Classification of the intention to generate a shoulder versus elbow torque by means of a time–frequency synthesized spatial patterns BCI algorithm

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Abstract
In this paper, we attempt to determine a subject’s intention of generating torque at the shoulder or elbow, two neighboring joints, using scalp electroencephalogram signals from 163 electrodes for a brain–computer interface (BCI) application. To achieve this goal, we have applied a time–frequency synthesized spatial patterns (TFSP) BCI algorithm with a presorting procedure. Using this method, we were able to achieve an average recognition rate of 89% in four healthy subjects, which is comparable to the highest rates reported in the literature but now for tasks with much closer spatial representations on the motor cortex. This result demonstrates, for the first time, that the TFSP BCI method can be applied to separate intentions between generating static shoulder versus elbow torque. Furthermore, in this study, the potential application of this BCI algorithm for brain-injured patients was tested in one chronic hemiparetic stroke subject. A recognition rate of 76% was obtained, suggesting that this BCI method can provide a potential control signal for neural prostheses or other movement coordination improving devices for patients following brain injury.

1. Introduction
Brain–computer interface (BCI) techniques have developed rapidly in the last two decades [1]. These techniques have great potential for providing a non-muscular communication channel for people who lack muscle control or have movement disorders, by interacting with neural prostheses or other devices. In BCI studies, scalp electroencephalogram (EEG) is a potential control signal for determining a subject’s motor intention, because it offers a noninvasive and convenient way to examine, with high temporal resolution, the electrophysiological changes produced by brain structures. Currently, applications of scalp EEG based BCI techniques focus on efficiently decoding the user’s intention to control the movement of a cursor on a screen, by measuring different types of EEG signals (visual evoked potential (VEP) [2], P300 [3], steady-state VEP [4], spontaneous rhythms [5, 6] or self-regulated slow cortical potential shifts [7]). These applications have targeted a small population namely fully locked-in patients. Other BCI studies attempt to classify different movement intentions. These studies target a wider range of clinical populations, as BCI could be used for the control of prostheses or other devices. Currently, BCI approaches in these studies are mainly applied to classify the imagination of left versus right hand movements or to predict whether subjects are typing or not [8–13] (please refer to [14] for a recent review of BCI research). These BCI studies may be among the simplest in the applications related to movement intention classification, considering that the former type of study aims to separate movement...
intensions, whose cortex representations are on opposite hemispheres about 10 cm apart, whereas the latter one aims at detecting a movement versus resting condition. In these studies, achieved recognition rates range from 67% to 95%.

In an effort to be one step closer to the goal of BCI-controlled prostheses or other devices, we investigated whether BCI techniques are able to separate motor tasks controlled by two closely neighboring areas in the cortex, such as the shoulder and elbow areas (about 10 mm apart in the cortex). This problem has never been explored and is very challenging because motor tasks involving one joint usually result in a certain level of muscle coactivation at the other. Furthermore, because of the redundancy present in the human musculoskeletal system (i.e., more muscles involved in the generation of torque than the number of degrees of freedom present at a joint [15]), one can generate the same motor task using an infinite number of combinations of muscle activation patterns. Therefore, it is possible that subjects use more than one strategy to complete a single motor task, which makes our task, i.e. off-line classifying a subject’s intention to generate an isometric shoulder abduction (SABD) versus elbow flexion (EF) torque based on single-trial scalp EEG analysis, more difficult.

In order to achieve a high recognition rate, a well-designed BCI algorithm is required. A BCI algorithm usually includes effective signal feature extraction and discrimination algorithms. For signal feature extraction, autoregressive coefficients describing the time-varying characteristics of signals and power spectral densities representing the power of a certain frequency band in a time segment are widely used. As for the discrimination techniques, there are linear (e.g. linear discrimination analysis [16], signal space projection [17], common spatial patterns [18, 19], etc) and nonlinear classifiers [11, 20] (e.g. distinction sensitive learning vector quantization (DSLVQ) [21, 22], support vector machine [23] and hidden Markov model [24]).

In our study, we extracted features from spontaneous rhythmic EEG activity. It has been found that programming and planning of motor actions are typically accompanied by a task-specific, localized and short-lasting power decrease of rhythmic activity labeled as event-related desynchronization (ERD) [25]. Reports have shown that the generation of motor commands can modulate ERD features in the sensorimotor cortex [26]. Specifically, the sources of $\beta$ frequency band (12–24.5 Hz) are mostly centered in the anterior bank of the central sulcus [27] and reflect cortical somatotopic organization [28]. Moreover, the ERD features were found to change as a function of time and to be frequency dependent [29, 30]. All these features of ERD require detailed time–frequency signal analysis. Considering the sensitivity of ERD to timing, frequency and localization, we adopted the BCI strategy proposed by Wang et al [8] using subject-specific time–frequency features and feature-weighted linear discrimination. Furthermore, due to the possibility that subjects may use different strategies when performing the same task, we modified the algorithm by disassembling the dataset into a couple of subsets each with different covariance complexity before applying the main BCI method. By applying this modified algorithm, we showed that we could achieve an average classification accuracy of 89% in four healthy subjects for classifying the mental intention of a shoulder or elbow task. This result suggests that a time–frequency synthesized spatial patterns (TFSP) BCI algorithm [8] using noninvasive scalp EEG is a promising approach even when applied to a challenging classification problem.

2. Method

2.1. Experimental protocol and data recording

Four healthy, right-hand dominant subjects were involved in this study; each gave written informed consent prior to participating. Subjects sat on a Biodex chair with straps crossing their chest and abdomen to prevent trunk and pelvis motion during the experiment. They were casted at the wrist and secured to a six degrees of freedom load cell with the shoulder 75° abducted and 40° flexed and the elbow 90° flexed.

Subjects were first trained using visual feedback to self-initiate the generation of shoulder abduction (SABD) or elbow flexion (EF) torques from rest up to 25% of their maximum voluntary torque, 5–7 s after an auditory cue signaling the beginning of the trial. Once subjects were able to perform the tasks, visual feedback was removed and data collection was performed. Subjects were required to complete 100–120 trials of torque generation in the direction of SABD or EF in several randomly ordered blocks (20–30 trials for each block) without visual feedback. In an effort to avoid fatigue, rest periods were provided for 15 s between trials and 20 min between each block.

The EEG signals were recorded from 163 electrodes by a BioSemi Active II system (BioSemi, Amsterdam, The Netherlands) with a sampling rate of 1024 Hz. A pair of electrodes was placed above and below the right eye to detect eye movements. At the same time, the force and moment data at the wrist were measured by a six degrees of freedom load cell (JR3 Inc., Woodland, CA) and were converted online into elbow and shoulder torques. A TTL signal was sent to synchronize the collection of torque and EEG signals when the torque in the required direction exceeded 0.15 N m.

2.2. Data preprocessing

The 163-channel EEG signals were imported into the Brain Vision Analyzer V1.04 (Brain Products GmbH, München, Germany) for signal preprocessing. EEG signals in noisy channels, within intervals of eye artifacts, or with drifting artifacts were first manually eliminated from further analysis. The remaining signals were aligned with the off-line detected onset of torque, and then segmented from 1800 ms to 60 ms prior to the onset of torque. The segmented EEG signals were then run through a multi-stage processing procedure: (1) re-referencing to the common average, (2) low-pass filtering (9th order Butterworth filter, cutoff frequency at 50Hz), (3) baseline correction, and (4) de-sampling to 256 Hz. In order to increase the signal-to-noise ratio (SNR), a finite-difference surface Laplacian (SL) transformation [31] was...
applied to each channel as a spatial high-pass filter to reduce the smearing effects caused by the head volume conductor. As a result, peripheral electrodes were removed and preprocessed EEG signals in the inner 131 electrodes were exported to a MATLAB software program for BCI classification.

2.3. BCI algorithm for the classification of intention in generating shoulder/elbow torques

We used the leave-five-out cross-validation method (i.e., dividing the whole dataset into multi-folds with five trials per fold for each of the motor tasks) to train and test the BCI algorithm. Using this method, one of the folds was taken iteratively as the testing data and the rest of folds were used as the training data.

2.3.1. Time–frequency weighted synthesized classification based on correlation of spatial patterns (the main classification).

The main BCI process is based on the work of Wang et al [8]. Briefly, EEG signals ranging from 5 to 34 Hz were first decomposed into a series of frequency bands using a group of constant $Q$ value ($Q = 4$) band-pass filters. Each of the filters is overlapped with the center frequency of the previous one to obtain the starting frequency of the consecutive one. Subsequently, the Hilbert transform was used to extract profiles of the oscillatory activities, and the resulting profiles were then divided into equal-length intervals (55 ms of each interval) with a 50% overlap. By dividing signals in both frequency and time domains, EEG signal were presented in time–frequency grids. In our study, the time–frequency grids consist of 13 frequency bins and 61 time segments. Following the divisions, we calculated the instantaneous power (i.e., integration of the profile) in each of the time–frequency grids in the spatial domain, and thus, a spatial pattern denoted as $p(t, f)$ was formed in this specific time–frequency grid, where $t$ and $f$ are the indices of time and frequency bins, respectively. By generating spatial patterns in all the time–frequency grids, an original recorded single-trial EEG signal was represented in a new spatial, time and frequency space by frequency grids, an original recorded single-trial EEG signal as grids in the spatial domain, and thus, a spatial pattern denoted (i.e., integration of the profile) in each of the time–frequency grids set of different trials could have different time–frequency feature patterns. Therefore, we added a presorting procedure to divide EEG trials for each motor task into two subsets according to the covariance complexity, denoted as $C_c$, of each of the single-trial EEG signals, which was calculated as follows [32]:

$$C_c = -\frac{1}{\log N} \left[ \sum_{j=1}^{N} V_j \log V_j \right],$$

where $V_j = \frac{1}{\log N}$ and $S_j$ is in the $j$th eigenvalue obtained using a principle component analysis. The mean of the covariance complexities for all EEG trials was used as the dividing line (i.e., trials with covariance complexities larger than the mean formed the first subset and those with smaller covariance complexities formed the second subset).

Within each subset, we generated a characteristic pattern, resulting in a total of four characteristic patterns (i.e., $P_{\text{ABD}(t,f)}$, $P_{\text{ABD}(t,f)}$, $P_{\text{ABD}(t,f)}$, and $P_{\text{ABD}(t,f)}$). Subsequently, when applying equation (1) on each time–frequency grid, the spatial pattern $p(t, f)$ was compared with all of the four characteristic patterns. The result of the similarity judgment, $S_p(t, f)$, was set to 1 if the testing pattern $p(t, f)$ had the maximum similarity to one of the two characteristic patterns of SABD; otherwise, $S_p(t, f)$ would be equal to –1. Finally, we used equation (3) to get the classification result for a single trial. The overall flow chart of our modified algorithm is illustrated in figure 1.

$$R(p) = \text{sign} \left[ \sum_{i=1}^{N} \sum_{j=1}^{N} W(t, f) * S_p(t, f) \right],$$

where $p$ represents the spatial pattern of a testing trial. A positive $R(p)$ indicates that the current trial is a SABD-related event, while a negative one indicates a EF-related event.

2.3.2. The modified BCI method by quantifying covariance complexity (presorting procedure).

Due to the possibility that subjects may use different strategies for the same motor task, it is possible that the EEG signals elicited at different trials could have different time–frequency feature patterns. Therefore, we added a presorting procedure to divide EEG trials for each motor task into two subsets according to the covariance complexity, denoted as $C_c$, of each of the single-trial EEG signals, which was calculated as follows [32]:

$$C_c = -\frac{1}{\log N} \left[ \sum_{j=1}^{N} V_j \log V_j \right],$$

where $V_j = \frac{1}{\log N}$ and $S_j$ is in the $j$th eigenvalue obtained using a principle component analysis. The mean of the covariance complexities for all EEG trials was used as the dividing line (i.e., trials with covariance complexities larger than the mean formed the first subset and those with smaller covariance complexities formed the second subset).

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Figure 1. Flow chart of the presorting and main classification processes of our BCI approach. SABD and EF refer to shoulder abduction and elbow flexion, respectively.

Figure 2. Mean value and standard deviation of the covariance complexities for the generation of SABD and EF torques in the four healthy subjects. The black (blue) and gray (red) bars represent the mean of the covariance complexities in the two data subsets.

3. Results

The means and standard deviations of the covariance complexities in the two subsets for the generation of SABD and EF torques in each of the subjects are shown in figure 2. In this figure, the black (blue) and gray (red) bars represent the covariance complexities of the first and second subsets, respectively. In subject 1, there is a larger difference between the means of the covariance complexities for the two subsets, suggesting that strategies in this subject for the same task differ more than those in the other subjects (e.g., subjects 2 and 4). Therefore, the presorting procedure may be more useful in improving recognition rate in subject 1. We will provide supportive evidence for this argument later.

Figure 3 shows the subject-specific time–frequency weight distribution obtained by the training process. A larger weight (represented by the red color) indicates that a greater contribution was provided by the corresponding time and frequency grid. As showed in figure 3, the subjects have different time–frequency patterns for the generation of SABD and EF torques. However, for all subjects, except subject 4, the α (8–12 Hz) or β (12–24.5 Hz) bands provide the highest contributions.

Figure 4 shows the differential mode of characteristic pattern (DMP) defined as \( WP_{\text{Abd}} - WP_{\text{Ef}} \), where \( WP_{\text{Abd}} \) and \( WP_{\text{Ef}} \) represent weighted synthesized characteristic patterns for SABD and EF in the sensorimotor cortices, respectively. These two weighted synthesized characteristic patterns were calculated as a weighted summation of the characteristic pattern reflecting the features of the event-related power change in time, frequency and spatial domains [8]. The first column of figure 4 shows the DMPs resulting from the non-modified algorithm and the next two columns (DMP1 and DMP2) are derived separately from the two sub-datasets when using the modified algorithm. Quantitatively, we calculated the correlation between DMP1 and DMP2. Results showed that the correlation coefficient for subject 1 (~0.32) was smaller compared to the other three subjects (subject 2 (0.82), subject 3 (0.74) and subject 4 (0.86)). This result is in accordance with results reflected by covariance complexities (see figure 2), which also shows the biggest difference in covariance complexity between two subsets in this subject. Additionally, there was a remarkable improvement (12%) for subject 1 by using the modified algorithm in table 1, which shows the recognition rate obtained by using non-modified (I) (i.e., method without presorting procedure) and modified (II) (i.e., method with presorting procedure) methods. In conclusion, a higher average recognition rate (89%) was obtained using the modified BCI methods to separate the intention of shoulder abduction (SABD) and elbow flexion (EF) torque generation as opposed to the non-modified BCI method (85%) in the four healthy subjects we studied.
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Figure 3. Time–frequency weights distribution derived from training procedure for each subject. Frequency band was divided into 13 frequency bins (1: 5.3–6.8 Hz; 2: 6.0–7.7 Hz; 3: 6.9–8.8 Hz; 4: 7.8–10.0 Hz; 5: 9.0–11.5 Hz; 6: 10.2–13.2 Hz; 7: 11.7–15.0 Hz; 8: 13.4–17.2 Hz; 9: 15.3–19.6 Hz; 10: 17.5–22.5 Hz; 11: 20.0–25.7 Hz; 12: 22.8–29.3 Hz; 13: 26.0–33.5 Hz). Time interval from 1800 ms to 60 ms prior to the onset of torque (denoted as time point 0) was divided into 61 segments (1: −1800 to −1745 ms; ...; 10: −1554 to −1449 ms; ...; 20: −1280 to −1226 ms; ...; 30: −1007 to −952 ms; ...; 40: −734 to −679 ms; ...; 50: −460 to −405 ms; ...; 60: −159 to −105 ms).

Figure 4. The differential-mode characteristic pattern (DMP) in the sensorimotor area obtained from the non-modified method (column 1) and the two DMPs obtained from the modified algorithm (columns 2 and 3). DMP1 and DMP2 are derived from the two subsets of each subject. In each panel, the dashed line roughly separates left and right hemispheres and the small black dots are electrode positions.

4. Discussion

In this study, we successfully achieved a high recognition rate (89%) when classifying the intention of generating a shoulder versus elbow motor task. This recognition rate is comparable to results achieved in previous studies using BCI approaches to separate left versus right hand movements (67–95%), however, for motor tasks that are known to have much closer spatial representations on the motor cortex. To achieve the high recognition rate, we applied an efficient time–frequency feature extraction and feature-weighted classification BCI method [8]. This method has the advantage that features
in time, frequency and spatial domains are all taken into account.

4.1. Frequency band differences between the two motor tasks

Subject-specific information in both frequency (5–34 Hz) and time (1800–60 ms before the onset of torque) domains was extracted and weighted. When generating the time–frequency weigh matrix, we assumed that an important time–frequency grid should have a high similarity to the characteristic pattern through all the trials. This assumption is based on the observation that the time–frequency pattern in a certain location at the cortex for a fixed strategy of a motor task is constant [33]. Our results showed important contributions from lower $\alpha$ (5–8 Hz), $\alpha$ (8–12 Hz) and $\beta$ (12–24.5 Hz) bands, although different subjects showed a different distribution of the weights. Contributions from $\alpha$ and $\beta$ are consistent with widely accepted results that the Rolandic $\mu$ (10–13 Hz) and central $\beta$ (14.5–18 Hz) rhythms are two important rhythmic activities showing characteristic spatiotemporal patterns during the imagination, planning and execution of movements [20, 34–39], although different users may have their own specific and optimal frequency bands [40].

An important contribution from lower $\alpha$ band was also found in our results. It was reported that desynchronization of lower $\alpha$ band is sensitive to expectancy, temporal attention, cognitive processes [41–45] and memory functions [46]. Therefore, the contribution from lower $\alpha$ band observed in our study (figure 3) may indicate that the difference associated with cognitive processes of temporal awareness, anticipation and motor memory between the two tasks may also be important for the classification.

4.2. Determination of movement onset

The time–frequency features preceding motor tasks require timing of torque onset. We envision the use of EMG or motion sensor signals in the future application of our approach. Although in this study we extracted time features in a window from 1800 to 60 ms prior to the onset of torque, the important time intervals are from 1800 to 150 ms (see figure 3). The discrimination of task about 150 ms before the onset of torque would give enough time for online applications in future studies.

### Table 1. Recognition rates for four subjects by using non-modified (I) and modified (II) weighted time–frequency synthesized classification algorithms.

<table>
<thead>
<tr>
<th>Subject no</th>
<th>Recognition rate I (%)</th>
<th>Recognition rate II (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>78</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>85</td>
<td>86</td>
</tr>
<tr>
<td>3</td>
<td>87</td>
<td>91</td>
</tr>
<tr>
<td>4</td>
<td>90</td>
<td>89</td>
</tr>
<tr>
<td>Mean</td>
<td>85</td>
<td>89</td>
</tr>
</tbody>
</table>

4.3. The rationale for using a presorting procedure

Due to the redundancy of a multi-joint motor task, subjects may use different strategies and thus cause a difference of time–frequency patterns from trial to trial. To overcome the reduction of recognition rate caused by using different strategies, the covariance complexity of a signal was used to separate the whole training datasets into two subsets. The covariance complexity has been found to be correlated to physiological conditions [47, 48] and sensitive to changes of behavior state [49]. By using the presorting procedure, two time–frequency features for each motor task were obtained in each of the tested subjects. Comparing the DMP of different subjects (see figure 4), we found the lowest correlation coefficients in subject 1 among all of the four subjects. Accordingly, this subject also showed the highest difference of covariance complexity between the two subsets and the highest improvement in recognition rate achieved by using the modified BCI method. Although by adding the presetting procedure, we only obtained notable improvement in one subject, this additional procedure would not cause significant decrease in the recognition rate even if subjects use a single strategy for a given motor task. In this study, we separated the database into two subsets. If necessary, the presetting procedure of the database can be generalized to multiple subsets. The determination of the number of subsets could be based on the number of motor strategies used by the subject and the accompanying improvement in recognition rates.

4.4. Relative importance of time/frequency and spatial domains using the TFSP BCI algorithm

In this study, the features in time–frequency domain were weighted, while features in spatial domain were treated equally. We chose to use this method because EEG has good temporal resolution, which may provide redundant and/or irrelevant information in time–frequency domain for the classification, and thus an optimization process could be useful for obtaining a high recognition rate. Our results showed different weights for different users and an important contribution from lower $\alpha$, $\alpha$ and $\beta$ bands. These may indicate that differences in both the motor planning and performance and cognitive activity related to the two motor tasks, like temporal attention, motor memory and motor learning, could be important for the classification. Furthermore, location information was used by comparing the distance between the spatial pattern of a single-trial EEG and the characteristic patterns. Although EEG signals from our 163-channel system have a spatial resolution of about 1–2 cm on the scalp, a previous study in our lab has reported that using a high-density scalp EEG recording system (128 electrodes), one can separate cortex representation of shoulder versus elbow motor tasks [50]. Therefore, the spatial information could also contribute to the classification. Future research testing the relative effect of electrode location as well as the number of electrodes on the performance of our BCI algorithm is envisioned.
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Table 2. Lesion location and Fugl–Meyer score for the stroke subject.

<table>
<thead>
<tr>
<th>Patient</th>
<th>Age</th>
<th>Sex</th>
<th>Affected hand</th>
<th>Dominant hand</th>
<th>Site of lesion</th>
<th>Time to exp.</th>
<th>Fugl–Meyer score</th>
<th>Mirror movement</th>
<th>Sensory loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>S2</td>
<td>51</td>
<td>F</td>
<td>R</td>
<td>R</td>
<td>L. dorsal lateral SMA and subcortical white matter</td>
<td>5 years</td>
<td>35/66</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

SMA: supplementary motor area.

4.5. Future applications of our BCI algorithm in neurologically impaired subjects

An important future application of BCI will help patients who lack muscle control (such as patients with spinal injury) or suffer from movement disorders (such as patients with medium to severe motor impairment due to a stroke or cerebral palsy), by interacting with neural prostheses or other devices. To test this possibility quantitatively, we also tested the predictive power of the modified BCI method in one chronic hemiparetic stroke subject (see table 2 for subject information). A recognition rate equal to 76% was achieved. This recognition rate is lower than those achieved in healthy subjects. The reduction could be a result of brain reorganization following the stroke. Recent results from our laboratory have suggested that there is a significantly greater overlap between cortical current distributions during the generation of SABD and EF torques in chronic stroke as opposed in healthy subjects [51, 52]. The increased cortical overlap in stroke subjects may increase the difficulty of predicting torque generation in stroke subjects. In order to achieve high levels of prediction accuracy, even in chronic stroke subjects, BCI algorithms that combine a powerful feature extractor with an efficient classifier are required. As discussed above, the TFSP method weights the time and frequency information, but not the spatial information (i.e., a simple linear classifier comparing the distance between the spatial pattern of a single-trial EEG with the characteristic patterns is used, which treats the contribution from each electrode equally). A nonlinear classifier may provide more power to discriminate between the two different motor tasks. In addition, using an optimal subject-specific electrode combination may improve the efficiency and practicality of the BCI approach. The number of training trials necessary for obtaining an effective and stable feature pattern also needs to be investigated. In the future, we hope to design such an advanced BCI approach that improves the prediction of elbow versus shoulder torques in stroke subjects.

4.6. Conclusion

In summary, using a combination of the time–frequency synthesized spatial patterns BCI algorithm [8] and high-density scalp EEG signals, we successfully predicted the intention of generating SABD or EF torques in healthy subjects. This BCI approach was also tested in a single chronic hemiparetic stroke subject and demonstrated that it could provide a promising control signal for neural prostheses or other movement coordination improving devices for neurologically impaired subjects.

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