VIRTUAL REALITY UPPER LIMB MODEL CONTROLLED BY EMG SIGNALS

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Abstract. This work presents the design and development of a six-channel system for acquisition and conditioning of electromyographic signals collected in the upper limb. The main objective of the work is to create a system that can be used as rehabilitation and training instrument for potential users of myoelectric prostheses. Using software rendering, feature extractions, classifier training and design of the mechanical model of the human arm, with the running movements of flexion, extension, pronation and supination of the forearm and the grasp in a reality environment virtual, providing rehabilitation therapy to different patients.

1. Introduction
Assistive technologies have emerged in recent years in order to provide rehabilitation devices for people with varying degrees of disability. Especially for upper limb amputees, or patients with reduced mobility and control, several devices have been developed and find clinical application [1]. Nowadays, the construction of prosthetic systems as extensions of any human body limb has huge improvements, which present essential features such as: flexibility, aesthetic, lightweight and multi-functionality.

Many robot systems for upper limbs rehabilitation have been developed, such as MANUS system, which has two degrees of freedom (DOF) for active control of force-feedback, and conducted clinical tests with successful results [2]. Specifically designed for neurorehabilitation, the ARMin device [3] is an exoskeleton with 6 DOF, in which the patient is positioned in a wheelchair and the arm is attached to the structure to complete the exercise sequence. It allows a complete position control and preserves the natural biomechanics of the elbow and shoulder joints, assuring the patient comfort. The ArMin is equipped with force and position sensors and has three functioning modes: movement therapy mode, game therapy mode and ADL training mode. Another alternative for upper limb rehabilitation is the use of Virtual Reality (VR) tools, providing visual feedback to the user, by the repetitive exercises or in game like tasks. In this area is important to cite the works of Adamovich et al [4] and Morrow et al [5], between others.

Similarly, science and engineering have made significant advances in the area of digital signal processing, especially surface electromyographic signals (sEMG) and its applications in the control of active devices. Moreover, sEMG are used as control input in devices [6] designed for post-stroke rehabilitation programs, or Virtual Reality (VR), using the information contained in the signal about the intentionality of the user and the muscular force involved.

The main objective of this work is to design a system capable of acquire sEMG signals, digitalise and process them, to be used as a control input to a virtual object that represents a model of the upper limb. This VR object emulates the user’s movements, providing a training system for potential prosthesis users or to patients with reduced mobility in the upper limb, by repetitive exercises or tasks performed in the VR environment.

A customized circuit was designed to acquire the six channels sEMG of the upper limb, constructing a data base of ten normally limbed subjects. Software was developed under Matlab®/Simulink® that performs the A/D conversion, processing and classification of user intent,
done by an artificial neural network (ANN). Finally a control strategy for real-time simulation is performed and the virtual reality animation allows the visualization of upper limb movements, to validate the results.

The paper is organized as follows: Section II explains the design and developing of the acquisition stage, the database, the sEMG signal processing, feature extraction and simulation of the VR object. In Section III, the results of sEMG signals classification using different combinations of features parameters are showed and finally, the conclusions are exposed.

2. Materials and Methods

2.1. Design and developing of the acquisition circuit

The block diagram of Figure 1 provides an overview of the building blocks of the front-end circuit that amplify the information contained in the sEMG signals and that way separate them from any noise. The sEMG signal is captured by disposable surface electrodes (Ag-AgCl), which are highly stable and the electrolytic gel junction provide a very low noise level. They are connected to the amplification stage using shielded cables, supporting mobility. An embedded instrumentation amplifier, INA 129, of Texas Instruments® was used, setting the gain in 950V/V. For electrical safety conditions, an optical isolation stage was interposed between the subject and the devices connected to the (electric) voltage line, feeding the circuit with two batteries of 9 Volts. Then, signals are filtered by a 4th order bandpass Butterworth filter, in Sallen-Key structure, with cutoff frequencies between 10Hz and 500Hz. The circuit was designed with six acquisition channels. Only four of them were used for the classification of movements, leaving the possibility of acquiring sEMG signals from other muscles with other purposes. The A/D conversion is performed by a PCI 6024-E from National Instruments® board, with a sample frequency of 1KHz [7].

![Figure 1: Block diagram of the designed system.](image)

2.2. Database

After previous informed consent, sEMG data corresponding to six classes of motion were collected from 4 volunteers, all normally limbed subjects, (3 male, 1 female, 27 ± 3 years old). Electrodes were placed in *brachial biceps*, *brachial triceps*, *brachioradialis* and *pronator teres*, during flexion, extension, pronation and supination of the forearm, and grasp, all them interspersed with rest. The users were prompted to perform the movements by a video, which assures the task execution in the programmed time. The test is divided into two sequences; one is used for training the classifier and the other one for validation. Also, an extra session is done by the subjects to control the virtual arm in real time.
2.3. **EMG Processing, Feature extraction and Classification.**

All digital processing is performed using the Matlab/Simulink® software. In order to avoid the electrical line interference a digital notch filter was used, with a cutoff frequency of 50 Hz and a Q factor of 250. Due to the accumulative properties of the sEMG descriptors, it is very important to remove the noise of baseline, in order to avoid erroneous control commands (Fig. 2). The data was segmented into non overlapped windows of 50 ms (N samples) to obtain a feature vector of each segment. Several sEMG features are described in bibliography, in temporal or frequency domain [8]. However, the choice of the best feature vector was made selecting those descriptors that better represent the information contained in the signal, without detriment of the real-time performance. The features selected are good estimators of the muscular force developed during contraction. These are:

*Energy:*

\[ E = a \sum_{i=1}^{N} x_i \]

*Integral of Absolute Value:*

\[ IAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \]

*Willison Amplitude:*

\[ WAMP = \sum_{i=1}^{N} f(|x_i - x_{i+1}|) \quad f(x) = \begin{cases} 1 & \text{if } x > \varepsilon \\ 0 & \text{otherwise} \end{cases} \]

*Waveform Length:*

\[ wl = \sum_{i=1}^{N} |\Delta x_i| \quad \Delta x_i = x_i - x_{i-1} \]

The continuous feature vector resulting (Fig. 3) is suitable for the use as control reference. The classification was implemented by an ANN, using a multilayered backpropagation learning algorithm. We implemented a network of three hidden layers with 16, 12 and 8 neurons in each and 6 neurons in the output layer. Figure 4 shows the training vectors corresponding to a sequence of the six described movements.

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Figure 2: Up: Raw sEMG signals. Down: sEMG filtered and without noise baseline.
2.4. Virtual Model of the Upper Limb.

The next stage is the upper limb modeling, represented by cylindrical and spherical rigid bodies, with the SimMechanics® and Virtual Reality® toolboxes [9]. Firstly, the tasks, movements and dimensions of the upper limb need to be defined. Inertial parameters, mass and center of gravity were calculated according with the average of the measurements made in the volunteers. Also, bodies’ moment of inertia, degrees of freedom and coordinate axis must be specified in the toolbox, to use the virtual reality environment. The signals obtained in the classification stage are translated to control commands by a PID control system, controlling the VR model actuators that emulate the behavior of the upper limb. These actuators include rotational joints in the elbow, wrist and fingers.
The elbow joint was used as reference to the forearm segment and hand, which are represented by a cylinder and a sphere. Fingers were represented only by two segments. Finally, sensors and actuators blocks inserted in the model provide the interaction tool with the others Simulink blocks (Figure 5). The control is implemented by a PID controller.

![Block diagram of the Upper Limb Model in SimMechanics®](image)

3. Results

The ANN validation was done offline with the data for that purpose. Table 1 shows the average percentage of positive ratings (APPR) per volunteer, calculated by the porcentual relation between the number of successful movements and the total number of movements, by one hundred.

| VOLUNTEER 1 | VOLUNTEER 2 | VOLUNTEER 3 | VOLUNTEER 4 |
|-------------|-------------|-------------|-------------|
| APPR [%]    | 69,75       | 92,5        | 72,75       | 82,5        |

Table 1: APPR considering E, IAV, WAMP and WL.
It is noted that the average ranges from 69.75% to over 92%. The variability among volunteers is attributed to sEMG signals which differ from causes such as the location of electrodes, layout and individual physiology, among others.

In order to reduce the computational time, only WAMP and IAV features were taken into account, and Table 2 presents these results. It is possible to see that the volunteer 2 increase slightly the average score, while the remainders suffer moderate decrease.

| VOLUNTEER 1 | VOLUNTEER 2 | VOLUNTEER 3 | VOLUNTEER 4 |
|-------------|-------------|-------------|-------------|
| APPR [%]    | 49.5        | 93.75       | 56          | 76.25       |

Table 2: APPR considering WAMP and WL.

Table 3 presents the effect occurred when only the WAMP is extracted from the signals, showing a significant decrease of the APPR, especially in a couple of volunteers that are under the range of accepted values.

| VOLUNTEER 1 | VOLUNTEER 2 | VOLUNTEER 3 | VOLUNTEER 4 |
|-------------|-------------|-------------|-------------|
| APPR [%]    | 31.25       | 84.5        | 50.25       | 70.75       |

Table 3: APPR considering WAMP

From the above, it is possible to conclude that efficiency and good performance of the classifier depends more on the feature extraction stage, than for the classifier in itself. The virtual model was tested online with all subjects, demonstrating a good performance and acceptance. The users do not report any lack of controllability, nevertheless the system is not able to correctly identify the grasp state in all situations. (To see an experimental session, please visit http://www.youtube.com/watch?v=bGsZUq_8mYA)

4. Conclusions and Discussion

The system proposed can be used as a complete training rehabilitation device, due to its portability, lightweight and embedded signal conditioning. The algorithms and model developed in Matlab has the potentiality to be compiled as executable software, and used in any personal computer. The control objective of this work was accomplished and also, a versatile and documented sEMG signals database was obtained.

The different stages of signal processing (pre-processing, feature extraction and classification) provide a control signal that was used in the actuators of the virtual model. By the results presented, it was demonstrated that the use of a feature vector, consisting of E, IAV, WAMP and WL, generates the best results in the classification process. The use of ANN is one of the best alternatives to the sEMG signal classification, by their ability to learn and solve problems that are not linearly separable. This allowed us to get offline classification rates higher than 70%. The virtual model of the upper limb was built with SimMechanics®, providing a VR environment in which is possible to perform online experiments and check the results obtained offline.

We conclude that this system can be used as wearable robot simulator, for upper limb rehabilitation and also as training stage for potential users of myoelectric prostheses. Future works include the use of microcontrollers, inclusion of programmed tasks in the VR environment and shoulder simulation, in order to add more degrees of freedom to the model. Also, the system must be tested with people with upper limb disabilities.
Figure 6: The virtual model performed with the V-RealmBuilder Toolbox®, which simulates online the movements made by the volunteers

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