Platform for Multimodal Signal Acquisition for the Control of Lower Limb Rehabilitation Devices

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Abstract: Patients with some sort of motor disability may benefit from robotic rehabilitation since it can provide more control, accuracy and variety of training modes. This enhances the efficiency of the rehabilitation and, therefore, the recovery of the patient. Assistive devices, like exoskeletons or orthoses, can make use of physiological data, such as electromyography (EMG) and electroencephalography (EEG), in order to detect the movement intention. Combination of data can potentially improve the adaptability of assistive devices with respect to the individual demands. Different methods can be applied depending on the neuromuscular disorder, therapy or assistive device. In this work, we present a multimodal interface which integrates EEG, EMG and inertial sensors (IMU) signals. Experiments were conducted with healthy subjects performing lower limb motor tasks. The aim of the proposed system is to analyze the movement intention (EEG signal), the muscle activation (EMG signal) and the limb motion onset (IMU signal). An experimental protocol is proposed. The results obtained showed that the system is capable to acquire and process the biological signals synchronously. Results indicated that the system is able to identify the movement intention, based on the EEG signal, the movement anticipation, based on the muscle activation, and the limb motion onset.

1 INTRODUCTION

The number of individuals with some sort of lower limbs disability due to several reasons as stroke and spinal cord injuries is increasing (Tsukahara et al., 2009). Such disabilities can also lead to secondary problems, like wheelchair dependence, osteoporosis and bedsores. Therefore, these disorders are likely to decrease the quality of life. In order to recover or enhance the lower limbs functions, rehabilitation programs are the most used treatment (Ju et al., 2005).

Robots have been introduced in rehabilitation as a potential tool to implement physical therapies since they can assist therapists performing repetitive movements (Denève et al., 2008).

Exoskeletons or orthoses are assistive devices often used in robotic rehabilitation. Besides all the challenges brought from the structural design and construction, the assistive devices should support self-initiated movements for intuitive interaction. This is desired in systems controlling neuroprosthetic or neurorobotic devices that aim to assist patients with motor disabilities as naturally as possible, i.e. reducing the impact of the assistive technology (Ibáñez et al., 2013). This can be achieved by adapting the control of the device with respect to the patient's intention (Kirchner et al., 2014). Those devices can make use of physiological data in order to detect or predict limb movement. The combination of such data can be used to improve the reliability of assistive rehabilitation robotic systems.

The integration of physiological data-based recognition into the control of an assistive technical device has a great advantage which is the earliness of prediction (Muralidharan et al., 2011). A prediction of movement onset that was based on EEG analysis can, for example, be confirmed by the detection of muscle activity and corroborated by measuring the limb

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motion onset. Thus, a multimodal system provides not only the intention to move but also shows the actual execution of the movement and the position of the lower limbs during the rehabilitation. Thus, it is possible to characterize a volitional movement from its planning to its execution (Gallego et al., 2012). This approach was implemented in different studies.

Rocon et al. proposed functional compensation of upper limb tremors with a soft wearable robot using EEG, EMG and IMU analysis (Rocon et al., 2010). Ibanez et al. proposed an adaptive and asynchronous EEG-based system for online detection of the intention to move in patients with tremor (Ibáñez et al., 2013). Kirchner et al. showed that the combination of EEG and EMG can potentially be used for movement prediction and improve the adaptability of assistive technical devices through an offline analysis (Kirchner et al., 2014).

In this study it is proposed a multimodal platform that enables the synchronization and the analysis of electroencephalographic (EEG) signal, electromyographic (EMG) signal and Inertial Measurement Unit (IMU) signal. The aim is to analyze the movement intention, the muscle activation and the effective movement of lower limbs through EEG, EMG and IMU signals, respectively.

This paper will have the focus on the architecture of the synchronization, and implementation of an offline analysis, of EEG, EMG and IMU data, acquired in a lower limb movement task, in order to identify the activation steps. An experimental protocol, which involves sensors placement, is proposed for the tasks performed by healthy subjects. The platform can be used in the development of interfaces for rehabilitation robotics devices aiming at adapting their control with respect to the patient's intention.

2 MATERIALS AND METHODS

The equipment used to acquire the EEG and EMG data was the BrainNet® BNT-36 (Lynx Eletronica, Brazil). It is based on the requirements of general safety for medical electrical equipment and has the approval of the entities responsible for regulation of medical products.

EEG signal was recorded using a international 10-20 system cap. The positions used were Fp1, Fp2, F7, F3, Fz, F4, F8, C3, Cz, C4 and Pz.

A bipolar channel was used to acquire a surface EMG (sEMG) signal. Passive Ag/AgCl gel electrodes were positioned on the right subject's thigh, according to the international protocol SENIAM (Hermens et al., 1999) at the rectus femoris muscle, as it can be seen in Figure 2.

Tech MCS®(Technaid, Spain) was used to acquire the inertial signals. This system provides real time spatial orientation for each sensor. Two IMUs were used in the experiments.

2.1 Control Architecture for Data Acquisition

A C#-based software was developed for the integration of both commercial systems described above. It uses the UDP communication protocol to send and receive data packages from BrainNet® BNT-36. A library, provided by the manufacturer of the Technaid system to capture data through the USB computer port was also used. The data were synchronized and saved in a computer and processed offline. The data acquisition of the software developed was validated using the calibration sinusoidal signal provided by Brainet® BNT-36 and also by controlled experiments doing rotations of the IMUs. A representation of the system developed can be seen in Figure 1.

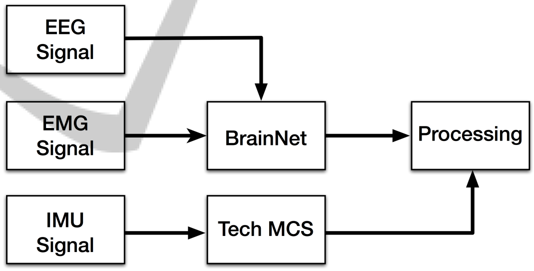

Figure 1: Representation of the platform proposed.

Figure 1 represents the proposed platform, as it is can be seen, the software proposed integrates the EEG, EMG signals acquired using the BrainNet® BNT-36 with the IMU signal acquired using the Tech MCS® system. All data were synchronized and saved in a computer for a offline processing, as illustrated.

The sampling frequency of the BrainNet® BNT-36 was set to 600Hz, the maximum possible value. The sampling frequency of the Technaid system was set to 50Hz, compatible with the leg movement performed in the experiments. The data processing is made by MATLAB®-based software.

2.2 Experimental Protocol

Three female and one male, healthy and right-handed, subjects with ages between 22 and 24 performed the experiments. The proposed experiment was developed according to the protocol approved by Research

Ethics Committee of Federal University of Espírito Santo Health Sciences Center (Project n. 214/10).

During the experimental session, subjects were comfortably seated with hands resting on the legs and with feet suspended, without touching the ground. The angle between thigh and shank was assumed to be 90°. The calibration of the inertial system occurs in this step. An acoustic signal indicates the end of the calibration and the beginning of the experiment. After about 10 seconds, another acoustic signal indicates that the subject is allowed to perform the extension and flexion of the knee using both legs, from rest position up to maximum extension. The Figure 2 illustrates a subject during the experiment wearing all sensors.

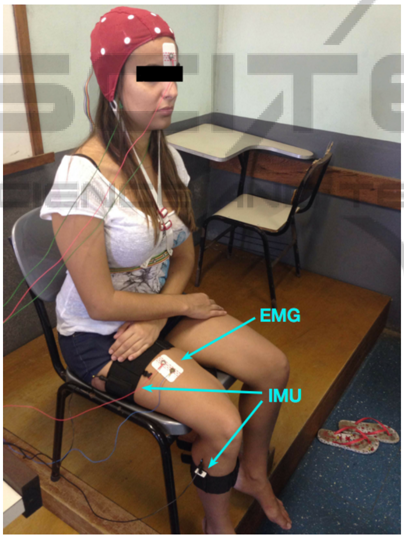

Figure 2: User wearing the complete set of sensors during an experimental session.

The inertial sensors were positioned on the right thigh and shank of the subject. The placement protocol doesn't require specific placement or any alignment between the sensors because the alignment was done virtually during the data processing. The only recommendation was to place the sensors on the external part of the leg, as it can be seen in Figures 2 and 4. The movement was assumed to be only in the shank.

The protocol selected for the experiments defines a self-chosen moment after hearing the acoustic indication to start the movement. The subject thinks and immediately executes the task. The examiner asks to the subject to perform the movement slowly and to keep the eyes open, avoid blinking and swallowing. Each experiment was composed by 30 trials of extension and flexion movement and one trial lasts approximately 30 seconds. A graphical representation of one trial can be seen in Figure 3.

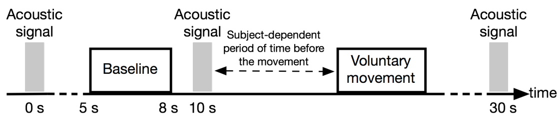

Figure 3: Graphical representation of one trial.

Figure 3 illustrates one trial of the experiments performed. As it can be seen, there is a subject-dependent period of time before the voluntary movement, after the second acoustic signal.

3 SIGNAL PROCESSING

The signal processing was made of two different ways. To EEG signal, a multi-trial analysis was performed while the EMG and IMU signals analysis were a single-trial. Making not possible the presentation of these three signals together.

3.1 EEG Signal Processing

EEG signal was used to estimate the movement intention of the subject. In order to achieve this estimative, the Event Related Desynchronization (ERD) characteristic was evaluated by the classical method described by (Pfurtscheller and Lopes da Silva, 1999).

The signals were filtered at μ and β bands by Butterworth 4th order bandpass filters and the energy was obtained.

The EEG signals were then analyzed under a percentage scale based on a baseline, represented in Figure 3. The baseline was evaluated between the 5th and the 8th seconds of the experiment, while the subject was resting before the second acoustic signal.

3.2 EMG Signal Processing

EMG signal was used to estimate the muscle activation of the subject during the experiment. For each trial, the data was preprocessed with a variance filter defined by the Equation 1. In Equation 1, N is the length of the window used for filtering, x is the EMG raw signal and v is the EMG preprocessed signal. This processing was chosen for preserving the initial muscle activation moment and for providing enough differentiation between the rest and contraction positions, as described by (Kirchner et al., 2014; Tabie and Kirchner, 2013).

An adaptive threshold classifier, as described by the Equation 2, based on the mean and standard deviation, obtained in the baseline evaluates the initial muscle activation. The signals were processed on windows with a length of 10 samples with 90% of overlapping.

$$v(t) = \frac{1}{N-1}\sum_{i=0}^{N}[x(t-i)]^2 - \left(\frac{1}{N-1}\sum_{i=0}^{N}x(t-i)\right)^2 \quad (1)$$

$$T(t) = m_N(t) + pd(t)_N \quad (2)$$

In Equation 2, T is the threshold, m is the mean value, d is the standard deviation and p the sensitivity factor of the threshold. N represents the length of the window used to obtain the mean and the standard deviation. The moment of muscle activation is defined when the first window, between a predetermined number of consecutive windows, exceeds the threshold. For each subject a leave-one-out cross validation analysis of the data was performed and for the parameters optimization a grid search was used.

3.3 IMU Signal Processing

IMU signal was used to detect the movement onset, i.e. the beginning of the limb displacement, and to measure the angles of the knee joint. The three clinical knee rotations occur: flexion/extension, abduction/adduction and internal/external rotation (Favre et al., 2009). The thigh and shank can be represented by links and the clinical rotations by β, γ and α, respectively, as illustrated in Figure 4.

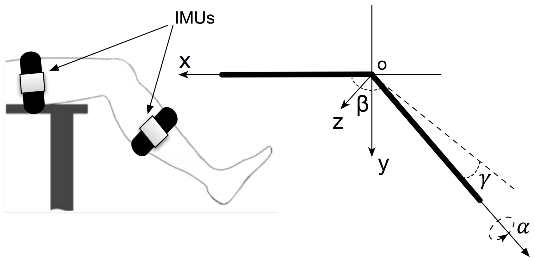

Figure 4: Inertial sensors placement, link-segment representation of the leg and clinical rotations.

The angles measured between the thigh and the shank were the relative angles between the sensors. In order to measure these angles, the world reference frame of the shank sensor was transformed to reference frame of the thigh sensor.

The sensors were supposed to be aligned in x and z axes and to have an angle equal to 90° between the y axis when the calibration of the inertial system occurs, as described in the experimental protocol and illustrated in Figure 5.

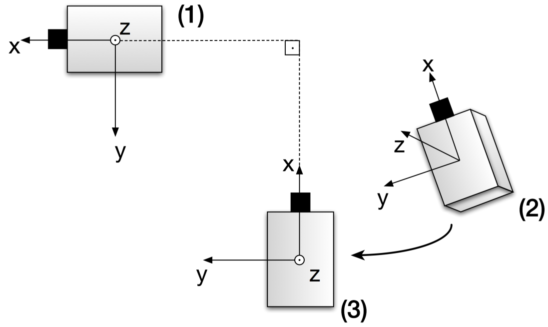

Figure 5: Representation of the virtual alignment between the inertial sensors.

A virtual alignment between the sensors was done, achieving this configuration, in order to provide a placement protocol regardless of sensors position. Figure 5 shows the real shank IMU represented by (2), the virtual shank IMU represented by (3) and the thigh IMU is represented by (1).

The data from the IMUs were analyzed using a threshold in order to determine the start of effective movement. The data were also converted into Euler angles in order represent the angles of the knee joint movement along the tasks.

4 RESULTS AND DISCUSSION

In Figure 6, the relative energy of μ and β bands of the EEG signal is shown for the subject two. The first five seconds were not shown because they represent a signal stabilization and should not be taken into account. The last five seconds were not shown because the trials were synchronized to the first moment of movement along the trials, thus some samples had to be discarded in the end of each trial. The ERD characteristic can be seen in all channels, mainly in the Cz, C3 and C4, which are positioned on the motor cortex. In these channels the relative energy reaches a decrease of approximately 80% in the μ band. The ERDs are seen, approximately, from the 10th second on. This is consistent with the movements performed in the experiments.

In Figure 7, one trial of EMG, preprocessed with a variance filter, of the subject two is shown. The time scale is the same of Figure 6. An initial muscle activation can be seen in the 11th second, approximately. The end of the muscle activation occurs in the 13th second, approximately. This is consistent with the time that the subject perform the extension and flexion of the knee.

In Figure 8, the Euler angles related to the IMUs signals for the same subject are shown. The angles

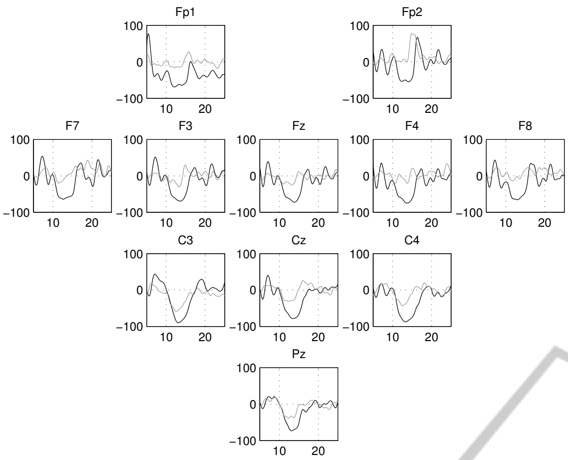

Figure 6: Relative energy of μ (black) and β (gray) bands, in percent scale vs. time in seconds, obtained by an average of 30 trials.

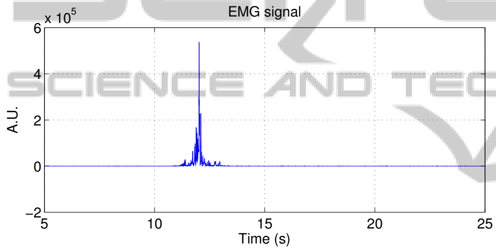

Figure 7: One trial of EMG signal preprocessed with a variance filter.

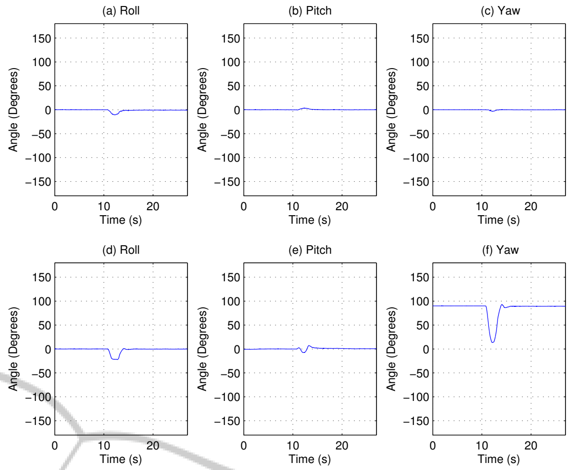

Figure 8: One trial of IMU signals from both sensors, showing Roll (a), Pitch (b) and Yaw (c) for the thigh sensor, and Roll (d), Pitch (e) and Yaw (f) for the shank sensor.

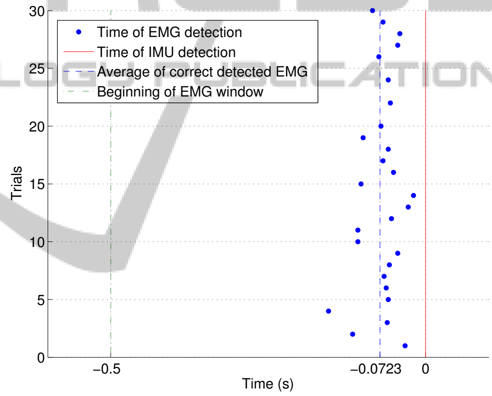

Figure 9: Distribution of prediction times for EMG-based movement prediction for the subject three.

are related to the thigh sensor in calibration position. In this figure, above, are shown the thigh sensor angles. As it can be seen, only a small displacement occurs. Thus, the movement can be considered only in the shank. Below, the shank sensor angles are shown. As it can be seen, mainly displacement occurs in Yaw, which is related to the extension and flexion. The initial value was 90°, as considered in the experimental protocol and obtained with the virtual alignment. The final value depends on the subject's extension. A small displacement occurs in Roll and Pitch, which is consistent with the clinical knee rotations. As it can be seen, the initial limb displacement occurs, approximately, in the 11th second.

In Figure 9, the distribution of prediction times for EMG-based movement prediction for the subject three is shown. Time point zero corresponds to the physical movement onset, represented by the red line. The dash-dot green line at time $-0.5s$ indicates the range up to where predictions based on EMG were allowed. The movement onset up to the line at time $-0.5s$ was considered the EMG-window. The dashed blue line represents the mean of EMG-based time predictions, which in this case was $72.3ms$ before the movement onset. Only the classifications in the EMG window are shown.

The classification results are summarized in Table 1. In Table 1 it is shown the accuracy of the EMG classifier and the mean time of initial activation, taking into account only classifications inside the EMG-window with the standard deviation. The accuracy is defined by the Equation (3).

$$Ac(\%) = \frac{N_{EMGW}.100}{N_T} \tag{3}$$

Where Ac is the accuracy of the system, N_{EMGW} is the number of trials in which the EMG is classified in the EMG window and N_T is the total number of trials per experiment. As it can be seen, the accuracy range was 46.67% up to 93.33%. The system can classify the activation before the EMG window, inside the EMG window, after the movement onset or can not identify the activation. Thus, for the subject

Table 1: Classification results of EMG-based prediction for all subjects. The accuracy of the classification and the mean time of EMG-based prediction inside the EMG-window with the standard deviation.

Subject	Accuracy (%)	Time (ms)
1	70.00	-91.60 ± 91.30
2	46.67	-90.90 ± 130.70
3	93.33	-72.30 ± 46.20
4	57.67	-52.25 ± 51.40
Average	66.92	-76.74 ± 79.90

one and, mainly, for the subject three, is reached a high level of accuracy. According to (Kirchner et al., 2014), activations before the EMG-window were considered false positives. Taking into account all the classes of classification, regardless of whether the detection anticipates or not the movement onset or the detection is classified before the EMG-window, 100% of the trials were detected by the EMG classifier for all subjects.

The difference of accuracy between the subjects is directly related to the EMG time of activation, since it defines the position of the EMG classification between the classes. The EMG time of activation depends on many factors and vary between subjects and trials, as it can be seen in Figure 9 and according to the results achieved by (Kirchner et al., 2014).

The execution of the movement depends on many motor unit-related parameters, e.g. twitch force, contractile speed, axonal conduction velocity, fatigue resistance, among others (Pons, 2008). Furthermore, the surface electromyographic also depends on the skin-electrode coupling which contributes to different signals between subjects. Based on the study of these characteristics, the length of the EMG-window can be adapted for each subject. This can decrease the number of wrong classifications of false positives. For subjects whose accuracy is lower, the movement prediction can be complemented by an EEG-based prediction.

Depending on the type of neuromuscular disorder and state of therapy, both, single EEG or single EMG-based movement prediction, might no longer result in good performance. In this case, the combination of multimodal data should be even more relevant (Kirchner et al., 2014).

5 CONCLUSIONS

A multimodal platform for lower limb studies in rehabilitation based on EEG, EMG and IMU signals was developed. An experimental protocol, applied in healthy subjects to acquire data from the platform, was also proposed. An offline analysis of the data generated by this system in a lower limb movement task was showed.

The analysis estimates the subject's movement intention evaluating the ERD characteristic in the EEG signal and the muscle activation in the EMG signal. The beginning of the movement was evaluated by IMUs data, which also measure the angles between the thigh and the shank of the subject during the tasks performed.

The accuracy and the mean time showed the feasibility of the interface proposed. Under a qualitative analysis and based on the Figures 7, 8 and 9, the system proposed was capable to acquire, synchronize and process the combined signals. Thus, the platform proposed can be used in the study and development of multimodal interfaces. Prosthesis or orthoses whose purpose is motor rehabilitation, adapting the control of devices with respect to the patient's intention, can be developed with the platform proposed.

Results presented here were achieved in an offline processing. In future work, a single trial algorithm whose purpose is to analyze the EEG signal in order to find MRPs will be applied. A platform which uses online detection of EEG and EMG data will be applied to an exoskeleton, which is currently under development.

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