Preliminary Study to Detect Gait Initiation Intention Through a BCI System

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Abstract: In this paper is presented an experiment designed to detect the will to perform several steps forward (as walking onset) before it occurs using the electroencephalographic (EEG) signals collected from the scalp. The preliminary results from five users have been presented. In order to improve the quality of the signals acquired some different spatial filters are applied and compared. In the future, the improved Brain-Computer Interface of this paper will be used as part of the control system of an exoskeleton attached to the lower limb of people with incomplete and complete spinal cord injury to initiate their gait cycle.

1 INTRODUCTION

There is a range of longer-term problems that a person who has suffered a stroke might continue to face after they have left hospital. Patients with stroke normally have communication, cognitive, emotional, physical or visual problems so they need attendance or even rehabilitation. However, there is other disabilities as people with spinal cord injury or multiple sclerosis that involve lost of voluntary mobility. Therefore, the research community has to do a huge effort to find solutions to restore their capacities or, at least, to facilitate new technology with the aim of improving their lives.

For this reason, Brain-Computer Interfaces (BCIs) have seen a rapid development during the last years as an assistive technology. BCIs are an alternative communication method for people with a severe motor disability as they allow generating control commands with the only help of the thoughts (Guido Dornhege and Muller, 2007; Nicolelis, 2001). Therefore, BCIs could increase their independence and also could improve their quality of life.

Current technology allows collecting and processing EEG signals that occur just before performing an action and thus we can know the intention to perform a movement (Bai et al., 2011). It can be used to assist subject movements whenever he/she wishes which is one of the great practical advantages of this approach. In a motor rehabilitation process, it can make a big improvement since it would be possible to share efforts between the subject and, for example, an exoskeleton attached to the lower limb (Moreno et al., 2011). This coordination between the will to execute a movement and the performance of the action itself increases the likelihood of the brain to create new communication channels due to neuronal plasticity (Kolb et al., 2011). Through this, the effects of rehabilitation increase a greater extent in a much shorter time frame.

This paper has been developed under the BioMot project - Smart Wearable Robots with Bioinspired Sensory-Motor Skills (FP7-ICT-2013-10) funded by the Commission of the European Union, which pretends to control an exoskeleton attached to the lower limb of the disabled user capturing and processing their electroencephalographic (EEG) signals. As part of this challenge, our purpose is to activate the controlled gait cycle of the exoskeleton using the intention to walk of the user. Therefore, the EEG signals will be analysed in order to detect the intention of the gait onset and this will be turn into an activation command of the exoskeletons engines or a stimulus over the leg muscles with Functional Electrical Stimulation (FES). At the moment, the focus is on the system to detect the intention to start walking and initially, only healthy subjects have performed the test.

For our knowledge, there are two phenomena extensively used in BCI related to the motor intention. On the one hand, a kind of Movement-Related Cortical Potential (MRCP) which is a slow potential called Bereitschaftspotential or readiness potential (Shibasaki and Hallett, 2006) but this paper will not take into consideration this phenomenon. On

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the other hand, the event-related desynchronization (ERD) characterized by a decrease in the spectral power of EEG signals in mu and beta frequency bands (Pfurtscheller and da Silva, 1999). This phenomenon starts up to 2 seconds before the movement onset and it ends more or less when the movement is finished. After that, the spectral power recovers its magnitude generating the event-related synchronization (ERS).

2 MATERIALS AND METHODS

2.1 Test Description

Five healthy subjects between 22 and 29 years old (26.50 ± 3.15) performed one session. All voluntaries had normal vision and hearing and no history of neurological or psychiatric disorders. Each subject was instructed to remain at rest on their two legs during at least 5 seconds to have enough information to be used as resting time (or baseline) and then to perform several steps forward. However, the user could begin the movement whenever they want after the restricted period (limited to 10 seconds). No interface guides the subject but they know when a task starts through an advice from the experimenter.

8 runs with 10 repetitions each have been performed. Between each run there is one or two minutes of break time and between repetitions there is a few seconds. The user has to wear several measurement equipments to register the EEG signals and the kinematic of the user. Then, a cap with EEG electrodes, a backpack with the electronic devices that registers the EEG signals and 7 Inertial Measurement Units (IMUs) distributed over the lower limb are used. These devices are connected to a laptop which is over a cart managed by the experimenter. Therefore, the experimenter pulls the cart while the user is moving forward to keep around 1.5 meters between the user and the cart. In Fig. 1 it is possible to see an example of test.

2.2 Experimental Set Up

The system architecture is composed by a Brain-Computer Interface (BCI) that will capture and process EEG signals to command, in the future, an exoskeleton attached to the lower limb and seven Inertial Measurement Units (IMUs) managed by the Motion Capture System (Technaid S.L.), which are distributed over the lower body to register kinematics. Both acquisition systems are synchronized.

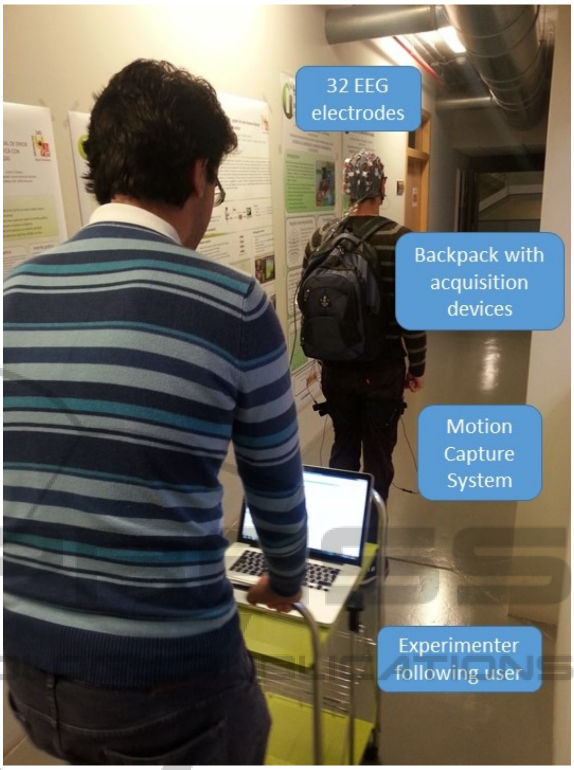

Figure 1: The user is wearing the cap, the backpack and the Motion Capture System while the experimenter follows him with the cart and the computer.

2.2.1 Brain-Computer Interface

The EEG signals are registered through 32 active electrodes. These electrodes are placed using a cap (g.GAMMAcap, g.tec medical engineering, GmbH, Austria). This cap is very useful as it allows an easy placement of the electrodes. The 32 electrodes are placed following a uniform distribution over the scalp. According to the International 10-10 System, the position of the electrodes is the following: FZ, FC5, FC3, FC1, FCZ, FC2, FC4, FC6, C5, C3, C1, CZ, C2, C4, C6, CP5, CP3, CP1, CPZ, CP2, CP4, CP6, P3, P1, PZ, P2, P4, PO7, PO3, POZ, PO4 and PO8. This distribution of the electrodes is shown in Fig. 2. These electrodes are the g.LADYbird model, sintered Ag/AgCl crown with a 2-pin safety connector. These electrodes need a conductive gel that comes in contact the scalp with the sensor. The ground sensor is located in AFz and the reference is placed on the earlobe. The signals of the 32 electrodes are acquired through two commercial g.USBamp devices from g.tec synchronized by using g.INTERsync device and they have two preamplifiers g.GAMMAbox. Each amplifier has 16 channels and the sampling frequency used to register the signals is 1200 Hz.

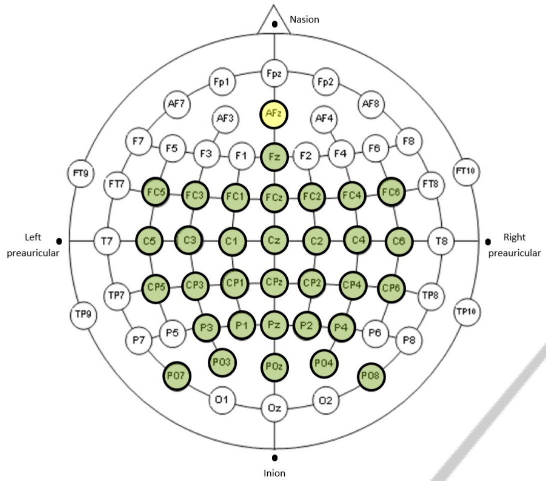

Figure 2: Placement of the 32 electrodes over frontal and parietal lobes.

2.2.2 Motion Capture System

The motion capture system Tech MCS is a complete wireless motion analysis system. It manages the seven IMUs of the company Technaid which are used in our experiments and they are placed as Fig. 3 shows. The sampling frequency used is 30 Hz. Each Tech IMU integrates three different types of sensors as an accelerometer, a gyroscope and a magnetometer. A sophisticated and robust algorithm, calibrated also taking into account changes in temperature, results in a very precise and robust estimation of 3D orientation, even during changing environmental conditions.

2.3 Signal Processing

The EEG signals voltage is around a few microvolts, consequently the signals are easily affected by other sources of voltage that are not the cerebral activity as ocular or muscular movements. Therefore, it is necessary to reduce the undesirable contribution of each electrode using some temporal and frequency filters. In this sense, the EEG data is filtered with two frequency filters that eliminate the power line interference, the DC component and some artifacts. Then, a 50 Hz Notch filter and a 4th order Butterworth from 1 to 100 Hz filter are used. Thus, the information of mu and beta (8-30 Hz) and surrounding frequencies are isolated. Moreover, due to the proximity of the EEG electrodes and the numerous neural connections, the signal acquired per each electrode is partially affected by the potential produced in other location of the scalp. Hence, in this paper two different spatial filters are used to reduce that neighbour contribution.

On the one hand, a Common Average Reference

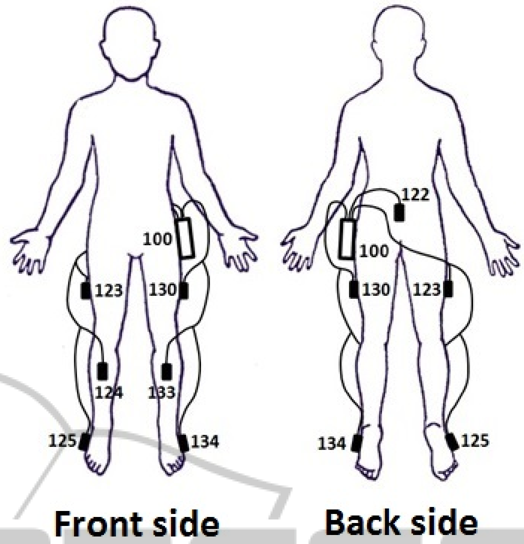

Figure 3: IMUs distribution. 100: Tech HUB; 122: Lumbar; 123: Right quadriceps; 124: Right biceps; 125: Right foot; 130: Left quadriceps; 133: Left biceps; 134: Left foot.

(CAR) is used (Alhaddad, 2012). This spatial filter consists of subtract the 32 EEG channels mean data to each channel. Therefore, it is expected that the information processed per electrode comes from itself, reducing the contribution of the remaining electrodes.

On the other hand, a Laplacian (LAP) algorithm is applied for all electrodes (McFarland et al., 1997). This algorithm uses the information received from all the remaining electrodes and their distances from them. The visual result is a smoother time signal which should contain only the contribution coming from the particular position of the electrode. The Laplacian is computed according to the formula:

$$Vi^{LAP} = Vi^{CR} - \sum_{j\varepsilon Si} g_{ij} V j^{CR} \qquad (1)$$

where Vi^{LAP} is the result of applying this algorithm to the electrode i, Vi^{CR} is the electrode i signal before the transformation and,

$$g_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{j\varepsilon Si} \frac{1}{d_{ij}}} \qquad (2)$$

where Si contains all the electrodes except from the electrode i and d_{ij} is the distance between i and j electrodes.

In order to compare, a third option without any spatial filter (NOF) is used.

2.4 Features Extraction and Classifier

The EEG data are cut from 5 seconds before each movement onset sample to 1 second after it. Only these data will be analysed to distinguish between premovement and resting time. Then, the first three seconds will be used as resting data and the last three seconds as premovement data. To know the starting sample, the data acquired from the IMUs are used. An automatic searching method based on the first change in the curve obtained from IMUs is implemented. The number of IMU is higher than needed in this experiment because other lines of research in BioMot take under consideration kinematics.

Later, the selected EEG data per each task is fed into a 7th order autoregressive process that returns a vector with the estimated coefficients a of a linear regression model per a EEG channel. This vector is calculated as follows:

$$x(n) = 1 + \sum_{i=1}^{6} a_i x(n-i) \tag{3}$$

where x is the EEG data and a is the vector of estimated coefficients.

Therefore, these coefficients are used to train a Support Vector Machine (SVM) classifier. SVM is an approach where the objective is to find the best separation hyperplane, which provides the highest margin distance between the nearest points of the two classes to separate them.

3 RESULTS

The system is tested using an 8-fold cross validation with each run as a fold. This statistic analysis performs all combinations of 7 runs to train the SVM classifier and uses the other one to test it. In each iteration, the number of correct and incorrect detections are added and, at the end, the following three statistical index are calculated:

$$TPR = \frac{\text{Premovement data correctly detected}}{\text{Number of premovement data}} * 100 \tag{4}$$

$$FPR = \frac{\text{Resting data incorrectly detected}}{\text{Number of resting data}} * 100 \tag{5}$$

$$ACC = \frac{\text{Tasks correctly detected}}{\text{Number of tasks performed}} * 100 \tag{6}$$

The results obtained per each user with the two spatial filters and no one are summarized in Table 1. In view of the results, it is possible to say that when a spatial filter is used the FPR and the ACC are

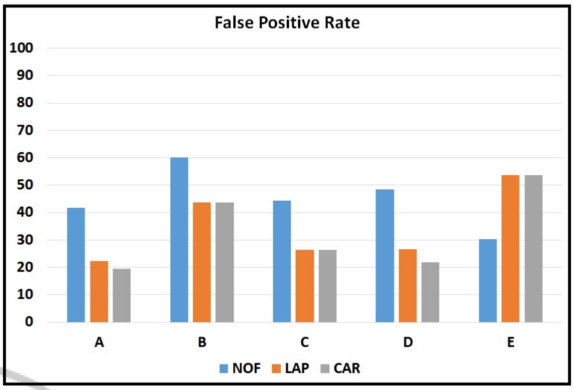

Figure 4: False Positive Rate (FPR) in all users with the different filters: no filter (NOF), laplacian filter (LAP) and common average reference filter (CAR).

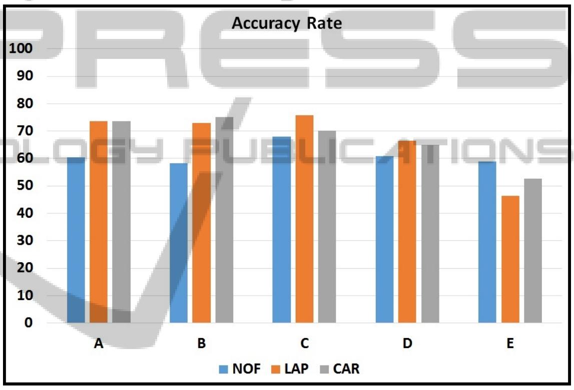

Figure 5: Accuracy Rate (ACC) in all users with the different filters: no filter (NOF), laplacian filter (LAP) and common average reference filter (CAR).

improved (around 11% and 6% respectively), except user E who is an abnormal case as it is shown in figures 4 and 5. However, there is not significant differences in TPR average. Leaving out user E and NOF, TPR is better using LAP filter but FPR is lower using CAR and at the end, the accuracy of the system is similar with both filters. Therefore, the difference between LAP and CAR filter is not significant but at least, according to ACC, it is better than NOF. In average, TPR and FPR are around 68% and 34% (respectively) using any filter. However, there is huge differences between users and for example, user B reaches 93.75% of TPR while user D only achieves 51.56% with the same spatial filter. Then, the system has to be improved in both index with more complex signal processing to achieve better features and a more stable system.

Table 1: Results of the 8-fold cross validation.

	TRUE POSITIVE RATE			FALSE POSITIVE RATE			ACCURACY RATE		
USER	**NOF**	**LAP**	**CAR**	**NOF**	**LAP**	**CAR**	**NOF**	**LAP**	**CAR**
A	62.50	69.44	66.67	41.67	22.22	19.44	60.42	73.61	73.61
B	77.08	89.58	93.75	60.08	43.75	43.75	58.33	72.92	75.00
C	80.56	77.78	66.67	44.44	26.39	26.39	68.06	75.69	70.14
D	70.31	59.38	51.56	48.44	26.56	21.88	60.94	66.41	64.84
E	48.21	46.43	58.93	30.36	53.57	53.57	58.93	46.43	52.68
MEAN	**67.73**	**68.52**	**67.52**	**45.00**	**34.50**	**33.01**	**61.34**	**67.01**	**67.25**

4 CONCLUSIONS AND FUTURE WORKS

In this paper a system to detect the intention to start walking has been presented. According to the results obtained from five healthy users, the system has to be improved to achieve better TPR and FPR. If the system is able to predict each movement with a really low FP rate, the classifier output could serve as a command to activate the engines of an exoskeleton or a FES system to start walking. Therefore, in a rehabilitation process an exoskeleton could be used to support the lower limbs while the user carries out mentally walking intentions. The relationship between the cognitive process to perform such movement and the real movement could improve the rehabilitation due to cerebral plasticity.

Therefore, other methods to characterize the EEG signals before the movement onset will be studied. For example, it is possible to calculate the power spectral and to extract the best component of each user to be used as feature. Moreover, a frequency filter narrower could be applied in order to isolate the mu and beta frequency bands which are involved in ERD phenomenon. Furthermore, ERD can be used purely as theory indicates (a relative decrement of power spectral in a special frequency band measured in percentage). Usually, EEG signals have some artifacts like eye blinks or muscle activity that should be removed. In particular, eye movements could be removed from EEG signals recording the electroculagraphy (EOG) signals using 2 bipolar electrodes (horizontal and vertical channels) and then reducing their contribution through a linear regression which relates EEG and EOG signals (Kenemans et al., 1991). Moreover, artifacts due to neck movements can be easily seen in EEG signals due to their magnitude, so it is possible to add a voltage threshold to avoid it.

The population of this experiment and also the number of sessions will be increased. Furthermore, patients with complete and incomplete spinal cord injury will perform the experiment in order to test the system and to evaluate the performance. It is expected that some patients keep their brain procedures related to the intention of movement as healthy people although they could be weaker or allocated in other brain area (Wei et al., 2011). Then, a real-time test with a better system will be performed both healthy as patient users.

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