Automating a Labour Performance Measurement and Risk Assessment:
An Evaluation of Methods for a Computer Vision based System

by
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Declaration

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Abstract

This thesis brings together productivity and risk assessments through innovative design, development and evaluation of a unique system for retrieving and analysing data. In the past, although the link between them is well-documented, these assessments have largely been dealt with as separate antagonist entities.

A broad evaluation of the existing traditional and technological support systems has been conducted to identify suitable methodologies along with a common technological platform for automation. The methodologies selected for the productivity and risk assessments were; work sampling and the revised NIOSH lifting equation respectively.

The automation of these procedures is facilitated through computer vision and the use of a range imaging Kinect™ camera. The standalone C++ application integrates two tracking approaches to extract real-time positional data on the worker and the work-piece. The OpenNI and OpenCV libraries are used to perform skeletal tracking and image recognition respectively. The skeletal tracker returns positional data on specific joints of the worker, while the image recognition component, a SURF implementation, is used to identify and track a specific work-piece within the capture frame. These tracking techniques are computationally expensive. In order to enable real time execution of the program, Nvidia's CUDA toolkit and threading building blocks have been applied to reduce the processing time.

The performance measurement system is a continuous sampling derivative of work sampling. The speed of the worker's hand movements and proximity to the work-piece are used to classify the worker in one of four possible states; busy, static, idle, or out of frame. In addition to the worker based performance measures, data relating to work-pieces are also calculated. These include the number of work-pieces processed by a specific worker, along with the average and variations in the processing times.

The risk assessment is an automated approach of the revised NIOSH lifting equation. The system calculates when a worker makes and/or breaks contact with the work-piece and uses the joint locations from the skeletal tracker to calculate the variables used in the determination of the multipliers and ultimately the recommended weight limit and lifting index. The final calculation indicates whether the worker is at risk of developing a musculoskeletal disorder. Additionally the information provided on each of the multipliers highlights which elements of the lifting task contribute the most to the risk.

The user-interface design ensures that the system is easy to use. The interface also displays the results of the study enabling analysts to assess worker performance at any time in real time. The automated system therefore enables analysts to respond rapidly to rectify problems. The system also reduces the complexity of performing studies and it eliminates human errors. The time and costs required to perform the studies are reduced and the system can become a permanent fixture on factory floors. The development of the automated system opens the door for further development of the system to ultimately enable more detailed assessments of productivity and risk.

Opsomming

Produktiwiteit en risiko evaluerings word in hierdie tesis saam hanteer deur die innoverende ontwerp, ontwikkeling en evaluering van 'n unieke stelsel vir die meting en ontleding van data. Alhoewel die skakel tussen hulle goed gedokumenteer is, word hierdie evaluering as afsonderlike antagonistiese entiteite hanteer.

'n Breë studie van die bestaande tradisionele en tegnologiese ondersteuningstelsels is gedoen om toepaslike metodes te identifiseer, om 'n gemeenskaplike tegnologiese platform vir outomatisering daar te stel. Die metodes wat gekies is vir die produktiwiteit en risiko bepalings is onderskeidelik werk monsterneming en die hersiende NIOSH opheffing vergelyking.

Die outomatisering van hierdie prosedures word gefasiliteer deur middel van rekenaar visie en die gebruik van 'n Kinect™ 3D kamera. Die selfstandige C++ program integreer ‘n dubbelvolgings benadering om in reële tyd posisionele data van die werker en die werk-stuk te kry. Die OpenNI en OpenCV biblioteke word onderskeidelik gebruik om skeletale volging en beeld erkenning uit te voer. Die skeletale volger bepaal posisionele data van spesifieke gewrigte van die werker, terwyl die beeld erkenning komponent, 'n SURF implementering gebruik om 'n spesifieke werk-stuk binne die opname raam te identifiseer en te volg. Hierdie volgings tegnieke is berekenings intensief. Om werklike tyd uitvoering van die program te verseker, is Nvidia se CUDA gereedskapstel en liggewig boublokke geimplementeer.

Die produktiwiteit meting-stelsel is 'n aaneenlopende monsterneming benadering van werk monsterneming. Die spoed van die werker se handbewegings en nabyheid aan die werkstuk word gebruik om die werker te klassifiseer as in een van vier moontlike toestande; besig, staties, onaktief of buite die raam. Benewens die werker gebaseerde metings, word daar ook data oor werkstukke bereken. Dit sluit in die aantal werkstukke verwerk deur 'n spesifieke werker, sowel as die gemiddelde en variasie in verwerkings tye.

Die risiko-berekening is 'n outomatiese benadering van die hersiende NIOSH opheffing vergelyking. Die stelsel bereken wanneer die werker kontak maak en/of breek met die werkstuk en maak gebruik van die gewrigsposisies wat die skeletale volger aandui om die veranderlikes wat in die vermenigvuldigers gebruik word te bepaal. Die vermenigvuldigers word gebruik om die aanbevole maksimum gewig en die opheffing indeks te bereken. Die opheffing indeks dui aan of daar ‘n risiko vir die werker is om muskuloskeletale versteuring te ontwikkel. Benewens dui die vermenigvuldigers aan watter elemente die grootste bydra tot die risiko van die opheffingstaak maak.

Die gebruiker-koppelvlak-ontwerp verseker dat die stelsel maklik is om te gebruik. Die koppelvlak vertoon ook die resultate van die studie sodat ontleders op enige tyd werker prestasie kan evalueer in reële tyd. Die outomatiese stelsel stel dus ontleders in staat om vinnig te reageer sodat probleme reggestel kan word. Die stelsel verminder ook die kompleksiteit vir die uitvoering van studies en dit elimineer menslike foute. Die tyd en koste vereis om die studie te doen, word verminder en die stelsel kan ‘n permanente instelling op fabriekvloere geword. Die ontwikkeling van die outomatiese stelsel maak die deur oop vir verdere ontwikkeling van die stelsel om uiteindelik daartoe te lei dat meer gedetailleerde evaluering van produktiwiteit en risiko bepaal kan word.

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Nomenclature

AABB	Axis Aligned Bounding Box
API	Application Programming Interface
CMOS	Complementary Metal–Oxide–Semiconductor
CUDA	Compute Unified Device Architecture
DALY	Disability Adjusted Life Year
GUI	Graphical User Interface
GPU	Graphics Processing Unit
HSE	Health and Safety Executive
LI	Lifting Index
LBP	Low Back Pain
LPM	Labour Performance Measurements
MODAPTS	Modular Arrangement of Predetermined Time Standards
MOST	Maynard Operation Sequence Technique
MSD	Musculoskeletal Disorder
MTM	Methods Time Measurement
MVTA	Multimedia Video Task Analysis
NIOSH	National Institute for Occupational Safety and Health
OCRA	Concise Expose Index
OSHA	Occupational Safety and Health Administration
OWAS	Ovako Working posture Analysis System
PDA	Personal Digital Assistant
PC	Personal Computer
PMTS	Predetermined Motion Time System
PSM	Physiological Status Monitoring
RANSAC	RANdom Sample and Consensus

REBA	Rapid Entire Body Assessment
RFID	Radio Frequency Identification
RGB	Red Green Blue
RNLE	Revised NIOSH Lifting Equation
RTLS	Real-time Location Sensing
RULA	Rapid Upper Limb Assessment
RWL	Recommended Weight Limit
SDK	Software Development Kit
SIFT	Scale-Invariant Feature Transform
SOP	Standard Operating Procedure
SSP	Static Strength Prediction
SURF	Speeded-Up Robust Features
TBB	Threading Building Blocks
TSS	Technological Support Systems
USB	Universal Serial Bus
UWB	Ultra Wideband
WMSD	Work Related Musculoskeletal Disorder

1. Chapter 1
Introduction

1.1 Introduction to the report

This section provides the background for the project and highlights the importance and necessity of the project. It also states the aims and objectives of this project and defines the boundaries within which the project was undertaken. The key terms in the project description are also defined.

1.2 Background

The competitive and dynamic climate of global markets places significant pressure on companies. If companies are to remain profitable they need to continuously improve their service delivery. Effectively this entails producing higher quality products, quicker and at a lower cost to customers. The need to continuously improve and remain competitive is complicated further by technological developments. These developments frequently bring about changes; including updates and improvements to software, hardware and labour components in the production lines. In order to assess these improvements, various studies relating to the workforce and machinery need to be conducted.

In many developing countries automation is mostly restricted to large scale enterprises. The result is that many companies are still heavily dependent on labour. If companies are to remain profitable and competitive, the workforce needs to be highly productive. In many cases the performance of the workforce can be improved but for this to happen it firstly needs to be measured.

Numerous approaches for measuring labour performance have been developed. These methodologies have been extensively documented and utilised in production sectors around the world. The evaluation of labour performance typically identifies problem areas in the production process such as the under and overutilization of workers. The measurements also provide information relating to the manufacturing time along with the manufacturing costs of items. They also enable the determination of capacity. The basic function of performance measurements is to identify and evaluate possible changes so that productivity on factory floors is improved, where productivity is broadly defined as; Measurement of the efficiency at which components in the system convert inputs into outputs.

These traditional methods are supervisor intensive and have not developed much in concept since the introduction of work sampling in 1935. Traditionally the labour performance measurement has been done manually, using clerks or analysts to record observations. This traditional method is both time consuming, tedious and expensive. The techniques are also fairly intricate and require training in the various methods. The result is that the cost of performing analyses are high and subsequently many smaller companies only utilise measurements to a very limited degree or fail to perform studies at all.

The driving force to increase productivity and maximize work-force utilization places strain on the workers. The excess pressure results in overexertion and work related musculoskeletal disorders (WMSD), such as Low Back Pain (LBP). These incidents form a significant financial burden in terms of direct costs such as compensation payments and in terms of indirect costs which originate from the reduction in productivity and disability [**1**,**2**]. In most industrialized countries, the costs of compensation for WMSDs account for at least one half of all workers compensation costs [**1**].

Approximately 70% of the global population suffers from LBP at some time in their lives [**3**,**4**]. Worldwide, in 2001, 37% of this fraction was attributed to occupational risk factors. The fraction varied between 21%-41% among regions and was higher in developing countries. LBP is one of the more common and most costly types of work injuries [**2**]. In the United States of America it amounted to 25% of all compensation payments and was the most costly [**5**]. Furthermore, it was the second most frequent reason for visits to the physician, the fifth-ranking cause of admission to hospital, and the third most common reason for surgical procedures [**6**]. The combined effect of occupational stressors were estimated to cause 818,000 Disability Adjusted Life years (DALYs) lost annually to LBP [**4**].

The National Research Council identified four work-related risk factors that show consistent and positive associations with the occurrence of LBP. These risk factors include [**7**]:

1. Manual materials handling
2. Frequent bending and twisting
3. Heavy physical load
4. Exposure to whole body vibration

Subsequent research has also found a positive association between other factors and LBP including [**5**,**1**]:

5. Awkward or extreme postures
6. Static postures
7. High once-off or accumulated forces on the spine

Over and above these physical causalities, psychological factors, such as stress and lifestyle factors have also been evaluated. Research has indicated that a positive correlation exists between poor social support in the workplace, low job satisfaction and the reporting of LBP. However, psychological factors in private life such as family support have not shown a positive correlation to the recording of back pain [**6**].

A substantial global effort has been made to reduce the occurrences of LBP. National and international laws and standards, such as ISO 11228-1: 2003 prescribe the methods for risk assessment associated with manual material handling [**8**]. These tools and systems pre-empt LBP cases by addressing the identified risk factors. A myriad of traditional and technological methods have been developed specifically to reduce the prevalence of LBP cases. The traditional methods are supervisor intensive, making them time consuming and tedious to perform. As technology has become available new methodologies and systems have been developed that aid and simplify the analysis of work elements. Many of the traditional and technological support systems that have been developed will be covered in this thesis.

The link between the labour performance measurements and risk assessments is well documented, yet the assessments are dealt with as separate antagonist entities. A number of technological developments with similar bases have been applied to both assessments. The wealth of technology narrows the gap between the assessments, indicating that the combination of the assessments is a distinct possibility.

A number of developments and improvements have been made to the traditional measurements techniques. Of particular interest is the non-invasive means of gathering data, such as the use of interactive video footage systems. These systems have ensured an improvement in the accuracy of performing labour performance measurements. [**9**] Similar technology has also been applied to assess WMSDs [**10**]. The biggest limitation of this approach is that the equipment and software required for the video analysis is rather expensive and as a result have not been implemented extensively.

The concept of using a video camera has merit. During the past few decades the computer scene has seen an exponential increase in the capacity and capability of computers. Furthermore the technological developments in cameras, particularly in range imaging cameras, enable the low cost image processing depiction of three-dimensional scenes. The reduced costs of hardware have also resulted in booming open source communities. These developments have dramatically reduced the costs and complexities of image processing. Real time image processing has already been applied in both performance measurements and risk assessment fields [**11**,**12**,**13**]

The wealth of available technology poses an excellent opportunity for the innovative development of a basic system that with minimal cost and effort can be used to evaluate labour performance and risk within in a workplace.

1.3 Aim

The aim of this thesis is to design and develop a system that is capable of autonomously and non-invasively gauging labour performance while also reducing the prevalence of musculoskeletal disorders.

1.4 Problem statement

This thesis was undertaken with the objective of automating both a traditional labour performance measurement and risk assessment. This requires the selection of a suitable technological platform and the assessment of the platform's ability in the context of the proposed automation procedures. The automation includes both the data gathering and analysis phases of the traditional measurements.

Additional objectives include improving the traditional approaches by reducing the time, costs and complexity associated with evaluating labour assessments. Ultimately, these improvements would ensure that the assessments would be available to a wider audience. The proposed systems should address the limitations of the exiting automated systems.

The data and results provided by the automated system should offer analysts an opportunity to improve the productivity of most organisations within the production sector. The results should also serve as reference for eliminating or reducing the risks that certain lifting tasks pose on workers.

1.5 Justification

Analysts in industry spend a significant amount of time gathering and analysing data relating to the workforce. The introduction of commercially available technological support systems has in many cases simplified the data gathering and/or analysis process. The vast majority of these systems use intrusive means of capturing data while the majority of non-intrusive devices function off-line.

There are very few commercially available tools that enable real time and non-intrusive monitoring of workers. The only real time, non-intrusive data gathering and/or analysis systems are based on computer vision. These systems enable the extraction of positional data of workers in real time by using live feeds from cameras linked to computers. The most recent development of low cost 3D range imaging cameras has resulted in rapid growth and development of open source image recognition libraries.

The availability of technological developments, such as computer vision enables the automation of the labour assessment methodologies proposed by this research.

1.6 Delimitations

The literature study does not cover all the techniques. Regarding Labour Performance Measurements (LPM) it is limited to those techniques requiring the identification of larger movements, and therefore excludes an evaluation of derived techniques such as predetermined time systems. The study also does not cover all topics relating to musculoskeletal disorders, but is limited to those that evaluate the prevalence of LBP.

The influence of ergonomic factors within the workplace are not considered, these include but are not limited to noise, lighting and temperature. The influences of these factors are considerable with regard to productivity and allowances. As a result they need to be dealt with separately.

The system that is developed in this thesis draws on existing methods and libraries. The functionality of these methods are tested within the context of this thesis, however the fundamental basis is not evaluated. It is assumed the basis and prior testing of the applied methods is scientifically sound.

Throughout the development and write-up of this thesis, new libraries and software packages have been launched. Due to the rapid development occurring in the computer vision field, it was detrimental to progress of the thesis to keep updating to the latest software releases. This thesis was therefore conducted with fixed software versions, which at the conclusion of the thesis was already out-dated. The same applies to new hardware. New cameras have become available over the course of the thesis. The hardware available at initiation of the thesis was the hardware used throughout the thesis.

A vital component of the thesis is the determination of contact between the worker and the work-piece. Due to the nature of the image recognition algorithm as well as the programming complexity, contact is determined with an axis aligned approach. This approach requires approximate alignment between the work-piece and the camera's co-ordinate system.

The system has been created to only track a single work-piece and a single worker within the capture frame at a time. Although the system has been created to be as stable as possible, errors relating to incorrect use have not been considered.

Worker performance ratings used in the calculation of standard times have been excluded from consideration. The average processing times calculated by the system are therefore not equal to the standard times.

1.7 Limitations

The thesis is constrained by both time and budget. The time constraints are 1800 working hours and the budget was limited to R70 000.

1.8 Definition of terms

Numerous terms used in this thesis have been explicitly defined here in order to prevent confusion as well as to provide a richer understanding of the text.

Effective

The system is effective if it is capable of fulfilling its purpose and therefore ultimately produces the desired results [**14**].

System

A system is an organized and co-ordinated method or procedure that has been formulated to accomplish a specific task. In the context of this thesis, the system refers to the group of interrelated and interdependent hardware and software components that are functionally connected and grouped together in order to execute the required analyses [**14**].

Productivity

It is defined as the measure of efficiency with which an activity converts inputs into value added outputs. Productivity is a relative measure. As a result the values themselves have little meaning. The values need to be compared with one another in order to be used [**15**,**16**].

Labour performance measurement (LPM)

Performance measurement is defined as the assessment of how well organizations are managed and the value of the services delivered [**17**]. In the context of this thesis LPM refers to the determination and evaluation of labour utilization, standard times as well as variations in working speed. Therefore how well workers are managed. The usefulness of LPM is determined by its ability to facilitate the improvement of productivity in the organization.

Risk Assessment

Risk is any event in which the outcome is uncertain and something of human value is at stake [**18**]. Risk is therefore a function of the likelihood and probability of an occurrence. In this thesis the term risk assessment is a contracted version of a longer phase and it is used specifically to describe the group of systems and techniques that quantify the risks of developing work related musculoskeletal disorders.

Labour assessments

The term labour assessment has been coined to simplify referring to both the LPM and the risk assessment.

Work related musculoskeletal disorder (WMSD)

Musculoskeletal disorders (MSD) refer to conditions that involve the nerves, tendons, muscles, and supporting structures of the body [**19**]. WMSDs, refers to the subset of MSDs that can be attributed to occupational stressors, including physical, psychosocial and individual risk factors [**10**] The specific area of interest in this thesis is the impact of exposure to physical factors in the workplace on the upper extremity and the lower back.

Traditional measurement

These are manually performed studies. They are typically the original concept.

Analysts

Refers to any individual that performs an assessment on workers.

Technological support system (TSS)

These are tools, devices and systems that have been created to simplify or automate labour assessments. They are not always linked to traditional measurements and may be unique systems.

Online (Real-time)

Refers to systems which guarantee responses within strict time constraints [**20**]. These systems are therefore capable of gathering and manipulating data before returning the results to the user within a set time from the moment they occur. In the context of this thesis the limit would be a few seconds.

Throughout the testing section numerous similar terms are used. In order to minimize confusion, this small section defines the most important terms.

Error

All measurements, regardless of the device used and type of measurement are only approximations. The deviations are referred to as errors. In an attempt to provide a distinction between the values of interest, wherever relevant other terms have been used.

Accuracy

It is the closeness with which the measurement of an element matches the true or actual value. It is calculated according to Equation 1. Accuracy takes systematic errors, random errors and resolution into account. The accepted value is defined by the measurement of the parameter with a system of known accuracy and precision.

$$X_{accuracy} = \left|\bar{X}_{measured} - X_{accepted}\right| \ldots (1)$$

Noise

It represents the closeness with which repeated measurements of an element returns the same results. Due to the nature of this system, the term noise is substituted for precision. This is a result of the jumpiness of the data retrieved from the Kinect™ sensor. Noise per definition represents any unwanted addition to a signal. Two types of noise are presented:

- **Average noise** (Noise) is calculated as the standard deviation. It is calculated according to Equation 2. Where *E* denotes the average of expected value of X.

$$noise = \sqrt{E[X^2] - \mu^2} \ldots (2)$$

- **Maximum noise** which provides information on the maximum discrepancy of the measured value. It is calculated according to Equation 3.

$$Max\ noise = Max(X_{measured}) - Min\ (X_{measured}) \ldots (3)$$

Systematic failures or errors

It refers to occurrences of factors which decrease the efficiency of the measurement system. These are consistent in that they are always prevalent under certain conditions [**21**].

Random errors

Are present in all systems and occur at random points in time. These are inherent in all systems and cannot be eliminated [**21**].

Relative Error

The ratio of the absolute error of the measurement to the accepted measurement, as indicated in Equation 4 The relative error expresses the "relative size of the error" of the measurement in relation to the measurement itself [**21**].

$$E_{relative} = \frac{X_{accuracy}}{X_{accepted}} \ldots (4)$$

1.9 Structure

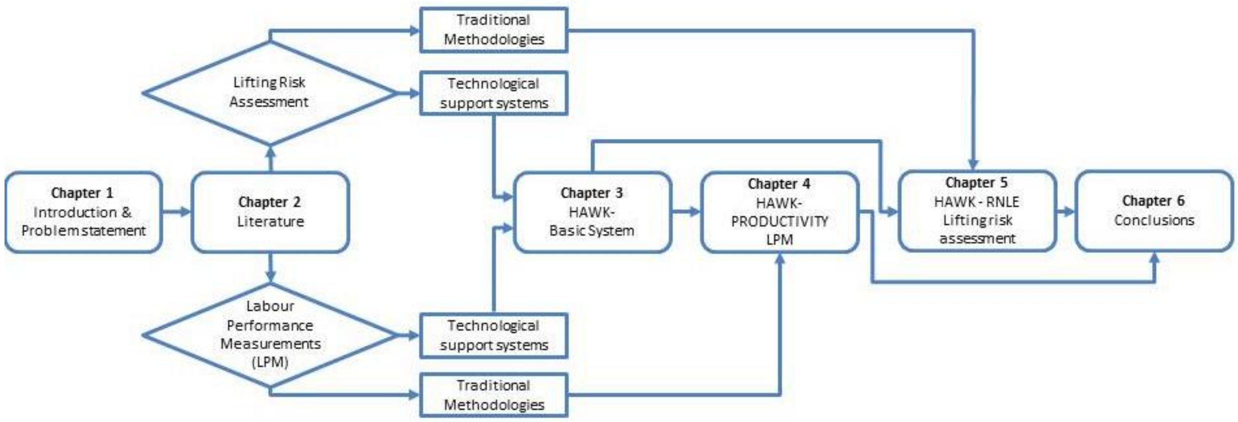

Figure 1: Roadmap for the document

Chapter 1 provides the backbone for the project by indicating its importance. It also highlighted the aims and objectives and defined the boundaries within which the project was undertaken. The key terms in the project's description were also defined.

Chapter 2, as indicated in Figure 1, is separated into two primary categories; Labour performance measurement and risk assessments. These fields are further subdivided into the investigation of traditional methodologies and technological support systems. The concurrent investigation of both techniques is ultimately used to identify a common technological basis which will facilitate the automation of suitable traditional methodologies.

Chapter 3 introduces the concept for automation of the labour assessments. Following the basic concept, an investigation is conducted to identify hardware and software components with the desired characteristics. Chapter 3 covers the development of the basic computer vision based system, which can be broken down into three distinct components; worker-tracking, work piece tracking and contact determination. Each of these components is comprehensively tested to indicate the capabilities and limitations of the system.

Chapter 4 covers the automation of a LPM. The traditional work-sampling basis of the study, originally flagged for automation in Chapter 2, is discussed. Chapter 4 presents the process whereby the raw inputs from the basic system in Chapter 3 are processed to reveal information on the labour performance. The chapter concludes with testing on the system.

Chapter 5 covers the automation of the RNLE which was selected for automation of a risk assessment in Chapter 2. The traditional approach is comprehensively discussed and it provides the framework for the development of the automated version. Raw data from the basic system introduced in Chapter 3 is used to calculate the task variables of the RNLE. The results of tests done on the system are compared to the results of existing studies on human capabilities.

Chapter 6 provides a summary of the finding of the study. It also includes recommendations for future work.

2. CHAPTER 2
Literature Study

2.1 Introduction

The aim of this section is to discuss, describe and compare the existing approaches and tools used to automate the measurement of labour performance and assess the risk of developing WMSDs. It is important to note that LPM and risk assessment are separate fields. They are brought together in this thesis because of their correlation and importance of considering them mutually.

There is constant and on-going effort being made to increase the productivity and maximize utilization of the workforce. Opportunities for improvement are often unveiled by gauging the current status of the workforce with LPMs. These measurements provide valuable information relating to standard times, rest allowances and utilization of workers. However, there is a risk that pressure to increase productivity could result in overexertion. There is also a risk that workers will adopt unsafe material handling practices in an attempt to save time. If workers develop WMSDs it could become a significant financial burden to companies. It is therefore important to ensure that tasks are safe and fall within the limits specified by the respective risk assessments.

One of the complexities is to establish the boundaries for a system that is capable of automating both labour performance measurements and risk assessment. The subsequent extensive literary research provides direction and guidelines for the selection of methodologies and hardware.

The literature can be divided into two distinct subtopics. Within both the LPM and risk assessment fields two approaches for executing studies exist:

- Traditional measurements
- Technological support systems

The traditional measurements use observers or analysts to gather and analyse data manually while technological support systems make use of technological advances to simplify or improve the data gathering and/or data analysis phases of the measurements.

The investigation of existing traditional LPMs and risk assessment methodologies provides valuable insight into the important characteristics that would need to be measured in the automated system. In addition understanding of the foundations of these measurements is vital in assessing their suitability for automation.

Technological developments have resulted in the creation of numerous systems that support the measurement and analysis phases of these measurements. A few fully automated systems have also been developed. The research of these systems brings to light the advantages, disadvantages and limitations relating to the use of each of these systems.

By considering the objectives of the project along with the evaluation of the traditional and technological support systems, a framework for the development of an effective and fully automated system is created.

2.2 Measurement methodologies

Numerous measurement methodologies have been developed to measure labour performance and to assess the risks of developing WMSDs. Many of the methodologies that have been developed for these assessments have similarities. Similar systems have been grouped together in order to provide a coherent structure for the literature review. The different approaches are categorised under the groups represented in Figure 2.

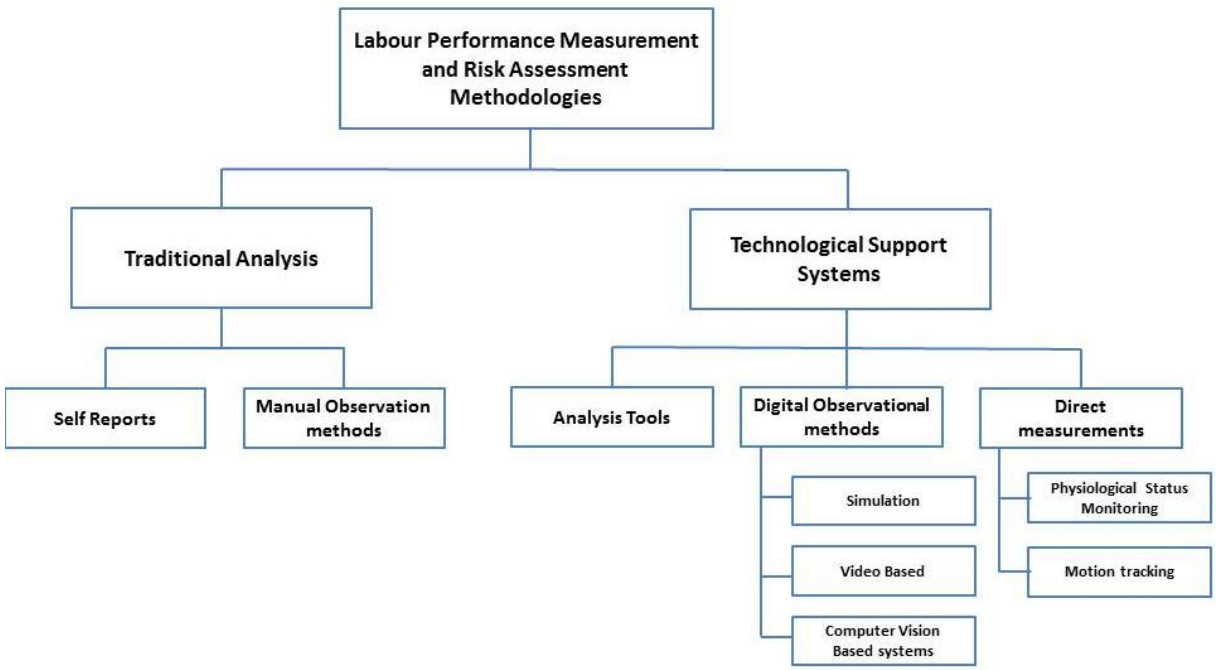

Figure 2: Methods for measuring labour performance and assessing risks

Traditional measurements are observer based approaches and include self-reports and manual observation techniques. Technological support systems utilise specialised hardware and/or software to retrieve and/or analyse data relating to the workers. These methods can be further classified as analyses tools, digital observational methods or direct measurements.

The analyses tools section includes systems and programs that have been specifically developed to reduce the complexities associated with the gathering and processing of data. Digital observational methods rely on the modification of digital inputs, to noninvasively extract data relating to workers. These approaches include computer vision or simulation based approaches. Direct measurements are only used to perform risk assessments. These systems utilize sensors or markers placed directly on the worker to extract data.

The various systems and approaches all have advantages and disadvantages, which along with the nuances between the assessment methodologies, are highlighted in the remainder of this chapter. The primary function of the methodologies is to enable companies to identify areas in which improvements can be made. In the context of this thesis the methodologies specifically enable decision makers to make clear and concise decisions regarding the workforce. The methodologies also enable companies to gauge the impact of changes that have been implemented.

The effectiveness of the study is directly related to the inherent accuracy and relevance of the methodology. The time frame within which the analysis is conducted is equally important. The study will only be relevant if the time frame is truly representative of the working conditions. It follows that inaccurate or poorly timed measurements would result in warped decisions from management.

The time delay between the measurement and feedback of data is also important. Online and Offline systems have been developed and both approaches have merits. The advantage of the online approach is that problems and risks can be identified in real time. However, offline systems typically provide more and richer data. The trade-off between the two systems should be considered.

2.3 Traditional Analyses

Traditional analysis refers to observer based techniques. The observer is required to record measurements, perform calculations and analyse tasks and results. There are two categories: Self-reports and manual observation.

2.3.1 Self-reports

The data used in self-reports is generated and analysed by the worker. In labour performance measurements, self-assessments are often performed according to a sampling approach. The worker periodically records what he or she is doing at random predetermined times. A statistical analysis of the captured data provides insights into the time the worker is spending on various tasks [**22**].

Self-assessments are also used in the risk assessment field. In contrast to the statistical bases used in the LPM field, data is typically gathered from reports that workers make regarding physical and psychosocial factors. Other methods of data collection include interviews and questionnaires. Most recently, workers have been using video recordings of themselves and web based questionnaires [**10**].

2.3.2 Manual observational techniques

A variety of tools and methods have been developed that require an analyst to manually gather and analyse data. These tools typically form the basis of specific labour assessment fields as they represent the original concepts and methods [**10**]. A significant number of these approaches are widely used in industry and have been thoroughly scrutinised in academic circles. The investigations and assessment of approaches in this section will identify the most suitable candidates for automation.

In general the traditional measurements are typically practical for a wide range of applications. The biggest limitation is the influence of biases and inter-observer variability. These methods are also typically better suited for simple pattern tasks.

The basic execution of manual observational techniques starts well before the initiation of a study. Analysts are required to plan studies which also include preparatory work. For example, in LPMs this can entail determining the number of observations and the time at which measurements are to be taken.

Once the study is initiated the data is logged on task sheets and various calculations are performed on the data. The logging and analysis approaches will differ according to the assessment used. The data analysis phase can either be processed manually or with the aid of analysis tools. These tools have been specifically developed to simplify the processing of data and are widely available on the internet. One of the most common tools is an online calculator. The analyst simply inputs the recorded data into the specified cells and the calculator generates the results.

The following subsections provide insight into the manual observation techniques as used to asses LPM and risk assessments.

2.3.2.1 Labour performance measurement

There are numerous labour performance measurement techniques available to analysts. These include [**23**]:

1. Time and motion studies
2. Work sampling
3. Subjective evaluations
4. Reviewing records
5. Combinations of the techniques

Of these, only time studies and work sampling lend themselves to automation. These techniques will be discussed and compared in the following sub-sections.

Predetermined motion and time systems (PMTS) offer an alternative to the traditional labour performance measurements for establishing time standards. In contrast to time studies where the analyst times and subjectively rates the performance of an operator, PMTS requires the analyst to break a task down into its component actions. Time values are then assigned to each specific component action. Finally the analyst calculates the component times together to establish the standard time.

There are a number of PMTS standards in existence today. The first PMTS was the methods-time measurement (MTM) released in 1948. Later Modular Arrangement of Predetermined Time Standards (MODAPTS) released in 1966, and Maynard Operation Sequence Technique (MOST) released in 1972, also gained popularity. At present, numerous variations of the MTM and MOST standards exist. These were developed to extend the range of application. Each of the various versions is suited to the assessment of specific tasks [**22**,**24**,**25**,**26**].

The PMTS methods require detailed analyses of the tasks. The methods therefore provide valuable detail on how the task is done. This enables the identification of possible areas for improvement. The methods also provide more accurate standard times. This results because the subjective evaluation of worker performance in work sampling and time studies is not required.

The automation of PMTS would certainly be valuable, and could be used to improve productivity. The methods are however limited to the establishment and optimization of production times. The objective of this project is the real-time autonomous monitoring and assessment of the workforce. Due to the limited information provided by the methods, no further research was conducted.

Time and motion study

Time study is a methodology used to determine the standard time required to complete a task. The basic methodology involves [**22**,**27**,**28**]:

1. Selecting an average worker that has been trained in the specific task to be analysed.
2. Documenting the working conditions and other details relevant to the study.
3. Breaking the task down into subcomponents. The subcomponents are selected to be as small as possible without influencing the accuracy of the study. The analyst uses both sight and sound to determine when a subcomponent is started and ended.
4. Once the aforementioned steps are completed, the study is started using either a continuous or snapback timing method.

The calculated times are then deemed to be a fair representation of the time required to complete a given task, as it takes allowances and delays into consideration [**22**,**27**].

Time studies enable management to make effective decisions aimed at improving the efficiency of the entities operating within the system. It is important to realize that accurate time studies yield positive results and inaccurate time studies can create many problems [**22**,**27**].

Work sampling

Work sampling offers an alternative method for determining standard times and allowances. It therefore provides similar information to that acquired from time studies. However, it differs from time studies, in that it is an indirect measurement method [**22**,**29**].

The fundamental principle of work sampling is that it is based on the laws of probability. Work sampling was developed for the first time in 1935 by L.H.C. Tippet. It is the activity of taking randomly distributed observations of workers or machines with the primary objective of determining their utilization. This is achieved by classifying workers and machines as occupying one of a possible number of states at the time of the observation. The states are specified prior to the study.

The basic methodology involves [**22**,**27**]:

1. The objective of the study as well as the population of the study needs to be clearly defined. A list of the reasons why the study is being considered should be compiled.
2. The organization and its components to be studied need to be understood.
3. The different classification fields for the study need to be classified and documented.
4. Design and create a work sampling form that will be used in the study.
5. A preliminary estimate for critical factors needs to be determined. These can be derived from historical data or from a pilot study.
6. The desired accuracy of the study needs to be specified by the analyst. The analyst specifies two values that influence the accuracy of the study:

    - The confidence interval
    - The tolerance.
7. The estimate of the number of samples required for the work sampling study can then be determined.
8. Determine the frequency of the observations.
9. Folders for observers need to be prepared. Included in the folder should be the schedules, forms and layout plans.
10. The observers need to be trained.

A result of the statistical basis of work sampling is that the accuracy of the results is linked to the number of samples taken in the study. It is also influenced by the time period over which the assessment is performed [**23**]. The sampling basis of work studies enables analysts to observe multiple workers at the same time. As a result, work sampling can provide reasonably accurate representations of the conditions in the work environment at a fraction of the cost and without the drawbacks of continuous monitoring [**29**,**22**,**23**].

It is important for the analyst to understand the operations of the company so that an appropriate time frame for the study can be selected. Furthermore, the analyst needs to select a sample size that represents the true conditions of the system, while also understanding the capabilities of the observer. Some standards have been developed to aid in making selections about the number of samples in the study. One such guideline is to limit the number of observations to less than 8 per hour [**23**].

The objective of work sampling should be to attain unbiased results. These results should represent the true conditions of the individual under study. With the understanding that statistical methods form the basis of work sampling, the input data needs to be random and unbiased [**29**]. If these conditions are not met, the data will not deliver reasonable results. These inaccuracies can include [**30**]:

- Continuity errors - Small changes in input data represent small changes in the output data.
- Consistency errors - Similar runs will not reflect similar results.

Comparison of traditional time studies and work sampling

From the comparison in Table 1, it is clear that both techniques have a number of advantages and disadvantages [**29**,**22**,**23**].

Table 1: Comparison between work sampling and time studies

Time studies	Work Sampling
Easy to understand	The statistical basis of the study may be difficult for workers and/or management to comprehend.
Requires extensive knowledge and understanding of the task	Does not require an understanding of the task
Subject to both observer and worker biases	The effect of biases is limited because it is only present when performance ratings are selected
Accurate timing figures are obtained	Enough samples need to be made to ensure that the desired accuracy of the final results are achieved
One task analysed at a time and therefore labour intensive.	Multiple work stations observed at the same time, therefor fewer observers required
Cyclic variations are not as well compensated for	Observations typically made over an extended time period which decreases the effects of cyclic variations
Study is a continuous uninterrupted process and tedious to perform	The study can be interrupted at any time with a minimal effect on the results, and therefore not as tedious
Establishes a systematic understanding of job tasks and therefore facilitates the determination of the best methods which aid in the development of training programs.	Provides no specific information about the job
Hawthorn effect is likely to influence results	Hawthorne effect is less likely due to the large number of observations made
Analyst does not move between workers	It is not an economical solution if workers are spread out over a wide area

The two techniques also have a number of similarities. The systems play an important role in identifying labour costs. However, If multiple analysts are used the results could be invalid. Variations could result from inconstant ratings of worker performance. In work sampling there could also be additional variability in the level of detail recorded by analysts. For both methodologies the reliability of the results is dependent on the number of trails or observations taken by analysts.

The comparison has provided valuable insights into the advantages, disadvantages and limitations of each methodology. The single biggest difference between the methods is the complexity of cycle recognition algorithms that would need function reliably in the automation of time studies. However, this does not exclude it from consideration.

The selection of a methodology for automation is delayed until after the subsequent evaluation of the exiting technological support systems.

2.3.2.2 Risk assessment

A large number of risk assessment methodologies have been developed. The majority assess several critical physical exposure factors. Table 2 represents a comprehensive list of techniques and corresponding critical exposure factors as developed by David [**10**].

Since the development of revised NIOSH lifting equation in 1993 there has been a trend towards developing methodologies that consider the contribution of a number of the factors leading to WMSDs. The combined impact of these factors is represented in as a concise exposure index [**31**].

In Table 2 three candidate methodologies are highlighted. These methodologies were considered for selection due to their complete coverage of the exposure factors. It is important to note that the whole body vibration, although a known cause of LBP does not form a serious risk in manufacturing environments. The vast majority of exposure originates from non-occupational sources such as use of motor vehicles [**32**]. It is therefore not considered in the selection of a methodology.

Table 2: Exposure factors assessed by different methods [10]

Technique	Posture	Load/Force	Movement frequency	Duration	Recovery	Vibration	Others
OWAS	X	X					
Checklist	X						
RULA	X	X	X				
NIOSH Lifting Equation	X	X	X	X	X		X
PLIBEL	X	X					X
The Strain Index	X	X	X	X			X
OCRA	X	X	X	X	X	X	X
QEC	X	X	X	X		X	X
Manual Handling Guidance	X	X	X	X	X		X
REBA	X	X	X				X
FIOH Risk Factor Checklist	X	X	X	X			X
ACGIH TLVs	X	X	X	X			
LUBA	X						
Upper Limb Disorder Guidance,HSG60	X	X	X	X		X	X
MAC	X	X	X				X

The Revised NIOSH Lifting Equation

The Revised NIOSH Lifting Equation (RNLE) is widely used in industry to reduce the risk of LBP associated with manual lifting. Additionally it also reduces the possibility of shoulder and arm pain. It provides an empirical method for calculating the maximum mass of an object to be lifted. This mass represents the load that the vast majority of all healthy workers could lift over a substantial period of time, without an increased risk of developing lifting related LBP [**3**].

The load constant, which represents the maximum allowable load that can be safely lifted by the majority of the population under ideal conditions, is diminished by a number of factors. These factors include the location of the load, the coupling and frequency of lifts.

The fundamental inputs are positional and time data from a few key-points on the worker's body and the work-piece. A number of existing technologies are capable of retrieving accurate positional data automatically. Furthermore, the calculations are also fairly straightforward. As a result the methodology lends itself well to automation.

The concise expose index

The concise expose index (OCRA index) is similar in concept to Revised NIOSH lifting equation [**31**]. The daily numbers of actions actually completed are compared with the corresponding number of recommended actions.

The recommended number of actions is represented by a constant, which is diminished by a number of risk factors including; force, posture and recovery periods [**31**].

Due to the similarities with the revised NIOSH lifting equation, OCRA should lend well towards automation. However, the frequency basis of the method results in complexities. Determining cycles automatically requires the implementation of pattern recognition algorithms. These algorithms are often excessively complex, particularly in cases where repeatability needs to be high [**33**].

The manual material handling guideline

The manual material guideline covers the majority of manual handling activities. It applies to lifting, lowering pushing and pulling and handling tasks while seated. The item being carried may also be inanimate or animate. The broad application area of the guideline provides valuable and practical advice to employers, managers and safety officers on reducing the risk of developing WMSDs from manual handling [**34**].

The manual guideline uses a comprehensive checklist to assess tasks. A checklist is provided in the guidelines. However, these checklists are often modified to suit specific departments where the assessments are conducted. The assessments do not provide safe limits for lifting. However, work outside the guidelines increases the risk of developing WMSDs [**35**].

The function of the guideline is to use the assessments to make necessary changes in order to reduce the risks. It is important to understand that there is no such thing as a completely safe manual handling operation. It is however the responsibility of the employer to reduce the demands of the job if it is practical to do so. As the risk of injuries increase, the operation under question is be evaluated in finer detail and consequently the risk of injury is reduced as much as practically possible [**34**].

Work elements are evaluated closely to identify elements where improvements can be made. These improvements can relate to any one or a combination of the following [**35**] [**36**]:

- The weight and characteristics of the load
- The task and organization of work
- The layout of the workplace and equipment
- The work environment
- The individual's ability and training

The checklist basis of the study has the advantage of simplifying the analysis of tasks. However, it also results in a loss of detail. Checklists are only viewed as the first step in the execution of risk assessment. Additional information or expert assistance may be required in the assessment of more complex risks. The simplification that makes the checklists such a popular choice for manual studies is the reason why it is not considered as a suitable option for an automated system [**36**].

2.4 Technological Support Systems

2.4.1 Labour performance measurement

In performing traditional work assessments, a large amount of time is spent on carrying out simple tasks, such as calculating percentages, timing elements, preparing for studies and determining the number of observations required. Over the years, Technological Support Systems (TSSs) have been developed that simplify and reduce the time required to perform the data gathering and processing phases of traditional studies while also increasing the accuracy of the results. In addition these methods address many of the barriers which impede work measurements [**37**,**22**]. These barriers are introduced in Section 2.4.1.1.

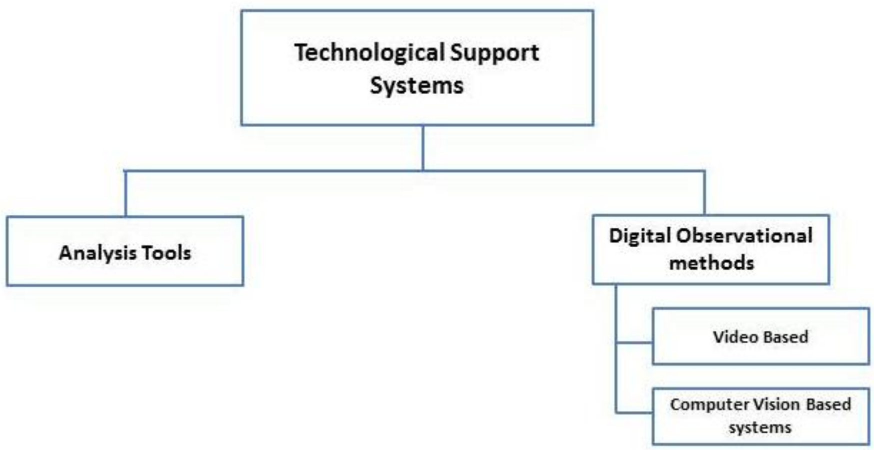

Figure 3: Technological support systems for labour performance measurement

The TSSs that specifically relate to labour performance measurement are depicted in Figure 3. The analysis tools are software and hardware systems that simplify the execution of traditional studies. The digital observational techniques include; video based systems, which enable a more detailed analysis of workers and computer vision based systems, which are capable of fully automating the labour performance methodologies [**13**,**12**].

2.4.1.1 Barriers impeding traditional work measurement

All workplaces have inherent barriers preventing the efficient execution of traditional work measurements. These can be sub-categorized into social and technical categories. Within each of the categories are four subtopics. These subtopics discuss the complexities that must be overcome for the effective execution in work environments. It is important to understand that in these subtopics are not independent and may not cover all the issues in every workplace [**37**].

The following list indicates represents the subtopics and a brief description [**37**]:

Social

1. Hierarchy of organization structure

   The alienation that occurs when initiatives are passed down from top management without involving the staff is damaging to any work measurement study.
2. Lack of full support

   Everyone involved in the study must support it. Lack of support can originate in management, due to the cost implications of executing a study. Others are senior leadership that believe their employees will not buy into such a project.
3. Reluctance to measure

   A strong resistance to changing from soft estimates, based on educated guesses, because on self-efficacy and performance satisfaction. Self-efficacy is an estimate of how well an individual could function in a new environment. Performance satisfaction is the worker's estimate of how well tasks are being done at present.
4. Fear of job loss

   The purpose of work measurements is to identify possible areas for improvement. For the workers being assessed, there is an assumption that if the studies show that they cannot keep up with the standard, they will be fired. The result is that workers will try to hinder the process, for example tamper with the computer used to store and analyse data.

Technical

1. Tedium of the measurement process

   The time and effort required to firstly observe the worker, and then to transfer written observations into an electronic document where the analysis is conducted. As the observation period increases, so does the time required to transfer the information onto the computer.
2. Variation of work methods

   As jobs and tasks become more complex, the variations in base times increase. For certain tasks, workers may have a unique method which could be slightly faster or slower than the rest of the department. These inaccuracies lead to variations in cost for the company and also unreliable delivery times.
3. Ambiguity of process elements

   This occurs in cases where the analyst is not familiar with the task. As a result the worker cannot determine which elements are independent of one another. For complex work it could take months to acquire the in-depth knowledge of the task.
4. Shortage of needed samples

   As the analyst collects more samples, so the accuracy of the study increases. For elements with greater variability, more samples should be taken. Due dates often force analysts to take fewer measurements, resulting in inaccuracies.

A few of the barriers listed above are not prevalent in work sampling. The notable exclusions are a reduced fear of job loss. This results because the worker is not constantly being observed and timed with a stopwatch. In addition analysts are also required to establish a possible task list beforehand. As a result this reduces the problems of ambiguity of the process elements.

2.4.1.2 Analysis tools

Performing measurements by traditional methods are inefficient and tedious. An effective improvement to the traditional approaches is to upgrade the technology used to perform the study. In this case replacing stopwatches, forms and pens with modern hand held devices that are better suited to quick and accurate data gathering. A variety of systems utilizing recent hardware developments have been created. Amongst these there are two distinct groups; systems using Microsoft Excel, and systems using custom software [**37**].

Analysis tools in time studies

Numerous systems and software packages that minimize the effort of performing time studies are commercially available. These systems have gained popularity primarily due to the fact that they eliminate much of the hassle of clerical transcription while also improving the accuracy of computations.

Royal J. Dosset Corp created a system that uses a data writer to collect data electronically and then uploads the data directly onto a computer on which the analysis is performed. Another system CITS/APR created by C-four utilizes hand held computers to collect data. This system offers a more detailed analysis than the system created by Royal J. Dosset Corp and interfaces with Microsoft Excel. A drawback of these systems is that they require specialized hardware which is not readily available [**38**,**22**,**39**].

Over the years software was developed to fit the current technology. The systems requiring specialised data capturing hardware were largely overshadowed as programs running on general purpose Personal Digital Assistants (PDAs) gained popularity. PDAs are lightweight hand-held multifunctional devices that accommodate the uploading of various applications. In addition, as opposed to the specialized data writers PDAs were widely commercially available.

These applications simplified the data gathering process and also eliminated the need to enter the data into a computer. This in turn saved a considerable amount of time. A few examples include Palm CITS by C-Four, Quicktimes™ and Timer Pro™ by Applied Computer Services, Inc. and UmtPlus by Laubrass Inc. [**37**,**22**].

UmtPlus requires that prior to recording observations the analyst enters an extensive list of the expected work tasks into the PDAs memory. Each entry is displayed on the PDA screen as an icon. During the study the analyst clicks on the respective icon. As the study is completed the analyst records this by clicking on the icon for the next operation. The tool then stores the amount of time in its database [**37**].

Timer Pro™ utilises Microsoft excel to conduct the study. The analyst captures time values by clicking on an empty cell with a mouse or PDA pen. The system then records the current system time from a continuously running clock into the selected cell. The analyst enters a description of the activity into the adjacent cell. Upon completion of the study, the analyst has an Excel file which can later be processed for analysis [**37**].

The recent bloom in the App, smartphone and tablet market have resulted in another popularity shift towards Apps, which are typically low cost or in some cases free programs that can be run on smart phones and tablets. They offer similar capabilities to the programs developed for PDAs. Time Motion Study by Graphite, Inc. and Time Study Pro by Enteq Systems are Android based Apps. Time study Pro is a time study, work study analysis and reporting tool. The program utilizes an Android based time study device coupled with a hosted website for analysis, reporting and standard derivation. Similar applications are available for numerous other operating systems such Time Study 1.2 by Time study LLC which runs on the iOS operating system [**40**].

Analysis tools in work sampling

The development of analysis tools for work sampling has followed a similar trend to that of time studies. Numerous systems have been developed which aid the analyst in performing work sampling studies. The analysis tools have been shown to save an estimated 35% of the cost required to perform work sampling manually. The significant saving result from the inherent clerical effort required in work sampling studies. The clerical effort includes, but is not limited to, calculating percentages and accuracies, plotting data on control charts, determining the number of observations required, determining the number of trips and the time of these trips to an area each day [**40**].

There are several software packages commercially available. WorkSamp by Royal J. DossetCorp. has a built in beeper to signal for data entries at random intervals, several different summary reports and an RS233C connection to upload data onto a PC. A slight disadvantage is the use of the custom-build hardware which is used to record data [**40**,**22**].

Other packages make use of more flexible PDAs to collect data, such as the *SamplePro* and *UmtPlus* applications developed by *Applied Computer Services Inc*. and *Laubrass* Inc. respectively. Similar to the recent shift towards Apps for smart phones and tablets as mentioned for time studies, a number of Apps for work sampling are also available, both Sample Pro Professional by Applied Computer Services Inc. and UmtPlus by Laubrass Inc. can be downloaded from App markets [**40**,**22**,**41**].

WorkStudy+ by Quetech Ltd. as with most of the other systems can be downloaded for number of operating platforms, including Android, iOS, Windows Mobile and for tablet PCs. In addition to having built-in timers the system allows the user to view and edit any recorded observation at any time and also review the statistical information on the data gathered so far. An unlimited number of samples can be recorded and the system enables seamless integration with Excel and it includes powerful and customizable statistical reporting. Completed studies can be directly imported into Microsoft Excel or further analysis. The feature sheet taken off their website is included in Appendix 1 [**42**].

Closing remarks on analysis tools

The investigation of the existing analysis tools identified that there are numerous systems available for a wide range of budgets and applications. The accuracy and flexibility of the systems vary greatly. All of the systems ultimately simplify the data collection, transcription and analysis phases of work assessments.

The use of these systems alleviates some of the boundaries which impede work assessments. The most important factor is the amount of time saved with each data entry. This saving result from the simplification facilitated through the use of modern devices, which ultimately condense the recording and transcribing processes of traditional studies into a single click on the screen of the device being used. This process therefore eliminates much of the non-value adding time. In addition the job security concerns are alleviated because stopwatches which are seen as symbols hierarchy and scrutiny of evaluation are replaced by docile and ambiguous smart-phones, tablets or PDAs. The use of these modern tools also indicates that the upper management is willing to financially back the initiative. [**37**]

2.4.1.3 Digital observational tools

Video based

Video based time study software is used to aid the analysis of time studies. The system requires a video camera to be set up to monitor a workstation. After the desired footage has been recorded, the video is then read into the program at which point it can then be analysed.

Multimedia Video Task Analysis (MVTA) by Nexgen Ergonomics enables the user to interactively identify breakpoints in the video record at any desired play speed. MVTA then automatically produces time study reports and computes the frequency of occurrence of each event as well as postural analysis for work design [**9**].

Video Time Study by Productivity Concepts Inc. is in many ways similar to MVTA. The software also enables analysts to speed up and slow down videos enabling frame by frame analysis of the captured data. The system then automatically captures work times and calculates averages. Analysts can also mark and calculate distances [**43**].

In addition to performing time study and analysing videos, Video Time Study can be used to create standard procedures and training videos. The system enables the creation of a data base for managing a company’s time studies and training videos. The significant advantages of the system are that it enables the analyst to highlight and calculate value added and non-value added operations. It also allows analysts to study two screens simultaneously [**43**].

In contrast to the two systems discussed previously, ProPlanner’s ProTime Estimation software allows users to perform both traditional and predetermined time studies such as MTM and MODAPTS and then merge the results. There are however also a number of similarities. Similar to Video Time Study analysts can classify and colour code elements as value added and non-value added time. The System also generates pie charts indicating waste [**43**,**44**].

The ProTime Estimation software accepts the majority of popular predetermined time standards and enables users to modify the standards, and even create their own. Users can import customized time elements for each process and also create formulas to compute complex machining times, which increases accuracy of studies [**44**].

The advantage of the ProTime Estimation system is that the analysts can quickly estimate process times from the various PMTS. The system is also unique in that it enables the comparison of different PMTS. The outputs of each study can be saved as individual files that can be edited by multiple users [**44**].

The video based approach has a few notable advantages. It enables very accurate timing of work elements. It also enables richer data to be captured which results because the analyst can speed up and slow down the captured data at will. The video based systems discussed here, all facilitate the exporting of data to Microsoft Excel for further analysis and reporting. Most of the systems have advanced reporting capabilities. This simplifies the creation of performance reports, further adding to time saving.

There are also a few disadvantages of video based systems. The systems are expensive and in most cases operating the program is not as simple as the developers claim. Lastly, the results of studies, as with most of the analysis tools, are only available well after the data is gathered.

Computer vision systems

The existing technological support systems aid analysts in preparing for studies as well as processing data and generating reports. The analyst is therefore still required to take and record observations. In this section, two computer vision based systems are investigated. These systems, as developed by van Blommestein [**13**] in 2010 and von Petersdorff [**12**] in 2011 aim to automate the observation phases of the work sampling and time study and methodologies respectively.

The development of these systems has been facilitated by the recent developments in computer vision. Computer vision includes methods for acquiring, processing, analysing and understanding images. High-dimensional data from the real world is translated into numeric information, which we can then manipulate to enable the tracking of specific items in the video capture frame [**45**].

There are numerous methods and libraries in which computer vision algorithms can be developed to enable tracking of a worker. The algorithms that were used to automate the two methodologies are based on different methods and also utilise different open source libraries.

Automation of the work sampling methodology

The system used to automate the work sampling consists of a number of low cost web cameras linked up to a central computer via high-speed and long-range USB extenders. The cameras are set up at certain workstations in a production process. The computer runs a standalone C++ application. The application uses a random function to determine when measurements are to be taken.

The worker that is being monitored wears a uniquely coloured glove on his/her dominant hand. The video camera footage is converted to pixel matrix using Open Source Computer Vision (OpenCV). This matrix is then filtered and analysed, enabling the tracking of the glove as indicated in Figure 4. The location and time data of the glove's position in the frame are determined at maximum capable frame rate of the system for a sampling period of 10 seconds. The sampling duration was determined to be adequate for classification from the tests performed on the system. This data is then written to a text file which is exported to a spread-sheet application for analysis [**13**].

The speed of the worker's hand over a sampling period is used to classify the operator as one of three possible states; idle, busy or out of frame. After the required number of samples has been collected the data is then exported into a spreadsheet application. The spreadsheet application generates a report of the labour utilization which is sent to the analyst for review. [**46**].

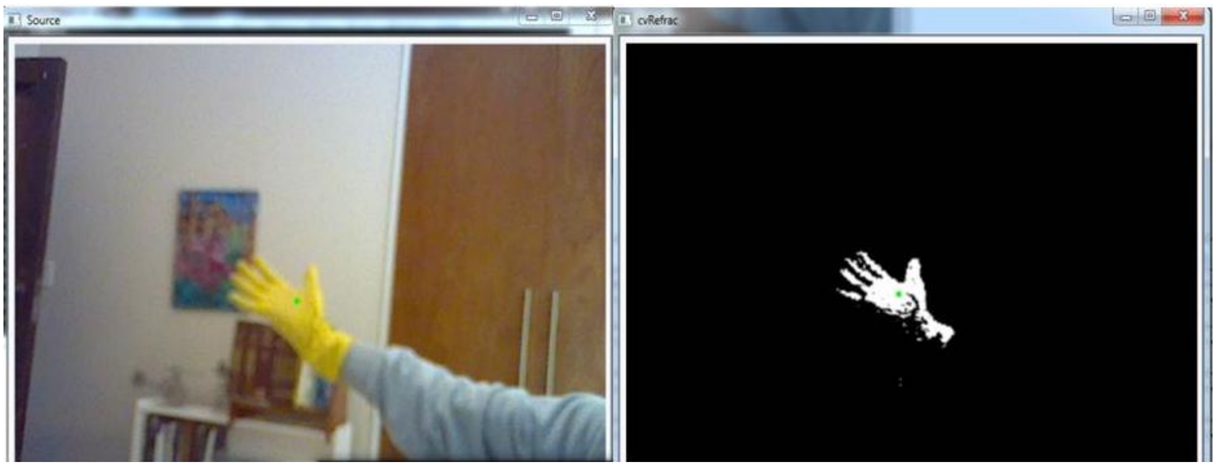

Figure 4: Screenshots of both the source and the filtered images. The green dot is located at the centre of the filtered object [13]

Two sets of tests were performed on the system. The first tests were performed in a controlled lab environment and the second involved field testing the system in a confectionary factory in Wellington.

The controlled tests were conducted which required the worker to occupy a particular state for a set amount of time. These tests were conducted under constant lighting with no similarly coloured items within the capture frame. The largest classification errors, which involved incorrectly classifying the users state was less than 6%. The total classification errors for the experiment were 2% [**46**].

The controlled tests indicated that;

- Under ideal conditions, and
- For tasks requiring frequent and large hand movements,

The system was capable of reliably returning positional data and that this information could be used to differentiate between the three states [**46**].

In the field test four cameras were set up at different stations in the production line. Two cameras where set up above the processing line and the remaining two above the packaging department. The workers that were studied were located at a specific station for the duration of the study. A blue nitrile glove was worn on the right hand by the individual under study.

In the top left of the image is the bandwidth filter as configured to track the glove worn by the worker. Below this is the capture frame. On the worker's glove a green dot is visible. This green dot is the point that is tracked and used in the analysis, it is however off-centre. This is a result of a small amount of interference resulting from the other similar coloured items in the capture frame, such as the worker's collar and hair cap. On the right of the screen is a console window. The console window is red in the image indicating that that a samples data is being recorded to a text file.

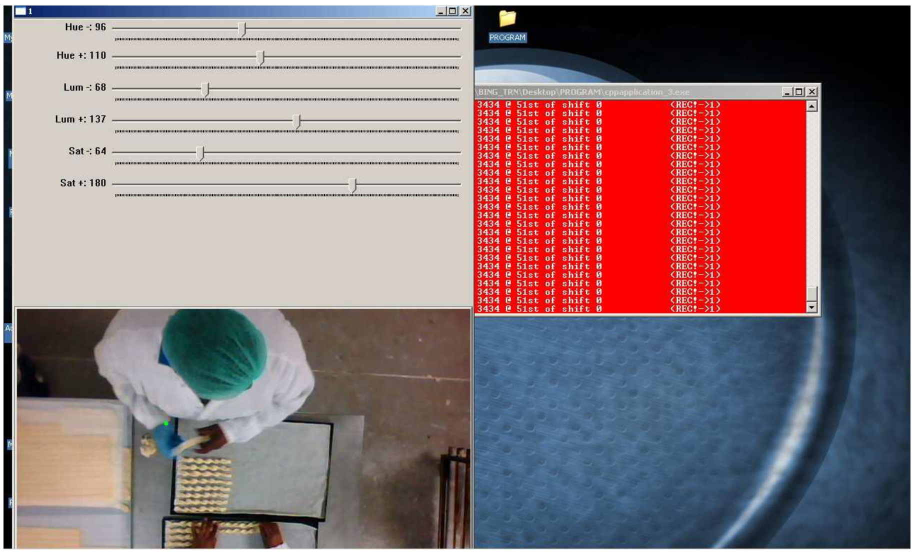

Figure 5: Screen shot of the computer screen at the factory [46]

The graph in Figure 6 represents the data that was captured by one of the cameras during the first shift of the study. It provides broad overview of the occurrences within one of the processing shifts. It can be seen that movement was recorded for most of the period. Furthermore, the 19:30 – 20:00 production break period is clearly visible (which includes the 19:33:56 – 19:59:26 time interval, with low peaks). Within this period the workers cover the work in process with blue plastic sheets. These sheets are passed through the filter and result in the small amount of movement being recorded, also termed noise. Fortunately humans are rarely as motionless as inanimate objects and a distinction can be made. In the final analysis of the data, this noise is excluded from the calculations by increasing the upper limit of the out of screen classification speed. The presence of the blue food covers does however increase the number of incorrect classifications. This issue could be simply remedied by wearing different coloured gloves.

The periods during which the worker was idle or out of screen, can clearly be seen by the troughs in the graph. As an example, it can be seen from the graph that at 16:20:59 the moving average speed of the worker is relatively small. This indicates that the worker was idle and therefore not working. At 19:15:44 the speed is zero and the user was therefore out of screen. If the idle time or the out of screen time is excessive the causes for these occurrences should be investigated by the production manager.

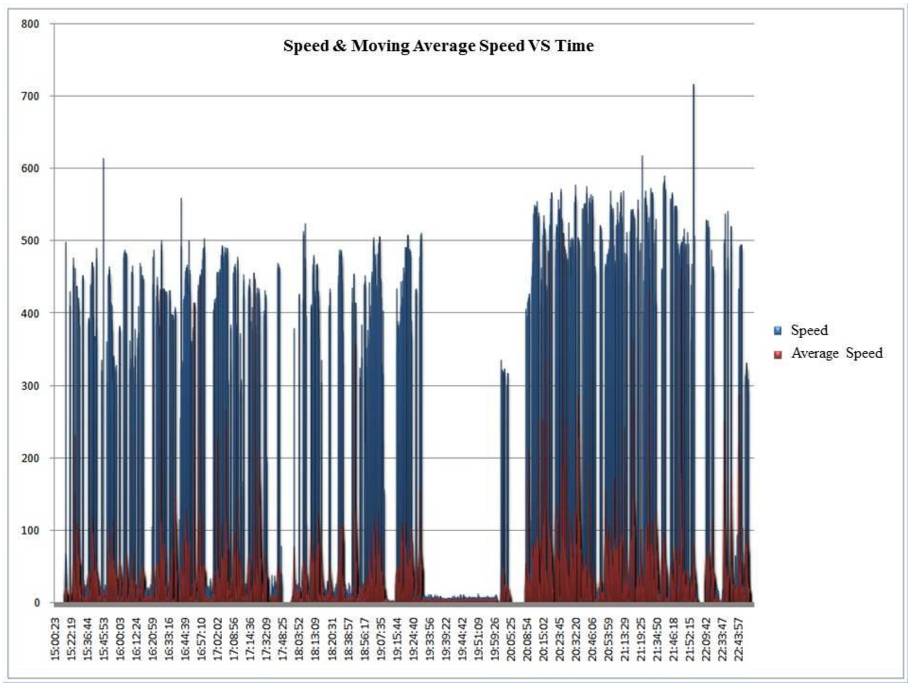

Figure 6: Graph of the data recorded for a shift during the study [46]

The field testing of the system provided valuable information of the system, highlighting the limitations, advantages and disadvantages. From the tests done on the system, it is evident that the system adequately classifies an operator as in one of the three possible states: *idle*, *busy* or *out of screen* [**46**].

From these classifications workforce utilization (U) can be computed by dividing the number of observations classified as busy (n_{busy}) by the total number of observations of the study (n_{total}), as indicated in Equation 5 [**47**].

$$U = \frac{n_{busy}}{n_{total}} \ldots (5)$$

The system also enables the determination of a fair standard allowance time. If it is assumed that the proportion of measurements classified as being out of screen is acceptable, then it can be assumed that avoidable delays are those which take place while the operator is seated at his station, but is not working. The avoidable delays are determined by Equation 6 [**47**].

$$\mathrm{D_{avoidable}} = \left(\frac{\mathrm{n_{stationary}}}{\mathrm{n_{total}}}\right) \ldots (6)$$

Table 3 includes the classification data, along with the utilisation, avoidable delays and out of frame values are shown for a processing shift of the case study.

Table 3: Results from the first shift of the case study

Number of Samples	334
Out of Frame	34
Number of Samples for Analysis	272
Idle	47
Busy	191
Noise	62
Percentage Utilization	70.22
Percentage Avoidable Delays	17.28
Percentage Out of Frame Ratio	12.5

The automated system also provides information on the variation in working speeds over a shift, between shifts and on different days of the week. The system does however have a number of limitations. If standard times are to be calculated, data on the number of items processed by a specific station needs to be determined manually by reviewing job sheets by manually counting the number of items processed. This problem is carried through from the traditional method of performing studies [**40**].

There are many advantages of utilising an automated system to perform work sampling. These advantages are summarised in Table 4.

Table 4: Advantages of automated sampling

Advantage	Reasons
Time saving	Observer not required; Data entry not required
Fewer resource requirements	No observers
Higher accuracy	More samples per day possible; Multiple stations analysed in parallel
More accurate representation of the work environment	Hawthorne effect minimal; More data available
Lower cost	Observers expensive
Can become a permanent installation	No time frame after which it must leave the organization
Data on the activity velocity is available.	Velocity of the worker recorded
Flexible	Determine machine utilization; Any number of cameras

There are also a number of disadvantages of the system; these are represented in Table 5: Disadvantages of automated sampling Table 5.

Table 5: Disadvantages of automated sampling

Disadvantages	Reasons
Setting up the camera filter is a hassle	Time consuming; Determining acceptable noise is difficult
Glove may influence the performance of the operator	Cause discomfort; Difficulties with performing fine tasks
Less detail available than in manual work sampling	More states identified in manual studies

Automation of the time study methodology

The system used to automate the time study methodology consists of a Microsoft Xbox Kinect™ camera, connected via USB to a computer. The Microsoft Kinect™ camera uses structured infrared light to create a dense digital three dimensional representation of a scene. The computer runs a standalone executable C++ application. The Kinect™ camera is used alongside Open source Natural Interaction (OpenNI) software to perform skeletal-tracking on the worker. Data gathered from the joints represented by the worker's hands are parsed over a period of time to automatically find significant nodes, as displayed in the scene represented in Figure 7. The system then records node visits and performs a pattern detection algorithm to extract the work cycle being performed. The system detects and records these cycles if they are performed subsequently, and calculates the time between cycles. Worker performance is calculated and real time feedback is given to the worker via a simple colour scale after each completed cycle. This data is gathered in a log file for later analysis. Calculations and algorithms are performed as simply as possible to enable the analysis to execute in real-time [**12**].

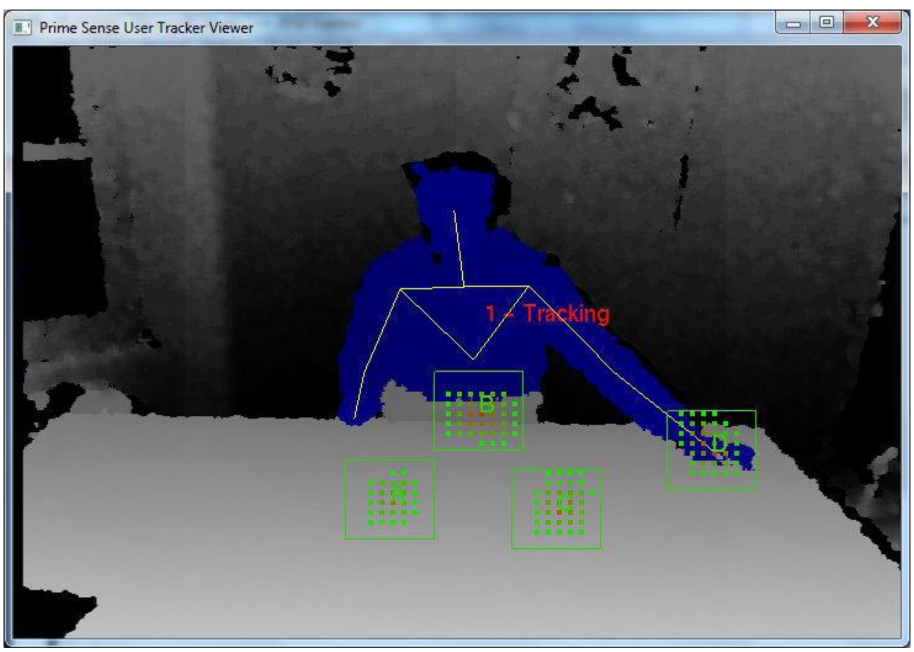

Figure 7: Screenshot of training complete and bin locations fixed

In order to determine the effectiveness of the proposed solution, a simple assembly task in Figure 8 emulating an assembly task was designed. It involved retrieving LEGO® bricks from bins located on the workbench, assembling the bricks in a specific manner, and placing the completed assembly in a bin to the right hand side of the worker. The Kinect™ camera was placed on a tripod approximately 2.5 meters away from the worker, at a height of 1.8 meters. A laptop, which served as the execution platform for the program as well as the feedback mechanism to the worker, was placed to the left of the worker. Concurrently, a human analyst observing was given a stop-watch timer, and was told to note the time of each completed assembly. Only the time-study aspect of the project was assessed.

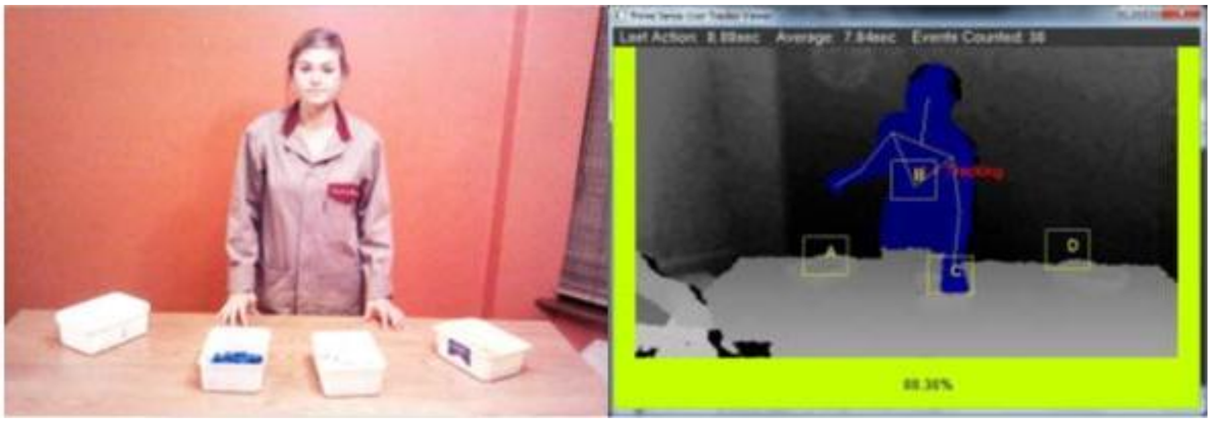

Figure 8: (*left*) Image seen by the camera of test, (*right*) Screenshot of the performance feedback screen

The testing provided insight into the capabilities of the program as well as the limitations, advantages and disadvantages. The results of the tests are represented in Table 6. From the tests it was shown that the system was capable of automating the time study method reasonably accurately. More than 95% of the work cycles were recognised and timing variation between the manual and automated study was less than 2%. The time taken to train and the number of training cycles needed was also deemed to be acceptable.

Table 6: Automated time study testing results

Description: Assemble two LEGO® blocks using right hand		
	Operator	**Kinect™ System**
Number of Events Recorded	50	45
Number of Training Cycles Required	-	3
Number of Failed Recognitions	-	2
% Recognition Excluding Training	-	95.60%
Average Time Recorded(sec)	8.08	8.09
Time Taken to Train (sec)	-	25.98

A specific limitation of the automated system was the accuracy of skeletal-tracking data when the worker's body was partially obscured or when the worker was handling objects. The Kinect™ occasionally struggled to keep an accurate lock on the user in these situations. This was especially detrimental during the training of the system, which due to the method of cycle recognition used was sensitive to such behaviour [**12**].

A number of advantages of utilising an automated system were also identified. These advantages are summarised in Table 7.

Table 7: Advantages of the automated time study system

Advantage	Reasons
Time saving	Observer not required; Data entry not required
Fewer resource requirements	Analyst not required to identify sub- elements or time elements
More accurate representation of the work environment	Tests can be performed for longer periods
Lower cost	Observers expensive
Can become a permanent installation	Equipment can be setup at various work stations

There are also a number of disadvantages of the system; these are represented in Table 8.

Table 8: Disadvantages of the automated time study system

Disadvantages	Reasons
Inaccurate skeletal tracking	Kinect was not designed for the uses described in this project; Tracking fails when hand comes in contact with work surfaces
Cycle recognition algorithm inflexible	Coding difficult; Cycle recognition failed in some instances
Less detail available than in manual time studies	Sub-elements cannot be timed accurately; Only total assembly time recorded
Limited flexibility	Only standard times calculated; Only one product can be worked on at a time

2.4.2 Comparison between two computer vision LPMs

A comparison of work sampling and time studies is represented in Table 9. From the comparison, it is clear that both techniques have a number of advantages and disadvantages. The two techniques also have a number of similarities.

Table 9: Comparison between work sampling and time studies

Time Studies	Work Sampling
Approximate system cost: R 2000 (Kinect™ camera)	Approximate system cost: R 6800 (2 x USB extenders + 4 x web cameras)
Limited impact on accuracy as compared to traditional studies	Increased accuracy compared to traditional study. Due to increased number of observations and extended duration of the study
Easy to understand	The statistical basis of the study may be difficult for workers and/or management to comprehend
Accurate timing figures are obtained	Enough samples need to be made to ensure that the desired accuracy of the final results are achieved
Difficulty in programming robust flexible cycle identification and recognition algorithms. More computational power required	Simple coding procedures and less computational power required
Less detail available as compared to traditional methods - Only information on work cycle time provided	Less detail available regarding the specific activity of the worker compared to traditional methods.
Calculates the standard cycle time for a simple task	Calculates worker utilisation and allowances
Feedback given to worker	No real time feedback
System is intrusive. The computer screen faces analyst and the camera is large	Less intrusive, cameras mounted above the workers
One task analysed at a time,	Multiple work stations observed at the same time
Worker needs to be calibrated to enable tracking	Glove needs to be worn by worker to enable tracking
Requires worker to work at fixed location	Requires worker to work at fixed location
Tracking fails when hand is placed on work surface	Tracking fails when similar coloured device enters frame
Cyclic variations are not as well compensated for	Observations typically made over an extended time period which decreases the effects of cyclic variations
Helps to identify labour costs	Helps to identify labour costs
Simple set up procedure	More complicated setup procedure, set up filters and input initial valuables for variables
Requires extensive knowledge and understanding of the task	Does not require an understanding of the task

2.4.3 Risk assessment

Figure 9 depicts the three categories under which the systems technological support systems for risk assessment can be categorised.

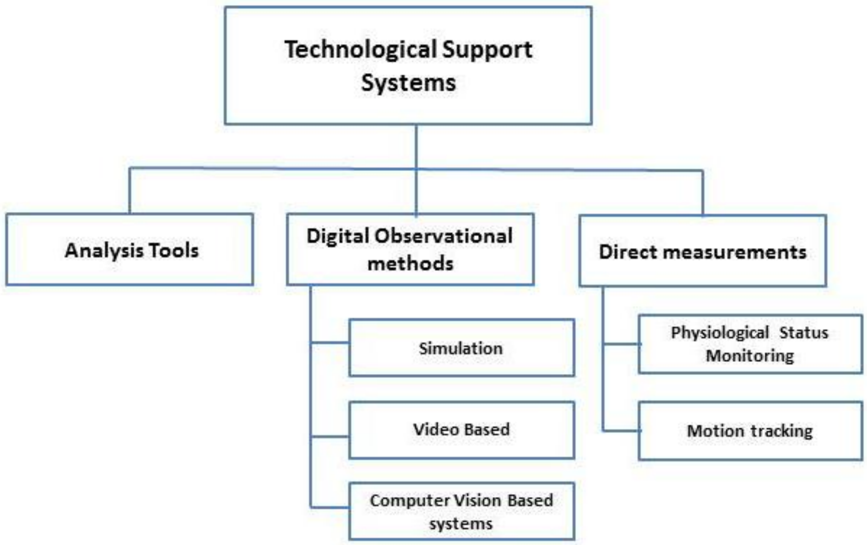

Figure 9: Technological support systems for risk assessments

The analysis tools are limited to the simplification of the data gathering and analysis processes. The direct and digital observational techniques are significantly more complex. Direct measurements require workers to wear specialised hardware devices, whereas digital observational techniques are reliant on simulations, video footage and/or computer vision technology to track workers. These systems can be further subdivided into online and offline systems. Online systems provide feedback in real time while offline systems involve capturing and storing data for analysis at a later date.

2.4.3.1 Analysis tools

Numerous software developments have been made to simplify the data gathering and analysis of traditional studies. These systems range from free online calculators to extensive and costly programs covering a multitude of risk indexes.

Free online calculators and checklists are available for many of the traditional risk assessment methodologies. These free online applications simplify the analysis phases of calculations and also eliminate calculation errors. An online RULA Calculator hosted on the RULA website enables users to select the appropriate limb positions and relevant weighting factors. Once complete the system returns the score which indicates if the worker is at risk [**48**]. Online calculators for Revised NIOSH lifting equation (RNLE) such as the calculator hosted by the Canadian Centre for Occupational Health and Safety, require analysts to input the measured values for the appropriate variables. From these variables, the calculator calculates each of the multipliers and returns the recommended weight limit (RWL) [**49**].

Although PDA's have largely been phased-out by the recent technological developments of smartphones and tablets, a few applications are still available. Pocket Lift developed by Kevin Culp is a PDA application that analyses back injury risks according to the RNLE. The application is similar to the online calculators and requires the analyst to physically measure each variable. The advantages of the application include; context-sensitive help that enable analysts to click on any of the variables to retrieve a description and limits of the variable. The application is also capable of assessing single and multiple lifting tasks. [**50**]

The popularity of smartphones and tablets has resulted in the development of a large number of apps. Apps are available for a variety of platforms including Android, iOS, Windows mobile and others. The functionality of the apps varies greatly. The most basic apps are based on the online calculators and checklists. The OSHA Warehouse Safety Checklist: Manual Lifting/Handling app for example, provides a solution checklist for manual handling hazards [**51**]. The NIOSH Lift Index app, as with the online calculators, requires the analysts to input measured values for each of the variables. The system therefore assumes that the users have professional training in the application of the revised NIOSH Lifting equation. The mobile nature of the app is an advantage and it can be used as a quick and easy reference tool for use in occupational situations [**52**].

Pocket Ergo® is an internet based application that includes a number of ergonomic assessments for office and industrial applications. The software can be used on an iPad, Android tablet, smartphone, computer or laptop. The office assessments include:

- Computer Workstation Quick Configure Calculator
- THS Office Assessment Checklist
- OSHA Office Assessment Checklist

The industrial assessments include:

- Anthropometry (Standing and Seated)
- Revised NIOSH Lifting Equation (RNLE)
- Utah Back Compressive Force Model
- Push Force Calculator
- Pull Force Calculator
- Carry Force Calculator
- RULA (Rapid Upper Limb Assessment)
- REBA (Rapid Entire Body Assessment)
- Strain Index (SI)
- Grip and Pinch Strength
- Industrial Ergo/Material Handling Assessment Checklists
- Guide to Performing Industrial Ergonomics Assessments

Analysts can navigate between the Office and Industrial tabs to access assessments of interest. Each of the assessments includes a brief description of when and how to conduct the assessment. It should be noted that the system assumes that analysts are reasonably familiar with the assessments.

Pocket Ergo® bridges the gap between the basic smartphone applications and more advanced computer based systems. It is essentially a mobilization of systems such as ErgoEasy Professional, which is a computerization of existing risk assessment methods.

ErgoEasy Professional assessments include; Check-List OCRA, OCRA Index, REBA, RULA, Strain Index, NIOSH Lifting Index and the Snook-Ciriello Pushing-pulling and carry assessments. The system reduces the analysis time and also eliminates the errors that traditionally occur during the analysis and calculation phases. The ease of use simplifies the ergonomic analyses and the in-depth understanding of methodologies is not required. This makes the analyses easier to perform. The system also enables simulation of interventions and redesigns of workplaces which is not possible in the paper based counterpart [**39**]. ErgoIntelligence™ Upper Extremity Assessment (UEA) by Nexgen ergonomics is another example of an advanced computer based system. The multitude of assessments incorporated in the system includes; RULA, REBA, Strain Index, OCRA Index and the Cumulative Trauma Disorders Risk Index [**41**].

2.4.3.2 Direct measurements

Direct measurements require the worker to wear specialised hardware devices to capture data on the worker's location. Both online and offline systems have been developed. The two main groups include; Motion tracking and Physiological Status Monitoring (PSM) devices.

Motion tracking

Motion tracking systems utilize sensors or markers placed directly on the workers to gather data. The markers and sensors are placed at specific locations on the worker and track the position and angular movement of different body segments [**10**]. Sensor based systems use devices such as gyroscopes and accelerometers. MVNBIOMECH by Xsens, represented in Figure 10, is an example of a sensor based 3D human kinematic measurement system. Marker based systems use optical, fibre-optic, sonic or electromagnetic markers placed at specific locations on the subject and a number of appropriate scanning devices to extract data [**53**]. Figure 10 shows a close up of optical markers. In conjunction with the markers the systems utilises a number of cameras to perform the assessment. Each marker needs to be seen by at least 3 cameras [**54**].

The motion tracking systems provide data on 3D location, velocity and acceleration. The systems can be used to identify whether workers are required to assume awkward postures. They can also be used to determine the time that individuals spend in different postures during the course of their working day and for ambulatory monitoring of occupational work [**55**].

Figure 10: (*Left*) MVN BIOMECH 3D kinematics measurement system [56], (*Right*) Close up of optical markers [54]

Motion tracking systems appear to be more suited to the investigation of task simulations, as opposed to investigation at industrial locations. This is primarily because the sensors are directly attached to the worker and as a result may cause discomfort and modification of the workers behaviour. Motion tracking systems provide large quantities of accurate data. The problem with the enhanced data gathering is that considerable time is required for processing, analysing and interpreting data. As a result many analysts consider the systems to be impractical. Furthermore, costs of the systems are substantial. These costs include both the initial and subsequent maintenance and operation costs. The operation costs result from the necessity to have highly skilled technical staff to operate the systems effectively [**10**].

Physiological status monitoring devices

There are a variety of different Physiological Status Monitoring devices (PSM) systems commercially available. BioHarness™ BT by Zephyr represented in Figure 11 , ECG:PSM by Quasar and EQ-01 by Hidalgo are a few examples. These systems can autonomously and remotely monitor the physiological status of a worker with a minimal impact on their ability to perform routine activities. PSMs measure a number of physiological factors, including [**57**,**58**,**59**]:

- Skin temperature
- Heart rate
- Breathing rate
- Activity Posture

Figure 11: Physical features of the BioHarness™ BT by Zephyr [60]

The data captured by the devices can be transmitted through mobile and fixed networks to computers where specialised software processes and analyses the data. The devices therefore enable remote monitoring in work environments [**57**]. Studies have indicated that the devices are capable of providing reliable information in real world applications [**58**,**59**].

In order to evaluate the probability of musculoskeletal injuries physiological and motion data are recorded. This includes the Heart rate which was calculated from the electrocardiograph and the thoracic bending angle. The thoracic bending angle is derived from the gravity compensated measurements provided by the tri-axial accelerometers [**57**]. One disadvantage of using the accelerometers to approximate bending angles and position is drift. Drift becomes considerable if the measurements are taken over a period of time [**55**].

The problem with PSM devices is that it does not identify the location where the unsafe lifting events occur [**59**]. In order to address this limitation Cheng [**59**] developed a system that makes use of Real-Time Location Sensing (RTLS) to provide data on the location of the worker. This in turn enables the determination of the location where the awkward or unsafe bending procedures takes place. The RTLS was accomplished by utilizing an Ultra Wideband (UWB) system. UWB is an active Radio Frequency Identification (RFID) technology that records the location of resources in real time. A tag is placed on the worker being analysed, the tag then communicates with multiple antennas that are strategically located in the workplace. A central processing hub triangulates the incoming radio frequencies from the antennas and thereby determines the location of the worker.

2.4.3.3 Digital observational techniques

Digital observation techniques include numerous methods for non-intrusively assessing lifting risks. These methods range from simulation based models, through to real time ambulatory computer vision based systems that utilise skeleton tracking algorithms to estimate joint locations of the workers.

Simulation

Simulation systems such as Safework™ and JACK™ enable the determination and design of various work elements prior to performing the work. These systems therefore eliminate the need to expose workers to potentially hazardous tasks. Model of the work station and the lifting tasks generally need to be developed [**55**]. An example of a lifting task assessed in JACK is depicted in Figure 12.

JACK, developed by the Computer Graphics laboratory of the University of Pennsylvania, requires the analyst to construct a model of the work environment, the operator and the tasks. The model can then be used to support the analysis and improvement of ergonomic facets from anthropometrical and biomechanical viewpoints. These include product design and organisation of the workplace. The combined use of the tools available in JACK supports an integrated and multifactorial analysis of the work system. As an example, it can identify the optimum arrangement of devices and equipment [**8**].

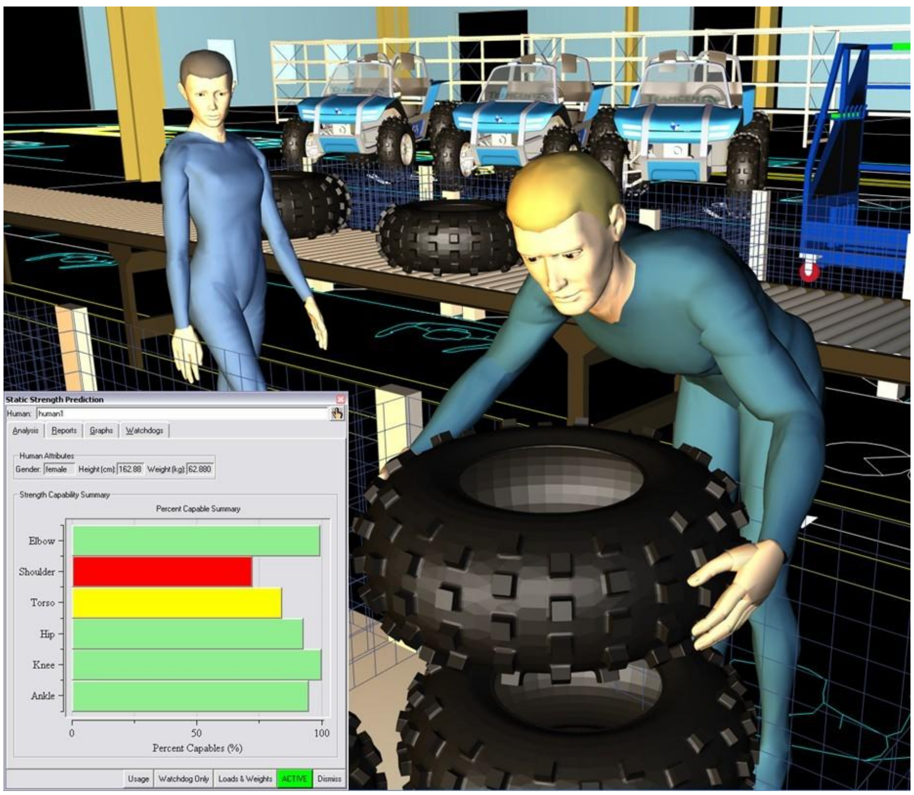

Figure 12: Jack simulation of lifting a tyre [61]

JACK's task analysis tool kit includes a vast range of risk assessment tools. In addition it also incorporates predetermined time standards (MTM-1), which are used to establish standard times. The risk assessment tools provide feedback on acceptable ergonomic thresholds which are used during product and process design. The toolkit includes; Fatigue analysis, lower back analysis, manual material handling, NIOSH lifting analysis, Ovako working posture analysis (OWAS), Rapid upper limb assessment (RULA), Static strength prediction (SSP) and ForceSolver [**62**].

Unfortunately a precise comparison between traditional methods and the results of the simulation model are not possible. However the evaluations on a general level seem to be consistent and the simulated models accurately identify activities as potential sources for risk [**8**].

In situations where there is high variability, either between operator's techniques or between the tasks that are performed, the use of simulation software cannot replace the role of the analyst. It could however be used to support the risk assessment as it makes it possible to understand the impacts and effects that various changes would have. In many cases the simulation must be seen as an aid to the traditional assessment. One significant disadvantage of the simulation based approach is that analysts may not have a thorough understanding of the methods on which the packages are based. This could negatively impact the use of the results as well as the consequent identification of corrective measures [**8**].

Video based

A number of video-based systems have been developed that asses the postural variation of dynamic activities. These systems use videotapes or computers to record worker movements in real time for a work period that represents the work activities. Dedicated software is then used to analyse the data of several joint segments simultaneously. A number of dimensions may be determined, such as distance of movement, angular changes, velocities and accelerations [**10**].

The analysis may include the use of biomechanical models that represent the human body as a set of articulated links in a kinetic chain and use anthropometric and postural data to calculate intersegment moments and forces. These range in complexity from two-dimensional static models to three-dimensional dynamic models.

The costs of the above-mentioned systems can be substantial, and they require extensive technical support from highly trained staff for effective operation. They can be time consuming to use in practice and have been found more suitable for use in recording and analysing simulated tasks, rather than for conducting practical assessments in the workplace.

Computer vision systems

Computer vision is one of the most recent technological developments that have been applied to the risk assessment of WMSD. Computer vision refers to the field that involves translating high dimensional data from the real world into numeric or symbolic information. This enables the manipulation of images thereby facilitating the tracking of objects and people. Numerous algorithms and libraries have been developed for tracking purposes.

By making use of computer vision algorithms and libraries, it is possible to non-invasively approximate joint locations, and therefore joint angles of a worker. A few approaches for tracking workers have been investigated and developed. The most recent approaches utilize low cost range imaging cameras. These cameras are capable of returning 3D co-ordinates of any pixel in the capture frame.

Gonsalves developed a system that uses 3D range imaging cameras [**63**]. The system is computationally inexpensive and as a result it enables robust and real time tracking of workers. The human target is identified via background subtraction. A threshold value, determined from grey level histograms was then used to separate the human target from the background. To threshold on its own is not enough to get clear foreground images. In order to eliminate excess noise a median filter and erosion is used. The Centroid of the human target is determined and tracking is achieved via the use of a particle filter. A star skeleton model is applied to the filtered object. It identifies extreme points on the boundary of the filtered object. The extreme points were then connected to the centroid. The model is used to evaluate the posture of construction workers while performing simple tasks such as lifting a box. The system could be used to determine whether workers are maintaining the correct posture.

Another system developed by Ray uses a Kinect™ camera [**55**]. The system provides a method for integrating posture analysis of workers with a predefined set of rules to categorize work tasks as ergonomic or non-ergonomic. The system illuminates the risk of LPB and WMSD due to awkward postures. It makes use of a linear classification model to classify and estimate the worker's postures in real time (stand, squat, bend and crawl) and then uses rules from literature to determine when workers are at risk.

Martin et al. developed a system that uses a Kinect™ camera and the Microsoft software development toolkit (SDK) to approximate the joint locations of a worker. The system consisted of several design iterations. It is based on the Occupational Safety and Health Administration (OSHA) model. The model provides valuable information on correct lifting techniques and it also provides a method for calculating the maximum weight that can be safely lifted by worker, the Recommended Weight Limit (RWL). In addition to returning the dynamic RWL the system also calculated the time spent in awkward postures, which include [**11**]:

- Hands above shoulders
- Hands below knees
- Arms extended past 135 degrees

A screenshot of the system is represented in Figure 13. In the capture frame the skeletal tracking model is clearly discernible.

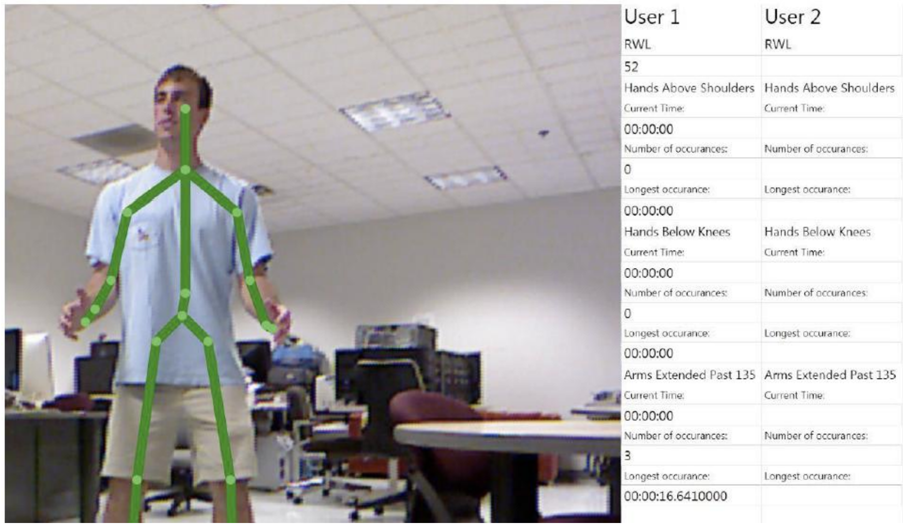

Figure 13: Screenshot of the ergonomic monitoring system developed by Martin et al. [11]

A variety of computer vision based algorithms and approaches have been applied to accomplish worker tracking and thereby address the issue of reducing the incident rate of WMSDs. The systems that have been developed are used for training workers on correct lifting techniques and for ambulatory monitoring of workers. The most popular tool is range imaging cameras, such as Microsoft® Kinect™ and the accompanying open source libraries. Its popularity in this field can be attributed to its ability to non-invasively extract joint location data in real time. Additionally the hardware is relatively cheap and numerous open source libraries are available to developers. The libraries drastically reduce the time and complexity associated with developing systems.

The existing skeletal tracking libraries were developed for natural interaction as a result there are numerous limitations of using them. Even under ideal conditions noise is significant, for this reason the data is often passed through one or a series of filters. However joint tracking can still become excessively noisy or fail altogether under the following conditions [**55**]:

- When body parts are occluded from the camera's view
- When body parts come into contact with other objects in the capture frame
- When there is natural light present
- When the camera or worker are at extreme angles

As a result the systems use is limited to indoor environments with little or no natural light present. Furthermore contact with foreign items, such as work surfaces needs to be avoided. Positioning of the camera is also important. The camera also needs to have a direct viewing angle of the worker.

2.5 Comparing techniques

A brief generalized comparison between the manual observation and technological support system approaches is represented in Table 10. The comparison highlights some of the advantages, disadvantages, and indicates situations in which the two approaches are applicable.

Table 10: Comparison between manual and technological support systems

Manual Observation	Technological support systems
Low cost	Higher costs due to software and hardware
Biases	No biases
Tedious to perform	Tediousness depends on system used
Variation between different analysts	Minimal variation as the system is constant
Better suited to assess static or repetitive tasks	Some systems provide opportunity to evaluate more complex tasks
Less reliable data	Provide more reliable data
Fairly simple to perform	Require extensive technical support from highly trained staff for effective operation
Practical for use in a wide range of workplaces	More suitable for use in controlled environments due to the noise levels in an uncontrolled environment
Data collected and analysed later on	Capable of real time measurement and providing warnings for unsafe execution of task
One on one observation	Multiple workers can be monitored simultaneously

From the comparison in Table 10, it is clear that the approaches are better suited under various conditions. It is also important to emphasise that most manual observation techniques and technological support systems vary significantly. Some of the methods discussed in this thesis require highly skilled analysts and an extensive use of resources to conduct the studies, while other techniques, specifically the more general observation-based assessments, are preferred when the analyst has minimal time and resources at their disposal [**10**].

Due to the vast number of systems that have been developed and their suitability for use in specific studies, selecting approaches becomes arduous. The following factors were considered important in the selection of a suitable technique [**64**]:

- The features of the system
- The feasibility of the system with regards to assessing worker performance and identifying causes
- The level of detail required
- Variation in performance and exposure distributions within and between different workers

These considerations provided the foundations for selecting a basis on which the system was developed. By defining the initial objectives of the systems, a suitable approach was selected and the system developed. An effort was also made to elevate many of the limitations identified in the comparison in Table 10.

2.6 Selection of a technological base and methodologies

In order to select an appropriate method for assessing labour performance while also minimizing the impact of LBP the following goals and objectives for the system were defined:

- Real time operation
- Low cost
- Minimal impact on the worker's ability to perform his tasks, preferably non-intrusive
- At least as accurate as manual studies
- Easy to use, setup, understand and operate
- Addressing as many performance factors and causes for LBP as possible

The system will be used in the manufacturing environment, the system will therefore be limited to use indoors.

These objectives were used in conjunction with considerations for selecting a suitable technological basis, described in Section 2.5. Of all the TSS discussed only computer vision adheres to the objectives of this thesis and overlaps between the LPM and risk assessment.

Existing computer vision systems have indicated that low cost and real-time operation is possible. Additionally computer vision enables the development of intuitive graphic user interfaces (GUI), which can simplify the execution of labour assessments. The biggest advantage of computer vision is that it is capable of extracting non-invasive tracking workers.

Selecting the methodologies for automation was done by evaluating the existing traditional methods. The features of the methods were considered along with the suitability for automation via computer vision. The selection is further complicated by the dual nature of the system. The approaches selected should ideally share a common structure.

2.6.1 Selecting a labour performance measurement system

The choice between the selection of either time studies and work sampling was delayed until after the evaluation of TSS. A comparison between the two existing computer vision based systems is included in Table 9. The comparison highlighted numerous limitations and advantages of the respective systems. By taking various elements from both existing approaches and addressing some of the limitations, a proposal for an improved system is developed.

The proposed system draws on both the work sampling and time study methodologies. It can be described as a continuous work sampling methodology, utilizing a Kinect™ camera, to non-invasively extract 3D joint location data from workers. Image recognition is used to track the work-piece so that processing time information can be extracted. The continuous approach enables real time feedback to analysts, and also eliminates restrictions imposed by the statistical bases of work sampling.

2.6.2 Selecting a risk assessment methodology

Table 2 indicated the exposure factors assessed by the various methods. From the study of the existing traditional risk assessments, a single candidate methodology for automation was selected. The methodology is the Revised NIOSH Lifting Equation (RNLE). The characteristics that make it suitable for selection include [**3**]:

- The majority of the exposure factors are addressed
- The calculations are simple mathematical expressions
- The solution is a tangible value which provides insight into the severity of the lifting task

The basic principle of the RNLE is that the load constant, which is the maximum allowable load that can be safely lifted by the majority of the population, is diminished by a number of factors. These factors include the location of the load, the coupling and frequency of lifts. The fundamental inputs are positional and time data, which as a result of the equation, lends itself well to automation.

It was decided that the RNLE would be best suited for automation in a computer vision system because only time and location data of a few key joints on the worker’s body and the work-piece is required. The same basic system for the LPM could therefore be applied to the RNLE.

2.7 Conclusion

The literature reviewed in this chapter considered a multitude of traditional and technological support systems used for:

1. Assessing the risks of developing LBP
2. Measuring labour performance

The study identified computer vision as a suitable technological platform for the automation of both labour assessments. Ultimately the RNLE was selected for risk assessments and a continuous classification work sampling methodology for labour performance measurement. The following chapter covers the development of the shared technological platform.

3. Chapter 3

HAWK - The Basic System

3.1 Concept of automation

Recent technological advances and developments in computer vision offer us an opportunity to automate numerous industrial engineering practices. The automation of procedures is important because analysts spend a large portion of their time gathering data. By automating the data gathering procedures a significant amount of time and resources are spared.

The system must be capable of:

- Measuring labour performance continuously in real-time
- Assessing if lifting tasks are hazardous, according to the Revised NIOSH Lifting equation

The system proposed for the automation consists of a Kinect™ camera linked to computer that runs a standalone C++ application. The Kinect™ camera is a 3D camera which observes depth by making use of an infrared emitter and receiver. The Kinect™ camera will be used in conjunction with the OpenNI and OpenCV libraries. This combination of hardware and software will enable the tracking of:

- Hands, feet and shoulder location of the worker
- Work-piece

OpenNI will be used to perform skeletal tracking. Data on the specific joints of interest can be extracted as needed. OpenCV will be used for image recognition purposes, ultimately identifying a predetermined item within the user defined workspace. The data on the location of the worker's hands and work-piece will be analysed in real time in order to identify the moment the worker makes or breaks contact with the work-piece. Contact will be determined through Arvo's box-sphere intersection test. These contact points are crucial to both worker assessments [**65**,**45**,**66**,**67**].

For the RNLE the contact points represent the initiation and conclusions of lifts. At these instances the positional data of the worker's hands and feet need to be recorded, so that the variables and multipliers can be calculated. The number of contacts also indicates the number of lifts that have been conducted, which is used in the frequency calculations [**5**].

For the labour assessment the location and speed of the worker's hands and the work-piece can be used to answer the following questions [**40**]:

- Is the worker in contact with a work-piece?
- Is the worker at his/her station without a work-piece in front of him/her?
- Is the worker at his/her station but not in contact with a work-piece in front of him/her?
- Is the worker away from his station?
- How long has the work-piece been in the frame?
- How much time has the worker been in contact with the work-piece?
- At what speed is the worker working on the work-piece?

This information is then used to determine:

- Worker Utilization
- Number of items processed thus far
- Standard times
- Allowances
- Variations in working speed over the shift
- Variation in processing time of a single item

3.2 The system

The system relies on both hardware and software components to enable the real time execution of the labour assessments.

The hardware used in this project is limited to a 3D range imaging device. USB extenders, such as the Icron ranger 2212 unit could prove valuable in industry as they are capable of extending USB 2.0 devices over 100m. For the sake of this project range extenders have not been included [**13**].

The core software components used in the development of the system are the OpenNI SDK and OpenCV libraries. A number of performance enhancing libraries and architectures such as Compute Unified Device Architecture (CUDA) and Threading building blocks (TBB) are used to speed up processing and ultimately enable the real time execution of the labour assessments. The assessments were compiled in C++ using QT creator IDE

3.2.1 Hardware

Motion tracking 3D sensors are technological innovations enabling the development of the system used in this project. There are a few motion sensing devices commercially available:

- Kinect™ by Microsoft [**68**]
- Xtion by Asus [**69**]
- Carmine by PrimeSense [**70**]

The motion tracking devices all create a depth scene using a near-infrared structured light. The devices measure the “time of flight” after the light reflects off objects. In addition some deviation of the structured light occurs. This deviation assists in producing a finer image of the object’s 3D texture as shown in Figure 14. The depth image functionality allows for simple extraction of 3D co-ordinates and ultimately the ability to perform marker-less skeletal tracking. Natural Interaction (NI) is developing rapidly and has already been applied in many fields. The rapid advancement is largely attributed to the large open source NI community.

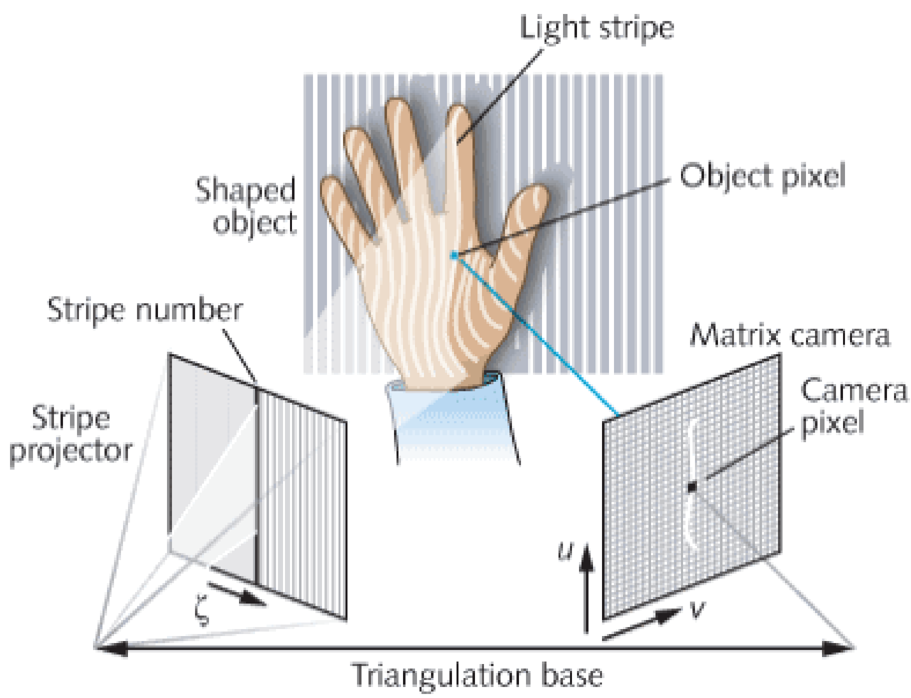

Figure 14: Structured light 3D scanning by measuring distortion in projected stripe patterns [12]

At the initiation of this project only the Kinect™ and Xtion were commercially available. One of which needed to be selected for the system. The Xtion is a PC-compatible device similar to Kinect™. The device also uses most of the same hardware and PC drivers. It was designed solely for application development whereas the Kinect™ camera was just a gaming peripheral. There were however no significant advantages of the device over the Kinect™ camera. The Kinect™ device was ultimately selected because more information was available, and because it was widely commercially available while the Xtion was available from Asus South Africa.

Kinect™

The Kinect™ device was first released for the Xbox 360 video game console in November 2010. Shortly after the original release PrimeSense, the company behind the technology used in the Kinect™ camera, launched the Open Natural Interaction (OpenNI) website (December 2010). The website provided an extensive manual along with the source drivers and Application Programming Interface (API). This enabled the Kinect™ device to be used on the computer and also in the development of unique applications. In June 2011 Microsoft released the Kinect™ software development toolkit (SDK) for Windows 7®, which also enabled the device to be used in the development of applications. The selection of a suitable SDK is dealt with in Section 3.3.1.

The Kinect™ camera, represented in Figure 15, was the first solution that introduced range imaging technology to open source motion sensing applications. It was chosen as the primary vision system due to its novel method of extracting 3D co-ordinates from the capture frame and the potential for marker-less human joint tracking. In addition the Kinect™ camera is fitted with a standard USB connector and can therefore be used with computers, provided that the drivers are installed.

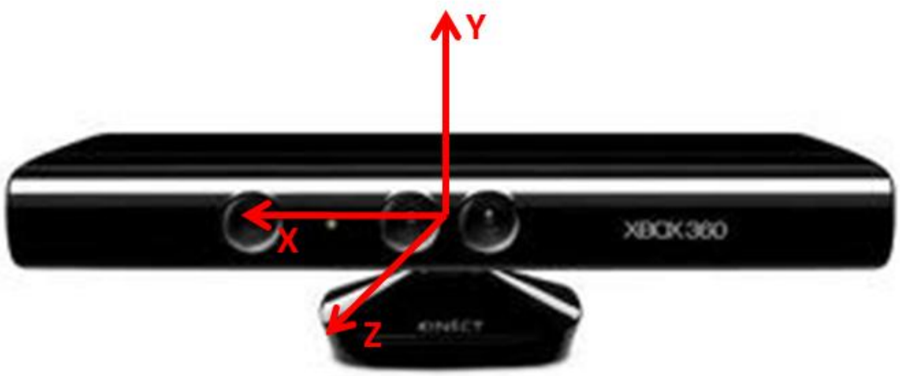

Figure 15: Microsoft Xbox 360 Kinect™ camera and the corresponding co-ordinate system [71]

The Kinect™ camera was originally developed to facilitate controller free gaming. Users would use their gestures and voice commands to control the gaming environment. Tracking, which in the past was done by distinguishing between colour and texture was drastically simplified by the depth dimension provided by the Kinect™ camera. This dimension was calculated by measuring the time of flight of the near-infrared light [**72**].

The ease of tracking players is attributed to the fact that the depth dimension allows players to be easily differentiated from the rest of the scene. The image on the left of Figure 16 shows the pattern of the near-IR light as it is projected onto the scene. The camera then measures the time of flight of the reflected light. By calculating the time it takes for the light to return the distance to the item can be determined. In addition to the time of flight principle the Kinect™ also assesses the deformation of the encoded pattern. This deformation assists in generating a more detailed image of the 3D objects. The Kinect™ camera has an on-board processor which uses algorithms to process the data to render the three-dimensional image. The images on the right and centre of Figure 16 are depth depictions of the scene captured by the camera [**72**].

Figure 16: (*Left*) IR image of scene, (*Centre*) Distance image, (*Right*) Colour coded point cloud [73]

The joint-tracking used by the Xbox is a sophisticated per-frame, per-pixel classification system utilizing decision forests and a training set of over 500 000 images. Microsoft research has released parts of the skeletal tracking code to the public for 3rd party application development, and for use by the scientific community. The access to skeletal tracking libraries has resulted in the Kinect™ camera quickly being adopted and applied to a wide variety of fields [**74**].

Kinect™ features

The Kinect™ device has the following features:

- RGB camera with 8-bit VGA resolution
- 3D depth sensor which is VGA resolution with 11bit depth providing 2048 levels of sensitivity
- Motorised tilt capable of tilting 27˚upwards and downwards
- Multi-array Microphone

The hardware layout of the Kinect™ device is shown in Figure 17. The Kinect™ retrieves 3D scene information by continuously-projecting a near-IR structured light onto the scene. The reflected light is then captured by the CMOS sensor. The Kinect™ device encodes information in light patterns as they are transmitted. The deformations of the light pattern are observed, and the sophisticated PrimeSense PS1080 on board microchip returns the 3D co-ordinates of any pixel within the scene [**12**].

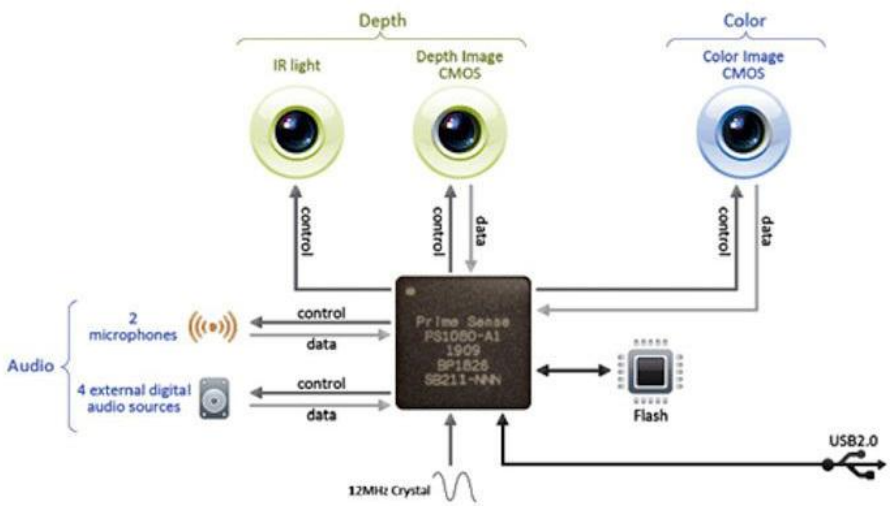

Figure 17: Internal processing layout of the Kinect™ [71]

The 3D capabilities of the camera therefore stem from the systems infrared laser projector and a monochrome CMOS sensor. As a result the system reproduces the scene which is mostly invariant to visible lighting. The primary nominal specifications for the Kinect™ camera are shown in Table 11 [**75**].

Table 11: Kinect™ hardware specifications [75]

Property	Value
Angular Field-of-View	57˚Horizontal, 43˚Vertical
Frame rate	Approximately 30 Hz
Nominal spatial range	640 x 480 (VGA)
Nominal depth range	0.8 m - 3.5 m
Nominal spatial resolution (at 2m)	0.003 m
Nominal depth resolution (at 2m)	0.01 m
Nominal random error (at 2m)	0.008m
Device connection type	USB (+ external power)

Kinect™ accuracy, resolution and precision

The accuracy, precision and resolution provide valuable insights into the suitability of the camera for the purposes of this project.

A number of experiments have been conducted to determine the accuracy, resolution and precision of the Kinect™ camera. Khoshelham evaluated the accuracy of the Kinect™ camera by comparing the point cloud with a high end laser scanner's (FARO LS 880) point cloud. The laser scanner has an accuracy of 0.7mm at 10m. The relationship between true and measured distances was near linear. The results indicated that the point cloud of a calibrated Kinect™ sensor does not contain large systematic errors when compared with the laser scanning data [**76**].

The depth resolution of the camera is defined as the smallest distance between two successive measurements. The resolution gets coarser as the distance between the camera and item is continuously increased. The resolution decreases from approximately 2.5cm at 3m and to 7cm at 5m. This quadratic reduction in resolution makes it an important consideration in determining the range and required resolution for the application [**75**,**76**]. Kozono et al. showed that the variation between different Kinect™ devices was less than 0.46% for five cameras in the distances ranging from 0.5 – 2m [**77**].

Even if the camera is kept still and the distance to a stationary object is measured, there is some variation, or noise in the measured depth values. The standard deviation these values give us the systems precision, or random error. The errors increase quadratically from a few millimetres at 0.5 m to about 4 cm at the 5m the sensor.

From the evaluation of the accuracy, precision and resolution of the camera, it is clear that data should be acquired within a 1m – 3.5m distance from the camera. Beyond 3.5m the data is rapidly degenerated by the influence of noise and resolution. Furthermore it is also important for the IR camera and the RGB camera to be calibrated. This will eliminate misalignments and distortions in the point cloud [**75**,**76**].

Comments on Kinect's™ suitability

The Kinect™ camera's performance specifications indicate that it is a suitable choice for use in this system. The single biggest disadvantage of the device is its cost. The device is significantly more expensive than traditional web-cameras with the same resolution. However the ability to reliably perform marker less tracking of workers and the ability to return 3D co-ordinates of any point within the capture frame ensure that the advantages outweigh the disadvantages.

3.2.2 Software

The applications developed for risk assessment and labour performance measurement are called the HAWK-RNLE and HAWK-PRODUCTIVITY applications respectively. Collectively they are referred to as the HAWK systems or applications. The applications are coded in C++ using the Qt creator 4.8.0 IDE. Qt was selected as it provides a simple and intuitive means of creating Graphical User Interface (GUI) applications. It also integrates seamlessly with Microsoft Visual studio 2008.

A number of libraries and applications were used in this development of the HAWK applications in order to enable the real time execution of the applications.

- OpenNI - Facilitates skeletal tracking
- OpenCV - Enables item tracking
- CUDA - Utilizes the GPU to speed up item tracking algorithm
- TBB - Enables parallel processing increasing the processed speed of the application

The system was developed in segments. Each of the segments represented a significant component that would be used in the automation of labour assessments. For each segment a number of sub-objectives were listed. These would ultimately ensure that the system had the functionality required by the final system and could also be tested. Each of the following segments was developed sequentially:

1. Worker Tracker - Skeletal tracking
2. Item Tracker - Work-piece tracking
3. Contact - Box-sphere intersection

3.3 Worker tracker

The tracking of workers is accomplished with OpenNI's skeletal tracker. The primary advantage of skeletal tracking is the ability to non-intrusively extract joint location data of a worker. However, the presence of the camera cannot be ignored. The camera is likely to intrude into the worker's normal routine and although the intrusion would appear to be small in comparison with solutions requiring workers to wear special clothing, devices and markers. The response of workers to the camera will need to be assessed.

This section includes:

- The selection of an SDK
- The development of a C++ GUI application
    - Uses OpenCV to draw small circles on the points that are tracked on the worker's hands.
    - Enables the user to select a file name for the text file to which the x,y and z-co-ordinates of the worker's hands and feet will be recorded in mm along with the time of the observation.

    - Uses the mounting information of the Kinect™ camera information to translate and rotate the relative measurements into absolute measurements to some absolute reference point defined by the analyst.
- Testing the accuracy and precision of the system in order determine its suitability for use in this project

3.3.1 Selecting an SDK

There are two SDK's that can be used to perform human joint tracking with the Kinect™ Camera.

1. Official Kinect™ for Windows SDK [**78**]
2. OpenNI SDK [**65**]

Over the duration of this thesis numerous releases and enhancements have been created to improve and develop both the OpenNI and the Kinect™ for Windows SDKs. This section discusses the advantages, disadvantages and considerations used in the selection of a SDK at the initiation of the project.

There is no discernible difference in tracking accuracy of the two SDK's. The underlying skeletal tracking algorithm is however different. The official SDK utilises a more sophisticated method, in that it can perform predictive tracking of a worker's joints. This makes it better at dealing with awkward poses and in cases when the camera loses track of the worker, the predictive tracking yields more accurate results. The increased accuracy comes at the cost of generating more false positives, in some cases it results in the tracking of inanimate objects as workers. The official SDK is also computationally more expensive. This is reflected in tests comparing the two SDKs which showed that OpenNI has a consistently higher frame-rate. The official SDK tracks more body locations than OpenNI, however it does not preserve bone lengths. This in turn means that the dimensions of the skeleton fitted on the worker can vary between frames [**79**,**12**].

Both SDKs enable access to low level data streams of the depth sensor and RGB (colour) camera sensor. The SDK's enable the tracking of multiple workers, although in this thesis only one worker will be tracked within the capture frame at a time. Originally OpenNI required the worker to assume a calibration pose prior to the initiation of tracking; this was remedied in subsequent releases. The OpenNI skeletal tracker also allows for torso-only tracking, something which the Microsoft Kinect™ for Windows SDK has yet to implement. The official SDK therefore requires the entire body of a subject to be visible within a scene whereas OpenNI facilitates upper-body tracking. As it is foreseen that most work operations will be performed by a worker which at least at times will be obscured by work surfaces, this is an important feature in the selection of the SDK, particularly in the productivity measurement. OpenNI is completely supported across platforms, whereas Kinect™ SDK only runs on windows. This is a significant advantage as it results in additional flexibility. The open source basis of OpenNI provides users with greater access to functions. It was also released earlier than the official SDK, as a result there was more support and information available at the start of this thesis [**79**,**12**,**65**,**68**].

The SDK that best aligned with the objectives for this thesis was the OpenNI SDK. The primary reasons for its selection include:

- Torso only tracking
- Higher frame rate
- Open source nature of the SDK

3.3.2 The worker tracker application

One of the objectives on the system was to simplify the labour assessments. This simplification, in addition to the execution of studies also refers to the operation of the HAWK systems. The use of GUIs improves the quality of human-computer interactions. The GUI makes it easier for the analyst to assign input values and also to monitor key values independently from the compiler. The GUI approach was used from the initiation of the project in order to test the usability of the GUI.

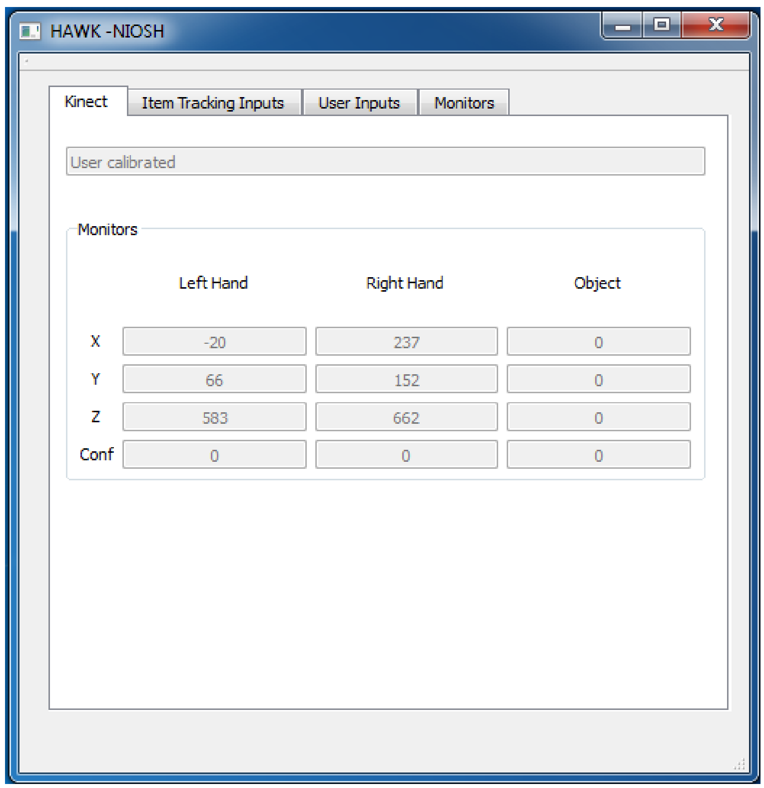

Figure 18: Graphical user interface for the worker tracker

In Figure 18, four tabs are visible at the top of the frame: *Kinect™*, *Item tracking inputs*, *User inputs* and *Monitors*. For the worker tracker phase of the systems development only the *Kinect™* tab was used. The ultimate function of the tabs is to enable analysts to scroll between uncluttered tabs at any time, prior to and during assessments.

The upper line-edit box returns information pertaining to the state of the worker tracker. The possible states include; *User lost*, *Calibration stated* and *User calibrated*. This feedback enables a visual evaluation of the responsiveness of the system to workers entering the frame.

Below this is a table containing co-ordinate data. Data is provided for the worker's right and left hands in mm. Once the item tracker is developed, positional data of the work-piece will be included. The co-ordinates provided in the table are based on Kinect's™ co-ordinate system, which is indicated in Figure 15. The last row of the table is the confidence values, which are either one or zero. The values are one if skeletal points are positively identified and zero otherwise.

In order to facilitate an evaluation of the data and to plot graphs, the co-ordinate data along with the time of the observation in milliseconds is recorded to text files. The data stored in the text files can be exported to spread sheet programs such as Microsoft Excel where it is analysed.

Tracking circles are plotted using OpenCV. These circles are plotted on the hand locations tracked by the system. These circles enable close monitoring of the system's behaviour as the worker moves around in the capture frame. Reductions in accuracy or precision can be identified. The visual representation of the system is used to establish operational guidelines.

3.3.3 Testing of the worker tracker

The tracking assesses the accuracy and precision (referred to as noise) of the worker tracker as it is used in this system. The study will yield data pertinent to the evaluation of the Kinect™ based worker tracker within the context of the HAWK-RNLE and HAWK-Productivity systems.

A fundamental issue with the worker-tracker is that there appears to be a difference between measurements taken when the worker is in contact with items and when free-standing. This is attributed to the Kinect's™ range sensing basis. Therefore, simple accuracy tests, in which the worker makes contact at predefined locations, cannot be conducted exclusively. Tests which assess free-standing positional accuracy and noise also need to be conducted.

These tests are complex as they require the use of another system for comparison. The second system needs to be capable of accurately returning positional data of a worker in a free-standing position. This would therefore either require the use of an alternative scanning device, such as one of the Vicon systems or the use of devices mounted on the worker. An example of which is the MVNBIOMECH system which was discussed in Section 2.4.3.2. This suit uses accelerometers or gyroscopes to derive positional data [**80**,**56**]. A Movin suit was available but the complexity of setting up the system and extracting data was a deterrent. Additionally, drift was a significant challenge limiting the accuracy of data [**56**]. Extensive further searches of alternative methods ultimately identified the Motoman® SDA10 robot as a possible solution to this complex problem. If it was possible to track the robot, very accurate positional data could be extracted for comparison. Furthermore, setup time and simplicity of the study would be dramatically reduced.

The only limitation of the Motoman® is the fact that it only provides data on the end effectors, which in theory is equivalent to a person's hands. For the HAWK-RNLE data on the worker's feet is also required. Due to the contact between the feet and the floor, the worker's feet could be susceptible to deviation. Additional comparative testing of the worker's feet also needs to be conducted.

The worker tracker testing is divided into two parts.

1. Freestanding tests conducted on the Motoman® SDA10.
2. Testing done on a worker, where the worker's feet were placed at predefined locations.

3.3.3.1 Motoman® SDA10 test

Background

The Motoman® SDA 10 is a dual arm robot with human torso like appearance and flexibility. The SDA10 robot has 15 axes of movement, seven per arm and one for the trunk. It has accuracy and repeatability of 100µm. The data sheet for the robot is included in Appendix 6. The high accuracy and human like appearance make it an ideal candidate for the test.

Methodology and equipment

For the testing procedure, only one small modification to the robot was made. This was the addition of a cardboard box, which appears as a head to the HAWK system. This was vital to the tracking procedure. Identifying the Motoman® as a worker requires the analyst to move the robot. Occasionally, small movements of the Kinect™ camera were required for the identification process. Although the system does identify people easier it is still straight forward to track the Motoman robot.

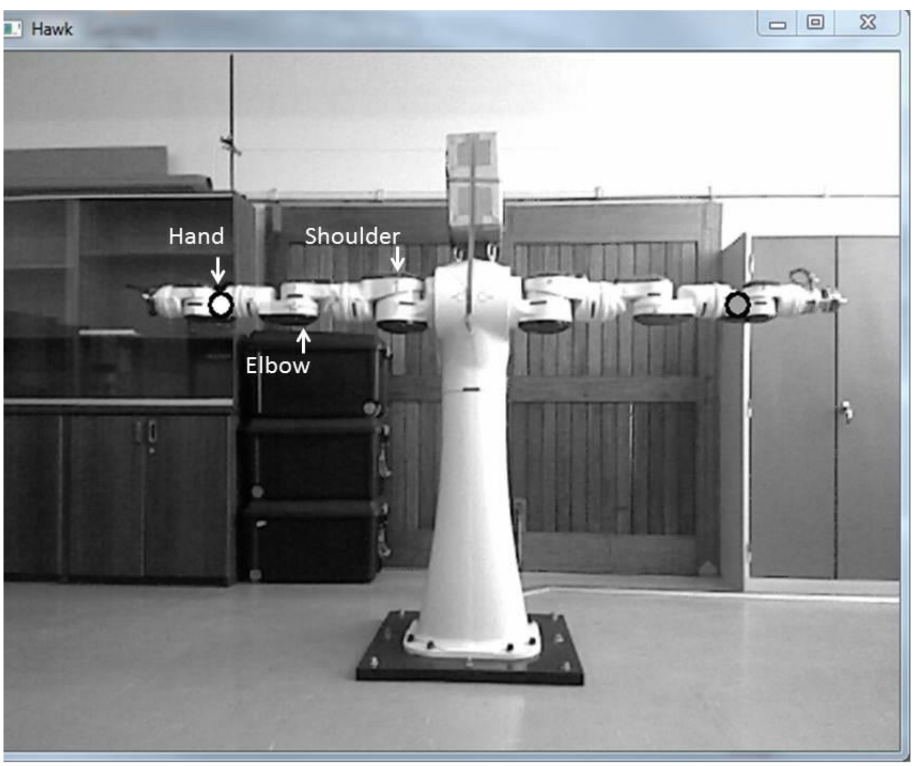

Figure 19: Tracking the Motoman SDA10

When the Motoman® was tracked for the first time, it was apparent the worker-tracker identified the hands as one of the joints and not as the end effector. A screenshot of the first tracking is represented in Figure 19. This deviation is ascribed to the calibration process. In order to minimize the complexities that would arise by conducting testing under the calibration in Figure 19. The Motoman® robot was used in tool mode. The tool mode is a specific setting that keeps the end effectors orientation constant even as the rest of the joints move. The tool position used in this study is represented in Figure 20. The end effectors are always facing forward in this case. A short screen recording of the worker-tracking tracking the Motoman® robot in tool mode is included on the DVD.

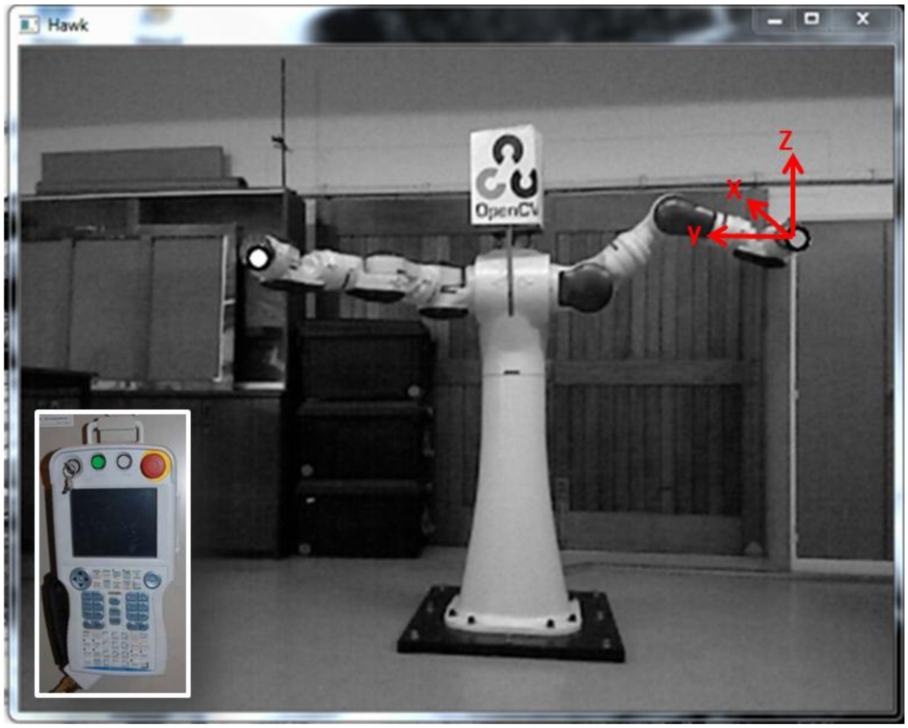

Figure 20: Motoman® DX100 dynamic controller and SDA10 robot with end effectors in the tool mode and co-ordinate system indicated

The Motoman® SDA10 robot is controlled with the Motoman® DX100 dynamic controller, which can be seen in Figure 20. The controller has a number of built-in features vital to the success of this experiment. The tool setting has already been highlighted however other features are equally important. Core to the execution of this experiment is the function that enables movement along an axis at a predefined speed. This feature manipulates the motors so that the end effector moves along the desired axis with negligible deviation of the other two axes. The user defined speed is advantageous in that movements can be slowed down to ensure that the tracking is as accurate as possible. The controller also displays the 3D co-ordinate measurements of the end effector, which are used to evaluate the accuracy of the worker-tracker.

Prior to the execution of the test the starting location, sequence and approximate distance of the movements needed to be determined. This is required to ensure that movements are reasonably large. The sequence and distance of the movements as well as the starting position were established through experimentation.

The co-ordinate systems of the Motoman® SDA10 and the Kinect™ camera are different. The Motoman® co-ordinate system for the right arm is represented in Figure 20. Due to the comparative nature of this test, alignment of the co-ordinate systems is important. The Kinect™ camera's motor is automatically set to 0˚ upon initiation of the HAWK program. The alignment around the other axis was approximated with the naked eye, by trying to get the base of the robot aligned with the bottom of the capture frame. An example of this alignment is represented by the red lines in Figure 21.

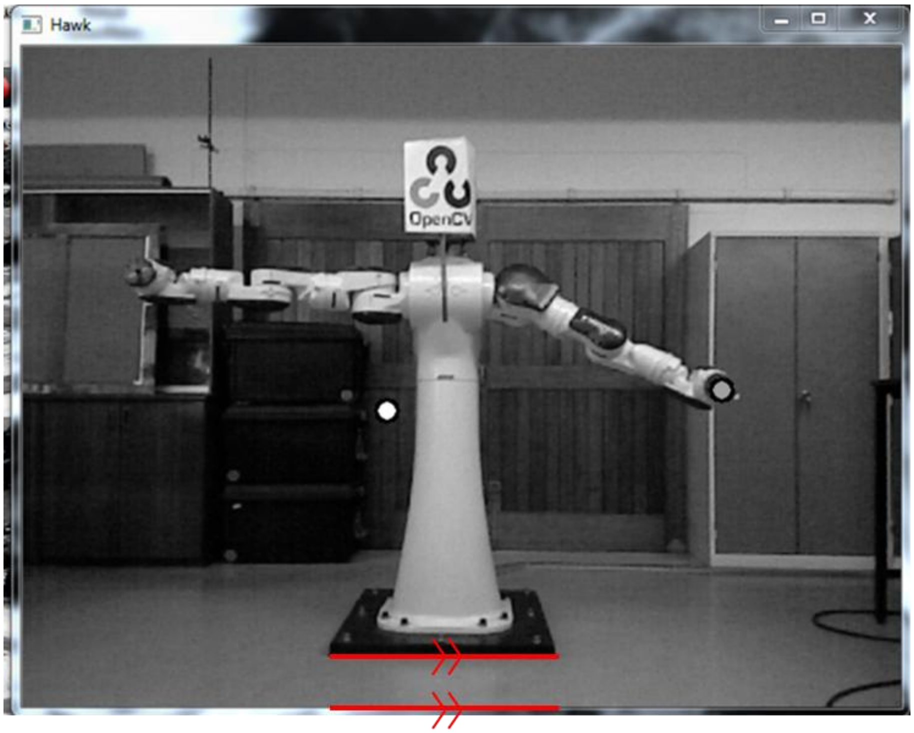

Figure 21: Motoman® tracking and alignment

Data gathering and analysis

The test involves moving the right robot arm along each axis individually. After each movement is completed, the end effector remains static for a few seconds before making the next movement. At each location the positional information is recorded off the display of the controller.

From the starting position depicted in Figure 21, the first movement according to the Motoman® co-ordinate system is in the positive *y* direction then the negative *z* direction and finally in the negative *x* direction. From this point the movements are then reversed. Movements are therefore made in the opposite *x, z* and y directions. After each movement the positional data, as supplied by the dynamic controller is recorded and later compared with the logged worker-tracker data.

The raw data recorded by the HAWK-PRODUCTIVITY system is displayed in Figure 21. From the figure, the movements in the various directions can clearly be identified. The lines are smooth indicating that the system noise is minimal. There is however a small, yet noticeable dependence between the movements. Consider the first movement; as the arm moves closer to the centre of the frame (measured in the *x*-axis), so the system records a slight movement towards the camera (reduction along the *z*-axis). This dependence between measurements is small yet noticeable at most positional data changes. It is attributed to a slight misalignment between the two co-ordinate systems.

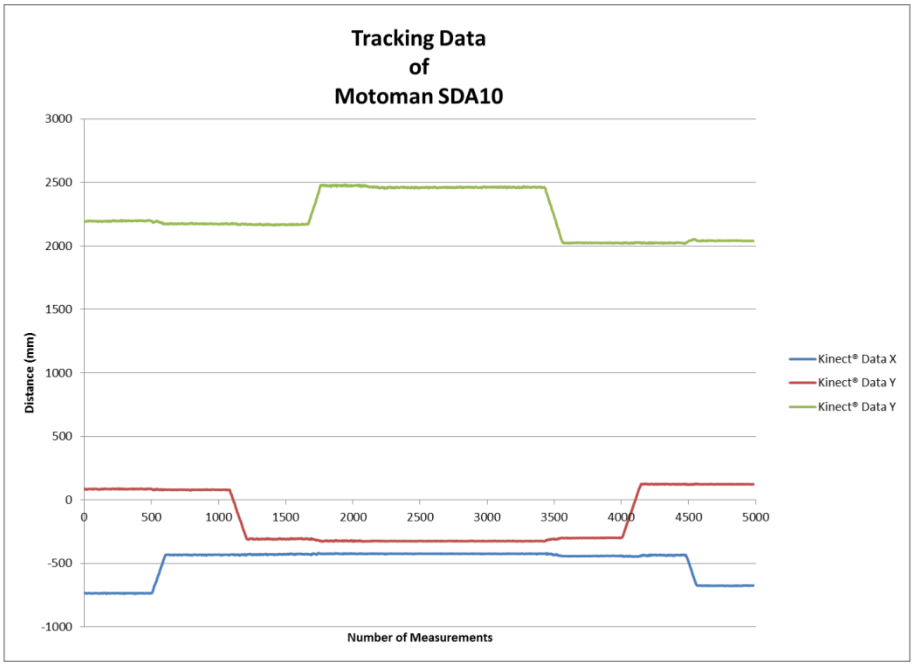

Figure 22: Raw data worker tracker recorded

The test on the Motoman® robot aims to establish the accuracy with which the worker-tracker can measure distances. It also indicates the inherent noise of the worker-tracker. Accuracy is calculated by comparing the average distance moved, as logged by the HAWK-system with the highly accurate data provided by the Motoman® DX100 dynamic controller. The noise calculation is divided into two parts. The first is the average noise. This is calculated as the standard deviation during each static period. The second measure is the maximum static deviation. This is calculated as the maximum of the differences within each of the static positions. The actual distances measured by the Motoman® robot and the Kinect™ camera, along with the accuracy and noise measurements are represented in Table 12. The experiment was conducted at approximately 2.2m.

Table 12: Accuracy and noise for the Motoman® SDA10 test

		Motoman® SDA10	Kinect™	Accuracy (Difference)	Noise (Std. Deviation)	Noise (max Deviation)
X Increment (mm)	X	339	301	38	**5**	**11**
	Y	0	-6	6	2	12
	Z	0	-21	21	3	15
Y Increment (mm)	X	0	4	4	5	12
	Y	-429	-387	41	2	10
	Z	0	-7	7	3	17
Z Increment (mm)	X	0	6	6	2	11
	Y	0	-15	15	3	14
	Z	-293	307	14	4	20
Z Increment (mm)	X	0	-19	19	1	8
	Y	0	23	23	2	12
	Z	444	-451	7	5	17
Y Increment (mm)	X	0	7	7	2	11
	Y	462	424	37	1	9
	Z	0	-1	1	5	11
X increment (mm)	X	-250	-240	10	3	12
	Y	0	0	0	1	8
	Z	0	18	18	3	19

From the data represented in Table 12 it is clear that there are some notable variations in the measurement of distances. The accuracy column shows the difference between the measurements of each system. The average difference between measurements along the axis of manipulation is 24.6mm and the maximum 41mm. This is a considerable deviation considering the actual distances moved. The maximum error represented 11.1% of the actual distance while the average was 6%.

In contrast to the relatively poor accuracy, the noise is minimal. The noise was a maximum of 5mm. This clearly indicates that the system calibrated and tracked the Motoman® SDA10 well. It also indicates that there was very little interference from external sources such as sunlight. The maximum noise during the static pose periods was 20mm. This represents the maximum deviation of the distance as measured by the worker-tracker during the static poses.

Discussion

A large number and variety of experiments have been conducted that asses Kinect's™ accuracy. Accuracy experiments on inanimate objects provide an indication of Kinect's™ capabilities. Experiments by [**77**] indicate that a calibrated Kinect™ camera is highly accurate. For the purpose of this thesis, an evaluation on the accuracy of the worker tracker needs to be conducted. As previously mentioned there are a number of ways in which this can be assessed. There have however only been limited attempts to quantify these aspects, and the results of the studies that have been conducted are not freely available.

It is important to stress that this is not the only test of the worker-trackers accuracy and noise. There are two more tests that are conducted in subsequent sections. These tests are performed on people and will provide more information relating to the accuracy and precision capabilities in both free-standing and contact situations.

The test performed with the Motoman® SDA10 indicated that the system is capable of good precision measurement. The test also highlighted the low accuracy, which was partially attributed to a small misalignment between the axes. Closer inspection indicated that in all but one of the cases the worker tracker under estimated the distance moved. The only case in which it over estimated the distance was along the z-axis, which occurred when the end effector was closer to the centre of the frame. The accuracy of the second movement along the z-axis was very high compared to those in the x-and y-directions, which were underestimating the distance reasonably consistently except for the last x measurement. The deviations resulted because the robot was used in tool mode, in which the end effector was held perpendicular to the robot's forearm. As the arm moves towards the outer limit of the capture frame, the side portion of the end effector becomes visible to the camera, leading to a slight inward displacement in the identification of the centre of the hand. The variance of the final measurement in the x-direction is attributed to the reduction in the angle as the end effector was approximately 140mm closer to the camera at this measurement.

The study on the Motoman is a unique approach and it has a number of advantages and features that made it the ideal candidate for the evaluation of accuracy of the hands. There are however also a number of disadvantages. The arms of the Motoman robot are physiologically different to humans. As a result it was required to use the robot in tool mode, as depicted in Figure 20. This is suspected to be a reason for the limited accuracy of the study.

Although the accuracy returned by the program was not ideal, apparent correlation between results and low system noise warrant further experimentation to evaluate the suitability for application of the system.

3.3.3.2 Human testing

All testing conducted on people were done in normal working clothes, which is typically long pants, shoes, a shirt or an overall.

Background

In addition to the testing done on the Motoman® SDA10 robot, additional data was collected in a set of experiments designed to evaluate the positional accuracy of the worker tracker. There are a number of aspects to the tracker that need to be considered.

1. The average time taken to track the worker
2. The accuracy and precision of the tracker

There are two primary difficulties with testing on humans. The first is the inherent inability to remain perfectly motionless. The second is the difficulty of extracting accurate positional data. Equipment to do this is not widely available or in many cases not very accurate.

The human testing component primarily focused on the position of the worker's feet.

Calibration time

In the HAWK-PRODUCTIVITY system, time losses reduce the accuracy of the study. In order to evaluate the time losses, a simple experiment was conducted that measured the time between the worker entering the capture frame and the commencement of tracking.

The test involved letting a worker enter the capture frame at command. A stopwatch was used to evaluate the time it takes from the moment the worker enters the frame until the worker is calibrated and tracking has commenced. The average time of ten measurements on a 2.8GHz Core 2 Duo with 4GB RAM was calculated as 2.55 seconds. The minimum was 2.22 seconds and the maximum 2.83 seconds. The test indicated that the system was fairly consistent. The average time it takes to lose the worker, as he exits the screen is almost instantaneous.

This test was executed under ideal conditions. There were no surfaces obstructing the worker from direct view of the Kinect™ sensor. Additionally the item tracker was not enabled. These factors could increase the time losses of the calibration process.

Human foot tracking accuracy and noise

Methodology

Testing the accuracy and noise of the worker tracker involved moving to predefined locations. These locations were marked with outlines of the worker's boots. Once at the location, the worker remains stationary in that position for a short duration before moving to the next location. The predefined locations were approximately aligned with the axes of the Kinect™ camera. There were three locations:

- Origin
- Increase in the x-direction
- Decrease in the z-direction

The boot outlines, drawn on A3 paper were placed in the locations shown in Figure 23. The floor tiles were used to ensure alignment between the sheets. Once the pages were stuck in place with masking tape, the distance between corresponding points on the outlines were measured with a DEVON® LM80 digital laser distance meter which has a measuring accuracy of 2mm. These distances were recorded for comparison later on.

Figure 23: Worker tracker accuracy and noise test

Data gathering and analysis

The worker was calibrated at position 1 indicated in Figure 23. He remained stationary for a few moments before stepping in the positive *x*-direction towards position 2. Once his feet were aligned with the outlines, the worker indicated the alignment by briefly moving his hands around before remaining stationary for a few moments. The next movement was in the negative *z*-direction to position 3. Once again after ensuring alignment, the worker moved his hands around and then remained stationary for a few moments. Finally the worker returned to position 1 where the worker remained stationary until the application window was closed by the analyst.

The brief arm movements indicated the points at which the data needed to be cut. In this way the small movements made during the final positioning is excluded from the final analysis. Due to the nature of the experiment, and the difficulty of exactly aligning the boots with the traced outlines, some accuracy was lost to misalignment. The test should however still provide an indication of the worker tracker's ability.

Accuracy is calculated by comparing the average distance moved, as logged by the HAWK-PRODUCTIVITY system with the data measured by the DEVON® LM80. The noise calculation is divided into two parts. The first is the average noise. This is calculated as the standard deviation at each position. The second measure is the maximum static deviation. This is calculated as the maximum of the differences within each of the static positions. The experiment was conducted within the normal operating range, between 2.2m and 3.2m

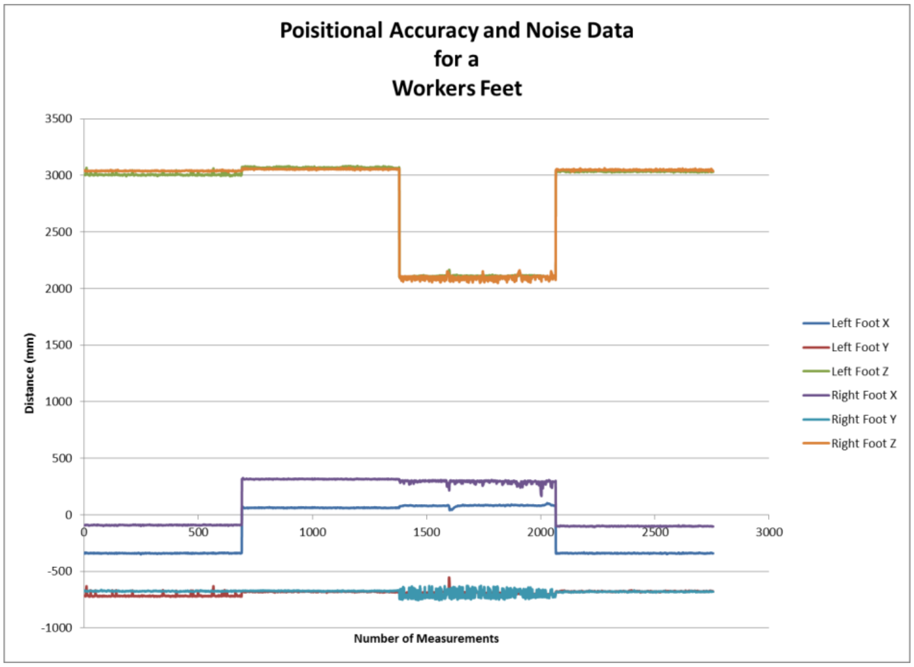

Figure 24: Accuracy and noise testing on a worker's feet

In Figure 24 a significant distortion occurs as the worker moves towards the camera. This increase in noise is owed to system failure, in which the worker-tracker struggles to fit the calibrated skeleton onto the worker. This deviation needs to be avoided. A possible solution is to evaluate and set the range in which the noise is minimized.

In the first section of the graph in Figure 24, the system falsely registered a difference in the location of the worker's feet. The skeletal tracker identified the left foot as being lower down and closer to the camera than the right foot. This is impossible on a level floor aligned with the camera's axis. In this experiment the fact that the tracking error is later corrected indicates that this is a systematic error. This type of error is referred to as an off-set error. In the first section, the average error for the *y*-co-ordinate between the left and right feet was 39.9mm and for the *z*-co-ordinate, 32.7mm. After the initial off-set error is corrected, the alignment improved. Calculations on the remaining data indicate that the error reduced to 7.2mm and 14.9mm for the *y* and *z* co-ordinates respectively. Dealing with this type of error is difficult; it is sporadic and cannot be controlled. A similar problem is the dependence between measurements, discussed in Section 3.3.3.1. There is no existing solution for this.

Off-set and dependence errors are dependent on the specific worker-tracker that is being used. A comprehensive study, which is beyond the scope of this project, is required to assess the severity and prevalence of these errors for the numerous skeletal tracking algorithms. For the purposes of this thesis, the evaluation of accuracy and noise are the single most important factors, as they indicate whether the system can be used to perform the desired productivity and risk assessments.

Table 13: Accuracy and noise for the foot accuracy test

			Kinect™	Actual	Accuracy (Difference)	Noise (Std. Deviation)	Noise (Max Deviation)
X Increment	Left Foot	X	402	448	46	3	20
		Y	35	0	35	12	99
		Z	64	0	64	10	73
	Right Foot	X	407	448	41	3	19
		Y	2	0	2	3	22
		Z	16	0	16	4	26
Z Increment	Left Foot	X	19	0	19	8	140
		Y	-10	0	10	12	156
		Z	-960	-907	53	8	72
	Right Foot	X	-25	0	25	20	229
		Y	-29	0	29	32	155
		Z	-961	-907	54	18	115
X and Z Increment	Left Foot	X	-421	-448	27	8	139
		Y	13	0	13	13	157
		Z	924	907	17	8	82
	Right Foot	X	-391	-448	57	21	227
		Y	23	0	23	32	154
		Z	954	907	47	19	117

From the data represented in Table 13 it is clear that there were excessive variations in the measurement of distances. The accuracy column shows the deviation between the measurements. The average difference between measurements along the axis of manipulation is 42.7mm and the maximum 57mm. This is a considerable deviation considering the actual distances moved. The maximum error represented 12.7% of the actual distance while the average was 9.5%.

In contrast to the study done on the Motoman SDA10, the testing on humans yielded relatively large amounts of noise. The noise was considerable with the maximum noise along a specific axis being 32mm and the maximum deviation 229mm. Systematic errors are primarily responsible for the inflated value. As a result the measurements cannot be improved once recorded. In Section 3.3.3.2, a range assessment was conducted to identify the range of distances from the camera that minimizes the systematic errors.

From Table 13 it can be seen that the data for the right foot during the first movement, in the absence of errors, is in line with the data from the Motoman experiment. The noise was 3mm and the maximum 20mm. This information provides valuable information when executing a run of the project, reflecting the importance of:

- Good quality calibrations
- Selecting an appropriate distance from the camera

- Understanding that external factors can influence the results

Range establishment

In order to identify the specific range at which feet tracking was most stable noise an experiment was conducted. The worker was required to make incremental movements by taking a step back with both feet and then remaining stationary for a few seconds. A graph of the results is depicted in Figure 25.

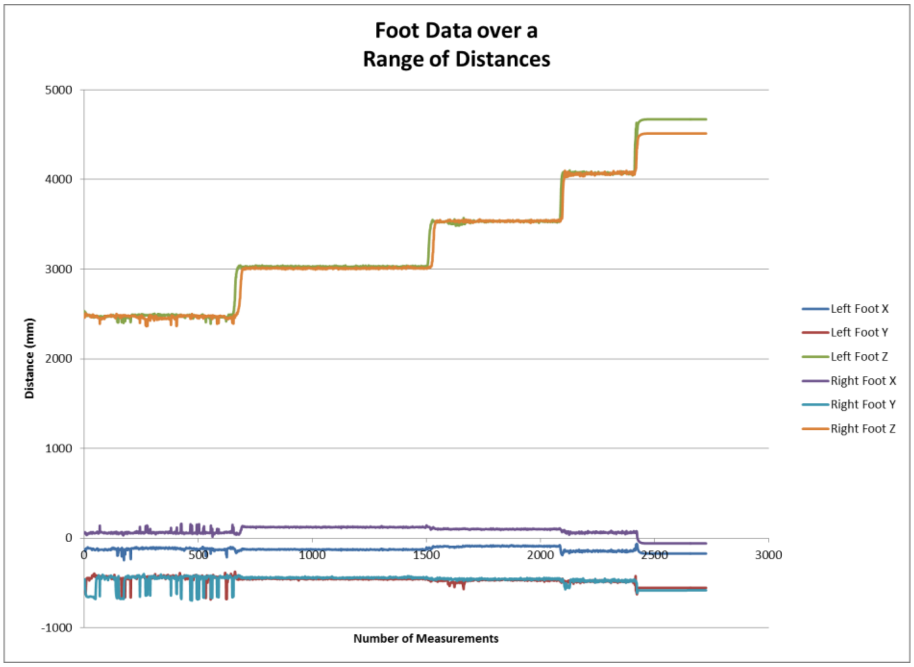

Figure 25: Noise of foot data used to identify a functional range

In Figure 25 a significant amount of noise is present at approximately 2.5m. At 3m the amount of noise decreases significantly and tracking is smooth. The amount of noise appears reasonable up to 4m at which point noise increases markedly. At approximately the 4.5m the worker tracker fails. The conclusions that are drawn from this experiment are that in systems requiring foot tracking data the worker needs to be calibrated and tracked between 3-3.5m from the Kinect™ camera.

It is explicitly stated that the optimal range for tracking of the worker's hands are different. This results because the worker tracker is capable of torso only tracking. The system therefore bypasses the failures that plague the foot tracking. A visual analysis of the hand data corresponding to the foot data in Figure 24 is included in Appendix 7. Note that the hand tracking data is not subject to the same tracking failures as the feet. The practical range for hand tracking is therefore between 1.5-3.5m.

Discussion

The human testing primarily revolved around the foot data although a basic visual analysis on the worker's hands was also conducted. There are a number of differences between the hand and foot data, the most notable and important of which is the optimal range for tracking.

- Feet, 3 - 3.5m

- Hands, 1.5 - 3.5m

The primary reason for evaluating the feet is the fact that they could be placed at pre-set locations and remained motionless for a predetermined amount of time. It is not possible to do same with the hands without either using fixed contact points or an alternate system, such as Vicon or Movin [**56**,**80**]. The fixed contact point concept was originally investigated and numerous alternatives considered, ultimately the range sensing basis of the Kinect™ along with the worker-tracker fitment render the method infeasible. The remaining option is the use of an alternative data gathering method. These methods are complex and in many cases not accurate enough to be used as a comparison. Ultimately the information obtained from the Motoman® SDA10 test offers a reasonable comparison to assess the systems capability in free-standing postures.

Hand and feet tracking tests indicated significant errors in tracking accuracy. This lack of accuracy is particularly detrimental for the proposed HAWK-RNLE. The sensitivity of the RNLE demands accurate extraction of joint location data. The specific case in interest is the ability of the system to accurately retrieve joint location data under contact conditions. The suitability in terms of accuracy for the automation of the RNLE is therefore suspended until after the contact testing.

There are a number of factors that influence the accuracy of results. In the tests the factors were selected to reflect typical factory conditions. External factors include:

- Type of clothing
  - Typical work clothes and overalls that workers would wear in a factory setting were used.
    - Loose clothing reduces the accuracy of joint location placement.
- Natural light
  - All tests were conducted indoors with natural light blocked to the maximum extent possible.
    - Natural light interferes with the Kinect™ sensors and results in increased noise.
- Gloss or reflective surfaces
  - No surfaces were specifically excluded.
    - Reflective surfaces cause interference with the Kinect™ sensors and result in increased noise or tracking failures.

Internal factors:

- The specific skeletal tracker used
- The quality of the calibration process
- The distance from the camera
- Alignment between the co-ordinate systems

A few of the factors influencing the accuracy of the results cannot be controlled by analyst. These factors result in the inherent noise and inaccuracy of the system. Other factors can be controlled without interfering with the worker’s ability to perform the required tasks. Analysts should attempt to create the optimal environment for data gathering. This includes setting the device up at the correct distance, aligning the co-ordinate systems as well as blocking out natural light and removing any unnecessary reflective surfaces.

3.4 Item tracker

Tracking of work-pieces within the capture frame is facilitated through the use of image recognition algorithms. Image recognition is a large sub-component of the computer vision field. Computer vision is the field that enables the manipulation of images by converting high-dimensional data from the real world into numeric or symbolic information. The computer vision field includes methods or acquiring, processing, analysing and understanding images.

Image recognition refers to the specific problem of trying to establish whether an image contains a specific feature or object. The objective of this section is to identify a method for real time and robust identification of a work-piece within the capture frame. This task can be easily accomplished by humans. This is significantly more challenging for computers. There are a number of constraints limiting the computer's ability to achieve this [**81**,**82**].

Existing methods are limited by strict constraints and can only be applied for simple shapes and in most cases also need to adhere to strict constraints, such as well-defined illumination background, scale and orientation [**83**].

Image recognition applications can be classified into three groups [**66**]:

- Object recognition
  - The objects recognized within the capture frame are pre-defined or learned. The recognition therefore involves the matching of features.
    - Example: Extraction of dimensional or positional data of an object.
- Identification
  - Objects are only recognized individually.
    - Examples: fingerprint identification, handwriting recognition, checking vehicles number plates.
- Detection
  - Images are processed and analysed to identify a specific condition. This method is often used to identify smaller regions of interest for further analysis by more computationally expensive techniques for deeper analysis.
    - Examples: Manufacturing defect detection or the detection of a vehicle in an automatic road toll system.

In order to track work-pieces, object recognition algorithms were considered. A variety of methods and algorithms are available for work-piece tracking. All object recognition approaches can be divided into three distinct steps: detection, description and matching. For real time execution on household computers, each of the three steps needs to be done quickly [**81**].

The selection of an appropriate technique was largely decided by the speed, reliability, and robustness characteristics. The selected approach should be able to detect and describe stable and repeatable dominant features that are invariant to changes in scale, rotation, viewpoint, noise and illumination. Ultimately a selection needed to be made between two recent approaches; Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF). These approaches represent a significant improvement in the field. Bauer et al. compared various implementations of the SIFT (Lowe, LTI-Lib sift++, Harris) and SURF (SURF, SURF-d) approaches. The study evaluated both the invariance to the changes as well as the runtime efficiency [**84**].

The number of correct matches found per second for changes in rotation, noise, scale, illumination and perspective are represented, for the different SURF and SIFT implementations, in Figure 26. The SURF implementations outperformed the SIFT implementations in terms of the number of correct matches made per time interval. It should also be noted that the SIFT approach does however produce more and better quality key-points and descriptors.

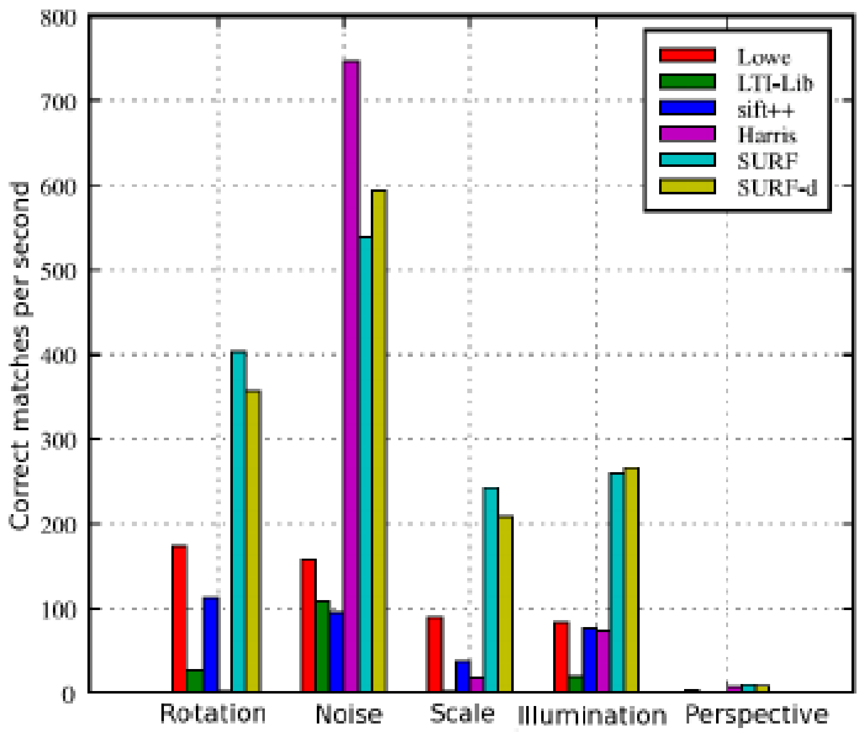

Figure 26: Number of correctly found matches per second for all of the conducted tests and algorithms [84]

Selecting a suitable approach largely depends on the application. If computing time is important then SURF is the preferred approach. Bauer et al. indicated that the superior runtime performance of SURF outweighs the slightly better feature quality of SIFT. Bay et al indicated that SURF also excels in a variety of important aspects, including robustness and reliability. It is also invariant to changes in image size and rotation [**81**]. There are certain cases in which other approaches would yield better results. Juan et al. showed that for large image rotations SURF lacks performance. However, their study showed that SURF is fast and robust in most cases [**85**].

3.4.1 SURF

The real time requirements of the HAWK system place an emphasis on speed. SURF superior performance regarding the number of positive matches per time unit along with the ability to select the item to be tracked in real time resulted in its selection. Other alternatives, such as Haar training execute matching of features is even faster than SURF. However, these approaches require training of classifiers which takes many hours [**82**,**86**].

The increased performance of SURF results from [**81**]:

- The use of an intermediate image representation called the integral image
- Fast-Hessian matrix-based detector
- Distribution-based descriptor

The three phases of the SURF implementation in object recognition [**81**,**86**] :

Detection This refers to the identification of interest points, which are distinct locations within the capture frame. The interest points include features where the contrast with the surroundings are significant, examples include: blobs, T-junctions and corners.

SURF uses a basic Hessian-matrix approximation. This is effectively used with integral images to significantly reduce computation time. The detector is, under different viewing conditions able to reliably and repeatedly identify the same interest points.

Description By evaluating the neighbourhood of each interest point a descriptor can be created. The descriptor is essentially a feature vector.

The Description phase in SURF firstly involves setting a reproducible orientation which reflects the information within a circular region around each interest point. After this a square region, aligned to the established orientation, is constructed. This square is broken down into either 64 or 128 subsections which form the SURF descriptor.

In many citations, rotation invariance is not necessary. An upright version of SURF (U-SURF) bypasses the identification of the reproducible orientation for each interest point. This reduces the computational expense, making it faster to compute while also remaining Robust for rotations of ±15˚.

The SURF descriptor is distinctive and concurrently robust to; noise, detection displacements, geometric deformations and illumination changes.

Matching The matching phase involves aligning of the descriptor vectors. It is done based on the distance between the vectors. The time required for matching is directly dependent on the dimensionality of the descriptor. For rapid matching fewer dimensions are preferred, however this also makes it less distinctive.

The enhanced performance of SURF with regard to execution time is largely attributed to the use of the integral images. The integral image is an intermediate image representation. It is derived from the input image and it reduces the number of operations required for simple box convolutions. It also makes computation time invariant to changes in scale [**81**].

The SURF detector is based on the determinant of the Hessian matrix. Bay et al. showed that the performance of the detector was comparable and in some cases better than some of the best interest point detectors. In addition, even without dedicated optimizations, almost real-time execution of the algorithm was possible without a reduction in performance. This is the single biggest advantage making SURF the preferred approach for the online approach of the HAWK system [**81**].

The SURF descriptor outperforms numerous of other algorithms in terms of speed. This is attributed to the simplicity along with the use of integral images. Finally, the matching step is enhanced by Laplacian based indexing strategy. This enables faster matching without compromising performance [**81**].

Additional Information and the mathematics behind the algorithm are provided by Bay et el. [**81**]

3.4.2 OpenCV SURF_GPU

Due to the popularity of and effectiveness of SURF, there are a few open source SURF libraries that have been developed and are available on the internet. These libraries include OpenCV's SURF and OpenSURF implementations. The use of these open source libraries significantly reduces the complexity of developing the item-tracker [**87**,**86**].

OpenCV's SURF_GPU implementation was selected for use in this project due to its ability to make use of the GPU's processing capabilities. Computing successive octaves of a Hessian matrix is computationally expensive. In order to address this problem Nvidia's CUDA™ toolkit is utilized to port this intensive algorithm to the Graphics Processing Unit (GPU). GPU's have a parallel architecture and as a result excel in matrix operations. This in turn drastically reduces the execution time, ultimately moving towards enabling real time execution of the SURF algorithm [**88**].

SURF_GPU was used in the development of the HAWK system as a feature detector and descriptor. Matching was then accomplished by Brute-force matching and finally Random Sample and Consensus (RANSAC) was used to minimize error matching and obtain the optimal transformation matrix between images. Ultimately the weighted centre of the corresponding positive matches is determined and used in the tracking of the item.

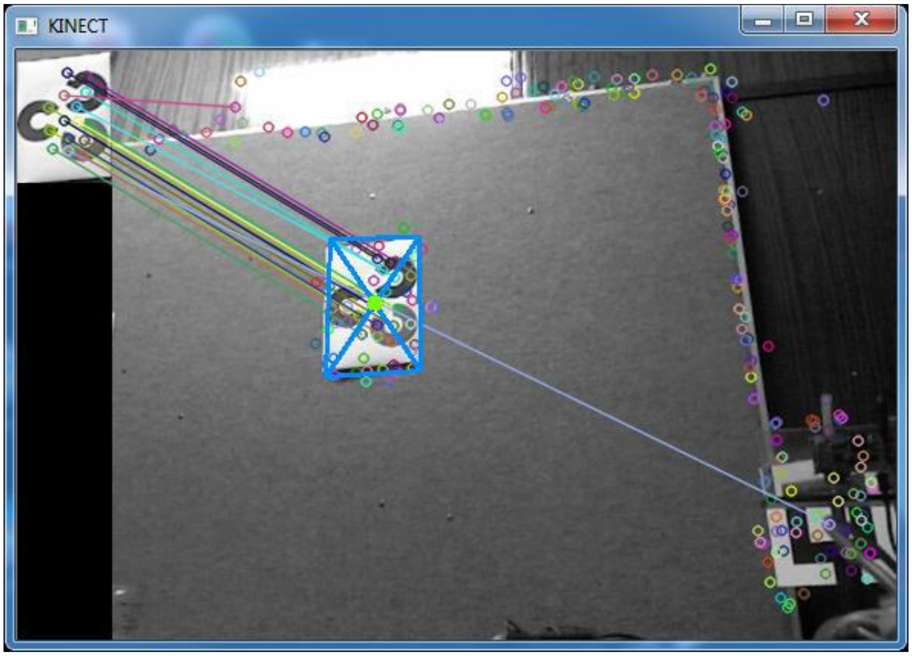

Figure 27: Tracking a logo with OpenCV SURF_GPU implementation

Figure 27 is a visualization of an early tracking procedure. The circles represent interest points in the image. The lines drawn between the OpenCV logo in the top-left of the capture frame and the logo in the frame represent the matched interest points. In order to save computational costs in the final versions of the HAWK systems, the linking lines are no longer drawn, and the interest points are represented in black and white. OpenCV's SURF_GPU implementation works on grey scale images. It captures a frame from the camera and converts it into grey scale. Functions are used to firstly set the parameters of the algorithm and then to extract unique key-points and descriptors from an image. These are then used to identify whether the same image is present in the capture frame, as represented in Figure 27 [**89**].

OpenCV SURF_GPU parameters and user inputs

The SURF_GPU class is included in Appendix 3. The class SURF_GPU is capable of storing results in the GPU and CPU memory and it provides functions to convert results between CPU and GPU versions. In The GPU results are stored in GpuMat format.

Prior to the initiation of the SURF detector and descriptor, the user is required to set a number of parameters [**89**]:

- **Extended** (Boolean)
    - 0 - The basic descriptors, of 64 elements each will be computed.
    - 1 - The extended descriptors of 128 elements each will be computed. The extended version is computationally significantly more expensive. For real time applications it should be avoided.
- **Upright** (Boolean)

  - 0 - The detector computes orientation of each feature.
  - 1 – The orientation is not computed. This is significantly quicker and can be used if rotations remain below 15˚.

The HAWK system is a real time application. As a result emphasis is placed on reducing computational cost. The *Extended* and *Upright* parameters are pre-set within the HAWK program to 0. This results in a balance between flexibility and processing speed. If the frame rate is deemed to be too low, the processing speed can be maximized by setting *Upright* to 1. The limitation of the *Upright* version is the flexibility with regard to rotation.

A few parameters, shown in the GUI in Figure 30, can be set by the analyst using the HAWK system. These values will vary according to the scene and the item that is being tracked [**89**].

- **Hessian Threshold**
  - This is the threshold for the interest point detector. Only those features with values larger than the Hessian Threshold are retained by the detector.
  - The larger the value, the less interest points will be found.
  - Values will vary depending on the image contrast.
    - The default value is 100
    - Values range between 50 – 600
    - Good values are typically between 300 to 500
- **Octaves**
  - The number of a Gaussian pyramid octaves that the detector uses.
  - If you want to get very large features, use the larger value. If you want just small features, decrease it.
    - By default the value is set to 1
    - Values range between 1-10
- **Octave Layers**
  - The number of images within each octave of a Gaussian pyramid.
    - It is set to 3 by default.
    - Values range between 1-10

Once the user has set the parameters to appropriate values the SURF implementation can execute the detection, description and matching phases. Error matches are removed through the use of RANdom Sampling And Consensus (RANSAC).

3.4.3 Random Sample and Consensus

The SURF feature matching algorithm produces false matches called outliers which typically originate from ambiguous features or background clatter. The RANdom Sample and Consensus (RANSAC) algorithm is used to efficiently remove outliers, thereby minimizing error matching and concurrently improving the clustering results.

RANSAC is an iterative algorithm which is used to approximate the planer surface of a user selected work-piece from the bunch of matches provided by the SURF algorithm. The probability of providing an acceptable approximation increases with each additional iteration. The RANSAC algorithm is non-deterministic and therefore only provides an acceptable result with a certain probability.

RANSAC uses a sampling approach to oust outliers. The algorithm iteratively selects a random subset from the original matches. The mathematical basis of the implementation is included in Appendix 4. The implementation in the HAWK system is summarised in the following steps [**90**]:

1. Randomly select a cluster size of matched-interest-points.
2. Calculate the relative states (Position: x_0, y_0, z_0 and Rotation: Ψ, ϑ, φ) of the plane representing the 2D work-piece. The assumption is made that the all matched interest points are co-planar.
3. The selected points are re-projected according to the derived states. The re-projection enables the evaluation of relative states by considering the difference between the matched-interest and re-projected points.
4. If the re-projected points fall within a predefined tolerance, defined by the standard deviation of the discrepancies, then the origin of the projected plane is returned for tracking.
5. Otherwise, repeat steps 1 through 4. The maximum number of repetitions will be N, the user defined bailout number.

The number of iterations before bailout, N, is ideally calculated according to Equation 7. The value *P* (typically set to 0.99) is the user defined probability that at least one of the random samples does not include an outlier. *v* represents the probability of observing an outlier and *m* the minimum number of points required [**90**]:

$$N = \frac{log(1-p)}{log(1-(1-(v)^m)} \ldots (7)$$

One of the fundamental bases of the HAWK systems is the axial alignment between the work-piece and the camera. As a result the work-piece should always be near perpendicular to the capture frame. The number of parameters that need to be estimated and the corresponding computational cost are therefore significantly reduced. The tolerance basis of the RANSAC implementation results in some flexibility with regards to rotation around the axis. The degree of rotation is limited by the tightness of the back-projection error defined by the analyst.

The primary reason why RANSAC is applied is because of its ability to perform robust estimation of the origin of the work-pieces planer surface. The origin corresponds to the centre-point of the user selected work-piece as described in Section 3.4.4.2 . It can therefore accurately derive the centre-point of the work-piece in the presence of many outliers, as would typically be present in factory environments.

RANSAC also has a few disadvantages. There is no defined upper limit on the time required to compute the origin of the plane and in cases, such as the applied implementation, where the number of iterations are bounded then the solution provided could be sub-optimal. Another disadvantage is the complexity associated with the setting of case specific threshold values. RANSAC is also only capable of estimating one model for each data set.

The RANSAC method offers a trade-off between the processing time and the probability of returning a reasonable planer approximation. Fortunately RANSAC is a highly parallelizable search algorithm and can thus be executed on all available CPUs with Intel's Threading Building Blocks (Intel® TBB). Parallel processing ensures that the results are improved without requiring additional processing time.

3.4.3.1 Threading building blocks

Threading Building Blocks (TBB) by Intel® is a widely used C++ library used for task parallelism. It enables users to utilize multicore performance. To utilize the multicore processing capabilities provided by Intel® TBB, OpenCV libraries with TBB enabled need to build. The process of building the new libraries can be found in Appendix 5. Without TBB installed, OpenCV applications only utilize the processing power of a single computer core. By Installing OpenCV with Intel® TBB, the library automatically uses threading to utilize all the available cores. This significantly speeds up computing of computationally expensive algorithms [**91**,**92**].

The reductions in computing time vary greatly between different scenes and computers. Furthermore TBB is only applied to the RANSAC component of the Item tracker. An early version of the HAWK program enabled analysts to toggle Intel® TBB on and off. The results of toggling Intel® TBB on a constant scene are represented in Figure 28. This basic experiment enables a crude demonstration of the impact that TBB has on processing speed. The single frame example indicates that Intel® TBB facilitated a reduction of more than 3.5 times the original duration. The impact of Intel® TBB on the Items tracker frame rate is small. This is because the processing time of the threaded RANSAC component is in the order of 100 times less that the SURF algorithm.

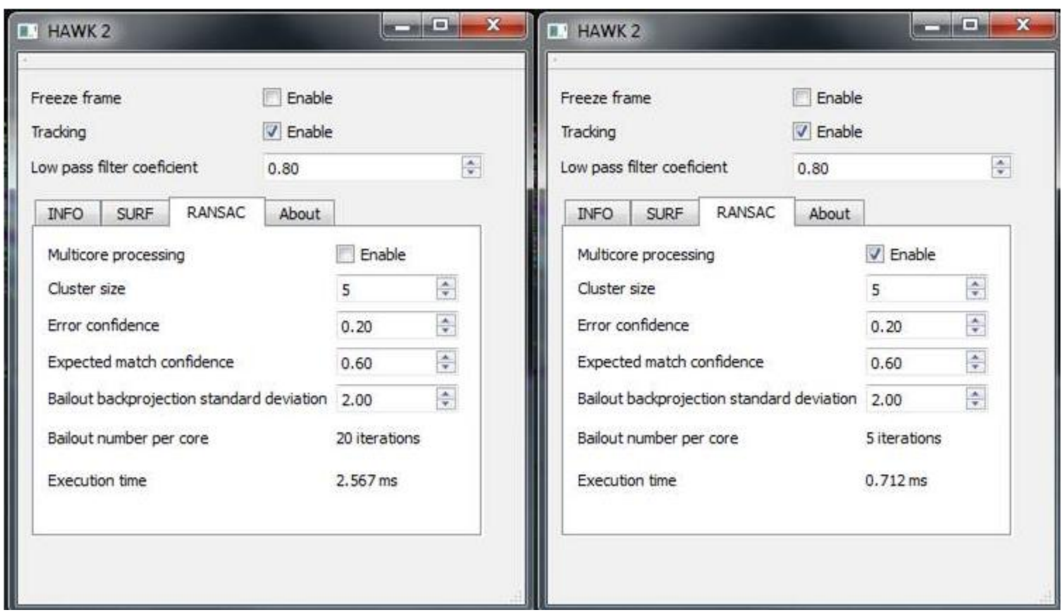

Figure 28: Reduction in execution time enabled by TBB

3.4.3.2 Variables

The RANSAC variables must be adjusted, in the GUI depicted in Figure 30, for each different scene. The variables must be selected so that the item-tracker can reliably and accurately identify the work-piece in a reasonable amount of time.

- **Cluster size**
  - The number of points randomly selected
  - Default value 6
  - Values vary between 5 and 20
  - The number of points always has to be smaller than the total number of features identified even in the absence of the work-piece.
- **Bail-out number**
  - The number of iterations before the algorithm exists the loop.
  - Default value 500
  - Values vary between 1 and 10 000
  - The value determines the maximum time spent attempting to identify the plane. As the value increases so does the probability of identifying an acceptable solution.
  - Analysts should select larger values as the proportion of outliers to inliers increases.
- **Back projection error**
  - The limit against which the standard deviation of the re-projected points are tested
  - Default value 10
  - Values vary between 1 and 300
  - Smaller values yield more accurate results.
  - The value also controls the degree to which angular deviations are accepted.
- **Low pass co-efficient**
  - A simple decimal value which filters the centre-point estimation.
  - The value represents the percentage of the previous location along with current location.
  - Default value 0.50
  - Values between 0.00 and 1.00
  - The lower the value the more noisy the centre point estimation.

3.4.4 Discussion

The SURF_GPU implementation used in conjunction with RANSAC to minimize error matching and speeded up through the use of Intel® TBB, provides real time 2D tracking data on a user defined item in terms of pixel values.

If the focal length f of the camera is known, along with the pixel co-ordinates x_{cam} and y_{cam} and a single true measurement, in this case Z_{real}, then the co-ordinates in mm can be determined according to Equations 8 and 9:

$$X_{real} = \frac{Z_{real}\, x_{cam}}{f_x} + c_x \ldots (8)$$

$$Y_{real} = \frac{z_{real}\, y_{cam}}{f_y} + c_y \; \ldots (9)$$

In order to retrieve the 3D co-ordinates in mm, the system retrieves the depth information at the pixel location of the centre point. This depth information can be retrieved from two sources; the depth-map and the point-cloud. The depth-map was used as it uses less memory and therefore enhances the processing speed of the application. Once the depth in mm is extracted, the x and y co-ordinates in mm are determined.

The principle behind the extraction of the x and y co-ordinates in mm is represented in Figure 29.

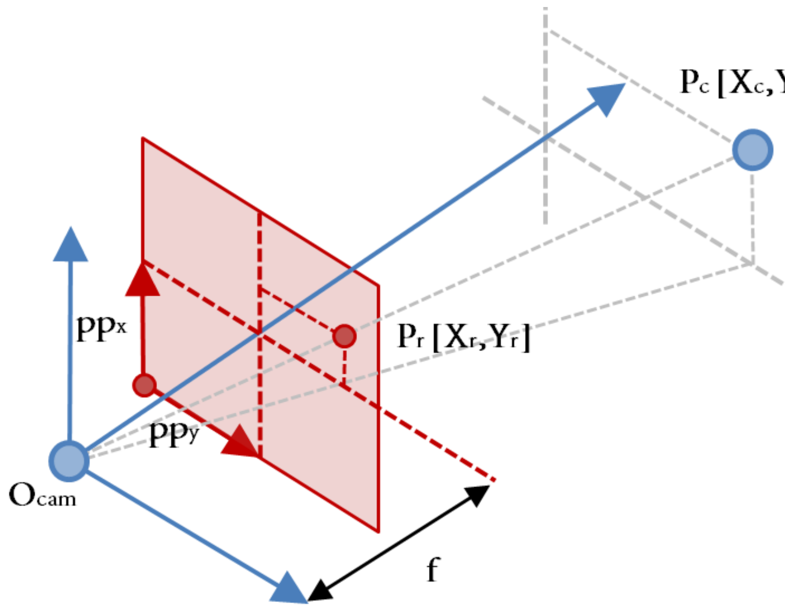

Figure 29: Pin-hole camera model

In this way the 3D co-ordinates in mm of the centre point of projected plane can be determined. The locations of the extreme points of the axis-aligned work-piece are also points of interest for establishing contact between the worker and the work-piece. These points are derived when the analyst draws the bounding box around the item to be tracked as described in Section 3.4.4.2. The pixel values are then scaled in the same manner as the centre point, according to equations 9 and 10.

3.4.4.1 Item tracking inputs with the GUI

Within the GUI there is a unique tab for the item tracker. The tab is depicted in Figure 30. The tab houses all of the pertinent user inputs for both the SURF and RANSAC algorithms. The tab also contains a dial for tilting the Kinect™ camera. The dial enables the analyst to tilt the camera upwards or downwards in order to ensure optimal view of the workstation, prior to selecting it. The maximum angular variation of the device is +-27˚. If the motor is used to tilt the camera, the co-ordinate system will be altered. The values need to be transformed in order to remain within the user defined co-ordinate system established by the base of the camera.

The Kinect™ motor rotates through an angle *Θ* around the *X-axis*. The *Y* and *Z* measurements therefore need to be compensated. This is done by transforming the *Z* and *Y* co-ordinates through the direction cosine matrix of the mounting angles of the camera *Θ*. The transformation matrix is represented in Equation 10. The Y co-ordinate is further offset by the mounting height of the camera. This is done so that the ground level is registered as approximately 0mm.

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -sin\theta \\ 0 & sin\theta & \cos\theta \end{bmatrix} \ldots (10)$$

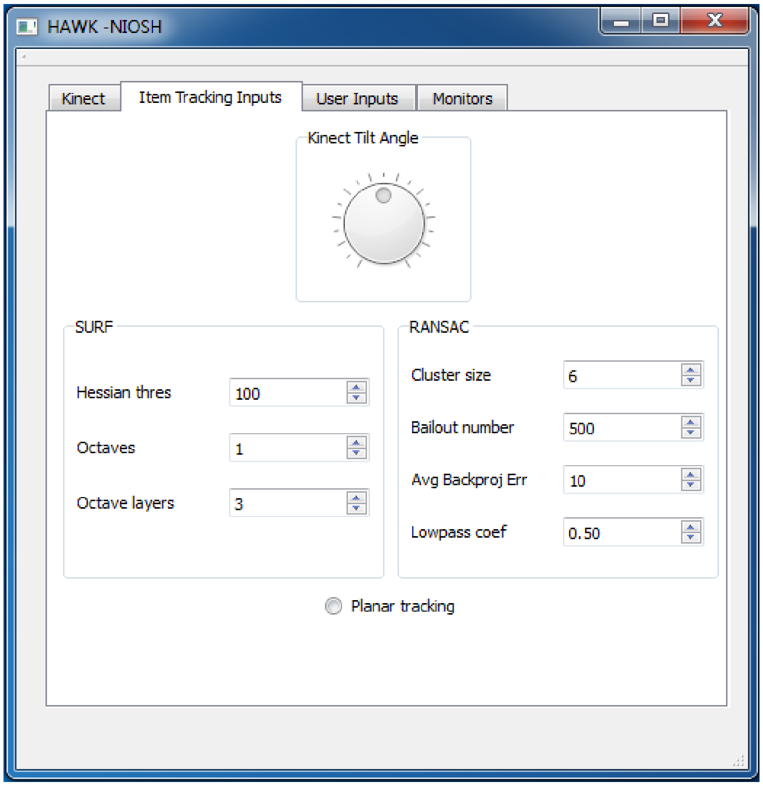

Figure 30: GUI for SURF and RANSAC inputs

The final feature on the GUI is the planar tracking radio button. After the variables are set and the workspace and work-piece have been selected, then worker is required to click on the planar tracking radio button in order to initiate tracking. The process of selecting the work-space and the work-piece are discussed in the subsequent sections.

3.4.4.2 Operating the item tracker

The operation of the item tracker is fundamental to the HAWK systems. Users are required to

- Select the work-space
- Select the work-piece
- Setting the user inputs for the SURF and RANSAC algorithms

Each of these selections is vital in ensuring accurate and reliable tracking of work-pieces.

Selecting the workspace

The first step in tracking a work-piece involves selecting the workspace within which tracking will take place. This principle was incorporated to ensure that only one work-piece is within the workspace at any given time. This is required because the RANSAC algorithm is only capable of estimating one model for each data set [**90**].

The user defined workspace enables multiple items, such as inventory piles to be within the capture frame but outside of the workspace. As an example, in Figure 31 there are two OpenCV logos. The scene has been selected in such a way that only one logo is present in the scene.

The workspace principle has the added advantage of increasing the matching speed of the item tracker. The increase in speed will correlate to the reduction in the workspace size. A disadvantage is that workers will be restricted to working within the workspaces, and they will not be able to see the boundaries that have been selected. The system will therefore only be suited to fixed workstation environments or short duration studies.

Figure 31: Selecting the tracking space

In Figure 31, the workspace is defined by the black bounding box. It is defined by depressing the right control button of the mouse at the desired origin of the scene. The analyst then, with the button depressed drags the box to the desired dimension upon which the button can be released. The scene can be reselected at any point in time

Analysts must always define the workspace larger than the maximum size of the work-piece. This includes cases where the work-piece will be brought closer to the camera. It is suggested that analysts select the workspaces with the work-piece appearing in its largest state

Selecting the work-piece

Figure 32: Selecting the work-piece

Once the workspace has been defined the analyst selects the work-piece. This is achieved by placing the inner angle of the crosshair on the outer corner of the image or item to be tracked. Once aligned the left mouse button key is depressed. A white rectangle, as shown in Figure 32, will be created as the curser is dragged across the image. Again the inner angle of the crosshair must be aligned to the outer corner of the image, as demonstrated in Figure 33. At this point the mouse button must be released.

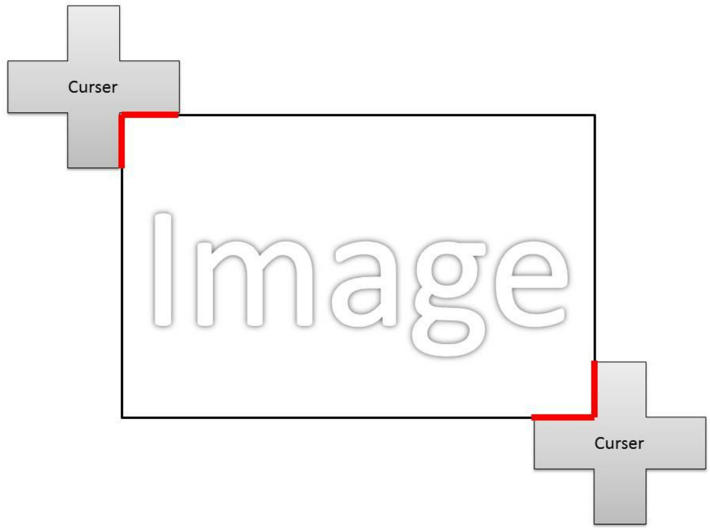

Figure 33: Curser location for selection for the work-piece

The accuracy with which the item is selected is largely dependent on the alignment between the work-piece and the capture frame. The bounding box is aligned with the capture frame. As a result, if the item is to be accurately selected both the Kinect™ camera and item need to be aligned.

The bounding box drawn around the work-piece makes it easy to detect any angular deviation. Humans have an enhanced ability to align two line segments. This ability is referred to as Vernier acuity and it is significantly better than normal visual acuity. Angular deviations are easier to spot as the length of two lines increase. As a result the ability to identify misalignments is also improved as the item increases in size relative to the capture frame.

It is suggested that analysts select work-pieces as close as possible to the camera, while still falling within the user defined workspace. Similar to the workspace selection, the item may be reselected at any time. This is useful if the item was poorly selected or if a different work-piece is to be tracked.

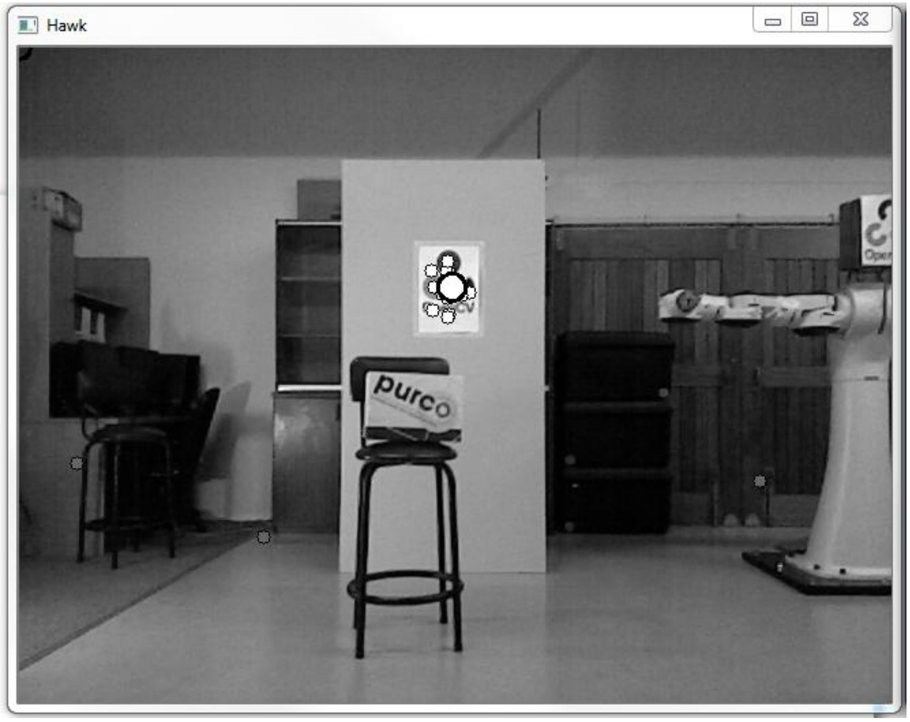

Figure 34: Item tracker tracking the selected work-piece

In Figure 34, the item tracker has been initialized and is currently tracking the selected item in real time. The item tracker's ability to match features and eliminate outliers is depicted by the large white circle which is drawn in the centre of the item. The circle will change to grey if RANSAC fails to identify the planer surface within the bail-out number.

The smaller white and grey circles are plotted for all query points. The visual elimination of error matching is indicated by distinguishing between matches falling within a single standard deviation (68%) of the centre point of all matches and those that do not. These are filled in white and grey respectively. The purpose of this depiction is to aid the analyst in selecting the input variables.

3.4.5 Item tracker testing

This section determines the suitability of the item-tracker for the desired application. The tests include assessment of:

1. Processing speed and accuracy
    - Time required to initiate tracking
    - Accuracy of selecting the work-piece
    - Matching speed, measured by the frame-rate
2. Scale considerations
    - The minimum size and distance from the camera of the work-piece
3. Lighting considerations
    - Although SURF is invariant to lighting, these experiments are done in order to evaluate the functional operating range

4. Rotation considerations

3.4.5.1 Processing speed and accuracy

The processing speed of the item tracker refers to the inner-efficiencies of the system. It includes consideration of the time between selecting the work-piece and the commencement of tracking as well as the frame-rate of the item-tracker under operation. The accuracy refers to the closeness with which the user selected work-piece matches the actual dimensions.

Time required to initiate tracking

The time required to initiate tracking is largely determined by the GPU used. The SURF algorithm needs to be mapped to the GPU which takes a few seconds, typically less than five seconds. Once the algorithm has been mapped the user can reselect the workspace or the item and tracking will commence almost immediately.

The exact duration between selecting the work-piece and the commencement of tracking has not been included as it varies significantly between different computers and only needs to be conducted once at the initiation of the study.

Matching Speed, measured by the frame-rate

The frame-rate is dependent on:

- Processor
    - RANSAC runs on all available cores of the CPU
    - The processing speed and number of cores therefore influences the frame-rate
- GPU
    - The SURF_GPU implementation runs on the GPU
    - The processing speed and number of cores therefore influences the frame-rate
- The user inputs which control the number of features
    - As the number of key-points increases, so does the processing time
    - The ratio of inliers to outliers also affects the speed
- The size of the work area
    - Smaller work areas results in fewer outliers and therefore speeds up the frame-rate

Due to that vast array of influencing factors, a specific frame-rate could not be determined. In order to gauge the capabilities of the item-tracker, the minimum frame rate from the entire set of item tracking tests was determined. On a 2.8 GHz Quad Core processor with 12 GIG RAM and an NVidia GeForce 9600GT graphics card the minimum frame rate was 21 frames per second. The frame rate will decrease significantly when the other components of the HAWK systems are running simultaneously.

Accuracy of selecting the work-piece

A simple experiment was conducted which required an analyst to select an A3 approximate axis aligned work-piece for tracking. The selection process was repeated 20 times at each of the three different distances. The selection testing provides an indication on the combined effect of the user-error and the focal length conversion error which results when converting from pixel to mm co-ordinates.

Table 14: Item selection accuracy

	Actual		1.75m		2.4m		3.2m	
	x	Y	x	y	x	y	x	y
Average (mm)	297.0	420.0	296.6	420.5	298.4	421.0	301.6	418.1
Standard Deviation (mm)	-	-	2.2	3.2	3.9	3.9	5.8	6.3
Maximum error (mm)	-	-	8.1	12.0	13.8	13.9	22.6	21.1

The results of the study are represented in Table 14. The accuracy of the selection is good and as expected the error increases as the work-piece is moved further away. The increased error results from the increased difficulty of selecting the work-piece that appears smaller.

3.4.5.2 Constants

In all of the experiments relating to the item tracker, there are a number of variables that are set at constant values. These are represented in

Table 15. A description of these variables is presented in Sections 3.4.2 and 3.4.3.2.

Table 15: Constants for item tracker testing

Sample size	800
Cluster size	6
Bailout number	500
Back Projection error	10
Low pass Coefficient	0.5
Hessian Threshold	100
Octaves	1
Octave layers	3

There are also environmental factors that could influence the results. The most important of which is natural light. In order to minimize the influence of natural light, it was blocked out to the furthest extent possible. Others, such as lustre could also have an impact. All tests were conducted on a plain sheet of paper with a logo printed on it and in the same environment, to offer maximum stability during these tests.

3.4.5.3 Item size and distance from the camera

One of the biggest limitations of using the SURF based approach is that the work-piece needs to have unique features. Additionally the work-piece also needs to be large enough so that the features can be descripted and matched. The feature based methodology means that at a certain size distinct features are no longer identified. This is similar to the human eye, where at a certain distance a distinction between black and white lines, a predefined distance apart, cannot be made and the item appears grey.

As the item size decreases so too does the number of features. As a result the location of the work-piece is determined by fewer interest points. The result is noisy data.

Figure 35: Testing on minimum item size

In Figure 35, screenshots of the scale test are provided. The tests were all conducted at a distance of 2.322m. The various size logos were printed onto A3 paper and stuck down within the boundaries marked on the board with masking tape. What is clearly visible is the tracking dot being off-set from the centre of the logo. As this logo decreased in size the number of features decreased and the off-set increased. In the right most capture-frame the system could not identify or match any features.

Table 16: Results from testing on item size

Scale	100%	75%	50%	25%
Size (mm)	420 x 297	210 x 98.5	105 x 49.25	52.5 x 24.625
Light meter (Lux)	66	64.8	65.4	64.5
Standard Deviation (mm)	5.74	9.02	14.45	NA

From the data represented in Table 16 it is clear that the size of the work-piece is an important consideration. From the data collected from the item-tracker a standard deviation was calculated. A visible trend is the increase in the standard deviation as the item decreases in size. As a result the relative error increases considerably as the item size decreases. The relative error is calculated by dividing the standard deviation in the x and y directions by the item dimensions, and then taking the average, we see that the relative error increases from 1.57% at 100% scaling to 26.34% at 50% scaling.

From this analysis it is clear that at a fixed distance the tracking data will be more accurate for larger items. Practically the work-piece will typically be small relative to the capture frame. For the remainder of the tests on the item tracker the item is A3 or 420 x 297mm.

The increased noise due to the reduction in size also occurs as distance between the work-piece and the Kinect™ sensor is increased. In this case the noise is exaggerated due to the nonlinearity of the Kinect™ depth sensor. This nonlinearity is represented in Figure 36. From the graph it is evident that the Kinect™ camera's precision drops quadratically with respect to distance. The graph also indicates that the standard deviations increase non-linearly.

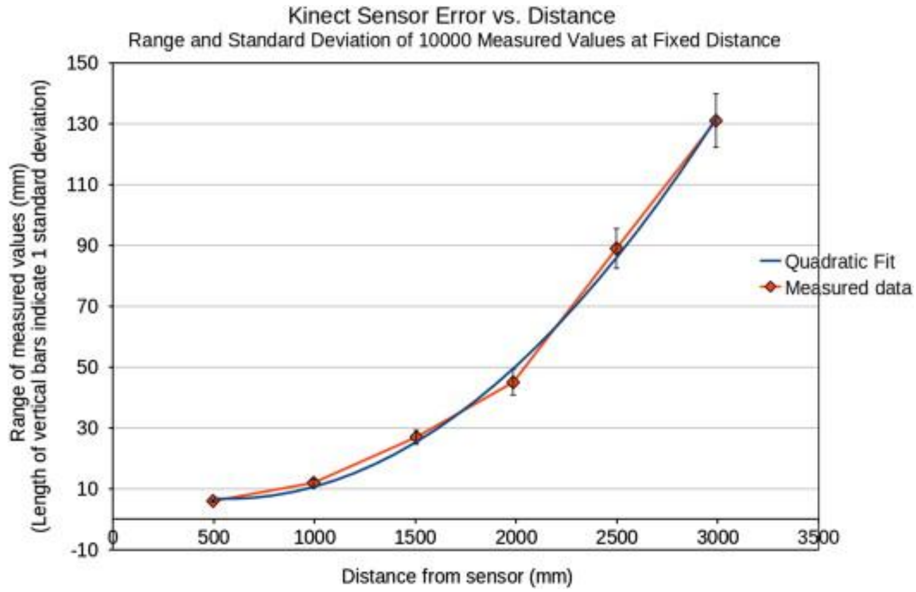

Figure 36: Kinect™ depth sensor precision with distance. Measured values show quadratic relationship between the distance to the depth camera and the range and standard deviation of depth values [93]

The screenshots in Figure 37 show the item tracker in operation at various distances. As the distance increases the number of matches decreases. The result is an increase in noise. However, due to the non-linearity of the Kinect™ depth sensor this increase in noise is exaggerated.

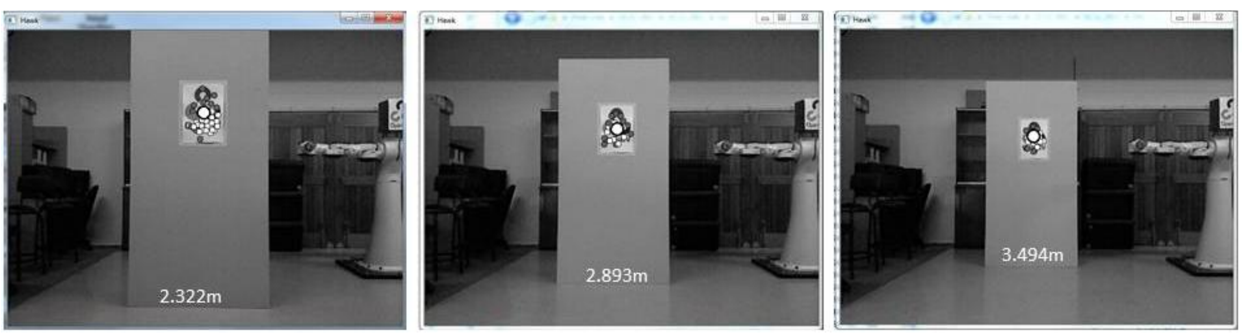

Figure 37: Testing the impact on distance from the camera

An important consideration in this experiment was the determination of the range at which data would be collected. Two primary factors were considered, the optimal human testing range for both hands and feet and the accuracy and precision of the Kinect™ camera. Ultimately the test needed to cover the range at which the HAWK systems would be used. Due to the loss of precision and the notable increase in noise of the worker tracker over 3.5m this was selected as the upper limit. The lower limit was selected as the minimum distance that an average worker would be completely visible.

Table 17: Distance test data

Distance (m)	2.322	2.893	3.494
Light meter (Lux)	67.5	67.1	66
Standard Deviation (mm)	5.74	9.62	10.80

The data in Table 17 indicates that under constant environmental conditions the noise increases considerably as the distance between the Kinect™ camera and the object increases, in this case almost doubling over the range.

It is clear that the optimal location, in terms of item tracker testing is closer to the camera. However, for the worker tracker, when the feet are tracked, the operating range is between 3-3.5m.

3.4.5.4 Lighting

The SURF algorithm is invariant to lighting. However other factors that accompany lighting are suspected causes for deviations, such as lustre. The purpose of this experiment was to evaluate the extent to which the item-tracker is influenced by the amount of illumination incidents on the work-piece. The aim was to derive recommended operating limits which would yield the smallest deviation.

The experiment involved keeping the A3 printed logo at a distance of 3.494m from the Kinect™ camera while varying the illumination levels. The illumination ranges from around 100Lux to 5Lux, screenshots of the data capturing process are depicted in Figure 38. The lighting was provided by a combination of six fluorescent diffuse light fittings, typical in many South African factories and a desk lamp. The Tenmars® TM201 light level test meter was then positioned on the centre of the logo and the illumination was recorded. In each test, 800 measurements were used to derive a standard deviation.

Figure 38: Testing the impact on lighting on noise

From the screenshot in Figure 38, it is clear that the item-tracker is capable of identifying and matching features over a broad illumination range. The first time that the illumination becomes a problem is when the illumination falls below 10 Lux. At 5 Lux, which is an extreme low light condition, the item tracker is incapable of tracking a work-piece.

Table 18: Illumination level test

Light meter (Lux)	102.1	81.2	66	27.2	11.8
Standard Deviation (mm)	15.00	15.98	10.80	11.64	13.12

The data from this experiment is summarized in Table 18. The data indicates that although there is some variation in level of noise, the item tracker can be reliably used over a wide range of lighting conditions. This is a significant advantage, and coupled with the worker tracker's ability to track workers in these lighting conditions ensures flexibility. The data does indicate that an illumination range exists which would yield improved results. The range is between 30-60Lux. Below 30Lux the contrast becomes problematic, particularly if the luminosities are closely spaced. Above 60Lux, glare becomes an issue. It should be noted that this limit will be largely influenced by the reflectivity of the work piece. In this experiment the upper limit could not be determined.

3.4.5.5 Selection modes

The work-piece's size relative to the capture frame varies with the distance to the Kinect™ camera. As a result the location of the work-piece during selection is an important consideration. There are two alternative modes of selection:

1. Credit selection
2. Deficit selection

In credit selection, the work-piece is selected at the optimal location in order to generate the maximum number of features. This is closer to the camera. In contrast, deficit selection involves selecting the work-piece at the location where the majority of the work will be conducted.

The two approaches are investigated by making incremental movement in the z-axis. The observations from these simple experiments play a vital role in establishing a suitable protocol for system testing later on. Screenshots of the approaches are represented in Figure 39.

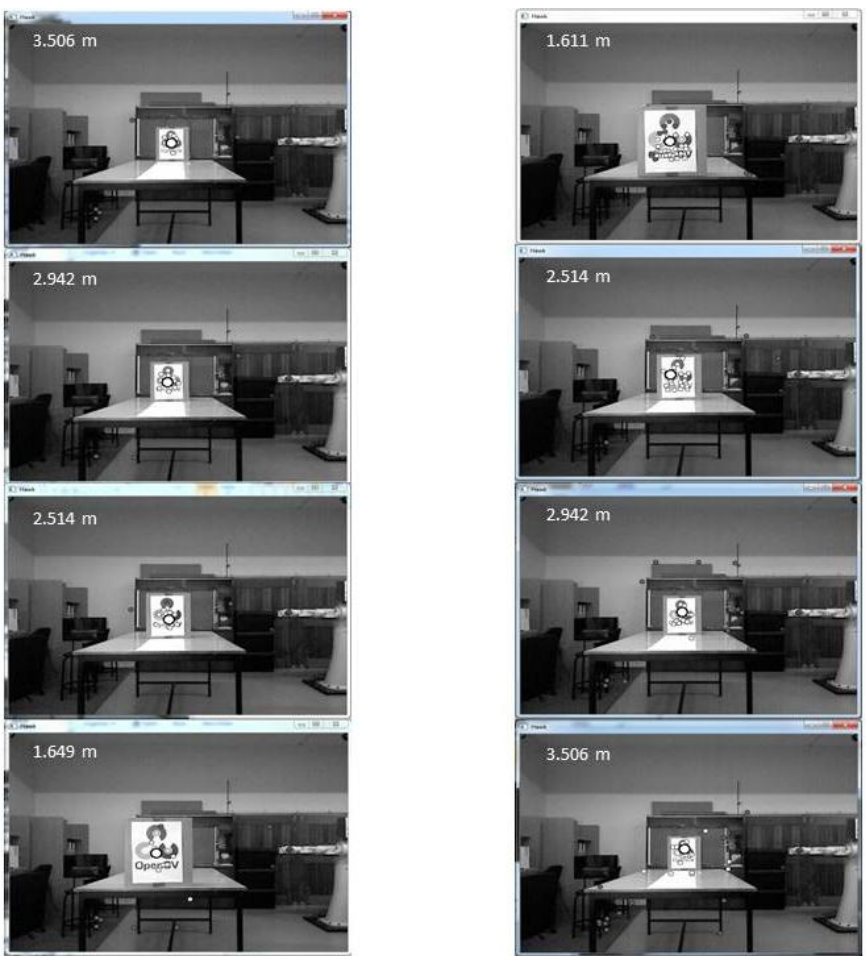

Figure 39: (*Left*) Deficit selection, (*Right*) Credit selection

Deficit selection results in the identification of fewer features. This results in slightly noisy data due to the increased influence of single matches. However the proportion of inliers to outliers remains constant which results in more reliable and quicker identification of the work-piece.

In contrast credit selection identifies far more features. This has some advantages, such as resulting in smoother more accurate approximation of the work-piece. This approach also has disadvantages. The credit approach processes more interest points and also needs to filter out more outliers. This increases the time required to identify the work-piece and also increases the number of false positive matches.

For the purposes of this project it was decided that the deficit selection approach yielded better results. The work-piece should be selected at the location where the majority of the work is conducted.

3.4.5.6 The tracking limit

At a certain distance for each image, depending on its contrast and size, the item tracker is no longer capable of extracting features and as a result the matching processes can no longer take place. This applies to both credit and deficit selections. The tracking will fail at a set distance under specific conditions regardless of the selection criterion used. The failure to match/identify features is represented in Figure 40.

Figure 40: Tracking failure at 4.350m. (*Left*): Credit selection, (*Right*): Deficit selection

3.4.5.7 Rotation

Due to the axis aligned basis of this project the performance of the item-tracker with respect to rotation is not of paramount importance. The axis aligned basis significantly simplifies the programming complexity and reduces the computational cost. Ultimately this enables the real-time execution of the code. The ability to match the work-piece given slight angular deviations is however a desired attribute. The testing done in this section demonstrates that careful consideration of the methods and variables can produce the desired results.

The degree of rotation is dependent on the specific SURF algorithm used along with the RANSAC implementation. U_SURF is a simplified version of SURF that can be applied to cases where the orientation of the tracked item remains constant. The approach does facilitate a small degree of rotation of approximately 15˚. This tight limitation was considered along with the processing time, and ultimately the normal SURF_GPU implementation was selected for use. The processing time of SURF_GPU was determined to be fast enough. An added advantage is that it can facilitate larger angular deviations by carefully selecting a larger back projection error for RANSAC; refer to Section 3.4.3.2.

The rotation capabilities were tested by making incremental angular movements around each axis. The specific implementation used was the standard SURF_GPU and RANSAC with constants set according to

Table 15.

Figure 41: From left to right, Rotation testing around, x, y and z axis respectively

The tests indicated that the worker tracker was relatively insensitive to angular deviations. The worker tracker identified the work-piece for misalignments with Kinect's^{TM} co-ordinate system around each axis of approximately 40˚.

The approach therefore provides additional flexibility without incurring additional computational expense. A disadvantage is that more false positive matches will be recorded. This is demonstrated by the rotation around the x-axis. In the case where the work-piece is upside down, the item is identified when it should not have been. This false classification highlights the possibility of incorrectly classifying similar work-pieces.

The back-projection error along with the other variables needs to be carefully selected in order to ensure that the desired attributes for each individual case can be achieved.

3.5 Contact between the worker and the work-piece

The final common component between the HAWK systems is the determination of contact. Contact is used to:

- Identify when the worker is in contact with work-pieces and therefore productive
- Determine the origin and destination of lifts

The difference between the implementations in the HAWK systems is the determination of contact for either one or both hands. For the worker to be productive, only one hand needs to be in contact with the work-piece. In contrast, the RNLE only applies to two handed lifting tasks. As a results contact is tested for both hands.

Figure 42 represents the basic concept for contact determination. Contact is determined according to a simple box–sphere overlap test. The Axis Aligned Bounding Box (AABB) encompasses the work-piece and the sphere represents the worker's hands. Recall that the item-tracker is a planer-tracking algorithm. As a result the item tracker only returns the co-ordinates of the forward-facing surface. If contact is to be determined, the analyst is required to enter a depth (*z*) dimension into the system.

Figure 42: Conceptual representation of contact determination

The specific implementation used is Arvo's axis aligned box sphere intersection test. The spheres plotted around the worker's hands are defined by the 3D co-ordinates of the centre points LH and RH for the left and right hands respectively. M*in* and *max* represent the minimum and maximum 3D co-ordinates of the work-piece.

Arvo's method determines the shortest distance between the worker's hands and the work-piece. This distance is then compared to the radius of the sphere representing the worker's hand. If it is smaller the worker is in contact with the work-piece. Following is the pseudo-code for the algorithm [**94**,**67**]:

BoxSphere(LH,RH,min,max)
$dL = 0$
$dR = 0$
$\boldsymbol{for\ each}\ i \in \{x, y, z\}$
$\quad \boldsymbol{if}(LH_i < min_i)$
$\quad\quad eL = LH_i - min_i$
$\quad\quad dL = dL + eL^2$
$\quad \boldsymbol{Else\ if}(LH_i > max_i)$
$\quad\quad eL = LH_i - max_i$
$\quad\quad dL = dL + eL^2$
$\boldsymbol{for\ each}\ j \in \{x, y, z\}$
$\quad \boldsymbol{if}(RH < min_j)$
$\quad\quad eR = RH - min_j$
$\quad\quad dR = dR + eR^2$
$\quad \boldsymbol{Else\ if}(RH_j > max_j)$
$\quad\quad eR = RH_j - max_j$
$\quad\quad dR = dR + eR^2$
If $(sqrt(dL) < r)$ $\boldsymbol{Return}$ $LH\ contact\ true$
If $(sqrt(dR) < r)$ $\boldsymbol{Return}$ $RH\ contact\ true$

3.5.1 Background

Contact determination is one of the most important aspects of the system. If contacts are to be reliably and accurately assessed, there are a few attributes that need to be considered.

- The system uses an axis aligned box-sphere contact test
- The skeletal tracker is not designed for contact with surfaces

Contact between the worker and the work-piece is determined with Arvos's box-sphere intersection test. This is an axis aligned approach. As a result the accuracy of the contact data is influenced by the alignment between the work-piece and the camera.

A significant disadvantage of the worker-tracker is that the skeletal tracking algorithm was not designed to track individuals when they come into contact with surfaces. On the contrary, the depth sensing ability of the Kinect™ device is fundamental in effectively differentiating workers from the rest of the scene [**72**]. As a result, when contact is made with work surfaces, partial or complete tracking failure can occur. This in turn means that as the worker makes contact with the work-piece the accuracy of the positional data of the worker's hands decreases significantly, an example of this is represented in Figure 43.

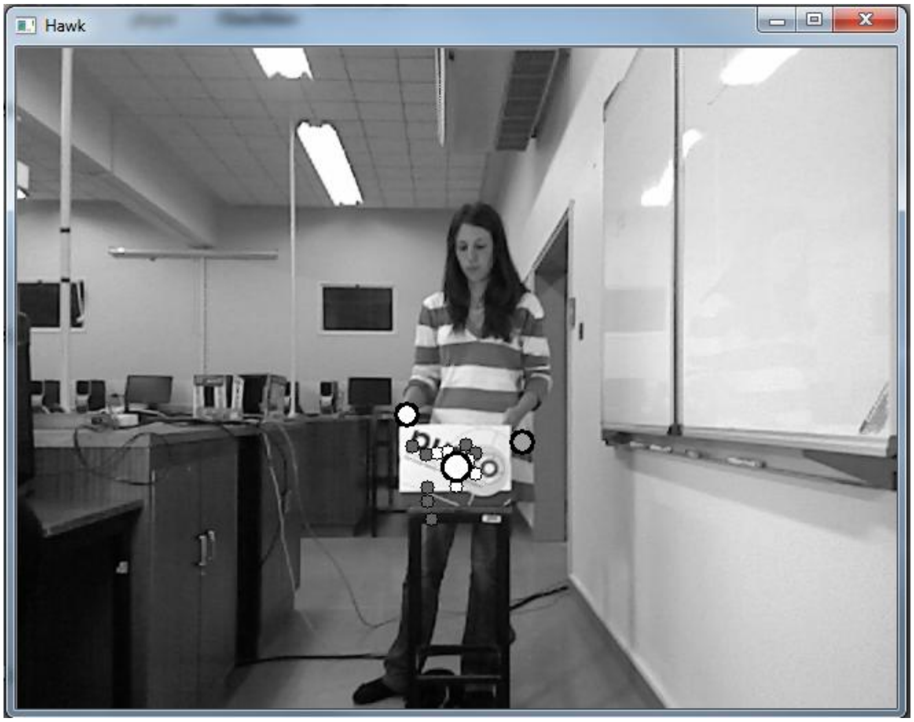

Figure 43: Tracking inaccuracy as contact is made with the work-piece

In Figure 43 the worker's hands are clearly not registered correctly by the system. In addition to the inaccuracies, noise is also present. Noise is seen as notable jumps of the tracking circle, when the hand is stationary.

3.5.2 Computing speed

The computing speed is measured by the frame-rate. It is calculated by counting the number of recordings in each second of the logged data.

Refer to Section 3.4.5.1 for a description of the factors that ultimately influence the effective frame rate of the system. Due to the number of influencing factors, a singular example value is meaningless.

In order to provide a more representative value, the minimum frame-rate was determined from all of the contact tests. The minimum frame rate represents the maximum time taken for the system to track a worker, a work piece as well as establish whether contact is made.

The computer used was a 2.8GHz Core 2 Duo with 4GB RAM and any Nvidia GForce 850Ti graphics card. The minimum recorded frame-rate was 9Hz.

3.5.3 Contact radius considerations

The tracking limitation of the skeletal tracker in contact situations necessitates the contemplation and assessment of a number of options and factors relating to the contact registration process. These factors vary according to the desired attributes of the program and include:

- The use of filters
- Noise in contact conditions
- The accuracy of the worker tracker in contact conditions
- Anthropometry
- Type of hand grasp

The demands of HAWK-RNLE and PRODUCTIVITY systems differ. As a result each system will have slightly different contact methodologies. In the HAWK-PRODUCTIVITY system contact is registered and broken as soon as one hand comes into contact with the work-piece. In the HAWK-RNLE system both hands need to be in contact, as required by the RNLE.

3.5.3.1 HAWK-RNLE contact considerations

In the HAWK-RNLE system, the positional data must be as accurate as possible at contact while also minimizing the probability of contact classification errors. For this system the contact radius is established by investigating the accuracy and noise of the system under contact. The investigation into the system noise provides data vital to the establishment of the contact radius. The accuracy study yields data pertinent to the system's capability of deriving accurate positional data of the worker's hands. The distance between the worker's hands and the work-piece at contact are also vital and some of the typical hand grasps have been investigated to determine if any alterations to the contact radius are necessary.

3.5.3.2 HAWK-PRODUCTIVITY contact considerations

In the HAWK-PRODUCTIVITY system, contact typically refers to working on the work piece, and occasionally using hand grasps to move the work piece out of the capture frame. As a result, anthropometric data of a representative population and standard system noise provide data for the establishment of an upper limit for the contact radius.

3.5.3.3 General contact considerations

The various factors influencing the selection of a methodology and contact radius will be covered in the subsequent sections. Ultimately the goal is to increase accuracy and to minimize classification errors, which are:

- Type 1: Contact classified as false, when it is true
- Type 2: Contact classified as true, when it is false

One of the primary concerns is selecting one of three options regarding the positional data of the hand at contact for the HAWK-RNLE program:

1. Use the first measurement once contact has been established
2. Use an average of an array of measurements which directly correlates to the number of measurements made to establish if contact is made
3. The final option is to use the item's dimensions to determine the location of the hand grasps

The easiest way to ensure reliable contact registration is to set the radius large enough so that it will still register contact when the noise increases as the worker comes into contact with the work-piece. There are a few problems with using such a simplified approach. The first problem is that as the radius increases in size, so the positional accuracy decreases and the number type 2 errors increases. Conversely, if this radius selected is too small then the number type 1 errors increases.

A possible way of reducing the contact radius, while also improving reliability involves storing an array of the minimum distances between the worker and the work-piece. The average of these values is calculated and compared against the predefined contact radius. In this way a more accurate contact determination with a smaller contact radius can be achieved. The disadvantage of this approach is that the detection is delayed. The delay is related to the size of the array, and the processing capabilities of the computer. The selection of the array size is therefore important. If the array is too small, the number of type 1 and type 2 errors increases. If the array is too large, although it will be more stable, it could fail to identify short duration contacts.

Prior to the evaluation and assessment of contacts, it is important to understand that there are external variables that will affect the results, and can only be controlled to a limited degree. These variables include.

- Calibration quality
- Selection of the work-piece
- Distance from the camera
- Person to person variability
- Alignment of the camera and work-piece

In selecting a suitable contact radius, it is also important to consider that the skeletal tracker does not perfectly track the centre of the hand.

3.5.4 Anthropometry

As a point of departure, the theoretical maximum possible distance for contact between the worker's hand and the work-piece can be calculated. Assuming that the worker-tracker returns an exact location for the middle of a worker's hand then the maximum distance for contact can be calculated as the anthropometric dimension from the middle of the hand to the maximum reach of the middle finger of the biggest worker. This distance was calculated for a 95th percentile male according to Equation 11 [**95**].

$$Contact\ radius = Hand\ length - wrist\ to\ center\ of\ grip\ length \ldots \quad (11)$$

The anthropometric data used in this calculation is taken from the RSA Military Standard 127 Volume 1 which is based on the measurement of 1614 males across the various ethnic groups. The contact radius for the 95 percentile male is 125 mm [**95**].

It is unlikely that the worker will ever be in contact with the work-piece with his or her fingers only. The figure on its own is also of little value, and the actual contact radius will need to be adjusted according to the other factors, such as the system accuracy, noise and the type of grip used. The figure does however serve as a reference for an upper limit of the radius.

3.5.5 Type of grip

The item-tracker of the HAWK systems is limited to tracking medium to large work-pieces. As a result material handling practices will typically result in the use of hand grasps represented in Figure 44. The distance between the centre of the hands and the work-piece will therefore always be closer than 125 mm, defined for the extended position. The exact distance will vary according to the location and type of the hand grasp used on the work-piece [**22**,**49**].

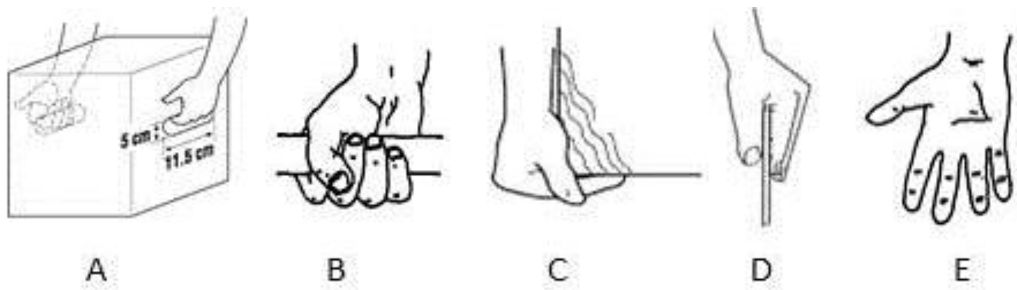

Figure 44: (*A*) Hook grip, (*B*) Power grip, (*C*) Ledge grip, (*D*) Palm pinch, (*E*) Finger or flat hand press

In Figure 44 it can be seen that the actual distance between the middle of the hand and the work-piece is never more than a few centimetres. The selection of a suitable contact radius does however also require the consideration of the systems accuracy and noise.

3.5.6 Accuracy evaluation

Evaluation of the worker-tracker's accuracy under contact conditions poses a significant challenge. This is due to the fact that accurate data on the worker's hands would need to be acquired via another method so that comparison between measurements can be made.

Due to the lack of access to suitable equipment, an approach similar to the one used in the Motoman® tracking case was used, see Section 3.3.3.1. The basic methodology involves measuring a distance along one axis, and comparing this to the known value. The worker makes contact at the corners of the work-piece. The index fingers and thumbs are held at right angles to each other and pressed against the periphery of the work-piece, as shown in Figure 45.

In this way the x and z-dimensions of the work-piece are measured individually. Measurement of the y-dimension was excluded as the grip would require awkward postures. Furthermore it is based on exactly the same principles as the x-dimension. The differences between these two dimensions would therefore be negligible. In contrast the z-dimension needs to be assessed as it is retrieved on a different basis and also has a different resolution.

Figure 45: (*Left*) Contact accuracy determination for z dimension, (Right) Contact accuracy determination for x dimension

Prior to performing the accuracy test, a number of test contact situations were made in order to observe the system. Through this visible assessment, it was determined that the accuracy improved as the hand speed approaching the work-piece decreased. Furthermore hand position also influenced the accuracy, as a general rule, the more visible the hand the better the accuracy. These two requirements limit the use of the system to some degree. Unfortunately there are currently no solutions elevating these limitations.

The results of the accuracy test are summarized in Table 19. The actual column provides the dimensions as measured by, and used in the system. The actual values deviate slightly from the physical dimension, which is measured with a tape measure. For the z-co-ordinate these values are the same. This is because the user is required to enter this value into the program. The average measured and standard deviation columns represent the average distance and standard deviation of the measurements. The maximum deviation column is the maximum error between the measured and physical distances.

Table 19: Accuracy test results summary

	Actual	Physical	Avg. Measured	Std. Deviation	Max. Deviation
X (mm)	322	314	315.41	5.96	10.02
Z (mm)	260	260	241.58	11.57	36.74

From the data in Table 19 it is clear that under good conditions, the system is capable of fairly accurately identifying points of contact. A graphical representation of the actual and measured distances is provided in Figure 46. The difference in accuracy of the z-measurements is partially attributed to the increased difficulty of the testing procedure. The test subject reported that she felt less consistent with the z-measurements. It was also observed that the worker’s hands were in contact with the side of the box as opposed to the edges. This deviation is clear as the values under estimated the z- dimension.

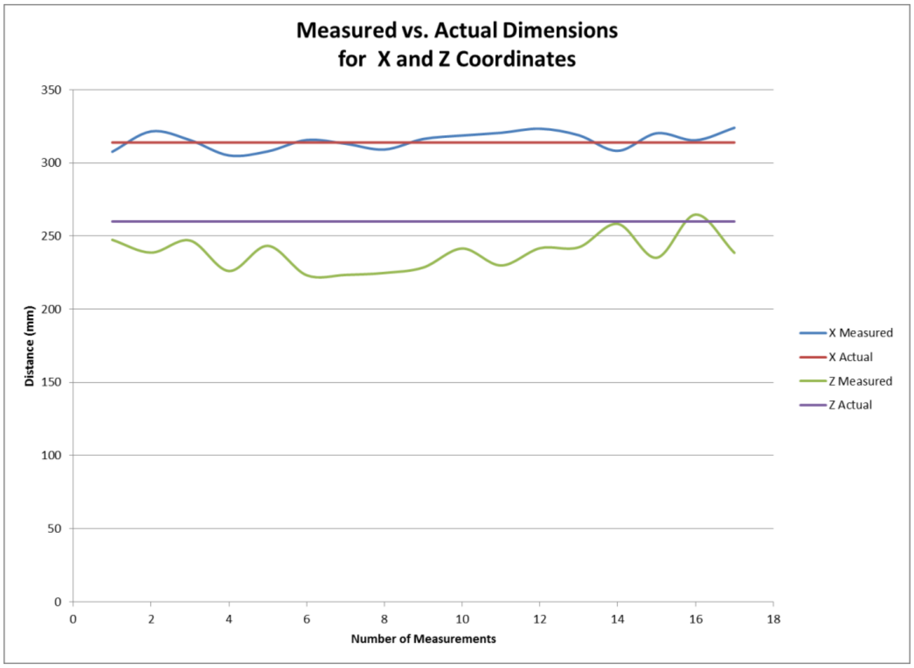

Figure 46: Measured and actual distances in the x and z directions for the contact test

It should be noted that the worker tracker tracks the centre of the worker's hands. As a result, there is a small discrepancy in the measurements. The hand positions used in this test were chosen specifically to minimize the distance between the worker's hands and the work-piece.

3.5.7 Data collection after contact

The accuracy of measurements is influenced by specific data used. A number of options are available. The purpose of the tests conducted in this section is to identify the approach that yields the best results. In order to assess the different approaches, contact needs to be identified by the system.

Through preliminary testing it became apparent that single measurements yielded too many type 1 and 2 errors. As a result a moving average approach was implemented. For contact to be detected, the moving average distance, for 10 measurements, between the worker's hands and the work-piece needed less than 100mm.

Once contact has been detected, the positional accuracy of the worker's hands is dependent on the specific measurements used. The test assessed 17 x-axis measurements according to the hand locations depicted in Figure 45. Three alternatives for data collection were assessed:

1. The Single Measurement approach
    - Use only the first measurement after contact is established.
    - The average distance was calculated as 315.41mm, with a standard deviation of 5.96mm.
2. The Moving Average 5 approach
    - Take an average of the first 5 measurements after contact is established.

- The average distance was calculated as 317.51mm with a reduced standard deviation of 4.77mm.
- As expected, the use of multiple measurements yielded more accurate results and it represents a slight improvement over the single measurement approach.

3. The Moving Average 10 approach
   - Use the same 10 measurements originally used to establish contact.
   - The average distance was calculated as 338.01mm with a standard deviation of 12.08mm.
   - This method yielded significantly poorer results. This is attributed to the inclusion of measurements prior to the actual contact.

The results of this assessment are represented in Figure 47. The moving Average 10 approach tended to overestimate the dimension of the work-piece. The overestimation results because the first few of the ten measurements include the data of the worker approaching the item. The deviations from the actual dimensions are also larger than the other approaches, which tended to be far more accurate. This is attributed to the fact that measurements are only taken once contact has been established.

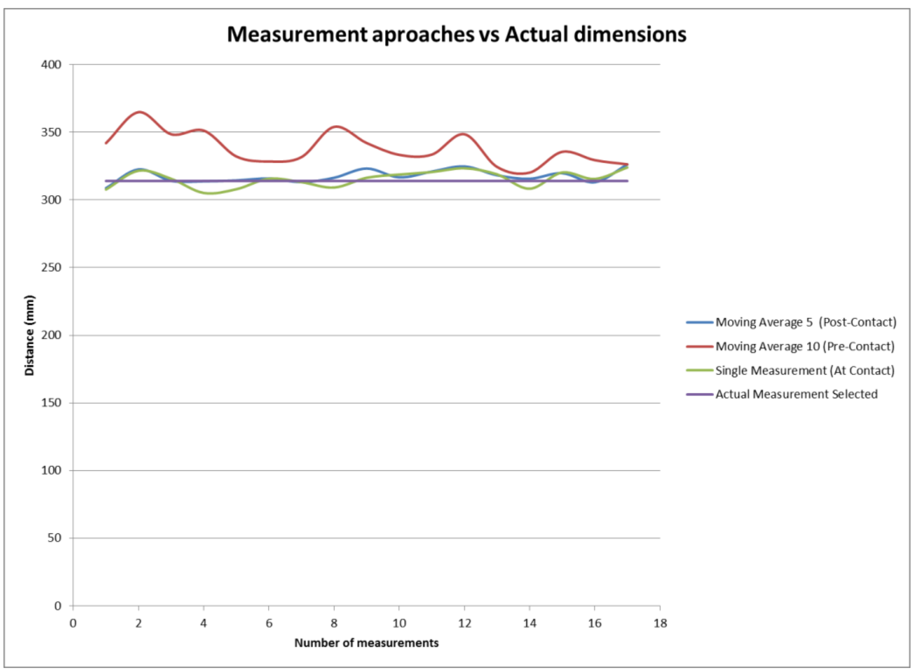

Figure 47: Measurement approaches at contact points

From the assessment in Figure 47, it is clear that the Moving Average 5 approach yielded the best results. Interestingly the single measurement method, which is the simplest method to implement, performed fairly well. For the single measurement approach the maximum deviation from the sample was 10.02mm, which is better than the 12.23mm for the Moving Average 5 approach. Considering the additional complexity, the time delays and the additional memory that will be required to store arrays of the measurements, it was decided that a single measurement would be used.

3.5.8 Noise evaluation

In order to assess the noise under contact conditions, a comparative test was conducted comparing the contact noise to the free-standing noise.

- The freestanding test was conducted with the worker standing as still as possible at approximately two meters from the Kinect™ camera.
- The contact test involved the worker remaining in contact with the box, in the position shown in Figure 48. This was also done at a distance of approximately two meters from the Kinect™ camera.

For both the free-standing and contact cases, a thousand measurements of each of the 3D co-ordinates of both hands as well as the work-piece were retrieved. The tests were conducted at the same distance from the camera to minimize the variance in noise, which increases as the distance from the camera increases.

Figure 48: Photograph of the hand positions used in the contact test

For the free-standing test, when the worker was in a stationary position, the standard deviation was calculated to be 9.18mm. In Figure 48 data relating to a contact test is represented. This data represents a segment of time during which the worker remained stationary and in contact with the work-piece in the pose shown in Figure 48. The standard deviation for the worker's hands was 34.76mm, whereas for the work-piece it was 4.59mm.

A single tracking failure in contact conditions can clearly be seen in Figure 49 as the deviation from the horizontal trend. The increase in the standard deviation is attributed to the failure of the worker tracker. Prior to the failure, the noise is similar to the free-standing result and in this experiment it was 8.04mm.

Although tracking failures do occur occasionally in the free-standing positions, they are far more common in contact situations. After the tracking failure, the positional accuracy of the tracking data improves, however, it does not return to the same value prior to the failure. This inconsistency along with the failure clearly illustrates the limitation of using the Kinect™ camera and worker tracker in contact situations.

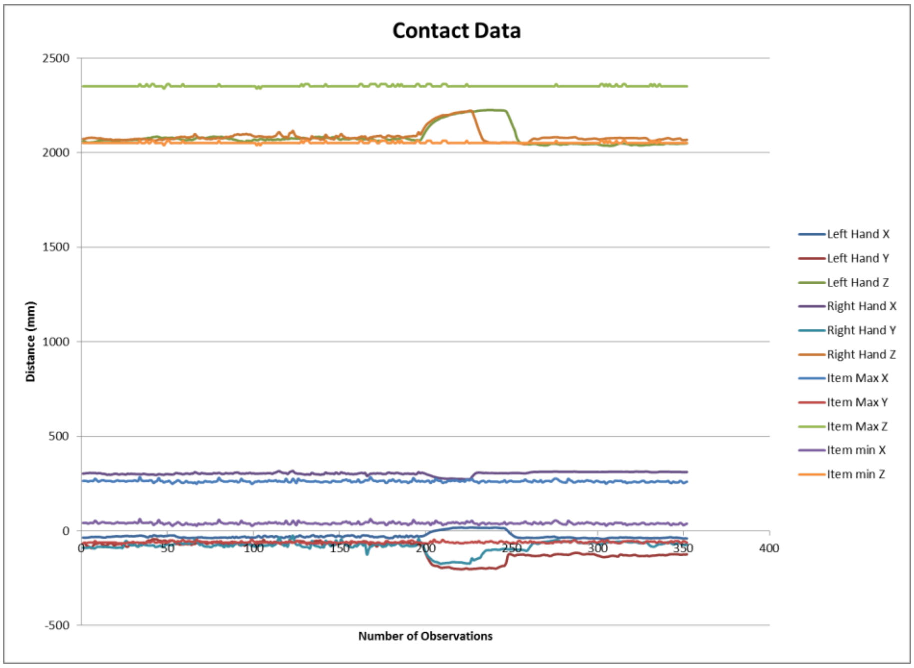

Figure 49: Failure of the worker tracker in contact

Tracking failures are influenced by a number of factors which makes measuring the frequency and severity difficult. Failures are influenced by:

- The calibration of the worker
- Speed at which the worker approaches the box
- The hand location at contact

The deviation that occurs in failures is typically in the direction of the work-piece. This is a result of the way the tracker works, which then perceives the work-piece as a part of the worker's hand. From the failure in Figure 48 the maximum absolute deviation for both hands is 194.18mm. This value demonstrates the systems incapability of reliably providing accurate and consistent positional data in contact situations. It should be noted that because the direction of deviation tends towards the work-piece, tracking failures do not influence the establishment of contact.

3.5.9 Setting the contact radius

In order to set a reliable contact radius, the distance between the centre of each of the worker's hands, *RH* and *LH*, and the nearest point on the axis aligned work-piece is evaluated. This evaluation takes place during actual contact between the worker and the work-piece. The method of evaluation is Arvo's axis aligned bounding box, which is the same as the method used for contact determination. The basic algorithm is represented below. *Min* and *max* represent the minimum and maximum dimensions of the work-piece along each axis.

BoxSphere(LH,RH,min,max)

$dL = 0$

$dR = 0$

$\boldsymbol{for\ each}\ i\ \in \{x, y, z\}$

$\boldsymbol{if}(LH_i < min_i)$

$eL = LH_i - min_i$

$dL = dL + eL^2$

$\boldsymbol{Else\ if}(LH_i > max_i)$

$eL = LH_i - max_i$

$dL = dL + eL^2$

$\boldsymbol{for\ each}\ j\ \in \{x, y, z\}$

$\boldsymbol{if}\left(RH < min_j\right)$

$eR = RH - min_j$

$dR = dR + eR^2$

$\boldsymbol{Else\ if}\left(RH_j > max_j\right)$

$eR = RH_j - max_j$

$dR = dR + eR^2$

$\boldsymbol{Return}\ (sqrt(dL), sqrt(dR))$

By considering the maximum distance that either of the worker's hands is from the work-piece, we can establish a limit that will minimize type 1 and 2 errors. As stated earlier, a possible way to reduce the contact radius is to use a moving average of a predefined number of measurements. The maximum and average contact radii for both the single and moving average measurements are summarized in Table 20.

Table 20: Contact radii

	Max	Average
Single measurement (mm)	94.4	54.5
Moving average of 10 measurements (mm)	80.1	54.2

Based on the results in Table 20, the number of type 1 errors can be reduced by setting the contact radius at 100mm for single measurements and 85mm if a moving average is used. Included in these dimensions is a small tolerance of approximately 5mm. This tolerance could be increased or decreased depending on a number of factors. The tolerance can be increased in cases where:

- A different hand grasp is used
    - The distance between the worker's hands and the work-piece increases
- The worker makes contact with the work-piece with his/her hands extended
    - Consider the upper limit of 125mm for the 95 percentile male
- The selection of the work-piece is difficult

- The work-piece orientation changes
- The contact takes place further away from the camera
- If the speed of the task is high
- The hand location is such that it is partially obscured

If the contact radius is increased the number of type 2 errors increases. The user should ultimately try to keep the radius as small as possible, while minimizing the number of errors. The HAWK-PRODUCTIVITY program is more sensitive to type 2 errors as only one hand is required to register a contact. As a result the contact radius should be small enough to have an acceptable number of type 2 errors.

In the HAWK-RNLE, a contact will only be registered when both hands are within the contact radius, and it is only broken once both hands are beyond the contact radius. As a result the tolerance could be decreased for more accurate results. The contact radius should not be too small, as this can lead to delays in identifying contacts and an increase in type 1 errors.

3.6 Conclusions on components

This chapter comprehensively covered the testing of the subcomponents of the system including:

- Worker-tracker
- Item-tracker
- Contact between the worker and the work-piece

Testing was mostly done by observation, specifically through controlled experimental recordings and systematic field observations. Prior to any of the tests, short pilot studies were conducted to identify any possible pitfalls.

The ultimate goal was to execute experiments under controlled conditions. However, due to the nature of the project there were too many variables to enable replication of all conditions over the duration of the study. The variables and environmental factors that could be measured were recorded for each of the experiments.

A variety of comparative studies were conducted in which results from existing methods were compared to those from the HAWK systems. The selection of comparative methodologies was done by considering the availability of instrumentation along with the operational complexity and accuracy. If no information was available on the instruments validity and reliability, it was immediately excluded. The techniques with the highest level of precision were applied correctly in order to avoid errors. To improve the reliability, multiple measurements were taken and the average value used.

The testing conducted on the sub-components of the system yielded valuable information on the performance capabilities of the system. These factors where used to determine the suitability for use within the proposed HAWK-RNLE and HAWK-PRODUCTIVITY systems. Additionally it also aided in the establishment of operational protocols that should be followed in the execution of the final tests.

The testing done on the components indicated that the system was capable of:

- Real time item selection
- Tracking of the worker and work-piece at a reasonable capture rate
- Reliable contact determination

Exact figures are not provided as the systems performance is dependent on the computer and GPU used in the experiments. The results are deemed reasonable with respect to the objectives of the system, on a 2.8GHz Core 2 Duo with 4GB RAM and any Nvidia graphics card that can be used with CUDA.

The operational protocols are largely determined by the systems constraints and limitations. The most fundamental limitations at this point are

- The resolution, accuracy and precision of the Kinect™ device
- The functional range of the system for the HAWK systems
    - For the HAWK-PRODUCTIVITY system, only the worker's hands and the work-piece need to be in the capture frame. The functional range is between 2 and 3.5m
    - The HAWK-RNLE system required tracking of the worker's feet. The functional range is between 3 and 3.5m
- Visibility of the worker
    - HAWK-PRODUCTIVITY system the worker can be stationed behind a desk or workbench. The item tracker is capable of torso only tracking.
    - In the HAWK-RNLE the entire worker must be visible to the camera. The worker's feet should not be obstructed by any objects
- Complexity of setting the values for the item-tracker
    - Setting the inputs to the SURF and RANSAC algorithms requires a basic understanding of the algorithms. These values also need to be set for each different case.
- The Minimum item size
    - The minimum size is dependent on the contrast in the image and the size of the features. As a general rule when operating close to the 3.5m limit items, the item should be at least $0.1m^2$.
- Axis aligned approach
    - The system is restricted to reasonable alignment with the capture frame. Misalignments can lead to significant errors.
    - A rotation invariant version is possible; however the computational cost will increase dramatically.
- Visibility of the contact
    - The accuracy of the hand location at points of contact is better if the hands are partially visible to the camera. Hands grasps from behind the work-piece, may lead to errors.
- Only one work-piece in the capture frame at any one time
    - The system can only identify one item within the user defined workplace at a time. This has significant restrictions on the practical use in the HAWK–RNLE implementation where work-pieces need to be tracked from the origin to the destination of lifts.

The testing indicated that the subcomponents, if used according to the principles summarized here should yield reasonable results in the HAWK systems.

4. Chapter 4

The HAWK-PRODUCTIVITY system

4.1 Introduction

This chapter introduces and describes the underlying methodology used to calculate and evaluate labour performance autonomously in real time. The chapter also encompasses the extensive testing of the HAWK-PRODUCTIVITY system.

4.2 The concept of continuous sampling

Recall from Section 3.1 that the basic principle behind the automation of the LPM in this thesis is to utilize co-ordinate data of a worker and a work-piece to classify the worker's action as in one of a number of states. The concept of classifying the worker as one of a number of mutually exclusive states is derived from the work sampling methodology.

The states of the HAWK-PRODUCTIVITY system are similar to those used in traditional studies although the number of states is reduced. This results because:

- The camera cannot follow the worker around, and can therefore only classify the worker's state when the worker is in the capture-frame.
    - Example: the camera cannot determine whether the worker is on a restroom or fatigue break, it can only determine that the worker is out of the capture frame.
- The classification process requires the consideration of a number of variables. Considering additional variables would significantly complicate the system.
    - Example: Human analysts can easily differentiate between cleaning and maintenance actions. For the automated systems, this would require an ability to distinguish between either; the actions required for the tasks or between the maintenance and cleaning equipment.

The information on the worker occupying the various states is used to calculate various performance indicators, including [**22**]:

- **Percentage utilization** - Measure the duration that workers are active or delayed
- **Allowances** - Establish rest allowances for workers
- **Time standards** - Establish time standards for manual tasks
- Measure working time and performance index on manual tasks

The biggest departure from traditional work sampling methodology is that rather than taking random observations, the HAWK-PRODUCTIVITY system continuously classifies the workers as in one of the states. Therefore whereas work sampling requires statistical analysis of the number of classifications in each state, the continuous approach of the HAWK-PRODUCTIVITY system analyses the time spent in each of the states. The accuracy of the continuous approach is therefore not dependent on the number of measurements but rather on the time delays that occur while classifying the worker as in one of the possible states.

4.3 Work sampling

Due to the correlations between the HAWK-PRODUCTIVITY system and work sampling, an investigation of the basic principles of work sampling provides insight into the logic behind the classification process. In addition the methodology also indicates what calculations are conducted in the establishment of labour performance indicators. Furthermore the basic concepts of work sampling also highlight complexities and limitations of the traditional work sampling methodology, many of which could be elevated through the continuous sampling approach.

4.3.1 Probability and classification theory

Prior to investigating the derivations for the performance indicators, the basic statistical basis for work sampling is introduced. Work sampling is based on the theory of probability. At a random observation point a state can either be present or absent, for example, a worker can either be productive or not. The data follows a binomial distribution represented in Equation 12 [**22**].

$$P(x) = \frac{n!}{x!(n-x)!} p^x q^{n-x} \; \ldots (12)$$

Where *p* = probability of an event

q = 1-p

n = number of observations

As *n* becomes large, as typically required in work sampling, the binomial distribution in Equation 12 approaches that of a normal distribution.

A fundamental component in work sampling is the selection of the number of observations, *n* to estimate the probability of an event, *p.* Elementary sampling theory indicates that the probability calculated for each observation should fall within $p \pm 1.96$ standard deviations ($z_{\alpha/2}$) approximately 95% (*CI*) of the time. This theory is used to calculate the number of samples required for the desired accuracy of the study.

The distribution has a mean = *p*, and a standard deviation of σ_p, given by Equation 13,

$$\sigma_p = \sqrt{\frac{pq}{n}} \; \ldots (13)$$

The acceptable limit of error *l*, in Equation 14, is defined by the term $z_{\alpha/2}\sigma_p$ at a $(1 - \alpha) \times 100\%$ confidence error.

$$l = z_{\alpha/2}\sigma_p = z_{\alpha/2}\sqrt{\frac{pq}{n}} \ldots (14)$$

The *l* value determines the desired precision of the results. The difficulty is that *l* is dependent on the mean of the data, which is often initially unknown. It is therefore suggested that the analyst define the *l* in terms of an overall precision. This value will then be adjusted and corrected for when the *p* value changes. The following example best demonstrate the use of an overall precision value. In order to ensure a +-5% precision on a task, then *l* = 0.05*p*.

Solving for *n* yields Equation 15, this is used for determining the number of samples required in the study.

$$n = z_{\alpha/2}^{2}\frac{pq}{l^{2}} \ldots (15)$$

As *n* increases so does the accuracy of the measurements. The accuracy of work studies are therefore limited by the number of samples that can be taken per day. The accuracy of the data is also influenced by the period over which the measurements are taken. This leads to another requirement of work sampling. The observations need to be taken over as long a period of time preferably over several days or weeks. This ensures that the data is more representative of the true performance of the analyst.

4.3.2 Performance indicators

The traditional labour performance indicators established through work sampling include [**22**]:

- Operator utilization
- Allowances
- Standard time

The derivations of these indicators require the reliable classification of a worker as one of a number of states. For the simplest case, these states include: Busy and idle.

4.3.2.1 Operator utilization

Utilization refers to the proportion of time that the worker spends performing productive work. According to the work sampling theory, it is calculated by dividing the number of observations classified as busy (n_{busy}) by the total number of observations (n_{total}) of the study as shown in Equation 16 [**47**].

$$U = \frac{n_{busy}}{n_{total}} \ldots (16)$$

The utilization figure is primarily used to assist with determining costing and possibilities for improvement.

4.3.2.2 Allowances

A number of different allowances and delays occur in working environments, some of which are mandated and others which could be avoided. These interruptions can be broken down into three distinct classes:

- Personal needs
  - Meals, restroom and water breaks
- Fatigue
  - Metabolic demands that can affect the strongest workers on the lightest work
- Unavoidable delays
  - Tool problems and breakages, supervisor interruptions, material variations

Allowances are calculated by dividing the number of measurements in each of the classes (n_{class}) by the total number of number of busy observations (n_{busy}) as shown in Equation 17. This value equals the percentage allowance that should be given to a worker for the specific class of work being studied.

$$A = \frac{n_{class}}{n_{busy}} \ldots (17)$$

The different elements that enter into personal, fatigue and unavoidable delays can be kept separate, and an equitable allowance can be determined for each class [**22**].

4.3.2.3 Standard time

The calculation of the standard time requires a number of consecutive calculations. The first step is determining the Observed Time (*OT*) in Equation 18. It is calculated by dividing the total time of the study (*T*) by the number of units produced during that time (*P*). This is multiplied this by the ratio of observations during which the worker was busy. Due to the random observation methodology of work sampling, data on the number of items processed is not directly available. Analysts are typically required to retrieve this data from the job cards or physical counts [**22**].

$$OT = \left(\frac{T}{P}\right)\left(\frac{n_{busy}}{n_{total}}\right) \ldots (18)$$

The observed time needs to be normalized according to the effort of the worker. The normal time (*NT*) is calculated by multiplying the observed time by an average performance rating, as shown in Equation 19 [**22**].

The performance rating ($\bar{R}$) describes how quickly or slowly the worker was working relative to a qualified and experienced worker working at standard performance without overexertion while adhering to the correct method under normal environmental conditions. A number of alternative rating systems exist. In selecting an approach analysts must comprehend the importance of the accuracy of the rating [**22**].

The simplest approach involves assigning a percentage rating to a worker's performance for each observation. This rating is recorded and averaged. This rating represents the average performance of the observed worker for the duration of the study.

$$NT = OT\left(\frac{\bar{R}}{100}\right) \ldots (19)$$

The standard time (*ST*) is calculated by adding allowances calculated in Equation 17 to the normal time, as indicated in Equation 20 [**22**].

$$ST = NT(1 + A) \ldots (20)$$

4.4 Automation

The derivation of performance indicators in the HAWK-PRODUCTIVITY system is based on the work sampling methodology. As a result the worker under analysis needs to be classified as in one of a number of mutually exclusive states. This classification process is conducted by considering the 3D co-ordinate data of the worker's hands and the work-piece along with the time between frames provided by the worker-tracker and item-tracker set forth in Chapter 3. Data on the time spent occupying each of the states can then be used to determine the percentage utilization and other performance indicators as described in Section 4.3.2. The only difference is that whereas work sampling is based on the number of observations the HAWK-PRODUCTIVITY system is based on the time spent in each of the states.

Due to the use of both a worker and an item tracker, two distinct categories of information are provided by the HAWK-PRODUCTIVITY system:

- Worker based measures, which includes data on the time spent:
    - Out of frame
    - Idle
    - Productive
    - Static
- Work-piece based measures, which includes data on:
    - Number of frames
    - Average processing time
    - Standard deviation of processing times

In order to facilitate the automation process, the HAWK-PRODUCTIVITY system uses a fewer states than typically used in traditional studies. As a consequence, erroneous classifications will have a bigger impact on the performance indicators. It is also emphasised that the values on the worker's states provided by the HAWK-PRODUCTIVITY system are relative measures and on their own have little meaning. The values therefore need to be compared with one another to be understood. Furthermore, the system cannot identify specific problems, it only indicates that problems exist and indicates under which classification the concerns occur. It falls to users of the system to understand the classifications and the correctly interpret the data.

4.4.1 Worker based measures

From the tracking data of the work-piece and the worker, the following questions can be answered:

- Is the worker inside or outside of the capture frame?
- Is the work-piece within or outside the user's defined workspace?

Provided that the worker and the work-piece are present, some additional manipulations and calculations yield the following information:

- Is the worker in contact with the work-piece?
- Are the worker's hands moving above or below a certain speed?

The answers to these questions are used to classify the worker as in one of four possible states. The criteria for the classification of each of the states are depicted in Table 21. Each of the states is exclusive and at any point in time a worker can only occupy one specific state.

Table 21: Classification states criteria

State	Worker	Work-piece	Contact	Speed
Out of Frame	NO	N/A	N/A	N/A
Idle	YES	NO	N/A	N/A
Productive	YES	YES	YES	N/A
Productive	YES	YES	NO	>LIMIT
Static	YES	YES	NO	<LIMIT

The states are based on a number of assumptions, some of which are carried forward from earlier work done by van Blommestein et al. [**13**]. In the subsequent sections the four states used in the HAWK-PRODUCTIVITY system are discussed extensively.

4.4.1.1 Productive

A worker can only be classified as productive if a work-piece is located at the workstation. The total productive time is the accumulation of two classifications:

1. The time that the worker is in contact with the work-piece
2. The time that the average hands' speed, while a work-piece is present within the workspace, is greater than the user specified threshold value.

The total productive time is used in the determination of utilization, as indicated in Equation 21. The equation is similar to Equation 16, however (n_{total}) is replaced by the total duration (T_{total}) of the study and (n_{busy}) is replaced by the total productive ($T_{productive}$) time logged by the system.

$$U = \frac{T_{productive}}{T_{total}} \ldots (21)$$

The total productive time would also be used in the establishment of standard times. Recall that the first step in calculating the standard time, is calculating the observed time (OT). Where (p) is the number of units produced during the study.

$$OT = \frac{T_{productive}}{p} \ldots (22)$$

The (OT), represented in Equation 22, then needs to be normalised by factoring in the effort of the worker as indicated in Equation 19. Following this, the standard time can be calculated by adding the allowances to the normal time, according to Equation 20.

The performance step rating poses a significant challenge and is a stumbling block in the automated system. A new methodology for performance rating needs to be developed with the information provided by the HAWK-PRODUCTIVITY system. The authors proposed that the worker's average hand speed for the productive portion that the work-piece spends in the workspace could be used as an indicator of effort. The evaluation of this rating methodology falls outside the scope of this thesis, and it forms a part of the proposed future work.

Contact with the work-piece

Assumption

A worker is classified as productive if the worker is in contact with the work-piece. Contact is registered when either of the worker's hands comes within a predefined distance from the work-piece, see Section 3.5.

Justification

It is unlikely that a worker will spend a considerable proportion of the study in contact with the item while resting or being unproductive. It is therefore reasonable to assume that if the worker is in contact with the work-piece then he/she is doing productive work.

Using the worker's hand-speed to distinguish between productive and resting (static) states was considered. However, the concept was discarded from the classification process for a number of reasons:

- Tracking failures would lead to false classifications, see Section 3.5.8.
- Hand location will in many cases be partially or completely obscured from view of the camera.
- The hand movements are typically small while in contact with the work-piece, differentiating between productive and idle is difficult due to the inherent noise of the worker tracker.

Comments

There are few possible sources of error in the contact classification process. False identification of contact breaks poses the biggest risk. The use of multiple measurements in the determination of contact reduces the possibility of many errors to statistical improbabilities. Analysts must carefully select:

- Contact radius
- Number of measurements
- Proportion of positive matches

Each of these is fundamental in the determination of contact. For selection of the contact radius see Section 3.5.9. Correct selection will ensure minimal classification errors.

Another source of error is the systematic errors inherent in the worker tracker. If the worker tracker fails to identify the hand location, the hand is automatically assumed to be next to the worker's side as shown in the Motoman test in Figure 21. If this occurs the system could incorrectly classify the worker as static while the worker is in fact in contact with the work-piece.

Hand speed productivity

If a work-piece is identified within the user defined workspace then workers will either be classified as productive or static. The classification is determined by comparing the average hand speed (S_i), over a predefined number of frames (n), to a user defined threshold speed. The hand speed is calculated according to Equation 23 and the average according to Equation 24.

$$S_i = \frac{\sqrt{(LHx_i - LHx_{i-1})^2 + (LHy_i - LHy_{i-1})^2 + (LHz_i - LHz_{i-1})^2} + \sqrt{(RHx_i - RHx_{i-1})^2 + (RHy_i - RHy_{i-1})^2 + (RHz_i - RHz_{i-1})^2}}{2 \times Time\ between\ frames} \ldots (23)$$

$$Average\ speed = \frac{\sum_{i=1}^{n} S_i}{n} \ldots (24)$$

The selection of the array-size (*n)* and the threshold speed will vary for different tasks. The influencing factors are the time required for placing components and the magnitude, speed and frequency of hand movements.

Assumption

Provided that there is a work-piece within the work area, the worker can be classified as productive if his/her average hands' speed is greater than a predefined threshold.

Justification

A study conducted by van Blommestien indicated that the hand speed of a worker could be effectively used to establish whether the worker is productive or static. A limitation of the system was the prevalence of classification errors when the worker moved his/her hands while performing non-productive work. The HAWK-PRODUCTIVITY system reduces the prevalence of classification errors by requiring a work-piece to be present within the work area [**46**].

Workers are automatically classified as productive while in contact with a work-piece. For many work elements the worker may be required to break contact with the work-piece to reach the component bins or tool racks. During these reaches the worker is productive. The speed consideration ensures that the worker will be classified accordingly.

Work conducted without a work-piece in the work area is supplementary and although it may be unavoidable, it does not form part of the income producing activity and should be minimized.

Comments

The reliability and responsiveness of the system is controlled by two user defined parameters; the threshold speed and the number of measurements.

The threshold speed determines the reliability of the classification between static and idle. The minimum value is constrained by the inherent noise of the worker-tracker. Figure 36 depicts the quadratic increase in the variation of measured values for the Kinect™ device. As a result, as the distance increases, it becomes increasingly difficult to determine whether the worker is static or making small productive hand movements.

The selection of the threshold speed requires consideration of the number of measurements used to calculate the average speed against which the threshold is tested. The number of measurements determines the responsiveness of the productive/static classifications. The actual hand speed at the moment components or tools are touched reduces to near zero. In order to avoid false classifications of static, the calculated average should include measurements of the reaching hand speed. The reaching hand speed is significantly larger than the noise of the worker tracker. As a result the system takes longer to change from a productive to a static state.

The speed classification of productive is only responsive and reliable for fast hand movements with a short picking duration. Fast hand movements are defined relative to the inherent noise of the worker-tracker. Fast hand movements will typically be an order of magnitude larger than the inherent noise. For shorter picking durations, the number of samples can be decreased, which will result in more responsive state changes.

There are a few sources of possible error in the speed productivity classification. Workers moving their hands around while being unproductive result in incorrect productive classifications. However, it is unlikely that the worker's hand movements while idle will often exceed the magnitude and frequency while working. Another error occurs in cases where a picking or placing activity takes longer than usual or the worker-tracker fails. In these cases the worker may incorrectly be classified as static. In order to minimize the number of classification errors, the threshold speed and number of measurements (*n*) needs to be set carefully.

4.4.1.2 **Static**

Interruptions that occur while working on a work-piece can either result from unavoidable or avoidable delays. Unavoidable delays will be determined by tool breakages or supervisor interruptions. Avoidable delays include social visits with other workers and idleness without overcoming fatigue.

In many work-environments, tool problems and supervisor interruption will form a negligible proportion of measurements. In these cases the total static duration can be used to calculate the avoidable delays. Note that no allowance is provided for avoidable delays.

Assumption

If a piece is within the work-area and the worker is stationary or near stationary, then it is assumed that the worker is static and therefore unproductive.

Justification

The study conducted by van Blommestein indicated that by comparing the hand-speed of a worker to a pre-set limit, that a worker can be reliably classified as productive or static (unproductive). This results because it would be impossible for a worker to perform productive work if his hands are motionless [**46**].

Comments

Establishing whether a worker is motionless is complicated by the noise of the worker tracker. Noise results in low speeds being registered while the worker is motionless. The noise makes it difficult to distinguish between slow or small hand movements and stationary postures.

The static state is therefore applicable to stationary or slow hand movements. The limit for static classification is determined by the user defined threshold speed. Erroneous classifications of productive while static and visa-versa are minimized when the hand movements are fast.

4.4.1.3 Idle

The worker will not be performing productive work when he has no work-piece to work on. Provided that there is a sufficient supply of work over the duration of the study, and the worker is not required to clean or perform any maintenance during the period, then it could be assumed that the worker is resting while no work is located at his station. This value could then be used to calculate the fatigue allowance, ($A_{fatigue}$) according to Equation 25, where (T_{idle}) is the total time logged in the idle state.

$$A_{fatigue} = \frac{T_{idle}}{T_{Productive}} \dots (25)$$

Assumption

While workers are at their respective stations without work-pieces they are assumed to be idle.

Justification

This classification is additional to the states originally used by van Blommestein et al. The state serves to provide additional information and also to minimize the prevalence of false productive classifications. [**13**].

The amount of time that a worker spends at his workstation without a work-piece represents the amount of time that the worker is not performing value-added work.

Large idle times indicate:

1. Work-piece shortages (bottleneck)
2. Worker has taken his time retrieving work-pieces
3. Long set-up times
4. Lengthy maintenance and cleaning processes

The HAWK-PRODUCTIVITY system is incapable of determining what activity the worker is doing during the period. The worker's hand-speed was considered as a means of providing further detail on the worker's activity. The concept is similar to the productive/static classification. The hand speed would be used to differentiate between *workers waiting for work* and *set-up* or *maintenance* states.

The concept of using the hand-speed to define additional states was discarded for a number of reasons:

- The system currently only tracks a single work-piece, set-up times are therefore excluded from consideration.
- The proportion of idle time to the rest of the study is typically fairly small.
- The speed consideration will require the user to define a *threshold speed* and the *number of samples* used to establish the average speed. This adds complexity to the system operation.
- Workers may try to keep themselves busy when no work is available. Workers are likely to move around and fidget resulting in erroneous classifications.
- Furthermore the classifications are delayed. As a result the more states, the more delays and possible sources of error and confusion.

The simple classification of an idle state provides valuable insight into the proportion of time that the worker is without a work-piece in the capture frame. The reasonableness of this value is fundamental in identifying:

- Lack of work
- Low worker productivity
- Excessive cleaning and maintenance practices

Comments

The classification of idle also considers a set of data on the presence of the work-piece within the work area. This is necessary because the work-piece is not always positively identified. In cases where the work-piece is positively identified within the capture frame, a value of one is recorded and zero if it is not. The average value for a user-defined sample in calculated and compared to a threshold value. If the value is greater than the threshold then the work-piece is positively identified, otherwise it is logged as lost.

The identification of the work-piece plays a vital role in minimizing the number of erroneous classifications. The threshold value and number of measurements needs to be carefully selected by the analyst to ensure that the system is both robust and responsive.

As the number of measurements increases so does the reliability of the classifications, but the responsiveness decreases. The threshold value will depend on the user inputs for the SURF and RANSAC algorithms. It should be noted that the selection variables and threshold values can have a dramatic impact on the responsiveness of the classification. Moving into the idle state may take significantly longer or shorter than exiting from the state.

4.4.1.4 Out of frame (Allowances)

A worker will be out of the capture frame when he leaves his workstation for personal needs, this includes bathroom and water breaks. If the worker does not leave the work-station for other reasons, then this value can be used to calculate personal allowances ($A_{personal}$) according to Equation 26, where ($T_{out\ of\ frame}$) is the total time in which the worker was logged as being out of frame.

$$A_{personal} = \frac{T_{out\ of\ frame}}{T_{Productive}} \ldots (26)$$

Assumption

It is assumed that all time spent out of the capture frame are for allowance breaks.

Justification

Once the worker leaves the capture frame, the system is incapable of determining the purpose of the exit. For this reason all exits from the capture frame are logged under allowances. Workers that work at fixed workstations throughout a shift will only leave their stations for personal, restroom and meal breaks.

In order to ensure that unnecessary exits from the capture frame are kept to a minimum. The stock piles and inventory bins that workers retrieve work-pieces from and pack them onto must be within the capture frame. The managers on production floors are traditionally responsible for ensuring that workers are located at the correct stations throughout shifts. They are required to assume the additional responsibility of ensuring that workers do not change stations or move out of the confines of the capture frame.

Comments

The HAWK-SYSTEM takes time to calibrate workers and also to loose workers once they leave the frame, as a result the accuracy of the data is dependent on the frequency of the exits from the frame. The best results are for longer duration exits and entries, which are typical for bathroom and meal breaks.

The system cannot be used in cases in which the worker leaves the frame regularly to retrieve work-pieces or other work related activities.

4.4.1.5 Special cases

In cases where the work-piece is too small to be tracked, or cases where the worker is doing other work which does not involve a specific work-piece, an approach similar to the system developed by van Blommestein et al is advised. In this case only information on the worker's hand-speed is used to differentiate between the three different states, productive, static and out of frame [**13**].

The advantage of the HAWK-PRODUCTIVIY system as compared to the original concept is the use of 3D co-ordinate data in mm, as opposed to 2D pixel values. The HAWK-PRODUCTIVIY system therefore enables comparisons between different studies. This is attributed to the fact that the Kinect™ camera is less sensitive to changes in distance between the worker and the camera. Recall that for reliable comparisons, the studies should however be conducted at similar ranges due to the reduction in resolution and increase in noise that accompanies increasing distance from the camera.

4.4.1.6 New measures

The classification process requires the extraction of 3D co-ordinate data of the worker's hands along with the system time data at the moment the measurement is taken. As a result the data can be extracted that is not available in traditional studies.

- 3D co-ordinate data can be used to calculate the distance travelled by a worker's hand.
  - Positional data could be evaluated and used to improve tasks.
- The speed data can be analysed and variations in working speeds over a shift, between shifts and on different days of the week can also be calculated.
  - This information could be used to establish improved job scheduling over shifts and on different days according to a worker's productivity.

Although it falls outside the context of this study, an investigation into possible means of utilizing this additional data is proposed.

4.4.1.7 Conclusions

In strictly controlled work environments the time spent occupying the various states can be used to calculate allowances and, if the workers effort can be rated, the standard time. In addition to the possible application in calculation of the established labour performance indicators, the information on the time spent within each of the states carries valuable information and should be used as relative measures and diagnostic tools. Analysts should evaluate whether the time spent in any of the unproductive states is reasonable. If any of the values are deemed to be excessive or abnormal, they should be investigated further and the causes identified.

Core to the assessment is the percentage utilization, which indicates the total proportion of the study that the worker spends producing work-pieces. The value represents the amount of time that workers are producing value added work, and as a result should be maximized. A small utilization value could indicate over staffing, or mismanagement. On the contrary, excessive values, could point to understaffing and overexerting the workforce.

The basic information provided on the time spent occupying the various states, and the deductions that can be made provide ample opportunity to improve performance of the workforce.

4.4.2 Work-piece based measures

In addition to the worker based measures, data regarding the work-piece is also calculated by analysing the co-ordinate and system time data provided by the item-tracker. The information derived for the work pieces includes:

- Number of items processed
- Average processing time
- Standard deviation of the processing time

The number of items processed could be used in the calculation of the observed time, as indicated in Equation 22, and ultimately the standard time. It also provides analyst with an indication on the production quantities. This is useful for determining whether orders will be completed on time, or if the job needs to be expedited or slowed.

The average processing time represents the time that the average work piece spends at a workstation. This value indicates of the time required to manufacture a specific work piece. Note that this is not related to the standard time. The value should be used as a relative measure, whereby the average proceeding time can be compared between different workers. Ideally the variations between workers should be small. Large variations could indicate problems with training and a need for revised standardised operating procedures.

The standard deviation of the processing times (S_N), as calculated according to Equation 27, indicates the variability associated with the processing of a particular item. (x_i) is the observed processing times, $\bar{x}$ is the average processing time, and N is the number of items processed thus far.

$$S_N = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \ldots (27)$$

Large variations can be indicative of processing problems such as material variations, tool problems or a lack of training and could therefore require revisions to the standard operating procedures.

As with the worker based measures, the values cannot identify specific problems, however they can indicate that problems exist, thereby warranting intervention or further investigation by human analysts.

4.5 The graphical user interface

The user interface of the HAWK-PRUDUCTIVITY system is divided into four tabs. The first two, labelled Kinect™ *and Item Tracking Inputs* are common to both the HAWK-PRODUCTIVITY and HAWK-RNLE systems, and have been introduced in Figure 18 and Figure 30.

The *User Inputs* tab, depicted in Figure 50 includes a list of values that the analyst must enter prior to initiation of the productivity assessment. The study is initiated by clicking on the large *Calculate* button at the bottom of the list.

The first input on the GUI is a radio button for *pose calibration*. If the radio button is selected the worker will be required to assume the calibration pose prior to the initiation of the study. The use of a pose calibration locks the dimensions of the worker and results in less tracking failures. The disadvantage is that if the worker exits the frame, he will have to assume the calibration pose upon re-entry. Due to the nature of the productivity assessment, in which workers can leave the capture frame for personal breaks, the default is to automatically calibrate the worker without the posing.

Analysts are required to use a measuring device to measure the *mounting height* of the camera, defined by the midpoint of the lens, and also the *item depth*. Recall that the item tracker is a planar tracking algorithm. In order determine whether the worker is in contact with the item the analyst is therefore required to enter the depth dimension for the work-piece. The analyst must also define the *contact radius*. More information on setting the contact radius is included in Section 3.5.9.

The *low pass filter* value is used to smooth the hand tracking data. The contribution of the previous measurement is defined by the low pass filter value. As the value increases, the contribution of the previous measurement increases. As a default the value is set as 0.50.

The analyst must also enter a value for the *Work Speed Threshold*. This is the threshold value against which the worker's hand speed is compared in order to classify the worker as either static or productive. This value will increase with increasing distance from the camera.

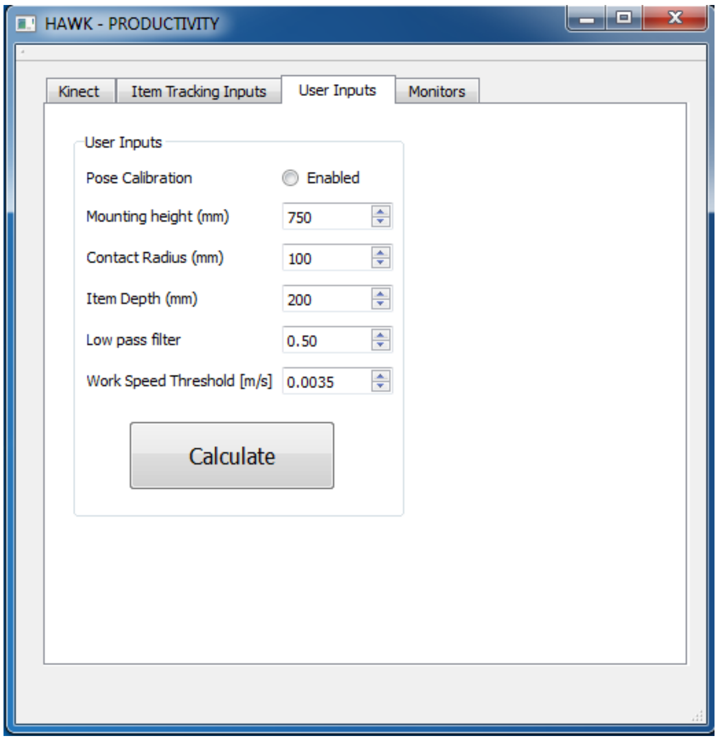

Figure 50: User inputs tab of the HAWK-PRDUCTIVITY GUI

A number of values have been purposefully excluded in order to minimize the complexity of the GUI. These values include:

- *Number of frames for contact*
  - The number of frames for which the minimum distance between the worker's hands and the work piece is calculated and then compared to the *contact radius*. The default value is 10 frames.
- *Number of frames for productivity*
  - The number of frames for which the average speed is calculated and compared against the *Work Speed Threshold*. The default is set at 40 frames.
- *Number of frames to detect item*

    - The number of frames over which the presence of the item, either a 1 or 0, is summed and then divided by the number of frames. This percentage of positive identifications is compared against the *percentage to detect item.* The default is set at 30 frames.
- *Percentage to detect item*
    - Threshold value against which the proportion of positive identifications of the item are compared. The default is set at 0.30.

The default values indicated for each of the tasks where determined after considerable testing. The values represented here were used in all of the tests conducted on the HAWK-PRODUCTIVITY system and will be suitable for a number of tasks. For tasks with frequent state changes the values should be adjusted to increase the responsiveness, Note however that by reducing the number of samples the reliability will decrease. These values therefore need to be carefully selected by an operator familiar with the system. The values can be adjusted within the header file named DON_CONSTANTS.

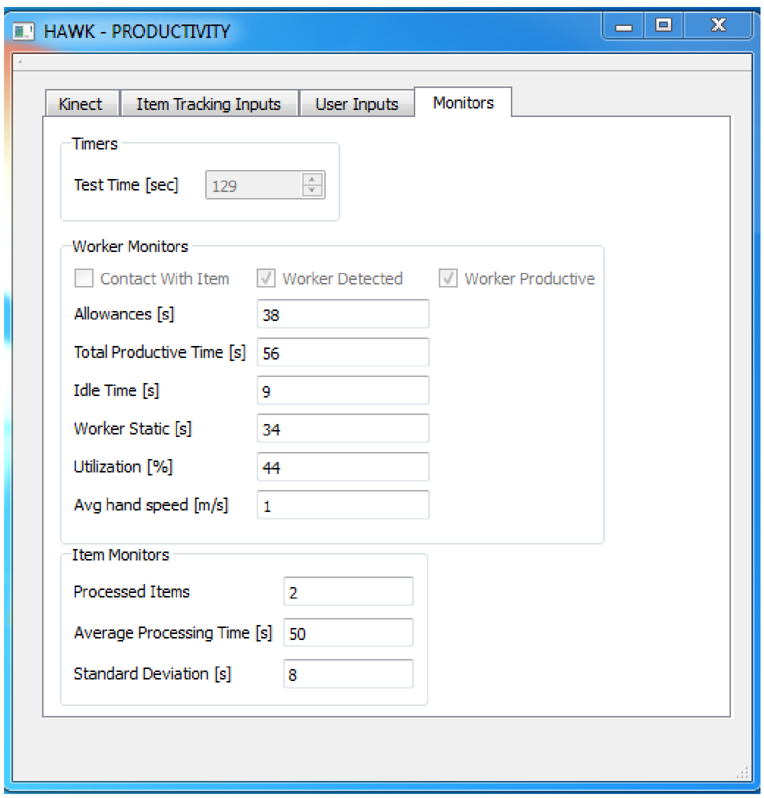

Figure 51: Item monitors tab of the HAWK-PRDUCTIVITY GUI

The *Monitors* tab of the HAWK-PRODUCTIVITY GUI is represented in Figure 51. The information in this tab can be divided into three subsections, the total *test time*, *worker monitors* and the *item monitors*. This is the tab that will invariably be selected for display directly following the initiation of the study.

- ***Test time***
    - The test time represents to total cumulative duration of the study in seconds. It is based on the system time and as a result is not directly linked to the other timers.

- ***Worker Monitors***
  - The worker monitors includes three checkboxes. The checkboxes indicate the state of the worker and serve as diagnostic tools. The *Contact With Item* checkbox is selected when the system registers contact between the worker and the item. The *Worker Detected* indicates when the system is tracking the worker. This is useful for indicating if at any time the system loses the worker. It is also useful for evaluating the time it takes for the system to lose the worker after exiting the capture frame. The final checkbox, *Worker Productive* indicates when there is a work piece in the frame and the worker is moving faster that the threshold speed. These values should to determine if any adjustments to the input values are required.
  - *Allowances* - The cumulative time that the worker is out of frame.
  - *Total Productive Time* -The cumulative time that the worker is in contact with the item, and the time that the worker's hand speed is greater than the threshold speed.
  - *Idle Time* - The cumulative time that there was no work piece within the capture frame
  - *Worker Static* – The cumulative time that the worker's hands speed is less than the threshold speed.
  - *Utilization* – The proportion of time that the worker is registered as productive.
  - *Average hand speed* – The average speed over the period defined by the *Number of frames for productivity*
- ***Item Monitors***
  - *Processed Items* – The total number of items that have moved through the user defined work-area
  - *Average Processing Time* – The average of the processing times
  - *Standard deviation* – The standard deviation of the processing times

4.6 Testing

There are two primary tests relating to the assessment of the HAWK-PRODUCTIVITY system.

1. Small item test - Involves work that is done on small items that cannot be tracked.
2. Large item test - Work done which includes large work-pieces that can be tracked by the item tracker.

The small item tests are an extension of the work done by van Blommestein et al., and although the methodology of the HAWK-PRODUCTIVITY system is slightly different, the basic principles remain. The basic concept involves monitoring the hand speed of the worker. By taking the average hand speed over a number of measurements and comparing this to predetermined limits, the worker can be classified as in one of three states; productive, static, or out of the capture frame [**13**].

The large item tests are essentially full system tests and require the tracking of a work-piece. As a result additional information is provided:

- Time that the worker has been in contact with the item

- Number of items produced
- Average processing time per Item
- Standard deviation of the processing time

It should be noted that there is an overlapping between the small and large item testing. The small item principles are also used in the full system test to determine whether the worker is productive or static.

4.6.1 Small item test

The small item test involves a simple task of assembling a number of LEGO® bricks in a pre-set order. The worker retrieves LEGO® bricks from component bins and assembles a number of similar structures adjacent to each other. The locations of the component bins and a close-up of one assembled row are depicted in Figure 52. Consequent rows are built a single space apart and in identical fashion to the first row.

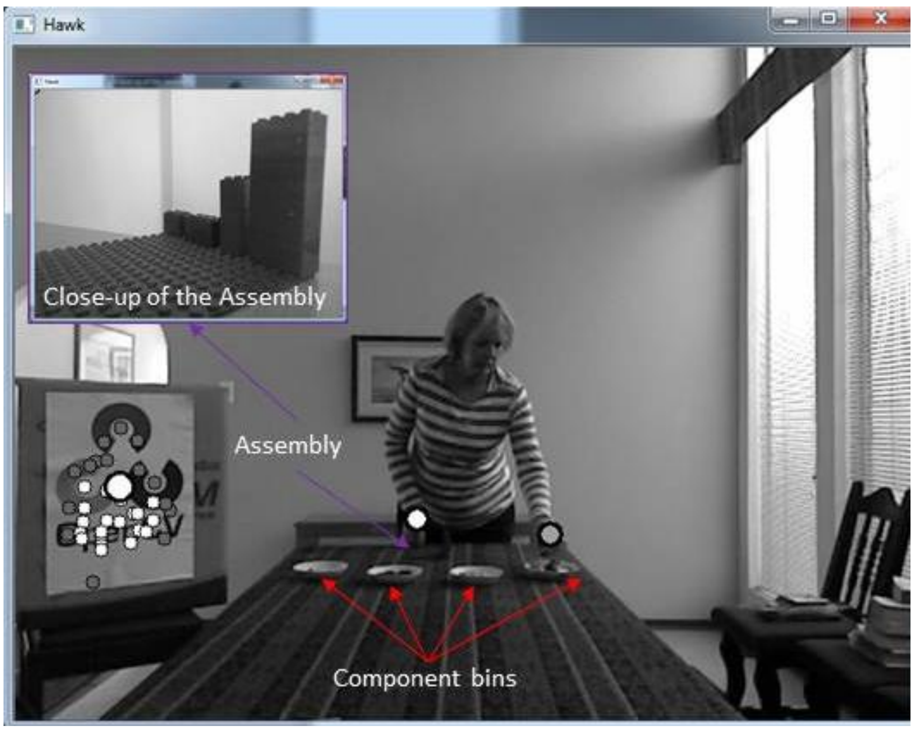

Figure 52: Small item assembly test

The test was designed to assess measurements of:

- Allowances
- Productive time
- Static time

The allowance is the total amount of time that the worker is away from the workstation, which is practically taken as the time the worker is not tracked by the camera.

The productive time is the total time that the average speed of both hands is above the predefined limit and the static time is the amount of time that the worker is near stationary, or below the predefined limit. If the worker is stationary, due to the Kinect™ sensors inherent noise, a small amount of movement is still registered by the system. Differentiating between the productive and static states therefore requires the establishment of a threshold limit. In order to minimize classification errors, this limit is selected to be slightly larger than the maximum noise of the Kinect™ camera. Recall that the magnitude of the noise increases with increasing distance from the camera.

Initial testing indicated problems of using the speed between two successive frames. Due to the high sampling frequency of the HAWK system, typically around 6-10Hz, while the worker placed a LEGO® block, the hand movements were small and the system registered the worker as stationary. As a result it was necessary to utilise an average speed over a longer time period, as was done in the colour tracking system developed by van Blommestein et al. [**13**]. The exact duration will vary between tasks, according to the frequency and magnitude of the reach and place cycles. In this test, due to continuous sampling basis and programming complexity, the representative duration was taken as a number of frames. The number of frames used was 30 and the threshold limit was set at 0.0035m/s.

4.6.1.1 Design

For this test the worker will originally start outside of the capture frame. After approximately two minutes the worker will enter the frame and after calibration remain stationary for a minute before repositioning himself in an alternative pose and remain stationary for another minute. The worker will then complete the assembly task after which he will again remain stationary before exiting the capture frame. After a while the worker will re-enter. This concludes a single instance of the testing procedure and it takes approximate ten minutes.

The test scenario represents an exaggerated and compacted workday in an assembly factory. The worker will spend some time in each of the states. The aim is to establish if the system is capable of reliably differentiating between the different states. In order to assess the performance of the worker the individual tests are recorded and the actual times are compared with those recorded by the system.

4.6.1.2 Analysis

The comparison between the HAWK-PRODUCTIVITY and the actual times provided information on the time delays between the identification of different states. Typically these delays include

- Time to calibrate the worker
    - There is a time delay between the worker entering the capture frame and the initiation of the skeletal tracker. As a result the worker could already be productive by the time he is calibrated.
    - The time required for calibration varies depending on the environmental conditions.
    - As a general rule, the worker should be as visible as possible to the camera. Larger movements also aid in the calibration proses.
- Time loss as the worker leaves the capture frame

  - The system does not immediately lose the worker upon exiting the capture frame. This can take as long as ten seconds
  - During this time the worker is incorrectly classified as static or productive.
- Settling time between the productive and static states
  - Due to the use of the average of multiple measurements to determine the state of the worker there is a delay in the switching of timers.
  - In the tests conducted here 30 frames are considered. As a result data from approximately 4 seconds earlier influences the current classification.

In addition to the delays there are also a few errors that occur.

- Tracking failures occur intermittently.
  - These failures are attributed to the contact nature of the experiment. The failures include:
    - Failure of the worker tracker to identify the worker's hand
    - Incorrect identification of the hand's location.
  - Tracking failures resulting in a false productive classification are less prevalent than those resulting in the false static classifications. Tracking failures in context of this experiment fail to identify hand movements ultimately resulting in the incorrect classification.
- Movement errors
  - Occasionally the worker will make a movement that is not work-related,
    - Adjusting to a more comfortable position while static
    - Leaving the frame

The accumulated errors of the test are represented in Table 22. These errors represent the closeness with which the HAWK system approximates results and the magnitude of the errors associated with changes of classification. The individual results in the table indicate considerable errors, however due to the inherent balancing effect of the state changes; the final results are remarkably accurate. The complete table, with actual times and the times measured by the HAWK-PRODUCTIVTY system is included in Appendix 15.

Table 22: Measurement errors of the small item assembly test

Step	Comments	Accumulated Total Error		
		Allowance (sec)	Static (sec)	Productive (sec)
1	Move into the frame, time lost to calibration	3	0	0
2	Remain stationary with fingers pressed against the table	3	-8	8
3	Cross arms	3	-12	10
4	Perform the assembly task	3	3	-11
5	Cross arms	3	1	-10
6	Leave frame	3	-4	-5
7	Totals	-1	-1	-1

An evaluation of the screen recording, which is included on the DVD, indicated that state changes were reliably identified. The time required to register state changes was measured using a stopwatch and recorded. In the absence of tracking failures the times were reasonably consistent. The average time to recognize a state change from static to productive was 1.25 seconds with a standard deviation of less than a quarter of a second. The time required to change from productive to static was longer at 3.15 seconds and the standard deviation was less than half a second. The difference in state changeover delays results because hand speeds during reaches are typically far larger than the threshold limit. As a result they have greater influence on the average hand speed. If the constants are chosen poorly, the system can be either hypo or hyper-sensitive

An area where variability is at its greatest is during the assembly process. The system is most reliable when the work cycle is fairly constant and the hand movements are fairly large. The classification errors of productive work for the assembly task were 12% (157s measured vs. 178s actual). This means that 12% of the time that should have been classified as productive, was incorrectly classified as in another state. More than half of this error is attributed to a slow first state change. The remaining error occurred in a single tracking failure which resulted in a state change time from productive to static of 8.34 seconds.

4.6.1.3 Discussion and conclusion

The selection of constants used in the differentiation of the different states will ultimately vary from task to task depending on:

- The speed, magnitude and frequency of the movements of a task
- Distance from the Kinect™ camera

The selection of limits is fairly intricate, as a general rule the limit should be set as low as possible while minimizing classification errors. The Kinect™ camera should be setup as close as possible to the worker while ensuring that the worker fits into the capture frame. If this is not possible, the basic principle is that the limit should increase as the distance between the worker and the camera increases. This is because the noise increases quadratically with increasing distance from the camera. If the frequency, speed and/or magnitude increase, the number of frames can be decreased. The system will respond quicker to state changes if fewer frames are used.

In preliminary tests it was observed that if the worker struggles with the placement process then the lack of movement registered by the system will result in the incorrect classification of the state. This indicates that the system will not be able to correctly classify the worker's state for small and slow movements.

Due to the nature of the program and the use of individual timers, there is a small amount of data lost as different timers are switched on and off. From the experiments conducted, the time losses are around 1%.

4.6.2 Large item test

In this section the individual elements are tested independently and are concluded with a complete system test.

4.6.2.1 Contact

The first test conducted is the contact determination test. The worker is required to make contact with the work-piece and after 30 seconds break contact, as illustrated in Figure 53. After a further 30 seconds the worker makes contact with the work-piece yet again repeating this cycle three times. The screen recording of the experiment is analysed to determine the final results.

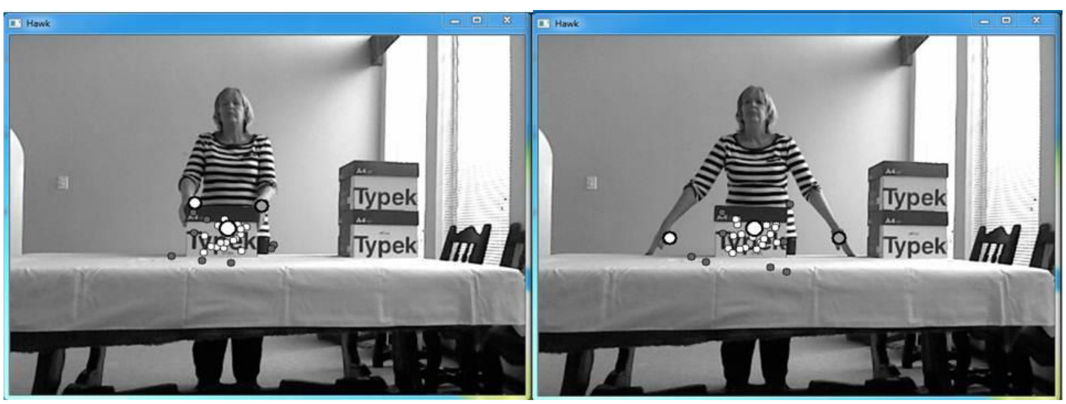

Figure 53: (*left*) Worker in contact with the work-piece, (*right*) Worker stationary and not in contact with the work-piece

In this simple experiment the work-piece remains within the capture frame. As a result the worker can only be classified as productive or static. The worker is productive when in contact with the work-piece and static during the non-contact motionless phase. The results of the experiment are represented in Table 23.

Table 23: Contact test results

	Actual	Measured
Productive	90	89
Static	90	88

From Table 23 it is apparent that a small amount of data is lost during the classification process. However, the data indicates that the system is capable of accurately classifying the worker as productive when he or she is in contact with the work-piece.

4.6.2.2 Number of Items processed

A simple test was conducted to assess the reliability of the item counter. The experiment involved moving a work piece into and out of the work area 50 times. The value recorded by the system was then compared to the actual amount. Figure 54 depicts a screenshot at the conclusion of the experiment. The GUI clearly indicates that 50 items have been processed with an average processing time of 5 seconds. Throughout the experiment the processing time and standard deviation remained constant.

The results of the experiment indicate that the system is capable of accurately counting the number of items produced. The reliability of the system is largely dependent on the user inputs of the item-tracker. The balance between the back projection error and the cluster size was most important. As a general rule, the back projection was set as low as possible. Once this was done, the user would increment the cluster size up to a point where the item tracker would occasionally lose the work-piece, even when perfectly aligned within the work-space. This approach minimizes the number of false classifications.

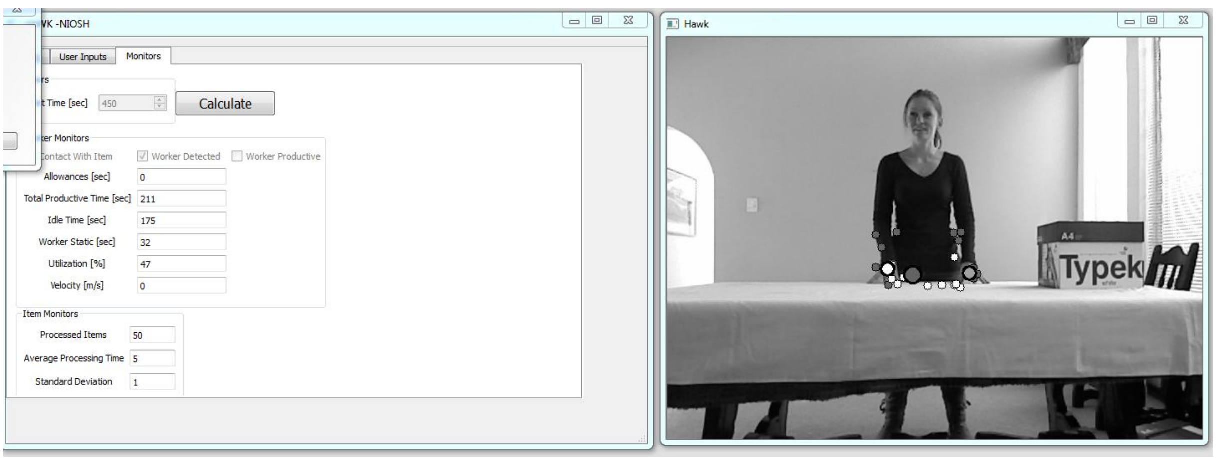

Figure 54: Item counter testing

From the experiment it was clear that there was a notable delay between identifying and losing the item. In this case, due to the short processing time of 5 seconds, the 30 frames required to detect the item is excessive. This value should be adjusted for shorter cycles, where it will have a larger influence on the results.

4.6.3 The final system test

The final test is designed to replicate the conditions of an assembly task. The worker is required to assemble a subcomponent and then fit the subcomponent onto the final product and execute a finishing activity. The testing assesses the system’s ability to accurately time and differentiate between the following states, under conditions resembling those of a factory:

- Allowances
- Total productive time
- Idle time
- Worker static

See Section 4.4.1 for the interpretation of each of these states.

In addition to the worker based information, the test also assesses the system's ability to accurately and reliably obtain data relating to the work-piece:

- Number of Items processed
- Average processing time

4.6.3.1 Design

The worker is required to build two rows of structures with LEGO® bricks. The components are located in component bins directly in front of the worker. The completed structures were then removed from the green base and placed through the corresponding holes cut into the top of the main assembly, as demonstrated in Figure 55. The main assembly which is tracked is a paper box, as used in Figure 54. The construction of the LEGO® bricks is designed to replicate the simple construction of a sub-assembly while pushing the sub-components through the corresponding holes replicating an attachment procedure between the sub and main assemblies. After each of the structures has been assembled into the box, the worker is required to draw a 10 x 10 mesh of lines 1cm apart. A completed mesh is drawn in Figure 55. The mesh represents a finishing action. Once completed, the box is moved out the work-area and placed in a holding position where it is ready for the next process.

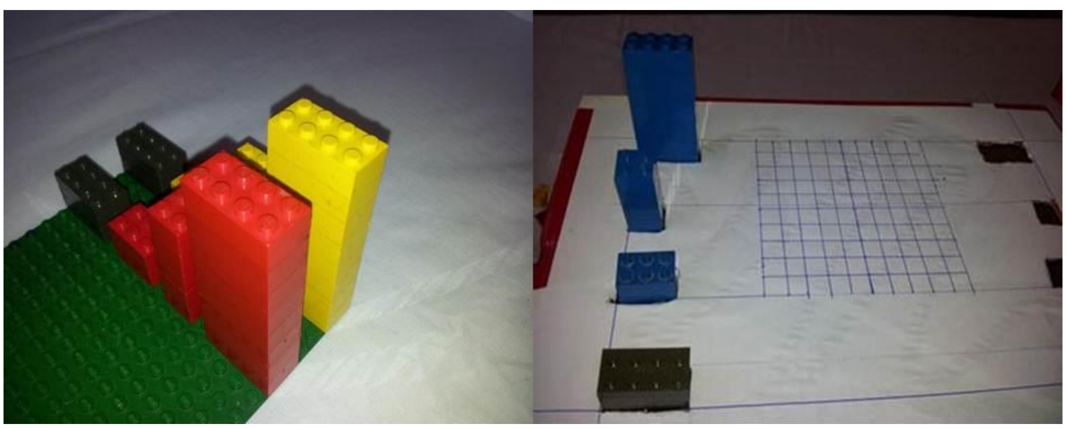

Figure 55: (*Left*) Construction of the LEGO® bricks, (*Right*) Placing the LEGO® bricks through the corresponding holes and a fully constructed mesh drawn.

The study was subdivided into three runs:

1. 13 minutes 22 seconds
2. 12 minutes 23 seconds
3. 13 minutes 13 seconds

Together a total of 38 minutes and 58 seconds of data was collected and analysed. During each run the worker would spend time in each of the classification states, with the majority of time spent being productive. In each run the worker completed three main assemblies. The exact time spent in each state was unscripted and would be determined in the final analysis. This analysis required a thorough investigation to identify the exact point at which state changes take place.

The test started with a work-piece in the frame. This was required because the work piece needed to be selected for tracking. Prior to this, the analyst firstly defined the work-area. The work area in this case was constant and as a result was drawn fairly tightly around the work piece. After selecting the work piece and enabling the item tracker, the analyst adjusted the input values for the RANSAC algorithm. The back projection error was made as small as possible while increasing the cluster size to the point that the item was occasionally lost. The item was then moved out of the work area to evaluate the response of the item tracker. If it lost the item and identified it immediately upon re-entry, then the study could be initiated. It is possible to adjust these values at any time during the test, however this is not recommended.

Upon initiation of the study a screen recording application was used to record the experiment and operation of the system. The specific screen recorder used was BB Flashback Express Recorder [**96**]. The screen recording approach was chosen as it eliminates synchronisation issues that would be encountered if an external camera was used to monitor the task. Additionally it enables close monitoring of the system's response to changes in the worker's behaviour. There is however one significant disadvantage of the approach. The processing power and memory used by the screen recording software does have an impact on the effectiveness of the HAWK-PRODUCTIVITY program.

4.6.3.2 Analysis

The screen recordings were closely examined in BB Flashback Express player. The software resembles a video editor, and although it cannot be used to perform edits like cropping and deleting parts of the video, the user is able to scan and select frames individually in the toolbar. This feature enables the user to select specific frames easily. This facilitates accurate determination of the exact points at which the state of the worker changes. A screen shot of the software in operation is included in Appendix 8. The player uses a unique .fbr file format. The software does however enable exporting of the recording to .avi files. This export function was used to create the videos on the DVD [**96**].

The recordings of each test were assessed individually. The analysis is broken down into two components. For each test, data is gathered and assessed on:

1. Item Monitors
2. Worker Monitors

Item Monitors

The accuracy with which the system calculates the average processing time is calculated by comparing the actual and measured values. The actual amount of time is calculated by recording the time at which the work piece enters the frame and as soon as the worker picks up the completed item. The measured data is retrieved from the GUI. Values are tabulated and the average error is determined. The results of the analysis are represented in Table 24.

Table 24: Accuracy of the average processing time determination

	Actual	Measured	Error
Processed Items	9	9	0%
Average Processing time (s)	205.8	209.7	1.9%

From the results in Table 24, it can be seen that the system is capable of estimating the processing time with an error of 1.9%. It should be noted that the error is specific to this task, as it is primarily dependent on the time delay required for the item-tracker to lose the item. In this case 30 frames, approximately 4 seconds of data are considered in order to establish whether the item is in the work area. This is a fairly large quantity and can be reduced to increase responsiveness. It will however reduce the reliability of the detection. In the tests conducted the system was 100% reliable and the error acceptable.

The information returned to the analyst via the GUI can be misleading if incorrect data is recorded by the system. False data could include item tracking failures, in which the item is not recognised, or lost by the system, ultimately resulting in false classification of items as complete. In order to minimize the likelihood of these errors, the analyst should select suitable input values for the item tracker. Additionally the number of frames used in the identification of the item should be as large as possible, while ensuring reasonable responsiveness. Another source of possible errors includes workers leaving a work piece in the work area while taking a break. Workers should be requested to avoid this.

The item monitors provide valuable data on the actual flow of work-pieces through a specific work station. The HAWK-PRODUCTIVITY system also provides information on the standard deviation of the processing time. This gives the analyst an indication on the variability of the processing times for a particular item.

Worker Monitors

The actual time spent by the worker in each state was taken as the time, to the nearest second, at which the worker's state changes. The description of the various states is represented in Table 25.

Table 25: Description and motivation behind the various classification states

State	Initiation Conditions	Motivation
Productive	The point at which the worker starts moving provided that there is a work-piece in the capture frame.	If the worker's hands are moving while there is a work piece in the frame it is likely that he is doing productive work.
	The moment that the worker makes contact with the work-piece.	If the worker is in contact with the work piece it is unlikely that the worker will be resting. It is therefore reasonable to assume that the worker is being productive.
Static	The moment the worker's hands stop moving.	If there is a work piece in the capture frame and the worker is not in contact with the work piece or his hands are stationary then the worker is resting and therefore unproductive.
Idle	The instant at which the worker picks up an item to move it out of the frame.	If there is no work piece in the frame then the worker will not generate revenue. Ideally workers should not spend as little time as possible without work-pieces.
Allowance	The moment at which the worker's body leaves the capture frame.	As soon as the worker leaves his workstation. The system cannot possibly determine what the worker is busy doing. In most cases workers will only leave their workstations for personal allowances.

The actual state changes for each test were then plotted onto a timeline, shown in Figure 56. The timelines clearly define the worker's state for each period. The timeline was used in the determination of the total time spent in each state.

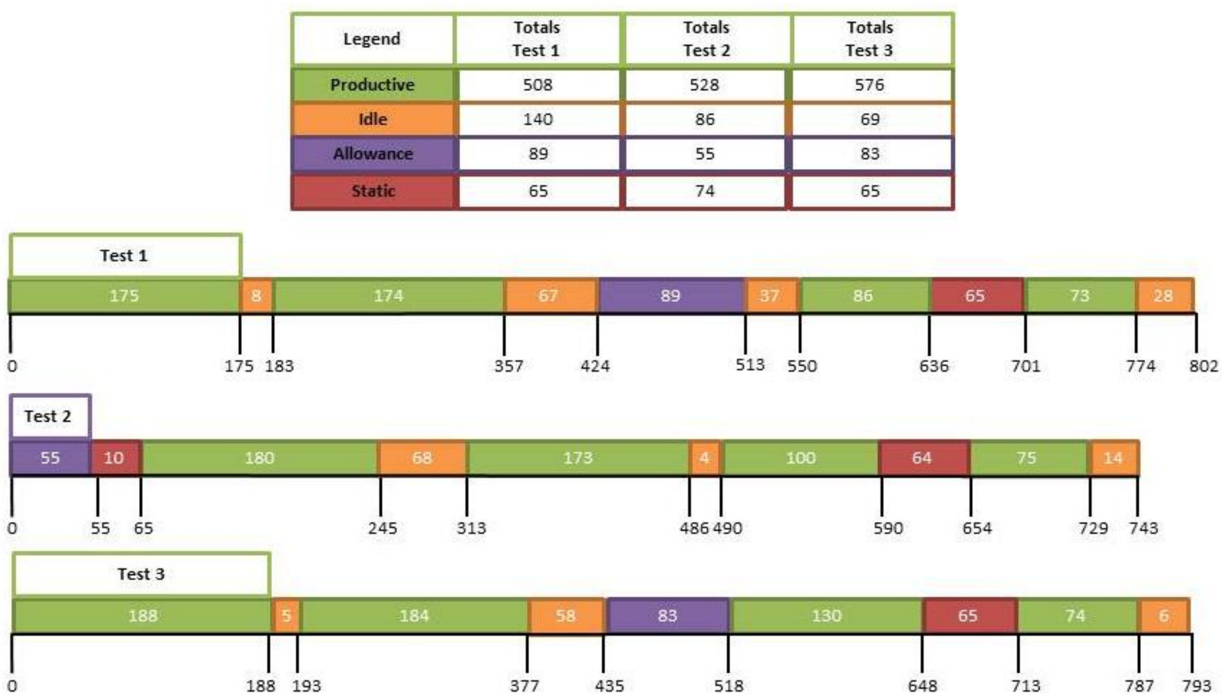

Figure 56: Timelines of the actual time spent in each state (all units in seconds)

The actual total time spent in each state, as derived from the timeline along with the values recorded by the system are represented in Table 26. The errors between the actual and measured values are also included in the table.

The data on the total duration indicates small timing issues within the system. In the tests the timers resulted in a loss of 1.1% of the data. The cause of the errors is attributed to the use of individual timers for each of the states. Due to the fact that the errors are relatively small, the time losses were not addressed. A discussion on each of the classifications states follows.

Table 26: Complete system test data

	Actual	Measured	Error
Total duration(s)	2338	2313	-1.1%
Allowances (s)	227	232	2.2%
Total Productive time (s)	1593	1612	1.2%
Idle time (s)	314	283	-9.9%
Worker static (s)	204	186	-8.8%
Utilization (s)	68.1%	69.7%	
Processed Items	9	9	0%
Average Processing time (s)	205.8	209.7	1.9%

Idle time

The results in Table 26 indicate that the system understated the idle time by nearly 10%. The magnitude of the error is attributed to the manner in which the values have been selected. This results because a number of frames are used to detect the item. The ratio of positive identifications required to register the item as present in the test was 0.3. Under good conditions, this ratio is close to 1 when the item is in the work-area and close to 0 when it is outside. Due to the fact that 30 frames are considered, the system takes a few seconds longer to lose the item than it does to identify it. The responsiveness can be adjusted by changing the number of frames and the ratio used to classify the state of the item. Any adjustment should also consider the impact on the reliability of the system.

Note that in order to remain consistent; the initiation conditions as described in Table 25 have been applied. As a result, when the worker moves a work-piece out of the work-area and immediately retrieves a new work piece, the worker is classified as idle, when in reality the worker is then being productive for the entire cycle. This results in an exaggeration of the idle time. The magnitude of which depends on the ratio between the time that the work piece spends in the frame and the time required to reach, retrieve and place the work piece.

In this experiment the average placing and retrieving process took six seconds, while the average time each work piece spends in the work-area was 206 seconds. The underestimation that this causes on the productive time was therefore less than 3%. The system will only return reasonably accurate results for small ratios. For large ratios a possible solution is estimating the time required for the placing and retrieving cycle. This can be multiplied by the number of items processed by the system. This value could be subtracted from the idle time and added to the productive time.

Static time

The other state that contributed a considerable error was the worker static time. A closer investigation indicated that the error of almost 9% is misleading.

A complex classification issue arises between the time the worker enters the frame and assumes a state at the workstation. In most cases this will be correctly classified as idle time. However, in the second test the worker left a work piece in the work area while taking an allowance break, as depicted in Figure 56. Upon returning to the station, the worker was calibrated and moved to assume a static position for a few seconds before starting productive work. As a result the worker was neither stationary nor productive between 55-63 seconds. The first four seconds were lost to calibration of the worker. A further four seconds was spent moving towards the workstation and finally the worker only remained stationary for 2 seconds. This duration was so short that the system classified the worker as stationary for less than a second before indicating that the worker was productive once more.

The errors for the first and third tests are -5% and 3% respectively, while for the second test the error was -23%. If the static classification during those controversial few seconds was done differently; with only 2 seconds being classified as static and the remaining 8 seconds as productive, the final results, indicate significantly reduced errors. These are represented in Table 27.

Table 27: Altered Static and productive times for test two

	Actual	Measured	Error
Allowances (s)	227	232	2.2%
Total Productive time (s)	1603	1612	0.6%
Idle time (s)	314	283	-9.9%
Worker static (s)	194	186	-4.1%
Utilization (s)	68.6%	69.7%	

The worker will always move into and out of the static state from a productive state. This can occur via two modes; either through contact with the item or by exceeding the threshold speed.

The input values selected for this test as well as the nature of the criterion causes a delay in the classification of the worker as static. This delay is longer than the delay to change back to the productive state. This results because as the worker moves to assume a stationary position, the hand speed is typically significantly larger than the inherent noise on which the speed criterion is based. 40 measurements are considered in the productivity/static consideration. As a result there is a delay in the time taken for influence of large hand movements to be sufficiently diminished. The counterpart is the accelerated exit from the static state.

The discrepancy between the times required to enter and exit the static state results in an underestimation of the measured value. This underestimation is off-set by false classifications of static when the worker is being productive. Examples of these false classifications along with the delay are depicted in Figure 57. In this case 8 seconds of false classifications are added to the measured static time. The total measured static time is eventually 2 seconds longer than the actual time.

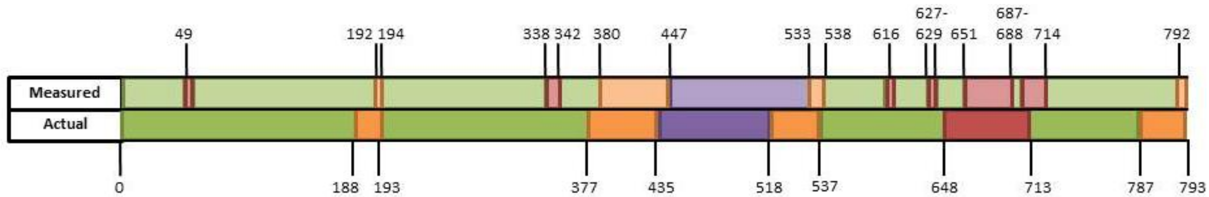

Figure 57: Timeline of actual vs. measured values

There are two primary sources for false classifications.

1. The first is tracking failures of the worker-tracker
2. Reduced processing speed

Tracking failures can occur when the worker is free-standing or in contact with a surface. The result is that hand locations are incorrectly recorded and the total amount of movement registered falls below the limit resulting in a static classification. A failure of this type occurs between 338-342 seconds in Figure 57. Fortunately in most cases the worker tracker is corrected as soon as the worker makes the next considerable movement with their hands.

The second source of error occurs as the worker slows down. A reduced processing speed would typically occur when workers spend an excessive amount of time picking components or tools. The increased period between reaches results in an increased risk of false static classifications. By considering the timelines for the three tests in Figure 56, it can be seen that the processing time in the third test, which is the timeline used in Figure 57, was significantly longer. It can be seen in Figure 56 that the worker was working slower in this test. If the worker spends too much time picking components, such as at 49, 616, 627-629 seconds then the worker is briefly classified as static until the next reach motion.

Productive time

In Table 26 the error of 1.2% indicates that the system is capable of accurately calculating the total productive time. There are however a few errors and delays in the responsiveness of the timer.

The time delays for the initiation of the productive timer vary for the different states. In terms of the static state the delays for initiation are typically shorter than that for stopping. The reasons have been discussed in the section on static time.

The pattern for the idle time is similar. The reason for this is that the worker is in contact with the item as it is brought into the frame. As a result the productive timer is initiated as soon as the item is detected. There is a small delay that results due to:

- 30% of 30 frames are required to identify the item (Minimum 9 frames)
- 10 frames used to establish contact

These two considerations are not related and run concurrently. The result is that the system took approximately 10 frames or just over a second to initialize the productive timer, as depicted in Figure 57 at 193 and 537 seconds. The exact time required will vary according to the processing capabilities of the computer. The process of exiting from a productive to an idle state takes significantly longer. This is due to the fact that at least 70% of 30 frames must fail to positively identify the item. This in turn means that at least 21 frames will be required to enter the static state from the productive state. This will be around 2.33 times as long as the identification process.

There are a few possible sources for false classifications. The likelihood of some errors has been reduced sufficiently through the use of multiple measurements. A few errors are however still prevalent. The comparison between the actual and measured values in Figure 57 includes an example of a false classification of productive while the worker is static. Between 687-688 seconds the worker changed his pose from resting his hands on the table to crossing his arms. The system is incapable of differentiating between productive and unproductive hand movements. This results because if there is a work piece located within the work area, the system classifies all hand movements above the threshold speed as productive.

Another possible source of error is tracking failures such as those for the worker's feet in Figure 24. These tracking failures occur when the system is incapable of fitting the skeletal model onto the worker. In all of the tests conducted, this type of error never occurred for the worker's hands. This could still become an issue if the worker does not completely fit within the capture frame and hand-movements are done near the boundary of the capture frame.

The final error occurs if the worker exits the frame while leaving a work piece in the frame. In this case the time required the worker to exit the capture frame will also be incorrectly classified as productive time.

Allowance

Allowances are measured as total amount of time the worker spends outside the capture frame. The timeline in Figure 57 indicates that there is a significant delay between the time the worker leaves the frame and the initialisation of the allowance timer. The delay in the initiation and exit from the allowance state is the largest of all of the states.

In the third of the system tests, the time delay between the worker exiting the frame and the system registering the exit was 12 seconds. This delay was largely balanced out by the time delay to calibrate the worker again. In this case the time delay was 15 seconds. The net result is a three second error between the actual and measured values. This counterbalancing effect is the reason for the total allowance error of only 2.2%.

The screen recording program increases the time required to loose and recalibrate the worker. Tests run under similar conditions without the screen recorder resulted in reduced times. In most cases the calibration took between four and seven seconds and the time to lose the worker between three and five seconds. However due the occasional failure to calibrate the worker properly on the first attempt, the maximum calibration time was twelve seconds. The presence of these errors could result in considerable overestimates.

The significance of the errors will be increased if:

- The frequency of exits increases
- The time spent out of the frame decreases

It is therefore important to ensure that the worker is predominantly located at his station.

4.6.3.3 Discussion and conclusions

The final system test indicated that HAWK-PRODUCTIVITY system was capable of accurately and reliably calculating the average processing time and number of items produced at a specific workstation. The ability to return information on the work-pieces requires:

1. The camera must be set up at a suitable distance from the workspace, ensuring that enough features can be identified on the work piece without compromising the performance of the worker tracker.
2. The workspace needs to be carefully defined, thereby ensuring:
   a. That there is never more than one work piece within the work area.
   b. That all work conducted on work-pieces must take place within the user-defined workspace.
3. The user inputs for the item tracker, must be appropriately selected for the task, so that:
   a. The work piece is reliably identified when it is in the frame
   b. It is not falsely identified when it is out of the frame.

These guidelines should be followed in order to ensure that the work piece is not inadvertently lost. Incorrect losses of the work piece could have significant consequences by misleading analysts. As a result, reliability is emphasised. In order to improve reliability, the program considers a number of measurements to classify the work piece as either present or absent. In the tests 30% of 30 frames needed to positively identify a work piece to register the work piece as present. Note that the use of multiple measurements decreases the responsiveness in the identification of work-pieces. As a result there is a small discrepancy (1.9%) between the actual and measured production times.

The full system testing also indicated that the system was capable of differentiating between the productive, static, idle and allowances states. In order to ensure more reliable definition of the worker's state, multiple measurements were considered. A consequence of the use of multiple measurements is the slight delay that occurs in the transition from one state to another. A summary of the criteria used for the classification is included in Table 28.

Table 28: Classification criteria and sources for delays in the full system tests

State	Criteria
Allowances	Worker tracker must lose the worker (3-5 seconds),or identify and calibrate the worker (4-7 seconds)
Productive (contact)	30% of 30 frames must positively identify a work-piece to identify the item Minimum distance between worker's hands and the work piece calculated over 10 frames are compared to the contact radius of 100mm.
Productive (Speed)	Average hands' speed of 40 frames must be greater than the 0.0035m/s limit
Static	Average hands' speed of 40 frames must be less than the 0.0035m/s limit
Idle	The work piece must not be identified. At least 70% of 30 frames must not have a work piece

For the full system testing, emphasis was placed on reliability. The result is that the time delays to register changes between states became notable. The impact that these delays have on the final results are directly linked to the duration that the worker spends in each of the states. As the duration decreases the errors become relatively bigger. The final system testing done required the worker to change states frequently. Although the errors were not negligible, they were considered to be reasonable. If the time spent in each state increases as it is expected to do in the real world, then the magnitude of errors is expected to decrease.

It is important to highlight the fact that that the processing power used by the screen recording software has an impact on the effectiveness of the program. Close observation identified a slightly reduced frame rate and indicated that the calibration of workers entering the screen is significantly affected. Delays were experienced in the testing, and in some cases the calibration required the worker to make unnatural movements. The advantages of using the screen recording software as opposed to filming the test independently with another camera out-weigh the disadvantages. The screen recording eliminates synchronisation issues between the systems which can be avoided. Furthermore the system's response to changes in the worker's behaviour can be evaluated easily.

4.7 Conclusions

The testing done on the system indicated that the system could be used for the assessment of workers working on small or large items. The small item test enables the system to be used in cases where work-pieces are too small to be effectively tracked by the item tracker. This therefore ensures that the HAWK-PRODUCTIVITY system can be used to asses a wider variety of tasks.

The large item test has many benefits over the simple small item implementation. In addition to providing information relating to the work-pieces, the large item implementation has the added benefit of producing fewer erroneous classifications. The most notable are those hand movements made when there is no work piece within the frame. In this small item implementation, these movements would falsely be classified as productive, whereas in the large item test the worker would be classified as idle.

The testing indicated that the HAWK-PRODUCTIVITY system was capable of reliably determining the state of the worker. However noticeable delays were identified between the state changes. These delays result because, for reliability, the system considers multiple measurements for state changes. As a consequence, the responsiveness has been affected. Due to the nature of the classification criteria, the delays do balance each other out to a limited degree; however the errors are still significant. The magnitude of the errors can be reduced by using smaller data sets in the classification process. This should be done with caution as this will influence the reliability of the classifications.

In addition to the delays, erroneous classifications also occur. Examples of which are depicted in Figure 57. The classification errors include cases where the worker is incorrectly classified as:

- Productive while static
    - The errors occur when making unproductive hand movements. The hand movements are then incorrectly logged as productive.
- Static while productive
    - Tracking failures cause hand locations to be being incorrectly determined. As a result the amount of movement registered falls below the threshold speed.
    - The worker's hands slow down, as would typically occur if the worker spends an unusual amount of time picking components.

Unfortunately, due to the systematic roots of the errors, nothing can be done to eradicate or reduce their prevalence. Although the errors do influence the results, they represent a fairly small component relative to the duration of the study.

4.7.1 Results

The results of the full system test indicated that the continuously updating GUI provided a suitable depiction of the results. The testing also indicated that the system was capable of returning reasonably accurate information on the worker and item monitors.

The results of HAWK-PRODUCTIVITY system should be used as relative measures, where deviations in the values indicate problems. Recall that due to the limited number of states used, the results cannot identify specific root causes for problems. It can only indicate that problems exist. A further investigation can be focused to some degree as the state under which the problem was identified is known.

Information provided on the worker monitors can be used to determine if a worker is spending an unusual or excessive amount of time in any of the states. Most importantly it provides a simple means of assessing; how much time the worker spends at his workstation and how much of that time is spent working on work-pieces, indicated by the percentage utilization. A simple evaluation of the time spent in each of the states could indicate problems, of which there are many sources:

- Large idle times could indicate:
    - Lack of work, which could be caused by
        - Upstream bottleneck operations
        - Problems with suppliers
    - Low worker productivity
    - Excessive cleaning and maintenance operations
- Excessive static times could indicate:

  - Poor work ethic
  - Frequent supervisor interruptions
  - Tool problems
- High allowances could indicate:
  - Poor management of workers, whereby workers are taking too many breaks

In addition to the data on the worker monitors, which is available in traditional studies, the HAWK-PRODUCTIVITY system also provides additional information on the work piece. The item monitors provides valuable information regarding the production quantities and the processing times. These values also contain valuable information on the presence of problems that cannot be identified by the worker's states. A few examples include:

- If the production quantities decrease and/or processing times increase then analysts should also consider the information on the worker's states. If the values are within the normal range. The variation could be the result of:
  - Reduced performance
  - Lack of proper training or standard operating procedures (SOP)
- Large standard deviations in the processing times require further analysis. Causes could include:
  - Material variations
  - Lack of training or SOP
- Workers that display significantly faster processing times should be assessed to identify the reason for the enhanced performance. If the causes can be identified by manually assessing the worker, then the SOP can be revised.
- The number of items completed can be used to assess the progress of a specific order.

Although it would be optimistic, it was mentioned that that in extremely controlled workplaces that the system could be used to calculate the rest allowances for workers. The calculations are based the following assumptions:

- Personal allowances for all the time the workers spend out of the frame.
- Fatigue allowances for the time that workers spend without a work piece at the station.
- Unavoidable delays for the time that workers are motionless while there is a work piece in the frame. Provided that there are no avoidable delays.

Due to the strict requirements of the assumptions, the allowances were excluded from consideration in the testing done on the HAWK-PRODUCTIVITY system. This also played a part in the exclusion of the calculation of standard time, which was eventually excluded due to problems with performance rating of the workers. A possible solution for performance rating was set forth and forms part of the future work. The proposal involves analysing the hand speed data while the worker is working on a work piece. The measured hand speed would then be compared to a reference value, thereby providing accurate performance ratings.

4.7.2 Comparison to existing automated LPMs

The evaluation of the existing automated systems developed by van Blommetein et al. and von Petersdorff in Section 0 brought to light certain limitations and advantages of the systems. The proposed system draws on the existing strengths of the approaches and addresses many of the limitations. A comparison with the existing approaches is represented in Table 29 [**13**,**12**].

Table 29: A comparison with existing techniques: The HAWK-PRODUCTIVITY system's strengths and weaknesses.

Time Studies	Work Sampling	HAWK-PRODUCTIVITY system
Limited impact on accuracy as compared to traditional studies	Increased accuracy compared to traditional study. Due to increased number of observations and extended duration of the study	**Increased accuracy, due to continuous sampling and ability to implement system over an extended time**
Easy to understand	The statistical basis of the study may be difficult for workers and management to comprehend	**Easy to understand - Continuous sampling requires no statistical explanation**
Accurate timing figures are obtained	Enough samples need to be made to ensure that the desired accuracy of the final results are achieved	**Due to the continuous basis, theoretically accurate timing figures can be retrieved**
Difficulty in programming robust flexible cycle identification and recognition algorithms.	Simple coding procedures.	**Simple coding procedures.**
Less detail available as compared to traditional methods - Only information on Work cycle time provided	Less detail available regarding the specific activity of the worker compared to traditional methods.	**Less detail as compared to traditional measures, but more compared to the existing automated approaches**
Calculates the standard cycle time for a simple task	Calculates worker utilisation and allowances	**Calculates the total productive time, idle time, static time, time out of frame, percentage utilization, allowances, number of items produced, average processing time, standard deviation of processing time.**
Feedback given to worker	No real time feedback	**Real time assessment enabled via the GUI**
Worker needs to be calibrated to enable tracking	Glove needs to be worn by worker to enable tracking	**No calibration required to enable tracking**
Cyclic variations are not as well compensated for	Observations typically made over an extended time period which decreases the effects of cyclic variations	**System can be set up for the maximum duration required**
Requires extensive knowledge and understanding of the task	Does not require an understanding of the task	**Does not require an understanding of the task**
Simple set-up procedure	More complicated set-up procedure, set up filters and input initial valuables for variables	**More complicated set-up procedure, setting item tracker variables and input initial values for variables**
Computational expensive, One task analysed at a time,	Less computational expensive, Multiple work stations observed at the same time	**Computationally very expensive, only one task is analysed at a time, due to the computational expense**

A notable disadvantage of the HAWK-PRODUCTIVITY system, as with all automated approaches is that there is less detail available than in manually performed studies. However, the benefits of the automation far outweigh the disadvantages. The automated systems save analysts time and therefore costs in the data capturing and transcription phases of traditional studies. Furthermore the automated systems significantly simplify and also reduce the tediousness of measuring labour performance.

There were however a number of problems and limitations with the existing systems. From the comparison in Table 29 it is clear that the HAWK-PRODUCTIVITY system represents a significant improvement of the existing systems and in addition to addressing many of the limitations, it also provides additional information.

5. Chapter 5

The HAWK-RNLE system

5.1 Introduction

This chapter introduces and discusses the Revised NIOSH Lifting Equation (RNLE). The chapter includes the methodology used to automate the procedure along with the testing of the HAWK-RNLE implementation.

5.2 Revised NIOSH lifting equation

This section provides background information on the derivation and formulation of the revised NIOSH Lifting equation RNLE. Following the formulation are the limitations within which the equation can be applied. The multifactorial nature of the algorithm results in varying sensitivity between the risk factors. As a result the sensitivity of the components in the equation is introduced. This is followed by an investigation into the accuracy with which of trained human analysts to can measure the variables. This information forms the basis for the development of the automated HAWK-RNLE system.

5.2.1 Background

Lifting tasks pose significant risks on workers and result in a significant global economic burden because of time off due to work related injury. The RNLE is widely used in industry to reduce the risk of LBP associated with manual lifting. In addition it also reduces the possibility of shoulder and arm pain. It provides an empirical method for calculating the maximum weight of an object to be lifted. This weight represents the load that the vast majority of healthy workers could perform over a substantial period of time, (up to eight hours) without an increased risk of developing lifting related LBP [**3**].

The components of the RNLE are defined by three criterions indicated in Table 30. Because each of the criterion may provide an unique load limit for a specific task the equation was based on the most conservative load limit allowed by any individual criterion [**3**]. The RNLE therefore considers the impact of a range of risk factors, and combines them in a concise lifting index [**31**].

Table 30: Criterion used to develop the revised NIOSH Lifting Equation [3]

Discipline	Design Criterion	Cut-off value
Biomechanical	Maximum disc compression force	3.4 kN
Physiological	Maximum energy expenditure	2.2 - 4.7kcal/min*
Psychophysical	Maximum acceptable weight	Acceptable to 75% of female workers and 99% male workers

* The energy expenditure limit varies according to the vertical height of the lift and the duration of continuous lifting.

It is important to note that the RNLE does not consider all factors attributing to LPB. It does not include exceptions or adjustments for whole body vibration, static postures, high once-off forces on the spine and psychological factors. A study conducted by Waters et al. indicated that personal and psychological factors did not have a significant effect on the reporting of LBP [**97**].

5.2.2 Revised NIOSH lifting equation formulation

The lifting index (LI) provides an indication of the physical stress associated with a lifting task. It is defined as the ratio of recommended weight limit (RWL) to the load weight, as shown in Equation 28 [**5**].

$$LI = \frac{Load\ Weight}{RWL} \ldots (28)$$

The RWL is the principle product of the RNLE. It is based on a multiplicative model that provides weighting for six task variables. The weightings are expressed as coefficients that serve to decrease the load constant (LC), which represents the maximum load weight to be lifted under ideal conditions and is equal to 23kg. The RWL is defined in Equation 29 [**5**].

$$RWL = LC \times HM \times VM \times DM \times AM \times FM \times CM \ \ldots (29)$$

A brief description of the multipliers is included in Table 31. The principle behind the establishment of each of the multipliers is provided by Waters et al. [**3**].

Table 31: Description of multipliers

Symbol	Name	Interpretation
LC	Load Constant	Maximum load weight that can be lifted by the majority of healthy individuals under ideal conditions
HM	Horizontal Multiplier	Varies according to the horizontal location of the load
VM	Vertical Multiplier	Varies according on the vertical location of the load
DM	Distance Multiplier	Varies according to the vertical distance that the load is moved
AM	Asymmetry Multiplier	Varies according to the angle of asymmetry between the worker's hands and feet
FM	Frequency Multiplier	Varies according to the number of lifts conducted over the work duration and also depends on the vertical location of the load
CM	Coupling Multiplier	Varies according to the quality of the hand to object gripping method as well as on the vertical location of the load

The multipliers are calculated according to the equations represented in Table 32. The multipliers are dependent on measurable descriptors called task variables. A description of the measurement process for each of the task variables is included in the table and supported by the visual depiction in Figure 58. The constraints for each of the task variables are also included in the table. A compressive description and justification for the task variables and corresponding constraints is provided by Waters et al [**5**].

Table 32: Equations, constraints and variable descriptions for RNLE multipliers [5,98]

Multipliers	Task Variables	Variable Description	Equation	Constraints
LC	-	-	23Kg	-
HM	H	Measured from the midpoint of the line joining the inner anklebones to a point projected directly below the mid-point of the hand grasps defined by the knuckle of the third metacarpal.	$\frac{25}{H}$	V must be greater than 0. If H < 25cm then H is set to 25cm. If H> 63cm then HM is set equal to 0.397
VM	V	The vertical height of the hands above the floor, measured as the mid-point between the hand grasps as defined by the knuckle of the third metacarpal.	$1-(0.003\|V-75\|)$	V must be greater than 0. If V >175 cm then VM is set equal to 0.
DM	D	The vertical travel distance of the hands between the origin and destination of lifts.	$0.82+\left(\frac{4.5}{D}\right)$	D must be greater than 0. If D<25 then D is set equal to 25cm. If D >175cm then DM is set to 0
AM	A	It is the angle between the asymmetry line and the sagittal plane. Where the asymmetry line is defined as the line that joins the midpoint between the inner ankle bones and the point projected on the floor directly below the hand grasps. The sagittal line is the line passing through the mid-point of the inner ankle bones and lying on the mid sagittal plane as defined by the body in the neutral position with no twisting or rotation.	$1-(0.0032\times A)$	A must be greater than 0. If A>135˚ then AM is set equal to 0.
FM	F ,V and the duration of continuous lifting	F - The average number of lifts per minute over a 15 minute period. V - The vertical height of the hands above the floor (as above). Duration – one of three categories; Short duration(<1hr), Moderate duration(1hr<Duration<2hr) or Long duration(2hr<Duration<8hr)	Appendix 9 Table 47	-
CM	V and the Coupling type	V - The vertical height of the of the hands above the floor(as measured above) Coupling type - can either be: Good, Fair or Poor. It is determined according to the decision tree in Appendix 9 Figure 69**.**	Appendix 9 Table 46	-

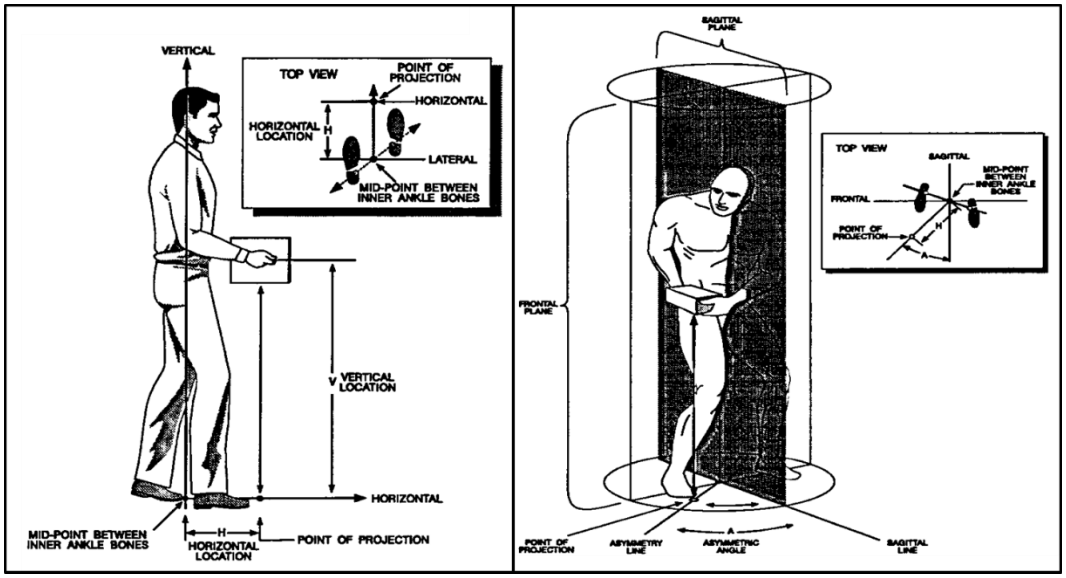

Figure 58: Graphical representations of the measurement of task variables.
(*Left*) Graphical representation of hand location, (*right*) Graphical representation of angle of asymmetry [5]

Studies evaluating the RNLE have indicated that a significant portion of the studies yield results that exceeded the constraints of the RNLE. The studies have also shown that more than two thirds of the studies conducted exceed the RWL and as a result would need to be redesigned. These results are attributed to the stringent limits set for the horizontal distance and the maximum allowable frequency [**99**,**8**].

In a recent study by Waters et al. the HM was modified for cases in which the horizontal distance (*H*) exceeded the original constraining limit of 63cm [**98**]. For cases where *H* exceeded 63cm it was set equal to 63cm. This is justified by the fact that in most cases in which the limit was exceeded the worker stepped forward and therefore centred their weight over one foot, as a result the horizontal distance to the L5/S1 joint was maintained at approximately 63cm [**98**].

Assessments of the RNLE have indicated that the LI was a useful predictor of risk in lifting related LBP [**98**,**97**]. The RNLE can therefore be used to reduce the risk of lifting related LBP by evaluating tasks and determining if changes need to be implemented. The RNLE can then be used to assess the redesigned task. If it is impossible to make the task acceptable, devices such as mechanical-assist devices should be implemented [**7**].

The RNLE is only applicable to a limited subset of lifting related tasks. Specifically, it only applies to lifting tasks in which both hands are used to move the load. As with any technique, it can only be applied in conditions falling inside the boundaries within which it was developed. Waters et al. provided the following summary of limitations under which the equation was invalid [**5**]:

- Lifting or lowering with one hand
- Lifting or lowering for over 8-hours
- Lifting or lowering while seated or kneeling
- Lifting or lowering in a restricted space
- Lifting or lowering unstable objects
- Lifting or lowering while carrying, pushing or pulling
- Lifting or lowering with wheelbarrows or shovels
- Lifting or lowering with high speed motion
- Lifting or lowering with unreasonable foot/floor coupling factor
- Lifting or lowering in an unfavourable environment (19-26˚C and 35-50% humidity)

5.2.3 Sensitivity analysis

In order to enable effective identification of problem areas and interventions with the use of the RNLE, accurate data needs to be extracted. Limited accuracy and precision could have far reaching consequences and result in poor allocation of funding and resources for improvements [**100**].

Consider the range of possible values of each of the multipliers and also the range of measurements for the variables. This information is used to determine the magnitude that a single unitary increase in the variable has on the multiplier. This information is depicted in Table 33. This simple assessment indicates that some values are more sensitive to changes in the location of loads than others. The most sensitive is the horizontal multiplier.

Table 33: Range of possible values for variables and multipliers

Multiplier	Range of possible Variable values	Range of possible Multiplier values	Average change in multiplier value per cm
HM	25cm – 63cm	0.40 - 1	0.016
VM	0cm – 175cm	0.70 - 1	0.002
DM	25cm – 175cm	0.85 - 1	0.001
AM	0˚ - 135˚	0.57 - 1	0.003 per degree
CM	-	0.90 - 1	-
FM	-	0.13 - 1	-

In order to demonstrate the sensitivity of the RNLE, we consider the sensitivity of the multipliers and the effect that measurement errors have on the RWL. The impact of the measurement error is demonstrated by considering the differential of the multiplier ($f'(x)$) and the assumed error (Δx) as shown in Equation 30 [**100**].

$$f'(x)\Delta x \ldots (30)$$

This approach provides a reasonable estimate for small errors since;

$$f(x + \Delta x\ ) \approx f(x) + f'(x)\Delta x \ldots (31)$$

Consider the following simplified scenario. If an analyst makes a measurement error in the determination of horizontal distance (*H)*, and all of the multipliers are equal to 1, then the RWL will be calculated according to Equation 32.

$$RWL = 23 \times \left(\frac{25}{H}\right) \dots (32)$$

The differential is provided by Equation 23.

$$RWL = -23 \times \left(\frac{25}{H^2}\right) \dots (33)$$

A measurement error of a single centimetre at a distance of 25cm results in a reduction of the RWL of 0.92kg. It should be noted that the error is nonlinear and as a result the sensitivity will be reduced as the measured distance increases. For example at 63cm the sensitivity reduced to 0.14kg per centimetre error. The simple demonstration of the sensitivity highlights the importance for accurate results. As a further indication on the influence of accuracy, an error of 10 cm in the measurement of the horizontal location can lead to an error of 30% in the RWL [**101**,**100**].

The sensitivity evaluation in this case is overly simplified and in some cases conservative. This results because in some cases single measurements are used in the calculations of multiple variables. The resulting impact of the errors is therefore echoed.

5.2.4 Measurement accuracy of human operators

Considering the significance of the sensitivity of the algorithm, it is also important to consider the human capabilities with regards to executing the measurement of the parameters for the RNLE. Of particular interest are the magnitude of the measurement errors and the prevalence of systematic errors.

The magnitude of errors is an important consideration in justification for the proposed automated system. The preliminary studies conducted in Chapter 3 have indicated the system's limitations constraining the accuracy of the extracted data.

Studies conducted by Waters et al. and Dempsy et al. revealed the prevalence and magnitude of errors recorded by trained human analysts [**102**,**100**]. The tests are mostly similar, however they differ in a few vital areas such as the task variables that are measured as well as the training provided to the analysts.

5.2.4.1 Methodology

Both tests required the participants to attend a training session. After a set duration, the trainees measured the variables for a simple, well controlled lifting task of a cardboard box. Prior to the testing, reference measurements were taken by NIOSH experts. Due to the controlled nature of the experiment the reference measurements are deemed to be significantly more accurate and subject to less variability than those measurements traditionally taken in the workplace. The worker doing the lifting was instructed to perform the task consistently in order to enable repeatable measurements. The workers used to perform assessments were all graduates with experience in collecting field data. The worker performing the lifting activity did not pause while measurements were taken as is normally done in industry [**102**,**100**].

Both studies were performed with significant control and as a result data was collected at both the origin and destination of lifts. The overlapping measurements included:

- Vertical height at the origin
- Vertical height at the destination
- Horizontal location at the origin
- Horizontal location at the destination
- Asymmetry angle at the origin
- Asymmetry angle at the destination

The study conducted by Waters et al. involved training 27 analysts for seven hours on a one day course and eight weeks later assessing the accuracy with which they measured variables for an asymmetric lifting task. The test also required workers to select the coupling quality (good, fair, or poor). The range of values, the mean, and standard deviation was determined for each of these measurements and also for the LI. The results of the study are represented in Appendix 10 Table 48 [**102**].

The study conducted by Dempsy et al. involved training eight analysts prior to data collection. The analysts underwent a 4-hour training session. A trained volunteer performed five simulated lifting/ lowering tasks [**100**]:

1. Symmetric lift
2. Asymmetric lift
3. A palletizing operation consisting of three asymmetric lowering tasks

In addition to the variables already mentioned, the study also required analysts to physically weigh the work-piece and also to determine the frequency component. The results of the study are represented in Appendix 10 Table 49.

5.2.4.2 Findings

The studies indicate that users could, with the aid of formal training in the measurement of parameters of the RNLE, accurately make the required measurements. The studies also indicated that the analyst's ability to measure the required parameters was effected by the duration of training as well as the complexity of the task being analysed [**102**,**100**].

The preliminary testing of the HAWK system indicated the limitations of the system with regards to accuracy and precision. The use of the HAWK system in the automation of the RNLE is partially justified by the variability and measurement errors of trained human observers indicated in the study conducted by [**102**]. As an example, the measured asymmetry angles at the destination of lifts were 7.9˚ larger than the reference value and the maximum deviation from the reference was 17˚. Another example is the 10.5cm maximum deviation from the reference vertical height of the load. In addition to the measurement errors, systematic errors were also reported. For the first task in Appendix 10 Table 49 the standard deviation for vertical height at the destination of the lift was 25.3 cm. This was attributed to an error in understanding the measurement strategy [**100**].

The results of the studies, represented in Appendix 10 Table 48 and Table 49 indicated that the variability in the LI was constant across all conditions. The studies concluded that individuals could be trained effectively in a single day, ultimately enabling the accurate measurement of parameters for the RNLE. It should be noted that the findings could have been different if the studies were conducted at an actual worksite, in which the analyst would be required to make more decisions and also how the frequency, duration would be determined, The improper classification of the work duration could vary in the RWL by as much as 40%. The data provided by Waters et al. and Dempsy et al. will be compared with the tests done on the RNLE, specifically with regards to the measurement of parameters.

5.3 Automation

This section discusses an existing computer vision based assessment that calculates the RWL. Numerous problem areas within the system are highlighted, ultimately justifying the development of the proposed HAWK-RNLE system. The methodology of the HAWK-RNLE system is thoroughly discussed and problem areas are identified. The section also introduces the user inputs tab and the results tab of the GUI.

5.3.1 Existing system

Martin et al. developed a real time ergonomic monitoring system using a Kinect™ sensor. As part of the system the RWL was calculated on a continuous basis. The updated RWL was displayed on the GUI in real time. The authors proposed that the system be used for training purposes, indicating the effect that bending or stooping movements have on the RWL. The authors concluded that the dynamic RWL is practical for the training purposes in a controlled environment [**11**].

The study provided some insights into the use of the Kinect™ cameras [**11**]:

- A notable increase in noise was recorded when joints were occluded from view. The authors attempted to use two Kinect™ cameras to address this problem. They were unable to combine the data and were limited to selecting which of the cameras' data to use for the calculation of the RWL.
- The system reported tracking failures for certain movements and also interference that occurs when the worker comes into contact with work-pieces. The failures resulted in noisy tracking data. Due to the continuous nature of the system the RWL was erratic at times.
- The errors and noise were reduced in cases where the worker held his hands out further in front of his body.
- The accuracy decreases as the angle of twisting increases. The Kinect™ should be used as close to perpendicular as possible and at approximately hip height.

In addition to the RWL the system also calculates other factors, such as the time the worker spends with his hand below his knees. For the purposes of this thesis, we only consider the RNLE component, which is riddled with flaws and concerns [**11**]:

- No consideration is given to the procedure where origin and destination of the lift needs to be defined. As a result the RWL continuously updated even when lifts are not conducted. Analysts would therefore need to monitor the RWL continuously and record it at the origin and destination of lifts. The need to continuously monitor the system would require an analyst to be present through-out the studies. As a result the objective of reducing the costs of performing the studies cannot be achieved.
- The accuracy and reliability of each of the multipliers was not indicated. In contrast, simple general and intuitive tests, such as moving the arms away from the body and twisting the body were conducted to assess whether the RWL decreased and increased as expected.
- There is no information provided on the implementation of the constraints of the variables.
- No indication is provided into how the vertical travel distance could be obtained.
- There is no mention on the discrepancy between the proposed method, which uses the approximate locations of the hands and feet and the locations prescribed by the RNLE. These include the inner ankle bones and the third metacarpal.
- The author defines the asymmetry angle as the angle of twist. [**5**] Specifically notes that the angle of symmetry is not defined by the foot location or extent of body twist but defines it by the location of the work-piece relative to the worker's mid-sagittal plane, where the mid-sagittal plane is defined by the neutral posture. The authors do not describe how the neutral position is defined.
- There is no possible means of collecting the data to determine the lifting frequency. In the system it is set to 5 lifts per minute and duration of less than 1 hour.

The extensive list of possible problems indicates significant room for improvement. It should be noted that the Microsoft SDK was used because it provided extensive documentation and did not require a calibration pose to initiate skeletal tracking. The performance on the skeletal trackers could therefore be different. In the conclusions of the study one of the desired features specified by the client included better lift evaluation [**11**].

5.3.2 The concept of automation

The RNLE requires the measurement of a number of parameters at the origin and, if significant control is required, at the destination of lifts. The origin of lifts is recorded as the moment the worker makes contact with an item, and the destination, the moment contact is broken.

Data on the worker's hands and feet along with data on the item's location are extracted at the origin and destination of lifts. This information is used to calculate most of the variables used in the calculation of the multipliers. In order to calculate the angle of asymmetry, additional information on the shoulders' locations needs to be extracted. This information needs to be extracted while the worker is in the neutral position, with no bending or twisting of the trunk. This is achieved by requiring the worker to assume a calibration pose prior to the initiation of the study. Directly after the calibration is completed, the positional information is recorded.

The frequency multiplier requires data on the number of lifts per minute. This is achieved by firstly counting the number of lifts that have been completed and then dividing this by the total duration of the study. The number of lifts is iterated each time the worker breaks contact with the work-piece, provided that the work-piece has moved.

5.3.3 The automation process

The study is initiated by the worker assuming his location at his workstation. The worker then assumes the phi–pose indicated in Figure 59. As soon at the worker is calibrated the co-ordinate data of the shoulders' locations is archived. The worker is requested to assume a neutral body position prior to assuming the calibration pose. As a result the line between the shoulders' positions is a reasonable approximation the line perpendicular to the 2D projection of the mid-sagittal plane. The co-ordinates of the shoulder are used to establish a gradient m_1. This gradient is later used in the determination of the angle of asymmetry. The use of the shoulder locations is derived from the method proposed by Okimoto et al. for the measurement of the variables of the RNLE [**101**].

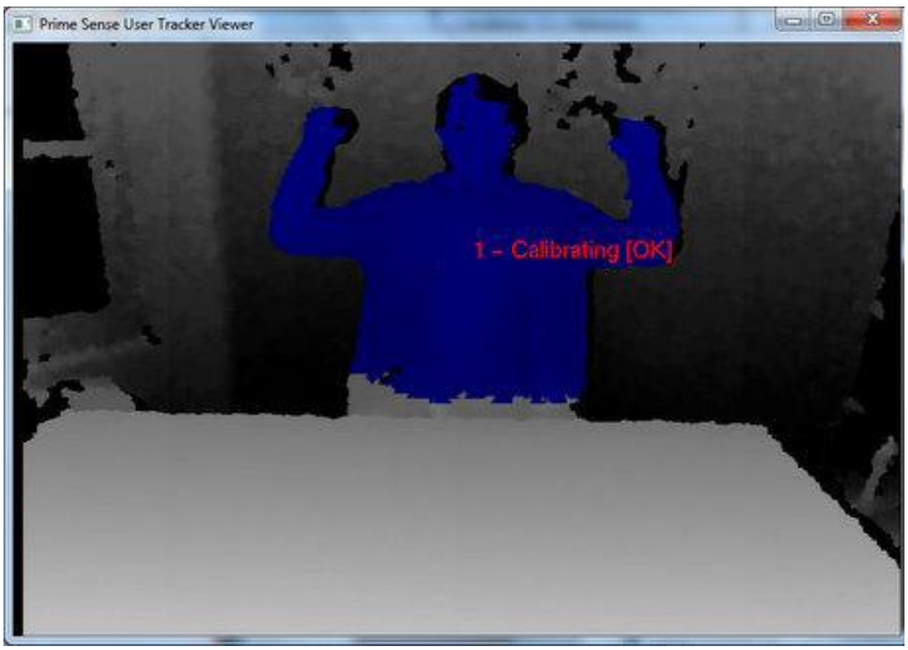

Figure 59: Worker in the phi-pose required for calibration

The work-area also needs to be defined and the work-piece selected. This can be completed before or after calibration of the worker. However because the system pauses while mapping the SURF algorithm of the item-tracker to the GPU, the analyst performs the preferred selection prior to asking the worker to assume the calibration pose.

In this case the work area must encompass the origin and the destination of the lift. This will ensure that the work piece can always be tracked. Recall that the processing speed of the application will be improved by selecting the area as small as possible. The work area should be defined, so that it is not unnecessarily large.

After the item has been selected the analyst must select appropriate values for the variables of the SURF and RANSAC algorithms. See Section 3.4.2 and Section 3.4.3.2 for more information. The user is also required to enter additional information into the GUI prior to the initiation of the study. A screenshot of the user inputs tab of the GUI is included in Figure 60. To create order, the user inputs have been divided into the following subsections:

- General Inputs
- RNLE Inputs
- File Recording
- Kinect™ Tilt Angle
- Calculate

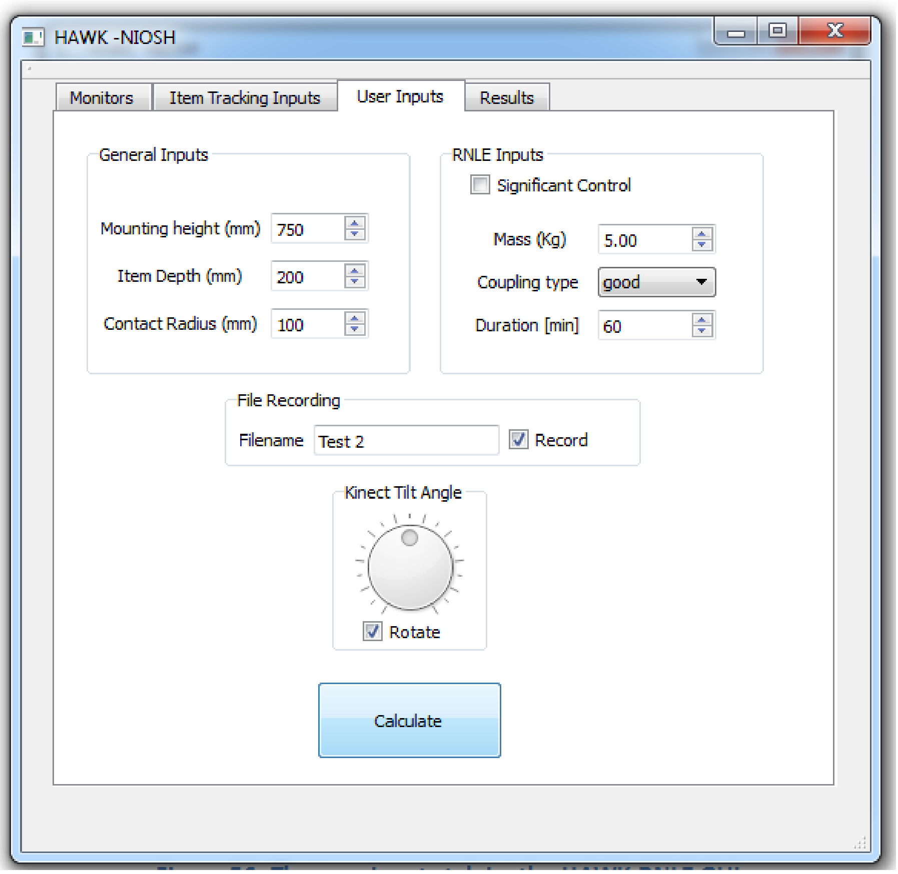

Figure 60: The user inputs tab in the HAWK-RNLE GUI

General Inputs

The general inputs are all numerical inputs. Analysts can either enter the values directly or by means of the up and down arrows of the double spin boxes. The values currently depicted are the default values.

- **Mounting Height -** The mounting height of the camera is an important consideration in normalising the measured values. The normalization enables the implementation of the constraints of the RNLE. The mounting height needs to be measured accurately.

- **Item Depth** - Recall that the item-tracker is a planer-tracking algorithm. As a result the analyst is required to enter a depth dimension for the work piece. The depth dimension is used in determining contact.
- **Contact Radius -** The contact radius can be adjusted depending on the requirements of the study. It can be reduced to minimum of 85mm for slow lifting tasks with good viewing angle from the camera.

RNLE Inputs

The HAWK-RNLE is not capable of measuring every parameter required by the RNLE. The parameters that cannot be measured include:

- **Significant control** - If significant control is required at the destination of the lift then the checkbox needs to be ticked. Significant control is typically required if:
  - The worker has to adjust his grip near the destination of the lift
  - The worker has to momentarily hold the item at the destination
  - Worker has to carefully place or guide the load at the destination
- **Mass** - The user is required to enter the mass of the item being lifted. The user will therefore require a scale to weigh the item prior to the study. The mass of the item is used in the calculation of the LI.
- **Coupling type** – This is the quality of the hand to object coupling and can either be good, fair or poor. The decision tree in Appendix 9 Figure 69 is used to determine which of the states it is. The classification is selected from a dropdown list.
- **Duration of work** – The duration of the lifting task in minutes can be entered, the system will then automatically classify the work duration as one of the three classifications:
  - Short – Less than 60 minutes
  - Moderate – Greater than 60 but less than 120 minutes
  - Long – Greater than 120 Minute but less than 480 Minutes.

File recording

Contact data at the origin and destination of lifts are automatically recorded by the system. However, In addition to this the user has the opportunity to use the file recording function to record raw positional data to a text file with the user specified name in the line edit box.

The data recorded by this function includes:

- Time in hours, minutes, seconds and milliseconds
- 3D co-ordinates of the Item
- 3D co-ordinates of both left and right
  - Shoulders at calibration
  - Hands
  - Feet

An example of this file is represented in Appendix 11. This .txt format of the file enables simple export procedure to Microsoft Excel, or any other spreadsheet applications, where the data can be assessed.

Kinect™ tilt angle

The Kinect™ motor can be tilted by dragging the dial to the preferred angle in order to gain an improved viewing angle of the worker. The Rotate checkbox is selected by default. It ensures that the measured co-ordinates are transformed through the direction cosine matrix of the mounting angles of the Kinect™ camera as represented in Section 3.4.4.1. The mounting height also forms part of this normalization process and off-sets the measurements so that the floor is defined as 0mm.

It is suggested that the tilt angle remain 0 where possible and that the camera be mounted at approximately half the worker's height. From RSA Military Standard 127 Volume 1 the average of both 5th percentile female and 95th percentile male is 836mm [**95**]. Most desks are around 750mm, which is close enough to provide a suitable platform.

Calculate

The calculate button must be clicked in order to initiate the study. If input variables are changed, the study must be re-initiated by pressing the calculate button.

5.3.4 Methodology

The equations for the multipliers and interpretations of the variables are indicated in Table 32. In the automated system the variables are calculated according to the equations in Table 34. Note that the joint locations used in the calculations of the variables in the HAWK-RNLE are slightly different to those represented in Figure 58 as posed by Waters et al.. This results because the worker tracker does not provide data on the locations the inner ankles or the third metacarpal. As a result the midpoints of the worker's hands and feet, which are the nearest tracking points to the proposed locations, are used.

In light of the sensitivity of the RNLE the discrepancy between the foot and ankle location will have a notable impact on the results. The impact of the hand locations will be significantly less. This is because the mid-point of the hand, returned by the worker-tracker is reasonably close to third metacarpal as used by Waters et al [**5**].

Where:

LF	Left foot
RF	Right foot
LH	Left hand
RH	Right hand
LS	Left shoulder at calibration
RS	Right shoulder at calibration
I	Centre point of the user defined plane
$_x$	X co-ordinate
$_y$	Y co-ordinate
$_z$	Z co-ordinate
$_o$	Origin of lift
$_d$	Destination of lift
m_1	Gradient of the line perpendicular to the mid-sagittal plane.
m_2	Gradient of the asymmetry line, the line joins the midpoint between the worker's feet and the midpoint between the hand-grasps
Theta	Intermediate angle used in the calculation of the angle of asymmetry

Table 34: Calculations of variables in the HAWK-NIOSH system

Variable	Computational calculation
LC	23kg
H	$\sqrt{\left[\frac{(LF_x + RF_x)}{2} - \frac{(LH_x + RH_x)}{2}\right]^2 + \left[\frac{(LF_z + RF_z)}{2} - \frac{(LH_z + RH_z)}{2}\right]^2}$
V	$\frac{LH_y + RH_y}{2}$
D	$I_{y_d} - I_{y_o}$
A	$m_1 = \frac{(LS_z - RS_z)}{(LS_x - RS_x)}$ $m_2 = \frac{\left[\frac{(LH_z + RH_z)}{2} - \frac{(LF_z + RF_z)}{2}\right]}{\left[\frac{(LH_x + RH_x)}{2} - \frac{(LF_x + LF_x)}{2}\right]}$ $Theta = 57.2958 \times \left\lvert \text{atan}\left[\frac{m_1 - m_2}{1 - m_1 m_2}\right]\right\rvert$ $A = 90^{\circ} - Theta$
FM	Lookup Table 47 in Appendix 9
CM	Lookup Table 46 in Appendix 9

Figure 61 graphically depicts a top view of for the measurement procedure. The values provided in this image are used in the calculation of the horizontal distance and also in the measurement of the angle of asymmetry.

The horizontal distance is defined by the line segment joining the mid-point between the worker's feet and midpoint of the coupling. The gradient of this line, termed the asymmetry line is used in conjunction with the gradient of the line perpendicular to the mid-sagittal line, to determine the angle of asymmetry. Numerous alternatives for defining the worker's mid-sagittal plane were considered. One alternative was to assume that the worker's mid-sagittal plane could be defined perpendicular to the capture frame. This would be partially justified by the axis aligned basis of the HAWK system. However, in order to allow for angular deviations, it was decided that the system should ask for a calibration pose prior to the study. At the instant the worker is calibrated the joint location data of the worker's shoulders is logged. The shoulder locations are used to define the mid-sagittal plane as proposed by Okimoto et el. [**101**].

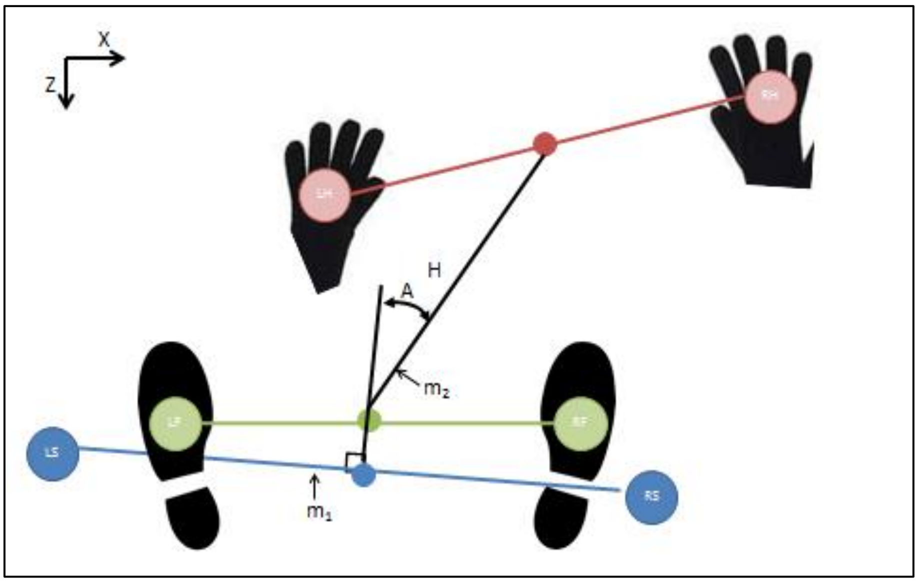

Figure 61: Conceptual representation of the system

The measurement of vertical height and the travel distance are much simpler. The graphical depiction of the vertical height is represented in Figure 58. Note that the measurement of travel distance is different to the method posed by Waters et al. The reason for this alteration is that the positional data on the item is significantly better than the hand location when in contact with the item [**5**].

The vertical height is also used when looking up the values for the frequency and coupling multipliers. The user inputs of the coupling quality and the measured vertical height are used to lookup the coupling multipliers in a table represented in Appendix 9 Table 46. The frequency multiplier is calculated in a similar fashion. However, it also required the measurement of the lifting frequency per minute. As per the methodology proposed by Waters et al, the duration of the traditional study is 15 minutes. During this period the system calculates the number of lifts by iterating a counter after each time a lift is completed. Once the study is completed the total number of recorded lifts is divided by the duration of the study. This value along with the duration of the lifting task, entered into the GUI by the analyst, and vertical height of the load are used to lookup the frequency multiplier in a table represented in Appendix 9 Table 47 [**5**].

The remaining multipliers are calculated by firstly comparing the measured values against the constraints and finally plugging the measured variables into the appropriate equations. The constraints and equations are represented in Table 32. The multipliers and the corresponding RWL and LI are ultimately returned to the analyst via the GUI. These values, along with the variables are also logged in test files.

5.3.5 The graphical user interface of results

The results of the study are displayed in the results tab of the GUI, as depicted in Figure 62. The GUI is divided into two sections, a results sections and a multipliers section. The GUI also features a radio button that indicates when the system registers contact between the worker and the work piece. This enables analysts to determine whether the system is responding as desired and at what range the contact is being registered. It also serves as a diagnostic tool, indicating if at any time contact is broken when the worker is still in contact with the work piece. Similarly the number of lifts is a displayed primarily as a diagnostic tool for the system. If the number of lifts is incorrectly calculated it will have notable impact on the resultant frequency multiplier, and consequently on the RWL and LI. Analysts should therefore monitor the value at the initiation of the study to ensure that the variables for the item-tracker and the contact radius are suitable for the task being analysed.

Multipliers

The multipliers subsection provides data on the values of each of the multipliers. The HAWK-RNLE only applies to single-task manual lifting jobs. As a result, the system can only be used to measure variables that do not differ significantly in between tasks [**5**].

In the traditional studies the analyst only records a single set of parameters, however in the automated system the parameters are calculated and recorded to text files for each lift. Due the nature of the HAWK-RNLE system and the presence of noise it is suggested that the average value be calculated for a study. The GUI serves as a quick reference and observation for the analyst, as a result it was decided that the values represented in the GUI should be continuously updated for each lift. Recall that the frequency multiplier cannot be calculated until the study is completed. The logged results therefore need to be analysed after the study. The logged data can easily be exported to Microsoft Excel where frequency multiplier can be factored in and the average values calculated.

The information on the multipliers enables analysts to identify where the specific areas of concern are for specific lifting tasks. The magnitude of a multiplier relative to the others indicates the relative contribution on the RWL. As a result, improvements should be focused on the smaller values first [**5**].

Limits

The limits subsection displays information on the RWL and the LI recorded by the system.

The RWL represents the maximum weight that a worker can safely lift for the specific lifting technique currently being used. As a result the value can be used to aid the redesign of existing tasks and new tasks. It can be used to adjust the maximum weight of the work piece or in other cases where the work-pieces weight cannot be altered; it can serve as a reference for the optimization of task variables [**5**].

The LI can be used to gauge the relative magnitude that a specific task or job places on workers. As the LI increases the proportion of the population that can safely perform the task decreases. In the most recent study on the efficacy of the RNLE to predict risk of LBP due to manual lifting, Waters et al. [**98**] conducted a study on 677 subjects conducted in 125 manual lifting jobs. The results indicated that the LI was a means of determining whether a specific job had a high risk of LBP due to lifting. Workers continuously performing lifting tasks with a LI of greater than 1.0 had a significantly higher risk of having LBP lasting for more than a week within any 12 month period than a person in a non-lifting job. The study also indicated an increased risk where the LI was between 2.0 and 3.0. The LI therefore enables a comparison between tasks, as such it could be used to rank order tasks within a facility, whereby the most hazardous tasks, indicated by the largest LIs are addressed first [**5**].

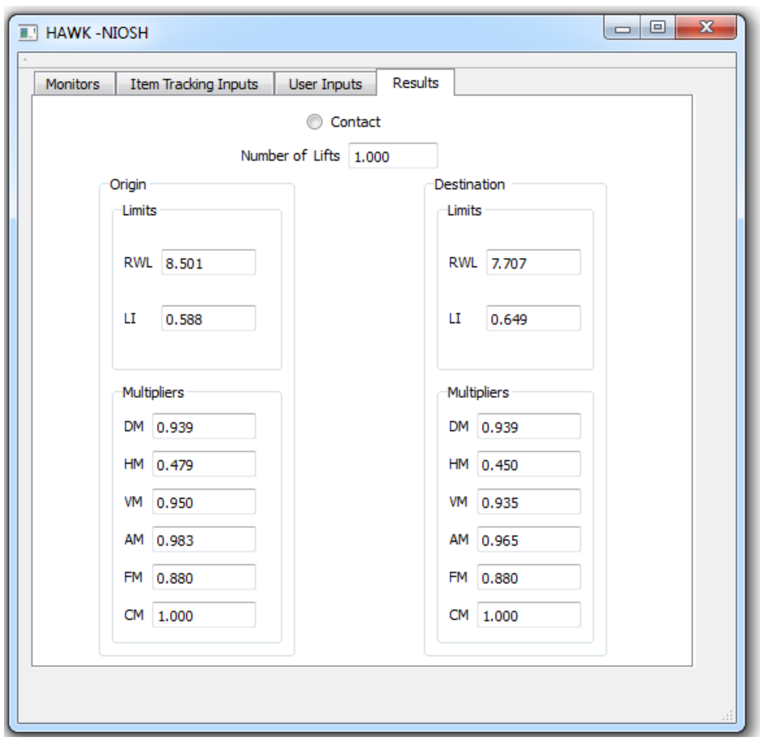

Figure 62: Results tab of the GUI

The screenshot depicted in Figure 62 was taken at the completion of the study, when the frequency component is also displayed. Prior to the completion of the study, because the frequency multiplier cannot be calculated the line edit box for the frequency multiplier is left blank. Similarly if the analyst does not check the checkbox for significant control in the user inputs tab then the significant control line edit boxes remain empty as shown in Appendix 14.

5.3.6 Problem areas

The following are problem areas in the functional automation of the RNLE.

- Determining the lifting frequency
- Obstructions to the cameras viewing angle
- Worker tracker is not suitable for bending assessments

Determining the frequency multiplier

One of the significant limitations of the HAWK-RNLE system is the fact that only one work-piece may be in the frame at any point in time. As a result the algorithm can only be applied to the lifting of a single specific item. This in turn means that the system cannot practically be used to assess the lifting frequency for repetitive lifting or lowering tasks such as palletizing operations.

The lifting frequency has however still been implemented in a conceptual manner. Each time the worker completes a lift, defined by the breaking of contact with the work-piece, a counter is iterated. The number of lifts are used to determine the lifting frequency, which along with the work duration specified by the analyst, is ultimately used in the calculation of the frequency multiplier [**5**].

Obstructions to the cameras viewing angle

On a practical level the worker and work piece will likely be obstructed at some point during the lifting process. The lifting process will always result in the work piece, which will typically be large, obstructing the worker.

The obstructions can lead to loss of accuracy or failures of the worker and item trackers. This can lead to incorrect classification of the destinations and origins of lifts.

Worker tracker is not suitable for bending assessments

It has been recorded that Kinect™ based skeletal trackers cannot accurately measure body locations and joint angles for bending and squatting positions typically associated with lifting tasks [**55**].

5.4 Testing

The following section covers the testing procedures used to assess the HAWK-RNLE system. The testing was conducted in two distinct phases;

- Preliminary testing
    - Assessed the basic functioning of the system as well as the implementation of the constraints.
- Final system testing
    - Involved performing a symmetric and an asymmetric lifting task. A manual study was conducted to provide reference values against which the measured values could be compared.

5.4.1 Preliminary test

The preliminary test required the worker to perform a number of lifts in order to gauge the response of the system.

5.4.1.1 Procedure

The HAWK-RNLE creates a text file, contact_data.txt, within the root folder of the application to which data on the origin of lifts are recorded. If the analyst selects significant control, another text file, destination_data.txt, is created to which data on the destination of lifts are recorded. After the completion of each lift, data on the variables and multipliers at the origin and destination of the lift are recorded to the respective text files. The data from the text files was exported to Microsoft Excel where the data was analysed to:

1. Ensure that the system only recorded data when the worker made and broke contact with the work piece.
2. Assess that the variables increased and decreased correctly corresponding to changes in the horizontal, vertical and angular locations of the load.
3. Ensure that the following constraints were applied correctly.
   - If H < 25cm then H is set to 25cm. Tested by picking the item up between the legs.
   - If H > 63cm then HM is set equal to 0.397. Tested by picking the item up as far forward as possible.
   - If D < 25 then D is set equal to 25cm. Tested by making and breaking contact with the item without moving it.
   - If D > 175cm then DM is set to 0. Tested by picking the item up from the ground and placing it on a shelf that is higher than 175 cm.
   - If V > 175 cm then VM is set equal to 0. Tested by making contact with the item on a shelf that is higher than 175 cm.

5.4.1.2 Findings of the preliminary test

The preliminary testing indicated problems with the accuracy of the data at contact break points. The inaccuracies results because multiple measurements are considered to register contact breaks. As a result the hand locations used in the calculation of the variables were nowhere near the work piece. The solution that was implemented to overcome this problem was to store a history of co-ordinate measurements for the worker and work piece. Once contact with the item was broken, a user defined historical data point is then recalled. The historical point is defined by the number of frames. As a result the physical time will vary according to the processing speed. Recall from Section 3.5.7 that the state of contact is determined by evaluating the average distance of the last 10 frames. As a result, once contact has been broken, the worker will still have been in contact with the work piece 10 frames ago. 10 frames is the default used in the system, it can however be adjusted if desired. A preliminary assessment indicated that the method provided significantly increased accuracy and reduced the variance.

Observation of the worker's hands location indicated that the hand tracking reliability drops significantly while the lift is executed. This results because the worker tracker cannot effectively differentiate between the worker's hands and the work piece. This is a systematic flaw, and no solution was available. This is likely to result in reduced accuracy of the results, specifically at the destination of lifts.

The preliminary testing indicated that the constraints were also correctly applied to the measured variables. The testing also indicated that the variables and the resultant RWL and LI responded correctly according to increases and decreases in the respective variables. The testing also indicated that the multipliers where calculated correctly from the measured variables.

5.4.2 Final testing procedure

The final test includes the assessment of symmetric and asymmetric single lifting tasks. The lifting tasks are similar to the lifts conducted in the experiments conducted by Waters et al, and Dempsy et al. [**102**,**100**]. For each of the lifting tasks three sets of continuous lifting and lowering cycles were conducted. Multiple sets enabled an evaluation of the consistency of the system. Each set was conducted over a period of five minutes. After each lifting or lowering action the worker briefly broke contact with the work piece before picking up the item and completing the next lift or lowering activity.

The tests provide insight into the accuracy and precision with which the system can measure the variables used in the calculation of the RWL and the LI. In order to enable comparisons with respect to accuracy and precision accurate reference values need to be measured.

5.4.2.1 Reference values

In order to assess the accuracy of the data measured by the HAWK-RNLE system a set of reference measurements need to be made. Due to the nature of the experiment it would not be possible to perform a traditional study concurrently. This results because only one human can be in the frame at any one time. The analyst therefore cannot enter into the capture frame to record measurements.

These reference measurements should be measured under controlled conditions so that the results are significantly more accurate and less variable than measurements traditionally recorded in the workplace. Analysts only measured the variables after a worker had repeated the lift for a sufficient duration of time to be able to repeat the lift consistently.

Apparatus

The two lifting tasks required the worker to lift a 5kg cardboard box (221mm high, 314mm wide and 260mm deep) with cut-outs. The cut outs were 76mm wide and 25mm high [**100**].

To make the reference measurements the analyst needs the following equipment [**101**]:

- Drafting paper 120cm x 100cm
- Masking tape
- Pen
- A meter stick
- Protractor
- Set square
- Plumb bob

Procedures

In order to extract accurate and reliable reference measurements, a measurement process needed to be selected and followed. The applications manual of the RNLE developed by Waters et al. describes the process yet it does not provide specific guidelines for the measurement process [**5**].

As a result the procedures proposed by Okimoto et al., represented in Table 35 were followed [**101**]. Note that no consideration is provided for establishing the lifting frequency, the duration of the lifting task and consequently the frequency multiplier.

Table 35: Steps in the proposed procedure to obtain the variables of the NIOSH Lifting Equation (NLE) [101]

Step	Description
1	Have the worker position himself to pick up the object and remain immobile in that position. Take photographs and film the site.
2	Determine the V value by measuring from the floor to the Coupling midpoint (M_C).
3	Define the location of the Coupling midpoint (M_C) and project it onto the floor.
4	Trace the outlines of the worker's feet on the drafting paper, using a ballpoint pen. Project the points of the ankles (AR and AL) onto the floor, using a plumb bob.
5	Determine the midpoint of the Ankles (M_A).
6	Join points MC and MA to obtain H (the line segment M_C M_A).
7	Measure the line segment *"M_C\`M_A"* to determine the value of H.
8	Project the shoulder points (S_R and S_L) onto the floor with the aid of a plumb bob. *With the worker in a neutral position, using as reference points the outer edges of the shoulder blades (S_R and S_L), identify the midpoint of the Shoulders (M_S). With the aid of a T-square placed on the MS point (the worker's mid-sagittal line), draw a straight line perpendicular to the line segment S_R and S_L.
9	Using a protractor, measure the angle formed between the H to the average sagittal line.
10	Classify the Coupling *according to the "decision tree for coupling quality" represented in Appendix 9 Figure 69
11	Measure the variables at the origin of the lift. Also measure the variables at both the origin and destination of the lift if the lifting action requires significant control at the destination.
12	Determine the value of D (Vertical Travel Distance covered by the object), through $V_d - V_o$ when the object is lifted or $V_o - V_d$ when the object is lowered.

The drafting paper needs to be laid down in the work area so that the projections of the body positions can be drawn and so that the necessary lines can be drawn and measured. If the drafting paper cannot be placed under the work area it should be folded in such a way that it is laid against the base of the obstruction. Consider that there should be enough space to mark off the projection of the mid-point of the coupling.

A complication in the process described in Table 35 arises if there is an obstruction below the plane on which the midpoint of the coupling was determined. This would typically be the case when the worker initiates a lift from a table. In order to project the mid-point of the coupling M_c onto the drafting paper a derivation of the methodology provided by Okimoto et al. is applied.

The methodology provided here is only valid if a reference, such as the edge of the table is present. Furthermore it is only valid if the table is level. Firstly, the mid-point of the coupling M_c needs to be marked on the work surface, then using the edge of the table as a reference, align one edge of the set square with the edge of the table. The other edge should pass through the point M_c. Measure and record the perpendicular distance to the point M_c. The Plumb bob must then be used to project the location of the corner of the set square onto the drafting paper. Another arbitrary point along the edge of the table must also be projected onto the drafting paper with the plumb bob. The analyst can then fold out the drafting paper and draw a line joining the projections of the edge of the table. The set square must be aligned with the projected edge of the table and the projected mark before the projection of the point M_c on the sheet can be measured and marked [**101**].

After the measurement of the reference values the worker would then be required to consistently repeat the lifting process enabling repeatable measurements. In order to decrease variability for the assessment by the HAWK-RNLE system, the worker was required to align his feet with the outlines drawn in the measurement of the reference values before assuming the calibration pose thereby initiating the study. The outlines of the work-piece at the origin and destination of lifts were marked with tape for the same reason.

5.4.2.2 Considerations

One of the fundamental problems indicated through testing of the basic HAWK system was the range considerations and the influence on noise of the worker tracker, depicted in Figure 25. The test indicated that the optimal range for calibration and foot tracking was between 3-3.5m from the Kinect™ device. The problem that occurs is that at these distances the reliability of the item tracker is significantly reduced, the problem is exaggerated when the work piece is moving. The reduction in the number of features for an A3 size work piece is represented in Figure 37. As a result for smaller work-pieces, the tests cannot be reliably conducted at the optimal range of distances. In the tests a compromise was made whereby the camera was set up as close to the optimal range as possible while the item-tracker could still identify enough features to enable reliable tracking.

The contact radius is also a matter of concern. See Section 3.5.9 for contact radius determination. The tests indicated that the contact radius could set at 85mm when the moving average of 10 measurements is used. The problem is that the work-piece was stationary throughout this test. When the worker is moving with the work piece in hand there is a significant reduction in the quality of the measured positional data. This results because skeletal tracking is fundamentally achieved though analysis of the depth image. As a result the worker tracker does not know what to track as the worker's hands. The result is that the 85mm limit could be too small. If the contact radius is set too small the HAWK-RNLE system will falsely identify the destinations and origins of lifts. As a result, to ensure that the system is as reliable as possible, a more conservative value should be implemented. The use of an increased contact radius is justified by the nature of the system:

- Origin data is a single measurement taken directly after contact has been established.
- Destination data is taken as a single historical data point before contact is broken. The default is 10 frames.

The contact radius will have a negligible effect on the accuracy of the results provided that the worker's hands move further than the contact radius in 10 frames (Maximum of either; the number of frames used to establish contact or the historical data point).

The influence of the reduction in tracking accuracy while performing the lift appears worse than in is. Recall that data is only retrieved at the origin and destination of lifts when the load is stationary. As a result the system does not experience the significant deviation in its results.

The systematic errors inherent to the system are unavoidable. An awareness of their existence will result in more reliable and accurate data being collected

5.4.2.3 Symmetric lifting task

The first lifting task assessed is a simple symmetric lowering task. The worker picks the work-piece up from the stand and carefully places it at the predefined location on the floor as shown in Figure 63. The worker then breaks contact with the work-piece before picking it up off the ground and carefully placing it back onto the stand. This cycle is repeated for five minutes and repeated 3 times. In total 33 lifts were measured. The task requires significant control and data was therefore recorded at the origin and destination of lifts. Note that only data relating to the lowering activity is presented here. The data for the lifting component is included on the DVD.

Due to the continuous nature of the test, no consideration is given to the calculation of the frequency multipliers. Furthermore the coupling quality is determined by the analyst via the decision tree in Appendix 9 Figure 69 and entered into the GUI. The calculations have been excluded from this study.

Figure 63: Screenshots of the symmetric lowering task. (*Left*) Origin on the stand, (*Right*) Destination on the floor

Figure 63 depicts the approximate moment that the worker makes and breaks contact with the work-piece. The drafting paper on which the manual study is conducted is visible beneath the worker. The drafting paper contains the outlines of the worker's feet which serve as a reference to ensure that variability between the studies is minimized.

The multipliers at the origin of the lift, defined by the moment the worker makes contact with the work piece on the stand is represented in Table 36. Included in the table is information on the reference and measured values.

Table 36: Symmetric lifting task results at the at the origin of the lift on the stand

	Reference	Measured	Standard Deviation	Difference	Relative Error
HM_o	0.58	0.69	0.05	0.11	18.20%
VM_o	0.93	0.96	0.00	0.03	2.83%
DM_o	0.88	0.88	0.00	0.00	0.20%
AM_o	1.00	0.99	0.01	-0.01	-0.86%
RWL_o	**11.00**	**13.30**	**0.88**	**2.30**	**20.75%**

From the data it is apparent that the horizontal multiplier has a detrimental effect on the calculated RWL. However, from the data in Table 38, it is apparent that numerically, the horizontal distance represents a smaller error than the vertical distance. The horizontal distance is however the most variable. This is indicated by the standard deviation. Both the distance and asymmetry multipliers appear to be reasonable and are calculated satisfactorily.

It should be noted that the reasons for the discrepancies between the reference and measured values will be conducted after introducing all of the relative data from both the symmetric and asymmetric tests. This is because the data in many cases is correlated and as a result cannot be discussed or evaluated independently. An example of the correlation can be seen in Table 37 which provides the reference and measured values at the destination of the lift. In this case the vertical multiplier represents a much smaller error even though the standard deviation is constant. The error appears to be linked to the magnitude of the measured vertical height.

Table 37 Symmetric lifting task results at the destination of the lift on the ground

	Reference	Measured	Standard Deviation	Difference	Relative Error
HM_D	0.57	0.54	0.03	0.03	-4.71%
VM_D	0.84	0.84	0.00	0.00	0.32%
DM_D	0.88	0.88	0.00	0.00	0.18%
AM_D	1.00	0.97	0.01	0.03	-2.93%
RWL_D	**9.15**	**8.54**	**0.40**	**0.61**	**-7.07%**

The results in Table 38, enables a comparison between the HAWK-RNLE and trained human analysts. The table includes data on variables of the RNLE, measured at the origin and destination of a symmetric lifting task. Although the tasks that have been analysed are not identical, the error and standard deviations does provide insights into the capabilities of HAWK-RNLE system.

Table 38: Comparison between traditional study and the results of the HAWK-NIOSH system for a symmetric lifting task [100]

	Manual Studies				HAWK-RNLE			
	Reference	Measured	Error	Standard deviation	Reference	Measured	Error	Standard deviation
H_O	48.3	40.3	8	-5.5	43.1	36.52	6.58	3.05
H_D	83.8	80.3	3.5	-9.1	44.1	46.65	-2.55	2.55
V_O	25.4	21	4.4	-2.5	97.17	88.35	8.82	1.22
V_D	99.1	85.2	13.9	-25.3	20.3	21.19	-0.89	1.21
D	73.7	64.2	9.5	-	75.50	73.35	-2.15	0.68
A_O	0	0	0	0	0	2.68	-2.68	3.63
A_D	0	0	0	0	0	9.16	-9.16	3.89

5.4.2.4 Asymmetric lifting task

The asymmetric lifting task involves a worker retrieving the work-piece from his side and placing the object on a stand located directly in front of him as depicted in Figure 64. After selecting the work-piece and setting up the parameters for the item-tracker the worker enters the frame and carefully places his feet within the outlines used to derive the reference values.

After carefully placing the item on the stand the worker breaks contact. After a short period the worker picks the item off the stand and places it back on the table, where after breaking contact once again, repeats the cycle over a five minute sample. The worker repeats the entire process three times. Only data on the cycle from the table to the stand is presented here. Data on the other cycle is available on the DVD.

The task requires significant control and due to the nature of the test, the frequency and coupling multipliers are not calculated.

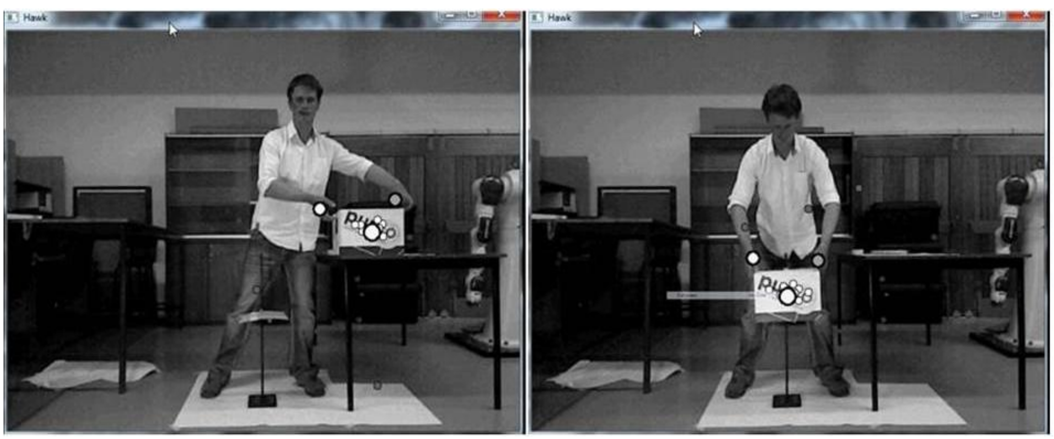

Figure 64: Screenshots of the asymmetric lifting task. (*Left*) Origin on table, (*Right*): Destination on stand

The reference and measured multipliers at the origin of the lift are provided in Table 39. Considerable errors are recorded for lifts originating from asymmetric locations. The largest and most variable errors occur on the measurement of the horizontal multiplier. There is also a notable over estimation on the asymmetry angle.

Table 39: Asymmetric lifting task results at the at the origin on the lift on the table

	Reference	Measured	Standard Deviation	Difference	Relative Error
HM_o	0.40	0.53	0.06	0.14	34.36%
VM_o	0.93	0.95	0.00	0.02	2.14%
DM_o	0.98	0.97	0.00	-0.01	-0.75%
AM_o	0.83	0.78	0.01	-0.04	-5.41%
RWL_o	**6.90**	**8.90**	**1.05**	**2.00**	**28.83%**

The reference and measured values for the multipliers at the destination of the lift in represented in Table 40. The data in this table can be compared to the data measured at the origin of the symmetric lift to identify any possible differences between data retrieved at the origin and destination of lifts.

Table 40: Asymmetric lifting task results at the at the destination of the lift on the stand

	Reference	Measured	Standard Deviation	Difference	Relative Error
HM_D	0.61	0.71	0.06	0.10	16.79%
VM_D	0.98	0.96	0.01	-0.02	-2.24%
DM_D	0.98	0.97	0.00	-0.01	-0.75%
AM_D	1.00	0.97	0.03	-0.03	-3.08%
RWL_D	**13.43**	**14.75**	**1.40**	**1.32**	**9.83%**

In order to facilitate a comparison between variables measured by the HAWK-RNLE and trained human analysts for an asymmetric lifting task, data from a study conducted by Dempsy et al. is tabulated alongside the results from the HAWK-RNLE system. Data for the variables at the origin and destination are provided. Note that the two tasks are not the same and as a result the physical measurements are not significant, they have been included to provide context to the measured error and standard deviation [**100**].

Table 41: Comparison between traditional study and the results of the HAWK-NIOSH system for an asymmetric lifting task [100]

	Manual Studies				HAKK-RNLE			
	Reference	Measured	Error	Standard deviation	Reference	Measured	Error	Standard deviation
H_O	45.7	47	1.3	-7.8	63	46.89	16.11	4.84
H_D	68.6	65.1	-3.5	-17.6	41.3	35.36	5.94	2.99
V_O	22.9	21.1	-1.8	-2.5	97.5	90.85	6.65	1.58
V_D	99.1	95	-4.1	-2.6	69.5	62.16	7.34	3.27
D	76.2	73.9	-2.3	-	28	29.34	1.34	0.64
A_O	0	0	0	0	54	67.99	-13.99	3.92
A_D	48	51.6	3.6	-7.2	0	9.62	-9.62	8.25

5.4.2.5 Discussion of results

The following sections discuss the discrepancies and performance of the system in terms of; standard deviations, errors and relative errors with respect to each of the multipliers. Within the sections the appropriate variables and the associated performance measurements are also discussed.

Distance multiplier

The distance multiplier (DM) is calculated differently in the HAWK-RNLE system than proposed in literature. Rather than using tracking information from the worker tracker the distance that the work piece travelled between the origin and destination was used. The results were exemplary with a relative error of less than a percent as shown in Table 37 and Table 40. In addition to closely estimating the distance travelled, the standard deviation of the measured value was by far the smallest of the multipliers and variables. The maximum resultant error of -2.15cm is better than the error of 2.3 cm [(99.1-22.9)-(95-21.1)] measured by human analysts as represented in Table 38 and Table 41.

Vertical multiplier

The vertical distance (VM) also represents a significant error even though the relative error of the multiplier is significantly smaller. This is a result of the reduced sensitivity of the multiplier.

The error between the measured and reference measurements varies significantly between the different tasks, however note that for a specific vertical height error it is fairly constant. As the vertical height increases so does the error. The increasing error consistently underestimates the measured value. As an example consider the three values for the origin of the lift for the symmetric lift from tables in Appendix 12. The errors are 9.11cm, 7.19cm and 9.95cm at a further corroborated by the data relating to the asymmetric lifting task in which the errors were 7.68cm, 6.88cm and 7.45cm at a vertical height of 69.5.

The vertical height could be made significantly more accurate by simply adding an additional ten percent to the measured value.

Table 42: Modified vertical distance with respective errors

Reference	Measured	Error	Measured + 10%	Error
97.5	90.85	6.65	99.94	2.44
69.5	62.16	7.34	68.38	-1.12
97.17	88.35	8.82	97.19	0.02
20.3	21.19	-0.89	23.31	3.01

The results in Table 42 indicate the significant impact that the simple process of adding ten percent to the measured values will have. The error of the measured values is then better than the manually performed studies which indicated an average error of 4.1cm in Table 41. It should be noted that this process increases the error at lower heights. However, due to the relative nature of the manipulation the resultant impact on the vertical multiplier will be small.

Asymmetry multiplier

The angle of asymmetry poses a significant challenge, because it requires the calculation of:

- The gradient of line perpendicular to the mid-sagittal plane
- The mid-point between the worker's feet
- The mid-point between the hand grasps

Due to the number of possible sources of error, it is therefore expected that the angle of asymmetry will be more variable than the other variables already introduced.

If the worker-tracker selects the shoulder joints poorly, an error will off-set all of the results of the study. Poorly selected shoulder joint locations can result from poor alignment of the worker or measurement errors. Due to the significant impact that the shoulders' joint location has on the final results, accurate data is very important. Other sources of error include tracking failures and measurement errors of the worker's hand and or feet.

Consider the symmetric lifting task represented in Table 38. At the origin of the lifting task the average errors are fairly small and constant measuring 2.06˚, 3.07˚ and 2.91˚ respectively as shown on Appendix 12. The errors at the destination of lifts are considerably larger. This is attributed to one of the bending postures assumed by the worker. The worker-tracker is incapable of accurately identifying the location of the worker's feet. This is also indicated in the variance of the horizontal multiplier. The largest measurement error at the destination was 11.7˚. Interestingly the standard deviation is similar to the standard deviation at the origin and if a single anomaly in the data is removed then the standard deviation reduces to 0.93˚. The system therefore measures a constant significant error with remarkable precision. The source of the error is attributed to the bending actions of the worker.

The standard deviation of the angle of asymmetry for a reference angle of 0˚ is between 3.5˚ and 4˚. The magnitude of the deviation can be attributed to one or two measurement anomalies which result in the recording of significantly larger angles than normal. These errors result from noise in the worker tracker and occur at both the origin and destination of lifts.

The noise and measurement errors are also magnified by the discrepancy between the traditional RNLE and the HAWK-RNLE, which uses tracking location data on the worker's feet rather than projections of the inner ankle bones. As a result the foot locations are closer to the coupling mid-point. This results in an exaggeration of the angle of asymmetry. This is best demonstrated through the analysis of the asymmetry multiplier (AM) for angular deviations. In each of the cases the measured value exceeded the reference values. The final of the three runs indicated significant deviations. The errors for the three runs, as depicted in Appendix 12 were 7.17˚, 9.16 to 25.1˚ respectively. The standard deviations were not significantly different to the values for the symmetric lifts. This variability in the error for the final run is attributed to poor identification of the shoulder joint locations. A possible solution is to return the angle of alignment relative to the camera's axis to the analyst. From this the analyst can determine whether or not the mid-sagittal plane is suitably measured. In this way if alignment is deemed excessive the worker can be requested to recalibrate.

Horizontal multiplier

The relative error of the horizontal multiplier (HM) indicates that it is the most significant source of error. This is mostly due to the sensitivity of the multiplier, see Section 5.2.3. The sensitivity of the multiplier and the use of the worker's feet locations as opposed to the projections of the inner ankle bones results in significant errors.

The distance between the feet locations tracked by the HAWK-RNLE and the inner ankle bones will vary for different individuals depending on the size of their shoes. For the worker analysed in this study, consider the origin of the symmetric lift where the worker is near upright. The results of all runs are included in Appendix 12. The horizontal distances that results in the considerable error, are consistently underestimated in all three tests (6.13cm, 6.92cm and 6.68cm). The consistency on the error for upright poses is also indicated by the asymmetric test where the average discrepancy at the destination on the stand indicated in Table 41 was 5.94cm and 6.13cm at the origin on the stand, the data for which is on the DVD.

In theory the error could be dramatically reduced either finding a skeletal tracking algorithm capable of returning joint location data on the ankle or alternatively offsetting the measured value by a constant value.

If we consider the destination on the ground represented in the symmetric test the results appear to be significantly better than the origin. The measured distance overestimates the horizontal distance by only 3.72cm resulting in a considerable reduction in the relative error. Note that although the relative error is smaller, it is incorrectly achieved. In the bending posture represented in Figure 63, the worker tracker is incapable of reliably tracking the worker's feet and other joint locations [**55**]. The inability to reliably track workers in bending postures is compounded by the fact that the worker's feet are obscured from view. In the tests, the worker's feet locations are fortuitously identified at a location that reduces the relative error. The error would however be increased if the ankle locations were used in the assessment.

The asymmetric lifting task provided interesting findings. Most notably was the dramatic underestimation of the horizontal distance to the load. Between the various runs the average measured distance also varied significantly (13.96cm, 21.91cm and 12.46cm) while the standard deviation of 4.84cm, did not deviate as much from the results of the symmetric test. The average measured value was 16.11cm less than the reference value. This is nearly three times as large as the errors for the symmetric task. Furthermore the worker was completely visible to the camera and was not bent over in any way as shown in Figure 64. A possible explanation for the significant error is provided by a study conducted by Martin et al. , who used two Kinect™ cameras and found that in cases where the camera viewing angle was not straight onto the worker or the worker twisted away from the camera, that the accuracy decreased with increasing misalignment [**11**].

5.4.2.6 Frequency and coupling multipliers

In order to assess if the system was capable of calculating the frequency and coupling multipliers three short tests were conducted which required a worker to perform simple lifts:

1. The worker was required to perform a single lift in the compressed minute long assessment. The analyst set the duration on the lifting task to 240 minutes. The coupling multiplier was set as poor.
2. In the second test the worker performed four lifts in the minute long assessment. The duration of the lifting task entered into the GUI was 90 minutes and a fair coupling was selected.
3. In the final assessment the worker performed 10 lifts in the minute long assessment. The duration was set to 60 minutes and the good coupling quality was selected.

The results of the assessment are indicated in Figure 65. In all cases the vertical distance was less than 750mm.

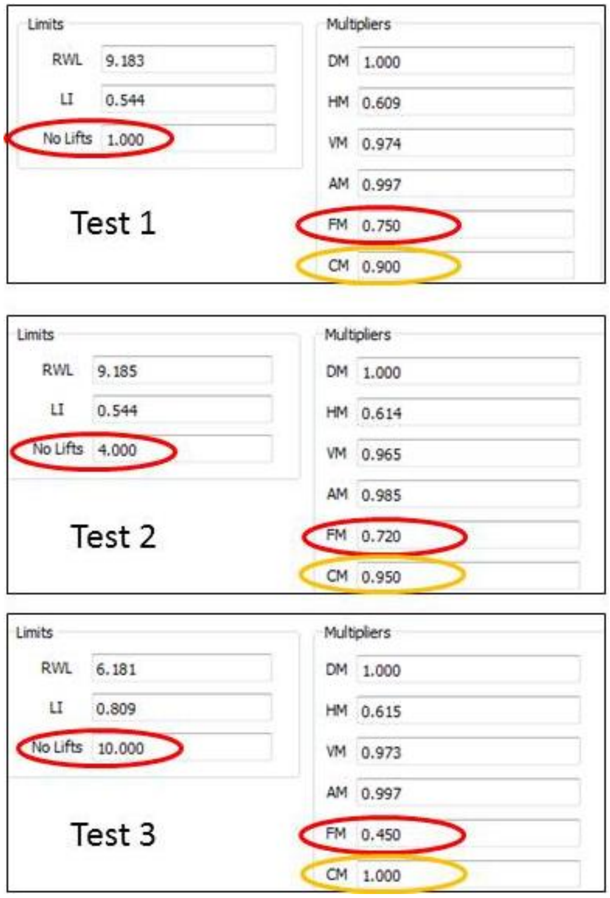

Figure 65: Screenshots of the GUI reflecting results of the frequency and coupling multiplier tests. (*Top*): Test 1, (*Middle*): Test 2, (*Bottom*): Test 3

The simple tests indicated that provided that the variables for the item tracker and RNLE were entered correctly that the system was capable of correctly determining the frequency and coupling multipliers as validated in the tables in Appendix 9.

The red ellipses highlight the data pertinent to the calculation of the frequency multiplier and the orange ellipses the coupling multiplier. Recall that the vertical location is also used in the calculation of both the frequency and coupling multipliers. In Section 5.4.2 the measurement error was indicated as being approximately proportional (10%) to the measured height. For lifting tasks conducted close to the 75cm height, the recorded measurement would incorrectly classify the state up to a height of approximately 83.33cm. The measurement error of the vertical location could therefore lead to increased errors resulting from the influence on the frequency and coupling multipliers. The accuracy of the vertical height, particularly around 75 cm is therefore vital. The solution is to off-set the measured values by ten percent.

Users are required to enter values into the GUI that cannot be calculated automatically. The multipliers are therefore susceptible to the same errors as manual studies. This requirement also means that the analyst needs to be familiar with the RNLE methodology and the task being analysed. The only input value for the coupling multiplier is the coupling quality which needs to be looked up in the decision tree depicted in Appendix 9 Figure 69. The coupling quality is therefore decided by the analyst. Waters et al. indicated that in their experiment there was a significant disagreement between the classification of the coupling quality and 41% of the participants rated the coupling as poor when the reference was defined as fair. These discrepancies will also be carried into the HAWK-RNLE system. The analyst is also required to enter the duration of the lifting activity, which is used in the calculation of the frequency multiplier. The analyst will therefore be required to have knowledge of the task that is being performed. Unfortunately very little data is available on the performance of workers in determining the factors of the frequency multiplier.

5.5 Discussions and conclusions

The HAWK-RNLE system was originally proposed as an attempt to improve, simplify and reduce the errors related to performing studies manually. This chapter introduced the RNLE as an established and accepted method for reducing the prevalence of LBP and other less significant WMSDs.

This chapter introduced the RNLE and provided information on the formulation and function of the equation, while also outlining the boundaries within which the equation is valid. Due to the complex nature of the algorithm, in which each of the multipliers is calculated according to a different equation, the sensitivity of the algorithm was introduced. This section emphasised the impact that even small measurement errors have on the resultant RWL.

Two studies were introduced that assessed the accuracy with which trained individuals could measure the variables of the RNLE [**100**,**102**]. The results of these studies indicated that there were considerable errors in the measurement of certain parameters. There was also a systematic error recorded whereby an analyst incorrectly interpreted the measurement strategy, this error had a significant impact on the results. These discrepancies and limited accuracies justified the development of the HAWK-RNLE system. The results of these studies also serve as a reference against which the HAWK-RNLE could be tested.

An existing system developed by Martin et al. automating the calculation of the RWL first introduced in Section 2.4.3.3 was investigated in order to ascertain whether an existing automation of the RNLE existed. Numerous fundamental errors were found with the system. The RWL was continuously updated with each frame, the system therefore does not follow the methodology of the RNLE described by Waters et al. which records variables at the origin and, if significant control is required, at the destination of lifts [**3**]. Other problems were also identified and no information was provided on the method used to calculate variables or results [**11**].

The opportunities for improvement ultimately resulted in the description of the concept for automating the RNLE according to the method developed by Waters et al. [**3**]. In most cases the variables in the HAWK-RNLE were calculated according to the method set forth by Okimoto et el. [**101**]. A single small modification to the methodology was implemented in order to reduce variability of the calculated distance travelled. Rather than using the vertical height of the worker’s hands, data on the work-piece’s location was used as it was subject to less variability.

Two tests were conducted; a simple symmetric lowering task and an asymmetric lowering task. In order to derive a reference value against which the results for the HAWK-RNLE system could be compared, a manual study was conducted prior to system testing. The manual study was conducted according to the method proposed by Okimoto et al. The study was performed under controlled conditions and the results were accepted as being suitably accurate [**101**].

The RWL for each of the tests are represented in Table 43. Due to the cyclic nature of the lifts, the RWL is provided for both origins and destinations. From the data in the table it is clear that the measured RWL represents a significant error. Considering the manual study conducted by Waters et al, and the results in Appendix 9 Table 48, the average error at the destination was less than 0.5kg and the maximum error was 1.7kg. This is notably less than the RWL calculated by the HAWK-RNLE system.

Table 43: Reference and measured RWL for the different tests

		Reference	Measured	Standard deviation	Error
Symmetric	Origin Stand	11	13.3	0.88	2.29
	Destination Floor	9.15	8.54	0.4	0.61
	Origin Floor	9.37	8.56	1.57	0.82
	Destination Stand	10.76	11.58	0.51	0.83
Asymmetric	Origin Table	6.9	8.9	1.05	1.99
	Destination Stand	13.43	14.75	1.4	1.32
	Origin Stand	13.43	14.84	1.16	1.41
	Destination Table	6.9	9.03	1.67	2.12

The testing done on the HAWK-RNLE indicated that there are a multitude of measurement errors.

- Tracking the worker's feet and hands rather than the inner-ankle bone and the third metacarpal
- Inherent tracking errors in the vertical multiplier
- Incapability of the worker-tracker to reliably track workers when bending or twisting
- Possible errors in frequency calculation as the work-piece is obstructed or accidental contact of the worker with the work-piece

The tests identified the need for adjustments to the measured data. This included offsetting the measured foot location by 6cm and correcting the vertical distance by multiplying the measured value with a factor of 0.1. The offset is required because the skeletal tracker returns the worker's foot and not ankle location. The single largest contributor to the measured error was the horizontal distance. The impact that this has is demonstrated through a simple example by adjusting the data for the origin of the lift at the stand for the symmetric lifting task. The revised results are represented in Appendix 13. The adjustments resulted in a reduction in the measured RWL to 11.33, which is significantly closer to the reference value and in fact better that manually performed studies. It therefore indicates that symmetric lifts where the worker is near upright can accurately be assessed by the system.

The impact of the revisions, when the work-piece is on the floor and for asymmetric lifts it is however not as positive. The RWL error at the destination on the floor increases to 1.66Kg from 0.61Kg. This is due to the inherent nature of the worker-tracker, whereby the accuracy of joint location data reduces when the worker is bending and/or twisting [**11**,**55**]. The system posed by Ray et al. identified the limitation of using skeletal trackers for bending postures and therefore performed posture classification and only estimated body poses when the worker was standing [**55**].

Although the reduction in accuracy has been noted in literature, empirical data on the magnitude of the reduction has not been provided. The tests performed in this case indicated that the systematic limitations were a stumbling block for the automation of the RNLE which is specifically designed to assess the risk of LBP for lifting activities which would require bending and twisting actions. As a result the HAWK-RNLE can only reliably be applied to lifts conducted where the worker and work-piece are completely visible to the camera. Furthermore the lift needs to be conducted near upright with minimal rotation.

In order to demonstrate the worker tracker's response to bending actions, data on a worker's right hand and foot were plotted for a bending action. The results of the simple experiment are included in Figure 66. Throughout the bending motion the worker's feet remained perfectly stationary, however the data indicates that around halfway through the bending motion, the system incorrectly identified a large jump in the negative y-direction, which would indicate the foot being pushed through the ground. A possible solution to the tracking failure would be to lock the worker's feet co-ordinates as soon as the worker hands are identified as being lower that the workers knees. Note that the y co-ordinate of the foot is not used in the RNLE. However the x and z co-ordinates are and corresponding to the failure they also undergo noticeable deviations in the positive x and z directions. Figure 66 also indicated that all of the foot co-ordinates are unstable during the entire bending motion, although the deviations are significantly less than the deviations when fully bent over, they would still influence the results. It should be noted that the hand location seems to be tracked correctly and are not influenced by the failure.

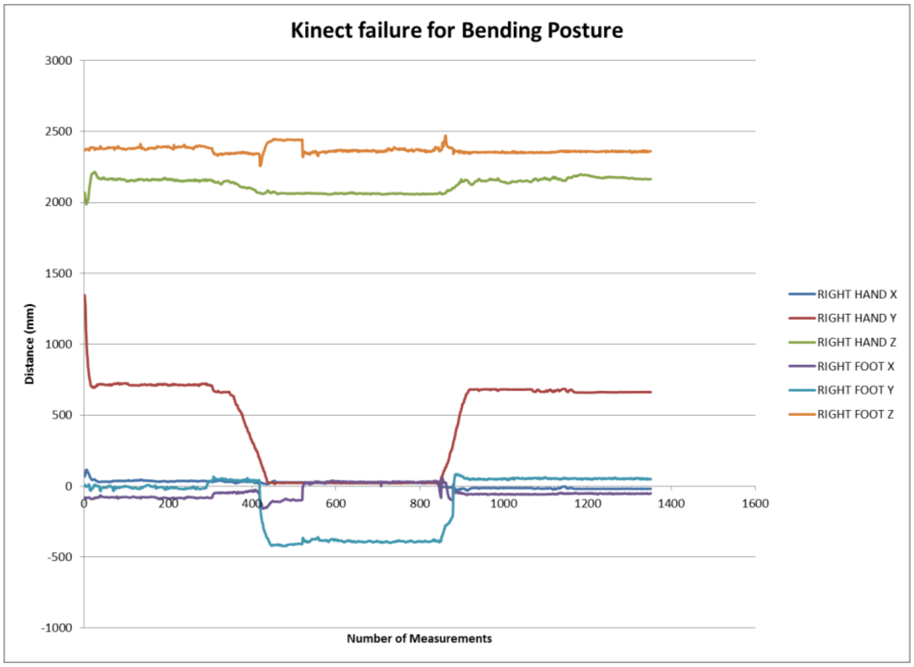

Figure 66: Demonstration of the worker trackers response to bending postures

The HAWK-RNLE in its current form cannot be used to calculate RNLE accurately enough, and in enough situations to be used as a practical tool in industry. In addition to the limitations of the skeletal tracker with regard to bending and twisting other practical concerns include:

- Generally lifting tasks will take place near shelves, workbenches and packaging tables. As a result workers will typically be partially be obscured from view, if they can be viewed at all.
- The worker tracker does not perform well when it is in contact with surfaces.
- In order to calculate the frequency multiplier, the system will require additional functionality of tracking multiple items.

Although not a functional success, the HAWK-RNLE addressed many of the errors related to the system developed by Martin et al. [**11**]. In addition the ability of tracking the work-piece and the worker in real time enabled accurate and reliable determination of contact points. The HAWK-RNLE system is therefore capable of capturing data at the origin and the destination of lifts according to the method proposed by waters et al [**5**]. It also enables the determination of the number of lifts. The use of the calibration pose serves as a reference for the calculation of the angle of asymmetry, and allows for angular misalignments.

In order to develop a system capable of accurately and reliably automating the RNLE, advancements in the skeletal tracking field are required. The natural interaction (*NI*) field is developing rapidly, and it seems reasonable to assume that significantly improved hardware and software will be available to developers in the near future. It is likely that these developments will address widely reported concerns on the accuracy and reliability of skeletal tracking for rotation and bending postures. Another area that required attention is the reliability under contact conditions. This could be achieved by incorporating other image recognition techniques, such as colour filtering, to aid in differentiation between surfaces and certain parts of the body [**11**,**55**].

6. Chapter 6

Discussions Conclusions and Recommendations

6.1 Introduction

This thesis introduced the link between:

1. The pressure to increase labour productivity
2. The increased strain that results on the work-force. (Specifically with reference to the lifting of work-pieces)

The pressure often results in overexertion and WMSDs, such as LBP. An investigation into the financial implication of these incidents indicated that LBP formed a significant financial burden in industry. The costs ascribed to LBP originate from both direct costs such as compensation payments and indirect costs which originate from the reduction in productivity. As a result companies are faced with a need to measure and optimize labour performance without subjecting employees to hazardous tasks.

This thesis was undertaken with the objective of identifying a suitable technological platform for the automation of both a traditional labour performance measurement (LPM) and risk assessment. The common platform aims to bring together LPM and risk assessments. The automation of both data gathering and analysis phases of traditional measurements in most instances will reduce the time, costs and complexity associated with executing labour assessment.

If the systems are capable of providing accurate data on the labour performance and risk assessments, then the system would enable most organizations within the production sector to measure labour performance, and with the same basic system measure the risk that certain lifting tasks pose on workers.

6.2 Summary and discussion

The literature study in Chapter 2 introduced a wide variety of existing:

1. Traditional methodologies
2. Technological support systems

The aim of the study was to identify suitable candidate methodologies for automation. Simultaneously the chapter identified computer vision as the platform with the most desirable characteristics. The most important of which was the ability to non-invasively track workers in real time. This ability is attributed to the range imaging capabilities of the Kinect™ camera and the open source libraries for Natural Interaction.

The labour assessment methodologies were selected by considering the range of factors covered by the methodology and the information provided by the results. By weighing up the advantages and assessing the suitability for automation of the various methodologies, work sampling was selected as the basis for LPM and the revised NIOSH Lifting Equation RNLE for risk assessment.

Basic system

With the methodologies and platform selected, a basic system capable of providing the raw data required for the labour assessments was created. The raw data included co-ordinate data on the

- Worker's hands, feet and shoulders
- Work-pieces centre point and dimensions

The basic system consisted of a Kinect™ camera linked to a central computer. The computer would run a C++ application that uses OpenNI libraries and OpenCV libraries to facilitate worker and item tracking respectively.

- Worker tracker utilises a skeletal tracking algorithm to return positional data on specific joints of the worker.
  - OpenNI SDK was chosen for the worker tracker.
    - It enables torso only tracking.
    - It provides a higher frame rate.
- The item tracker uses an image recognition algorithm to identify and track a specific work-piece within the capture frame.
  - A SURF implementation was chosen as the basis for the item tracker.
    - It does not require significant training periods and therefore facilitates the near real time selection of a work-piece.
    - The SURF_GPU algorithm was used with Nvidia's CUDA toolkit to enable real time execution. CUDA maps the SURF algorithm to the GPU which excels in matrix operations. The GPU computing has the added benefit of reducing the load on the computer's processors.
    - The SURF algorithm error matching is efficiently removed with a RANSAC algorithm.

In order to speed up processing further Threading Building Blocks (TBB) by Intel® was used to enable task parallelism. Normal OpenCV applications only utilize the processing power of a single computer core. By Installing OpenCV with Intel® TBB enabled, the library automatically uses threading to utilize all the available cores. The use of these performance enhancing tools were fundamental in ensuring the real time capabilities of the system. The enhancement is further improved by the ability of the user to select a subset of the capture frame as the workspace. The item tracker only evaluates the pixel within the smaller workspace. As a result computation time is further reduced.

For both the labour assessments, namely performance measurement and risk assessment the HAWK system, developed as the common platform of this thesis, would need to establish whether the worker was in contact with the work-piece. This was achieved through a simple box-sphere intersection test. An axis aligned bounding box is drawn around the work-piece by the analyst. The minimum distance between the centre of the either of the worker's hands and the box is continuously calculated. Whenever the minimum distance is less than the contact radius, defining the sphere around the worker's hand, the worker is in contact with the sphere.

HAWK-PRODUCTIVITY

The HAWK-PRODUCTIVITY system, as a labour performance measurement, is fundamentally similar to work sampling in that workers are classified as in a number of states. The biggest difference is that the automated system continuously monitors the worker, as opposed to recording a number of observations.

The basic principle of the automated productivity assessment is that the worker will be classified as in one of the following states: productive, idle, static, or out of frame, according to the locations of the worker and the work-piece. The speed of the worker's hand movements is also considered. The information on the time spent in each of the states is used to determine the utilization of the specific worker. In addition to the information on the time spent in the various states, information on the work-pieces is also provided. This includes:

- The number of work-pieces produced
- The average processing time
- The standard deviation of the average processing time

The information on the time spent in the various states and the number of items will be used as relative measures. Variations in the measurements will indicate the presence of problems, and indicate if further investigations are required.

HAWK-RNLE

The HAWK-SYSTEM is an automation of the existing RNLE. The RNLE is a multiplicative model in which a number of task variables are measured and expressed as multipliers. The multipliers are coefficients that serve to decrease the load constant, which represents the maximum load that can safely be lifted under ideal conditions. The task variables are measured at the origin, and if significant control is required, at the destination of lifts.

In the HAWK-RNLE system, prior to the initiation of the study, the worker is required to assume a calibration pose. As soon as the worker is calibrated, the locations of the worker's shoulders are recorded. This information is used to establish the mid sagittal plane of the worker defined while in the neutral position. This process is required to determine the angle of asymmetry for asymmetric lifts.

The moment the HAWK-RNLE system registers contact with the item and if significant control is applied the moment contact is broken, the system records data on the worker's hands and feet, and the item. Each time contact is broken, a counter for the number of lifts, is incremented. The number of lifts and the duration of the study are eventually used to determine the frequency multiplier at completion of the study.

The analysis of the recorded data yields information on the various multipliers and also on the principle product of the RNLE, the RWL, which represents the maximum load that can safely be lifted for the assessed technique.

6.3 Findings

The most important findings identified through the testing done on each of the three main sections of this thesis, the basic system, The HAWK-PRODUCTIVITY and the HAWK-RNLE are briefly discussed in the following section.

Basic System

The testing in chapter 3 was divided into three sections:

- Worker tracker
- Item tracker
- Contact

Worker tracker

A novel method of extracting data was used to assess the accuracy and the noise of the worker tracker. The worker tracker was used to track a Motoman SDA10 robot. The robot is anatomically similar to a human torso, and as a result the worker tracker was capable of tracking the robot. The robot has a very accurate positioning system and therefore offers an accurate measurement against which the information of the worker tracker can be compared. The results indicated that the accuracy of the skeletal tracker was not as good as expected. The maximum discrepancy that was indicated was 41mm.

Testing was also done on human operators, specifically on the worker's feet. The test was conducted in order to gauge the accuracy of the foot tracking while in contact with the floor. It has been reported in literature that skeletal trackers loose accuracy in contact situations [**12**]. The testing was conducted by comparing the actual travel distance, measured by an analyst to the measurements recorded by the HAWK system. The maximum deviation was found to be 57 mm which is a notable error (12.7% of the actual distance) The tests also indicated the optimal range for foot tracking as being between 3m-3.5m, whereas hand tracking is stable over a wider range of values, 2m -3.5m.

Item tracker

The work-piece needs to have features on it to enable tracking. As a general rule high contrast and larger features result in more reliable tracking. Due to the contrast basis of the algorithm it has been ascertained that it can operate in a wide range of lighting conditions.

The user tracker is a planer tracking algorithm. As a result the tracker only returns the 2D pixel co-ordinates of the centre of the user selected work-piece. In order to determine the depth dimension, the depth value for the centre point of the work-piece is retrieved from the depth-map. The focal length principle can then be used to translate the pixel co-ordinates to mm co-ordinates.

Prior to the initiation of tracking, the analyst is required to manually select the work-piece by using the mouse to drag a bounding box around the work-piece. The distance between the maximum and minimum x and y co-ordinates were logged in order to assess the accuracy with which the user selected the work-piece. The average error over the range of distances was 3.8mm and the maximum error was 22.6mm. The contact radius is therefore a minimum 3.7 times larger than the maximum error. As a result the dimensions of the work-piece can be selected accurately enough to enable reliable contact determination, provided that the co-ordinate systems of the box and the camera were aligned. This also indicated that the value for the focal length was accurate. After selecting the work-piece, there is a time delay of less than five seconds that occurs before tracking can commence. This delay results as the algorithm is mapped to the GPU.

Scale tests were conducted to identify the maximum distance that a specific size item could be placed from the camera. The reliability of the item tracker increases with an increasing number of features. As the work-piece's size decreases relative to the capture frame, fewer features can be identified on the work-piece. Testing indicated that the absolute minimum area covered by the work-piece at 3.5m should be $0.1m^2$.

Although SURF is invariant to changes in rotation, the RANSAC implementation in this thesis is not. The system can therefore only tolerate a limited degree of rotation, which is fundamentally controlled by the back projection error. Making the back projection error too large should be avoided as this will increase the probability of false identification of the work-piece. Due to the axis aligned nature of the task, the back-projection error is suggested to be set as small as practically possible. The implementation of a rotation invariant version is exponentially more complicated and computationally more expensive.

Contact

Contact is determined through Arvo's box axis aligned box sphere intersection test. The tests indicated that the minimum contact radius could be 85mm. The tests also indicated that a single data point after the establishment of contact provided suitably accurate positional data.

HAWK-PRODUCTIVITY

The testing done on the system indicated that the system could be used for the assessment of workers working on small or large items. The small item test ensures that the system can be applied to a broader spectrum of tasks. The large item implementation provides significantly more data. The accuracy of the data is also increased due to the reduction of incorrect classifications. Furthermore it also provides reasonably accurate data on the work-pieces. The information on the work-pieces provides valuable insights into problems and progress on the production lines and is information that is not available in traditional studies.

The tests indicated that the HAWK-PRODUCTIVITY system was capable of reliably determining the state of the worker. There were however noticeable delays between the actual and measured state changes. The delays result from the use of multiple measurements which were incorporated to increase the reliability of the classifications. As a result of the delays, the system will work best for tasks where the worker spends longer periods in each state. In addition to the delays, tests also indicated that there were a few errors in the static and productive classifications. These result when the worker makes unproductive movements, or when the worker-tracker fails. Unfortunately, due to the systematic roots of the errors, nothing can be done to eradicate or reduce their prevalence.

A notable disadvantage of the HAWK-PRODUCTIVITY system, as with all automated approaches, is that there is less detail available than in manually performed studies. However, the benefits of the automation far outweigh the disadvantages. The continuous basis of the HAWK-PRODUCTIVITY system ensures that it bypasses the inherent inaccuracies of traditional work sampling. The automated systems save analysts time and therefore costs in the data capturing and transcription phases of traditional studies are reduced. Furthermore the automated systems significantly simplify and also reduce the tediousness of measuring labour performance.

The HAWK-PRODUCTIVITY system addresses many of the limitations of the existing automated systems. In addition it also provides significantly more information, and therefore offers analysts a better opportunity to identify problem areas and ultimately improve productivity.

HAWK-RNLE

Numerous fundamental errors were found with an existing system developed by Martin et al. automating the calculation of the RWL. A fundamental issue was that no consideration is given to the procedure where origin and destination of the lift needs to be defined. The HAWK-RNLE addressed many of the problems of the existing approach [**11**].

To assess the capabilities of the HAWK-RNLE two tests were conducted;

- Symmetric lowering task
- Asymmetric lowering task

Manual studies were conducted in the parallel with the tests. The errors found in the two studies were compared with the manual studies and an assessment of the accuracy with which trained individuals could measure the variables of the RNLE [**100**,**102**].

The testing indicated that there are a number of shortcomings of using the worker tracker for the assessment of lifting tasks. The first error was the use of the worker’s feet and hands rather than the inner-ankle bone and the third metacarpal. The hand location would only result in a small error. In contrast the foot location represents a notable error. The solution that was proposed was to offset the measured foot locations by 6cm in the z-direction. This can only be done if the worker is perpendicular to the camera. The tests also identified the need for other adjustments to the measured data. This included correcting the vertical distance by multiplying the measured value with a factor of 0.1.

The adjustments resulted in a significant reduction in the error for lifts where the worker is near upright. The results indicated that the HAWK-SYSTEM actually outperformed human analysts. This is however only the case when the worker is near upright. The worker-tracker is incapable of correctly tracking workers for bending postures. The worker-tracker also indicated significant loss in accuracy for twisting postures.

Due to the limitation imposed by the limited flexibility of the worker-tracker, the HAWK-RNLE in its current form cannot be used to calculate RNLE accurately enough, and in enough situations to be used as a practical tool in industry. Although not a functional success, the HAWK-RNLE addressed many of the errors relating to the system developed by Martin et al.

6.4 Concluding remarks

The concept of tracking both a worker and a work-piece is a new and novel concept and it provides a rich source of data and if the worker-tracking information was more accurate, it would be an effective tool for the assessment of lifting risks and should provide better data for performance measurement. Nevertheless the system indicated that it is possible to track a worker and a work piece consecutively. This thesis also brought together two methodologies under a common platform. These two methodologies could, if desired, easily be combined within a single application, in which the user could then select the desired assessment.

At present the biggest limitation is the skeletal tracker in bending and twisting postures. As soon as an improved technique is released, the HAWK-RNLE will take a considerable leap towards being a marketable tool.

The advantages of the general system include

- Simple selection of the workspace and the work-piece
- GUI facilitates easy data entry
- Results provided to analysts in real-time via the GUI in real time
- Data logged to .txt files can easily be exported to Excel for further analysis or plotting of graphs

Disadvantages:

- Complexity with installing the drivers and supporting software to enable use of the system
- Complexity of selecting the inputs of the SURF and RANSAC implementations for reliable tracking
- Ability to only track a single item

HAWK-PRODUCTIVITY

The features that enable the HAWK-PRODUCTIVITY system to perform effectively include; the lack of need for a calibration pose and the torso only tracking. As a result the worker will be calibrated automatically each time he/she re-enters the capture-frame and the worker can work at a work bench where his legs are completely obscured from view.

The HAWK PRODUCTIVITY System has a number of advantages, as indicated in Table 44:

Table 44: Advantages of the HAWK-PRODUCTIVITY system

Advantage	Reasons
Time savings	Observation, transcription and analyses not required
Low cost	Analysts are expensive
Fewer resource requirements	Analysts required for a shorter duration
Continuous monitoring	No statistical loss of data. Easier to understand the statistical based studies
Continuous feedback	Analysts can identify problems faster
Can become a permanent installation	No time frame after which it must leave the organization.
Additional information provided	Number of items, average processing time, deviation in processing time

The system also has a number of disadvantages as indicated in Table 45:

Table 45; Disadvantages of the HAWK-PRODUCTIVITY system

Disadvantage	Reasons
Less detail available than manual work studies	More states identified in manual studies. Calculation of standard time and allowances
Timing inaccuracies and reliability	Overly conservative values lead to large errors, responsive state changes result in reliability issues.
Interpretation of the data	There are many possible causes for variation. Because analysts will not always be present they may be misled by the data.

HAWK-RNLE

In order to develop a system capable of accurately and reliably automating the RNLE, advancements in the skeletal tracking are required. The natural interaction (*NI*) field, primarily responsible for skeletal tracking is developing rapidly. It would be reasonable to assume that significant improved hardware and software will be available to developers in the near future. It is likely that these developments will address widely reported concerns on the accuracy and reliability of skeletal tracking for rotation and bending postures. Another area that requires attention is the reliability under contact conditions. This could be achieved by incorporating other image recognition techniques, such as colour filtering, to aid in differentiation between surfaces and certain parts of the body.

An advantage of the HAWK-RNLE is that whereas manual studies only take one set of measurements, the automated system can take the average of a number of lifts. For repetitive lifts this will result in more reliable values. The skeletal tracking provides information on the size of the individual. As a result there is an opportunity to modify the RNLE measurement to suit the stature of the individual being analysed

6.5 Future work and recommendations

The following list includes simple improvements and additions to the existing system that would enhance the system's ability to perform the aforementioned techniques:

- Tracking multiple work-pieces within the capture frame
- Having a library of features, so that more than one type of work-piece can be tracked

- Facial recognition of workers, so that different workers can be analysed individually

6.5.1 Development of new measures

There are a number of new measures that can be created simply by including simple additional calculations to the existing system. The existing classification process requires the extraction of 3D co-ordinate data of the worker's hands along with the system time. As a result the distance and speed data can be extracted and used as proposed:

- 3D co-ordinate data can be used to calculate the distance travelled by a worker's hand while working on a specific work-piece.
    - The data on the distance travelled could be evaluated and used to improve tasks. If the distance travelled by the hand is minimized, then the travel time should theoretically also be reduced.
- The worker's hand-speed can be analysed while working on a work-piece.
    - The average speed data can be used to rate a worker's performance.
- A log of the hand speed data can be kept and analysed.
    - This will provide information on the variations in working speeds over a shift, between shifts and on different days of the week.
    - This information could be used to establish improved job scheduling according to a worker's productivity.

Each of these proposed measurements would need to by thoroughly investigated and extensively tested.

6.5.2 Development of a rotation invariant version

A core feature of the HAWK system is the axis aligned nature of contact determination and item tracking. There are two primary reasons for selecting an axis aligned approach. Firstly, the computational cost of a rotation invariant system would be significant. Secondly, the programming complexity also increases drastically. Other reasons included the limited accuracy of the skeletal tracker in contact situations, and the contact radius concept, which is reasonably tolerant to small misalignments. The limitation is that if the back projection error of RANSAC is selected to be very tight, the item could easily be lost for small misalignments. In order to enhance the robustness of the system and ensure that it can be used in more situations, a rotation invariant version should be developed. This will require the implementation of:

- Rotation invariant RANSAC algorithm
- Oriented bounding box sphere intersection test

6.5.3 Technological upgrades

The Kinect™ camera is bulky and as a result requires an external power source. As a result it is not ideal for mounting in workplaces. The biggest disadvantage of the Kinect™ sensor is its intrusive nature. A more compact device would be preferred for work environments. As soon as a small OpenNI-compliant 3D depth sensor is commercially released it should be incorporated. An interesting prospect for range imaging cameras is Capri 1.25. It is small enough to be built into mobile devices and like the Kinect™ it is an embedded device and can perform skeletal tracking and object recognition [**70**].

The computer vision field is developing at a rapid rate. It is suggested that the OpenNI SDK 2 architecture should be used. This latest release has the following advantages: [**65**]

- Supports latest generation of short range 3D sensors
    - Short range sensors could be more practical for factory monitoring, and specifically item tracking.
    - By using hand tracking and item recognition, similar information to the data provided by the HAWK-PRODUCTIVITY system could be provided.
- More flexible: depth units control, exposure control, etc.
- Better backwards compatibility
    - This simplifies the upgrading process significantly.
    - Technology is developing very rapidly and the system needs to be updated.
- Large offer of third party middleware libraries: Body Tracking, 3D Reconstruction, Object Recognition, Analytics, and many more
    - The inclusion of object recognition libraries would therefore no longer require the addition of OpenCV.

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Appendix 1

Quetech Ltd.

the work measurement company

Take a Tour Buy Support Company

Home Overview Features Demo

WorkStudy+ Features

Feature Overview

WorkStudy+ has been designed to be easy to learn and use, and yet packed with powerful features to handle any work measurement data collection project. Here are just some of the reasons why WorkStudy+ is the right tool for your organization:

- Accurate collection of time study and sampling data
- No need to manually transcribe data to PC
- Easy to learn intuitive user interface
- Seamless integration with Excel
- Powerful and customizable statistical reporting
- Available for Android, Windows Mobile and Tablet PCs

Data Collection Features

WorkStudy+ has the data collection features that allow virtually unlimited flexibility in what is collected and how it is collected:

- Record unlimited number of observations
- Time study multiple subjects at the same time
- Performance rate (speed rate) individual observations
- Track numeric unit counts and job cycles
- Track value added and non-value added time for lean analysis
- Automate selection of successive elements for repetitive studies
- Enter verbose comments for any recorded observation
- Interrupt and resume any recorded observation
- Use built-in random timers for random sampling studies
- Collect auditing information, even during a time study
- View and edit any recorded observation at any time
- View statistical information about collected data at any time, even during a study

Setup and Analysis Features

Setting up studies and analyzing recorded data in WorkStudy+ is quick and easy:

- Create, edit and manage any number of time studies and sampling studies
- Create or edit element (task) lists on the PC or on directly on the handheld device
- Assign meaningful names and descriptions to your elements (tasks)
- Visually identify individual elements by configuring colors, fonts and layout
- Organize elements and element groups within element lists in a hierarchical fashion
- Easily standardize and share element lists among team members and handheld devices
- Import completed studies directly into Excel or Access for further analysis
- Generate custom statistical reports within Excel in seconds

Appendix 2

How to: Set up OpenNI and NITE on Windows

Phase	Source file in directory
0	-
1	avin2-SensorKinect-faf4994.zip
2	openni-win32-1.5.2.23-dev.msi
3	nite-win32-1.5.2.21-dev.msi
4	sensor-win32-5.1.0.41-redist.msi
5	-
6	KinectXMLs.zip
7	-
8	-
Troubleshooting	avin2-SensorKinect-faf4994\Bin\SensorKinect091-Bin-Win32-v5.1.0.25.msi

http://entreprene.us/2011/03/21/how-to-set-up-openni-and-nite-on-windows/

PrimeSense, the company behind Kinect, released OpenNI framework and NITE middleware. The whole hacked Kinect setup can be done on the Windows platform in a matter of 20-30 minutes now. Check out the process below to get going.

Phase 0
Uninstall any previews drivers, such as CLNUI. *If you want to use multiple drivers and not create a pain every-time, check the end of this tutorial for the way to do it.*

Phase 1

- Download **Kinect Drivers** and unzip the folder.
- Open the unzipped repository and move to Platform\Win32\Driver.
- Run **dpinst-x86.exe** (if you have a 32-bit processor) or **dpinst-amd64.exe** (if you have a 64-bit processor).

Drivers are now installed in your PC.

Phase 2
Download and install the latest stable or unstable OpenNI Binaries from OpenNI website.

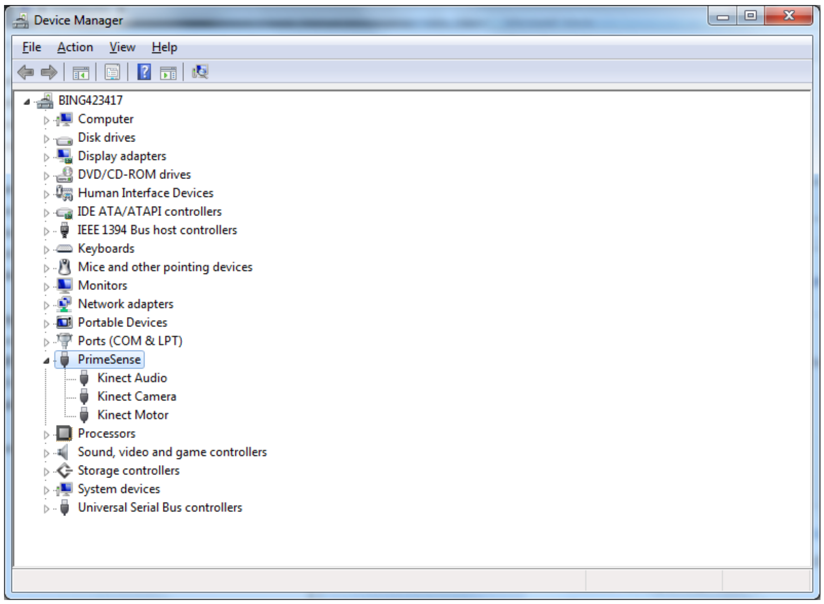
Phase 3
Download and install the latest stable or unstable OpenNI Compliant Middleware Binaries (NITE) from OpenNI website. The installation process will ask for a product key. Not to worry, enter the following key to it: **0KOIk2JeIBYClPWVnMoRKn5cdY4=**

Phase 4
Download and install the latest stable or unstable OpenNI Compliant Hardware Binaries from OpenNI website.

Note: Stable releases are older. Unstable ones are newer. Mind the trade-off.

Phase 5

- Plug in your Kinect device and connect its USB port with your PC.
- Wait until the driver software is found and properly installed.
- Under Device Manager it should look something like this:



Phase 6 – *the following process is optional yet it is advised to be followed*

- Download the **KinectXMLs file** and unzip. The extracted folders contain totally four XML files which are going to replace the ones OpenNI installed (the XMLs provided simply contain the license key and the correct Kinect camera resolution).
- Navigate to **KinectXMLs\OpenNI** folder and copy the SampleConfig.xml file. Navigate to**C:\Program Files\OpenNI\Data** (if you have a 32-bit processor) or **C:\Program Files (x86)\OpenNI\Data** (if you have a 64-bit processor) and replace SampleConfig.xml with the one you copied.
- Navigate to **KinectXMLs\NITE** folder and copy the Sample-Scene.xml, Sample-Tracking.xml and Sample-User.xml files. Navigate to **C:\Program Files\Prime Sense\NITE\Data** (if you have a 32-bit processor) or **C:\Program Files (x86)\Prime Sense\NITE\Data** (if you have a 64-bit processor) and replace Sample-Scene.xml, Sample-Tracking.xml and Sample-User.xml with the ones you copied.

The XML files used here are generated and provided by www.studentguru.gr people. We provide a trackback link.

Phase 7

Go to **C:\Program Files\OpenNI\Samples\Bin\Release** (or C:\Program Files (x86)\OpenNI\Samples\Bin\Release) and try out the existing demo applications. Also try the demos found in **C:\Program Files\Prime Sense\NITE\Samples\Bin\Release** (or C:\Program Files (x86)\Prime Sense\NITE\Samples\Bin\Release), too. If they work properly, then you are done! Congratulations!

Phase 8

The installation and setup of OpenNI and NITE is finished. You can try out the basic APIs by following the links below.

- **C:\Program Files\OpenNI\Bin** (or C:\Program Files (x86)\OpenNI\Bin) and
- **C:\Program Files\Prime Sense\NITE\Bin** (or C:\Program Files (x86)\Prime Sense\NITE\Bin)

OpenNI is the primary assembly you'll need when developing Natural User Interfaces applications.

Troubleshooting

If you are still running into problems with the basic demoes, then try the steps given below:

- Omit performing step 1.
- Follow steps 2, 3 and 4.
- Download **Kinect Drivers**, unzip and navigate to Bin folder. Run SensorKinect-Win32-5.0.0.exe.
- Follow steps 5, 6, 7 and 8.
- Finish.

Installing multiple drivers

You can now have various Kinect drivers installed concurrently. Here's how to achieve this:

- Open Device Manager.
- Right click Kinect Camera under PrimeSensor.
- Select "Update driver software"
- Select "Browse my computer for driver software" and "Let me pick from a list of device drivers on my computer".
- Select the driver of your preference (eg. **CLNUI**).
- You are through.

Appendix 3

```
class SURF_GPU
{
public:
    enum KeypointLayout
    {
        X_ROW = 0,
        Y_ROW,
        LAPLACIAN_ROW,
        OCTAVE_ROW,
        SIZE_ROW,
        ANGLE_ROW,
        HESSIAN_ROW,
        ROWS_COUNT
    };

    //! the default constructor
    SURF_GPU();
    //! the full constructor taking all the necessary parameters
    explicit SURF_GPU(double _hessianThreshold, int _nOctaves=4,
         int _nOctaveLayers=2, bool _extended=false, float
_keypointsRatio=0.01f);

    //! returns the descriptor size in float's (64 or 128)
    int descriptorSize() const;

    //! upload host keypoints to device memory
    void uploadKeypoints(const vector<KeyPoint>& keypoints,
        GpuMat& keypointsGPU);
    //! download keypoints from device to host memory
    void downloadKeypoints(const GpuMat& keypointsGPU,
        vector<KeyPoint>& keypoints);

    //! download descriptors from device to host memory
    void downloadDescriptors(const GpuMat& descriptorsGPU,
        vector<float>& descriptors);

    void operator()(const GpuMat& img, const GpuMat& mask,
        GpuMat& keypoints);

    void operator()(const GpuMat& img, const GpuMat& mask,
        GpuMat& keypoints, GpuMat& descriptors,
        bool useProvidedKeypoints = false,
        bool calcOrientation = true);

    void operator()(const GpuMat& img, const GpuMat& mask,
        std::vector<KeyPoint>& keypoints);

    void operator()(const GpuMat& img, const GpuMat& mask,
        std::vector<KeyPoint>& keypoints, GpuMat& descriptors,
        bool useProvidedKeypoints = false,
        bool calcOrientation = true);
```

```
    void operator()(const GpuMat& img, const GpuMat& mask,
        std::vector<KeyPoint>& keypoints,
        std::vector<float>& descriptors,
        bool useProvidedKeypoints = false,
        bool calcOrientation = true);

    void releaseMemory();

    // SURF parameters
    double hessianThreshold;
    int nOctaves;
    int nOctaveLayers;
    bool extended;
    bool upright;

    //! max keypoints = keypointsRatio * img.size().area()
    float keypointsRatio;

    GpuMat sum, mask1, maskSum, intBuffer;

    GpuMat det, trace;

    GpuMat maxPosBuffer;
};
```

Appendix 4

The planar Homography transformation matrix is given below:

$$\begin{bmatrix} x_t' \\ y_t' \\ z_t' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} & x_0 \\ h_{21} & h_{22} & h_{23} & y_0 \\ h_{31} & h_{32} & h_{33} & z_0 \end{bmatrix} \begin{bmatrix} x_r \\ y_r \\ z_r \\ 1 \end{bmatrix} \ldots (1)$$

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \frac{\begin{bmatrix} x_t' \\ y_t' \end{bmatrix}}{z_t'} \ldots (2)$$

Since all the points are coplanar this reduces to:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \frac{\begin{bmatrix} h_{11}x_r + h_{12}y_r + x_0 \\ h_{21}x_r + h_{22}y_r + y_0 \end{bmatrix}}{h_{31}x_r + h_{32}y_r + z_0} \ldots (3)$$

For points can then be used to populate an information matrix:

$$\begin{bmatrix} -x_{1r} & -y_{1r} & 0 & 0 & x_{1t}x_{1r} & x_{1t}y_{1r} & -1 & 0 & x_{1t} \\ 0 & 0 & -x_{1r} & -y_{1r} & y_{1t}x_{1r} & y_{1t}y_{1r} & 0 & -1 & y_{1t} \\ & & & & \vdots & & & & \\ -x_{Nr} & -y_{Nr} & 0 & 0 & x_{Nt}x_{Nr} & x_{Nt}y_{Nr} & -1 & 0 & x_{Nt} \\ 0 & 0 & -x_{Nr} & -y_{Nr} & y_{Nt}x_{1r} & y_{Nt}y_{Nr} & 0 & -1 & y_{Nt} \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{21} \\ h_{22} \\ h_{31} \\ h_{32} \\ x_0 \\ y_0 \\ z_0 \end{bmatrix} = 0 \ldots (4)$$

The un-scaled state solution is the kernel or null space of the information matrix computed with singular value decomposition. The scaling factor can be obtained through the Euler angles locked within the direction cosine matrix.

$$\Psi = tan^{-1}\left(\frac{h_{12}}{h_{11}}\right) \ldots (5)$$

$$\varphi = tan^{-1}\left(\frac{h_{31}\, sin\Psi \; - h_{32}cos\Psi}{h_{22}\, cos\,\Psi - h_{21}sin\Psi}\right) \ldots (6)$$

$$scaling = tan^{-1}\left(\frac{h_{22}\, cos\Psi \; - h_{21}sin\Psi}{cos\,\Psi}\right) \ldots (7)$$

$$\theta = sin^{-1}\left(\frac{h_{31}}{Ncos\varphi\; cos\Psi} - tan\varphi\; tan\Psi\right) \ldots (8)$$

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{\begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix}}{scaling} \ldots (9)$$

The standard “bailout” deviation computed for the back-projection error, assuming a null mean Gaussian distribution, then becomes:

$$\sigma_{error} = \sqrt{\frac{\sum_{i=0}^{N}\left(\left(\frac{h_{11}x_{ir} + h_{12}y_{ir} + x_{i0}}{h_{31}x_{ir} + h_{32}y_{ir} + z_{io}} - x_{it}\right)^2 + \left(\frac{h_{21}x_{ir} + h_{22}y_{ir} + y_{io}}{h_{31}x_{ir} + h_{32}y_{ir} + z_{i0}} - y_{it}\right)^2\right)}{N}}$$

Appendix 5

How to: Set up OpenCV for Microsoft Visual C++ 2008 Express on Windows with TBB enabled

Phase	Source file in directory
0	-
1	OpenCV-2.1.0-win.zip
2	cmake-2.8.7-win32-x86.exe
3	tbb30_221oss_win.zip
4	-
5	-
6	-

A more complete installation guide is given at http://opencv.willowgarage.com/wiki/InstallGuide

Phase 0

Download and install Microsoft Visual C++ 2008 Express edition from http://www.microsoft.com/download/en/default.aspx

Phase 1

Download OpenCV 2.1 source files for Windows from the following link and extract http://sourceforge.net/projects/opencvlibrary/files/opencv-win/2.1/OpenCV-2.1.0-win.zip/download

Phase 2

OpenCV must be built with TBB enabled. Download and install cmake-GUI **[add to PATH]** from http://www.cmake.org/cmake/resources/software.html

Phase 3

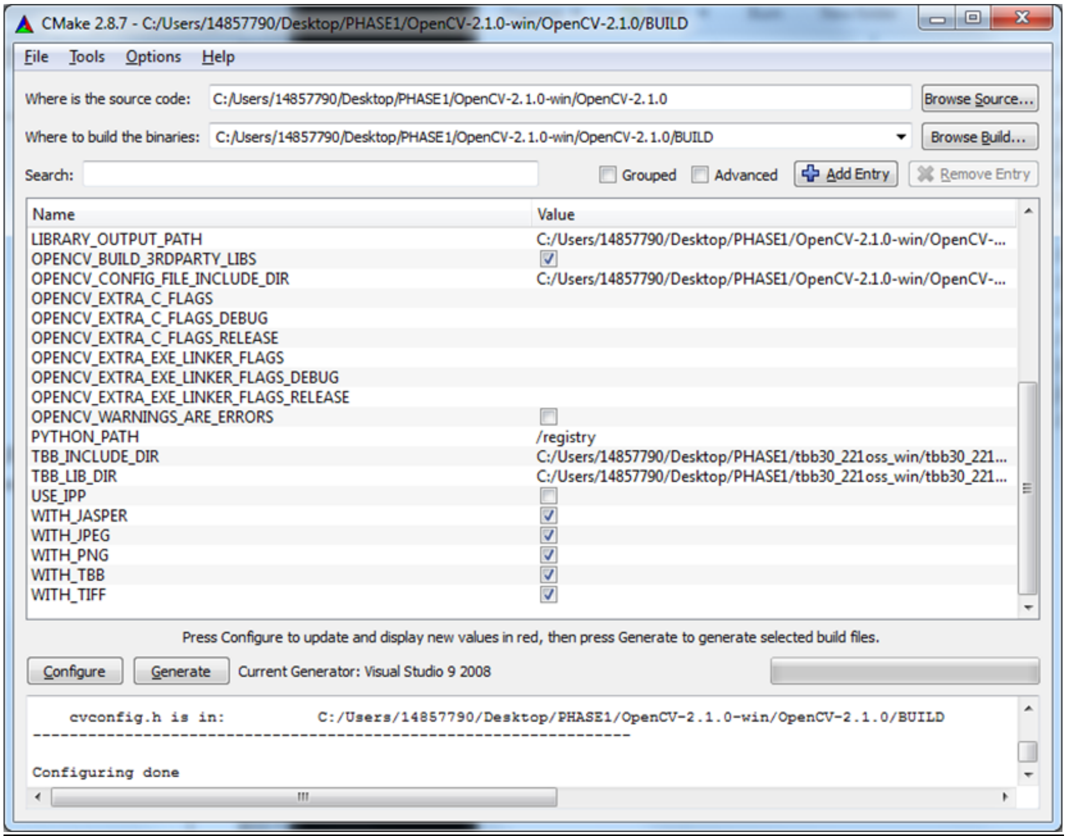
The source files for Intel Thread Building Blocks also needs to be downloaded from http://threadingbuildingblocks.org/file.php?fid=77

Phase 4

- Open cmake-gui
- Select the OpenCV cmakelist directory **[Browse Source…]**
- Create a new BUILD file in the latter directory and select **[Browse Build…]**
- Click **Configure**.
    - Generator for this project : **Visual Studio 9 2008**
    - **Use default native compilers**
- **WITH_TBB** must be toggled on. Click Configure again and specify the **TBB_INCLUDE_DIR**
- Click **Configure** twice. If all goes well nothing should be displayed in red and the window must look something like the following:
- Click **Generate**

Phase 5

- Go to the BUILD directory and open the **OpenCV.sln** file in VS C++ 2008
- Toggle **Debug/Release** for respective versions. [Debug by default]
- **Build Solution**
- In the Solution Explorer, select the **INSTALL** project, right-click -> Project Only -> Build Only INSTALL



Phase 6

- OpenCV needs to be added to the System Path
  - **Start -> Computer -> Properties -> Advanced system settings -> Environment Variables...**
  - Under **System variables -> New...**
    - Variable name : **OPENCV_INCLUDE**
      - Variable value [eg]: **C:\Users\14857790\Desktop\PHASE1\OpenCV-2.1.0-win\OpenCV-2.1.0\BUILD\include\opencv**
    - Variable name : **OPENCV_LIB**
      - Variable value [eg]: **C:\Users\14857790\Desktop\PHASE1\OpenCV-2.1.0-win\OpenCV-2.1.0\BUILD\lib**

Appendix 6

SOLUTIONS IN MOTION •

MOTOMAN

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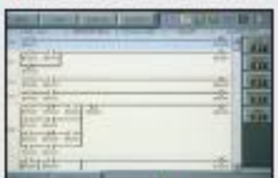
MACHINE TENDING

THRU-ARM CABLE AND HOSE ROUTING



LADDER EDITOR

Motoman's revolutionary slim, dual-arm SDA10 robot provides "human-like" flexibility of movement to meet your automation needs

ASSEMBLY • PACKAGING • HANDLING
MACHINE TENDING • PART TRANSFER

SDA10

Payload: 10 kg/arm

FEATURES & BENEFITS

- Both robot arms can work together to accomplish intricate tasks
- Single NX100 robot controller directs movement of all 15 axes of the robot
- Handles 10 kg (22.1 lb) payload per arm; 20 kg (44.1 lb) payload possible when using both arms
- Best-in-class wrist performance characteristics for your most demanding material handling tasks
- Repeatability: ±0.1 mm (±0.004")
- Reach: 985 mm (38.8") per arm from centerline of base rotation to tool mounting surface (total 1,970 mm P-point to P-point)
- Opens up a wide range of applications to be performed by robots
- Thru-arm hose and cable routing

Slim, Dual-Arm Robot with "Human-Like" Flexibility

Providing "human-like" flexibility of movement and fast acceleration, Motoman's slim, dual-arm SDA10 robot is strong, quick and agile. Powerful actuator-based design and best-in-class wrist characteristics make the SDA10 robot ideally suited for a wide variety of assembly, part transfer, machine tending, packaging and other handling tasks that formerly could only be done by people.

The unique SDA10 features 15 axes of motion (7 axes per arm, plus a single axis for base rotation). Internally routed cables and hoses reduce interference and maintenance, and also make programming easier.

The space-efficient, highly flexible SDA10 robot features a 10 kg (22.1 lb) payload per arm, a 985 mm (38.8") horizontal reach per arm, 1,440 mm (56.7") vertical reach per arm, and a repeatability of ±0.1 mm (0.004").

Both robot arms can work together on one task to double the payload or handle heavy, unwieldy objects. The two manipulators can perform simultaneous independant operations. A Motoman dual-arm robot can hold a part with one arm while performing operations on the part with the other arm, and can also transfer a part from one of its arms to the other with no need to set the part down.

Advanced NX100 Controller

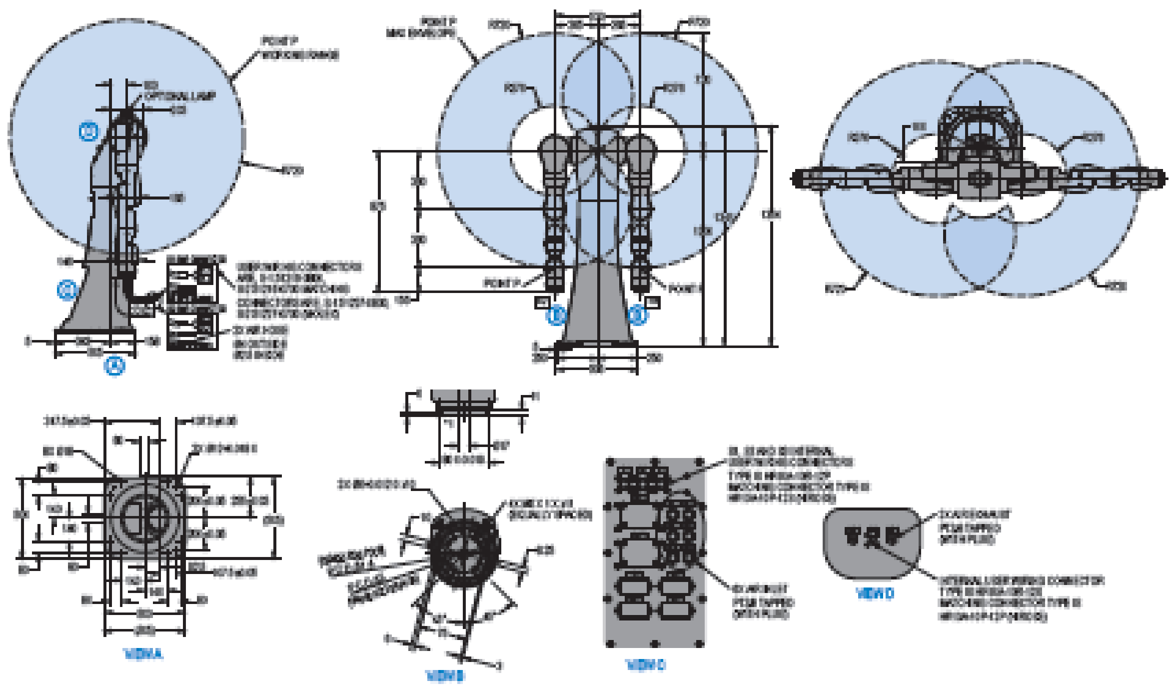
The SDA10 robot is controlled by the Motoman NX100 robot controller that features a robust PC architecture, Windows® CE programming pendant, and easy-to-use INFORM III programming language.

The NX100 offers unmatched multiple axes control capability to maximize flexibility while minimizing cost of integration and eliminating risk of robot collisions. Dual-channel safety features include enhanced E-stop functionality, integrated speed monitoring, manual brake release switches, and compliance with both ANSI/RIA R15.06-1999 and Canadian safety standards.

The NX100 controller offers unmatched connectivity through standard Ethernet and other network options, including: DeviceNet, ControlNet, Profibus-DP, and EtherNet/IP. The programming pendant features a color touch-screen display that can be configured as a custom HMI (Human Machine Interface) with buttons and status indicators.

SDA10 Robot

All dimensions are metric (mm) and for reference only. Please request detail drawings for all design/engineering requirements.



SDA10 SPECIFICATIONS

Structure		Articulated
Mounting		Floor
Controlled Axes		15 (7 axes per arm and 1 rotary axis)
Payload		10 kg (22.1 lbs)/arm
Horizontal Reach per Arm		985 mm (38.8")
Horizontal Reach (P-point to P-point)		1,970 mm (77.6")
Vertical Reach		1,440 mm (56.7")
Repeatability		±0.1 mm (±0.004")
Maximum Motion Range	Rotation-Axis (Waist) S-Axis (Lifting) L-Axis (Lower Arm) 7th-Axis (Lower Arm Twist) U-Axis (Upper Arm) R-Axis (Upper Arm Twist) B-Axis (Wrist Pitch/Yaw) T-Axis (Wrist Twist)	±170° ±180° ±110° ±170° ±135° ±180° ±110° ±180°
Maximum Speed	Turning-Axis S-Axis L-Axis 7th-Axis U-Axis R-Axis B-Axis T-Axis	130°/s 170°/s 170°/s 170°/s 170°/s 200°/s 200°/s 400°/s
Approximate Mass		220 kg (485.1 lbs)
Power Consumption		2.7 kVA
Allowable Moment	R-Axis B-Axis T-Axis	31.4 N•m 31.4 N•m 19.6 N•m
Allowable Moment of Inertia	R-Axis B-Axis T-Axis	1 kg•m² 1 kg•m² 0.4 kg•m²

NX100 CONTROLLER SPECIFICATIONS*

Structure	Free-standing, enclosed type
Dimensions (mm)	650 (w) x 1,200 (h) x 650 (d) (25.6" x 47.2" x 25.6")
Approximate Mass	150-250 kg (330.8-551.3 lbs.)
Cooling System	Indirect cooling
Ambient Temperature	During operation: 0° C (32° F) to 45° C (113° F) During transit and storage: -10° C (14° F) to +60° C (140° F)
Relative Humidity	90% max. non-condensing
Primary Power Requirements	3-phase, 240/480/575 VAC at 50/60 Hz
Grounding	Grounding resistance: ≤100 ohms Separate ground required
Digital I/O NPN-Standard PNP-Optional	Standard I/O: 40 inputs/40 outputs consisting of 16 system inputs/16 system outputs, 24 user inputs/24 user outputs Enabled to 1,024 inputs/1,024 outputs
Position Feedback	By absolute encoder
Drive Units	Servo packs for AC servo motors
Accel/Decel	Software servo control
Program Memory	60,000 steps, 10,000 ladder instructions
Pendant Dim. (mm)	199 (w) x 338 (h) x 60 (d) (7.8" x 13.3" x 2.4")
Pendant Playback Buttons	Teach, Play, Remote, Servo On, Start, Hold, Emergency Stop, Edit Lock (Play Mode Enabled on Controller)
Concurrent I/O Ladder	10,000 instructions
Multi Tasking	Up to 8 concurrent jobs
Fieldbus	DeviceNet Master/Slave, AB RIO, Profibus, Interbus-S, M-Net, CC Link, EtherNet IP/Slave
Ethernet	10 Base T/100 Base TX
E-Stop	Controlled stop
Safety	Dual-channel Emergency Stop Pushbuttons, 3-position Enable Switch, Manual Brake Release Meets ANSI/RIA R15.06-1999 and Canadian safety standards

*See NX100 Controller data sheet (DS-320) for complete specifications

MOTOMAN

a YASKAWA company

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Appendix 7

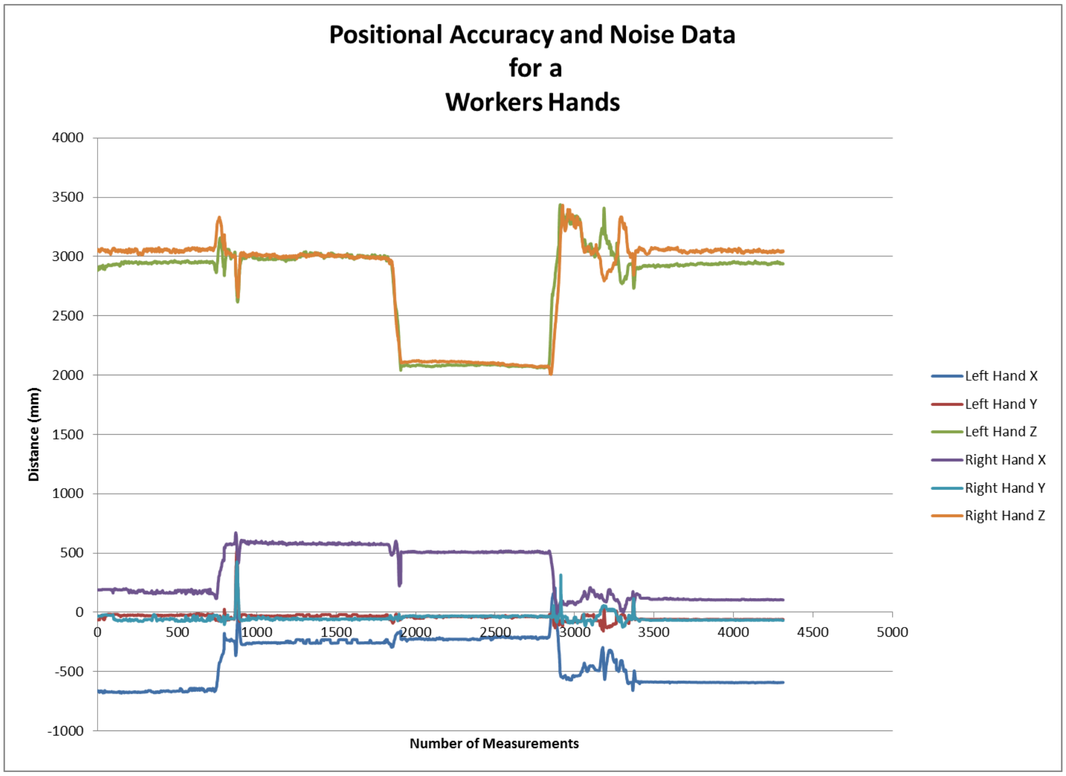

Figure 67: Positional accuracy and tracking noise of workers hands

Appendix 8

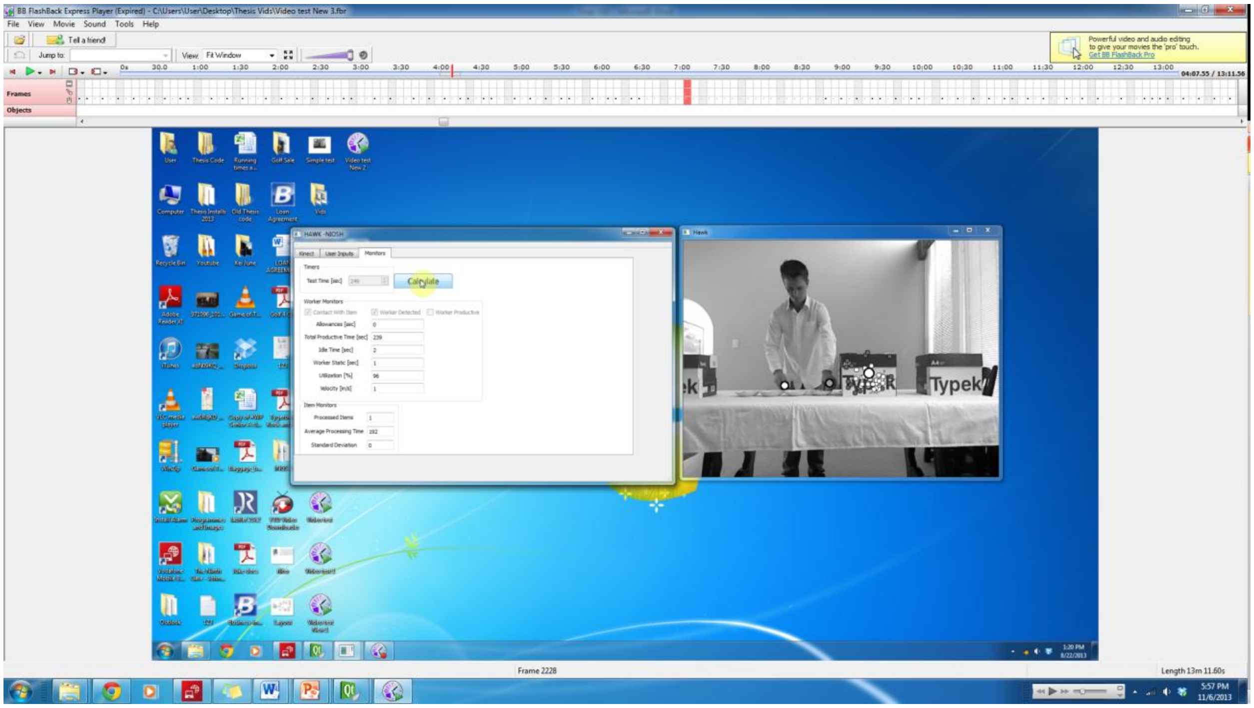

Figure 68: Screenshot of the BB FlashBack Express Player

Appendix 9

Coupling Multiplier

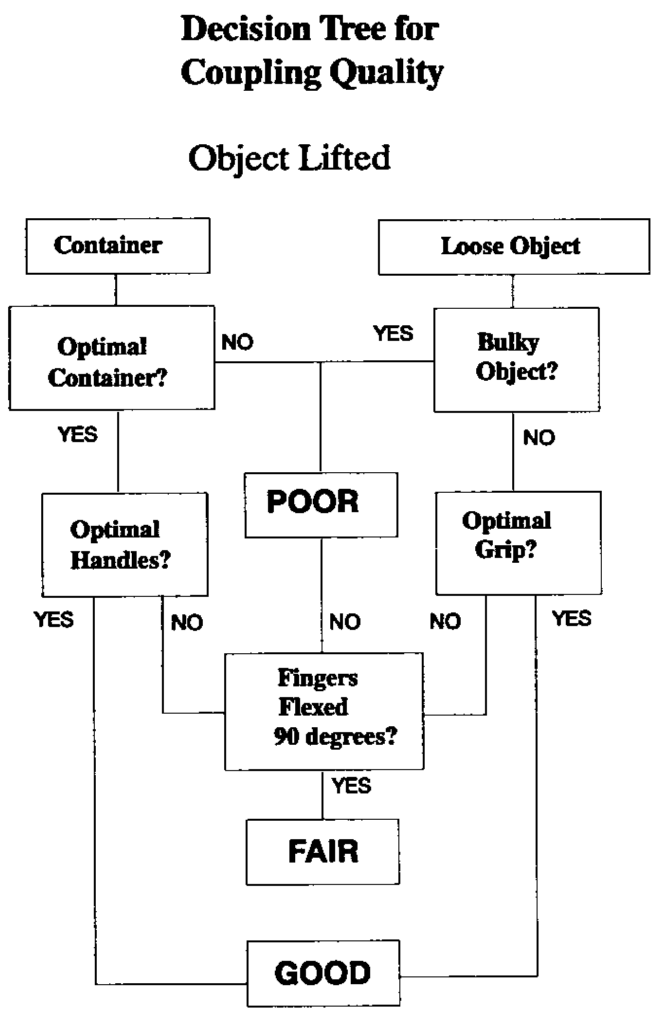

Figure 69: Decision tree for coupling quality [5]

Table 46: Coupling Multiplier [5]

Coupling type	Coupling Multiplier	
	V<75cm	V>75cm
Good	1.00	1.00
Fair	0.95	1.00
Poor	0.90	0.90

Frequency Multipliers

Table 47: Frequency Multiplier

Frequency Lifts/min (F)	Work Duration					
	≤1hour		>1hour but ≤ 2 hours		> 2 hour but ≤ 8 hours	
	V<75	V ≥75	V<75	V ≥75	V<75	V ≥75
0.20	1.00	1.00	0.95	0.95	0.85	0.85
0.50	0.97	0.97	0.92	0.92	0.81	0.81
1.00	0.94	0.94	0.88	0.88	0.75	0.75
2.00	0.91	0.91	0.84	0.84	0.65	0.65
3.00	0.88	0.88	0.79	0.79	0.55	0.55
4.00	0.84	0.84	0.72	0.72	0.45	0.45
5.00	0.80	0.80	0.60	0.60	0.35	0.35
6.00	0.75	0.75	0.50	0.50	0.27	0.27
7.00	0.70	0.70	0.42	0.42	0.22	0.22
8.00	0.60	0.60	0.35	0.35	0.18	0.18
9.00	0.52	0.52	0.30	0.30	0.00	0.15
10.00	0.45	0.45	0.26	0.26	0.00	0.13
11.00	0.41	0.41	0.00	0.23	0.00	0.00
12.00	0.37	0.37	0.00	0.21	0.00	0.00
13.00	0.00	0.34	0.00	0.00	0.00	0.00
14.00	0.00	0.31	0.00	0.00	0.00	0.00
15.00	0.00	0.28	0.00	0.00	0.00	0.00
>15	0.00	0.00	0.00	0.00	0.00	0.00

Appendix 10

Table 48: Summarized results from the measurements of a test lift (n = 27) [102]

Measured Parameters of NIOSH Equation										Calculated lifting index	
Task		Weight (kg)	**Vertical location$_O$**	**Vertical location$_D$**	**Horizontal location$_O$**	**Horizontal location$_D$**	**Asymmetry$_O$**	**Asymmetry$_D$**	**Coupling**	**LI$_O$**	**LI$_D$**
1	Reference	22.7	129.5	74.9	58.4	38.9	70	46	F	3.8	2.1
	Range		119-135	66-81	51-65	33-46	58-78	40-63	16F/11P	3.4-4.3	1.8-2.5
	Mean		128.3	74.4	58.2	39.6	65.5	54	59%F,41%P	3.8	2.2
	Standard deviation		3.4	3.8	2.6	3.2	4.8	6.6		0.2	0.3
	Mean of difference from reference		1.2	0.5	0.3	0.7	4.5	7.9		0.5	0.4
	Students *t*-value		1.9	0.6	0.5	1.1	4.9	6.2			
	Probability that mean of difference is zero		0.06	0.43	0.62	0.26	1E-04	1E-04			
	Maximum Difference from reference		10.5	8.9	7.4	7.1	12	17			
	Maximum % effect on the RWL		3	3	6	12	4	5			

Table 49: Comparison between the reference and measured values for the five tasks [100]

		Measured Parameters of NIOSH Equation								Calculated lifting index	
Task		**Weight**	**Vertical location$_O$**	**Vertical location$_D$**	**Horizontal location$_O$**	**Horizontal location$_D$**	**Asymmetry$_O$**	**Asymmetry$_D$**	**Frequency**	**Lifting Index$_O$**	**Lifting Index$_D$**
1	Reference	5	25.4	99.1	48.3	83.8	0	0	6	0.8	1.2
	Measured	4.9	21	85.2	40.3	80.3	0	0	6.5	0.6	1
	Standard deviation	0.4	2.5	25.3	5.5	9.1	0	0	2.5	0.2	0.4
2	Reference	5	22.9	99.1	45.7	68.6	0	48	4	1.3	1.9
	Measured	4.9	21.1	95	47	65.1	0	51.6	5.3	1.3	1.8
	Standard deviation	0.4	2.5	2.6	7.8	17.6	0	7.2	2.8	0.2	0.5
3	Reference	5	149.9	25.4	66	58.4	50	61	4	2.3	2
	Measured	4.9	125.4	20.6	48.4	53.5	39.4	37	5.3	1.4	1.5
	Standard deviation	0.4	47.2	3.8	15.9	18.4	8.6	11.7	3.8	0.8	0.7
4	Reference	5	124.5	50.8	66	58.4	50	61	4	2	1.8
	Measured	4.9	105.9	47.5	52.1	53.9	39.4	40.1	5.3	1.3	1.3
	Standard deviation	0.4	33.9	8.6	21.8	19.1	8.6	7.6	3.8	0.7	0.7
5	Reference	5	99.1	76.2	66	58.4	50	61	4	1.6	1.4
	Measured	4.9	90	65.4	50.6	53.2	39.4	40.1	5.3	0.9	1
	Standard deviation	0.4	33.2	20.7	18.2	17.7	8.6	7.6	3.8	0.8	0.9

Appendix 11

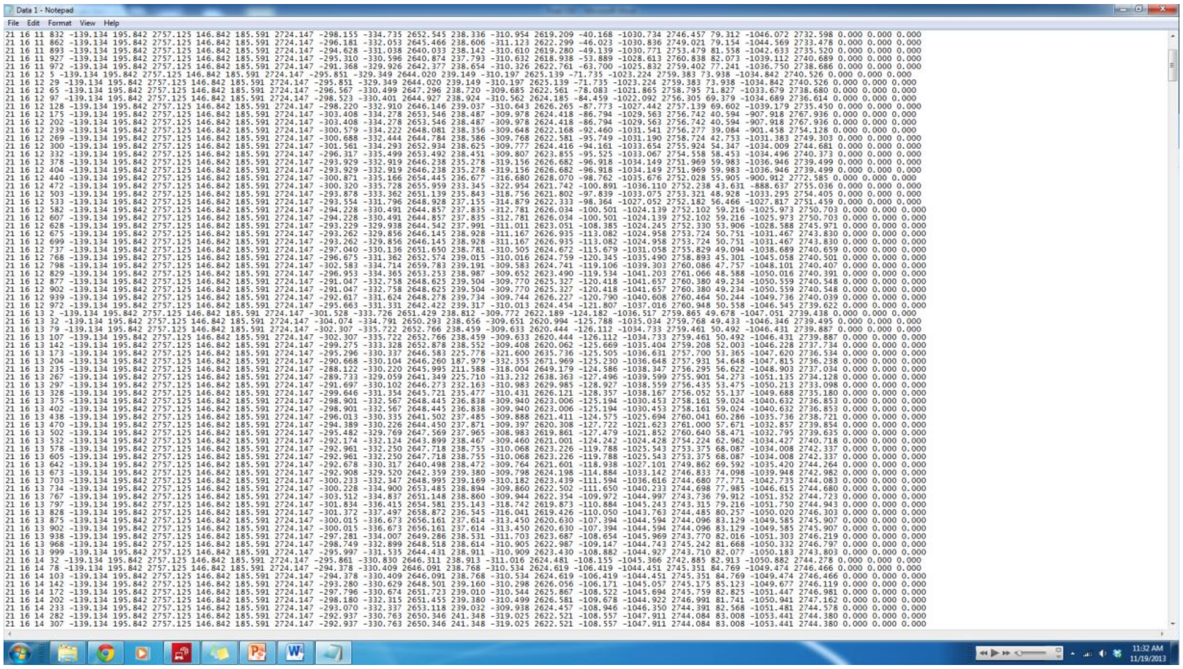

Figure 70: Screenshot of a text file populated with system times and coordinate data of a worker and a work piece

Appendix 12

Test 1

	Scenario 1	Measured	Standard Deviation	Difference		Scenario 1	Measured	Standard Deviation	Difference	Error
					LC	23	23			0.00%
H	47.10	40.97	3.41	-6.13	**HM**	0.53	0.61	0.05	0.08	14.97%
V	97.20	87.25	1.23	-9.95	**VM**	0.93	0.96	0.00	0.03	3.20%
D	75.50	74.82	1.03	-0.68	**DM**	0.88	0.88	0.00	0.00	0.06%
A	0.00	2.06	1.70	2.06	**AM**	1.00	0.99	0.01	-0.01	-0.66%
	Table				**FM**	1.00	1.00			
	Table				**CM**	1.00	1.00			
					RWL	10.02	11.82	1.15	1.80	17.93%

Test 2

	Reference	Measured	Standard Deviation	Difference		Reference	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	41.10	34.18	4.03	-6.92	**HM**	0.61	0.73	0.05	0.12	20.24%
V	97.20	87.89	0.92	-9.31	**VM**	0.93	0.96	0.00	0.03	2.99%
D	75.50	72.93	0.48	-2.57	**DM**	0.88	0.88	0.00	0.00	0.24%
A	0.00	3.07	7.56	3.07	**AM**	1.00	0.99	0.01	-0.01	-0.98%
	Table				**FM**	1.00	1.00			
	Table				**CM**	1.00	1.00			
					RWL	11.49	14.12	0.78	2.63	22.91%

Test 3

	Reference	Measured	Standard Deviation	Difference		Reference	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	41.10	34.42	1.70	-6.68	**HM**	0.61	0.73	0.04	0.12	19.41%
V	97.10	89.91	1.50	-7.19	**VM**	0.93	0.96	0.00	0.02	2.31%
D	75.50	72.30	0.54	-3.20	**DM**	0.88	0.88	0.00	0.00	0.30%
A	0.00	2.91	1.64	2.91	**AM**	1.00	0.99	0.01	-0.01	-0.93%
	Table				**FM**	1.00	1.00			
	Table				**CM**	1.00	1.00			
					RWL	11.49	13.95	0.70	2.46	21.39%

Average

	Reference	Measured	Standard Deviation	Difference		Reference	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	43.10	36.52	3.05	-6.58	HM	0.58	0.69	0.05	0.11	18.20%
V	97.17	88.35	1.22	-8.82	VM	0.93	0.96	0.00	0.03	2.83%
D	75.50	73.35	0.68	-2.15	DM	0.88	0.88	0.00	0.00	0.20%
A	0.00	2.68	3.63	2.68	AM	1.00	0.99	0.01	-0.01	-0.86%
	Table				FM	1.00	1.00			
	Table				CM	1.00	1.00			
					RWL	11.00	13.30	0.88	2.30	20.75%

Figure 71: Tables relating to the origin of a lift of the stand for the symmetric lifting test

Test 1

	Scenario 1	Measured	Standard Deviation	Difference		Scenario 1	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	63.00	49.04	5.56	-13.96	HM	0.40	0.51	0.06	0.11	28.47%
V	97.50	91.29	1.27	-6.21	VM	0.93	0.95	0.00	0.02	2.00%
D	28.00	29.18	0.48	1.18	DM	0.98	0.97	0.00	-0.01	-0.66%
A	54.00	63.16	3.41	9.16	AM	0.83	0.80	0.01	-0.03	-3.54%
	Table				FM	1.00	1.00			
	Table				CM	0.95	0.95			
					RWL	6.56	8.24	1.07	1.68	25.55%

Test 2

	Scenario 1	Measured	Standard Deviation	Difference		Scenario 1	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	63.00	41.09	5.91	-21.91	HM	0.40	0.61	0.08	0.21	53.32%
V	97.50	90.05	1.86	-7.45	VM	0.93	0.95	0.01	0.02	2.40%
D	28.00	29.53	1.09	1.53	DM	0.98	0.97	0.01	-0.01	-0.85%
A	54.00	61.71	4.34	7.71	AM	0.83	0.80	0.01	-0.02	-2.98%
	Table				FM	1.00	1.00			
	Table				CM	0.95	0.95			
					RWL	6.56	9.91	1.429649703	3.35	51.02%

Test 3

	Scenario 1	Measured	Standard Deviation	Difference		Scenario 1	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	63.00	50.54	3.06	-12.46	HM	0.40	0.49	0.03	0.10	24.65%
V	97.50	91.20	1.59	-6.30	VM	0.93	0.95	0.00	0.02	2.03%
D	28.00	29.32	0.34	1.32	DM	0.98	0.97	0.00	-0.01	-0.74%
A	54.00	79.10	4.01	25.10	AM	0.83	0.75	0.01	-0.08	-9.71%
	Table				FM	1.00	1.00			
	Table				CM	0.95	0.95			
					RWL	6.56	7.48	0.654282677	0.92	13.98%

Average

	Scenario 1	Measured	Standard Deviation	Difference		Scenario 1	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	63.00	46.89	4.84	-16.11	HM	0.40	0.53	0.06	0.14	34.36%
V	97.50	90.85	1.58	-6.65	VM	0.93	0.95	0.00	0.02	2.14%
D	28.00	29.34	0.64	1.34	DM	0.98	0.97	0.00	-0.01	-0.75%
A	54.00	67.99	3.92	13.99	AM	0.83	0.78	0.01	-0.04	-5.41%
	Table				FM	1.00	1.00			
	Table				CM	1.00	1.00			
					RWL	6.90	8.90	1.05	1.99	28.83%

Figure 72: Tables for the assessment of the asymmetric lifting task at the origin of the lift from the table

Appendix 13

Table 50: Revised results for the origin of the symmetric lifting task with the proposed improvements implemented

	Reference	Measured	Standard Deviation	Difference		Reference	Measured	Standard Deviation	Difference	Error
					LC	23	23			
H	43.10	42.52	3.05	-0.58	HM	0.58	0.59	0.05	0.01	1.42%
V	97.10	88.35	1.22	-8.75	VM	0.93	0.96	0.00	0.03	2.81%
D	75.50	80.68	0.68	5.18	DM	0.88	0.88	0.00	0.00	-0.43%
A	0.00	2.68	3.63	2.68	AM	1.00	0.99	0.01	-0.01	-0.86%
	Table				FM	1.00	1.00			
	Table				CM	1.00	1.00			
					RWL	**11.00**	**11.33**	**0.88**	**0.32**	**2.92%**

Appendix 14

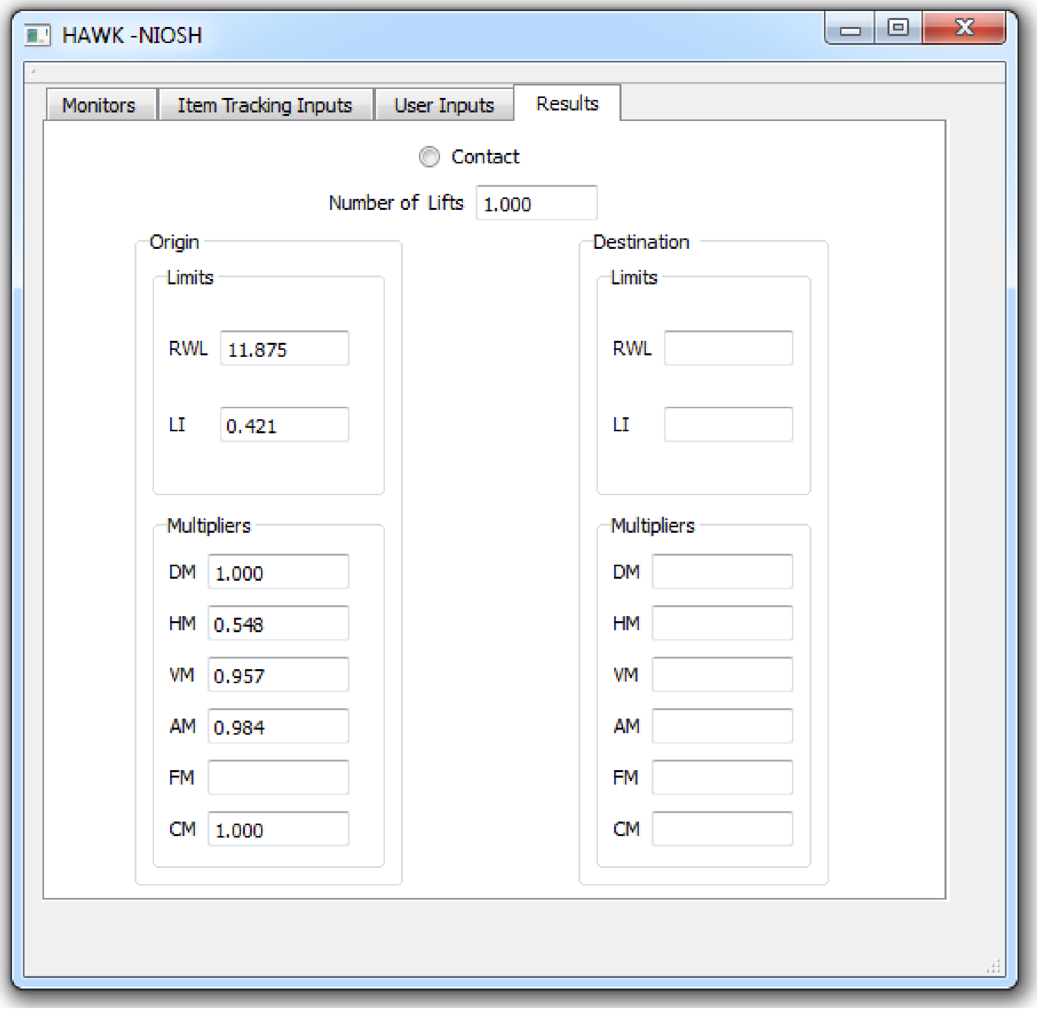

Figure 73: HAWK-RNLE results tab for an uncompleted assessment not requiring significant control

Appendix 15

Table 51: Actual and measured times for the small item test of the HAWK-PRODUCTIVTY system

		Actual			HAWK-PRODUCTIVITY			Total Error		
Step	**Comments**	**Allowance**	**Static**	**Productive**	**Allowance**	**Static**	**Productive**	**Allowance**	**Static**	**Productive**
1	Move into the frame	122	0	0	125	0	0	3	0	0
2	Remain stationary	122	51	0	125	43	8	3	-8	8
3	Cross arms	122	124	0	125	112	10	3	-12	10
4	Perform the assembly task	122	124	178	125	127	167	3	3	-11
5	Cross arms	122	141	178	125	142	168	3	1	-10
6	Leave frame	122	165	178	125	161	173	3	-4	-5
7	Totals	174	165	178	173	164	177	-1	-1	-1