ANNALS OF GULF MEDICINCES

https://publie.frontierscienceassociates.com/index.php/gulf

AGM

E-ISSN: 2616-9231

Evaluation of Subjective and Objective Levels of Drowsiness, it's Rating and its Relation with Facial Dynamics

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A R T I C L E I N F O

Article history:
Received:28 January, 2019
Accepted: 21 February, 2019
Online:14 March, 2019

Keywords:
Driver drowsiness,
Dynamic face changes,
ORD,
CSR

DOI: 10.37978/agm.v2i1.269

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A B S T R A C T

Objective: *To determine the subjective and observed levels of lethargy and changes in facial dynamics.*

Materials and Methods: *This study was conducted at Department of community medicine, Services Institute of Medical Sciences Lahore for one-year duration from January 2017 to December 2018. The changes in facial dynamics, such as changes in eyes, lips and eyebrows, were tested in KKS (Karolinska Sleepiness Scale) in twenty-five drivers. And ORD (drowsiness observer rating). Repeated ANOVA measurements and repeated MANOVA measurements were used to analyze the data. In addition, a neural network and Viola-Jones were used to detect facial features. PERCLOS (percentage of eye closure), blink frequency and blink time were examined to see eye parameters. The size of the open mouth during sleep was examined for oral parameters. When examining the eyebrows, the number 50 indicates that the eyebrow is in the normal position. For eyebrows above the normal position, a range of 50 to 55 was specified; In addition, 45-50 was found to be a defined range for normal eyebrows.*

Results: *Descriptive statistics of dynamic changes in the mouth and eyes showed increased drowsiness while driving, as well as changes in the eyes and mouth. However, statistical findings made while driving showed that dynamic eyebrow changes had a clear expression with a continuous trend. Similar studies on data obtained from CSR and ORD showed that both parameters increased at the same time and lethargy level. There was also a significant relationship between facial expressions and lethargy.*

Conclusion: *This study will be an effective and efficient tool for alerting and detecting sleep in a timely and accurate manner.*

Introduction

Detecting drowsiness can help reduce road fatalities. Studies have shown that 1.3 million people and more than 20-50 million people were killed in road accidents, respectively (1-2). Statistics published by the US National Road Safety Administration. Laws (NHTSA, in English) states that 100,000 accidents occur each year solely due to driver numbness. Road accidents cost 1,550 deaths and 71,000 judges, and their costs exceed 12.5 billion.Road accidents in urban and suburban areas are mainly caused by human factors. According to statistics, human error is the main cause of 90-95% of car accidents. Driver fatigue is expected to cause up to 25% of accidents, in particular 60% of fatal or harmful road accidents. In a study of 107 randomly selected vehicles carried out by the National Road Safety Administration (NHTSA), drowsiness of drivers was the main cause of 58% of car accidents (3).

Driver fatigue in the Pakistan is the main cause of 20% of road accidents. In recent years, the use of intelligent systems and wireless sensors has been widely used to monitor and report vehicle and driver status (WSN). Intelligent vehicles have improved the driving experience(4). This development, gears, braking system, steering wheel and so on. This is the result of computer programs and software projects. AD hoc networks were the first systems that developed automatic vehicle control, the delay in responding to changes in the environment was the weakness of these systems. When the driver drives a vehicle, sufficient time is important to react(5).

Well-known car companies have developed many techniques for detecting driver's lethargy, especially at night. These techniques are attributed to various weaknesses and advantages. Techniques developed to promote driver fatigue are divided into three groups:

1) Mathematical and statistical surveillance systems, 2) Vehicle monitoring systems, 3) Crew using sensor networks, and 4) Intelligent driver fatigue detection systems (6).

In 2009, Hosking and Liu developed a vigilance level detection system. This system detects driver fatigue using a model based on facial features. In addition, signals such as the sleep threshold are reported by Barbato et al. In this study, EEG was extracted based on wave analysis. Connor and colleagues investigated the risk of serious car accidents such as runways due to driver drowsiness in 2002, and proposed techniques based on intelligent systems (7-8).

Various studies used techniques to detect driver drowsiness to reduce the number of road accidents; such systems detect the drowsiness and alertness of the driver by shaking the steering wheel or seat. The following parameters were used to determine the sleep state:

1) Based on physiological signals (ECG and EEG)

2) Depending on drive performance (number of lines and distance between cars)

3) Based on the facial expression.

Physiological methods perfectly detect high precision drowsiness. However, in these methods, some sensors should be created in the body, which can be inconvenient for the user. The methods based on the controller performance require a lot of time and therefore no micro-layers are detected. Scientists often used the study of significant changes to detect drowsiness.

Materials and Methods

In the Department of community medicine, Services Institute of Medical Sciences Lahore for one-year duration from January 2014 to December 2014. This experimental study was conducted in twenty-five professional drivers In Lahore. Inclusion criteria include no visual impairment (without glasses), two years of driving experience and normal appearance (no abnormal beard or mustache). In this context, participants were randomly selected.

The virtual reality driving simulator was placed in a quiet room controlled by temperature and sound to take photos of the driver. The test was carried out on the AKIA-BI 301 driving simulator model (Fig. 1). When the drivers started driving the simulator, face photos were taken to discover drowsiness. The vehicle was temporarily asked a few minutes before the test. Then the subjects were asked not to use the simulator realities and to use the vehicles in accordance with traffic regulations.

At the starting point, a camera was installed to take pictures of the features of the subjects, and CSR appeared every ten minutes without a break. The observer performed ORD at the same time every ten minutes. The test was carried out at 9 am. and 12:00 to check the circadian rhythm. The controlled light of oncoming vehicles was simulated by a bright light collision that reduced subjective drowsiness. The camera and simulator were constantly monitored during the test to avoid interference. Install the camera and simulator continuously, avoid interference. The test ended when all the wheels went off the road. Then, software was created to take pictures of the eyes, eyebrows and lips and to verify dynamic changes of facial features based on information. Dynamic face features consist of closing the eyes (PERCLOS), flashing time and flashing frequency.

Fig. 1: Driving simulator model AKIA-BI 301

When recording deviations from normal conditions, eyebrows and lips were observed. After pairing and synchronization, data from previous studies were used in basic models of dynamic facial changes.

As a popular fast algorithm, the Viola-Jones algorithm has been used to immediately detect objects and facial expressions (especially around the eyes) and to help detect numbness. In this algorithm, the head is perceived as an oval-shaped area due to the relationship of the diameters with the eye opening, and the final goal is the option with a color and shade similar to human color.

Taking into account the position of the eyes on the face, the upper part of the right eye and the left eye were examined. Then the changes in the white part and colors of the students were examined. To detect open and closed eyes, and to shake and reduce the volume of data, the eye images were changed to binary. In the open eye, due to the dark colors of the pupil and eyelashes, the proportion of dark pixels from top to bottom is greater than in the closed eye. Before converting the image into binary form, normalization based on lighting was performed.

In addition, erosion and expansion joints operators were used to remove small blackheads. Finally, the ratio of black pixels to full pixels of the top and bottom was calculated and used to detect closed eyes.

Open mouth size changes due to stretching were the main reason for approaching the open month in this study. The location of the mouth was transferred to the Fuzzy C-Means (FCM) unit, a grouping method in which part of the data was divided into two or more groups. At this stage, the calculations belonged to group centers and member functions with spectral amplitude. An independent analysis was required to calculate the correct number of groups. This goal was achieved by multiple iterations of FCM for a spectrum of group number hypotheses and selection of relevant pages based on the importance of the group. In the next step, this information was transferred to a special FCM. Special information produced by FCM is used to eliminate image noise. To determine the cluster per pixel, demagnetization after c-FCM convergence was performed, and the results revealed FCM output in binary format image, which leads to lip detection.

Two more tests were carried out to test the accuracy of lip detection. The first test started from the middle part of the lips and from the second test as the calculated value of the angle between the position of the lips and the area between the eyes. The central area of the lips is perpendicular to the area between the eyes.

The ratio of the area of the mouth and the degree of open mouth was used to determine the size of the open mouth in various frames, such as:

1) $DoO = w / h = w / (h \times \cos\Theta)$

where

"W" = rectangle width (distance between two lip corners)

"H" = height of the lip rectangle calculated as the distance between the upper and lower lines

Changes in the open mouth of the rectangle with stretching can be obtained by calculations. As expected, the size of the open mouth during stretching has been particularly changed.

When examining the eyebrows, the number 50 indicates that the eyebrow is in the normal position. A range of 50 to 55 for eyebrows above the normal position and a range of 45 to 50 for eyebrows below the normal position was specified. This means that the highest forehead is +5 and the lowest forehead -5. The output from this section is moved to another software section to extract and recognize the properties of the areas detected in the previous section. These functions are considered to be controller functions and are stored in personal files provided by the software. In order to examine the level of dynamic facial features changes, recorded frames were examined. Finally, the data were combined according to lethargy, CSR and ORD. Due to the multidimensional analysis of these variables over time, the need to determine the level of sleep and lethargy was provided by the statistical model.

Results

The method was applied to 32 suburban bus drivers aged 26 to 60, and 25 of them felt asleep during the test. When the ride began, a camera was placed in front of the driver, a picture was taken and ORD was taken every ten minutes. In addition, CSR data was obtained at the same time every ten minutes. Next, the relationship between information on various parameters was examined. The demographic characteristics of these controllers are presented in Table 1.

Table 1: Demographic Characteristics of participants

Demographic Characteristics	Mean±SD	Minimum	Maximum
Age	37.2±10.95	26	60
Years of smoking	7.26±6.4	0	20
BMI	24.03±2.64	19.6	29.4
Work experience	10.32±7.39	2	25

Eye characteristics during drowsiness

According to signals from the eyes, the MLP neuron system was used to determine and determine the level of lethargy. There were two entrances to the nervous system: first, the eyes were closed to get excellent features and information about drowsiness. Secondly, the rate and duration of flashes and insomnia were excellent. As shown in Fig. 2, PERCLOS and the blink frequency tend to increase and decrease accordingly when the driver gets tired over time (Fig. 2).

After examining descriptive statistics of eye dynamics, a significant increase in eye drowsiness was observed over time. Based on the assumption of global rejection, the Greenhouse-Geisser test was used to confirm the changes. A significant change was observed at the significance level of 5% of eye dynamics over time ($F2.74, 65.86 = 135.26$, $P <0.001$, Partial $Eta2 = 0.849$). In other words, it has been claimed to have a significant effect on time and increase in sleepiness over time. In addition, the quadratic coefficient Eta showed that this variable determines about 85% of the total variance of this model.

Characteristics of sleepy lips

According to FIG. 4, there is a significant relationship between mouth dynamics and time progression. Furthermore, according to the Green-house-Geisser test, there was a significant change in mouth dynamics over time ($F3,47.8.47 = 89.59$, $df = 2.42$, $P <0.001$, partial $Eta2 = 0.789$).

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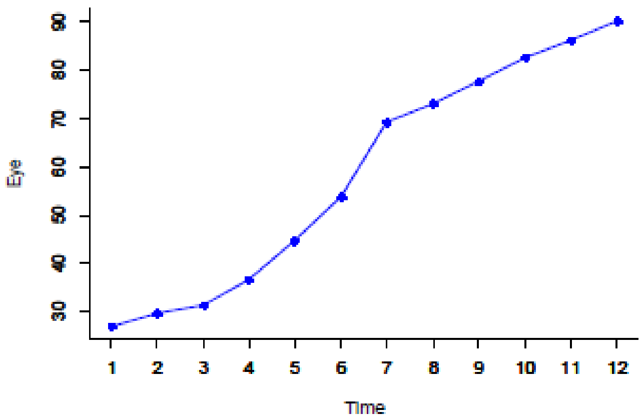

Fig. 3: changes of eyes dynamics in time

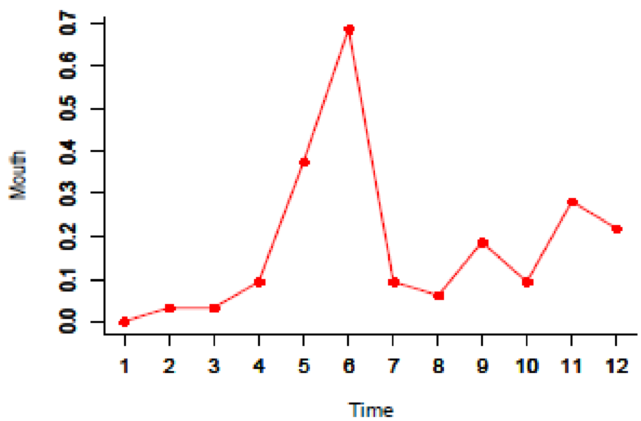

Fig. 4: Dynamic changes of mouth in time

The dynamics of eyebrows during drowsiness

Figure 5 shows dynamic eyebrow changes over time. According to statistical analysis, no significant relationship was found between progress over time and dynamic eyebrow changes.

CSR and ORD data at rest

CSR and ORD had a direct correlation with the level of drowsiness and increased rapidly after 60 minutes (Fig. 6). CSR, ORD, MANOVA Measurements were repeated to test the relationship between levels of drowsiness. The results showed that time had a significant impact on both CSR and ORD. It is worth noting that these two variables explained 98% of the total variance. The linear combination of both dependent variables was significantly different during the study periods (F (22.10) = 22.52, P <0.001; Wilkslambda = 0.02; Partial stage 2 = 0.98). According to CSR calculations, sleep changes over time (F (3.8,90.4) = 178.3, P = 0.001, partial Eta2 = 0.81) and ORD (F (3.8.90.4) = 178, 3, P = 0.001, partial Eta2 = 0.79). Equivalent comparisons were made with the Bonferroni correction because of the importance of time. CSR and ORD results showed that many pairs were significantly different.

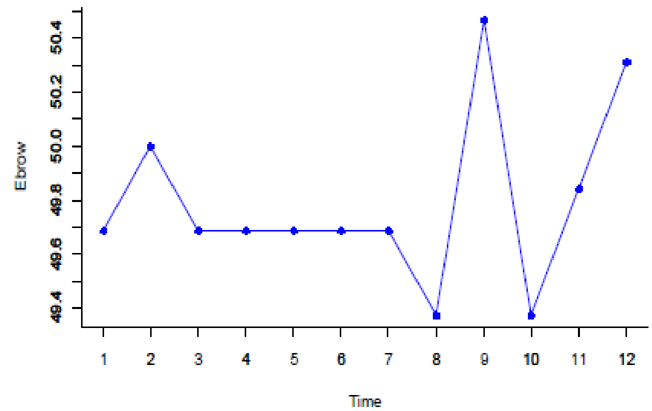

Fig.5: Dynamic changes of eyebrows in time

Relationship between CSR and ORD results and eye, mouth and eyebrow dynamics

MANOVA, CSR and ORD measurements were repeated to determine if there was a relationship between dynamic eye, mouth and eyebrow changes and changes in drowsiness while driving. The results showed that the time variable had a significant effect on facial expressions (eyes and lips) and dynamic CSR variables. Over 99% variance changes assigned to these variables. In this sense, there were significant connections between dynamic face changes and ORD; and between linear combinations of both dependent variables in 12 study periods (Table 2).

Table 2: Data related to KSS, ORD and their relationship with dynamics of eyes, mouth and eyebrow

Factors	Wilks'lambda	F(22,3)	P
Mouth – ORD	0.0002	513.98	< 0.001
Eye – ORD	0.0004	367.62	< 0.001
Eye – KSS	0.001	175.72	< 0.001
Eyebrow – ORD	0.001	234.3	< 0.001
Eyebrow – KSS	0.002	73.25	< 0.001
Mouth – KSS	0.001	250.1	< 0.001

Discussion

Driver numbness causes changes in facial and eye features, and many techniques and algorithms have been developed to recognize facial features that detect numbness. Lopar and Ribaric demonstrated the speed and precision of the Violla-Jones algorithm as a tool for monitoring facial features (9). These studies used image processing based on the Violla-

Jones algorithm to identify facial features, detect driver fatigue, and determine the level of driver warning. In addition, CSR, ORD and dynamic eye, mouth and eyebrow change parameters were used to increase the accuracy of the questionnaires. In a study by Belzaet al. Using CSR and ORD, a significant relationship was found between levels of drowsiness (10). Test results on many varieties showed an impressive impact of time on CSR and ORD. Both of these variables provided 98% of variance.

Dynamic changes in the eyes can be considered a key parameter in detecting fatigue and numerous studies have been conducted. According to the gradient of the charts, dynamic eye changes were directly related to the level of lethargy[11]. Kumar and Barwin applied the new method, while using eye dynamics, flash speed and Viola-Jones). This method can detect 92% of disk numbness and determine the disk. A direct relationship between sleep level and eye dynamics was observed. A 5% error rate in eye dynamics suggested a significant change over time. To get the right model, the GROUP INTERACTION test was used; The linear model provided 89% variance changes. However, the double comparison test showed that most of the 5% binary differences with BONFRONI correction were valid (12-13).

The purpose of this study was to create a hybrid model for detecting facial numbness. This study had its strengths and weaknesses[14]. The advantage of using this technique was the recognition of intelligent drowsiness by analyzing various criteria, long intervals and under the disk to detect drowsiness. It helps to identify the driver's sleep in real time, display important ads and reduce the number of cars accidents(15). The accuracy of this method was based on the right lighting and camera location. This method has been processed with high precision in real time compared to other methods (16). Another weak point was that we could not be sure of the driver's sleep because some drivers would have had false dreams and completed tests before others and could not change their position too much and could not detect the driver's eyes with light. bright. It was not possible.

Conclusion

CSR and ORD analysis showed dynamic changes in eye and mouth parameters when the driver was drowsy. This method can be an effective and effective tool for quickly and accurately detecting drowsiness.

Conflict of Interest: This study has no conflict of interest to declare by any author.

Disclosure: None

Human and Animal Rights: No rights violated.

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