Combining Motor Imagery With Selective Sensation Toward a Hybrid-Modality BCI

Lin Yao, Jianjun Meng, Dingguo Zhang, Xinjun Sheng, *Member, IEEE*, and Xiangyang Zhu*

***Abstract*—A hybrid modality brain-computer interface (BCI) is proposed in this paper, which combines motor imagery with selective sensation to enhance the discrimination between left and right mental tasks, e.g., the classification between left/ right stimulation sensation and right/ left motor imagery. In this paradigm, wearable vibrotactile rings are used to stimulate both the skin on both wrists. Subjects are required to perform the mental tasks according to the randomly presented cues (i.e., left hand motor imagery, right hand motor imagery, left stimulation sensation or right stimulation sensation). Two-way ANOVA statistical analysis showed a significant group effect (F (2,20) = 7.17, $p = 0.0045$), and the Benferroni-corrected multiple comparison test (with $\alpha = 0.05$) showed that the hybrid modality group is 11.13% higher on average than the motor imagery group, and 10.45% higher than the selective sensation group. The hybrid modality experiment exhibits potentially wider spread usage within ten subjects crossed 70% accuracy, followed by four subjects in motor imagery and five subjects in selective sensation. Six subjects showed statistically significant improvement ($p < 0.0045$ Benferroni-corrected) in hybrid modality in comparison with both motor imagery and selective sensation. Furthermore, among subjects having difficulties in both motor imagery and selective sensation, the hybrid modality improves their performance to 90% accuracy. The proposed hybrid modality BCI has demonstrated clear benefits for those poorly performing BCI users. Not only does the requirement of motor and sensory anticipation in this hybrid modality provide basic function of BCI for communication and control, it also has the potential for enhancing the rehabilitation during motor recovery.**

***Index Terms*—BCI, hybrid modality, motor imagery (MI), selective sensation (SS).**

I. Introduction

A BRAIN-computer interface (BCI) provides a nonmuscular channel for humans to communicate and control with the external world, and it paves the way to retrieve motion functions for those suffering from locked-in syndromes or amyotrophic lateral sclerosis [1]. There is growing research interest in improving classification accuracy [2]–[5], enabling mass usage of BCI systems [6]–[8], and solving the "BCI-illiteracy" problem in which BCI control does not work for a portion of users [9]–[11]. BCI diversity and software algorithms may provide a way to solve these problems. Various BCI modalities have been proposed in the literature, such as motor imagery (MI) [12], steady-state visual evoked potentials (SSVEPs) [13], P300 evoked potentials [14], sensory motor rhythm [15], steady-state somatosensory evoked potentials (SSSEPs) [16], and selective sensation (SS) [17]. While there are pros and cons in different BCI modalities [18]–[20], a hybrid BCI may lead to a novel way to achieve better performance [21]. Allison *et al.* [10] reported that a hybrid approach adopting MI and SSVEP yielded the highest classification accuracy (81.0%), compared with SSVEP (76.9%) or MI (74.8%) alone. In addition, a hybrid task-based approach that combined MI and the P300 potential into a single hybrid feature was proposed for target selection [22], with 94% accuracy. This hybrid paradigm was also successfully employed to control a brain-actuated simulated and real wheelchair [23]. In Pfurtscheller's work, MI was combined with SSVEP for orthosis control, which presented promising results with a much lower rate of false positives per minutes during resting periods in comparison with SSVEP BCI alone [24].

MI and SS are both based on the dynamics of brain oscillations described as event-related (de)synchronization (ERD, ERS) [25], which have a strong correlation not only with active or imagined movement [26]–[28], but also with sensory stimulation processing [29], [30]. For instance, motor imagery of hand movements accompanies contralateral ERD and ipsilateral ERS [31], while selective attention modulates somatosensory oscillations in alpha, beta bands [32], which results in significantly increased beta ERD/ERS due to attentional effects. Motor imagery and SS are two distinctive cognitive processes, which may have different dynamics represented in EEG signals. The former is for activating efferent neural pathways with mentally simulated motor output [25], and the latter is for selectively collecting and processing stimulation signals from afferent input [30], [32]. The hybridizing of motor and sensation intentions of the subjects and the corresponding brain oscillatory dynamics could enable a hybrid BCI, which combines imagined hand movement and stimulation sensation. The integration of these two neurophysiological signals is expected to enhance the spatial-temporal pattern discriminations corresponding to different mental tasks or strategies for improved BCI performance.

In this paper, vibrotactile stimulation is applied to subject's left and right wrists, and each subject is required to perform

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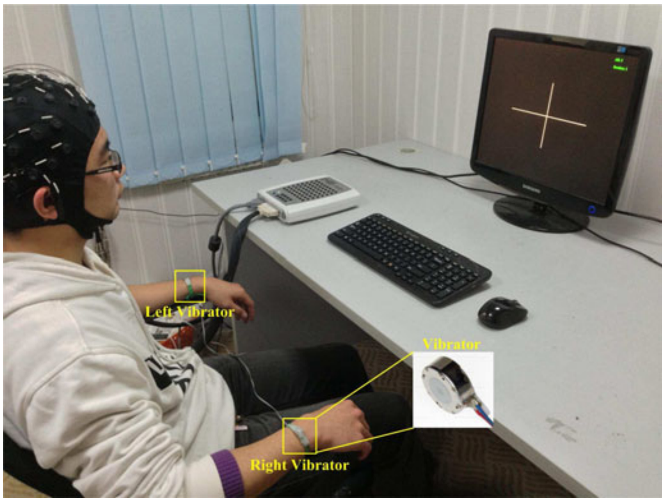

Fig. 1. Experimental setup: stimulation devices are attached to both wrists on the subject.

one of the four randomized mental tasks, i.e.,: right hand motor imagery, left hand motor imagery, right stimulation sensation, or left stimulation sensation. The focus of this paper is to present a hybrid BCI modality which combines motor imagery and SS as a feasible BCI methodology.

II. Method

A. Subjects

Eleven healthy subjects participated in these experiments (eight male/-three female, all right handed, average age of 25 years). Six subjects had previously participated a MI BCI experiment and a SS BCI experiment separately. The study was approved by the Ethics Committee of Shanghai Jiao Tong University, China. All participants signed informed consent forms before participation.

B. Stimulation Device

In this experiment, stimulation was applied to the wrist. The stimulation device produced a 23 Hz sine wave for the left wrist, and 27 Hz sine wave for the right wrist (both modulated with a 175 Hz sine carrier wave). Two types of mechanical receptors, Pacinian corpuscles and Meissner corpuscles were stimulated, which are sensitive to frequencies above 100 and 20–50 Hz, respectively [33].

Left and right wrists were simultaneously stimulated as shown in Fig. 1. The linear resonant actuators (10 mm, C10-100, Precision Microdrives, Ltd., typical normalized amplitude 1.4 G) were used for vibrotactile stimulation. The amplitude of vibration was individually adjusted within the range of 0.5 times to maximum amplitude of 11.3 μm at the resonant frequency. The subjects could feel the intense vibration with flutter sense, and it was modulated to a certain extent that the subject could concentrate on performing the predefined experimental tasks.

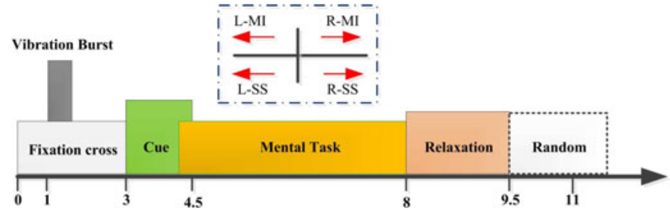

Fig. 2. Trial procedure of the experiment. Subjects performed the mental task according to the cue randomly presented in the screen, with upper left arrow corresponding to left motor imagery (L-MI), upper right arrow corresponding to right motor imagery (R-MI), lower left arrow corresponding to left stimulation sensation (L-SS), and lower right arrow corresponding to right stimulation sensation (R-SS).

C. EEG Recording

EEG signals were recorded using a SynAmps2 system (Neuroscan, USA). A 64 channel quick-cap was used to collect 62 channel EEG signals, and the electrodes were placed according to the extended 10/20 system. The reference electrode was located on the vertex, and the ground electrode was located on the forehead. An analog bandwidth filter of 0.5–70 Hz and a notch filter of 50 Hz were applied to the raw signals. Signals were digitally sampled at 250 Hz.

D. Experimental Paradigm

In the MI task, subjects were instructed to mentally simulate kinaesthetic movements of their own left or right hands depending on the cues without any actually moving. In the sensation task, subjects were required to SS on the indicated side of their hands as if stimulation on the attended side was stronger than the unattended side.

During the EEG signal recording, each subject sat in a comfortable armchair in an electrically shielded room. With forearms and hands resting in the armrest, the subject sat still while limiting eye blinks and avoiding facial or arm movements. The subject's task was to perform MI and SS according to a given cue. A total of 400 trials were performed by the subjects in ten runs, and subjects rested between the two runs. There were 40 trials in each run, and R-MI, L-MI, R-SS, L-SS (defined below) were randomly arranged with ten trials each. At the beginning of each trial, a "+" sign appeared in the center of the screen. At the first second, a vibration burst with the same intensity stimulated both hands to alert the user for the subsequent task, with the vibration pulse lasting 200 ms. Then, at the third second, a red cue pointing either up left (L-MI), up right (R-MI), lower left (L-SS) or lower right (R-SS) was presented visually on the computer monitor, which was superimposed on the "+" and lasted for 1.5 s. Subjects were instructed to perform the mental task after the cue arrow appeared. The mental task continued until the eighth second when the "+" disappeared. At the 4.5th second, vibrations were applied to both hands until the end of the mental task. Next there was a relaxation time period lasting for 1.5 s, during which the subjects relaxed and could blink his or her eyes. Finally, a random time period of 0 to 2 s was inserted after the relaxation period to further avoid subject's adaptation. The single-trial procedure is shown in Fig. 2.

TABLE I
CLASSIFICATION ACCURACY FOR EACH PAIR OF MENTAL TASKS FOR EACH SUBJECT

	R-MI,L-MI (%)	L-SS,L-MI (%)	R-SS,L-MI (%)	L-SS,R-MI (%)	R-SS,R-MI (%)	R-SS,L-SS (%)
s1	57.9±9.6	87.5±7.2	80.2±7.7	90.8±7.0	84.4±7.8	60.9±9.9
s2	68.4±10.5	63.4±11.1	77.7±9.1	79.0±8.0	75.7±9.3	72.6±9.3
s3	98.8±2.5	65.3±9.7	97.5±3.2	99.5±1.5	64.9±8.7	98.6±2.5
s4	62.6±9.7	64.2±9.7	70.3±8.4	79.3±8.0	62.3±8.4	72.6±10.1
s5	64.2±9.0	62.7±10.1	62.3±10.0	74.3±8.3	56.8±11.2	50.1±10.0
s6	69.2±10.6	53.8±9.1	74.7±8.9	80.6±9.4	52.0±10.1	82.1±8.4
s7	60.7±10.0	66.0±8.8	76.0±8.3	69.1±7.6	67.8±9.6	68.3±10.1
s8	68.0±9.8	82.5±8.8	82.6±8.1	92.7±5.7	78.0±9.0	77.2±8.3
s9	96.8±3.9	75.2±8.6	92.8±6.4	96.4±4.5	76.1±8.3	93.1±5.2
s10	90.4±6.8	72.4±8.8	84.7±8.2	80.8±9.1	66.2±10.1	68.0±9.8
s11	54.8±8.7	59.9±11.3	67.9±10.5	71.6±11.1	69.4±9.2	55.6±9.0
mean	71.9±15.8	68.4±10.0	78.8±10.4	83.1±10.2	68.5±9.6	72.6±14.8

E. Algorithms

The decoding algorithm for each two of the four mental tasks is based on the common spatial pattern (CSP). The CSP is a primary method used in MI-based BCI literature. Mathematically, it is realized by simultaneous diagonalization of the covariance matrices for the two classes [34], [35]. The raw EEG signal is represented as X_k with dimensions $ch \times len$, where ch is the number of recording electrodes, and len is the number of sample points, and k is the trial index. The normalized spatial covariance of the EEG can be obtained from

$$C_k = \frac{X_k X_k^T}{\mathrm{trace}(X_k X_k^T)} \tag{1}$$

where X_k^T denotes the transpose of the matrix X_k, and $\mathrm{trace}(X_k X_k^T)$ is the sum of the diagonal elements of the matrix $X_k X_k^T$. Let

$$C_l = \sum_{k \in S_l} C_k \qquad C_r = \sum_{k \in S_r} C_k \tag{2}$$

where S_l and S_r are the two index sets of the separate classes.

The projection matrix W is obtained from the augmented generalized decomposition problem, $(C_l + C_r)W = \lambda C_r W$. The rows of W are spatial filters; the columns of W^{-1} are spatial patterns. For the kth trial, the filtered signal $Z_k = W X_k$ is uncorrelated. In this paper, the log variance of the first three rows and last three rows of Z_k (corresponding to three largest eigenvalues and three smallest eigenvalues), are chosen as feature vectors, and linear discriminative analysis is selected as the classifier.

III. RESULTS

A. Hybrid Modality BCI

A hybrid modality BCI is defined in this paper as BCI decoding each subject's mental state from right MI to left stimulation sensation, hybridizing MI with SS (shown from Table I that R-MI versus L-SS yielded the highest mean accuracy across subjects).

The time interval was chosen from the fourth second to the seventh second from the beginning of the trial (the first to fourth second after the stimulus cue) for offline analysis of MI modality, SS modality, and proposed hybrid modality. The frequency band was chosen to cover the alpha and beta bands from 8 to 26 Hz, using a fourth-order Butterworth filter. The processing procedure was the same for all three modalities. A 10×10 fold cross validation was adopted to evaluate the classification accuracy of each modality as follows: first trials were randomly permutated (100 trials for class one and 100 trials for class two), then equally divided into ten partitions. Each partition was used as an unknown test set which was classified by the classifier trained with the remaining nine partitions, and achieved a classification accuracy for each partition. This process was repeated ten times, and generated 100 classification accuracy indexes. Table I outlines pairwise classification results of the four experimental tasks. A randomized complete block designs (RCBD) [36] was adopted to analyze the group effect of the three BCI modalities mentioned above (subjects as block factors, for within each subject the conditions were as homogeneous as possible so the treatments could be compared under relatively homogeneous conditions). Two-way ANOVA showed a significant group effect ($F(2,20) = 7.17$, $p = 0.0045$). Based on Benferroni-corrected multiple comparison test (with $\alpha = 0.05$), the hybrid modality group was 11.13% higher on average than the MI group with 95% confidence interval of [2.52% 19.73%], and was 10.45% higher than the SS group with 95% confidence interval of [1.84% 19.06%]. There was not a significant difference between the MI group and the SS group. One-way ANOVA with repeated measure and Benferroni-corrected p-value of 0.05/11 $=$ 0.0045 were utilized to evaluate different BCI treatments for each subject (Mauchlys̄ tests for the sphericity were done for repeated measures factors and in cases when sphericity was violated, significance tests were Greenhouse-Geisser corrected). Subjects s1, s2, s4, s5, s6, s7, s8, s9, s10, s11 showed significant differences among the three treatments in Fig. 3. The hybrid modality treatment was significantly better than both MI and SS among subjects s1, s2, s4, s5, s8, s11. Some subjects, having difficulties in both MI and SS performed well in hybrid modality reaching 90% accuracy level (e.g., s1, s8). Subjects s3 and

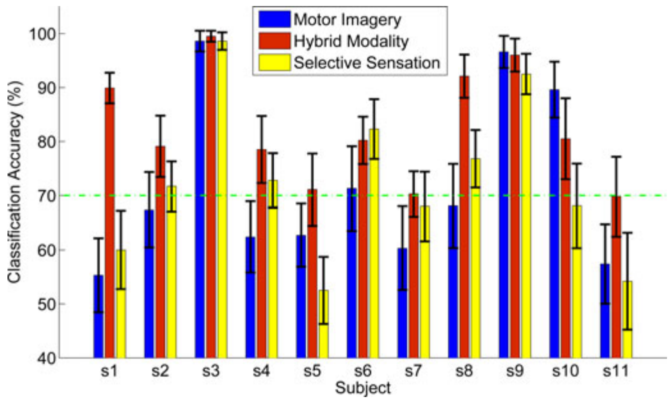

Fig. 3. Comparison of discrimination accuracy of motor imagery, selective sensation, and hybrid modality. Blue bars indicate the discrimination accuracy of left and right hand motor imagery (motor imagery). Yellow bars indicate the discrimination accuracy of left and right stimulation selective sensation (selective sensation). Red bars indicate the discrimination accuracy of left sensation and right motor imagery (hybrid modality). The green dash-dotted line indicates 70% accuracy.

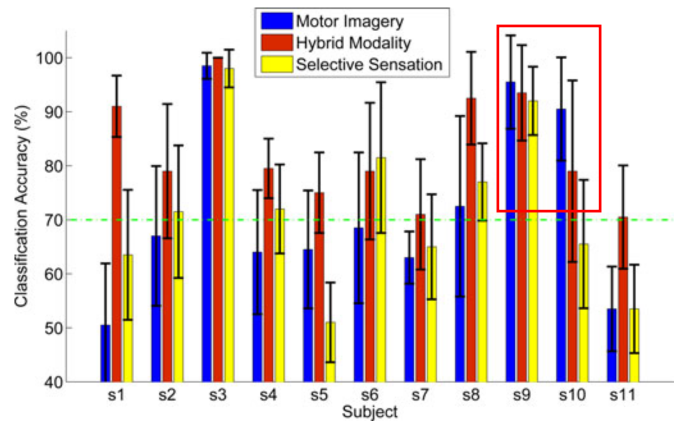

Fig. 4. Comparison of discrimination accuracy of motor imagery, selective sensation, and hybrid modality (temporal information incorporated). Blue bars indicate the discrimination accuracy of left and right hand motor imagery (motor imagery). Yellow bars indicate the discrimination accuracy of left and right stimulation selective sensation (selective sensation). Red bars indicate the discrimination accuracy of left sensation and right motor imagery (hybrid modality). The green dash-dotted line indicates 70% accuracy.

s9 demonstrated stable performance in all three modalities with above 95% accuracy. Subjects s6 and s10 showed better performance in SS and MI, respectively, and they gained reliable control in this hybrid modality with approximate 80% accuracy. Subject s7 showed better performance in hybrid modality. In general, the hybrid modality enabled wider user ranges and improved classification accuracy, generally enhanced performance for poorly performing BCI users.

10×10 fold cross validation was an efficient method to estimate the general classification accuracy of different BCI modalities, while the nonstationarity effect of the data might be obscured since training samples are drawn from the full time course of the experiment in cross validation [37]. Here we attempted to give another view considering the nonstationarity property of the data by performing a cross validation with a ten-fold chronological split. The 100 trials of each mental task were temporally sorted, and divided into ten partitions, each of which contained temporal information similar to actual BCI usage. As shown in Fig. 4, the classification results, which included with temporal information of the trials, were similar to that of Fig. 3, but with a relatively larger variance as a result of the chronological split in the cross validation maintaining the nonstationarity property of the data. There was also a significant group effect (F(2,20) $=$ 6.7, p $=$ 0.0059), and the hybrid modality group was 11.09% higher on average than the MI group with 95% confidence interval of [2.05% 20.14%], and was 10.86% higher than the SS group with 95% confidence interval of [1.82% 19.91%].

B. *Enhanced Discrimination in Spatial-Spectral-Temporal Space*

Time-frequency decomposition of each trial along each EEG channel was undertaken to construct the spatial-spectral-temporal structure according to predefined mental tasks. It was calculated every 200 ms with hanning tapper, convoluted with modified sinusoid basis in which the number of cycles linearly changed with frequency to achieve proper time and frequency resolution [38]. The R^2 index [39] was used to locate the discriminative information distribution among the spatial-spectral-temporal space between two corresponding mental tasks. The R^2 value distribution indicated which (frequency domain), where (spatial domain), and when (temporal domain) the EEG signal exhibited discriminative information, which was used to separate the two corresponding mental tasks. Subjects, who had difficulty in both MI and SS, demonstrated plain discriminative information among the spatial-spectral space as shown in Figs. 5 and 6 (note that R^2 was averaged along the temporal dimension corresponding to the fourth–seventh seconds from the beginning of the trial). While in this hybrid modality phase, discriminative information emerged out in the spatial-spectral space, and the discriminative information was localized in the sensorimotor area, which was responsible for motor output and processing of afferent input. Meanwhile, the R^2 value across the time and frequency domain at critical channels (such as C4 or C3) further showed how subjects gained control in this hybrid modality. Fig. 7 illustrates the discriminative information of a good BCI subject.

C. *Toward Four-Class Discrimination*

A one to one CSP algorithm was initially employed for four-class separation (L-MI, R-MI, L-SS, R-SS each with 100 trials). The baseline corresponded to $[-2\ 0]$ s before the appearance of the cues (i.e., the time interval of the first–third seconds from the beginning of the trial), while the taskline corresponded to [1 4] s after the appearance of the cues (i.e., the time interval of the fourth–seventh seconds from the beginning of the trial). The frequency band of [8 26] Hz was adopted to filter the EEG signals. Similarly, a 10×10 fold cross validation was conducted to evaluate the classification accuracy of the four-class recognition problem. Fig. 8 shows that taskline discrimination accuracy was significantly different from baseline discrimination (F(2,20) $=$ 182.97, $P < 0.0001$). Four subjects reached 60%

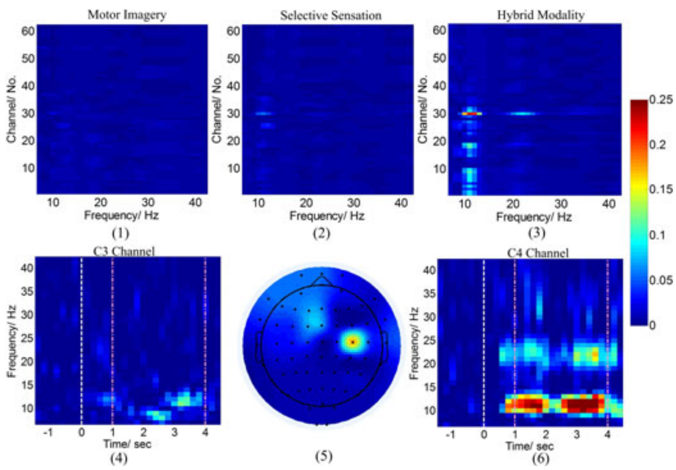

Fig. 5. R^2 value distribution in spatial-spectral-temporal space from subject s8. (1) R^2 value distribution across frequency and spatial domains in motor imagery task (R^2 was averaged along the temporal dimension corresponding to the fourth–seventh seconds from the beginning of the trial), the color bar indicates the R^2 values. (2) R^2 value distribution across frequency and spatial domains in selective sensation task. (3) R^2 value distribution across frequency and spatial domains in the hybrid modality task. (5) Topoplot at 12 Hz of R^2 value in the hybrid modality. (4)–(6) R^2 value distribution across time and frequency domains of channels C3 and C4 [corresponding to channel 26 and 30 in (1)] in the hybrid modality. The vertical white dashed line indicates the cue, and two vertical magenta dash-dotted lines correspond to the time interval used for classification, also equal to the fourth–seventh seconds from the beginning of the trial.

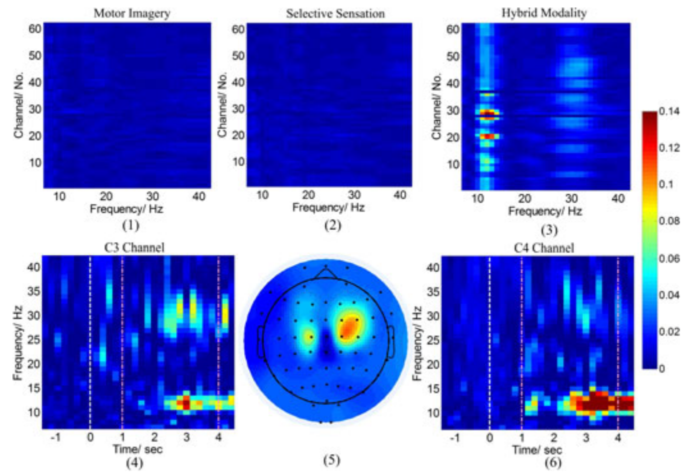

Fig. 6. R^2 value distribution in spatial-spectral-temporal space from subject s1. (1) R^2 value distribution across frequency and spatial domains in motor imagery task (R^2 was averaged along the temporal dimension corresponding to the fourth–seventh seconds from the beginning of the trial), the color bar indicates the R^2 values. (2) R^2 value distribution across frequency and spatial domains in selective sensation task. (3) R^2 value distribution across frequency and spatial domains in the hybrid modality task. (5) Topoplot at 12 Hz of R^2 value in the hybrid modality. (4)–(6) R^2 value distribution across time and frequency domains of channels C3 and C4 [corresponding to channel 26 and 30 in (1)] in the hybrid modality. The vertical white dashed line indicates the cue, and two vertical magenta dash-dotted lines correspond to the time interval used for classification, also equal to the fourth–seventh seconds from the beginning of the trial.

accuracy compared with 25% random probability level in the four-class problem, while subject s9 obtained a classification accuracy of 72.5%.

IV. Discussion

This study proposed a hybrid modality BCI combined cortical output activity (MI) with cortical activity related to afferent input (SS). It demonstrated significantly improved classification accuracy and better performance among a majority of subjects. Allison *et al.* [10] combined imagined movement and visual attention to form a hybrid BCI, and showed that a hybrid approach adopting MI and SSVEP yielded the highest classification accuracy (81.0%), followed by SSVEP (76.9%) and MI (74.8%). Some subjects with difficulty in MI BCI or SSVEP BCI attained effective communication in the hybrid task. In this paper, the hybrid condition also produced the highest average classification accuracy (83.1%), in comparison with the sole approach with MI (71.9%) or SS (72.6%). Some subjects, e.g., subject s1 and s8, turned out to be suitable BCI users achieving 90% classification accuracy in the hybrid condition. The hybrid modality seems to be a good choice for subjects with difficulty in gaining control through conventional MI BCI. The hybrid approach also presented a promising application in target selection [22], in which P300 and ERD features were hybridized. If the target is of interest, the user is instructed to pay attention to a flashing button and to maintain the idle state of MI in order to locate the target. In contrast, the user is instructed to perform MI without focusing on the flashing button. Upon this hybrid strategy, a 93.99% accuracy was attained to allow efficient target selection in the 2-D cursor control. In this experiment, only the ERD feature was used in the hybrid task, as the ERD feature not only reflects the motor intention but also reflects the sensation intention. The proposed strategy in the hybrid task was different from both of them, that is, increasing the left and right separation by instructing to perform different mental task (right MI and left stimulation sensation). In general, from the definition of the concept of hybrid BCI [21], at least one BCI should be involved in the hybrid task design. Like the hybrid car with two different types of engines for achieving energy efficiency, the hybrid BCI is a promising solution to improve overall user performance.

One of the challenging issues confronting BCI research is understanding and solving the "BCI Illiteracy" problem, in which BCI control does not work for some users (roughly 15%–30%). A neurophysiological predictor of BCI performance has been previously proposed [9], that is, the BCI feedback performance could be predicted upon two-minute recording of a "relax with eyes open" condition. This furthered our understanding of the "BCI Illiteracy" problem, and offered a novel way to discover poorly performing users. While training a subject to modulate rhythmic activity [40], machine learning to extract subject-specific patterns [6] and coadaptation of the subject and machine [8] have all been shown to reduce the number of poorly performing BCI users, the hybrid experiment design in this study has also shown the potential for reducing the number of the poorly performing BCI users. In the proposed experiment, the majority of the subjects crossed the 70% accuracy threshold in the hybrid approach, which might be provided as a supplementary intervention to tackle the "BCI-illiteracy" problem.

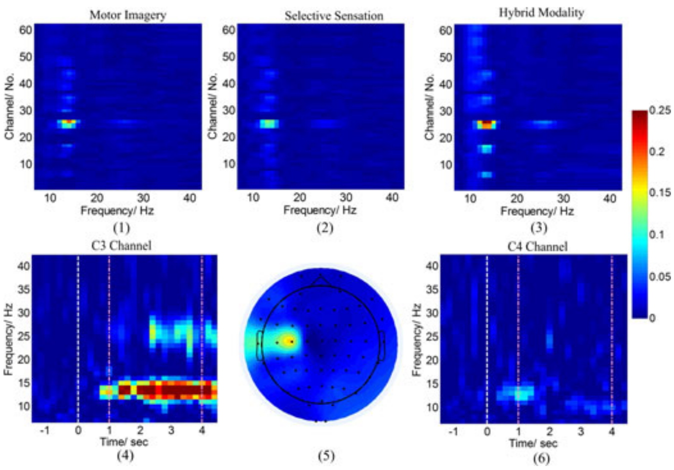

Fig. 7. R^2 value distribution in spatial-spectral-temporal space from subject s9. (1) R^2 value distribution across frequency and spatial domains in motor imagery task (R^2 was averaged along the temporal dimension corresponding to the fourth–seventh seconds from the beginning of the trial), the color bar indicates the R^2 values. (2) R^2 value distribution across frequency and spatial domains in selective sensation task. (3) R^2 value distribution across frequency and spatial domains in the hybrid modality task. (5) Topoplot at 12 Hz of R^2 value in the hybrid modality. (4)–(6) R^2 value distribution across time and frequency domains of channels C3 and C4 [corresponding to channel 26 and 30 in (1)] in the hybrid modality. The vertical white dashed line indicates the cue, and two vertical magenta dash-dotted lines correspond to the time interval used for classification, also equal to the fourth–seventh seconds from the beginning of the trial.

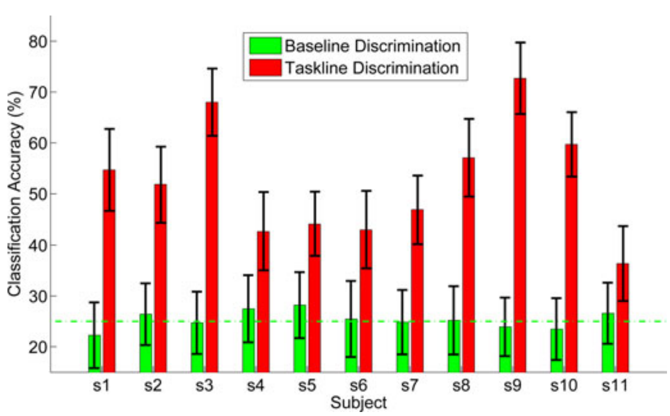

Fig. 8. Comparison of baseline and taskline discrimination in the four-class problem. The green dash-dotted line indicates 25% accuracy.

In all four mental task periods, the vibrotactile stimulation was applied to the subject's wrists, and the only difference was the mental tasks. The stimulation was primarily used to induce rhythmic changes with respect to the cortical process of the afferent input, a necessary component for constructing the SS BCI. Traditionally, MI BCI does not rely on sensory information but instead on spontaneous rhythms which can be modulated by the subject's mental activities. MI with stimulation in this experiment also showed discriminant information similar to MI without stimulation in the literature, and our previous work had also confirmed these findings [17], [41].

The proposed experimental paradigm required outside vibrotactile stimulation to induce cortical activity. Our experiment relied on the afferent neural pathway to perceive stimulation

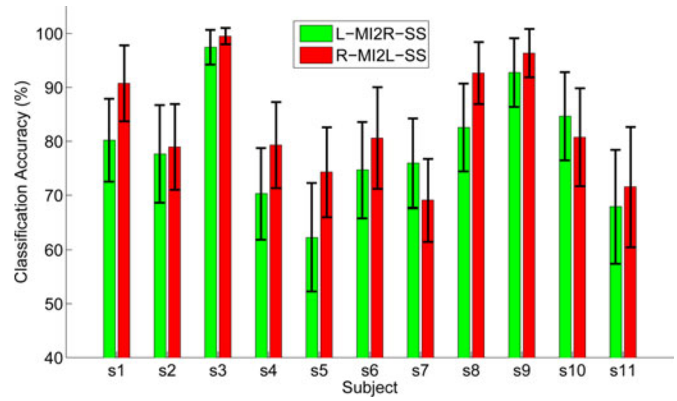

Fig. 9. Discrimination accuracy for each subject. The green bar indicates discrimination accuracy between left motor imagery and right stimulation sensation, and the red bar indicates discrimination accuracy between right motor imagery and left stimulation sensation.

instead of efferent neural pathways. This is similar to P300 based BCI, which requires intact afferent pathways to transmit the transient flickering stimuli to evoke P300 potentials and does not depend on efferent neural pathway for gazing direction of the eyes. It is also different from SSVEP-based BCI, which requires both efferent and afferent neural pathways. The proposed experimental paradigm is expected to work well for stroke patients with damaged motor movement but intact stimulation sensation ability. Additionally, this could be beneficial for rehabilitation, and for communication and control in aiding in daily activity tasks. Motor and sensory related cortical activity in this hybrid modality would enhance the sensory motor loop for functional recovery after disease onset, which is our intended application for future clinical trials.

It is interesting that the discrimination between right MI and left stimulation sensation is 4.3% higher on average than the one between left MI and right stimulation sensation as shown in Fig. 9, when choosing one motor task and one sensation task. According to one study, gating effects are lower in the dominant left hemisphere for right-handed subjects [42], and thus dominant hand control should reduce gating effects. As the attenuation effects were more evident in the right hemisphere, it is likely that left hand stimulation would be better captured. This phenomena and the motor-sensory interaction mechanism should be explored further [43].

The four-class separation results have the potential to form a multiclass BCI system [44], [45], though there is still room for improvement from advanced classification algorithms and improved experimental design. Our preliminary results of the four class discrimination using a one to one CSP algorithm have shown that it was significantly ($p < 0.001$) different from random guessing (25% accuracy), and can achieve up to 72.5% classification accuracy. For discrimination between unilateral motor and sensation, only four subjects crossed the 70% accuracy line. From the physiological point of view, motor and sensation processes were distinctive: one corresponding to efferent neural pathways, the other to afferent neural pathways. Since the EEG signals have poor spatial resolution and the primary motor cortex is close to the somatosensory cortex, separation of the two cognitive tasks might be difficult. This is also similar to the discrimination between left foot MI and right foot MI [46], in which the corresponding cortexes are very close to each other, causing difficulty in separating the two motor tasks. In the proposed research, only the ERD/ERS phenomena with basic CSP algorithm was used to deal with the classification problem between each of the two cognitive tasks. Steady-state somatosensory evoked potential (SSSEP) induced by periodic vibrotactile stimulation might increase the separation between unilateral side motor and sensation cognitive tasks. MI has been shown to decrease the SSSEP amplitude [47], while sensation has been shown to increase the SSSEP amplitude [48]. The hybridizing of the ERD/ERS and SSSEP features, might significantly increase the separation between these unilateral cognitive tasks. Introducing SSSEP was our initial goal of increasing the classification accuracy, but it is not yet found the SSSEP corresponding to the stimulation frequency. Some facts such as stimulation parameters and stimulation body side might explain our lack of SSSEP in this experiment. Our stimulating device produced a maximum amplitude of 11.3 μm at the resonant frequency, while an amplitude of 500 μm has been produced with a braille stimulator [49], showing a clear SSSEP. Also our vibration stimulation was applied at each subject's wrists compared to other studies, where the vibration stimulation was applied to the fingers or palms [16], [50], [51]. The discrimination of unilateral cognitive tasks would be critical points for further improvement of the classification accuracy of the four-class BCI, and this problem is worth of future investigation.

V. Conclusion

In this paper, we presented and validated a nonvisual hybrid modality BCI with improved classification accuracy and enhanced upper alpha EEG component discrimination localized near the sensorimotor cortex. This hybrid modality has potential for helping to solve the "BCI Illiteracy" problem. Experimental results demonstrated up to 72.5% accuracy in the four-class problem compared with 25% random chance. This hybrid modality BCI could also form a multiclass BCI system. The proposed hybrid BCI could be especially useful for individuals who have lost volitional gaze control for setting up a P300 or SSVEP based BCI. A motor and sensory combined hybrid BCI system might also be valuable for those deficient sensory-motor interaction, as the hybrid modality system would enhance the interaction of the sensory motor system. Future work should focus on extended clinical trials.

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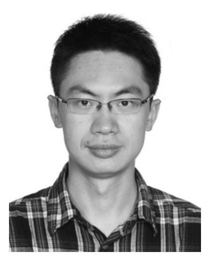

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