



Smartphone-based System for Driver Anger Scale Estimation Using Neural Network on Continuous Wavelet Transformation

H. R. Eftekhari*

Assistant Professor, Department of Computer engineering, Faculty of Engineering, Malayer University, Hamedan, Iran

ABSTRACT: Monitoring of the driver decreases accidents by reducing the risky behaviors and causes decreases the fuel consumption by preventing aggressive behavior. But this monitoring is costly due to built-in equipment. In this study, we propose a new model to recognize driving behavior by smartphone data without any extra equipment in the vehicles which is an important added value for smartphones. This recognition process is done in this paper based on the continuous wavelet transformation on accelerometer data. Then these patterns are fed to multilayer perceptron neural network to extend the information extracted from the corresponding features. Also the magnetometer sensor is used to detect the maneuvers through the driving period. Results show the accuracy of the proposed system is near 80% for pattern recognition. Driver scale based on a standard questionnaires regarding to driver angry scale (DAS), is also estimated by the proposed multilayer perceptron neural network with 3.7% errors in the average.

Review History:

Received: 24 November 2018
Revised: 6 February 2019
Accepted: 12 February 2019
Available Online: 1 February 2020

Keywords:

Risky behavior
Driver monitoring
Smartphone
Wavelet transformation
Multilayer perceptron neural network

1- Introduction

One of the most important causes of road accidents and deaths is inappropriate driving behavior. The statistics show that the cause of more than 70% of suburban accidents and 90% of urban accidents is vehicles' drivers' mistakes [1]. Also, about one-third of the human death on roads in the beginning of 2016 was due to the overturning of vehicles that directly related to improper driving behavior [2]. This also highlights the importance of monitoring and evaluating driving behavior. The studies suggest that monitoring the driver behavior and driving accidents' record can reduce the aggressive and hazardous driving behavior [3], which means a 20% reduction in accidents [4]. Also these behaviors, in addition to increasing accidents, will increase fuel consumption by 40% and reduce passengers' mental relaxation [5].

Hence, in order to monitor and evaluate the driver's behavior, some transport companies in commercial vehicles have used tools such as Global Positioning System and camera [6]. Also, some insurance companies have provided incentives for safe driving behaviors by equipping vehicles with evaluating sensors [7].

But the cost of equipment is the main cause for not extending this solution. Equipping vehicles by insurance companies or managing transport fleets would be costly for them. On the other hand, supply of equipment by drivers is not expected due to its high cost. In this case, installation of equipment is only possible in public transport fleets with legal compulsion, which will have certain consequences and dissatisfaction. The repair and maintenance costs of these systems reduced extendibility of these systems.

Today, on the one hand the use of smartphones is increasing. These devices include a set of sensors, such as accelerometers, gyroscopes, magnetometers and positioning tools. The presence of these sensors along with access to a variety of communication and telecommunication networks, as well as having an operating system and processor to run applications, provides a good ground for using this device in a variety of areas, such as transportation. Most importantly, users do not actually buy these devices for in-car surveillance or traffic analysis, but it's a value-added one. On the other hand, with the help of this tool, the cost of repair and maintenance is not paid by government and semi-government organizations for safety and traffic.

The previous researches show that smartphones can be used to various areas of intelligent transportation systems, such as travel mode detection, accident detection and driving behavior analysis [8-11]. One of these uses is to monitor driving behavior and evaluate it based on the driver's smartphone.

In Mostly Researches evaluation of driver behavior is calculated based on accelerations which are measured by smartphones accelerometer.

In [12], high acceleration in the vehicle direction and the lateral direction of the vehicle represents the driver's aggressive behavior. Also, [13] has shown that the drinking driver's risky behavior is detected by weaving and intensive turns. One of the disadvantages of this research is lack of attention to the difference between lane changes and turns acceleration.

*Corresponding author.

E-mail address: eftekhari@malayeru.ac.ir,

Generally, a slow turn more than an aggressive or risky lane change can make high acceleration to the vehicle, and hence the driver's cell phone.

On the other hand, unlike lane changes, left or right turning is not dependent on driving behavior, but depends on the road map from origin and destination of the trip. While frequent lane changes in direct paths represent a driver's risk behavior. In [14], taking into account the threshold for the peak obtained from the acceleration of the vehicle's lateral axis, the vehicle's sudden lane changes has been detected. The research did not any comparison or evaluation results. In [15], using the proposed algorithm converts the energy obtained from the accelerometer into an alphabetic sequence. Then, the pattern of driving aggressive behaviors, such as sudden left and right turns, was calculated and finally, the similarity of driver's behavior and aggressive behavior patterns are evaluated. The small set of aggressive patterns is most challenge of this study. Also, the proposed model has been evaluated in low dimensions and very limited samples, although the results had low accuracy. In [16], besides the use of positioning and accelerometer, this research have used the gyroscope and the magnetometer. Magnetometers and accelerometers' sensors are available on most smartphones, but a limited number of phones are equipped gyroscope sensors. They use Dynamic Time Warping (DTW) algorithm to compare time series and similarity between them.

According to previous researches, the driver's aggressive and risky behaviors are reflected in the frequency of lane change [17], the intensity of lane change [18] and accelerations and brakes [19].

So, driving risky and aggressive behaviors can be divided into three categories:

- The first category of frequent and unpredicted lane changes is one of the most important causes of sideswipe accidents, in addition this behavior disturb the other drivers focused.
- The second category is the driver's severe brakes, which in many cases cause chain accident due to lack of timely awareness and ability to control the rear vehicles.
- The third category is the fast acceleration of the vehicle, which increases the speed and reduces vehicle control over the turns, squares and slippery road.

Hence, monitoring these three categories of the driver behaviors will play an important role in reducing risky behaviors and accidents. However, other behaviors includes flashing headlights, sustained horn-honking, preventing other drivers from passing and passing on the road shoulder can indicate aggressive behavior [19]. In this study, we use accelerometers and magnetometers' sensors to identify the driver risky behavior pattern and determine the driver's anger score. First, by introducing a magnetometer-based feature, the intervals of the turns are extracted and removed. We then define the feature by applying a continuous wavelet transform on the accelerometer. Based on the defined feature and use of machine learning, we identify the pattern of the driver risky behaviors. In the next section, the architecture of the system, its phases, and the method of computing the features are expressed. In the fourth section, we evaluate the results of the model, and finally, we present the conclusion.

2- The Proposed Model

As shown in Figure 1, after activating the driving behavior detection system, cell phone sensors are stored and analyzed stored data after a period of time. The system can be activated either by the driver or automatically. The researches [20-23] have made it possible to detect in-car cell phone using low-power sensors. Therefore, automatic system activation is also possible.

The data of accelerometers and magnetometers' sensors are taken at 2 Hz sampling rate. This sampling rate will reduce battery consumption in storage and processing of data [20]. In the first phase, by introducing a feature on the data, the vehicle turns, including the right, left, U-turn, as well as the intense cell phone jerk, are detected by the use of cell phones. In the second phase, the remaining time intervals after removing noise data and vehicle turns are analyzed in a window

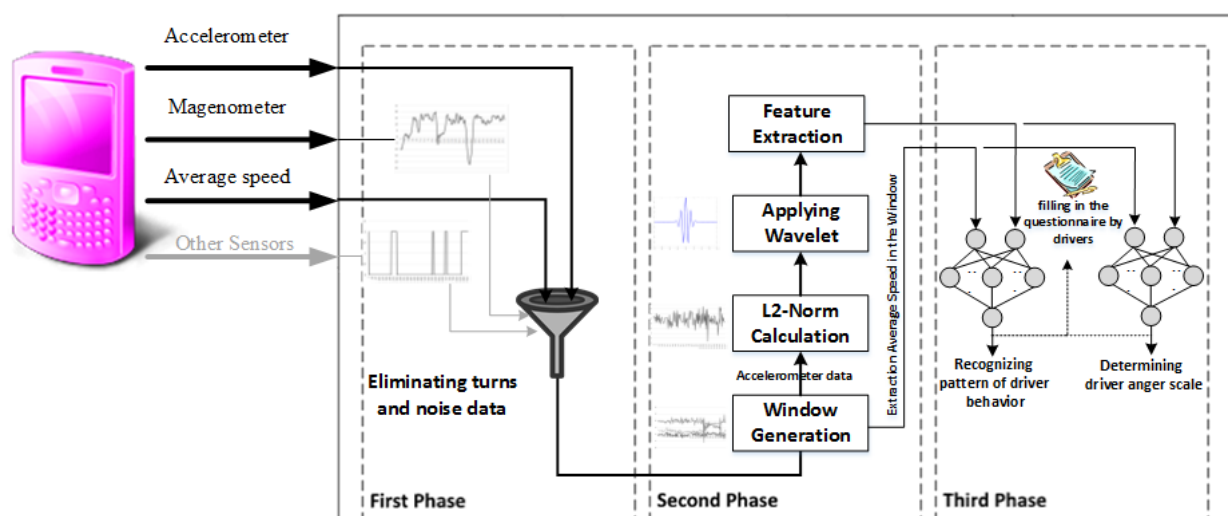


Fig. 1. The architecture of the proposed model

of 1800 samples. Hence, each window represents the individual's driving behavior in a straight path for 15 minutes. The result of the second phase is extraction of the feature which defined on the accelerometer. In this phase, also, the average speed of the vehicle is calculated. The average speed can be obtained in a range of 15 minutes from different methods. The easiest way is to use the mobile positioning such as GPS. Unlike accelerometers and magnetometers' sensors that are continuously active, cell phone location tool require activation by the user. Therefore, other methods such as the use of the cellular antenna positioning and Wi-Fi networks can be used to determine the average speed.

In the third phase, according to the results of the filled-in questionnaire for volunteer drivers, the neural network is trained to detect the pattern of driving behavior and determine anger score of the driver. After training the networks, the system is ready to evaluate driving behavior. Figure 1 shows the architecture of the proposed model.

2- 1- First phase: Removing turns and noise

On the one hand, risky behaviors are evaluated based on the value of acceleration on cell phones in the brakes, acceleration and lane changes; and on the other hand, acceleration to cell phones in slow-moving turns is usually more than weaving or even severe braking. Therefore, the data related to the turns, including U-turn, the left and right turn, should be removed from the acceleration analysis. In addition, the sudden jerks caused by cell phone mobility should also be identified and removed. These impacts bring high acceleration to the device.

In this phase, by introducing a magnetometer-based *noise detection feature (NDF)*, the intervals of sudden turns and jerks in the cell phone are identified and extracted. Most smartphones are equipped with a magnetometer and accelerometer data.

The introduced feature on the magnetometer examines the variance of the values of a 5-second interval including 10 registered samples. If the value of this feature exceeds γ threshold, it indicates that the interval had a turn or jerk of the cell phone. The procedure of detecting and eliminating time intervals involving the noise or vehicle turns and extracting a window is shown in Figure 2.

```

Window = function CreateWindow
(RowData(t0,tn))
//RowData include accelerometer
A(t)=(ax(t),ay(t),az(t))and
magenometer M(t)=(mx(t),my(t),mz(t))
values in 3 axes
during a driver trip from t0 to tn with 2
Hz sampling rate .
{ t=t0
l1=getLocation();
while t<tn-9
{
if NDF<
{ Window.Acc=Window.Acc+A(t)
Window.size++;
}
if Window.size==1800
{ l2=getLocation();
Window.AvgSpd=CalcAvgSpd(l1,l2);
return Window
}
t=t+1
}
}
    
```

Fig. 2. The procedure of detecting and eliminating noise and turn intervals.

The Equation 1 introduces this feature:

$$NDF = \sum_{k=x,y,z} \text{var}(m_k(i), m_k(i+1), \dots, m_k(i+9)) \geq \gamma \tag{1}$$

$m_k(i)$: The value of magnetometer in i th sample of k axis

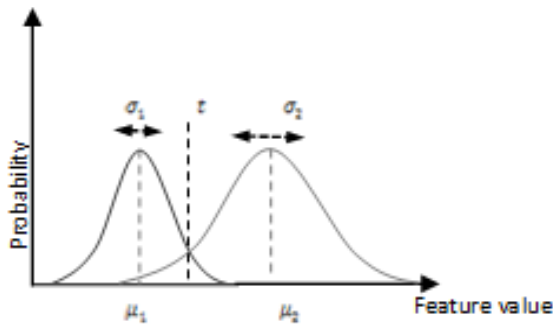


Fig. 3. Determining optimal threshold base on distribution function

Classifier	Threshold
The proposed method	69
Neural Network	70
Decision Tree	70
Naïve Bayes	63
Nearest Neighborhood	70

To determine the threshold for the feature, optimal thresholding method is utilized based on the minimum error. This method has been applied in image processing to recognize an object region from the background of the image [24]. There are two regions or two sets of data in the proposed feature. Firstly, values of NDF during turns, jerks and sudden movement of cell phone and secondly values of NDF in the brakes, acceleration and lane changes of the vehicle. The threshold is utilized to separate these two sets by determining a boundary between them. If the distribution function of these sets is determined, as shown in Figure 3, it is possible to separate them. Since according to the law of total probability, for each sample, one can write:

$$P(x) = \sum_{i=1}^2 P(x|S_i) \cdot P(S_i) = P(S1) \cdot p_{s1}(x) + P(S2) \cdot p_{s2}(x)$$

Where $P(S1)$ and $P(S2)$ are the prior probabilities of $S1$ and $S2$ sets and $p_{s1}(x)$ and $p_{s2}(x)$ are the probabilities of x belonging to $S1$ and $S2$, respectively. If t is considered as a threshold, the probability of error in each set is given by:

$$E_{s1}(t) = \int_{-\infty}^t p_{s2}(x) dx, \quad E_{s2}(t) = \int_t^{\infty} p_{s1}(x) dx$$

The total probability of false detection that must be minimized is as follows:

$$\text{Min } E(x) = P(s2) \cdot E_{s1}(x) + P(s1) \cdot E_{s2}(x) \tag{2}$$

To minimize (2), the following ordinary differential system should be solved:

$$\frac{dE(t)}{dt} = \frac{d \left(P(S2) \cdot \int_{-\infty}^t p_{s2}(x) dx + P(S1) \cdot \int_t^{\infty} p_{s1}(x) dx \right)}{dt} = 0$$

Based on the first fundamental theorem of calculus, we have:

$$P(S1) \cdot p_{s1}(t) = P(S2) \cdot p_{s2}(t) \tag{3}$$

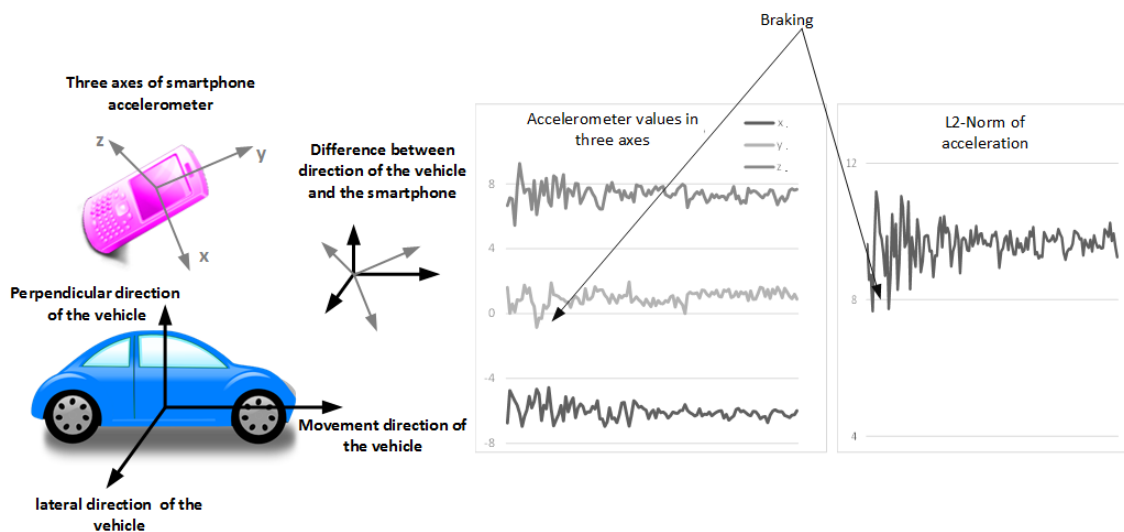


Fig. 4. The effect of acceleration of the vehicle on the accelerometer sensor of the smartphone

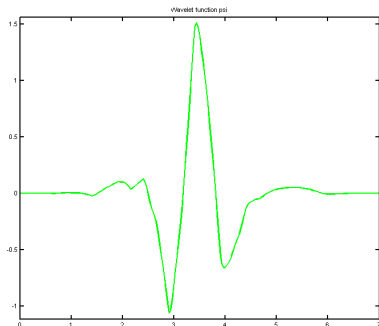
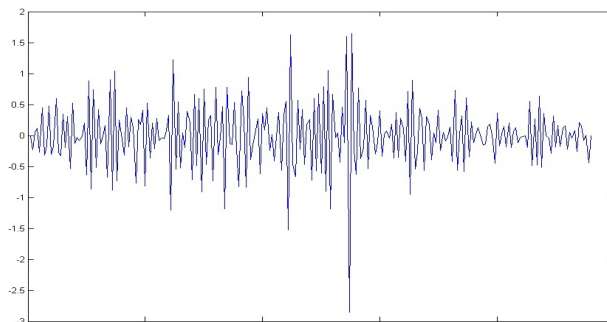


Fig. 5.A. Wavelet Symlet 4



B. Coefficient of continuous wavelet transformation for a window of driver behavior

Thus, after determining distribution functions of datasets and solving (3), the threshold t can be obtained. As a result of unpredictable probability of sets, the same probability can be usually considered for both $P(S1)$ and $P(S2)$. To determine thresholds, Equation (3) is applied based on the mean and the standard deviation values of datasets. Based on this, the sensor data obtained from more than 600 samples. Then, for each set, the best fit distribution function is estimated. The best threshold for NDF is given 69 by the proposed statistical method.

To validate thresholds obtained by statistical method, we applied and compared the accuracy of results. Based on this, an artificial neural network (NN), Decision Tree (DT), Naïve Bayes (NB) and KNN classifiers in MATLAB 2013b are applied for the binary classification of the data of the experiment given in Table 1. Note that the experimental threshold in learning machine techniques is obtained by smoothly increasing the value of the considered feature until the classes are changed.

The results show the value 70 is the most suitable threshold for equation (1). Table 1 shows that the obtained value for the threshold is given by the proposed statistical method is confirmed by machine learning methods.

In addition the above feature, the jerks which are generated by using the cell phone is also detected by other sensors such as proximity sensor or touch screen status. With combining these sensors with the feature, noise removal are more accurately. In our study, roads' bumps can also be effective on the proposed model. Passing bumps have three steps: slow down before bump, pass bump and increase speed after passing bump. Reducing and increasing the speed as well as other risky behaviors can be analyzed in the proposed model. Also, Mohan [10] has shown the acceleration of the vehicle's perpendicular axis increases when the speed of the vehicle during passing the bump is high. So the value of acceleration in perpendicular axis during passing the bump is also higher for aggressive drivers, and this acceleration difference effect on analyzing driver behavior.

2- 2- Second phase: Extracting wavelet feature

After applying the first phase filter and removing data related to the vehicle turn and cell phone jerks, the data derived from the accelerometer sensor will only include the driver's driving behaviors in straight paths. Two reasons cause changing the vehicle acceleration during a straight path. The first is changing the vehicle speed. Reducing or increasing speed changes acceleration in the vehicle direction. The second is lane changes, which causes acceleration changes in the lateral axis of the vehicle. The aggressive behavior involves sudden and intensive lane changings, acceleration and brake.

Given that the cell phone may not be aligned with the vehicle's direction, so the speed changes or lane changes may affect two or three directions of the vehicle's accelerometer sensors (See Fig. 4). To solve this problem, some researches have done the reorientation process before their analysis [10]. But the correction process itself is time-consuming and requires additional data. Therefore, in this study, we used L2-norm of acceleration of the three axes according to equation (4).

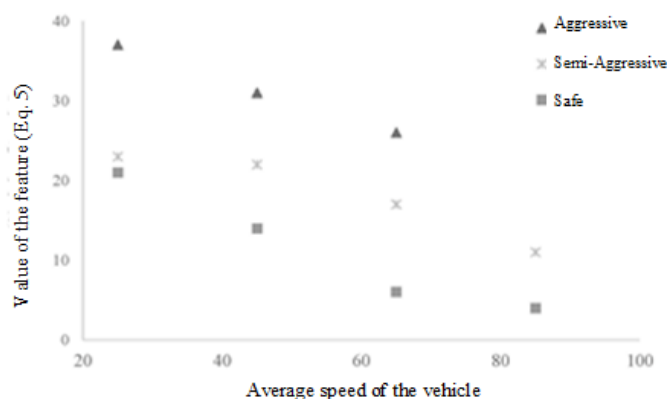


Fig. 6. The value of introduced feature (Eq. 5) for safe, semi-aggressive and aggressive drivers at different average speed

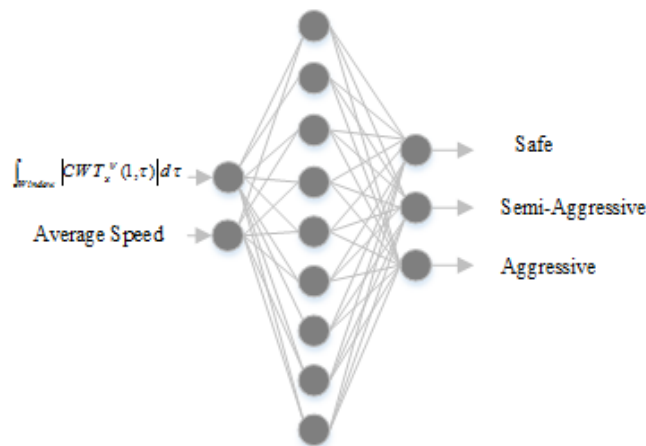


Fig. 7. The neural network for recognizing pattern of driver behavior

Table 2. Characteristics of drivers' vehicles and their smartphones and results of DAS questionnaire

Driver	Smartphone	Vehicle	DAS Scale	Driver	Smartphone	Vehicle	DAS Scale
1	Samsung	Samand	26	11	Samsung	Peugeot 405	42
2	Samsung	Pride	27	12	Samsung	Pride	43
3	Samsung	Pride	28	13	Samsung	Pride	43
4	Samsung	Peugeot	31	14	Lenovo	Pride	45
5	Samsung	Pride	34	15	Samsung	Samand	46
6	Samsung	Samand	36	16	Samsung	Pride	47
7	Samsung	Samand	39	17	Samsung	Pride	50
8	Samsung	Pride	39	18	Samsung	Persia	51
9	Lenovo	Pride	39	19	LG	Peugeot 206	52
10	Samsung	Samand	40	20	Nexus	Hyundai	53

Table 3. Confusion matrix

Target/ Output	Safe	Semi- Aggressive	Aggressive	Recall
Safe	30	5	2	81%
Semi- Aggressive	1	8	4	61%
Aggressive	0	2	14	87%
Precision	97%	53%	70%	79%

Table 4. The accuracy of different supervised learning algorithms

Method	Accuracy
Neural Network	79
Decision Tree	76
Naïve Bayes	69.5
Regression	44

$$a_{L2-norm} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{4}$$

a_x, a_y, a_z : The value of accelerometer in three different axes

As shown in Fig. 4, if the cell phone is not aligned with the car, the vehicle's brakes will change the values of the cell phone accelerometer on the three axes. L2-norm of the acceleration of three axes that is the resultant of these changes is equal to the deceleration of the vehicle in a brake.

Generating Window. In order to study the driver's high-risk behavior, it is necessary to evaluate at least 15 minutes of driving. Hence, the analysis will be done on the acceleration 1,800-sample window, which is equivalent to a 2-Hz sampling rate of 15 minutes.

The driver's behaviors include lane changes or speed changes (braking or acceleration) is with regard to traffic conditions and has a random nature. Hence, analyzing acceleration signal based on Fourier series which represents frequencies behavior at regular intervals, is not applicable. While the wavelet theory can detect localized phenomena in non-stationary time series. Hence, checking the presence of wavelets in a signal can indicate specific patterns throughout a signal. There are many famous wavelets such as Symlet, Haar and Mexican Hat. A continuous wavelet transformation of a signal such as $f(t)$ is equal to the following equation. Eq. (6) shows the continuous wavelet transform:

$$CWT_x^\psi(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-\tau}{s} \right) dt \tag{6}$$

where $\psi(t)$ is the mother wavelet, ψ^* denotes the complex conjugate of ψ , $s (>0)$ is the scale parameter and τ is the position parameter. Choosing the mother wavelet function is depended on the problem. We have used Symlet-4 wavelet in this study. Figure 5a shows the mother wavelet of Symlet-4. The coefficients of the continuous wavelet transformation of a window of driving behavior are extracted at this phase. Figure 5b shows an example of the values of these coefficients. As shown, lane changes or speed changes in the vehicle acceleration in continuous transformation coefficients appear as peaks.

Feature extraction. The two features of these peaks represent the driver's risky and aggressive behavior:

- The number of these peaks during a window, which indicates the number of drivers' lane changes or speed changes. The number of brakes and accelerations of an aggressive driver is higher than the number of brakes and accelerations of a normal driver in the same traffic situation [25]. This is also true of the driver's lane changes [26].
- The value of the peak indicates the maximum value of acceleration in vehicle brake and acceleration maneuver and the maximum lateral acceleration of the vehicle when during lane change maneuver. Obviously, this value for aggressive

Table 5. Result of the proposed model

Driver	DAS	Estimation	Error%	Driver	DAS	Estimation	Error%
1	26	28	7	11	42	42	0
2	27	28	3	12	43	41	4
3	28	31	10	13	43	45	4
4	31	31	0	14	45	44	2
5	34	34	0	15	46	49	6
6	36	35	2	16	47	48	2
7	39	39	0	17	50	48	4
8	39	40	2	18	51	48	6
9	39	35	10	19	52	48	7
10	40	42	5	20	53	53	0

Mean Percentage Error: 3.7 %

Table 6. Mean percentage error for different size of window

Driver	DAS	Estimated anger scale		
		840 samples	1800 samples	3600 samples
1	28	38	31	28
2	27	38	28	28
3	51	45	48	51
4	43	41	41	43
5	50	43	48	49
6	34	36	34	32
7	39	38	39	48
8	26	32	38	29
9	42	43	42	42
10	43	43	45	45
MPE		14 %	7 %	5 %

driver’s maneuvers is more than normal maneuvers [25].

The area under the continuous curve of the values obtained from the coefficients can be a good representation of the sum of the number of peaks and the maximum value of each peak. Accordingly, the integral of the curve of the peaks is considered as the feature of driving behavior. Regarding the discrete values of the coefficients, this integral is estimated as the sum of coefficients values. Eq. (7) shows how to calculate this feature.

$$\int_{W_{window}} |CWT_x^\psi(1, \tau)| d\tau = \sum_{\tau=\{1..1800\}} |CWT_x^\psi(1, \tau)| \tag{7}$$

Average speed feature. The value given by equation (7) for each driver may vary under different traffic conditions. Because in traffic congestion the number of brakes and lane changes increase in comparison with non-congestion condition. Hence, traffic volume affecting the values given by Eq. (7). Figure 6 shows the value of the feature for aggressive, semi-aggressive, and safe driving behavior at various speeds. The extraction of the traffic situation is complex at the moment of recording data based on the cell phone. For this reason, in this study, the average speed of the vehicle during a window is considered as representation of traffic condition. The average speed is calculated by simpler methods. All methods that record the position of a vehicle at the beginning and end of the window (including 15 minutes of driver behavior) are capable of calculating the average speed of the vehicle. The first is to use GPS. Although continuous activation of GPS increases battery consumption, it can be detected intervals when the cell phone is inside the car [20]. In these intervals, every 15 minutes, GPS is turned on for a limited time. Also, Wi-Fi based and BTS-based location services that are built-in functions deployed on Android can detect a vehicle’s location with an approximate distance of 100 meters at low battery consumption. This approximation is enough to calculate the average vehicle speed in a 15-minute interval.

2- 3- Third phase: Recognition driver behavior

According to the research, driving behavior has a direct relationship with the driver’s personality characteristics. Shakerinia and et al. [27] examined the personality characteristics of risky drivers and show significant relationship between anger

Table 7. The result of proposed model for a driver with 36 anger scale in different car.

Car	Manufacture	Estimated scale	Estimated pattern
Rana	Iran Khodro	38	Safe
405	Iran Khodro	32	Safe
L90	Saipa	37	Safe

personality trait and driving behavior which is similar to the research conducted in Shiraz by Haqshenas [28]. Ahmadpour and et al. [29]] has also shown that driving violations have significant relationship with the degree of aggression of the driver. The same study was conducted by Borairi and et al. [30].

One the well-known method to understand the driver's aggressive behavior is self-reporting questionnaires. In this questionnaire, different challenge scenarios are illustrate for the driver and his response to each scenario are collected. Several studies have been conducted to develop these questionnaires such as PDAS[31] and DBQ[32]. The most popular questionnaire for detecting the driver's aggressive behavior is DAS questionnaire [33], which includes 14 questions. In each question, the degree of anger in a scenario is determined by the driver through choosing a number between 1 and 5. Accordingly, the minimum scale of a driver is 14 and the maximum scale is 70. The final scale of a driver is calculated by the sum of the numbers obtained from the questionnaire. A scale of less than and equal to 42 shows safe driving behaviors and a scale of over 51 indicates the driver's aggressive behavior. According to a study by Kazemini et al. [34], this questionnaire have also been evaluated and validated in Iran. Meanwhile, the questionnaire has been evaluated in different countries with different cultures and has shown DAS questionnaire can represent the driver's aggressive behavior. Examples of these evaluations are Salman and et al. [35] in Spain; Lee [36] in China and Salman and et al. [37]] in Malaysia. Salman points out that the results of this questionnaire are very similar to the results of studies in Western countries such as New Zealand, Spain and the United States. We used the DAS questionnaire to evaluate and train our proposed model. In the following, Multi-Layer Perceptron (MLP) neural networks have been used to estimate the driver behavior patterns and determine the driver's anger scale.

Estimating driver's behavior by neural network. In this study is the feed forward back propagation MLP neural network has been used for estimating the pattern of driver's behavior. Trampberg [38] has shown that a three-layer neural network is capable of estimating any function. The structure of the neural network which estimating the pattern of driver's behavior is shown in Fig. 7. The network inputs include the feature value given by Eq. (7) and the average speed of the vehicle in the window. The middle layer of the network consists of 10 neurons with sigmoid activation function. And, the neural network also includes 3 outputs, which are equivalent to the safe, semi-aggressive and aggressive patterns, respectively. For each input (driver), three values are given by the neural network which indicate the similarity of driver's behavior to each three patterns. We consider the most similarity as the pattern of the driver's behavior.

DAS questionnaire is used to train the network. Those drivers with a scale of less than 42 are considered as safe drivers. Those drivers with a scale of more than 51 are labeled as aggressive drivers, and finally those drivers with a scale between 42 and 51 are considered as semi- aggressive drivers. For example, a driver with a scale of 38 is labeled (1, 0, 0) and a driver with a scale of 53 is labeled (0, 0, 1). We consider 70% of the samples to train the network and the rest are considered for generalization and validation of the data.

Estimating driver anger scale by neural network. For estimating the anger scale of drivers that given by the questionnaire, another the feed forward back propagation MLP neural network is considered. Unlike the previous neural network, this network has an output and its value is equal to the estimated driver's scale. The scale number is between 14 and 70. Also, ten neurons are considered in hidden layer the activation function is sigmoid. In order to train the network, the driver's questionnaire scale is used, the network inputs are proposed feature which introduced in Eq. (7) and the average speed of the vehicle in the window. In this network, 70% of samples are considered for training and the rest are considered for generalization and validation.

The driver behavior neural network recognizes the behavior of the driver in each 15-minute interval, while the driver anger scale neural network estimates the aggressive scale during all driving time based on the average aggressive scales in each 15-minute interval.

3- Evaluation Result

In order to evaluate the results, we collect more than 40 hours of driving of 20 different drivers volunteers ride different path at urban streets in Tehran. Nevertheless, Deffenbacher pointed out that the DAS questionnaire could be used in the same way in rural, suburban and urban environments [39]. After applying model and remove noises and turn maneuvers intervals, 60 windows of the driving behavior of 20 drivers are extracted.

Data is collected from different vehicles under different traffic conditions and different smartphones. All vehicles also had sedan cars. Table 2 shows characteristics of drivers' vehicles and their smartphones. The results of DAS questionnaire can also report in Table 2 as a number between 14 and 70 for each driver.

3- 1- Estimating risky driver behavior

The pattern recognition neural network estimates the behavior of the driver in a 15-minute time interval. The proposed

model can notify the output of the neural network to the driver during a trip. Regarding increased fuel consumption in risky and aggressive driving [5], this notification currently is informed by advanced and expensive equipment inside the car. This notification to drivers will reduce the aggressive and risky behavior and causes self-control. The network, which consists of 10 nodes in the hidden layer, categorizes driving behavior into three aggressive, semi-aggressive and safe patterns. In order to train and validate this network, drivers pattern which was identified by DAS questionnaire are considered. We consider 70% of the samples for training, 15% for the test and 15% for generalization. K-fold cross-validation method is also applied to test and train. For this purpose, the data are randomly divided into four distinct parts; three of them are used for network training, and the fourth part is considered as a network test. Table 3 shows the confusion matrix of the results. The last column in the Table 3 represents recall value for each behavior and the last row of the table represents precision value for each behavior. The accuracy of the neural network for training data is 81% and 79% for all samples for detecting the driver behavior patterns. Also, to evaluate other classification techniques, Regression, Decision Tree and Naïve Bayes are applied to samples. As shown in the table 4, the neural network provides better results.

3- 2- Determining driver anger scale:

In this section, the neural network-based model is provided to estimate the driver anger scale. This scale is given by DAS self-report questionnaires. The main problem with these questionnaires is their collection and analysis on a large scale. Also, when these questionnaires are considered as criteria for judgment of drivers, they will not be answered in an unbiased manner. The proposed model, by observing the driver behavior on different paths and several trips, can provide an appropriate estimation of the driver's anger scale.

$$MPE = 100\% \times \frac{1}{n} \sum_{i=1}^n \frac{s_i - p_i}{s_i} \quad (8)$$

s_i : Driver anger scale given by questionnaire for driver i
 p_i Output of neural network for driver i

In this model, the neural network is used a three-layer feed forward and back propagation MLP with 10 nodes of the hidden layer which uses sigmoid function for activation function. Unlike the pattern recognition network, the output of this network is a number that is determined the driver's anger scale. The network training is performed based on the scales given by DAS questionnaire. Also the mean percentage error measure which is defined as following equation is considered to evaluate results (8):

Table 5 shows the percentage error of estimated driver anger scale. According to the results the proposed model can be estimated the anger scale by cell phone sensors, with proper accuracy.

3- 3- Sensitivity analysis on window size

In order to study the effect of increasing the size of the time interval of driving behavior, we examined the different size of the window. In above, the window size is considered 1800 samples which are equivalent to 15 minutes of driving behavior. To analyze sensitivity of the proposed model, we examine results of the model when the window size is considered 840 and 3600 samples which is equivalent to 7 and 30 minutes of driving behavior, respect. Table 6 shows the mean estimation error in three networks. As shown, with increasing the window size, the accuracy of estimation increase. This increase is low for 1800 and 3600 window sizes, but the window size with 840 samples has led to a significant reduction in detection accuracy.

3- 4- Sensitivity analysis on different car

All vehicles are examined in this study has sedan cars. Therefore, in order to study the effect of the vehicle on the sensors of the cell phone, the behavior of a specific driver is evaluated on three different vehicles. The anger scale of this driver is 36 given by DAS questionnaire. Table 7 shows the outputs of the models that estimate the driving pattern and driver's anger scale in these three vehicles. The results show the model estimate safe pattern for the driver in each car which the questionnaire result confirms.

4- Conclusion

Aggressive and risky behaviors are one of the most important factor causes of driving accidents and deaths. One of the most effective ways to reduce these behaviors is to monitor the driver behavior. Hence, many public and commercial transportation fleets install equipment to monitor driving behavior in their vehicles. This monitoring, in addition to indirect reduction and control effect on the driver, can be considered as a criterion for driver rewards and punishments. Expensive built-in equipment is one of the challenges of this monitoring. In this study, we have used the driver's smartphone to analyze aggressive and risky behavior. Risky behaviors such as intense braking, fast acceleration and sudden and frequent lane changes can detect by the smartphone sensors, particularly the accelerometer. In this study firstly, by introducing a magnetometer-based feature, the vehicle turns including left/right turns and U-turns are discovered. Then, the intervals in which the vehicle passes a straight path are extracted. Then, a feature base on wavelet transformation of L2-norm of acceleration is introduced. According to this feature and the average speed of the vehicle, driver's behavior are evaluated. We consider two neural networks to recognize the pattern of driver behavior and to estimate driver anger scale. Training

and validating of models are based on DAS questionnaire. The results show that aggressive and risky behavior can be detected in a 15-minute of drivers behavior with near 80% accuracy. Not only the proposed model can detect the aggressive and safe behavior of the driver, but also has been able to provide a good ranking between drivers through estimating driver aggressive scale. This ranking can be used to assess drivers and encourage them to gradually reduce their aggressive behavior. The proposed model estimates the anger scale with a mean error of 3.7%. The results given by the proposed model can inform the driver as a warning to decrease risky behavior. This warning encourage the driver to driver safer and decrease fuel consumption.

Also, this scale can be provided a flexible measurement for the use of drivers in public transportation fleets. For example, a company can hire drivers whose scale is less than 36 or less than 30.

The last 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 state. 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 [40]. This study showed there is this dependency on both heavy and light traffic conditions.

Finally, it can be said that without any filling in a questionnaire by drivers, it is possible to extract the anger scale of drivers by using smartphones whilst collecting anger scale of drivers by different questionnaire is not applicable on a wide scale and under conditions where the driver may not answer in unbiased manner. So, insurance companies, taxi fleets' management, public and commercial transportation can base their data analysis on rewards and punishments for drivers to reduce risky behaviors.

References

- [1] Wiegmann DA, Shappell SA. (2003) *A Human Error Approach to Aviation Accident Analysis: The Human Factors Analysis and Classification System*. 1st ed. London: Ashgate Publishing.
- [2] Mehri, T. (2016) Interview on Police News Agency <http://news.police.ir/News/fullStory.do?Id=252579>
- [3]. Hickman, Jeffrey S., and E. Scott Geller. (2005): "Self-management to increase safe driving among short-haul truck drivers." *Journal of Organizational Behavior Management* 23.4 1-20.
- [4].P. I. J.Wouters and J. M. J. Bos, (2000) "Traffic accident reduction by monitoring driver behavior with in-car data recorders," *Accident Anal. Prev.*, vol. 32, no. 5, pp. 643–650,.
- [5]. Alessandrini, A., Cattivera, A., Filippi, F., & Ortenzi, F. (2012). "Driving style influence on car CO2 emissions". In 20th International Emission Inventory Conference - Tampa, Florida, August 13 –16.
- [6]. Seeing machines. (2016). Retrieved from <http://www.seeingmachines.com/>
- [7] Towergate . (2016). Retrieved from Towergate Underwriting Group Limited. Fair Pay a radical new approach to motor insurance: <http://www.fairpayinsurance.co.uk>
- [8] Eftekhari, Hamid Reza, and Mehdi Ghatee. (2018) "Hybrid of discrete wavelet transform and adaptive neuro fuzzy inference system for overall driving behavior recognition." *Transportation Research Part F: Traffic Psychology and Behaviour* 58: 782-796.
- [9] Zadeh, Roya Bastani, Mehdi Ghatee, and Hamid Reza Eftekhari. (2018) "Three-phases smartphone-based warning system to protect vulnerable road users under fuzzy conditions." *IEEE Transactions on Intelligent Transportation Systems* 19, no. 7: 2086-2098.
- [10] Mohan, P. V. (2008). "Nericell: Rich Monitoring of Road and Traffic Conditions using Mobile Smartphones". *Proceedings of the 6th ACM conference on Embedded network sensor systems*. ACM.
- [11] White, J., Thompson, C., Turner, H., Dougherty, B., & Schmidt, D. C. (2011). "Wreckwatch: Automatic traffic accident detection and notification with smartphones". *Mobile Networks and Applications*, 16(3), 285-303.
- [12] Vaiana, R., Iuele, T., Astarita, V., Caruso, M. V., Tassitani, A., Zaffino, C., & Giofrè, V. P. (2014). "Driving behavior and traffic safety: an acceleration-based safety evaluation procedure for smartphones". *Modern Applied Science*, 8(1), 88.
- [13] Dai, J., Teng, J., Bai, X., Shen, Z., & Xuan, D. (2010, March). "Mobile phone based drunk driving detection". In *Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, 2010 4th International Conference on-NO PERMISSIONS (pp. 1-8). IEEE
- [14] Fazeen, M., Gozick, B., Dantu, R., Bhukhiya, M., & González, M. C. (2012)." Safe driving using mobile phones". *IEEE Transactions on Intelligent Transportation Systems*, 13(3), 1462-1468.
- [15] Chaovalit, P., Saiprasert, C., & Pholprasit, T. (2013, November)." A method for driving event detection using SAX on smartphone sensors". In *IEEE International Conference on ITS Telecommunications (ITST)*, 2013 13th (pp. 450-455).
- [16] Johnson, D. A., & Trivedi, M. M. (2011, October). Driving style recognition using a smartphone as a sensor platform. In *International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2011 14th (pp. 1609-1615).
- [17] James, Leon. *Road rage and aggressive driving: Steering clear of highway warfare*. Prometheus Books, 2000.
- [18] Vaiana, R., Iuele, T., Astarita, V., Caruso, M.V., Tassitani, A., Zaffino, C. and Giofrè, V.P., "Driving Behavior and Traffic Safety: An Acceleration-Based Safety Evaluation Procedure for Smartphones," *Modern Applied Science*, 8(1), p.p88.,

2014.

- [19] Tasca, L. (2000). A review of the literature on aggressive driving research. Ontario, Canada: Ontario Advisory Group on Safe Driving Secretariat, Road User Safety Branch, Ontario Ministry of Transportation.
- [20] Eftekhari, H. R., & Ghatee, M. (2016). An inference engine for smartphones to preprocess data and detect stationary and transportation modes. *Transportation Research Part C: Emerging Technologies*, 69, 313-327.
- [21] Wang, S., Chen, C., & Ma, J. (2010, April). "Accelerometer based transportation mode recognition on mobile phones". In *IEEE 2010 Asia-Pacific Conference on Wearable Computing Systems* (pp. 44-46).
- [22] Reddy, S. e. (2010). "Using mobile phones to determine transportation modes". *ACM Transactions on Sensor Networks (TOSN)* 6.2: 13.
- [23] Chu, H., Raman, V., Shen, J., Kansal, A., Bahl, V., & Choudhury, R. R. (2014, January). I am a smartphone and I know my user is driving. In *Communication Systems and Networks (COMSNETS), 2014 Sixth International Conference on* (pp. 1-8). IEEE.
- [24] Kittler, J. and Illingworth, J., 1986. Minimum error thresholding. *Pattern recognition*, 19(1), p.41-47
- [25] Yang, Letian. (2007) "Driver speed and acceleration behavior on Canadian roads." PhD diss., University of Ottawa.
- [26] Huang, Ding-wei. (2002) "Lane-changing behavior on highways." *Physical Review E* 66.2: 026124.
- [27] Iraj Shakirinia, Mehri Mohammad Pour. (2010) "Relationship between personality traits, mental health and aggression with driving habits in high risk drivers". *Journal of Shahid Sadoughi University of Medical Sciences, Yazd, Iran*. Volume 18, Issue 3, Special Issue of the Conference on Risky Behaviors.
- [28] Hassan Haghsheni, Mary Hoseini, Masoumeh Jamshidi, Hamidreza Azizi. (2008) "The Relationship between Personality Characteristics and Driving Behavior in Shiraz City". *Hakim Research Journal, Autumn 87, 11th Edition, No. 3*
- [29] Mojgan Ahmadpour Ardeh Janni. (2015) "A survey on the relationship between personality traits and the degree of anger in people with driving violations". *Second Scientific Conference on Educational Sciences and Psychology, Social and Cultural Diseases of Iran*
- [30] Mahrokh Borairi, Alireza Esmaili. (2011, March) "The Role of Personality Characteristics in Risky Driving. 10th International Conference on Transport and Traffic Engineering
- [31] DePasquale, J. P., Geller, E. S., Clarke, S. W., & Littleton, L. C., (2001) "Measuring road rage: Development of the propensity for angry driving scale," *Journal of Safety Research*, pp. 32, 1– 16.
- [32] Reason J, Manstead A, Stradling S, Baxter J, Campbell K. (1990) "Errors and violations on the roads: a real distinction?," *Ergonomics*, Vols. 33.10-11: 1315-1332.
- [33] Deffenbacher, Jerry L., Eugene R. Getting, and Rebekah S. Lynch. (1994), "Development of a driving anger scale," *Psychological reports* 74. 83-91.,
- [34] Kazemeini, Takhtam, Ganbari Hashem Abadi, Bahram Ali, Modarress Gharavi, Morteza Esmaeilizadeh, Masoud. (2011) "The Effectiveness of Cognitive-Behavioral Therapy in Reducing Anger and Driving Aggression; *Journal of Clinical Psychology*, Vol. 10
- [35] Sullman, M.J., Gras, M.E., Cunill, M., Planes, M. and Font-Mayolas, S., (2007). "Driving anger in Spain. *Personality and Individual Differences*", 42(4), pp.701-713.
- [36] Li, F., Li, C., Long, Y., Zhan, C. and Hennessy, D.A., (2004). "Reliability and validity of aggressive driving measures in China. *Traffic injury prevention*", 5(4), pp.349-355
- [37] Sullman, M.J., Stephens, A.N. and Yong, M., (2014). "Driving anger in Malaysia. *Accident Analysis & Prevention*", 71, pp.1-9
- [38] Trappenberg TP (2002) "Fundamentals of Computational Neuroscience". Oxford University Press, Oxford
- [39] Deffenbacher, J.L., (2008). "Anger, Aggression, and Risky Behavior on the Road: A Preliminary Study of Urban and Rural Differences". *Journal of Applied Social Psychology*, 38(1), pp.22-36.
- [40] Hennessy, D.A. and Wiesenthal, D.L., (1997). "The relationship between traffic congestion, driver stress and direct versus indirect coping behaviors". *Ergonomics*, 40(3), pp.348-361

Please cite this article using:

H. R. Eftekhari, Smartphone-based System for Driver Anger Scale Estimation Using Neural Network on Continuous Wavelet Transformation, *AUT J. Math. Comput.*, 1(1) (2020) 113-124.
DOI: 10.22060/ajmc.2019.15327.1016



