Asynchronous BCIs for the Early Detection and Classification of Voluntary Movements: Applications in Stroke Rehabilitation

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Abstract. Stroke is a leading cause of permanent motor disability. At present, novel rehabilitation techniques focus on ways of promoting brain plasticity leading to functional rehabilitation of the patients. Among these techniques, the integration of Brain-Computer Interfaces in the rehabilitation process represents an encouraging area of active research. The measure of the brain signals during the execution of movements yields a relevant view of the motor-related amount of activity in specific areas of the brain. We expect that the combination of these brain signals with other sensors will lead to more natural interfaces between the patients and the rehabilitation devices, and to new means of tracking the patients' involvement in the rehabilitation process. We present here preliminar results and future studies using Electroencephalography signals in a rehabilitation system for stroke survivors.

1 Introduction

The damage of the cerebral neural networks in stroke patients can cause long-term severe motor disabilities. Following a stroke, a time-limited period of neuroplasticity is presented. During this time-window the rehabilitation exercises carried out by the patient may be critical to achieve a successful restoration of the motor function [1]. The development of Brain-Computer Interfaces (BCIs) in this context represents a promising area of research that aims to offer novel neurorehabilitation techniques, taking advantage of the real-time evaluation of the brain activity. In this regard, the BCI system is not intended to be used as a permanent assistive solution, but to take part in the rehabilitation process helping the patients recover their ability to perform motor actions without needing external devices. Two main groups of approaches are found in the literature dealing with the use of BCIs for motor neurorehabilitation: 1) Neurofeedback training, and 2) control of assisting devices with the movement-related EEG signals [2]. The first approach is focused on giving a feedback to the patients to guide their brain activity back

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to more normal patterns, which is expected to improve their motor function. The purpose of the paradigms used in this case is to help the patients to self-modulate their cortical sensorimotor rhythms and when possible, to increase their ipsilesional brain activity. The second approach aims at giving the patients a propioceptive feedback based on the brain activity observed over the cortical motor regions. The afferent information that this sensory feedback generates, as well as the visual assertion of the patient having voluntary control on the external assistive device moving the affected limb, are expected to induce central nervous system plasticity leading to functional recovery [2].

We propose here an Electroencephalography (EEG) based self-paced BCI to be integrated in the rehabilitation process of the upper-limb function of stroke patients. Our approach is aimed to be used as an additional source of information in a multimodal Human-Robot Interface (mHRI) controlling an orthosis during the rehabilitation of the upper-limb, and therefore it is related to the second of the two aforementioned strategies. The EEG-based system aims at characterizing with anticipation the patient's voluntary attempts to move. This prediction helps the mHRI to achieve a more natural behaviour by reacting synchronized with the patient's expectations of movement and by not requiring the patient to learn any new mental strategies unrelated to the task performed [3]. It is expected that such natural interface will strengthen the brain-muscle neural pathways due to the Hebbian learning theory, according to which simultaneous activations of parts of a neural network lead to increases in the synaptic strength between these parts [4]. Additionally, this BCI approach allows tracking the patient's involvement in the rehabilitation tasks by monitorizing the task-related sensorimotor cortex activation. This is expected to enhance the active participation of the patient in the rehabilitation process.

Nevertheless, in order for the EEG-based system to be useful as a part of the whole mHRI, it needs to be studied to which extent the EEG information preceding voluntary motor actions allows predicting the timing and planification of these tasks in stroke patients. Reliable EEG patterns that can be detected in a single-trial classification are required in order to achieve the aforementioned purposes with the BCI system. Therefore, we also propose using a BCI paradigm, prior to starting the rehabilitation process with an orthosis, to guide the patients on how to correctly perform voluntary actions eliciting premovement potentials robustly detectable in single-trials.

2 Development of BCI Algorithms

Two experimental sessions have been carried out in order to study the ability of the EEG signal to anticipate and characterize self-initiated movements in control subjects.

In the first experiment, the performance of an EEG-based detector of the intention to move was validated with control subjects and patients

Table 1 Recall (Rc) and Precision (Pc) results obtained in the task of classifying 7 analytical movements of the upper-limb: Shoulder Abduction (SA), Shoulder Extension (SE), Shoulder Rotation (SR), Elbow Extension (EE), Elbow Pronation (EP), Wrist Extension (WE), and Wrist Rotation (WR). Results with the six patients 01-06 are presented.

	SA		SE		SR		EE		EP		WE		WR	
	Rc(%)	Pr(%)	Rc(%)	Pr(%)	Rc(%)	Pr(%)	Rc(%)	Pr(%)	Rc(%)	Pr(%)	Rc(%)	Pr(%)	Rc(%)	Pr(%)
01	78.0	54.9	40.0	42.6	30.6	48.4	58.0	67.4	56.0	57.1	64.0	55.2	62.0	62.0
02	57.1	68.3	72.0	60.0	68.0	43.0	39.6	65.5	54.2	57.8	55.1	69.2	56.3	55.1
03	78.0	63.9	93.8	86.5	70.0	72.9	58.0	80.6	51.0	59.5	56.5	56.5	82.0	70.7
04	60.0	57.7	74.0	43.5	61.7	54.7	50.0	65.0	40.4	54.3	62.0	70.5	46.9	63.9
05	62.0	75.6	49.0	70.6	86.0	60.6	68.0	64.2	59.2	60.4	65.3	68.1	56.0	52.8
06	70.0	50.7	86.0	82.7	40.0	43.5	40.0	50.0	60.0	60.0	53.1	59.1	64.0	78.1

suffering from neurological diseases different from stroke. The system consisted of a Bayesian Classifier using as input the automatically selected logarithmic power values at specific scalp locations and frequencies. The average detection ratio was over 70% in the best cases and the number of false activations generated (average precision achieved was 42%) was reduced considering that a continuous evaluation of the system was performed and that 81% of the time measured corresponded to non-action/resting states of the subjects [5]. The features selected with most of the subjects in these experiments were spatially located in scalp positions contralateral to the moved limb and only in some cases was the ERD phenomenon significant in other regions. Therefore, movement intention detection may also be achieved in patients presenting altered cortical activity on an hemisphere due to injured cortical neural networks, although poorer results are expected in this case.

In the second experiment, a probabilistic classifier of analytical upper-limb movements was evaluated with 6 control subjects. The feature space used were the power values over 32 scalp positions and along the alpha and beta frequency bands. The windows where the features were extracted corresponded to the 2s intervals starting 1,5s before the onset of the movements and ending 0,5s after it. A genetic algorithm combined with a bayesian learning method were run to extract the optimal subset of features classifying the analytical movements (we applied a crossvalidation with 75% of the trials for the training). A Bayesian Classifier was built using the selected subset of features. The results obtained are shown in Table 1. For most of the tasks and subjects, both the precision and recall results exceded 50% ratio, showing encouraging performance of the classifier in order to be used to characterize movement strategies. Besides, in this case, the features selected to classify the analytical movements performed with one arm were spread all over the scalp. Therefore, positive results are also expected when applying a similar methodology with stroke patients.

3 Future Experiments

Both the aforementioned detector of the intention to move and the classifier of analytical movements have been designed to be integrated with Electromyography sensors and Inertial Measurement Units in a real-time mHRI. The final objective is to control a hand orthosis assisting the measured subjects in the performance of different rehabilitation tasks. The evaluation of this interface and its efficacy during the stroke rehabilitation process will be tested in future experiments.

Additionally, a BCI-based paradigm to help the stroke patients to learn how to control the movement-related cortical rhythms during the execution/attempt of volitional upper-limb tasks will be developed and evaluated. The objective of this additional experiment will be to test whether this training improves the Signal-to-Noise Ratio of the single-trial epochs to be used by the BCI integrated in the mHRI to detect and characterize movement actions before they start.

4 Conclusion

We describe here a research line being currently developed to integrate the BCI technology in the rehabilitation process of the upper-limb in stroke patients. The final goal of the study is to integrate the EEG-based information concerning the planning of voluntary movements of stroke patients in their rehabilitation therapies. Successful results proving the ability of the EEG signal to detect and classify volitional movements before they occur have already been obtained with control subjects. This demonstrates the potential use of EEG-based algorithms to extract brain patterns describing voluntary movement actions. Further work will be accomplished to test the ability of these systems to work with stroke patients and to develop a novel BCI paradigm aiming at enhancing the brain activity used to characterize the intervals preceding volitional actions.

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