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Fatigue Driving Detection of EEG Signals by LSTM Deep Neural Network with LPSD and DE

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***Abstract*—Fatigue driving detection has always been an urgent social problem to be solved, and many complex factors increase the difficulty of detection. Nowadays, more scholars choose to use multi-channel EEG signals for fatigue detection, which is accompanied by the development of deep learning networks. Here, we propose the deep Long Short Term Memory (LSTM) neural network with the Differential Entropy (DE) and Logarithm Power Spectrum Density (LPSD). We first divide the EEG signal into 8-s Hanning windows with 50% overlap, and then use the Short Time Fourier Transform(STFT) on the extracted time window to obtain 50 frequency sub-bands. Finally, LPSD and DE features are extracted from the frequency offspring obtained from the STFT and input into the deep LSTM neural network. The network can choose to learn more task related information by adding soft attention and extract effective time information from EEG signals,thereby improving the model's performance in detecting driving fatigue. In addition, we also collected EEG signals from 8 subjects in both awake and fatigued states,and used the PERCLOS index to judge the degree of fatigue. Using the collected dataset, we compared the effectiveness of the deep LSTM neural network with five other methods. The results indicate that the deep LSTM neural network has a better classification accuracy of 93.12%. It proves that the network has good performance in fatigue detection of EEG signals.**

***Index Terms*—EEG;Fatigue Detection;LSTM;DE;LPSD**

I. INTRODUCTION

Fatigue is a physiological state of a decrease in physical or mental activity,typically caused by continuous work and learning [1]. It is commonly divided into physical and mental fatigue [2]. Mental fatigue can lead to a sense of exhaustion, lack of concentration, and may cause the decline in work efficiency and the increase in the likelihood of accidents [3]. In daily life, driving fatigue is the most common form of mental fatigue. According to the surveys, there are about 20% of traffic accidents in the whole world related to fatigue driving every year [4]. So accurately detecting the driving fatigue and providing warnings has become an urgent problem to be solved.

So far, fatigue detection methods are mainly divided into three categories: subjective questionnaire survey (such as Karolinska Sleep Scale (KSS) [5], Psycho motor Vigilance Test (PVT) [6], human activity behavior detection method (such as facial expressions [7], head position [8]), detection methods based on physiological signals (such as electroencephalogram (EEG) [9], electrooculogram (EOG) [10], electromyography (EMG) [11], electrocardiogram (ECG) [12]). Wherein, subjective questionnaire surveys are easy to operate and have lower costs. However, it is unable to detect the status of subjects in actual time and has a high degree of subjectivity [13]. The human activity behavior detection method uses image recognition technology to capture facial expressions during human activity to detect fatigue. This method is affected by environmental lighting and cannot adapt to real-time environmental changes [14]. Physiological signals can correctly report the status of human activity in actual time. Among numerous physiological signals, it is known that EEG signals are considered as the "gold standard" for fatigue detection [15], It can correctly reflect the status of brain activity, refrain from the subjective influence caused by anthropogenic factors, and has high real time and responsibility. Above all, this paper focuses on the detection method of driving fatigue using the consecutive multi-channel EEG signals.

Recently, deep learning technology has been widely applied in image recognition [16], signal classification [17], and task target detection [18]. These models have high capacity and simple structure. Furthermore, some methods have also been achieved to turn into practical applications. Gao et al. [19] collected EEG signals from 8 subjects under fatigue state and constructed a novel EEG based spatiotemporal convolutional network for driving fatigue detection, which introduced core blocks to extract temporal features. Jiao et al. [20] used Conditional Wasserstein GAN to increase the data samples, and processed the EEG and EOG signals using LSTM. Budak et al. [21] constructed three different blocks to detect drowsiness, each using different methods to extract features. Then input the features extracted from the three blocks into LSTM for classification, and combine the results of LSTM with a major voting layer. This paper used different time windows of EEG signals to extract time information based on Differential Entropy (DE) and Logarithm Power Spectrum Density (LPSD). The deep LSTM network with soft attention was constructed for fatigue detection.

II. Experiment

In order to study effective fatigue characteristics, we designed a driving experiment to induce driver fatigue. By collecting EEG signals during the experiment, we could produce as many valuable raw datasets as possible. In the experimental design phase, we fully considered the impact of time and individual emotional factors on the experiment. Furthermore, we arranged the simulated driving scene as realistic as we can. In this section, subject communication, experimental plan, and data collection and preprocessing were introduced separately.

A. Subjects

During the experiment, 8 subjects (six males and two females) were selected for the experiment, all of them were between 22 and 25 years old. All subjects voluntarily participated in the experiment and had no physical or mental illnesses. This experiment required them to avoid taking anti fatigue beverages and psychotropic drugs that cause drowsiness during the experiment. Meanwhile, all subjects also maintained reasonable and healthy rest and sleep. The subjects must comply with all requirements so as to participate in the experiment. An indoor simulated driving platform was selected in the experiment. As some subjects had not been exposed to vehicle driving simulators, they needed to practice using driving simulators until they became proficient. If any discomfort occurred during the experiment, the subject would promptly stop driving and be arranged to rest.

B. Experimental design

Driving on the real highway and collecting EEG signals from drivers was a very dangerous thing. Therefore, the study simulated the real road driving scenario in the laboratory and selected Beijing China Joint Teaching Equipment Co. ltd.ZY-31D vehicle driving simulator as the simulation driving platform for the experiment. The simulation driving environment chose a circular highway with only a few vehicles on the road and a sunny day. Fig 1 shows the experiment settings.

For enhancing the fatigue feeling of the subjects, the experiment was conducted between 14:00 and 15:30, which is more likely to cause fatigue in the subjects. Each experiment lasted for 90 minutes for the subjects. The EEG signals of 64 channels were collected in a closed and quiet environment.

The PERCLOS index is used in the experiment to measure the fatigue level of the subjects. PERCLOS refers to the percentage of eye closure, which is widely used in measuring attention [22] and fatigue level [23]. The experiment uses the eye tracker to collect continuous blink time and 'CLOS' to calculate the PERCLOS,which is:

$$PERCLOS = \frac{blink + CLOS}{interval} \tag{1}$$

where 'CLOS' is the duration of eye closure.

The labeling method has a good effect on measuring fatigue in laboratory environments, but due to the high cost of eye

Fig. 1. Experimental settings.

trackers, it is not suitable for practical applications and is only used in this experiment to better improve the accuracy of model fatigue detection.

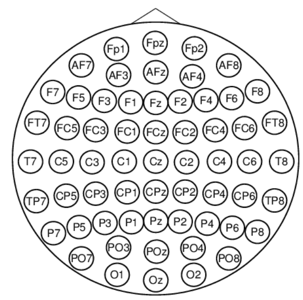

Fig. 2. The electrode location map in the international 10-20 system standard.

C. Data collection and preprocessing

The EEG collecting device was equipped with the the Neuroscan system with 64 electrodes at a sampling frequency of 1000 Hz. The electrode distribution was arranged according to the international 10-20 system standard, as shown in Fig 2. The Tobii Pro Fusion eye tracker was used to collect eye data from subjects, with a sampling frequency of 250Hz. During the data collection process, subjects were required to limit unnecessary physical activity, maintain smooth driving, and try to avoid vehicle collisions.

The EEGLAB toolbox was used to preprocess the original EEG signal. We reduced the sampling frequency to 100Hz and removed artifacts from the EEG signal through a 1-50Hz bandpass filter. Then, divided the EEG signal into 8-s Hanning windows with 50% overlap. Then used the STFT on the extracted time window with a resolution of 2Hz, and finally obtain 50 frequency sub-bands, where provided L windows for the STFT, T is the length of the EEG signals. About the PERCLOS index, we set the interval to 0.1s,and defined the

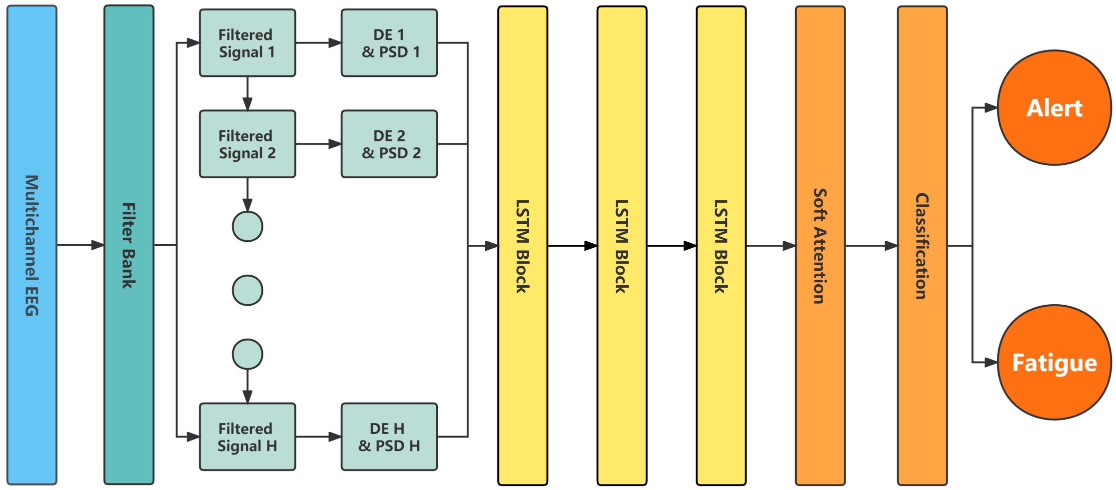

Fig. 3. The overview of fatigue detection of EEG signals.

PERCLOS index more than 0.7 as the fatigue state and less than 0.7 as the normal state.

III. Methodology

Fig 3 clearly illustrates our proposed fatigue detection method. First, used STFT on the time window extracted by the bandpass filter, and then DE and LPSD features were calculated on the STFT outputs which were 50 frequency sub-bands. Finally, the extracted features were sent to the deep LSTM network for classification.

A. Feature Extraction

The paper extracted two features: LPSD and DE. PSD is one of the typical methods for frequency domain analysis of EEG signals. It converts the amplitude of EEG signals over time into a spectrum of EEG signal power over frequency, thereby intuitively observing the distribution and changes of EEG signal rhythm. LPSD is used to extract the spectral features of EEG signals in the paper,as shown in Eq 2.

$$S_{xx}(\omega) = \lim_{T\to\infty} E[\left|\widehat{X}(\omega)\right|^2] \tag{2}$$

DE can measure the complexity of continuous signals. Assuming μ and δ^2 are the mean and variance of EEG signal x, DE calculation is shown in Eq 3.

$$\begin{aligned} DE &= -\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \log \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \mathrm{d}x \\ &= \frac{1}{2}\log 2\pi e\sigma^2 \end{aligned} \tag{3}$$

B. LSTM Network with Attention

LSTM is one of the RNN network that can learn both short and long-term dependency information from continuous sequence data. The LSTM network has been successfully used in the processing of EEG signals and has achieved good results. The paper inputs the EEG signal features (LPSD and DE) extracted from each frequency band of different time windows into L appropriate time steps. Then, through updating weights during the network training, determine which information to remember or forget, and learn the information of different LSTM cells (s_i),as shown in Eq 4.

$$h_i = LSTM(s_i), i \in [1, L] \tag{4}$$

where h_i is the output in the hidden state for each time step i. These outputs will be fed into the next layer of LSTM cells for higher-level feature learning.

To improve the temporal information of extracting EEG signals, we add the soft attention to the LSTM network. It evaluates the importance of all output information in the last layer of LSTM by assigning trainable attention weights α_i to each h_i. Thus, special time steps can be focused on by optimizing weights to obtain more task related information,as shown in Eq 5,6 and 7.

$$u_i = tanh(W_s h_i + b_s) \tag{5}$$

$$\alpha_i = \frac{exp(u_i)}{\sum_j exp(u_j)} \tag{6}$$

$$v = \sum_i \alpha_i h_i \tag{7}$$

where the vector v is the output of the LSTM network, W_s and b_s are the trainable parameters.

C. Implementation

We finally built a three-layer LSTM deep learning network with soft attention, with a dropout rate set to 0.5 between each layer. Softmax was used for the classification of the model,and the loss function of the model selected the mean squared error. The Adam optimizer used default learning rates to help minimize losses. We used 100 epochs and 32 batch sizes to effectively train the deep network. The experiment was run by using TensorFlow on the NVIDIA GeForce GTX 3060 (6G) GPU . All hyperparameters have been systematically adjusted for optimal performance.

IV. Result and Discussion

The proposed Deep LSTM network has been trained to detect the fatigue status of each subject. For the collected data, we choose to use 5-fold cross validation to divide the data into training and testing sets. For each subject, 50% of the samples are randomly selected for training, and the remaining 50% was retained for testing. Finally, the performance of the model is obtained on 8 subjects. Fig 4 shows the performance of the Deep LSTM network model on fatigue data.

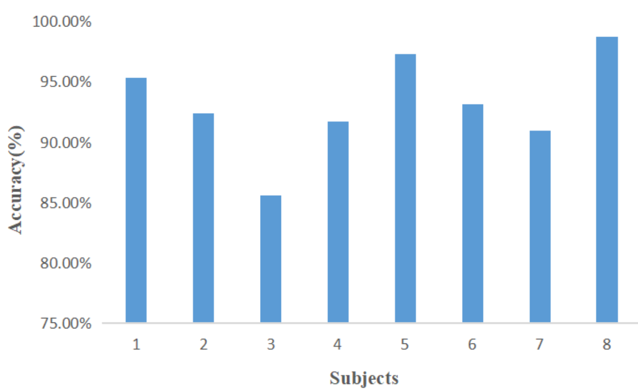

Fig. 4. The accuracy of the Deep LSTM network.

In Fig 4, the proposed Deep LSTM network is stable and effective throughout the collected dataset. The average accuracy reaches 93.12%. Among them, the accuracy of 5 subjects is higher than the average accuracy. Excluding some uncontrollable factors, the difference in accuracy among the subjects may be related to their own physical factors and the rest situation during the experimental days. The recognition accuracy of subject 5 is relatively low. We observed the fatigue label of the subject and found that the subject only developed mild fatigue at the end of the experiment. It also indirectly reflects the robustness of our proposed method in learning effective information from samples for recognition.

In addition, we compare the proposed method with several common structures and other existing works to ensure the reliability of the performance of our proposed method. From Table I, it can be seen that our proposed method has effective and reliable overall performance.

Based on the structural parameters proposed in the original paper, we reproduced these methods to analyze the EEG dataset we collected. These methods were designed for EEG signal analysis. As shown in Table I, our proposed method outperforms other EEG signal analysis methods on the self collected dataset. The result proves that our proposed deep LSTM neural network based on LPSD and DE has good performance.

TABLE I
The classification performance of EEG driving detection.

Method	Average Acc (%)
PSD-SVM	**74.25**
CNN-A [24]	**87.34**
CNN-B [25]	**89.38**
CNN-C [26]	**92.95**
LSTM [27]	**91.34**
OUR	**93.12**

V. Conclusion

Fatigue driving is an urgent social problem to be solved, and the development of deep learning has promoted the updating of task detection models. Therefore, we propose the deep LSTM neural network based on LPSD and DE to detect driving fatigue status from EEG signals. By extracting LPSD and DE features from the time window of EEG signals and inputting them into deep LSTM neural networks, the model's ability to process time information is improved. Compared with the other five models, our proposed deep LSTM neural network exhibits excellent performance in fatigue detection of EEG signals. Further work will focus on optimizing the network structure to improve the performance of the model and enhance the universality of deep LSTM neural networks in BCI systems.

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