Assessment of Drowsy Drivers by Fuzzy Logic approach based on Multinomial Logistic Regression Analysis

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Summary
The aim of this study is to investigate the effect of behavioral and physiological measures for predicting driver's drowsiness in order to develop an intelligent transportation system such as fuzzy logic for preventing fatal traffic accidents by evaluating the lack of driver's arousal level. In this paper, behavioral and physiological measures are considered but because of high costs of measuring physiological measures in laboratories, only behavioral measures are examined. Drowsy states of drivers were predicted by means of the multinomial logistic regression model which are independent variables and a dependent variable in order behavioral measures and driver's drowsiness, respectively. For better understanding of the multinomial logistic regression model related to drowsy states, all behavioral measures were entered into the model. It was found that behavioral measures were investigated with a significant coefficient of 0.05 according to statistical science which is ANOVA. From results of statistical view, prediction accuracy and probability of behavioral measures, it is clear that the most predicted behavioral measure is Neck bending angle (vertical) with regression coefficient (R2) 0.74, correlation coefficient 0.56, with probability of 0.78, and average prediction accuracy amongst drowsy groups 0.73, which represents a good fitness in the model. Furthermore, driver's sleep behavior in travel distances and weather conditions was simulated in fuzzy logic for understanding the effect of these conditions over driver's sleep behavior. Finally, Fuzzy logic showed that driver's sleep behavior in unsuitable weather such as rainy condition is affected in high risk of drivers's drowsiness level in comparison with light condition that drivers have lower drowsiness.

Keywords:
Traffic accidents, behavioral and physiological measures, driver's sleep behavior, Fuzzy logic.

1. Introduction

The growth of traffic accidents due to a reduction of arousal level of drivers has been a drastic issue for society. According to the United Nation statistics, annually, 1.5 million people died due to traffic accidents and approximately 20 to 50 million people were injured because of non-fatal accidents [1]. According to the US National Sleep Foundation (NSF) about 54% adult drivers have driven in drowsy states and 28% of them were completely at sleep [2]. Especially, from the view of researchers, there are different reasons for the causes of accidents like the fault of drivers, fault of pedestrians, mechanical pedestrians, bad road or bad weather conditions. But the fault of drivers is largely common. Recently, Intelligent transportation systems (ITS) have been used to improve the safety and efficiency of driver behavior. These systems have different tasks to control and monitor driver behavior [3]. Due to the important role of ITS in detecting driver error, there is an improved system that automatically recognizes driver errors such as fatigue. This improved and intelligent system is Fuzzy logic based on probability rules that was introduced by Lotfi Zadeh [4]. Fuzzy logic procedure to the contribution of intelligent transportation systems uses neural networks to simulate driver behavior characteristics like sleep behavior as a function of probability. The positive viewpoint of this artificial intelligent systems is that constantly evaluating driver behavior under environmental, and weather conditions. The major reason of the fault of drivers is fatigue [5]. The risk of accidents by drowsy condition is more four times than typical conditions. However, it is still just a lot. Unfortunately, it has been observed that a lot of light and heavy vehicle drivers drive in a drowsy state. Sleep disorders can increase traffic accidents related to drowsiness. The majority of people are not aware of sleep disorders. There are lots of safety, effective measures to control when drivers drive in the drowsy state. One of the methods that can contribute to accident prevention is simply done by police officers to stop dangerous drivers when they become suspicious about driver's fatigue by alcohol consumption or tiredness in roads [6]. Warning drivers due to the reduction in arousal level must be established to prevent any painful traffic accidents [7]. Recently, The growth of computer science and technology especially artificial intelligence systems has taken benefits to detect driver's drowsiness by simulating drivers behavioral measures as an intelligent vehicle systems [8]. The process of drowsiness detection is normally divided in 3 main categories: (1) vehicle detective system (2) evaluation of behavioral measures (3) evaluation of physiological measures [7]. The focus of this study is more on behavioral and physiological measures. In order to reduce road traffic accidents, behavioral measures (back pressure, foot pressure, neck bending angle (horizontal and vertical), COP movement of the driver seat and tracking error), and physiological measures (HRV (Heart Rate Variability), EEG (Electroencephalography), ECG

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(Electrocardiography)) for determining the decreased arousal level of drivers have been used [9,10]. Laboratory studies have shown that the subjective sleep and the EEG was significantly associated with the total hours of driving [11]. Objectively, the drowsiness of The participants under drowsy driving states by using HRV (heart rate variability) and EEG was evaluated. It was understood that there was a reduction in MPF (mean power frequency) - EEG when the arousal level of participants was low, respectively. However, prediction of the drowsiness on the basis of time series of the EEG-MPF was not possible [12, 13]. All these measures, which are being used, have the disadvantages of not being used in the daytime. Bayesian theory was used to predict the arousal level of drivers by using EEG, heart rate variability and tracking error in a driving simulator. However, this theory did not predict the arousal level [9]. A logistic regression model for physiological variables such as ECG or EEG and EOG to predict the level of consciousness (classified subjective sleep) with an approximate of 85% prediction accuracy achieved in the model [9, 10]. From the costs of test views, tools for the prediction of drivers drowsiness should have low costs and fast placing in cars . Behavioral measures such as tracking error, back pressure and foot pressure, COP (center of pressure) movement during the experimental tests are measured to assess such effective measures such as EEG, and MPF [14, 15]. Sometimes, it is helpful to use behavioral measures like oculography which means detecting driver's drowsiness by image processing by means of computers in laboratories [16].

2. Research Methodology

In this work, three issues were examined that include: 1. Using logistic regression model for the evaluation of driver's sleep behavior with high accuracy by driver's behavior measures. 2. The effect of correlation coefficients related to behavioral measures based on the probability and accuracy to determine the order of these measures in the model. 3. Comparison of the accuracy of predictions groups strongly sleepy or weakly sleepy. Based on the above studies, some requirements for predictive models that have been proposed include:

2.1. Participants in This Study

Because of some limitations of costs respects and accessibility of present students in dormitories near the sport sciences's faculty of Urmia university, all tests have been done in the center of computer of the sports' sciences faculty amongst 13 male students without any diseases for obtaining correct results in the age range of 21 to 25 years. The visual acuity of the participant was more than 20/20. They did not have any orthopedic or neurological diseases. The latter finding has explained the fact that sleep duration is more frequent among young and inexperienced people [17]. The participants took part in the experiment with the full knowledge. During the experiment, they were asked to stay up all night and go to the laboratory [18]. It was reported that there is a relationship between educational level and sleep involvement. Generally, high educated drivers have low risk of road accident [19].

2.2. Tools

A tool to measure the surface pressure applied to the driver seat is Nita. Nita has a screen to show and obtain the movement of COP. It is usually used to obtain pressure distribution over seat of vehicle. DKHs (goniometers) into the driver neck are built to measure the bending angle of the neck. Eight Nita pressure sensors for measuring foot and eight sensors for measuring bake pressure (back) are attached to the driver seat [18].

2.3. Experimental Method

Rating on drowsiness was assessed every 1 minute. Behavioral measures such as neck bending angle (horizontal and vertical), back pressure, the movement of COP on the driver seat and tracking error are in the driving simulator. The neck bending angle was sampled using a 10Hz frequency. The Foot pressure, the back pressure and COP on the seating surface were sampled with the frequency of 50Hz. The tracking error was measured every 1 second. Behavior measures in the above, under the low of arousal were simulated. The duration task of experiment number is different, because each participant has different sleep time range. To classify the degree of drowsiness, each experiment was implemented in 90 minutes [18]. Using behavioral measures in logistic regression, the prediction accuracy of drowsiness was examined in the following conditions: 1. Procedures for determining the behavioral measures in the prediction model. 2. Comparison of the prediction strongly drowsy, or weakly drowsy groups.

$$p(2) = \frac{e^{(b_0 + b_1 x_1(2) + \ldots + b_n x_n(2)}}{1 + e^{(b_0 + b_1 x_1(2) + \ldots + b_n x_n(2)}} \qquad (1)$$

$$p(3) = \frac{e^{(b_0 + b_1 x_1(3) + \ldots + b_n x_n(3)}}{1 + e^{(b_0 + b_1 x_1(3) + \ldots + b_n x_n(3)}} \qquad (2)$$

P(1: arousal) =1- P(2: a little drowsy) - p(3: very drowsy) (3)

In equations 1 and 2 where $x_1, x_2, x_3, \ldots, x_n$ are behavioral variables and n is number of behavioral variables in the model. Furthermore, $x_1(2), x_2(2), \ldots, x_n(2)$ represent the value of each evaluation measure when the subjective evaluation is equal to 2. Variables in equation 1 and 2, including, $x_1(3), x_2(3), \ldots, x_n(3)$ represent the value of each evaluation when the subjective evaluation is equal to 3. Based on P(1), P(2) and P(3) the probability of each subjective drowsiness is calculated. If the value of P(3) was the maximum in the model, it means that the risk of drowsiness will be high. As noted, the duration of the driving simulation due to the different range of participants sleepiness from 60 to 90 minutes change. Total number of variables (rating of psychological and behavioral measures) were between 60 and 90 minutes. The prediction accuracy defines as the proportion of the predicted value to the actual value. For example, If there are 81 times out of 90. The prediction accuracy is calculated as 0.9. Behavioral variables entered into the model in ascending order of the correlation coefficient. Correlation coefficients between the tracking error and five behavioral variables are (back pressure, COP movement, neck bending angle (vertical), neck bending angle (horizontal), and foot pressure). On the other hands, Behavior variables showed a good correlation of the tracking error is lower which has the priority in the model. To define the probability of behavior variables such as x and y, A logistic regression model was multinomial expressed as follows:

$$Y = \frac{e^{(ax+b)}}{1+e^{(ax+b)}} \tag{4}$$

In the model, a and b relate to logistic regression coefficient, respectively. The prediction accuracy of the behavior measures presented in Table 1. Also, in Table 2 using SPSS 17 software, statistical results amongst 13 students were evaluated and obtained. From Fig. 1, neck bending angle (vertical) has a high correlation coefficient rather than behavioral measures that denotes this measure will be one of the most popular reasons conducted to drowsy accidents. In addition, In Fig. 2, the probability of each behavioral measure was calculated by means of the multinomial regression logistic model, which driver's drowsiness level is determined by the probability of these measures, respectively.

Table 1: Prediction accuracy of behavioral measures

Behavioral measure prediction accuracy in the prediction model (%)			
Very drowsy	A little drowsy	Arousal	Independent variable
75.2	66.1	87.6	Back pressure (1)
68.8	73.4	75.8	COP movement (2)
84.4	76	46.6	Neck bending angle(horizontal) (3)
76.3	79.5	63	Neck bending angle (vertical) (4)
46.5	81	59	Foot pressure (5)
56.1	83	39.1	Tracking error (6)

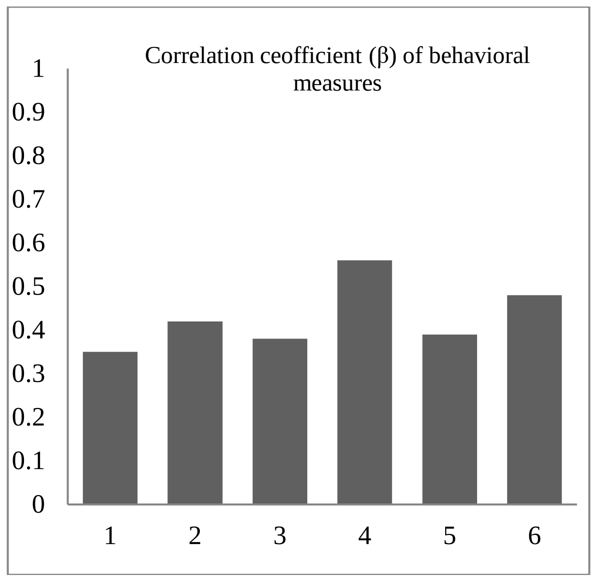

Fig. 1 Correlation coefficient between behavioral measures

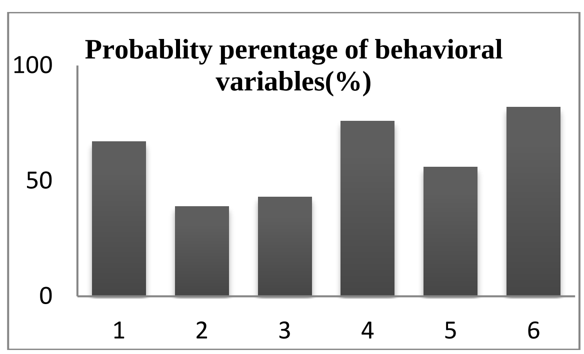

Fig. 2 Behavioral measures probablity (%)

Table 2: Statistical results for each behavioral measure

α (Significant coefficient)	T - test	β (Correlation coefficient)	B (unstandardized coefficient)	R^2 (Regression)	F Statistical value	Behavioral variable
0.021	3.9	0.35	0.3	0.78	543.124	Back pressure (1)
0.045	4.1	0.42	0.2	0.81	496.356	COP movement (2)
0.01	2.08	0.38	0.31	0.79	456.478	Neck bending angle(horizontal) (3)
0.03	4.05	0.56	0.76	0.74	382.896	Neck bending angle (vertical) (4)
0.02	3.05	0.39	0.39	0.92	312.942	Foot pressure (5)
0.01	5.1	0.48	0.72	0.89	279.630	Tracking error (6)

2.4. Literature Review of Proposed Method

2.4.1 Concept of Fuzzy Logic

Fuzzy theory was introduced by Lotfi Zadeh in 1965 with the perception of uncertainty and certainty which has significant applications [4]. Fuzzy theory can be used for evaluating uncertain problems in engineering views. In roads, because there are no exact evaluation systems to predict the driver behavior, all intentions have been made to apply fuzzy logic systems in managing the driver behavior under different conditions. The Fuzzy logic composes of the fuzzy inference system (FIS), membership functions (MF), rule editors, a ruler viewer, and a surface viewer and defuzzification for evaluation of all parameters involved, including inputs, and outputs [20]. Fuzzy logic system composes of membership function, fuzzy logic operators are divided as and, if then rules. Generally, there are two FIS membership functions which involve of Mamdani and Sugeno types [21]. It has also more flexibility with unsharp and vague boundaries [22]. In recent years, Fuzzy logic in washing machines, microwave ovens and industrial process control has been used dramatically [23]. Defuzzification operation converts results from fuzzy interference engine to numerical values [22]. The reason for choosing fuzzy inference system is to simulate driver's sleep state exactly by placing tools for measuring behavioral measures because multinomial logistic regression might not predict driver's drowsiness. Another advantageous of using this system is that controlling driver's behavior is each time is possible and results from input variables come into assessment to prevent any fatal accidents. By installing tools over vehicles, monitoring driver's behavior by online cameras and videos are easy.

2.4.2 Fuzzy Inference System (FIS) and Membership Function

Fuzzy logic operators are and, if- then rules. Generally, there are two FIS membership functions which involve of Mamdani and Sugeno types [25]. In this study, a Mamdani FIS was used to evaluate driver's sleep behavior. The degree of membership of fuzzy logic is between 0 and 1. In this work, the Gussian membership function has been used as shown in Fig. 3.

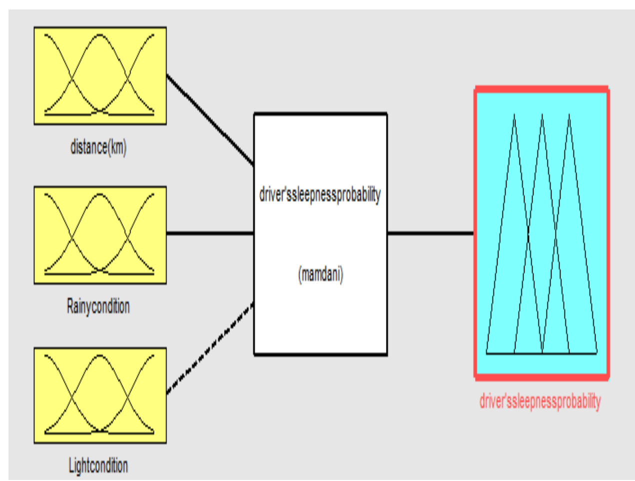

Fig. 3 Mamdani fuzzy logic inference system

2.4.3 Fuzzy Rule Base

Fuzzy logic rules are used on the basis of a human expert. There are 13 fuzzy rules for evaluation of driver's sleep behavior (see Table 3). Fuzzy logic rules are explained in the following form :

For example: Rule-1: if the value of distance is "few" and light condition is "low" and in rainy condition is "low" then driver's sleep behavior is "arousal" as shown in Table

3. Notice that low and high mean the quality of weather and environmental conditions.

Table 3: Fuzzy Logic rules of Driver's Sleep behavior

	Distance (km)	Light condition	Rainy condition	Driver's Sleep behavior
1	few	low	high	arousal
2	few	high	medium	A little drowsy
3	many	high	high	very drowsy
4	many	medium	medium	arousal
5	medium	medium	medium	A little drowsy
6	medium	medium	high	A little drowsy
7	many	low	high	Very drowsy
8	few	high	medium	Very drowsy
9	medium	high	high	Very drowsy
10	Many	high	low	Very drowsy
11	few	low	high	A little drowsy
12	Few	medium	medium	arousal
13	many	high	low	arousal

2.4.4. Driver's Sleep Behavior Fuzzy Logic System

Driver's ability plays an important role in determining safety to prevent fatal accidents. There are many features that associated with the driver's behavior such as: weather condition, driver's sleep characteristics, environmental conditions, travel distance, and, etc.… Due to the importance of these parameters, a fuzzy system has some inputs and outputs for assessment of the driver behavior.

2.4.4.1. Input and Output Parameters in Fuzzy Logic System

In this study, the input parameters are weather condition, environmental condition, travel distance which were categorized in numerical values of low, medium and high and they are rainy condition (see Table 4), light condition (see Table 5), and travel distance (see table 6). For considering the output parameters, only diver's sleep behavior (see Table 7) characteristics have been considered because these cause many fatal traffic accidents. For running fuzzy logic, outputs are the probability percentage of behavioral variables which were displayed in Fig. 2.

Table 4: input variables of rainy condition

low	medium	high
[0-3]	[3-6]	[6-10]

Table 5: input variables of light condition

low	medium	high
[0-4]	[5-8]	[8-10]

Table 6: input variables of travel distance (km)

few	medium	many
[0-100]	[100-200]	[200-300]

Table 7: Output variables according to the probability of behavioral variables for driver's sleep behavior

Arousal	A little drowsy	Very drowsy
[0-0.3]	[0.3-0.6]	[0.6-1]

3. Results and Discussion

As explained in the paper, under the symptom of physiological state which follows the symptom of psychological state and traffic accident risks are high, apparently. If the psychological symptoms of the driver was diagnosed rapidly, it can be estimated that whether drivers are in the danger of physiological symptoms or not. So, determination of the prediction accurate classification of the subjective sleepiness for each measurement is necessary to ensure while driving. In Fig. 4, prediction accuracy for each behavioral measure in arousal, a little drowsy, and very drowsy groups has been obtained from Table 1, generally. It is desirable to see what measure could have high accuracy.

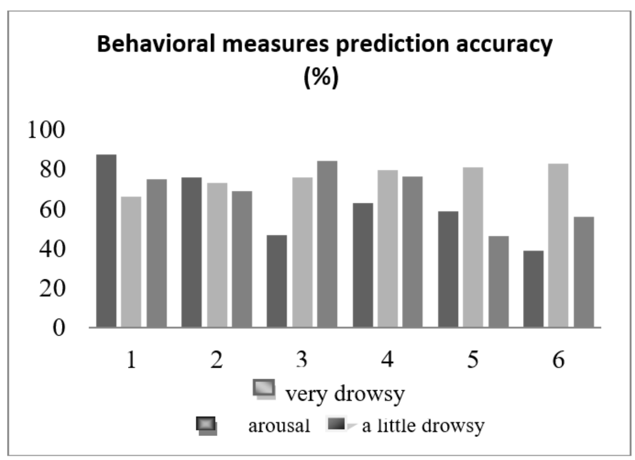

Fig. 4 Behavioral measures prediction accuracy

After designing driver's intelligent controlling system or Fuzzy logic. It simulates to evaluate the influence of the input parameters on the driver's sleep behavior as an output. As shown in Fig. 5, the density of the driver's sleep behavior (z-axis) is small which means driver's sleep behavior is arousal when the environmental condition (light) (y-axis) is large and distances (x-axis) are also large. However, the driver' sleep behavior tend to increase when distances are many and also the weather condition (rainy) is being increased (see Fig. 6). It means that the weather and environmental conditions have directly impacts on the driver's sleep behavior to be very drowsy. From Fig. 5 and Fig. 6 we can observe that z axis is the driver's sleep behavior, with a probability value between 0 and 1: categorization represents the level of drowsiness. A value between 0 and 0.3 represents an arousal driver. A value between 0.3 and 0.6 indicates a little drowsy driver, a value between 0.6 and 0.1 indicates that driver is very drowsy (see Table 7). Whatever driver's sleep behavior increases, it means that driver's state is very drowsy and there is a high risk of accident. From Fig. 7, it could be understood that in rainy conditions, driver's sleep behavior is more dangerous than in light conditions which have no dust, no rain and etc… For validity of outputs, normalization test according to Kolmogorov-Smirnov Test in Table 8 has been done and it was found that all results are normal. In Table 9 paired sample statistics test have been done to denote statistical characteristics of results between driver's sleep level in light and rainy condition. Furthermore, in Table 10, there is a comparison between rainy and light conditions of driver's sleep behavior that it was considerable with 2- tailed significance that means there is a significant difference for diver's sleep behavior by applying fuzzy logic to simulate these conditions for drivers to predict the level of drowsiness. It is considerable which has 95% confidence interval of difference (see Table 10). From Fig. 7, outputs of fuzzy logic simulation for driver's sleep behavior demonstrate the probability of driver's drowsiness in rainy condition is high and it would cause traffic accidents in unsuitable weather. However, in light condition this behavior is low.

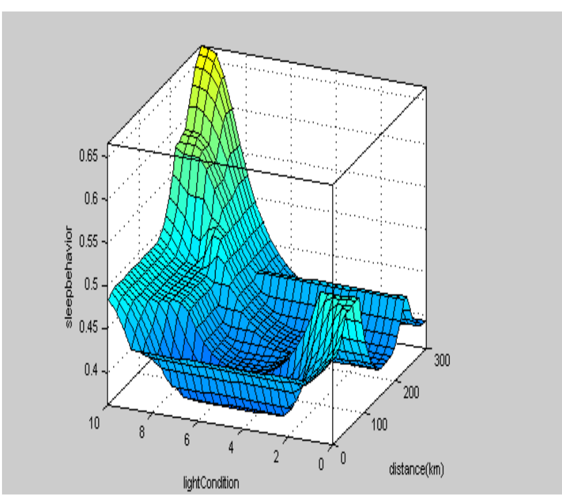

Fig. 5 Influence of weather condition (light) and distance on driver's sleep behavior

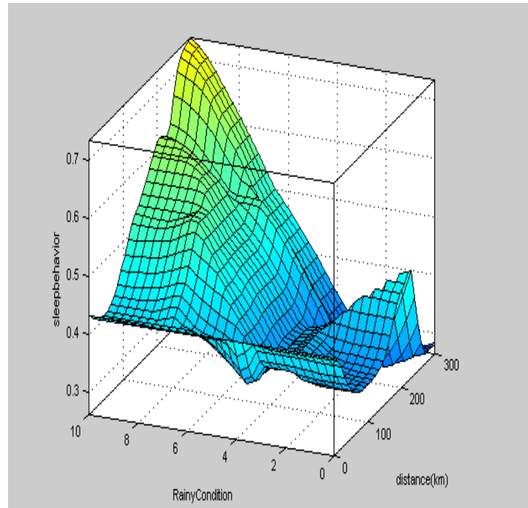

Fig. 6 Influence of weather condition (rainy) and travel distance on driver's sleep behavior

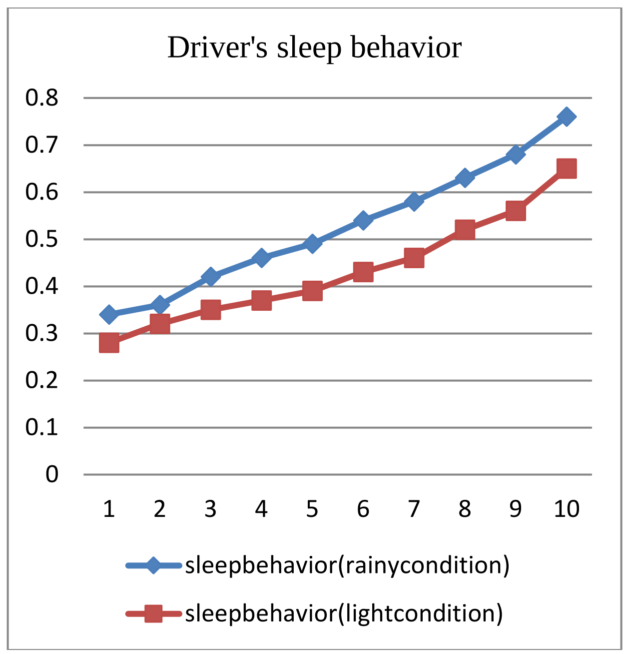

Fig. 7 Outputs of Driver's sleepBehavior in different conditions in Fuzzy Logic Simulation

Table 8: Kolmogorov-Smirnov Test for validating normal data

		RainyCondition	LightCondition
N		10	10
Normal Parameters[a,b]	Mean	.5260	.4330
	Std. Deviation	.13802	.11567
Most Extreme Differences	Absolute	.103	.145
	Positive	.103	.145
	Negative	-.089	-.093
Kolmogorov-Smirnov Z		.325	.458
Asymp. Sig. (2-tailed)		1.000	.985

a. Test distribution is Normal.

b. Calculated from data.

Table 9: Paired Samples Statistics

	Mean	N	Std. Deviation	Std. Error Mean
RainyCondition	.5260	10	.13802	.04365
LightCondition	.4330	10	.11567	.03658

Table 10: Paired Samples Test

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Rainy condition Light condition	.093	.028	.0087	.07332	.1127	0.11	9	.000

4. Conclusion

Application of an artificial intelligent system (Fuzzy logic) in transportation is a solution for investigating dangerous drivers in roads. Artificial intelligent systems plan based on human thoughts. This utility helps to find out the reason of mortal traffic accidents, mostly. Fuzzy logic takes into account to advance intelligent transportation systems. In this article, the state of drowsiness was determined experimentally. Various factors for fatigue and drowsy detection, including psychological (mental), behavioral and physiological measures have been considered. In addition, defects and their effectiveness were examined. Using these measures into the multinomial logistic regression model will determine a growth in the development of intelligent systems to determine effective variables in the driver sleep prediction for the evaluation of the influence of environmental, and weather conditions on driver's sleep behavior. According to proposed method for driver's drowsiness, driver's sleep behavior was evaluated and predicted by the fuzzy logic. Obviously, results indicated that the risk of deadly traffic accidents in sleep duration significantly increases because of the reduction in the arousal level of drivers. Therefore, the multinomial logistic regression model can firstly categorize driver's drowsiness for each behavioral measure with high prediction accuracy (see Fig. 4) to predict the effective measure on accidents when drivers have different sleepy groups. Subsequently, the fuzzy logic system takes driver's drowsiness to evaluate the driver's sleep prediction. Apparently, fuzzy logic approved that drowsy state (sleep duration) grows when there are many distances and weather condition is rainy. However, the drowsy states for the driver's sleep behavior which regularly diminishes when environmental condition is light in many distances. From results, it was understood that driver's sleep behavior in light condition has a significant difference in comparison with rainy condition (see Tables 9 and 10). Moreover, rainy and light conditions for driver's sleep behavior approved that drivers in many distances under rainy condition has the worst state of drowsiness which means there is a high risk of accident (see Fig. 7). For being aware of validity of results, all of them were analyzed by SPSS 16 software, and it was obtained that multinomial logistic regression developed fuzzy logic system of driver's sleep behavior to predict the probability of driver's drowsiness correctly.

Recommendation

This study tends to be applied to examine the safety of drivers according to their behavioral characteristics to investigate the reason of drowsy accidents and also evaluation of these behaviors could be easy by applying fuzzy logic for controlling driver's sleep behavior. In the future, this work will be utilized by traffic police and safety and prevention research organizations .

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References

[1] Global Status Report on Road Safety. World Health Organisation (WHO): Geneva, Switzerland, 2009.
[2] Drivers Beware Getting Enough Sleep Can Save Your Life This Memorial Day; National Sleep Foundation (NSF): Arlington, VA, USA, 2010.
[3] Fernandez, S. and Ito, T. Driver Behavior Model Based on Ontology for Intelligent Transportation Systems. IEEE 8th International Conference on Service-Oriented Computing and Applications. 2015, p.1 – 5.
[4] Zadeh, L.A. Fuzzy set, Information and Control. 1965, 8(1):338–353.
[5] Nazeem, K.M. and Sekar dash, S. Experimental Investigation on the performance of Drowsiness manipulation using driving simulators.International Conference on Circuit, Power and Computing Technologies [ICCPCT], 2015, p. 1-5.
[6] Radun, I., Ohisalo, J., Radun, J., Wahde, M. and Kecklund, G. Driver fatigue and the law from the perspective of police officers and prosecutors. Journal of Transportation Research Part F. 2013;18(1):159–167.
[7] Sahayadhas,A., Sundaraj, K., and Murugappan, M. “Detecting Driver Drowsiness Based on ensors: A Review. ” Sensors Journals. 2012, 12(1):16937 – 16953.
[8] V. Rajput, M. and Bakal, J. W. Execution Scheme for Driver Drowsiness Detection using Yawning FeatureInternational Journal of Computer Applications, 2013. 62(6).
[9] Murata, A., Matsuda, Y., Moriwaka, M. and Hayami, T. An Attempt to Predict Drowsiness by Bayesian Estimation. 2011, In Proceeding of SICE (Society of Instrument and Control Engineers), p. 58-63.
[10] Murata, A., Koriyama, T. and Hayami, T. Basic Study on the Prevention of Drowsy Driving Using theChange of Neck Bending Angle and the Sitting Pressure Distribution. 2012, In Proceedings of SICE, p. 274-279.
[11] Kecklund, G. and Akersted, T. Sleepiness in Long Distance Truck Driving: An Ambulatory EEG Study of Night Driving. Ergonomics. 1993; 36(9):1007-1017.
[12] Murata, A. and Hiramatsu, Y. Evaluation of Drowsiness by HRV Measures—Basic Study for Drowsy Driver Detection. 2008, In Proceedings of IWCIA(International Workshop on Computational Intelligence and Applications), p. 99-102.
[13] Murata, A. and Nishijima, K. Evaluation of Drowsiness by EEG Analysis-Basic Study on ITS Development for the Prevention of Drowsy Driving. 2008, In Proceeings of IWCIA, p. 95-98.
[14] Murata, A., Koriyama, T., Ohkubo, Y., Moriwaka, M. and Hayamai, T. Verification of Physiological orBehavioral Evaluation Measures Suitable for Predicting Drivers' Drowsiness. 2013, In Proceedings of SICE, p. 1766-1771.
[15] Murata, A., Nakatsuka, A. and Moriwaka, M. “Effectiveness of Back and Foot Pressures for AssessingDrowsiness of Drivers. 2013, In Proceedings of SICE, p. 1754-1759.
[16] Wertz, J., Francois, C. and G. Verly, J. Validation of a new automatic drowsiness quantification system for drivers. 5th International Conference on Applied Human Factors and Ergonomics (AHFE), July 19-23, 2014, Poland.
[17] Sagberg, F. Month-by-month changes in accident risk among novice drivers. 24th International Conference of Applied Pscyhology, San Francisco. 1998.
[18] Murata, A. and Naitoh, K. Multinomial Logistic Regression Model for Predicting Driver's Drowsiness Using Only Behavioral Measures. Journal of Traffic and Transportation Engineering. 2015; 3(1):80-90.
[19] Murray, A. The home and school background of young drivers involved in traffic accidents. Journal of Accidents and Preventation. 1998; 30(2):169–182.
[20] Kusan, H., Aytekin, O. and Ozdemir, I. The use of fuzzy logic in predicting house selling price. Expert Systems with Applications. 2010; 37(3): 1808–1813.
[21] ER Brown, JE Haddock, RB Mallick and Lynn, TA, “Development of a mixture design procedure for stone matrix asphalt (SMA)”, report, no. 97–3, 1997, National Center for Asphalt Technology (NCAT), Auburn, USA.
[22] K. Wang, F. Liu. Fuzzy set-based and performance-oriented pavement network optimization system. Journal of. Infrastruct. Syst. 1997;3(4): 154–159.
[23] H. Is¸ik and S. Arslan. The design of ultrasonic therapy device via fuzzy logic. Expert Systems with App. 2011; 38: 7342–7348.
[24] M. Omid. Design of an expert system for sorting pistachio nuts through decision tree and fuzzy logic classifier. Expert Systems with Applications. 2011; 38: 4339–4347.
[25] Akkurt, I., Basyigit, C., Kilincarslan, S. and Beycioglu, A. Prediction of photon attenuation coefficients of heavy concrete by fuzzy logic. Journal of the Franklin Institute. 2010; 347(9): 1589 –1597.