A Minor Project Report on

Inferring Driving Behavior

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under the guidance of

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<u>DECLARATION BY THE STUDENT</u>

I, **Navami K,** hereby declare that the project entitled "**Inferring Driving Behavior**" was carried out by me during the **summer** term of the academic year 2014 – 2015. I declare that this is my original work and has been completed successfully according to the direction of my guide Mr. **Nitin Dileep Salodkar, Samsung R& D Institute- Bangalore** and as per the specifications of NITK Surathkal.

Place: Bangalore

Date: 8 July 2014

(Signature of the Student)

Abstract

We consider the problem of inferring driving behaviour. Previous work in this field has required the deployment of dedicated sensors on vehicles and/or on the roadside, or the tracking of mobile phones by service providers. A driving behaviour inference system using smartphone sensors like gyroscope, accelerometer and GPS data can determine drivers speed and acceleration profiles as well as recognize driving events. Driving events, viz. turns (left, right and U) and overtake etc. are well defined and characterised by sensors like z-component of gyroscope, vehicle speed etc. and hence, can be detected by using supervised learning algorithms. This information can be used to monitor and improve driving efficiency through a voice-enabled smartphone app. Event recognition rates of 70.59%, 65.77%, 69% and 76% were achieved for left, right, u turns and overtake respectively. Our system differs from past driving pattern recognition since we fuse data from multiple sensors into a single classifier. Additionally, drivers speed and acceleration profiles is are determined to aid in the feedback process. The system is a completely mobile, effective and inexpensive way to detect and recognize driving events. Therefore, the system can be easily distributed to a wide audience due to the ubiquitous nature of smartphones.

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1 Introduction

Steady development of motor vehicles during the 20th century had a lot of impact on human life, providing much greater mobility for people and products and thus enabling progress in many other fields. However, it is not possible to keep up rapid increase in vehicle speed and availability, with appropriate changes in road infrastructure/conditons and in humans driving capabilities. On the contrary, road congestion has become an obstacle for economic development and, even worse, vehicle accidents have become one of the major causes of death.

Vehicle driving is an act of operating and directing the course of a vehicle. For many humans, driving is a very easy process, perceived as a natural extension of their capabilities. However, driving is a complex decision-making process due to the multidimensionality of the problem (space-time), the complex relationships between the major entities involved in driving (driver, vehicle, and environment) and the dynamic nature of these entities (for example, the driving capabilities of a person vary depending on their age, the time of day, their mental, physical, and emotional state, etc.).

In a 2009 study by the American Automobile Association (AAA) Foundation for Traffic Safety, "As many as 56% of deadly crashes between 2003 and 2007 involve one or more unsafe driving behaviors typically associated with aggressive driving"[6]. These actions include excessive speeding, improper following, erratic lane changing and making improper turns. Currently many companies, including the Department of Motor Vehicles (DMV), utilize call service systems with How am I driving? bumper stickers on their vehicle fleets to monitor driver safety. These systems claim that drivers who know they are being monitored are less likely to engage in distracted or unsafe driving, however, today these systems are ineffective due to the fact that many states prohibit use of cell phones while driving. In order to report an erratic driver, one would need to remember both the number to call and the vehicle ID, or have a passenger report the information. However, as cited by the most recent "Journey to Work" report by the US Census Bureau, 76% of workers drive alone, which means that in most cases, a passenger would not be available to report a drivers behavior. Recently, auto insurance companies such as Progressive have started placing cameras in vehicles to lower insurance rates and monitor driver safety. Similar to vehicle fleet monitoring, insurance companies have also observed that people drive better when being monitored. The systems being deployed in vehicles, such as those created by San Diego-based company DriveCam, have a very high startup cost. According to an editor at Limousine Charter and Tour Magazine, the fleet units are roughly $1000 each, and the company requires a minimum of 20 units to order. The company also charges $30 per month to keep the units online, which makes this an infeasible option for smaller fleets. Family units are also costly, at around $500 per unit with a $30 monthly fee.

For effective driving and in order to promote driver safety, we,find that a drivers behaviour is relatively better when being monitored, when feedback of specific driving events is provided, and when reports of potentially aggressive events are recorded for better understanding. Several companies offer products for fleet management and individual use in order to monitor driving behaviour using expensive cameras and equipment, but we believe that we can create a system that is inexpensive, accessible, and intelligently uses the sensors available on a mobile phone.

We use the term “driving event” to refer to any major change in vehicle attitude or speed, such as a left or a right turn, a stop, making a U-turn, etc. From the decision-making point of view, driving events are demanding as they require the driver to act on vehicle controls while, at the same time, the relationship between the vehicle and the environment (road infrastructure) is far more complex than between events. In these circumstances, driving safety margins are very small and even a minor disturbance can cause an accident situation. Accordingly, driving events have a very significant role in driving safety research.

2 Literature Survey

2.1 *Background*

Determining driving style has importance in the field of driver safety, driver monitoring, reporting, and insurance claims; it can also be used to assist in holistic sensing for intelligent Driver Assistance Systems (DAS). The Laboratory for Intelligent and Safe Automobiles (LISA) has conducted many research experiments focusing on a driver's style, behaviour and intentions [2], [4] and their correlation with driver predictability and responsiveness in various driving situations [5]. Driving style has impact on both the predictability of the driver in certain situations, as well as their compliance with feedback from a DAS. There have been a few works on DAS that use smartphone as a platform. For example, [1] identifies driving style as aggressive or non-aggressive(typical) using Dynamic Time Warping. In [3], authors propose 'Nericell' system, that monitors road and traffic conditions using mobile smartphones.

Support Vector Machine (SVM) [12], is proposed to provide well learning functionality in practical application, for instance, character symbol identification, image classification and induction as well as analysis of biological evolution, and have been identified as a standard tool that is often used in machine learning and data mining.

2.2 *Outcome of Literature Survey*

Driver safety monitoring is not only important for fleet management, but also for monitoring new drivers and assessing performance of drivers during training sessions. Driver safety can be inferred from driver behaviour, which is characteristically driver's profile and the nature of driving events. In order to overcome the high cost of these commercial systems, we have created a novel application for recognizing types of driving events using only the sensors on a mobile phone. In the proposed system, in addition to driving event detection, we detemine driver's speed and acceleration profile which enable us to provide effective feedback to driver using voice assistance systems. An inexpensive, versatile smartphone sensor platform goes a long way as an excellent alternative to current camera equipped fleet management systems.

2.3 *Problem Statement*

We intend to determine certain aspects of users driving behaviour, namely speed and acceleration profiles as well as the driving events like turns, overtake etc. with analytics and processing of smartphone sensor data.

2.4 *Objectives*

- Identifying speed and acceleration profile of a user. Speed profile is the amount of time spent in a particular speed bucket, the time of day at which the time was spent. For example, rush and non-rush hours would typically be the time of day, one would be interested in. Similar definition follows for acceleration profile.

- Inferring driving events like turning (left/right turns, U turns) and overtaking behaviour. The window length (in time) for these events would define how fast an event occured and hence driver's agressive/non-aggresive behaviour can be deduced.

3 Methodology and Work Done

3.1 *Sensor Data Collection*

The latest mobile phones are equipped with many useful inputs for research, including:

- Camera(primary & secondary)
- Microphone
- 3-axis Accelerometer
- 3-axis Gyroscope
- Proximity
- Magnetometer
- GPS

just to name a few. These devices are powerful, inexpensive and versatile research platforms that make instrumenting a vehicle for data collection accessible to the general public as well as academia.

All the above smartphone sensor readings were logged at 1Hz and driving events like left, right, u turns and overtake were manually labelled and saved in persistence storage for further processing. As the events were manually labelled, supervised learning algorithms can be applied, as well as the results can be verified to achieve good event recognition rates.

3.2 *Feature Identification*

The coordinate system used by android sensorAPI for smartphones is shown in Fig. 3.1. We follow the same conventions.

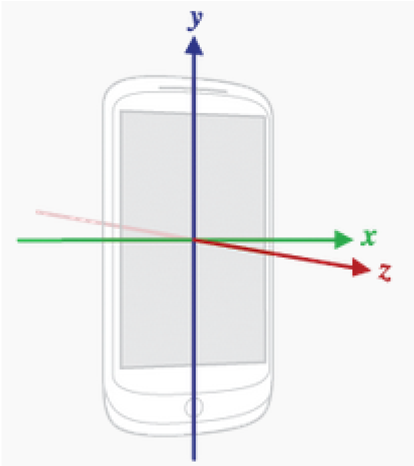
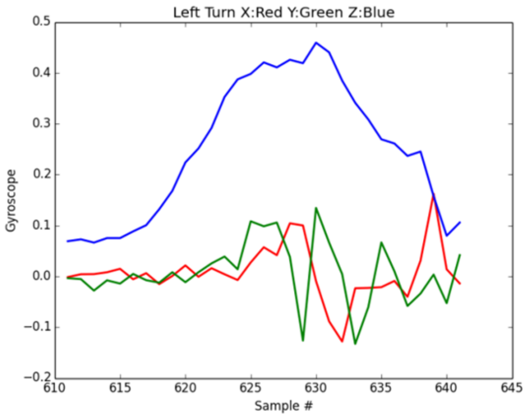
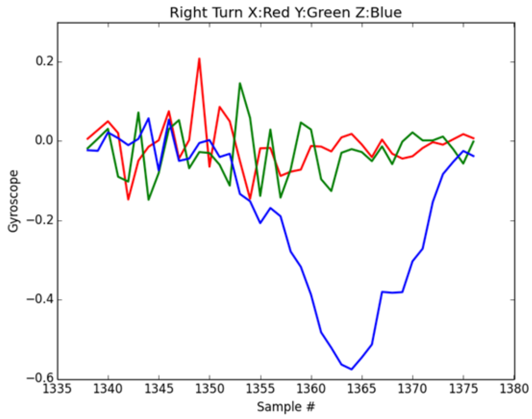


Figure 3.1: **Phone Coordinate System**

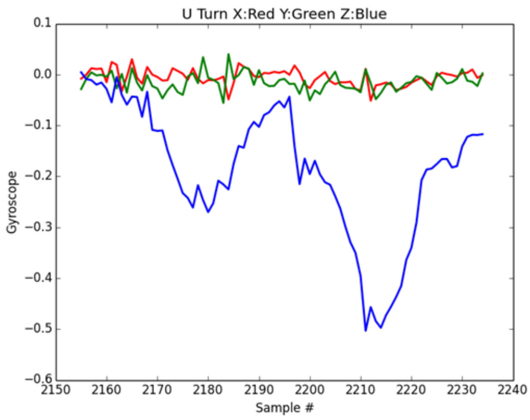
When a turn is taken, since the phone tends to rotate according to the motion of the vehicle, the rate of rotation around an axis that's perpendicular to the horizontal(z- in our case) shows a peak value. In case of left turn, the sensor shows maximum value at the point of turn as it is in anti-clockwise direction, as depicted in Fgure 3.2a. Similary, for a right turn, it shows minimum at the point of turn, as rate of rotation is clockwise, shown in Figure 3.2b. An overtake is identified with a smaller z-gyroscope signals representing lane changes , show in Figure 3.3a. Also, overtake is characterised by an initial increase in speed, shown in Figure 3.3b. Thus, z-gyroscope and GPSSpeed would define an overtake.



(a)

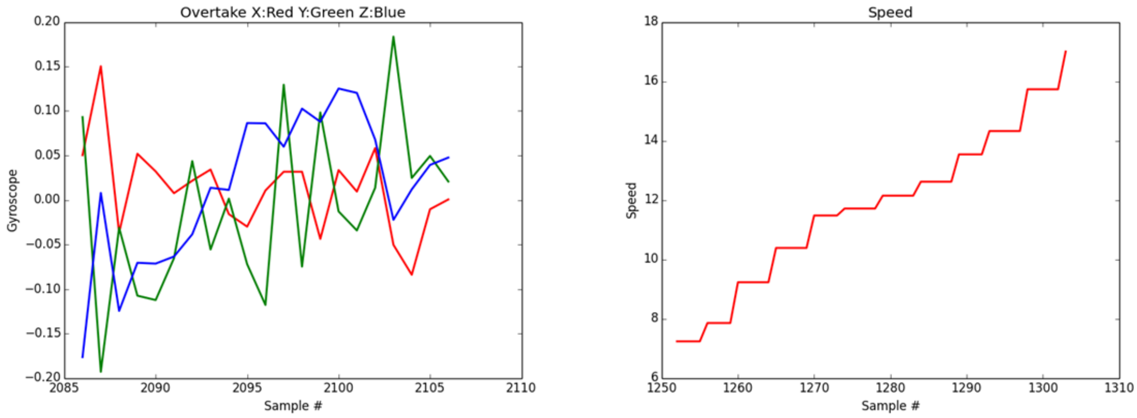


(b)



(c)

Figure 3.2: **z-component of gyroscope showing characteristic signals for (a)left turn (b)right turn and u-turn**



(a) (b)

Figure 3.3: **(a)z-component of gyroscope showing characteristic signals for overtake (b)speed increase during overtake**

3.3 *Event Detection using SVM Classifier*

Support Vector Machine (SVM) supervised learning technique used to implement classifiers for event detection. This method has following advantages:

- Uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.
- Versatile: different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.

3.4 *Evaluation*

Speed and acceleration profiles of driver are identified from GPSSpeed and accelerometer sensor values, using map-reduce framework operations on the given dataset. For left, right and U turns, we identified z-component of Gyroscope as the defining feature. As shown in Fig. 3.2a, this was verified with patterns showed while plotting Gyroscope-z against sample numbers(time sequenced) for each type of turns. The sensor dataset was smoothed by binning to reduce noise as well as normalized since SVM is scale-variant. SVM classifiers were coded to differentiate these events(classes) from normal driving, using scikit-learn tool available for python. The selected machine learning algorithm, SVMs parameters were tuned to achieve higher accuracies. Rbf kernel with class_weight as 'auto' and C (regularisation parameter) as 10.0 was found to be most optimal. As an alternative to supervised learning described above, the characteristic signals for different driving events could be employed for online learning (i.e. in smartphone itself) using low CPU intensive operations. An application that would detect the pattern of gyroscope-z in moving window can efficiently determine turns without the overhead of svm learning.

4 Results and Discussions

The identified speed profile provides a good understanding of users driving style. The aggregate speed and acceleration profiles of all users can be used to give effective feedback to the driver using a voice enabled smartphone app. For example, a use-case of app might look like "The typical driving speed for this non-rush hour is 40 kmph, you are driving at a slower pace". Figure. **??** shows the amount of time spent by a user in different speed buckets.

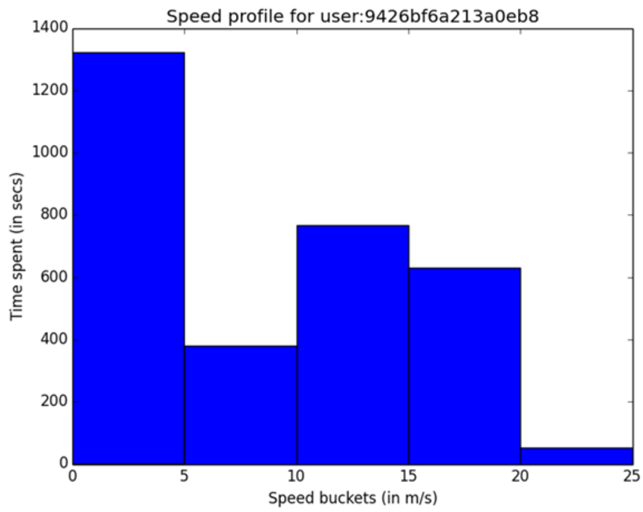


Figure 4.1: **Speed profile for a user**

The confusion matrices for all driving events are shown below.

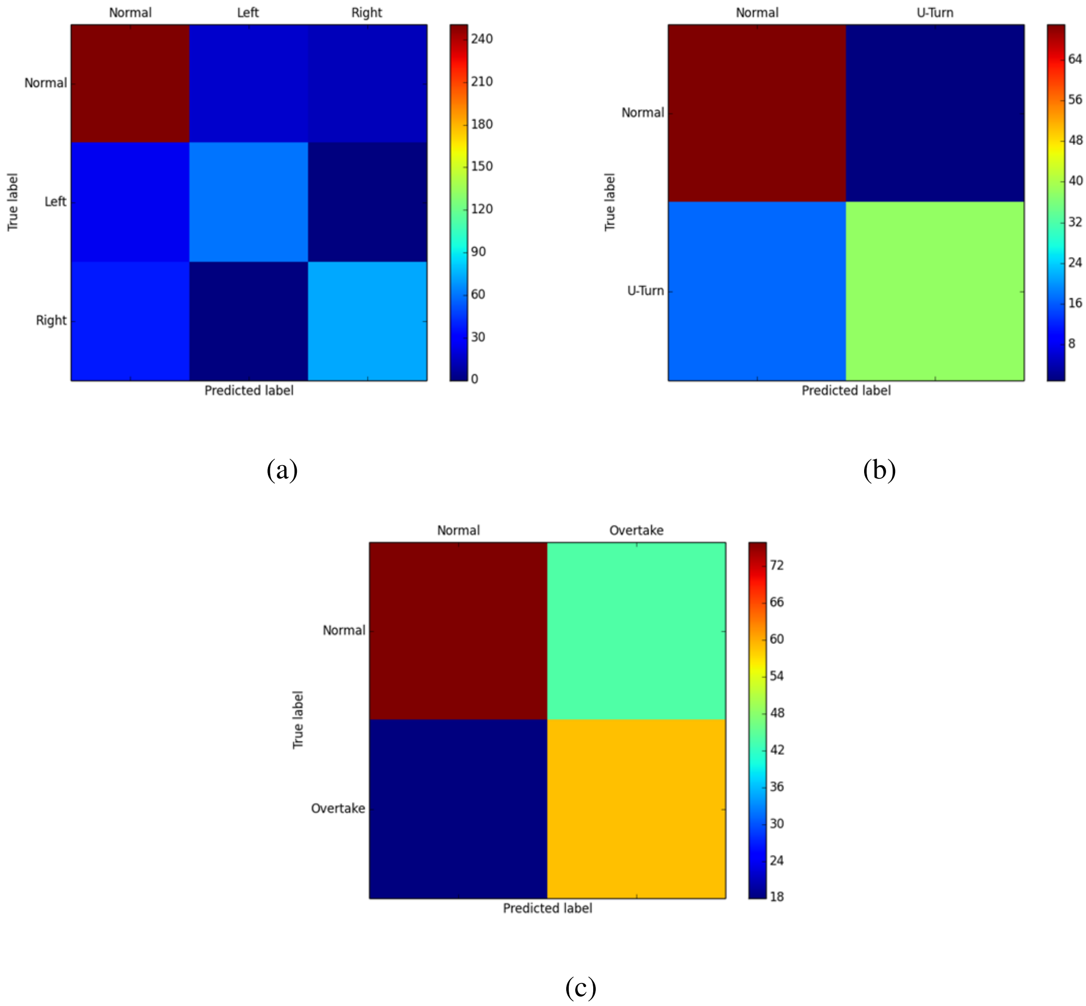


Figure 4.2: **Confusion matrices for evaluation (a) Left, right and normal classes (b)U-Turn and normal classes (c) Overtake and normal classes**

As shown in Table. 1 classifiers for left and right turns showed an accuracy of 80.5% whereas accuracy was 68.53% for overtake manoeuvre. In case of overtake detection, sensor fusion of gyroscope and speed improved the accuracy from 55.5% to 68.53%. Also, class recognition rates were achieved as shown in Table. 2.

Table 1: **Events detection is validated with below accuracies**

	Accuracy(%)
Turn	80.5
Overtake	68.5

Table 2: **Events detection is validated with below class recognition rates**

	Class Recognition Rate(%)
Left turn	70.59
Right turn	65.77
U turn	69
Overtake	76

5 Conclusion and Future Work

We conclude that the combination of gyroscope-z, are the signals best suited for defining and detecting turns. Sensor fusion of z-gyroscope and speed provide good result for overtake. This sytem serves as a novel tool that can be easily and inexpensively distributed to a wide audience due to the ubiquitous nature of smartphones. The system actively detects and records events that characterize a drivers behaviour, thereby giving effective feedbacks, and further promoting driver safety. Our research shows that the sensors available in smartphones can detect movement with similar quality to a vehicle CAN bus, and therefore make it a viable and inexpensive utility for vehicle instrumentation. We believe the smartphone platform is a valuable addition to a Driver Assistance System, not only because of its advanced sensors and ability to recognize driving behaviour, but also because of its access to global networks via its alwayson internet connection.

In the future, we could use unsupervised learning algorithms instead of their supervised counterparts for event detection. Also, event detection can be expanded to include flyovers, traffic signals, honks etc.

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