Multivariate Multiscale Entropy: An Approach to Estimating Vigilance of Driver

Kawser Ahammed [1,*] and Mosabber Uddin Ahmed [2]

[1]Department of Electrical and Electronic Engineering, Jatiya Kabi Kazi Nazrul Islam University, Trishal, Mymensingh, Bangladesh kawser@jkkniu.edu.bd

[2]Department of Electrical and Electronic Engineering, University of Dhaka, Dhaka, Bangladesh

mosabber.ahmed@du.ac.bd

Abstract

Various driver's vigilance estimation techniques currently exist in the literature. But none of them estimates the driver's vigilance in the complexity domain. In this research, we propose the recently introduced multivariate multiscale entropy method to fill the above mentioned research gap. We apply this technique to differential entropy features of electroencephalogram and electrooculogram signals to detect driver's vigilance. Also, we employ it to the percentage of eye closure values to analyse the driver's cognitive states (awake, tired and drowsy) in the complexity domain. The contribution of this research is to efficiently classify the driver's cognitive states using a new feature based on multivariate multiscale entropy. The experimental complexity profile curves show the statistically significant differences ($p < 0.01$) among brain electroencephalogram, forehead electroencephalogram and electrooculogram signals. Moreover, the difference in the multivariate sample entropy across all scales in awake (1.0828 ± 0.4664), tired (0.7841 ± 0.3183) and drowsy (0.2938 ± 0.1664) states are statistically significant ($p < 0.01$). Also, the support vector machine, a machine learning technique, discriminates the driver's cognitive states with a promising classification accuracy of 76.2%. Therefore, the complexity profile of driver's cognitive states could be an indicator for vigilance estimation.

1. Introduction

Humans possess different mental states through which they interact with their surrounding complex environments. Vigilance, which means the ability to maintain more careful attention for the monotonous task, especially to notice possible danger, is one of the mental states of humans. Unfortunately, machines are incapable of interacting with surroundings and generally interact with users through a process known as Human-Computer Interaction (HCI) [1]. The purpose of HCI is to provide information for computers by converting brain activity into control signals so that the machine can respond simultaneously [2]. If a brain-computer interaction system works effectively, it could assess the high vigilance of the human brain.

Accidents that occur due to the loss of vigilance by drivers are common phenomena for some occupations such as driving buses, trucks, high-speed trains and air planes[1]. In these circumstances, high vigilance analysis is necessary to prevent the occurrence of drowsiness, sleepiness or fatigue by continuously

---

*Corresponding author. Email: kawser@jkkniu.edu.bd

observing the driver's mental state [3]. Hence, we can use the recently introduced multivariate multiscale entropy (MMSE) method for analyzing high vigilance.

There are various vigilance estimation techniques based on the video, multi-sensor and physiological signals [4, 5] in the literature. As the implementation of video and multi-sensor based approaches is arduous, researchers consider several physiological signal based techniques [3, 6–10] for vigilance estimation. Moreover, physiological signal based methods are considered as most fruitful, effective, and promising for vigilance estimation. Also, most of the physiological signals are an indicator of the transition between wakefulness to sleepiness. [11, 12].

In addition to the above mentioned methods, different entropy approaches [13, 14] have already been studied to determine the alertness of humans. However, all of these methods have been used in the time domain instead of the complexity domain. Therefore, we have introduced the MMSE method in this research and applied it to a dataset [1] to characterize the driver's vigilance in the complexity domain.

The organization of this paper is as follows: In section 2, we describe in detail the dataset along with data processing and the methods. The methods include multivariate multiscale entropy and multivariate sample entropy algorithm. We also mention some parameters and information to determine the complexity of multivariate time series. In section 3, we discuss the results along with corresponding statistical analysis. We describe the discussion and conclusion in sections 4 and 5 respectively.

2. Materials and Methods

2.1. Dataset

The data used in this research was collected from [1]. The EEG signals (CP1, CPZ, CP2, P1, PZ, P2, PO3, POZ, PO4, O1, OZ, and O2) from posterior site and the EEG signals (FT7, FT8, T7, T8, TP7, and TP8) from temporal site were recorded simultaneously using Neuroscan system with a 1000 Hz sampling rate according to the international 10-20 system. The GND electrode was located posterior to FPz and the REF electrode was located between Cz and CPz. At the same time, forehead EOG signals were recorded using Neuroscan system with a 1000 Hz sampling rate. The downsampling rate of EEG signals was 200 Hz to reduce computational complexity.

The EEG signals were preprocessed with a band-pass filter between 1 Hz and 75 Hz to reduce noise and artifacts. Short-time Fourier transform with a 8 s non-overlapping Hanning window was used to extract five EEG frequency bands: delta(1-4 Hz), theta(4-8 Hz), alpha(8-14 Hz), beta(14-31 Hz) and gamma(31-50 Hz). For each frequency band, the differential entropy (DE)

features [1] (efficient EEG features) were extracted. DE features were also extracted from the total frequency band (1-50 Hz) with a 2 Hz frequency resolution.

The five frequency bands might not be able to capture detailed vigilance dynamics. Therefore, the spectral features with higher frequency resolution were also extracted. For avoiding over-fitting with too high feature dimensionality, choosing a frequency resolution of 2 Hz was a trade-off. As DE proposed in [15] showed superior performance for vigilance estimation compared to conventional power spectral density features, we used it for vigilance estimation. The data processing steps mentioned above are shown in Figure 1. Also, a detailed description of the dataset will be found in [1].

2.2. Multivariate Multiscale Entropy

The MMSE evaluates multivariate sample entropy over different time scales and deals with the different embedding dimensions, time lags, and amplitude ranges of data channels in a rigorous and unified way. The MMSE [16, 17] is performed through the following steps:
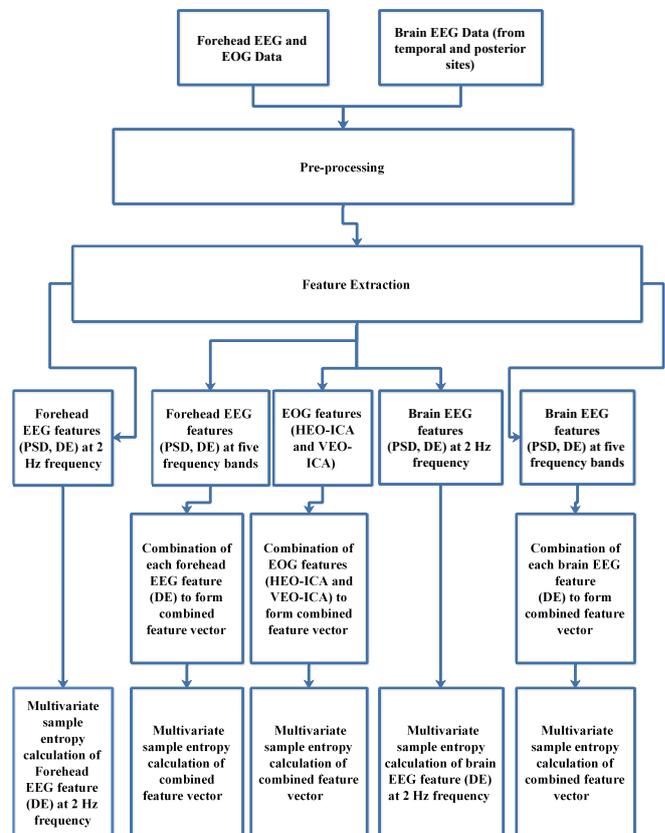
Figure 1. Data processing

(i) To define temporal scales of increasing length, apply the coarse-graining process to the c-variate time series $\{x_{l,i}\}_{i=1}^{N}$, $l = 1, 2, ..., c$, where N denotes the number of samples in each variate (channel). For a scale factor ξ, the elements of the multivariate coarse-grained time series are calculated as:

$$u_{l,k}^{\xi} = \frac{1}{\xi} \sum_{i=(k-1)\xi+1}^{k\xi} x_{l,i} \qquad (1)$$

where $1 \leq k \leq \frac{N}{\xi}$.

(ii) To plot multivariate sample entropy (MS_{En}) as a function of the scale factor ξ, calculate multivariate sample entropy for each coarse-grained multivariate $u_{l,k}^{\xi}$.

2.3. Multivariate Sample Entropy Calculation

The MS_{En} is the prerequisite for performing MMSE analysis over a number of data channels. For a c-variate coarse-grained time series $\{U_{l,k}^{\xi}\}_{k=1}^{\frac{N}{\xi}}$, $l = 1, 2, ..., c$, the MS_{En} [16, 17] is performed through the following steps:

(i) Form $(N' - n)$ composite delay vectors $U_m(i) \in \mathbb{R}^m (m = \sum_{l=1}^{c} m_l)$, where $i = 1, 2, ..., N' - n$, $N' = \frac{N}{\xi}$ and $n = max\{M\} \times max\{\tau\}$.

(ii) To determine the distance between any two composite delay vectors $U_m(i)$ and $U_m(j)$, define the maximum norm as $d[U_m(i), U_m(j)] = max_{p=1,...,m}\{|u(i + p - 1) - u(j + p - 1)|\}$.

(iii) Estimate the frequency of occurrence, $A_i^m(r) = \frac{1}{N'-n-1}C_i$ and define a global quantity, $A^m(r) = \frac{1}{N'-n} \sum_{i=1}^{N'-m} A_i^m(r)$, where $d[U_m(i), U_m(j)] \leq r$, $j \neq i$, r denotes a threshold value and C_i represents the number of calculated instances.

(iv) Extend the dimension of multivariate delay vector $U_m(i)$ from m_l to $m_l + 1$ for a specific random variable l, remaining the dimension of the other variables unchanged. As a result, a total of $c \times (N' - n)$ vectors $U_{m+1}(i)$ in $\mathbb{R}^{m+1}$ are obtained.

(v) Calculate the frequency of occurrence $A_i^{m+1}(r) = \frac{1}{c(N'-n)-1}Q_i$ and define a global quantity $A^{m+1}(r) = \frac{1}{c(N'-n)} \sum_{i=1}^{c(N'-n)} A_i^{m+1}(r)$, where Q_i denotes the number of calculated vectors for a given $U_{m+1}(i)$, such that $d[U_m(i), U_m(j)] \leq r$, $j \neq i$.

(vi) Finally, for a tolerance level r, Multivariate sample entropy is calculated by $MS_{En}(M, \tau, r, N') = $

$-ln[\frac{A^{m+1}(r)}{A^m(r)}]$, where MS_{En} denotes the multivariate sample entropy, $M = [m_1, m_2, ..., m_c]$ is the embedding vector, and $\tau = [\tau_1, \tau_2, ..., \tau_c]$ represents time lag vector.

2.4. Selection of Parameter values

While estimating multivariate sample entropy, we need to chose several parameters by introducing their constraints. For example, each channel of multivariate data exhibits different embedding parameters m_l and τ_l. Besides, the threshold parameter r needs to be set some percentage of the standard deviation of the normalized time series. In this research, we have chosen the value of $r = 0.4 \times$ (standard deviation of the normalized time series) with trial and error for better separation among MMSE curves.

2.5. Complexity Analysis of multivariate time series

From the MMSE plots (multivariate sample entropy as a function of the scale factor), the complexity of multivariate time series [16, 17] can be inferred as follows:

(i) If the sample entropy values of a multivariate time series are higher than those of the other time series for the majority of the scale factors, the multivariate time series will be more complex than another one.

(ii) If the signal in hand only contains useful information at the smallest scale, then the multivariate entropy values of the signal decrease monotonically for the scale factors.

3. Results

3.1. EEG (Brain and Forehead) and EOG Based Vigilance Estimation

This subsection analyses the temporal (FT7, FT8, T7 and T8), posterior (POZ, PO4, O1 and OZ), forehead, a fusion of temporal and posterior (T7, T8, PO3 and POZ) EEG and EOG signals in terms of complexity. To analyse these signals using MMSE, we had to choose the value of some parameters ($[m_1, m_2, m_3, m_4]$= embedding vector, $[\tau_1, \tau_2, \tau_3, \tau_4]$= time lag vector) as $m_1 = 1, m_2 = 1, m_3 = 1, m_4 = 1, \tau_1 = 1, \tau_2 = 1, \tau_3 = 1, \tau_4 = 1$.

From figure 2(a), 2(b), 2(c) and 2(d), it is noticeable that the multivariate sample entropy values of forehead EEG signals are higher compared to the temporal, posterior, brain (fusion of temporal and posterior) EEG and EOG signals for the majority of the scale factors. As the multivariate sample entropy values are higher for the majority of the scale factors, the forehead EEG signals contain correlations across multiple time scales and are, therefore, more complex compared to the
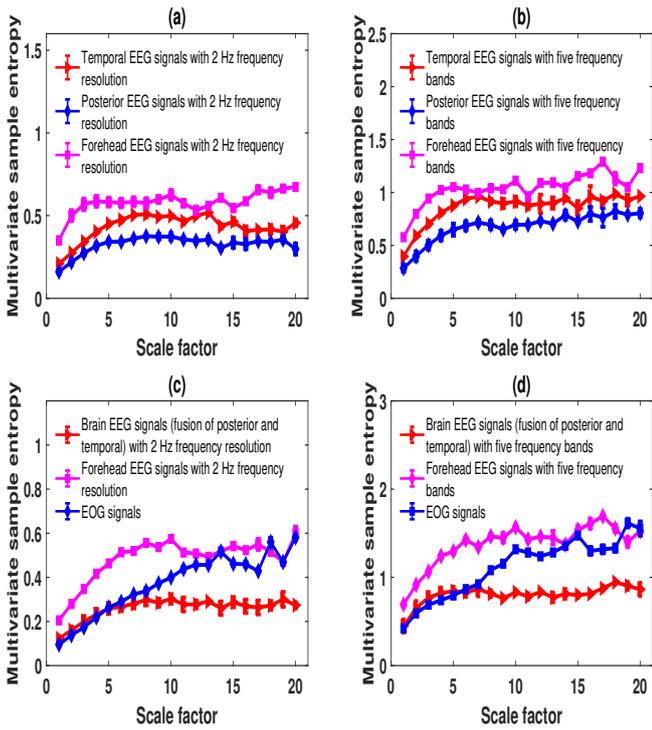
Figure 2. MMSE analysis (a) For temporal, posterior and forehead EEG time series with 2 Hz frequency resolution (b) For temporal, posterior and forehead EEG time series with five frequency bands (c) For fusion of temporal–posterior EEG, forehead EEG with 2 Hz frequency resolution and EOG time series (d) For fusion of temporal–posterior EEG, forehead EEG with five frequency bands and EOG time series, each with 885 sample numbers. The points on the curves represent mean value and error bars represent the standard deviation.

temporal, posterior, brain EEG (fusion of temporal and posterior) and EOG signals.

3.2. Statistical Analysis of EEG (Brain and Forehead) and EOG Based Vigilance Estimation

This subsection discusses the statistical analysis of EEG (Brain and Forehead) and EOG data. Firstly, we apply the One-way ANOVA (analysis of variance) test to EEG data to find the statistically significant difference among the forehead, temporal and posterior EEG signals. We find statistically significant difference among the above mentioned signals because of the ANOVA test results, $F = 35.03 > F_{crit} = 3.24$, effective size=0.64, $p < 0.01$ (null hypothesis rejection) at 2 Hz frequency resolution. We also find $F = 32.21 > F_{crit} = 3.24$, effective size=0.62, $p < 0.01$ (null hypothesis rejection) at 5 Hz frequency resolution.

Secondly, we again apply the One-way ANOVA test to forehead EEG, Brain EEG (fusion of temporal and posterior) and EOG data. Similarly, we find the statistically significant difference among the above

mentioned signals because of $F = 19.09 > F_{crit} = 3.16$, effective size=0.40, $p < 0.01$ (null hypothesis rejection) at 2Hz frequency resolution and $F = 54.91 > F_{crit} = 3.20$, effective size=0.42, $p < 0.01$ (null hypothesis rejection) at 5 Hz frequency resolution.

3.3. Vigilance Estimation Based on Cognitive States (Awake, Tired and Drowsy)

In this subsection, we analyse the driver's cognitive states (awake, tired and drowsy) in the complexity domain. According to the percentage of eye closure (PERCLOS) index [1] shown in Table 1, we use two threshold values (0.35 and 0.7) to categorize the EEG data into awake, tired and drowsy states. To analyse cognitive states using MMSE, we choose the value of embedding vectors ($[m_1, m_2]$) and time lag vectors ($[\tau_1, \tau_2]$) as $m_1 = 1, m_2 = 1$ and $\tau_1 = 1, \tau_2 = 1$.

Figure 3 shows that the multivariate sample entropy values of awake state are higher compared to tired and drowsy state for the majority of the scale factor. As the multivariate sample entropy values of awake state are higher compared to tired and drowsy state, the awake state contains correlations across multiple time scales and is, therefore, more complex compared to tired and

Table 1. Splitting of EEG data into three classes (awake, tired and drowsy)

PERCLOS label	Cognitive States
0< PERCLOS label <0.35	Awake
0.35< PERCLOS label <0.75	Tired
0.75< PERCLOS label ≤1	Drowsy
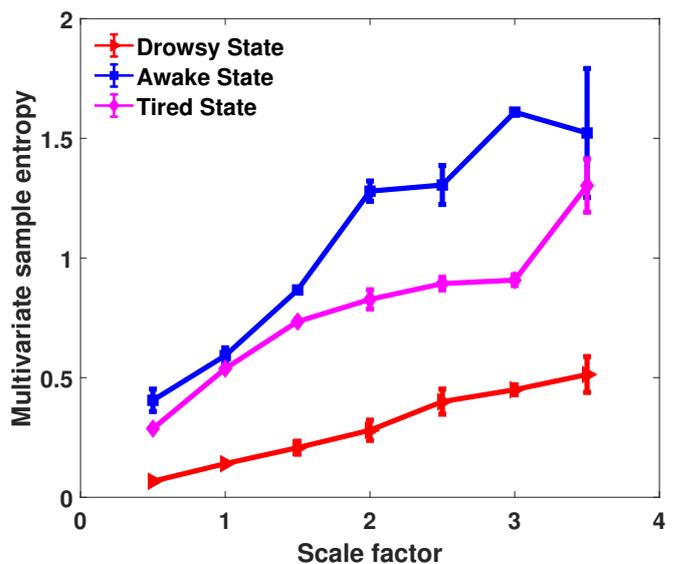
Figure 3. MMSE analysis of awake, tired and drowsy state. The points on the curves represent mean value and error bars represent the standard deviation.

drowsy state. This fact implies that a driver could show higher vigilance in the awake state compared to tired and drowsy state.

3.4. Statistical Analysis of Cognitive States

In this subsection, we analyse the cognitive states using statistical tests. At first, we apply the ANOVA test to PERCLOS values to investigate whether the cognitive states are statistically significantly different or not. We find that cognitive states are statistically significantly different because of the ANOVA test results, $F = 121.18 > F_{crit} = 3.26$, effective size=0.87, and $p < 0.01$ (null hypothesis rejection). Also, we apply Student's t-test following multiple comparisons to find which two groups are statistically significantly different. We again find that the awake and tired states are statistically significantly different because of the t-test results, $t = 5.48 > t_{crit} = 2.11$. The tired and the drowsy states are statistically significantly different because of the, $t = 8.37 > t_{crit} = 2.09$. Also, the awake and drowsy states are statistically significantly different due to $t = 20.6 > t_{crit} = 2.07$.

Although the MMSE method efficiently classifies the cognitive states in the complexity domain (Fig.3), we justify the classification ability of the MMSE method using SVM. We use multivariate sample entropy values of cognitive states as the attributes of SVM. We use 5-fold cross-validation to avoid biased classification and classification learner APP of MATLAB R2016b to classify cognitive states using SVM. We use SVM as it provides a promising classification accuracy compared to other classifiers. The confusion matrix of SVM is shown in Table 2 for the cognitive states. From the confusion matrix, we can say that the SVM has classified the cognitive states with a promising classification accuracy of 76.2%. Moreover, the awake state has been identified with a sensitivity of 57.1% and a specificity of 92.9%. Similarly, the drowsy state has been recognized with a sensitivity of 100% and a specificity of 85.7%. The tired state is detected with 71.43% sensitivity and 85.7% specificity. Besides, we find a statistically significant difference ($p <0.01$) in cognitive states using One way ANOVA test.

Table 2. Confusion matrix of SVM classifier output

True/Predicted	Awake	Drowsy	Tired
Awake	4	1	2
Drowsy	0	7	0
Tired	1	1	5

4. Discussion

In this study, we have developed and applied MMSE method to EEG, EOG and eye movement data for vigilance estimation. Although different types of research studies [18, 19] have already been performed for on-road real driving tests, many other scenarios, such as actor's performance in the theatre, require vigilance estimation. In future, we will apply our method to such kinds of real world scenarios to explore further application areas of MMSE. Also, the data used in this study were acquired in the context of driving rather monotonous a priori (driving on a highway). Hence, the MMSE method could be limited to this study context and could be less relevant in driving contexts of higher mental load (e.g. driving in a city).

The experimental results demonstrate that our approach can achieve comparable results with the conventional methods [20, 21]. The approaches proposed in [20, 21] detected the vigilance of drivers with an accuracy of 83.6% and 88.6% respectively. In this study, vigilance estimation has been performed without considering any neurofeedback. In future, we will focus on neurofeedback in a high vigilance task. Also, we could explore different optimization algorithms as proposed in [22, 23] to optimize the support vector machine for better classification accuracy.

In this research, we propose a novel method based on complexity science to characterize traditional EEG, forehead EEG, and EOG. The forehead EEG signals provide higher complexity compared to others in the complexity domain. Besides, the awake state shows higher complexity compared to tired and drowsy states in the complexity domain. It is also intuitive that cognitive loads are higher in the awake state compared to tired or drowsy states. As the signals in tired or drowsy states become more regular and thus, have less information, they show lower complexity values. In future, we could use these complexity features for building a vigilance estimation system.

5. Conclusion

In this paper, we introduce complexity profile based on multivariate multiscale entropy for characterizing driver's cognitive states (awake, tired and drowsy) along with brain EEG, forehead EEG and EOG signals. The MMSE analysis curves clearly show that forehead EEG signals reveal higher complexity compared to brain EEG and EOG signals. Moreover, the complexity profile curves along with statistical tests (t-test and one-way ANOVA test) demonstrate that the multivariate sample entropy values of awake state are significantly different from those of tired and drowsy state. Therefore, the MMSE method could be utilized practically to monitor continuous attention.

References

[1] Zheng W-L, Lu B-L, A multimodal approach to estimating vigilance using EEG and forehead EOG,

Journal of Neural Engineering **14**:1, 2017

[2] Brunner C, Blankertz B, Cincotti F, Kübler A, Mattia D, Miralles F, Nijholt A, Otal B, Salomon P, Müller-Putz GR, BNCI Horizon 2020 – Towards a Roadmap for Brain/Neural Computer Interaction. In: Stephanidis C., Antona M. (eds) *Universal Access in Human-Computer Interaction. Design and Development Methods for Universal Access. UAHCI 2014*, Lecture Notes in Computer Science, **8513**:475, 2014

[3] Ma J-X, Shi L-C, Lu B-L, Vigilance estimation by using electrooculographic features, *In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, **6591**, 2010

[4] Zhu X, Zheng W-L, Lu B-L, Chen X, Chen S, Wang C, EOG based drowsiness detection using convolutional neural networks, *In: International Joint Conference on Neural Network*, **128**, 2014

[5] Fuletra JD, Bosamiya D, A survey on drivers drowsiness detection techniques, *International Journal on Recent and Innovation Trends in Computing and Communication* **1**:816, 2013

[6] Bulling A, Ward JA, Gellersen H, Tröster G, Eye movement analysis for activity recognition using electrooculography, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **33**:741, 2011

[7] Shi L-C, Lu B-L, EEG-based vigilance estimation using extreme learning machines, *Neurocomputing* **102**:135, 2013

[8] Shi L-C, Duan R-N, Lu B-L, A robust principal component analysis algorithm for EEG-based vigilance estimation, *In: 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. **6623**, 2013

[9] Shi L-C, Jiao Y-Y, Lu B-L, Differential entropy feature for EEG-based vigilance estimation, *In: 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. **6627**, 2013

[10] Shi L-C, Lu B-L, Off-line and on-line vigilance estimation based on linear dynamical system and manifold learning, *In: 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. **6587**, 2010

[11] Huo X-Q, Zheng W-L, Lu B-L, Driving Fatigue Detection with Fusion of EEG and Forehead EOG, *In: International Joint Conference on Neural Networks*, **897**, 2016

[12] Zhang N, Zheng WL, Liu W, Lu BL, Continuous Vigilance Estimation Using LSTM Neural Networks. In: Hirose A, Ozawa S, Doya K, Ikeda K, Lee M, Liu D (eds) *Neural Information Processing. ICONIP 2016*. Lecture Notes in Computer Science, **9948**, 2016

[13] Shi LC, Jiao Y-Y, Lu BL, Differential Entropy Feature for EEG-based Vigilance Estimation. *In: 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. **6627**, 2013

[14] Srinivasan V, Eswaran C, Sriraam N, Approximate entropy based epileptic eeg detection using artificial neural networks, Trans. Infor. *Technology in Biomedicine* **11**:288, 2007

[15] Shi L-C, Jiao Y-Y, Lu B-L, Differential entropy feature for EEG-based vigilance estimation, *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, **6627**, 2013

[16] Ahmed MU, Mandic DP, Multivariate multiscale entropy: A tool for complexity analysis of multichannel data, *Phys. Rev. E* **84**:061918, 2011

[17] Ahmed MU, Mandic DP, Multivariate Multiscale Entropy Analysis, *IEEE Signal Processing Letters* **19**:91, 2012

[18] Chen Z, Bamidis PD, Chouvarda I, Bekiaris E, Monitoring sleepiness with on-board electrophysiological recordings for preventing sleep-deprived traffic accidents, *Clinical Neurophysiology* **118**:1906, 2007

[19] Haufe S, Kim J-W, Kim I-H, Sonnleitner A, Schrauf M, Curio G, Blankertz B, Electrophysiology-based detection of emergency braking intention in real-world driving, *Journal of Neural Engineering.* **11**:056011, 2014

[20] Correa AG, Orosco L, Laciar E, Automatic detection of drowsiness in EEG records based on multimodal analysis, *Med Eng Phys* **36**:244, 2014

[21] Nguyen T, Ahn S, Jang H, Jun SC, Kim JW, Utilization of a combined EEG/NIRS system to predict driver drowsiness, *Sci Rep* **7**:43933, 2017

[22] Abualigah L, Yousri D, Abd Elaziz M, Ewees A A, Al-Qaness M A, Gandomi A H, Aquila optimizer: a novel meta-heuristic optimization algorithm, *Computers & Industrial Engineering*, 157, 107250, 2021.

[23] Abualigah L, Diabat A, Advances in sine cosine algorithm: a comprehensive survey, *Artificial Intelligence Review*, 54(4), 2567-2608, 2021.