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*Research article*

# A fatigue driving detection method based on local maximum refined composite multi-scale normalized dispersion entropy and SVM

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**Abstract:** Multi-scale dispersion entropy (MDE) has been extensively applied to capture the nonlinear features of electroencephalography (EEG) signals for fatigue driving detection. However, MDE suffers from information loss and limited robustness during the extraction of EEG signal nonlinearities. To address these issues, a fatigue driving detection approach integrating local maximum refined composite multi-scale normalized dispersion entropy (LMRCMNDE) with support vector machines (SVM) is introduced. To begin, the refined composite multi-scale dispersion entropy (RCMDE) technique is presented. Next, the segmented averaging in the coarse-graining process is substituted with local maximum calculation to alleviate information loss. Finally, normalization of the entropy values is performed to enhance the robustness of feature parameters, leading to the formation of LMRCMNDE. LMRCMNDE serves as the feature descriptor for fatigue driving EEG signals, while SVM is employed for classification. Compared with the MDE-SVM and RCMDE-SVM approaches, the LMRCMNDE-SVM method achieves higher recognition accuracy, reaching up to 98%. The proposed method can effectively identify the fatigue state of drivers and provide a new reliable detection method for automatic fatigue driving detection.

**Keywords:** fatigue driving; electroencephalogram signals; local maximum refined composite multi-scale normalized dispersion entropy; support vector machine; pattern recognition

## 1. Introduction

Driver fatigue constitutes one of the most critical factors contributing to traffic accidents and fatalities, with estimates suggesting that 10–30% of fatal road accidents can be attributed to fatigued driving [1]. Statistical evidence reveals that fatigue-related crashes account for at least 100,000 traffic incidents annually in the United States, and in China, fatigue ranks as the second leading cause of road accidents [2]. Despite its significant impact, fatigue lacks a precise scientific definition and quantifiable measurement standards. Electroencephalogram (EEG) signals have gained prominence in driver fatigue research owing to their cost-effectiveness, safety, and high temporal resolution [3,4]. Despite the contact-based nature and inherent limitations of current EEG acquisition methods, EEG remains unparalleled in its ability to directly capture the electrophysiological dynamics of cortical neurons, thereby serving as the definitive standard for fatigue detection. EEG signals directly reflect cortical fatigue dynamics, capturing real-time variations in drivers' neurological states. Breakthroughs in EEG-based fatigue detection methodologies hold significant implications for developing effective monitoring and early warning systems, which could potentially revolutionize road safety paradigms [5,6].

Scholars in driver fatigue detection have progressively explored nonlinear analytical approaches for EEG signal characterization, revealing that entropy-based metrics effectively capture dynamic variations in drivers' neural patterns [7–9]. For instance, Liu et al. [10] employed multi-scale sample entropy (MSE) as an EEG feature for drowsiness detection, achieving a classification accuracy of 72.7%. However, MSE's computational complexity and time-intensive nature render it unsuitable for real-time applications. This limitation prompted the adoption of multi-scale permutation entropy (MPE) for automated fatigue detection through nonlinear EEG feature extraction [11]. While MPE demonstrates advantages in computational efficiency, its coarse-graining process considers only ordinal patterns yet disregards amplitude information [12,13]. To overcome these constraints, Azami et al. [14] developed multi-scale dispersion entropy (MDE) as an enhanced nonlinear analytical framework. MDE not only preserves computational efficiency but also incorporates amplitude characteristics during time series complexity assessment [15]. Subsequent applications in Reference [16] demonstrated the advantages of MDE and its variants over other MSE and MPE algorithms as well as their potential in EEG-based automated fatigue detection. MDE has great potential in automated EEG-based fatigue detection. Nevertheless, MDE's reliance on segmented mean calculations for coarse-grained sequences introduces information loss vulnerabilities [17]. Furthermore, increasing scale factors reduce sequence length, resulting in unstable entropy calculations with reduced accuracy, ultimately compromising EEG signal classification performance [18]. To overcome the aforementioned limitations, this study proposes a novel fatigue detection method that integrates local maximum refined composite multi-scale normalized dispersion entropy (LMRCMNDE) with a support vector machine (SVM) classifier. Initially, the refined composite multi-scale dispersion entropy (RCMDE) serves as the foundation for the proposed method. Subsequently, the traditional piecewise averaging in the coarse-graining procedure is replaced by a local maximum strategy. The entropy values are then normalized to mitigate issues such as information degradation and weak robustness found in traditional MDE. The enhanced LMRCMNDE algorithm is applied to extract characteristic features from EEG signals associated with fatigue driving, and with the integration of the SVM's benefits—such as high computational efficiency and suitability for real-time applications—the system enables the automatic identification of driver fatigue.

This paper introduces a fatigue driving detection method utilizing LMRCMNDE for feature extraction and SVM for classification. The contributions of this paper are as follows:

1) Proposing the novel LMRCMNDE algorithm, which extracts entropy features more effectively than existing MDE and RCMDE methods.

2) Applying LMRCMNDE to extract features from EEG signals related to fatigue driving,

enabling automatic driver fatigue identification when combined with an SVM classifier.

3) Demonstrating through comparative experiments that the LMRCMNDE-SVM approach achieves higher accuracy than MDE-SVM and RCMDE-SVM in distinguishing between alertness, fatigue, and drowsiness states.

## 2. Principles and methods

### 2.1. MDE

Given a one-dimensional time series $x_n$ of length N (where n=1,2,3...N), the data is transformed into a new series using the normal cumulative distribution function (NCDF). This operation ensures that all sequence values fall within the interval [0, 1], as illustrated in Eq (1):

$$y_n = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x_n} e^{\frac{-(t-\mu)^2}{2\sigma^2}} dt \tag{1}$$

Where $\sigma$ symbolizes the standard deviation, whereas $u$ corresponds to the time series' average amplitude and $x_n$ represents the EEG signal. Then, the linear algorithm shown in Eq (2) is used to map $y_n$ to $Z_n^c$.

$$z_n^c = round(c \cdot y_n + 0.5) \tag{2}$$

In this context, the round function is applied to perform numerical rounding. Given the embedding dimension $m$, number of discrete categories $c$, and time delay $d$, the embedding vector $z_i^{m,c}$ is formulated accordingly, as presented in Eq (3).

$$\begin{aligned} & z_i^{m,c} = \left\{ z_i^c, z_{i+d}^c, \ldots, z_{i+(m-1)d}^c \right\}, \\ & i = 1,2,\ldots N - (m-1)d \end{aligned} \tag{3}$$

In which $z_i^c = v_0, z_{i+d}^c = v_1, \ldots, z_{i+(m-1)d}^c = v_{m-1}$; subsequently, each $z_i^{m,c}$ is mapped to $\pi_{v_0 v_2 \ldots v_{m-1}}$, as shown in formula (4), to compute the relative frequency of each $\pi_{v_1 v_2 \ldots v_{m-1}}$. The dispersion pattern $\pi$ is a combination of symbol sequences that represent the local amplitude variation of a signal.

$$p(\pi_{v_0 v_1 \ldots v_{m-1}}) = \frac{Number(\pi_{v_0 v_1 \ldots v_{m-1}})}{N - (m-1)d} \tag{4}$$

In Eq (4), $N-(m-1)$ represents the total number of embedding vectors, and $Number()$ denotes the number of mappings. Finally, the dispersion entropy (DE) is derived based on the Shannon entropy formula.

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

Figure 1 illustrates the coarse-graining process applied to the original signal. During this process, the signal $x_n$ is divided into several non-overlapping windows, and the average value of the data points in each segmented window is calculated to obtain the coarse-graining time series $M_{k,j}^{(\tau)}$.

$$M_{k,j}^{(\tau)} = \frac{1}{\tau} \sum_{n=(j-1)\tau+k}^{j\tau+k-1} x_n \quad 1 \le j \le \frac{N}{\tau}, 1 \le k \le \tau \tag{6}$$

Based on Eqs (1)–(4), the expression for MDE is

$$MDE(x, m, c, d, \tau) = DE(M_k^{(\tau)}, m, c, d) \tag{7}$$

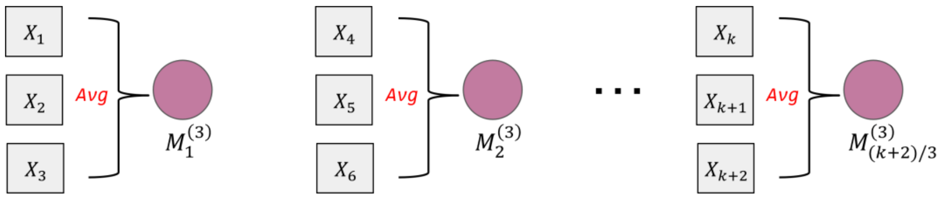



**Figure 1.** The coarse-graining diagram of MDE when $\tau$=3.

*2.2. LMRCMNDE*

When implementing coarse graining in MDE, the averaging computation over non-overlapping segments tends to neutralize nonlinear transient features in original signals, resulting in information loss. Furthermore, increasing scale factors lead to shorter coarse-grained sequences, consequently reducing entropy value stability. To overcome the limitations of MDE, we initially present RCMDE. The formulation of RCMDE is

$$RCMDE\left(\mathrm{M}_{\mathrm{k}}^{(\tau)}, \mathrm{m}, c, d\right) = \sum_{\pi=1}^{c^m} \overline{p(\pi_{v_0 v_1 \ldots v_{m-1}})} \ln\left(\overline{p(\pi_{v_0 v_1 \ldots v_{m-1}})}\right) \tag{8}$$

In Eq (8), $\overline{p(\pi_{v_0 v_1 \ldots v_{m-1}})} = \frac{1}{\tau} \sum_{1}^{\tau} p(\pi_{v_0 v_1 \ldots v_{m-1}})$.

As shown in Figure 2, the coarse-graining process now uses a local maximum approach instead of a segmented average, addressing the problem of information loss. Additionally, based on the coarse-graining process shown in Figure 2, $\tau$ groups of sequences are generated, which resolves the issue of sequence shortening and enhances the stability of the entropy values. The expression for the local maximum calculation of the coarse-grained sequence is

$$y_{k,j}^{(\tau)} = \max(abs(x_{(j-1)\tau+k} : x_{k+j\tau-1})) \qquad (1 \le j \le [N/\tau], 1 \le k \le \tau) \tag{9}$$

Finally, the entropy values are computed and normalized to improve the stability of the feature parameters, forming the LMRCMNDE.

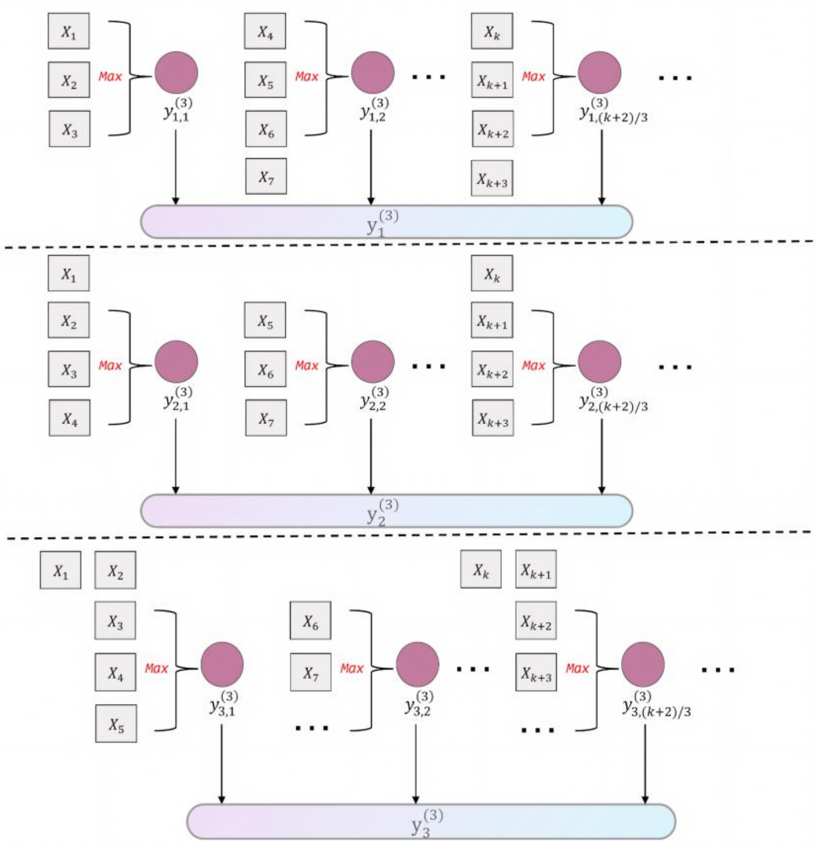



**Figure 2.** LMRCMNDE coarse-graining diagram when $\tau$=3.

### *2.3. The proposed fatigue driving detection scheme*

To enhance the recognition accuracy of fatigue driving detection, this section presents a method combining LMRCMNDE and SVM. The LMRCMNDE-SVM framework is illustrated in Figure 3, with the following steps outlining the procedure:

1) EEG signals related to fatigue driving are taken from the online emotional EEG database of Shanghai Jiao Tong University as experimental data.

2) The LMRCMNDE algorithm is used to extract the relevant features from the EEG signals. The generated feature set is randomly split into training and testing samples. The training set is then used to build an SVM-based fatigue detection model. This leads to the construction of an automatic LMRCMNDE-SVM detection model.

3) To evaluate the method's effectiveness, the test samples are input into the trained model to obtain the recognition accuracy and performance. The performance of MDE-SVM, RCMDE-SVM, and LMRCMNDE-SVM are then compared through analysis.

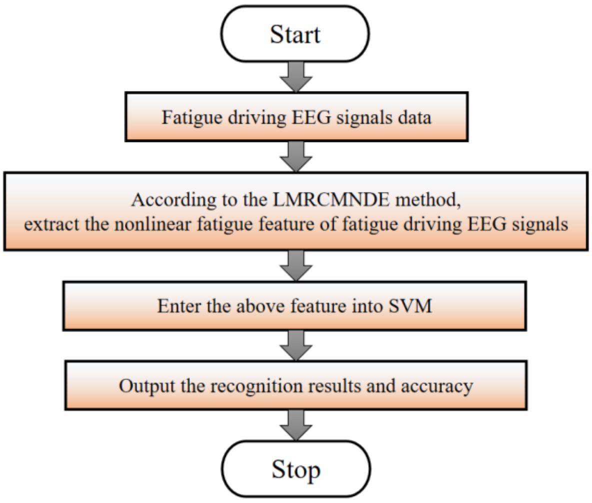



**Figure 3.** Flowchart illustrating the LMRCMNDE-SVM-based fatigue driving detection process.

## 3. Results and analysis

### *3.1. Dataset and parameter settings*

This study utilizes EEG data from the SEED-VIG emotional EEG dataset [19], which was released by Shanghai Jiao Tong University. The dataset was collected by simulating a real driving environment, as shown in Figure 4. In total, 23 participants were recruited for the simulation, and after data screening, EEG data from 21 participants were obtained. Of these participants, 13 participants were tested at midday and 8 participants were tested at night, with each participant undergoing a test lasting 118 minutes. EEG data was recorded at a sampling rate of 200 Hz, yielding 1,416,000 total sampling points per participant. This study primarily focuses on the automatic detection of EEG signals in wakefulness, fatigue, and drowsiness states, involving feature extraction and classification from these three states in the dataset. For each type of signal, 1024 sampling points were collected in each set of data. Figure 5 displays the time-domain waveforms of these EEG states. In the SVM pattern recognition part, RBF was selected as the kernel function. Meanwhile, the penalty factor $c$ and kernel parameter $g$ were defaulted as 1 and 90, respectively.

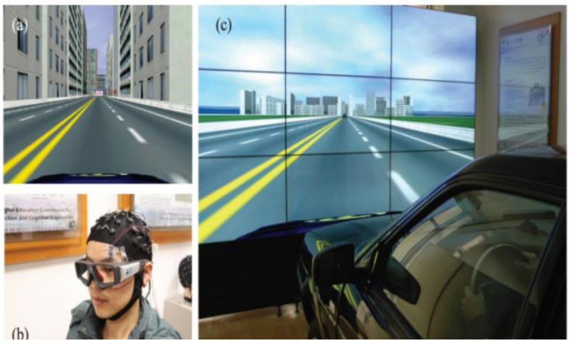
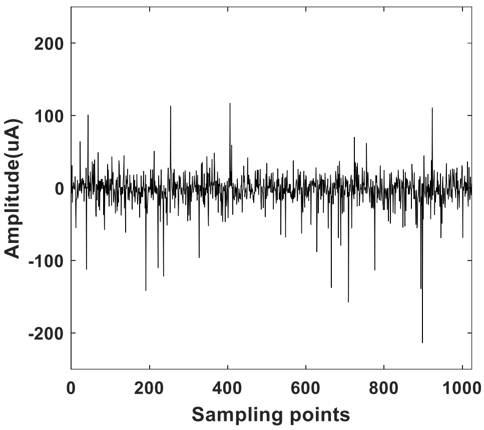
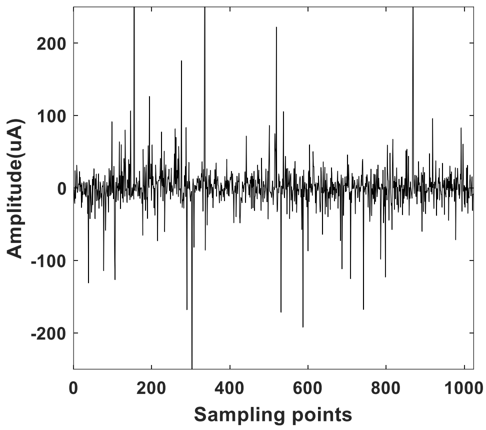


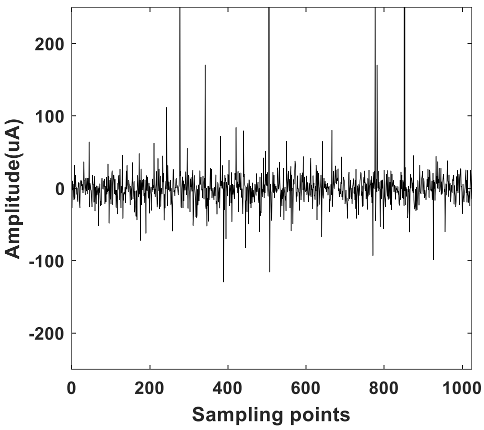

**Figure 4.** Simulation driving test process.




(a) EEG time-domain diagram in wakefulness state




(b) EEG time-domain diagram in fatigue state

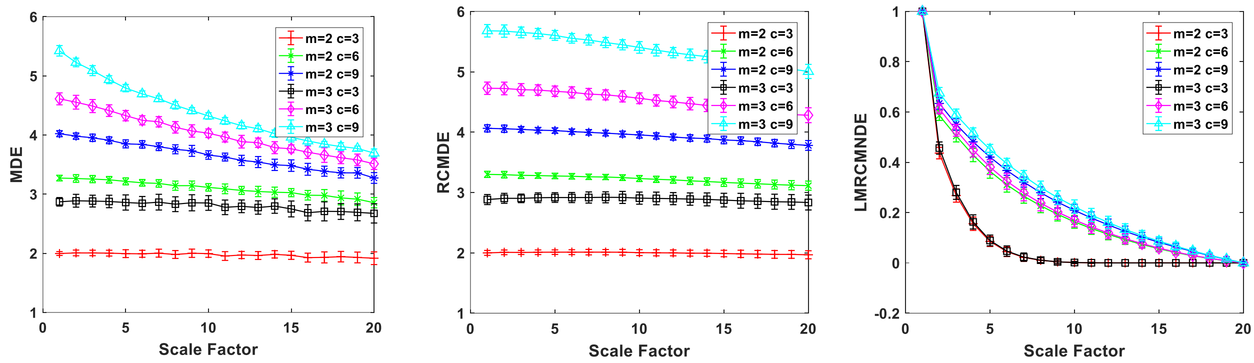



(c) EEG time-domain diagram in drowsiness state

**Figure 5.** EEG time-domain diagram of subjects in wakefulness, fatigue, and drowsiness states.

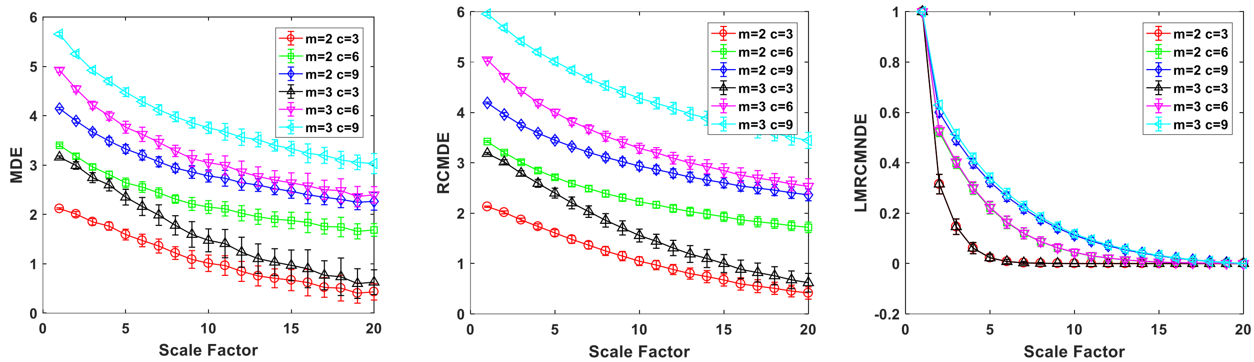
*3.2. Simulated signal analysis*

The LMRCMNDE calculation depends on the embedding dimension $m$, the number of categories $c$, and the delay time parameter d. Azami et al. [14] suggest that $m$ is typically set within the range of 2 to 3, $c$ is selected as an integer between 3 and 9, and d is set to 1. To highlight the effectiveness of the LMRCMNDE approach, a comparative analysis is conducted on the entropy values produced by MDE, RCMDE, and LMRCMNDE across various parameter settings. Simulated signals, including Gaussian white noise and 1/f noise, are selected for the analysis. Figures 6 and 7 illustrate how the mean and standard deviation curves vary for the simulated signals when analyzed with MDE, RCMDE, and LMRCMNDE. Figures 6 and 7 reveal that, for the noise signal with a flat power spectral density, the MDE, RCMDE, and LMRCMNDE curves all show a downward trend as the scale factor increases. However, for 1/f noise, the decline observed in the MDE and RCMDE curves is relatively mild, whereas the LMRCMNDE curve exhibits a pronounced downward trend as the scale factor increases. This suggests that MDE and RCMDE fail to effectively capture the multi-scale characteristics of 1/f noise, resulting in the loss of critical data. In contrast, LMRCMNDE effectively captures multi-scale features from different types of noise, thus overcoming information loss. Additionally, variations in the embedding dimension and the number of categories significantly affect the MDE and RCMDE curves, whereas the LMRCMNDE results remain largely stable across different settings. This demonstrates that the normalization process in LMRCMNDE reduces the impact of parameter selection on entropy value fluctuations, thereby enhancing the robustness of the feature parameters. Finally, it is evident that RCMDE and LMRCMNDE exhibit smaller standard deviations compared to MDE when analyzing the three entropy curves. This is attributed to the refined composite process, which, to some extent, reduces entropy value fluctuations.




(a) MDE (b) RCMDE (c) LMRCMNDE

**Figure 6.** Curve of mean and standard deviation for gaussian white noise under various features.

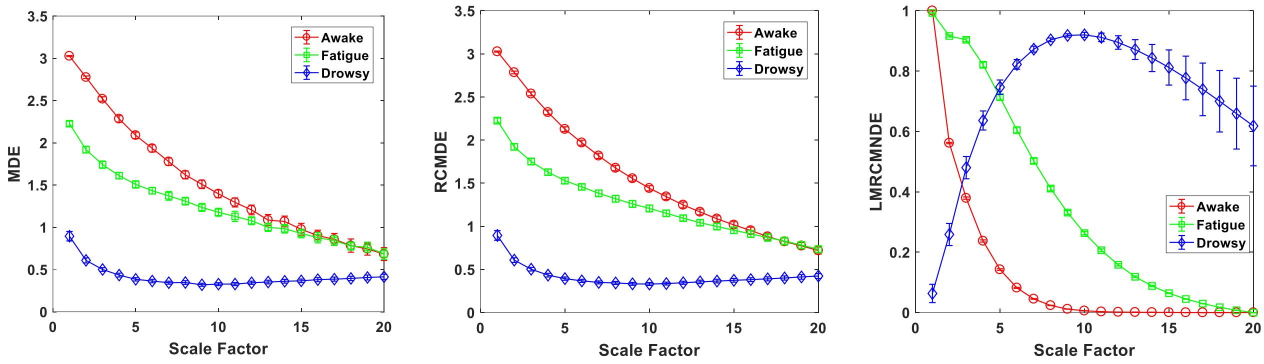



(a) MDE (b) RCMDE (c) LMRCMNDE

**Figure 7.** Curve of mean and standard deviation for 1/f noise under various features.

### *3.3. EEG signal analysis*

The participants' brain electrical signal data were collected under three states: wakefulness, fatigue, and drowsiness. Using MDE, RCMDE, and LMRCMNDE, we extracted the entropy features from 300 EEG signals, including 100 wakefulness signals, 100 fatigue signals, and 100 drowsiness signals. According to the references [20,21], the embedding dimension is set to 3, the number of categories is 3, and the time delay is 1. As shown in Figure 8, these features describe MDE, RCMDE, and LMRCMNDE for scale factors 1–20 in different EEG states. From Figure 8, it is evident that the MDE and RCMDE curves for wakefulness and fatigue signals still overlap, creating substantial challenges in detecting fatigue during driving. In contrast, the LMRCMNDE entropy curves clearly distinguish the wakefulness, fatigue, and drowsiness states across most scales, with their mean-standard deviation curves showing virtually no overlap. This finding indicates that LMRCMNDE can effectively capture nonlinear abrupt-change information in EEG signals.




(b) MDE (b) RCMDE (c) LMRCMNDE

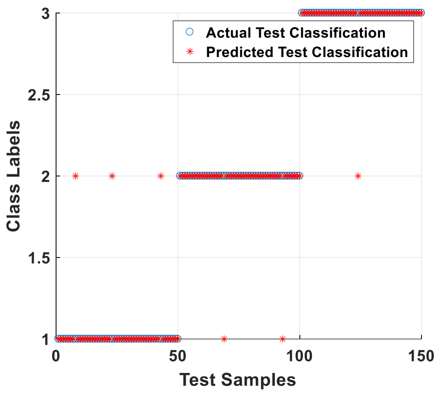
**Figure 8.** Curves of mean and standard deviation for EEG signal features in various states.

### *3.4. Driver fatigue classification*

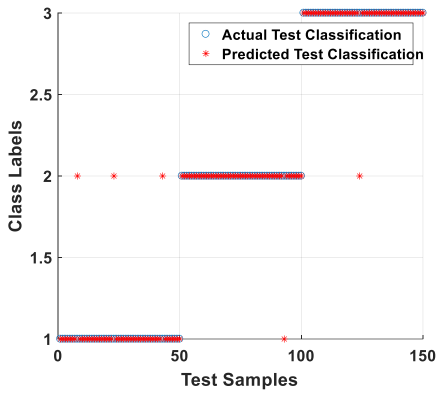
SVM [22,23] were employed to classify the MDE, RCMDE, and LMRCMNDE feature parameters extracted from the aforementioned EEG signals. A total of 150 EEG samples (50 for each state: wakefulness, fatigue, and drowsiness) were randomly chosen as training data, while the other 150 samples were reserved for testing. In the SVM classifier, the penalty factor $c$ and the kernel parameter $g$ were set to 1 and 90, respectively.

Figure 9 presents the fatigue-driving classification results obtained by MDE-SVM, RCMDE-SVM, and LMRCMNDE-SVM, where the vertical axis values 1, 2, and 3 represent the wakefulness, fatigue, and drowsiness states, respectively, and the horizontal axis represents the EEG sample index. Evidently, six samples were misclassified by the MDE-SVM approach, five by the RCMDE-SVM model, and only three by the LMRCMNDE-SVM, highlighting the superior effectiveness of the proposed method.

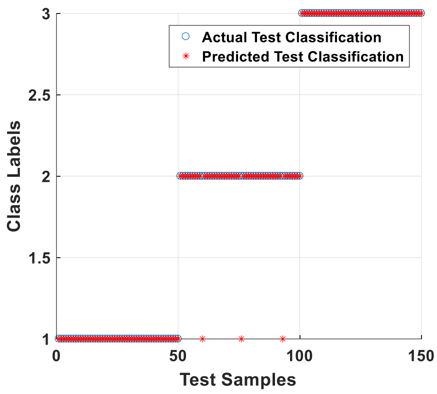
Furthermore, Table 1 presents the fatigue-driving classification accuracy and running time for the MDE-SVM, RCMDE-SVM, and LMRCMNDE-SVM methods. Relative to the MDE-SVM and RCMDE-SVM approaches, the proposed LMRCMNDE-SVM framework achieved a higher classification accuracy (98%), further demonstrating its effectiveness in capturing the nonlinear characteristics of EEG signals under fatigue conditions. In terms of running time, LMRCMNDE and RCMDE exhibit lower computational efficiency than MDE, as the refine-grained composite process enhances entropy stability but increases the algorithm's computational load to some extent. Nevertheless, LMRCMNDE operates faster than RCMDE, as it replaces the mean calculation in coarse graining with a local maxima approach, thereby reducing computations and enhancing efficiency.




(a) MDE-SVM




(b) RCMDE-SVM




(c) LMRCMNDE-SVM

**Figure 9.** Fatigue classification outcomes based on MDE-SVM, RCMDE-SVM, and LMRCMNDE-SVM approaches.

**Table 1**. Comparison of classification performance among different driver fatigue detection methods.

| Methods | Awake | Fatigue | Drowsy | Recognition Rate | Running time |
|---|---|---|---|---|---|
| MDE-SVM | 47/50 | 48/50 | 49/50 | 96% | 1.393356 s |
| RCMDE-SVM | 47/50 | 49/50 | 49/50 | 96.67% | 9.332018 s |
| LMRCMNDE-SVM | 50/50 | 47/50 | 50/50 | 98% | 5.656751 s |

## 4. Discussion

The proposed LMRCMNDE-SVM method demonstrates significant advancements in fatigue driving detection by addressing the limitations of traditional MDE and RCMDE approaches. The analysis of the analog signal in Figures 6 and 7 indicates the integration of local maximum calculations and normalization in the coarse-graining process effectively mitigates information loss and enhances the robustness of entropy-based feature extraction. The results in Figures 8 and 9 and Table 1 indicate that the classification accuracy of this method reaches 98%, verifying that LMRCMNDE-SVM is superior to the existing entropy methods in distinguishing between wakefulness, fatigue and drowsiness states. This high accuracy is attributed to the method's ability to capture nonlinear transient features in EEG signals, which are critical for reliable fatigue detection.

To further demonstrate the advantages of the method proposed in this paper, a comparison was made with multiple methods in references [24–28], mainly focusing on the parameters of recognition accuracy, recall rate and F1 value. As shown in Table 2, the comparison results of multiple methods applied to the SEED-VIG EEG dataset are presented. It can be clearly seen that the recognition accuracy of the method proposed in this paper is higher than that of the existing CSF-GTNet, T-A-MFFNet, LGGNet, LAG, and HCS-TENET methods, reaching 0.98. The recall rate and F1 value parameters of the proposed method are 0.98 and 0.9799 respectively, slightly lower than those of the HCS-TENET detection method, and significantly better than the other four methods. Although the HMS-TENet method has achieved good results, it requires the integration of EEG and EOG. In practical applications, the EOG signal is vulnerable to environmental interference and the model complexity is relatively large. The proposed LMRCMNDE-SVM method improves entropy calculation through local maxima and normalization, directly solving the classification problem of fatigue-related EEG signals. The above comparison proves the advantages of the method proposed in this paper.

There are still some limitations of LMRCMNDE-SVM. The coarse-grained improvement of LMRCMNDE increases the computational complexity of MDE to a certain extent. Additionally, the recognition performance is also related to parameters such as the embedding dimension and the number of categories. In the future, it is planned to adopt intelligent optimization algorithms to adaptively select parameters, which may further enhance reliability.

**Table 2.** Comparison of the effectiveness of various methods on classification.

| Methods | Recognition accuracy | Recall rate | F1 value |
|---|---|---|---|
| CSF-GTNet[25] | 0.8392 | 0.8951 | 0.8761 |
| T-A-MFFNet[26] | 0.8565 | 0.8637 | 0.8653 |
| LGGNet[27] | 0.8389 | 0.8627 | 0.8548 |
| LAG[28] | 0.8515 | 0.8876 | 0.8756 |
| HCS-TENET[24] | 0.9796 | 0.986 | 0.983 |
| LMRCMNDE-SVM | 0.98 | 0.98 | 0.9799 |

## 5. Conclusions

In response to the limitations of the MDE method in extracting nonlinear EEG features, this paper proposes an LMRCMNDE-SVM approach for fatigue driving detection, which is validated using both simulated and real EEG signals. The simulation results indicate that, relative to MDE and RCMDE, LMRCMNDE effectively minimizes information loss during complexity analysis and reduces entropy fluctuations caused by parameter variations, thereby enhancing the robustness of the extracted features. Furthermore, experimental analysis on EEG data reveals that LMRCMNDE more effectively extracts the nonlinear characteristics of fatigue-driving signals and, when combined with SVM, achieves a recognition accuracy of 98%—a significant improvement over traditional MDE-SVM and RCMDE-SVM methods—thus providing a more precise differentiation between wakefulness, fatigue, and drowsiness. Overall, the proposed LMRCMNDE-SVM framework not only overcomes the limitations of previous methods but also provides a robust and reliable solution, showing broad potential for application in fatigue driving detection.

Although the proposed LMRCMNDE algorithm demonstrates strong performance in fatigue driving detection, its effectiveness in other domains remains unverified. Further experimental validation is required. Consequently, the author will prioritize research into extending the LMRCMNDE algorithm's application for feature extraction in nonlinear time series.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

## Acknowledgments

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## Conflict of interest

The authors declare there is no conflict of interest.

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