Recognition of driving manoeuvres using smartphone-based inertial and GPS measurement

Jarrett Engelbrecht, Marthinus J. Booysen, Gert-Jan van Rooyen
MTN Mobile Intelligence Lab
Department of Electrical and Electronic Engineering
Stellenbosch University
Stellenbosch, South Africa, 7600
Email: {15608301,mjbooysen,gvrooyen}@sun.ac.za

***Abstract*—The ubiquitous presence of smartphones provides a new platform on which to implement sensor networks for ITS applications. In this paper we show how the embedded sensors and GPS of a smartphone can be used to recognize driving manoeuvres. Smartphone-based driving behaviour monitoring has applications in the insurance industry and for law enforcement. The proposed solution is suitable for real-time applications, such as driver assistance and safety systems. An endpoint detection algorithm is used on filtered accelerometer and gyroscope data to find the start- and endpoints of driving events. The relevant sensor data is compared against different sets of manoeuvre signal templates using the dynamic time warping (DTW) algorithm. A heuristic method is then used to classify a manoeuvre as normal or aggressive based on its speed and closest matching acceleration and rotation rate templates.**

I. Introduction

Worldwide, more than a million deaths are caused by road accidents per year [1]. The World Health Organization predicts that road fatalities will rise to become the fifth leading cause of death by 2030 [1]. Research done in the United States shows that, in more than 50% of fatal road accidents, unsafe driving behaviours were involved [2]. Road accidents are caused by a variety of factors, but aggressive driving behaviour is one of the major causes.

In the last decade, various companies have been developing solutions to monitor a vehicle and its driver's behaviour [3]–[5]. However, these solutions are expensive and intended for fleet management, and there is little incentive for individuals to buy them. However, the increasingly ubiquitous presence of smartphones – with their variety of sensors – presents the possibility to easily implement vehicle monitoring systems on a large scale.

Most modern smartphones have a variety of embedded sensors — typically an accelerometer and gyroscope, and light, proximity and magnetic sensors, as well as a microphone, camera and Global Positioning System (GPS). This variety of sensors make many sensing applications possible. An example of such an application is gesture recognition, which is used to answer a call when bringing the phone to one's ear, or paging through a document by the wave of a hand [6], [7]. In a similar way, different activities such as walking, running, cycling and driving can be detected and classified using the inertial sensors of a phone that is carried in a user's pocket [8].

Vehicle monitoring is an attractive sensing application for smartphones. For instance, drivers can be monitored to make them aware of their potentially dangerous driving behaviour. Anonymous participatory sensing could also enable identifying areas where accidents are more likely to occur [9].

Smartphones' connectivity also allows for the implementation of other vehicle monitoring features, such as traffic monitoring, traffic re-routing and accident reporting. Accident detection is possible using only the sensors in a modern smartphone, as shown by White et al. [10]. The swift automatic reporting of road accidents to authorities can prevent fatalities by minimizing the response time of emergency services. Additionally, using a machine-to-machine (M2M) communication platform would allow the redirection of other drivers away from an accident. Notifying drivers that they are approaching an accident scene could also increase their alertness and warn them to slow down, thereby preventing further accidents.

The remainder of this paper is organized as follows: Section 2 presents the current state of the art of smartphone-based monitoring systems; Section 3 describes the design of a proposed driving manoeuvre recognition system; Section 4 provides the experimental approach and results; and Section 5 presents the concluding remarks.

II. State of the art

In this section, a brief overview is given of the current literature on smartphone-based monitoring systems used in vehicles. The literature mentioned is mostly relevant to driver behaviour monitoring, and some systems also employing road condition monitoring. The techniques and sensors used in the more recent projects are listed in Table I.

Johnson and Trivedi [9] developed one of the first complete driver behaviour monitoring systems on a smartphone. Their system can detect and classify a number of aggressive and non-aggressive driving manoeuvres when placed in a vehicle, by only using the internal accelerometer, gyroscope, magnetometer and GPS of a smartphone. Although the system can identify aggressive driving manoeuvres, it does not draw any conclusions from them. Their intent is to use the system to support a holistic driver assistance system (DAS) by providing it with additional information.

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TABLE I
SUMMARY OF TECHNIQUES AND SENSORS USED BY SMARTPHONE-BASED VEHICLE MONITORING SYSTEMS.

Reference	Detection technique	Sensors used
Mohan [11]	pattern matching, orientation calibration	accelerometer, microphone, GPS
Dai [12]	pattern matching, orientation calibration	accelerometer, gyroscope
Johnson [9]	endpoint detection, DTW	accelerometer, gyroscope, magnetometer, GPS
Eren [13]	endpoint detection, DTW, Bayesian classifier	accelerometer, gyroscope, magnetometer
Fazeen [14]	pattern recognition	accelerometer, GPS
White [10]	pattern matching	accelerometer, microphone, GPS

Eren et al. [13] also implemented a smartphone-based driving manoeuvre detection system similar to Johnson and Trivedi's [9] approach. However, they expanded the system by adding a driving style characterization feature that labels a person's driving style as either safe or unsafe with a given probability.

Dai et al. [12] developed a smartphone-based system that specifically detects drunk driving. This is achieved by detecting and positively identifying a combination of dangerous driving manoeuvres associated with drunk driving.

Fazeen et al. [14] implemented a DAS entirely on a smartphone. The system records and analyses various driver behaviours and external road conditions, and advises a driver on dangerous vehicle manoeuvres. In addition to the driver behaviour monitoring feature, Fazeen et al. [14] also added a road condition characterization and mapping feature to their system that uses a smartphone's GPS and accelerometer.

Mohan et al. [11] developed a comprehensive road and traffic monitoring system, named Nericell, which also employs smartphone sensors to detect certain driving manoeuvres and road conditions.

White et al. [10] developed the WreckWatch accident detection system for a smartphone. It detects a vehicle collision by applying threshold filtering to accelerometer and microphone samples from the smartphone. Data recorded before and during an accident is sent via GSM to a centralized server. Important information about an accident can then be relayed to the relevant authorities from a stored database on the server.

The literature distinguishes between driving manoeuvre recognition and driving behaviour classification. A system could detect various manoeuvres, but not necessarily infer anything from them, whereas another system may be able to classify a driver's behaviour from detected driving manoeuvres. These different systems demonstrate the variety of driving behaviour classifications that can be made. A person's normal driving style can be classified as safe or risky, fuel-efficient or inefficient, skilled or unskilled — and recommendations can be given accordingly to improve their driving. On the other hand, a person's driving behaviour can sometimes differ from normal due to certain circumstances. A person could be driving under the influence of alcohol, drugs or other sensory impairments. In such situations drivers could be warned of their dangerous behaviour, and with their consent, the relevant authorities could be notified of their location.

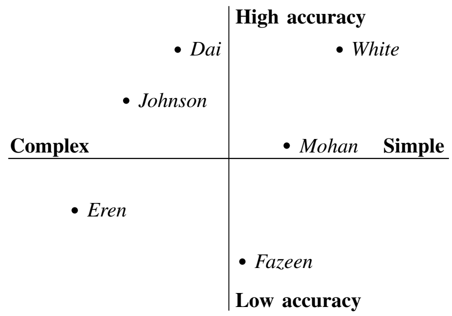

Fig. 1. Qualitative comparison of the systems' accuracy versus simplicity.

A. Accuracy versus simplicity

It is impractical to quantitatively compare the performance and power consumption of the different systems. All of the systems were implemented on different smartphones that have varied sensors and computing power. The test studies were performed in various countries with different road and traffic conditions. Their methods of establishing the ground truth for tests were not necessarily the same and could vary due to subjectivity.

Figure 1 shows a qualitative comparison of the accuracy versus simplicity of the different systems. A system that achieves high detection accuracy with a simple algorithm is considered superior. The assumption is that a simpler system uses less resources and therefore consumes less power. The experimental and empirical test results of the systems as given in each paper were used to compare detection accuracy, although the testing procedures differed as mentioned. The perceived simplicity of each system is based on what each system is trying to detect, what sensors it uses and how its algorithms function.

WreckWatch of White et al. [10] is empirically proven to be virtually 100% accurate and is the simplest system, because it only detects accidents and nothing else. The road condition monitoring feature of Mohan et al. [11] is more accurate than that of Fazeen et al, and its implementation is simpler.

The drunk driving detection of Dai et al. [12] is the most accurate, achieving a false negative rate of virtually 0%. Dai et al. [12] implemented a simple yet effective pattern matching approach that requires very little computation. Essentially, only the difference in subsequent values on the relative longitudinal and latitudinal axes are calculated. If the difference exceeds a certain threshold, an aggressive driving manoeuvre is assumed. The algorithm used by Nericell of Mohan et al. [11] works in a similar manner. Both systems consume less than 12% of the phone's battery life-cycle.

In contrast, Johnson and Trivedi [9], as well as Eren et al. [13], implemented a more complex pattern recognition approach derived from speech recognition techniques. Their

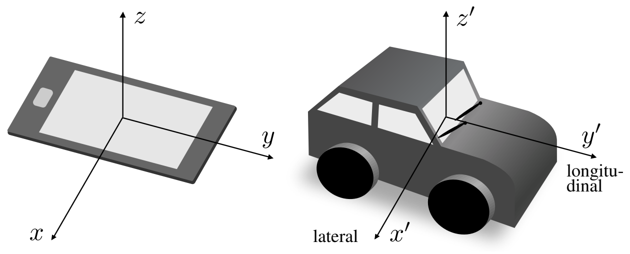

Fig. 2. Smartphone and vehicle coordinate system.

systems perform well, achieving a true positive rate of 97% and 93%, respectively. Although it can not be explicitly proven here, the simpler approaches are likely to consume less power while achieving similar performance to the more complex approaches. Arguably, Dai et al. [12] accomplished the same functionality as Eren et al. [13] with a simpler algorithm, as both systems can infer a certain aspect of a driver's behaviour from detected driving manoeuvres.

The systems of Mohan et al. [11] and Dai et al. [12] were developed on hardware and software that are now considered obsolete, yet their systems were simple and accurate. This suggests that in the last decade, the accuracy of embedded sensors used in smartphones has either not improved significantly, or it does not result in better manoeuvre recognition. The computing power and efficiency of modern smartphones, however, has increased dramatically, which provides headroom for more complex solutions. Therefore there is still merit in implementing a more complex approach as used by Johnson and Trivedi [9]. Especially if the accuracy could be improved to such an extent as to have very few false negatives (FN) or false positives (FP).

B. Contributions and best practices

In terms of contributions made, Dai et al. [12] and Mohan et al. [11] were the only authors to implement a procedure to calibrate the system to any arbitrary orientation of the smartphone. All of the other systems assume that the smartphone is placed in a fixed position within a vehicle. Automatic virtual reorientation of a smartphone's axes to a vehicle's axes is considered a best practice for any smartphone-based vehicle monitoring system.

III. System design

The proposed algorithmic approach used to detect aggressive driving is discussed in this section. The hardware setup used to collect driving data with which the system was developed and tested is also described.

The vehicle's axes are denoted as x', y' and z' in the directions as shown in Figure 2. The smartphone's axes are denoted as x pointing towards the right and y to the top from the phone's front, while z points out orthogonal to the screen. The system assumes the smartphone's axes are aligned with the vehicle's axes. Readings from the accelerometer's three axes (x, y, z) are denoted as a_x, a_y and a_z. Readings from a gyroscope's three axes are denoted as ω_x, ω_y and ω_z. Accelerometer readings are expressed in terms of the acceleration from gravity, g (9.8 m/s^2), and gyroscope readings in terms of rotation rate (rad/s).

A. Aggressive driving model

Aggressive driving is considered as deliberate behaviour by a driver to perform any manoeuvre in such a manner that increases the risk of a road accident. Such deliberate driving behaviour often involves exceeding the speed limit.

In developing countries, such as in Africa, roads and vehicles are generally not as well maintained as in North America and Europe. Speeding is thus a bigger contributing factor to road accidents in Africa then typically elsewhere. Enforcing speed limits in rural areas proves to be difficult, because of typical budgetary constraints of law enforcement agencies in Africa. Making drivers aware of the danger of speeding has always been a top priority of road safety initiatives, such as the Arrive Alive campaign in South Africa. Drivers are unfortunately not always aware they are driving too fast for the shape of the road they are on. The goal is therefore to make a driver aware of unsafe speeds for the specific road they are on using their own smartphone.

Our aggressive driving model is consequently based on the angle of a turn, the lateral force exerted on the vehicle and it's speed through the turn. The gyroscope, accelerometer and GPS of a smartphone is used accordingly to obtain the required information.

B. Recognition algorithm

For the recognition of lateral driving manoeuvres, the a_x acceleration and rotation rate ω_z are used. The accelerometer and gyroscope are continuously sampled at a rate of 20 Hz, in line with [9].

Figure 3 shows a block diagram of the system. The accelerometer output is band-pass filtered to remove sensor noise and the gravitational force vector, as its direction changes slowly when the vehicle's roll and pitch changes while driving. The gyroscope output is low-pass filtered to remove noise.

In order to detect manoeuvres, the start and end of driving events are determined by using the endpoint detection algorithm. For lateral manoeuvres, a simple moving average (SMA) of ω_z is continuously calculated over 40 samples. The beginning of a lateral event is detected if the SMA goes above a set threshold. The previous 40 and succeeding samples of ω_z are concatenated until the SMA falls below the threshold, signifying the end of the event. The samples of a_x are also saved during the same time window. An event is dismissed if it is less than 2.5 or more than 15 seconds long. This is to keep the system from hanging on potentially erroneous or noisy data. The length boundaries were established empirically to detect most valid events.

When a valid driving event has been detected, the signals recorded during the event are compared to a set of templates using the dynamic time warping (DTW) algorithm [15]. DTW finds an optimal alignment between two signal vectors with different lengths. Consider a matrix of the Euclidean distance

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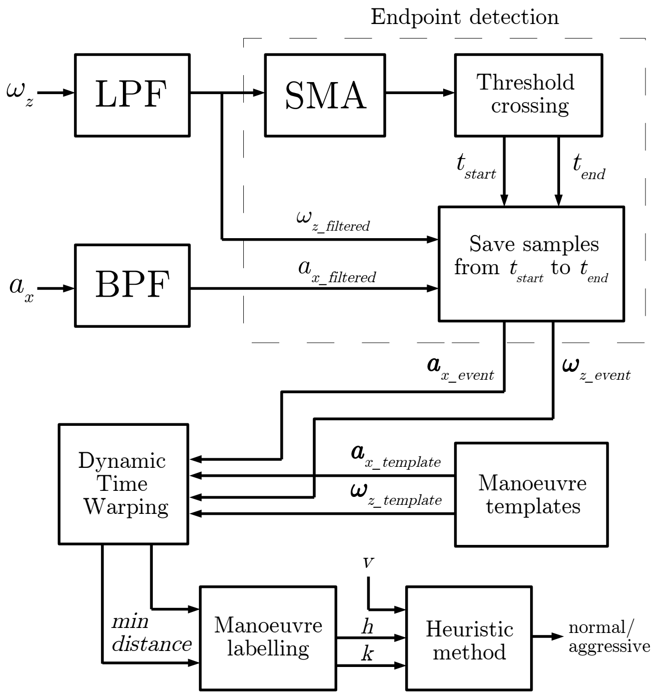

Fig. 3. Block diagram of the system.

between each point of two signal vectors, as seen in Table II. Both vectors start at the bottom left corner. An optimal warping path constitutes the minimum sum of distances, while adhering to monotonicity, boundary and step size conditions. The template with the lowest minimum-distance warp path to the detected event is the closest match.

C. Empirical classification

The acceleration and rotation rate templates are discrete Gaussian signals with fixed lengths that were created from collected driving data. The ω_z templates indicate the angle of a turn. It allows the system to classify a left or right bend from 1 to 3, based on the closest matching ω_z template — with 1 indicating an easy bend, 2 a medium bend and 3 a sharp bend. Similarly there are six a_x templates with increasing amplitudes.

TABLE II
DTW COST MATRIX SHOWING OPTIMAL WARPING PATH.

Template									Minimum-distance	***0***
0	0	-1	-2	-3	-4	-4	-2	-1	-1	***0***
1	1	0	-1	-2	-3	-3	-1	***0***	***0***	1
2	2	1	0	-1	-2	-2	***0***	1	1	2
4	4	3	2	1	0	***0***	2	3	3	4
3	3	2	1	***0***	***-1***	-1	1	2	2	3
3	3	2	***1***	0	-1	-1	1	2	2	3
1	1	***0***	-1	-2	-3	-3	-1	0	0	1
0	***0***	-1	-2	-3	-4	-4	-2	-1	-1	0
Measured	**0**	**1**	**2**	**3**	**4**	**4**	**2**	**1**	**1**	**0**

A heuristic method is used to label any recognized turn as taken normally or aggressively, based on the vehicle's speed (obtained from the GPS) and matching a_x and ω_z template. From experimental results it was evident that two conditions need to be satisfied to classify a turn as aggressive:

1. $v > 50(3 - h)$
2. $k > 4 \vee k > (h + 2)$

where v is the vehicle's speed in km/h, h is the labelled bend severity (1–3) and k is the a_x template number (1–6).

D. Hardware setup

A Samsung Galaxy S3 smartphone was used for driving data collection. A simple data logger Android application was developed that samples the accelerometer and gyroscope at 20 Hz. Although a higher sampling rate is possible, it increases power consumption, and 20 Hz was considered fast enough for the proposed system. The application saves the sensor samples and GPS data to an SQLite database.

In order to validate the smartphone's data, an Arduino board was used to also log data from a dedicated GPS and inertial measurement unit (IMU) to an SD card.

IV. EXPERIMENTAL RESULTS

The collected data set and tested system performance is presented in this section.

A. Data collection

Six individuals were asked to drive a pre-determined route while subjective labelling of their turns were performed by hand. A route of 15 km was chosen that has varying bends and up- and downhill parts. The route necessitates drivers to manage their speed as straighter sections are followed by several sharp bends. All the distinct bends were annotated by hand on a map with a severity of 1, 2 or 3. The route has 55 identified bends — 28 right and 27 left bends. Route notes were used to label how the driver took each bend: normally or aggressively. Although the labelling was done subjectively, it was kept consistent for each driver.

The raw data was post-processed and valid data was successfully extracted and labelled for 387 bends. Overall, the endpoint detection algorithm successfully detected 95% of the left and right bends. The data was split in a 66%/33% ratio for training and test data respectively. The training data set was used to create gyroscope and accelerometer signal templates for the three bend severities taken both normally and aggressively. Twelve templates were thus created from the gyroscope and accelerometer data in total.

B. System performance

The test data set was used to obtain the results given in Table III. For the driver labelled as most aggressive from first-hand observation, the classifier achieved a FN and FP rate of 80% and 10.5%, respectively. Figure 4(a) shows the lateral acceleration of a one minute section where 4 of his aggressive turns occurred. The vehicle's average speed was 85 km/h through this section.

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TABLE III
CLASSIFICATION RESULTS.

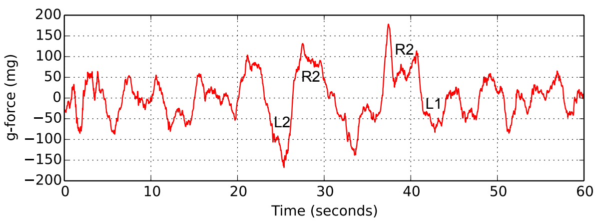
Bend severity classification:							
Accuracy	= 83.7%						
Aggressive manoeuvre classification:							
Precision	= 64.3%						
Recall	= 37.5%	TP	FP	=	9	5
Specifity	= 95.2%	FN	TN		15	100
Accuracy	= 84.5%						

Figure 4(b) shows the lateral acceleration of another driver for the same section of road as in Figure 4(a). All of the second driver's turns were observationally labelled as normal, and his average speed was 70 km/h through the section. The lateral acceleration never exceeded $0.1g$, whereas with the aggressive driver the acceleration exceeded $0.1g$ for all four turns. The classifier achieved a FN and FP rate of 0% and 5.9%, respectively, for this driver.

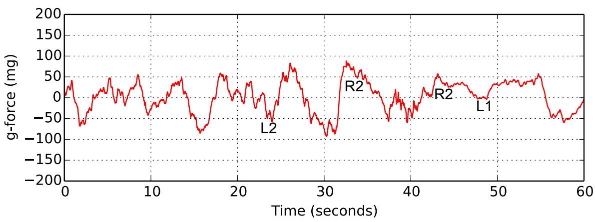
With 24 aggressive turns out of 129 in the test set, the aggressive turn labelling heuristic achieved a FN and FP rate of 62.5% and 4.8%, respectively. Although the FN rate is high, a lower FP rate is desirable. It is biased to label a driver as aggressive based on falsely identified aggressive manoeuvres. The heuristic was tuned to obtain the least false positives, at the expense of missing many true positives (TP). Although the sample size was small, it is clear that the classifier's precision and recall is poor and could be improved. The strength of the system is that it can definitely be expanded to recognize other manoeuvres by preparing relevant templates for the same or other axes of the sensors.

V. CONCLUSIONS

This paper presents a driving manoeuvre recognition and classification system that is suitable for implementation on a smartphone. The recognition algorithm can successfully detect turns of varying severity by comparing the gyroscope signal to a template set, using dynamic time warping. The system can also label each recognized turn as taken normally or aggressively by the driver. The system can be expanded to recognize a variety of manoeuvres. Such a system could be used to monitor a driver over a long period and give him feedback on how to drive safely. The prevalence of smartphones also allows such a system to be easily and cost-effectively deployed on a large scale. In future work we will compare the accuracy of the proposed manoeuvre classification approach to that of other machine learning techniques.



(a) Aggressive driving



(b) Normal driving

Fig. 4. Band-pass filtered lateral acceleration of left (L) and right (R) turns labelled with the bend severity (1–3).

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