

Combining speed and acceleration to detect reckless driving in the informal public transport industry

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Abstract—The informal transport industry in Sub-Saharan Africa is notoriously dangerous, leading to many fatalities annually. This paper presents an innovative way of monitoring driver behaviour, in real-time, by taking into account road design standards, vehicle dynamics, and passenger comfort. Two models are presented that each combines acceleration and speed data into an erratic driving detection algorithm. The first model is developed through the evaluation of empirical results taken from trips in a minibus taxi, and subjectively gauging recklessness from a passenger’s perspective. The second model presents a novel use of commonly used civil engineering principles, used in road design. Evaluation of the models, using actual minibus data, demonstrates that both successfully detect reckless driving, but the second model proves to be simpler and less processor intensive.

I. INTRODUCTION

In sub-Saharan Africa in general, and South Africa in particular, the minibus taxi sector dominates the informal public transportation system and has grown enormously in the last 20 years. Not only is it the most available mode of transport, it is also affordable to the public. In 2008 it held 67.9% of the collective transport market share [1]. The sector originally evolved to meet the demand of mobility, but unfortunately, a crucial obligation that has fallen victim to the incentive of personal wealth, is personal safety.

The World Health Organization (WHO) African Region [2] has some of the world’s highest road traffic fatality rates globally with more than 32 deaths per 100,000 population annually making it the 9th leading cause of death in the region. The African region has less than 2% of the world’s registered vehicles, but almost 20% of the global traffic deaths. An 80% increase in traffic deaths between 2000 and 2020 is predicted in [3]. According to the March 2011 Road Traffic Report [4], there are 285,858 registered minibuses in South Africa, of which 1,408 were involved in fatal collisions during 2010-11, with 1,795 fatalities.

What makes this tragedy especially unjust is who the victims are: the poor, who have few other options due to the inadequate public transport network in sub-Saharan Africa. The damage extends to other vehicles involved in minibus accidents, and more broadly affects the economy, through the large number of employees and breadwinners lost in the senseless carnage.

The research in [5] and [6], have found that being monitored leads to safer driving behaviour. Seven key characteristics of a well performing urban transport system were

identified by [7], with affordability and safety being the first two characteristics.

Sudden changes of direction, or travelling at a high speed around curves, or braking and accelerating result in forces acting on a vehicle and its passengers. Rapid acceleration decreases the driver’s ability to react as a result of increased speed and limited reaction times. High g-force values around a curve can also result in side slip and loss of control over the vehicle. An increase in speed reduces the possibility to respond in time when necessary and therefore, the possibility to avoid a collision become smaller as speed increases. A special maximum speed limit of 100km/h has been set for minibus taxis, 20km/h lower than the norm on highways, due to the high number of fatalities.

This paper presents an innovative way of monitoring driver behaviour using an electronic unit with two sensors, namely a GPS and accelerometer, and theoretical models, which includes both acceleration and speed data, to detect and report erratic driving of a minibus taxis. To aid in the reconstruction of accidents, the electronic system also contains a storage facility, which is used as a black-box. Driver behaviour and warning notifications are transmitted to an online platform in real-time and also delivered as an audible notification inside the vehicle.

II. RELATED WORK

Numerous studies have been completed on driving behaviour and modelling thereof. The main differences between these studies are in the specific application area and the sensing method employed. A summary of previous work on driver behaviour detection with the research goal and modelling techniques can be found in Table I. An overview of the work done on driver modelling over the past few decades is given in [8]. This overview focused on automatic vehicle control or driver assistance, such as path following, lane change assist and overtake assist. In [9] a system named Intelligent Driving Recognition with Expert System (IDRES) is proposed, which uses a two-level rule-based system that uses measurements from vehicle mounted cameras that face the road to determine lateral position delimiting the lanes of the road.

Recently, research focus has shifted from visual monitoring to the use of vehicle-mounted motion sensors. Visual monitoring makes use of cameras to monitor the driver’s behaviour, and radar and lasers to determine the vehicles speed and position relative to obstacles on the road. Motion sensors, such as accelerometers and gyroscopes, measure the vehicle’s acceleration, in g-force, and orientation, in

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degrees. The popularity of these sensors is mostly due to their simplicity, robustness, and low cost.

Driving patterns classification using Hidden Markov Models (HMM) is proposed by [10] as a framework for machine learning for modelling and recognizing driver behaviour. Information sensed from a steering wheel angle sensor, brake pedal, speedometer, acceleration throttle, gear and GPS unit are used as inputs for the HMM. An adaptive assistance system to determine or predict driver's behaviour using HMM has been developed by [11]. Four cameras are installed in the vehicle (view of front, rear, driver head, and his feet) to monitor the vehicle's sensors (speedometer, steering wheel, acceleration throttle and brake pedal) and the driver.

A Neural Network (NN)-based model for driving pattern classification is proposed by [12]. Bi-axial accelerometer and GPS data are combined to characterize driving patterns using neural networks. A geo-referenced database was developed empirically to compare positioning data to disregard outliers and anomalies.

An embedded sensory system to measure the comfort in public transportation system has been developed by [13]. The system consists of a tri-axial accelerometer, global positioning system (GPS) receiver, temperature sensor and SD Card storage. Three techniques were proposed to determine the comfort level: threshold detection of acceleration peaks; threshold-jerk detection based on the derivative of acceleration (jerk); and comfort assessment from weighted RMS accelerations based on the standard ISO2631-1.

A number of studies have looked at the reconstruction of accidents and accident analysis/prevention. In [14] an erratic driving detection system using Fuzzy Logic is proposed. This system consists of a 3-axis accelerometer, a camera and an on-board diagnostics (OBD-II) reader, which provides the fuzzy logic model with speed and engine readings. The system output is a driving-risk level ranging from 1 to 3.

Portable or mobile (Smartphone) driving detection systems have become increasingly popular since they only need to use sensory data acquired from the GPS, accelerometer, gyroscope and/or magnetometer that are available in a typical Smartphone. Moreover, processing can be performed on the device.

To monitor road and traffic conditions (e.g. speed bumps, braking, and honking), [15] present Nericell, a system that performs sensing through Smartphones using the internal sensing components (accelerometer, microphone, GSM modem and GPS receiver). In [16] driver behaviour is estimated using these sensors (accelerometer, gyroscope and magnetometer). A threshold determines the occurrence of an event and a Dynamic Time Warping (DTW) algorithm compares the occurred event to a set of predefined templates to find an optimal path. Bayesian classification is used to determine how risky or safe the driving habits of the driver are.

In [17] drunk driving manoeuvres are detected by comparing a driver's driving to typical predefined drunk driving patterns. The pattern recognition algorithm makes use of a Smartphone's accelerometer and gyroscope. A DTW and Smartphone based sensor-fusion system, utilizing Euler rep-

resentation, has been proposed by [6] to distinguish between safe and unsafe behaviour.

Table II summarises the sensors used by each of the proposed approaches to measure behaviour.

A. Contribution

Although various contributions have been made in the field of modelling driver behaviour, there are shortcomings in the research field: existing approaches lack an algorithm where the relationship between speed and acceleration are taken into account to accurately identify reckless driving.

By taking road design standards, vehicle dynamics, and passenger comfort into account, this paper proposes two theoretical erratic driving detection models. The first model is designed empirically and the second model from road design standards. The proposed algorithms combine acceleration and speed data into an erratic driving detection algorithm. Despite being commonly used in road design, these road-centric principles have never been used to evaluate vehicle-based recklessness. An evaluation of this model is presented using data captured in a minibus taxi.

TABLE I
SUMMARY OF GOALS AND TECHNIQUES OF RELATED DRIVER
BEHAVIOUR SYSTEMS

Goals of behaviour modelling system	Behaviour modelling technique	Ref.
recognise driver manoeuvres from data sensors	rule based	[9]
machine learning framework for modelling and recognizing driver manoeuvres	graphical models, HMMs and CHMMs	[10]
adaptive assistance system to determine/predict drivers' behaviour	HMM	[11]
classify driving patterns using neural networks	neural networks	[12]
evaluate the comfort in public transportation	three algorithms: Threshold detection, jerk detection and Comfort index measurement	[13]
record driving events and detect unsafe driving behaviours	Fuzzy Logic	[14]
monitor road and traffic conditions using mobile Smartphones	threshold detection	[15]
understand the driver behaviour using Smartphone sensors	endpoint detection, DTW, Bayesian classification	[16]
detect and alert dangerous vehicle manoeuvres related to drunk driving	pattern recognition	[17]
investigate driver behaviour as safe or unsafe	DTW, Bayesian classification	[6]

III. MODEL DESIGN

This section discusses two models that combine speed and acceleration into an erratic driving detection system. In both models, raw acceleration data is filtered using an exponential moving average (EMA). An EMA is chosen as the low pass filter (LPF) since it results in shorter lag than a simple moving average [18], and is given by

$$y_f[n] = \alpha x[n] + (1 - \alpha)y[n - 1] \quad (1)$$

TABLE II
SUMMARY OF SENSORS USED BY RELATED DRIVER BEHAVIOUR SYSTEMS

	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[6]
accelerometer	-	✓	-	✓	✓	-	✓	✓	-	-
gyroscope	-	-	-	-	-	-	-	✓	✓	✓
magnetometer	-	-	-	-	-	-	-	✓	-	✓
GPS	-	-	-	✓	✓	✓	✓	✓	✓	✓
camera	✓	-	✓	-	-	✓	-	-	-	-
GSM module	-	-	-	-	-	-	✓	-	-	-
speedometer	-	✓	✓	-	-	-	-	-	-	-
acceleration throttle	-	✓	✓	-	-	-	-	-	-	-
brake pedal	-	✓	✓	-	-	-	-	-	-	-
steering wheel	-	✓	✓	-	-	-	-	-	-	-
CAN-bus reader	-	-	-	-	-	✓	-	-	-	-

where $y_f[n]$ is the output of the LPF to find the EMA, $x[n]$ is the current sample and $\alpha = \frac{2}{N+1}$ with N the sample period. The LPF sampling time is $20Hz$, since the accelerometer samples at $20Hz$. Other sampling times were evaluated, but this sampling time proved to work well, since engine noise and other high frequencies were filtered out without affecting any relevant data.

Long distance (highway) and short distance (urban) accelerometer and GPS data were collected, and several differences were observed:

- As expected, taxis travel at higher speeds on highways than in urban areas. Taxis travelled at over $140km/h$, which is $40km/h$ over the legal speed limit.
- Variations in longitudinal acceleration is more frequent in urban areas, since taxis regularly stop to pick up passengers. Long-distance taxis are loaded early on a long distance journey and they don't stop often.
- Lateral acceleration variations are more frequent in urban areas, since the radius of curves on highways is larger than in urban areas. Taxis also frequently pull over to the side of the road to pick up passengers in urban areas.
- At a high speed, the same g-force feels more dangerous than at a lower speed. This is confirmed from road design principles where maximum lateral acceleration thresholds are reduced with an increase in speed.

Minibus taxi driving events can be classified into urban events and highway events. An urban event is a pull-over, sharp turn or sharp braking. The duration of an acceleration event is expressed as Δt . These events have smaller Δt than highway events. Highway events include: circular curve following, swerving and sharp braking. The highway events have a longer Δt since the radius of a circular curve (R) is larger on highways and it takes a vehicle therefore longer to go around a curve. Braking from high speeds also result in longer Δt .

It is therefore clear from above observations that the developed model must accommodate both urban and highway events. The following two proposed models meet this requirement, augmenting the acceleration data with vehicle speed information.

The first model was developed by evaluating empirical results taken from trips in a minibus taxi, and subjectively

gauging recklessness from a passenger's perspective. The second model is based civil engineering principles used in road design.

A. Erratic driving detection model from jerky manoeuvres

The model developed is based on the rate of change of acceleration (jerk); that is, the derivative of acceleration with respect to time. The functional diagram in Fig. 1 shows the process of determining erratic driving.

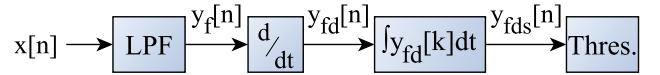


Fig. 1. Functional Diagram for lateral and longitudinal acceleration

Sustained high peaks over an empirically determined Δt relates to irregular driving manoeuvres. We therefore determine the gradient of acceleration, i.e. the jerk, from the empirically specified Δt , which is given by

$$\frac{dy_f(t)}{dt} \Big|_{t=nT_s} = y_{fd}[n] = \frac{y_f[n] - y_f[n-1]}{T_s} \quad (2)$$

where T_s is the sampling period of the differentiator. Substituting (1) into (2) gives the complete jerk equation, namely

$$y_{fd}[n] = (1 - \alpha)y_{fd}[n-1] + \alpha f_s(x[n] - x[n-1]) \quad (3)$$

The jerk samples are summed ($y_{fds}[n]$) over a moving window to identify high concentrations of acceleration, which indicates a lateral or longitudinal driving event

$$y_{fds}[n] = \sum_{k=n}^W |y_{fd}[k]| \quad (4)$$

Acceleration peaks relate to sudden, or erratic driving manoeuvres and a threshold determine if the peak exceeds the 'safe' margin. The thresholds were determined from evaluating empirical results while taking an actual passenger's perspective into account. The erratic acceleration thresholds are categorized into six different identified thresholds. The thresholds decreases with an increase in speed, as seen in table III. For speed above $100km/h$ the taxi driver is committing a traffic violation as mentioned in section I.

TABLE III
ERRATIC ACCELERATION THRESHOLDS

speed (km/h)	threshold (mg)
< 40	200
41 – 60	180
61 – 80	160
81 – 100	140
101 – 120	120
121 <	100

B. Erratic driving detection from road design standards

Roads are designed in accordance with design guidelines with the objective to optimize efficiency and safety while minimizing cost and environmental damage.

Worn out tyres, heavy rainfall and relatively light rain after a long dry spell, reduces the friction between the road and vehicle's tyres. This applies particularly to areas where the road surface is polluted by rubber and oil spills, as is the case in urban areas and the immediately surrounding rural areas. For the purposes of design, it is desirable to select a friction coefficient lower than the limit at which skidding is likely to occur, since any of these circumstances are likely to occur.

1) *Lateral threshold*: The safety of a curve is most significantly influenced by the curve radius in road design. A minimum curve radius is desired to minimize the cost and environmental damage.

A vehicle moving around a circular curve experiences a radial force, usually referred to as the centrifugal force [19]. There is also outward radial force acting towards the centre of the curvature as a result of centripetal acceleration. Roads are designed with an incline to balance the centripetal acceleration. This inclination of the roadway is known as superelevation. The amount of centripetal acceleration depends on the side friction between the tyres and the road and the vehicles weight along the inclined surface. The forces acting on the vehicle can be seen in Fig. 2. The centrifugal force, F_c is given by

$$F_c = \frac{W a_c}{g} = m a_c = m \frac{v^2}{R} \quad (5)$$

where

- m mass of vehicle
- a_c acceleration for curvilinear motion
- v speed
- R radius of the curve
- W weight of the vehicle
- g acceleration of gravity

When the vehicle in Fig. 2 is in equilibrium with respect to the incline (vehicle moving forward, but neither up nor down the incline); we can obtain the horizontal force components, which is given by

$$F_c \cos \alpha = W \sin \alpha + W f_s \cos \alpha \quad (6)$$

where f_s is the coefficient of side friction. From eq. (5) we get

$$R = \frac{v^2}{g(\tan \alpha + f_s)} \quad (7)$$

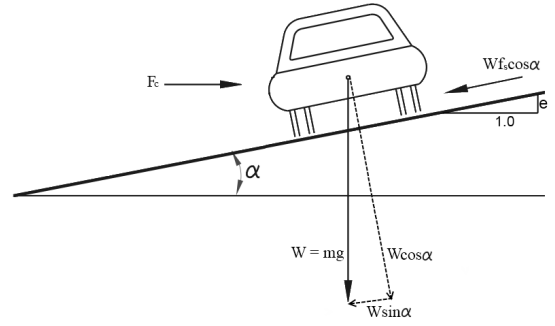


Fig. 2. Forces acting on a vehicle travelling on a horizontal curve section of a road.

and $\tan \alpha$ is known as the rate of superelevation (e) [19]. The equation in (7) can therefore be written as

$$g(e + f_s) = \frac{v^2}{R} = a_c \quad (8)$$

A conservative approach is to take the rate of superelevation as zero (no incline), which results in

$$\frac{a_c}{g} = G = f_s \quad (9)$$

where G is the g-force. The coefficient of side friction according to [20] is

$$f_s = 0.21 - 0.001V \quad (10)$$

where V is the vehicle speed in km/h and is therefore chosen as the lateral threshold for erratic driving events.

2) *Longitudinal threshold*: A deceleration rate of $3.5m/s^2$ (relates to $0.35G$) is recommend by [21] although most drivers stop at a rate higher than $4.5m/s^2$ when confronted with the need to stop for an unexpected object in the roadway. This is a conservative and comfortable deceleration rate for most drivers and is within a driver's capability to stay within the road lane and maintain steering control during the braking manoeuvre on wet surfaces. This rate is therefore chosen as the longitudinal threshold for erratic driving events.

IV. RESULTS

This section evaluates the two models proposed in section III, based on experiments completed in a minibus. Acceleration and GPS (speed and location) data was collected in a minibus taxi that travelled from Cape Town to Aberdeen, Eastern Cape (total distance: 580km, travelling time: 6 hours). Acceleration data was captured on the prototype's SD-card, and post-processed with MATLAB. The raw accelerometer data is filtered using the LPF with $N = 20$ samples, and $\alpha = 0.0476$ (see (1)).

We have collected and processed 36 hour's total lateral and longitudinal acceleration data from 41 minibus taxis, of which 25% is from urban driving. As an example to test and demonstrate the effectiveness of the two models, a section of the road was identified where the most lateral g-force was exerted on the minibus taxi, and this event was also regarded the most erratic for the journey (see Fig. 3). The data plotted



Fig. 3. Google Earth speed plot of a minibus taxi travelling eastwards

in Fig. 4 to 9 reflects this segment, which constitutes a 5 minute period in the trip.

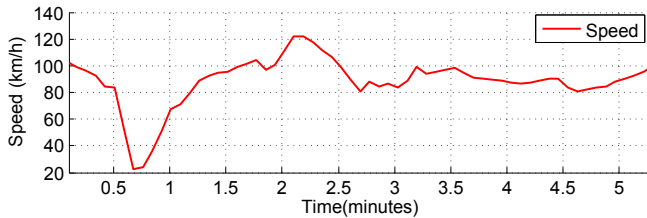


Fig. 4. Speed of the minibus taxi

The minibus taxi's speed through this section is shown in Fig 4. An average speed of 91km/h is maintained, amidst a speed limit of 50km/h. On the straight (nr. 1 in Fig. 3), before the left turn, a top speed of 122km/h was reached, 22km/h above the absolute maximum legal limit for minibus taxis.

The acceleration values for the same road section, filtered according to the LPF from section III, is illustrated in Fig. 5. Left and right turns in Fig. 3 respectively relate to negative and positive values in Fig. 5.

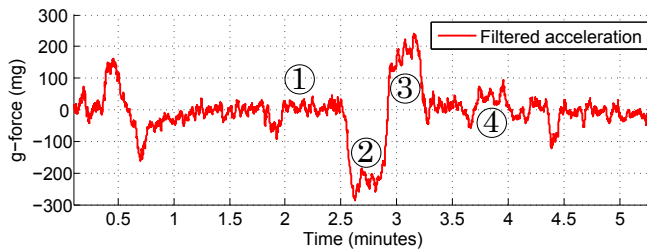


Fig. 5. Low pass filtered acceleration of a minibus taxi. Left (nr. 2) and right (nr. 3) turns respectively relate to negative and positive values.

The plot clearly illustrates the high acceleration experienced through the turns. What the plot also shows is a weakness in the approach of using only an accelerometer threshold, without considering speed, to model reckless driving – the initial peaks in acceleration occur at low speed, and does not constitute a reckless event.

A. Empirical jerk model

The differentiated acceleration data, i.e. the jerk, is illustrated in Fig. 6. The peak jerk values correspond to the

sustained acceleration peaks in Fig. 5. It can also be observed

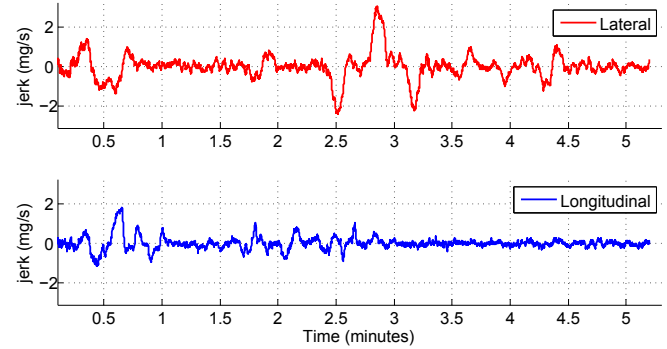


Fig. 6. Lateral and longitudinal jerk derived from the filtered acceleration

that the effect of the duration of the peaks in acceleration is exaggerated, giving more weight to the two erratic events that occur at 2.5 and 3 minutes. The summed values of the

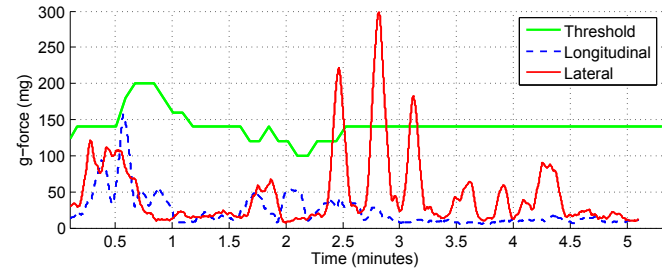


Fig. 7. Lateral and longitudinal summed acceleration. Lateral acceleration crossing the threshold and therefore detecting an erratic driving event at 2.5, 2.75 and 3.2 minutes.

jerk, which essentially partially integrates the jerk back to acceleration, is illustrated in Fig. 7. This figure also shows the speed-dependent threshold, which is noticeably raised at the low speeds in the first minute. The high levels at 2.5, 2.75, and 3.2 minutes exceed the thresholds, and show that erratic events has occurred. No longitudinal erratic events were identified as seen in Fig. 7.

B. Road design model

The model designed from road design standards was applied on the same data set used in section IV-A. The same erratic events were identified, but with a more efficient algorithm. The threshold to detect the erratic event is based on road design and not only from passengers' perspective. The implementation of this model on real time data proved to be simple to realise with low memory and processing usage.

Fig. 8 shows the dynamic threshold for the data set with the corresponding lateral acceleration. A clear erratic event occurred between 2.5 and 2.75 minutes, and again between 3 and 3.25 minutes. A small erratic event occurred at 0.4 minutes, which can be ascribed to the conservative assumptions used in road design. The longitudinal acceleration with the road design erratic driving threshold can be seen in Fig. 9. No erratic driving events were identified. Longitudinal erratic events are less often identified on highway data since the minibus taxis stop less frequent than in urban regions.

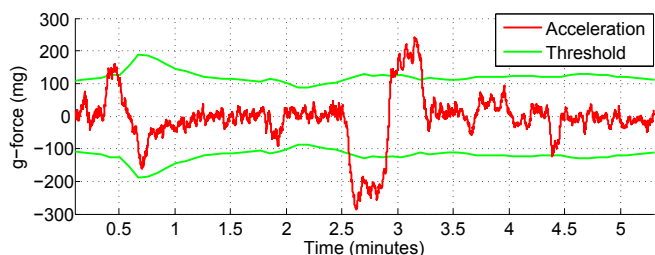


Fig. 8. Lateral acceleration with road design lateral threshold. Erratic driving detected between 2.5 and 2.75 minutes and between 3.0 and 3.25 minutes.

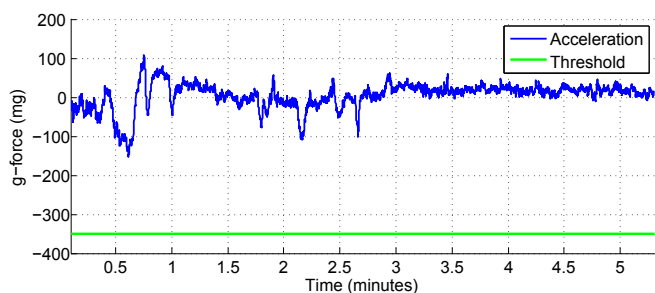


Fig. 9. Longitudinal acceleration with road design longitudinal threshold. No erratic events detected.

V. CONCLUSION

This paper presents two models that combine acceleration and speed into an erratic driving detection system. The first model is developed from the evaluation of empirical results, and is based on passengers experience and captured data. The second model implements design standards, traditionally used only in road design, to create a theoretical erratic driving detection model. Both approaches clearly distinguish between normal driving and erratic driving in urban and highway environments. The second model is more flexible and less processor intensive. The simplicity and robustness of the models makes both ideal for driver behaviour sensing in the informal public transport industry in Sub-Saharan Africa. In future work we will develop a combined model which is less dependent on a subjective measure of recklessness and takes into account the number of passenger in the minibus taxi using an occupancy detection system [22].

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