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

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Abstract

Recent BCI applications stroke motor rehabilitation have raised important concerns regarding the type of brain activity which one would train in agreement with an evidence-based approach in rehabilitation. In this pilot study we proposed an offline analysis on EEG data acquired during a BCI-assisted motor imagery training performed by a stroke patient, with the aim of defining an index for the evaluation of the training achievements across session. The proposed *h* parameter would be independent from the selected BCI training setting and would better describe the physiological properties of the patterns generated during training, allowing a more appropriate evaluation of the training achievements than the behavioral performance (i.e. percentage of hit target).

1 Introduction

Nowadays, Brain Computer Interface (BCI) represents a promising technology to support motor and cognitive rehabilitation after stroke. In such rehabilitative context, BCI application aims at increasing the neuroelectric or metabolic brain responsiveness, which in turn would lead to a better recovery of function.

The Electroencephalographic (EEG) -based BCI operated by motor imagery (MI) can provide a valuable approach to support mental motor practice to enhance arm motor recovery after stroke [Mattia et al., 2012]. However, as stroke cortical lesions may result in a functional reduction/derangement of neuroelectrical activity generated over the ipsilesional hemisphere there is a need for further implementation of the procedures for recognition of those EEG patterns which are reinforced during the BCI-supported training of MI. Furthermore the online classification of trials as successful and failed also relies on a arbitrary choice of parameters and gains that do not strictly reflect the intrinsic properties (i.e. the level of desynchronization of SMR) of the patterns of activity recorded during the training.

The aim of this study was to define an index which would be independent from the settings adopted for the online control and thus, would describe the properties of neuroelectrical activations across BCI training sessions more appropriately than the hit rate (behavioral performance). To this purpose, we performed an offline analysis of EEG data sets acquired from stroke patients who underwent a MI-assisted BCI training aiming at promoting functional motor recovery of the paralized upper limb [Pichiorri et al., 2011]. The estimated index was monitored across training sessions and used to sort trials according to their intrinsic properties.

2 Methods

2.1 Experimental design

EEG data were collected from 14 stroke patients (age: 64 ± 8 years; first ever, unilateral stroke causing hemiparesis/plegia) who underwent a BCI-assisted MI training. The training was preceded by an EEG screening session. EEG signals were recorded from 61 scalp positions (sampling rate 200 Hz) and such data were used to extract the features for the online control. Such control features were spatially selected only over the damaged (stroke) hemisphere (two channels) within an EEG frequency range relevant for sensorimotor function (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 (sampling rate at 200 Hz) during training were collected from 31 electrode positions (fronto-central, central, centro-parietal and parietal lines).

2.2 Offline analysis

After frequency (1-60 Hz band-pass and 50 Hz notch filters) and spatial (Common Average Reference; CAR) signal filtering, the power spectral densities (PSD) over all channels were computed by means of the Welch method [Welch, 1967]. We defined the new parameter h describing the activity associated to the selected features, elicited during each trial. The parameter is defined as follows:

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

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 were set at the same value ($\alpha=\beta=0.5$).

The parameter h was computed for each trial over the total of 12 training sessions and the distribution of h was built for each session (see Figure 2). The median of such distributions was considered as a synthetic descriptor of the features and was used to *monitor* the EEG pattern evolution session by session. We also evaluated 3 percentiles for each single distribution: 25% (first quartile), 50% (median) and 75% (last quartile) to investigate how trials would be distributed according to the h parameter. For each of the considered percentile, the overall trials were then separated into two groups: one group included all trails associated with h values below the h threshold relative to the percentile under investigation and the second group included all remaining trials.

To identify the spatial distribution of the spectral activity related to the selected trials, we computed the statistical scalp maps by contrasting the MI and baseline PSD values (student's t-test; significance level 5%) relative to each trail for the trained 2Hz-frequency range. False Discovery Rate correction for multiple comparisons was applied to avoid the occurrence of type I errors [Benjamini et al., 2001].

3 Results

The results are showed for one exemplary training data set acquired form a stroke patient with left affected hemisphere whose selected features were C3 and Cp3 electrode position at frequency bin of 10-12 Hz.

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The graphs in Figure 1 show the trend of the *h* median values relative to each trial (left panel) and of the correspondent hit rate percentage (behavioral performance) (right panel) as a function of training sessions. In particular, Figure 1 shows that the median follows the positive outcome of the training with a decreasing trend along the investigated sessions. The hit rate, instead, after large oscillations in the first half of training sessions, saturated around 90% for the second half, not showing a clear trend along the intervention.

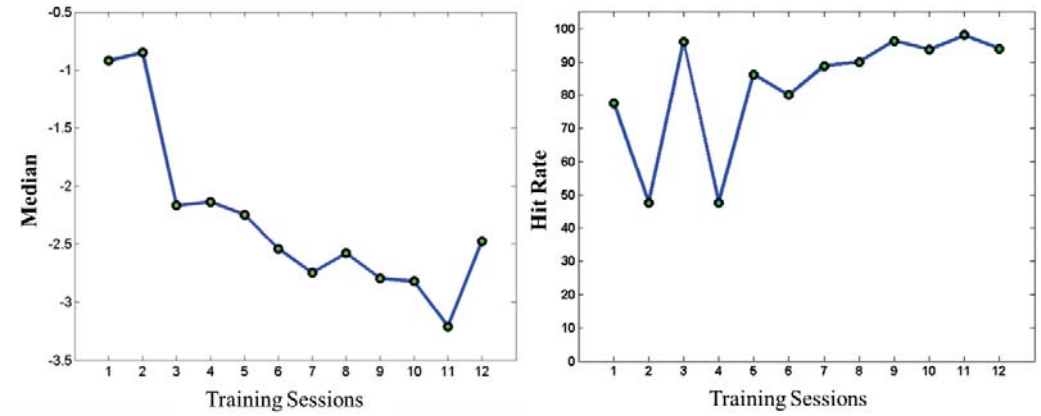

Figure 1: Median value of *h* parameter (left panel) and hit rate percentage (right panel) across training sessions.

The Figure 2 illustrates the distribution of the *h* parameter (top panel) and the relative statistical scalp maps (bottom panel) obtained from the second training session data set, considering the two groups of trials divided by the median. Note that only the statistical scalp map relative to the trials distributed to the left of the median (i.e. stronger desynchronization) showed a significant pattern (blue color in the left side map) as compared to that relative to the trials distributed to the right of median.

4 Discussion and Conclusion

In this study we defined a new parameter (*h*) to measure the MI-induced desynchronization during BCI training for motor rehabilitation after stroke. The *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 and suggested an increase of spectral desynchronization associated to MI across training. The statistical scalp maps obtained from trials to the left of the median provided a topological description of the activation underlying the execution of "good" trials (desynchronization). It was possible to achieve such result from the very early sessions thanks to the use of the *h* index.

Such preliminary results suggest that the proposed approach could be useful 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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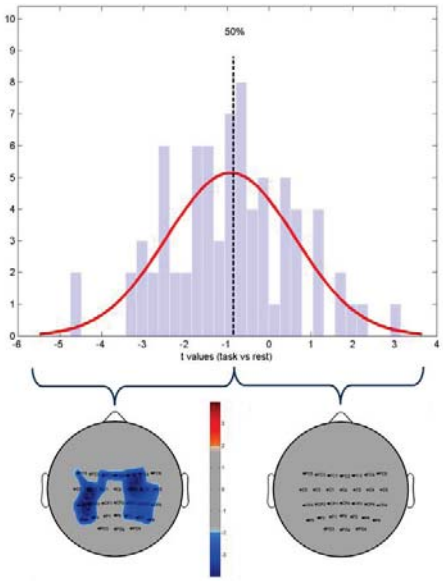

Figure 2: Distribution of the *h* parameter (top panel) and statistical scalp maps (bottom panel) obtained from the second training session data set. Top panel: dashed line indicates the median (percentile 50%). Bottom panel: the color bar codes for t-value associated with each pixel: gray color = not significant differences between baseline and task trial PSD values; hot (yellow-red) = significant synchronization; cold (blue) = significant desynchronization.

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