Mental Fatigue Classification Using EEG Signals based on XGBoost

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Abstract

Fatigue is a common physiological and psychological state that affects human cognition and behavior. Electroencephalography (EEG) signals provide non-invasive biological information about brain activity. In this study, we aimed to use the Extreme Gradient Boosting (XGBoost) algorithm, a powerful machine learning technique, for EEG-based mental fatigue classification. We collected EEG data from 10 participants who performed a cognitive task under mental fatigue and non-fatigue conditions. We preprocessed the raw EEG data by filtering, denoising, and feature extraction to enhance signal quality and reliability. Then, we built an XGBoost classifier to differentiate between fatigue and non-fatigue states. Our research has significant implications for understanding the mechanisms of fatigue and improving human performance in various domains.

Keywords

Mental Fatigue; XGBoost; EEG; Classification; Recognition.

1. Introduction

Fatigue refers to a decline in work capacity caused by excessive exertion[1], and it can manifest as physical or mental fatigue, weakness, and weariness. It can be triggered by various factors such as prolonged labor, exercise, mental stress, or sleep deprivation. One specific type of fatigue is mental fatigue (also known as cognitive fatigue), which results from sustained attention, thinking, or decision-making. Mental fatigue can impair cognitive function, mental state, and physical health. Existing methods for classifying mental fatigue can be divided into two main categories. The first category relies on subjective ratings of fatigue levels based on different stages of alertness and sleepiness. For example, Peiris proposed a four-level scale of fatigue: normal state, mild fatigue, moderate fatigue, and severe fatigue; but did not specify how to measure or distinguish these levels [2]. The second category uses objective indicators of fatigue derived from specific analysis methods, such as physiological signals or behavioral performance, and then quantifies and interprets them.

EEG band changes have been shown to be strongly associated with mental fatigue in many studies, and they indicate that EEG is a promising tool for assessing mental fatigue [3]. However, these studies mainly focused on vehicle driving in simulated settings [4]. Despite the high prevalence of mental fatigue induced by long-term high-stress conditions in some occupations, the EEG signal changes underlying this phenomenon remain poorly elucidated.

The aim of this study was to use the XGBoost classifier, a powerful machine learning technique, to examine the mental fatigue variations during a long-term stress condition by recording EEG using 32 electrodes distributed over the head. We evaluated mental fatigue in a real-life intellectually challenging competition using different measurement methods: self-rating scale and reaction time in Go/No-Go and Stroop task; and we validated the EEG analyses by comparing them with these methods. Our hypothesis was that mental fatigue would be present, and that the XGBoost classifier would be able to distinguish it.

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2. Materials and Methods

2.1 Participants

We recruited 8 male and 2 female volunteers, aged 19–22 years (mean = 20.5, and SD = 0.82), from the South Central Minzu University who participated in the National Undergraduate Electronics Design Contest. The inclusion criteria were: good general health, absence of neurological diseases and psychiatric disorders, and no history of hearing and visual impairment. All participants gave written informed consent to the experimental procedures before the experiment. They were not allowed to consume any alcohol, caffeine, or nicotine products during the experiment.

2.2 Procedure

We used three subjective and objective measurement tools to assess their mental fatigue during a 5-day electronics design competition. The National Undergraduate Electronic Design Contest is an annual contest that requires the undergraduates to complete a project within 5 days. The contest is a highly competitive and beneficial opportunity for the participants' career and education prospects. The high stakes of the contest create significant pressure for the students; and they lead to the accumulation of mental fatigue.

The experimental procedures for each assessment are illustrated in Figure 1. Before the assessment, participants completed the Stanford Sleepiness Scale and reported their sleep duration. Then they were fitted with the EEG device and their room lights were dimmed. Next, we recorded their resting-state EEG for a 5 min with eyes closed. Participants were instructed to sit in a chair, remain quiet and calm, empty their mind, and minimize their movements except for pressing the button. Finally, they performed the Go/No-Go and Stroop tasks.

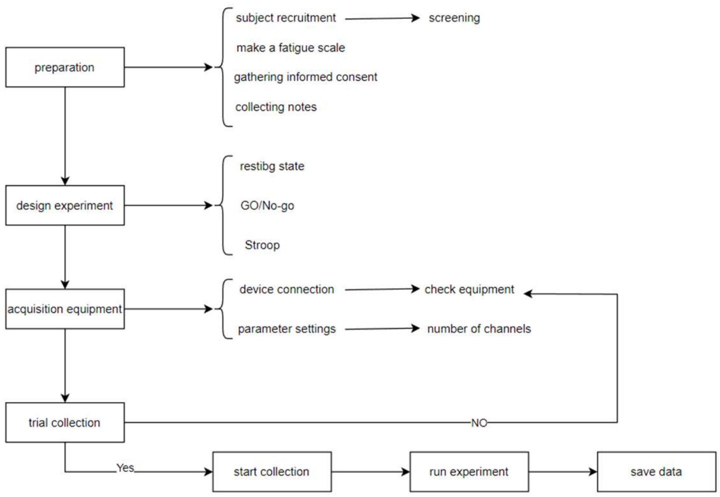

Figure 1. Experimental procedures.

2.3 EEG Recording

We collected EEG data from 32 electrodes following the standard 10-20 system. We used the ActiveTwo EEG amplifier and electrode cap from BioSemi, Netherlands, to acquire the EEG signal. The signal was sampled at 2048 Hz with a resolution of two microvolts. We ensured that the impedance level was below 5 kΩ before processing.

2.4 Fatigue Assessment

The tasks were separated by an interval of 1000 ms, and they lasted for 50 ms each. The standard oddball sequence had a white background in the visual stimulation paradigm. The target stimuli were the English letters in the Go/No-go task and the Chinese characters with color in the Stroop task. We instructed the participants to press a button with their finger of their dominant hand as quickly as

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possible when they detected the deviant stimuli. The reaction time was measured as the time difference between the stimulus onset and the button press onset; and we used the mean reaction time (RT) of the participants in each task as a metric.

3. Methods

Figure 2 shows the data processing pipeline for the EEG signals. We preprocess the raw EEG data to improve its quality and reliability. The preprocessing steps include filtering, bad channel removal, artifact removal, and re-referencing. Then we select the relevant channels and augment the data. We obtain enough sample data for feature extraction and classifier training. Finally, we generate the classification results as output.

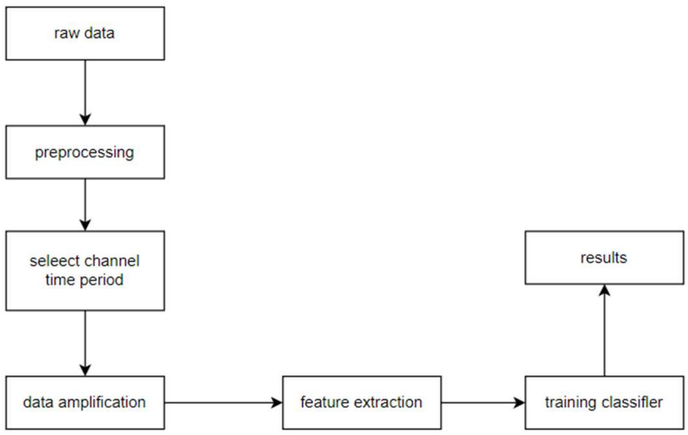

Figure 2. Data Processing Pipeline

3.1 Data Preprocessing

We preprocess the raw EEG data, to reduce noise and artifacts and improve the quality and accuracy of the signals. We use the MNE-Python library for EEG signal preprocessing that consists of four steps: bad channel removal, re-referencing, filtering, and artifact removal. First, we employ an interpolation method to identify and restore the data at the bad channel locations using the signals from neighboring electrodes. Second, we use an average reference method to mitigate the influence of reference electrodes and enhance the signal consistency across different channels. Third, we apply notch and bandpass filters to the EEG signals after bad channel removal and re-referencing. The notch filter removes the powerline interference, while the bandpass filter extracts the desired frequency range of the EEG signals. Finally, we use independent component analysis (ICA) to remove eye movement artifacts from the EEG signals. ICA separates the mixed signals into independent components and allows us to identify and remove components related to eye movements. These preprocessing steps clean the EEG signals and reduce artifacts, resulting in a purified EEG dataset for further analysis and interpretation.

3.2 Data Splitting and Augmentation

We use the leave-one-out method for prediction strategy, where we leave out each sample from the original dataset and use it as a test sample while training on the remaining samples. We repeat this process for each sample in the dataset. The leave-one-out method helps us to better understand the characteristics and patterns of each sample, and to reveal the similarities and differences among them. It also provides a reliable and unbiased estimate of model performance.

We also use data augmentation to increase the size and diversity of the training data because the samples were insufficient for the classifier. We average similar samples to create new samples. This superimposed averaging method captures the commonalities and generalized features among the samples. It increases the number of samples in the dataset and improves the training effectiveness of the model.

The data augmentation method has the advantage of using the information in the existing data to generate new samples with similar features. By augmenting the dataset, the model can be trained better, resulting in improved generalization ability and robustness. Moreover, this method has a wide range of applications and can be used not only for fatigue state recognition but also for other pattern recognition tasks in different domains.

3.3 XGBoost

XGBoost was used as the classifier. XGBoost is a powerful and efficient machine learning algorithm that is mainly used for regression and classification problems [5]. It is based on the gradient boosting framework, which iteratively trains a series of decision tree models for prediction [6].

XGBoost has great flexibility and performance advantages in data preprocessing, feature engineering, and model training. It can handle different types of data and automatically handle missing values. Moreover, XGBoost provides feature importance analysis and model interpretation capabilities. XGBoost is an additive model consisting of kbase models, assuming that the tree model to be trained at the t-th iteration is ft(x), we have:

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_x(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i). \tag{1}$$

Where the first i represents the prediction result of sample i after t iterations, the second i represents the prediction results of the first t-1 trees, and the third i represents the model (function) of the t-th tree.

The boosting tree model is initialized and fitted initially during training. Then, in each iteration of the training process, we compute the residuals between the current predictions and the actual values, and we generate a new regression tree by fitting the residuals [7]. The core idea of this training process is to continuously add new trees, and to learn a new function with each added tree to better fit the previous errors. Figure 3 shows the XGBoost EEG classification process.

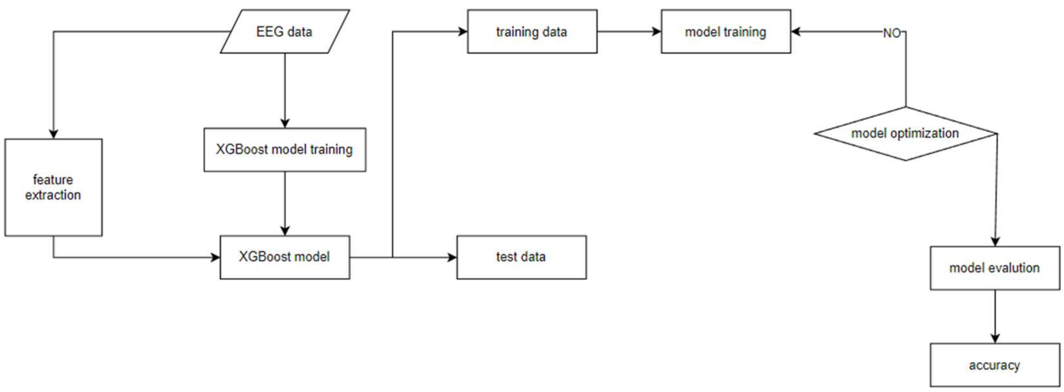

Figure 3. XGBoost Classification Flowchart

4. Results

4.1 Reaction Time statistics

The average reaction time and accuracy rate for both conflict and non-conflict stimuli are calculated for the fatigued participants. An extreme data point is excluded, and then the mean values are obtained.

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To further explore the relationship between conflict and non-conflict stimuli, paired-sample t-tests are conducted.

The t-test for the Go/Nogo experiment showed that, the accuracy rate under the Go stimulus condition was significantly higher than the accuracy rate under the Nogo stimulus condition ($P=0.0012<0.05$). The t-tests for the Stroop experiment showed that there was a significant difference between the reaction times and accuracy rates of the conflict and non-conflict stimuli. The reaction time of the conflict stimuli was significantly longer than that of the non-conflict stimuli ($P=0.017<0.05$). The accuracy rate of the conflict stimuli was significantly lower than that of the non-conflict stimuli ($P=0.027<0.05$).

Table 1. Go/No-go andStroop Experiment Statistics

Task	Stimulus	Accuracy	Reaction Time
Go/No-go	Go	0.99±0.01	434.77±65.90
	NoGo	0.96±0.04	
Stroop	Conflict	0.93±0.14	605.04±176.32
	Noconflict	0.99±0.08	541.30±120.76

The results indicate that participants exhibited significant differences in reaction time and accuracy between the color-word incongruent condition and the color-word congruent condition, demonstrating a strong effect of semantic interference. The color-word Stroop task is widely used to measure cognitive inhibition [8], and its successful application in this study's Stroop experiment confirms the effectiveness of the experimental setup.

4.2 Signals after Preprocessing

Figure 4(a) shows the power spectral density plot after preprocessing. The figure shows that the filtering effect of the high-frequency part is significant, and the energy is mainly concentrated in the low-frequency of 10~15Hz interval. Figure 4 (b)shows one participant's EEG data after preprocessing. From figure 4, we can observe that the P300 is significant with this event. The figure 4 shows that P300 gradually disappears after 500ms. Therefore, we chose the 0~500ms interval segment as the feature of the sample for the subsequent classifier. We also downsampled the sampling rate from 2048Hz to 200Hz to reduce the computation amount.

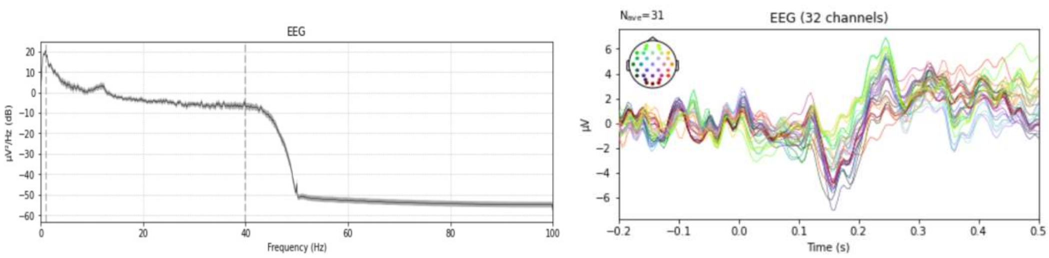

Figure 4. (a) The power spectral density of EEG. (b) The evoked related potentials after preprocessing of all channels

4.3 Classification Results

Table 2 shows the accuracy of EEG signal recognition using the XGBoost classifier. The accuracy ranges from 65% to 75%, which indicates that the classifier can classify the EEG signals correctly to some extent, but there is still room for improvement.

Table 2. Classification Accuracy

	Sbj1	Sbj2	Sbj3	Sbj4	Sbj5	Sbj6	Sbj7	Sbj8	Sbj9	Sbj10
Cz	0.73	0.55	0.75	0.74	0.69	0.74	0.56	0.55	0.72	0.69
P3	0.58	0.69	0.68	0.72	0.65	0.58	0.65	0.68	0.68	0.75
PO3	0.67	0.63	0.56	0.68	0.72	0.63	0.59	0.54	0.59	0.59
P4	0.64	0.53	0.65	0.58	0.67	0.62	0.69	0.54	0.67	0.58

5. Conclusion

This study employed the XGBoost-based approach for fatigue state recognition and conducted comprehensive data processing through preprocessing and feature extraction of the EEG signals. Based on the data collection and analysis, the following conclusions can be drawn: Firstly, the preprocessing steps played a crucial role in improving the quality and reliability of the EEG signals. The application of filtering, bad channel removal, artifact removal, and re-referencing significantly reduced noise and interference in the signals, providing a more accurate data foundation. Secondly, the selection of feature extraction methods played an important role in fatigue state recognition.

The fatigue state recognition was achieved through training the XGBoost classifier in this study. This research provides a reference solution for various fields such as traffic safety, work efficiency, and health management, and holds practical significance for a better understanding of fatigue mechanisms and improving the quality of human life.

Acknowledgments

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