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Research Paper

An Expert System for Evaluation Driver Behavior Based on Fuzzy Fusion of Smartphone Sensors

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Abstract
Monitoring and evaluating driving behavior indirectly reduces accidents and fuel consumption. But this evaluation is not available due to the need for expensive equipment. In this study, an expert system is presented which allows fuzzy evaluation of drivers` behaviors by using smartphone sensors. The proposed model, first identifies different types of maneuvers such as changing lane, road ramps, turning left or right based on cell phone sensors fusion. Then, the expert system uses fuzzy C-mean clustering technique to determine the overall behavior of the drivers into two categories, aggressive and safe, based on the type of maneuver and the lateral acceleration during the maneuver. Results show fusion of smartphone inertial measurement sensor (IMU) sensors based on the adaptive neuro fuzzy inference system (ANFIS) detect correctly the type of maneuvers near 96%. Also, in order to validate the results of assessing driver behavior, the well-known Driver Anger Scale questionnaire is used. The output obtained from the proposed model confirms the results of the questionnaire.

Keywords: Driver behavior, Vehicle Maneuvers Detection, Sensor fusion, Smartphone sensor, Intelligent transportation system

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1. Introduction

One of the most important factors of an accident is the aggressive behavior of the driver, e.g. sudden maneuvers. This magnifies the importance of monitoring and evaluating drivers` behaviors. Researches show that monitoring the behavior of a driver and logging the driving events mitigates dangerous and aggressive driving behaviors [Hickman,2005] and consequently reduces 20% of the accidents [Wouters,2000]. Moreover, in addition to increasing the number of accidents, aggressive behaviors can lead to a 40% increase in fuel consumption and mitigating the mental convenience of the passengers [Alessandrini et al. 2012].

Therefore, in order to monitor and evaluate the driver`s behavior, some transportation companies incorporate tools like GPS and camera into their commercial vehicles [Yuniar et al. 2020] [Zhang,2021]. Moreover, some insurance companies equip vehicles with several sensors to evaluate drivers` behaviors. This evaluation has provided a measure to determine the rewards for safe driving behaviors [Troncoso et al. 2011].

However, the cost of the equipment installed and maintained in vehicles is one of the most important reasons to prevent the expansion of this approach. On the other hand, today, using smartphones is increasingly growing. These tools are a set of various sensors, e.g. accelerometers, gyroscopes, and location tools like GPS. The existence of these sensors and access to communication and telecommunication networks, as well as an operating system and processor to execute applications provide an appropriate context to use this device in various domains like transportation [Castrogiovanni et al. 2020] [Gjoreski et al. 2020] . More importantly, users do not practically buy these devices for in-vehicle monitoring or traffic analysis; this application is considered as an added value. Also, governments and organizations involved in safety and traffic do not expense for maintenance and upkeep equipment.

In order to monitor and evaluate the driver`s behavior by smartphones, maneuvers including changing lane and turning to left or right are identified and the behavior of the driver during these maneuvers is evaluated. Vaiana and et al. [Vaiana et al. 2014] show that high acceleration in the movement and lateral direction of the vehicle is an indicator of the driver`s aggressive behavior. In this study, GPS has been employed to determine the steering rate and the acceleration of the two aforementioned directions. The problem of this idea is that acceleration is computed using the speed variations of GPS. GPS information has a low accuracy and low updating rate. Moreover, using this sensor requires access to relevant satellites, which is not possible for some passages like tunnels. Second, the acceleration of the vehicle for an aggressive lane change is much lower than slowly turning to the left or right. Therefore, without taking into account the type of the maneuver, detecting the aggressive of the driver causes many mistakes.

Considering a threshold for the peak obtained from the lateral axis acceleration of the vehicle, [Fazeen et al. 2012] detects sudden lane changes of the vehicle. Regarding driver behavior detection, this research presents no results for comparison. Moreover, this research merely employs the smartphone accelerometer to detect maneuvers, which does not show sufficient accuracy [Johnson, 2011]. Using the SAX algorithm, Chaovalit [Chaovalit ,2013] transforms the energy level obtained from the accelerometer into an alphabetic string and extracts the string pattern of the driver`s aggressive behaviors, like suddenly turning left or right. Finally, it tries to find patterns in the string of the driver`s behavior. Sections which are highly similar to one of the patterns are detected as aggressive maneuvers. However, this model is evaluated in limited samples which lead to a low accuracy of results. In addition to applying GPS and accelerometer, gyroscope and magnetometer is also employed in [Johnson, 2011]. Gyroscope shows the angular velocity of its rotation and is more sustainable in detecting rotation and maneuver. Magnetometer measure magnetic fields around the device including earth magnetic field. So it can use as a digital compass in smartphones. The aforementioned study exploits the DWT[2] algorithm to compare time series and obtain their similarities. In this study, turn corresponds to 90 degree rotation and U-turn corresponds to 180 degree rotation. Whereas some turns to left or right make less than 90 degrees changes in orientation sensor and the same problem for U-turns. This matter has caused low accuracy in detection of U-turn maneuvers. This study does not investigate road curves and difference between them and lane changes or turns.

One of the challenges mostly noticed in mentioned and other related researches are dividing behaviors into aggressive and normal by determining a precise threshold; while the driver`s behavior is a fuzzy spectrum and subjective and it is not possible to determine a threshold between aggressive and normal behaviors.

The contributions of our study include the following:

- Previous studies did not have a criterion for validating results and only labeled behavior based on defined thresholds. In this study, results are validated by the well-known driver angry scale (DAS) questionnaire.
- In other research approaches, a specific and rigid threshold on acceleration was considered for high-risk or aggressive behavior that leads to some misclassification, but in this study we consider fuzzy logic, which is able to consider the qualitative aspects of human knowledge and imprecise of insights .
- In similar work that analyze of the driver behavior, expensive equipment which installed inside the car is used, while in this study, the driving behavior is recognized by driver's mobile phone.
- In major researches, supervised learning has been used to learn the model. While in this study, unsupervised learning techniques have been used to detect driver behavior. However, for validation, the final results were compared with the output of the questionnaire.

The architecture of proposed model and their stages are presented in section 2. In section 3, results of the model is evaluated and final section ends the paper with a brief conclusion.

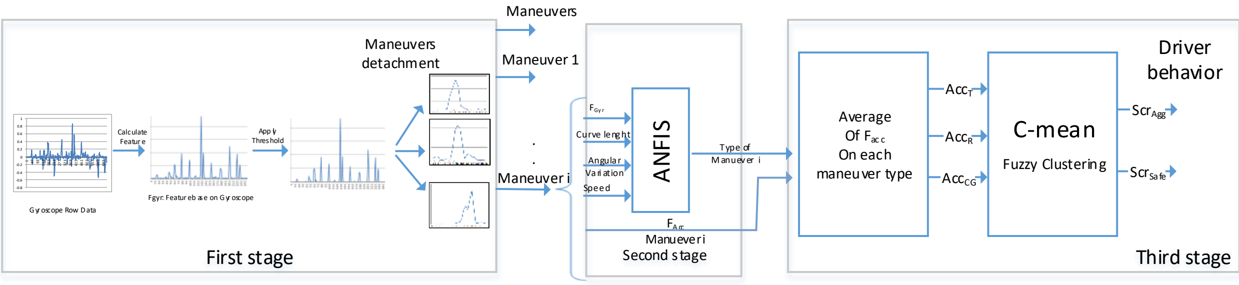


Figure 1. Architecture of expert system including third stages

2. Model Architecture

The architecture of the model consists of four stages. Figure 1 presents an overview of the architecture of the model. As we can see, in the first stage, a feature based on the gyroscope is introduced and a threshold is defined to detect the occurrence of a maneuver. In the second stage, a neuro fuzzy network recognize the type of the maneuver based on the gyroscope and angular variation. In the third stage, the lateral acceleration values of the vehicle and type of

[2] Dynamic Time wrapping

the maneuver considered as the input of the unsupervised fuzzy clustering algorithm. The output of this stage, the driver's behavior is assigned to safe or aggressive clusters.

In this paper, we assume that the smartphone is located inside the vehicle and its orientation is aligned with the vehicle direction (Fig 2). In addition, there is not any movement and jerk in smartphone during data recording and all noisy intervals are removed. These assumptions are not limited, because in the previous studies these limitations are solved as the following:

- It is simple to detect the time intervals that the smartphone is inside the vehicle, e.g., in [Eftekhari, 2016] or [Dabiri, 2018] by mode detection, this can be done simply.
- There are different methods to reorient the smartphone to align with the vehicle direction [Promwongsa, 2014] .Once the orientation matrix is estimated; the IMU measurements can be rotated to the vehicle frame. To visit a survey of these methods, see Section IV of [Wahlström, 2017]
- Detecting and removing the noise and the irrelevant data are possible, see e.g., [Eftekhari, 2018] for details.

The details of third stages of the proposed model are presented in the following.

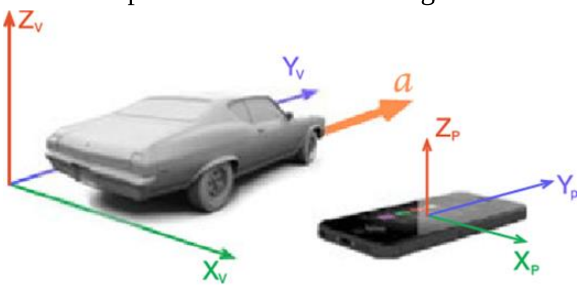


Figure 2. Aligned smartphone orientation with the vehicle direction

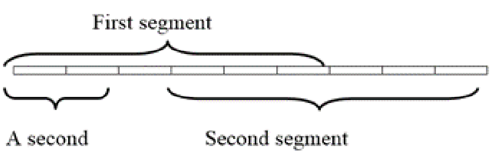
2.1. First Stage: Maneuver Detection

In the proposed model, the smartphone is installed on the dashboard. For maneuvers, the angular velocity along axis Z presents distinguished changes. To track these changes, gyroscope data are evaluated through segments. According to Figure 3.a, a segment includes 6 samples of sensor data during 3 seconds (i.e. 2 Hz sampling rate). Moreover, two consecutive segments are overlapped by 3 samples. F_{Gyr} is introduced as a feature on the gyroscope. The considered feature is the summation of the square of samples of the perpendicular axis (Z) in each segment, as mentioned following formula:

$$F_{Gyr} = \sum_{i=1}^{6} gyr_i^2 \qquad \text{rad/sec}$$

Where gyr_i is gyroscope value of the perpendicular axis in the i-th sample of a segment.

When a maneuver occurred, the value of this feature increases (See Figure 3.b). So, by determining a threshold α, when the interval which F_{Gyr} is higher than the threshold specifies a maneuver. The support vector machine (SVM) algorithm is used to determine the threshold. Accordingly, 0.05 is obtained for α . By applying α threshold, maneuvers intervals are detached and values of accelerometer, orientation, and gyroscope sensor data during these intervals are sent to the next stage.



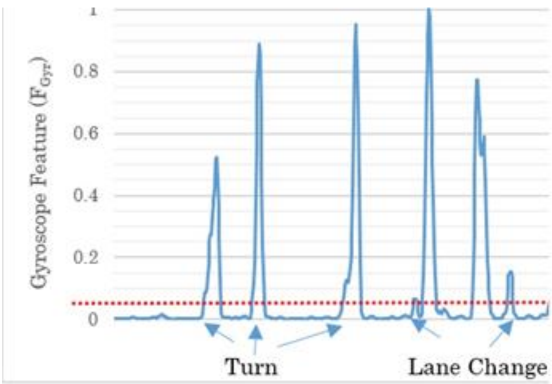


Figure 3. a) A segments includes 6 samples during 3 seconds. b) Values of introduced feature on gyroscope sensor data

2.2. Second Stage: Maneuver Type Detection

After extracting intervals which a maneuver was performed, it is required to determine the type of the maneuver. This stage is performed using the fusion of vehicle speed, gyroscope and magnetometer sensors through an adaptive neuro fuzzy inference system.

The major different of maneuvers will be the degree of angular variation (θΔ) of the vehicle corresponding to the north geographical direction. However, this angular variation may generally occur without any turn maneuver. Therefore, this feature in fusion with the gyroscope features can be an indicator of the type of the maneuver.

Based on the geometrical characteristics of the road, the driver's behavior on a left or right turn differs from the entrance or exit freeway ramps. Figure 4.a shows the difference between a road ramp curve and a turn. The F_{Gyr} and lateral acceleration values in these two maneuvers are different.

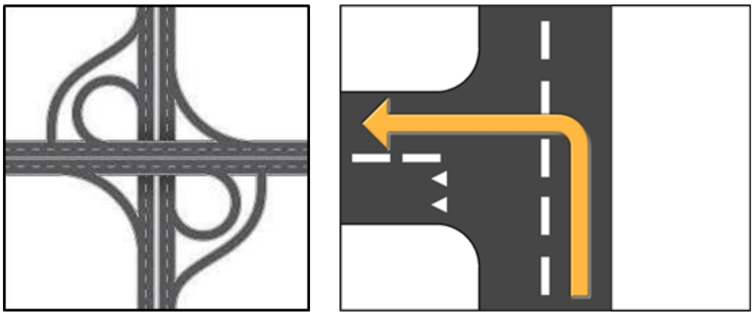


Figure 4. Ramp curve versus turn curve

Therefore, before analyzing the vehicle's lateral acceleration in driver maneuvers, a distinction must be made between the types of maneuvers.

To determine maneuver type, the following features of each maneuver are applied into an ANFIS:

- The peak of F_{Gyr} in the maneuver range.
- The length of the curve of $\mathrm{F_{Gyr}}$ in the maneuver range.
- The angular variation in the maneuver range (θΔ).
- The average speed of vehicle during the maneuver.

The ability of ANFIS as an approximator capable of neural network based training and local approximation based on the Sugeno fuzzy model has led to the formation of membership functions and fuzzy inference engine in accordance with the training data. The reason for using the fuzzy model is that the system is not sensitive to a certain threshold value for indicators.

The five layers of these adaptive neuro fuzzy networks are as follows:

First layer: The above four features are inputs of this layer. Nodes in this layer are adaptive, and the output of this layer is a Gaussian membership function. The parameters (a, b) are obtained during network training. The output values of the nodes of this layer are calculated as follows.

$$O_{1.j} = \mu_{x_i.j}(y) = exp\left(-\left(\frac{y-a}{b}\right)^2\right)$$
$$i = 1.2.3.4 \quad j = 1.2.3$$

For each input, three membership functions are considered, i represents the number of inputs and j represents the number of membership functions of each input.

Second Layer: This layer contains nodes that create inference rules. In this layer, the number of nodes is equal to the number of nodes of first layer. Nodes in this layer is fixed. The outputs of these nodes are defined as the following production of the outputs of the previous layer. For each node we will have:

$$O_{2.j} = w_j = \prod_i \mu_{x_i.j}(y)$$

$$i = 1.2.3.4 \qquad j = 1.2.3$$

Multiplying the membership functions represents the operator "AND" in fuzzy logic, which is another form of conditional implementation in fuzzy logic (Mamdani implication).

Third layer: In this layer, the number of nodes is equal to the number of rules. Each node in this layer represents the amount of excitation of a rule relative to the excitation of all the rules. In fact, the values of $w_j$are normalized in this layer.

$$O_{3.j} = \overline{w}_j = \frac{w_j}{\sum_j w_j} \qquad j = 1.2.3$$

Fourth layer: Each node in this layer is adaptive. The parameters $p_{i,j}$ that can be obtained by the learning process; Jang et al. [27] propose a hybrid method to find these parameters associate with learning parameters a and b in first Layer. The outputs of these neurons can be defined as the following:

$$O_{4.j} = \overline{w}_j \left(\sum_i p_{i.j}.x_i + p_{i+1.j} \right)$$

$$i = 1.2.3.4 \quad j = 1.2.3$$

Fifth Layer: The single node of this layer is fixed and its output can be defined as the following summation over all incoming signals from the previous nodes:

$$O_5 = \sum_j O_{4.j} = \sum_j \overline{w}_j \left(\sum_i p_{i.j}.x_i + p_{i+1.j} \right)$$

$$i = 1.2.3.4 \qquad j = 1.2.3$$

Figure 5 shows the five-layer structure of ANFIS.

The output of the ANFIS determines the type of maneuver. Table 1 shows the confusion matrix of the results. As can be seen, the neuro fuzzy network has been able to detect the type of maneuver with an accuracy of 95.5%. In similar studies, this accuracy was 89% [Eftekhari,2018].

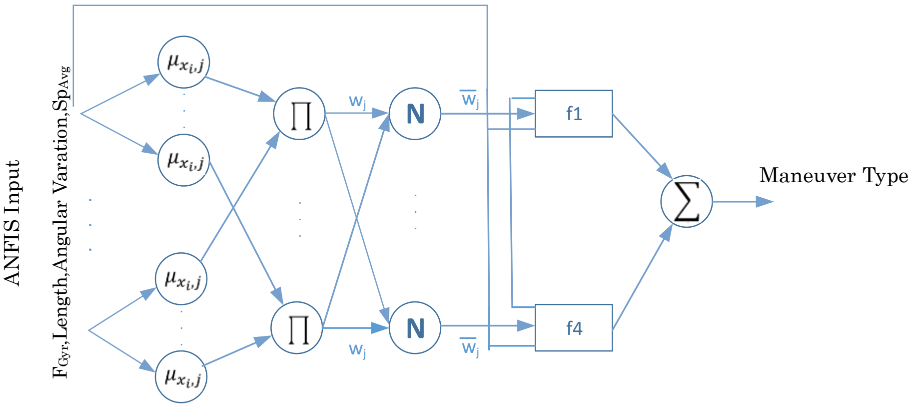


Figure 5. The ANFIS layers for estimation maneuver type

Table 1.Confusion Matrix for detecting maneuver type based on the proposed neuro fuzzy network

	Lane change	Ramp curve	Turn
Lane change	39	0	1
Ramp curve	3	46	3
Turn	0	0	69
	Accuracy	95.5	

2.3. Behavior detection

An aggressive driving is described as “Operating a motor vehicle in a selfish, pushy, or impatient manner, often unsafely, that directly affects other drivers” [NCHRP,2003].According to the definition above, two points must be taken into account:

Firstly; the aggressive behavior is a fuzzy concept and does not explain through a numeric or rigid threshold.

Secondly; it is subjective, depends on the expert opinion, and is a perception of the general behavior of the driver.

Therefore, we cannot consider a specific threshold for aggressive maneuvers. On the other hand, aggressive behavior detection for a particular maneuver may have low accuracy and evaluating and judging the general behavior of a driver during a trip is easier and more accurate.

Results show determining the aggressiveness and the non-aggressiveness of the driver`s behavior during a maneuver directly related to the acceleration of the lateral axis of the vehicle [Vaiana et al. 2014] [Fazeen et al. 2012]. So, $F_{Acc}$ is considered to detect driver`s behavior during a maneuver.

F_{Acc} is also the summation of the square of accelerometer samples of the lateral axis (X) in each segment, as mentioned following formula:

$$\mathrm{F_{Acc}} = \sum_{\mathrm{i}=1}^{6} \mathrm{Acc_i^2} \qquad \mathrm{m/sec^2}$$

Where $\mathrm{Acc_i}$ is accelerometer value of the lateral axis in the *i-th* sample of a segment.

However, the important point is that acceleration value is not merely sufficient to detect aggressive or non-aggressive behavior. As mentioned earlier, the value of F_{Acc} during a lane change or ramp curve by aggressive driver maybe is less than the value of this feature during a left or right turn by safe behavior. So, the type of the maneuver also must be considered for determining behaviors.

In this stage, following features of each maneuver are considered:

- The peak of F_{Acc} in the maneuver range.
- The type of the maneuver

In the proposed model, drivers' behavior is stored and evaluated at intervals of 30 minutes of their driving. During each trip, the driver performs maneuvers, including turning, entering the ramp or changing lanes, the type of maneuvers being determined through the neuro fuzzy network which described in previous section. Then the value of attribute A is calculated for each maneuver.

In the next step, the average of feature F_{Acc} is calculated for each type of maneuver during a driver trip. Therefore, for each trip, a driver gets three numbers, which represent the average of feature F_{Acc} for turns, ramps and lane changes.

These three numbers are calculated from the following equation:

$$Acc_T = Average\left(\sum_{i\in\{All\ Turn\ Maneuvers\ \}} F_{Acc}(i)\right)$$

$$Acc_R = Average\left(\sum_{i\in\{All\ Ramp\ Maneuvers\ \}} F_{Acc}(i)\right)$$

$$Acc_{LC} = Average\left(\sum_{i\in\{All\ Lane\ Change\ Maneuvers\ \}} F_{Acc}(i)\right)$$

Then, using a fuzzy clustering, the extent to which all drivers' trips belong to each of the clusters of aggressive and safe behavior is determined. The importance of this section is that the learning algorithm is unsupervised and the algorithm has no information or training on drivers' scores. The algorithm can be used to evaluate the driver's behavior based on determination membership degree to safe or aggressive clusters for each trip. Scr_{Safe}, Scr_{Agg} scores represent these degrees for each trip, respectively.

2.4. Validation Model

One of the challenges that is mainly seen in similar studies is the lack of validation of the results. Most of the researches have only separated and clustered the drivers' behavior, while in this study, the results obtained from the proposed model have been compared with the evaluation of the questionnaire completed by the driver.

For this purpose, we have used the DAS questionnaire [Deffenbacher, 1994] which is a well-known questionnaire to assess driver behavior. This questionnaire consists of 14 questions, each question with five Likert scale answers. The scale given by this questionnaire is between 14 and 70. According to the reference article, if the number obtained for a driver is less than 42, it is considered safe driver behavior, and if this number is higher than 51, it is considered aggressive driver behavior.

The results given by implementing the fuzzy clustering algorithm of the previous section for driver is compared with the results of the questionnaire completed by them and a direct relationship is observed between the two.

3. Results

In order to experiment the proposed model, the data is collected by installing a mobile phone on the vehicles of a taxi service agency during 10 days. Drivers were also unaware of the content of the stored data. The data were recorded using software Androsensor [Androsensor,2021], which is installed on a n8000 Samsung smartphone, and the collected data have been analyzed on MATLAB 2013. The DAS questionnaire is also completed by the drivers, and the scale obtained for each driver is shown in Table 2. Then half-hour intervals are extracted from a driver's driving.

In order to be able to generalize and validation of results in any traffic situation, driving behavior in different road conditions and on a variety of roads has been evaluated. Appendix A shows the type of road and the average speed on each road, as well as the average lateral and longitudinal acceleration to each driver. Also in Appendix B the G-G diagram for each driver are shown.

In the next step, using the F_{Gyr} threshold, first the interval in which the maneuver occurred was determined then the type of maneuvers was determined based on the neuro fuzzy network that described on section 2-2 and the Acc_T , Acc_R, Acc_{LC} value for each trip is determined. Table 2 shows the score for seven driver during all trips.

In the next step, by applying the C-mean fuzzy clustering algorithm on these data, two clusters is created with the centers stated in Table 3. Based on these clusters, Scr_{Safe} and Scr_{Agg} for each driver is calculated.

Figure 6 shows the results. As can be seen, the drivers whose scale of the questionnaire is less than 42 and according to the reference article are considered as calm drivers, mostly have a value of Scr_{Agg} higher than Scr_{Safe}. In contrast, for drivers with a scale greater than 50, the proposed model shows higher Scr_{Agg} than Scr_{Safe} . In the case of drivers whose scales ranged from 42 to 50, some of the drivers' trips are more aggressive behavior (larger Scr_{Agg}) and some are more safe behavior (larger Scr_{Safe}).

Table 2. Characteristic of drivers including DAS questionnaire scale and Acc_T . Acc_R, Acc_{LC} values

Drivers	Driver anger scale	Acc_T	Acc_R	Acc_{LC}
1	27	3.0	1.5	1.9
2	28	5.9	7.2	1.5
3	34	5.6	6.9	1.5
4	43	6.7	10.4	2.3
5	44	7.3	7.6	0.8
6	50	7.0	11.4	2.7
7	51	9.8	11.5	2.3

Table 3. Aggressive and safe cluster center according to Acc_T. Acc_R, Acc_{LC} values given by C-mean

Cluster	Acc_T	Acc_R	Acc_{LC}
Safe behavior	5.2	5.7	1.5
Aggressive behavior	7.7	10.7	2.3

This evaluation can be used to determine a measure for discounts and penalties of the annual car insurance. For instance, the annual insurance of drivers who have “safe” behaviors include more discounts, while drivers with “aggressive” behaviors are deprived of the annual discounts. Moreover, it can be used as a measure for public transportation fleet management to make decisions regarding hiring or continuing working with their drivers. Moreover, by mandating the usage of “safe” drivers in commercial vehicles, legislators can take precautions to increase the road safety.

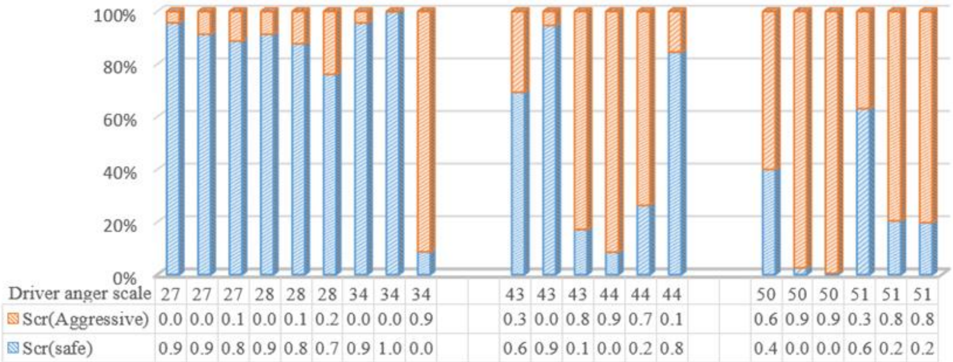


Figure 6. Scr_{Safe} **and** Scr_{Agg} **values for each trip**

4. Conclusion

Driving behavior evaluation is a type of driver monitoring which indirectly mitigates dangerous and aggressive behaviors and consequently reduces the number of accidents and fuel consumption. On the other hand, this evaluation can be used to encourage and punish drivers in form a discounts and penalties of car insurance or introduce special scores regarding drivers of public transportation fleets.
However, due to the expensive equipment, this evaluation is not welcomed by insurers or fleet management and drivers. In this study, the driver`s behavior was analyzed using smartphones. The characteristics of this device include its widespread usage and imposing no additional costs for their users.
Several sensors like the accelerometer, gyroscope, and magnetometer can properly reflect the driver`s behavior. In this study, driving maneuvers, e.g. changing lane, turning left or right and road ramp are detected using the fusion of sensors through neuro fuzzy inference engine. Using the proposed model, more than 95% of maneuvers were detected. In the other hand, detecting driver behavior e.g. the aggressive or safe driver, is subjective. After recognizing the maneuver type, based on the maneuvers performed by the driver during a trip and its lateral acceleration in these maneuvers, the overall behavior of the driver is evaluated.
The expert system uses the observation of different drivers' behaviors and based on C-mean fuzzy clustering, divides the drivers' behavior in half an hour trips into two categories: aggressive and safe.
In order to validate the results obtained from the diagnosis of a driver aggressiveness during trips, we used the DAS questionnaire. In conclusion, it is shown that in the case of drivers who behaved calmly according to the questionnaire and their questionnaire scale was less than 42, the expert system also evaluated their behavior in the relevant cluster. Also, drivers who have a scale above 50 and are considered aggressive driver according to the questionnaire are mainly evaluated by the expert system in its appropriate cluster. In the case of drivers who had a scale between 42 and 50, they were evaluated in the aggressive cluster in some trips and in the safe cluster in some.
The another point that can be considered as a challenge for the proposed model is the effect of the trip purpose on driving behavior. For example, having to hurry on business trips or relaxing on vacations may affect the results of the evaluation. In this regard, one should distinguish between the driver’s trait, which is related to his personality and the driver’s state, with his temporary and momentary sate. Psychological research shows a significant relationship between these two concepts. As an example, Hensy has shown that the stress of a driver, which can be the result of being in a

hurry or staying in traffic, depend on his trait [Hennessy.1997].

This evaluation can be used to determine a measure for discounts and penalties of the annual car insurance. Moreover, it can be used as a measure for public transportation fleet management to make decisions regarding hiring or continuing working with their drivers.

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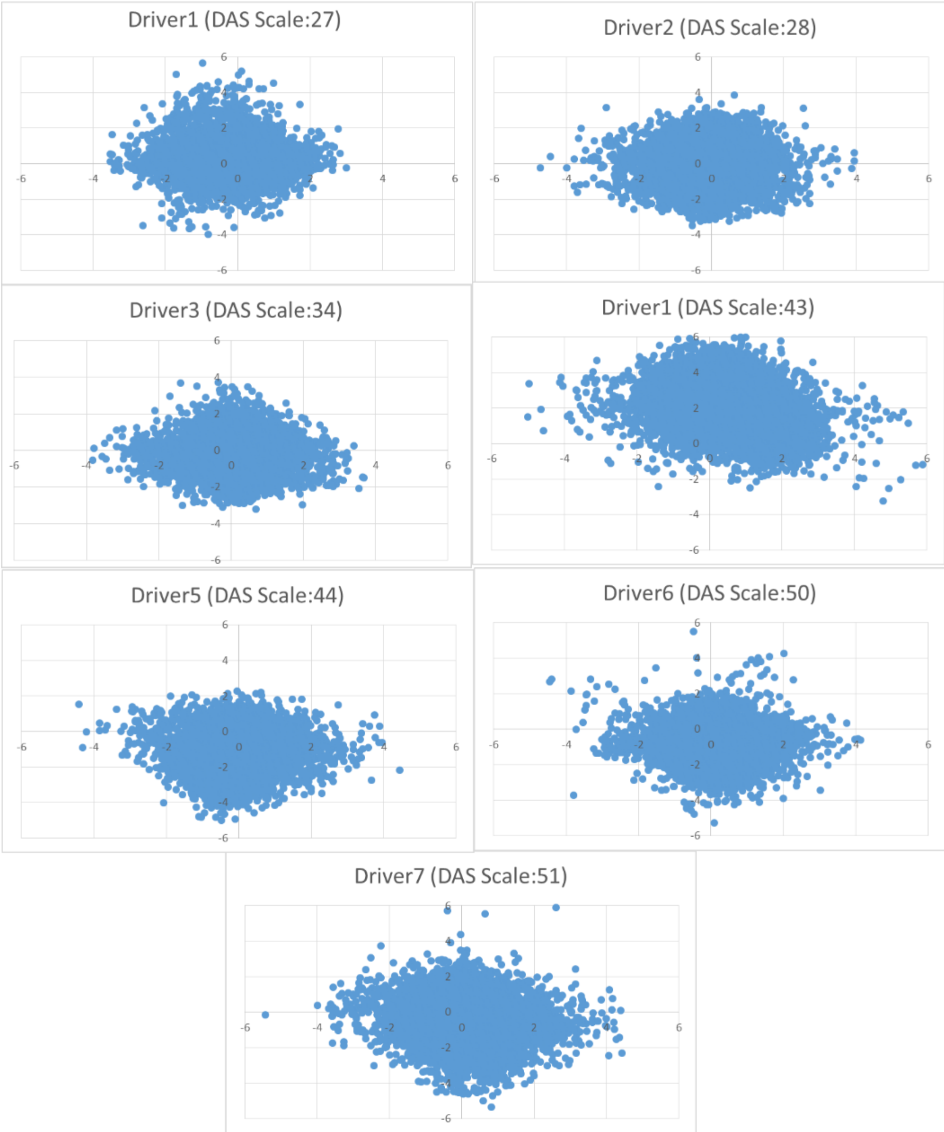
6. Appendix A

Drivers	Road Type	Average Speed (km/h)	Average of longitudinal acceleration (m/sec^2)	Standard deviation of longitudinal acceleration (m/sec^2)	Average of lateral acceleration (m/sec^2)	Standard deviation of lateral acceleration (m/sec^2)
1	Arterial	25.1	-0.215	0.56	0.15	0.85
2	Highway	23.7	0.1	0.45	0.35	0.6
3	Street	12.5	0.01	0.61	0.12	0.61
4	Street	16.8	0.05	0.5	0	0.57
5	Arterial	23.5	-0.01	0.49	0	0.37
6	Street	24.4	-0.06	0.4	0.03	0.46
7	Arterial	35	-0.05	0.4	0	0.46
8	Highway	59.8	-0.02	0.4	0	0.51
9	Street	18.6	0.06	0.55	-0.01	0.5
10	Arterial	22.6	0.05	0.48	0	0.34
11	Highway	55	-0.02	0.42	-0.02	0.45
12	Street	12.7	0.13	0.41	-0.01	0.4
13	Arterial	22.1	0.05	0.49	-0.03	0.32
14	Highway	56	0.06	0.42	0.02	0.36
15	Highway	58	0.02	0.41	0.01	0.35

7. Appendix B

Figure shows the G-G diagram for each driver. In this diagram, the vertical axis represents the longitudinal acceleration of the vehicle and the horizontal axis represents the lateral acceleration of the vehicle. In other words, acceleration and braking are equivalent to positive and negative values on the y-axis and the turning to the right and left is equivalent to positive and negative values on the x-axis.


Driver1 (DAS Scale:27)
Driver2 (DAS Scale:28)
Driver3 (DAS Scale:34)
Driver1 (DAS Scale:43)
Driver5 (DAS Scale:44)
Driver6 (DAS Scale:50)
Driver7 (DAS Scale:51)