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Fatigue EEG Classification Study Based on Convolutionally Constrained Boltzmann Machine

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Abstract: As the demand for the detection of brain fatigue state grows, portable EEG instruments are becoming more and more critical in related research. In this study, we designed a 1-back task paradigm to induce fatigue EEG signals using the EmotivEpoc+14 EEG instrument. The EEG dataset was built based on the subjective rating scale rating scores of the KSS scale and the behavioral analysis results. Construct an improved convolutionally constrained Boltzmann machine model, introducing convolutional operations to the visible and hidden layers to achieve weight sharing. Feature selection using principal component analysis method combined with Pearson's coefficient to retain highly correlated features. Self-training-semi-supervised learning method is used to train the model, and the results show that the features extracted from the C-RBM model achieve 89% and 91% classification accuracy in the frontal and occipital lobes. After reducing the channels it is used for SVM and RF classifiers with the best results, SVM achieves 93% classification accuracy of HM + PSD + PE for occipital lobe and RF achieves 92% classification accuracy of HM + PSD + WE for occipital lobe. This shows that the combination of the C-RBM model proposed in this paper with SVM and RF classifiers can effectively use the reduced dimensionality channel features for fatigue detection, which provides a reference for fatigue detection of feature combinations for sparse channels.

Keywords: N-back, C-RBM, semi-supervised learning, EEG classification.

1. Introduction

With the development of the times and social progress, fatigue has become a common physiological and psychological state of people, which is widely existed in daily life and has a significant impact, so the research on fatigue has a better prospect and important significance. In the field of transport, driver fatigue is one of the major causes of traffic accidents. According to statistics, a large number of traffic tragedies are related to fatigue driving, and improving the accuracy of detecting driver fatigue can effectively reduce the occurrence of such accidents. In industrial production, worker fatigue can lead to operational errors, reduce productivity, and even cause serious safety accidents, so it is crucial for enterprises and factories to ensure that workers work in a sober state for safe and effective production. EEG signals, as a kind of physiological signals, can directly reflect the changes of brain nerve activity and contain key characteristic information related to fatigue state. Research on fatigue EEG can provide insight into the physiological mechanisms of the brain during fatigue, provide scientific and reliable fatigue assessment methods for related fields, and thus safeguard people's lives and improve productivity and quality of life.

Currently, the methods of fatigue EEG assessment are divided into subjective and objective assessment. Subjective assessment methods are usually used: Piper Fatigue Scale, Karolinska Sleepiness Scale [1] , Epworth Sleepiness Scale [2, 3] , Stanford Sleepiness Scale [4] . This approach relies on the subjective feelings of the subjects to judge the degree of fatigue, which is susceptible to the interference of a variety of factors, so the combination of objective assessment methods can more comprehensively and objectively reflect the actual fatigue status of the subjects. Objective assessment methods mainly include psychological indicators, behavioral characteristics and physiological signals. EEG, as a physiological signal, can directly reflect brain activity with high sensitivity and objectivity, and is regarded as the 'gold standard' for fatigue detection [5] , and is usually used in studies to detect human brain load and fatigue status.

At present, the research on fatigue EEG is getting more and more attention and importance at home and abroad, and some better results have been achieved. Peng [6] et al. achieved the approximation of EEG by wavelet analysis, and the sample entropy value was used as the key feature, and the accuracy of fatigue recognition was increased from 65.1% to 87.7% compared with the traditional entropy method. Luo [7] et al. collected the prefrontal fatigue EEG signals with adaptive multi-scale entropy feature extraction algorithm, and the fatigue driving detection accuracy reached 95.37%.Hu [8] et al. used AdaBoost classifier for fatigue prediction with fuzzy entropy, sample entropy, approximate entropy, spectral entropy, and combinatorial entropy, and proved the best performance as fuzzy entropy and combinatorial entropy. Liu [9] et al. induced fatigue through a 2-back task and used the Relief F algorithm to calculate the weights of the features of each channel, selected the upper half of the weight order as the common channel and combined it with the SRDA classifier to classify the time-frequency fusion features, which reduced the number of computational channels and improved the accuracy of the mental fatigue detection. The DE-GFRJMCMC model proposed by Guo [10] et al utilizes the empirical mode decomposition (EMD) and the improved reversible jump Markov chain Monte Carlo (RJMCMC) algorithms to filter out the optimal subset of features and combines them with the K Nearest Neighbors (KNN) classifier to achieve the highest recognition accuracy of 96.11% ± 0.43%. Hu [11] et al. on the other hand, used multiple entropy features of a single EEG channel as inputs to a gradient boosting decision tree (GBDT), achieving the highest average recognition rate of 94.0% for the three classifiers of k-nearest neighbors, support vector machines and neural networks.

In summary, there are relatively few studies on the feature combination of fatigue EEG signals for sparse channels, so this paper proposes a model construction method, which introduces the convolution structure into the restricted Boltzmann machine model, and after dimensionality reduction by using principal component analysis, combined with Pearson coefficients, retains the features with strong correlation as the input of the classifier. A self-training semi-supervised learning algorithm is used to train the CNN classifier, and several iterations are finally used in SVM and KNN machine learning classifiers with fatigue detection and classification, aiming to find the optimal combination of features for the sparse channel and the classifier with the best performance.

2. Fatigue EEG Acquisition Process and Pre-processing

(1) Self-assessment of fatigue status

The Karolinska Sleepiness Scale (KSS), a scale that enables subjects to autonomously assess their level of fatigue, has been widely validated and successfully applied to the field of EEG signal research[1]. In this study, a sample of 16 subjects was used to calculate their KSS scores, which are rated as fatigue with a KSS score greater than or equal to 5. As shown in Table 2.1 below, 87.5% of subjects experienced fatigue after completing the 1-back experiment. The results showed that the experiment successfully induced fatigue EEG, which could be used as a sample of fatigue state.

Table 2.1 Comparison of KSS scores before and after the 1-back task

Participants	KSS Scores	
	Before 1-back	After 1-back
1	1	7
2	0	8
3	2	5
4	1	7
5	3	6
6	0	4
7	1	5
8	2	8
9	0	7
10	2	6
11	1	7
12	3	8
13	0	6
14	0	5
15	2	7
16	1	4
Fatigue realisation rate		87.50%

(2) N-back experimental design

In this paper, in the laboratory, the EEG signals before and after the N-back experiment were collected from 16 participants using the EEG EmotivEpoc+14. The N-back task paradigm can be used to assess the effects of cognitive aging, fatigue, and stress on individuals[12]. In this paper, a 1-back experimental paradigm is chosen, using shapes of different colors as stimulus elements at different locations. A sequence of 30 images is presented, each for 3 seconds, with an empty screen for 2 seconds, before the next image appears. Subjects are asked to judge whether the current stimulus is consistent with the previous stimulus. The sequence of stimuli is shown in Figure 2.1. The final result of the mean response time and average correct response rate for 16 participants was combined with subjective rating to determine subject status.

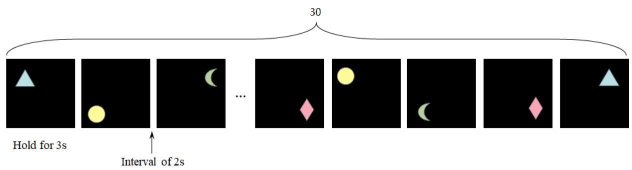

Figure 2.1 Design diagram of the stimulation sequence

The results showed that the average reaction time of the 16 participants gradually increased with the increase of duration, and the response accuracy also gradually decreased. Therefore, it was proved that the brain fatigue of the subjects was successfully induced, and their EEG signals could be used for subsequent classification studies. Figure 2.2 shows the overall process framework

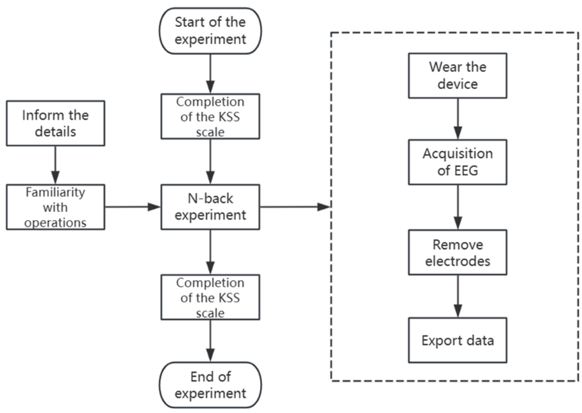

Figure 2.2 Framework diagram of the overall flow of the experiment

(3) EEG signal pre-processing

The acquired raw signals are interfered by noise, artefacts or other electrophysiological signals, which to a large extent will directly affect the data quality and analysis results. Therefore, pre-processing of EEG signals is a very necessary process before EEG characterization.

The acquired raw signal can be interfered with by noise or artifacts, which can directly affect data quality and analysis results. Therefore, the preprocessing of EEG signals is a very necessary process prior to EEG signs. In order to effectively eliminate the interference, the empirical mode decomposition algorithm and the adaptive filtering of the digital filter are selected to denoise the original signal. The purpose of EMD decomposition is to decompose a signal x(n) into M intrinsic mode functions (IMF) and a residual. The expression of the original signal x(n) after EMD decomposition is: [13, 14].

$$X(n) = \sum_{1}^{m} c_m(n) + r_m(n)$$

$c_m(n)$: represents the order m modal function. $r_m(n)$: represents the residuals that ultimately meet the criterion.

In this paper, we chose to continue to remove artifacts such as ocular and electromyography with FastICA. FastICA expects to find a separation vector that maximizes the latent non-Gaussian features of multidimensional data in an efficient way, so as to achieve blind source separation [15]. The iteration formula is as follows:

$$W_{K+1} = E[xg(W_K^T)] - E[g'(W_K^T x)]W_K$$
$$g(u) = ue^{(-u^2/2)}$$

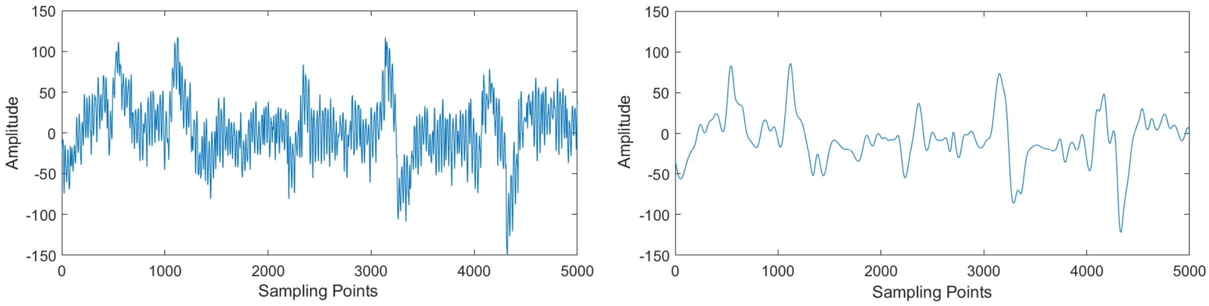

Figure 2.3 Comparison of EEG signals before and after filtering and artifact removal

3. Characteristic Extraction

(1) Time-domain characterization

Hjorth parameters are a set of time-domain parameters used to characterize signals and have important applications in analyzing the correlation between EEG signals and states such as fatigue. It mainly consists of three parameters: Hjorth Activity (HA), Hjorth Mobility (HM) and Hjorth Complexity (HC) [16].

Hjorth Activity is used to measure the intensity or energy level of a signal. The Hjorth mobility characterizes the major frequency components of the signal. The Hjorth complexity reflects the rate of change in the frequency of the signal. Therefore, the Hjorth parameter can be well used to analyze the time-domain characteristics of EEG signals[17].

(2) Frequency-domain characterization

Frequency domain characteristics mainly analyze the information of frequency characteristics from the perspective of frequency domain. Power spectral density is used to characterize the distribution characteristics of signal power, which can visualize the change in signal power with frequency. Therefore, in this paper, the Welch method is used to obtain the power spectral density, and the power spectral density of the original EEG signal and each rhythm wave is calculated separately, and then the power spectral density of different frequency bands is superimposed and integrated as the final extracted feature. [18].

Based on the acquired EEG, the frequency domain power spectral density waveforms of some brain regions were intercepted as shown in Figure 3.1 below.

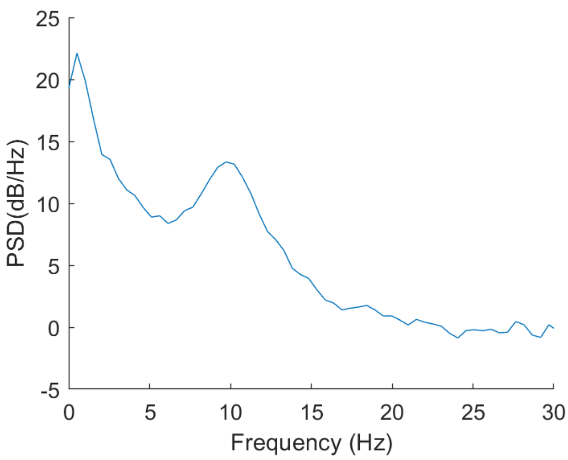

Figure 3.1 Waveforms for extracting the power spectral density of the EEG signal

The energy spectrum is a function used to describe the distribution of signal energy in the frequency domain. It represents the variation of the signal energy with frequency and visualizes the amount of energy contained in different frequency components of the signal. The energy spectrum provides a clear picture of how much each frequency component of the signal contributes to the total energy. Figure 3.2 shows the distribution of the EEG energy spectrum.

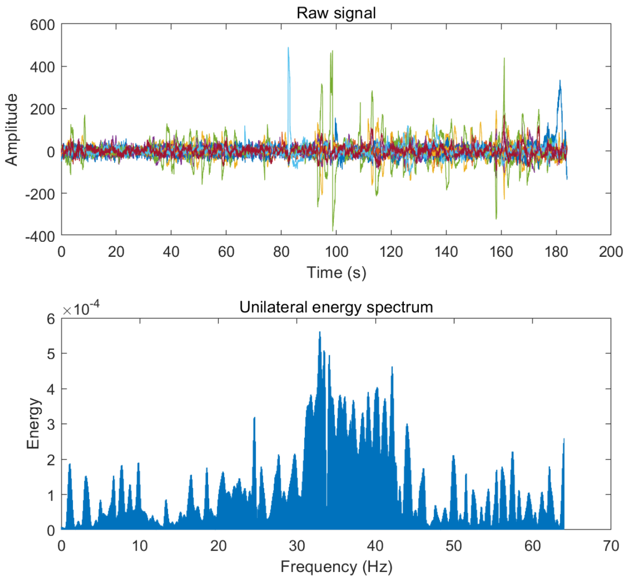

Figure 3.2 Schematic of the energy spectrum distribution of the EEG signal.

(3) Time-frequency domain characterization

Time-frequency analysis can effectively integrate the feature information in the time and frequency domains to more comprehensively analyze the characteristics of the signal. Wavelet packet transform is a commonly used method for EEG time-frequency analysis, and its advantage is the deep decomposition of low-frequency sub-band, which makes up for the lack of high-frequency sub-band decomposition. When using wavelet packet transform to process the signal, the signal will generate a series of wavelet packet coefficients according to different scales and frequencies, which can accurately reflect the composition of the signal in different frequency bands[19] . Figure 3.3 below shows the wavelet packet reconstructed EEG signal in the corresponding frequency band.

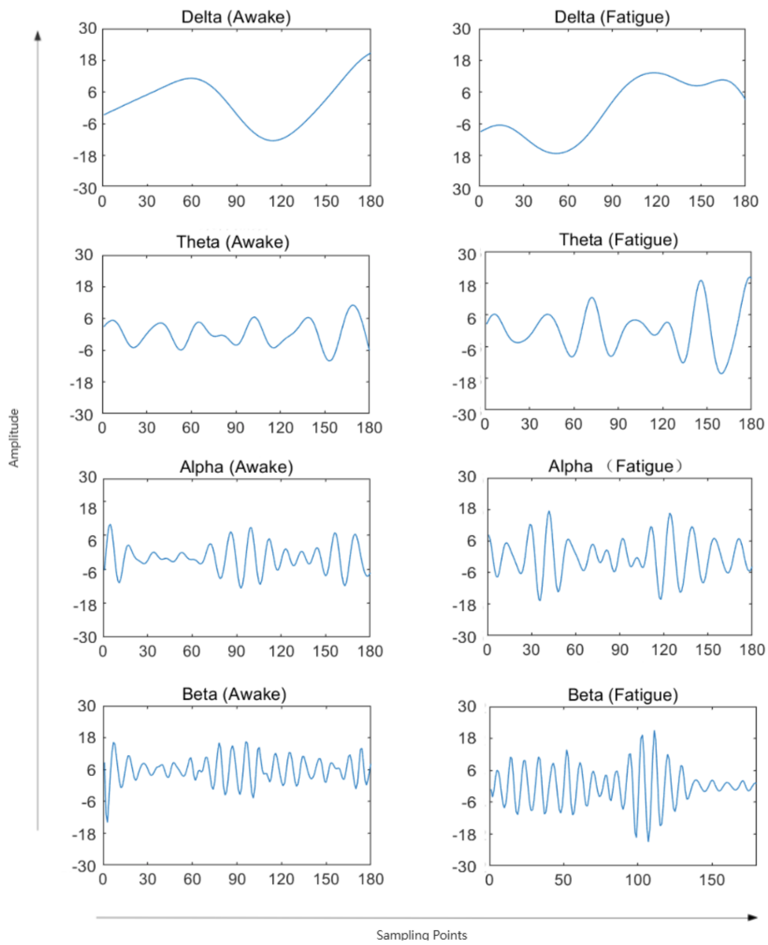

Figure 3.3 Schematic of wavelet packet reconstruction of δ, θ, α and β waves

(4) Nonlinear characterization

EEG signals are chaotic and nonlinear, and nonlinear dynamics analysis has become a common and popular method to study EEG signals. Commonly used nonlinear dynamics methods include correlation dimension, Lyapunov exponent, entropy analysis and complexity analysis. In this paper, approximate entropy, sample entropy [20, 21], fuzzy entropy [22, 23] and wavelet entropy [24] are chosen for characterization.

4. C-RBM Modeling and General Framework for Fatigue Detection

(1) General framework of C-RBM modeling

The constrained Boltzmann machine is a generative stochastic neural network based on energy functions, consisting of visible and hidden layers with unconnected nodes within the layers and fully connected nodes between the layers[25]. However, in the face of diverse application scenarios, it is necessary to improve and extend it to adapt to different task requirements thus optimizing the model performance. Therefore, in this paper, the convolution operation is innovatively introduced into the hidden layer of the restricted Boltzmann machine, where each hidden unit is connected to only one local region of the visible layer to realize spatial weight sharing. This greatly reduces the number of parameters in the model and the computation becomes faster, thus mining potential local features more accurately. Figure 4.1 shows a flowchart of the general framework of the convolutionally constrained Boltzmann machine model and classifier to implement fatigue prediction.

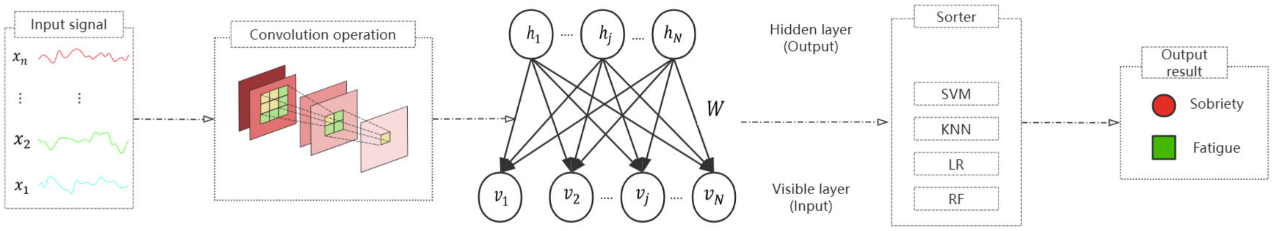

Figure 4.1 Convolutionally constrained Boltzmann machine and classifier model flowchart

(2) Feature selection

The focus of this chapter is to categorize the fatigue EEG signals from different channels. In order to investigate whether there is an intrinsic correlation between individual channels and these extracted features, the brain areas where the electrodes are located are divided into several regions: the brain areas corresponding to electrodes AF3, AF4, F7, F8, F3, and F4 are categorized as frontal lobes; the brain areas where electrodes FC5 and FC6 are located are defined as the central brain areas; The brain regions corresponding to electrodes T7 and T8 were categorized as temporal lobes; the brain regions corresponding to electrodes P7 and P8 were categorized as parietal lobes; and the brain regions corresponding to electrodes O1 and O2 were designated as occipital lobes.

As the extracted multidimensional features may have redundancy and thus affect the accuracy of classification, we chose to downscale the features by principal component analysis before detecting fatigue, and remove the complicated irrelevant features as input features for classification. Principal Component Analysis (PCA) is the process of reusing highly correlated variables and transforming them into several highly representative composite variables, i.e., principal components. They are independent and unrelated to each other, so they can reflect most of the information of the variables and the feature information does not overlap with each other, which is a good solution to the problem of feature redundancy [26]. In this paper, we choose to extract the first, second and third features as the principal components, combined with the Pearson coefficient to retain the highly correlated features for the next study.

Pearson correlation coefficient (Pearson correlation coefficient) can well reflect the correlation between variables [28]. In this paper, 13-dimensional features such as time-frequency entropy are combined two by two for Pearson correlation coefficient analysis. Figure 4.2 Heat map of feature correlation coefficient matrix corresponding to EEG data of selected subjects, where red represents positive correlation, blue represents negative correlation, and the depth of color represents the strength of correlation. From the figure, it can be seen that: Hjorth mobility is negatively correlated with Hjorth complexity, power spectral density, energy spectrum and sample entropy, and Hjorth complexity and sample entropy; Hjorth mobility is positively correlated with sample entropy, power spectral density, energy spectrum and wavelet entropy. Therefore, Hjorth complexity and energy spectrum features are excluded and the remaining features with no significant correlation are analyzed in the next step.

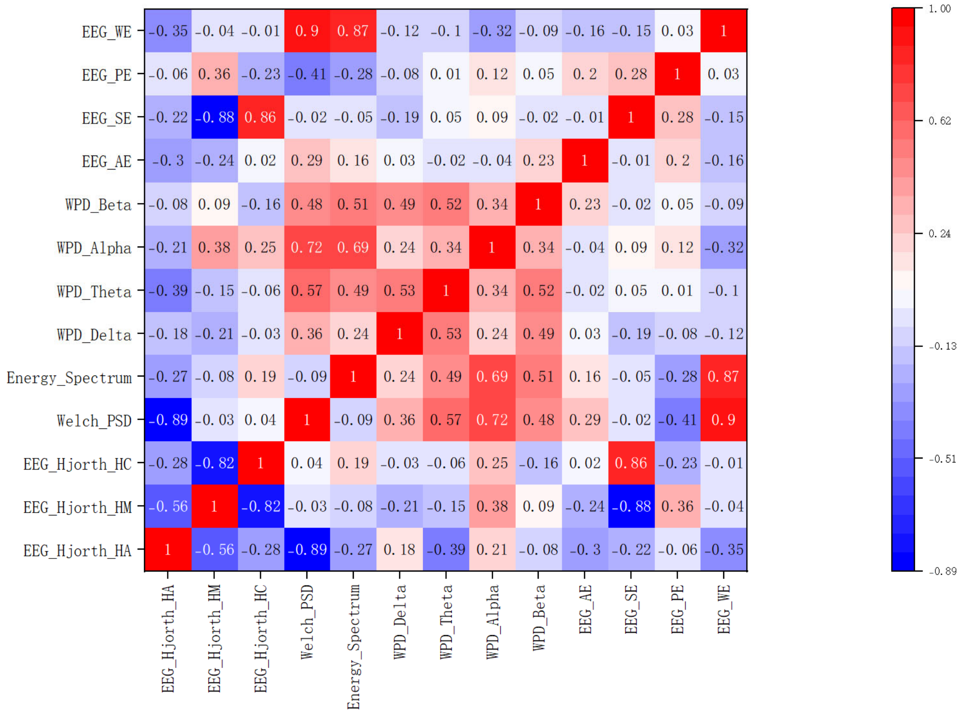

Figure 4.2 Heat map of correlation coefficients between different combinations of features

(3) C-RBM Fatigue Detection Study

In this paper, a classification model based on self-training-semi-supervised learning is proposed. The CNN is used as the initial classifier, 32 5×5 convolutional kernels are selected for the convolutional layer and moved step by step, the ReLU function is selected for the activation layer, the window of the pooling layer is set to 2×2, the step size is set to 2, and the learning rate is set to 0.001. After that, the dataset is divided into the training set and the test set according to the ratio of 3:7, and the confidence threshold is set to 0.8, and the data with a higher value than 0.8 are added into the test set as pseudo-labeled data. The confidence threshold is set to 0.8, and data higher than 0.8 are added to the test set as pseudo-marked data. Data less than 0.8 will continue to participate in the training until the preset number of iterations is reached. Finally, a new test set is formed, which serves as the target input for SVM and KNN classifiers to predict fatigue EEG. Figure 4.3 below shows the general framework diagram. Table 4.1 compares the fatigue EEG classification accuracy results for different channels after feature selection.

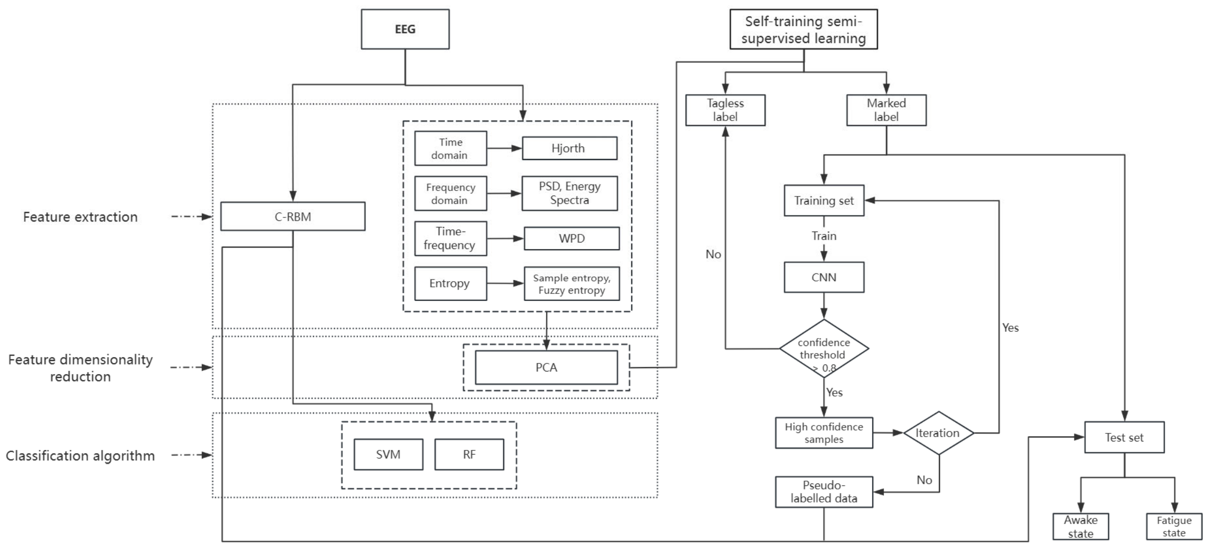

Figure 4.3 General framework diagram of self-training-semi-supervised learning classification model

Table 4.1 Fatigue EEG classification accuracy for different channels in 16 subjects

Participants	Classification accuracy for different channels				
	Frontal area	Central area	Temporal area	Parietal area	Occipital area
1	0.92	0.89	0.83	0.87	0.91
2	0.87	0.87	0.92	0.9	0.94
3	0.82	0.79	0.84	0.87	0.97
4	0.96	0.9	0.95	0.84	0.84
5	0.91	0.79	0.88	0.94	0.95
6	0.84	0.83	0.75	0.83	0.88
7	0.95	0.86	0.79	0.92	0.97
8	0.88	0.92	0.83	0.95	0.83
9	0.94	0.89	0.72	0.82	0.91
10	0.83	0.76	0.81	0.76	0.87
11	0.92	0.91	0.86	0.91	0.83
12	0.91	0.84	0.76	0.84	0.94
13	0.85	0.89	0.91	0.89	0.89
14	0.81	0.88	0.84	0.88	0.97
15	0.9	0.75	0.79	0.81	0.86
16	0.86	0.83	0.91	0.83	0.95
Average	**0.89**	0.85	0.84	**0.87**	**0.91**

From the above table, it can be seen that the average classification accuracy of frontal, parietal and occipital lobes is higher, reaching 89%, 87% and 91%, respectively, which determines that the number of channels can be appropriately reduced to analyze and classify fatigue EEG features, and the following use of different classifiers focuses on the fatigue detection of the sparse channels and the features after dimensionality reduction. In this paper, Welch's method, wavelet packet transform and fuzzy entropy method are used to extract the power spectrum and sub-band feature information of δ, θ, α and β of the EEG signals, respectively, and compare the fatigue detection of the frontal lobe, parietal lobe and occipital lobe with the classical binary classification SVM classifiers and the trained CNN classifier model, respectively, and the comparison of the classification results is shown in the table below:

Table 4.2 Mean classification accuracy in different brain regions

Feature extraction	Classifier	The average accuracy rate of the frontal lobe
Wavelet packet transform	SVM	68.7%
Welch and Fuzzy entropy	SVM	65.2%
Wavelet packet transform and Fuzzy entropy	SVM	79.5%
C-RBM	SVM	78.1%
C-RBM	CNN	85.3%

Feature extraction	Classifier	The average accuracy rate of the parietal lobe
Wavelet packet transform	SVM	67.3%
Welch and Fuzzy entropy	SVM	62.5%
Wavelet packet transform and Fuzzy entropy	SVM	77.5%
C-RBM	SVM	76.2%
C-RBM	CNN	84.7%

Feature extraction	Classifier	The average accuracy rate of the occipital lobe
Wavelet packet transform	SVM	68.9%
Welch and Fuzzy entropy	SVM	64.8%
Wavelet packet transform and Fuzzy entropy	SVM	79.2%
C-RBM	SVM	78.6%
C-RBM	CNN	86.9%

As can be seen from Table 4.2, the traditional method using SVM classifier achieves good results with an average accuracy close to 78% for all three brain regions. This indicates that with the a priori experience of manually selecting features, the SVM classification model is able to obtain a high classification accuracy. And the classification accuracy of C-RBM + CNN for all three channels reaches about 85%, which is about 7% higher than the C-RBM + SVM model. It is proved that the trained initial classifier achieves higher accuracy on sparse channels, based on which fatigue is detected and evaluated using SVM and RF classifiers for this test set.

(4) Analysis of feature classification results of different classifiers for sparse channels

The classification results of the overall fatigue EEG features of different channels were analyzed above, and after dimensionality reduction, it was found that the frontal, parietal and occipital lobes had higher classification accuracy. Therefore, the subsequent fatigue detection is mainly performed on the channels of these three brain regions to find the model that can have better fatigue detection performance for different combinations of temporal entropy features in the case of sparse channels. The classifier is accomplished using support vector machines and random forests, and the core ideas of the two classifiers are briefly described below.

The core idea of support vector machine is to explore an ideal hyperplane in the high-dimensional data space, which can clearly delineate the data belonging to different categories. The decision function of the optimal hyperplane is formulated as follows:

$$f(x) = sgn\left(\sum_{i=1}^{l} a_i y_i (x_i, x_j) + b\right)$$

The core idea of random forest is to draw random samples from the training set and each subset is used to train a decision tree. At each node of each decision tree the features to build the tree are randomly selected. For the classification task, assume that the random forest has N trees, and the nth tree is predicted by $\hat{y}_n$, and the final prediction is:

$$\hat{y} = argmax_c = \sum_{n=1}^{N} I(\hat{y}_n = c)$$

Based on the features after the screening of the original signal, this paper retains the feature information with a total of 11 dimensions of time-frequency entropy, and uses 2 classifiers for fatigue detection of the remaining features. The penalty parameter c of SVM is set to 10, the kernel function selects radial basis kernel function, and the gamma parameter is set to 0.02. The number of n_estimators decision tree of RF is selected to be 30, the maximum depth of max_depth decision tree is set to be 10, the minimum number of samples inside min_samples_split is set to be 5, and the learning rate is set to be 0.02. The time-frequency entropy features are categorized into HA and HM, PSD, AE, SE, PE and WE are combined into 8 feature combinations, which are classified and compared with SVM and RF classifiers respectively, as shown in Figure 4.3 below.

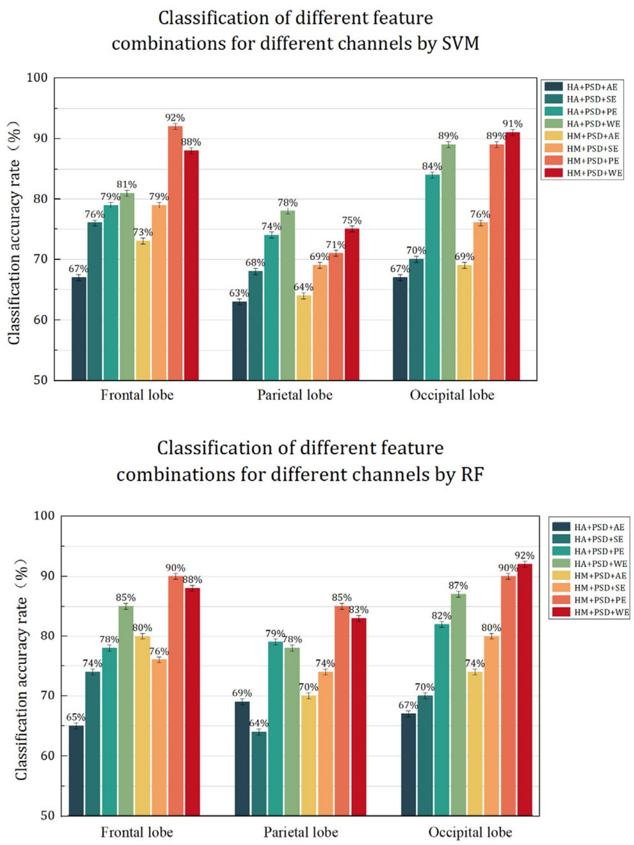

Figure 4.3 Comparison of classification accuracy of SVM and RF for different channels and combinations of features

As can be seen in Figure 4.3, it can be seen that the accuracy of the frontal and occipital lobes is slightly higher than that of the parietal lobe, and the best feature combinations for classification are HM + PSD + PE and HM + PSD + WE, followed by HA + PSD + PE and HA + PSD + WE. This indicates that the feature combinations of Hjorth parameter, power spectral density with fuzzy entropy and wavelet entropy for frontal and occipital lobes have obvious advantages in fatigue detection in this paper.

5. Conclusion

In today's neuroscience and brain-computer interface research field, the characterization of fatigue EEG is becoming more and more important. Fatigue state in special scenarios such as driving and working at heights not only affects the daily life of an individual, but also may lead to safety hazards in serious cases, so it is of crucial importance to accurately recognize fatigue EEG signals.

In this paper, 16 subjects were selected to participate in a 1 - back task paradigm to induce their fatigue EEG state, in which subjects were asked to judge whether the previous stimulus was the same as the current stimulus and give a response. As the task progressed, the subjects' visual and central nervous system were highly focused, which led to the presentation of EEG signals specific to the fatigued state. Based on the average reaction time and average correct response rate combined with the fatigue index value F as the objective assessment results, the trend of change is consistent with the subjective assessment of the KSS scale, which proves that brain fatigue has been successfully induced.

In order to extract effective features from complex EEG data, this paper adds a convolution operation to the restricted Boltzmann machine, aiming to use convolution operations to better identify features in localized regions. PCA and Pearson's coefficient are applied to correlate the features, remove redundant features, filter out the features that are highly correlated with fatigue EEG, and select the time-frequency entropy features of frontal, parietal, and occipital lobes as the input features for classification and recognition. Afterwards, the convolutional neural network (CNN) classifier was trained based on self-training and semi-supervised learning, making full use of a small number of labeled samples and a large number of unlabeled samples, and repeatedly iterating to optimize its own weight parameters, so that the average classification accuracies of frontal, parietal, and occipital EEG signals finally reached 89%, 87%, and 91%, respectively. On this basis, support vector machine (SVM) and random forest (RF) classifiers were further used to reclassify the time-frequency entropy feature combinations after feature selection, aiming to find more explicit feature combinations with higher classification accuracy. The experimental results show that the frontal and occipital regions perform slightly better than the parietal lobe in terms of classification accuracy, especially for the two feature combinations of HM + PSD + PE and HM + PSD + WE. SVM achieves a classification accuracy of 93% for the occipital lobe with HM + PSD + PE, and RF achieves a classification accuracy of 92% for the occipital lobe with HM + PSD + WE. This fully demonstrates that the model of C-RBM extracting features constructed in this paper and the combination of SVM and RF classifiers have better fatigue detection effect on the two combinations of features after channel reduction, which provides an effective reference and feasibility for the subsequent sparse channel detection of fatigue EEG.

Discussions:

(1) Most of the methods used in this study to induce fatigue EEG are based on small-scale data sets, which inevitably lack diversity and representativeness. Due to the differences in experimental environments, types of tasks, and groups of subjects, the EEG data may vary, and the individual's own habits and genetic factors may also have an impact on the EEG signals. In the future, we can try to collect detailed information of individuals, construct a model based on the EEG data of some individuals, and then test it with the EEG data of the rest of the subjects to check the validity of the model, and then explore the unique fatigue characteristics model.

(2) In this study, only the states of the first and last stages of the subjects were selected as the research data, and although the accuracy of the dichotomous classification task is quite impressive, it is possible to find an intermediate state between these two states, and multiple fatigue level classifications can be attempted in the future.

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