Screening for abnormal heart sounds and murmurs by implementing Neural Networks

by

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Declaration

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part submitted it at any university for a degree.

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Abstract

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This thesis is concerned with the testing of an "auscultation jacket" as a means of recording heart sounds and electrocardiography (ECG) data from patients. A classification system based on Neural Networks, that is able to discriminate between normal and abnormal heart sounds and murmurs, has also been developed . The classification system uses the recorded data as training and testing data. This classification system is proposed to serve as an aid to physicians in diagnosing patients with cardiac abnormalities. Seventeen normal participants and 14 participants that suffer from valve-related heart disease have been recorded with the jacket. The "auscultation jacket" shows great promise as a wearable health monitoring aid for application in rural areas and in the telemedicine industry. The Neural Network classification system is able to differentiate between normal and abnormal heart sounds with a sensitivity of 85.7% and a specificity of 94.1%.

Uittreksel

**Sifting vir abnormale hartklanke en geruise
deur die implementering van Neurale Netwerke**

*("Screening for abnormal heart sounds and murmurs
by implementing Neural Networks")*

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Hierdie tesis het te make met die toets van 'n "stetoskoop baadjie" as 'n manier om hartklanke en elektrokardiografie (EKG) data van pasiënte te bekom. 'n Klassifikasiesisteem wat gebasseer is op Neurale Netwerke, wat die data wat met die baadjie opgeneem is gebruik as leer- en toetsdata, is ook ontwikkel . Sewentien normale deelnemers en 14 deelnemers wat lei aan klep-verwante hartsiektes is met die baadjie opgeneem. Die "stetoskoop baadjie" toon baie potensiaal as 'n drabare gesondheidsmonitering sisteem, spesifiek vir gebruik in verafgeleë gebiede en in die telemedisyne industrie. Die klassifikasiesisteem is bevoeg om te diskrimineer tussen normale en abnormale hartklanke en geruis met 'n sensitiwiteit van 85.7% en 'n spesifisiteit van 94.1% en is beoog as 'n hulpmiddel vir dokters om hartabnormaliteite te diagnoseer.

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- Thanks to Dr Renier Verbeek for helping us finalise the positions of the stethoscopes on the jacket.

Dedications

To Carine

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Nomenclature

Constants

$\exp =$	$2.718\,281\,828$
$j =$	$\sqrt{-1}$

Variables

AN	approximation at level N
A_2	aortic component of the second heart sound
α	regularisation parameter or momentum term (indicated in text)
b	bias in ANN
C	Fourier coefficient magnitude
$CW(t,\omega)$	Choi-Williams distribution of a time-domain signal
$CWT(b,a)$	Continuous Wavelet Transform of a signal
DN	detail at level N
δw_j^r	correction term in estimation of unknown weights
E	energy of a signal
ε	error function of ANN
$\varepsilon_{\mathbf{p}}$	error function of weights in ANN
F_{ratio}	ratio of frequency bands
f	frequency
f_{analysis}	frequency intervals
f_s	sampling frequency
$g(n)$	ECG signal after first-order derivative operator and MA filter have been applied
$g_1(n)$	ECG signal after first-order derivative operator have been applied
$h^*\left(\frac{t-b}{a}\right)$	complex conjugate of wavelet function
i	index operator

J	cost function of ANN
k	counter in algorithms
k_r	number of neurons in layer r of ANN
L_d	length of diastole
L_s	length of systole
M	size of moving-average filter
M1	first group of identified murmur
M2	second group of identified murmur
μ	learning rate of ANN
N	length of signal or size of FFT (indicated in text)
n	index operator
$n(t)$	noise signal
$o(t)$	original uncorrupted signal
P	power of a signal
P_2	pulmonary component of the second heart sound
$\overline{Q}$	vector containing indices of start-points of QRS wave of ECG
QRS_{start}	start of QRS-complex in ECG wave
$RMS(f)$	root-mean-square value of a function f
r	layer in ANN
S	indices at $f_s = 2000$ Hz
$\overline{S}$	vector containing indices of end-points of QRS wave of ECG
S_1, S_2, S_3, S_4	first, second, third and fourth heart sounds
$S_{1\text{duration}}$	duration of the first heart sound
s	indices at $f_s = 100$ Hz
$s(t)$	time-domain signal
$sign(x)$	signum operator on a signal x
σ	factor to reduce interference terms or standard deviation
T	threshold value
T_n	noise threshold value
$T_{\text{P-wave}}$	duration of atrial depolarisation wave in ECG
$T_{\text{P-Q interval}}$	time between start of P-wave and start of QRS-complex in ECG
$T_{\text{P-Q segment}}$	time between end of P-wave and start of QRS-complex in ECG
T_{QRS}	duration of QRS-wave in ECG

$T_{\text{Q-T interval}}$	time between start of the QRS-wave and end of the T-wave in ECG
$T_{\text{Q-Tc}}$	corrected Q-T interval duration according to Bazett's formula
T_{RR}	R-R interval duration in ECG wave
T_s	signal threshold value
$T_{\text{S-T segment}}$	time between end of QRS-wave and start of T-wave in ECG
$T_{\text{T-wave}}$	duration of ventricular repolarisation wave in ECG
τ	time step at which window function is centred
$\text{V}N$	ECG chest electrode position for $N = 1, 2, \ldots, 6$
v_j^r	input to activation function of node j in layer r in ANN
$W(t, \omega)$	Wigner distribution of a time-domain signal
w_{jk}^r	weight in ANN from node k in layer $r-1$ to node j in layer r
$w_j^r(\text{new})$	new estimate of unknown weight
$w_j^r(\text{old})$	current estimate of unknown weight
$w^*(t - \tau)$	complex conjugate of window function
$X(f)$	Fourier coefficient
x	signal value
$\overline{x}$	vector of indices of values of g greater than zero or distribution mean
$x(i)$	individual sample i of recorded signal
$x_{\max}$	maximum value of recorded signal
$x(t)$	time-domain signal
y_j^r	output of node j in layer r in ANN

Abbreviations

ANN	artificial neural network
AR	auto-regressive
ARMSCOR	Armaments Corporation of South Africa
AV	atrio-ventricular
CHR	Committee for Human Research
CI	cardiac index - normalised
CVD	cardiovascular disease
CWD	Choi-Williams distribution
CWT	continuous wavelet transform

DFT	discrete Fourier transform
DWT	discrete wavelet transform
db$n$	Daubechies wavelet of order n
ECG	electrocardiography
EF	ejection fraction estimate
EPCI	ejection phase contractility index
ES	ejection sound
FFT	fast Fourier transform
FNF	false-negative fraction
FPF	false-positive fraction
FT	Fourier transform
FWT	fast wavelet transform
HMM	hidden Markov model
HR	heart rate
ICA	independent component analysis
ICG	impedance cardiography
IDWT	inverse discrete wavelet transform
ISDN	integrated services digital network
ISI	inotropic state index
kg	kilogram
MA	moving-average
MC	midsystolic click
MRC	Medical Research Council
msec	millisecond
OS	opening snap
OTRI	Online Telemedicine Research Institute
PC	personal computer
PCA	principal component analysis
PEP	pre-ejection period
RMSS	RSA Military Steering Committee
RR	respiratory rate
SARS	severe acute respiratory syndrome
SI	stroke index - normalised

SOF	statistical overlap factor
STFT	short-time Fourier transform
SURE	Stein's unbiased estimate of risk
TFC	thoracic fluid conductivity
TNF	true-negative fraction
TPF	true-positive fraction
USB	universal serial bus
VET	ventricular ejection time
VSAT	very small aperture terminal
WD	Wigner distribution

Chapter 1

Introduction

1.1   Motivation

Every 12 minutes someone in South Africa suffers a heart attack; every 12 minutes someone suffers a stroke. One in three men and one in four women will have a heart condition before the age of 60 [1]. According to the World Health Organisation estimates of 2003, cardiovascular disease accounts for approximately 16.7 million deaths globally, which equals over 29% of all deaths globally [2]. The mortality rate in South Africa due to cardiovascular disease (CVD) is 199 per 100000 people and the total mortality rate is 481 per 100000 people [1] [3]. Thus the mortality rate due to CVD accounts for 41% of the total deaths in South Africa. In the United States of America 5 million people are diagnosed with valvular heart disease each year.

These facts alone show that CVD is a major global threat and any development to aid the prevention of these diseases is of great importance. Along with the increase in CVD, the ability of physicians to diagnose heart disease by auscultation is also decreasing [4]. Proficiency in auscultation is a difficult skill to master, since heart and lung sounds are short-duration sounds and several sounds occur in a short time interval [5]. Also the human ear is poorly suited for cardiac auscultation and does not enable the physician to obtain both qualitative and quantitive information about heart sounds [6]. For this reason, any means that will aid physicians in making better diagnosis will prove extremely beneficial. Tavel [7] evaluated the use of electronic stethoscopes and visual displays of heart sounds and came to the conclusion that it can aid physicians in diagnosing and can also be used in educational circumstances. For example, the acquired signals can be stored, played back at a later stage and transmitted to distant sites. According to Tavel, the application of signal analysis also shows promise for clinical application in cases such as the assessment of the severity of aortic stenosis and in the differentiation between innocent and organic murmurs

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[1]These statistics are pre-2002

[7].

Many pathological conditions of the cardiovascular system cause murmurs and aberrations in heart sounds much before they are reflected as other symptoms such as changes in the electrocardiogram (ECG) signal [8]. Early detection of these sounds is therefore critical to the diagnosis and sufficient treatment of patients that suffer from these types of cardiovascular diseases.

Auscultation with a stethoscope is a well-known occurrence to each of us that has visited a physician. It all began in the early 1800's when the French physician René Laînnec had to examine a female patient that showed symptoms of heart disease. According to Dr. Laînnec "the patient's age and sex did not permit direct application of the ear to the chest", as was the norm in examining heart and lung sounds in those days [9]. Determined to do his utmost for the patient, Laînnec rolled up a sheet of paper to form a tube and pressed this against the patient's chest and held his ear to the other side. He later said that he "was surprised and gratified at being able to hear the beating of the heart with much greater clearness and distinctness than ever before"[9].

The first "electronic stethoscope" was developed in 1910 by S.G. Brown in London. He was actually trying to overcome a problem in long distance telephony where the telephone signals could not be transmitted further than 20 miles [9]. He developed a repeater, amplifier and receiver that would allow transmission over 50 miles and further. As an experiment, heart sounds were transmitted to physicians in various parts of London and all of them reported that the received sounds were just as clear as when they were physically examining the patient. Mr. Brown concluded that "this trial proved that it is now possible for a specialist to examine a patient in the country and to arrive at a correct diagnosis"[9].

In many rural areas very few or no health care facilities exist. According to the Medical Research Council of South Africa, the South African government is "committed to providing basic health care to all South African citizens" and "to achieve this goal, the government has identified telemedicine as a strategic tool for facilitating the delivery of equitable health care and educational services". Just as Mr. Brown did in the early 1900's, it is our aim to deliver recorded data from patients in rural areas to physicians in faraway locations to aid in the diagnosing and treatment of these people.

1.2   Objectives

The primary objective of this project is to:

- Develop a classification scheme based on Neural Networks to screen for abnormal heart sounds. The system has to use the data recorded by an "auscultation jacket". The

data has to be denoised and useful information (features) has to be extracted from the recordings. The system must be tested with unknown data.

The secondary objective of this project is to:

- Test and validate the concept of the auscultation jacket as a means to record all the necessary information from a patient and determine the validity of its use as an application in the telemedicine industry.

1.3 Thesis outline

Chapter 2 presents a literature review covering the basic principles of the cardiovascular system, how the different heart sounds are produced and gives an introduction to auscultation and phonocardiography. The current methods used to analyse heart sounds such as the Fourier Transform and the Wavelet Transform are discussed, as well as other techniques. Neural Networks and its application to heart sound classification is briefly discussed and other classification techniques used for heart sounds are also mentioned.

In Chapter 3 the hardware used in the recording procedure is discussed. The development of the auscultation jacket is also discussed in some detail.

Chapter 4 discusses the methodology used in the analysis of the recorded heart sounds. This includes the denoising of the data, the extraction of individual cycles from the data by using the ECG signal and the extraction of the features used in the classification system. Some of these features include the extraction of the individual first and second heart sounds, the extraction of the time difference between the different components of the second heart sound and the extraction of extra heart sounds.

The theory behind Neural Networks and their application to this study is presented in Chapter 5. The construction and training of the Neural Network as well as Statistical Overlap Factor (SOF) as a feature reduction technique are discussed.

The report concludes in Chapter 6 with an evaluation of the techniques used in the feature extraction process and an evaluation of the classification system. Application to the telemedicine industry is discussed.

Chapter 2

Literature review

This chapter presents an overview of the human circulatory system, how the heart works, how heart sounds are produced and where to listen for them. Signal processing techniques used in the analysis of heart sounds are discussed, as well as methods implemented in different classification schemes to differentiate between normal and abnormal heart sounds as well as individual pathologies.

2.1   The cardiovascular system

Two circuits exist through which blood flows in the human body, namely the systemic circuit and the pulmonary circuit. Both of these circuits begin and end at the heart. The pulmonary circuit carries blood to and from the lungs while the systemic circuit carries blood to and from the rest of the body. Figure 2.1 shows a schematic view of the circulatory system. These two circuits are interconnected, so the blood that passes through one circuit, has to pass through the other as well.

There are three types of vessels that transport blood. *Arteries* (efferent vessels) carry blood away from the heart while *veins*(afferent vessels) carry blood to the heart. *Capillaries* are small, thin-walled vessels between the smallest arteries and veins that permit the exchange of nutrients and gases between the blood and the surrounding tissues [10].

The human heart is situated in the middle of the chest with the apex (bottom) shifted slightly to the left. The heart consists of four chambers: the left and right atria and the left and right ventricles. Each atrium and its corresponding ventricle is separated by an atrioventricular (AV) valve. The right atrium and right ventricle are separated by the tricuspid valve and the left atrium and left ventricle are separated by the mitral (bicuspid) valve. The two ventricles and the arteries that carry blood from the are also separated by valves. The right ventricle and the pulmonary artery are separated by the pulmonary valve, while the left ventricle and the aorta are separated by the aortic valve. A frontal-section of

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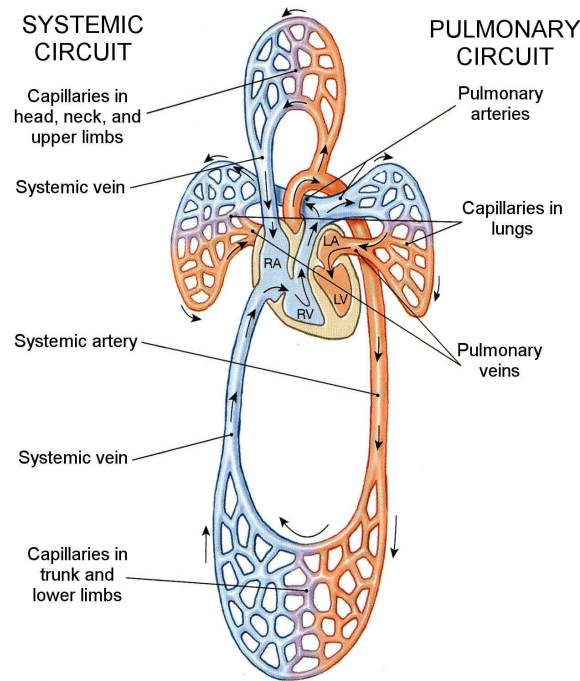
Figure 2.1: Cardiovascular circulatory system [10]

the heart is shown in Figure 2.2.

The right atrium receives deoxygenated blood from the body via the superior and inferior vena cavae. From the right atrium the blood is pumped through the tricuspid valve to the right ventricle, from where it goes through the pulmonary valve into the pulmonary artery, which takes the blood to the lungs where it receives oxygen. The oxygenated blood is transported to the left atrium via the pulmonary vein. The oxygenated blood is pumped through the mitral valve to the left ventricle. When the left ventricle contracts, the blood is pumped through the aortic valve into the aorta, from where it is distributed to the rest of the body.

2.2 The cardiac cycle

The cardiac cycle can be divided into two phases for any chamber of the heart. These two phases are known as *systole* (contraction) and *diastole* (dilation). During systole, the chamber pushes blood into an adjacent chamber or arterial trunk. During diastole, the chamber relaxes and is filled with blood.

A cardiac cycle begins with atrial systole which lasts for approximately 100 msec. At this time, the ventricles are partially filled with blood and the atrial contraction fills the ventricles. After the 100 msec of atrial systole, ventricular systole and atrial diastole begins. Ventricular systole lasts for 275 msec and atrial diastole for 700 msec. During ventricular systole, the pressure in the ventricles increases and forces the mitral and tricuspid valves
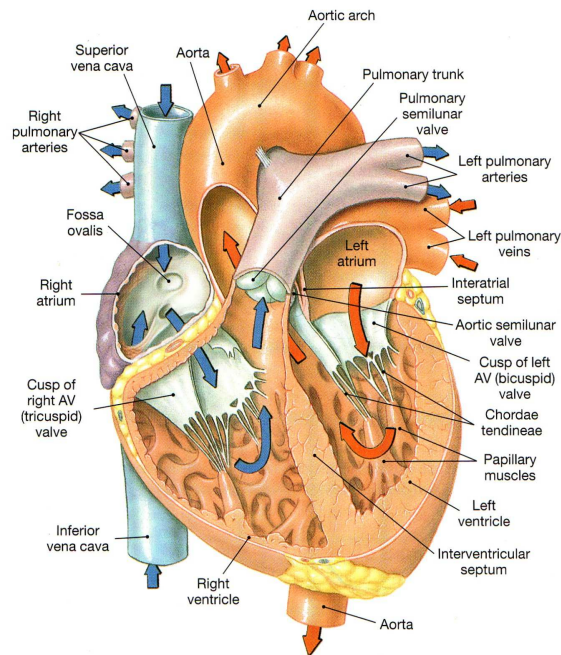
Figure 2.2: Frontal-section of the human heart showing the internal anatomy [10]

shut. The high pressures also force open the pulmonary valve and the aortic valve and the blood flows into the pulmonary artery and aorta. At this point, ventricular diastole begins and the ventricles as well as the atria are in diastole. The pressures in the ventricles decline and fall below the pressures in the pulmonary artery and aorta and the pulmonary valve and aortic valve close as a result of this. As ventricular pressure continues to fall, the pressure drops below the pressure in the atria and the mitral and tricuspid valve open, allowing blood to flow from the major veins through the atria to the relaxed ventricles. When atrial systole begins another cardiac cycle, the total time that has passed from the start of the previous atrial systole is approximately 800 msec. The ventricles are roughly 70% filled at this time [10]. Atrial systole contributes a relatively small amount to ventricular volume and this explains why individuals that have severely damaged atria can continue to lead normal lives, while damage to one or both ventricles can leave the heart unable to maintain adequate cardiac ouput [10].

2.3 Heart sounds

There are four different heart sounds known as S_1, S_2, S_3 and S_4. S_1 and S_2 are the normal sounds one associates with a heartbeat. In the "lubb-dupp" sound one associates with a heart sound, "lubb" corresponds to S_1 and "dupp" corresponds to S_2. Contradictory explanations exist as to the origin of these sounds. It was historically believed that S_1 and S_2 were produced solely by the closure of the mitral and tricuspid and the aortic and
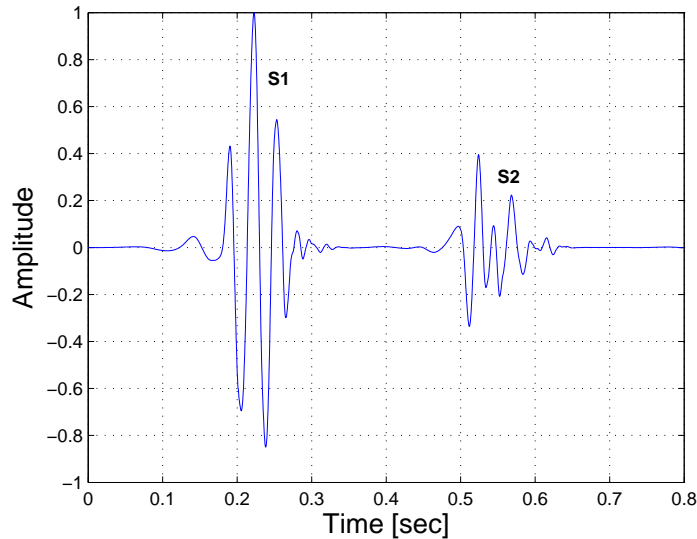
Figure 2.3: Single cardiac cycle showing S_1 and S_2

pulmonary valves, respectively. Recently it has been accepted that the externally recorded heart sounds are produced by vibrations of the whole cardiovascular system triggered by pressure gradients [11].

According to Rangayyan [11], S_1 can be split into four parts. The first component is due to the initial contraction of the ventricles as they move blood towards the atria thereby sealing the AV valves (mitral and tricuspid valves). The second component of S_1 can be attributed to the closure of these valves and the resulting deceleration of the blood that is moved to the atria by the contraction of the ventricles. The aortic and pulmonary valves then open as a result of the increased pressure in the ventricles and the third component of S_1 may be attributed to the oscillation of blood between the root of the aorta and the ventricles. The fourth component of S_1 may be due to turbulence of blood flowing through the aorta.

S_2 is caused by the closure of the aortic and pulmonary valves. The primary vibrations of S_2 occur in the arteries due to the deceleration of the blood as the aortic and pulmonary valves close, but the ventricles and atria also vibrate due to transmission of vibrations through the blood, valves, etc. Figure 2.3 shows a single normal cardiac cycle where S_1 and S_2 have been indicated.

The third heart sound (S_3) can sometimes be heard and is due to the sudden termination of the ventricular rapid-filling phase. S_3 is usually low-pitched and best heard at the apex of the heart [12]. If a third heart sound is heard in healthy young adults, it is usually diagnosed as "physiological". This is especially prevalent in athletes that have a slow pulse and a large stroke volume [1]. In older patients, the presence of a third heart sound usually indicates

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[1]The stroke volume is the amount of blood ejected by a ventricle during a single heartbeat [10].

impaired ventricular function if there are other signs of cardiac failure [12]. A third heart sound can originate from either ventricle and the one responsible is usually deduced from the circumstances, rather than the quality of the sound [12].

The fourth heart sound (S_4) occurs at the same time as, and is due to, atrial systole. It can be heard only in the presence of a sinus rhythm [2]. Phonocardiography can detect a quiet S_4 in many normal subjects but it tends to become particularly prominent when a hypertrophied [3] left atrium pumps blood through an unobstructed mitral valve into a stiff left ventricle. These conditions are most often fulfilled in ischaemic heart disease or systemic hypertension [12]. S_4 is usually a low-pitched sound and best heard at the apex of the heart. In patients with a sufficiently slow heart rate it is sometimes possible to make out fourth, first, second and third heart sounds, but as the heart rate increases, the third and fourth sounds tend to merge [12].

2.4 Auscultation and phonocardiography

Heart auscultation (listening to heart and lung sounds of a patient through a stethoscope) is the primary method by which physicians diagnose a patient as having an underlying pathology associated with heart diseases. When auscultating a patient, one listens at specific locations on the thorax and back. Only the thorax positions will be discussed here, since we are dealing with heart sounds. Lung sounds are heard when auscultating the back. Figure 2.4 shows the positions of the actual valves as well as the auscultation positions. The aortic valve is situated in the middle of the chest between the aorta and left ventricle but is best heard in the second intercostal space (between the 2nd and 3rd ribs) to the right of the sternum (the bone in the middle of the chest). The pulmonary valve is situated between the pulmonary artery and right ventricle and is best heard in the second intercostal space to the left of the sternum. The tricuspid valve, situated between the right atrium and right ventricle is best heard at the fifth intercostal space (between the 5th and 6th ribs) just to the left of the sternum, while the mitral valve that separates the left atrium and ventricle is also best heard in the fifth intercostal space but further to the left of the sternum.

There is, however, a widespread belief that the skill of auscultation is of secondary importance since the same information can be obtained through newer technological means [16]. The reason auscultation remains a primary method by which to diagnose patients, is due to the higher costs and limited availability of other screening procedures such as an electrocardiogram (ECG) and an echo-cardiogram. Together with the overall bedside

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[2]Sinus rhythm is a term used in medicine to describe the normal beating of the heart, as measured by an electrocardiogram (ECG)[13].

[3]Enlargement or overgrowth of an organ or part of the body due to the increased size of the constituent cells. Hypertrophy occurs in the biceps and heart due to increased work [14].
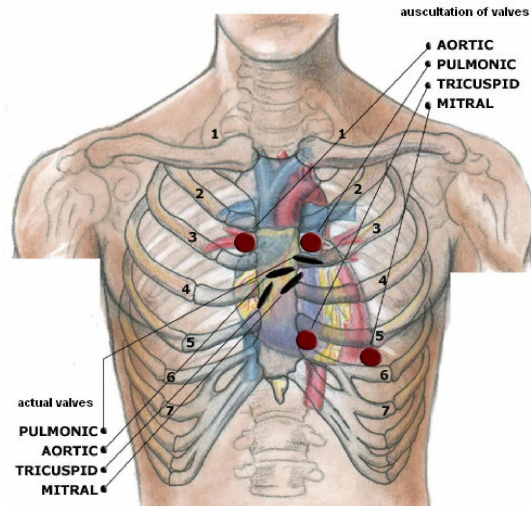
Figure 2.4: Actual heart valve positions together with auscultation positions [15]

examination, the use of the stethoscope is not only cost-effective, but is also not totally replacable by alternative technological methods [7]. However, auscultation is a very difficult skill to acquire and the necessary skills to make a proper diagnosis take years of practice to develop [17]. The human ear is also poorly suited for cardiac auscultation [6]. The conventional stethoscope also cannot store, play sounds back, offer a visual display, process the acoustic signal and transmit the sounds simultaneously to multiple listeners [7].

Phonocardiography is the graphical recording of the vibrations caused by the beating human heart. A microphone or piezo-electric sensor is placed on the thorax of a patient and the vibrations caused by the beating heart are recorded and displayed as a sound wave. Having digital recordings of patients' heart sounds will prove beneficial in a multitude of ways. First of all, it can be played back simultaneously to multiple listeners, which is ideal for the training of auscultation skills. The teaching of cardiac auscultation skills seems to be a difficult process as noted in [7], where it is stated that (referring to the lack of after-recording playback):

> *"This lack of a common "audio platform" is the most serious obstacle to effective teaching of cardiac auscultation, a deficiency that has reached serious proportions throughout our educational institutions."*

The unnecessary referrals of patients with innocent murmurs,[4] etc. to cardiac specialists by general practitioners poses a big problem, since this constitutes extra money and time that have to be spent by both parties concerned. According to de Vos [18], any unnecessary referrals should be minimised because:

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[4]Innocent heart murmurs are murmurs found in people with normal hearts and are harmless [18].

1. Specialists are a very scarce and expensive resource that should be used only when required.

2. The distribution of specialists and medical practitioners are not in ratio with the regional demographic composition. The distribution of specialists are economically driven with poorer regions having a much larger people-to-specialist ratio.

3. The anxiety of the patient and family can be minimised if unnecessary referrals are eliminated.

2.5   Previous research

2.5.1   Signal processing techniques

A multitude of different techniques have been implemented to analyse and characterise heart sounds. These include Fourier analysis, Short-time Fourier analysis, Wigner distributions, Choi-Williams distributions and Wavelet analysis.

The Fourier Transform (FT) is used to determine which frequencies are contained in a given time-domain signal. Fourier coefficients are indicative of the frequency content of a signal and are calculated by:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-2j\pi ft}dt \tag{2.5.1}$$

At a more practical level, the Discrete Fourier Transform (DFT) is implemented to calculate the Fourier coefficients for discrete signals. Discrete signals comprise most of the signals one works with, since they are recorded by a computer. The formula by which the Fourier coefficients are calculated for discrete signals is:

$$X(m) = \sum_{k=0}^{N-1} x(k)e^{\frac{-2j\pi mk}{N}} \tag{2.5.2}$$

where $m = 0, 1, ..., \frac{N}{2}$, N is the size of the FT one wishes to calculate. The value N effectively determines the resolution of the FT. For example, if you have a signal that has been sampled at $f_s = 2000$ Hz, the frequencies at which the FT will be calculated is determined by [19]:

$$f_{\text{analysis}}(m) = \frac{mf_s}{N} \tag{2.5.3}$$

For example, if you perform an 8-point FT on your data, the first frequency term will be calculated at a frequency of $\frac{1 \times 2000}{8} = 250$ Hz, the second frequency term will be calculated

at a frequency of $\frac{2\times2000}{8} = 500$ Hz etc. If you decide to perform a 512-point FT on your signal instead, the first frequency term will be calculated at a frequency of $\frac{1\times2000}{512} = 3.91$ Hz, the second frequency term will be calculated at a frequency of $\frac{2\times2000}{512} = 7.81$ Hz, etc. Thus the larger N, the better the resolution of the FT that is calculated. However, the size of the FT that you wish to calculate is bounded by the length of the signal that is being analysed.

The Fourier coefficients are calculated for a set of pre-defined frequencies, as determined by equation 2.5.3. At each frequency, the time-domain signal is multiplied by a complex exponential function and integrated over all time to yield the corresponding Fourier coefficient. If the Fourier coefficient is relatively large, the time-domain signal contains a major component of the frequency that is currently under consideration. Should the Fourier coefficient be relatively small, the contribution of the frequency under consideration is small. If the signal does not contain a component of a specific frequency, the Fourier coefficient will be zero. The complex exponential function $e^{-2j\pi ft}$ is defined as:

$$e^{-2j\pi ft} = \cos(2\pi ft) - j\sin(2\pi ft) \tag{2.5.4}$$

This definition implies that any time-domain signal can be represented as a sum of sine and cosine functions at specific frequencies. The FT of a signal is computed in a fast and efficient manner by the Fast Fourier Transform (FFT), which is an algorithm developed by J.W. Cooley and J.W. Tukey in 1965. The details of the algorithm will not be discussed here and can be found in [20].

The frequency information is very important, since different actions of the heart (e.g. the opening or closing of valves) will produce sounds at different frequencies. It is thus critical to have the frequency information contained in a heart sound at your disposal in order to identify certain pathologies. Bhatikar *et al.* [21] used the FT coefficients as input to a classification scheme differentiating between innocent and pathological murmurs and obtained a correct classification rate of 83% sensitivity and 90% specificity. Refer to Section 2.5.2 for a definition of sensitivity and specificity.

The major drawback of Fourier analysis is the fact that all temporal information in the signal is lost [22]. The FT can only be applied to a signal if it is assumed that the signal is stationary [6]. A stationary signal is defined as a signal whose statistical properties do not change with time [23]. Heart sounds exhibit extremely non-stationary characteristics and Fourier analysis is thus not suited for the analysis of these signals [24]. Figure 2.5 shows the FFT of the denoised normal heart recording in Figure 2.3. The recording was done at the 4th right intercostal space.

In an effort to correct the disadvantage (that temporal information is lost) of the FT, the Short-Time Fourier transform (STFT) was developed. The STFT is implemented by
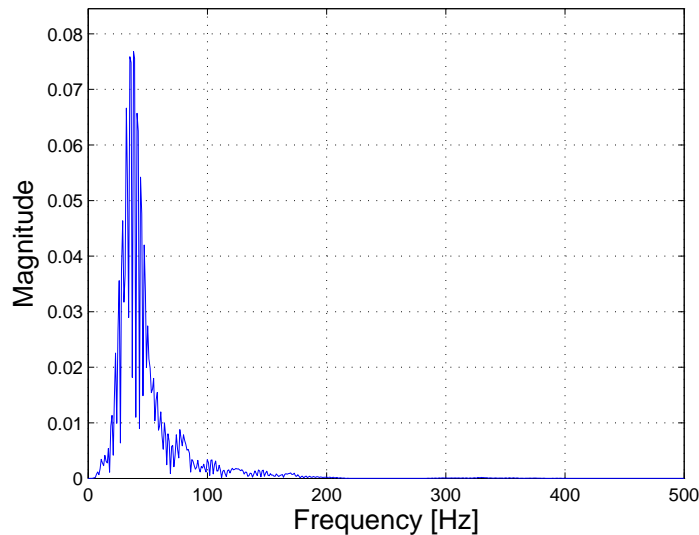
Figure 2.5: FFT of recorded heart sound

performing the FT on only a small part of the signal. The signal under analysis is subdivided into a number of small records where it is assumed that each sub-record is stationary. The signal is multiplied by a short-duration time window that is centered on the time instant of interest. This is called windowing. The window is subsequently slid along the time axis to cover the entire duration of the signal and to obtain an estimate of the spectral content of the signal at every time instant. The formula by which the STFT is computed is:

$$X(\tau, \omega) = \int_{-\infty}^{\infty} [x(t)w^*(t - \tau)]e^{-j2\pi ft}dt \qquad (2.5.5)$$

The STFT cannot track very sensitive changes in the time direction [25] and hence is not suitable for the analysis of the non-stationary and rapidly changing heart signals. However, Turkoglu *et al.* [26] used the STFT to calculate the features that were used as input into their classification algorithm for heart sounds. The authors used a back propagation neural network as their classification scheme and obtained a correct classification rate of 94% for normal heart sounds and 95.9% for abnormal heart sounds. The STFT of the recorded signal in Figure 2.3 is shown in Figure 2.6. The window that was used is a Hanning window with a duration of 64 ms and an overlap between windows of 32 ms.

The Wigner Distribution (WD) is another technique that provides a two-dimensional view of the frequency and the temporal information of the signal under analysis. It provides better resolution than the STFT, but is limited by the appearance of cross-terms. These cross-terms are due to the non-linear behaviour of the WD and bear no physical meaning [6]. The WD has also been evaluated by Bentley *et al.* [27] as a time-frequency technique to extract information from recorded native and bioprosthetic heart sounds. The WD is
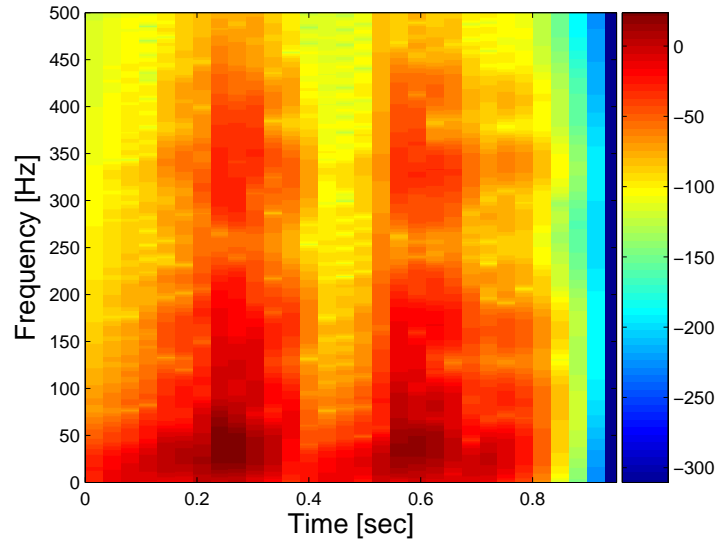
Figure 2.6: STFT of recorded heart sound

calculated by:

$$W\left(t,\omega\right) = \int x^*\left(t - \frac{1}{2}\tau\right) x\left(t + \frac{1}{2}\tau\right) e^{-j\omega t} d\tau \qquad (2.5.6)$$

Figure 2.7 shows the WD of the signal in Figure 2.3. It can be seen that at 0.4 sec there is a component present that is not physically present in the recorded sound. This is the cross-terms mentioned previously. Thus the WD is unsuitable for analysis since these cross-terms may alter the information extracted from the signal.

The Choi-Williams Distribution (CWD) is another technique capable of displaying time-
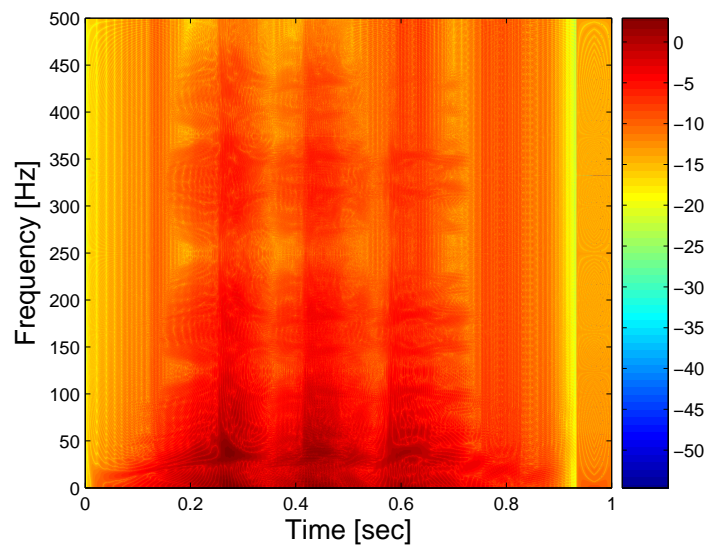
Figure 2.7: Wigner distribution of recorded heart sound
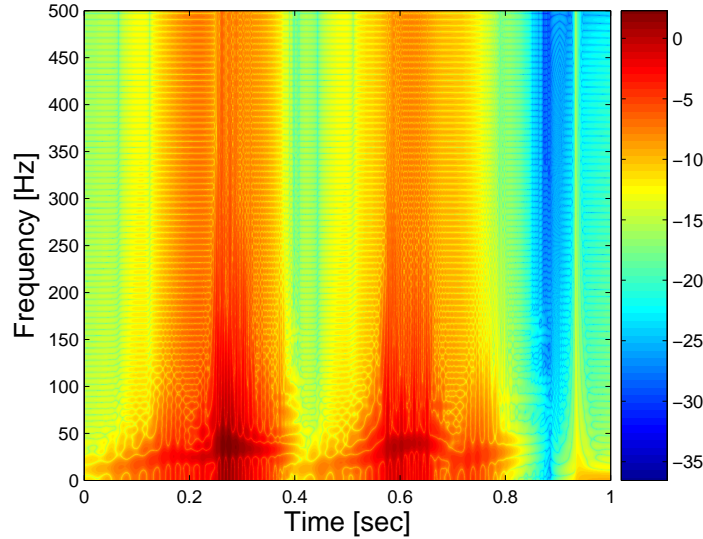
Figure 2.8: Choi-Williams Distribution of recorded heart sound

frequency information of heart sound signals. The CWD is calculated by [28]:

$$CW\left(t,\omega\right)=\sqrt{\frac{2}{\pi}}\int\int_{-\infty}^{\infty}\frac{\sigma}{|\tau|}e^{-2\sigma^{2}(s-t)^{2}/\tau^{2}}x\left(s+\frac{\tau}{2}\right)x^{*}\left(s-\frac{\tau}{2}\right)e^{-j2\pi\omega\tau}ds\ d\tau \qquad (2.5.7)$$

The difference between the CWD and the WD is the use of the kernel function $\sqrt{\frac{2}{\pi}}\frac{\sigma}{|\tau|}e^{-2\sigma^{2}(s-t)^{2}/\tau^{2}-j2\pi\omega\tau}$. In the WD the kernel function is $e^{-j\omega t}$. The use of σ in the CWD kernel function reduces the interference problems without reducing the resolution [27]. Figure 2.8 shows the CWD of the signal in Figure 2.3. The value for σ used in these calculations was $\sigma = 6.061$. It can be seen that the interference at 0.4 sec is significantly reduced in the CWD, while the resolution still remains significantly better than the STFT.

Wavelet analysis provides a time-scale representation instead of a time-frequency representation of the signal under analysis. Scale can be thought of as the inverse of frequency, where the low scales constitute the high-frequency components and the high scales the low-frequency components. When switching between frequency and scale, the scale cannot simply be inverted to yield the frequency. Instead, one has to think in terms of pseudo-frequencies to determine which frequencies a specific scale represents. To calculate the pseudo-frequency associated with a specific scale, equation 2.5.8 can be used:

$$F_{a}=\frac{F_{c}}{\Delta a} \qquad (2.5.8)$$

where F_{c} is the wavelet centre frequency, a is the specified scale and F_{a} is the pseudo-frequency corresponding to scale a. It is attempted to associate with each wavelet a purely
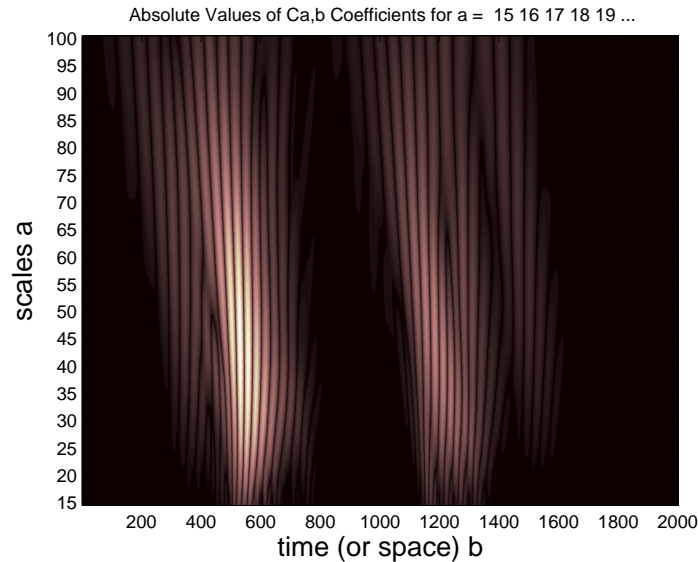
Figure 2.9: Continuous Wavelet Transform (CWT) of recorded heart sound

periodic signal that captures the main oscillations of the wavelet. This is done to simplify the subsequent analysis of the frequency content of the wavelet, since this signal contains the main frequency component of the wavelet. The frequency of this signal is the wavelet centre frequency, F_c, and this frequency maximises the FFT of the wavelet modulus [29].

Calculating the wavelet transform consists of breaking up a signal into shifted and scaled versions of an original (mother) wavelet, similar to Fourier analysis which breaks up the original signal into sinusoids of different frequencies. The continuous wavelet transform (CWT) is calculated by:

$$CWT(b, a) = \frac{1}{\sqrt{a}} \int h^* \left(\frac{t - b}{a} \right) s(t) \, dt \qquad (2.5.9)$$

An original mother wavelet is chosen from a pre-defined set of wavelets, or a custom wavelet can also be constructed. The wavelet is then stepped through the signal, multiplied with the signal at every time instant of interest and integrated to yield a wavelet coefficient. The scale of the wavelet is then changed to compress or dilate it. The new wavelet is then stepped through the signal again, multiplied by the signal and integrated to yield wavelet coefficients. This process is repeated for the set of scales that one has decided upon. If the coefficient that has been calculated is relatively large, the signal contains a component that is similar to the wavelet at that specific scale. The CWT of the signal in Figure 2.3, computed for scales 15 to 100, is shown in Figure 2.9.

The Discrete Wavelet Transform (DWT) computes the wavelet coefficients for a dyadic scale sequence. This means that the wavelet coefficients are only calculated for scales based on the power of 2 e.g. $2^1, 2^2, 2^3$, etc. This implies that wavelet coefficients are only calculated
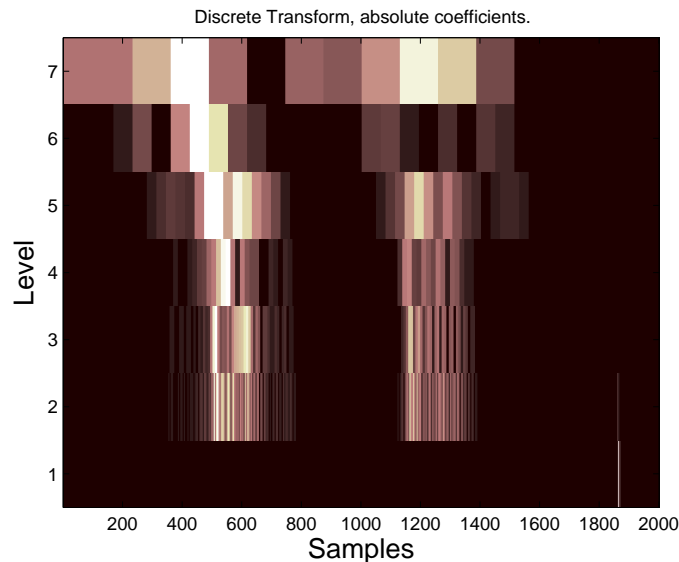
Figure 2.10: Discrete Wavelet Transform (DWT) of recorded heart sound

for scales $= 2, 4, 8, 16$, etc. The resolution of the DWT is not as good as the resolution of the CWT, but the computation time is far shorter since the coefficients are not calculated for every scale. Nevertheless, the analysis is equally accurate as the CWT [29]. Figure 2.10 shows the DWT of the signal in Figure 2.3. The wavelet used was the Daubechies wavelet of order 7, and the breakdown level was also level 7. This means that the coefficients were calculated for scales of $2^1, 2^2, ..., 2^7$.

Mallat developed an efficient way to implement the DWT by using the subband coding scheme [30]. This is known as the Fast Wavelet Transform (FWT). The signal under analysis is broken down into low-frequency (approximations) and high-frequency (details) components by passing the signal through a low- and high-pass filter respectively. At each breakdown level, the signal bandwidth is split in half. For example, if you have a signal sampled at 2000 Hz, the maximum frequency present in the signal is 1000 Hz according to the Nyquist criterion. This means that after the first set of filters in the DWT, the approximations will contain the components between 0-500 Hz and the details will contain the components between 500-1000 Hz. For the following breakdown level, the approximation of the previous level is broken down further, yielding another set of approximations and details. The approximation of this level contains the frequency components between 0-250 Hz and the details the frequency components between 250-500 Hz. This process continues until the remaining samples are equal to one. The signal has to be downsampled at each level to ensure that the number of samples at the breakdown level is half the amount of samples contained in the signal that is passed through the filters. If this is not done, one ends up with twice the amount of data that one started with, since convolving a signal with a filter yields the same number of samples of the original signal. Every second sample is

thus kept to ensure the correct sizes at each level. This process is explained graphically in Figure 2.5.1.
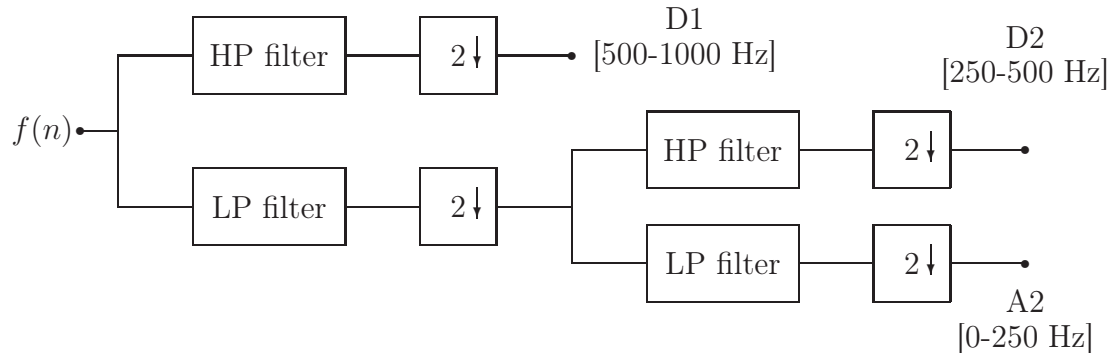
Figure 2.11: Graphical presentation of FWT implementation

In the literature reviewed, wavelets have been used extensively to denoise phonocardiogram signals or highlight certain features in the signals. Debbal and Bereksi-Reguig [25] showed that the number of major components present in each sound of the second heart sound (A_2 and P_2) can be identified. The frequency range and the localisation of these sounds can also be determined by use of the continuous wavelet transform. Doppler heart sounds were decomposed using wavelet analysis and certain components were implemented in a neural-network based classification scheme [26]. These authors obtained a correct classification rate of 94% using these components. Messer *et al.* [24] studied the effects of different wavelets on denoising recorded heart sounds. They found that certain wavelets from the Coiflet, Daubechies and Symlet families provide the best results. The best denoising results were obtained by implementing wavelet analysis together with averaging[5].

Other techniques that have been implemented to extract information from heart sounds, include the Hilbert Transform [24] and homomorphic filtering [31].

2.5.2 Classification techniques

Artificial Neural Networks (ANNs) are the primary tool implemented in the classification of heart sounds [32; 33; 34; 35; 36] although other techniques, such as Hidden Markov Models (HMMs), have been implemented as well [37]. ANNs are adaptive systems that can model complex non-linear systems [38]. Refer to Chapter 5 for a detailed discussion of ANNs. As an example, Cathers [32] used the heart sound amplitude envelope as input to the ANN.

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[5]This is when a number of points in a signal is replaced by the average of all those points concerned.

The output of the system was a 3 x 1 column vector. The sequence

$$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

denoted a normal heart sound whereas the sequence

$$\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

denoted a systolic murmur. The ANN is thus trained to give these outputs for the correct inputs, so that when it is presented with similar input data, it will give the same output, classifying the heart sound as either normal, or as a systolic murmur, for instance.

In a study performed by Bhatikar *et al.* [21] to distinguish between innocent and pathological murmurs, the input to the ANN was the frequency spectrum of the heart sound that consisted of the 252 bins in the discrete energy spectrum with a range of 0-252 Hz and a bin-size of 1 Hz. In this case, the output was a single number, either 0 or 1, where 0 indicated an innocent murmur and 1 indicated a pathological murmur. The network consisted of 252 input neurons, 15 hidden layer neurons and 1 output neuron. The authors obtained a correct classification rate of 83% sensitivity and 90% specificity. Sensitivity and specificity are defined as:

$$\text{Sensitivity} = \frac{\text{\# of true positives}}{\text{\# of true positives} + \text{\# of false negatives}} \quad (2.5.10)$$

$$\text{Specificity} = \frac{\text{\# of true negatives}}{\text{\# of true negatives} + \text{\# of false positives}} \quad (2.5.11)$$

Sensitivity specifies the percentage of unhealthy patients that are recognised as unhealthy and specificity determines the number of healthy patients that are recognized as healthy [34].

In other studies, Leung *et al.* [36] obtained a sensitivity of 97.3% and a specificity of 94.4% in classifying innocent and pathological systolic murmurs. The authors used a probability neural network in classifying their data.

Akay *et al.* [35] achieved a sensitivity of 85.5% and a specificity of 88.9% in detecting coronary artery disease. The authors used a Fuzzy Min-Max Neural Network in their study. The fuzzy min-max classification neural netork is an on-line supervised learning classifier that is based on hyperbox fuzzy sets. Tripathy [39] used a feed-forward neural network trained with the backpropagation algorithm to differentiate between normal heart sounds

and certain pathologies. A correct classification rate of 81.86% was obtained.

HMMs have mainly been used in the field of speech recognition. When working with HMMs, one has a sequence of observable events, or observed vectors, that have been generated by a Markov model. The Markov model consists of a set of states and these states produce a certain observation vector/s. In the Markov model, state is changed every time unit and each time the state is changed, an observation vector is generated that depends on the probability of that observation vector being produced. The transition from one state to another is also determined by the probability that such a transition will occur. The HMM then calculates the best sequence of states that maximises the probability of generating the specific observation sequence. El-Hanjouri *et al.* [37] achieved a correct recognition rate of 99.1% in classifying pathological heart sounds by implementing HMMs. HMMs were also used in [40] to segment heart sounds into their constituent parts.

Other classification techniques implemented in phonocardiogram analysis includes decision-tree classifiers. Pavlopoulos *et al.* [41] achieved a correct classification rate of 90% in discriminating between aortic stenosis and mitral regurgitation.

Voss *et al.* [42] achieved a correct classification rate of 100% for patients suffering from moderate or severe aortic stenosis and a correct classification rate of 75% for patients suffering from mild aortic stenosis. Their desicion-making scheme was based on a linear discriminant function being applied to the feature vectors extracted from the heart sounds.

Bentley *et al.* [27] used Bayes' decision rule in classifying their data as either normal or abnormal. They obtained a correct classification rate of between 61% and 100%, depending on which feature extraction method was followed.

Chapter 3

Hardware and Data Acquisition

This chapter describes in broad terms the procedure followed in the design of the auscultation jacket. The hardware implemented as well as the procedure followed in recording the patient data is discussed.

3.1 Stethoscopes

It was desired to record the heart sounds from patients in order to develop an automated screening procedure capable of differentiating between normal and abnormal heart sounds. There are different methods of obtaining the heart sounds from a patient. It could be done via the use of a digital stethoscope or an accelerometer. Accelerometers are not as widely used as digital stethoscopes, but have been implemented in studies to record heart and lung sounds [43].

Conventional analogue stethoscopes are mainly used for auscultating patients in hospitals and clinics. A conventional analogue stethoscope simply converts sound waves into pressure waves that can be heard and processed by the human ear and is shown in Figure 3.1. Digital stethoscopes can work on two different principles;(a) implementing a microphone to convert the acoustic waves generated by the beating heart to electrical signals;(b) using a piezo-electric crystal in converting the sound waves to electric signals. Most phonocardiograph transducers implement the *crystal* piezo-electric or *dynamic* piezo-electric microphones [44]. For this project, the digital stethoscopes implemented were designed and supplied by GeoAxon. The stethoscopes made use of a condenser microphone to convert the pressure waves to electrical signals and the microphone used in the stethoscope was the *Panasonic WM-61 B back electret condenser microphone*. These microphones have a range of $20 - 20000$ Hz and a flat frequency response up to 5000 Hz. The data sheet for the microphone is given in Appendix B.

A normal condensor microphone uses a capacitor to produce a change in voltage. One of

Figure 3.1: Conventional analogue stethoscope [45]
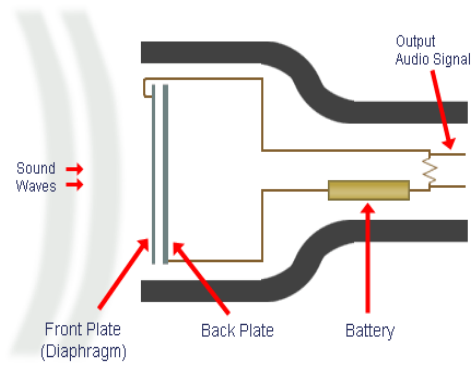
Figure 3.2: Standard condenser microphone [46]

the materials used in the capacitor is the diaphragm. As sound waves reach the diaphragm, it moves back and forth, thereby changing the distance between the two plates of the capacitor. As the distance decreases, the capacitance increases, producing a charge current;when the distance increases, capacitance decreases and a discharge current is produced. The change in voltage across a resistor is measured and converted to an audible sound (refer Figure 3.2). In order to produce the charge or discharge current a voltage is required and is normally supplied by a battery in the microphone or by phantom power [46].

In the back electret microphone a dielectric material is placed behind the diaphragm on the backplate of the microphone housing (refer Figure 3.3). This dielectric material serves as the capacitor. The only difference between a normal condenser microphone and an electret condensor microphone is that the latter does not require an external voltage source to produce the charge and discharge currents, since the voltage is manufactured into the dielectric material [46].

The stethoscopes used in this study are USB-enabled stethoscopes. The stethoscopes connect to the PC via the USB connection and each stethoscope is registered by the computer as a separate recording device. The analogue-to-digital conversion of the signal takes
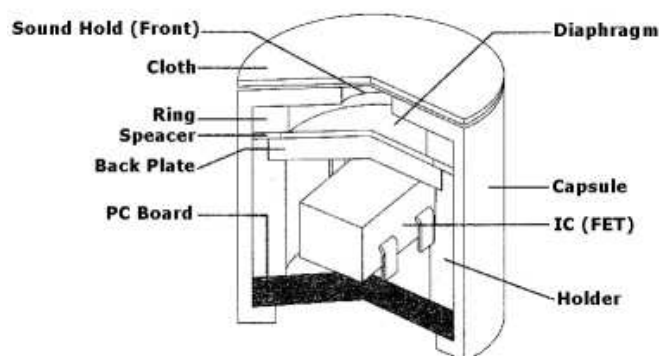
Figure 3.3: Back electret condenser microphone [47]

Figure 3.4: Digital stethoscope used in study
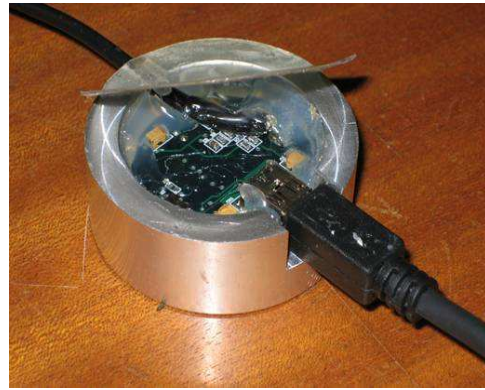
Figure 3.5: Inside view of digital stethoscope

place in the stethoscope itself. These digital signals were then recorded by a computer, using recording software. The digital stethoscopes used in the study are shown in Figure 3.4. Figure 3.5 shows the electronic chip inside the digital stethoscope. The recorded signals were sampled at 16-bit and 2000 Hz.

3.2 Auscultation jacket

When auscultating a patient or recording the heart sounds of a patient, only one position is normally listened to or recorded at a specific time. This is not necessarily a deficiency, but during the research it was decided to obtain a "snapshot" of the heart (or lungs) of a patient by simultaneously recording the heart and lung sounds at the positions where a physician would normally auscultate a patient. To achieve this, 21 digital stethoscopes were embedded into a jacket to record the heart and lung sounds of a patient.

The result is the "auscultation jacket" that is capable of recording the heart and lung sounds at all the necessary positions simultaneously, as well as a 12-lead ECG (refer to Figure 2.4). An Impedance Cardiogram (ICG) was also built into the jacket but due to unforeseen hardware problems the ICG could not be recorded with the jacket but had to be recorded separately. Please refer to Appendix A for a detailed explanation of ECG and ICG technology.

3.2.1 Previous approaches

Similar approaches to the auscultation jacket have been developed previously. These include designs from companies such as *Stethographics Inc.*, *Tapuz Medical Technology Ltd.* and *Medes.*

Stethographics Inc. developed a multi-channel stethograph that consists of 14 stethoscopes embedded within sponge. The sponge is placed behind the patient's back and two

seperate stethoscopes are placed on the patient's chest. All recordings are done simultaneously, which will make true comparisons possible and provides the basis for three-dimensional analysis and display. Figure 3.6 shows the multi-channel stethograph from *Stethographics Inc.*.

Tapuz Medical Technology Ltd. developed a universal ECG electrode belt, which has six ECG electrodes moulded into the structure. The electrode positions correspond to the positions where the chest electrodes would be placed for a normal 12-lead ECG. Fitting sockets for the leads onto the electrodes are provided for. Figure 3.7 shows this ECG belt.

Medes is a French organisation that has been working on the *VTMAN* project. The objective is to enhance the autonomy of patients by integrating medical equipment in the patients' clothes. This achievement should significantly reduce the medical follow-up of patients who are medically dependent and should contribute to optimising medical procedures [50]. Figure 3.8 shows some of the different elements of the *VTMAN* project.

3.2.2 Design procedure

In the design of the jacket, it was difficult to decide where the positions for the stethoscopes and electrodes in the jacket should be. The positions of the stethoscopes should coincide with the auscultation locations as explained in section 2.4, as well as some of the positions

Figure 3.6: *Stethographics Inc.* multi-channel stethograph [48]
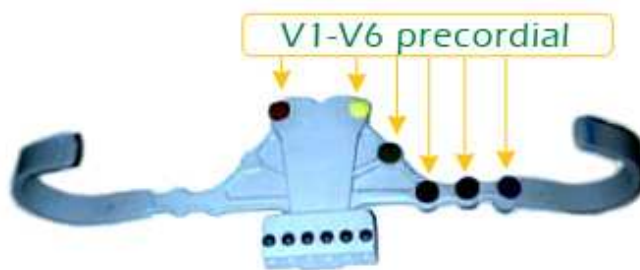
Figure 3.7: *Tapuz Medical Technology Ltd.* ECG belt [49]
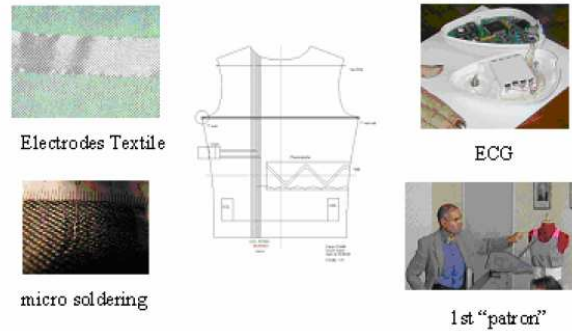
Figure 3.8: *Medes - VTMAN* project [50]

where the ECG electrodes should be placed. These positions proved to be extremely difficult to pin down, since these positions differ from person to person.

The final positions were decided upon with the help of a medical doctor, Dr Renier Verbeek. A tight-fitting shirt was worn by a volunteer of average build and the normal auscultation positions were indicated on the shirt. These markings resulted in 18 possible auscultation/ECG/ICG positions on the torso and 14 auscultation/ECG positions on the back. The positions marked were converted to a sketch and can be seen in Figure 3.9.

It was decided that all of these positions were not necessary and the final positions decided upon are shown in Figure 3.10. These positions are the most likely auscultation positions, as well as the positions of the ECG and ICG electrodes. These positions were thus deemed sufficient to obtain all data necessary to make a proper diagnosis.

The physical size of the jacket was based on anthropometric data obtained from the *RSA Military Steering Committee* (RMSS), which forms part of the *Armaments Corporation of South Africa* (ARMSCOR). The data used is contained in the *RSA-Mil-Std. 127 Volume*
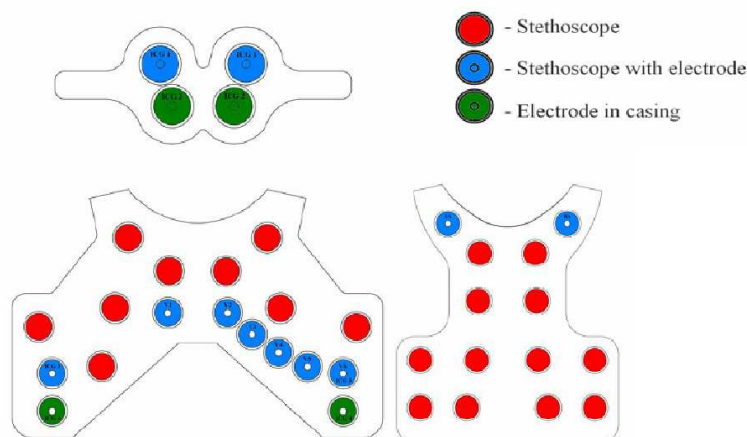
Figure 3.9: Initial positions for stethoscopes and electrodes in jacket
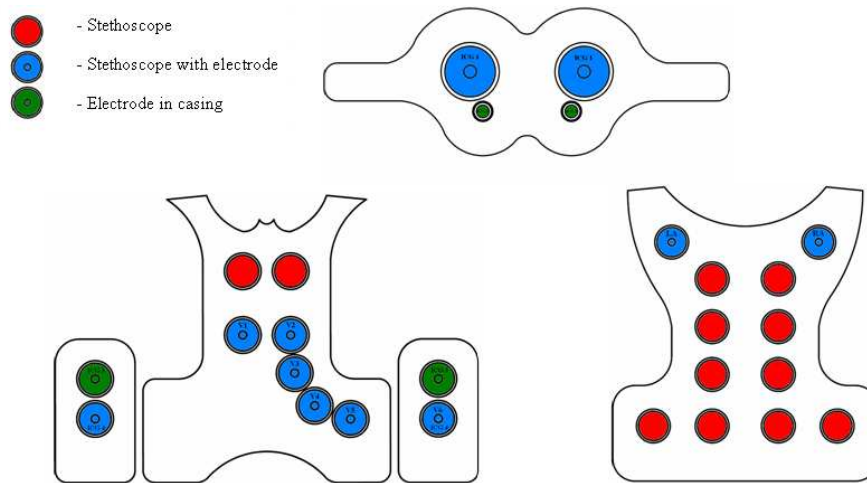
Figure 3.10: Final positions for stethoscopes and electrodes in jacket

1 and measurements based on the 50th percentile was used. It was thus ensured that the jacket will fit the greater part of the South African population.

3.2.3   The auscultation jacket

The jacket consists of a neck piece, front piece, back piece and two side pieces. The neck piece contains two stethoscopes with electrodes embedded and two smaller electrodes for ICG purposes. The left side piece contains two stethoscopes with electrodes embedded. The top stethoscope serves a dual purpose: it serves as the electrode at the V6 position for the ECG, as well as the electrode that measures the impedance during the ICG. The bottom stethoscope serves as one of the electrodes that generate the small current that is sent through the thorax during the ICG procedure. The right side piece contains one stethoscope with an electrode embedded and one stethoscope casing with only an electrode. The front piece contains seven stethoscopes. Five of these stethoscopes have electrodes embedded, since they serve the purpose of the V1-V5 electrodes needed for the ECG purposes. The back piece contains 12 stethoscopes that are situated in a symmetrical pattern for the recording of the lung sounds. Figures 3.11 and 3.12 show the inside and outside of the front piece of the jacket. The inside and outside of the back piece is shown in Figures 3.13 and 3.14 respectively.

Some of the stethoscopes are stereo stethoscopes, i.e. two stethoscopes connect to the PC via one USB cable. One stethoscope uses the left channel and the other the right channel in the recording procedure. Figure 3.15 shows a pair of these stethoscopes. This was done so that the total number of USB cables running to the PC remain at a minimum. Please refer to [51] for a detailed explanation of the procedure followed during the design of the jacket.
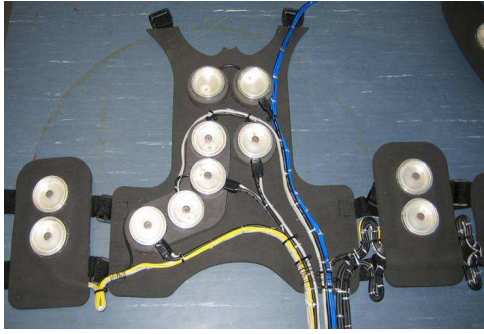
Figure 3.11: Front piece of jacket (inside)
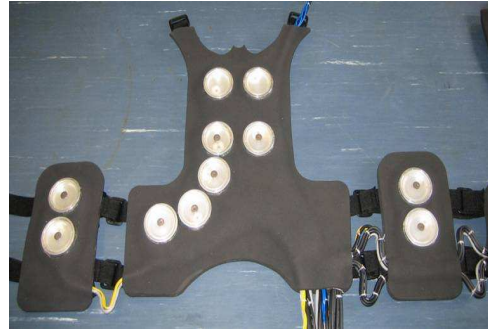
Figure 3.12: Front piece of jacket (outside)

The electrodes necessary for the ECG and ICG purposes were built into the jacket, except for two of the limb leads necessary for the ECG. If the auscultation positions coincided with the position for an electrode, the electrode was simply embedded into the stethoscope. This proved to be a satisfactory approach, since the ECG recorded with the jacket was of a good standard. The system used for the ECG recording was supplied by **IQteq** and the system

Figure 3.13: Back piece of jacket (inside)

Figure 3.14: Back piece of jacket (outside)

Figure 3.15: Dual stethoscopes

for the ICG recording by **Hemo Sapiens Inc**. A sample ECG recording of a normal patient is shown in Figure 3.16.

3.3   Data acquisition

The aim was to record the heart and lung sounds of 60 male volunteers, 30 of them patients with no heart problems and 30 of them patients with valve-related heart disease or some form of auscultatory abnormality. The design of the jacket did not accommodate the recording of female test subjects. A study protocol, explaining the goals as well as the procedures followed during the course of the study, was submitted to the Committe for Human Research (CHR) of the University of Stellenbosch. The study protocol was approved by the CHR and the project number is N06/02/030.

To establish whether a participant belonged to the normal or abnormal study group, each participant had to be individually examined by a physician for any auscultatory abnormalities and undergo a 12-lead ECG and an echo-cardiogram. All patients had to sign a consent form before the recording and examination procedure took place. Each patient was also fitted with a 3-lead ECG, that could simultaneously be recorded with the stethoscope data, built by **GeoAxon**. This served as a trigger to determine when S_1 was produced. The further use of this information is explained in Chapter 4.

The inclusion criteria for the participants were:

- 60 kg < mass of participant < 110 kg

- Participants above 18 years of age

Figure 3.16: Sample 12-lead ECG recorded with auscultation jacket

- Participants who had given written informed consent

- Patients determined fit to participate in this study by a physician

- Patients with a normal echo-cardiogram

- Patients with have an abnormal echo-cardiogram

- Any person willing to participate in this study, i.e. any person from the Mechanical Engineering Department, Tygerberg Hospital, or any person who was aware of the study and wished to take part

The exclusion criteria for the participants were:

- 60 kg > Mass of participant > 110 kg

- Participants without written informed consent

- Patients found physically unfit for the study

- Subordinates to any of the researchers

Unfortunately, due to time limits, not all sixty volunteers could be recorded. Thirty-four normal volunteers were recorded, but the data of only 17 of these patients could be used in the analysis procedure. This was due to the positions in which the patients were recorded being changed after it was realised that the number of positions in which the recordings were being done was not necessary. Ideally all the volunteers had to be recorded in the same positions so as to not bias the results in any way. Another reason for omitting some of the recorded data is that some of the data was still too noisy to extract any meaningful information despite the denoising procedure. Of the 21 abnormal patients recorded, only 14 patients' data could be used due to either the data that have been recorded being too noisy despite the denoising procedure, or that the ECG recorded with GeoAxon's ECG was too noisy and artifacts were produced that corrupted the data.

Each participant was fitted with the jacket and was asked to lie on his back on an examination bed. The patients were recorded in 3 supine positions:

1. Patient breathing normally

2. Patient holding breath at end of expiration

3. Patient holding breath at end of inspiration
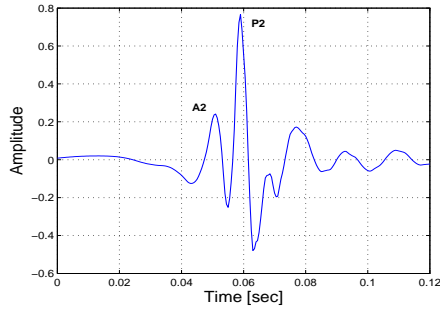
Figure 3.17: S_2 at expiration
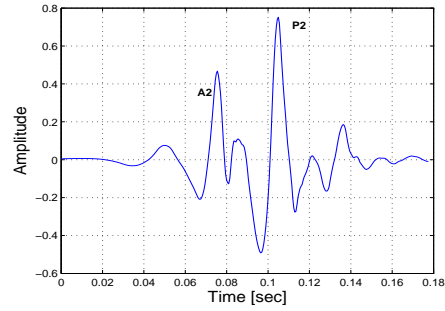
Figure 3.18: S_2 at inspiration

Positions 2 and 3 were performed so as to determine whether the splitting of S_2 widens during inspiration or vice versa. As was explained in section 2.3, the second heart sound is produced by the closure of the aortic and pulmonary valves (refer Figure 2.2), in that order. In some cases it is possible to hear the split between the closure of these two valves. During expiration the split is virtually inseparable, but during inspiration the pulmonary component, P_2, tends to be delayed [12]. During inspiration, the intrathoracic pressure decreases, below atmospheric pressure, to allow air into the lungs. This drop in intrathoracic pressure leads to the expansion of the lungs, the cardiac chambers and superior and inferior vena cavae [52]. Due to this expansion of the chambers, the pressure inside the right atrium and the veins leading to the right atrium are decreased. The venous return can be defined as:

$$VR = \frac{P_V - P_{RA}}{R_V} \quad (3.3.1)$$

where VR is the venous return[1], P_V is the pressure inside the vena cava, P_{RA} is the pressure inside the right atrium and R_V is the venous resistance [52]. It can easily be seen from equation 3.3.1 that a decrease in P_{RA} will lead to an increase in VR. It has to be noted that the decrease in P_V during inspiration has to be smaller than the decrease in P_{RA} to facilitate an increase in venous return.

Due to this increase in venous return, the right atrium and ventricle fill slightly more with blood and consequently it takes slightly longer to eject this blood during systole. Because of the slightly longer ejection period, the pulmonary valve stays open a bit longer and this leads to a split in the second heart sound that is audible in normal healthy people. Splitting of the second heart sound occurs in patients with heart disease as well and may be a good indicator of whether heart disease is present. Figures 3.17 and 3.18 show the extracted second heart sound of a patient at expiration and inspiration respectively. The aortic and pulmonary components are shown (A_2 and P_2 respectively) and it can be seen that the split increased noticably with inspiration.

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[1]Venous return is defined as the amount of blood reaching the right atrium during a single beat in the cardiac cycle [52].

Splitting of S_2 occurs when there is obstruction to emptying of the right ventricle, as in *pulmonary stenosis* (when the pulmonary valve does not open properly). It may also occur if there is delayed electrical activation of the right ventricle as in *right bundle branch block* [12]. These diseases tend to increase the split of S_2, but the split still increases with inspiration and decreases with expiration.

Fixed splitting of S_2 also occurs e.g. in patients who suffer from *atrial septal defect*. In patients who suffer from *atrial septal defect* there is a hole in the muscle wall (septum) that seperates the atria from each other. This causes blood to flow from one atrium to the other. In cases such as these, the right ventricle has to pump harder to compensate for the loss of blood to the left atrium. This causes the pulmonary valve to stay open longer, but the split is fixed during inspiration and expiration since the blood moves between the atria permanently.

Reversed splitting of S_2 can also occur. That is when the pulmonary valve closes before the aortic valve and the split increases during expiration and decreases during inspiration. This commonly occurs in patients who suffer from *hypertrophic obstructive cardiomyopathy*. This is when a portion of the *myocardium* (the heart muscle) is enlarged. It may also occur in *left bundle branch block* and in *aortic stenosis*, but can be difficult to detect since the aortic component is very soft due to the rigidity of the stenosed valve [12].

The amplitude values of the recorded heart sounds were normalised by:

$$\overline{x}(i) = \frac{x(i)}{x_{\max}} \qquad\qquad (3.3.2)$$

where $x(i)$ is the current value under consideration and $x_{\max}$ is the maximum value of the specific recording. The recording software recorded the values in decibels, but after the normalisation procedure all recorded values were between -1 and 1. All the stethoscopes were first connected to a custom-built 28-port USB hub from which only four cables connected to the PC. These four cables then transmitted all the recorded information to the computer. The hub is shown in Figure 3.19.

After the recording procedure, the ICG recording was performed on each patient. ICG technology is based upon a drop in the thoracic resistance during each beat of the heart. The resistance drops because, during ejection of the blood, the red blood cells align themselves in a parallel fashion thereby making the blood more conductive [53]. Please refer to Appendix A for a detailed explanation of ICG technology.
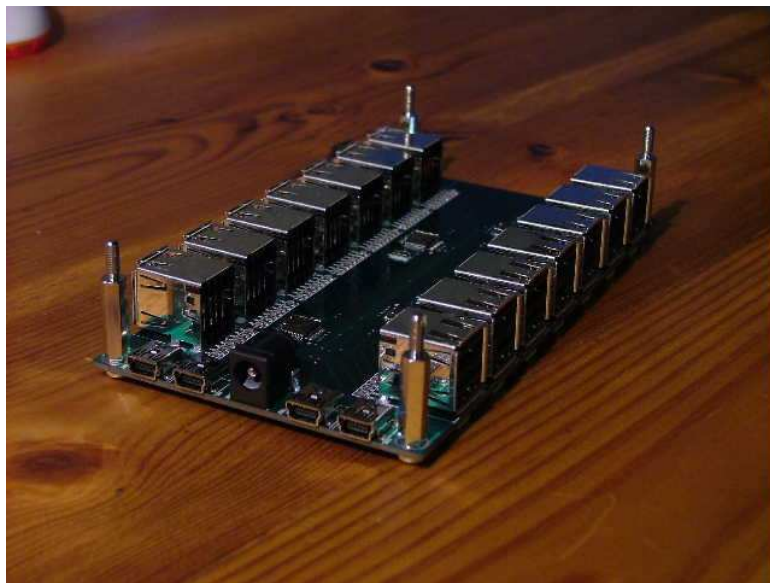
Figure 3.19: 28-port USB hub used to connect stethoscopes to computer

Chapter 4

Methodology

The analysis procedure of the recorded heart sounds will be discussed in this chapter. This includes denoising of the recorded data, preprocessing of the data and the feature extraction. The whole process is outlined in Figure 4.1 and each section will be discussed separately.
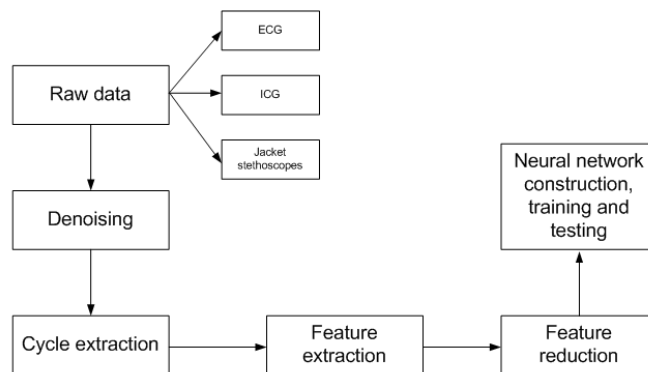
Figure 4.1: Implemented methodology

4.1 Denoising of recorded data

Recording of the data took place at Tygerberg Hospital in the Western Cape. During the recording procedure the recorded signals were contaminated by noise and this had to be removed. It was attempted to keep the environment as quiet as possible but some noise was still recorded. The noise was due to voices, people in the halls of the hospital as well as the physical examination taking place right next to the recording area. The denoising methods used are shown schematically in Figure 4.2.

The frequencies of interest in recorded heart sounds are in the range of 50 - 650 Hz. Due to this, the recorded signals were bandpass filtered. The lower cut-off frequency was 25 Hz and the upper cut-off frequency was 700 Hz. Figure 4.3 shows the original recorded

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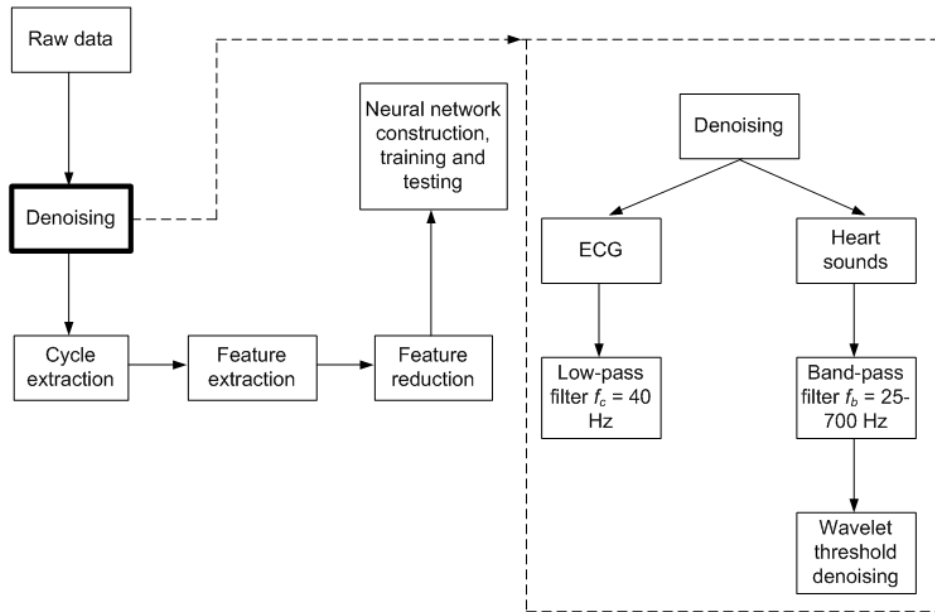
Figure 4.2: Denoising methods implemented

signal and Figure 4.4 shows the signal after it was bandpass filtered. The signal was sent through the filter, reversed and sent back through the filter so that zero phase distortion would be present at the end of the filtering process. The signal shown is a signal recorded with the auscultation jacket at the 4th left intercostal space. The recorded ECG signals (IQteq and GeoAxon) were also filtered. These signals were low-pass filtered with a 4th order Butterworth filter with a cut-off frequency of 40 Hz so as to remove any electrical noise that might have occurred.
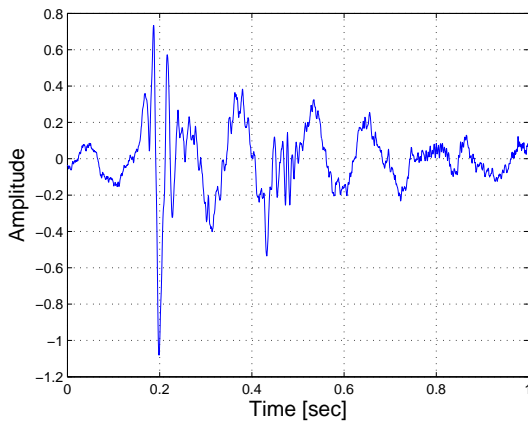
Figure 4.3: Original recorded signal
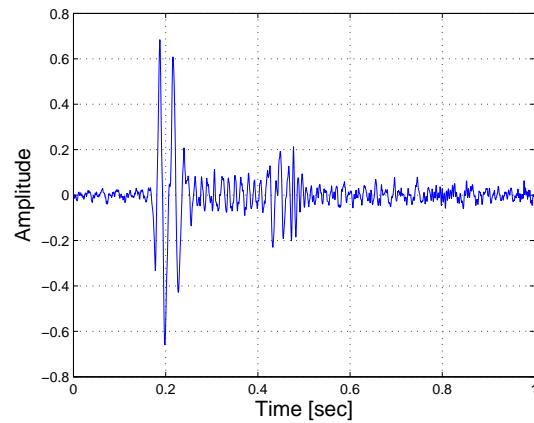
Figure 4.4: Bandpass filtered signal
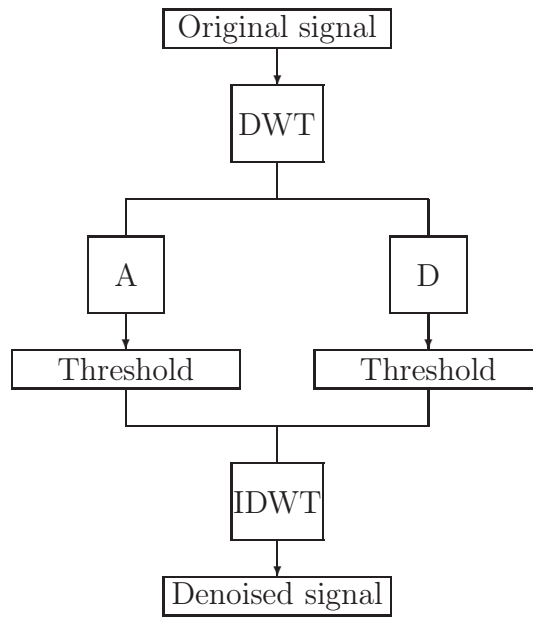
Figure 4.5: Flowdiagram of wavelet threshold denoising technique

4.1.1 Wavelet threshold denoising

After the signals were bandpass filtered, the signal were denoised with the wavelet threshold denoising method. The wavelet threshold denoising technique is a relatively simple and effective technique for denoising data. It has been used by de Vos [18] and Messer *et al.* [24] in denoising phonocardiograms. When using the wavelet threshold technique, the wavelet is first broken down to a specified level by the discrete wavelet transform. The threshold is then applied to the approximation and detail coefficients. The signal is reconstructed by the Inverse Discrete Wavelet Transform (IDWT) and the denoised signal is produced. The process is described figuratively in Figure 4.5.

Two types of thresholding techniques exist, hard thresholding and soft thresholding. Hard thresholding is defined as (x being the signal value, T being the threshold value) [24]:

$$x = \begin{cases} x \text{ if } |x| > T \\ 0 \text{ if } |x| \leqslant T \end{cases} \tag{4.1.1}$$

and soft thresholding is defined as (x being the signal value, T being the threshold value) [24]:

$$x = \begin{cases} sign\,(x)\,(|x| - T) \text{ if } |x| > T \\ 0 \text{ if } |x| \leqslant T \end{cases} \tag{4.1.2}$$
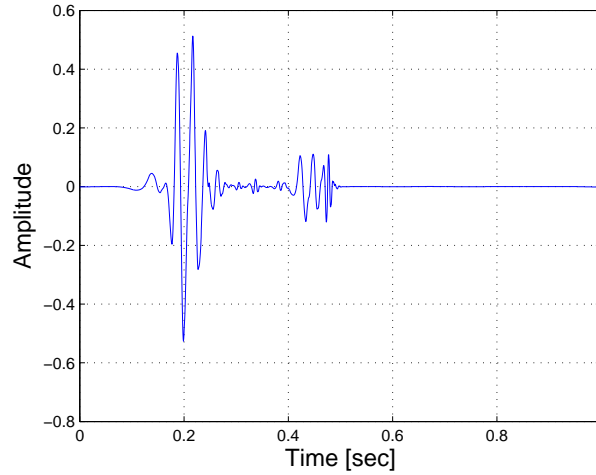
Figure 4.6: Wavelet threshold denoised signal

Coefficients of the DWT that lie below the threshold value are removed and the resulting coefficients are then reconstructed to constitute the denoised signal. This is a very powerful concept, because signals with energy concentrated in a small number of wavelet dimensions will have coefficients that are relatively large compared to any other signal present that has its energy concentrated over a larger number of wavelet dimensions [22]. Applying the thresholding operation to the DWT will, therefore, effectively remove any unwanted signal or noise, even if the instantaneous frequency spectra of the two signals overlap.

When using the threshold denoising technique, the following assumptions are made [54]:

1. The recorded signal is modelled as: $x(t) = o(t) + n(t)$ where $x(t)$ is the recorded signal, $o(t)$ is the original uncorrupted signal and $n(t)$ is the noise signal.

2. The energy of the original signal is effectively captured in a transform whose values lie above a specified threshold $T_s > 0$.

3. The transform values of the noise signal have magnitudes that lie below a specified threshold T_n that satisfy the following condition $T_n < T_s$.

The result of denoising by the wavelet threshold method for the signal shown in Figure 4.4 is shown in Figure 4.6. For the denoising of the recorded data, Stein's Unbiased Estimate of Risk (SURE) was used to calculate the threshold value. The calculated threshold value was multiplied by 0.3 to reduce the value, since the larger value resulted in some signals losing the first or second heart sound. In some instances this value was still a bit large and removed some murmur information as well, but setting this value lower resulted in more signals that were not denoised properly. It was thus decided to adhere to the selected threshold and apply that to every signal processed.
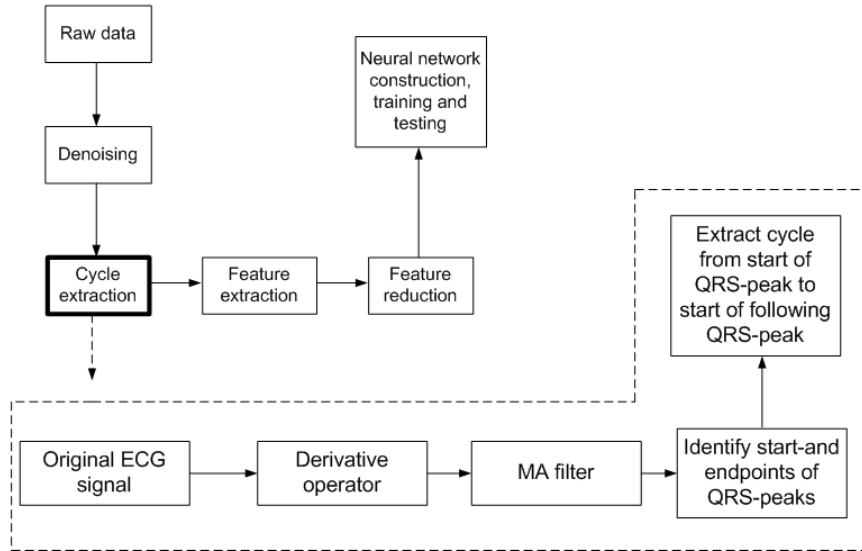
Figure 4.7: Cycle extraction flowdiagram

A second technique was used to calculate a threshold value. The standard deviation, σ, of the first-level detail coefficients was calculated. It is assumed that most of the noise is captured at this level, since it contains the high-frequency components. The threshold is then set to $T = 4\sigma$ as suggested in [54]. The larger of the the two calculated threshold values was chosen as the value to use in the denoising procedure.

4.1.2 Cycle extraction

After the recorded signals had been denoised, four cycles of heart sounds were extracted. This was done by identifying the QRS-peaks in the ECG recordings to identify the onset of a heartbeat cycle. The process is outlined in Figure 4.7. The detection algorithm used is based upon a weighted and squared first-derivative operator and a moving-average (MA) filter and is described by Rangayyan [11]. The first-derivative operator accentuates the areas of greatest change (the QRS-peaks) and attenuates the slow-varying components. The MA filter smooths the signal further to attenuate any small artifacts or noise that may still be present. The signal after applying the filtered-derivative operator is:

$$g_1(n) = \sum_{i=1}^{N} |x(n-i+1) - x(n-i)|^2 \, (N-i+1) \qquad (4.1.3)$$

where $x(n)$ is the ECG signal and N is the width of a window within which first-order differences are computed, squared and weighted by the factor $(N-i+1)$. Further smoothing of the result was performed by an MA filter over M points. The signal after application of the MA filter:

$$g(n) = \frac{1}{M} \sum_{j=0}^{M-1} g_1(n-j) \qquad (4.1.4)$$

The recorded ECG signals were resampled to $f_s = 100$ Hz, since this makes the calculation considerably faster. The window widths were set to $N = 1$ and $M = 5$. In Rangayyan [11] the window widths were set to $N = M = 8$. This, however, resulted in the QRS-peaks being smoothed to such a degree that the start of S_1 was calculated incorrectly by roughly 100 msec. The window widths were thus changed to avoid this. Figures 4.8, 4.9 and 4.10 show the original recorded ECG signal recorded by GeoAxon's ECG, the signal after the first-derivative operator and the signal after smoothing with the MA filter respectively.

After this procedure, the starting-points and end-points of the peaks were identified. All values below 15% of the maximum value in the signal were first set to zero in order to
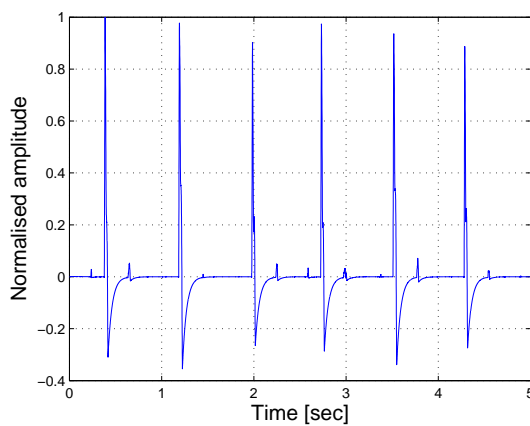
Figure 4.8: Original recorded ECG
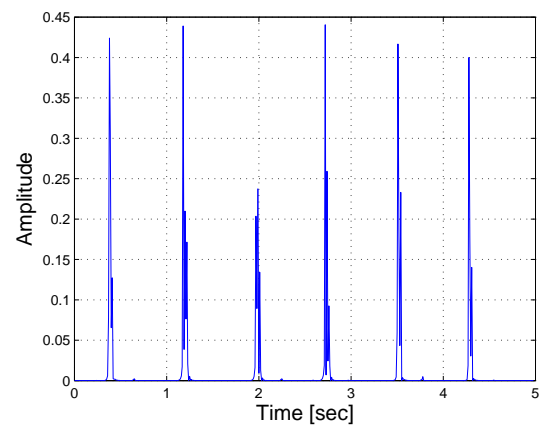
Figure 4.9: ECG signal after first-derivative operator applied
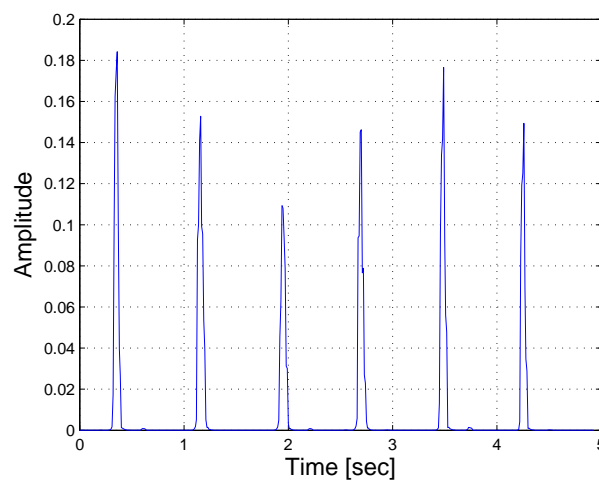
Figure 4.10: ECG signal after first-derivative operator and smoothing MA filter
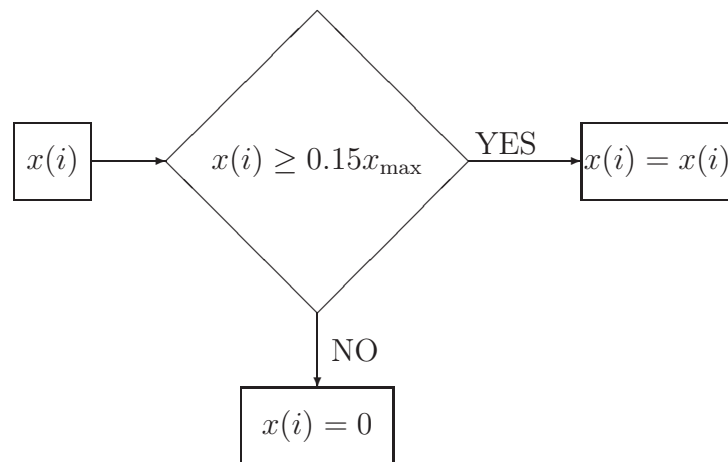
Figure 4.11: Algorithm to set all values below 15% of maximum value to zero

remove any artifacts in the signal. This algorithm is shown in Figure 4.11 where $x(i)$ is the function value and $x_{\max}$ is the maximum function value.

The algorithm to detect the starting-points and end-points of the QRS-peaks is explained in Figure 4.12. Here the vector $\overline{x}$ contains the indices of all the values of g (after the bottom
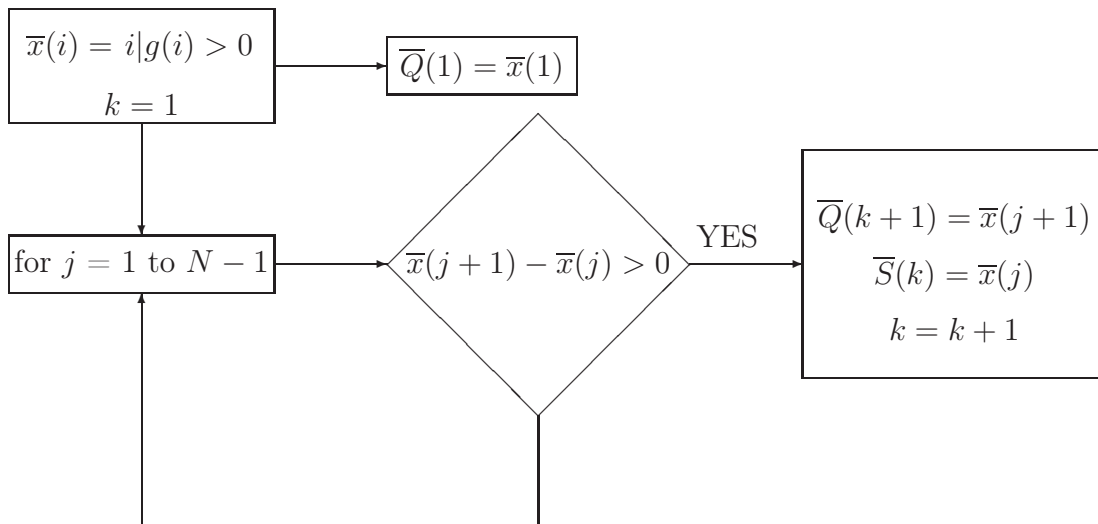
Figure 4.12: Algorithm to detect QRS starting-points and end-points

15% have been removed, refer equation 4.1.4) that are greater than zero. The vector $\overline{Q}$ contains the indices of the starting-points of the QRS-complex and the vector $\overline{S}$ contains the indices of the end-points of the QRS-complex. N is the length of the vector $\overline{x}$.

The indices of the starting-points and end-points of the QRS-peaks were identified. To extract four cycles of the recorded heart sounds, the indices had to be reworked to the sampling frequency $f_s = 2000$ Hz. This was done by equation 4.1.5.

$$S = \frac{2000 \times s}{100} \tag{4.1.5}$$

where s is the sample indices at $f_s = 100$ Hz and S is the sample indices at $f_s = 2000$ Hz. In cases where a patient suffers from atrial fibrillation or any other disease that results in an unstable heartbeat, the extracted heart cycle might not contain all the necessary information. In order to extract four cycles that contain information that is comparable to one another, the interval duration of a cycle was calculated and compared to the interval prior to that and the interval next to it. If these ratios fell within the range, $0.85 \leq Interval \leq 1.15$, the centre cycle was extracted. If none of the heart cycles fell within that ratio, 4 cycles were simply extracted from the first QRS-peak to the fourth QRS-peak.

4.2 Feature extraction

It was decided to follow a more physiological process during the feature extraction process. This implies that the features extracted are features that a physician would listen to when auscultating the heart. It was then attempted to describe these features in a mathematical manner so that they might be used in the classification process. The feature extraction process is described schematically in Figure 4.13.

4.2.1 Ratio of power between S_1 and S_2

The power ratio of S_1 to S_2 as a feature was decided upon, since this indicates where S_1 or S_2 is the loudest. The second heart sound should be loudest at the 2nd intercostal space near the base of the heart and the first heart sound at the fifth intercostal space near the apex of the heart. This is a result of the sound of the closing valves radiating through the thorax. Refer to Figure 2.4 and Section 2.4 for an explanation. If S_1 increased in intensity (louder than S_2 at the base), it might indicate the following [55]:

- Anaemia, pregnancy, anxiety, fever and hyperthyroidism, which in turn result in increased contractility and myocardial tension development.

- Mitral stenosis: S_1 may be louder due to mitral valve leaflet thickening and scarring.
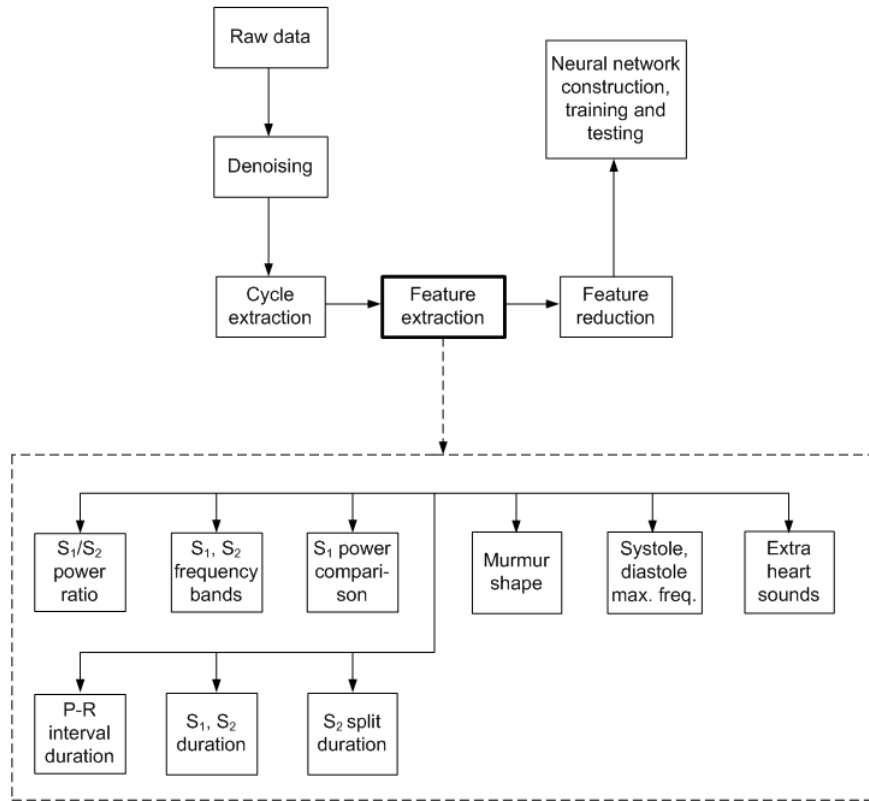
Figure 4.13: Feature extraction process

- The opening of mitral valve at the onset of ventricular contraction. This occurs when there is a short P-R interval in the ECG (between 0.11-0.13 seconds).

If S_1 is decreased in intensity (S_2 louder than S_1 at the apex) it may indicate the following:

- Impaired ventricular contractility, which means a decrease in myocardial tension development, that could indicate congestive heart failure.

- Severe mitral stenosis, which results in complete mitral valve immobility.

- The mitral valve is nearly closed at the onset of ventricular contraction. This results in a prolonged P-R interval (> 0.2 seconds).

To calculate the power ratio, the first and second heart sounds had to be extracted first. The extraction of S_1 and S_2 was based on the timing relationships of the heart sounds to the ECG. The extraction process is shown schematically in Figure 4.14.

The start of the first heart sound can be taken as the start of the QRS-complex in the ECG [11]. Refer to Appendix A for an explanation of the constituent parts of the ECG. The QRS-complexes have been identified as explained in Section 4.1.2. It was decided to use the power ratios of three consecutive cycles and calculate the average power ratio between
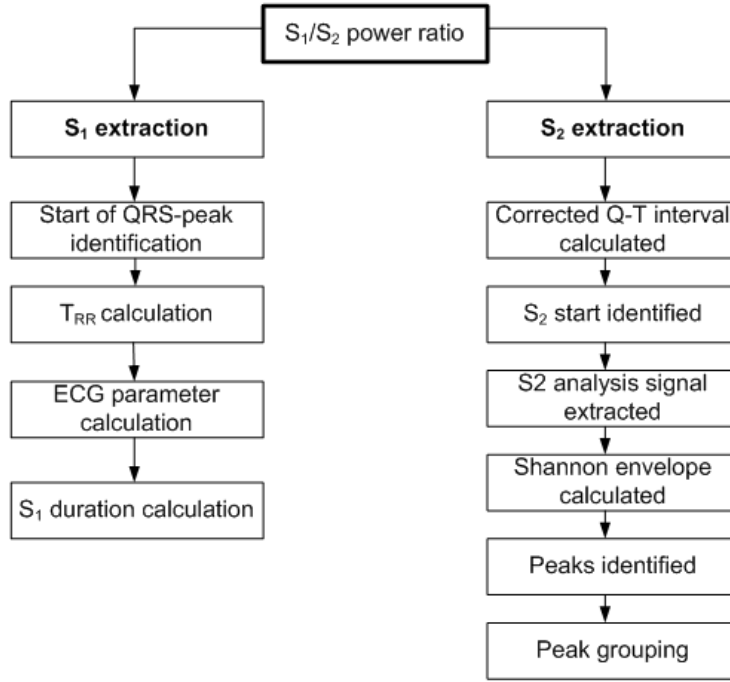
Figure 4.14: Procedure followed to extract S_1 and S_2

S_1 and S_2 at the apex and the base of the heart. This was done to ensure that the ratio calculated is representative of the actual beating of the heart. The start of S_1 can be related to the QRS-complex by keeping in mind that ventricular contraction forces blood upwards, which, in turn, closes the mitral and tricuspid valves (resulting in the main component of the S_1 sound). The end of S_1 cannot be attributed to any specific event in the ECG. We know that the start of the T-wave corresponds to ventricular repolarisation [10], which means that the ventricles relax and cause the aortic and pulmonary valves to shut, thereby causing S_2. The end of S_1 thus has to occur prior to that. It was decided to calculate the end of S_1 as:

$$S_{1 \text{ end}} = QRS_{\text{start}} + 1.5 \times T_{\text{S-T segment}} \tag{4.2.1}$$

This ensures that enough of the information contained in S_1 is extracted without containing a portion of S_2.

Burke and Nasor [56] developed second-order equations to calculate the time relationships of the different components of the human electrocardiogram. The equations developed for the different sections of the ECG (refer Appendix A) are (all times are in seconds):

$$T_{\text{P-wave}} = 0.57T_{\text{R-R}}^{1/2} - 0.33T_{\text{R-R}} - 0.14 \tag{4.2.2}$$

$$T_{\text{P-Q segment}} = 0.56T_{\text{R-R}}^{1/2} - 0.33T_{\text{R-R}} - 0.17 \tag{4.2.3}$$
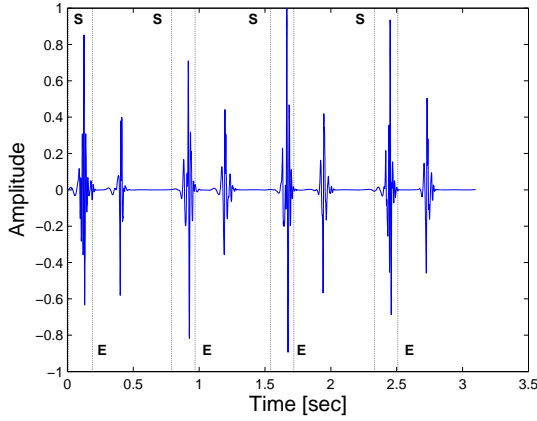
Figure 4.15: Identified S_1's for a patient with a normal heart
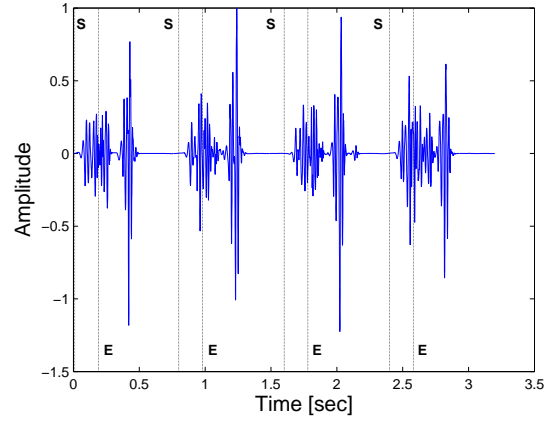
Figure 4.16: Identified S_1's for a patient with an abnormal heart

$$T_{\text{P-Q interval}} = 1.12 T_{\text{R-R}}^{1/2} - 0.65 T_{\text{R-R}} - 0.31 \tag{4.2.4}$$

$$T_{\text{QRS}} = -0.02 T_{\text{R-R}}^{1/2} + 0.02 T_{\text{R-R}} + 0.08 \tag{4.2.5}$$

$$T_{\text{Q-T interval}} = 1.65 T_{\text{R-R}}^{1/2} - 0.84 T_{\text{R-R}} - 0.46 \tag{4.2.6}$$

$$T_{\text{T-wave}} = 1.29 T_{\text{R-R}}^{1/2} - 0.66 T_{\text{R-R}} - 0.42 \tag{4.2.7}$$

$$T_{\text{S-T segment}} = 0.34 T_{\text{R-R}}^{1/2} - 0.17 T_{\text{R-R}} - 0.10 \tag{4.2.8}$$

This approach proved to be very uncomplicated and efficient in extracting the first heart sound. The start and end of S_1 are shown in Figure 4.15 (for a normal heart sound) and in Figure 4.16 for an abnormal heart sound, where **S** denotes the start of S_1 and **E** denotes the end of S_1. The corresponding extracted first heart sounds are shown in Figures 4.17 and 4.18 respectively.

For the extraction of the second heart sound, the procedure was not as straightforward. The start of S_2 was taken as the end of the T-wave in the ECG. The end of the T-wave can be taken as the start of S_2 since this is when the ventricles start to relax and the pressure in the ventricles drop [11]. This action causes the aortic and pulmonary valves to shut, since the pressure in the aorta and the pulmonary artery is higher than the pressure in the ventricles. In calculating the end of the T-wave, the start of the QRS-complex was identified and the duration of the Q-T interval was added. The corrected Q-T interval, Q-Tc, was used in the calculation. This is equal to the Q-T interval divided by the square root of the
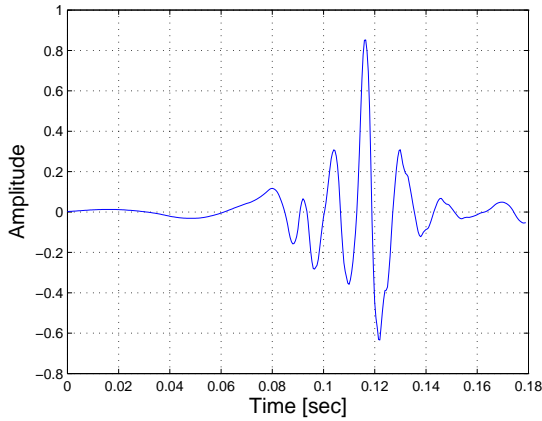
Figure 4.17: Extracted S_1 for a patient with a normal heart
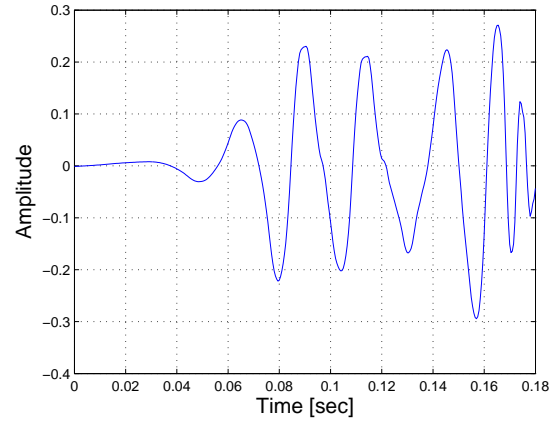
Figure 4.18: Extracted S_1 for a patient with an abnormal heart

R-R interval, according to Bazett's formula [57]:

$$T_{\text{Q - T}_c} = \frac{T_{\text{Q - T interval}}}{\sqrt{T_{\text{R - R}}}} \tag{4.2.9}$$

After the start of S_2 had been identified, 300 ms of the recorded heart signal were extracted from 40 ms prior to the calculated start of S_2. This was deemed sufficient to capture the second heart sound as well as a bit extra of diastole, since the average duration of S_2 is about 150-200 ms. The reason for starting 40 ms prior to the identified start was to compensate for the error in the calculation of the end of the T-wave, as well as to accommodate fluctuations in the heartbeat of patients. The starting-points of S_2 for an abnormal patient are indicated in Figure 4.19 and Figure 4.20 shows the 300 ms of signal extracted from 40 ms prior to the identified start of S_2. As can be seen in Figure 4.20, S_2 as well as a diastolic murmur, is present in the extracted portion of the signal. It must be attempted not to identify murmurs as S_2 falsely.

The end of the second heart sound cannot be attributed to any specific event in the ECG. Thus a different approach was needed. To do this, it was decided to calculate an energy envelope of the extracted signal to determine where the majority of the energy is situated, since this would most likely correspond with the second heart sound. The Shannon energy was used to calculate the envelope, since it intensifies the medium intensity signals and attenuates the effect of low intensity signals much more than that of high intensity signals [58]. This aspect makes it much easier to extract medium intensity signals (such as heart sounds embedded in noise) from the recordings. Liang *et al.* [58] showed that the Shannon energy performed the best in comparison to other techniques such as the Shannon entropy, absolute value and normal energy (taking the square of the function values) in obtaining a decent envelope of the recorded heart sound. The Shannon energy envelopes of

the extracted signals for an abnormal patient are shown in Figure 4.21. The bottom 25% of the envelope values were discarded to eliminate small noise that might interfere in the extraction process.

Due to the possibility of noise, it was decided to identify the peaks in the Shannon energy envelope and group the peaks together. If two peaks were less than 40 ms apart, it was assumed that they formed part of the same group. If not, they were put into separate groups. The energy of the different groups were then calculated and the group with the highest energy was extracted as S_2. This assumption proved to be sufficient in extracting the correct group as S_2. Figure 4.22 shows the identified peaks for a patient with an abnormal heart and the corresponding identified groups. It can be seen that each component identified in Figure 4.20 forms its own separate group (with the murmur forming two groups).

The energy of the different groups were calculated by:

$$E_{\text{group}} = \sum_{i=1}^{N} x(i)^2 \tag{4.2.10}$$

where $x(i)$ is the amplitude of a specific peak i, and N is the number of peaks in a specific group. The energy values for S_2, the murmur (M_1 and M_2) and S_1 are shown in Table 4.1. Figure 4.23 shows the extracted second heart sound.

Now that both S_1 and S_2 had been extracted for three heart cycles at each location and in each recording position, the power ratio between S_1 and S_2 could be calculated. The power of each of the extracted heart sounds was calculated by calculating the energy and
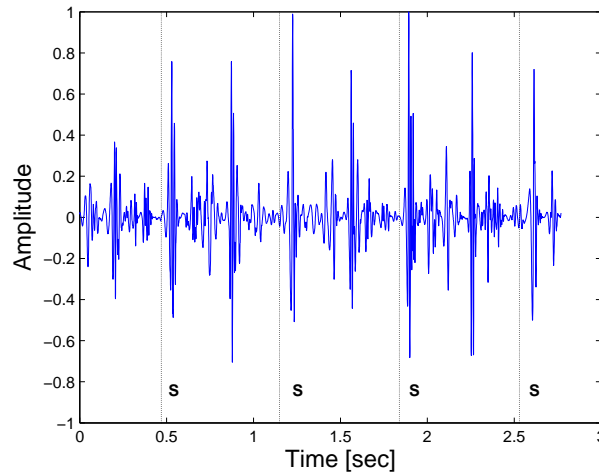
Figure 4.19: Start of S_2 identified for a patient with an abnormal heart
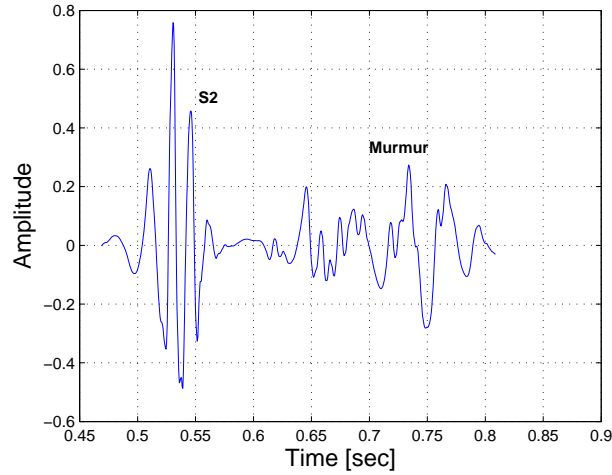
Figure 4.20: Extracted portion of signal for S_2 extraction

dividing it by the duration of the extracted sound as in equation 4.2.11:

$$P_{\text{heart sound}} = \frac{\sum_{t=0}^{N} x(t)^2}{t_{\text{total}}} \qquad (4.2.11)$$

where $x(t)$ is the heart sound amplitude at a specific time instant t, t_{total} is the duration of the heart sound and N is the length of the signal. This calculation was performed for each extracted sound at a specific location. The average power of the three extracted sounds was calculated and used as the feature. The heart sounds recorded at the 2nd left and right intercostal spaces and 5th and 6th left intercostal spaces were used in this calculation, since S_2 should be the loudest at the base of the heart (2nd left and right intercostal spaces) and S_1 should be the loudest at the apex of the heart (5th & 6th left intercostal spaces). The
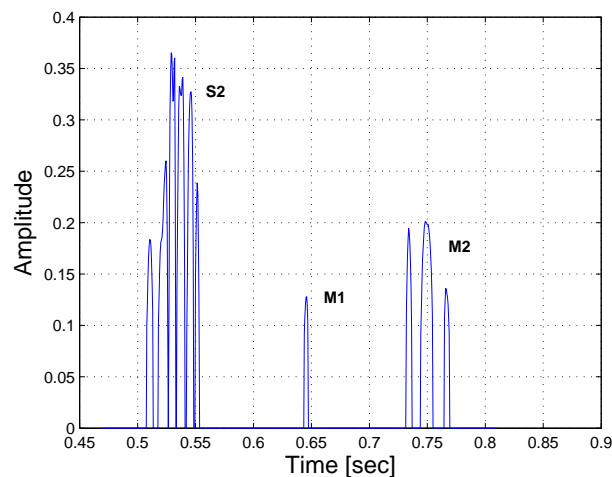
Figure 4.21: Shannon energy envelope of a patient with an abnormal heart
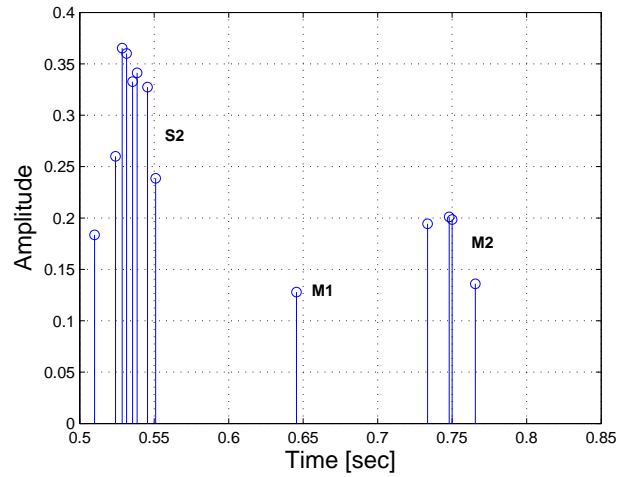
Figure 4.22: Identified peaks in the Shannon energy envelope of a patient with an abnormal heart

Energy value	
S_2	0.76
M_1	0.02
M_2	0.12

Table 4.1: Energy values of different components in extracted second heart sound signal
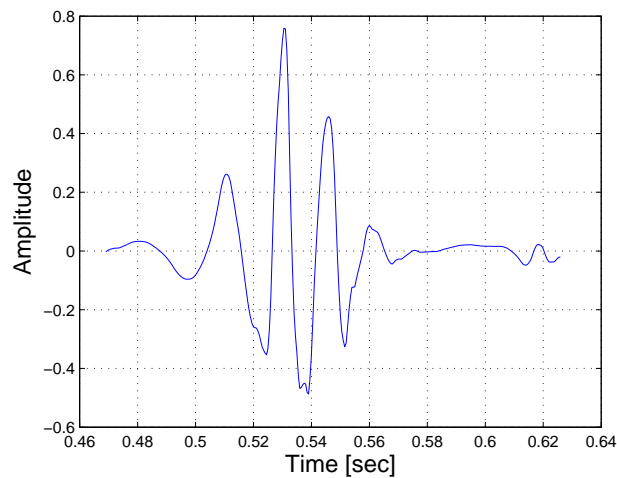
Figure 4.23: Extracted second heart sound for an abnormal patient

power ratio thus contributed to a total of four features used in the classification process.

Other studies that have also successfully identified the different heart sounds in the phonocardiogram have been published . Liang *et al.* [58] obtained 93% correct identifcation ratio in splitting the heart cycle into S_1, systole, S_2 and diastole. The algorithm was based on the normalised average Shannon energy of the phonocardiogram signal. The correct S_1's

and S_2's were identified by a cardiologist and then compared to the heart sounds extracted by the algorithm. Haghighi-Mood *et al.* [59] segmented the heart sound by using an auto-regressive (AR) model to estimate the power spectral density of the signal and calculate the energy in specific frames of the signal. The authors did not obtain statistical results in quantifying the validity of their algorithm. Huiying *et al.* [8] developed an algorithm for detecting S_1, systole, S_2 and diastole from the phonocardiogram signal. The discrete wavelet transform was used to calculate intensity enevelopes of the signals and identify components within the envelope. A correct identification ratio of 93 % was obtained. The correct locations of S_1 and S_2 were identified by a cardiologist and the result was then compared to the S_1's and S_2's extracted by the algorithm. The algorithm developed in this study have not yet been assessed by a cardiologist, but preliminary results show that the algorithm extracts S_1 and S_2 correctly in approximately 90% of the cases. This was determined by visual inspection.

4.2.2 Frequency band ratio of S_1 and S_2

It was deemed necessary to extract the frequency information from S_1 and S_2 as well, since S_2 is normally higher pitched (higher frequency) than S_1 [55] and a noticeable deviation from this could indicate pathology. Johnson *et al.* [60] extracted frequency bands in their study of the systolic murmur of aortic stenosis. It was decided to follow the same approach in this study, as this would identify heart sounds that have higher frequency content than normal.

The FFT of each extracted S_1 and S_2 was calculated. The magnitudes of the Fourier coefficients in the frequency range between 0-100 Hz as well as between 100-800 Hz were summed. These two values were then divided to yield a ratio that describes the frequency content of the extracted signal as in equation 4.2.12.

$$F_{\text{ratio}} = \frac{\sum_{f=0}^{100} C}{\sum_{f=100}^{800} C} \qquad (4.2.12)$$

where C indicates the Fourier coefficient magnitude at a specific frequency f. The higher this value, the more normal the extracted heart sound should be, since normal heart sounds should not contain frequencies higher than about 100 Hz. Should this ratio be low, it should indicate that higher than normal frequencies are present and could be an indication of a murmur. Figure 4.24 shows the FFT of S_1 for a normal and an abnormal patient and Figure 4.25 shows the FFT of S_2 for a normal and an abnormal patient.
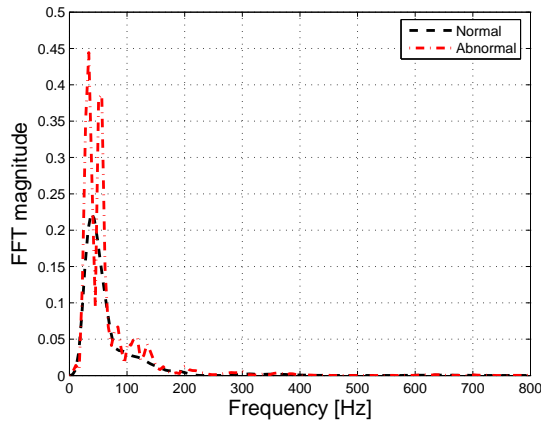
Figure 4.24: FFT of S_1 for a normal and an abnormal patient
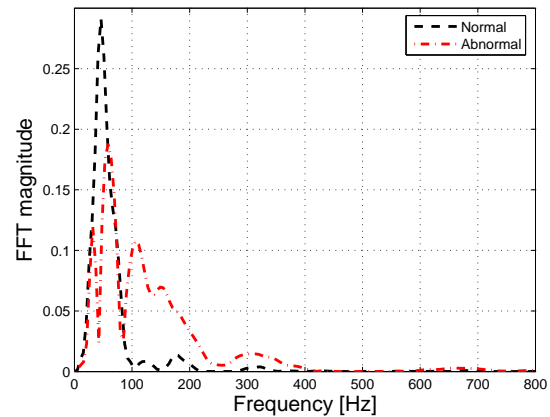
Figure 4.25: FFT of S_2 for a normal and an abnormal patient

4.2.3 Power comparison between first heart sounds of different cycles

Variation in the intensity of S_1 from beat-to-beat is also an indication of abnormality [55]. S_1 varies from beat-to-beat when the position of the mitral and tricuspid valves is variable at the onset of ventricular contraction. This occurs in patients with atrial fibrillation[1], third degree heart block [2] and ventricular pacemakers [55]. No fixed relationship exists between atrial excitation and ventricular contraction. The position of the mitral and tricuspid valves at the beginning of ventricular systole varies, sometimes being partially shut and at other times being completely open, resulting in a variation in the intensity of S_1.

The power of S_1 was calculated for the phonocardiograms, as explained in Section 4.2.1. The ratios between the first heart sounds of the different cycles were calculated and the average of the three ratios was taken to yield the feature used in the classification process. The recordings at the 5th and 6th intercostal spaces were used in the calculation, since this is where S_1 should be heard most clearly (refer Section 2.4).

Figure 4.26 shows 4 cycles of a patient with the first heart sounds indicated. It can be seen that the amplitude of the different S_1's differ from beat-to-beat. Figure 4.27 shows the recorded ECG of the patient. Lead V_1 shows the characteristic "ripples" that are present during atrial fibrillation. This patient suffers from severe mitral stenosis, as was confirmed by an echocardiogram, which causes atrial fibrillation [12]. The ratios were calculated as $\frac{Cycle2}{Cycle1}$, $\frac{Cycle3}{Cycle2}$ and $\frac{Cycle3}{Cycle1}$. The average of these three values was calculated for the recordings

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[1]Atrial fibrillation occurs when the atria are not depolarised in a rhythmic manner. Multiple electrical impulses spread across the atria causing the atria to contract at random rates and in effect "flutter" [61].

[2]Third degree heart block, also known as complete heartblock, is when the electrical impulse that activates atrial and ventricular contraction does not pass through the AV node. This leads to the ventricles not necessarily contracting after the atria but at their own rhythm. The QRS-complex of the ECG thus does not necessarily follow the P-wave [62].
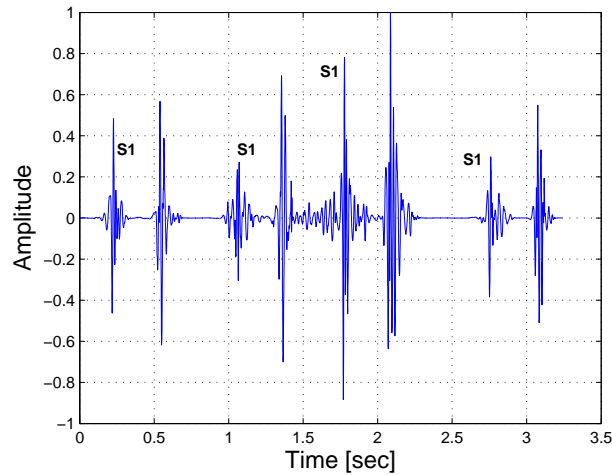
Figure 4.26: Three heart cycles of abnormal patient to illustrate S_1 beat-to-beat variation
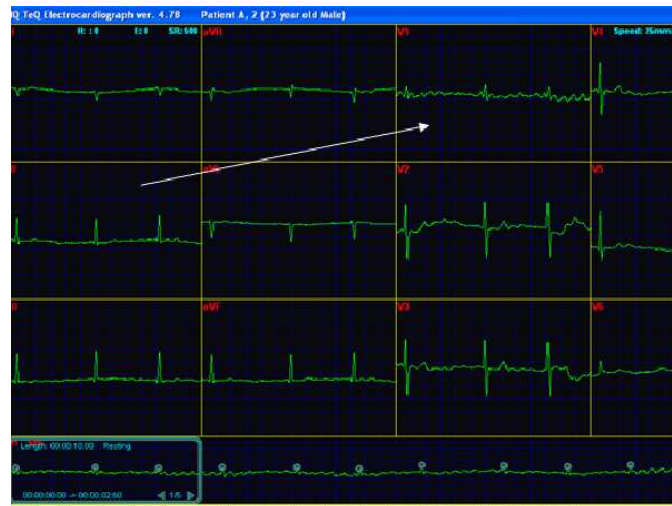
Figure 4.27: ECG of patient that suffers from atrial fibrillation (see lead V_1)

at the 5th and 6th intercostal spaces as features.

4.2.4 Duration of P-R interval of electrocardiogram

Another way of determining whether S_1 is increased or decreased in intensity, is by calculating the P-R interval of the electrocardiogram. The P-R interval is defined as the period from the start of the P-wave to the start of the QRS-complex in the human electrocardiogram. That is, from the onset of the atrial depolarization to the onset of ventricular depolarization [63]. The impulse originates from the SA node, spreads across the atria, reaches the AV node, moves down the interventricular septum into the Purkinje fibres, resulting in contraction of the ventricles. Refer to Appendix A for a detailed explanation of the electrical conduction system of the human heart and the human electrocardiogram.

Abnormal patient	P-R interval [sec]	Normal patient	P-R interval [sec]
1	0.14	1	0.16
2	0.15	2	0.15
3	0.15	3	0.15
4	0.15	4	0.17
5	0.14	5	0.16
6	0.15	6	0.17
7	0.16	7	0.16
8	0.14	8	0.16
9	0.15	9	0.17
10	0.15	10	0.15

Table 4.2: Calculate P-R intervals for normal and abnormal patients

The normal duration for the P-R interval is between 0.12 and 0.20 seconds. According to Werener *et al.* [55] a short P-R interval (0.11-0.13 seconds) is indicative of an increase in intensity of S_1. A loud S_1 is produced when the mitral valve is wide open at the onset of ventricular contraction resulting in a "louder" sound when the increase in ventricular pressure closes the mitral valve. This is a logical consequence of the mitral valve having less time to close due to the quicker onset of ventricular contraction. An increase in the P-R interval (> 0.2 seconds) results in a decrease in the intensity of S_1, as this implies that the mitral valve is almost closed at the onset of ventricular contraction, resulting in a "softer" sound [55]. The mitral valve has more time to close due to the delayed onset of ventricular contraction.

The P-R interval (in seconds) was calculated by the equation presented in [56]:

$$T_{\text{P-R interval}} = 0.30 T_{\text{R-R}}^{1/2} - 0.12 T_{\text{R-R}} - 0.02 \tag{4.2.13}$$

The values were calculated for recording position 1 (patient supine breathing normally) and the values for the normal and abnormal patients are shown in Table 4.2. The values are only shown for 10 patients of the normal and abnormal group respectively.

4.2.5 Duration of S_1 and S_2

The next feature that was extracted was the duration of S_1 and S_2. S_1 is normally of longer duration than S_2 [55] and any deviation to this could indicate pathology.

4.2.6 Duration of S_2 split

It was decided to extract the duration of the split of S_2 as a feature to be used in the classification process. The duration of the split of S_2 is indicative of some pathologies, as

explained in Section 3.3. The problem was how to identify the two components of S_2 and measure the time difference between them. Debbal *et al.* [25] investigated the differences between the components of the second heart sound of a normal heart, a patient that suffers from *aortic-coarctation* and a patient that suffers from *mitral stenosis*. The aortic and pulmonary components were identified by using the continuous wavelet transform (CWT), but no automatic identification algorithm was presented in the study.

It was decided to identify the aortic and pulmonary components by also using the CWT, but to add a degree of automaticity to the algorithm. When calculating the CWT of a signal, a set of coefficients that indicate the degree of comparison of the signal to the analysing wavelet at a specific scale and at a specific instant in time are generated. By taking the absolute values of these coefficients, a "comparison envelope" is obtained. This indicates where in frequency and time the major components of the analysed signal is situated. The higher in value the coefficient, the higher the degree of comparison at that specific scale and time instant.

The CWT of the extracted second heart sounds (refer Section 4.2.1) was calculated and the absolute values taken to obtain the envelope. The Daubechies wavelet of order 7 (*db*7) was used and the scales at which the CWT was calculated, were from 5 to 100. This corresponded to pseudo-frequencies between 14 and 277 Hz. It was assumed that the two highest peaks corresponded to A_2 and P_2, as was done in [25]. To obtain the time difference between the two components, the highest peak was first identified. It was then stepped through the entire data set to identify the second highest peak. The maximum points were identified and subsequently set to zero until two maxima differed by 10 msec or more. This maxima was then identified as the second peak. The absolute value of the time difference between the two components was then taken as the time difference between A_2 and P_2. According to Werner *et al.* [55], A_2 and P_2 differ by 10-20 msec during expiration and 40-50 msec during inspiration during normal conditions. The 10 msec time difference ensured that the two peaks were identified during inspiration as well as expiration. Figure 4.28 shows the "comparison envelope" as viewed from the top (a contour plot), with the two peaks identified (the X's) for an abnormal patient. The timing difference between these peaks was calculated as 12.5 msec.

4.2.7 Determining the shape of systolic and diastolic murmurs

Murmurs can either be classified as *systolic murmurs* or *diastolic murmurs*, depending on where in the cardiac cycle the murmur occurs. Depending on which pathology causes the murmur, the shape of the murmur may vary. For instance, the intensity of the murmur might increase from its origin (crescendo murmur) or decrease from its origin (decrescendo murmur) or it may be a combination of the two. The intensity of the murmur may also stay
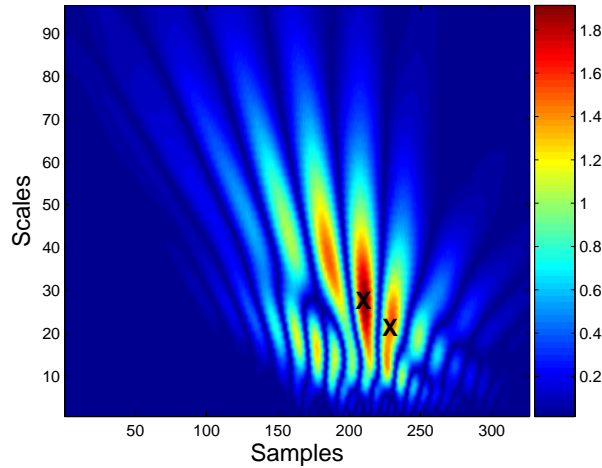
Figure 4.28: CWT coefficients with peaks indicated that correspond to $A2$ and $P2$ of the second heart sound
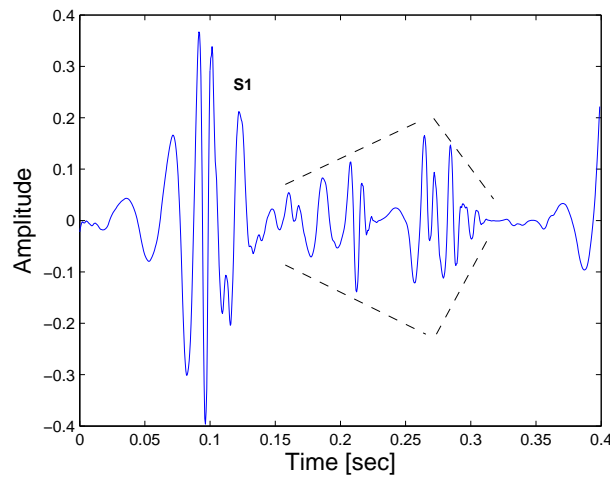
Figure 4.29: Ejection systolic murmur of a patient suffering from aortic stenosis, showing the crescendo-decrescendo nature of the murmur

constant for the duration of the murmur.

Systolic murmurs can be divided into *ejection systolic murmurs*, *pansystolic murmurs* and *late systolic murmurs*. **Ejection systolic murmurs** occur due to turbulent bloodflow through stenotic aortic and pulmonary valves. The murmur increases to a crescendo at more or less the middle of systole and then decreases (decrescendo) and ends just before the start of S_2. Pathologies that exhibit such murmurs are *aortic stenosis*, *pulmonary stenosis* and *atrial septal defect*. Figure 4.29 shows the recording of a patient that suffers from moderate aortic stenosis. The crescendo-decrescendo shape of the murmur can clearly be seen as indicated by the dashed lines.

Pansystolic murmurs are murmurs that extend throughout systole. The murmurs
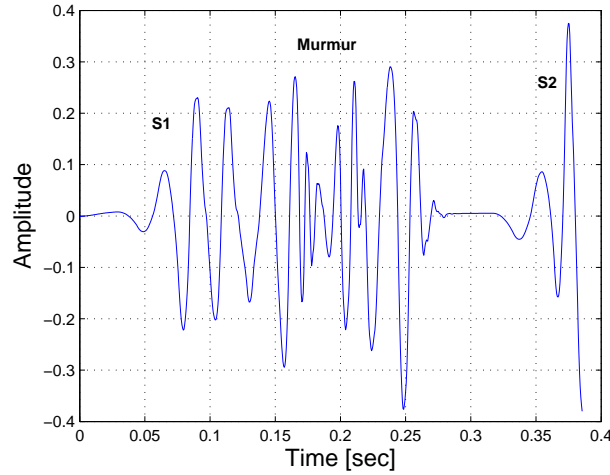
Figure 4.30: Pansystolic murmur of a patient suffering from mitral regurgitation

have a slight accentuation in mid-systole, but the ejection systolic murmur is more pronounced. This type of murmur is caused by blood leaking through a valve that is not closed properly during ventricular contraction, such as in *mitral regurgitation* or *tricuspid regurgitation*. It may sometimes occur in patients that suffer from *ventricular septal defect* in which the hole between the left and right ventricles is relatively small. The murmur starts simultaneously with S_1 and extends throughout systole and may even obscure a bit of S_2 [12]. Figure 4.30 shows the recording of a patient that suffers from mitral regurgitation. The pansystolic nature of the murmur can clearly be seen. It obscures S_1, extends throughout systole and ends just before S_2.

To calculate the shape of the murmur it was decided to extract the systole and diastole portions from the heart cycle, break them up into three sections and calculate the root-mean-square value (rms-value) of each. The rms-value of a function is defined as [64]:

$$RMS(f) = \sqrt{\frac{\int_a^b f^2(x)dx}{b-a}} \tag{4.2.14}$$

By calculating three values, one can draw a line which shows whether the murmur is either increasing (crescendo), decreasing (decrescendo), a combination of the two (crescendo-decrescendo), or if it stays constant throughout systole or diastole. Figure 4.31 shows the extracted systole component from the cardiac cycle of a patient. Three sections are indicated and it can easily be seen that the murmur is of a decrescendo nature. The calculated rms-values are presented in Table 4.3. From the values in Table 4.3 it can be seen that the murmur is of a decrescendo nature, since the line that is plotted through the three values has a negative gradient.

This process was repeated for each of the three extracted cardiac cycles of both systole
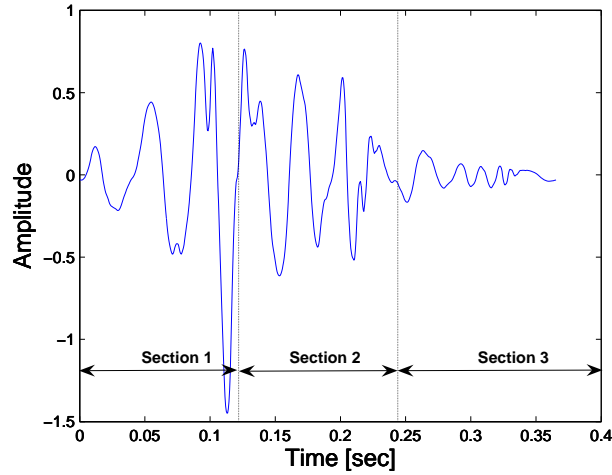
Figure 4.31: Systole extracted from the cardiac cycle showing three sections for which rms-value are calculated to determine shape of murmur

Section	rms-value
Section 1	0.46
Section 2	0.33
Section 3	0.07

Table 4.3: RMS-values of different sections of systole of an abnormal patient

and diastole. The recordings used in the calculations were the recordings at the 2nd left and right intercostal spaces and the recordings at the 5th and 6th left intercostal spaces. It was thought necessary to use the recordings, since some murmurs are heard at one location, but not at another. Since three values for each section of either systole or diastole of a recording were obtained (due to the tree cycles that were extracted), it was decided to take the average of the three calculated values to use as a feature. This was done in order to reduce the number of features used, as well as to obtain an overview of the nature of the murmur under consideration. The average was simply calculated by taking the sum of the three values and dividing the total by three. This process resulted in a total of 24 features being generated; 12 of them from the systole part of the cardiac cycle and 12 of the diastole part of the cardiac cycle.

4.2.8   Calculating maximum frequency in different sections of systole and diastole

The maximum frequency in each section of systole and diastole was calculated. The FFT of each extracted section was calculated and the frequency with the maximum amplitude was identified and extracted. This was done for all three extracted cycles of the recorded
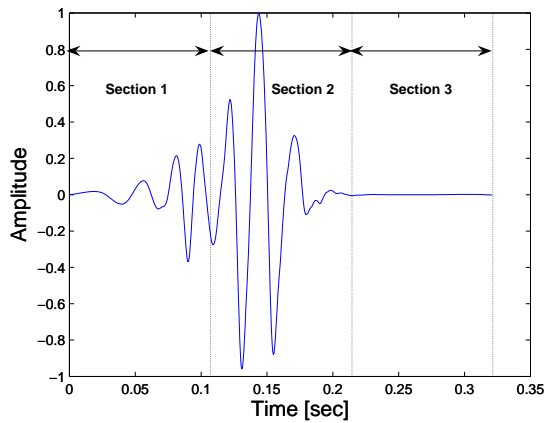
Figure 4.32: Systole extracted from normal patient with subsections indicated
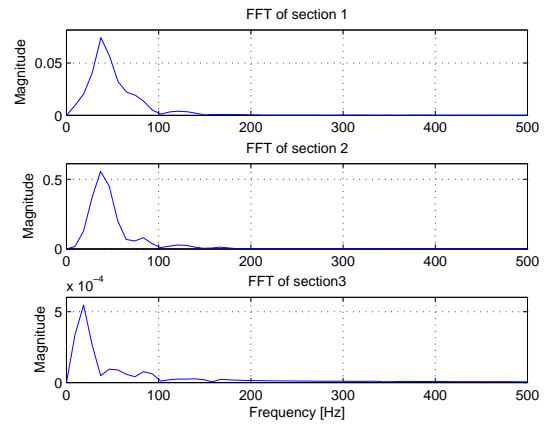
Figure 4.33: FFT of each subsection in systolic region of cardiac cycle for a normal patient

phonocardiogram.
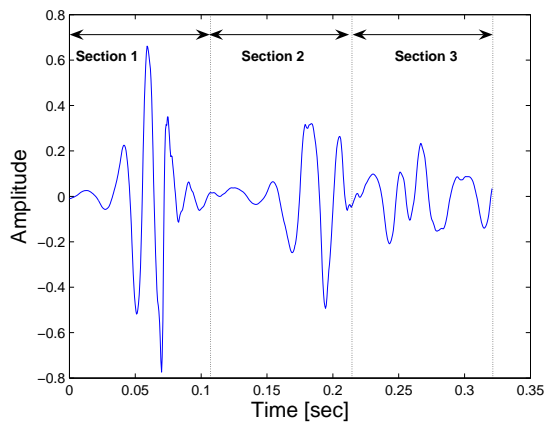
Figure 4.34: Diastole extracted from abnormal patient with subsections indicated
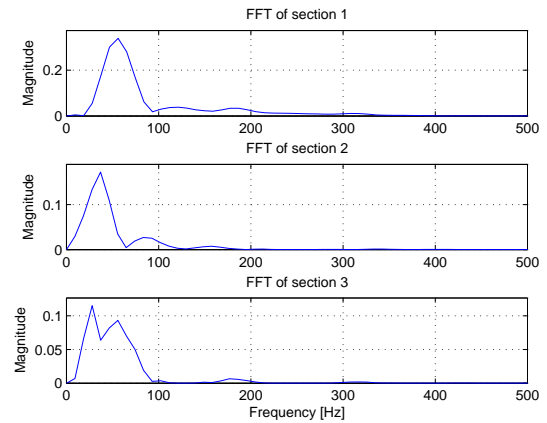
Figure 4.35: FFT of each subsection in diastolic region of cardiac cycle for an abnormal patient

The recordings used for the calculations were the recordings at the 2nd left and right intercostal spaces, the 4th left and right intercostal spaces and the 5th left intercostal space. Figure 4.32 shows the extracted systolic portion of the cardiac cycle of a patient with no abnormalities, with the different sections into which it was subdivided, indicated. Figure 4.33 shows the FFT of each subsection. Figure 4.34 shows the diastolic portion of the cardiac cycle of a patient that suffers from aortic regurgitation, with the different sections indicated. Figure 4.35 shows the FFT of each different subsection.

4.2.9 Identifying extra sounds: ejection sound, midsystolic click and opening snap

When auscultating the heart, extra sounds that should not be present during normal functioning of the human heart may occur. These sounds include the *ejection sound, midsystolic click* and the *opening snap.*

Extra heart sounds can be attributed to specific events in the cardiac cycle and therefore occur at specific times during the cardiac cycle. **Ejection sounds** are high-pitched sounds that follow S_1 by 0.04-0.06 seconds [55] and can be attributed to abnormalities of the aortic and pulmonary valves [12]. Ejection sounds associated with the aortic valve are primarily due to congenitally bicuspid aortic valves or congenital aortic stenosis, and are principally due to the opening of the abnormal valves [12]. Ejection sounds due to abnormal pulmonary valves are most commonly due to pulmonary stenosis, but can also be heard in patients with idiopathic dilatation [3] of the pulmonary artery, or with pulmonary artery dilatation caused by pulmonary hypertension [12].

Midsystolic clicks are extra heart sounds that occur in midsystole. The most common cause of a midsystolic click is mitral valve prolapse, where one of the mitral valve leaflets moves into the left atrium during systole causing an extra sound. This is caused by elongation or rupture of the chordae tendinae (muscles that hold the valve in place) [12].

Opening snaps are high-pithced sounds which occur in patients who suffer from mitral stenosis. The hardened (stenosed) valve moves forward towards the left ventricle at the beginning of diastole as the pressure decreases, resulting in an extra sound prior to S_1 [12].

To check whether any of these extra sounds were present, it was argued that within the interval in which the sounds would occur, the power of the sections would be higher if these sounds were present than if they were not present. The systolic and diastolic regions of each cardiac cycle were identified and broken up into different sections, as shown in Figure 4.2.9, to search for these extra sounds. *ES* refers to the ejection sound, *MC* to the midsystolic click and *OS* to the opening snap. S_1s refers to the start of S_1 and S_1e to the end of S_1. The same numbering is applicable to S_2.

For the *ejection sound*, 0.06 seconds was extracted from the end of S_1. The power was calculated, as was done in Section 4.2.1, by using equation 4.2.11. For the *midsystolic click*, the portion of systole from $\frac{L_s}{4}$ to $\frac{3L_s}{4}$, with L_s being the length of systole, was extracted, and the power calculated by equation 4.2.11. The *opening snap* follows A_2 by 0.03-0.15 seconds [12]. To search for any opening snap sounds, 0.15 seconds were extracted from the end of S_2 and the power of the extracted section was calculated by equation 4.2.11. This was done for each of the three extracted cardiac cycles and the average of the three cycles was

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[3]Idiopathic dilatation of the pulmonary artery is an uncommon cause of a large main pulmonary artery. The reason for the enlargement of the artery is unknown. [65]
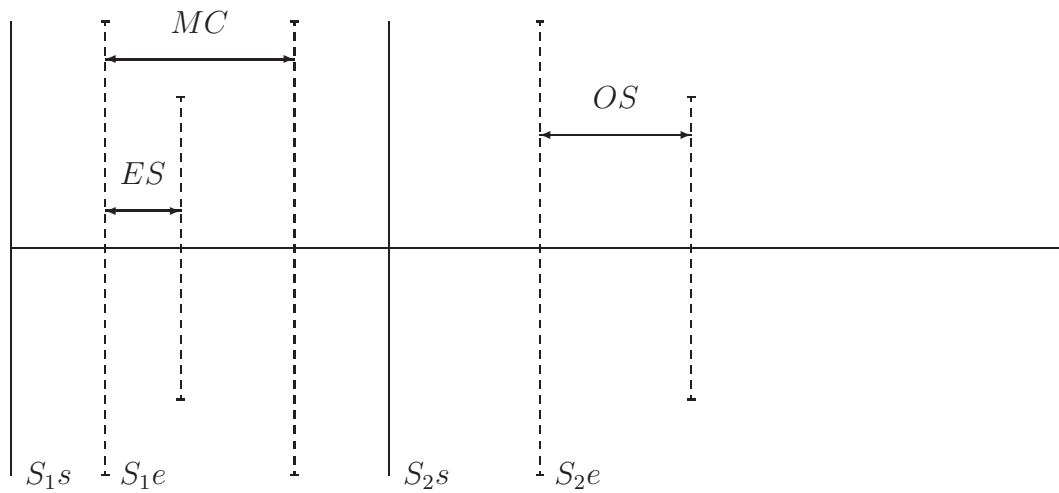
Figure 4.36: Splitting of heart cycle

Abnormal			
Patient	**ES power [1/sec]**	**MC power [1/sec]**	**OS power [1/sec]**
1	8.96	67.26	21.59
2	60.41	38.30	0.30
3	215.16	32.96	0.16
4	18.25	1.78	0.11
5	48.88	263.01	2.94

Table 4.4: Average power of different sections to search for extra heart sounds (Abnormal)

calculated. For the ejection sound calculations, the recording at the 2nd right intercostal space was used, for the midsystolic click, the recording at the 5th left intercostal space was used and for the opening snap, the recording at the 4th right intercostal space was used. Tables 4.4 and 4.5 show the calculated power of the different sections for abnormal and normal patients respectively. The values are shown only for five patients of each group. Figure 4.37 shows an extracted heart cycle with the sections indicated, where MC refers to the midsystolic click search area, ES refers to the ejection sound search area and OS refers to the opening snap search area.

Normal			
Patient	**ES power [1/sec]**	**MC power [1/sec]**	**OS power [1/sec]**
1	23.37	184.88	0.11
2	21.10	77.37	0.01
3	75.68	202.18	23.61
4	62.45	175.56	0.01
5	42.26	257.70	0.22

Table 4.5: Average power of different sections to search for extra heart sounds (Normal)
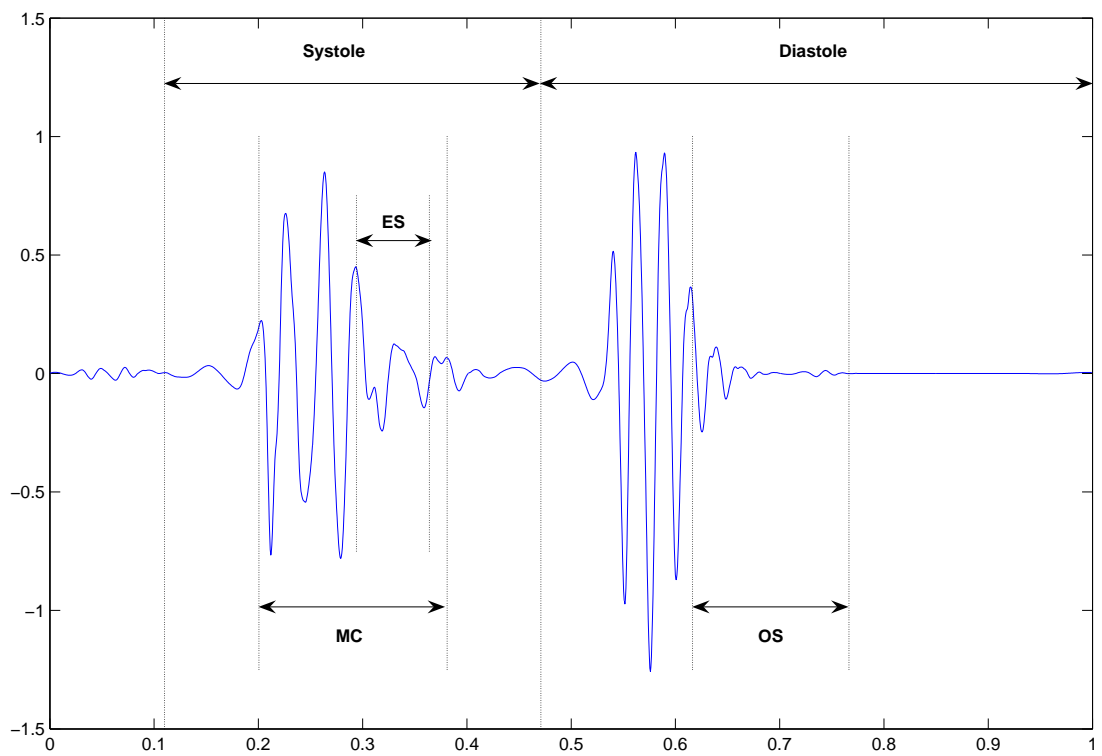
Figure 4.37: Cardiac cycle shown with extra sounds search areas

Chapter 5

Feature selection and classification

This chapter describes the method used in reducing the dimension of the input vector to the classification scheme. Neural Networks are introduced as the classification scheme used, the theory is discussed and some preliminary results are given. Statistical Overlap Factor (SOF) is discussed as the feature reduction technique. The process is described schematically in Figure 5.1.
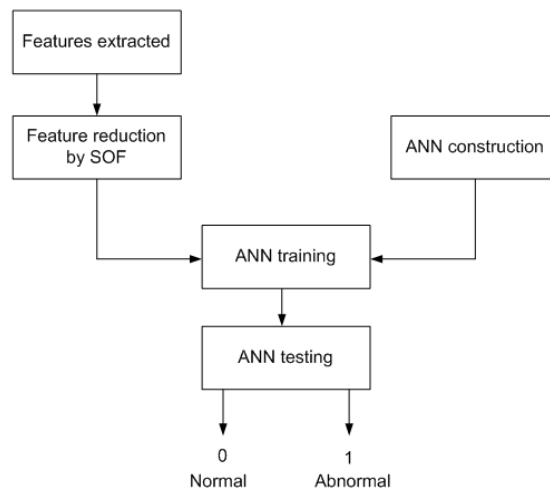
Figure 5.1: Feature reduction and ANN training and testing methodology

5.1 Feature selection

It was decided to reduce the extracted features as input to the classification scheme to a smaller set, since it was deemed unnecessary and computationally intensive to have a large set of features as input. A variety of feature reduction methods exists: Principal Component Analysis (PCA), Independent Component Analysis (ICA) and the Statistical Overlap Factor

(SOF). SOF was used to reduce the features in this project, since it was easy and efficient to implement and proved to have satisfactory results.

5.1.1 Statistical overlap factor

The Statistical Overlap Factor (SOF) is used to determine the variability or degree of separation between two distributions, and is defined as [66]:

$$SOF = \left| \frac{\bar{x}_1 - \bar{x}_2}{(\sigma_1 + \sigma_2)/2} \right| \tag{5.1.1}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the means of distributions x_1 and x_2, and σ_1 and σ_2 are the respective standard deviations. The higher the SOF, the better the degree of separation between the two distributions [66].

As an example, the SOF of two of the features extracted in Section 4.2 will be shown. This will illustrate the degree of separation between the features from the different groups (normal and abnormal). The reason for implementing the SOF to reduce the features is to extract those features that differ most from one another in the respective groups. This will ensure a better performance in classification.

The number of features extracted in Section 4.2 amounted to a total of 70 features. The number of features used in the eventual classification scheme was reduced to 3. This was determined experimentally and proved to produce the best results. To determine the amount of features, the network was trained and tested with a different number of hidden nodes and features to establish which combination provided the best results. The network was trained and tested with 2, 3, 4 and 5 input features and 10, 15 and 20 hidden neurons.
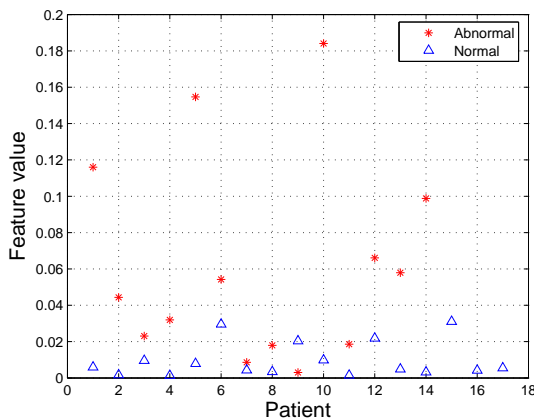
Figure 5.2: Values of feature that exhibited the greatest degree of separation between the normal and abnormal groups
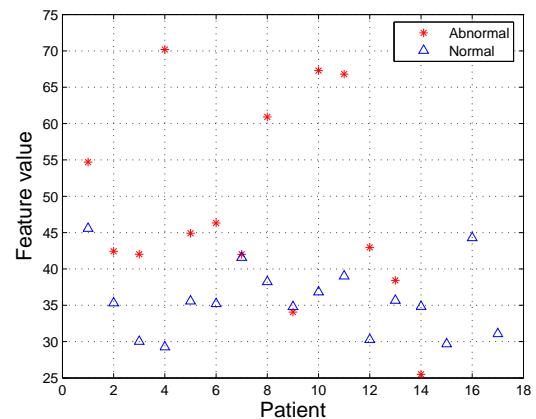
Figure 5.3: Values of feature that exhibited the smallest degree of separation between the normal and abnormal groups

Number of features	Run 1	Run 2	Run 3	Run 4	Run 5	Desired value
2	0.1369	0.1525	0.1430	0.1506	0.1764	0
2	0.3437	0.2698	0.3137	0.2857	0.2347	1
3	0.2644	0.2568	0.2987	0.2445	0.2584	0
3	0.8097	1.0350	0.8700	0.8711	0.9298	1
4	1.0121	1.1424	0.9547	0.8631	0.9969	0
4	0.5409	0.6969	0.7510	1.0214	1.0392	1
5	1.0853	1.0280	0.9760	0.9397	0.9478	0
5	0.5270	0.2885	0.1480	0.2345	0.2271	1

Table 5.1: Network outputs for network with 15 hidden neurons and 2, 3, 4 and 5 input features

Feature	SOF
RMS-value of 3rd section of diastole - 2nd IC right	1.6153
RMS-value of 3rd section of diastole - 2nd IC left	1.6153
Max frequency of 1st section of diastole - 4th IC right	1.3869

Table 5.2: Selected features and their respective SOF

Each combination was tested five times to determine if repeatable results were achieved. The network was trained to give an output of 0 for a normal heart sound and an output of 1 for an abnormal heart sound. The number of features to be used were selected on the basis of the number that gave the most correct and repeatable results, i.e. if the network gave results that varied between 0 and 1 and the results for each training and testing run were more or less in the same range, that number of features were selected. Table 5.1 shows the results for the testing run for a network with 15 hidden nodes and 2, 3, 4 and 5 input features respectively. It can clearly be seen that 3 features as input provided the best results.

The three features that were used in the final classification scheme are shown in Table 5.2. Figure 5.2 shows the different values for the RMS-value of the third section of diastole of the recording at the 2nd right intercostal space. Figure 5.3 shows the different values for the maximum frequency of the first section of diastole of the recording at the 4th intercostal space. The SOF calculated for the first feature was 1.6153 and for the last feature was 1.3869. Tables B.1 and B.2 in Appendix B show the full set of extracted features and their respective SOF.

5.2   Artificial Neural Network classification

Artificial Neural Networks (ANNs) are mathematical models inspired by biological nervous sytems. ANNs attempt to simulate the learning process of biological systems, and can learn to recognise certain inputs to produce particular outputs [67]. Therefore, ANNs are commonly used for pattern detection and classification of signal features.

ANNs consist of multiple interconnected processing units, known as neurons, arranged in two or more layers. The simplest network consists of an input layer and an output layer, as shown in Figure 5.4. The circle in the output layer represents a single neuron. The input layer has one input and the output layer has one output. The output neuron normally contains a transfer function that changes the input to a certain output. The transfer function is denoted by the symbol f. Normally ANNs contain one or more hidden layers. A hidden layer is another layer of neurons inserted between the input and output layers.

Feed-forward networks (FFNs) are the simplest type of multiple-layer ANNs. A FFN consists of an input layer, one or more hidden layers and an output layer. As the name implies, a specific layer is only connected to the layer in front of it, no feedback or layer-skipping is present. A simple FFN with one hidden layer is shown in Figure 5.5. One can see that a specific layer is only connected to the layer in front of it.

Associated with each neuron is a specific transfer function. In Figure 5.5 the transfer function is denoted by f. A variety of transfer functions can be used in the neurons, each with its own benefits. The selected transfer functions have to be differentiable, though. The most common transfer functions used is the family of *sigmoid* transfer functions [68]. A typical representation is,

$$f(x) = \frac{2}{1 + e^{-ax}} - 1 \tag{5.2.1}$$

which belongs to the family of hyperbolic tangent functions. These functions are known as *squashing functions*, since their output is limited in a finite range of values [68]. The output of the function in equation 5.2.1 varies between -1 and 1. Figure 5.6 shows the function for different values of a.

The learning process of the ANN can either be *supervised* or *unsupervised*. During *supervised* learning, a target output value is set for each input given to the ANN. The ANN then tries to minimise the error between the output it calculates and the desired response by minimising a certain cost function. The cost function can be any function that is dependent on the calculated output of the network and the target values. This is done by iteratively adjusting the weights and biases of each neuron until a specified tolerance has

Input layer   Output layer
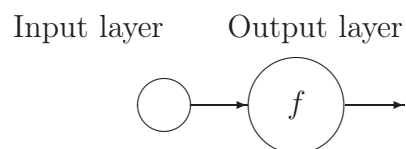
Figure 5.4: ANN with an input layer and an output layer
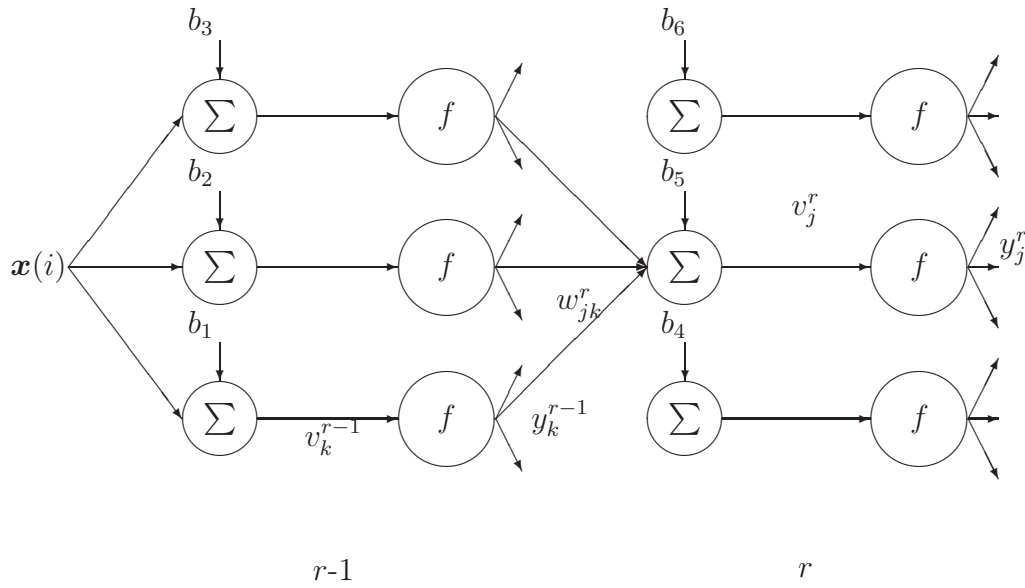
Figure 5.5: ANN with one hidden layer
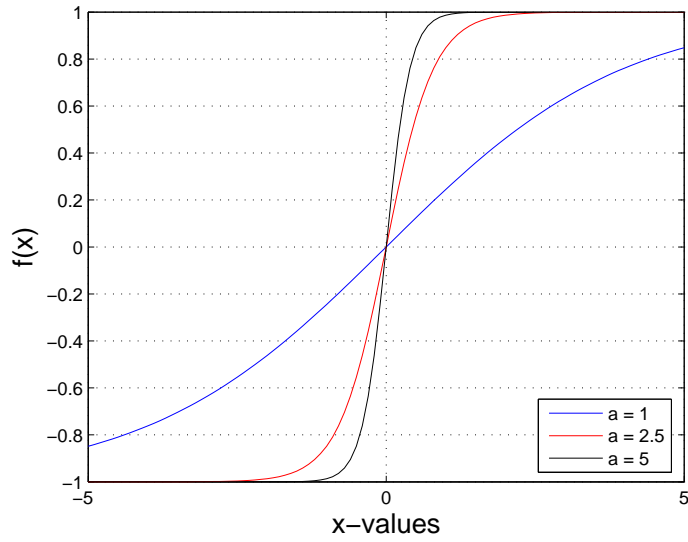
Figure 5.6: $f(x) = \frac{2}{1+e^{-ax}} - 1$ for $a = 1, 2.5, 5$

been met. During *unsupervised* learning the weights and biases are adapted only according to the inputs, since no target values are available for training purposes. The biases for each neuron are indicated as b_1, b_2 etc.

The most common way in which the weights are calculated and adapted, is probably the *backpropagation* algorithm [68]. Standard backpropagation is a gradient descent algorithm[1] in which the network weights are adjusted in accordance with the negative of the gradient of the cost function. The term "backpropagation" refers to the manner in which the gradient is computed for nonlinear multilayer networks. The gradient is first calculated for the last layer of the network and subsequently moved to the first layer, hence the term *backpropagation.*

During training, when an input vector $\boldsymbol{x}(i)$ is applied to the input, the output of the network will be $\widehat{\boldsymbol{y}}(i)$, which is different from the desired value $\boldsymbol{y}(i)$. The weights of the connections are computed such that an appropriate cost function,$\boldsymbol{J}$, which is dependent on the values $\boldsymbol{y}(i)$ and $\widehat{\boldsymbol{y}}(i)$, $i = 1, 2, \ldots, N$, is minimised [68]. In Figure 5.5 the weight vector of the jth neuron in layer r can be denoted by $\boldsymbol{w}_j^r$, which includes the thresholds. The weight between neuron k in layer r-1 and neuron j in layer r is denoted by w_{jk}^r, which states that the weight is applicable from neuron k to neuron j in layer r. The weight vector for neuron j in layer r is defined as $\boldsymbol{w}_j^r = \left[w_{j0}^r, w_{j1}^r, \ldots, w_{jk_{r-1}}^r \right]^{\text{T}}$, where k_{r-1} are the number of neurons in layer r-1.

At each iteration the weight vector is updated by

$$\boldsymbol{w}_j^r(\text{new}) = \boldsymbol{w}_j^r(\text{old}) + \Delta\boldsymbol{w}_j^r \qquad (5.2.2)$$

where $\boldsymbol{w}_j^r(\text{old})$ is the current estimate of the unknown weights and $\Delta\boldsymbol{w}_j^r$ is the correction term to obtain the new estimate of the weights $\boldsymbol{w}_j^r(\text{new})$.

5.2.1   The backpropagation algorithm

The backpropagation algorithm works as follows (refer to Fifure 5.5):

- *Initialisation*: Initialise all the weights with small random values.

- *Forward computations*: For each of the training feature vectors $\boldsymbol{x}(i)$, $i = 1, 2, \ldots, N$, compute all the $v_j^r(i)$, $y_j^r(i) = f(v_j^r(i))$, $j = 1, 2, \ldots, k_r$, $r = 1, 2, \ldots, L$, from

$$v_j^r = \sum_{k=1}^{k_{r-1}} w_{jk}^r y_k^{r-1}(i) + w_{j0}^r \equiv \sum_{k=0}^{k_{r-1}} w_{jk}^r y_k^{r-1}(i) \qquad (5.2.3)$$

where k_r is the number of neurons in layer r and L is the number of layers. By definition $y_0^r(i) \equiv 1$, $\forall\, r, i$; so as to include the thresholds in the weights [68]. For the

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[1]Please refer to Appendix C for an explanation of the gradient descent algorithm.

output layer, $r = L$ and $y_k^r(i) = \hat{y}_k(i)$, $k = 1, 2, \ldots, k_L$, i.e. the outputs of the neural network, and for $r = 1$, $y_k^{r-1}(i) = x_k(i)$, $k = 1, 2, \ldots, k_0$, i.e. the network inputs. k_0 is the number of nodes in the input layer [or the length of $\boldsymbol{x}(i)$].

Compute the cost function for the current estimate of weights from

$$J = \sum_{i=1}^{N} \varepsilon(i) \tag{5.2.4}$$

where

$$\varepsilon(i) = \frac{1}{N} \sum_{m=1}^{k_L} e_m^2(i) = \frac{1}{N} \sum_{m=1}^{k_L} (f(v_m^L(i)) - y_m(i))^2 \tag{5.2.5}$$

and $y_m(i)$ is the target value of output neuron m, and k_L is the number of neurons in the last layer of the network, layer L. In this case, the function $\varepsilon(i)$ is the mean-squared error function. Equation 5.2.4 thus states that the cost function is defined as the sum of the N values that the function ε takes on for each training pair, $(\boldsymbol{x}(i), \boldsymbol{y}(i))$. Other functions can be used for $\varepsilon(i)$ as well, such as the sum of squared errors defined as:

$$\varepsilon(i) = \frac{1}{2} \sum_{m=1}^{k_L} (f(v_m^L(i)) - y_m(i))^2 \tag{5.2.6}$$

or the cross-entropy function defined by:

$$\varepsilon(i) = \sum_{m=1}^{k_L} (y_m(i) \ln \hat{y}_m(i) + (1 - y_m(i)) \ln(1 - \hat{y}_m(i))) \tag{5.2.7}$$

- *Backward computations*: For each $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, k_L$ compute $\delta_j^L(i)$ from:

$$\delta_j^L(i) = e_j(i) f'(v_j^L(i)) \tag{5.2.8}$$

where f' is the first derivative of transfer function f.

and subsequently compute $\delta_j^{r-1}(i)$ for $r = L, L-1, \ldots, 2$, ($r = 1$ is the input layer) and $j = 1, 2, \ldots, k_r$ from:

$$\delta_j^{r-1}(i) = e_j^{r-1}(i) f'(v_j^{r-1}(i)) \tag{5.2.9}$$

where

$$e_j^{r-1}(i) = \sum_{k=1}^{k_r} \delta_k^r(i) w_{kj}^r \tag{5.2.10}$$

where $w_{kj}^r = w_{jk}^r$. The subscript kj simply states that the calculation is moving from neuron j to neuron k (i.e. backwards, as would be expected).

- *Update the weights*: For $r = 1, 2, \ldots, L$ and $j = 1, 2, \ldots, k_r$ calculate the new estimate of the weights from equation 5.2.2 where

$$\Delta \boldsymbol{w}_j^r = -\mu \sum_{i=1}^{N} \delta_j^r(i) \boldsymbol{y}^{r-1}(i) \tag{5.2.11}$$

where μ is defined as the learning rate of the training scheme.

5.2.2 Backpropagation variations

The convergence speed of the backpropagation scheme can sometimes be very slow [68] and therefore variations to this scheme have been developed. Some of these variations include the use of a *momentum term*, the use of an *adaptive learning rate*, the *delta-delta* rule and the *delta-bar-delta* rule. Only the *momentum term* and *adaptive learning rate* strategies will be discussed here.

5.2.2.1 Backpropagation with a momentum term

When the convergence of the cost function is slow with the backpropagation algorithm, it is usually due to the fact that the change of the cost function gradient is highly oscillatory between successive iterations [68]. To overcome this, a momentum term can be added to the algorithm. This updates the weights and smooths the oscillatory behaviour and speeds up convergence. The weights are then updated by:

$$\Delta \boldsymbol{w}_j^r = \alpha \Delta \boldsymbol{w}_j^r(old) - \mu \sum_{i}^{N} \delta_j^r(i) \boldsymbol{y}^{r-1}(i) \tag{5.2.12}$$

The constant α is the *momentum factor* and usually takes on a value between 0.1 and 0.8 [68]. This approach was attempted with the training of the network in this study, but did not give satisfactory results.

5.2.2.2 Backpropagation with an adaptive learning rate

The adaptive learning rate was also attempted with the training of the network in this study and had very good results and was thus adopted as the training algorithm for the network. This variation works on the principle that the learning rate, μ, is adapted, depending on

Parameters			
μ	r_i	r_d	c
4×10^{-7}	1.15	5×10^{-6}	1

Table 5.3: Neural network training algorithm parameters

the value of the cost function at successive iteration steps. The process can be described as

$$\frac{J(t)}{J(t-1)} < 1, \ \mu(t) = r_i \mu(t-1)$$

$$\frac{J(t)}{J(t-1)} > c, \ \mu(t) = r_d \mu(t-1)$$

$$1 \leqslant \frac{J(t)}{J(t-1)} \leqslant c, \ \mu(t) = \mu(t-1)$$

where $J(t)$ is the cost function at iteration t, r_i is the factor by which the learning rate, μ, is increased, r_d is the factor by which the learning rate is decreased and c is just a limiting factor by which the current and previous cost function ratio is allowed to differ. Typical values are $r_i = 1.05$, $r_d = 0.7$ and $c = 1.04$ [68]. The values used in this study are presented in Table 5.3 and were determined experimentally.

5.3 Construction and training of the neural network

For this study, a FFN with two hidden layers was implemented. The input layer consisted of 3 nodes (the 3 input features), the hidden layers consisted of 10 and 5 neurons respectively, with the *logarithmic tangent function* as activation function. The formula of this function is:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{5.3.1}$$

The output layer consisted of one neuron with a linear function as activation function (this function simply gives the same value as output and input). As stated previously, the training function used was the backpropagation algorithm with the adaptive learning rate.

In certain circumstances, networks might be overtrained. This implies that the network memorises the training data and produces the correct outputs, but does not have adequate generalisation capabilities, i.e. it does not produce the correct results for new data. Several methods to improve the generalisation capabilities of networks do exist, and one of these methods is called *regularisation*. *Regularisation* tries to shrink the size of the weights, since large weights lead to irregular error surfaces when sigmoid functions are used as activation

functions [69]. During regularisation the cost function is calculated by:

$$J = \alpha \sum_{i=1}^{N} \varepsilon(i) + (1 - \alpha)\varepsilon_p(\boldsymbol{w}) \tag{5.3.2}$$

where $\varepsilon_p(\boldsymbol{w})$ is the error function, dependent on the weights of the network and is equal to:

$$\varepsilon_p(\boldsymbol{w}) = \frac{1}{K} \sum_{k=1}^{K} w_k^2 \tag{5.3.3}$$

and α is the regularisation parameter. This method improved the results and hence was implemented in the final network structure. In the final network structure α was set to 0.5, giving equal importance to the weights and the network errors.

The number of features to be used in the network were determined, as explained in Section 5.1.1. The number of hidden layers and nodes in the hidden layers were determined by trial-and-error. The configuration that provided the best results were two hidden layers with 10 and 5 nodes respectively. The network was trained by implementing a variation of the leave-one-out algorithm, as was done in [70] and [39]. Thirteen abnormal data sets and 16 normal data sets were randomly selected as training data and one normal data set and one abnormal data set were selected as test data. This process was repeated 50 times in order to test a wide variety of combinations of normal and abnormal datasets.

It had to be decided which threshold would be used to differentiate between normal and abnormal data, e.g. for a threshold of value t, all values below t would be set to 0 and all values equal and above t would be set to 1, where t is a value between 0 and 1. One way of determining the optimal threshold value is by constructing a Receiver Operating Characteristic (ROC) curve. An ROC curve is a measure of how well a specific decision-making system classifies between different classes. It is based on detecting the optimal threshold to distinguish between two probability density functions. The aim is to maximise the true-positive fraction (TPF) while at the same time minimising the false-positive fraction (FPF). The TPF is the number of patients who are classified correctly as having the disease, i.e. the *sensitivity*. The FPF is the number of people who have the disease, but are classified as not having the disease. The FPF is related to the true-negative fraction (TNF) by the following relation:

$$FPF + TNF = 1 \tag{5.3.4}$$

The optimal threshold was calculated as 0.35, producing a TPF of 0.8571 and a FPF of 0.1765. However, it was noted that the FPF was 0 and TPF was 0.7857 at a threshold of 0.4 and, therefore, it was decided to examine the threshold in this range more closely to
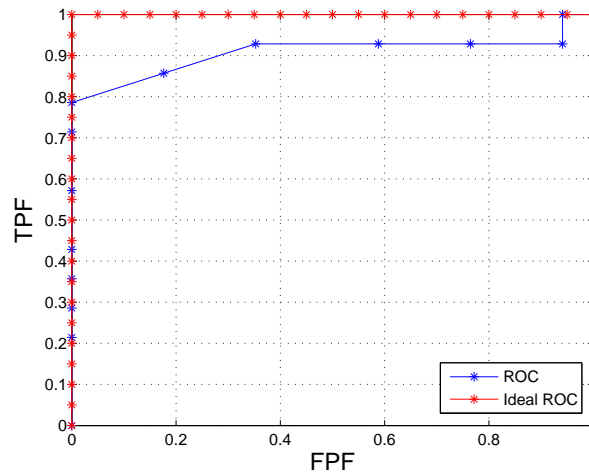
Figure 5.7: ROC curve for classification scheme used

ascertain if better results could be achieved. The thresholds in the range from 0.4 to 0.25 were varied in steps of 0.01 and, indeed, better results were achieved. Thresholds equal to 0.39 and 0.38 resulted in a FPF of 0.0588 and a TPF of 0.8571 and were thus deemed as the optimal.

A measure of the effectiveness of a specific test is given by the area under the ROC curve [11]. This value can only be between 0 and 1. The closer this value is to 1, the better the test. The area under the curve in Figure 5.7 was calculated as 0.9076, which indicates that the test is of a very good standard. The ideal curve is also shown in comparison with the ROC curve of this test.

The optimal threshold value was calculated to be 0.38, resulting in a TPF of 0.8571 and FPF of 0.0588. This in turn resulted in a sensitivity of:

$$\text{Sensitivity} = TPF = 85.7\%$$

and a specificity of:

$$\text{Specificity} = (1 - FPF) \times 100\% = (1 - 0.0588) \times 100\% = 94.1\%$$

This means that 85.7% of the abnormal patients were classified correctly as abnormal and 94.1% of the normal patients were classified correctly as normal.

Chapter 6

Conclusions and Recommendations

Problems regarding the cycle and feature extraction processes, as well as the ANN, are discussed and possible solutions are presented. An overview of the positive and negative aspects of the auscultation jacket and its application to telemedicine is also given.

6.1 Data analysis and classification system

6.1.1 Cycle extraction

In some instances cycle extraction was not possible, since the ECG recorded simultaneously with the heart sounds produced artifacts as shown in Figure 6.1. When this signal was passed through the first-derivative operator and the MA filter (refer Section 4.1.2) it produced artifacts that were incorrectly labelled as QRS-peaks and this resulted in the extraction of incorrect cycles. Recordings in which the ECG did not record properly, had to be discarded and could not be used in the training of the Neural Network. Figure 6.1 shows the originally recorded ECG signal after it had been low-pass filtered (refer Section 4.1). Figure 6.2 shows the signal after it had been passed through the first derivative operator and MA filter (refer Section 4.1.2). It can clearly be seen that peaks are presented that cannot be attributed to QRS-peaks.

One might ask why the threshold was not simply increased. In some instances the amplitude of the consecutive QRS-peaks differed from the maximum peak amplitude to such an extent that when the threshold was increased, the peaks were also removed and the cycle extraction process missed some cycles. Because of the fact that the successive ECG cycle intervals were compared with one another, these intervals fell outside the allowed range and resulted in no extracted cycles. All such erroneous cycles as mentioned had to be discarded.

Two ECG recordings were taken, because it was only realised after the ECG had been built into the jacket that the ECG recording would be needed to identify the start of S_1.

70
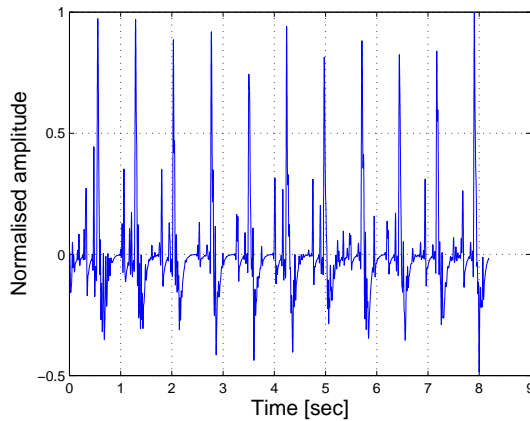
Figure 6.1: Recorded GeoAxon ECG showing artifacts that prohibited cycle extraction
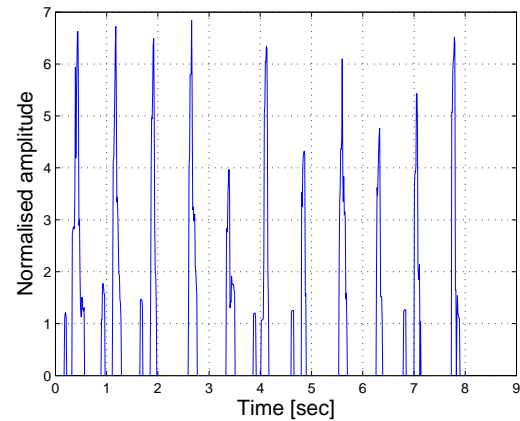
Figure 6.2: QRS-peaks with artifacts that resulted in wrongly extracted cycles

Because this was only a prototype of the auscultation jacket, it was the easiest and quickest solution to the problem to record an extra ECG together with the stethoscope data instead of attempting to access the recording process of the built-in ECG and trying to synchronise that with the recording of the stethoscopes. This would be the most sophisticated solution and would nullify the effects of artifacts. This procedure should definitely be attempted in the following version of the auscultation jacket.

6.1.2   Denoising

The denoising procedure of the recorded heart sounds presented a problem in that if the wavelet threshold was set too high, some of the information was discarded. The use of high- or low-pass filters did not solve this problem either, since the noise frequencies were in the same range as the frequencies of interest. Averaging was not used and might provide better results as indicated in [24].

Some of the stethoscopes (especially the stethoscopes at the 2nd left and right intercostal spaces) did not make sufficient contact with the patient's skin. This resulted in "noisy scrathes" in the data, as the patient's chest moved up and down during breathing. This situation was exarcebated if the patient had a significant amount of chest hair. Figure 6.3 shows the recording of a normal patient at the 2nd right intercostal space, where the stethoscope did not make sufficient contact with the skin. Figure 6.4 shows the recording at the 4th right intercostal space for the same patient, where the stethoscopes did make sufficient contact with the patient's skin. Figures 6.5 and 6.6 show the denoised signals. It can be seen that no information could be extracted from the recording at the 2nd intercostal space in comparison to the recording at the 4th intercostal space. The recording at the 2nd intercostal space (and thus the whole feature set) could thus not be used to train the Neural
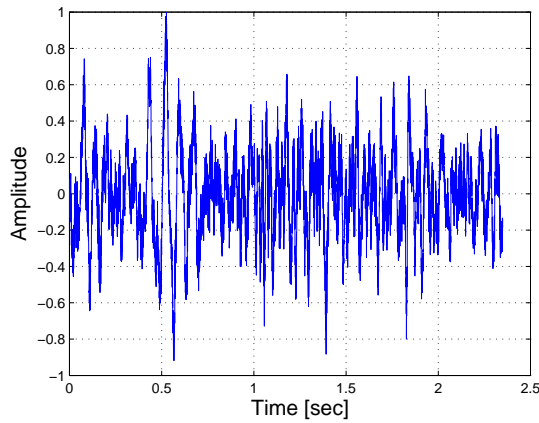
Figure 6.3: Recording of normal patient at 2nd right intercostal space showing noise generated by insufficient contact between stethoscope and skin
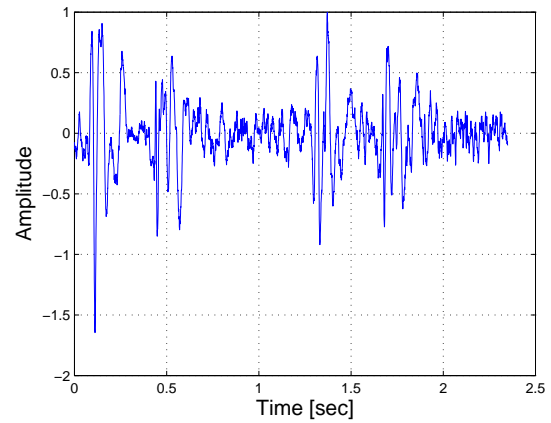
Figure 6.4: Recording of normal patient at 4th right intercostal space showing that less noise is generated with sufficient contact between stethoscope and skin

Network.
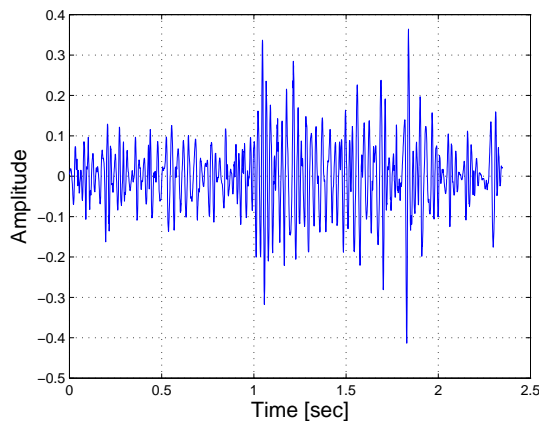
Figure 6.5: Denoised recording showing that no information could be extracted due to poor original recording
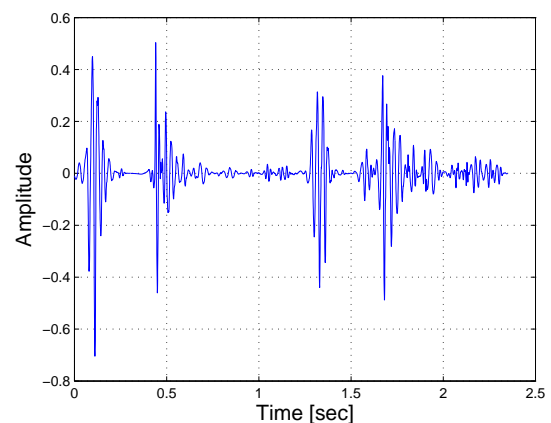
Figure 6.6: Denoised recording showing sufficient information to be extracted

6.1.3 Feature extraction

6.1.3.1 Duration of S_2 split

The calculation of the S_2 split proved to be more difficult than initially anticipated. The procedure implemented in section 4.2.6 gave reasonable results but in some instances the correct peaks in the CWT were not identified sufficiently. For example, if a value that
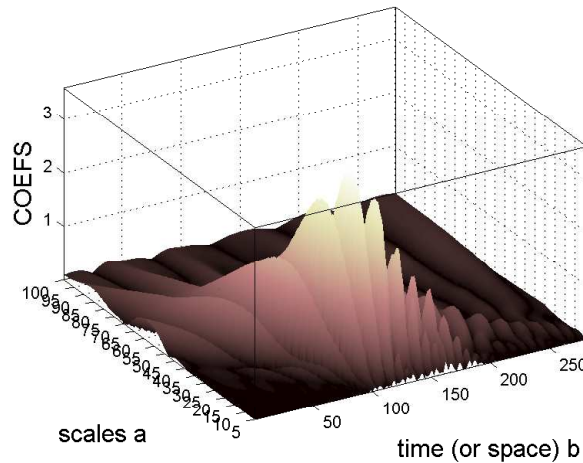
Figure 6.7: CWT of S_2 showing multiple peaks

differed from the maximum value by 10 msec was situated in the range of the first peak and was greater in value than the second peak, this value would have been incorrectly labelled as the second component of the S_2 split.

No easy solution to this problem seems to exist, since no automated algorithm that is capable of detecting two peaks in a graph of the kind shown in Figure 6.7 currently exists. To identify the peaks in 95% of these situations correctly and automatically will need further research and possibly the construction and training of another neural network to determine the relationship between these two peaks.

Other techniques that have been implemented by other researchers to identify A_2 and P_2 include the use of the carotid pulse [11]. The carotid pulse is a pulse signal recorded over the carotid artery. The algorithm proposed by Rangayyan [11] uses the dicrotic notch in the carotid pulse as an indicator of where S_2 should start. Synchronised averaging is then used to enhance the appearance in time of A_2, since it will most likely occur at the same time relative to the start of S_2. During inspiration the relative timing of P_2 changes, and because of this, P_2 should be minimised by the averaging process.

6.1.4 Classification system

The biggest problem with the classification system is the lack of training data. Unfortunately, time limits prohibited the collection of more data and the structure of the neural network can only be truly evaluated once there is enough training data (probably 100 sets or more). The fact that the system is capable of distinguishing between normal and abnormal heart sounds despite the small amount of training data, holds big promise that the approach followed in the construction and training of the classification system is the correct one.

Other classification techniques should also be investigated, as they may lead to better

results than ANNs. Other techniques that have been implemented in other studies, include decision tree classifiers [41], linear discriminant functions [42] and Hidden Markov Models [37]. *Unsupervised* pattern classification techniques such as the k-means algorithm and the maximin-distance algorithm could also be researched. Feature reduction techniques such as principal component analysis and independent component analysis should also be considered.

The features that were eventually used as inputs to the ANN only evaluated information from the diastolic region of the heart cycle. It was decided to train and test the ANN with systolic information added to the inputs, to determine whether this would increase the sensitivity and specificity of the ANN. Different combinations of systolic data, together with the diastolic information already present, was presented to the ANN as input data. Satisfactory results were not achieved. This can be attributed to the fact that there is not sufficient discrimination between the systolic data of the normal and abnormal heart sounds that enables the ANN to properly discriminate between the two classes. Better recording procedures and denoising procedures could improve this result.

6.2 Recommendations concerning the auscultation jacket

Since this is only the first attempt at a prototype of the auscultation jacket, numerous improvements could be made. The greatest weakness of the jacket is that the stethoscopes, and thus the electrodes embedded into the stethoscopes, move relative to the body surface as the patient breathes. This in turn, causes the ECG recorded with the jacket to be unreliable. The afore-mentioned is the reason why not more of the ECG information was used as features in the classification scheme. Examples of these are the height of the P-wave, where the P-wave occurs with respect to the QRS-complex, whether the QRS-complex is inverted or not, etc. All of these features could be used to extend the screening capabilities of the jacket beyond simple auscultation abnormalities. The screening of other cardiovascular diseases such as myocardial infarction (heart attack) which may be diagnosed by a significant decrease in the R-wave amplitude due to the loss of tissue would also be possible.

The side pieces of the jacket also present a problem. They move around and do not necessarily correspond to the correct position for V6. To correct this problem it is proposed that the stethoscopes should be fitted with double-sided tape that is capable of fixing the position of the stethoscope (and thus the electrode) to the skin surface of the patient. This material should be of such a nature that it could be easily removed from the stethoscope between recordings.

The two stethoscopes, which correspond to the auscultation positions at the 2nd left

and right intercostal spaces (pulmonary and aortic areas respectively), present a two-fold problem. Firstly, these two stethoscopes are the main reason why the jacket cannot be used on women. The current size of the stethoscopes prohibit the stethoscopes from making sufficient contact with the body between the breasts. The second problem is that these two stethoscopes do not make sufficient contact with some male patients when they are in the supine positions. This leads to noisy data that cannot be used. It is proposed that the contour surface of the jacket be changed in such a way that it follows the contour of the body better. This could be done by installing an inflatable bladder, that can press the stethoscopes down until sufficient contact is made, in the jacket . Each stethoscope could also have its own inflatable bladder and could be inflated individually. However, this concept brings about a number of problems, such as the number of pipes needed to inflate the jacket, whether it would be possible to seal off the bladder to avoid leakage, what size pump would be needed to inflate the jacket, etc. All these factors will have to be taken into account and assessed individually before making use of this idea. Another idea is to embed the stethoscopes in sponge that is thicker at the positions that correspond to the 2nd left and right intercostal spaces. This would also ensure that better contact is made with the skin. Another strap could also be inserted on the side of the jacket at the height of the 2nd intercostal space. This strap could then be tightened around the body to ensure that sufficient contact is made with the skin at these locations.

The number of cables is also a definite problem. Keeping in mind that this was a first attempt at a prototype, the number of cables was not a major problem, but it would be more practical to reduce the number of cables. Implementing wireless technology could pose a solution. The hub to which the stethoscopes and ECG are connected, could be placed on the jacket instead of hanging loose, as it is in the current prototype.

As the jacket was fitted on healthy as well as unhealthy patients, it was noted that if the patient is significantly weakened, as in the case of someone with severe valvular heart disease, it gets difficult to fit the person with the jacket. Since it is proposed to develop this jacket to be used on patients who do suffer from valvular or other heart disease, this problem is something that has to be considered and addressed.

Other aspects to think about are the stethoscopes themselves. During the recording process the diaphragms of some of the stethoscopes became dislodged because of multiple usage. The ECG electrode gel reacted with the glue that held the diaphragms in place and this also aggravated the problem. To counter this, the diaphragm could be built into the stethoscope by creating a small slot on the inside of the stethoscope casing and inserting the flexible diaphragm. The diaphragm could also be discarded, since it only acts as a low-pass filter and any noise that is recorded can be filtered out after the recording.

The stethoscopes are also very bulky and add a lot of weight to the jacket although the casings are manufactured of aluminium. It might be beneficial to consider using accelerom-

eters instead of microphones to record the heart sounds, as they are much smaller, but this still has to be researched. Accelerometers have been used in a previous study to record lung sounds as described in Pourazad *et al.* [43]. The authors used two Siemens EMT 25 C piezoelectric contact accelerometers to record the lung sounds.

6.3 Application to telemedicine?

Telemedicine is defined as "the use of telecommunication technology (involving audio, video, and graphic data) to deliver healthcare services, health education, and administrative services to sites that are physically distant from the host or educator" [71]. According to the Medical Research Council of South Africa, the South African government is "committed to providing basic health care to all South African citizens" and "to achieve this goal, the government has identified Telemedicine as a strategic tool for facilitating the delivery of equitable healthcare and educational services".

Telemedicine has proved useful and necessary in developing countries. In India, for example, the Online Telemedicine Research Institute (OTRI) has made a great impact on the lives of people. In January of 2001, an earthquake hit the city of Bhuj in Western India and left thousands dead and homeless. Within a day, the OTRI in Ahmedabad established satellite telephone links and set up all equipment necessary to provide emergency medical care through telemedicine. Ahmedabad is 300 km from Bhuj. The satellite phones were soon replaced by VSAT with phone lines and ISDN. A fully-fledged telemedicine system was used for teleconsultation in pathology, radiology, and cardiology over ISDN lines, and between district hospitals near Bhuj and other in Ahmedabad. Seven-hundred and fifty sessions consisting primarily of X-rays and ECGs of patients, were transmitted in one month to specialists in Ahmedabad [71].

Although telemedicine has proved helpful in some cases, it also has its limitations. In some areas, the infrastructure is extremely poor and it is very difficult to implement a telemedicine centre in an area that has little or no infrastructure. The problem is that physicians tend to leave the rural areas for bigger cities and improperly trained technicians are left in charge of health facilities. These technicians rarely have any experience working on computers [72]. In the Alto Amazonas province of Peru, 64.9% of the healthcare personnel have never used a computer and 89% of the healthcare personnel have never used e-mail. It may be argued that since Peru is also a developing country, more or less the same conditions exist in South Africa. This poses a big problem in setting up a telemedicine centre in the rural areas of South Africa.

No roads, administrative problems (information being sent has to be paid for by the health staff themselves) and no feedback to the rural health centres are just some of the

challenges in such areas. A delay of 13 months on the arrival of information is common practice in these areas. Many healthcare personnel have to pay their travel costs themselves. On average this accounts to 17% of his or her salary [72]. The use of electronic mail could reduce the amount of time needed to travel by coordinating certain travels with others. Training of healthcare personnel could also be improved by supplying the information better and faster to rural areas. 59% of the healthcare staff in Alto Amazonas said they do not attend courses because the information arrives too late or not at all.

On the practical side, many of these areas do not have electricity, no public telecommunication infrastructure, have limiting purchasing power, maintenance costs are high due to the poor infrastructure and few well-trained people in managerial positions are available. To combat this, any telemedicine equipment installed has to fulfil the following conditions [72]:

- Be highly robust

- Any technological platform must demand low infrastructure, maintenance and operation costs

- Low energy consumption

- Technical personnel will have to be trained in system management, maintenance, and repair

However, in sub-Saharan Africa telemedicine has been implemented in several countries to address the extremely poor medical infrastructure. Sub-Saharan Africa is home to 33 of the 48 least developed countries in the world and telemedicine would thus have far-reaching effects in these countries by making proper healthcare accessible to everyone [71].

The final aim of the auscultation jacket is to distribute the jacket to rural areas that do not have sufficient healthcare facilities. Patients will then be recorded with the jacket and the data will be sent via a communication link to physicians who are able to interpret the data and provide feedback on each patient. Many factors have to be taken into consideration before such a system can be implemented, but the possibility is real and will have far-reaching positive effects if the process is managed and implemented correctly.

6.4   Other applications

The application of the auscultation jacket can be expanded to include educational applications as well. For instance, if patient contact is prohibited or limited due to a specific disease as in [73] where patient contact was prohibited due to severe acute respiratory syndrome (SARS), the monitoring of patients could be done with the help of the auscultation

jacket. In the mentioned study, cardiac sounds were recorded with Littmann model 4000 stethoscopes and played back to students to assist in teaching auscultation skills. The auscultation jacket could have been implemented to record all the heart and lung sounds, ECG and ICG for educating purposes at a later stage.

The auscultation jacket, together with the classification system, can be used as a training tool for students to determine whether a patient has cardiovascular (or pulmonary) pathology or not. According to Tuchinda *et al.* teaching cardiac auscultation skills has been difficult "due to time constraints and the impracticability of examining large numbers of patients with cardiac pathology"[74]. A database consisting of recordings made with the auscultation jacket can be made and students can thus access recordings made at different locations on the body in their own time. This would enable them to make their own diagnosis and check it against the results of the classification system. This eliminates the need for examination of a large number of patients. The doctor-patient relationship is a very necessary and important one and it is not proposed to do away with this relationship.

According to March *et al.* "the ability of many of today's health care professionals to correctly identify normal and abnormal heart sounds continues to diminish" [4]. The auscultation jacket and classification system can help overcome this obstacle by providing diagnostic information to physicians who are uncertain of a specific pathology.

Appendices

Appendix A

Relevant technologies

Many techniques that are used to diagnose heart disease exist. These techniques include electrocardiography (ECG), echo-cardiography, impedance cardiography (ICG), nuclear stress testing, coronary angiogram, computed tomography (CT) scan, PET (positron emission tomography)/CT scan and magnetic resonance imaging (MRI). Only the ECG, echo-cardiography and ICG will be discussed here.

A.1 Electrocardiogram (ECG)

The Electrocardiogram (ECG) measures the electrical activity of the human heart. The electrical impulses that make the heart contract spread across the heart in a specific manner and any deviation from this could indicate pathology. To explain and understand the ECG waveform, the electrical system of the heart first has to be explained. Refer to Figure A.1 for a diagram of the heart and its electrical system. A normal ECG graph is shown in Figure A.2. This ECG was recorded with the auscultation jacket. The heart's pacemeaker is the Sinoatrial (SA) node. Action potentials [1] are generated here and travel from here through the rest of the electrical system. The action potential first travels down the anterior, middle and posterior internodal tract as well as Bachmann's bundle. In doing so, the muscle cells of the atria depolarise (the action potential is raised from -90 mV towards 0 mV) and the atria begin to contract. This corresponds to the P-wave in the ECG waveform and is shown as section C in Figure A.2. The P-wave has a duration of $60-80$ ms. When the action potential arrives at the AV node, there is a delay of approximately $60-80$ ms [11]. This is known as the P-Q segment and is shown as section D in Figure A.2. The action potential now travels down the left and right bundle branches in the interventricular septum, into the conduction pathways (also known as Purkinje fibres). As the action potential moves upward through

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[1]A change in the membrane potential of cells (from the normal -90 mV), initiated by a change in the membrane permeability to sodium ions [10].
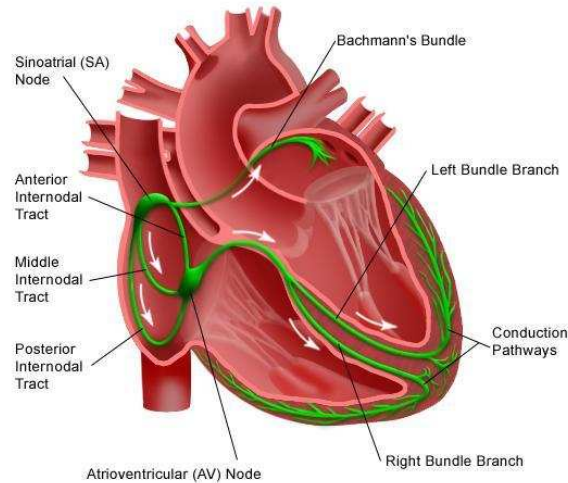
Figure A.1: Schematic of the electrical system of the human heart [75]

the heart from the apex, the ventricles contract, resulting in the QRS-complex in the ECG waveform (section E in Figure A.2) lasting about 80 ms. The QRS-complex is relatively large in comparison to the other waveforms in the ECG, since the mass of the ventricles is much larger than the mass of the atria. The action potential duration of ventricular muscle cells is relatively long $(300 - 350$ ms) [11]. This results in a section of little activity after the QRS-complex known as the S-T segment (section F) and lasts for about $100 - 120$ ms. Repolarisation (membrane potential of cardiac muscle cells return to -90 mV) of the ventricles lasts for about $120 - 160$ ms and can be seen in the ECG as the T-wave (section G). Section A is known as the P-Q interval and shows the electrical potential of the atria. Section B is known as the Q-T interval and shows the electrical potential of the ventricles during a single cardiac cycle.

Sometimes a U-wave is present after the T-wave (not present in Figure A.2), but the origin of the U-wave is still a topic of debate [76]. Three hypotheses exist on the genesis of the U-wave: late repolarisation of Purkinje fibres, late repolarisation of other portions of the left ventricle and alteration in the normal action potential shape by after-potentials, which are most likely generated by mechano-electric feedback [76]. The U-wave has the same polarity as the T-wave in normal subjects; when the polarity of the U-wave is reversed, it is, therefore, of great clinical importance [76].

The electrical potentials are measured by electrodes placed on the surface of the skin. The electrodes are placed at different positions on the body, depending on which ECG configuration is being used, e.g. 12-lead ECG, 6-lead ECG, 3-lead ECG or 1-lead ECG. For a 12-lead ECG 6 electrodes are placed on the thorax in the V1-V6 positions (refer to Figure A.3). For the remaining four electrodes there are two possible combinations: one electrode
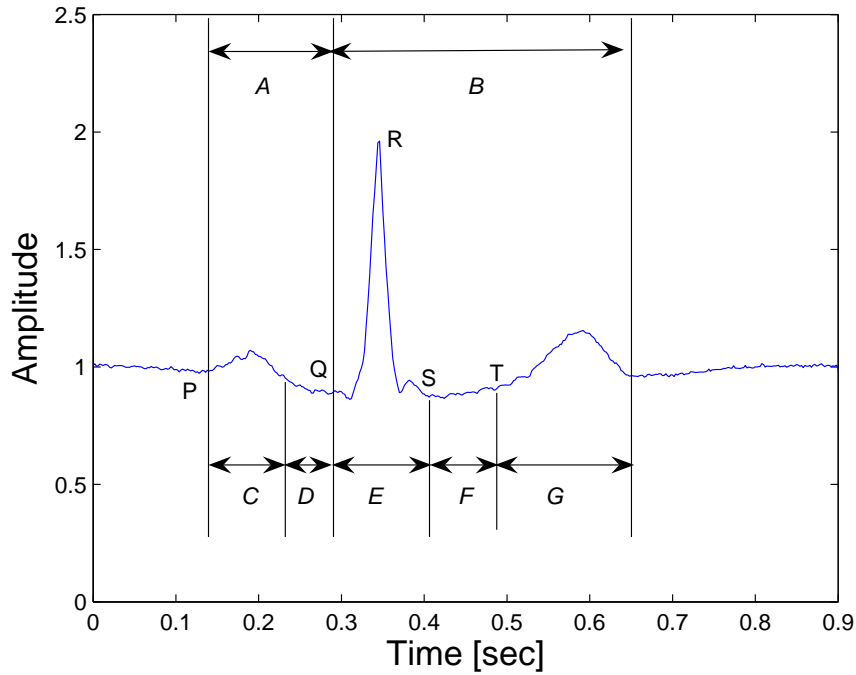
Figure A.2: Normal ECG wave

can be placed on each wrist and foot, or one electrode can be placed on each shoulder and hip (refer to Figure A.4 and Figure A.5).

The graphs that are displayed on the standard ECG recording correspond to how the action potentials spread through different axes of the heart. In effect, one looks at how the heart contracts from different angles around the heart. Specific patterns are associated with each view and any deviation from this could indicate pathology. The different axes are shown in Figure A.6.

To understand how the deflections for specific axes are formed, the volume conductor principle has to be explained. Consider a mass of ventricular muscle placed in a bath of salt
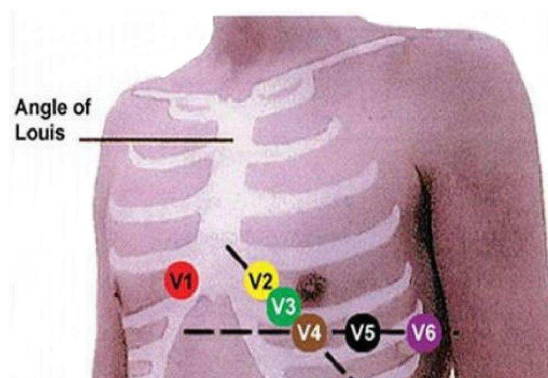
Figure A.3: V1-V6 positions [77]
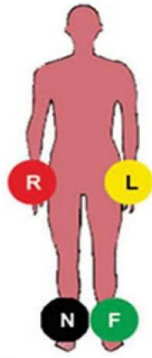
Figure A.4: Configuration for ECG electrodes on wrists and feet [77]
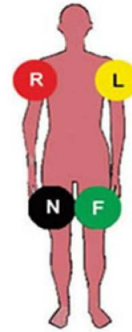
Figure A.5: Configuration for ECG electrodes on shoulders and hips [77]

water. In the resting state of the ventricular muscle, the outside of the cells is positively charged with respect to the inside of the cell. For heart muscle cells, the resting membrane potential (RMP) is approximately -90 mV [10]. If two electrodes are placed on either side of the ventricular mass, no potential difference will be measured between the electrodes, as in Figure A.7. When an action potential spreads across the heart (from negative to positive in this case), however, some of the muscle cells on the left side of the ventricular mass is charged negatively with respect to the inside (due to the in- and outflow of sodium and potassium ions) and a positive deflection is measured on the positive electrode.

A.1.1   Atrial depolarisation

Atrial depolarisation starts with the activation of the SA node. As the wave of depolarisation spreads across the atria, some of the muscle cells are negatively charged with respect to the inside (depolarised) and some of the muscle cells are still at their RMP(polarised) and, therefore, positive with respect to the inside. A positive deflection is thus seen on the ECG
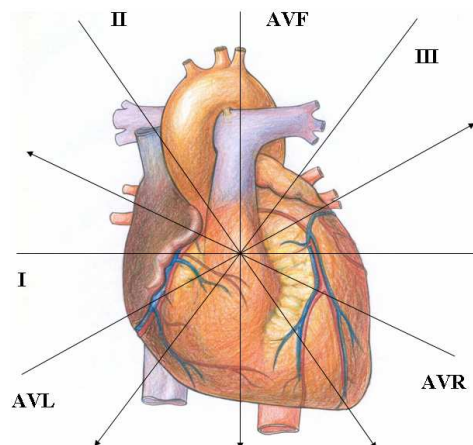
Figure A.6: Heart axes as viewed by different leads
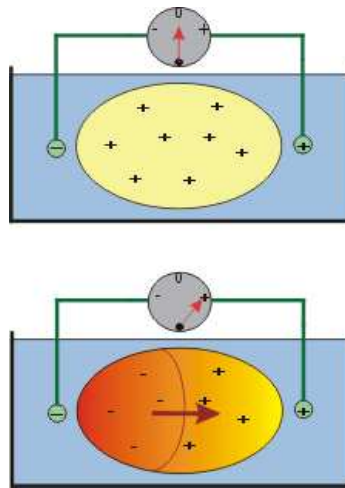
Figure A.7: Potential difference between two sides of ventricular muscle mass is zero when there is no depolarisation wave, and positive when depolarisation moves towards the positive electrode [78]

tracing. Once all of the atrial muscle cells are depolarised, the net potential difference is again zero and no deflection is seen. Figure A.8 explains this, as well as the spread of the repolarisation wave schematically. When repolaristaion occurs, the opposite happens. The muscle cells that were first depolarised are first to repolarise and their net charge with respect to the inside of the cell is once again positive. Because the cells that are still negative are now closer to the positive electrode, and a net negative potential difference exists between the two electrodes, a negative deflection is seen in the ECG tracing. Once all the cells are positive with respect to the inside (repolarisation has stopped), the net potential difference is zero and no deflection is seen on the ECG tracing.
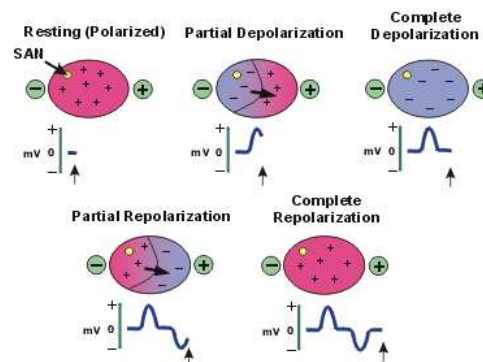
Figure A.8: Spread of atrial depolarisation and repolarisation waves and resulting deflections in ECG tracing [78]
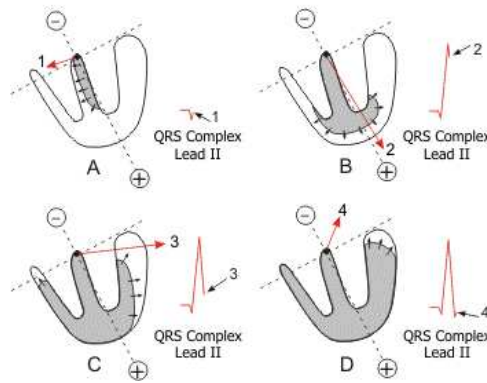
Figure A.9: Spread of ventricular depolarisation wave showing resulting deflections in ECG tracing [78]

A.1.2 Ventricular depolarisation

The spread of the repolarisation wave across the ventricles is as shown in Figure A.9. This explanation is based on lead II of the ECG axis. The ventricular depolarisation waves originate at the AV node and first spread down the interventricular septum through the left and right bundle branches (refer Figure A.1). The septum thus depolarises from left to right, as shown in sketch A of Figure A.9. When viewing Figure A.9, it should be kept in mind that the left side of the heart is to the right of the sketch. The plus and minus in each sketch shows the position of the positive and negative electrodes for the lead II orientation. The mean electrical vector is orientated in such a way that it moves away from the positive electrode and the result is a negative deflection in the ECG tracing. This corresponds to the Q-wave in the QRS-complex.

The repolarisation wave now moves further down the septum and reaches the apex of the heart and begins to move through the Purkinje fibres (sketch B in Figure A.9). The mean electrical vector is almost parallel to the orientation of lead II and moves towards the positive electrode, thus resulting in a considerable positive deflection in the ECG tracing. This corresponds to the R-wave in the QRS-complex of the ECG tracing.

Next the wave moves up the ventricles, almost totally depolarising the right ventricle and partially depolarising the left ventricle. This is because the left ventricle is much larger than the right ventricle. The mean electrical vector is orientated as shown in sketch C of Figure A.9 and results in a small positive deflection in the ECG tracing. The last regions to depolarise are the topmost areas of the ventricles and the resulting mean electrical vector points upwards (towards the negative electrode) and to the left, resulting in a minor negative deflection in the QRS-complex (the S-wave).

During ventricular repolarisation, the cells that were depolarised last are the first ones to repolarise, therefore, the repolarisation waves move in the opposite direction to the depolarisation waves, thus resulting in a positive deflection in the ECG tracing, whereas
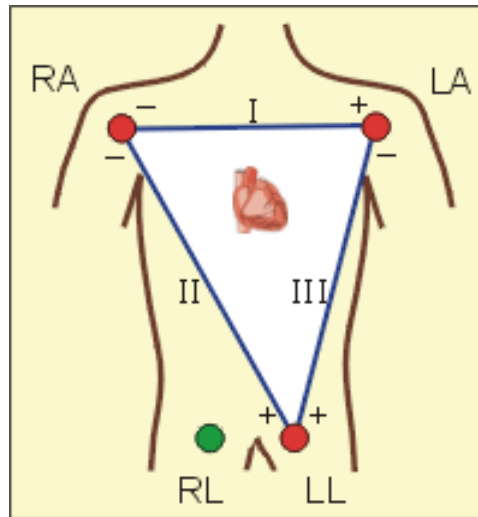
Figure A.10: Standard bipolar limb leads for a 12-lead ECG configuration [78]

atrial repolarisation results in a negative deflection in the ECG tracing.

As the heart contracts (depolarises), a multitude of depolarisation waves spread across the heart. The mean electrical vector is the sum of all these vectors (waves) of depolarisation at a specific instant in time [78]. Physicians often refer to the *mean electrical axis* of a patient. This refers to the average of all the mean electrical vectors and is normally in the range of $0°$ to $+90°$. If the mean electrical axis is less than $0°$ it is termed *left axis deviation* and may be indicative of diseases such as *inferior myocardial infarction* or *left anterior hemiblock* [57]. If the mean electrical axis is greater than $+90°$ it is termed *right axis deviation*. In order to determine the mean electrical axis, one should first find the electrical axis that is biphasic (equal positive and negative deflections). Next, the electrical axis that is perpendicular to the afore-mentioned axis, that has a net positive deflection, should be established. The latter axis is then the mean electrical axis.

A.1.3 The lead system

The volume conductor principle also applies when viewing the deflections of a specific ECG lead (or axis). For the different ECG axes (I, II, V1, aV_F etc.), the positive and negative electrodes are placed at different locations on the body and, thus, different deflections will be seen by each one. For example, the standard bipolar limb leads are known as Leads I, II and III and their electrodes are placed on the body as shown in Figure A.10.

As can be seen in Figure A.10, for lead I the positive electrode is situated on the left arm (LA) and the negative electrode is situated on the right arm (RA). For leads II and III the positive electrode is situated on the left leg (LL) and the negative electrodes are placed on the right arm and left arm respectively. Together these three leads form what is known as Einthoven's Triangle and examine the depolarisation of the heart from different angles and
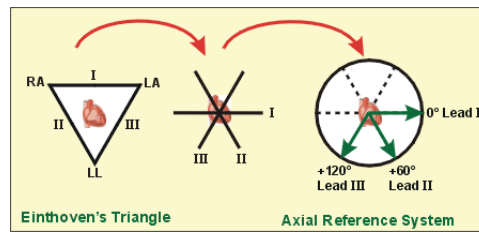
Figure A.11: Einthoven's Triangle and the Axial Reference System [78]

together they form the Axial Reference System, as shown in Figure A.11. According to the volume conductor principle, a wave of depolarisation that is moving towards the positive electrode of lead I, will produce a positive deflection in lead I. The same applies to all the other leads. If the wave of depolarisation moves towards a positive electrode, a positive deflection will be seen and if the wave of depolarisation moves away from the positive electrode, a negative deflection will be seen. Just the same, if a wave of **repolarisation** moves towards the positive electrode, a negative deflection will be seen, whereas if the repolarisation wave moves towards the negative electrode, a positive deflection will be seen. These rules are universally accepted and apply to all ECG measurements [78].

The leads aV_R, aV_L and aV_F are known as the unipolar augmented limb leads. They are termed "unipolar" because there a single positive electrode is referenced against a combination of all the other limb electrodes [78]. The positive electrodes are situated on the left arm (aV_L), right arm (aV_R) and left leg (aV_F). The position of these electrodes and their positions on the Axial Reference System are shown in Figure A.12.

The three limb leads and the three augmented limb leads view the electrical activity of the heart form the frontal plane. In addition to this, there are 6 precordial unipolar chest leads (V_1 - V_6) that view the electrical activity of the heart in a plane perpendicular to the frontal plane. Their position on the chest and in the perpendicular plane is shown in Figure A.13.

The deflections in these tracings are produced in the same way as for all the other leads. Leads V_1 and V_2 view the anterior septal region of the heart, leads V_3 and V_4 view the anterior apical (apex) region of the heart and leads V_5 and V_6 view the anterior lateral region of the heart.

A.2   Echo-cardiography

The echo-cardiogram uses ultrasound waves to examine the heart of a patient. An echo-cardiogram is also used in evaluating the fetus of a pregnant female. Ultrasonic gel is applied to the thorax of the individual on the area of interest to aid in the transmitting of the ultrasonic waves. A transducer then sends ultrasonic waves through the body and these
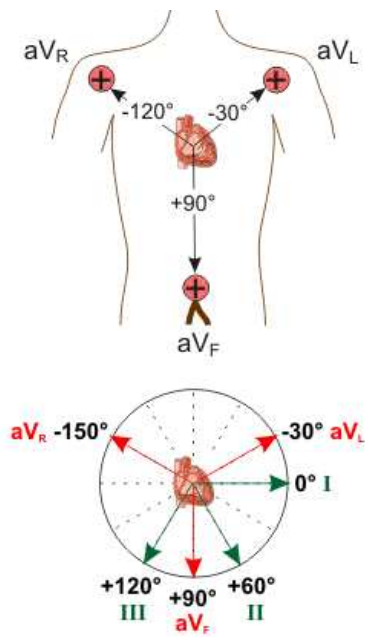
Figure A.12: Unipolar augmented limb leads position [78]
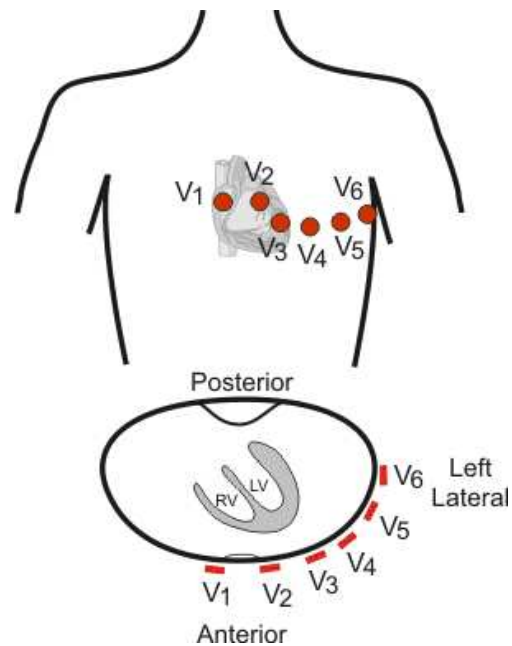
Figure A.13: Precordial unipolar chest leads positions [78]

are reflected back by the heart, collected by the transducer and transformed to an image of the heart.

The single dimension (1-D) echo-cardiogram is known as M-mode echo-cardiography. In M-mode echo-cardiography a narrow beam is directed towards the region of interest and the output is the movement of the structures through which the beam passes as a function of time. Characteristic patterns are associated with certain pathologies such as mitral stenosis and pericardial effusions, which are easily recognised [12].

A more advanced type of echo-cardiography, 2-D echo, gives a two-dimensional sectional view of the heart. This is probably the most well-known type of echo-cardiogram. In this type of echo-cardiogram the transducer beam moves across the chest wall in a sweeping manner, updating the picture with each sweep. The transducer can either be of the sweeping or rotating type. In the rotating transducer the head has a multitude of transducers inside a liquid-filled dome. One transducer emits a beam and receives the echo back and the next transducer in line takes over and does the same and so on and so forth. In this manner the picture is continuously updated so that the movement of the structures are displayed in real-time [79]. Figure A.14 shows how the transducer beam sweeps across the heart and the resulting image formed. Figure A.15 shows an echo-cardiogram of the four chambers of the heart.
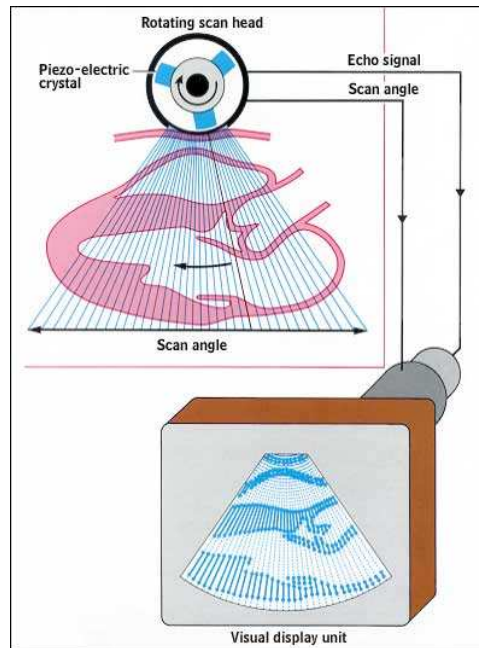
Figure A.14: Sweeping of echo-cardiography transducer beam and how resulting image is formed [79]
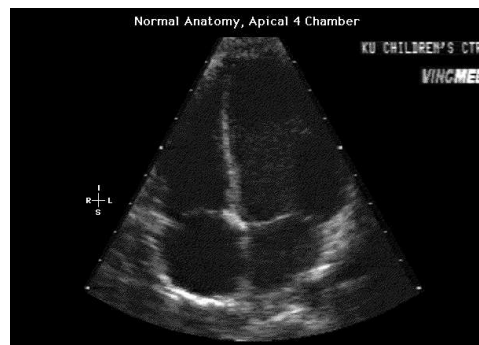
Figure A.15: Echo-cardiogram of normal heart showing different chambers [80]

A.3 Impedance cardiography (ICG)

Impedance cardiography is a technique by means of which the resistance of the thorax to a small current is measured. From this measurement, parameters such as cardiac output, stroke volume, etc. are calculated. Eight electrodes are placed on the thorax and neck for use in the measurements (see Figure A.16). The inner electrodes (white & red) are the sensing electrodes, while the outer electrodes (black & green) are the source and sink of the measurement current. The white electrodes must be placed along the line of the root of the neck and the red electrodes are placed on either side (midaxillary line) of the patient at the xiphoid process level (diaphragm level). The black electrodes are placed above the white electrodes at 5 cm distance and the green electrodes are similarly placed below the
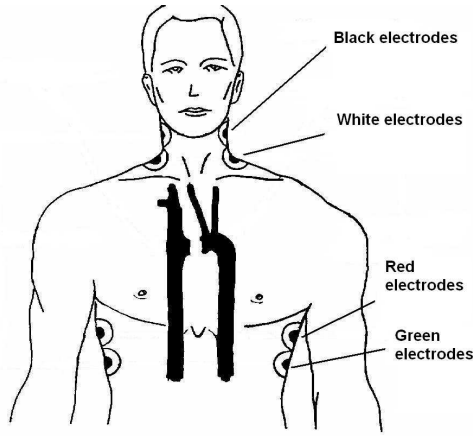
Figure A.16: Electrode positions for ICG measurements

red electrodes.

A high-frequency current (65 kHz, 7 μA RMS) is introduced between the black and the green electrode pairs. The current flows through the thorax, parallel to the spine, primarily through the aorta and superior and inferior vena cavae, since this is the path of least resistance. Due to this high-frequency current, a high-frequency voltage is developed across the thorax and sensed by the white and red electrode pairs. This voltage is directly proportional to the impedance of the thorax [81]. As the impedance, known as Thoracic Electrical Bioimpedance (TEB), in the thorax changes, the changes are measured and certain parameters are calculated.

Before one starts an ICG test, the height(H) in cm and weight(W) in kg of the patient have to be entered into the program. The ideal weight of a male of the specified height is calculated by:

$$W_{\text{ideal male}} = 0.524 \times H - 16.58 \tag{A.3.1}$$

The volume of electrically participating tissue (VEPT) is then calculated as:

$$VEPT_{\text{male}} = \frac{(0.17 \times H)^3}{4.25} \times (1 + 0.65 \times (\frac{W}{W_{\text{ideal male}}} - 1)) \tag{A.3.2}$$

The body surface area (BSA) is calculated from the DuBois & DuBois [81] formula as:

$$BSA = W^{0.425} \times H^{0.725} \times 0.007184 \tag{A.3.3}$$

The stroke index (SI) [2] and cardiac index (CI) [3] can then be calculated by:

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[2]The amount of blood pumped by the left ventricle in one heart beat interval, indexed by the BSA $[ml/m^2]$.

[3]The amount of blood delivered by the heart to the body in one minute, indexed by the BSA $[l/min/m^2]$.

$$SI_{\text{actual}} = \frac{2}{BSA} \times \frac{VEPT_{\text{male}}}{6800} \times SI_{\text{TEBCO}} \qquad \text{(A.3.4)}$$

and

$$CI_{\text{actual}} = \frac{2}{BSA} \times \frac{VEPT_{\text{male}}}{6800} \times CI_{\text{TEBCO}} \qquad \text{(A.3.5)}$$

where SI_{TEBCO} and CI_{TEBCO} are standardised values for a male of height (H) = 180 cm and weight (W) = 80 kg, transmitted by TEBCO and are equal to 49 ml/m^2 and 4.9 $l/min/m^2$ respectively.

The parameters that were measured are (definitions were obtained from [53; 82; 81]):

- **Heart rate**: The heart rate is the number of times the heart beats in one minute and is measured in beats per minute.

- **Ventricular ejection time (VET)**: VET is the time from aortic valve opening to closure during the systolic portion of the cardiac cycle. The duration of VET is shortened by heart failure.

- **Pre-ejection period (PEP)**: PEP represents the time from onset of electrical activity of the heart (measured by the start of the QRS-complex) to the opening of the aortic valve (the onset of left ventricular ejection). PEP is shortened by hyperadrenergic[4] states and prolonged by heart failure.

- **Thoracic fluid conductivity (TFC)**: This is the total conductivity of the thorax, measured at 65 kHz between the root of the neck and the diaphragm. TFC represents the total contribution of all the conductive fluids in the thorax.

- **Ejection phase contractility index (EPCI)**: This represents a combination signal and takes into account the maximum rate of volumetric change of blood within the aorta and the maximum rate of alignment of red blood cells. The measurement is normalised by TFC to produce a per second rate.

- **Inotropic State Index (ISI)**: ISI represents a normalised image of maximum acceleration of aortic blood flow and is measured in $1/sec^2$.

- **Ejection Fraction (EF)**: This is the percentage of blood held within the ventricle at the end of diastole, which is ejected into the vasculature.

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[4]Adrenergic refers to a synaptic terminal that releases norepinephrine upon stimulation [10]. Hyperadrenergic will then refer to such a state when abnormally large amounts of norepinephrine is released upon stimulation.

- **Stroke Index (SI)**: The SI is the volume of blood pumped by the left ventricle, over one heart beat interval indexed by the body surface area (BSA). It is measured in ml/m^2.

- **Cardiac Index (CI)**: This is the amount of blood pumped by the left ventricle in one minute, indexed by the body surface area (BSA) and is measured in $l/min/m^2$.

- **Respiratory Rate (RR)**: This is the number of breaths per minute.

Appendix B

Data sheets and data tables

The data sheet for the condenser microphones used and tables with the extracted features and their respective SOF are given. The selected features are indicated.

Feature	SOF	Selected(Y/N)
RMS-value of 3rd section of diastole - 2nd IC right	1.6153	Y
RMS-value of 3rd section of diastole - 2nd IC left	1.6153	Y
Max frequency of 1st section of diastole - 4th IC right	1.3869	Y
S_1 duration	1.3213	N
P-R interval duration	1.2296	N
RMS-value of 2nd section of diastole - 2nd IC right	1.1271	N
RMS-value of 2nd section of diastole - 2nd IC left	1.1271	N
Frequency band ratio of S_2	0.9828	N
Max frequency of 2nd section of diastole - 2nd IC right	0.9289	N
Max frequency of 2nd section of diastole - 2nd IC left	0.9289	N
RMS-value of 2nd section of systole - 5th IC left	0.9142	N
Max frequency of 3rd section of systole - 2nd IC right	0.9033	N
Max frequency of 3rd section of systole - 2nd IC left	0.9033	N
Average power of S_1 to S_2 ratio - 2nd IC right	0.8986	N
Average power of S_1 to S_2 ratio - 2nd IC left	0.8986	N
RMS-value of 2nd section of diastole - 6th IC left	0.7827	N
Max frequency of 2nd section of systole - 5th IC left	0.7801	N
Max frequency of 3rd section of diastole - 2nd IC right	0.7434	N
Max frequency of 3rd section of diastole - 2nd IC left	0.7434	N
Average power of S_1 to S_2 ratio - 5th IC left	0.7245	N
RMS-value of 3rd section of diastole - 6th IC left	0.6951	N
Average power of S_1 to S_2 ratio - 6th IC left	0.6941	N
Max frequency of 1st section of systole - 4th IC right	0.6859	N
Max frequency of 2nd section of systole - 4th IC left	0.6754	N
Ejection sound power	0.6511	N
Max frequency of 3rd section of diastole - 4th IC left	0.6496	N
RMS-value of 2nd section of systole - 6th IC left	0.6415	N
RMS-value of 2nd section of systole - 2nd IC right	0.6389	N
RMS-value of 2nd section of systole - 2nd IC left	0.6389	N
Max frequency of 1st section of systole - 4th IC left	0.6207	N
Max frequency of 3rd section of diastole - 4th IC right	0.5942	N
RMS-value of 3rd section of systole - 2nd IC right	0.5619	N
RMS-value of 3rd section of systole - 2nd IC left	0.5619	N
S_1 beat-to-beat power comparison - 5th IC left	0.5345	N
Max frequency of 1st section of systole - 2nd IC right	0.5314	N

Table B.1: Extracted features and their respective SOF

Feature	SOF	Selected(Y/N)
Max frequency of 1st section of systole - 2nd IC left	0.5314	N
Max frequency of 3rd section of systole - 4th IC right	0.5255	N
Midsystolic click power	0.4822	N
Max frequency of 2nd section of diastole - 4th IC left	0.4655	N
A_2- P_2 split timing - 2nd IC right	0.4416	N
Max frequency of 1st section of diastole - 4th IC left	0.4345	N
RMS-value of 1st section of systole - 5th IC left	0.4244	N
Max frequency of 2nd section of diastole - 4th IC left	0.4147	N
RMS-value of 3rd section of diastole - 5th IC left	0.4126	N
Max frequency of 3rd section of systole - 4th IC left	0.4121	N
Frequency band ratio of S_1	0.4115	N
RMS-value of 1st section of diastole - 2nd IC right	0.4101	N
RMS-value of 1st section of diastole - 2nd IC left	0.4101	N
Max frequency of 3rd section of diastole - 5th IC left	0.3972	N
Max frequency of 2nd section of systole - 2th IC right	0.3932	N
Max frequency of 2nd section of systole - 2th IC left	0.3932	N
Openingsnap power	0.3931	N
RMS-value of 1st section of systole - 6th IC left	0.3800	N
RMS-value of 1st section of diastole - 5th IC left	0.3534	N
Max frequency of 2nd section of systole - 4th IC right	0.3253	N
Max frequency of 1st section of systole - 5th IC left	0.2810	N
S_1 beat-to-beat power comparison - 6th IC left	0.2790	N
Max frequency of 1st section of diastole - 5th IC left	0.2719	N
RMS-value of 2nd section of diastole - 5th IC left	0.2324	N
Max frequency of 3rd section of systole - 5th IC left	0.2311	N
RMS-value of 3rd section of systole - 6th IC left	0.2183	N
S_2 duration	0.1979	N
Max frequency of 2nd section of diastole - 5th IC left	0.1820	N
Max frequency of 1st section of diastole - 2nd IC right	0.1360	N
Max frequency of 1st section of diastole - 2nd IC left	0.1360	N
A_2- P_2 split timing - 2nd IC left	0.1104	N
RMS-value of 3rd section of systole - 4th IC right	0.1014	N
RMS-value of 1st section of diastole - 6th IC left	0.0595	N
RMS-value of 1st section of systole - 2nd IC right	0.0218	N
RMS-value of 1st section of systole - 2nd IC left	0.0218	N

Table B.2: Extracted features and their respective SOF (continued)

Appendix C

Gradient descent algorithm

The *gradient descent algorithm* is an optimisation technique by which the minimum of a function is found. If the maximum of the function is sought, the method is known as the *gradient ascent algorithm.*

The gradient descent algorithm starts by having an initial estimate of the minimum point of the function, say $J(\zeta_1, \zeta_2) = J(\boldsymbol{\zeta})$. The new $\boldsymbol{\zeta}$ is calculated by

$$\boldsymbol{\zeta}^{\text{new}} = \boldsymbol{\zeta}^{\text{old}} + \Delta\boldsymbol{\zeta} \tag{C.1}$$

where

$$\Delta\boldsymbol{\zeta} = -\mu\frac{\partial J\left(\boldsymbol{\zeta}\right)}{\partial\boldsymbol{\zeta}} \tag{C.2}$$

where μ is positive [68]. Figure C.1 shows the contour plot of a function with the minimum of the function indicated by **X**. If the initial point is chosen at $\boldsymbol{x}_1$, the *gradient descent algorithm* searches in the direction of the negative of the gradient. The gradient at the point $\boldsymbol{x}_1$ is shown as a straight line and the negative of the gradient at that point is in a direction perpendicular to the gradient at that point. The algorithm then calculates the new values of $\boldsymbol{\zeta}$ and moves to the following point, say $\boldsymbol{x}_2$. The process is then repeated until the minimum value of the function is reached, say point X.

The amount by which the function steps towards the minimum at each iteration is dependent on the learning rate μ, as shown in equation C.2. If the learning rate is too large, the algorithm might miss the minimum by overstepping, whereas convergence may take a long time if the learning rate is too small [68]. If the learning rate is chosen correctly, the algorithm converges to a point where the gradient is zero. This might not necessarily be the global minimum of the function, but it might be a local minimum or a saddle point.
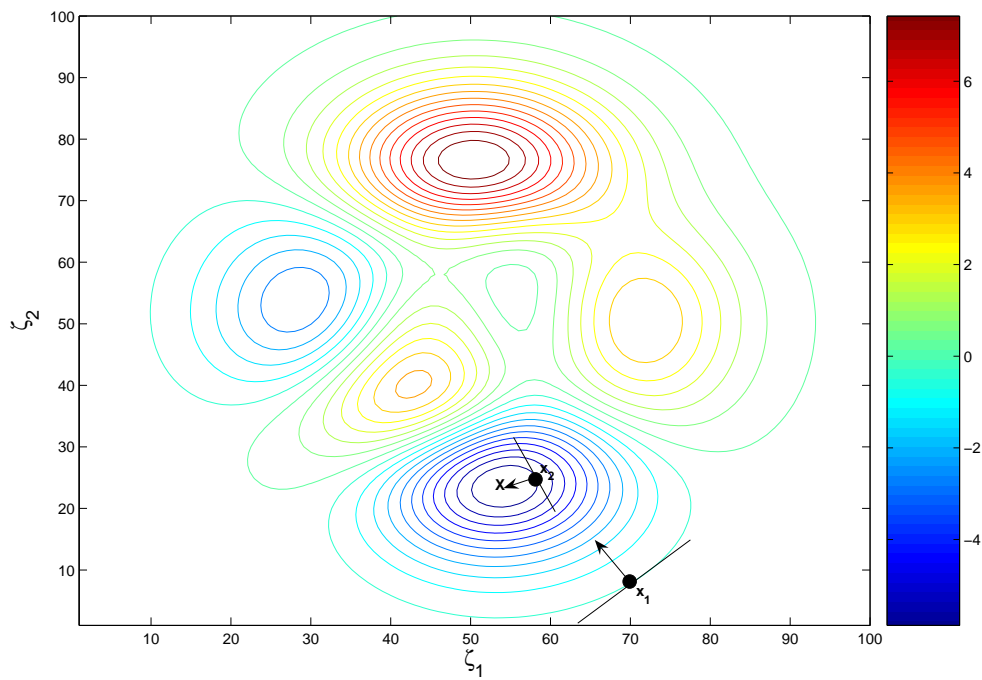
Figure C.1: Contour plot of function, showing how *gradient descent algorithm* steps towards the minimum function value

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