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Recognizing Motor Imagery Between Hand and Forearm in the Same Limb in a Hybrid Brain Computer Interface Paradigm: An Online Study

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ABSTRACT Brain computer interfaces (BCIs) based on motor imagery (MI) play an important role in helping to improve and restore the loss of physical function. However, traditional MI-BCIs are limited to the motion intention of gross limb, which places many restrictions on their applications. This study proposes a hybrid paradigm based on MI and the steady-state somatosensory evoked potential, with the aim of improving the spatial resolution of MI recognition. Twelve subjects participated in this study. They performed MI tasks under MI and hybrid conditions. In the MI condition, subjects only performed MI tasks, whereas, in the hybrid condition, they received an electrical stimulus while performing the same tasks. Under the hybrid condition, subjects were required not to pay extra attention to the electrical stimulation. The MI task included imagining clenching the right hand and lifting the right forearm. The classifier was built using the filter bank common spatial pattern algorithm and a support vector machine, and online experiments were used to verify the recognition of two MI tasks. During the online experiments, all subjects were able to output different commands at a recognition accuracy far higher than the random level. The average classification accuracy of the hybrid condition reached 76.39%, with a maximum value of 88.34%, which was about 11% higher than that of the MI condition. Moreover, based on offline data, the classification performance using the event-related desynchronization (ERD) feature under the hybrid condition did not differ significantly from that under the MI condition, indicating that the introduction of electrical stimulation did not interfere in the separability of ERD. The proposed paradigm improved the efficiency of decoding multiple MI locations within a single limb. Despite the introduction of external stimuli, users could still drive the new system in the same way as MI in traditional MI-BCI.

INDEX TERMS Motor imagery, event-related desynchronization (ERD), steady-state somatosensory evoked potential (SSSEP), hybrid brain–computer interface.

I. INTRODUCTION

Brain-computer interfaces (BCIs) provide a direct connection between the brain and the external environment [1], and can offer additional options for severely paralyzed patients to live more independently. Motor imagery (MI)-BCI, which can recognize the user's subjective motion intention without the need for external stimulation, is one of the most important paradigms in this field [2], [3]. Studies have shown that MI could induce event-related desynchronization/synchronization (ERD/ERS) of electroencephalography (EEG) signals at a particular frequency band in the sensorimotor cortex [4]. This ERD feature can be used to identify the user's motion intention, which can be transformed into a computer operation command. Its many clinical applications have proved that MI-BCI shows great potential in recovery post-stroke [5], [6].

Previous studies have shown that MI-BCIs can recognize MI tasks of different body parts, such as left hand, right hand, both hand, and feet [7], or a combination of these [8].

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However, at present, MI-BCI is very imprecise about the body location of an MI. For example, a classic MI-BCI can distinguish between MI of the left and the right hand with very high accuracy, but it is much less successful regarding the distinction between the right thumb and the right forefinger. Therefore, current MI-BCI systems are capable of only simple control, and improving the spatial resolution of MI recognition is the most important and challenging issue in the MI-BCI field. However, until now, most research on MI-BCI control with high spatial resolution has been based on invasive collection technology [9], [10]. In recent years, only a few studies have used EEG to address this problem. For example, Liao *et al.* analyzed the EEG signals of subjects who actually performed the flexion of one finger and found that the average decoding accuracy in each pair of fingers was 77.11% [11]. In another example, Edelman *et al.* used an EEG source imaging method to distinguish the MI tasks of four different gestures in the right wrist [12]. Although these studies showed the potential of EEG as a solution to this problem, they were limited by a lack of online validation owing to the complexity of the algorithm or other reasons.

On the other hand, to improve MI-BCI performance in the general sense, including factors such as robustness, classification efficiency, and size of command set, the hybrid strategy shows promise [13]. Hybrid BCI combines multiple paradigms – for example, P300 and MI – to decode the user's intent. Based on the sequence of these paradigms, serial and parallel types were proposed. Serial hybrid BCI often uses one type of signal as a switch to control another signal. For example, Pfurtscheller *et al.* reported that using foot MI as a brain switch to turn on/off a steady-state visual evoked potential (SSVEP)-based BCI could reduce the false positive rate of opening and closing the orthosis [14]. Parallel BCI also contains two types. The first involves establishing a number of different classifiers to identify different features for the expansion of degrees of freedom. For example, Li et al. designed a hybrid paradigm that combined MI and P300 to realize two-dimensional movement of a cursor. The P300 signal was used to control the vertical movement, while the left/right hand MI tasks were used to control the horizontal movement [15]. The second type involves establishing a classifier to recognize combined EEG features to improve recognition accuracy. Allison et al. showed that employing both ERD and SSVEP achieved a significant improvement in classification accuracy, with an increase of ~6% [16]. Although the hybrid paradigm has some advantages over the single MI paradigm, many limitations exist. In the case of serial BCI, extra tasks are added to the BCI operation, thereby reducing the efficiency of information transfer. In the case of parallel BCI, users need to pay attention to both tasks at the same time, which not only leads to extra attention consumption, but also easily weakens each separate signal. Both increase the operation complexity and affect the user's experience.

However, in recent years, the steady-state somatosensory evoked potential (SSSEP) has been proposed. This can be modulated by focusing on different somatosensory stimulation, allowing an SSSEP-based BCI system to be established [17]. Our previous study showed that the recognition accuracy of combined MI and SSSEP was significantly higher than that of using individual features [18]. Compared with the other approaches to hybrid MI-BCI, such as SSVEP and P300 as described above, the combination of SSSEP with MI-BCI has a potential advantage in terms of attention consumption. Owing to the neural paths of motor cortex and sensory cortex being closely connected, the motion intention of a specific body location would increase the sensory response in the same location. Thus, an MI task would induce changes in SSSEP response in the same location, without the need for users to pay extra attention to external stimulation. In this sense, the hybrid MI-SSSEP paradigm not only improves performance, but also maintains the imaginative way of the original MI-BCI.

In this study, our hypothesis is that the MI-SSSEP paradigm could improve the spatial resolution of MI recognition. We chose two adjacent locations in the same limb for MI, right hand and right forearm, to test this hypothesis. In order to avoid possible problems of confidence in offline analysis, we built an online MI-SSVEP BCI system to carry out the experiment. We also performed a control experiment based on the MI paradigm only for comparison.

II. MATERIALS AND METHODS

A. SUBJECTS

In this experiment, the data were collected from 12 healthy subjects (six males, six females, right-handed, and ranging in age from 20 to 25 years). All subjects were required to have training and were informed about the experimental procedure before the formal experiment. This study was performed after obtaining written informed consent from the subjects and approved by the department of biomedical engineering, Tianjin University.

B. EXPERIMENTAL PROCEDURE

During the experiment, subjects sat on a comfortable chair in a relaxed posture, with their right palm facing upward and forearm flat on a bracket. There were two experimental conditions, MI and hybrid. In the MI condition, subjects only performed MI tasks, whereas in the hybrid condition, they performed the same MI task while simultaneously receiving an electrical stimulus. The MI task included imagining clenching the right hand and lifting the right forearm. The experimental paradigms for the two conditions are shown in figure 1(a); each trial lasted eight seconds. The visual cue appeared in the center of the computer screen. At the beginning of each trial, a white circle appeared for two seconds, which reminded the subject that the experiment was about to begin. After the white circle disappeared, a red circle appeared for one second to remind the subject to prepare. At the third second, the subjects immediately performed the corresponding MI tasks for four seconds, according to the

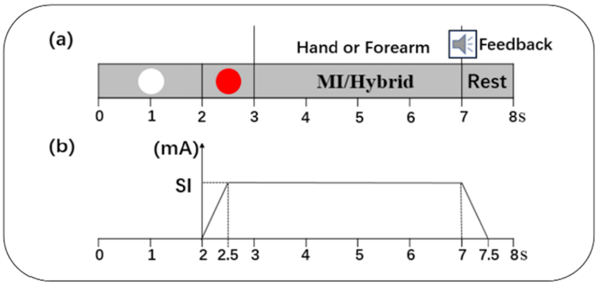

FIGURE 1. Experimental paradigm. (a) Trial structure for MI and hybrid conditions in online and offline sessions, respectively. Voice feedback existed only in online sessions. In the hybrid condition, subjects performed the MI task following the cues, while at the same time they received an electrical stimulus at the right wrist. In the MI condition, subjects only performed MI tasks. The MI task began at the third second; subjects performed the MI task according to cues for 4 seconds. "Rest" indicates a one-second rest before the next trial. (b) Electrical stimulation started from the second to the 7.5th second for the hybrid task. "SI" indicates stimulation intensity, which was individually determined and remained fixed for 4.5 seconds.

word "hand" or "forearm". Then, the word "Rest" appeared for one second, during which the subject relaxed and waited for the next trial. Under the hybrid condition, the electrical stimulation lasted for 5.5 seconds, from the 2nd second to the 7.5th second in each trial. The stimulation strength reached the pre-set current strength within 0.5 seconds (figure 1(b)). In addition, subjects were asked not to pay attention to electrical stimulation and to only perform MI tasks in the same mode as under MI conditions.

The experiment contained eight runs, each consisting of 15 "hand" and 15 "forearm" tasks with randomized order. Each run lasted for four minutes, and subjects had a break of about five minutes between runs. The entire experiment lasted about 80 minutes. Each experimental condition (MI and hybrid) contained two runs, which meant a total 30 trials for each task. In the first four runs, subjects performed offline experiments without voice feedback. In the following four runs, subjects performed online experiments for the validation of the feasibility of the proposed method and the voice feedback of "hand" or "forearm" on the seventh second of each trial was provided to let subjects know the recognition result. It takes about 4 seconds from imagining begin to the result feedback. Throughout the experiment, subjects were asked to avoid any body movements and to reduce eye blinks during the task to minimize artifacts. The whole experiment was done in a quiet and undisturbed environment.

The electrical stimulation used to induce SSSEP in this study was a biphasic current pulse of 200 μ s duration. Two self-adhesive ECG electrodes were placed on the right wrist, mainly acting on the right median nerve [19]. Studies have reported that stimulation frequencies near 21 and 26 Hz induce the largest SSSEP amplitudes [20]. However, we set the stimulation frequency to 31 Hz in order to have a clear difference between SSSEP and ERD [18]. In order to successfully induce SSSEP, the intensity of stimulation for each subject was adjusted to produce a slight thumb twitch before the experiment [21]. The current strength for the 12 subjects involved in this experiment varied from 1.8 to 3.8 mA, and no subjects felt pain.

C. EEG RECORDING AND ONLINE PROCESSING

EEG signals were recorded by a SynAmps2 system (Neuroscan, USA). Sixty-four Ag/AgCl scalp electrodes were placed according to the international 10/20 system. The ground electrode was located on the forehead, and the reference on the nose. EEG signals were band-pass filtered between 0.5 and 100 Hz with a sampling frequency of 1000 Hz. Impedance of each channel was kept below 5 kΩ. In addition, a notch filter with 50 Hz was used to remove power frequency interference during data acquisition. In the pre-processing stage, the raw data was down-sampled at 200 Hz and then spatially filtered by the common average reference (CAR).

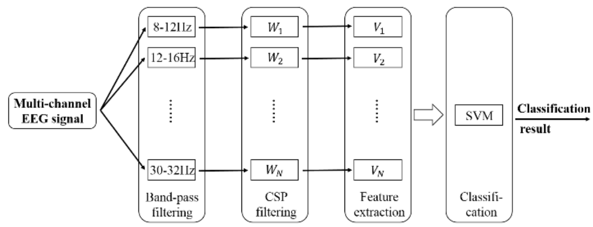

FIGURE 2. Architecture of the filter bank common spatial pattern (FBCSP) machine learning approach.

In order to extract ERD and SSSEP features distributed at different frequencies, a filter bank common spatial pattern (FBCSP) algorithm based on multi-frequency component spatial filtering was used in this study [22]. As shown in figure 2, EEG data is divided into components of different frequency bands by N band-pass filters in the FBCSP algorithm. Spatial filtering is performed using a two-class common spatial pattern (CSP) algorithm by linearly transforming the EEG using [23]

$$v_i = w_i^T x_{i,b} \tag{1}$$

where $x_{i,b}$ denotes the single-trial EEG from the ith band-pass filter of the bth trial; $w_i (i = 1, 2, \ldots, N)$ denotes the CSP projection matrix and T denotes transpose operator; each task uses only the eigenvectors corresponding to the m largest eigenvalues as spatial filters. The feature vector for each trial is denoted as $V = [v_1, v_2, \ldots, v_N] V \in \mathbb{R}^{1\times(N*2m)}$ where $v_i \in \mathbb{R}^{2m} (i = 1, 2, \ldots, N)$ is extracted for each EEG component separately.

EEG data from 0.5 to 3.5 seconds after the imaginary cue onset were extracted for recognition [8]. Data collected from the offline experiments were used to build the FBCSP filter as described above, and the filtered data was then used to build a classifier with a support vector machine (SVM), using the LIBSVM software package [24]. In the online experiments, EEG data from each trial were processed with this filter and classifier to obtain the recognition result. All programs were compiled and run on the MATLAB platform.

D. OFFLINE ANALYSIS

For further comparison, classification performance of the offline data was also evaluated. The whole offline dataset was divided into training sets and testing sets by a 10-fold cross-validation strategy. Based on the training set, the FBCSP spatial filter and the SVM classifier were computed, and the classification accuracy was then calculated on the test set using this filter and classifier. Finally, classification accuracy was calculated by averaging 10-fold.

To analyze the difference in classification performance when using the ERD or SSSEP features individually, we used FE to depict the ERD features and FS to depict the SSSEP features. FE corresponds to the frequency bands of 8-12, 12-16, 16-20, 20-25, and 25-30 Hz and FS corresponds to the frequency band of 30-32 Hz. We also used FC to depict the combined features, which contained all of the above frequency bands. In order to ensure the consistency of the feature dimension of the classifier, we use FC for feature extraction under MI and hybrid conditions.

Event-related spectral perturbation (ERSP) was used to analyze EEG features in the time-frequency domain, which could provide ERD/ERS/SSSEP patterns of different tasks [25]. ERSP was defined as follows:

$$ERSP(f, t) = \frac{1}{n}\sum_{k=1}^{n}\left(F_k(f, t)^2\right) \tag{2}$$

where n represents the number of trails, and $F_k(f, t)$ indicates the spectral estimation at frequency f and time$t$ for the kth trial [25]. The short-time Fourier transform (STFT) with a Hanning-tapered window was used to calculate the ERSP (dB) in EEGLAB [26]. The mean power changes in a baseline period (3 seconds before MI onset) were subtracted from each spectral estimate in order to produce the baseline-normalized ERSP. For each task under different conditions, we analyzed the mean ERSP of all subjects in three key channels - C5, C3, and C1 - which were displayed from −3 to 5 seconds between 1 and 40 Hz. "0" represented the moment when the subjects began to imagine.

Spatial filtering is helpful to amplify the changes under different conditions. We calculated the spectrum of the data spatially filtered with the FS band. First, the raw EEG data were filtered on each channel through the FS band-pass filter, and then the multiple channel data were spatially filtered by W_h and W_f, respectively. Here, W_h and W_f are CSP filters corresponding to the largest eigenvalue for the hand and forearm imagined tasks, respectively. Finally, we analyzed the filtered data in the time-frequency domain and calculated their separability.

The R^2 coefficient was used to measure the separability of two tasks. The point-wise R^2 coefficient is defined follows [11]:

$$R^2 = \left(\frac{\sqrt{N_1 \cdot N_2}}{N_1 + N_2}\frac{mean\{x_i \mid y_i = 1\} - mean\{x_i \mid y_i = 2\}}{std\{x_i\}}\right)^2 \tag{3}$$

where N_1 and N_2 represent the trial numbers of two categories, respectively; x_i refers to the ERSP at a particular time and frequency, and y_i refers to the two categories. The maximum R^2 coefficient represents the max separability of two MI tasks in different frequency bands.

E. STATISTICAL ANALYSIS

Statistical analyses were conducted using the SPSS software (IBM SPSS Statistics, IBM Corporation). We used a paired t-test to test the difference in classification accuracy between different conditions and features. Paired t-tests for classification accuracy were performed according to standard procedures and followed normal distribution. We also tested the difference in ERSP values between different tasks and frequency bands. A false discovery rate (FDR) correction was applied to multiple tests. Here, for the data that did not follow the normal distribution, we used the wilcoxon rank sum test instead of the paired t-test for statistical analysis. The alpha level was set to 0.05.

III. RESULTS

A. CLASSIFICATION PERFORMANCE

Table I outlines the classification accuracy of all subjects in this experiment. The left panel depicts the results under the online condition, and the right panel depicts the result under the offline condition. First, the left panel shows that all subjects could output the control commands with effective recognition accuracy during the online operation. The average classification accuracy of the hybrid paradigm reached 76.39 %, with a maximum value of 88.34% and a minimum value of 60%. This was not only significantly higher than would be expected with chance selection, but also significantly higher than that of the MI condition, with an increase of 11.66% ($p = 0.0003$). This result indicates that the hybrid method proposed in this paper can effectively improve the spatial resolution of MI recognition in different parts of the same limb.

Second, we further analyzed the offline results. As can be seen from the table I, using the FC band, the average classification accuracy of the hybrid paradigm was 78.42%, which was higher than that of the MI paradigm by 9.31% ($p = 0.0231$) with a significant difference. This is consistent with the online result. Moreover, we calculated the classification performance using only ERD or SSSEP features under MI and hybrid condition. In the MI condition, the mean accuracy for using ERD was 70.60%, which was not significantly different from the use of FC band ($p = 0.0819$). For using SSSEP, the mean accuracy was 58.20%, which was slightly higher than the random level, indicating that there was no SSSEP feature under MI condition. In the hybrid condition, the mean accuracy using ERD was 71.31%, while that using SSSEP was 71.83%; there was no significant difference between the two ($p = 0.4541$). However, the performance using both ERD and SSSEP features was significantly better than using ERD or SSSEP alone ($p = 0.0276$ and 0.0231, respectively). This indicates that merging these two features could effectively improve the recognition performance.

TABLE 1. Classification accuracies for each subject during the experiment.

subject	Online Test		Offline Test					
	MI-FC (%)	Hybrid-FC (%)	MI-FC (%)	Hybrid-FC (%)	MI-FE (%)	MI-FS (%)	Hybrid-FE (%)	Hybrid-FS (%)
S1	66.67	85.00	71.33	89.00	76.67	60.00	92.00	87.67
S2	70.00	76.67	83.33	78.00	90.00	61.67	72.67	71.00
S3	56.67	61.67	54.33	67.33	51.67	45.00	67.00	60.33
S4	63.34	71.67	64.00	73.67	63.33	68.33	69.67	64.67
S5	61.67	63.34	59.33	82.33	60.00	55.00	79.33	54.67
S6	58.33	76.67	69.33	65.00	66.67	61.67	63.67	60.33
S7	73.34	85.00	75.00	82.00	75.00	61.67	73.67	76.67
S8	70.00	80.00	75.33	86.00	73.33	61.67	81.33	73.00
S9	63.34	85.00	59.33	87.00	65.00	56.67	55.67	94.00
S10	81.67	83.34	88.67	91.67	93.33	56.67	75.67	86.00
S11	53.34	60.00	62.33	53.00	61.67	60.00	57.00	50.33
S12	58.34	88.34	67.00	86.00	70.56	50.00	68.00	83.33
mean±SD	64.73±8.03	76.39±10.02	69.11±10.22	78.42±11.58	70.60±12.09	58.20±6.13	71.31±10.27	71.83±14.06

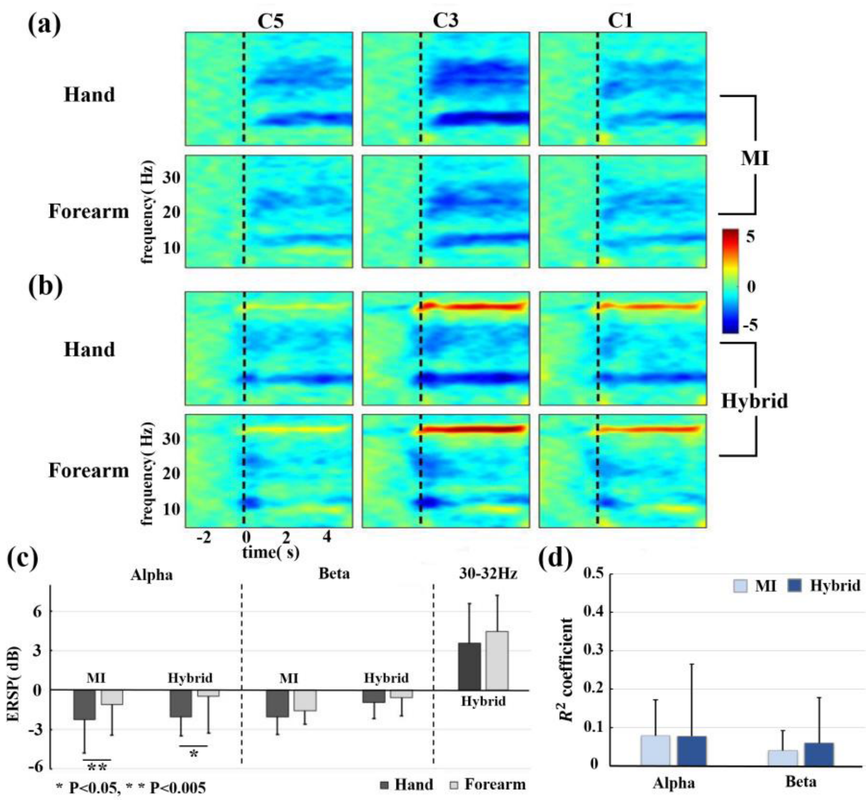

FIGURE 3. Averaged time-frequency maps across all subjects at three channel locations, and the mean ERSP on channel C3. (a) MI condition. Black dashed line indicates the onset of the MI task. Blue color indicates the ERD phenomenon. (b) Hybrid condition. Red color indicates the SSSEP phenomenon. (c) The mean ERSP on C3 for alpha, beta, and SSSEP bands during two MI tasks of the experiment. (d) The R^2 coefficients of ERSP value between hand and forearm in different frequency bands.

We also found that the recognition performance under the MI condition was similar to that of using the separate ERD feature under the hybrid condition. A paired t-test revealed no significant difference ($p = 0.3175$), which indicated that the SSSEP in the hybrid paradigm had no influence on the separability of ERD feature.

B. TIME-FREQUENCY ANALYSIS OF EEG

Figure 3 shows the average time-frequency maps of all subjects at the C5, C3, and C1 channels under both experimental conditions. The maps of MI and hybrid conditions (figure 3(a) and figure 3(b), respectively) present a clear long-lasting alpha and beta rhythm desynchronization from task

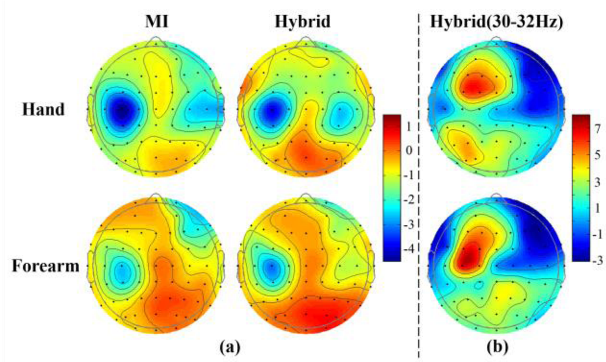

FIGURE 4. Topographical distributions of ERD and SSSEP patterns for a typical subject. (a) ERD patterns for MI and hybrid conditions. (b) SSSEP patterns for hybrid condition. 'Hand' indicates hand imagination task. 'Forearm' indicates elbow imagination task.

onset. Compared with the MI conditions, the hybrid condition showed a long-lasting SSSEP phenomenon at 31 Hz, indicating that the SSSEP feature was successfully induced by electrical stimulation in this study. This result shows that, under the hybrid condition, co-existence of two EEG features (ERD and SSSEP) was obtained. All three channels showed similar phenomena.

We further analyzed the average ERSP values of different bands at a typical channel, C3, as shown in figure 3(c). First, in the alpha band, the paired t-test showed a significant difference in the ERSP values between hand and forearm under the MI condition ($p = 0.0068$), which is similar to the result under the hybrid condition ($p = 0.0299$). This indicates that the features of the two MI tasks are separable. Second, in the beta band, the ERSP values of different tasks under MI conditions and Hybrid conditions did not show significant differences, indicating that the difference of ERSP values under MI and hybrid conditions were similar. We further calculated the R^2 coefficients of the ERSP values between the two MI tasks in different frequency bands (figure 3(d)). There were no significant differences in the R^2 coefficients between the two conditions in either band ($p = 0.9840$ and 0.6030, respectively). This showed that although the overall ERD phenomenon of the hybrid condition was weaker than that of the MI condition, its separability had not decreased. This result also explained why the recognition performance when using the ERD feature only under the hybrid condition was close to that obtained under the MI condition, which shown that the induced SSSEP features do not affect the ERD features. In addition, although there was no significant difference between MI tasks in the 30-32Hz band, a certain degree of separability still can be seen.

Figure 4 shows the topographical distributions characteristics of the ERD and SSSEP patterns under MI and hybrid conditions. It can be seen from figure 4(a) that the ERD phenomenon of the two conditions was mainly concentrated in the brain function area of the hand, and has obvious contralateral dominant characteristics. Compared with the MI condition, the ERD presented under the hybrid condition was weaker. As shown in figure 4(b), under the hybrid condition, the 31 Hz SSSEP phenomenon was concentrated on the left sensorimotor function area, indicating that the SSSEP feature has the same spatial correspondence characteristics as the MI-induced ERD feature. And the SSSEP feature induced by the forearm task was stronger than the hand.

As the mean ERSP values of the two MI tasks did not differ significantly in the SSSEP band, we further analyzed the spectrum of spatially filtered data for the SSSEP band. As shown in figure 5(a), after CSP filtering, the two MI tasks showed significant differences at 31 Hz. This result indicates that the method of spatial filtering can greatly enhance the separability of SSSEP. In addition, the maximum R^2 coefficient was at 31 Hz, with the maximum values of 0.3679 and 0.4439, respectively (figure 5(b)), indicating that the SSSEP feature has strong separability after spatial filtering. Also, we can from figure 5(c) that the high weight was distributed on left brain areas for different MI tasks according to topographic maps of spatial patterns W_h and W_f. And it showed a significant difference between different spatial filters. This result further verifies that the classification performance of the SSSEP feature alone is comparable with that of the ERD feature alone.

From the above analysis, it can be seen that the new paradigm not only maintains the separability information of the original MI paradigm, but also can obtain additional and comparable separability information. Owing to this increase in separability information, the classification performance can be significantly improved.

IV. DISCUSSION

In this study, we proposed a novel approach to recognize MI between two parts – hand and forearm – of the same limb. The online results showed that subjects could easily learn how to control a BCI to output two commands by MI in the upper limb on one side. Given the low signal-to-noise ratio of the EEG signal, it is very difficult to obtain a high spatial resolution in MI-BCI [27]. To our knowledge, this is the first online study using MI-BCI to identify two adjacent parts of one upper limb. In most hybrid paradigms that combine ERD and SSSEP, the MI tasks of different parts on the same limb are not studied [28], [29], so we do not compare. Based on this approach, future studies may be developed to further improve the spatial resolution of MI identification, for example, MI between different fingers.

It is important to emphasize that the subjects performed the same MI task under two different conditions. Although subjects in the hybrid condition were exposed to electrical stimuli, they were not required to make any active responses to these stimuli. This meant that users could control the hybrid BCI in the same way as they would control a traditional MI-BCI; that is, they did not need to pay any extra attention or perform any additional operations. In this study, although we did not use any questionnaire to compare attention levels between the proposed hybrid paradigm and the traditional MI paradigm, most of the participants reported that

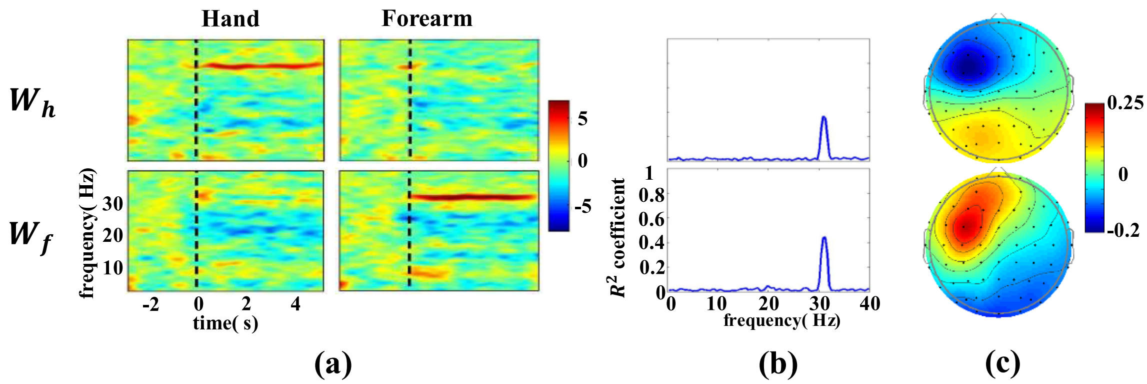

FIGURE 5. Averaged spectrum and R^2 coefficient after CSP filter processing and the spatial pattern of a typical subject. (a) Averaged spectrum of spatially filtered data for the SSSEP band under the hybrid condition. W_h and W_f are spatial filters corresponding to the largest eigenvalue for hand and forearm MI tasks, respectively. (b) The R^2 coefficient of spatially filtered ERSP for different frequencies between hand and forearm tasks. The above corresponds to W_h and the below corresponds to W_f. (c) The spatial pattern of one subject for SSSEP band during hybrid condition. The upper is corresponding to W_h and the lower is W_f.

the electrical stimulation did not interfere with the execution of their MI tasks. Therefore, it appears that the proposed paradigm in this study maintains the active operation method of MI-BCI, which makes it significantly different from other hybrid approaches.

To the best of our knowledge, functional electrical stimulation (FES) has shown a certain potential in stroke rehabilitation. Related studies have shown that MI-BCI-FES rehabilitation training system is more effective than traditional FES for stroke rehabilitation [30] [31]. This type of stimulation, including waveform and intensity is a safe design that does not cause patient's obvious uncomfortable feelings. Since the waveform and phase parameters of the ES used in this study were consistent with FES, and the SI was much lower than that of the general FES, even if the stimulation is applied on the patients who are more sensitive, it will not cause obvious uncomfortable feelings. Therefore, this stimulation method has reliable safety and adaptability.

As described in the text, the SSSEP feature incorporated in this study is a somatosensory response induced by ES, so it required the user's somatosensory feedback to still exist. It is true that not all people have somatosensory feedback, mainly in patients with severe tetraplegia accompanied by sensory impairment. Since MI-BCI is mainly used in the rehabilitation of patients, such as locked-in syndrome (LIS), amyotrophic lateral sclerosis (ALS), or stroke, it is necessary to discuss the applicable population of the system.

Studies have shown that for most patients who suffer LIS or ALS, although they lose voluntary gaze control, their somatosensory system still works [32] [33]. Hence, they can use the somatosensory system to modulate brain activity and generate the SSSEP feature. For stroke patients, studies have shown that according to the Erasmus modification of the Nottingham Sensory Assessment for the upper extremity (EmNSA-UE) [34], the levels of sensory impairment of patients were classified in three groups, namely severe, mild and none [35]. Therefore, at least some patients can have sensory feedback. In addition, during the recovery process, the patient's somatosensory is may slowly recovered, so at least some patients can maintain sensory function at a certain stage. Therefore, the hybrid BCI paradigm proposed in this study is suitable for patients with motor impairment whose somatosensory system is still sound. In the future work, the feasibility of this system in different degree of somatosensory damage can be explored.

In our previous study of the MI-SSSEP paradigm, we placed electrical stimuli of different frequencies on the left and right limb during the execution of the MI task [18]. In particular, we applied a 26 Hz stimulus on the left wrist and a 31 Hz stimulus on the right wrist, while the subject imagined opening and closing their left hand or right hand. The results showed that, under this condition, the SSSEP responses could be modulated by the MI executed on the same location. However, in this study, we only introduced one channel of electrical stimulus. The results indicate that the SSSEP response was different between the two MI tasks, especially after the spatial filter processing. This suggests that the distance between the location at which the MI is executed and the location at which the stimulus is delivered is an important factor in the modulation of SSSEP responses. On the one hand, this result provides new approach to BCIs using somatosensory signals. On the other hand, it indicates that it is unnecessary to exert stimuli of different frequencies on every location of the MI, allowing the system complexity to be significantly reduced and improving the user experience.

V. CONCLUSIONS

In this study, we developed a novel hybrid paradigm to decode motion intention of hand and forearm on the same limb, and verified the feasibility of the system through online experiments. Both ERD and SSSEP features were included in the hybrid condition. Compared with MI, the decoding performance of the hybrid condition showed a significant improvement. Our research shows that the introduction of somatosensory stimulation into MI-BCI helps to improve the spatial resolution, which provides a new way to boost BCI efficiency.

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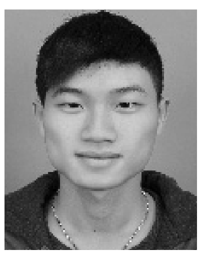

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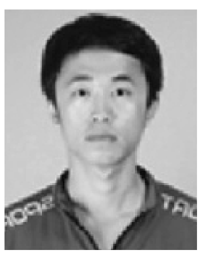

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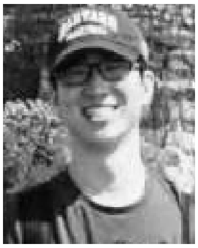

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