34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Detection of Event-related Desynchronization during Attempted and Imagined Movements in Tetraplegics for Brain Switch Control

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Abstract— **Motor-impaired individuals such as tetraplegics could benefit from Brain-Computer Interfaces with an intuitive control mechanism, for instance for the control of a neuroprosthesis. Whereas BCI studies in healthy users commonly focus on motor imagery, for the eventual target users, namely patients, *attempted* movements could potentially be a more promising alternative. In the current study, EEG frequency information was used for classification of both imagined and attempted movements in tetraplegics. Although overall classification rates were considerably lower for tetraplegics than for the control group, both imagined and attempted movement were detectable. Classification rates were significantly higher for the attempted movement condition, with a mean rate of 77%. These results suggest that attempted movement is an appropriate task for BCI control in long-term paralysis patients.**

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) enable people to drive devices directly with their brain signals, without producing any overt behaviour. The BCI decodes brain activity, usually obtained with an electroencephalogram (EEG), and converts this information to a sensible output such as a command for a device or computer. This technique allows people to communicate their intentions in a very direct way and is especially useful for people with severely disabled motor functions, such as tetraplegics [1].

A commonly used paradigm is the detection of the mu- and beta rhythm event-related desynchronization and -synchronization in the motor cortex following executed or imagined movements [2], e.g. to distinguish between left-hand and right-hand (imagined) movements. In so-called 'brain switch'-type BCIs however, the system is not distinguishing between two different tasks as such but merely detects one specific mental state from the 'baseline' state in which the user is not intending any communication. In a movement-based brain switch, the brain state during one motor imagery or execution task is to be differentiated from all other states [3]. Not only can the user refrain from performing a specific mental task when there is no need for system use or change, but also the distinction between one motor task and a baseline state may be more robust than the distinction between two different types of motor task [4]. This is especially useful in control applications with a high demand of accuracy. For instance, in one study a spinal cord injury patient was able to control a grasp neuroprosthesis with a motor imagery-based brain switch [5].

Although the number of BCI studies involving patients is limited, this line of research is gradually receiving more attention [6]. Interestingly, in most studies patients are asked to imagine their movements only. Even though no actual motor output is visible, attempting a certain movement rather than imagining it may feel more natural to the patient and perhaps even generate a stronger brain response. It was shown with fMRI that cortical activation patterns of attempted movement in tetraplegics correspond well to those of executed movement in heatlhy controls [7]. Kauhanen et al. [8] asked patients to attempt movement execution. The investigators were able to detect the time-locked lateralized readiness potential during movement planning in tetraplegics for control of a BCI.

Unfortunately, such precise time domain responses rely on a cue-based system. For use in an asynchronous setting with a more natural way of controlling a device [9], [10], frequency information would be more appropriate. In the current study two things were investigated:

- Whether movement-related frequency information from EEG is detectable in patients who have lost sensory and motor control of their limbs more than a decade ago
- How classification results of patient's attempted movements relate to the classification results of their imagined movements

II. METHODOLOGY

A. Subjects

Ten male tetraplegic patients (mean age 48.9 yrs) and twelve male controls (mean age 45.9 yrs) participated in the study. All patients had a complete lesion at C5-C6, with the exception of one patient with a complete lesion at level C4-C5. The time since the injury varied between 11 and 40 years (mean 25.2 yrs). The protocol was approved by the institutional review board and all participants gave informed consent. After data collection, one patient and one control were excluded from the data set due to insufficient signal quality.

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This work was supported by the BrainGain Smart Mix Programme of the Netherlands Ministry of Economic Affairs and the Netherlands Ministry of Education, Culture and Science and by the Netherlands Organization for Scientific Research (NWO).

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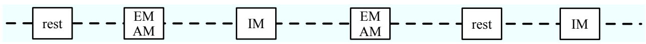

Fig. 1. Experimental sequence. Each sequence consisted of two 'rest' trials, two 'imagined movement' (IM) trials and either two 'movement' (EM) or two 'attempted movement' (AM) trials. The dotted lines represent the random intertrial intervals.

B. Materials and Procedure

Subjects were presented with six sequences of movement tasks, each sequence consisting of six trials (Fig. 1). Each trial lasted 15 seconds, during which participants had to follow the instructions on the screen. The three types of task participants were asked to perform were 'rest' (do nothing), 'movement' (tap your fingers and thumb continuously) and 'imagined movement' (imagine tapping your fingers and thumb continuously). When patients received the instruction of 'movement' they were asked to attempt performing the actual movement even though the movement could not really be executed. Each type of movement was performed 12 times with the trials equally divided over all sequences. Instructions were presented randomly, with the restriction that the first sequence trial was always 'rest'. Intervals between trials lasted between 27 and 33 seconds to ensure sufficient recovery time for the simultaneously recorded haemodynamic signal (results not presented here). Total recording time per participant, including short breaks, was approximately 30 minutes.

EEG was recorded with an 8-channel passive system (TMSi, Enschede, the Netherlands), the electrodes placed on positions C3, FC3, C5, CP3, C4, FC4, C6 and CP4 according to the 10/20 system. Data was sampled at 2048 Hz and acquired with the Fieldtrip toolbox in Matlab [11]. All patient recordings and two control recordings took place at the participant's homes, the remaining control experiments were conducted at the institutional lab.

C. Analyses

After downsampling the EEG data to 256 Hz and removing the DC offset, linear detrending was performed to remove slow drifts. Trials were split into 3-second segments. Bad segments of data were automatically identified and rejected, based on a signal variance measure. This reduced the average number of segments available for analysis by 5.6% to 57 segments per subject per condition. For each segment, the power spectral density was computed for 8 to 24 Hz using Welch's method with a 4 Hz frequency resolution [12]. The derived power spectral features (5 frequency bins x 8 channels) were used for classification with an L_2-regularized linear logistic regression classifier [13]. The classifier's performance was evaluated with 10-fold cross-validation for three binary problems to distinguish each individual movement condition from the 'rest' condition: 1) 'executed movement' versus 'rest' (controls only), 2) 'attempted movement' versus 'rest' (patients only) and 3) 'imagined movement' versus 'rest' (both groups).

To determine statistical significance, a one-tailed dependent samples t-test was used for comparison of classification performances between conditions within both subject groups.

For visualization of the discriminative information between the classes in each of the binary classification problems, the average area under the ROC curve (AUC) for both the patients and the control group was calculated for the 9-13 Hz (mu) and 17-21 Hz (beta) frequency bands.

III. RESULTS

In the control group, a mean classification rate of 82% (SE 2%) was obtained for movement imagery when distinguishing it from the baseline 'rest' condition, whereas for the patient group this rate was much lower at 66% (SE 4%). However, a rate of 77% (SE 3%) was obtained for the 'attempted movement' condition in patients, with individual rates ranging from 66% to 90%. All rates are shown in Table 1. Average classification performance in the patient group was significantly larger for 'attempted movement' than for 'imagined movement' ($p = 0.001$). In the control group, a similar effect was observed with a lower performance for the 'imagined movement' condition than for the 'movement' condition ($p = 0.01$).

The Area Under the Curve plots (Fig. 2) show a power decrease in the mu and beta bands in all movement conditions as compared to rest, with an overall stronger response for the control group. However, a comparable pattern is seen within both groups: less discriminative information is present in the imagery condition than in either attempted or executed movement. The plots indicate a slight bias towards the left hemisphere in the attempted movement condition in the patient group. It could however not be determined whether this is a generic effect.

IV. DISCUSSION

In this study we have shown that movement-related EEG signals can be detected in patients who have lost their ability to move on average twenty-five years ago. Specifically, when they actually attempt to perform finger movements, this results in significantly higher classification rates as compared to when they only imagine making the movements.

All tetraplegic participants in this study had retained at least some form of movement in their upper extremities,

TABLE I
CLASSIFICATION RATES PER SUBJECT GROUP PER CONDITION

Control group			Patient group		
Subject	Execution	Imagery	Subject	Attempt	Imagery
1	88	90	1	83	76
2	89	91	2	77	74
3	91	92	3	72	53
4	84	80	4	66	58
5	92	87	5	67	56
6	74	73	6	79	78
7	84	71	7	90	80
8	77	71	8	80	57
9	91	88	9	80	66
10	88	75	-		
11	89	81	-		
mean	86	82	mean	77	66

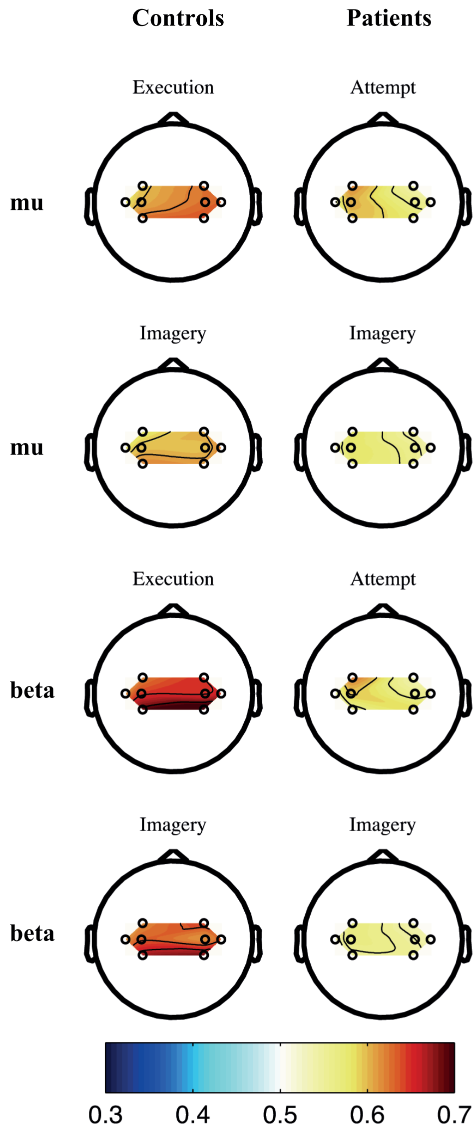

Fig. 2. Average Area Under the Curve plots for controls and patients per frequency range and movement condition. For visualization purposes, values were interpolated for the areas between electrodes. This is a plot of discriminative information where a value of 0.5 indicates no discriminative information between two conditions. Values <0.5 indicate the feature used for classification is smaller in the 'rest' condition whereas values >0.5 indicate the feature is larger in the 'rest' condition. As expected, for all channels the values are >0.5, indicating a decrease in power when executing, imagining or attempting movement (i.e. event-related desynchronization).

mostly their wrists. Although none could execute the fingertapping movement, in attempting to do so the wrist or other arm muscles may have been slightly activated. This could, at least partly, explain the difference in EEG response between movement attempt and imagery, similar to the difference between movement execution and imagery in healthy individuals. Future research in patients with different levels of tetraplegia could possibly reveal whether the level of retained movement ability indicates the strength and thus detectability of EEG responses for attempted movement.

As the patients have been paralyzed for many years, their overall lower brain response to motor tasks as compared to the response in healthy subjects is not very surprising. Nevertheless, in patients as well as healthy participants, motor imagery is less informative than a task in which motor execution is actually intended. Motor imagery requires active suppression of movement and is often regarded a difficult task altogether. Our results indicate that movement execution in healthy users may be more representative of movement attempt in patients than movement imagery, even though classification performance in the patient group is generally lower than in the control group.

Since in the current study only spectral features in the EEG are used, obtained during continuous rather than brisk movements, temporal precision is of lesser importance for detection. Therefore, this task would be more suitable for use in an asynchronous BCI than a task relying on a very precise time-lock. Moreover, the current results were obtained with only 8 EEG channels, allowing for a fast setup and therefore practical use.

In conclusion, attempted movement has proven to be a robust task for tetraplegics to control a BCI and could potentially be implemented in an asynchronous brain switch paradigm.

ACKNOWLEDGMENT

The authors thank Twente Medical Systems International for providing the EEG system used in this study.

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