A new descriptor of neuroelectrical activity during BCI–assisted Motor Imagery-based training in stroke patients*

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Abstract— **In BCI applications for stroke rehabilitation, BCI systems are used with the aim of providing patients with an instrument that is capable of monitoring and reinforcing EEG patterns generated by motor imagery (MI). In this study we proposed an offline analysis on data acquired from stroke patients subjected to a BCI–assisted MI training in order to define an index for the evaluation of MI-BCI training session which is independent from the settings adopted for the online control and which is able to describe the properties of neuroelectrical activations across sessions. Results suggest that such index can be adopted to sort the trails within a session according to the adherence to the task.**

I. Introduction

Brain Computer Interface (BCI) techniques have developed to different applications, including a support to motor and cognitive rehabilitation. New scientific questions and requirements arose as a consequence of these new approaches, to face the twofold need to improve the understanding of the effects of a neurofeedback-based training on brain cortical activity and to improve the efficacy of the intervention by a strategy defined ad hoc for such a purpose.

With respect to BCI for communication and control, whose aim is to maximize the accuracy and the reliability of the recognition of the user's intention, EEG based BCI application for rehabilitation purposes are specifically aimed to increase the neuroelectrical responsiveness of specific regions of the brain, to enforce the recovery of impaired functions. For instance, EEG-based Brain Computer Interfaces (BCI) operated by Motor Imagery (MI) can provide a valuable approach to support mental motor practice to enhance arm motor recovery after stroke [1]. As stroke lesions may result in a functional reduction of activity of the ipsilesional hemisphere associated with a correspondent increase in the contralesional one, rehabilitation strategies aim at increasing the excitability of the affected hemisphere and/or decreasing that in the unaffected [2]. The adherence to the task is aided by an appropriate features selection, aimed to increase motor-related neuroelectrical responsiveness of the affected hemisphere. However, such features are necessarily limited to a restricted number of channels, while the correct desynchronization pattern is not monitored during the training. While monitoring the cortical activity of the subject during the training is important for the aforementioned purposes, the effects of the online classifications of trials in successful and failed relies on arbitrary choices of parameters and gains instead of on intrinsic properties of the activity recorded during the training.

The aim of this study is to define an index for the evaluation of MI-BCI training session which is independent from the settings adopted for the online control and which is able to describe the properties of neuroelectrical activations across sessions more appropriately than the hit rate. Moreover, such index is aimed to sort the trails within a session according to the adherence to the task, in a fashion independent from the settings and allowing comparisons between "good" and "bad" trials, to improve understanding of the effects of neuroplasticity during the training.

To reach this goal, we performed an offline analysis of EEG data acquired from stroke patients during a MI-BCI training for the rehabilitation of the upper limb motor function. The proposed index was monitored across training sessions and used to sort trials according to their intrinsic properties.

II. Methods

A. Experimental design

EEG data were collected from 14 stroke patients (age: 64 ± 8 years; first ever, unilateral stroke causing paresis or plegia of the affected upper limb) who underwent the BCI-MI training. The training was preceded and followed by two screening sessions (PRE, POST). During these sessions, EEG signals were recorded from 61 scalp positions, sampling rate 200 Hz: data from screening PRE were used to choose control features for BCI training. The features were spatially selected over the damaged hemisphere (two channels) at frequency ranges typical of sensorimotor rhythms (10-15 Hz). The training protocol included 4 weeks of MI-based BCI training (3 sessions per week), during which the patient was asked to control the movements of a virtual representation of his own stroke-affected hand throughout the imagination of simple hand movements (visual neurofeedback). Each training session included 4 up to 8 runs (20 trials per run). Trials consisted of a baseline period (4 sec) followed by MI (max 10 sec). EEG signals during the training were collected from 31 positions

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(frontocentral, central, centroparietal and parietal lines). Sampling rate was set to 200 Hz.

B. *Offline analysis*

After frequency filtering (1-60 Hz band-pass and 50 Hz Notch filters) and CAR (Common Average Reference) spatial filtering, the power spectral densities (PSD) over all channels were computed by means of the Welch method [3]. We defined the new parameter *h* describing the activity associated to the selected features, elicited during each trial. The parameter is defined as follows:

$$h = \alpha \times t(ch_1, bin) + \beta \times t(ch_2, bin) \quad (1)$$

where channels ch_1 and ch_2 and *bin* (2Hz-frequency range) are the features selected during the initial screening for each subject, α and β are multiplicative constants ($\alpha+\beta=1$), while t is the result of the Student's t test performed, for each trial, between the values of the PSD associated to the samples of task phase and those of baseline phase. The constants α and β allow to weigh in a different way the contributions from the two channels, but in this study we chose to set them to the same value ($\alpha=\beta=0.5$).

The parameter *h* was calculated for each trial of the 12 sessions. For each session it was then possible to build the distribution of *h*. We took the median of the obtained distributions as a synthetic descriptor of the features, that was used to monitor the rehabilitative intervention session by session.

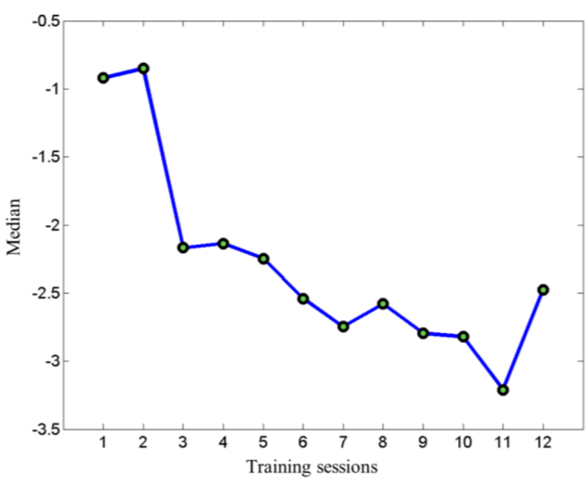

Figure 1. Median value of *h* as a function of training sessions.

After the first overall assessment of the *h* distributions by means of the median, we investigated three percentiles of each distribution: 25% (first quartile), 50% (median) and 75% (last quartile). This step was aimed to understand how trials are distributed according to the parameter *h*. By considering each percentile, the trials were divided into two groups, based on the value of the parameter *h*. The first group included trials for which *h* was smaller than the threshold associated to the percentile under examination, while the second included all the others.

After dividing the trials in the two groups, we computed the statistical scalp maps associated to the trained 2Hz-frequency range. These maps were obtained with Student's t-test on trials (significance level 5%) computed between MI and baseline PSDs. False Discovery Rate correction for multiple comparisons was applied to the statistical tests to avoid the occurrence of type I errors [4]. This procedure allowed to highlight spectral activity related to the task during selected trials.

III. RESULTS

In this study we show the results obtained with EEG data acquired from a representative stroke patient (left affected hemisphere) subjected to the BCI–assisted MI training. The features selected for this patients are as follows: channels C3, Cp3; frequency bin 10-12 Hz.

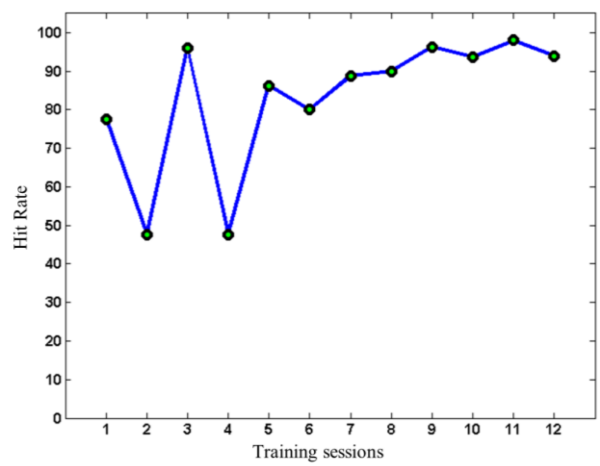

Figure 2. Hit rate as a function of training sessions.

For each training session, parameter *h* was computed for each trial and a histogram was constructed. The first evaluation of the distributions obtained was performed by means of the median. In figure 1, the trend of the median is shown as a function of training sessions. A comparison with the correspondent hit rate across sessions is also provided (Figure 2). As described in the previous section, to understand how the trials were distributed with respect to the investigated parameter, we focused on three percentiles relative to the first quartile, the median and the third quartile. The results obtain for the median in the second session is shown in figure 3: the scalp is seen from above with the nose pointing the upper part of the page and the color of each pixel codes for the correspondent t-value (gray for not significant differences, hot and cold color scales for the level of significant synchronization and desynchronization, respectively). The scalp map obtained with trials distributed to the left of median (i.e. stronger desynchronization) shows a significant pattern, while the scalp map on the right does not reveal significant activations. The other percentiles have not shown the same performance.

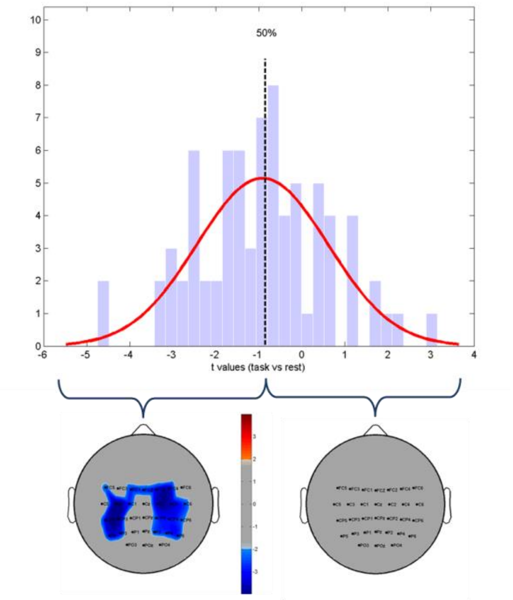

Figure 3. On the top the distribution of parameter *h* for one session is shown, dashed line indicates the median (percentile 50%). On the bottom statistical scalp maps obtained with trials distributed to the left and to the right of the median. The color of each pixel codes for the correspondent t-value: gray for not significant differences, hot (yellow-red) and cold (blue) color scales for the level of significant synchronization and desynchronization, respectively. The two maps are related to the trained 2Hz-frequency range (10-12 Hz).

IV. Discussion

The described study was aimed to the definition of a new descriptor of neuroelectrical activity during BCI-assisted MI training. In particular the new parameter *h* was defined as a function of features selected for the training of motor imagery as a rehabilitative intervention after stroke. This parameter in associated to the signals acquired from electrodes positioned over the damage hemisphere and to the frequency ranges typical of sensorimotor rhythms. In particular it is function of the value of *t* obtained for each trial with a Student's t test between samples associated to MI-task execution and baseline phase samples. This value is therefore a measure of the desynchronization elicited by the patient and specific of the function trained during the rehabilitative intervention. *h* distribution associated to each session allowed to evaluate how the trials are distributed with respect to the parameter. The median of the distributions proved to be more stable than the hit rate as a descriptor of the trend of the training sessions. Indeed while the hit rate is characterized by an oscillatory trend during the first half of the training followed by a nearly constant trend, the median showed a decreasing trend with few oscillations. Furthermore variations of parameter h (as well as the median) are related to a direct interpretation of the changes induced by training. Indeed the median decrease session by session suggests an increase of spectral desynchronization associated to the MI task execution. The statistical scalp maps obtained from the trials to the left of the median provided a topological description of the activation underlying the execution of "good" trials which is in agreement with the physiology of the trained function. It was possible to achieve such result from the very early sessions thanks to the use of the *h* index.

V. Conclusion

Such preliminary results suggest that the proposed procedure may have a future role in helping understanding the neuroplasticity at the basis of a neurofeedback based training and in optimizing a BCI based intervention for neurorehabilitation purposes. In fact, future developments of the new described methodology will be oriented to the definition of an automatic procedure to detect the correct and specific threshold between successful and failed trials for the online analysis during MI-based BCI training.

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