Using EEG Signals to Detect the Intention of Walking Initiation and Stop

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Abstract. The ability of walking brings us a great freedom in our daily life. However, there is a huge number of people who have this ability diminished or are not even able to walk due to motor disabilities. This paper presents a method to detect the voluntary initiation and stop of the gait cycle using the ERD phenomenon. The system developed obtains a good accuracy in the detection of the rest and walking state (70.5 % and 75.0 %, respectively). Moreover, the average detection of the onset and ending instants of the gait is detected with a 65.2 % of accuracy. Taking into account the number of intentions of initiation and stop of the gait, the system reaches a good True Positive Rate (around 65%) but obtaining a still improvable False Positive Rate (15.4 FP/min in average). By reducing this factor, this detection system can be used in future works to control a lower limb exoskeleton or a wearable robot. These devices are very useful for rehabilitation and assistance procedures in patients with motor problems affecting their lower limb.

Keywords: EEG Signals · Gait analysis · ERD · Movement detection

1 Introduction

Brain-Machine Interfaces (BMI) represent a great help for people with disabilities or motor damage. Due to spinal cord injury, stroke or other causes, these patients might not have the chance of performing movements as common as picking up a glass of water or walking. Different methods have been applied in order to use BMIs to solve, or at least reduce, this kind of impediments [1,2]. Electroencephalographic (EEG) systems allow the measurement of the brain activity over the motor cortex while subjects are performing motor tasks [3,4]. This information can be used to control lower limb exoskeletons or wearable robots, providing an alternative communication path between the brain (by detecting the patient's movement intention) and these devices [5,6].

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Current technology allows registering and processing EEG signals that occur just before performing an action and thus it is possible to know the movement intention [7,8,9]. This methodology allows assisting motor movements when it is necessary. The detection of these movement intentions can be very useful in motor rehabilitation processes. For instance, through this detection, an exoskeleton attached to the lower limb [10,11] could allow patients with disabilities to walk. The coordination between the desire 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 [12]. Using this phenomenon, the effects of rehabilitation could increase more efficiently.

There are two widely used neurophysiological phenomena that begin before a voluntary action: the Bereitschaftspotential (BP or readiness potential) and the Event-Related Desynchronization (ERD). The slow potential BP is generally described as a decrease in the component closest to the DC component in EEG signals [13]. On the other hand, ERD represents a decrease in the spectral power of the EEG signals in the *mu* and *beta* frequency bands [14]. In this paper, a methodology to detect the walking intention onset using a non-invasive system based on ERD is presented. The main goal is the development of a system which allows controlling an exoskeleton attached to the lower limb. These system could be applied for both functional rehabilitation and assistance of walking.

2 System Architecture

The designed system is able to detect four different human gait states: *Relax*, *Start*, *Walking* and *Stop*. To that end, a motion capture system is used to analyze lower limb kinematic data to obtain real indices of these states. Afterward, the brain activity is analyzed to detect the current state in each moment. The brain signals are acquired using a non-invasive BMI system which provides 32 EEG channels.

2.1 Brain-Machine Interface

EEG signals are recorded through 32 active Ag/AgCl electrodes (g.LADYbird model - g.tec Medical Engineering GmbH, Austria) distributed over the scalp. These electrodes are placed on the positions 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 according to the International 10/10 System and covering central and parietal regions. A monoauricular reference is placed on the earlobe and the ground is located on AFz. To ensure a better placement of the electrodes, a g.GAMMAcap (g.tec Medical Engineering GmbH) is used. This cap allows a quick placement of electrodes. Moreover, this system is able to reduce motion artifacts and electromagnetic interference. The EEG signals are amplified using two g.USBamp (g.tec Medical Engineering GmbH). The sample frequency used to acquire the signals is 1200 Hz. A computer software developed in MatLab (The MathWorks, Inc., Natick, MA, USA)

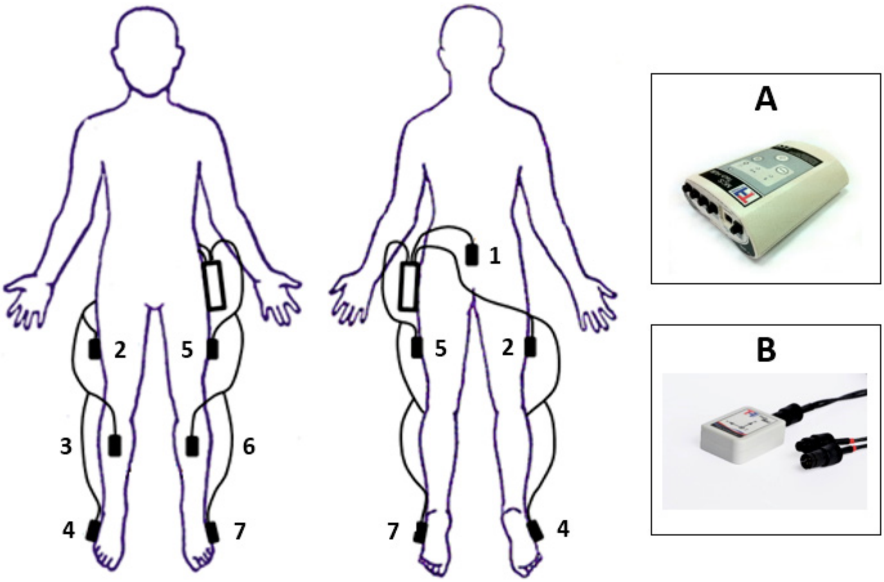

Fig. 1. INERTIAL MEASUREMENT SYSTEM. Position of the IMU sensors (1-Lumbar, 2-Right thigh, 3-Right leg, 4-Right foot, 5-Left thigh, 6-Left leg, 7-Left foot). Tech Hub that manages all the IMUs (A) and Inertial Measurement Unit (IMU) (B).

reads and processes the data acquired using the API (Application Programming Interface) provided by the manufacturer (gUSBamp MATLAB API).

2.2 Motion Capture System

The motion capture system used in this work is the Tech MCS (Technaid S.L., Spain). This product is a complete wireless motion analysis system. It manages seven Inertial Measurement Units (IMUs) which are used in the experiments (see Figure 1). Each Tech-IMU (Technaid S.L.) integrates three different types of sensors as an accelerometer, a gyroscope and a magnetometer.

In this work, the seven IMUs are distributed as follows: three sensors are placed on each lower limb (foot, thigh and leg) and the last one is placed on a lumbar position. Each IMU registers 19 variables corresponding to different parameters as rotation (nine parameters corresponding to the rotation matrix), acceleration (three parameters, m/s^2), angular velocity (three parameters, rad/s), magnetic field (three parameters) and temperature. Rotation parameters are used to detect gait initiations and stops. This data are acquired through a HUB that is connected to the PC USB port with a data acquisition frequency of 30 Hz.

3 Experimental Procedure

3.1 Test Protocol

To detect the different states of human gait, brain activity will be analyzed. For this purpose, a proper test protocol has been designed. The protocol consists of the execution, on a voluntary basis, of several changes in the gait state of the user. To that end the user performs, for each session, several initiations and stops of walking without using any external stimulus to indicate each of these changes. Voluntarily, users are asked to perform a total of 10 initializations and stops of the gait process, with a waiting period of more than two seconds between each of the changes. This requisite is applied to assure the minimum window time required to detect the onset and the end of movement using the ERD phenomenon (see Section 3.3).

Three male users aged between 22 and 29 years old (26.7±4.0) took part in the experiment. Each of them carried out a total of 8 runs per session with 10 complete cycles of motion (relax/start/walking/stop). All of them completed two sessions performed in two different days.

3.2 EEG Signals Processing

In order to enhance the EEG signals quality it is necessary to increase the signal-to-noise ratio. The amplifier includes several internal filters that can be applied to the input signals. Due to the fact that EEG signals are very noisy, two of these internal filters are applied. In the current work, a low pass filter with a cut off frequency of 100 Hz and a 50 Hz notch filter to eliminate the power line interference have been applied. Moreover, an 8th order Butterworth band pass filter programmed in MatLab from 5 Hz to 40 Hz is applied to remove artifacts and the DC component, preserving only the information of the frequencies of interest, which are *mu* and *beta* frequency bands (between 8 and 30 Hz).

Then, a spatial filter is applied to all EEG channels to reduce the contribution of the remaining electrodes in each channel and therefore to better isolate the information collected from each sensor. To do that, a Laplacian algorithm is applied to all the electrodes. This algorithm uses the information recorded from all the remaining electrodes and their distances to the sensor of interest. 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:

$$Vi^{LAP} = Vi^{CR} - \sum_{j \in Si} g_{ij} Vj^{CR} \tag{1}$$

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,

$$g_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{j \in Si} \frac{1}{d_{ij}}} \tag{2}$$

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

3.3 Data Selection

ERD is a phenomenon which refers to the decrease of the EEG signal power in the *mu* and *beta* bands related to the preparation and performance of voluntary motor tasks. This desynchronization starts about two seconds before the movement onset as it is stated in [14]. The study shows that ERD appears over the contralateral Rolandic region and becomes bilaterally symmetrical immediately before execution of a right hand movement. Although the movement performed in our experiment is not the same, we hypothesize that it may occur in the same time interval and also over the motor cortex. When the performance of the movement ends, the *mu* and *beta* bands recover the power and produce the event-related synchronization (ERS).

Typically, ERD-based research uses around two seconds width windows to analyze this phenomenon. As it is explained in Section 2.2, the kinematic data recorded are used to determine the current state of the walking cycle. The detection of the initialization and the stop of the gait allows the classification of the data in four different groups (Figure 2). Data between three seconds prior to gait onset and the onset itself is established as *Start* state. The same occurs with the *Stop* state, which is considered between three seconds prior to the end of the walking process and the end itself. Data between these states are considered as *Relax* state (between a *Stop* and a *Start*) and *Walking* state (between a *Start* and a *Stop*). With this procedure, a bigger amount of data is obtained for the *Walking* and *Relax* states (twice the size of *Start* and *Stop* data approximately). Using these data, the training model allows a better identification of these two states (*Walking* and *Relax*) avoiding false detection (False Positive or FP) of the *Start* and *Stop* states.

3.4 Feature Extraction

The four data groups obtained in Section 3.3 are segmented in windows of 1 second each 0.2 seconds (overlap of 0.8 seconds). Each window is processed separately to extract the features which represent the task. The selected EEG data are processed with a Fast Fourier Transform (FFT) to compute the spectral power. The features are the sums of three frequency bands, 8-12 Hz, 13-24 Hz and 25-30 Hz per each electrode which represent *mu* and *beta* bands, so 96 features define each class (32 electrodes, 3 features per electrode).

3.5 Classification

To determine the state of the walking cycle, a SVM-based (Support Vector Machine) classifier is used. The SVM classifier is a very useful technique for data classification [15]. To do the classification, SVM makes use of a hyperplane or

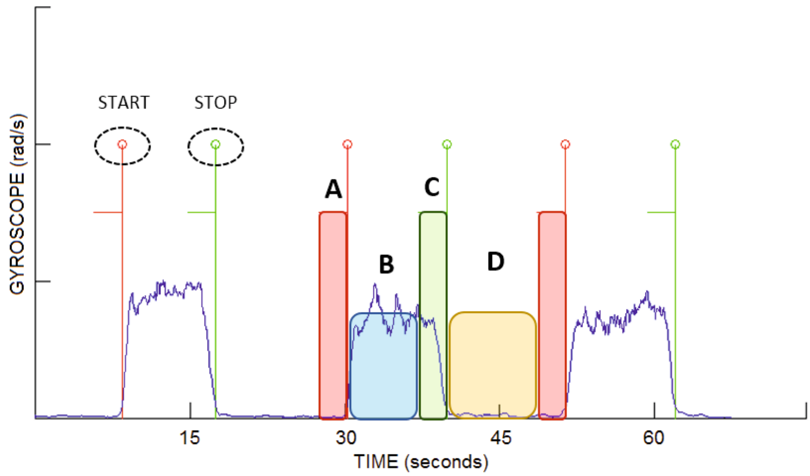

Fig. 2. DATA SELECTION. In this figure, the gyroscopes analysis is shown. *START* and *STOP* detections are marked. Moreover, the data used as *Start* (A), *Walking* (B), *Stop* (C) and *Relax* (D) are also represented.

groups of it in a very high (even infinite) dimensional space to distinguish the different classes to classify. The accuracy of the SVM-based classifier depends on the kernel used. In the case of a BMI system, generally a Gaussian kernel or a Radial Base Function (RBF) is applied [16]. In this case, a SVM-based system with a RBF kernel is used. A one-step multiclass strategy is used in the SVM system. In order to create the model and to detect the gait state, the data obtained following the procedure described in Section 3.4 are used.

After performing the classification of the four states (R:*Relax*, S:*Start*, T:*Stop* and W:*Walking*) the following confusion matrix is obtained:

$$\begin{array}{cc} & \textit{Detected} \\ & \begin{array}{cccc} R & S & T & W \end{array} \\ \textit{Real}\begin{array}{c} R \\ S \\ T \\ W \end{array} & \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \end{array}$$

where c_{11} is the *Relax* Success Rate, c_{22} the *Start* Success Rate, c_{33} the *Stop* Success Rate and c_{44} the *Walking* Success Rate. The *Relax* Error Rate and the *Walking* Error Rate correspond to c_{12} and c_{43}, respectively. The remaining elements of the confusion matrix do not affect a correct performance of the system, as a consequence, they are not taken into account when calculating the accuracy of the system.

To validate this system in the control of real devices such as an exoskeleton, two more parameters are defined: True Positive Rate (TP) and False Positive Rate (FP). TP represents the number of valid commands sent to the exoskeleton

Table 1. Cross validation results. *Relax* and *Walking* states

	SUCCESS RATE (%)		ERROR RATE (%)		FP/min
	Relax	Walking	Relax	Walking	
User A.1	65.5	75.3	8.2	3.8	16.6
User A.2	63.7	75.7	13.1	6.7	18.7
User B.1	84.7	86.4	6.7	9.6	17.7
User B.2	69.4	63.6	11.1	8.9	22.3
User C.1	72.5	75.9	3.3	3.7	10.3
User C.2	67.2	73.1	4.9	2.4	6.9
Average	**70.5**	**75.0**	**7.9**	**5.9**	**15.4**

divided by the total number movement intentions for the states *Start* and *Stop*, respectively. FP represents the number of incorrect detections during *Walking* or *Relax* divided by the time the user stays in the corresponding state.

4 Results and Discussion

The results for the classification of the different gait states are shown in Tables 1 and 2. These results are calculated offline, by analyzing the data after an 8-fold cross validation (each session run is used as a fold). In Figure 3, an example of classification is shown (User A, one fold). In order to design a useful detection system for the control of rehabilitation or assisting devices, it is important to obtain a reliable behavior in the execution of control commands (*Start* and *Stop* states in this case). As it was mentioned in Section 3.3, the method followed allows a better detection of the rest periods (*Relax* state) and the continuous walking (*Walking* state). In Table 1, the behavior of the system in the detection of these states is shown.

Firstly, columns labeled as "SUCCESS RATE (%)" show the system accuracy in the detection of *Relax* and *Walking* states. In columns labeled as "ERROR RATE (%)" the error in the classification of these states is shown. An erroneous *Start* detections during a *Relax* state or wrong *Stop* detections during walking are considered as an error (or False Positive). Finally, the number of False Positives detected per minute (column "FP/min") is represented. This parameter is very important in the design of this kind of control systems. The error rates show a good classification index regarding this parameter (7.9% in *Relax* periods and 5.9% in *Walking* periods). However, the number of FP/min is too high (15.4 FP/min on average). This parameter should be reduced to be useful in a real time application. Taking into account these accuracies, all the users obtained similar results. However, User C achieved lower FP/min than the rest of the users. Furthermore, Table 1 shows a good success rate for the *Relax* and the *Walking* periods for all users, reaching and average of 70.5% and 75.0% respectively.

On the other hand, in Table 2, the success rate for the *Start* and the *Stop* states are shown (columns labeled as "SUCCESS RATE (%)"). The number of

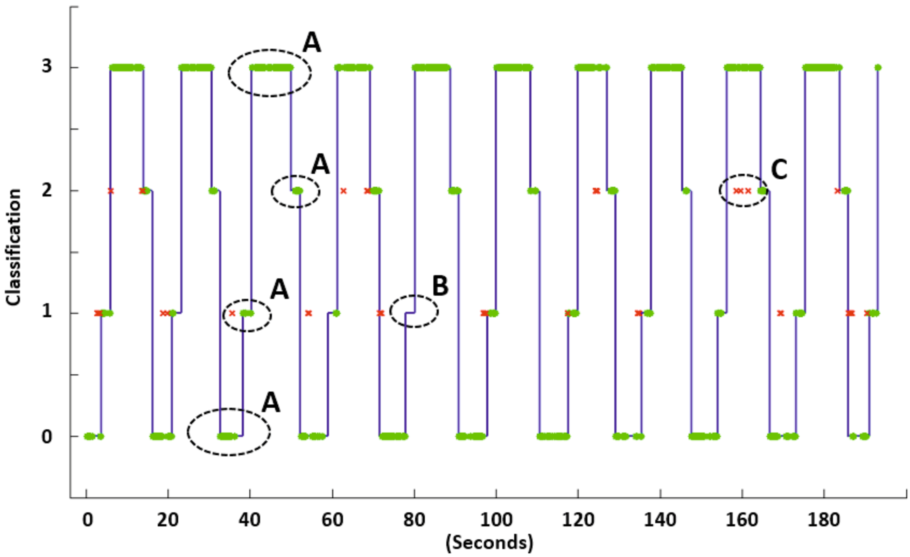

Fig. 3. DATA CLASSIFICATION. Y-axis represent the task performed (0-Relax, 1-Start, 2-Stop and 3-Walking). Data marked as A represent the correct detection of the four different states of the gait cycle. B is a not detected gait intention. C represents an error in the classification which provoke False Positives.

Table 2. Cross validation results. *Start* and *Stop* detection

	SUCCESS RATE (%)		TP rate (%)
	Start	Stop	
User A.1	34.4	26.3	82.2
User A.2	49.5	36.5	94.1
User B.1	32.2	16.4	62.9
User B.2	42.0	13.0	66.2
User C.1	15.1	8.5	55.8
User C.2	10.3	1.1	30.2
Average	**30.6**	**17.0**	**65.2**

events properly classified is represented in the "TP rate (%)" column. Regarding success rates, these values are not very high. However, this accuracy does not represent the actual control commands of the system, but the number of trials that have been detected inside the movement window selected to analyze movement intention (*Start* or *Stop*, according to the method explained in Section 3.3). In relation to the "TP rate (%)", User A obtained clearly a better classification than User B and a remarkably higher rate than User C, who achieved the worst results.

5 Conclusions

In this paper, a method to detect different states during walking activities is presented. The system shows the possibility of detecting gait onset and stop by using the brain activity measured from EEG signals. The system shows a good accuracy in the detection of these states but the number of False Positives is still to high to apply this methodology to a real-time system. Future works must reduce the number of FPs in order to increase the reliability of the system in real-time applications. With this improvement, the system could be applied to control a wearable robot in rehabilitation or assistance procedures performed with patients with motor disabilities. To reduce these FPs, other data features and classifiers must be tested.

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