Lower limb motor imagery EEG signals classification based on 1D-CNN-LSTM algorithm

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ABSTRACT

With the continuous development of the brain-computer interface (BCI) technology, the lower limb rehabilitation system based on Motor Imagery (MI) has gradually become a research hotspot in the field of rehabilitation. To recognize the lower limbs MI, this paper designed an experimental paradigm for MI lower limb MI and used the 1D-CNN-LSTM deep learning algorithm to classify lower limb movement features from MI EEG signals. Compared with classical machine learning algorithms, the results showed that 1D-CNN-LSTM has relatively higher accuracy. Meanwhile, the paper built a real-time lower limb rehabilitation system based on the 1D-CNN-LSTM algorithm, which verifies the effectiveness and feasibility of the algorithm. The system provides an advanced and effective solution for brain-computer interfaces based on MI.

Keywords: Motor Imagery, lower limb, 1D-CNN-LSTM, rehabilitation, EEG Signals

1. INTRODUCTION

As China's aging population aggravates the problem, the number of elderly people who have difficulty walking is also increasing, and the demand related to old age continues to increase. It is shown that there are more than 2 million new cases of stroke hemiplegia in China every year, and 75% of these survivors face a series of sequelae, such as muscle weakness and paralysis. Meanwhile, limitation of lower limb motor function caused by stroke, spinal cord injury, cerebral palsy and other diseases is also a common condition, which seriously affects the quality of patients 'life [1]. Significant progress has been made in investigating motor imagery-based brain-computer interface (MI BCI) systems for rehabilitation functions [2][3], offering entirely new possibilities for rehabilitation therapy [4].

The increasing amount of research related to classification algorithms for MI in MI BCI systems. The feature extraction methods that are commonly used in (MI-BCI) system are Common Spatial Patterns(CSP)[5], Filter Bank Common Spatial Pattern(FBCSP)[6], Power Spectral Density(PSD)[7], Wavelet Packet Transform(WPT)[8] Energy Entropy[9], etc. Classification methods are Support Vector Machines (SVM)[10], Neural Networks (NN)[11], etc.

Most of the MI research is geared toward categorizing left and right hand, not left and right leg. which is due to the fact that it is difficult to classify lower limb movements since the area of the cerebral cortex corresponding to lower limb movements is concentrated[12]. However, many people who lose the motor function of legs in the real life need to be rehabilitated or manipulate the equipment by MI-BCI. How to realize the high-precision classification of the lower limb will become a hotspot of further research.

In summary, this paper introduced One-dimensional Convolutional Neural Network combined with Long Short-Term Memory Network (1D-CNN-LSTM) deep learning algorithm for lower limbs MI classification. At the same time, based on the above algorithms, a real-time lower limb rehabilitation system was designed.

2. EXPERIMENT

2.1 System framework

During the experiment, subjects were given a task to simulate left and right leg flexion and extension movements through MI for a specified period. The MI experiment was written by the E-Prime software. Subjects performed an MI task of left-leg flexion or right-leg flexion depending on the arrow direction display on the computer screen in a random order. The experiment was divided into seven blocks. Each block contained 20 trials of left-leg flexion and 20 trails of right-leg flexion. Each trial was divided into three steps, which is shown in Figure 1.

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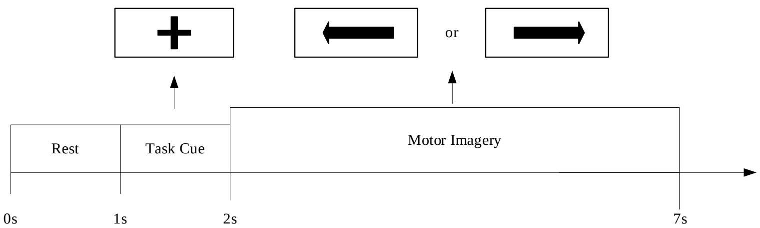

Figure 1. Experimental procedure for each trial in MI paradigm

During 0s-1s, it was the resting phase; during 1s-2s, it was the task cue phase, with no MI task required. Subjects would prepare for the next MI task when they saw the cue "+". From 2s-7s, subjects performed the MI action corresponding to the arrows direction randomly displayed on the screen, which lasted for 5s. When the screen showed an arrow to the left, subjects were required to continuously image of the left leg flexion; when an arrow to the right was shown, subjects were required to continuously image of the right leg flexion.

2.2 Data acquisition

The experimental data was obtained from 12 subjects aged 20-25 years, including 8 males and 4 females. The dominant hand of all subjects was the right hand. Prior to the MI experiment, each subject completed training experiments at least five times in one week. During the experiments, the MI EEG signals was acquired in a quiet, soundproof, well-lit and well-ventilated experimental room. Nine channels related to lower limb movement were collected, namely, F3, Fz, F4, C3, Cz, C4, P3, Pz and P4[13], where the channel placement is according to the 10-20 international standard, with a sampling rate of 1000 Hz.

2.3 Data preprocessing

Preprocessing was performed after obtaining the raw EEG signals. An averaging reference was used. Band-pass filtering from 0.5Hz-35Hz was performed. The sampling rate was reduced to 500Hz to improve computational efficiency. The data were divided into different events according to the MI task lasting for 5s and baseline correction was performed within each event. Artifacts such as electrooculogram were removed by Independent Component Analysis (ICA) to improve the signal-to-noise ratio of the EEG signals. Preprocessed data was used for the subsequent signal analysis.

3. METHODS

3.1 CNN

Convolutional Neural Network (CNN) is a class of deep learning neural networks. The convolutional layer and pooling layer are the core components of CNN. By stacking and alternating of these two kinds of layers, CNN can effectively capture the layer-level features in the image.

The weight sharing and translation invariance of the convolutional kernel enables them to learn similar features at different timestamps from the input signal. For multi-channel EEG signals, CNN can preserve the spatial topology among channels to better capture the relationship among channels. Therefore, CNN have better ability to extract EEG features, which has been widely used in MI classification. The unit structure of CNN is shown in Figure 2.

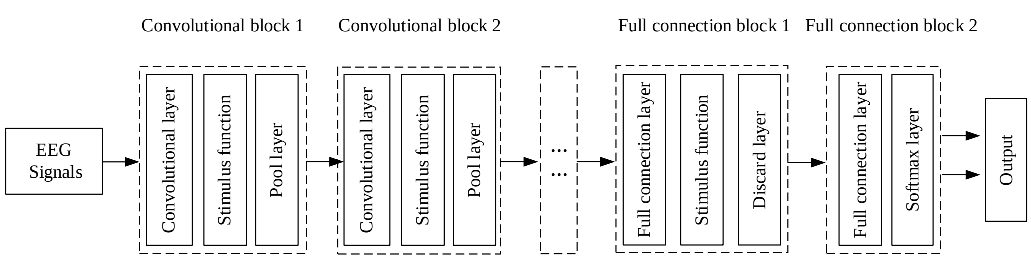

Figure 2. CNN unit structure diagram

3.2 LSTM

LSTM (Long Short-Term Memory) is a variant of Recurrent Neural Network (RNN) that aims to solve the modeling problem of long-term dependencies in traditional RNNs [14]. LSTM uses a cell state to store and convey information. The cell state remains constant along the time step, allowing the model to add or remove information selectively.

Each LSTM unit consists of a memory cell, a forgetting gate, an input gate, and an output gate, which is shown in Figure 3. These gates can retain, forget, or update information through the Sigmoid activation function and tanh layer, which is effectively solved the gradient vanishing problem, and enables LSTM to be able to effectively capture and utilize long-term dependencies in time series.

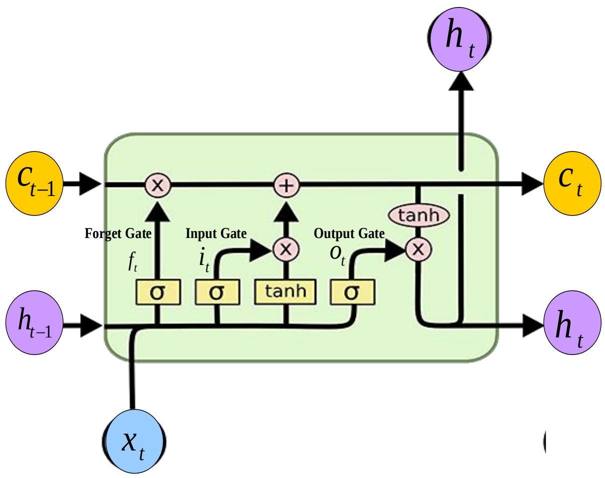

Figure 3. Structure of the LSTM unit. $C_{(.)}$: internal core state; $H_{(.)}$: exposed state; σ: Sigmoid function; $X_{(.)}$: input.

3.3 1D-CNN-LSTM

One-dimensional convolutional neural networks (1D-CNN) are a variant of CNN specifically designed to process one-dimensional sequential data[15]. Unlike 2D-CNNs used in traditional image processing tasks, 1D-CNNs can efficiently extract the temporal features and capture the local patterns of EEG signals through the convolutional kernels. The traditional CNNs can capture spatial features but ignore the temporal relationships in EEG signals. LSTM can better deal with the temporal information, but is difficult to capture the spatial features.

Therefore, combining 1D-CNN and LSTM could better adapt to analyze EEG signals at different frequency and temporal scales, improve the generalization of the model, enable the network to model EEG signals hierarchically, and improve the ability to learn complex features. It is a positive contribution to improve the classification accuracy and real-time performance of MI tasks. The data analysis process is based on the 1D-CNN-LSTM model, as is shown in Figure 4. In this combined model, one convolutional layer is reduced and LSTM is added to form the combined model. The 1D-CNN model focuses on the local feature extraction of time series data, and then the extracted features are passed to the LSTM model for long-term time series modeling. The model parameters are shown in Table 1.

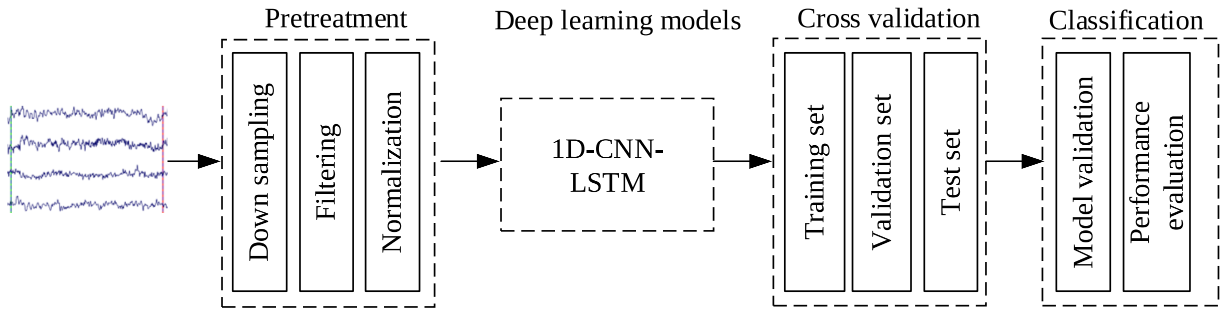

Figure 4. The data analysis process based on the 1D-CNN-LSTM model

Table 1. 1D-CNN-LSTM model parameters

Layer	Type	Filter	Kernel	Stride	Activation Function
1	Input	-	-	-	-
2	Convolution	256	5	1	ReLU
3	Max pooling	-	2	1	-
4	Dropout	-	-	Rate=0.3	-
5	Convolutional	256	5	1	ReLU
6	Max pooling	-	2	1	-
8	Dropout	-	-	Rate=0.3	-
9	LSTM	1	128	-	-
10	Dropout	-	-	Rate=0.3	-
11	LSTM	1	64	-	-
12	Dropout	-	-	Rate=0.3	-
13	Leveling	-	-	-	-
14	Dense	128	-	-	ReLU
15	Dropout	-	-	Rate=0.3	-
16	Dense	4	-	-	ReLU
17	Incentive	-	-	-	softmax

4. RESULTS

After preprocessing, the EEG data was normalized by Z-Score normalization and Min-Max normalization. The collected data was divided into training, validation, and test sets in the ratio of 8:1:1, which was used to build 1D-CNN-LSTM model.

4.1 Off-line analysis results

The accuracy and loss rate curves during the training of the 1D-CNN-LSTM model introduced in this paper are shown in Figure 5. From Figure 5(a), the horizontal coordinate represents the number of iterations and the vertical coordinate represents the accuracy. The training accuracy of the model finally converges to 70% after 50 training iterations, and the validation set accuracy also converges to 70%. From Figure 5(b), the vertical coordinate denotes the loss rate, and the model loss rate converges to about 15%.

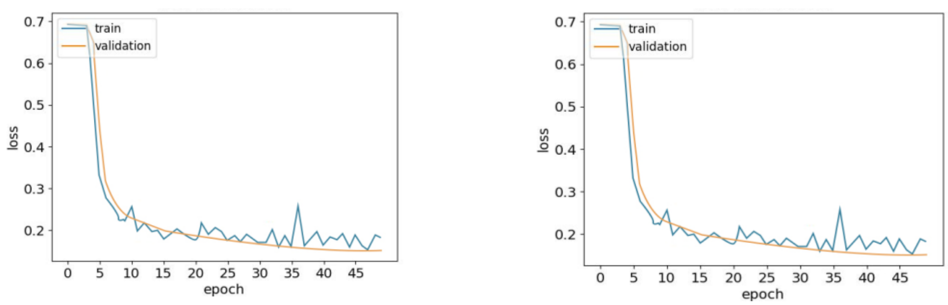

Figure 5. Accuracy and loss rate graphs during training of 1D-CNN-LSTM model. (a) Model Accuracy; (b) Model Loss Ratio

The classification accuracy of the collected EEG data through 1D-CNN-LSTM model for each subject is listed in Table 2, and the average classification accuracy was up to 63.75%. In comparison, we also used the traditional machine learning algorithm such as CSP-SVM and FBCSP-SVM, and the average accuracy reached 59.28% and 62.41%, respectively. It is suggested that the 1D-CNN-LSTM model has an advantage in the classification task of lower limb MI. Therefore, 1D-CNN-LSTM model was applied to construct the real-time system.

Table 2. Classification accuracy of CSP-SVM, FBCSP-SVM and 1D-CNN-LSTM model

Subject	CSP-SVM	FBCSP-SVM	1D-CNN-LSTM	Subject	CSP-SVM	FBCSP-SVM	1D-CNN-LSTM
S1	54.29%	57.50%	59.25%	S7	63.21%	65.71%	67.14%
S2	57.14%	60.36%	62.50%	S8	57.86%	62.14%	62.86%
S3	66.07%	70.36%	73.21%	S9	64.64%	66.43%	67.50%
S4	55.71%	58.21%	59.64%	S10	49.64%	53.93%	55.00%
S5	62.14%	65.00%	66.43%	S11	63.57%	65.71%	66.07%
S6	60.71%	63.93%	64.64%	S12	56.43%	59.64%	60.71%
				Mean ± Std	59.28% ±0.24%	62.41% ±0.21%	63.75% ±0.23%

4.2 Real-time system construction

In this paper, a lower limb MI rehabilitation system based on 1D-CNN-LSTM model was built, and the system structure was shown in Figure 6. The real-time system used the NeuSenW EEG acquisition device for EEG signal acquisition. We chose the same nine channels mentioned in section 2.2. The EEG signals were stored and analyzed in real-time. We performed the training phase and real-time feedback phase. Table 3 presents the classification accuracy of the real-time system for 10 subjects. It shows an average classification accuracy of 56% for the left leg movement, 58% for the right leg movement, and with an overall average classification accuracy of 57%, which suggests that the classification of the real-time system performs well.

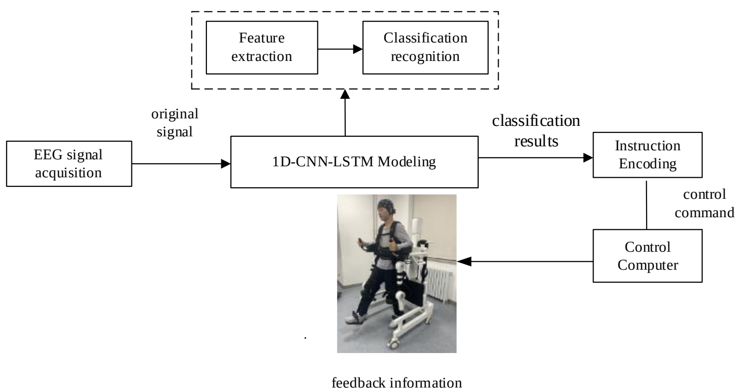

Figure 6. The Real-time system structure

Table 3. Left and Right leg Classification Accuracy of the Real-time System

Accuracy / Subject	left	right	Average	Accuracy / Subject	left	right	Average
S1	45%	50%	48%	S6	65%	55%	60%
S2	50%	55%	53%	S7	55%	60%	58%
S3	55%	60%	58%	S8	50%	55%	53%
S4	60%	60%	60%	S9	65%	60%	63%
S5	60%	65%	63%	S10	55%	60%	58%
				Mean ± Std	56% ±0.43%	58% ±0.18%	57% ±0.21%

5. CONCLUSIONS

This paper studied ID-CNN-LSTM deep learning algorithms for lower limb MI EEG signals, and compared with the traditional machine learning algorithms. It is found that 1D-CNN-LSTM model has higher performance compared to CSP-

SVM and FBCSP-SVM model in the respect of classification accuracy. We also used the adopted 1D-CNN-LSTM algorithm to build a lower limb rehabilitation real-time system based on MI EEG signals. The system realizes the use of MI EEG signals to control the left and right leg movements of a lower limb exoskeleton. The experimental results prove the feasibility of the real-time system. This system has potential rehabilitation applications, and provides an effective tool and methodology for theory and practice in the field of lower limb rehabilitation

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