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Driving Analytics – Data Science Approach based on Smartphone Vehicle Telematic Data

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ABSTRACT – *Driving takes place in the everyday life of many people around the globe. Driving analytics adaptations might increase overall security and lessen vehicle energy consumption and gas emissions. In this context, driver analytics and profiling try to better understand and potentially improve driver behavior, leveraging safer and more energy-aware driving. Driver monitoring and analysis or driver behavior profiling is the process of automatically collecting driving data (e.g., speed, acceleration, braking, steering, location) and applying a data science approach to generate a safety score for the driver.*

KEYWORDS: Driving analytics, advanced analytics, safety score, data science

1. INTRODUCTION

Many drivers are aware of the driving behaviors and habits that can lead to inefficient and unsafe driving (Ab Rashid & Ibrahim, 2017). However, it is often the case that these same drivers unknowingly exhibit these inefficient and unsafe driving behaviors in their everyday driving activity. There is an increasing number of studies that focus on the detection and identification of driving behavior patterns under various circumstances. Some of these studies involve in-vehicle data recorders (e.g., Toledo et al., 2008, Prato et al., 2009, Farah et al., 2013), which provide very detailed data regarding the vehicle and the driver. These studies focus on young drivers and driving patterns within the family. However, today's technology provides ubiquitous and affordable sensors (e.g., accelerometers and gyros in smartphones) that can provide reliable sensor platforms to monitor driving behavior, as shown by Antoniou et al. (2014). Other development such as by Johnson and Trivedi (2011) developed a system that recognizes a driver's profile using a smartphone.

Modern smartphones and tablets have powerful computing, communications, and sensing capabilities (Chu et al., 2014). In addition to being capable of performing complex computing tasks and communicating with each other wirelessly, smartphones and tablets have a rich set of onboard sensors, such as accelerometers, gyroscopes, GPS, and cameras. These sensors provide valuable information when investigating users' needs and behavioral patterns (Chu et al., 2014). Automobiles, a dominant means of transportation for several decades, are also beginning to be equipped with onboard sensors. These sensors, which provide Internet connectivity and vehicle condition monitoring, form a small ecosystem.

For this study, the following research questions are considered:

i. Which computational approaches exist to classify driver behavior?
ii. Which important parameters are suitable to classify drivers based on smartphone sensor data?

2. BACKGROUND STUDIES

Modern smartphones provide sensors suitable to collect data for driver profile analysis. Previous works show that properly preprocessed and handled smartphone sensor data are an interesting alternative to conventional black boxes for the monitoring of driver behavior.

Ferreira et al. (2017) considered driver profiling with different Android smartphone sensors like accelerometer, linear acceleration, magnetometer, and gyroscope. They implemented the classification with different machine learning algorithms like Artificial Neural Networks, Support Vector Machines, Random Forest, and Bayesian networks to assess which sensor/method assembly enables classification with higher performance. The results show that Random Forest performs the best followed by artificial neural networks. Bigger window sizes perform better results, and gyroscopes and accelerometers are the best sensors for their classification.

Singh et al. (2017) proposed a model for detecting sudden braking and aggressive driving behaviors with data collected from smartphone sensors. A dynamic time-warping technique is used for classification aiming for mobile devices with constrained resources. The proposed algorithm has an accuracy of 100% for detecting braking events, 97% for detecting left and right turns, and 86.67% for detecting aggressive turns.

Bejani & Ghatee (2018) proposed a driving style evaluation system called CADSE which is based on data from smartphone sensors. The system is evaluating different driving maneuvers on three successive time frames and additionally takes the context into accounts such as traffic conditions and car sensitivity. The extracted data is classified in the respective subsystem using different machine learning approaches such as decision tree, support vector machine, multi-layer perceptron, naive Bayes classifier, Radial basis function network, and k-nearest neighbors, additionally these algorithms are compared against each other to gather the most accurate algorithm for the individual tasks.

Rahman et al. (2019) investigated driving behavior with sensor data from smartphones such as accelerometers and gyroscopes. The data is classified using Bayesian Networks, random forest, and multi-layer perceptron in aggressive and non-aggressive driving events. The findings recommend both Bayesian algorithms for their great statistical execution and multi-layer perceptron for their fast and intelligent computing.

Yu et al. (2016) proposed a fine-grained abnormal driving behavior detection and identification system which make use of smartphone sensors for acceleration and orientation to train both a support vector machine and neuron network with empirically grounded data from real driving situations. The identification of abnormal driving events distinguishes between weaving, swerving, sideslipping, fast U-turns, wide radius turning, and sudden breaking. Furthermore, they investigate different impacts on the results such as training set size, traffic condition, road type, smartphone placement, and the sensors' sampling rate.

In what follows, we discuss the information flow of smartphone-based vehicle telematics in more detail. The process is illustrated in Figure 1 (Wahlström et al., 2017). Measurements can be collected from both built-in smartphone sensors and from external complementary sensor systems. Although vehicle-fixed sensor systems in many cases can offer both higher reliability and accuracy than their smartphone equivalents, they are often omitted to avoid the associated increase in monetary costs and logistical demands. Vehicle-fixed sensors are, however, indispensable in the more general field of vehicle telematics where they provide updates on the status of the vehicle's subsystems and describe driver characteristics (Wahlström et al., 2017). Table 1 shows the sensor technologies commonly utilized in smartphones.

TABLE 1: Smartphone sensors in telematics applications

Sensor	Measurement
GNSS	Position, planar speed, and planar course
Magnetometer	Magnetic flux density
Camera	Visual images
Microphone	Audio
Accelerometer	Specific force (non-gravitational acceleration)
Gyroscope	Angular velocity

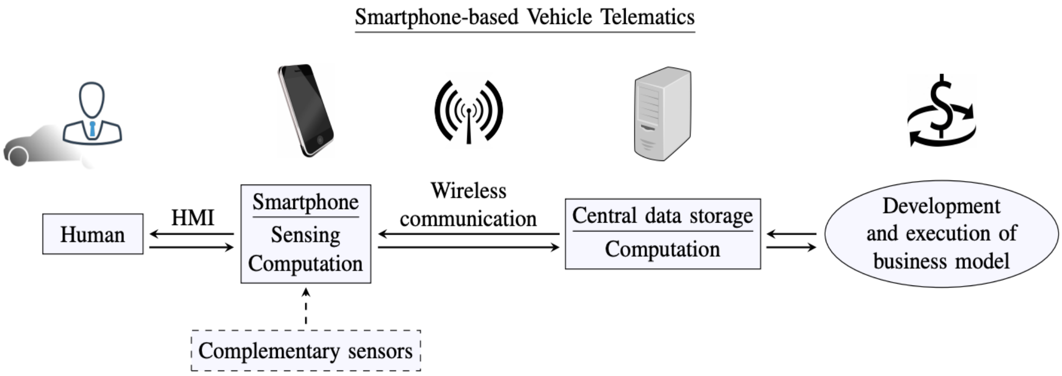

FIGURE 1: Process diagram illustrating the information flow of smartphone-based vehicle telematics (Wahlström et al., 2017)

3. VISUALIZATION OF DRIVING BEHAVIOR

The sensor frame and the navigation frame directions are reversed (the smartphone sensor frame's negative axis points in the direction of the navigation frame's positive axis). The reason for this is that the accelerometer measures relative acceleration (Wahlström et al., 2017). When the car accelerates in the forward direction the accelerometer experiences a force in the backward direction, which is analogous to the force that we feel pushing us back into the seat in an accelerating car. Reversing the axis makes sure that when the car accelerates in the forward direction a positive acceleration is measured by the smartphone accelerometer.

It can be deduced from the above discussion that two axes are important for the accelerometer and one axis is important for the gyroscope:

i. Accelerometer Z-Axis: Will record changes for acceleration and braking.
ii. Accelerometer X-Axis: Important for turns, U-turns, and swaps.
iii. Gyroscope Y-Axis: Will record the changes in the rate of change of heading

There is a clear difference between characteristics of acceleration along the x-axis for normal and aggressive maneuvers shown in Figure 2. The minimum value of x-axis acceleration for aggressive events tends to be much lower. The mean value and spread of x-axis acceleration values are also different. The acceleration along the z-axis shows the effect of braking which is more pronounced for aggressive maneuvers. The plot of the gyroscope y-axis which measures the rate of change of the car's heading has the same shape for both risky and normal events as expected. Upon closer inspection, the minimum value for aggressive events is lower and the spread of values is less.

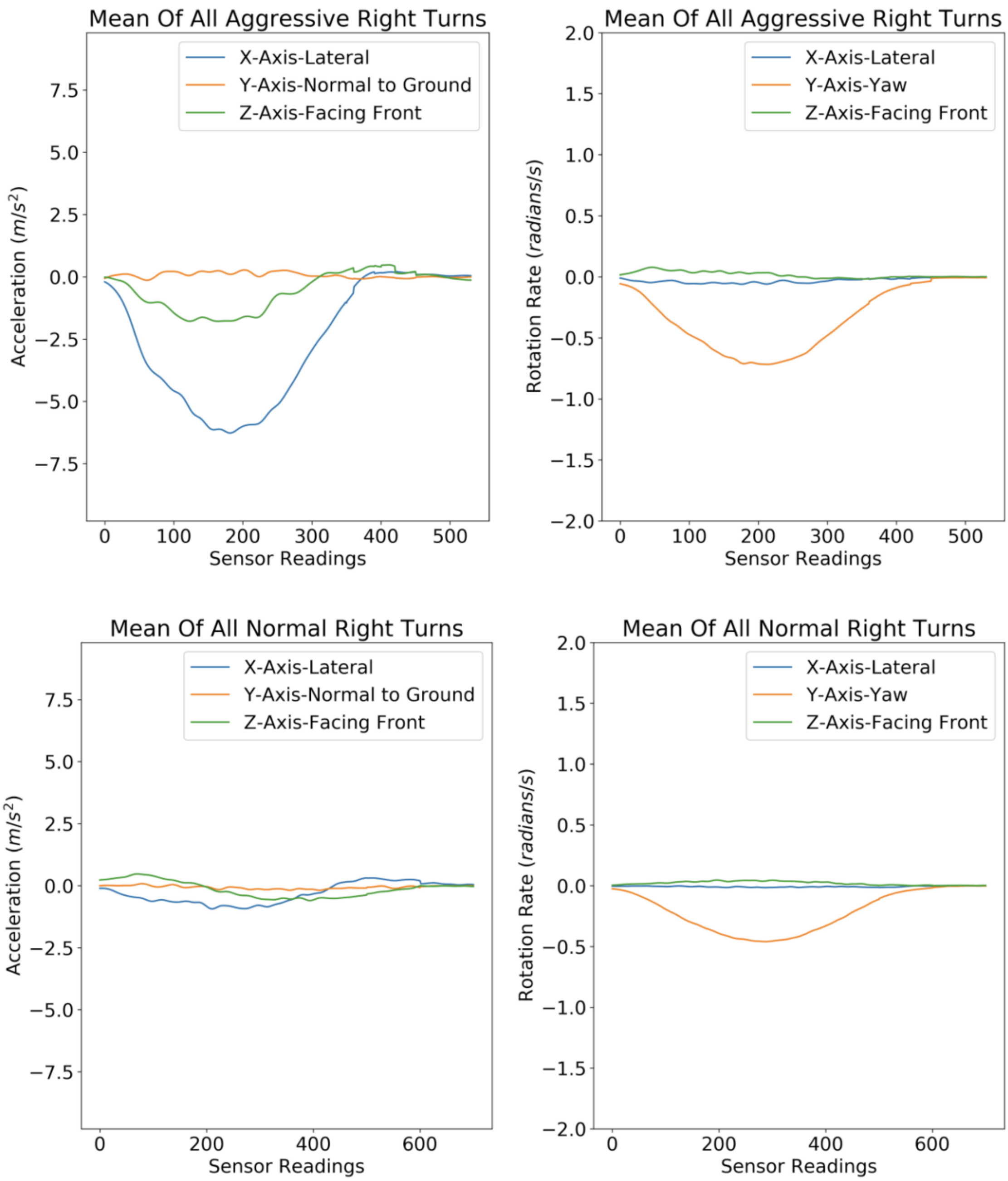

FIGURE 2: Visualization of aggressive turn right vs. normal turn right

The signatures between aggressive and normal accelerations do not show a stark difference at the first glance. This is probably due to the fact that the car being used has an automatic transmission and is not able to accelerate very aggressively in the first place. However, upon closer inspection of the signatures, certain features such as the max acceleration in the z-axis and the spread of acceleration values differ between normal and aggressive maneuvers (Figure 3).

The traffic conditions may affect the drivers' driving behaviors and further affect the performance of the existing method. The result during peak time and off-peak time will have an impact on driver behavior especially if the traffic condition is very bad. This is because, during peak time, the vehicles perform less aggressive actions due to traffic jams. Moreover, the driver's behavior is also affected by the weather and road conditions. Therefore, in the next section, we proposed a methodology for future experiments using weather conditions.

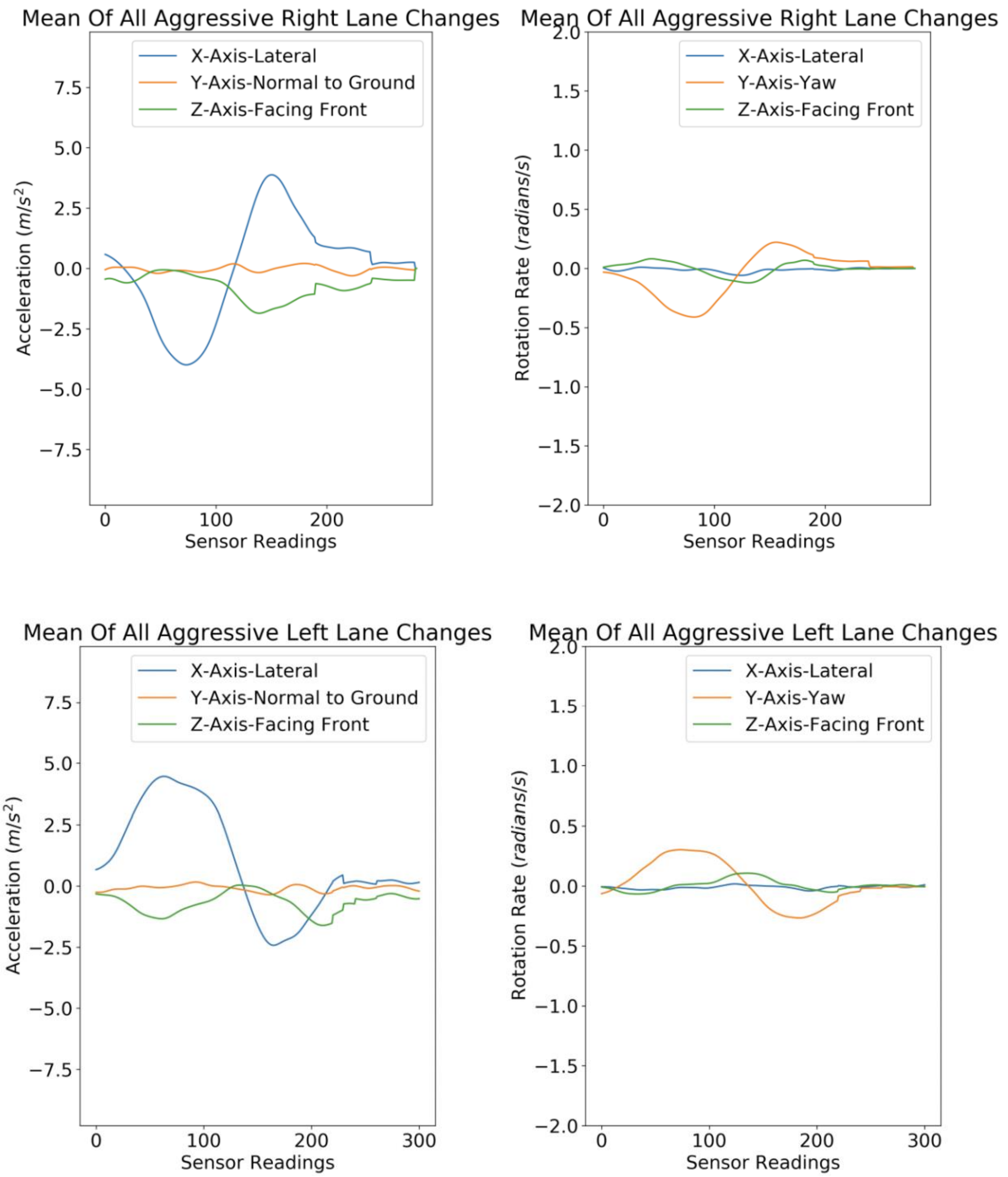

FIGURE 3: Visualization of aggressive lane change vs. normal lane change

4. PROPOSED METHODOLOGY

Based on the information from the literature review regarding common machine learning techniques and corresponding data gathered from smartphones, a reference model has been proposed that shows how the advanced analytics approaches can be used for personalized driver decision support systems (Kashevnik & Lashkov, 2018). When a driver is driving a car and uses the decision support system the smartphone takes place as a means of data collection.

The weather condition, particularly the adverse weather phenomenon, is one of the unsafe operation issues that could undermine the qualities in all aspects of road transportation and thus, increasing the risk of road accidents and casualties (Jawi et al., 2009). Very few researchers have compared the effect of reduced visibility due to fog and rain on the traffic parameters using field data since the vehicle-based traffic data and weather data. Most researchers have conducted driving simulator-based studies to identify the effect of adverse weather including fog and rain separately (Peng et al., 2018).

The information about how drivers react to the effect of weather change is crucial to the effectiveness of adverse weather warning systems. This study comprehensively will investigate the relationship between a driver's driving pattern and adverse weather based on field data collected by smartphone-based vehicle telemetric data and weather data.

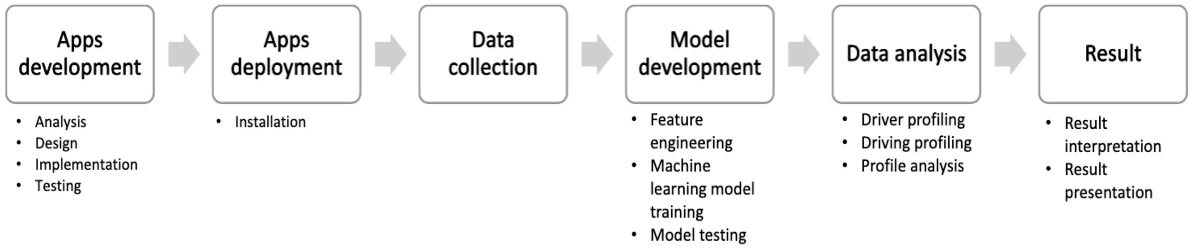

FIGURE 4: Process for driver decision support based on driving data analysis

The live data is then uploaded to a cloud to perform the driving behavior analytics. The computation is done by deep learning, which proves to be used in similar classification tasks. The behavior of distraction should be identified and based on that an appropriate recommendation should be provided to the affected driver via the smartphone. This would be an ideal "full use case" for the advanced analytics approach but, tests need to be conducted to verify if this kind of online behavior detection is viable in the real-world concerning computation time and resource usages such as battery or internet traffic. The computation time is of special interest in a driver safety system. After all, such a system should prevent accidents based on distracted driving but if the time to compute the live data and give a proper warning based on the detected behavior exceeds a certain time frame the recommendation might come too late for the driver to react to the situation accordingly. A more feasible way to deploy the machine learning-based identification of driver behavior in the current threshold-based model of the driver safety system is to use the extended knowledge about the driver behavior from the multi-layer perceptron to update the current thresholds of the driver safety system. Different driving styles and overall driving behavior might be perceived differently by varying drivers. If the individual driver labels their recorded and proposed behavior identification correct or incorrect, the system should find better fitting thresholds for the identification of distraction. This way a more personalized experience can be brought to the driver.

Ultimately, the participants themselves are the experts in this kind of behavior identification system and are encouraged to help with the classification of behavior by verifying the proposed detected behavior. By confirming the identified behavior, the associated data gets labeled accordingly and can be reused in the training of the system to classify the upcoming driving events even more precisely. A mentioned problem in literature with this kind of machine learning-based system is the challenge of getting a proper classification for a completely new driver with perhaps completely new behavior with which the current model is unfamiliar and therefore can´t identify the correct behavior with good accuracy. To address this problem the training of the general model for this system should be considered regularly with a growing database. As an example, when new participants use the application, and their data has been recorded retraining of the classifier is suitable starting with the step of Data-Preprocessing where the data is normalized, and perhaps incomplete data is deleted from the dataset. Afterward, a feature selection is performed to find the best set of features that lead to both a satisfying accuracy and a reasonable complexity regarding computation and time efforts. With those preceding steps done the prepared data can be used to perform training of the model to incorporate new behavior of new drivers into the system. This way the proposed model is not only doing its classification task based on a set number of drivers and their recorded data but also takes completely new driving styles and corresponding new drivers into account. Therefore, a personalized identification of the driver's behavior is realizable. Furthermore, there are certain stakeholders that can profit from the knowledge about the different driving behaviors of different drivers. For example, can the information be used to give fleet managers of logistics or taxi companies insight into the different driving behaviors of their drivers to incentive appropriate driving styles or conduct training measures to improve the driving behavior.

5. CONCLUSION

This paper aimed at investigating the identification of driver behavior with a smartphone-based system. Different machine learning approaches as well as many sensors are used to detect driver behavior. The developed driver decision support system can be extended with the proposed methodology of this paper by incorporating a multi-layer perceptron into the current threshold model. This way the classification of the behavior can help personalize the behavior detection and improve the overall accuracy in terms of identifying the abnormal driving behavior by the system. In the real world, the usage of machine learning-based classification of driver behavior with smartphone sensors can lead to increased accuracy of driver decision support systems, delivering a more personalized experience and lastly encourage every smartphone user to use this lightweight system compared to expensive and bounded to modern-cars-only driver decision support systems. Therefore, widespread use and acceptance of this technology seem possible. Not to mention that a machine learning-based classification task excel at working with a lot of data which would further improve the quality of the system in a widespread use case.

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