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Online Hand Movement Recognition System with EEG-EMG Fusion Using One-Dimensional Convolutional Neural Network

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Abstract— **Upper limb amputees face significant challenges in their daily lives due to the loss of hand or arm functionality. Researchers have developed upper limb prostheses to restore normal hand movements for them. Most hand movement recognition systems of prostheses use electromyography (EMG) as the input signal source, but ignore the interrelationship with electroencephalography (EEG), which may contain valuable movement-related information as well. In order to enhance the accuracy of hand movement classification, we proposed a hand movement recognition system based on a one-dimensional convolutional neural network (1D-CNN) that combines EEG and EMG as the input signal sources to increase the quantity of accessible information. In this work, we collected the EEG and EMG of five subjects during the hand movements and used a 1D-CNN based model to classify the preprocessed signals. The average accuracy of using EEG-EMG fusion is 96.59±2.63%, significantly higher than 74.99±8.24% of using single EEG and 90.31±7.16% of using single EMG. Then, we applied the model trained by offline experiment for online recognition, and controlled the Pepper robot to complete the corresponding hand movements. The average accuracy of online recognition can reach 93.00±4.85% by using majority voting method. The results indicate that the method of EEG-EMG fusion can effectively enhance the performance of hand movement recognition system, which promote the development of upper limb prostheses and contribute to the rehabilitation of upper limb amputees.**

I. Introduction

According to the statistics, there are 85.02 million disabled people in China, with over 24 million are physically disabled. For upper limb amputees, without the ability to complete hand movements, they not only have many restrictions in their daily activities but also have the problems like limited educational opportunities, financial constraints, and societal discrimination. In order to help upper limb amputees recover their physical capabilities, the development of upper limb prostheses has garnered widespread attention within the field of motor rehabilitation. The prostheses can predict amputees' movement intentions by their residual muscle contractions or neuroactivities and execute the hand movements for them.

In most studies of upper limb prostheses [1], electromyography (EMG) signals serve as the primary input signal source for hand movement recognition systems, which mainly include signal acquisition, feature extraction, and classification. Feature extraction is the process to convert raw data into a set of features by computation or conversion, including time domain [2], frequency domain [3], and time-frequency domain [4]. During the process of classification, machine-learning classifiers play a pivotal role in hand movement recognition systems. Tavakoli *et al.* [5] adopted SVM as a classifier in a two-channel EMG system to classify four gestures. Antuvan *et al.* [6] utilized LDA to exploit low-dimensional representation of EMG and tested in a two DOFs task, the online classification accuracy is 88.02%.

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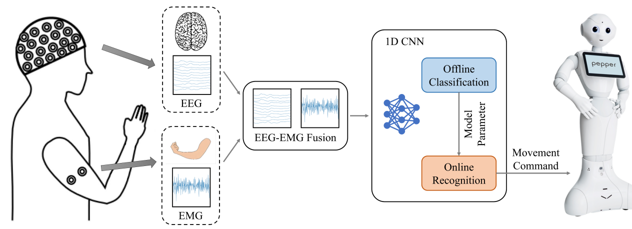

Fig. 1. Framework of the hand movement recognition system.

With the development of deep learning, deep learning models like convolutional neural networks (CNN) and recurrent neural networks (RNN), have been widely applied in various fields like computer vision [7], natural language processing [8], and disease diagnosis [9]. Compared with machine learning, deep learning as an end-to-end model, can reduce the process of feature extraction, and demonstrate a higher learning ability as well. Considering these advantages, deep learning can also be used for the decoding of neurophysiological signals. Srinivasan *et al.* [10] presented a CNN based model to classify four different finger flexion and rest position, the classification rate is 72.5%. Yamanoi *et al.* [11] used CNN to learn large-scale data and mounted this method on a myoelectric hand without the necessity of relearning.

However, for some upper limb amputees, the EMG signals of forearm limb cannot be acquired due to the absence of specific muscles. Due to the advantages of containing substantial movement-related information and being accessible for acquisition, electroencephalography (EEG) is also adopted in various movement-related studies, like motor imagery [12] or hand movement decoding [13].

In current research, most hand movement recognition studies are focused on the single-modal signals. However, the single-modal methods ignore the internal relationship between different neurophysiological signals during the movement process. Multimodality neurophysiological signals are

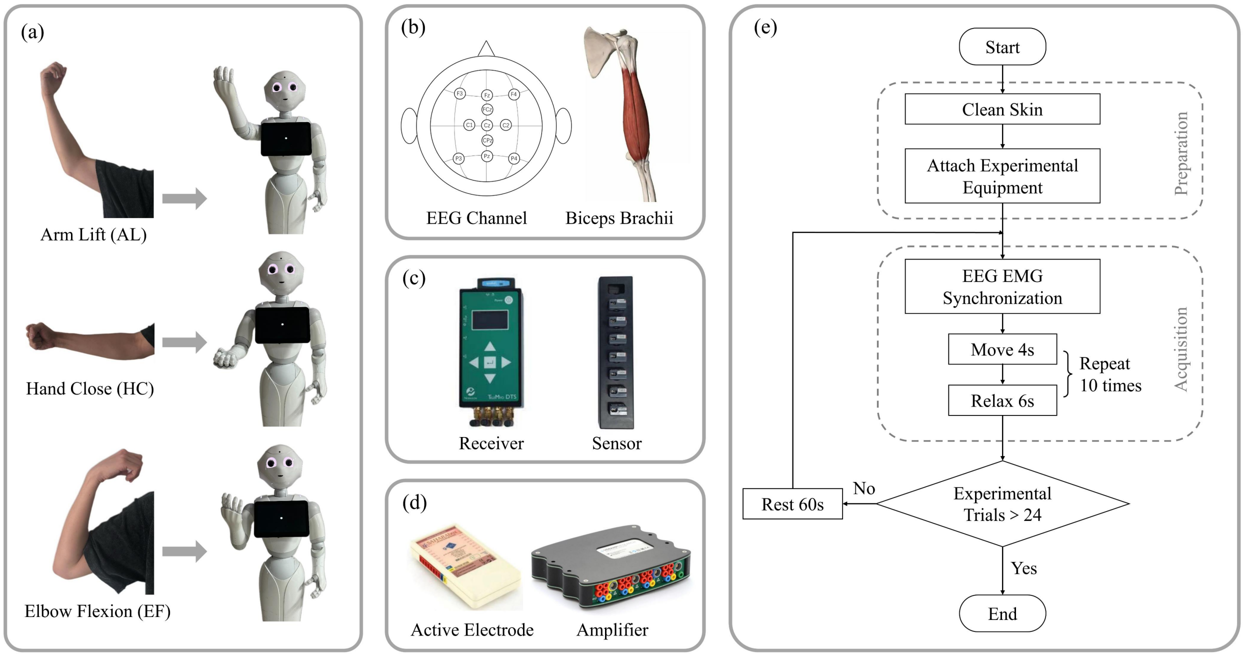

Fig. 2. Experimental outline. (a) Selected hand movements and corresponding postures of the Pepper robot. (b) The signal sources of EEG and EMG. (c) EMG acquisition equipment. Including a wireless receiver and wireless sensor. (d) EEG acquisition equipment. Including an active electrode system and an amplifier. (e) Experimental procedure. Before the acquisition, the sensors and electrodes are applied to the skin after cleaning. Each trial has ten experimental cycles, with 4s of motion and 6s of relax. Subjects rest for 60s between two trials and need to complete 24 trials in total.

used to compensate for the insufficient feature in single-modal signals. Ferdiansyah *et al*. [14] used EEG and EMG signals to classify three elbow joint movements, the results prove that the combination of EEG and EMG can raise testing accuracy to 85.20%. Xi *et al*. [15] proposed a method to improve the estimation of EEG-EMG coherence, enabling an accurate reflection of the coupling relationship between the cortex and muscles. Therefore, combining EMG and EEG for hand movement recognition system is considered as a promising approach to improve the classification accuracy.

In this study, we proposed a hand movement recognition system, including a deep learning model based on 1D-CNN with the advantages of simple computation and high efficiency, and employed multimodality neurophysiological signals to integrate more movement-related information, aims to improve the classification accuracy. Then we applied this system for online recognition and controlled the Pepper robot to complete the hand movements for real-time. The framework of the proposed system is shown in Fig. 1.

The rest of this paper is organized as follows. Section II describes the process of data acquisition. Section III introduces the method of preprocessing and classification. The results of offline classification and online recognition are presented in Section IV. Finally, Section V gives a brief conclusion and future work.

II. Experimental Setup

A. Gestures and Signal Source

Different hand movements can be completed through the contraction of various muscles on human arm. Considering that precise movements do not satisfy the practicality of most people, we choose three basic hand movements for recognition, which are fundamental to upper limb functionality in daily life, including arm lift (AL), hand close (HC), and elbow flexion (EF), as shown in Fig. 2(a).

The signal sources of EMG and EEG are shown in Fig. 2(b). The muscles need to be related to the chosen movements. At the same time, considering the potential of muscle loss in individuals with forearm amputees, we choose biceps brachii to collect EMG signals. For EEG, the event-related potentials are concentrated in the somatomotor cortex. Therefore, eleven electrodes in the center and around the somatomotor cortex are chosen to collect EEG signals, including F3, Fz, F4, FCz, C1, Cz, C2, CPz, P3, Pz, and P4.

B. Equipment

The experimental equipments used in this study are shown in Fig. 2(c) and (d). The EMG acquisition equipment is the TeleMyob2400 G2 signal acquisition and processing system of Noraxon, including wireless sensor (DTS EMG) and wireless receiver (TeleMyo DTS) two parts, the sampling rate is 1500Hz. The EEG acquisition equipment includes an active electrode system (g.SAHARAbox) and an amplifier (g.USBamp) of g.tec, the sampling rate is 256Hz.

In the online experiment, Pepper robot is used to simulate prostheses for control, which can complete the movements selected in this study by rotating the joint and closing hand. The postures of Pepper robot and corresponding hand movements are illustrated in Fig. 2(a).

C. Data Acquisition

Five college students mean aged 24±0.89 years participated in this experiment. All the subjects have no motor or

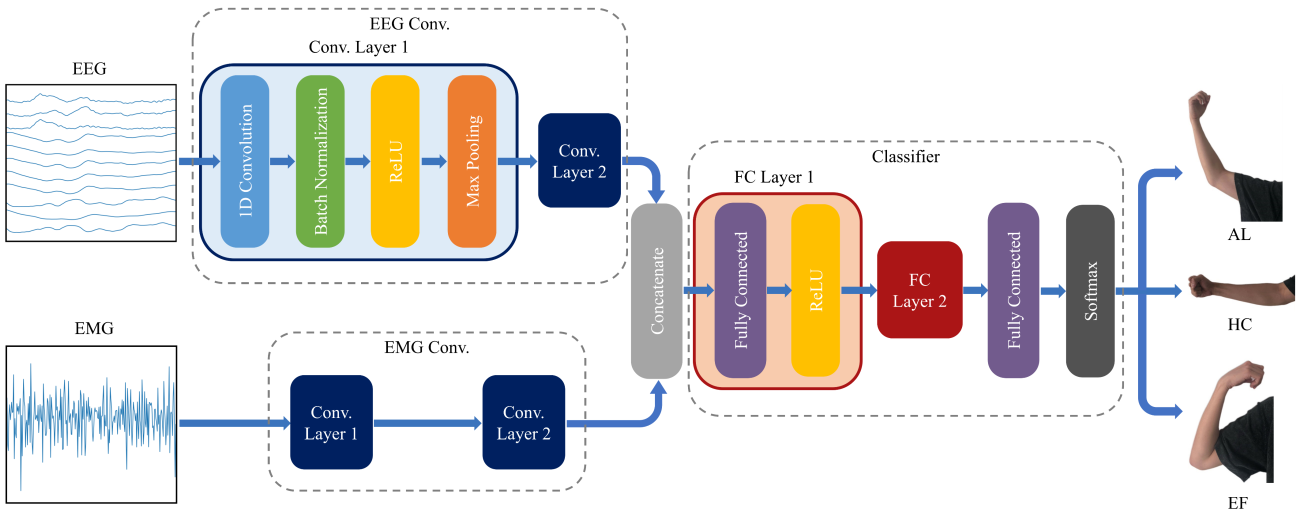

Fig. 3. The architecture of the proposed model. The input EEG and EMG are processed by two convolution layers respectively, which is comprised by four sub layers: 1D convolution, Batch Normalization layer, ReLU, and a max pooling layer. Then, the feature maps of EEG and EMG are concatenated before the fully connected layers, and Softmax functions are utilized to obtain the predicted probabilities of three hand movements.

mental disorders and provided informed consent to take part in the experiment.The experiment procedure is shown in Fig. 2(e). Since the acquisition equipment of EEG and EMG are different, the signals were synchronized before each trial of the offline experiment. Each trial consists of ten experimental cycles, with each cycle lasting for 10 seconds: 4 seconds of motion and 6 seconds of relax. In order to prevent muscle fatigue, subjects needed to rest for 60 seconds between two trials. To obtain sufficient experimental data, each subject was required to complete 8 trials for each type of hand movement, totaling 24 trials in the offline experiment.

During the online experiment, subjects were instructed to sit in the chair and focus on the computer screen. The program would randomly display one of three hand movements, subjects needed to perform the same movement follow the command. Each subject was required to complete 4 trials in the online experiment. Online experiment follows the same paradigm as the offline experiment. The only difference is the absence of the signal synchronization process, since the collection of EEG and EMG signals are simultaneous. Once the hand movement was classified, the predicted class was sent to the Pepper robot via TCP/IP protocol, and the Pepper robot would execute the corresponding task.

III. Method

A. Preprocessing

For the preprocessing of EEG, we remove the baseline to obtain the accurate EEG signals. Then, a band-pass filter of 0.5-45Hz is applied to reduce the noise. Additionally, we utilize independent component analysis (ICA) to remove electrooculography (EOG) and EMG artifacts caused by eye blinks or facial muscle activities during the experiment.

For the preprocessing of EMG, as the subjects need to move arms during the experiment, which could lose the electrode on their biceps brachii. Therefore, we delete the EMG signals with consecutive missing values exceeding 150 samples, along with the EEG signals in the same motion. Then we use a band-pass filter of 20-400Hz to reduce the noise. At last, the EMG signals are down-sampled to 256Hz to ensure consistent data dimensions with EEG.

In order to obtain the stable signals during the motions, we remove the initial and final 0.5 seconds of each motion as well as the relax part, retaining only the central 3 seconds of the signals during the motion as valid data. Then, the stable EEG and EMG signals are constructed to a series of data sequences by sliding window with the window length of 1000ms and the incremental steps of 100ms for classification.

B. Classification

CNN is a deep learning model with multiple convolution and pooling layers, and fully connected layer to integrate the extracted features. The convolution layer can extract the feature maps of the input sample, the expression of convolution is shown as

$$y_{i,j}^{l} = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \omega_{n,m}^{l-1} \times x_{i+n,j+m}^{l-1} + b \tag{1}$$

where $x_{i+n,j+m}^{l-1}$ and $y_{i,j}^{l}$ denotes the element at $(i+n,j+m)$ and (i,j) of layer $l-1$ and l, ω is a convolution kernel of size $N \times M$, $\omega_{n,m}$ denotes the weight at (n,m) of the convolution kernel, b denotes the offset of the convolution kernel.

Since the input EMG signals is one channel, we use one-dimensional (1D) convolution to process EEG and EMG, characterised by the fact that the convolution kernels slide only over the time dimension. As a lightweight model, 1D-CNN can reduce the computational complexity within the network and has a faster processing speeds as well, making it well-suited for the real-time applications [16].

The architecture of the model is shown in Fig. 3. In order to combine the features of multimodality signals, we use two convolutional modules to process EEG and EMG respectively, and combine them before the fully connected layers. The convolutional modules include two convolution layers respectively to extract the features, which are comprised by four sub layers: 1D convolution with the kernel width of 3 and stride of 1, a Batch Normalization layer to reduce overfitting, Rectified Linear Unit (ReLU) activation, and a max pooling layer with the size and stride of 2. ReLU activation functions are employed in the model to introduce non-linearity to the output of 1D convolution. Before the fully connected layers, the feature maps of EEG and EMG are concatenated, and flattened into vectors by three fully connected layers. At last, Softmax functions are utilized to obtain the predicted probabilities of three hand movements.

As for the training of the model, cross-entropy is chosen as the loss function, which can converge to the global optimal and has a fast convergence speed at the same time.

$$L = -\sum_{i=1}^{N} y_i log(p_i) \tag{2}$$

We use the stochastic gradient descent (SGD) algorithm with Nesterov momentum to optimize the parameters in the model. As an improved form of the SGD algorithm, it can not only avoid falling into local optimal parameters, but also reduce the oscillation to accelerate convergence. The SGD with Nesterov momentum can be expressed as

$$v_t = \beta v_{t-1} + (1-\beta)\frac{\partial L}{\partial(w_i + \beta v_{t-1})} \tag{3}$$

$$w_i = w_i - \eta v_t \tag{4}$$

where v_t denotes the current velocity, determined by the velocity and gradient of previous step, β denotes the momentum parameter, which is used to control the velocity change and the influence of local gradient on the overall motion.

To provide a comparison with single-modal signal input for evaluating the performance of the EEG-EMG fusion method, EEG and EMG signals are processed individually by the EEG or EMG convolutional module and Classifier, without the operation of concatenate before the fully connected layers. In this case, the classification results are based on the signal from a single modality.

Since the significant individual differences in the neurophysiological signals among different people, we use individual data to train specific classification models for each subject. Besides, in order to mitigate the randomness of the results, the method of K-fold cross validation is employed. In the process of the model training, the data are randomly divided into five equal parts, one of which is chosen as the test set, while the other four parts are the training set. The average accuracy of five times is calculated as the final result.

IV. Results

A. *Offline Experiment Results*

The offline classification results of using different signal sources are shown in Fig. 4. It can be seen that using EEG alone results in a low classification accuracy of 74.99±8.24% only. As the most widely used signal source in hand movement recognition research, using EMG alone can complete the classification task better, with a mean accuracy of 90.31±7.16%. The classification accuracy of EEG-EMG fusion proposed in this study is 96.59±2.63%, which is 21.60% higher than single EEG and 6.28% higher than single EMG. The results prove that the performance of EEG-EMG fusion shows a significant increase in accuracy over using single-modal signals, indicating that the method of combining EEG and EMG as input signal source can effectively improve the accuracy of hand movement recognition.

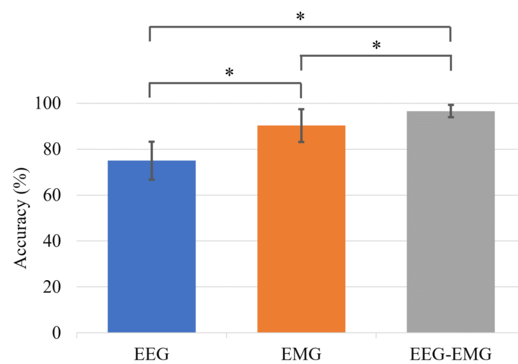

Fig. 4. The average classification accuracy of three signal sources and results of one-tailed Wilcoxon signed-rank test. (* indicates p-value < 0.05).

Evaluating the performance only by average accuracy could be biased, therefore, statistical analysis can provide a means to verify the results. In this study, we use one-tailed Wilcoxon signed-rank test [17] to examine the statistically significant differences between the performance of different signal sources. The results of one-tailed Wilcoxon signed-rank test are shown in Fig. 4, which show that there exist statistically significant differences among all the three signal sources (p-value < 0.05). The classification accuracy of EEG-EMG fusion is proved to be statistically significantly higher than single-modal signals, which also proves the validity of the proposed method in this study.

In order to assess the recognition performance of each hand movement, confusion matrix is utilized to calculate the class-specific precision. The confusion matrices of different signal sources are illustrated in Fig. 5. It should be noted that, by using single EEG, AL can be better distinguished from the other two hand movements, with a classification accuracy of 92.37%. However, there is a significant rate of confusion between HC and EF. For the confusion matrix of EMG, the best recognizable movement has changed into HC, can reach 95.82%. While the accuracy of the other two movements is relatively low, with only 88.60% of AL and 86.51% of EF. To combine the movement-related information contained in these two signals, using EEG-EMG fusion as input signal source can achieve high classification accuracy for both AL and HC. Compared with single-modal signals, the classification of all the three movements shows an increase in accuracy, with each of them exceeding 95.00%, indicating that the method of EEG-EMG fusion can make it possible to accurately recognize various hand movements.

To compare the features extracted by the model using different signal sources, we use Uniform Manifold Approximation and Projection (UMAP) [18] to reduce the dimensional-

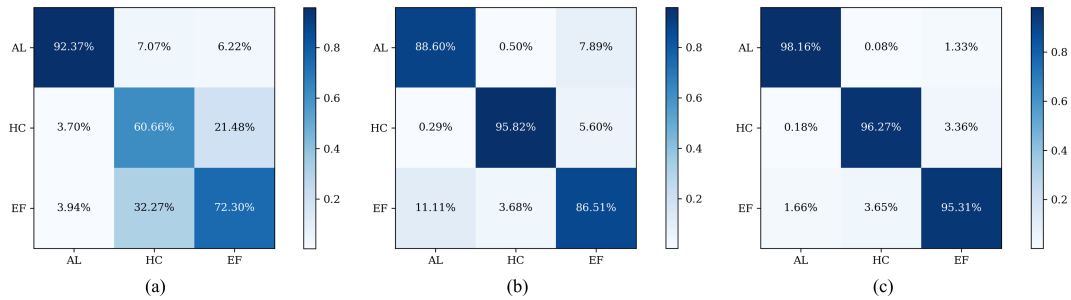

Fig. 5. The confusion matrices of three kinds of signal sources. (a) EEG. (b) EMG. (c) EEG-EMG.

TABLE I
THE PERFORMANCE COMPARISON WITH STATE-OF-THE-ART METHODS.

Method	Signal Source	Accuracy (%)					
		Subject1	Subject2	Subject3	Subject4	Subject5	Mean±Std
EEGNet [19]	EEG	78.29	51.08	78.53	72.28	83.08	72.65±11.32
EEG Conv. + Classifer	EEG	69.85	64.74	70.89	84.23	85.28	74.99±8.24
SVM [20]	EMG	67.42	99.89	93.35	71.73	91.45	84.77±12.79
EMG Conv. + Classifer	EMG	77.85	99.97	92.34	89.33	92.04	90.31±7.16
LSTM [21]	EEG-EMG	80.45	99.90	96.99	84.03	93.25	90.92±7.48
Spectrogram CNN [22]	EEG-EMG	92.28	**100.00**	96.65	95.14	78.05	92.42±7.61
Our Method	EEG-EMG	**92.91**	**100.00**	**97.85**	**98.02**	**94.17**	**96.59±2.63**

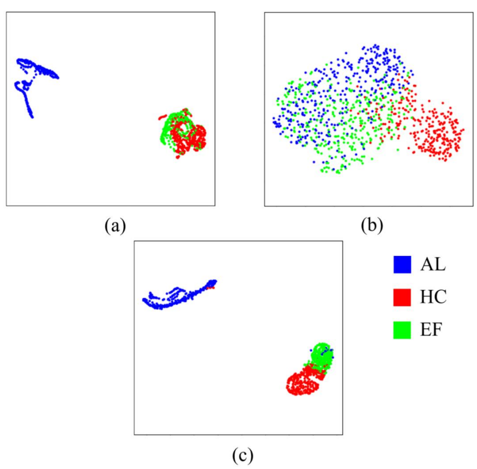

Fig. 6. UMAP visualization of the features learned by different signal sources. (a) EEG. (b) EMG. (c) EEG-EMG.

ity of the outputs of the penultimate fully connected layer and visualize the results. The UMAP visualization of the features learned by different signal sources are shown in Fig. 6. Like the confusion matrices, UMAP visualization shows a similar situation. The features of HC and EF extracted from EEG exhibit certain resemblance, same as the AL and EF features of EMG, resulting in a lower classification accuracy for these hand movements. Obviously, in the UMAP visualization of EEG-EMG fusion, the differences between the features of each hand movements become more straightforward, making it easier to distinguish three types of movements.

The comprehensive performance comparison of the proposed method with existing state-of-the-art methods is presented in Table I. In previous studies, Tortora *et al.* [21] used two Long-Short Term Memory (LSTM) running in parallel to decode EEG and EMG respectively, and integrated the predictions by calculating the Bayesian belief. Tryon *et al.* [22] proposed a spectrogram CNN model to classify the spectrogram images, which calculate the time–frequency domain representation of EEG and EMG by STFT. Beside, to assess the performance of single-modal signals under different methods, we also contrast the classification result of EEGNet [19], a novel compact CNN for EEG-based brain-computer interface (BCI) with using single EEG and the widely used machine learning method in EMG decoding, SVM [20] with using single EMG. A clear trend can be seen from the results, the classification accuracy of single EMG is found to be consistently higher than single EEG. During the experiment, muscles serve as the terminal execution units of subjects' movements, making the connection between muscles and hand movements more direct compared to the brain. Even though single EEG shows an inferior performance compared with single EMG, it still contribute positively to the EEG–EMG fusion method. Since the mean accuracy of each method based on EEG-EMG fusion always tend to surpass the single EMG, proved that EEG and EMG possess certain correlations and during hand movements. By combining EEG and EMG as the input signal source, the correlated information between the two signals can be effectively exploited. Meanwhile, when using EEG-EMG fusion, our method outperforms LSTM with 90.92±7.48% and the spectrogram CNN model with 92.42±7.61% in terms of classification performance.

B. Online Experiment Results

In the online experiment, we use the model trained by offline experiment to classify filtered EEG and EMG signals in real time and send the predicted results to Pepper robot via TCP/IP protocol. Voting method is widely used in the field of ensemble learning. In this study, we use majority

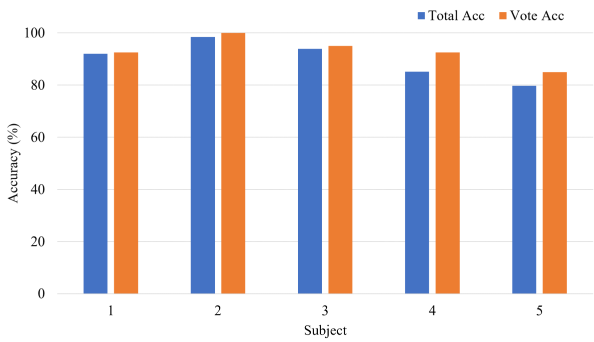

Fig. 7. The online recognition accuracy of 5 subjects. Total Acc is the average accuracy calculated by all sliding windows in each motion. Vote Acc is the average accuracy calculated by the predicted class determined by the majority voting method.

voting method to determine the predicted class from the classification results of all the sliding windows in one motion. The concept of majority voting is easily comprehensible: the predicted class is determined by the candidate with the highest proportion. In the real-time hand movement recognition system, even though the majority voting method could introduce a time delay, while it can improve the classification accuracy and enhance the stability at the same time.

The online recognition results of five subjects are shown in Fig. 7. The total accuracy is 89.86±6.63%, which is using the results of all sliding windows in each motion to calculate the mean accuracy, and the vote accuracy is 93.00±4.85%. Among all subjects, No. 4 and 5 show a notable improvement in recognition accuracy by using majority voting method, while the differences between vote and total accuracy of the other subjects are not significant. It can be seen that the total accuracy of No.4 and 5 is relatively low, therefore, a remarkable increasement can be achieved by majority voting. In addition, No. 2 wins the highest score with all motions have been successfully predicted, who achieves the top accuracy in offline classification as well. The least accurate result is from No. 5, with an accuracy of 85.00%, means 6 incorrect decisions are predicted out of 40 motions.

V. Conclusions

Towards the rehabilitation of upper limb amputees, a hand movement recognition system based on 1D-CNN was presented in this study, which combine EEG and EMG as the input signal source to improve the classification accuracy. According to the results evaluated in the 3-class hand movements classification, our method of EEG-EMG fusion achieved the highest classification accuracy of 96.59±2.63%. The proposed system was successfully implemented for real-time recognition and control of the Pepper robot, with a mean accuracy of 93.00±4.85%. The results show that the EEG-EMG fusion method can be applied to the current hand movement recognition system to improve the performance and contribute to the development of intelligent prostheses. In the future work, we will recognize more gestures and explore the impact of EEG-EMG fusion method on recognition results in some non-ideal scenarios like muscle fatigue and electrode displacement.

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