Poster: Your Phone Tells Us The Truth : Driver Identification Using Smartphone on One Turn

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ABSTRACT

Due to the extensive use of smart devices using them to study the driving behaviors has attracted a lot of researchers. This work demonstrates the problem of identifying drivers based on their driving style using smart phones. For this purpose the turns done by the drivers are being studied. Different sensors are embedded in the smart phones which are being used in order to extract some features to distinguish different drivers. Experiments are being done with four drivers and the results show that our system can distinguish them with high accuracy of 92% using only one turn.

CCS CONCEPTS

• **Human-centered computing** → **Mobile computing; Ubiquitous and mobile devices; Smartphones;**

KEYWORDS

Smart Sensing; Mobile Computing; Driver Behavior; Driver Identification

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1 INTRODUCTION

Driving behaviors have always been an interesting topic for researchers due to their rich information that can facilitate a broad range of applications. For instance, they can provide important information for insurance companies in different scenarios such as theft detection [3] and car accidents [1].

Driving data can be extracted using different platforms such as the embedded sensors in the car including brake, accelerate, signal,

rotation and etc. sensors or from the sensors embedded in the smart devices that people carry by themselves. These sensors can provide useful information about the status of the car such as its speed, the braking and acceleration behaviors and etc. Since the use of smart devices such as smartphones are becoming more pervasive every day, it is really convenient if these devices can be used for studying driving behaviors. For example if the owner of a car only wants specific people be able to drive her car by installing an application on the phone which is able to identify drivers she can find out if an unauthorized person has driven her car or not. In this work, we use smartphones as platform to obtain rich motion data corresponding to drivers. We focus on differentiate drivers by leveraging the sensors embedded in smartphones.

There are existing works that try to identify drivers based on different driving behaviors and sensing platforms. For example, embedded sensors in the car and On-Board Diagnostic (OBD-II) are used to analyze drivers' behavior and differentiate them [1, 3]. David *et al.* [3] analyze driving behavior on turns using the data coming from the different embedded sensors in the car and by extracting simple and complex features for each sensor data try to identify different drivers. In a similar work, Miro *et al.* by analyzing the car's sensor data and extracting different features they could get a very good accuracy in identifying different drivers. Even though such works can get a very high accuracy in identifying drivers, but accessing to sensors data from different car is different and developing a system for different models can be complicated. Zhang *et al.* [4] tries to leverage the data coming from both smartphones and sensors in the car for driver identification. However, the feature set used in this work is too large, which might not be convenient for mobile devices with limited resources. Also, for getting a good results it might need over 10 minuets of driving to collect data for training and testing. In this work, we focus on studying driving behaviors specially on turns and by analyzing turning maneuvers we aim to distinguish between different drivers. Toward this end, we develop a driver identification system that only uses the motion sensors embedded in smartphones, such as the accelerometers and gyroscopes. Compared to existing work, our system only requires low-cost sensors in pervasive smartphones and a small-sized driving data (e.g., a single turn), which make driving behavior-based driver identification practical for daily applications.

As mentioned before, turning maneuver is the main focus in this paper. Using turns is very helpful because it contains very

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Figure 1: Architecture of driver identification system

fine-grained information about how a driver makes a turn. The motion sensor data corresponding to a turn contain different and useful information such as braking and accelerating, before, during, and after the turn, steering the wheel and signaling other drivers which the combination of all of them can reflect a specific driving behavior and can show different driving preferences for different drivers. Our system extract 11 features by combination of the speed and acceleration data with the angle which can achieve a very good accuracy. Experiments are being done on four different drivers (2 males and 2 females) and we can achieve the accuracy of 92% between four drivers and 97% between two drivers. A summary of our contributions is listed below:

- Discovering of 11 new features that are very helpful in distinguishing between different drivers.
- Development of the system which can extract the features while drivers do turns and identify the drivers.
- Experiments are done with four different drivers and the designed system can identify between them with 92% accuracy.

2 APPROACH OVERVIEW

Generally, a driver should follow some specific behaviors for doing a turn which include: reducing speed, signaling other drivers, doing the turn by turning the wheel or in other words by changing the angle of the car, and then at the end increasing speed and completing the turn and come back to the horizontal position. While these coarse grain behaviors can be similar for different drivers, in fine grain investigation the drivers do not necessarily have the same behavior. In other words, if we look at the drivers behaviors in more detail we can see every driver has his/her own habit in doing the turn. Some of these factors that can be important in doing a turn are as follow:

- The distance from the edge of the road.
- The time when the driver signals other drivers.
- The speed before and during the turn.
- The time that the driver decreases its speed and its intensity.
- The radius of the turn.
- The speed after completing the turn.

Figure 2: Gyroscope Z-axis readings during a real trip.

- The place when the drivers starts rotating the wheel or in other words, the place when the driver starts changing the angle of the car.

Figure 1 shows the architecture of the proposed method. The system has some important steps which are as follow: preprocessing the raw data coming from the sensors in smartphone, detecting the turns, extracting features, analyzing the features with machine learning techniques in order to identify the driver, and then adding it to the driver's profile. In order to collect data for drivers a smart phone is installed in the car and different sensors data are being collected and stored in the phone. These sensors include Accelerometer, Gyroscope, Magnetometer, and GPS. The collected data from the sensors in the smartphone are inputted into the system. The Accelerometer sensor can provide information about the acceleration and braking and the Gyroscope sensor can provide information about rotation angle of the car.

Pre-processing Raw Data. Since the collected data from different sensors are signals they can encounter noises coming from non-smooth roads conditions or electric circuits in the car. Therefore, noises should be removed from the data. For this purpose, a low pass filter is designed to smooth the data. After removing the noise from the data, turns should be detected by the system. **Turn Segmentation.** To identify left or right turns we can use Gyroscope data. Gyroscope sensor provides us the signals along three axis X, Y, and Z. When the car is driving on the straight path the sensor reading on the Z axis is around zero. When the driver rotates the wheel, the sensor reading on the Gyroscope Z axis is not zero anymore. Therefore, Gyroscope Z axis can be used to identify the turns by setting a threshold on the sensor reading. In our system the threshold is set to "0.13" which is set based on the empirical experiments. In order to segment the Gyroscope data into different turns we should identify the points before and after each peak in the Gyroscope Z axis reading that reaches to zero or in other words we should find the start and end points of each peak.

Figure 2 shows an example of the Gyroscope reading on the Z axis and identifying the peaks corresponding to each turn on a sample route. **Feature Extraction.** As said before there are some factors different drivers have different preferences in speed, in braking, accelerating, and rotating the wheel while doing the turn. Therefore some interesting features can be extracted using sensor reading on the Accelerometer X and Y axis and Gyroscope Z axis.

- Accelerometer on X axis: When the car is driving on a straight path the acceleration on X axis is almost zero, but it experiences a centripetal force while doing a turn which causes a centripetal acceleration. Accelerometer on X axis

Ground Truth	D1	0.9026	0.06	0.008	0.017
	D2	0.037	0.9328	0.029	0.00
	D3	0.036	0.0	0.9279	0.036
	D4	0.021	0.028	0.014	0.9366
		D1	D2	D3	D4
		Predictions			

Figure 3: Confusion matrix of identifying four drivers

shows this centripetal acceleration which based on the following equation it depends on the rotation rate(ω), radius of the turn(r), and the speed of the vehicle(v).

$$a = \omega v = \omega^2 r = v^2 / r \quad (1)$$

Different drivers tend to rotate their wheel in different positions while doing a turn, some start turning the wheel sooner while others tend to drive straight to the turn and then turn the wheel. In addition, different drivers rotate the wheel with different speed. Based on these behaviors the shape of the acceleration on the X axis can be different and some interesting features can be extracted.

- Acceleration on Y axis. This axis gives information about braking and acceleration. By combination of these information with the rotation angle some interesting features can be extracted.
- Gyroscope on Z axis: As said before when the driver turns the wheel the gyroscope reading on Z axis will have nonzero values and is shaped like a bump. But this bump shaped figure depends on how fast and aggressive the driver turns the wheel can be different.

Identifying Drivers. After extracting the features set, it should be given to the machine learning technique to identify the driver. Then the feature set is being added to the driver's profile.

3 PERFORMANCE EVALUATION

3.1 Experimental Methodology

The experiments in this work are being done by four drivers with the ages between 25 to 40 and they are being driven a Dodge caliber 2007 which a Google Nexus Note 3 installed in the car to collect the data. The sampling rate of the application is 10 samples/sec. The drivers have been driving in a residential area on different days and different times.

3.2 Evaluation Results

Driver Identification Accuracy. In order to evaluate the proposed method, Gradient Boost Tree (GBT) classifier is being used. We build a binary classifier for each driver using the GBT. GBT is used because it is known to be robust with different types of features with different scales. Therefore we don't need to normalize our features before the classification [2] We use the GBT implementation from the SQBlib library. Figure 3 shows the confusion matrix for identifying between four drivers. Each entry C_{ij} shows the percentage of the number of driver i is predicted as driver j in

Figure 4: Impact of the training set size on the accuracy

the total number of i . The average accuracy of identifying drivers is shown in the diagonal entries. The average accuracy is 92% among 4 drivers. If the driver has more stable behavior while driving and specially turning the accuracy for identifying driver increases. In summary the results show that it is promising to use commodity smartphones sensors to identify drivers.

Impact of the Training Data Size. In this section we analyze the impact of the training data size on the classification accuracy. For this purpose, we change the percentage of the feature set that can be used for training the classifier and evaluate the performance of our system. Figure 4 shows the performance of our system with different training set size. As can be seen even with small training set our system can achieve 83% in identifying drivers. As the size of the training set grows the performance of the system improves. The size of the test set is still one turn. Therefore, by increasing the size of the test set, the performance of the system will increase as well. In other word, system can start collecting data when the driver starts driving and with small training set it can achieve a reasonable accuracy. For getting better results system can collect the data for more turns as the test set. All of this shows that the proposed system is completely applicable and doesn't need a long time for collecting data and build profiles for different drivers.

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