A Stable Method for Detecting Driver Maneuvers Using a Rule Classifier

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Abstract. Traffic accidents and vehicle mishandling are significant problems in road transportation, affecting human lives. Various studies suggest that driver behavior is a key factor in the most road accidents and contributes significantly to fuel consumption and emissions. Improvements in driver behavior can be achieved by providing feedback to drivers on their driving behavior. The identification of risky and wasteful maneuvers allows the evaluation of driver behavior. This allows the elimination of irresponsible drivers who pose a danger in traffic, and at the same time, it allows the reduction of maintenance and repair costs of the vehicle fleet. This paper presents the first stage of a driver profiling method based on the analysis of signals coming from the vehicle CAN bus and auxiliary device containing a GPS receiver and an IMU unit. No additional equipment is needed, what is an advantage of the proposed method.

1 Introduction

Around the world, road traffic is growing at a tremendous rate, year after year. This is due to economic needs, supply chains to hard-to-reach places or the convenience of individual car including car long- or short-term leasing and rental services. Unfortunately, the increase in traffic is also associated with an increase in the number of accidents involving drivers and other road users. Every year, thousands of people lose their lives or are seriously injured in road accidents. In Europe in 2019, according to European Union statistics, accidents occur on highways (9%), in urban areas (38%) and on rural roads (53%) [3]. Road accidents generate costs related to treatment and rehabilitation of people, repair of cars or repair of road infrastructure. This is always a big burden on the budget of any country. Any erroneous decision by a driver can lead to a dangerous traffic incident that must be effectively addressed. This problem becomes even more complex when the traffic is heterogeneous and involves different types of vehicles.

The issue of vehicle damage and insurance is very important from a business point of view because it always involves losses for the company. After an accident, the car must be repaired and tangible and intangible damages must

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be covered, which is often the cause of legal disputes. This is also important for car rental companies, where car recalls generate economic losses. In these types of companies, customers do not take care of the rental cars and often damage them through irresponsible driving or mishandling. Some of these behaviors are difficult to detect and only manifest themselves after some time in the poor condition of the vehicle. This user behavior is increasingly prompting companies to install devices in vehicles that monitor the driver's driving [6]. This makes it possible, in particularly drastic cases, to refuse to rent the vehicle again or, in the case of other companies, to send the driver to retraining courses

Most of the studies have used machine learning methods - artificial neural networks (ANN) and attention-based deep neural network (ADNet) [8], adaptive neuro-fuzzy inference systems (ANFIS) [2], convolutional networks (CNN) [5,9], functional principal component analysis (PCA) [4] with projection into a low dimensional space, as well as support vector machines (SVM) [6]. Most studies devoted to analyzing driver behavior focus on analyzing the age and gender of the driver, look at the impact of using additional devices while driving, check for the presence of vehicles on side streets, the intensity of pedestrian, bicycle or vehicle traffic in front of, from behind or from the opposite direction. A comprehensive review of these parameters, the reader can find in works [2,6,7]. The proposed solutions can mainly be used in laboratory simulators, where prediction of driver behavior can be measured, and then some recommendations can be formed. As a result, this leads to increased road safety by imparting this knowledge during driver training.

In real conditions, observation of driver's behavior (e.g. whether he uses cell phone) and observation of traffic where the vehicle is moving are not possible. This happens, for example, at car rental companies, where once a car is rented, the driver is not observed and their driving style is not recorded. This often leads to improper use of the vehicle, and sometimes to deliberate violations of road safety rules. As a result, this leads to frequent vehicle breakdowns and even road accidents. In general, driving can be divided into two basic categories: safe or aggressive driving. Safe (eco-friendly) driving results in lower CO_2 emissions, fewer fatalities, and safer roads. Aggressive driving results in more air pollution around the roads, more fuel consumption, more accidents, and less safety for road users.

Some driving simulator studies have analyzed driver behavior under various road conditions [6]. In addition, the study focused on driver behavior at intersections with traffic lights. Longitudinal acceleration and longitudinal speed were measured, as well as throttle pressure, deceleration during braking, and brake pedal force. However, these measurements were carried on simulators and have not been conducted under actual road conditions. Due to the above limitations, in our study, we analyze the data coming from the CAN (Controller Area Network) bus, an accelerometer, and a gyroscope. In our research, additional devices to detect eye, head and body movements have been eliminated. This is expensive equipment, not always installed, and not always effective. The use of road edge detection systems was also eliminated because shadows or road lighting limit the effectiveness of such a solution.

2 Data Logging

The driver's driving behavior is evaluated on the basis of driving parameters read from the CAN bus. The CAN (Controller Area Network) bus is an automotive bus standard designed to provide communication between microcontrollers and devices of a car. CAN is a serial communication bus using a two-wire twisted pair cable. Messages can be transmitted at a maximum rate of 1 Mbps. The CAN protocol gives high noise immunity and reliability [1]. In addition to CAN bus messages, data from additional sensors installed in the vehicle were used. The data from the sensors were synchronized with the CAN. The research used a precise three-axis digital accelerometer and gyroscope operating in three orthogonal directions: X, Y and Z. It is a so-called IMU (Inertial Measurement Unit) sensor. The idea of how such a sensor works on the car board is shown in Fig. 1.

Table 1. List of monitored driving parameters

Variables	Units	Source
Longitudinal velocity	m/s	CAN
Acceleration in X,Y,Z direction	m/s^2	IMU
Angular speed around X,Y,Z axis	°/s	IMU
Brake pedal force	N	CAN
Throttle opening angle	°	CAN
Clutch pedal force*	N	CAN
ABS, ESP, ASR Intervention	Yes/No	CAN
Turn signals	On/Off	CAN
Steering wheel angle	°	CAN
Geographical coordinates	°	GPS
Heading	°	GPS

*) for cars with a manual transmission

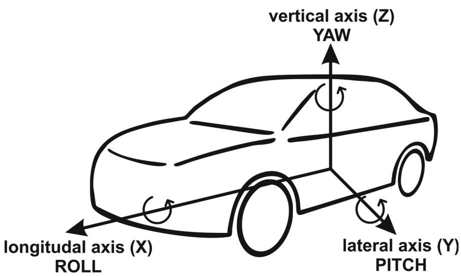

Fig. 1. Measured accelerations and rotations.

The parameters listed in Table 1 are measured using car's on-board equipment. Only the 3-axis accelerometer/gyroscope (MPU6050) and GPS sensor are installed as additional external devices. This reduces the cost of vehicle equipment.

2.1 Data Stream Forming

As mentioned before, our system is using at least three different data sources: the CAN bus (which actually transfers data from various in-car control units, like Engine Control Unit, ABS/ESP/ASR Unit, Chassis/Body Control Module and others), the 6 DoF IMU (3-axis gyroscope + accelerometer), and the GPS receiver. Some of these units send data in regular time periods, others send it on event based regime, and other need to be polled. Data send over CAN bus is often in a raw form, e.g. Analog-to-Digital converter (ADC) data. This really isn't a problem for classification algorithms, but different car manufacturers use different data scaling, so it is a good idea to scale these raw data to the physical units, so the resulting ML algorithm would be universal across different cars, and only data decoding routines need to be changed. The same concern is in case of IMU, global integrated circuits shortages may force choosing another IMU in the future, so it is safer to use unified (physical) units. The problem with GPS receiver is a little different, it returns its data in a well standardized NMEA 0183 format, yet if we want to approximate some values in the re-sampling process, it is required to decode these frames.

For the security reasons, on-board CAN bus devices can't be actively queried, as this might affect their functions, so we may only passively listen to the inter-node communication over a CAN bus, and capture frames containing relevant information, whenever they occur. The IMU device can be actively polled or be free running, as well as GPS, but GPS receivers are known to feed their data with a significant delay. This brings a problem of forming a data stream for a further analysis. Such a data stream preferably should have a constant time step, and contain no missing values. So, low or irregular sample rate parameters must be stored and updated once a new value occurs, and all streams should also be time adjusted to the GPS data stream (so delayed by a few seconds). Delay of GPS stream is constant and may be determined, by analyzing time offsets between wave forms of GPS reported speed, and ABS (CAN) reported speed.

2.2 Data Collection

Data for identifying and scoring various maneuvers was collected on a closed test track with two types of surface (concrete slabs, and skid plate), by several drivers assisted by a pilot, using a proprietary, multichannel data logging device, with a sampling rate up 100 Hz. Drivers were following the route prepared by road safety specialists. Additionally, during the experiment, the driver assistant (pilot) marked the beginning and end of each maneuver, using a digital tablet with specialized software. The result of one of such drives is shown on Fig. 2, where track marks are depicted as small triangles, and the bright area shows the skid plate. Tagged maneuvers are marked by colors (red - moving off, brown - sequence of turns, violet - left turn, blue - bypassing obstacle, orange - braking in left turn). The test track was driven in different configurations, and directions, 300 times, by randomly selected drivers (of different genders).

It should be noted that maneuvers manually selected by the assistant-pilot do not match perfectly with either the track markings or the maneuvers detected by GPS. It clearly follows from observation of trajectories in Fig. 2. Thus, their direct usefulness for machine learning is limited. They may, however, be used for verifying the correctness of maneuvers detected by our algorithm.

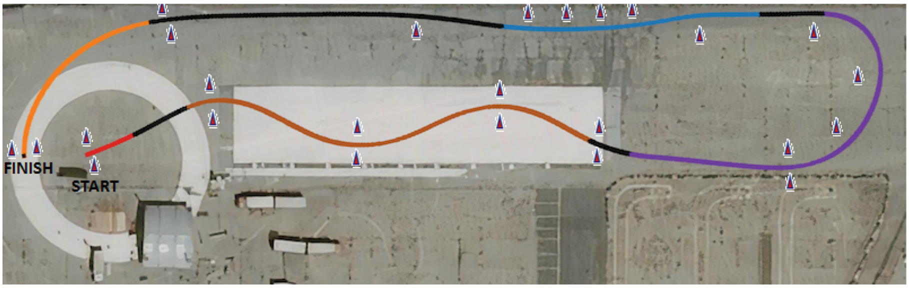

Fig. 2. GPS track tagged by a pilot with a maneuver markers. (Color figure online)

During the drive, data from the CAN bus, IMU and GPS were recorded. Based on these signals, it is possible to detect the type of maneuver the car driver is performing at any given time. The result of such detection can be seen on Fig. 3 (colors illustrate maneuvers detected by our software, red - moving off, violet - turning right, brown - turning left, green - braking).

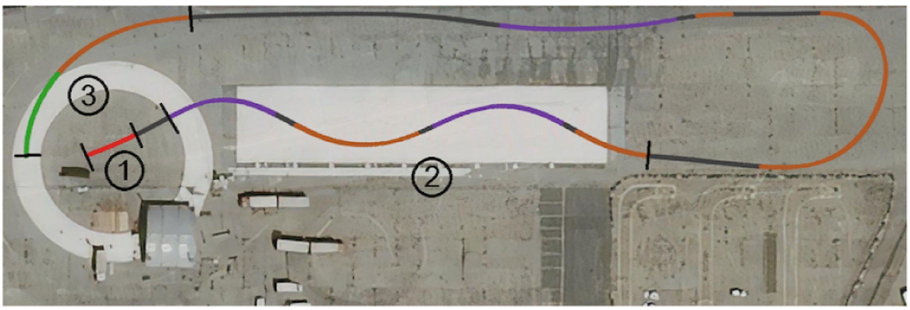

Fig. 3. GPS track tagged by software with detected maneuvers. (Color figure online)

Based on these measurements, a rule classifier model was built. The operations of the classifier present Algorithms 1, 2 and 3. Automatic detection of maneuvers has been done using experimentally established rules, which are based on observing the telemetry data. Effects of detecting 4 different maneuvers on 3 sections marked on Fig. 3 as ①, ②, and ③, have been shown, on the background of actual telemetric data from this drive, on Fig. 4, 5 and 6. It can be seen that the maneuver recognition based on the rule classifier is more accurate compared to GPS detection and assistant-pilot indications.

Algorithm 1. An algorithm for detecting car moving off

Input: $Speed, STaccelerationX, LTaccelerationX, ThrottleIncrease$
Output: $IsMovingOff$
  if $(!IsMovingOff \wedge ThrottleIncrease \wedge STaccelerationX >= 0.2 \wedge Speed < 5)$ **then**
    $IsMovingOff \leftarrow TRUE$
  else if $(IsMovingOff \wedge LTaccelerationX < 0.2)$ **then**
    $IsMovingOff \leftarrow FALSE$
  end if

Algorithm 2. An algorithm for detecting car making a turn

Input: $SteeringToLeft, SteeringToRight, GyroscopeZ$
Output: $IsTurningLeft, IsTurningRight$
  if $((!IsTurningLeft \vee !IsTurningRight) \wedge SteeringToLeft \wedge GyroscopeZ >= 0.5)$ **then**
    $IsTurningLeft \leftarrow TRUE$
  else if $(IsTurningLeft \wedge GyroscopeZ < 0.5)$ **then**
    $IsTurningLeft \leftarrow FALSE$
  end if
  if $((!IsTurningLeft \vee !IsTurningRight) \wedge SteeringToRight \wedge GyroscopeZ <= -0.5)$ **then**
    $IsTurningRight \leftarrow TRUE$
  else if $(IsTurningRight \wedge GyroscopeZ > -0.5)$ **then**
    $IsTurningRight \leftarrow FALSE$
  end if

Algorithm 3. An algorithm for detecting car braking

Input: $Speed, STaccelerationX, LTaccelerationX, ThrottleDecrease$
Output: $IsBraking$
  if $(!IsBraking \wedge BrakeIncrease \wedge STaccelerationX <= -0.4)$ **then**
    $IsBraking \leftarrow TRUE$
  else if $(IsBraking \wedge LTaccelerationX > -0.4)$ **then**
    $IsBraking \leftarrow FALSE$
  end if

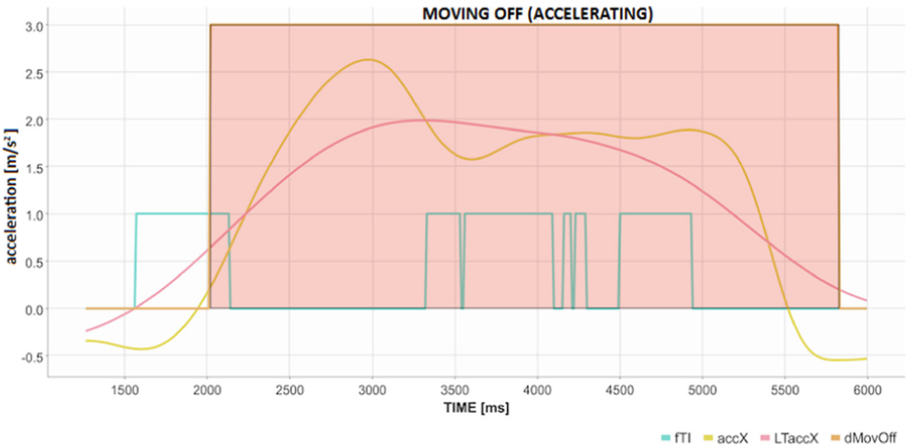

Fig. 4. Telemetry data for section ① (moving off/accelerating) from Fig. 3

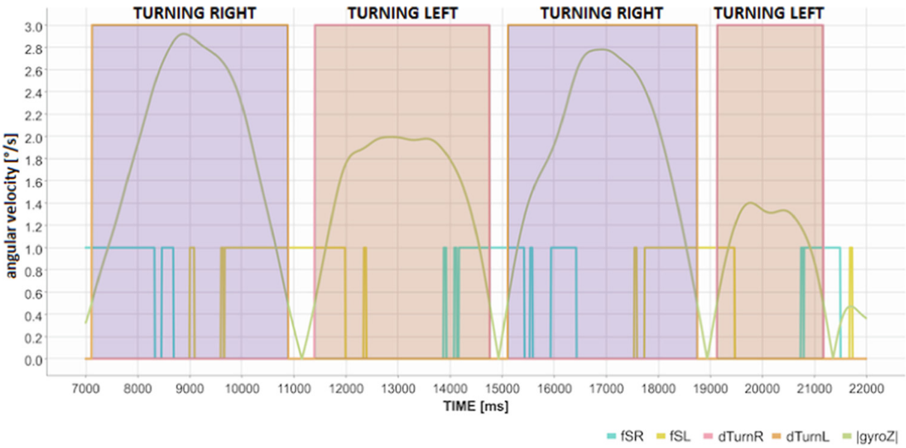

Fig. 5. Telemetry data for section ② (sequence of turns) from Fig. 3

The above graphs show the smoothed signals collected during driving, from the CAN bus and, the previously mentioned, IMU sensors. Names of these signals are collected in Table 2 which should be read together with Table 1.

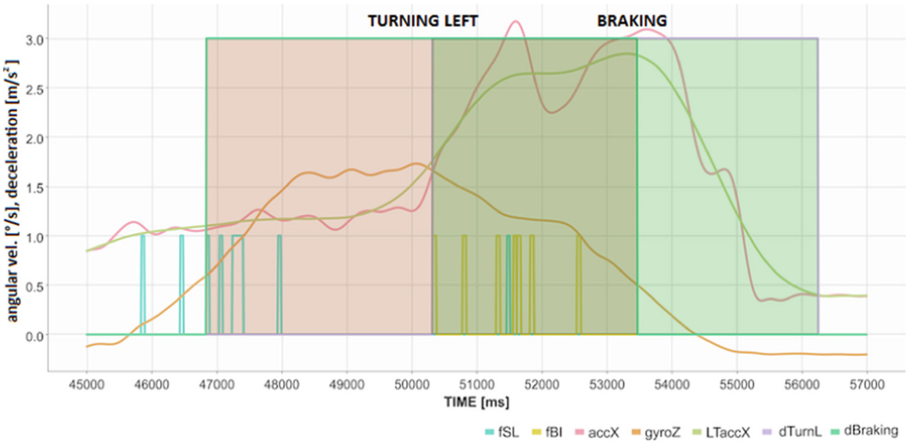

Fig. 6. Telemetry data for section ③ (braking while turning left) from Fig. 3

Table 2. Symbols used on graphs and in pseudocode.

Symbol on graph	Variable name	Description
$accX$	$STaccelerationX$	Momentary (short term) acceleration in X axis
$LTaccX$	$LTaccelerationX$	Averaged (long term) acceleration in X axis
$gyroZ$	$GyroscopeZ$	Angular speed around Z axis
fTI	$ThrottleIncrease$	Throttle is increasing
fBI	$BrakeIncrease$	Brake pressure is increasing
fSL	$SteeringToRight$	Steering wheel is turning right
fSR	$SteeringToLeft$	Steering wheel is turning left
$dMovOff$	$IsMovingOff$	Moving Off maneuver detection
$dTurnL$	$IsTruningLeft$	Turning left maneuver detection
$dTurnR$	$IsTruningRight$	Turning right maneuver detection
$dBrake$	$IsBraking$	Braking maneuver detection

3 Evaluation of the Model

The correctness of the maneuver detection rules was verified on 7 loops of a 3 km long public road under normal urban traffic conditions. The road was passed in different directions. The obtained maneuver detection rates in this environment are shown in Table 3.

Table 3. Detection rates of analyzed driving maneuvers

No	Maneuver	Detection rate
1	Moving off	100.0%
2	Turning left	85.5%
3	Turning right	95.0%
4	Braking	100.0%

As can be seen, the proposed method for detecting car maneuvers on the road gives very good results compared to the data collected by the on-board GPS device and the assistant-pilot. The slightly lower detection ratio of the left turns is probably related to the generally smaller turning radius of right turns, than left turns, due to right hand side traffic.

4 Conclusions and Further Work

Presented algorithm - maneuvers detection is only the first stage for assessing safety of maneuvers, and evaluating style of driving. It allows marking fragments of telemetry data stream, for secondary features extraction and further evaluation. In the future, the research presented in the article will be supplemented with the assessment of the driver's driving style. In future research, we plan to find an optimal set of parameters for detecting maneuvers and determining driver driving style. The driving style will be evaluated based on additional parameters such as driving speed, steering wheel jerking or acceleration. Such solutions are especially expected by companies with large fleets of vehicles, where repair and service costs are high.

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References

1. CAN Specification v2.0. Robert Bosch GmbH (1991)
2. Eftekhari, H.R., Ghatee, M.: Hybrid of discrete wavelet transform and adaptive neuro fuzzy inference system for overall driving behavior recognition. Transport. Res. F: Traffic Psychol. Behav. **58**, 782–796 (2018)
3. European Road Safety Observatory, European Commission: Annual statistical report on road safety in the EU 2020. https://ec.europa.eu/transport/road_safety/system/files/2021-07/asr2020.pdf. Accessed May 2022

4. Guardiola, I., Leon, T., Mallor, F.: A functional approach to monitor and recognize patterns of daily traffic profiles. Transport. Res. Part B: Methodol. **65**, 119–136 (2014)
5. Huang, X., Sun, J., Sun, J.: A car-following model considering asymmetric driving behavior based on long short-term memory neural networks. Transport. Res. Part C: Emerg. Technol. **95**, 346–362 (2018)
6. Karri, S.L., De Silva, L., Lai, D.T.C., Yong, S.Y.: Identification and classification of driving behaviour at signalized intersections using support vector machine. Int. J. Autom. Comput. **18**, 480–491 (2021)
7. Singh, H., Kathuria, A.: Profiling drivers to assess safe and eco-driving behavior - a systematic review of naturalistic driving studies. Accid. Anal. Prevent. **161**, 106349 (2021)
8. Xiao, W., Liu, H., Ma, Z., Chen, W.: Attention-based deep neural network for driver behavior recognition. Futur. Gener. Comput. Syst. **132**, 152–161 (2022)
9. Zheng, J., Suzuki, K., Fujita, M.: Car-following behavior with instantaneous driver-vehicle reaction delay: a neural-network-based methodology. Transport. Res. Part C: Emerg. Technol. **36**, 339–351 (2013)