Original

Driver Fatigue Detection using EEG Microstate Features and Support Vector Machines

Zahra Yaddasht (PhD Candidate)[1], Kamran Kazemi (PhD)[1]*, Habibollah Danyali (PhD)[1], Ardalan Aarabi (PhD)[2,3]

[1]Department of Electrical Engineering, Shiraz University of Technology, Shiraz, Iran
[2]Laboratory of Functional Neuroscience and Pathologies (UR UPJV 4559), University Research Center, University Hospital, Amiens, France
[3]Faculty of Medicine, University of Picardy Jules Verne, Amiens, France

ABSTRACT

Background: Driver fatigue detection is crucial for traffic safety. Electroencephalography (EEG) signals, which directly reflect the human mental state, provide a reliable approach for identifying fatigue.

Objective: This study aimed to investigate the effectiveness of EEG microstate analysis in detecting driver fatigue by analyzing variations in microstate features between normal and fatigued states.

Material and Methods: This analytical study aimed to develop a supervised machine learning approach for driver fatigue detection using EEG microstate features. EEG data were collected from 10 individuals in both normal and fatigued states. Microstate analysis was performed to extract key features, including duration, occurrence, coverage, and Microstate Mean Power (MMP), from four types of microstates labeled A, B, C, and D. These features were then used as inputs to train and test a Support Vector Machine (SVM) for classifying each EEG segment into either normal state or fatigue state.

Results: The classification achieved high accuracy, particularly when combining MMP and occurrence features. The highest accuracy recorded was 98.77%.

Conclusion: EEG microstate analysis, in combination with SVM, proves to be an effective method for detecting driver fatigue. This approach can be utilized for real-time driver monitoring and fatigue alert systems, enhancing road safety.

Citation: Yaddasht Z, Kazemi K, Danyali H, Aarabi A. Driver Fatigue Detection using EEG Microstate Features and Support Vector Machines. *J Biomed Phys Eng*. 2025;15(6):515-524. do: 10.31661/jbpe.v0i0.2501-1883.

Keywords

Fatigue; Driving Fatigue; Electroencephalography; EEG Microstate Analysis; Support Vector Machine

Introduction

Fatigue is a significant mental and physical concern that affects a driver's ability to safely control a vehicle. Therefore, the development of tools to detect early signs of fatigue and enable timely intervention is in high demand and has become a critical safety issue. To address this problem, researchers have utilized various physiological and behavioral biomarkers to develop sophisticated, non-invasive systems for fatigue detection. These methods include tracking eye movements, using Electrooculography (EOG), and measuring brain activity through Electroencephalography (EEG). Among these, EEG is considered the most commonly used signal since it can directly measure brain activity and assess fatigue status [1,2]. To design an effective driving fatigue detection system using EEG signals, it is essential to extract

*Corresponding author: Kamran Kazemi
Department of Electrical Engineering, Shiraz University of Technology, Shiraz, Iran
E-mail: kazemi@sutech.ac.ir

Received: 15 December 2024
Accepted: 2 February 2025

informative features from these signals.

There have been several EEG studies related to driving fatigue detection that have applied both classical machine learning and deep learning approaches [3,4]. Classical methods typically involve feature extraction followed by classification using algorithms, such as Support Vector Machines (SVM) [5,6]. Recent research on driver fatigue detection has utilized diverse methods to analyze EEG signals, including time-domain waveform feature analysis, frequency-domain functional spectrum analysis, and time-frequency-domain techniques, such as wavelet transform and Fast Fourier Transform (FFT) [3]. Additionally, nonlinear dynamics feature extraction methods, including wavelet entropy, permutation entropy, sample entropy, and fuzzy entropy, have also been utilized [4,7]. Moreover, network features derived from brain functional connectivity graphs based on EEG signals have been employed for driver fatigue detection [6].

The EEG microstates are brief, quasi-stable patterns of scalp electrical activity ranging from 80 to 120 milliseconds before transitioning to another state. They are related to large-scale neural networks and can quasi-synchronously reflect their activities [8,9]. EEG microstates are instantaneous representations of the global functional state of the brain and can reflect changes in global brain network activation. They are typically visualized through brain topography. While the number of microstates can vary between studies, four microstates are most commonly identified and used in EEG microstate analysis, which are labeled as A, B, C, and D [8].

Recent studies using EEG microstate analysis have revealed changes in brain activity, which can be used for detecting fatigue [10-11]. Baldini et al. [10] investigated fatigue in Multiple Sclerosis (MS) patients and found that activity in microstate F (associated with the salience network) decreased, while microstate B (linked to the visual network) increased in the fatigued subjects in broadband and beta bands. Li et al. [11] examined how mental fatigue affects EEG microstate patterns of aircraft pilots. Across four identified microstates, they found that fatigue increased the global explained variance and time parameters of microstate C, while decreasing the occurrence and coverage of microstate D. Furthermore, they found that transitions between different microstates happened with different probability, highlighting the effectiveness of EEG microstates in detecting mental fatigue.

Although different studies have revealed microstate changes in different diseases and mental states [12-15], few have focused on the potential of microstate-based features for detecting driver fatigue. In this study, we applied microstate analysis to extract relevant features from broadband-decomposed EEG signals to classify them into fatigue state or normal state. Key features, including average duration, occurrence per second, total time coverage, and Microstate Mean Power (MMP), were extracted from EEG signals of healthy subjects in both fatigue and normal states. These features were then used to train an SVM classifier for signal classification.

Material and Methods

The entire process of this analytical study, as illustrated in Figure 1, involved preprocessing EEG signals to remove artifacts and segmenting the continuous data into overlapping epochs. Each EEG segment subsequently underwent microstate analysis to identify distinct microstates. From these, temporal parameters including duration, occurrence, time coverage, and microstate mean power were extracted. Finally, the extracted features were used to train an SVM classifier to classify the segments into normal or fatigued states.

EEG Data recording and preprocessing

In this study, we used the EEG data recorded from 12 subjects aged between 19-24 years

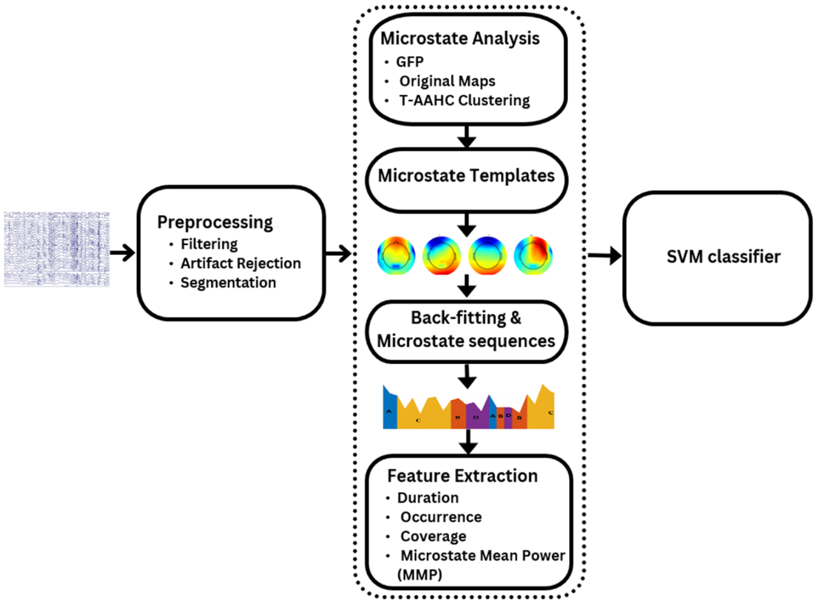

Figure 1: Block diagram of the proposed Electroencephalography (EEG) based fatigue detection method. The process includes preprocessing, EEG microstate analysis, feature extraction, and classification using an SVM classifier. (SVM: Support Vector Machine)

recruited from Jiangxi University of Technology [7], which is a publicly accessible EEG dataset, for method development and evaluation. The EEG recording was performed with a static driving simulator in a controlled lab environment in two phases. The EEG signals from the last 5 minutes of the first 20 minutes of driving were recorded and identified as the normal state. Participants then drove continuously for 40 to 100 minutes. Once the self-reported fatigue questionnaire indicated that the subject was in a driving fatigue state, the EEG recording was stopped. The last 5 minutes of recorded EEG signals were labeled as fatigue. EEG signals were collected using a 32-channel electrode cap, which comprised 30 active channels and 2 reference channels, based on the international 10–20 system. Data from all channels were referenced to two electrically connected mastoid electrodes at A1 and A2 and digitized at 1000 Hz. Eye movements and blinks were monitored by recording the horizontal and vertical EOG signals. Data preprocessing was conducted using Neuroscan's Scan 4.3 software. To reduce noise, the raw signals were filtered with a 50 Hz notch filter and a band-pass filter ranging from 0.15 Hz to 45 Hz [7]. Independent Component Analysis (ICA) was applied to decompose the EEG signals, allowing for the identification and removal of noise components associated with artifacts. The signal quality was then assessed visually, leading to the exclusion of two subjects due to the remaining artifacts in their signals. Consequently, we used the EEG data recorded from 10 subjects.

Finally, we segmented the continuous EEG signals into 5-second overlapping epochs with a 3-second overlap. From the EEG dataset for each subject, 295 segments in the normal state and 295 segments in the fatigue state were extracted. All segments (2,950 segments in the fatigue state and 2,950 segments in the normal state) were used for feature extraction using microstate analysis and classification to determine whether each segment belonged to a subject in a normal or fatigued state.

EEG microstate analysis

The Microstate EEGlab toolbox [16] was

used to segment the entire EEG into a discrete set of a limited number of prototypical topographies that remained quasi-stable for a short period of time (around 80–120 ms) before rapidly transitioning to a different topography. These short periods have been called microstates. The time domain microstate analysis is performed mainly in two stages: i) a segmentation process of EEG data to find the most representative template maps, and ii) the back-fitting process to fit these classes back to the EEG data [16]. In the first stage of microstate analysis, the Global Field Power (GFP) was computed (Equation 1) for each time point t of the entire EEG segment. GFP served as an indicator of the potential variance across all electrodes at each time point.

$$GFP\left(t\right)=\sqrt{\sum_{i}^{N}(V_i\left(t\right)-V_{mean}\left(t\right))^2\,/\,N_e} \qquad (1)$$

Where $V_i(t)$ and $V_{mean}(t)$ are the instantaneous and mean EEG signal across N_e electrodes at time *t*. We utilized all 30 EEG electrodes in microstate analysis to derive the GFP for each time point, which results in an oscillatory time series for GFP. Since scalp topographies remain stable around GFP peaks with the highest signal-to-noise ratio, these time points using data from all EEG electrodes were used for the clustering algorithm.

Then, topographic maps corresponding to the GFP peaks were extracted at specific time points and underwent Topographic Atomize & Agglomerate Hierarchical Clustering (T-AAH) analysis [16]. Compared to k-means clustering, T-AAHC offers more consistent identification of microstate classes [13]. The polarity of the microstate topography was ignored. Based on previous studies showing that four topographies are sufficient to represent whole-brain activity, the number of clusters was set to four (c=4) [8]. The Global Explain Variance (GEV) and the Cross-Validation (CV) criterion were used to determine the subject representative microstate topographies. These procedures were applied to the EEG of each subject. This process was applied separately to the EEG recordings from both normal and fatigue conditions, resulting in four distinct microstate classes (A, B, C, and D) per condition. These classes represent the most common topographic patterns in the EEG data for each state.

In the second stage, the back-fitting process was performed by assigning microstate labels to EEG samples based on their highest topographic similarity to the corresponding microstate prototypes. This similarity is measured using Global Map Dissimilarity (GMD). The GMD is a distance measure that is invariant to the strength of the signal and only considers how similar the topographical maps appear. This procedure enabled a detailed analysis of the EEG signals within the time series corresponding to the four identified microstates, facilitating a comprehensive understanding of the temporal dynamics and characteristics of the EEG data across different microstates. Back-fitting according to individual topographic maps provides an optimal fit between the EEG data and the maps.

Back-fitting and quantifying according to individual template maps have the advantage of providing an optimal fit between the chosen template and their respective EEG data. However, using a separate template for each subject increases feature variance and reduces the comparability of extracted individual microstate characteristics [16]. To address this, we selected a subject in the normal state as a reference and utilized their template maps for back-fitting all subjects. Following the back-fitting, we extracted appropriate features to classify the EEG segments into normal and fatigue states.

Feature extraction

Microstate sequences reflect the potential neural dynamics of brain activity as a symbolic time series and serve as the basis for extracting microstate characteristics. In this study, four types of features were extracted to classify each EEG segment as either a normal or fatigued state. The occurrence represents the mean number of times per second that a specific microstate remains dominant, reflecting the likelihood of the underlying neural activation being represented. The coverage refers to the percentage of the EEG segment's total analysis time during which a specific microstate remains dominant. The duration is defined as the average time that a specific microstate remains dominant, providing insight into the stability of the underlying neural configuration during either the normal or fatigue state [17]. Finally, the MMP quantifies the average signal power recorded at each electrode during a given microstate (A, B, C, or D), reflecting the corresponding brain activity. For an EEG signal $V_i(t)$ from the i^{th} electrode (i=1, ..., N_e electrodes), the mean power during a specific microstate is defined as:

$$MMP_i = \frac{1}{T}\sum_{n=1}^{T}\left(V\left(n\right)_i\right)^2 \qquad (2)$$

where $V(n)_i$ represents the EEG signal amplitude at time sample n for the i^{th} electrode, and T is the total number of time points within that specific microstate. This calculation yields 30 MMP features per microstate, resulting in a total of 120 features across all four microstates.

Feature extraction through microstate analysis generates 132 features for all microstates A, B, C, and D. To minimize variability that could affect classifier performance, Z-score normalization was applied [18]. This normalization step ensured that all features were scaled to a common range, thereby mitigating the impact of outliers and reducing the influence of individual differences.

Classification

SVM is a supervised machine learning method that aims to simultaneously minimize classification errors and maximize the geometric margin between classes. This is achieved by iteratively constructing an optimal separating hyperplane that distinguishes samples from two different classes. In this study, we used an SVM with a radial basis function (RBF) kernel, selected for its higher classification efficiency compared to other kernel types, to classify entire EEG segments as either normal or fatigued based on the extracted microstate features.

A stratified 10-fold cross-validation was applied to the EEG segments of each subject, with data from 10 subjects used for training and testing; specifically, 9 folds were combined for training, while the remaining fold from all subjects served as the test set. This process was repeated to k=10 times, with each fold serving as the test set exactly once, ensuring that all data points were used for both training and testing across the iterations.

Results

EEG microstates analysis

Figure 2 shows EEG microstate topographic maps of a selected subject in two distinct states: normal (top row) and fatigue (bottom row). Each map represents the spatial distribution of brain activity as reflected by characteristic microstate A, B, C, and D. The topography maps show differences between the two states. Figure 3 shows the temporal parameters (Duration, Occurrence, and Coverage) of the four microstates A, B, C, and D in normal and fatigue states obtained from microstate analysis. For microstates A, C, and D, Coverage increased during the fatigue state, while Duration and Occurrence showed slight decreases. In microstate B during the fatigue state, Coverage decreased along with Duration and Occurrence. Across all four microstates, Occurrence generally decreased in the fatigue state compared to the normal state.

Classification performances

Table 1 shows the mean classification accuracy obtained by tenfold cross-validation for three temporal microstate features and MMP across four microstates (A, B, C, and D) and their combined features of four

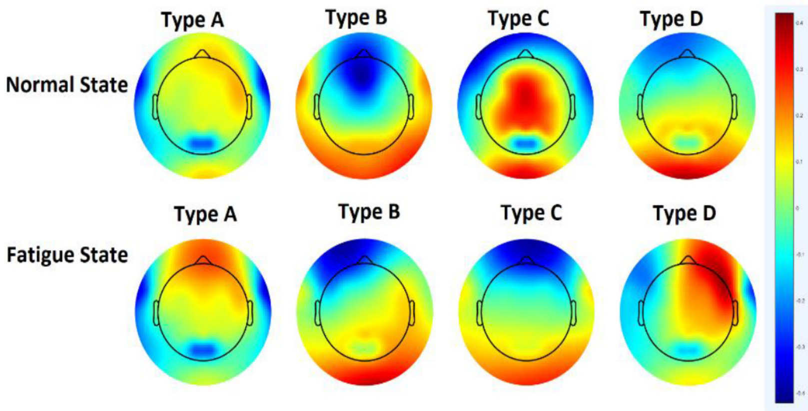

Figure 2: Topographies of the four microstates A, B, C, and D in the normal state (top) and the fatigue state (bottom).

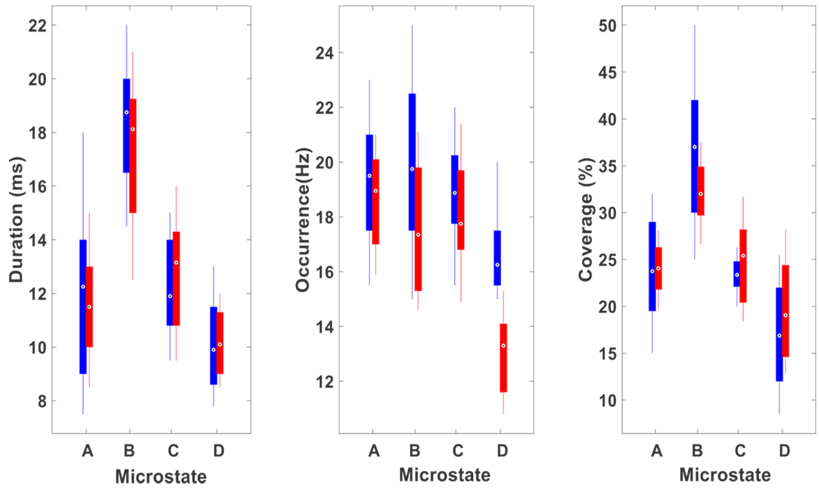

Figure 3: Comparison of Electroencephalography (EEG) Microstate Temporal Parameters in Normal and Fatigue States. Boxplots represent the Duration (millisecond), Occurrence (Hz), and Coverage (%) of microstates A, B, C, and D across 10 subjects, obtained from EEG microstate analysis. Blue boxplots correspond to subjects in the normal state, while red boxplots represent subjects in the fatigue state.

Table 1: Mean classification accuracy (±std) for classification of subjects in the normal state and fatigue state using microstate features: Duration, Occurrence, Coverage and Microstate Mean Power (MMP).

	Microstate A	Microstate B	Microstate C	Microstate D	Microstate A,B,C,D
Duration	55.25±3.92	60.50±2.94	61.73±4.16	61.78±3.90	72.77±4.02
Occurrence	54.65±4.03	66.63±4.33	70.40±3.63	60.19±3.92	76.68±3.32
Coverage	55.84±2.94	53.76±2.59	56.04±3.60	51.38±4.04	63.16±3.34
MMP	90.20±2.47	87.96±2.80	88.21±2.80	83.762±3.18	97.82±1.04

MMP: Microstate Mean Power

microstates using SVM. For individual microstates, Duration shows similar accuracy for microstates B, C, and D (60.50±2.94, 61.73±4.16, 61.78±3.90), slightly outperforming microstate A (55.25±3.92). Occurrence performs best for Microstate C (70.40±3.63), suggesting its superior role in differentiating states, while microstate A performs the least effectively for this feature. Coverage shows relatively similar accuracy across microstates, with microstate C (56.04±3.60) performing slightly better. However, the overall performance of this feature is less impactful compared to Duration and Occurrence. Microstate mean power proved to be the most effective feature compared to Occurrence, Duration and Coverage, consistently yielding higher classification accuracy across all microstates, with microstate A achieving the highest performance (90.20±2.47). These results underscore the varying contributions of individual features and microstates to the classification task.

Combining features from all microstates (A, B, C, and D) for the classification of the subjects into normal and fatigue states significantly enhances mean accuracy. For Duration, the combined accuracy has been improved to 72.77±4.02, and for Occurrence, it reached the highest accuracy of 76.68±3.32. Coverage, with less impact individually, showed a moderate improvement in accuracy when combined across all microstates (63.16±3.34). Microstate mean power achieves best accuracy when combining microstates, reaching 97.82±1.04. These results suggest that integrating microstate features leverages complementary information, improving classification performance and reducing variability.

Mean Classification Accuracy Using Combined Microstate Features

To identify the most effective feature set for achieving accurate classification, we analyzed the performance of different feature combinations. Table 2 presents the mean classification accuracy for differentiating between the normal and fatigue states using various combinations of microstate features.

The results show that by incorporating different features, the classification accuracy increased. The combination of temporal features consisting of Occurrence, Duration, and Coverage increases the accuracy to 80.50±4.14, highlighting the moderate classification potential of these temporal features. Incorporating mean instantaneous energy substantially improves performance, achieving a high accuracy of 97.82±1.04. Adding Occurrence to microstate mean power further enhances accuracy to 98.77±0.58. However, adding Duration and then Coverage leads to a small decrease in accuracy (98.74±0.45 and 98.56±0.84, respectively), indicating that combining too many features results in diminishing improvements.

These results show the critical role of

Table 2: Mean classification accuracy (±std) for classification of subjects in the normal state and fatigue state using combined features of Duration, Occurrence, Coverage and Microstate Mean Power (MMP).

Microstate A, B, C, D	Number of Features	Accuracy
Occurrence + Duration + Coverage	12	80.50±4.14
MMP	120	97.82±1.04
MMP + Occurrence	124	98.77±0.58
MMP + Occurrence + Duration	128	98.74±0.45
MMP + Occurrence + Duration + Coverage	132	98.56±0.84

MMP: Microstate Mean Power

microstate mean power as the most influential feature for classification. While adding Occurrence further improved performance, additional features, such as Duration and Coverage did not significantly contribute to accuracy. This analysis underscores the importance of feature selection in optimizing classification models, with the combination of microstate mean power and Occurrence emerging as the most effective feature set.

Discussion

In this study, we introduced a novel framework that utilizes microstate analysis to classify EEG data into normal and fatigue states, using SVM as the classifier. We evaluated the impact of different features extracted using EEG microstate analysis. Our results showed that classification accuracy, particularly with the inclusion of microstate mean power and Occurrence, significantly improved the accuracy of the classifier.

In the context of driver fatigue detection, EEG signals have been predominantly applied. EEG offers a direct measure of brain activity that can indicate changes in alertness and cognitive state. Recently, different driver fatigue detection approaches have been proposed. The developed methods were tested on collected datasets, including both public and private sources, with various validation strategies, such as k-fold cross-validation, leave-one-out cross-validation, and fixed splits. The studies utilized different numbers of EEG channels, suggesting a trade-off between system complexity and data richness. The classification accuracies ranged from 90.70% to 98.86%.

Min et al. [7] utilized multiple entropy-based features (spectrogram entropy, approximate entropy, sample entropy, and fuzzy entropy) as inputs to an SVM, achieving an accuracy of 98.75% on a 12-subject EEG dataset. Gao et al. [19] proposed the Relative Wavelet Entropy Complex Network (RWECN), which combines wavelet entropy and network-based features for classifying alert and fatigue states using Fisher Linear Discriminant Analysis (FLDA). Using EEG data from 30 effective channels, they achieved an accuracy of 95.5% on eight subjects with a 10-fold cross-validation strategy. Chen et al. [20] decomposed EEG signals into frequency bands using Wavelet Packet Transform (WPT). They analyzed functional connectivity differences between alert and fatigue states, identifying reduced frontal-to-parietal connectivity, lower clustering coefficients, and higher characteristic path lengths during fatigue, particularly in the alpha and beta bands. These network features were used to train SVM classifier, achieving 94.4% accuracy with 14-channel EEG data and 10-fold cross-validation on EEG segments from 14 subjects. Luo et al. [21] employed an adaptive multi-scale entropy method to extract features, including Adaptive Multi-scale Sample Entropy (AMSE), Fuzzy Entropy (AMFE), and Permutation Entropy (AMPE), from EEG data recorded at forehead electrodes (Fp1 and Fp2) for driver fatigue detection. Using SVM as the classifier, they achieved a 95.37% accuracy with AMFE, splitting the EEG signals into 80% training and 20% testing data from 16 subjects, with each signal segmented into 1-second intervals. Ren et al. [22] developed a Two-Level Learning Hierarchy (TLLH) using Radial Basis Function (RBF) networks, achieving a mean accuracy of 92.71% and an Area Under the Curve (AUC) of 0.9199. Gao et al. [23] applied the Short Time Fourier Transform (STFT) to obtain log-Mel spectrograms from EEG signals, which served as inputs to a Convolutional Recurrent Neural Network (CRNN) model. This approach achieved a maximum accuracy of 88.39% using EEG signals from 21 channels and 21 subjects. These studies highlight the growing emphasis on leveraging deep learning techniques for fatigue detection.

Although the developed method applied a range of features based on brain wave activity extracted from EEG signals, few studies have utilized EEG microstate analysis for the analysis of brain fatigue and the classification of driver fatigue detection. Our findings, based on EEG microstate analysis of 10 subjects, highlight the potential of EEG microstate analysis for driver fatigue detection. The results of our study, which extracted microstate feature sets and input them into the SVM classifier to classify the subjects into normal state and fatigue state, demonstrated high classification accuracy, particularly with the inclusion of microstate mean power and Occurrence. Specifically, the combination of microstate mean power and Occurrence achieved the highest accuracy (98.77±0.58).

Conclusion

In this study, we explored the possibility of applying EEG microstate analysis for driver fatigue detection. Based on microstate analysis, we extracted microstate features to classify normal and fatigue states using an SVM classifier. We found that features extracted from microstates, particularly microstate mean power and occurrence, can effectively classify EEG signals. Although this conclusion underscores the importance of microstate analysis for driver fatigue detection, we expect that this discovery can be verified by large-sample and multi-center experiments in the future. Furthermore, while traditional approaches like SVMs remain effective for specific feature sets, deep learning models such as convolutional neural networks have opened new possibilities for processing EEG data and could enhance predictive performance. We expected to apply different classifiers, especially deep learning models.

Authors' Contribution

Z. Yaddasht, K. Kazemi, H. Danyali, and A. Aarabi conceived and conceptualized the study. The methodology was designed by Z. Yaddasht, K. Kazemi, and A. Aarabi. Software development was performed by Z. Yaddasht, K. Kazemi, and A. Aarabi. Validation of the results was conducted by Z. Yaddasht, K. Kazemi, and A. Aarabi. Formal analysis was carried out by Z. Yaddasht. The original draft of the manuscript was prepared by Z. Yaddasht and K. Kazemi, while review and editing were performed by Z. Yaddasht, K. Kazemi, and A. Aarabi. Visualization was provided by Z. Yaddasht. Supervision of the research was carried out by K. Kazemi and A. Aarabi. Project administration was managed by K. Kazemi and A. Aarabi. All authors read, modified, and approved the final version of the manuscript.

Ethical Approval

Since the data supporting this study is openly available at https://figshare.com/articles/The_original_EEG_data_for_driver_fatigue_detection/5202739 (DOI: 10.6084/m9.figshare.5202739), the requirement for an additional code of ethics is not applicable.

Funding

This project was supported by the Cognitive Science and Technology Council (CSTC) of Iran under the grant number 8603.

Conflict of Interest

K. Kazemi, as the Editorial Board Member, was not involved in the peer-review and decision-making processes for this manuscript.

References

1. Guo F, Zhou Y, Wang X, Li W, Cai J. Literature review of driving fatigue research based on bibliometric analysis. *J Traffic and Transportation Engineering (English Edition)*. 2024;**11**(6):1401-19. doi: 10.1016/j.jtte.2024.03.005.
2. Fu S, Yang Z, Ma Y, Li Z, Xu L, Zhou H. Advancements in the intelligent detection of driver fatigue and distraction: A comprehensive review. *J Appl Sci.* 2024;**14**(7):3016. doi: 10.3390/app14073016.
3. Othmani A, Sabri AQ, Aslan S, Chaieb F, Rameh H, Alfred R, Cohen D. EEG-based neural networks approaches for fatigue and drowsiness detection: A survey. *Neurocomputing.* 2023;**557**:126709. doi: 10.1016/j.neucom.2023.126709.
4. Stancin I, Cifrek M, Jovic A. A Review of EEG Signal Features and their Application in Driver Drowsiness De-

tection Systems. *Sensors (Basel)*. 2021;**21**(11):3786. doi: 10.3390/s21113786. PubMed PMID: 34070732. PubMed PMCID: PMC8198610.

5. Imran MAA, Nasirzadeh F, Karmakar C. Designing a practical fatigue detection system: A review on recent developments and challenges. *J Safety Res.* 2024;**90**:100-14. doi: 10.1016/j.jsr.2024.05.015. PubMed PMID: 39251269.
6. Ardabili SZ, Bahmani S, Lahijan LZ, Khaleghi N, Sheykhivand S, Danishvar S. A Novel Approach for Automatic Detection of Driver Fatigue Using EEG Signals Based on Graph Convolutional Networks. *Sensors (Basel).* 2024;**24**(2):364. doi: 10.3390/s24020364. PubMed PMID: 38257457. PubMed PMCID: PMC10819416.
7. Min J, Wang P, Hu J. Driver fatigue detection through multiple entropy fusion analysis in an EEG-based system. *PLoS One*. 2017;**12**(12):e0188756. doi: 10.1371/journal.pone.0188756. PubMed PMID: 29220351. PubMed PMCID: PMC5722287.
8. Michel CM, Koenig T. EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *Neuroimage.* 2018;**180**(Pt B):577-93. doi: 10.1016/j.neuroimage.2017.11.062. PubMed PMID: 29196270.
9. Lehmann D, Strik WK, Henggeler B, Koenig T, Koukkou M. Brain electric microstates and momentary conscious mind states as building blocks of spontaneous thinking: I. Visual imagery and abstract thoughts. *Int J Psychophysiol*. 1998;**29**(1):1-11. doi: 10.1016/s0167-8760(97)00098-6. PubMed PMID: 9641243.
10. Baldini S, Sartori A, Rossi L, Favero A, Pasquin F, Dinoto A, et al. Fatigue in Multiple Sclerosis: A Resting-State EEG Microstate Study. *Brain Topogr.* 2024;**37**(6):1203-16. doi: 10.1007/s10548-024-01053-3. PubMed PMID: 38847997. PubMed PMCID: PMC11408556.
11. Li W, Cheng S, Wang H, Chang Y. EEG microstate changes according to mental fatigue induced by aircraft piloting simulation: An exploratory study. *Behav Brain Res.* 2023;**438**:114203. doi: 10.1016/j.bbr.2022.114203. PubMed PMID: 36356722.
12. Hua W, Li Y. Electroencephalography Based Microstate Functional Connectivity Analysis in Emotional Cognitive Reappraisal Combined with Happy Music. *Brain Sci.* 2023;**13**(4):554. doi: 10.3390/brainsci13040554. PubMed PMID: 37190519. PubMed PMCID: PMC10136627.
13. Guan K, Zhang Z, Chai X, Tian Z, Liu T, Niu H. EEG Based Dynamic Functional Connectivity Analysis in Mental Workload Tasks With Different Types of Information. *IEEE Trans Neural Syst Rehabil Eng.* 2022;**30**:632-42. doi: 10.1109/TNSRE.2022.3156546. PubMed PMID: 35239485.
14. Hu W, Zhang Z, Zhao H, Zhang L, Li L, Huang G, Liang Z. EEG microstate correlates of emotion dynamics and stimulation content during video watching. *Cereb Cortex.* 2023;**33**(3):523-42. doi: 10.1093/cercor/bhac082. PubMed PMID: 35262653.
15. Kim K, Duc NT, Choi M, Lee B. EEG microstate features for schizophrenia classification. *PLoS One.* 2021;**16**(5):e0251842. doi: 10.1371/journal.pone.0251842. PubMed PMID: 33989352. PubMed PMCID: PMC8121321.
16. Nagabhushan Kalburgi S, Kleinert T, Aryan D, Nash K, Schiller B, Koenig T. MICROSTATELAB: The EEGLAB Toolbox for Resting-State Microstate Analysis. *Brain Topogr.* 2024;**37**(4):621-45. doi: 10.1007/s10548-023-01003-5. PubMed PMID: 37697212. PubMed PMCID: PMC11199309.
17. Chen J, Zhao Z, Shu Q, Cai G. Feature extraction based on microstate sequences for EEG-based emotion recognition. *Front Psychol.* 2022;**13**:1065196. doi: 10.3389/fpsyg.2022.1065196. PubMed PMID: 36619090. PubMed PMCID: PMC9816384.
18. Apicella A, Isgrò F, Pollastro A, Prevete R. On the effects of data normalization for domain adaptation on EEG data. *J Eng Appl Artif Intell.* 2023;**123**:106205. doi: 10.1016/j.engappai.2023.106205.
19. Gao Z, Li S, Cai Q, Dang W, Yang Y, Mu C, Hui P. Relative wavelet entropy complex network for improving EEG-based fatigue driving classification. *J IEEE Trans Instrum Meas.* 2018;**68**(7):2491-7. doi: 10.1109/TIM.2018.2865842.
20. Chen J, Wang H, Wang Q, Hua C. Exploring the fatigue affecting electroencephalography based functional brain networks during real driving in young males. *Neuropsychologia.* 2019;**129**:200-11. doi: 10.1016/j.neuropsychologia.2019.04.004. PubMed PMID: 30995455.
21. Luo H, Qiu T, Liu C, Huang P. Research on fatigue driving detection using forehead EEG based on adaptive multi-scale entropy. *J Biomed Signal Process Control*. 2019;**51**(3):50-8. doi: 10.1016/j.bspc.2019.02.005.
22. Ren Z, Li R, Chen B, Zhang H, Ma Y, Wang C, Lin Y, Zhang Y. EEG-Based Driving Fatigue Detection Using a Two-Level Learning Hierarchy Radial Basis Function. *Front Neurorobot.* 2021;**15**:618408. doi: 10.3389/fnbot.2021.618408. PubMed PMID: 33643018. PubMed PMCID: PMC7905350.
23. Gao D, Tang X, Wan M, Huang G, Zhang Y. EEG driving fatigue detection based on log-Mel spectrogram and convolutional recurrent neural networks. *Front Neurosci.* 2023;**17**:1136609. doi: 10.3389/fnins.2023.1136609. PubMed PMID: 36968502. PubMed PMCID: PMC10033857.