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Original Article

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Detection of movement intention using EEG in a human-robot interaction environment

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Ernesto Pablo Lana, Bruno Vilhena Adorno, Carlos Julio Tierra-Criollo*

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Abstract **Introduction**: This paper presents a detection method for upper limb movement intention as part of a brain-machine interface using EEG signals, whose final goal is to assist disabled or vulnerable people with activities of daily living. **Methods**: EEG signals were recorded from six naïve healthy volunteers while performing a motor task. Every volunteer remained in an acoustically isolated recording room. The robot was placed in front of the volunteers such that it seemed [Times New Roman Regular 8,5 pt/ 10,2 pt - C0 M0 Y0 K100] ight arm, emulating a Brain Machine Interface environment. The volunteers were sea hout the experiment, outside the reaching area of the robot to guarantee safety. Three conditions are studied: observation, execution, and imagery of right arm's flexion and extension movements paced by an anthropomorphic manipulator robot. The detector of movement intention uses the spectral F test for discrimination of conditions and uses as feature the desynchronization patterns found on the volunteers. Using a detector provides an objective method to acknowledge for the occurrence of movement intention. **Results**: When using four realizations of the task, detection rates ranging from 53 to 97% were found in five of the volunteers when the movement was executed, in three of them when the movement was imagined, and in two of them when the movement was observed. **Conclusions**: Detection rates for movement observation raises the question of how the visual feedback may affect the performance of a working brain-machine interface, posing another challenge for the upcoming interface implementation. Future developments will focus on the improvement of feature extraction and detection accuracy for movement intention using EEG data.

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Keywords: Movement intention, Objective response detection, Statistical F test, Event-related desynchronization, Brain-machine interface.

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Introduction

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Bra[…]nonly considered as the ultimate means of interaction between humans and machines or computers (Allison et al., 2012; Doud et al., 2011; Hochberg et al., 2012; Sirvent Blasco et al., 2012). The idea of controlling our environment using brain activity opens the possibility for many potential applications using these interfaces. For instance, a potential use of a Brai[Times New Roman Regular 9,5 pt/ 11,5 pt - C0 M0 Y0 K100]BMI) is the assistance of severely disabled individuals in order to improve their communication skills, mobility, and general wellbeing (Hochberg et al., 2012; Lebedev and Nicolelis, 2006; Nicolelis, 2003; Pfurtscheller et al., 2003; Santos-Couto-Paz et al., 2013).

A significant amount of BMI research is based on non-invasive methods for the measurement of brain activity (Cecotti, 2011). In particular, electroencephalogram (EEG) is a method to measure overall cortical activity that is easy to setup, operate, and does not require a surgical intervention. However, the measurements EEG provide are polluted with noise coming from brain activity of no interest, as well as noise coming from other sources like muscle activity or external interferences. Hence, it is difficult to extract meaningful information from these measurements (Nicolelis, 2003; Nicolelis and Ribeiro, 2006). In fact, extracting specific information from EEG signals (e.g., the movement intention of a person) is a challenge that depends on the latest instruments, filtering, and processing methods available.

With focus on EEG data processing, this paper presents the development of a method for the detection of arm movement intention in a BMI setup. In order to do so, an experiment with six volunteers standing in front of a manipulator robot emulated a BMI environment. The purpose of this setup is to test the interference of a moving manipulator robot over the electrophysiological responses measured by EEG. Moreover, our goal is to test the detection algorithm over EEG data obtained within this environment and to identify further challenges towards the implementation of a BMI for self-feeding (Lana et al., 2013b).

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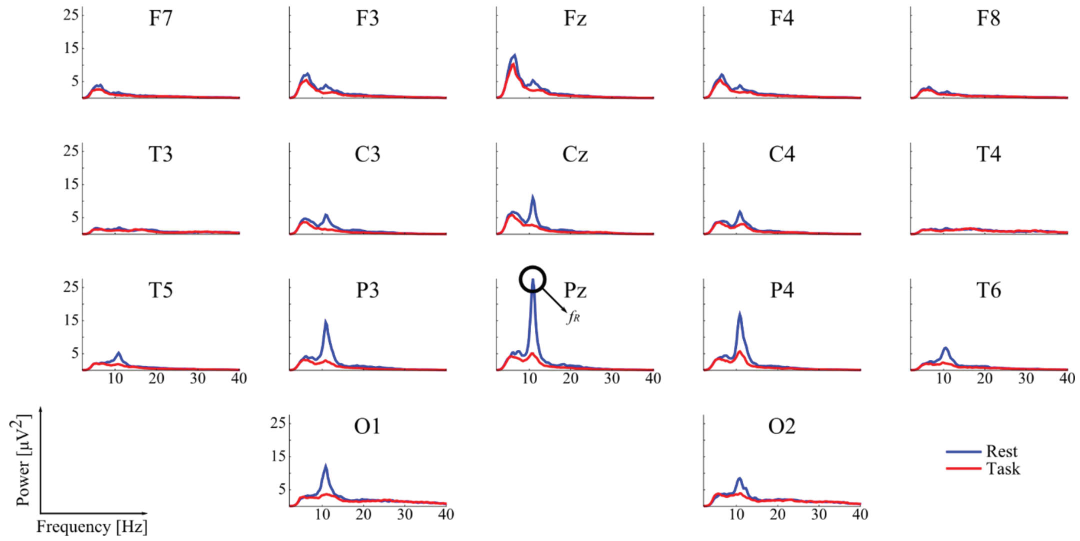

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Figure 5. Power spectrum comparison between rest and task states for volunteer S6 under condition MV.

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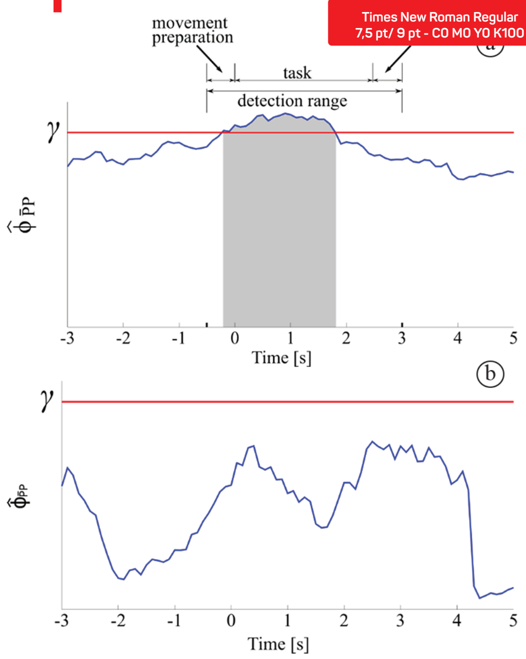

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Figure 6. Function $\hat{\phi}_{\bar{P}P}$ with (a) detection and (b) no detection of movement intention. The figure shows the results using five realizations of the task for volunteer S1 under co

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seconds before and five seconds after the task initiation, whereas Figure 6b shows the same function for a case when no detection occurs with the execution of the task.

In order to consider a particular detection as valid, we defined a time interval when the task condition must be detected. The detection range comprised

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Table 1. Reactive frequency for each volunteer.

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Volunteer	S1	S2	S3	S4	S5	S6
f_R [Hz]	10.6	8.2	9.8			

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the half of second before task execution (movement preparation), the actual time of execution, and the half-second after performing the task (latency) as depicted in Figure 6a.

We computed $\hat{\phi}_{\bar{P}P}$ for all the volunteers and conditions using 1 (single trial), 4, 8, and 12 trials for the detector. We determined the detection rate for every volunteer based on the time interval to consider a detection as valid (Figure 6a). The false positives were computed as the detections outside this interval.

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We determined the detection rate for all the volunteers and conditions of the study as the rate between the amount of valid detections over the total number of expected In general, the highest detection rate obtained was for condition MV (Figure 7b), followed by IM (Figure 7c) and finally ST (Figure 7a). We obtained detection rates ranging from 53 to 97%, when using four realizations of the task, in five of the volunteers for condition MV, in three of them for IM, and in two of them for ST.

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For imagery (IM), which is the condition to be used to command the BMI, the detection rates for three volunteers (S1, S2 and S5) are much lower than for the others (S3, S4 and S6). Furthermore, the detection rate does not improve significantly with the number of trials used in the detector for the volunteers with low detection rate. False positives varied among subjects, but all rates remained below 5% when using more than one trial for the detector.

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Different from most classifiers (Bai et al., 2007; 2011; Bhagat, 2014; Jiang et al., 2015; Kamavuako et al., 2015; Lew et al., 2012; 2014; Nikulin et al., 2008), the detector does not need training data to determine its parameters. The only previous knowledge needed for the SFT detector is the electrophysiological response, i.e., the only characteristic needed is the desynchronization present as a persistent feature related to movement intention, which is used to detect whether the volunteer intended a movement or not. This characteristic may be considered invariant among subjects and experiment conditions.

The BMI paradigm we use has two focuses: the triggering of high-level tasks by the electrophysiological activity of the BMI user obtained through EEG signals, and the execution and solution of several kinds of task by using robotic systems. Both of these aspects are treated as separate parts of our current research. However, we always keep a path that will allow the appropriate integration of these aspects into a single BMI.

As future work, we intend to extend and improve the proposed algorithm in order to detect more types of movement intention. In addition, we will explore other biosignal sources to increase the amount and robustness of control commands, as done in hybrid interfaces research (Allison et al., 2012; Fazli et al., 2012; Pfurtscheller et al., 2010).

Acknowledgements

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