A hybrid BCI based on EEG and fNIRS signals improves the performance of decoding motor imagery of both force and speed of hand clenching.
A hybrid BCI based on EEG and fNIRS signals improves the performance of decoding motor imagery of both force and speed of hand clenching

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Abstract

Objective. In order to increase the number of states classified by a brain–computer interface (BCI), we utilized a motor imagery task where subjects imagined both force and speed of hand clenching. Approach. The BCI utilized simultaneously recorded electroencephalographic (EEG) and functional near-infrared spectroscopy (fNIRS) signals. The time-phase-frequency feature was extracted from EEG, whereas the HbD [the difference of oxy-hemoglobin (HbO) and deoxy-hemoglobin (Hb)] feature was used to improve the classification accuracy of fNIRS. The EEG and fNIRS features were combined and optimized using the joint mutual information (JMI) feature selection criterion; then the extracted features were classified with the extreme learning machines (ELMs). Main results. In this study, the averaged classification accuracy of EEG signals achieved by the time-phase-frequency feature improved by 7%, to 18%, more than the single-type feature, and improved by 15% more than common spatial pattern (CSP) feature. The HbD feature of fNIRS signals improved the accuracy by 1%, to 4%, more than Hb, HbO, or HbT (total hemoglobin). The EEG–fNIRS feature for decoding motor imagery of both force and speed of hand clenching achieved an accuracy of 89% ± 2%, and improved the accuracy by 1% to 5% more than the sole EEG or fNIRS feature. Significance. Our novel motor imagery paradigm improves BCI performance by increasing the number of extracted commands. Both the time-phase-frequency and the HbD feature improve the classification accuracy of EEG and fNIRS signals, respectively, and the hybrid EEG–fNIRS technique achieves a higher decoding accuracy for two-class motor imagery, which may provide the framework for future multi-modal online BCI systems.

Keywords: EEG-fNIRS, hand clenching force and speed, motor imagery, joint mutual information (JMI), extreme learning machines (ELMs)

7 These authors contributed equally to the study.
1. Introduction

The brain–computer interface (BCI) is a type of technology that decodes user intentions and directly realizes device control using brain signals without the participation of the peripheral nervous system and muscles [1]. First proposed by Vidal in 1973 [2], BCI has acquired great developments in the past two decades [3–6]. This technology is used for the communication of locked-in patients and neurological rehabilitation of stroke patients [7, 8] as well as for the entertainment of healthy users [9, 10]. In the literature, several techniques have been used to analyze brain activities, including electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS).

EEG is the most used non-invasive brain signal for BCI systems because of its high temporal resolution and low cost. Here, the key step to achieve a high decoding accuracy is to extract task-relevant features. Many researchers have investigated the features of time, spatial, or frequency domains for EEG decoding, such as power spectral, band power, event-related de-synchronization/synchronization (ERD/ERS), and spatial patterns. However, few studies have focused on phase-domain features. Lachaux et al [11] introduced phase locking value (PLV) as a statistical measure to evaluate the phase synchrony phenomenon between two EEG channels, whereas Gysels et al [12] proposed that PLV is useful for spontaneous EEG classification during mental tasks. Moreover, Li et al [13] compared PLV with the phase interval value (PIV) for classification of motor imagery for BCI applications, and their results demonstrated that PIV performed better than PLV. In this study, time-, phase-, and frequency-domain features are combined to classify different motor imageries for BCI. Results show that the time-phase-frequency feature can significantly improve the classification accuracy.

fNIRS is another promising non-invasive approach for BCI systems since Coyle et al first applied it in BCI research in 2004 [14]. This technology measures de-oxyhemoglobin (Hb) and oxyhemoglobin (HbO) concentration changes by shining near-infrared light into the head (with two or more wavelengths) and measuring the diffusively reflected light changes that originate from physiological changes in the skin and cortex [15–18]. Although fNIRS signals provide an approach to investigating user intentions, an inherent time delay of hemodynamic response exists.

Most motor imagery-based paradigms currently use imagination of different limbs, such as the left and right hands, feet, and tongue [19, 20]. The ability to produce multiple control commands, however, may be limited. Although combining motor imageries with other mental tasks, such as word association and mental arithmetic, is one way to increase the command number [21], motor parameter imagery offers a more efficient approach to achieve this goal. Jochumsen et al [22] detected ankle dorsiflexion movement intentions associated with different levels of force and speed using movement-related cortical potential (MRCP). This study can detect different movement intentions with limited latencies, but this design is based on actual movement. Yuan et al [23] investigated the relationship between hand clenching speed and EEG activity and found that activities in alpha and beta frequency bands were linearly correlated with the hand clenching speed. However, it is unknown if hand clenching force and speed motor imageries can be distinguished. Consequently, this study investigates motor parameter imageries associated with both force and speed of hand clenching. This paradigm is a feasible approach in generating considerable BCI commands.

The hybrid BCI using the EEG–fNIRS combination can resolve the particular limitations of single modality and improve the classification accuracy. Fazli et al [24] demonstrated that the performance of motor imagery-based BCI can be enhanced by combining the measurements of EEG and fNIRS signals. In the current study, the hybrid EEG and fNIRS signals are recorded simultaneously and then combined to improve the classification accuracy of decoding motor imagery of both force and speed of hand clenching. Results demonstrate that the classification of motor imagery of both force and speed of hand clenching is possible, and that the EEG–fNIRS features can achieve accuracy levels of 89% ± 2%; further, this method is more accurate compared with that using single-modality features.

2. Materials and methods

2.1. Experiment paradigm

A paradigm based on motor parameter imagery associated with hand clenching force and speed is proposed in this study to increase the BCI command number. Unlike paradigms using motor imageries of different limbs, the two different motor imagery tasks in this study come from the same limb (i.e., the right hand). The hand clenching speed task refers to different hand clenching frequencies, such as 0.5, 1, and 2 Hz. Before the experiment, subjects practiced actual movements of different hand clenching speed levels using a metronome; they were instructed to become familiar with the feeling of different speed levels. However, during the experiment process, they were requested to perform different hand clenching speed levels of motor imageries without actual movement. electromyography activity was monitored to exclude those unqualified trials. The hand clenching force task refers to the different hand clenching forces of the right hand (e.g., 20%, 50%, and 80% of the maximum hand clenching force, MF). The MF of the right hand was measured using an electrical dynamometer. Subjects were required to increase the hand clenching force to a target value in 2 s and then maintain the force (figure 1). Before the experiment, subjects were performed substantial training until they could perform the movements appropriately.

Six right-handed neurologically healthy volunteers (three males and three females, average age: 26.8 ± 3.3 years)
participated in the experiment. All participants gave written informed consent to join the experiment. Among these subjects, subjects 1, 2, and 6 were trained with actual and imagery movements for a total of three times before the experiment, whereas subjects 3, 4, and 5 were only trained one time before the experiment. The experiment was approved by the Ethical Committee of the Shenyang Institute of Automation, Chinese Academy of Sciences.

To acquire considerable task-relevant brain signals for decoding motor imageries, the EEG and fNIRS signals were recorded simultaneously. In consideration of the time lag in the fNIRS response to cerebral activations [25], the time duration of a single trial is longer than the time used for traditional EEG paradigms. A single trial consists of four parts, i.e., baseline, cue, task, and rest period [figure 1(b)]. Owing to the inherent delay of hemodynamic response, the task duration was set to 10 s to ensure fNIRS signals reached the maximum values. The rest period lasted from 10 s to 12 s to eliminate the effect of periodic system error and make fNIRS signals return to base value.

2.2. Data acquisition

A total of 21 EEG electrodes and 24 fNIRS channels over the primary motor area and the supplementary motor area were used in this research [figure 2(a)]. The fNIRS probes contained two types, i.e., the light emitters (the red ones) and the light detectors (the blue ones). The locations between the emitters and the detectors were set as the measured channels. In our research, two 3 × 3 probe sets were used. The EEG electrodes were arranged in accordance with the 10–20 international system, and the fNIRS probe sets were arranged in accordance with the C3 and C4 locations of the EEG electrodes.

The EEG signals were acquired by Neuroscan Synamps2 at a sampling frequency of 1000 Hz, with A1 as the reference and Fpz as the ground. The electrode impedance was reduced to 5 K ohms before the experiment. The electro-oculogram (EOG) was also recorded to ensure that no EOG artifact existed during the motor imagery task period. Meanwhile, the fNIRS signals were acquired by ETG-4000 (Hitachi Medical Corporation, Japan) at a sampling frequency of 10 Hz. The illuminators emitted near-infrared light at two different wavelengths, i.e., 695 and 830 nm. The triggers were simultaneously sent to Synamps2 and ETG-4000 through parallel and serial ports. Although the received triggers of the two signal types may present a difference of a few milliseconds, such a difference does not affect the following analysis.
Every subject participated in three sessions of the experiment. Every session included 30 trials of the hand clenching speed motor imagery task and 30 trials of the hand clenching force motor imagery task. Given that the duration of a single trial was longer than that of traditional EEG paradigms, the number of trials in one session was correspondingly smaller.

2.3. Signal preprocessing

2.3.1. EEG. In order to reduce the computational cost, the EEG data were downsampled to 250 Hz, followed by a Chebyshev II low-pass filter with five orders at a cutoff frequency of 125 Hz to eliminate signal distortion. The data were then band-pass filtered with a band of 5 to 45 Hz. A small Laplacian filter [26] was used to improve the spatial resolution of the EEG data. This is expressed by

\[ V_j^L = V_j - \frac{1}{N} \sum_{k \in S_j} V_k, \]

where \( V_j \) is the \( j \)th channel, \( S_j \) is the surrounding channel set of \( V_j \), \( N \) is the size of \( S_j \), and \( V_k \) is the \( k \)th channel in \( S_j \). Previous studies have shown that mu rhythm and beta rhythm are effective for BCI control [27]. Thus, in this study, signals of 8 to 12 Hz and 18 to 25 Hz were extracted for classification.

2.3.2. fNIRS. The original fNIRS signals are optical intensity signals of two wavelengths. Thus, the concentration changes of Hb and HbO can be calculated with these optical signals using the modified Beer–Lambert Law, as shown in equation (2), where \( \varepsilon_{\lambda_{1/2}, HB/HBO} \) is the extinction coefficient of Hb/HbO under the corresponding wavelength, \( I_{\lambda_{1/2}}(t) \) is the light intensity at times \( t_1 \) and \( t_2 \), and DPF is the ratio of the actual path length of the optical photon to the illuminator-detector distance [28]. Values for the differential path length factors (DPF_{695}=6.51, DPF_{830}=5.86) and the extinction coefficients \( \varepsilon_{695, HB} = 1.9665, \varepsilon_{695, HBO} = 0.3120, \varepsilon_{830, HB} = 0.7804, \varepsilon_{830, HBO} = 1.0507 \) are obtained from [29, 30].

\[ \Delta C = \begin{pmatrix} \Delta C_{IB} \\ \Delta C_{HBO} \end{pmatrix} = \begin{pmatrix} \varepsilon_{1/2, HB} & \varepsilon_{1/2, HBO} \\ \varepsilon_{1/2, HB} & \varepsilon_{1/2, HBO} \end{pmatrix}^{-1} \begin{pmatrix} \log \frac{I_{1}\left(t_2\right)}{I_{1}\left(t_1\right)} \\ \log \frac{I_{2}\left(t_2\right)}{I_{2}\left(t_1\right)} \end{pmatrix} \frac{DPF_{I}d}{DPF_{I}d} \]

The low-frequency drift caused by probe movements in the concentration data was removed using a linear-detrend filter. The concentration data were then low-pass filtered using a Chebyshev II filter with five orders, at a cutoff frequency of 0.1 Hz to remove high-frequency artifacts, such as heart and breathing rates. After eliminating the physiological noise, the data were downsampled to 1 Hz to decrease feature space dimensionality.

2.4. Feature extraction

2.4.1. EEG. In this study, the time-frequency-phase feature is proposed to improve the classification of different motor imageries. Hilbert transform and the complex wavelet convolution are two methods used to obtain the phase information of a signal [11]. These two methods can obtain similar results [31]. The Hilbert transform method is adopted in this study.

The Hilbert transform of a signal \( x(t) \) can be obtained by convoluting with the function \( h(t) = 1/\pi t \) using

\[ y(t) = P \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau, \]

where \( P \) is the Cauchy principal value. The analytic signal of \( x(t) \) can be obtained using equation (2).

\[ z(t) = x(t) + iy(t) = A(t)e^{i\theta(t)}, \]

where \( \theta(t) \) is the imaginary unit, \( A(t) = \sqrt{x(t)^2 + y(t)^2} \) is the instantaneous amplitude (IA), and \( \theta(t) = \arctan(y(t)/x(t)) \) is the instantaneous phase (IP). The value range of \( \theta(t) \) is \([\pi, \pi]\). The instantaneous frequency (IF) can be obtained by \( \omega(t) = d\theta(t)/dt \). To achieve the correct IF, \( \theta(t) \) must be unwrapped by adding multiples of \( \pm 2\pi \) when absolute jumps of more than \( \pi \) occur between consecutive elements.

In this study, four feature types were included, i.e., power, IA, IP, and IF, which were combined together to construct the time-phase-frequency feature. The latter three features can be obtained from Hilbert transform. The topographies of IP and IF between hand clenching force and speed imagery are shown in figure 3.

To decrease the feature dimensions and improve the classification stability, the original features were averaged using a 0.5 s moving window with a step width of 0.125 s. After testing four window length and step width combinations (0.5 s to 0.125 s, 0.5 s to 0.2 s, 1 s to 0.125 s, and 1 s to 0.2 s), we found that the 0.5 s to 0.125 s combination yielded the best performance. The 0.5 s window length is reasonable in consideration of the varied nature of EEG signals, and the 0.125 s step width is enough for achieving fluent BCI device control. The averaged feature points between the time range of \([-0.5, 0.5]\) of all the channels are combined into a vector, and the original size of each feature type is 8 \( \times \) 21 = 168. To eliminate the degradation of the classifier performance caused by feature value range variance and obtain a high classification accuracy, each feature vector was normalized to the range \([-1, 1]\) using equation (5). The four normalized feature vectors were then merged into a single vector to construct the time-phase-frequency feature.

\[ \text{Feature}_{\text{norm}} = \left( \frac{\text{Feature} - \min(\text{Feature})}{\max(\text{Feature}) - \min(\text{Feature})} - 0.5 \right) \times 2, \]

2.4.2. fNIRS. Three types of concentration change signals are currently used in fNIRS-based BCI applications, i.e., Hb, HbO, and total hemoglobin (HbT, i.e., HbT = Hb + HBO), along with two optical intensity signals. The signal pattern...
HbD, i.e., the difference between HbO and Hb concentrations, was also employed in this study [32]. HbO and Hb concentrations are typically strongly negatively correlated with each other under normal circumstances [33]. In this work, we propose that HbD may amplify the amplitude of concentration changes due to cognitive tasks. The time courses of the four preprocessed fNIRS concentration signals activated by cognitive tasks are shown in figure 4.

The four concentration signals and two optical intensity signals of 24 channels from the [0 12] s period were extracted to construct the feature vectors. The original feature space of each signal consisted of $12 \times 24 = 288$ values. The features extracted from these six signal types were then normalized using equation (5).

2.5. Feature optimization

The existence of redundant information in the original feature space can significantly reduce the classification accuracy. Therefore, feature optimization is essential in improving the discriminative performance of a classifier. Feature extraction and feature selection are two typically used feature optimization methods [34]. Although feature extraction projects the original feature set to new features on the basis of transformations (e.g., principal component analysis [35]), feature selection methods select the best subset of the original feature set on the basis of some criteria. The disadvantage of the feature extraction method is that the newly created feature space is difficult to understand. Hence, the feature selection method was chosen in our research.

Depending on whether the classifier is included in the selection process, feature selection methods can be grouped into ‘wrapper’ and ‘filter’ methods [36]. On the one hand, the wrapper methods generally consider the classification accuracy of the classifier as the feature selection criterion, thus resulting in a high classification rate. However, its generalization capability is poor, and its computational burden is extensive. On the other hand, the filter method, based on joint mutual information (JMI) criterion, has been chosen in this study, because Brown et al [36] showed that this criterion provides the best tradeoff between accuracy and stability. In order to score the potential usefulness of a feature, the JMI criterion uses the equation given by

$$J_{\text{MI}}(X_k) = \sum_{X_j \in S} I(X_k; X_j; Y),$$

(6)

Figure 4. The time course of the four preprocessed fNIRS concentration signals activated during hand clenching force tasks.
Table 1. Decoding accuracies of different EEG feature types and their combinations.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Power</th>
<th>IA</th>
<th>IP</th>
<th>IF</th>
<th>Power-IA-IP-IF</th>
</tr>
</thead>
<tbody>
<tr>
<td>subj1</td>
<td>0.72 ± 0.13</td>
<td>0.72 ± 0.14</td>
<td>0.75 ± 0.07</td>
<td>0.81 ± 0.06</td>
<td>0.89 ± 0.07</td>
</tr>
<tr>
<td>subj2</td>
<td>0.73 ± 0.08</td>
<td>0.76 ± 0.07</td>
<td>0.78 ± 0.04</td>
<td>0.81 ± 0.02</td>
<td>0.86 ± 0.01</td>
</tr>
<tr>
<td>subj3</td>
<td>0.69 ± 0.05</td>
<td>0.69 ± 0.06</td>
<td>0.80 ± 0.02</td>
<td>0.80 ± 0.05</td>
<td>0.87 ± 0.06</td>
</tr>
<tr>
<td>subj4</td>
<td>0.62 ± 0.04</td>
<td>0.70 ± 0.08</td>
<td>0.83 ± 0.06</td>
<td>0.77 ± 0.02</td>
<td>0.88 ± 0.01</td>
</tr>
<tr>
<td>subj5</td>
<td>0.73 ± 0.03</td>
<td>0.73 ± 0.02</td>
<td>0.87 ± 0.09</td>
<td>0.82 ± 0.06</td>
<td>0.90 ± 0.07</td>
</tr>
<tr>
<td>subj6</td>
<td>0.73 ± 0.03</td>
<td>0.74 ± 0.07</td>
<td>0.82 ± 0.02</td>
<td>0.77 ± 0.06</td>
<td>0.88 ± 0.01</td>
</tr>
<tr>
<td>trained</td>
<td>0.73 ± 0.00</td>
<td>0.74 ± 0.01</td>
<td>0.78 ± 0.03</td>
<td>0.79 ± 0.02</td>
<td>0.88 ± 0.01</td>
</tr>
<tr>
<td>non-trained</td>
<td>0.68 ± 0.05</td>
<td>0.71 ± 0.02</td>
<td>0.83 ± 0.03</td>
<td>0.79 ± 0.02</td>
<td>0.88 ± 0.01</td>
</tr>
<tr>
<td>all</td>
<td>0.70 ± 0.04</td>
<td>0.72 ± 0.02</td>
<td>0.81 ± 0.04</td>
<td>0.79 ± 0.02</td>
<td>0.88 ± 0.01</td>
</tr>
</tbody>
</table>

Where \( X_i \) is the feature to evaluate, \( X_j \) is the feature that has been selected already, \( S \) is the selected feature set, and \( Y \) is the feature label. This equation stands for the information details of the algorithm can be found in [37].

2.6. Classification

In this study, the extreme learning machines (ELMs) were used to classify between hand clenching force and speed motor imageries of the right hand. ELMs are types of single-hidden layer feedforward neural networks (SLFNs) [38], which can be used for regression and multiclass classifications [39]. Unlike other feedforward neural networks that use gradient-based learning algorithms to tune all the network parameters iteratively, ELMs use an analytical approach by choosing the input weights randomly and then determining the output weights of SLFNs. The advantages of ELMs include extremely fast learning speed, small training error, and good generalization performance. Huang et al. [40] rigorously proved that the input weights and hidden layer biases of SLFNs with infinitely differentiable activation functions can be randomly assigned.

For a training set \( \mathcal{X} = \{ (x_i, t_i) \} \subseteq \mathbb{R}^N \), \( t_i \in \mathbb{R}^m \), \( i = 1, \ldots, N \), standard SLFNs with activation function \( g(x) \) and a hidden node number \( N \) are mathematically modeled next

\[
\sum_{i=1}^{N} \beta_i g(x_j) = \sum_{i=1}^{N} \beta_i g(w_i \cdot x_j + b_i) = t_j, \quad j = 1, \ldots, N, \tag{7}
\]

where \( w_i \) is the input weight vector that connects the input nodes and \( i \)th hidden node, \( \beta \) is the output weight vector that connects \( i \)th hidden node and the output nodes, and \( b_i \) is the bias of \( i \)th hidden node.

Equation (7) can be written in a compact format as

\[
H\beta = T, \tag{8}
\]

where

\[
H = \begin{bmatrix}
g(w_1 \cdot x_1 + b_1) & \cdots & g(w_1 \cdot x_1 + b_{\tau}) \\
\vdots & \ddots & \vdots \\
g(w_1 \cdot x_N + b_1) & \cdots & g(w_1 \cdot x_N + b_{\tau})
\end{bmatrix}_{N \times \tau},
\]

\[
\beta = \left[ \beta_1^T \quad \vdots \quad \beta_{\tau}^T \right]_T^T \quad \text{and} \quad T = \left[ t_1^T \quad \vdots \quad t_{\tau}^T \right]_T^T.
\]

When the input weight \( w_i \) and the bias \( b_i \) are given, the hidden layer output matrix \( H \) can be calculated. The output weight \( \beta \) can be calculated using the equation given by

\[
\beta = H^T T, \tag{9}
\]

where \( H^T \) is the Moore–Penrose generalized inverse of matrix \( H \) [41].

Liang [42] showed that although the accuracy of ELMs is comparable with that of support vector machines, ELMs require less computational cost and shorter training time.

3. Results

3.1. EEG

The classification accuracies between hand clenching force and speed motor imageries of the right hand are shown in table 1 and figure 5. When the power, IA, IP, and IF features are used alone, their decoding accuracies are 0.70 ± 0.04, 0.72 ± 0.02, 0.81 ± 0.04, and 0.79 ± 0.02, respectively. The phase feature (IP feature) and its derivative feature (IF feature) outperform the power and amplitude features. When the four features are used simultaneously, the classification accuracy can be increased to 0.88 ± 0.01. The CSP method performs a weighting of the electrodes to maximize the difference between two different motor tasks, and the channel variance of the filtered signal is used for the classification [43]. In this study, we find that the averaged classification accuracy using CSP is 0.73 ± 0.03, which is worse than that of the time-phase-frequency feature. This result demonstrates that using motor parameter imagery for BCI applications is possible and the time-phase-frequency method outperforms the traditional CSP method.

When the power and IA features are used, the average accuracy for the trained group is better than that for the non-trained group. However, when the IP and IF features are used, the average accuracy for the non-trained group is not worse than that for the trained group. Therefore, the phase feature...
may provide significantly different information compared to the amplitude feature.

3.2. fNIRS

The decoding accuracies using four concentration fNIRS features and two optical fNIRS features are shown in Table 2 and Figure 6. It can be seen that Figure 6(a) shows that different subjects have different feature types. The HbD feature can acquire the best accuracy compared with other features. For all subjects, the averaged accuracies of four concentration features (Hb, HbO, HbT, and HbD) are 0.73 ± 0.05, 0.73 ± 0.05, 0.70 ± 0.06, and 0.74 ± 0.05, respectively, indicating that the HbD feature can achieve a higher accuracy.

When the two optical features are used, the decoding accuracies are 0.70 ± 0.05 and 0.70 ± 0.06, respectively, which are lower than those of the four concentration features. The accuracy of the concentration-combined feature is higher than that of the optical-combined feature by 0.03, which implies that the concentration feature should be chosen preferentially.

3.3. EEG–fNIRS

To investigate the performance of the EEG–fNIRS merged feature, the four normalized EEG features and the four normalized fNIRS concentration features were combined into one feature vector, which was then optimized using the JMI feature selection criterion. The accuracy of the EEG–fNIRS merged feature and its comparison with the results of sole EEG and fNIRS features are shown in Table 3 and Figure 7, respectively. Although the accuracy of the merged feature can only be increased by 0.01 for the average of all the subjects, the accuracy is increased by 0.03 for subject 5 and by 0.05 for...
<table>
<thead>
<tr>
<th>Subject</th>
<th>Hb</th>
<th>HbO</th>
<th>HbT</th>
<th>HbD</th>
<th>Lam1</th>
<th>Lam2</th>
<th>Lam1-lam2</th>
<th>Hb-HbO-HbT</th>
<th>Hb-HbO-HbT-HbD</th>
</tr>
</thead>
<tbody>
<tr>
<td>subj1</td>
<td>0.76 ± 0.05</td>
<td>0.80 ± 0.09</td>
<td>0.79 ± 0.03</td>
<td>0.76 ± 0.01</td>
<td>0.77 ± 0.08</td>
<td>0.76 ± 0.01</td>
<td>0.79 ± 0.02</td>
<td>0.82 ± 0.06</td>
<td>0.80 ± 0.06</td>
</tr>
<tr>
<td>subj2</td>
<td>0.74 ± 0.08</td>
<td>0.77 ± 0.06</td>
<td>0.78 ± 0.02</td>
<td>0.78 ± 0.00</td>
<td>0.74 ± 0.06</td>
<td>0.76 ± 0.07</td>
<td>0.80 ± 0.06</td>
<td>0.77 ± 0.02</td>
<td>0.79 ± 0.04</td>
</tr>
<tr>
<td>subj3</td>
<td>0.64 ± 0.02</td>
<td>0.68 ± 0.02</td>
<td>0.63 ± 0.01</td>
<td>0.69 ± 0.01</td>
<td>0.62 ± 0.03</td>
<td>0.60 ± 0.02</td>
<td>0.67 ± 0.07</td>
<td>0.69 ± 0.01</td>
<td>0.69 ± 0.07</td>
</tr>
<tr>
<td>subj4</td>
<td>0.69 ± 0.08</td>
<td>0.68 ± 0.03</td>
<td>0.67 ± 0.04</td>
<td>0.67 ± 0.03</td>
<td>0.66 ± 0.08</td>
<td>0.68 ± 0.03</td>
<td>0.67 ± 0.04</td>
<td>0.67 ± 0.05</td>
<td>0.70 ± 0.05</td>
</tr>
<tr>
<td>subj5</td>
<td>0.75 ± 0.00</td>
<td>0.69 ± 0.07</td>
<td>0.68 ± 0.03</td>
<td>0.72 ± 0.02</td>
<td>0.72 ± 0.05</td>
<td>0.71 ± 0.06</td>
<td>0.75 ± 0.04</td>
<td>0.77 ± 0.04</td>
<td>0.76 ± 0.04</td>
</tr>
<tr>
<td>subj6</td>
<td>0.77 ± 0.05</td>
<td>0.79 ± 0.09</td>
<td>0.68 ± 0.06</td>
<td>0.79 ± 0.06</td>
<td>0.67 ± 0.02</td>
<td>0.67 ± 0.09</td>
<td>0.71 ± 0.05</td>
<td>0.77 ± 0.04</td>
<td>0.79 ± 0.03</td>
</tr>
<tr>
<td>trained</td>
<td>0.76 ± 0.01</td>
<td>0.78 ± 0.01</td>
<td>0.75 ± 0.05</td>
<td>0.78 ± 0.01</td>
<td>0.73 ± 0.04</td>
<td>0.73 ± 0.04</td>
<td>0.77 ± 0.04</td>
<td>0.79 ± 0.02</td>
<td>0.79 ± 0.00</td>
</tr>
<tr>
<td>non-trained</td>
<td>0.69 ± 0.05</td>
<td>0.68 ± 0.01</td>
<td>0.66 ± 0.02</td>
<td>0.69 ± 0.02</td>
<td>0.67 ± 0.04</td>
<td>0.66 ± 0.05</td>
<td>0.69 ± 0.04</td>
<td>0.71 ± 0.04</td>
<td>0.72 ± 0.03</td>
</tr>
<tr>
<td>all</td>
<td>0.73 ± 0.05</td>
<td>0.73 ± 0.05</td>
<td>0.70 ± 0.06</td>
<td>0.74 ± 0.05</td>
<td>0.70 ± 0.05</td>
<td>0.70 ± 0.06</td>
<td>0.73 ± 0.05</td>
<td>0.75 ± 0.05</td>
<td>0.76 ± 0.05</td>
</tr>
</tbody>
</table>
subject 6. Hence, the EEG and fNIRS features can supplement each other and improve the classification of different motor imagery tasks.

4. Discussion

4.1. Classification of sole EEG

Amplitude and phase are two aspects of a signal. Most features used in EEG-based BCI applications are focused on the amplitude aspect, such as band power, ERD/ERS, and CSP. In this study, IP feature and its derivative feature (IF) were compared with the amplitude feature and its square feature (power feature). The results show that when used alone, the phase feature outperforms the amplitude feature by approximately 10% for the average of all the subjects. When the amplitude and phase features are used simultaneously, the classification accuracy between hand clenching force and speed motor imageries can be improved to 88% for both trained and non-trained groups. The classification accuracy of time-phase-frequency also outperforms the results using CSP.
by 15%. The time-phase-frequency feature proposed in the current study can also be extended to time-spatial-phase-frequency feature by adopting the CSP method.

4.2. Classification of sole fNIRS

fNIRS is a new measurement method that can be used for BCI applications. Both concentration features and optical features were used in current research. After comparing the two feature types, the results demonstrate that the concentration signal outperforms the optical signal, implying that the concentration signal is more effective in reflecting brain activations than optical signals. Moreover, compared with the Hb, HbO, and HbT features, the HbD feature can obtain the best

<table>
<thead>
<tr>
<th>Subject</th>
<th>Hb-HbO-HbT-HbD</th>
<th>Power-IA-IP-IF</th>
<th>Hb-HbO-HbT-HbD &amp; power-IA-IP-IF</th>
</tr>
</thead>
<tbody>
<tr>
<td>subj1</td>
<td>0.80 ± 0.06</td>
<td>0.89 ± 0.07</td>
<td>0.89 ± 0.02</td>
</tr>
<tr>
<td>subj2</td>
<td>0.79 ± 0.04</td>
<td>0.86 ± 0.01</td>
<td>0.87 ± 0.02</td>
</tr>
<tr>
<td>subj3</td>
<td>0.69 ± 0.07</td>
<td>0.87 ± 0.06</td>
<td>0.87 ± 0.03</td>
</tr>
<tr>
<td>subj4</td>
<td>0.70 ± 0.05</td>
<td>0.88 ± 0.01</td>
<td>0.88 ± 0.01</td>
</tr>
<tr>
<td>subj5</td>
<td>0.76 ± 0.04</td>
<td>0.90 ± 0.07</td>
<td>0.93 ± 0.03</td>
</tr>
<tr>
<td>subj6</td>
<td>0.79 ± 0.03</td>
<td>0.88 ± 0.01</td>
<td>0.92 ± 0.03</td>
</tr>
<tr>
<td>trained</td>
<td>0.79 ± 0.00</td>
<td>0.88 ± 0.01</td>
<td>0.89 ± 0.02</td>
</tr>
<tr>
<td>non-trained</td>
<td>0.72 ± 0.03</td>
<td>0.88 ± 0.01</td>
<td>0.89 ± 0.03</td>
</tr>
<tr>
<td>all</td>
<td>0.76 ± 0.05</td>
<td>0.88 ± 0.01</td>
<td>0.89 ± 0.02</td>
</tr>
</tbody>
</table>

Figure 7. Decoding accuracies of fNIRS, EEG, and fNIRS-EEG merged feature. (a) Results for every subject; (b) Results for different groups.
The results show that when the EEG improves classification and checking whether this approach can significantly improve classification accuracy, and not to understand the neural mechanisms of functional brain activity. Our future work will thus examine a merged feature outperforms the sole EEG feature and the sole fNIRS feature. Although the classifier-level merged method has been widely used in previous studies [24], the feature-level merged method is more fundamental in improving classification performance. Furthermore, the optimized features offer cognitive neuroscience experts a convenient way of explaining the neuromechanism behind the optimized features.

EEG presents the neural electrical activity during brain activation, whereas fNIRS measures hemoglobin oxygenation information. There are three reasons why the EEG–fNIRS merged features can achieve better performance than sole EEG and sole fNIRS. First, when EEG and fNIRS are used simultaneously, more task-relevant information content can be enhanced about the motor imagery state of the subject. Second, these two techniques can complement each other in presenting cortex activation during motor imagery. Finally, feature optimization can also extract the most relevant features, which can separate hand clenching force and speed motor imageries.

4.3. Classification of EEG–fNIRS

The results in this paper show that when the EEG–fNIRS merged feature is used, the decoding accuracy can be improved by 1% to 5%. The best accuracy using the merged feature is 93% ± 3% for subject 5, which is high enough, considering that only one hand is used in the experiment. The merged feature outperforms the sole EEG feature and the sole fNIRS feature. Although the classifier-level merged method has been widely used in previous studies [24], the feature-level merged method is more fundamental in improving classification performance. Furthermore, the optimized features offer cognitive neuroscience experts a convenient way of explaining the neuromechanism behind the optimized features.

In conclusion, the paradigm of hand clenching force and speed motor imageries proposed in this study is feasible in increasing control command numbers for BCI applications. Furthermore, the EEG–fNIRS merged feature can better improve classification accuracy compared with the single-signal type approach.

Acknowledgments

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