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Complexity Analysis of Ocular Signal for Detection of Human Fatigue Using Small Datasets

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Abstract

The electrooculogram, often known as an EOG signal, can frequently be used to quantify the amount of drowsiness and exhaustion that a person is experiencing in their body. Electrooculogram signal analysis is primarily a process that does not include any invasive procedures and is used to evaluate the movement of the eye in both horizontal as well as in the vertical direction. The primary purpose of this research is to identify signs of exhaustion using the process of complexity analysis using non-invasive data collected from twenty people who are deemed to be in good physical and mental health. This investigation makes use of three distinct visual signals at three distinct frequencies, and it also considers three distinct time slots during the day. Based on real-time EOG signals that have been gathered in a non-invasive manner, oculo-parameters such as moving window fuzzy entropy and moving window dispersion entropy can be computed. According to the findings of the experiment, the level of complexity of both horizontal and vertical data steadily grows throughout the afternoon and evening as cue frequency steadily rises and we can ascertain the fatigue of the body. Drowsiness and exhaustion in humans may be caused by factors such as muscle stress, insufficient sleep, and a significant time gap between two different sleep cycles.

Keywords: Electrooculogram (EOG); Fatigue; Muscle stress; Visual cue; Moving window fuzzy entropy (MW-FuzzyEn); Moving window dispersion entropy (MW-DispEn).

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1. Introduction

Fatigue is the sensation of extreme physical and mental exhaustion. Increased rest intervals can help to reduce fatigue. Fatigue can be caused by a variety of physical and mental factors. Continuous physical activity might be regarded as a result of strenuous physical exertion or obligations that necessitate physical stamina and fitness. The gradual onset of drowsiness or weariness is usually caused by overstressed muscle tissues in the body [1]. Insufficient sleep and health are also factors [2]. Psychological exhaustion or mental weariness is a feeling of indirect reluctance to complete a bit of effort or duty. The inability to accomplish the activity with the optimal cognitive function will diminish. During every type of cognitive effort, mental fatigue is perceived gradually. In every circumstance, it is risky to engage in activities that necessitate complete focus, such as completing precise work, operating a vehicle, etc. For instance, a sufficiently exhausted individual may experience microsleep or a percentage of microsleep [3,4]. Fatigue describes muscular exhaustion, whereas sleepiness is the inability to remain attentive and awake [5,6]. Workload, work pressure, and duration, in addition to sleep deprivation and the length of the last sleep cycle, can all contribute to fatigue. Significant elements that contribute to exhaustion and drowsiness include diurnal rhythm, physical fitness, sleep quality, age, alcohol use, job schedule, working circumstances, and repetitive activity. Between 1 pm and 4 pm and 1 am and 6 am, people whose circadian rhythms are frequently synchronized with the biological clock had sporadic alertness deficits. The majority of road accidents that occurred during these times were a result of inattentiveness. Driving at night reduces the attentiveness or rather increases the risk factor in many folds than driving at day time because the probability of falling asleep enhances with the limited vision at night [7]. Drivers are frequently unable to assess their level of tiredness, resulting in accidents [8]. Falling asleep in the vehicle lowers the awareness of drivers regarding their surroundings and impairs their ability to respond. Also, driver fatigue impairs their capacity to make sound decisions [9]. There are precautions against drowsiness to deal with fatigue in a drowsy state. The most popular measures include stopping the car for a little period to take a nap, rest, eat, or drink tea, coffee, or an energy drink. It is also suggested that you wash your face or alter the ventilation in the car, switch drivers, and listen to music or the radio [10-12]. In addition, other countermeasures are implemented, such as requesting the co-passenger to initiate talking or making any phone call, however, these activities may generate direct distraction while driving. Avoiding night driving as well as prolonged driving may reduce the chances of road crashes considerably [7]. There are several physiological methods for quantification of drowsiness and fatigue. Several works of literature have suggested that ECG, EEG, EOG, EMG, GSR, and ST are well-known. Some hybrid techniques are also used which are the combination of two or more two methods. In commercially available drowsiness detection systems, vehicle-based measuring techniques are typically favoured over alternative approaches for monitoring the status of the driver in real-time [13]. But it is very difficult to mimic the actual driving environment in a controlled environment by using driving simulators. On the other way, the measurement of behavioural changes requires a different technique of image processing, which is highly dependent on the variation of light. Drivers' spectacles or sunglasses may also create a reflection or there may be insufficient foreground or background lighting. So, using physiological signal-based measurement of fatigue or drowsiness is very well accepted, but in that case, several electrodes are engaged to record the real-time signal. Out of all non-invasive biosignals, an EOG signal can be obtained by employing very a much smaller number of disposable electrodes. Some research [14] indicates that the electrooculogram signal has a decent per cent success rate, and it is conceivable to install as well as manage disposable electrooculogram electrodes as well as collect real-time data from participants such as a driver or operator to detect drowsiness and weariness. The objective of fatigue detection is primarily to reduce road accidents due to driver's inattentiveness during driving as well as to reduce any other possible fatal injuries that may occur to the operators due to fatigue.

The objective of the present work illustrated the detection of fatigue and drowsiness by complexity analysis. Here the entropy-based complexity analysis is used for finding out the fatigue and drowsiness. Fuzzy entropy is a useful tool for determining the complexity of non-stationary signal dynamics. It measures the degradation of energy. Another process of measurement of the regularity of a time series is dispersion entropy [15]. The acquired data with different cue frequencies on different time slots of the day is utilized for finding out those parameters for complexity measurement. By analyzing those parameters, the onset of fatigue and detection of fatigue and drowsiness is determined.

The following is the structure of the rest of the paper: Section 2 goes through the technique in-depth, section 3 goes over the experimental results and discussion, and section 4 goes over the concluding conclusions and future scope.

2. Methodology

2.1. EOG

EOG signal is a measurement of the corneal and retinal resting potential, which resides between the front and back of the human eye [16, 25, 26]. Disposable Ag-Agcl electrodes can be placed around the eye in various locations to obtain EOG. For acquiring the horizontal movement of the cornea, two electrodes are placed in the area of the hairline and the corner of the eye. The third electrode is placed on the forehead for providing the ground connection. Similarly, for acquiring the vertical movement of the cornea, electrodes are placed in quadrature with the axis of horizontal eye movement and the third electrode is placed on the forehead. The horizontal movement of the cornea is captured in the horizontal channel and vertical movement is captured by the vertical channel. The EOG signal varies in the range of micro-volt or mili-volt. The acquired EOG signal by the Biopac MP45 system is shown in Fig 1. and Fig 2.

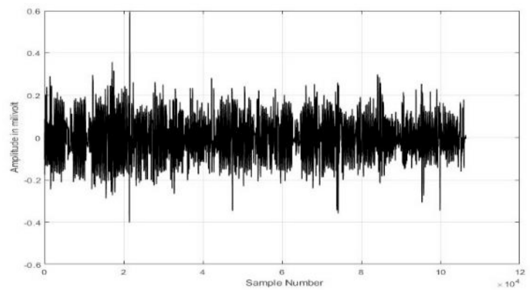

Fig. 1. Horizontal channel EOG signal acquired by Biopac MP45

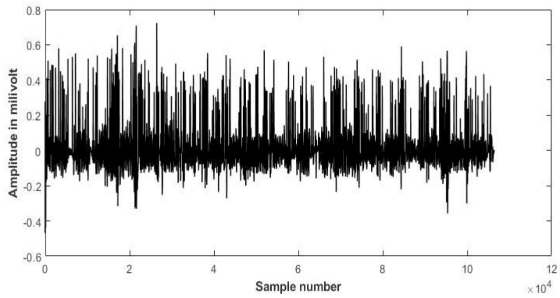

Fig. 2. Vertical channel EOG signal acquired by Biopac MP45.

2.2. Participants

Twenty individuals, consisting of thirteen males and seven females between the ages of 23 and 32, have freely participated in the study at the Biomedical Instrumentation Laboratory, NIT Durgapur. A total of three sessions were used to collect all of the experiment's data: morning (8 am to 10 am), afternoon (3 pm to 5 pm), and evening (7 pm to 9 pm). All subjects were asked for staying away from consuming alcohol the night before and smoke an hour before the EOG signal recording. The present work has been approved by the institutional ethics committee (IEC, NIT Durgapur), and the participants signed consent forms indicate that they are prepared to participate in the study and allow the use of their physiological data. They are also provided with satisfactory information on their questionnaire. Anthropometric and hemodynamic characteristics of the participants are shown in Table 1. Since mean (central tendency) and standard deviation (variability) are within the range with a narrow margin, it can be ascertained that the participants have high homogeneity in terms of factors influencing EOG signals such as age, Body mass index (BMI), etc.

Table 1. The anthropometric and hemodynamic characteristics of the candidates.

	Male		Female	
	Mean ± SD	Range	Mean ± SD	Range
Age (Years)	27.40 ± 2.55	23-32	24.00 ± 1.15	23-25
Mass (Kg)	66.50 ± 8.41	56-80	55.51 ± 0.58	55-56
Height (m)	1.69 ± 0.09	1.58-1.83	1.56 ± 0.02	1.55-1.58
BMI (kg/m2)	23.22 ± 2.18	19.4-26.6	22.75 ± 0.17	22.6-22.9
Basal HR (bpm)	71.91 ± 8.17	59.62-84.86	80.96 ± 6.01	74.31-87.85

2.3. Optical cue

In this experiment, we have introduced a series of patterns of a visual cue [17], which is a 530-second video clip, and all the participants are asked to track the cue [18, 19]. The cue consists of the movement of an optical ball in different directions on a mobile screen, and it also follows a variety of patterns. In this process of visual cue tracks, the movement of visual cues follow gazing, smooth pursuit and saccade. Here, a total of ten cue movement patterns are generated, each of which follows a predetermined shape for 16 seconds. To make a clear difference in the sensation of the shape of a cue in our brain, a mandatory gap of 10 seconds is provided by continuous gazing at the cue ball at the centre of the screen. The same gap is also provided at the start and end of the set of one cue pattern for a given frequency. The optical cue pattern is given as:

gazing → elliptical CW → gazing → elliptical CCW → gazing → rectangular CW → gazing → rectangular CCW → gazing → triangular CW → gazing → triangular CCW → gazing → numeric 8 CW → gazing → numeric 8 CCW → gazing → lemniscate CW → gazing → lemniscate CCW → gazing →→→ a repeat of cycle from elliptical CW

(CW: Clockwise, CCW: Counterclockwise)

2.4. Data acquisition

As illustrated in Fig 3, an EOG signal was obtained by an MP 45(Biopac) data acquisition device using a two-channel (The horizontal channel moves the cornea in a horizontal direction, and the vertical channel moves the cornea in a vertical direction, which is mostly the blink.). Fig 4 depicts the electrode implantation procedure. Medicos electrodes International Ltd's Ag-AgCl (silver- Silver chloride) replaceable electrodes MSGLT-05MG are securely connected to contact surface (skin). Three pinch leads red (positive), white (negative), and black (ground) of a general-purpose electrode lead SS2LB are snapped immediately onto disposable electrodes. The data collecting system sampled the signal at 2 kHz, and the EOG signal's bandwidth is 0 to 50 Hz, with amplitudes ranging from 100 to 3500 µvolts [20]. Fig 5 depicts the laboratory experimental setup for EOG data acquisition utilizing the Biopac MP 45, with the cue pattern displayed on a mobile screen via a VR platform.

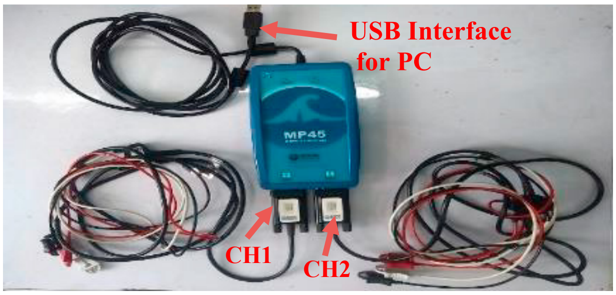

Fig.3 MP 45 (BIOPAC) Data acquisition system

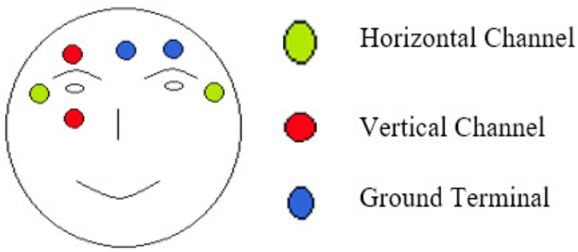

Fig.4 Electrodes position

Fig.5 Laboratory setup EOG Data recording by MP45 (BIOPAC)

During experiments, the subjects are instructed to engage in a massive cognitive activity, and the total process is evaluated to ensure that the experiment is running smoothly. After a sound sleep, the participants are requested to provide the first set of data around 8.30 a.m. After receiving the morning dataset from the targeted participants, they are requested to participate in the cognitive activity once more and they are asked to eat their lunch around 1 p.m., and then they are re-engaged with the pre-defined activities without taking a break until around 2 p.m. when we will collect the second set of data. Following the completion of the second round of data collection, participants were requested to engage in cognitive activity for at least four hours, and we collected the last set of data at 8 p.m. The participants were asked to sit in a chair steadily every time we took data. We took three sets of data in each slot, based on the three different frequencies of the cue. We've picked cue frequencies of 0.5Hz, 1Hz, and 2Hz. During the experiments, the participants are asked to restrain voluntary blinking as much as possible when they are following the cues.

The experiment was conducted under natural light during the day and diffused light during the evening. For the video clip, we employed a 5.5-inch mobile screen with visual cue patterns, and the phone was placed on a Virtual Reality platform for compact projection.

2.5. Data pre-processing

The range of frequency of the electrooculogram signal is 0-50 Hz. Noise removal from the acquired EOG signal using an appropriate noise filter that winnows out and mitigates noise components such as baseline wander from various sources such as respiration, muscle movement, and power line frequency interference (PLI) from cables carrying EOG signal is one of the most important steps in pre-processing the EOG signal. It improves the signal-to-noise ratio (SNR) for subsequent processing. For further analysis and processing, the acquired raw electrooculogram signal is usually filtered. Filtering is necessary to eliminate noise. Before it is filtered, the raw EOG signal is sampled down to 200 Hz. The filtering procedure involves the establishment of a Butterworth band pass filter of the third order with a high pass cut-off frequency of 0.1 Hz and a low pass cut-off frequency of 20 Hz respectively to get the EOG bandwidth between 0 to 20 Hz.

3. Result and Discussion

3.1. Fuzzy entropy

Most of the time, the complexity of a time series can be measured by using fuzzy entropy, because it works well and doesn't depend on the length of the data. But if we compare this process to sample entropy, we can see that it is a bit slower. Here, we analyzed the EOG signal in real-time by using a moving window with a sampling frequency of 1s. The fuzzy function is [21, 24]

$$\mu\left(d_{t_1t_2}, n, r\right) = \exp\left(-\left(d_{t_1t_2}\right)^n / r\right) \tag{1}$$

The function ϕ^m can be expressed as

$$\phi^m\left(x, n, r\right) = \frac{1}{N-m}\sum_{t_1=1}^{N-m}\frac{1}{N-m-1}\sum_{t_2=1, t_1\neq t_2}^{N-m}\exp\left(-\left(d_{t_1t_2}\right)^n / r\right) \tag{2}$$

Finally, fuzzy entropy (FuzEn) can be defined as a time-series as

$$FuzEn(x, m, n, r) = -\ln\left(\frac{\phi^{m+1}}{\phi^m}\right) \tag{3}$$

Typically, the parameters in the above calculation are m=2 (dimension), n=2 (power), and r=0.15*SD (tolerance).

3.2. Dispersion entropy

The dispersion entropy (DE) algorithm [22, 23, 27] has four basic steps for a given univariate signal of length N: $x=x_1, x_2,..., x_N$.

Applying the normal cumulative distribution function (NCDF) to express x to $y=y_1, y_2,...,y_N$ from 0 to 1 is the initial step. Then, using a linear approach, we assign each y_j a positive integer between 1 and c. To accomplish this, we utilize $z_j^c = round(c.y_j + 0.5)$. for each component of the mapped signal, where z_j^c denotes j^th component of the time series (classified) and rounding entails either reducing or increasing a number to the next digit.

For each embedding vector, $z_i^{m,c}$ with embedding dimension *m* and time delay *d* is created according to $z_i^{m,c} = \{z_i^c, z_{i+d}^c, \dots\dots\dots, z_{i+(m-1)d}^c\}$, where i=1,2,….,N-(m-1)d. Each time series $z_i^{m,c}$ is expressed (mapped) to a dispersion pattern $\pi_{v_0 v_1 \dots\dots v_{m-1}}$, where $z_i^c = v_0, z_{i+d}^c = v_1, \dots\dots, z_{i+(m-1)d}^c = v_{m-1}$. Number of different dispersion patterns that may be allocated to each time series $z_i^{m,c}$ is c^m, provided that the signal has m components and each component can be an integer between 1 and c.

For every feasible dispersion pattern in c^m, the relative frequency is calculated as:

$$p(\pi_{v_0 v_1 \dots\dots v_{m-1}}) = \frac{Number\{i \,|\, i \le N-(m-1)d, z_i^{m,c} \text{ has type } \pi_{v_0 v_1 \dots\dots v_{m-1}}\}}{N-(m-1)d} \tag{4}$$

The DE value with embedding dimension m, time delay d, and the number of classes c is calculated as follows, and always based on Shannon's concept of entropy:

$$DE(x,m,c,d) = -\sum_{\pi=1}^{c^m} p(\pi_{v_0 v_1 \dots\dots v_{m-1}}).\ln(p(\pi_{v_0 v_1 \dots\dots v_{m-1}})) \tag{5}$$

Generally, dispersion gives the spread of the data. Here, we analyzed the EOG signal in real-time by using a moving window with a sampling frequency of 1s.

3.3. Complexity analysis

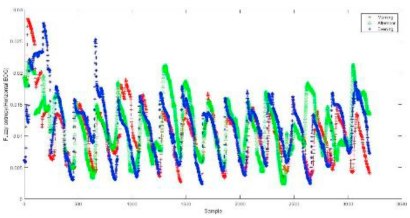

Fig.6 Fuzzy entropy of 1st set horizontal EOGs

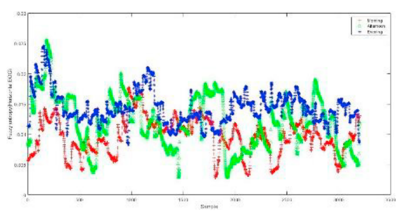

Fig.7 Fuzzy entropy of 2nd set horizontal EOGs

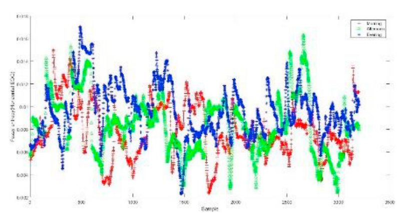

Fig.8 Fuzzy entropy of 3rd set horizontal EOGs

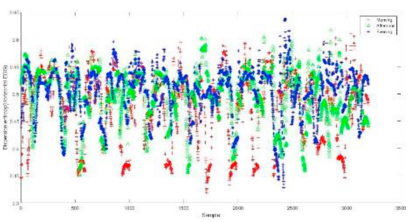

Fig.9 Dispersion entropy of 1st set horizontal EOGs

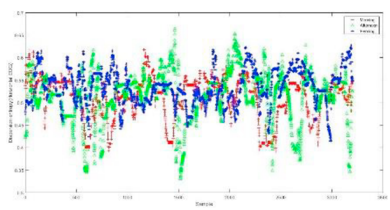

Fig.10 Dispersion entropy of 2nd set horizontal EOGs

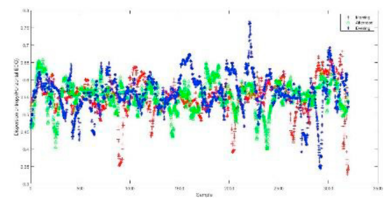

Fig.11 Dispersion entropy of 3rd set horizontal EOGs

In this present work, two types of entropies are evaluated for assessment of the complexity of EOG signals that came out from the horizontal channel of Biopac MP45. In Fig 6, we have tried to compare the plots of 1st set (0.5 Hz cue frequency) horizontal channel EOG signals. In these plots (Fig 6) the curve shown by 'red+' indicates the moving window fuzzy entropy for morning data, 'green^' indicates the same for afternoon data and 'blue*' provides the moving window fuzzy entropy for evening data. Similarly, Fig 7 and Fig 8 provide the moving window fuzzy entropies of data taken by increasing the cueing frequency to 1 Hz and 2 Hz respectively. The moving window dispersion entropies are evaluated in Fig 9,10 and 11. In these figures, we have tried to compare the complexity of EOG data taken by maintaining the cue frequencies at 0.5 Hz, 1 Hz and 2 Hz respectively and acquired in the morning, afternoon and as well as in evening. The comparison is expressed in Table 2.

Table 2. Comparison of different entropies of horizontal EOGs acquired in morning, afternoon and evening with different cue frequencies of a participant.

Entropy	0.5 Hz			1 Hz			2 Hz		
	Morning	Afternoon	Evening	Morning	Afternoon	Evening	Morning	Afternoon	Evening
Moving window fuzzy (average)	0.0104	0.0114	0.0115	0.0097	0.0119	0.0143	0.0079	0.0084	0.0096
Moving window dispersion (average)	0.4783	0.4966	0.5037	0.5100	0.5141	0.5328	0.5503	0.5521	0.5620

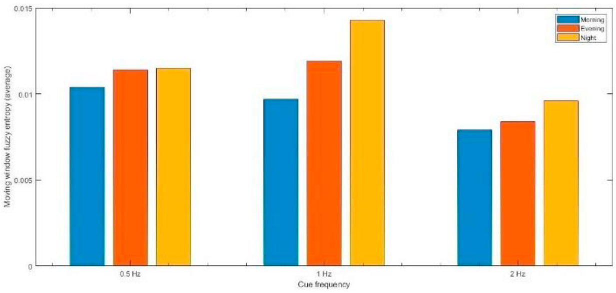

Fig.12 Moving window fuzzy entropy (average)

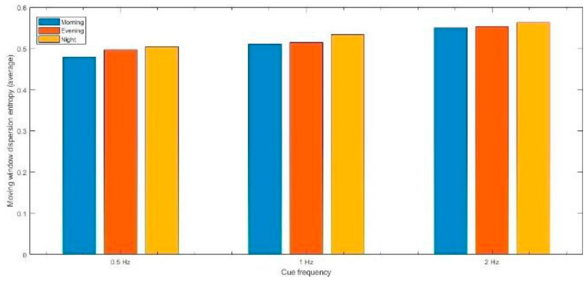

Fig.13 Moving window dispersion entropy (average)

From the table and the bar plots shown in Fig 12. and Fig 13., it is clear that with the cognitive load and when the time elapses, the complexity of the EOG signal increases gradually. In the present work, we have chosen visual cues of different frequencies and individual time slots of a given day (whole) and collected data from the participants accordingly. Horizontal EOG provides the voltage equivalent of saccades and gazing of the cornea with respect to Bruch's membrane. From the evaluation of entropies, for different cue frequencies, it has been observed that evening data shows higher complexity of signal than the afternoon data and as well as afternoon data shows higher complexity than the morning data. Generally, during attention, the candidate tries to observe the pattern of the visual cue as it appears and there might be homogeneity in the pattern of following the cue and that is reflected by a lesser amplitude in respective entropy. But when a person is tired or drowsy because of some microsleep or because they aren't paying attention to the patterns, the complexity, that is, the irregularity of the pattern following goes up a lot. This is shown by a higher amplitude in the respective entropy. We have tried to compare our result with the different recent techniques which are hybrid techniques with multi-feature and we can assure that complexity-based analysis with a single noninvasive biosignal is quite advantageous, because it plays an important role in the time of signal acquisition. The required data acquisition system can be fabricated in a portable and compact form in the form of eyeglass for real-time noninvasive data monitoring from the driver or operator.

4. Conclusion

In this work, different patterns of visual cues are used to detect muscle fatigue and drowsiness, and it works very well for monitoring the driver's or operator's condition and figuring out if he or she has tired muscles or not. The frequency of the pattern's movement is also changed, and three different frequencies are used to stimulate the cornea and help the eye follow the pattern. This method can be used to evaluate fatigue and drowsiness. Two measures, fuzzy entropy (moving window) and dispersion entropy (moving window) are utilized to analyze the EOG signal and draw a judgement on fatigue and drowsiness. The contribution to the work may be measured by the theme that by using only the EOG signal and complexity analysis of that we can reach the fair conclusive part that fatigue is induced or not. In the future, we will try to use classification techniques to cluster the different stages of fatigue and make an eye movement-based real-time warning system.

References

[1] E. Grandjean, “Fatigue in industry,” Brit. J. Ind. Med., vol. 36, no. 3, pp. 175–186, 1979.

[2] H. R. Colten and B. M. Altevogt, “Sleep physiology,” in Sleep Disorders Sleep Deprivation: An Unmet Public Health Problem,H. R. Colten and B. M. Altevogt, Eds. Washington, DC, USA: National Academy Press, 2006, ch. 2, pp. 33–54.

[3] R. Schleicher, N. Galley, S. Briest, and L. Galley, “Blinks and saccades as indicators of fatigue in sleepiness warnings: Looking tired?” Ergonomics, vol. 51, no. 7, pp. 982–1010, 2008.

[4] Bereshpolova, Y.; Stoelzel, C. R.; Zhuang, J.; Amitai, Y.; Alonso, J.-M.; Swadlow, H. A. (2011). "Getting Drowsy? Alert/Nonalert Transitions and Visual Thalamocortical Network Dynamics". Journal of Neuroscience. 31 (48): 17480–7. doi:10.1523/JNEUROSCI.2262-11.2011. PMID 22131409.

[5] P. Philip et al., “Fatigue, sleepiness, and performance in simulated versus real driving conditions,” Sleep, vol. 28, no. 12, pp. 1511–1516, 2005.

[6] M. Hirshkowitz, “Fatigue, sleepiness, and safety: Definitions, assessment, methodology,” Sleep Med. Clin., vol. 8, no. 2, pp. 183–189, 2013.

[7] P. Thiffault and J. Bergeron, “Monotony of road environment and driver fatigue: A simulator study,” Accident Anal. Prevention, vol. 35, no. 3, pp. 381–391, 2003.

[8] M. M. Mitler, M. A. Carskadon, C. A. Czeisler, W. C. Dement, D. F. Dinges, and R. C. Graeber, “Catastrophes, sleep, and public policy: Consensus report,” Sleep, vol. 11, no. 1, p. 100, 1988.

[9] S. Nordbakke and F. Serberg, “Sleepy at the wheel: Knowledge, symptoms and behaviour among car drivers,” Transp. Res. F, Traffic Psychol. Behav., vol. 10, no. 1, pp. 1–10, 2007.

[10] R. Friswell and A. Williamson, “Exploratory study of fatigue in light and short haul transport drivers in NSW, Australia,” Accident Anal. Prevention, vol. 40, no. 1, pp. 410–417, 2008.

[11] P. Gershon, D. Shinar, T. Oron-Gilad, Y. Parmet, and A. Ronen, “Usage and perceived effectiveness of fatigue countermeasures for professional and nonprofessional drivers,” Accident Anal. Prevention, vol. 43, no. 3, pp. 797–803, 2011.

[12] P. Thiffault and J. Bergeron, “Monotony of road environment and driver fatigue: A simulator study,” Accident Anal. Prevention, vol. 35, no. 3, pp. 381–391, 2003.

[13] L. Barr, H. Howarth, S. Popkin, and R. J. Carroll, “A review and evaluation of emerging driver fatigue detection measures and technologies,” in Proc. Int. Conf. Fatigue Manage. Transp. Oper., 2005, pp. 1–27.

[14] A. Colic, O. Marques, and B. Furht, “Commercial solutions,” in Driver Drowsiness Detection: Systems and Solutions. Springer, 2014, ch. 2, pp. 19–23.

[15] M. Rostaghi and H. Azami, "Dispersion Entropy: A Measure for Time-Series Analysis," in IEEE Signal Processing Letters, vol. 23, no. 5, pp. 610-614, May 2016, doi: 10.1109/LSP.2016.2542881.

[16] A. Nijholt, D. Tan, “Brain computer interfacing for intelligent systems,” IEEE intelligent systems Vol 23. (3), 2008, pp. 72-9.

[17] Das, A.K.; Kumar, P.; Halder, S.; Banerjee, A.; Tibarewala, D.N. A Laboratory Based Experimental Evaluation of Ocular Parameters as Fatigue and Drowsiness Measures. Procedia Comput. Sci. 2020, 167, 2051–2059. [CrossRef]

[18] S. Datta, A. Banerjee, M. Pal, A. Konar, D. N. Tibarewala and R. Janarthanan, "Blink recognition to detect the possibility of eye dystonia based on electrooculogram analysis," Proceedings of the 2014 International Conference on Control, Instrumentation, Energy and Communication (CIEC), Calcutta, 2014, pp. 186-190. doi: 10.1109/CIEC.2014.6959075.

[19] Anwesha Banerjee, Monalisa Pal, Shreyasi Datta, D.N. Tibarewala, Amit Konar, Eye movement sequence analysis using electrooculogram to assist autistic children, Biomedical Signal Processing and Control, Volume 14, 2014, Pages 134-140, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2014.07.010.

[20] Roy Choudhury S, Venkataramanan S., Harshal B. Nemade, Sahambi J.S., “Design and Development of a Novel EOG Biopotential Amplifier”, IJBEM Vol. 7, No. 1, 2005.

[21] H. Azami and J. Escudero, "Refined Multiscale Fuzzy Entropy based on Standard Deviation for Biomedical Signal Analysis", Medical & Biological Engineering & Computing, 2016.

[22] M. Rostaghi and H. Azami, "Dispersion Entropy: A Measure for Time-Series Analysis," in IEEE Signal Processing Letters, vol. 23, no. 5, pp. 610-614, May 2016, doi: 10.1109/LSP.2016.2542881.

[23] Hamed Azami, Luiz Eduardo Virgilio da Silva, Ana Carolina Mieko Omoto, Anne Humeau-Heurtier, Two-dimensional dispersion entropy: An information-theoretic method for irregularity analysis of images, Signal Processing: Image Communication, Volume 75, 2019, Pages 178-187, ISSN 0923-5965, https://doi.org/10.1016/j.image.2019.04.013.

[24] He, S., Sun, K. & Wang, R. Fractional fuzzy entropy algorithm and the complexity analysis for nonlinear time series. Eur. Phys. J. Spec. Top. 227, 943–957 (2018). https://doi.org/10.1140/epjst/e2018-700098-x

[25] M. M. Alam, M. M. S. Raihan, M. R. Chowdhury and A. B. Shams, "High Precision Eye Tracking Based on Electrooculography (EOG) Signal Using Artificial Neural Network (ANN) for Smart Technology Application," 2021 24th International Conference on Computer and Information Technology (ICCIT), 2021, pp. 1-6, doi: 10.1109/ICCIT54785.2021.9689821.

[26] T. Ravichandran, N. Kamel, A. A. Al-Ezzi, K. Alsaih and N. Yahya, "Electrooculography-based Eye Movement Classification using Deep Learning Models," 2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), 2021, pp. 57-61, doi: 10.1109/IECBES48179.2021.9398730.

[27] B. García-Martínez, A. Fernández-Caballero, R. Alcaraz and A. Martínez-Rodrigo, "Application of Dispersion Entropy for the Detection of Emotions with Electroencephalographic Signals," in IEEE Transactions on Cognitive and Developmental Systems, doi: 10.1109/TCDS.2021.3099344.