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EEG patterns during motor imagery based volitional control of a brain computer interface

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Abstract. ***In the context of EEG- based Brain-Computer Interface system (BCI), the aims of this study were (i) to describe differences in EEG activities that underline motor imagery based control of the cursor motion on a video screen and (ii) to provide a guideline to detect most promising BCI users on the bases of their pattern of features and their motor imagery ability. To this aim, we explored the EEG activity patterns generated at the end of a mu- (and/or beta-) rhythm based BCI training of nine subjects. Three different activity patterns related to the capability of the user to control the system were detected. These findings move up questions about the different motor imagery strategy and the mental processes that underlie this control.***

Keywords: Brain Computer Interface, Motor Imagery, EEG, Mu-rhythms, Feature Extraction

1. Introduction

Humans can learn to volitionally control the amplitude of the 8–13 Hz mu rhythm, as well as central beta (20–24 Hz) in a very short period of time ([Kuhlman, 1978; Sheikh et al., 2003]). This raises questions about the open architecture of neural systems producing mu rhythms, their ability to respond to cognitive, emotive, and motor imagery, and their ability to reorganize dynamically.

If the mu rhythm control in the EEG-based brain computer interfaces (BCIs) reflects direct access to the neural mechanisms generating these rhythms or indirect modulation of some general state of the brain is not clear yet. Based on these considerations, this study examines typical EEG patterns at the end of new users' BCI training (stabilization of performances): the key to learn volitional control of mu rhythms appears to be the gradual build-up of internal associations with the visual feedback and the strategies to control the cursor motion tend to focus on motor imagery [Neuper et al., 2006; Pineda, 2005] and attentional processing, which are closely related, as controlled processing [Decety, 1996].

2. Material and Methods

2.1. Recordings

Data were collected from 9 healthy subjects (mean age 30.2 ± 2.9) who underwent a series of recording while were trained to gain control over a sensorimotor rhythm based brain computer interface. A 61-channel cap was used to acquire the EEG signals and a subset of 1-3 channels (among C3, C4, CP3, CP4, Cz, CPz), re-referenced to the common average reference (CAR; the spatial filter used for training), was used to control the vertical movement of a cursor on a video screen (BCI2000 recording software, D2box task, [Schalk, 2004]).

An initial screening session was meant to define the EEG frequency peaks and scalp locations of each subject's spontaneous mu- and beta- rhythm activity during execution and kinaesthetic imagination of simple hand or foot movements. During this session, the subject was provided with any feedback (any representation of her/his μ/β rhythm) and she/he had to perform motor tasks just in an open loop.

During the following training sessions the subjects were asked to perform the same hand or foot kinaesthetic movement imagination they were asked during the screening session, but they were now fed back with a representation of their mu/beta rhythm activity (the cursor motion), so that they could learn how to improve its modulation as to move a cursor upward or downward respectively, towards appearing targets covering half screen (the cursor moved horizontally across the screen at a fixed rate, while the user controlled vertical movements). In Figure 1 the experimental setup during a typical EEG-based BCI training session is represented.

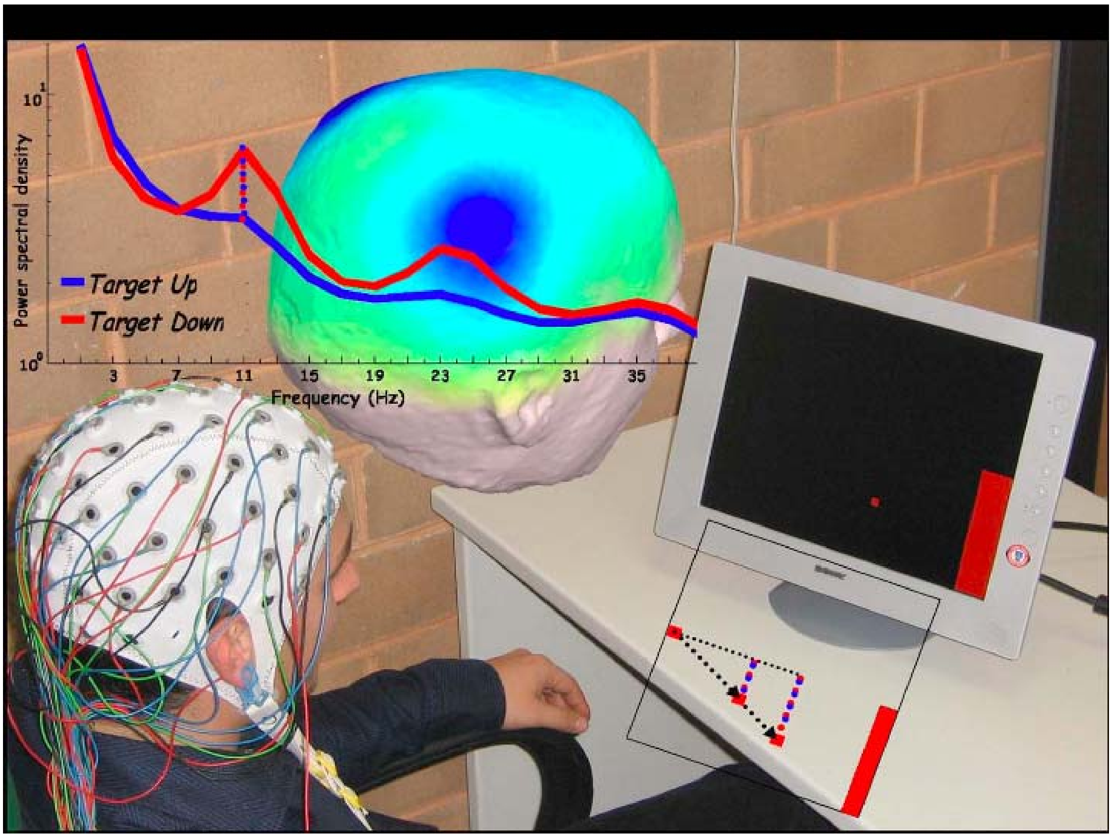

Figure 1. *Typical EEG-based BCI training session: the subject sat in a reclining chair facing a video screen and was asked to remain motionless during performance. He had to perform hands or feet kinaethetic movement imagination to bring up or down the cursor for correspondingly top or bottom targets.*

Training period consisted of 1-7 (depending on subjects) weekly sessions (six three min runs, 29 trials per run) and ended with stabilization of performances.

2.2. Data Analysis

Extraction of the EEG features from background noise was based on spatial filtering operations that improve the signal-to-noise ratio and on an autoregressive spectral estimation. At the end of each training session an offline analysis based on pairs of contrasts was performed to detect the most promising set of features, which will be used in the following session. A cross-comparison was performed between patterns obtained from all the subjects at the end of their BCI training. User performances was assessed by accuracy, namely the percentage of trials in which the target was hit and by the variable named r2, a parameter used to characterize BCI performance ([Wolpaw et al., 2002; Wolpaw and Mc Farland, 2004]). This variable is computed as the correlation between the amplitude of the signal used to control cursor movement and the target position (top or bottom). Data are reported in term of topographical and spectral analysis of R2 values.

3. Results

At the end of the training, all subject obtained a cursor control with stable performance ranging from 77% to 98% on average. On the basis of the EEG features used to control the cursor movement, users were classified in three groups. A first group (2 users) was able to control the BCI system since in the first training session by inducing both a desynchronization of mu- rhythm (12-16Hz) over the bilateral sensorimotor strip and a synchronization of beta rhythm (18-30Hz) over the vertex electrode lead (Cz). In the second group (4 subjects) the cursor movement was typically controlled only by the desynchronization of mu- or beta- rhythm over the bilateral sensorimotor regions. The training ended in 2-7 sessions, depending on subjects. Evolution of performances and EEG patterns at the beginning and at the end of the training for a representative subject in the second group are reported in Figure 2.

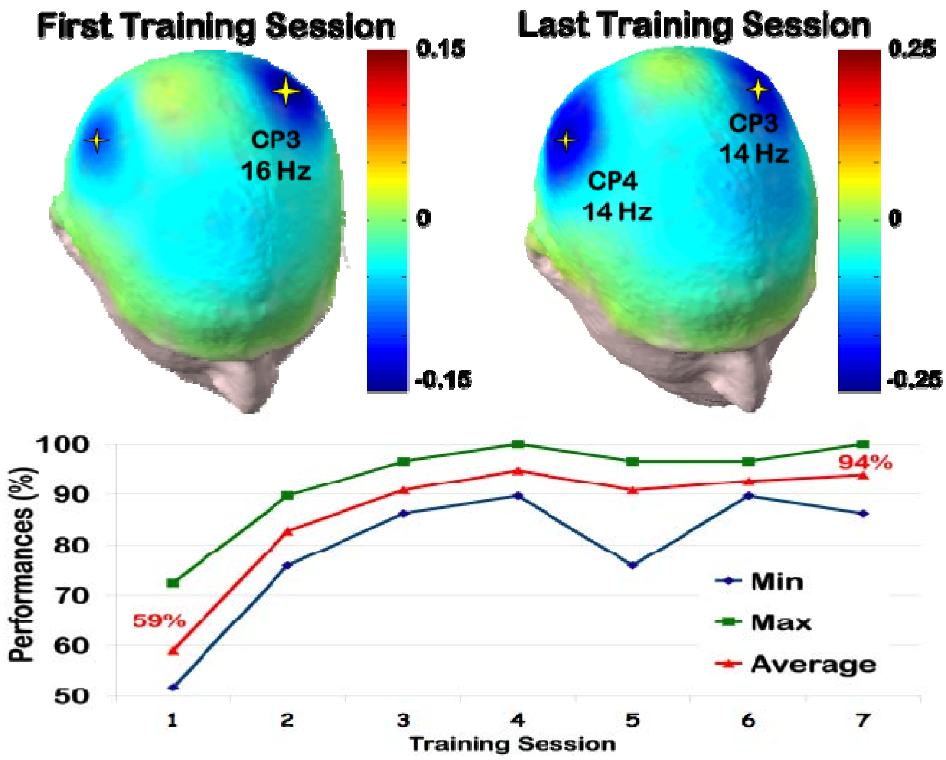

Figure 2.*Topographical distributions of r2 values are shown on the realistic head model and scalp envelope of the subject, obtained from sequential MRIs. Left and rigth top panels represent the EEG patterns for a representative subject in the second group respectively in the first and in the last training session. Evolution of performances are reported in the bottom panel.*

Finally, in the third group (3 people) the typical pattern consists in a desynchronization of beta activity over the mesial strip. They achieved a good control in 4-6 sessions, depending on subjects. Evolution of performances and EEG patterns at the beginning and at the end of the training for a representative subject in the third group are reported in Figure 3.

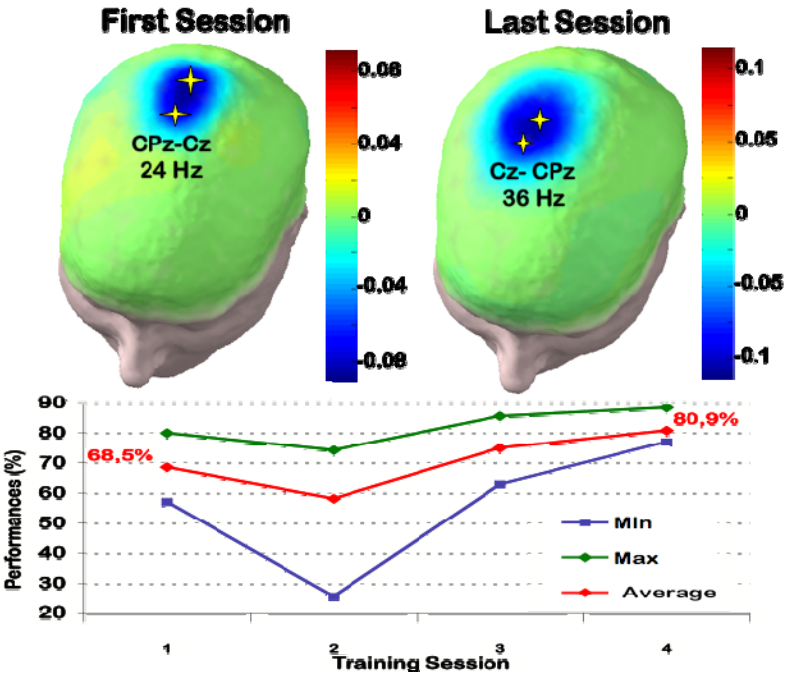

Figure 3. Topographical distributions of r2 values are shown on the realistic head model and scalp envelope of the subject, obtained from sequential MRIs. Left and rigth top panels represent the EEG patterns for a representative subject in the third group respectively in the first and in the last training session. Evolution of performances are reported in the bottom panel.

Each subject's features and performances in the last training session are reported in Table 1; EEG patterns and average of performances at the end of training for a representative subject in each group are reported in Figure 4.

	Subject	Control channels	Frequencies (Hz)	EEG Pattern	Performances (%)	Training Duration
Gruoup 1	S1	Cz - C3 - C4	26 - 12 - 12	S/D	98	1
	S2	Cz - C3 - C4	30 - 12 - 12	S/D	88,56	1
Group 2	S3	C3 - C4	12-Dec	D	89,22	3
	S4	CP3 - CP4	14 - 14	D	94	7
	S5	C3 - C4	24 - 24	D	95,5	2
	S6	CP3 - C4	18 - 18	D	89,7	4
Group 3	S7	Cz - CPz	20 - 20	D	95	6
	S8	Cz - CPz	36 - 36	D	80,9	4
	S9	Cz	22	D	77,16	5

***Table 1.** For each subject in each group are reported: the features used to control the cursor (Control channels and Frequencies), the EEG pattern (D=Desynchronization, S=Synchronization), the performances (percentage of trials in which the target was hit) and the duration of the training period (number of recording sessions). Different colours are used for different groups.*

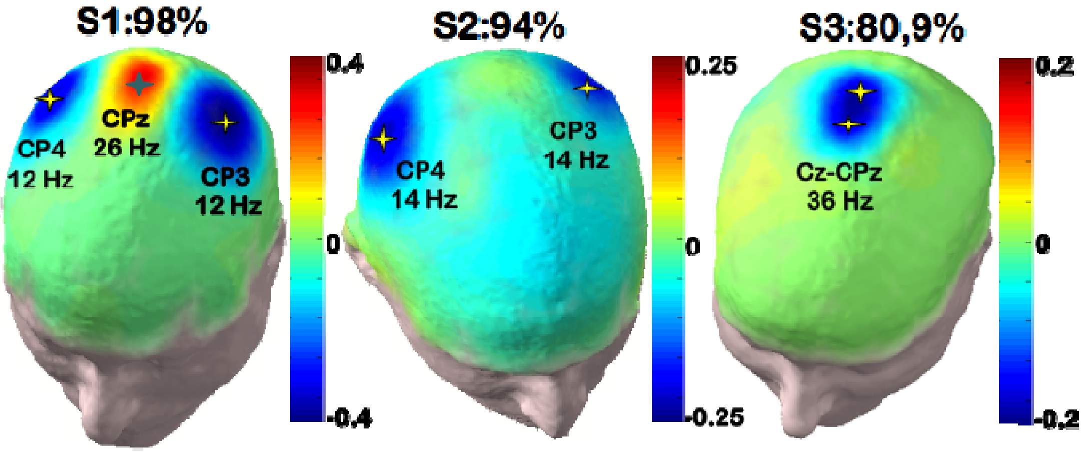

Figure 4.*Topographical distributions of r2 values are shown on the realistic head model and scalp envelope of the subject, obtained from sequential MRIs. Each panel represent the EEG patterns for a representative subject in the first (left panel), in the second (central panel) and in the third group (rigth panel). Each subject's EEG features and average of performances at the end of training are marked.*

4. Discussion

Comprehensive topographical and spectral analyses throughout user training are essential for detecting EEG patterns, which can function as BCI signal. Even if in all the subjects learning strategies tends to focus on motor imagery and seem to be correlated to the kinesthetic motor imagery capability, differences in the EEG activity that underlie the cursor control motion were detected and inter-group differences in the length of the training period were found. These findings reveal that this kind of motor imagery can be a natural capability or can be enhanced by means of neurofeedback learning strategies: the key to learning volitional control of mu rhythms appears to be the gradual build-up of internal associations with the visual feedback. Is still open the question about the possibility that the mesial activity detected in the first group of subjects is really related to a foot movement imagery rather than to the inhibition of the control related to an acquired capability (hands motor imagery).

Despite the differences in the EEG features used to control the cursor motion, all subjects achieve high- level control over their sensorimotor rhythms, thus indicating that inter-subject variability in the EEG reactivity do not prevent ability in controlling the system. On the other side, the findings of difference in the topography and frequency of EEG patterns and in the duration of the training period raise questions about what the subject actually does to control a cursor motion, that is the relationship between behaviours including motor imagery and the volitional modulation of the neural activity (Loetze and Halsband, 2006).

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