Driver categorization based on vehicle motion and trajectory data

András Mihály

MTA-BME Control Engineering Research Group,
Budapest University of Technology and Economics and
Institute for Computer Science and Control,
Hungarian Academy of Sciences, Budapest, Hungary
Email: mihaly.andras@mail.bme.hu

Péter Gáspár

Systems and Control Laboratory,
Institute for Computer Science and Control,
Hungarian Academy of Sciences, Budapest, Hungary
Email: gaspar.peter@sztaki.mta.hu

***Abstract*—The paper deals with categorization of different driving styles. The categorization is based on real-time simulator studies with several test drivers with different attitudes. The categorization of the drivers are based on the monitoring of the vehicle motion, detecting abrupt movements and speed limit violations. The goal of the study is to set up typical driving behavior categorizes, thus dangerous driver attitudes can be identified. The benefit of such driver categorization is that transportation companies can monitor their drivers using easily accessible data, which helps to avoid dangerous driving behaviors.**

I. Introduction

Driver identification and classification has been studied by several authors with very different methods. First of all, the observable driving signals can be divided into three major groups [13]: driver related (pedal and steering usage, eye and body movements, etc...), vehicle related (velocity, acceleration, engine speed, yaw rate, etc..) or vehicle-environment related (vehicle position in lane, following distance, yaw angle, etc...). Note, that several experiments are based on using driving signals from different groups listed above.

Thus, driver behavior can be measured with different sensors. It can be monitored directly by using on-board electronic devices, such as video cameras [5], [10]. By this mean, the body posture, eye and hand movements can be examined directly in order to classify drivers or to recognize dangerous driving situations. A number of studies has shown that inertial senors in smartphones can also provide data to detect driving events [14] and even to classify drivers [15].

Moreover, the vehicle CAN bus information can also be used to derive data regarding driver behavior. In [1] a classification method was introduced to identify driver behavior (quiet, normal, aggressive) in stop and go urban environment using vehicle data (throttle opening angle, brake circuit pressure, vehicle speed) and obstacle data measured by radar. A driving style recognition method with supervised learning (SVM) technique has been presented by [9], using inertial sensor data via CAN bus. Longitudinal accelerometer and gyro data was used for driver classification. In [3] steering wheel angle, brake status, acceleration status, and vehicle speed gained from the vehicle CAN bus was used to categorize driving events, identify driver distraction and behavior characteristics using Hidden Markov Models. In [7] the driver safety classification (timid, cautious, conservative, neutral, assertive, aggressive) was based on vehicle data gained by devices using CAN bus and OBD-II information as well as GPS data. Vehicle velocity, acceleration, jerk, engine speed data had been collected for every test driver on their routes and threshold values had been given to determine the number of violations in order to categorize the drivers. Note, that advanced driving simulators can also be applicable in driver behavior classification [6]. In [4] authors analyze and classify driver behavior related to distraction under secondary tasks.

Present paper deals with the categorization of the drivers based on simulator driving experiments. The categorization is based on easily accessible vehicle related data, i.e position, velocity, longitudinal and lateral acceleration. These data can be gained using the vehicle CAN bus and OBD-II information along with GPS data, but smartphone applications can also provide input data for the classification algorithm as well as additional gyro sensors fitted in the vehicle. The easy application is one of the most attractive property of the proposed categorization method. By this mean, forwarding agencies and transportation companies can monitor their drivers easily and efficiently, identifying drivers with bigger risk of causing accidents or using the vehicle less efficiently.

The structure of the paper is as follows. In Section II the real-time simulation environment is presented with the human-machine interface. Section III describes the method of driver classification based on trajectory analysis. Next, in Section IV the driving simulator experiments and the results of the classification are presented. Finally, some concluding remarks are given in Section V.

II. Simulation environment of the driver model

A hardware-in-the-loop, real-time simulation environment is applied in order to measure the signals generated by the subject drivers. The architecture of the simulator has already been introduced in [12], thus in this paper only a brief description is given. The driving simulator consists of a real car connected to the validated simulation environment of CarSim, see Figure 1. The signals of the real vehicle (the position of the accelerator and the brake pedal along with the steering angle) are read through the CAN network by using standard communication interface.

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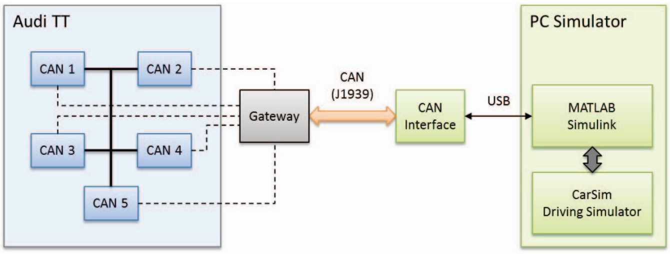


Fig. 1. Architecture of driving simulator

Based on the driver inputs, the Driving Simulator of CarSim generates the signals for the vehicle, while the real-time graphics of the environment is projected in front of the driver. The sound of the engine and the wheels, along with the working instruments of the dashboard creates a driving experience close to real life. One of the biggest advantage of the simulator, is that certain signals which are hard or impossible to measure in practice are also available, thus the inputs of the driver model can be gained. During the simulation, the test drivers drive along the selected road, while the important signals for the driver model are measured and saved for the identification procedure.

III. Defining driver behavior categorizes

In this paper, the driver measurements are performed using the simulator introduced in Section II. The driver categorization is based on trajectory analysis, similar to the method proposed by [2]. The aim of this type of categorization is to identify anomalous movements of the vehicle induced by the test drivers. Then, based on trajectory data the anomalous movement is further examined in order to decide, whether the abrupt motion of the vehicle is due to the property of the track, or it is caused by the abnormal behavior of the driver. Note, that in the categorization process of the drivers the vehicle speed and the actual speed limit is also considered.

In this paper, four driver categorizes are defined, typifying the common driver attitudes. These are the beginner driver, the defensive driver , the normal driver and the aggressive driver:

- Beginner driver: abrupt movements are detected even at places where other drivers did not generate such vehicle motion. Another property of this category, is that the driver does not exceed the speed limit by more than 20 percent.
- Defensive driver: abrupt movements are not detected and the speed limit is not exceeded by more than 20 percent. In case the driver meets these requirements, the comparison with other drivers is not necessary.
- Normal driver: abrupt movements are detected, but only at places where other drivers generate such vehicle motion. Another property of this category, is that the driver does not exceed the speed limit by more than 20 percent.
- Aggressive driver: abrupt movements are detected even at places where other drivers did not generate such vehicle motion. Another property of this category, is that the driver exceeds the speed limit by more than 20 percent, even in more than one occasion.

The abrupt movement of the vehicle induced by the driver is defined with longitudinal acceleration-deceleration and lateral acceleration thresholds. These values may differ greatly depending on the type of the road (urban road, highway, motorway), the curvature of the road, etc. (see [2], [18]). Thus, in order to evaluate the categorization of the drivers, it is very important to select proper values for the acceleration limits ans the velocity threshold as well. Speed limit violation is only considered when the driver exceeds the limit by more than 20 percent. The reason for this, is that in certain driving situations (takeover, lane change, hilly road, etc..) most of the drivers tend to exceed the speed limit in some extent.

The scheme of the driver categorization is shown in Figure 2. One of the possible benefit of the categorization process not mentioned above, is that driver models can be set up for different driver behaviors using identification methods, see [11], [16], [8], [17].

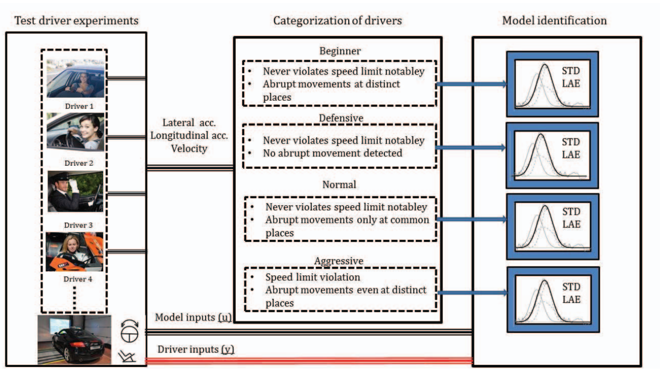


Fig. 2. Scheme of the driver categorization and model identification

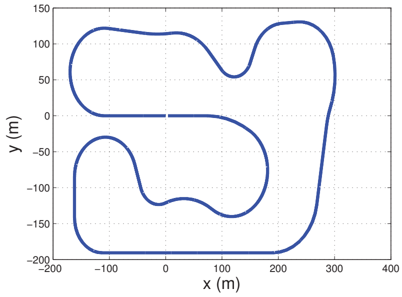
IV. Simulation results

The vehicle chosen for this simulation is a conventional small car, with the parameters shown in Table I. The vehicle is powered by an internal combustion engine producing 75 kW of maximum output, which drives the front axle of the vehicle through an automatic gearbox . The brakes of the vehicle are operated by a conventional hydraulic brake system.

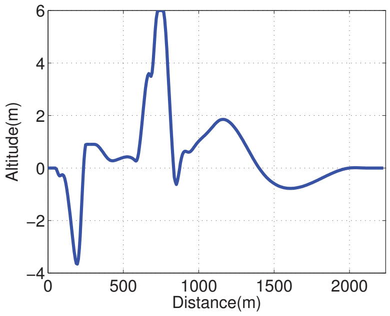
TABLE I
Vehicle parameters

Parameter	Value	Unit
Vehicle mass (m)	830	kg
Yaw moment of inertia (J)	1110.9	kgm^2
Distance from C.G to front axle (l_1)	1.103	m
Distance from C.G to rear axle (l_2)	1.244	m
Tread front (b_f)	1.416	m
Tread rear (b_r)	1.375	m
Height of COG (h_{COG})	0.54	m
Cornering stiffness front (c_1)	30	kN/rad
Cornering stiffness rear (c_2)	60	kN/rad
Aerodynamic drag co-efficient (c_w)	0.343	$-$
Front contact surface (A)	1.6	m^2

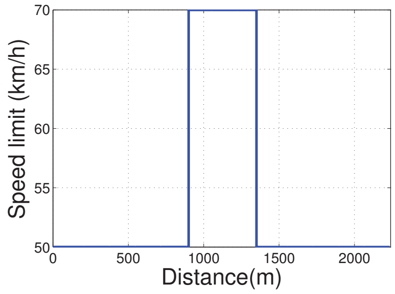
The characteristics of the racetrack are shown in Figure 3(a),(b). As it can be observed, the track contains several curves of different types as well as straight sections with uphills and downhills. Note, that speed limits were defined on the track as well, as it can be seen in Figure 3 (c).



(a) Racetrack X-Y plane



(b) Altitude



(c) Speed limit

Fig. 3. Simulation environment

The selected test drivers' age, gender, driving experience were all very different, representing a wide a range of driver behavior. The drivers were asked to drive the simulator introduced in Section II along the racetrack while the driver input and vehicle output signals were measured and saved, see Figure 4. Note, that the vehicle output data used in the classification method are easily accessible in a real life measurement using on-board electronic device such as GPS, gyro sensors or smartphone applications.

The inputs of the test drivers are shown in Figure 5. It can be seen in Figure 5 (a)-(b), that Driver 8 controls the throttle and the brake the most aggressively, while Drive 7 and Driver 10 also handles the throttle and the brake more heavily than

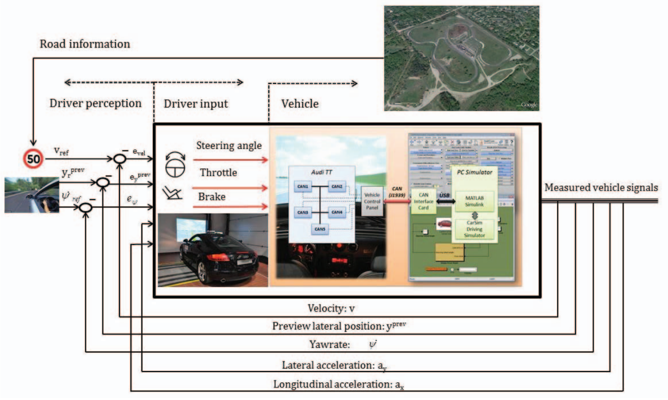
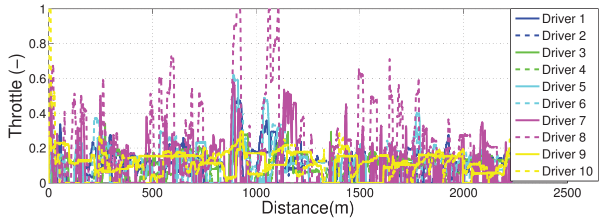
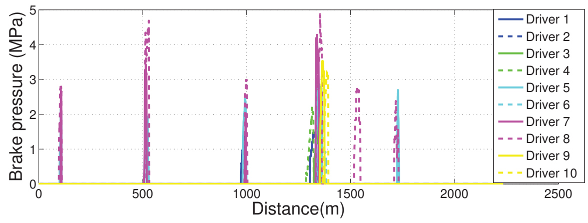


Fig. 4. Scheme of the driver measurement

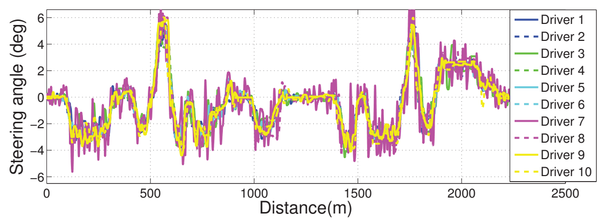
others. Compared to Driver 7-10, Driver 1-6 drives the vehicle with smoother pedal usage, which corresponds to the vehicle longitudinal acceleration data detailed later in Figure 7(b). The steering intervention of the drivers are shown in Figure 5(c). It is well demonstrated, that the angle of the steering for different drivers are very similar at certain points of the racetrack, however, the fluctuation and the steering speed can differ greatly. For example, there is plenty of jerk in the steering behavior of Driver 7 compared to the rest of the test drivers.



(a) Throttle



(b) Brake pressure



(c) Steer angle

Fig. 5. Input of the test drivers

The lateral error from the middle line of the racetrack is shown in Figure 6. It can be seen, that some drivers follow the track more conservatively (for example Driver 1), while other drivers tend to cut the curves with bigger freedom (for example Driver 2). Since the lateral error from the middle line is difficult and expensive to measure in real life applications, it is not used in this paper for classification.

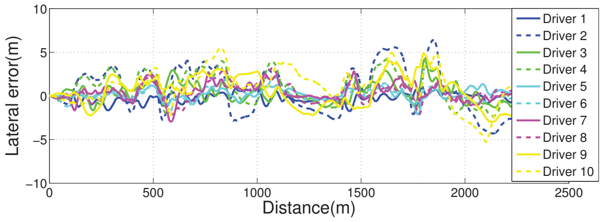
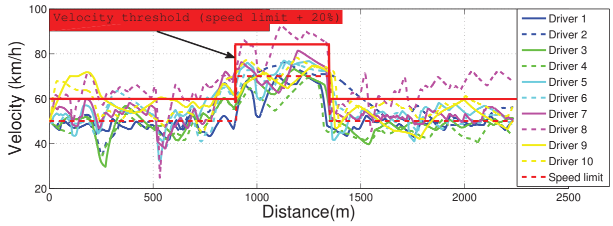
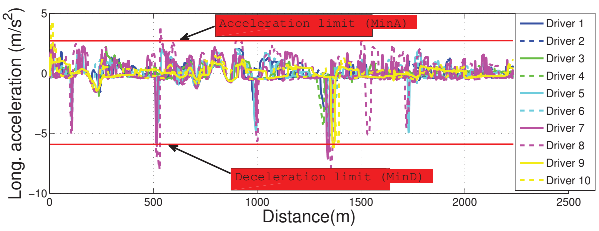


Fig. 6. Lateral error of the test drivers

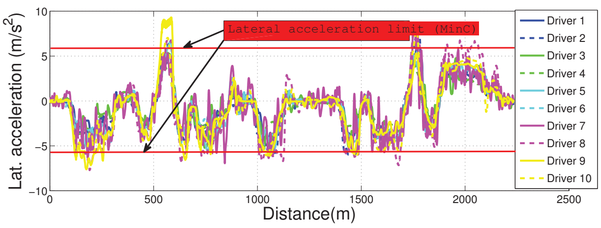
Next, the categorization method listed in Section III was evaluated for the test drivers. The acceleration and velocity profile for the test drivers along with the threshold values used for the classification are shown in Figure 7.



(a) Velocity



(b) Longitudinal acceleration



(c) Lateral acceleration

Fig. 7. Velocity and accelerations of test drivers

The vehicle velocities are shown in Figure 7(a) for the test drivers, along with the speed limit and the threshold values used for the categorization. It can be seen, that Driver 8 violates the threshold limit most frequently, but some other drivers also exceed this value at some part of the track.

For the longitudinal motion of the vehicle, the acceleration and deceleration limits used for the categorization has been separated, since the simulation vehicle (as every road vehicle) is capable of much higher rates of deceleration due to the fact, that the brake system of the vehicle is designed to be much stronger than the engine. In the categorization, the deceleration threshold has been selected to be 6 m/s^2(minD), while the acceleration limit was 3 m/s^2(minA). It is well demonstrated in Figure 7(b), that only few driver (Driver 7-Driver 10) violates these acceleration-deceleration limits, typically at some part of the track where a speed limit sign or an extreme curve is ahead of the vehicle.

For the centripetal acceleration of the vehicle the threshold value has been chosen to be 6 m/s^2 (minC). During the test drives on the track, this limit has only been violated in heavy cornering maneuvers, as illustrated in Figure 7(c). Once again, Driver 8 tends to violate this limit the most often, but Driver 9 exceeds it the most.

The offline categorization algorithm had run under MATLAB working with the distance, speed limit, longitudinal and lateral acceleration data of the vehicle records. The results of the different drivers are compared to each other, thus not only the abrupt movements are identified, but with the known position data it can be decided whether the anomalous behavior is distinct, or can also be identified for other drivers at the same point of the track. This is important information for the classification process, since a driver with abrupt movements can be classified as beginner, normal or aggressive, as detailed earlier in Section III. Note, that it is also very important to tune the acceleration and speed limit threshold values to the given route or even weather condition, in order to avoid fails classification using a too sensitive or insensitive values.

With the above detailed threshold values the drivers fall in different predefined categories (see Table II).

TABLE II
DRIVER CATEGORIZES PARAMETERS

Driver	Abrupt movements (s)	Speeding (s)	Category
1	0	0	Defensive
2	3.51	14.04	Normal
3	0	0.88	Defensive
4	0	0	Defensive
5	1.27	7.63	Normal
6	0	11	Defensive
7	3.86	5.14	Aggressive
8	16.86	83.3	Aggressive
9	9.01	20.91	Aggressive
10	4.88	19.14	Aggressive

As expected, Driver 8 is classified as aggressive driver, with the most abrupt movements and the longest speeding time. Note, that the speed limit is also violated by other drivers (Driver 7, Driver 9, Driver 10) categorized to be aggressive. On the other hand, although Driver 6 and Driver 3 also violates the speed limit for a short period of time, the lack of abrupt movements puts them in the defensive category. Moreover, that Driver 2 and Driver 5 violates the speed limit and makes abrupt movements as well, but are classified as normal drivers. The reason for this, is the abrupt motion is only detected at places where other drivers has also violated the acceleration limits. The classification of Driver 1 and Driver 4 as defensive is straightforward, since they didn't violate neither the speed limit, neither the predefined acceleration thresholds. Interestingly, no test driver has been categorized to be beginner. The reason for this, is that drives not violating the speed limit (Driver 1 and Driver 4) didn't violate the acceleration limits as well.

V. Conclusion

The paper presented an offline method for the categorization of drivers based on simulator experiments. The categorization was founded on searching abrupt movements of the vehicle and speed limit violations. Four driver category has been defined based on driver behavior, in which each driver has been compared to all of the other test drivers in order to identify anomalous maneuvers. The proposed driver classification can be used to monitor and identify dangerous drivers, but the measurements of the test drives can also be used to identify linear driver models considering both lateral and longitudinal dynamics.

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