Upper-limb muscular electrical stimulation driven by EEG-based detections of the intentions to move: A proposed intervention for patients with stroke

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***Abstract*— This study proposes an intervention for stroke patients in which electrical stimulation of muscles in the affected arm is supplied when movement intention is detected from the electroencephalographic signal. The detection relies on the combined analysis of two movement related cortical patterns: the event-related desynchronization and the bereitschaftspotential. Results with two healthy subjects and three chronic stroke patients show that reliable EEG-based estimations of the movement onsets can be generated (on average, 66.9 $\pm$ 26.4 % of the movements are detected with 0.42 $\pm$ 0.17 false activations per minute) which in turn give rise to electrical stimuli providing sensory feedback tightly associated to the movement planning (average detection latency of the onsets of the movements was 54.4 $\pm$ 287.9 ms).**

I. INTRODUCTION

The damage of neural networks in the brain caused by stroke may affect the functionality of limbs on one side of the body. Successfully recovering the ability to perform functional tasks with the affected limb depends mainly on the characteristics of the brain injury (size and location), and on the effectiveness of the rehabilitation therapy [1]. Around 30% of chronic stroke patients do not recover the arm and hand functionality despite intensive treatment and rehabilitation [2].

Novel therapies focusing on the neural rehabilitation of the patients may lead to an improvement of their condition in the long term. The use of Brain-computer interface (BCI) technology based on the electroencephalographic (EEG) activity has gained interest in this regard during the last years [3]. The EEG activity allows characterizing movement-related mental states at the exact moment they occur in the brain [4], which in turn may be used to supply patients with sensory feedback coupled with their expectations of movement. Supplying such tightly associated in time sensory feedback is postulated to induce plasticity in cortical regions targeting the damaged limb, which in turn leads to restoration of normal motor control [3]. In this regard, recent studies have proven the relevance of the proprioceptive feedback timing to achieve associative neural facilitation [5].

The Bereitschaftspotential (BP) is defined as a slow negative shift of the EEG amplitude over the central cortical areas that precedes voluntary movements (for a review see [6]). The BP has been used in previous studies to detect online the onsets of self-paced ankle dorsiflexions [4], and to trigger peripheral nerve stimulation during self-paced imagined movements [5]. In that case, it was showed that increased cortical excitability could be induced with a correct function of the EEG-based system. Although positive results have been achieved in the use of the BP to detect onsets of voluntary movements in healthy subjects, some limitations may also be considered. Firstly, the amplitude of the BP (5-10 μV) and the frequency band where it is contained (0.05-1 Hz) make this cortical pattern vulnerable to noisy environments and artifacts. Secondly, in patients with cortical damage such as stroke patients, altered BP patterns may be observed [7], which may affect the single-trial detection of the BP as compared to healthy subjects [8]. A possible way of boosting EEG-based systems aimed to detect the intention to move is to combine the BP with other EEG movement-related patterns providing complementary information. The event-related desynchronization (ERD) is a well-documented movement-related cortical pattern. For voluntary movements performed with the upper-limb, the ERD consists in a decrease of EEG signal power in the contralateral alpha (8-12 Hz) and beta (13-30 Hz) rhythms starting around 2 s before the onset of voluntary movements [9]. As in the case of the BP, the spatio-temporo-frequential distribution of the ERD observed when averaging a number of EEG segments preceding voluntary movements shows a distinguishable pattern [10], which may be useful to locate the onsets of these movements. In fact, previous studies have used the ERD pattern to anticipate voluntary movement events [11]. As in the analysis of the BP, the ERD pattern of stroke patients presents variations with respect to healthy subjects [12]. Therefore, it is of interest to study how stroke-related cortical changes may affect a BCI driven by these two different cortical patterns.

Here it is proposed an intervention for stroke patients in which electrical stimulation of upper-limb muscles is delivered according to EEG-based estimations of the onsets of voluntary movements. To this end, the sensorimotor rhythms and the slow cortical potentials are analysed. The combined function of the BCI system and the electrical stimuli is tested in single experimental sessions with healthy subjects and chronic stroke patients. To the authors' knowledge, this is the first time that precise temporal estimations regarding movement intentions are used to close the BCI loop with electrical stimulation in upper-limb functional movements performed by stroke patients. Results given are expected to serve as a partial validation of such intervention.

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II. METHODS

A. Participants

Two healthy subjects (right handed, 28 and 33 years old) and three chronic stroke patients were recruited to validate the proposed system. The patients' description can be found in Table I. None of the subjects measured had prior experience with BCI paradigms. The experimental protocol was approved by the Ethical Committee of the ''Universidad Rey Juan Carlos'' (Madrid), and warranted its accordance with the Declaration of Helsinki. All patients signed a written informed consent.

Code	Age	Gender	Stroke Type	Side	F-M
P01	69	M	Hemorrg	R	64
P02	52	F	Isquemic	L	126
P03	54	M	Isquemic	L	68

TABLE I

DESCRIPTON OF THE STROKE PATIENTS' CONDITIONS. (F-M REFERS TO FÜGL-MEYER SCALE)

B. Apparatus and experimental protocol

Movements of the affected arm (dominant arm for healthy subjects) were measured with three solid-state gyroscopes (Technaid S.L., Madrid, Spain), placed on the hand dorsum, the distal third of the forearm, and the middle of the arm. The data were sampled at 100 Hz.

EEG signals were recorded from AFz, F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2, P4, PO3, PO4 and Oz, (according to the international 10-20 system) using active Ag/AgCl electrodes (Acticap, Brain Products GmbH, Germany). The reference was set to the voltage of the earlobe contralateral to the arm moved. AFz was used as ground. The signal was amplified (gUSBamp, g.Tecgmbh, Austria) and sampled at 256 Hz.

The electrical stimuli were delivered at the anterior deltoids and triceps with a multichannel monopolar neurostimulator with charge compensated pulses (UNA Systems, Belgrade, Serbia). The common electrode was located at the oleocranon. Sub motor-threshold stimulation was used. Pulse width and frequency were set to 250 μs and 30 pps, respectively. The stimulator was controlled by a stand alone computer (OS QNX Software Systems, Ottawa, Canada) that received activation commands from the computer recording the EEG activity via a digital signal.

Each participant was measured during one session. Participants sat in a comfortable chair with their arms supported on a table. They were instructed to remain relaxed with their eyes open and their gaze fixated on a point on the wall. In the first part of the session ("TRAIN"), the participants were asked to perform self-paced reaching movements with the affected arm (the dominant arm for control subjects). During the resting periods between movements, participants were asked to remain relaxed for around 5-8 s. Participants performed 30 movements in this part. The data recorded was used to train an EEG-based detector of the onsets reaching movements. In the second part of the session ("INTERV") participants were asked to stare at a screen that presented three states in each trial. First the word "Rest" was printed on the screen for a variable period of time until the EEG-based detector showed negative (non-movement) estimations during at least 2 s. When that condition was reached, a blank screen was showed indicating the participants that they could initiate a movement whenever they wanted (trying to wait more than 3 s). When the participants initiated a movement, gyroscopic sensors detected it and the screen printed the word "Movement" until the movement ended. At this point, the trial was finished. During this process, electrical stimuli were delivered each time the EEG-based detector estimated that movement intention was detected, unless the "Rest" state was present (during this state, detections of movement intention were not listened). Participants were told that the electrical stimuli appeared whenever motor-related mental processes were observed. Electrical stimuli lasted 2 s if no movement was performed (wrong detections) and they lasted until the end of the movement if the movement was given concurrently with the detection. A total of 60 movements were performed during this phase.

C. Detection of the onset of the movements

To detect the actual onsets of the reaching movements, the data from the gyroscopic sensor in the arm were analyzed. Data were low-pass filtered (Butterworth, order 2, $<$ 6 Hz). The threshold amplitude for the detection of the onsets of the movements was set to 5 % of the peak amplitude in the training data.

D. Description of the classifier architecture and validation

Two classifiers (based on the movement-related ERD and BP patterns) were combined to estimate the instant at which the onsets of the movements were located (see Fig. 1).

A naïve Bayes classifier was used to detect the ERD pattern preceding the movements in each participant. Bandpass filtering (Butterworth, 3th order, 0.5 Hz $<$ f1, 35 $>$ f2) and small laplacian filter were used. The power values were estimated in segments of 1.5 s and for frequencies between 7-30 Hz in steps of 1 Hz. Welch's method was used to this end (Hamming windows of 1 s, 50 % overlapping). Power estimations were generated every 100 ms. The values obtained in the training run from -3 s to -0.5 s (with respect to the movement onsets) were labelled as resting state examples, whereas the estimations generated at t = 0 s were labelled as movement onset examples. The Bhattacharyya distance was used to select the 10 best features (channel/frequency pairs) to build the Bayesian classifier. The Bayesian classifier was trained with the training examples of the selected features and it was applied to the test data generating estimations of movement intention every 100 ms.

A similar procedure to the one proposed in [13] was used to detect the BP. In this case, a finite impulse response bandpass filter (0.05 Hz $<$ f1, 1 Hz $>$ f2, 15th order) was used. Three virtual channels were obtained by subtracting the average potential of channels F3, Fz, F4, C3, C4, P3, Pz and P4 to channels C1, Cz and C2. The average BP was computed for the three resulting channels using the training data. The channel showing the highest absolute BP peak was selected for the online BP-based detection of movement onsets. Finally, a matched filter was designed using the previously selected channel. To this end, the average BP pattern was extracted from -1.5 s to 0 s from the trials in the training dataset. During the online function, the matched filter was applied to the virtual channel of the validation dataset. The BP-based online estimations of movement intention were also made every 100 ms.

Outputs from ERD- and BP-based detectors were combined using a logistic regression classifier. Training examples of the resting condition were taken from estimations of the two detectors between -3 s and -0.5 s with respect to the movement onset. The output estimations of the ERD and the BP classifiers at the movement onset were used to model the movement state. The classifier generated estimations of the intention to move every 100 ms.

Finally, a threshold was applied to the output of the detector to decide at each moment whether movement intention was detected. The threshold was optimally obtained using the training dataset, following the criterion of maximizing the percentage of trials with a true positive (TP) and with no false positives (FP). The TP was defined as the percentage of trials with a movement detection contained in the time interval from -0.75 s to +0.75 s with respect to the actual onset estimated by the gyroscopes. Detections of the classifier during the resting intervals between movements were considered FP (activations during the intervals in which the screen showed the word "Rest" were also accounted as FP).

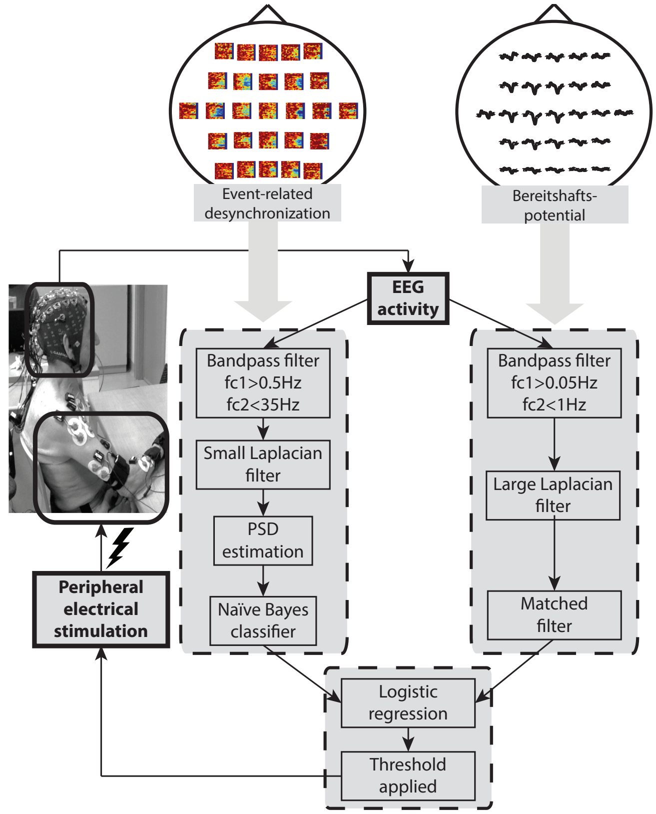

Fig. 1. Schematic representation of the system architecture

C01	C02	P01	P02	P3
C3/12Hz	C3/12Hz	CPz/22Hz	C6/20Hz	CPz/14Hz
CP2/16Hz	C3/11Hz	CPz/23Hz	C6/32Hz	CPz/15Hz
CP2/15Hz	C3/21Hz	C1/22Hz	C6/19Hz	CPz/13Hz
C3/23Hz	C3/20Hz	P3/12Hz	C6/18Hz	CPz/20Hz
CP2/17Hz	C3/17Hz	PO3/12Hz	C4/18Hz	CPz/16Hz
C2/14Hz	C3/18Hz	C1/23Hz	C6/22Hz	CP2/20Hz
FC1/14Hz	C3/19Hz	C1/21Hz	C2/21Hz	CP2/18Hz
C1/17Hz	CP3/10Hz	CPz/16Hz	C4/19Hz	Cz/23Hz
C1/16Hz	CP3/12Hz	CPz/15Hz	P4/10Hz	CP2/19Hz
FC1/20Hz	C3/10Hz	CPz/24Hz	FC1/11Hz	Cz/20Hz
C1	Cz	Cz	C2	Cz

TABLE II

FEATURES SELECTED BY THE ERD (FIRST 10 LINES) AND BP (LAST LINE) CLASSIFIERS FOR EACH PARTICIPANT (C CONTROL, P PATIENTS)

III. RESULTS

The features selected by the ERD and BP classifiers from the training dataset are presented in Table II. In the case of the ERD-classifier, features from contralateral central positions were selected to detect the movement onsets in the control subjects, whereas for the patients, different patterns of selected features were observed. The average BP curve obtained from the training dataset showed that, in participants C01 and C02, the BP peak was located at $t = -1.0$ ms and $t = 123.1$ ms, respectively, and in the patients, the BP peak was located at $t = 396.6$ ms (P01), $t = 119.6$ ms (P02), and $t = 56.4$ ms (P03).

Online results of the proposed EEG-based detector are shown in Table III. On average, 66.9 ± 26.4 % of the movements were correctly detected, giving rise to electrical stimuli associated to the movement intention. The number of false activations generated per minute (FP/min) was on average 0.42 ± 0.17, and the movement onsets were detected with average latencies of 54.4 ± 287.9 ms with respect to the actual onsets of the movements located with the gyroscopic sensors. Fig. 2 shows the latencies of all true positives with respect to the actual onsets of the movements in each subject, reflecting an organisation of the detections around the actual movement onset in the two healthy subjects and in P01, whereas delayed detections were obtained in most trials in patients P02 and P03.

IV. DISCUSSION AND CONCLUSIONS

This article presents an intervention for the upper-limb of stroke patients aimed at promoting associative facilitation at the motor cortex. The study shows results of a paradigm in which participants performed self-paced reaching movements with the arm and proprioceptive feedback was delivered by means of an electrical stimulator activated each time movement intention states were found in the EEG signal. At the same time, a visual feedback was presented to the participants to guide them through the intervention. The visual paradigm assured that the basal (resting) state was

Code	TP (%)	FP/min	Latency (ms)
C01	60.0	0.29	60.6±267.0
C02	90.0	0.32	30.6±303.1
P01	93.2	0.49	-56.4±156.1
P02	28.1	0.30	25.0±233.3
P03	63.3	0.69	139.5±350.0
Average	66.9±26.4	0.42±0.17	54.4±287.9

TABLE III

RESULTS OBTAINED WITH ALL SUBJECTS AND AVERAGE RESULTS

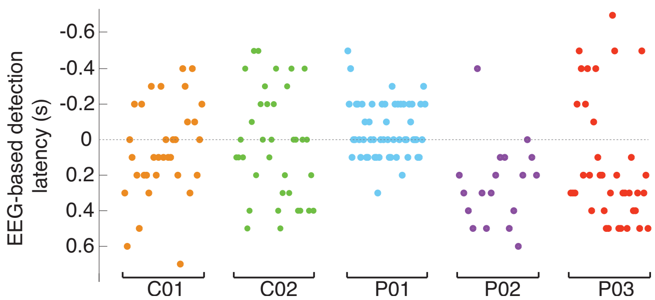

Fig. 2. Latencies of the true positives with respect to the actual onsets of the movements

reached after each movement, although this did not affect to the self-pace nature of the exercise. This way, a demanding protocol was achieved, which required a constant concentration of the participants in the task. This is the first time that the EEG-based online detection of the onsets of upper-limb movements in chronic stroke patients is used to trigger electrical stimulation.

It is concluded that a successful detection of the initiation of volitional actions with the arm can be obtained and that the electrical stimulation help to improve the specificity of the EEG-based detector (the number of false activations generated was lower than that observed in similar studies, e.g. [4]). Other authors have also provided evidence of improved decoding of motor-related cortical activity when the BCI sensorimotor feedback loop is closed [14]. Results here sustain this hypothesis and extend it by providing evidence of a maintained EEG-based reliable detection of movement onsets with temporal accuracy when subjects received electrical stimulation. Having a source of information regarding patients' intentions to move and with temporal accuracy is expected to improve BCI-based therapies, since it ensures the active participation of the patients in the rehabilitation task and implies a close interaction between movement-related cortical processes and external electrical stimuli. Furthermore, all subjects, except for P02, reported that they were able to control the electrical stimulation when they imagined instead of performed the reaching movements, which provides a rationale for using this kind of technology in patients without movement capacity. Since the onset of imagined movements cannot be precisely located, results with imagined movements were not extracted and are therefore not provided.

Finally, differences were observed between the healthy subjects and the patients. According to the features selected in each case and to the location of the BP peak, these differences were associated with altered BP and ERD patterns in the patients, which is in line with previous studies [7], [12]. In future studies, longitudinal experiments may be carried out with the patients performing multiple intervention sessions to study whether such approach results in improvements of functional scales.

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