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Performance of EEG Motor-Imagery based spatial filtering methods: A BCI study on Stroke patients

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Abstract

The study reports the performance of stroke patients to operate Motor-Imagery based Brain-Computer Interface (MI-BCI) in early post-stroke neurorehabilitation and compares three different BCI spatial filtering techniques. The experiment was conducted on five stroke patients who performed a total of 15 MI-BCI sessions targeting paretic limbs. The EEG data were collected during the initial calibration phase of each session, and the individual BCI models were made by using Source Power Co-Modulation (SPoC), Spectrally weighted Common Spatial Patterns (SpecCSP), and Filter-Bank Common Spatial Patterns (FBCSP) BCI approaches. The accuracy of FBCSP was significantly higher than the accuracy of SPoC *(85.1±1.9 % vs. 83.0±1.9 %; p=0.002)*, while the accuracy of FBCSP was slightly higher than the accuracy of SpecCSP (*85.1±1.9 % vs. 83.8±2.0 %; p=0.068)*. No significant difference was found between SPoC and SpecCSP *(p=0.616)*. The average false positive ratio was *16.9%, 17.1%, 14.3%*, while the average false negative was *15.5 %, 16.9 %, 15.5 %* for SpecCSP, SPoC, FBCSP, respectively. In conclusion, we demonstrated that the stroke patients were capable of controlling MI-BCI, with high accuracy and that FBCSP may be used as the MI-BCI approach for complementary neurorehabilitation during early stroke phases.

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1. Introduction

Despite current therapeutic and rehabilitative strategies, stroke remains one of the leading causes of mortality and disability in the elderly population worldwide [1–3]. One of the most common deficits after ischemic stroke is hemiparesis of the contralateral limb, especially upper limb motor disability is present in 80% of cases in the acute phase and more than 40% in the chronic phase [4].

The traditional neurorehabilitation treatments for motor damage in stroke patients, such as physical therapy and constraint - induced movement therapy, are based on techniques that aim to stimulate the use of the paretic limb. The underlying principle is that repetitive, active movements should induce mechanisms of cortical neuroplasticity, and improve the motor abilities of a subject [5,6]. These techniques require some residual movement of the affected limb. The problem arises when the remaining motor functions of the patients after stroke are too low and when the time window of enhanced neuroplasticity early after stroke has been closed (i.e., chronic stroke stage).

In these cases, the neuroplasticity induced by this motor practice can be extremely limited. For this reason, in addition to the motor training, additional strategies to potentiate neuroplasticity of motor areas are needed [7,8]. Furthermore, these strategies should be considered in early post-acute rehabilitation in which the brain's dynamic response to injury is heightened and rehabilitation might be particularly effective [9].

Motor imagery (MI) is one of the promising neurorehabilitation tools [10] which have been suggested to improve restoration of motor function after stroke, both in acute and chronic stroke phases [7,11]. It has been shown that MI can induces plastic changes to the basic neural mechanism underlying motor learning in the lesioned hemisphere [12,13]. In particular, MI tasks activate the sensorimotor areas that are active during actual motor execution [14] and induce a significant increase in cerebral blood flow velocity related to the neural activation during MI tasks [15]. Considering the correlation, at cerebral level, between executed and imagined movement, EEG-based MI brain-computer interface (BCI) systems seem to be promising tools to promote motor recovery after stroke, by exploiting the neuroplasticity phenomena induced on the motor cortex by the Motor-Imagery training [7,16].

The MI-BCI neurorehabilitation refers to the closed-loop detection of EEG MI Event-related desynchronization/synchronization (ERD/S) and transformation via spatial filtering and machine learning techniques to the visual feedback presented to the subject in real-time [17]. In this way, the subject becomes aware of the voluntary modulation of EEG oscillatory activity, and when coupled with the adequate stimulus and electrode settings, can target desired brain regions. Furthermore, it creates a more controlled rehabilitation environment since the MI induced oscillatory activity can be monitored to assess whether the patient performs the task correctly. However, due to anatomical differences and particularity of the stroke lesions, the precise spatial location of the electrode is hard to determine apriori. This can be approached by using more electrodes on the broader area and by means of data-driven spatial-filtering techniques to find the optimal ones [18].

The most commonly applied data-driven spatial filtering technique in the MI-BCI domain is the Common Spatial Pattern (CSP) [19]. The CSP algorithm assigns weights to each channel to maximize and minimize the variance for the two tasks, MI and rest, respectively. The CSP in the past decade has been further improved by introducing Filter Bank CSP (FBCSP) [20], Spectrally Weighted CSP (SpecCSP) [21], Source Power Co-Modulation (SPoC) [22]. In the FBCSP a series of CSP filters are designed for different frequency subbands producing frequency-specific task-related model, whereas the SpecCSP weights the spectral components to exploits interactions between frequency bands. Finally, the SPoC the variance (power) is optimized on the component space, instead of on the raw EEG data, as in the case of the previous two approaches. The average accuracy of these approaches exceeds 70% [23–26] and, in some cases, reaches 85% [27] in a healthy population.

The disadvantages of the abovementioned studies are that the BCI approaches have been tested only on a healthy population, and studies of performances on patients, similar to the one on Stroke patients reported in [28] or on Parkinson's disease patients [29] are quite rare. It cannot be overlooked that the clinical population is additionally characterized by EEG alterations in acute [29–32] and chronic phase [33] as well as by cognitive decline [34] and therefore, may present different BCI performance.

The MI-BCI neurorehabilitation in stroke patients was previously studied [35–37]. However, the performance of state-of-art spatial filtering methods has not yet been evaluated in the early post-stroke phase rehabilitation in which rehabilitation might be particularly effective.
This study aims to investigate the performance of MI-BCI approaches on stroke patients in the early post-stroke phase and to report a comparison of three selected approaches.

2. Materials and Methods

2.1. Study population and protocol

This study was conducted on five ischemic stroke patients (3M/2F 67±8 years) with motor deficits who underwent 15-session BCI neurorehabilitation in the early post-acute phase. The inclusion criteria were minor/mild unilateral anterior circulation ischemic stroke patients able to follow verbal instructions, communicate and perform the BCI tasks. Participants were recruited from the neurology clinic of Trieste University Hospital in the sub-acute phase (i.e. in the first two weeks after the stroke). Exclusion criteria were previous brain injury, hemorrhagic stroke, other serious medical conditions, history of non-controlled seizures, severe cognitive deficits (Montreal Cognitive Assessment - MoCA score < 19), severe aphasia, unilateral spatial neglect. No-age and sex limits were applied.

The study was conducted within the MEMORI-net Interreg ITS-SLO project. All recruited patients gave their signed informed consent to participate in the study. The study protocol was approved by the Regional Ethical Committee CEUR (Comitato Etico Unico Regionale, FVG, Italy) with approval number 118/2018. The research was conducted according to the principles of the Declaration of Helsinki.

2.2. Study population and protocol

The BCI protocol consisted of a total of 15 neurofeedback MI sessions with a duration of 1-1.5 hours each repeated 2-3 times per week. The session was split into two parts, the initial calibration phase where the patients had to perform MI, and the online where they had to control stimuli on the screen continuously. During the calibration phase to instruct patients to perform MI, an image of the limb was displayed for 5s over a cross-shaped icon at the centre of a monitor alternatively to a blank screen for the “rest” (Fig. 1a). The same task has been performed 35-40 times in each session.

During the feedback phase, the subjects had to interact with the personalized visual feedback, which consisted of the moving hand. The movement of the hand has been controlled by the continuous output of the linear classifier.

The performance of the BCI algorithms in this study has been evaluated on the data obtained during the calibration phase.

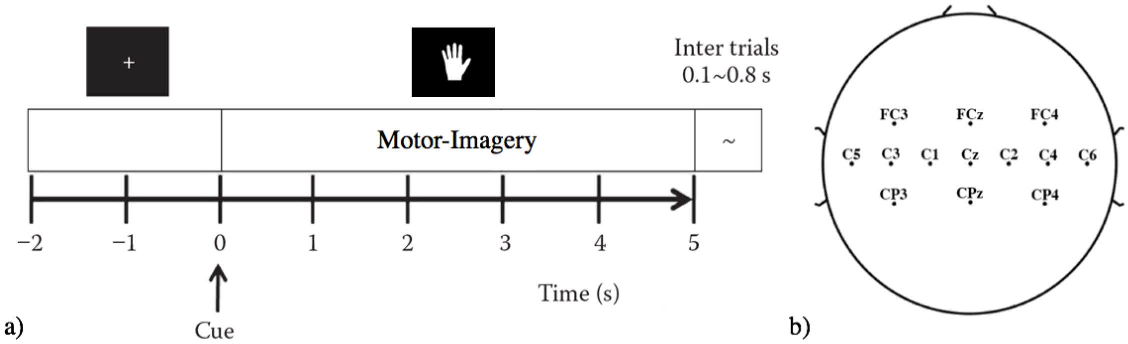

Fig. 1 (a) BCI stimulus design. (b) Electrode placement

The acquisition of 15 channel EEG was performed using SAM 32FO amplifier (Micromed S.p.A., Italy) and Ag/AgCl electrodes (FC3, FC4, FCz, Cz, C4, C3, CP3, CP4, CPz, C2, C4, C6, C5, O1, O2) with the placement reported in Figure 1b. The signals were recorded with 256 Hz sample frequency. In addition, two EMG electrodes were added to exclude any possible execution of a movement.

2.3. EEG pre-processing

The processing of EEG data was carried out using MATLAB (The MathWorks Inc., Natick, MA) and the BCI models were produced with the BCILAB [38] framework. All channels were filtered from 0.5 to 48 Hz with the 2nd order Butterworth bandpass filter and resampled to 128Hz.

2.4. BCI Approaches

The BCI approaches selected for this work were based on their reported performance on healthy individuals, which is in the case of SPoC 76% [24], SpecCSP 70-80% [39] and in the case of the FBCSP up to 90% [23–25]. Furthermore, we included only approaches that do not require a tedious tune-up of various parameters and the approaches where the model can be produced on standard portable computers in a reasonable time of 5-10min.

The SPoC (Source Power Comodulation) approach is the most advanced among the tested methods. Its advantage is that the log variance features are not extracted from the sensor data space (EEG raw data) but from a linear subspace, similar to one obtained with ICA [40], or beamforming algorithm [41]. The optimization algorithm is identical to the one used for Common Spatial Patterns (CSP) [19] with a difference that in the case of SPoC the variance is optimized on the component space, instead of on a raw EEG data. In that way, it is presumably less affected by noises and non-task related brain oscillatory activities. However, it may be more sensitive to artifacts with high variances, such as muscular contraction that can involuntarily co-occur during MI task, that can be misinterpreted as a task-related signal.

The second abovementioned algorithm is the SpecCSP, which is also an extension of the original CSP algorithm. It is designed for oscillatory processes where the exact frequency band is unknown so that the weights of the spectral components have to be assigned automatically. The SpecCSP is applicable to most oscillatory processes and, in comparison and in general, gives better results of the standard CSP algorithm.

Finally, the FBCSP [20] overcomes the spectral selectivity of the CSP by introducing the series of frequency filters (Filter Banks) to the pre-processing mechanism. Similarly, to the SpecCSP, also, in this case, the variance optimization on each subband creates a specific frequency and task-related model.

All three mention approaches exploit the interaction between frequency bands and show the best performances when the EEG activity is present on different scalp locations and on different subbands. This is particularly useful for MI task where the relative power of mu/beta is changed during the process of Event-related desynchronization/synchronization (ERD/S) [42]

At the end of the log-variance (power), features are fed to the regularized LDA classifier with automatic shrinkage parameter estimation [43].

2.5. Performance evaluation and Statistical analysis

The classification accuracy as a performance measure had been selected, and it was estimated using 10-fold chronological/blockwise cross-validation with five trials margin. Together with accuracy, the type I and type II errors are also reported.

Differences in classification accuracy and related type I (false positive ratio - FPR) and II errors (false negative ration - FNR) among selected approaches were tested by repeated ‑ measure analysis of variance (ANOVA). Bonferroni corrections were used for post hoc multiple comparisons.

3. Results

Table 1 reports the demographic and clinical summary of included patients. Fig. 2 shows the comparison of accuracy values obtained with three considered approaches for each subject and session. It can be observed the better performance of FBCSP method compared to SpecCSP and the SPoC. Mean±SD values and 95% confidence intervals of obtained accuracies were reported in Table 2.

Table 1. Patients' demographic and clinical data.

Age (Mean + SD) years	67 ± 8
Sex (F / M)	2 / 3
Lesion side (L / R)	3 / 2
NIHSS	4 ± 1.9
Fugl-Mayer	19.8 ± 1.6
MoCA	25.4 ± 1.3
MIQ-RS Visual Imagery Score	5.4 ± 1.1
MIQ-RS Kinesthetic Imagery Score	5.0 ± 0.75

Note: NIHSS - National Institutes of Health Stroke Scale; Fugl-Mayer; MoCA - Montreal Cognitive Assessment; MIQ-RS - Movement Imagery Questionnaire—Revised second version.

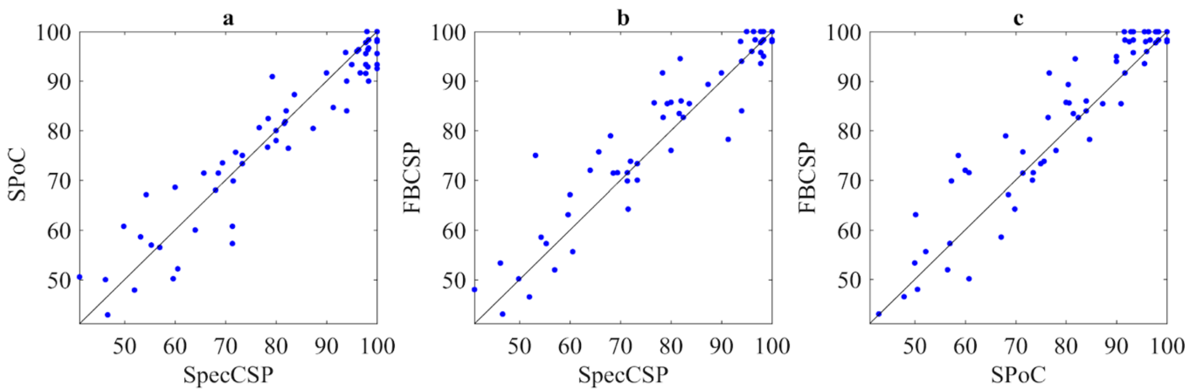

Fig. 2 Comparison of accuracy values (%) obtained with three considered approaches for each subject and session. (a) SPoC against SpecCSP, (b) FBCSP against SpecCSP, (c) FBCSP against SPoC.

The accuracy of FBCSP was significantly higher than the accuracy of SPoC (85.1±1.9 % vs. 83.0±1.9 %; p=0.002), while the accuracy of FBCSP was slightly higher than the accuracy of SpecCSP (85.1±1.9 % vs. 83.8±2.0 %; p=0.068) No significant difference was found between SPoC and SpecCSP (p=0.616). In addition, FBCSP presented better average performance over 15 sessions for each subject (Table 3). The average FPR was 16.9%, 17.1%, 14.3%, while the average FNR was 15.5 %, 16.9 %, 15.5 % for SpecCSP, SPoC, FBCSP, respectively.

Table 2. Mean ± SD values and 95% confidence intervals of obtained accuracies

	Accuracy	
BCI Approach	**Mean ± SD [%]**	**95% CI**
SpecCSP	83.8 ± 2.0	79.7 - 87.8
SPoC	83.0 ± 1.9	79.2 - 86.9
FBCSP	85.1 ± 1.9	81.3 - 89.0

Table 3. Average accuracy (%) over 15 sessions calculated for each subject. The highest for each subject was highlighted in bold.

Subject	SpecCSP [%]	SPoC [%]	FBCSP [%]
1	75.2	77.3	**78.3**
2	94.5	92.1	**95.1**
3	97.1	96.1	**97.6**
4	92.3	91.2	**92.4**
5	57.8	56.7	**60.7**

4. Discussion

The MI-BCI neurorehabilitation consists of the closed-loop detection of MI induced ERD/S that is further processed and presented back to the subject in the form of a combination of a visual, auditory or tactile stimulus. With a practice, reinforcement, and with different types of feedback and neurorehabilitation paradigms [44,45] targeting different sensory modalities, subjects can learn to modulate their neural activity voluntarily. The controlled modulation of neural activity via MI-BCI has been shown to positively affect cognitive capabilities and motor planning and execution in a healthy and clinical population affected by Parkinson's disease [46,47], Attention Deficit Hyperactivity Disorder [48,49], Autism spectrum disorder [50], etc.

The MI-BCI in stroke patients has been previously studied [35–37]. However, the studies that apply MI-BCI from a week to two from a stroke are rare or nonexistent. A window of time after a stroke is particularly important to have effective rehabilitation [9]. Still, the patients' physical conditions after stroke prevent them from performing a full set of motor exercises, and when they are physically ready, it is most likely that the stroke passed in the chronic stage. Therefore, it is important to exploit the aforementioned time window, during which the brain dynamics as a response to an injury is enhanced and when the MI-BCI, might be particularly useful. Nevertheless, there are no yet standardized procedures for BCI in general [51], and a similar demonstration of the performance of different spatial-filtering preprocessing BCI techniques on patients' strategies are quite rare [28,29].

Hence, the aim of the study is to investigate the performance MI-BCI approaches on stroke patients in the early post-stroke phase and to report a comparison of three selected approaches. In particular, this study focused on SpecCSP, SPoC, and FBCSP BCI approaches tested on five patients in the early post-stroke phase. The main finding of the study is that FBCSP showed better overall performances then SPoC and SpecCSP approaches.

The FBCSP showed significantly better performance than SPoC, while it presented a slightly higher accuracy than SpecCSP. The similar average accuracy between FBCSP and SpecCSP can be explained by the same objective function to optimize the interaction of specific frequency bands with relation to the scalp location, which in fact happens in the case of the MI, where the mu/alpha power is expected to decrease and beta increase (beta rebound) [19]. The possible reason for lower SPoC performance might be explained with the fact that the algorithm is designed to maximize components subspace, and since in post-Stroke period, noises (i.e., involuntary muscular activity) can happen simultaneously with the task, the approach might misinterpret such activity as a signal, which leads to poorer performance.

In addition to the classification accuracy, we have also investigated type I and type II errors. The performance of BCI systems is also reflected by False positives (type I error), which is defined as the existence of feedback without a subject's will. On the contrary, the False negatives (type II error) is less important to some extent, since the subject can voluntary try multiple times to perform the task to move the object on the screen, whilst the False positive gives the impression that the system works without their control, and can lead to a reduction of the motivation for participation in the rehabilitation.

Furthermore, we observe that the post-stroke patients were capable of controlling MI-BCI with higher accuracy in comparison to Parkinson's [29], where the mean accuracies were around 65%. The higher accuracy in post-stroke patients can be explained by the fact that there is no activation inhibition of the movement's execution for paretic limbs, as the subject could not move them. Therefore, the lack of inhibition mechanism makes the MI ERD/S more prominent and very similar to the actual movement [52] concerning the MI in other patients. Moreover, we can also argue that the MI task in stroke patients is clearer to comprehend since, in contrast to healthy individuals or Parkinson's disease, the "imagination" task in MI is vaguer [53].

5. Conclusion

This study demonstrates that the stroke patients were capable of controlling MI-BCI, with high accuracy and that FBCSP may be used as the MI-BCI approach for complementary neurorehabilitation during early stroke phases. However, results obtained and clinical efficacy of this type of rehabilitation should be confirmed in a larger clinical study.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest

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