Multivariate Multiscale Entropy: An Approach to Estimating Vigilance of Driver

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Research

Keywords: Complexity, Differential entropy, EEG, EOG, PERCLOS, Multivariate sample entropy feature, SVM

Posted Date: January 13th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-30557/v2>

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RESEARCH

Multivariate Multiscale Entropy: An Approach to Estimating Vigilance of Driver

Kawser Ahammed^{1*} and Mosabber Uddin Ahmed²

Abstract

Various driver's vigilance estimation techniques currently exist in literature. But none of them detects the vigilance of driver in complexity domain. As a result, we have proposed the recently introduced multivariate multiscale entropy (MMSE) method to fill this research gap. In this research, we have applied the MMSE technique to differential entropy features of electroencephalogram (EEG) and electrooculogram (EOG) signals for detecting vigilance of driver in complexity domain. The MMSE has also been employed to PERCLOS (Percentage of Eye Closure) values to analyse cognitive states (awake, tired and drowsy) in complexity domain. The contribution of this research is to show how a new feature called MMSE can efficiently classify the awake, tired and drowsy state of the driver in complexity domain. Another contribution is to demonstrate the distinguishing ability of the MMSE by validating it with applying multivariate sample entropy feature of cognitive states to support vector machine (SVM). The experimental MMSE analysis curves show statistically significant differences ($p < 0.01$) in terms of complexity among brain EEG signals, forehead EEG signals and EOG 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 SVM, a machine learning technique, has discriminated the cognitive states with the promising classification accuracy of 76.2%. As a result, the MMSE analysis of cognitive states can be implemented practically for vigilance detection by building a programmable vigilance detection system.

Keywords: Complexity; Differential entropy; EEG; EOG; PERCLOS; Multivariate sample entropy feature; SVM

1 Introduction

Humans possess different types of 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 unable to interact 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 through converting brain activity into control signals for computers so that the machine can respond simultaneously [2]. If a brain-computer interaction system works effectively, it can assess 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 this case, high vigilance analysis is necessary to prevent the occurrence of drowsiness, sleepiness or fatigue by continuously observing the driver's mental state [3]. This high vigilance can be analysed with the multivariate multiscale entropy (MMSE) method.

There are various methods of estimating vigilance in the literature. These methods can be referred to as video-based, multi-sensor based and physiological signals based [4, 5]. Since the implementation of both video and multi-sensor based approaches is arduous, various physiological signal based approaches, for example, eye movement [3, 6] and autonomic nervous system activity [7, 8, 9, 10], have been studied for vigilance estimation. Moreover, physiological signal based methods are considered as most fruitful, effective, and promising for vigilance estimation because most of the physiological signals are an indicator of transition between wakefulness to sleepiness [11, 12].

In addition to the above methods, there are different entropy approaches [13, 14] that have been studied to determine the alertness of humans. However, all of these methods have been analysed in time do-

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main instead of complexity domain. For this reason, the MMSE method has been introduced and applied to a multimodal dataset [1] to characterize the vigilance of drivers from electroencephalogram (EEG) and electrooculogram (EOG) signals in complexity domain.

The organization of the paper is as follows. In section 2, the materials and methods have been represented. The results have been described in section 3. The discussion and conclusion have been demonstrated respectively in section 4 and section 5.

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 standard electrode set up of Neuroscan systems was followed, where 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 were 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. EEG signals are usually analysed in the five frequency bands. However, these five frequency bands might not be able to capture detailed vigilance dynamics. Therefore, spectral features with higher frequency resolution are extracted. Also, to avoid overfitting with too high feature dimensionality, choosing a frequency resolution of 2 Hz was a trade-off. It means for every 2 Hz frequency range, DE features and power density (PSD) features were calculated. Since DE proposed in [17] showed superior performance for vigilance estimation compared to conventional power spectral density features, we used it for vigilance estimation. The data processing performed during this research has been shown in Figure 1. 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 calculation of MMSE [15, 16] is performed through the following steps:

- (i) To define temporal scales of increasing length, apply the coarse-graining process to the c -variate time series $\{x_{l,i}\}_{i=1}^N, l = 1, 2, \dots, c$, 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:

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

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 $\{U_{l,k}^\xi\}_{k=1}^{\frac{N}{\xi}}, l = 1, 2, \dots, c$, the MS_{En} [15, 16] 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 $i = 1, 2, \dots, N' - n$, $N' = \frac{N}{\xi}$ 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 $d[U_m(i), U_m(j)] = \max_{p=1, \dots, m} \{|u(i + p - 1) - u(j + p - 1)|\}$.
- (iii) Estimate the frequency of occurrence, $A_i^m(r) = \frac{1}{N' - n - 1} C_i$ and define a global quantity, $A^m(r) = \frac{1}{N' - n} \sum_{i=1}^{N' - n} A_i^m(r)$, 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, $M=[m_1, m_2, \dots, m_c]$ is the embedding vector, and $\tau = [\tau_1, \tau_2, \dots, \tau_c]$ represents time lag vector.

2.4 Selection of Parameter values

During the multivariate sample entropy calculation, several parameters have to be chosen by introducing their constraints. For example, for multivariate data, the individual channel exhibits different embedding parameters m_i and τ_i . Besides, the threshold parameter r needs to be set some percentage of the standard deviation of the original signal. To estimate vigilance of the driver using MMSE, we have chosen r with trial and error as 40% of the standard deviation of the original signal for better separation among MMSE curves.

2.5 Complexity Analysis of multivariate time series

The rule for measuring the complexity of multivariate time series [15, 16] from the MMSE plots (multivariate sample entropy represented as a function of the scale factor) is given below:

- 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.
- 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 EEG signals (FT7, FT8, T7 and T8), posterior EEG signals (POZ, PO4, O1 and OZ), forehead EEG signals, fusion of temporal and posterior EEG signals (T7, T8, PO3 and POZ) and EOG signals in terms of complexity with a view to estimating vigilance of driver. To analyse these signals using multivariate multiscale entropy (MMSE), 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) were chosen to calculate multivariate sample entropy. The value of the parameters were $m_1 = 1, m_2 = 1, m_3 = 1, m_4 = 1, \tau_1 = 1, \tau_2 = 1, \tau_3 = 1, \tau_4 = 1$.

From figure 2(a), 2(b), 2(c) and 2(d) it is observed that for the majority of the scale factors, the values of the multivariate sample entropy for forehead EEG signals are higher than the temporal EEG, posterior EEG, brain EEG (fusion of temporal and posterior)

Figure 1: Data processing

and EOG signals. Due to higher multivariate sample entropy values of forehead EEG signals for the majority of the scale factors, it can be said that forehead EEG signals contain correlations across multiple time scales and is, therefore, more complex than the temporal EEG, posterior EEG, brain EEG (fusion of temporal and posterior) and EOG signals.

Figure 2: MMSE analysis (a) For brain EEG (without fusion of temporal and posterior) and forehead EEG time series with 2 Hz frequency resolution (b) For brain EEG (individually temporal and posterior) and forehead EEG time series with five frequency bands (c) For brain (fusion of posterior and temporal) EEG and forehead EEG signals with 2 Hz frequency resolution and EOG time series (d) For brain (fusion of posterior and temporal) EEG and forehead EEG signals with five frequency bands and EOG time series, each with 885 samples numbers. The points on the curves represent mean value and error bars represent the standard deviation.

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

This subsection discusses the statistical analysis performed on EEG (Brain and Forehead) and EOG data. Firstly, One-way ANOVA (analysis of variance) test has been applied to EEG values to find whether the difference among the forehead, temporal and posterior brain EEG signals are statistically significant or not in terms of multivariate sample entropy values. After applying ANOVA test, we have found statistically significant difference because the ANOVA test gives the result of $F = 35.03 > F_{crit} = 3.24$, effective size=0.64, $p < 0.01$ (null hypothesis rejection) at 2 Hz frequency resolution. This test also gives the result of $F = 32.21 > F_{crit} = 3.24$, effective size=0.62, $p < 0.01$ (null hypothesis rejection) at 5 Hz frequency resolution.

Secondly, after implementing One-way ANOVA test, we can say that the difference among the forehead EEG, the fusion of temporal and posterior EEG and EOG are statistically significant in terms of multivariate sample entropy values as One-way ANOVA test provides $F = 19.09 > F_{crit} = 3.16$, 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)

This subsection categorizes EEG data into three cognitive states (Awake, Tired and Drowsy) with two thresholds (0.35 and 0.7) according to the PERCLOS index [1] shown in Table 1. To analyse EEG data using

Table 1: Splitting of EEG data into three categorizes (awake, tired and drowsy) with two thresholds (0.35 and 0.7) according to the PERCLOS index.

PERCLOS label	Cognitive States
$0 < \text{PERCLOS label} < 0.35$	Awake
$0.35 < \text{PERCLOS label} < 0.75$	Tired
$0.75 < \text{PERCLOS label} \leq 1$	Drowsy

MMSE, the value of some parameters ($[m_1, m_2]$ = embedding vector, $[\tau_1, \tau_2]$ = time lag vector) were chosen to calculate multivariate sample entropy. The value of the parameters were $m_1 = 1, m_2 = 1, \tau_1 = 1, \tau_2 = 1$.

From figure 3, one can state that multivariate sample entropy values of awake state are higher than both tired and drowsy state for the majority of the scale factor. Two (awake and tired) of these three cognitive states overlap with each other only for scale factor 2 and 7. This indicates that these three cognitive states can be identified by MMSE algorithm. Since the multivariate sample entropy values for the awake state are

Figure 3: MMSE analysis for awake state, tired state and drowsy state. The points on the curves represent mean value and error bars represent the standard deviation.

higher than both tired and drowsy state except for scale factor 2 and 7, it can be said that unlike tired and drowsy state, awake state contains correlations across multiple time scales and is, therefore, more complex than both tired and drowsy state. This fact also implies that a driver shows higher vigilance at the awake state than both tired and drowsy state.

3.4 Statistical Analysis of Cognitive States

In this subsection, we have analysed the PERCLOS values with statistical tests. To do this, two statistical tests (Student's t-test as well as the one-way ANOVA test), have been applied to cognitive states. At first, we have applied the ANOVA test to investigate whether the cognitive states are statistically significant or not in terms of multivariate sample entropy values. After applying ANOVA test, Student's t-test following multiple comparisons has been applied to find the information about which two groups are significantly different and which are not. In all cases, we have found that cognitive states are statistically significant because of the ANOVA test gives the result of $F = 121.18 > F_{crit} = 3.26$, effective size=0.87, and $p < 0.01$ (null hypothesis rejection) and t-test gives the result of $t = 5.48 > t_{crit} = 2.11$ for awake and tired state, $t = 8.37 > t_{crit} = 2.09$ for tired and drowsy state and $t = 20.6 > t_{crit} = 2.07$ for awake and drowsy state.

Although the MMSE method has classified the cognitive states in complexity domain, the classification

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

ability of the MMSE method have further been justified with the SVM. To do this, 7 mean multivariate sample entropy values of awake state, 7 mean multivariate sample entropy values of tired state and 7 mean multivariate sample entropy values of drowsy state are used as the attributes of SVM for the classification task. Here, we have used a 5-fold cross validation approach for measuring classification results and to avoid biased classification. To classify using SVM, we have used classification learner APP of MATLAB R2016b. In this research, SVM has been used as a classifier as it provided a promising classification accuracy compared to other classifiers. Since multivariate sample entropy values were the input of the SVM, it provided a confusion matrix as shown in Table 2 for the cognitive states. After analysing confusion matrix, it can be said that cognitive states have been classified with the promising classification accuracy of 76.2%. Moreover, the awake state has been identified with sensitivity of 57.1% and specificity of 92.9%. Similarly, the drowsy state has been recognised with sensitivity of 100% and specificity of 85.7%. The tired state is detected with 71.43% sensitivity and 85.7% specificity. Besides, statistically significant difference ($p < 0.01$) has been observed among cognitive states with One way ANOVA test.

4 Discussion

In this study, we have developed and applied MMSE method to EEG, EOG and eye movement data for vigilance estimation. Although various types of research [18, 19] have been done for on-road real driving tests, many other scenarios, such as actors performance in the theatre, require vigilance estimation. In future, we will apply our method to this type of real world scenarios to explore further application areas of MMSE. Also, the data used in this study was acquired in a context of driving rather monotonous a priori (driving on a highway). The validity of the method applied to this study can be limited to this study context and may 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, neurofeedback in high vigilance task should be investigated.

In this research, we propose a novel method based on complexity science to characterize traditional EEG, forehead EEG, and EOG. From the results, it can be inferred that forehead EEG signals can give higher complexity curves and easily distinguished in the complexity domain. Besides, different mental states like awake, tired or sleep states can also be distinguished in the complexity domain. It is also intuitive that cognitive loads are higher in awake states than tired or drowsy states. As a result, the complexity profiles for awake states are higher as in drowsy or tired states the signals become more regular and have less information thus have lower complexity values. This complexity features can give us complementary information for the future to build vigilance estimation system.

5 Conclusion

This paper represents a novel method (MMSE) for vigilance estimation. In this paper, characterization of the brain EEG signals, forehead EEG signals, EOG signals and cognitive states (awake, tired and drowsy) have been performed in terms of complexity and the results have been validated by statistical tests. The MMSE analysis curves have clearly shown that forehead EEG signals reveal higher complexity compared to brain EEG and EOG signals. Moreover, statistical tests (t-test and one-way ANOVA test) used to justify the MMSE results have shown that MS_{En} values of awake state are significantly different from those of tired state and drowsy state. From the experimental results, we have observed that vigilance of driver decreases when the driver goes to one of the states (tired or drowsy) from the awake state. The simulation results also indicate that the MMSE method can be utilized practically to monitor continuous attention.

Availability of data and material:

<http://bcmi.sjtu.edu.cn/home/seed/downloads.html#seed-vig-access-anchor>

Competing interests

The authors declare that they have no competing interests.

Funding

Not applicable

Acknowledgements

The authors are thankful to Wei-Long Zheng for providing SEED-VIG data which is not publicly available.

Author's Contributions

Kawser Ahammed: Conceived and designed the analysis framework, analyzed the data, drafted the manuscript, read and approved the final manuscript.
Mosabber Uddin Ahmed: Analyzed and interpreted the result, reviewed the manuscript critically, read and approved the final manuscript.

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Figures

Figure 1

Data processing

Figure 2

MMSE analysis (a) For brain EEG (without fusion of temporal and posterior) and forehead EEG time series with 2 Hz frequency resolution (b) For brain EEG (individually temporal and posterior) and forehead EEG time series with ve frequency bands (c) For brain (fusion of posterior and temporal) EEG and forehead EEG signals with 2 Hz frequency resolution and EOG time series (d) For brain (fusion of posterior and temporal) EEG and forehead EEG signals with ve frequency bands and EOG time series, each with 885 samples numbers. The points on the curves represent mean value and error bars represent the standard deviation.

Figure 3

MMSE analysis for awake state, tired state and drowsy state. The points on the curves represent mean value and error bars represent the standard deviation.