Classification of Four-class Motor Imagery Movements using Long Short-term Memory Network

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***Abstract*—In this study, we have developed a multi-channel dry-electrode EEG system to implement a brain computer interface (BCI) for discriminating four-class motor imagery signals. The EEG channels recorded from Fz, F3, F4, C3, Cz, C4, P3, and P4 positions, according to international 10-20 EEG system, were acquired and wirelessly transmitted to a personal computer. Five subjects were recruited in our experiment. All subjects were asked to perform right hand, left hand, right foot, and left foot imagery movements, 60 trials in each movement type. EEG data were segmented into epochs from 0sec to 8sec, anchored to time points of imagery movement cues. The segmented EEG epochs were pre-processed by means of morlet wavelet. A long short-term memory (LSTM) neural network with 64 LSTM cells were constructed to discriminate EEG signals recorded from different imagery movements. Among total EEG epochs, 80% were randomly chosen as training data and the rest of 20% were used as validation data. The detection accuracy has achieved 89% in our study.**

***Index Terms*—Brain computer interface (BCI); Long short-term memory (LSTM) neural network; motor imagery movement.**

I. Introduction

Paralyzed patients, such as stroke patients, brain injury patients, or amyotrophic lateral sclerosis (ALS), who are incapable of moving their limbs voluntarily, are unable to communicate with external environments. In order to help paralyzed patients to express their intentions, a technique denoted as brain computer interface (BCI), enables users to communicate via their brain waves. However, due to the large inter-individual variations of brain waves, the most challenge issue in designing a BCI system is to design an effective classifier for discerning brain wave patterns induced from distinct tasks. Several signal processing techniques or classifiers have been developed to achieve a high performance BCI system. Xu et al. (2011) developed enhanced probabilistic linear discriminant analysis (LDA) method to achieve multi-class classification BCI in motor imagery task [1]. Yazdani et al. (2009) applied k-nearest neighbor (KNN) to discriminate different mental task [2]. Hsu et al. (2017) adopted adaptive neuron-fuzzy classifier to classify four options in a phase-tagged steady-state visual evoked potential (SSVEP) based BCI system [3]. Kumar et al. (2017) used partical swarm optimization (PSO) for feature selection in a motor imagery BCI system [4]. Nevertheless, most motor imagery BCIs applied classifiers to classify only two imagery movements. Only few research groups engaged themselves in classifying four or more mental tasks. Accordingly, in this study, we adopted deep learning technique. A long short-term memory (LSTM) neural network was applied to classify four motor imagery tasks.

II. Materials and methods

Five healthy subjects, four males and one females, aged 25.2±3.3 years-old, were recruited in our study. All participants gave informed consent to institutional review board (IRB), Taoyuan General Hospital, Taiwan. An eight-channel wireless EEG system (InMex EEG, WellFulfill Co., Taiwan), electricity safety certificated by IEC 60601-1-2, was used to record motor related EEG signals. The EEG signals were recorded at 1kHz with 24-bits resolution. Each EEG dry electrode is constructed by 10 spring-loaded copper pins, and its biocompatibility has been certificated by ISO 10993. The eight-channel dry-electrode EEG system is shown in Figure 1.

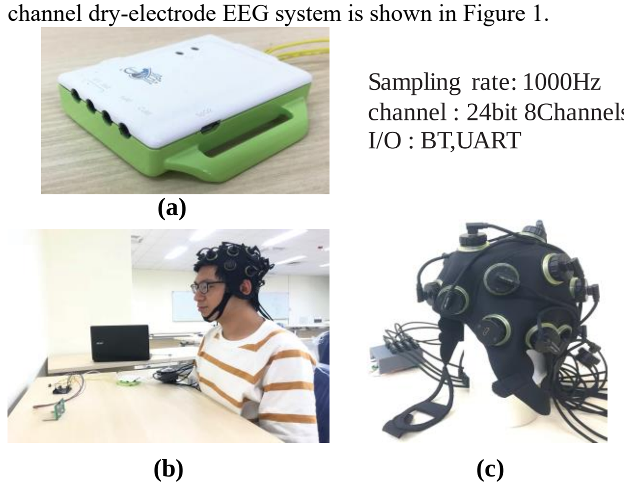

Figure 1. The photographs of the eight-channel dry-electrode EEG system. (a) The EEG amplifier. (b) The measurement environment. (c) The dry-electrode EEG cap.

Figure 2 illustrates the experimental paradigm of our study. Subjects were requested to sit comfortably in an arm chair. A 32-inch LCD monitor was placed 50cm in front of the subjects. Each epoch was designed with nine-second long. After the presence of a visual cue with a beep sound, the subjects were requested to perform a designated

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motor imagery task, preceded by a three-second silent-counting. In this study, the type of motor imagery task in each trial was indicated by the visual cue, which was one of the four imagery movements, including right hand, left hand, right foot, and left foot movements.

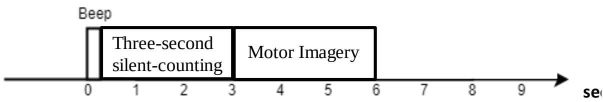

Figure 2. The experimental paradigm of our motor imagery movements.

The acquired EEG data were segmented into EEG epochs, from 0sec to 8sec anchored to the visual cue (or beep sound), which covered around one second preceding the onset of motor imagery movement and the whole period of motor imagery movement. The four second EEG epochs were preprocessed using morlet wavelet to obtain temporal-frequency features. The obtained temporal-frequency features were used as input data to train the LSTM neural network. Since EEG features usually have large fluctuations, the EEG signals were averaged every two seconds, in which the 0sec~8sec data were averaged to become four values, presenting the average values of 0sec~2sec, 2sec~4sec, 4sec~6sec, and 6sec~8sec. Considering the frequency information from 1Hz~37Hz, the input vector of each trial for LSTM will be 37 (frequency) ×8 (channel) ×4 (time information) which will be a vector with 1184 features. The signal preprocessing is shown in Figure 3.

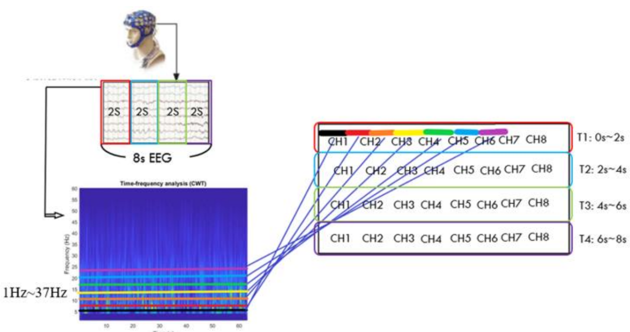

Figure 3. The signal preprocessing of EEG temporal-frequency features.

The LSTM model that we used in this study had 64 LSTM cells and 48 hidden neurons. The signal processing was written in python language on keras 3.0 platform with backend chosen as tensorflow 2.0. The LSTM model is shown in Figure 4.

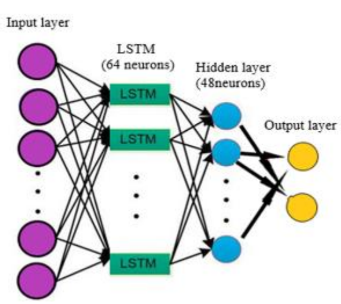

Figure 4. The LSTM model used in this study.

III. Results

Figure 5 presents the training and testing accuracies versus training epoch number in our study. It can be observed that the training accuracy has achieved higher than 95% after more than 125 training epochs. However, the testing accuracy achieved 89% after applying more than 175 training epochs.

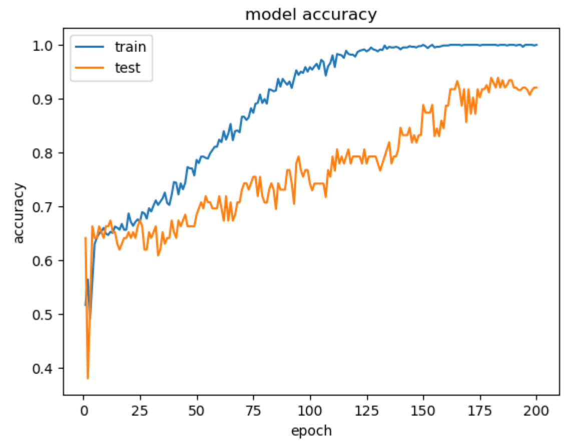

Figure 5. The training and testing results of LSTM neural network in our motor imagery BCI tasks.

Compared with the results obtained from support vector machine (SVM) or convolutional neural network (CNN), the accuracies of traditional SVM and the radial basis function (RBF) SVM were 0.52 and 0.67, and the detection accuracy for CNN was 0.77. The lower accuracies of SVM might be owing the causal relation embedded in the acquired EEG data. Though the utilization of the temporal-frequency features of whole EEG epoch as feature map for CNN could also include the causal information of motor imagery movement, however, the 2D CNN has to consider the topology arrangement of EEG features from different channels which has to find a way for optimizing the 2D arrangement. The results of SVMs, CNN and LSTM are shown in Table 1.

Table 1. The detection results of SVM, CNN and LSTM.

	SVM Model		**Deep learning**	
	SVM-linear	**SVM-rbf**	**CNN**	**LSTM**
Accuracy	0.52	0.67	0.77	0.89

IV. Conclusions

In this study, we have demonstrated the effectiveness of LSTM for classifying EEG data in a four-class motor imagery task. In addition to LSTM, the traditional SVM, RBF-SVM and CNN were also studied. Our study results showed the LSTM had achieved better detection results than the other three classifiers. In contrast to most previous motor imagery studies which only classified two motor imagery movements, the main contribution of this study is its high classification rate in discriminating four mental patterns. In the future, we will design biofeedback in our system to enhance the stimulation feedback of efferent-to-afferent neural loop. Other neural networks, such as reinforcement learning networks, will be adopted in our future studies.

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References and Footnotes

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