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A clinical evaluation on the spatial patterns of non-invasive motor imagery-based brain-computer interface in stroke

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Abstract—**This clinical study investigates whether the spatial patterns of hemiparetic stroke patients operating a non-invasive Motor Imagery-based Brain Computer Interface (MI-BCI) is comparable to healthy subjects. The spatial patterns for a specific frequency range are generated using the common spatial pattern (CSP) algorithm, of which is highly successful for discriminating two classes of EEG measurements in MI-BCI. The spatial patterns illustrate how the presumed sources project on the scalp and are effective in verifying the neurophysiological plausibility of the computed solution. The spatial patterns show focused activity in ipsilateral as well as contralateral hemisphere with respect to the hand by tapping or motor imagery in 2 BCI-artful healthy subjects and 12 BCI-naïve hemiparetic stroke patients. The results also show that neurophysiologically interpretable spatial patterns is more common in performing motor imagery compared to finger tapping by hemiparetic stroke patients. Hence, this shows that hemiparetic stroke patients are capable of operating MI-BCI.**

I. INTRODUCTION

Brain signals can be acquired by scalp-recorded electroencephalogram (EEG) non-invasively from a subject. Studies have shown that distinct mental processes such as Event-Related Desynchronization/Synchronization (ERD/ERS) [1] are detectable for both real and imagined motor activity on healthy subjects [2],[3]. Thus, Motor Imagery-based Brain Computer Interface (MI-BCI), which translates the mental imagination of movements into commands, provides a promising communication channel for stroke patients who suffer from motor disabilities.

The Common Spatial Pattern (CSP) algorithm [4],[5] is highly effective in constructing optimal spatial filters that discriminates two classes of EEG measurements in MI-BCI [5]. It is also capable of constructing spatial patterns based on the position of the electrodes for illustrating how the presumed sources project on the scalp, and for verifying the neurophysiological plausibility of the computed solution [4]. From the concept of the cortical homunculus, different areas of the cerebral cortex control movements of different body parts [6]. In addition, distinct areas of the cerebral cortex control movements on the contralateral side of the body [7]. Hence, spatial patterns of a motor action are verifiable with the specific region that controls the motor action [4].

However, the effectiveness of the CSP algorithm is highly dependent on the operational frequency band [8] due to the huge inter-subject variability of the brain signals [4]. Thus, setting a broad frequency range or manually selecting a subject-specific frequency range is commonly used with the CSP algorithm [9]. Recently, the Filter Bank Common Spatial Pattern (FBCSP) algorithm [10] has been developed to perform autonomous selection of operational frequency band that represents key temporal-spatial discriminative EEG characteristics for MI-BCI. Thus the FBCSP algorithm is used in this paper to compute the operational frequency band for generating the spatial patterns.

At present, there are reports of spatial patterns generated using the CSP algorithm on healthy subjects operating MI-BCI [4],[5],[11]-[15]. To the best of our knowledge, there are only a limited number of studies performed on stroke patients operating MI-BCI, but no clinical studies on the spatial patterns have been reported. Since stroke patients suffer from neurological damage, the portion of the brain that is responsible for generating ERD/ERS in MI-BCI could be compromised. As such, the issue remains as to whether the spatial patterns observed in healthy subjects are also present in stroke patients.

This paper addresses this issue by performing a clinical study of the spatial patterns of BCI-naïve hemiparetic stroke patients operating non-invasive MI-BCI. Hemiparetic stroke patients are recruited for this study because their motor impairment can be quantitatively measured using Fugl-Meyer Assessment (FMA) [16]. This preliminary study will be extended to include functional MRI evaluation in the near future. Since ERD/ERS are detectable for both imagined and real motor movements in healthy subjects [2],[3], it is more intuitive for hemiparetic stroke patients to perform hand tapping by the able arm and hand motor imagery by the paralyzed arm.

The remainder of this paper is organized as follows. Section II briefly describes the CSP and FBCSP algorithms used in this clinical study. Section III describes the experimental studies and presents the results. Section IV concludes with an analysis of the experimental results.

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II. COMMON SPATIAL PATTERN

The neurophysiological background of MI-BCI is that motor activity, both actual and imagined [17],[18], causes an attenuation or increase of localized neural rhythmic activity called ERD/ERS [1]. The *Common Spatial Pattern* (CSP) algorithm is highly successful in calculating spatial filters for detecting ERD/ERS [4]. The objective of spatial filtering employing the CSP algorithm [13] in MI-BCI is to compute the features whose variances are optimal for discriminating two classes of EEG measurements [13],[15].

The method employed by the CSP algorithm is based on the simultaneous diagonalization of two covariance matrices [13]. In summary, the spatially filtered signal $\mathbf{Z}$ of a single trial EEG $\mathbf{E}$ is given as

$$\mathbf{Z} = \mathbf{W}\mathbf{E}, \tag{1}$$

where $\mathbf{E}$ is an $N \times T$ matrix of EEG data for a single trial; N is the number of channels; T is the number of measurement samples per channel; and $\mathbf{W}$ is the CSP projection matrix. Equation (1) can be rearranged in the form of the semiblind source separation problem [19]-[21] to

$$\mathbf{E} = \mathbf{W}^{-1}\mathbf{Z}, \tag{2}$$

where $\mathbf{Z}$ is an uncorrelated vector of sources; and $\mathbf{W}^{-1}$ represents a time-invariant EEG source distribution [13]. The rows of $\mathbf{W}$ are thus the stationary spatial filters and the columns of $\mathbf{W}^{-1}$ represent the spatial patterns.

Equation (2) is a form of semiblind source separation [20] because the CSP algorithm is not really a source separation or localization method [11]. Prior to having a neurophysiological interpretation of the spatial patterns, it has to be kept in mind that the spatial filters $\mathbf{W}$ are optimized to maximize the variance of one class and minimize variance for the other. Hence, if there is a strong focus of the spatial pattern on the left hemisphere motor area that corresponds to the right hand imagery, it can be due to two possible reasons: It can either originate from an ERD during right hand imagery, or an ERS during left hand imagery or foot imagery due to an increase in the idle rhythm since the right hand is more relaxed [11].

To address the problem of selecting the operational subject-specific frequency band for the CSP algorithm, the FBCSP algorithm [10] is developed. The architecture of FBCSP (see Fig. 1 of [22]) comprises four stages: frequency filtering, spatial filtering, feature selection and classification. These four stages of EEG signal processing perform an autonomous selection of key temporal-spatial discriminative EEG characteristics using a machine learning approach.

III. EXPERIMENTAL RESULTS

This section describes the experiments performed in this study and presents the results. The spatial patterns of the subjects operating MI-BCI are generated by computing a cubic interpolation of the columns of $\mathbf{W}^{-1}$ from the CSP algorithm and illustrated with respect to the position of the EEG electrodes on the scalp. The operational subject-specific frequency band employed by the CSP algorithm is selected by concatenating the selected filter banks in the third stage of the FBCSP algorithm. The experiments comprises: a study on the spatial patterns of 5 BCI-artful healthy subjects who are experienced in operating MI-BCI from a publicly available dataset; a study on the spatial patterns of 2 BCI-artful healthy subjects who perform hand tapping versus hand motor imagery; and a study on the spatial patterns of 6 BCI-naïve left hemiparetic stroke patients and 6 BCI-naïve right hemiparetic stroke patients.

A. Publicly available BCI Competition III dataset IVa

The BCI Competition III dataset IVa [23] is collected from 5 BCI-artful subjects (labeled *aa*, *al*, *av*, *aw*, *ay*) who performed right hand and right foot motor imagery. The data for each subject comprises 280 trials of EEG measurements from 118 electrodes. Fig. 1 shows the spatial patterns and accuracy for each subject that are computed from EEG data extracted 0.5s to 2.5s after the visual cue.

The results show activity in the left hemisphere on right on right hand motor imagery for all 5 subjects, and focused activity in the centre vertex on foot motor imagery for subjects *al*, *aw* and *ay*. Hence, the spatial patterns illustrated

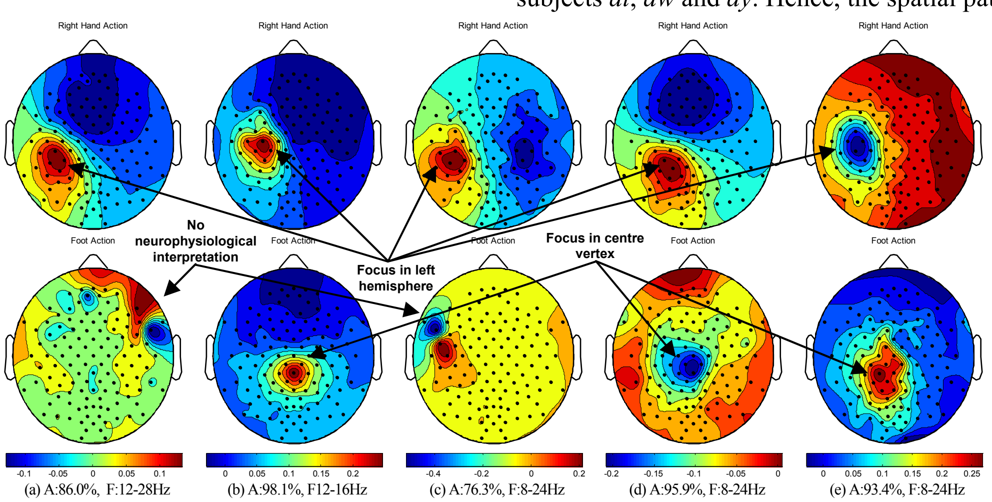
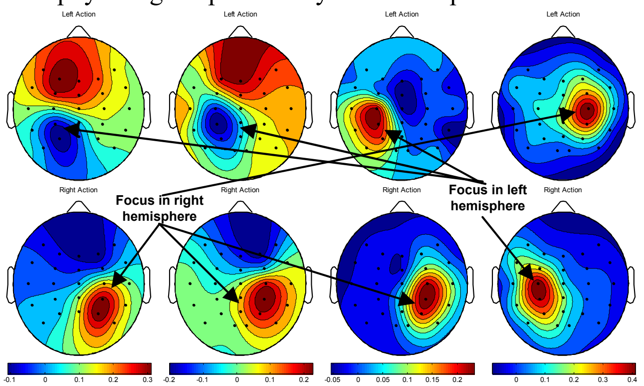


Fig. 1. Spatial patterns of BCI Competition dataset IVa for subjects (a) *aa*, (b) *al*, (c) *av*, (d) *aw*, and (e) *ay* respectively who performed right hand and foot motor imagery. The 10×10-fold cross-validation accuracy (A) and frequency band (F) are labeled below each pattern.

from CSP show how the presumed sources project on the scalp. The results also show that accuracy of *aa* and *av* are relatively inferior to the other 3 subjects, of which can be attributed to the absence of activity at the centre vertex. This result is consistent with the result in [8]. This demonstrates that the spatial patterns are also able to verify the neurophysiological plausibility of the computed solution.



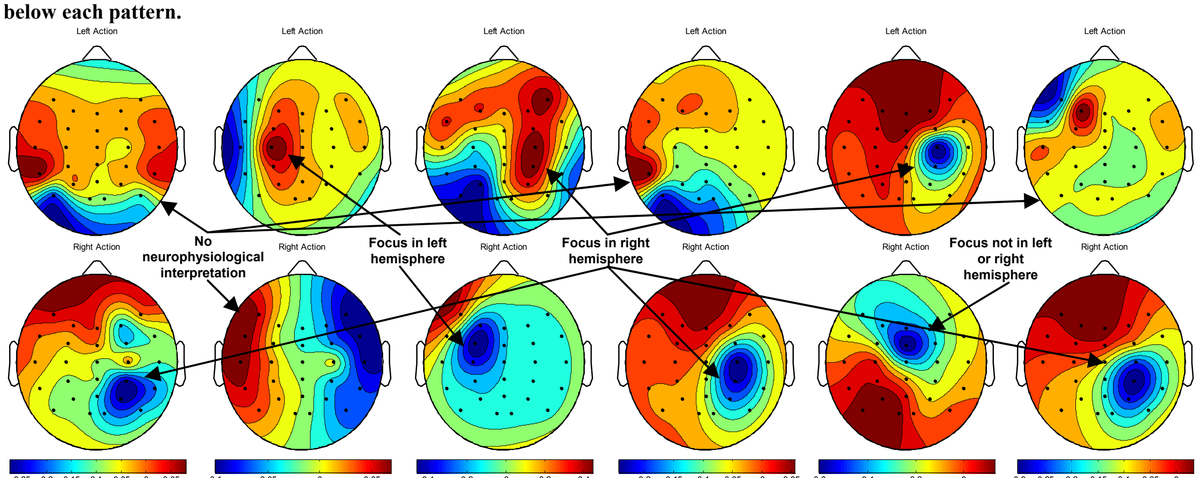
(a) A:83.5%, F:16-24Hz (b) A:77.4%, F:16-28Hz (c) A:76.9%, F:16-28Hz (d) A:92.8%, F:8-24Hz

Fig. 2. Spatial patterns of healthy subjects. (a) and (b) show subject *1* who performed hand tapping and hand motor imagery respectively, (c) and (d) shows subject *2* who performed hand tapping and hand motor imagery respectively. The accuracy (A) and frequency band (F) are labeled below each pattern.

B. *Tapping versus imagery from 2 healthy subjects*

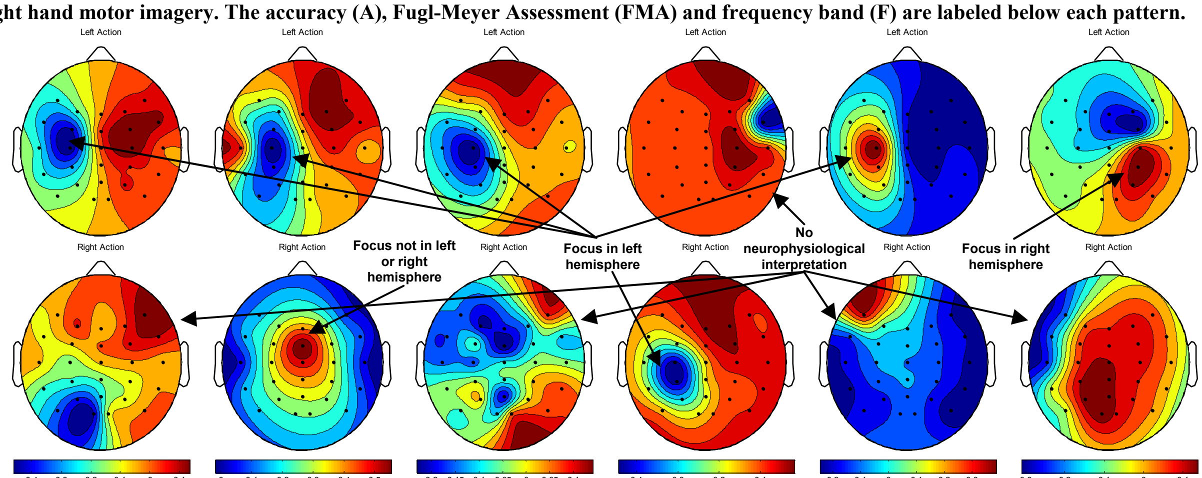
This dataset is collected using Neuroscan NuAmps from 8 BCI-artful healthy subjects. The data is collected with approval from the Ethics Approval Board. The subjects performed hand tapping and hand motor imagery separately. The description of this dataset and the results on the 10×10-fold cross-validation accuracy for each subject using FBCSP is presented in [22]. Fig. 2 shows and compares the spatial patterns of tapping versus imagery for 2 subjects computed from EEG data extracted 0.5s to 2.5s after the visual cue.

The results show focused activities in the left (right) hemisphere for left (right) hand tapping and motor imagery on subject 1 as well as for left (right) hand tapping on subject 2. The results also show focused activities in the right (left) hemisphere for left (right) motor imagery on subject 2. Hence, the results in Figs. (a)-(c) indicate that ERS is detected on the ipsilateral hemisphere, and Fig. 2(d) indicates that ERD is detected on the contralateral hemisphere; respective to the hand by tapping or motor imagery. This is consistent with the evidence in the literature that ERD/ERS are detectable for both real and imagined motor movements in healthy subjects [2].



(a) A:81.5%, FMA:8, F:8-20Hz (b) A:77.4%, FMA:6, F:4-8Hz (c) A:80.93%,FMA:15,F:12-40Hz (d) A:83.3%,FMA:27, F:8-20Hz (e) A:92.5%, FMA:22, F:8-20Hz (f) A:88.4%, FMA:7, F:12-20Hz

Fig. 3. Spatial patterns of right hemiparetic stroke patients. (a)-(f) show patients *1*, *2*, *3*, *6*, *18* and *29* who respectively performed left hand tapping and right hand motor imagery. The accuracy (A), Fugl-Meyer Assessment (FMA) and frequency band (F) are labeled below each pattern.



(a) A:77.2%, FMA:11, F:12-24Hz (b) A:72.3%, FMA:39, F:12-32Hz (c) A:83.2%, FMA:23, F:8-28Hz (d) A:72.4%, FMA:4, F:16-24Hz (e) A:86.6 %, FMA:6, F:12-24Hz (f) A:90.4%, FMA: 25, F:

Fig. 4. Spatial patterns of left hemiparetic stroke patients. (a)-(f) show patients *9*, *10*, *15*, *16*, *20* and *32* who respectively performed left hand motor imagery and right hand tapping. The accuracy (A), frequency (F) and patient's FMA are labeled below each pattern.

C. Tapping versus imagery from 12 hemiparetic stroke patients

This dataset is collected using Neuroscan NuAmps from 35 BCI-naïve hemiparetic stroke patients. The data is collected with approval from the Ethics Approval Board. The patients performed tapping on the able arm and motor imagery on the paralyzed arm. The description of this dataset and the results on the 10×10-fold cross-validation accuracy for each subject using FBCSP is presented in [22].

Figs. 3 and 4 show and compare the spatial patterns of 6 right hemiparetic stroke patients versus 6 left hemiparetic stroke patients. The results show focused activity in the ipsilateral as well as contralateral hemisphere respective to the hand by tapping or motor imagery for both left and right hemiparetic stroke patients. The results show no neurophysiological interpretation of the spatial patterns for 3 left and 4 right hand tapping versus 1 right and 1 left motor imagery. This shows that the neurophysiologically not interpretable spatial patterns, which correspond to background EEG activity, is present more in hand tapping than in motor imagery for BCI naïve hemiparetic stroke patients. 1 out of 6 patients shows activity in the contralateral hemisphere on the respective hand motor imagery for both left and right hemiparetic stroke patients. Interestingly, Fig. 3(e) show that patient *18* performed very well in operating MI-BCI (Accuracy=92.5%), but the focused activity for the right hand motor imagery does not show up on the left hemisphere. Since the patient's FMA is not very low (FMA=22), this result could suggest neuroplasticity at work.

IV. CONCLUSIONS

This clinical study investigates the spatial patterns of hemiparetic stroke patients versus healthy subjects in operating a non-invasive MI-BCI. The spatial patterns are generated from CSP whose operational frequency range is computed using FBCSP. The spatial patterns of 2 BCI-artful healthy subjects show focused activities in the contralateral as well as ipsilateral hemisphere respective to the hand by tapping or motor imagery.

The spatial patterns of 6 left and 6 right hemiparetic stroke patients who performed tapping on the able arm and imagery on paralyzed arm also show focused activities in the contralateral as well as ipsilateral hemisphere respective to the hand by tapping or motor imagery. The results also show that neurophysiologically interpretable spatial patterns are more common for motor imagery than for hand tapping. This shows that the spatial patterns of hemiparetic stroke patients are comparable with healthy subjects, and that they are capable of operating MI-BCI as reported in [22].

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