Biomedical Interface for the Control of Robotic Systems Using sEMG Signals

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***Abstract*—Surface electromyographic signals (sEMG) have contributed to the improvement of human well-being in applications such as rehabilitation devices, prosthesis and human machine interfaces. Systems based on sEMG signals require some form of machine learning algorithm for the recognition and classification of specific patterns in muscle activity. This paper introduces a framework that combines a classification algorithm and a real-time robotic simulation. The aim is to develop an interface capable of controlling robotic devices depending on the movement executed by the user in real time. For the classification stage, two common classifiers were evaluated using signals from a public database and signals from a proprietary database. Furthermore, a method where signals are divided into segments prior to feature extraction was evaluated. The performance of the complete system was evaluated using sEMG signals acquired and processed in real time.**

***Index Terms*—Electromyographic signals, robotic interface, neuronal networks, support vector machines**

I. Introduction

The study of bioelectric signals has contributed significantly to the development of medical assistance devices, whose objective is to improve the human well-being, both physical and psychological, of people with motor disabilities. For example, surface electromyographic signals (sEMG) are commonly used for actuation and handling of prostheses. Taking advantage of the information provided by this type of signals about the electrical activity generated in specific muscles, as mentioned in [1] and [2].

The great advantage of myoelectric control in prostheses and in other types of devices is that it offers automatic control. This means that manual activation or control via switches is not required as with assistive devices or prosthetics that require mechanical control. On the other hand, the acquisition of signals in a non-invasive way using surface electrodes, contributes to the comfort of the users who control these devices. Helping to improve the quality of life of people who require medical assistance devices.

The main goal of this work is the development of a biomedical interface for the control of robotic devices through the acquisition, filtering and analysis of surface electromyographic signals. To achieve this, the use of a classification algorithm is proposed, which allows separating sEMG signals according to their class, using feature vectors of the signal as input information. To ensure that this algorithm presented high performance, the performance of a classifier based on support vector machines (SVM) was compared with one based on neural networks (NN).

With a high-performance classification model, it is possible to implement an interface that simulates the behavior of a robotic system and an algorithm capable of translating the results of the classifier into commands. In order to visualize the manipulation of a robotic system according to the acquired sEMG signal.

This article proposes a framework composed of a series of stages that are presented below. Two main series of experiments are also presented, first using data from a public database. And the following using data from a proprietary database and data acquired in real time.

II. Background

A. Electromyographic Signals (EMG)

Electromyographic signals are bioelectric signals generated due to electrical activity that occurs in the muscle fiber during muscle contraction or relaxation. Specialists rely on EMG signals to detect pathologies related to neuromuscular activity and diseases. Such as muscular dystrophy, inflammation of the muscles, nerve damage, etc [3].

These signals produced by motor neurons when activating the muscles of the body generate voltages that are usually between 0 and 6 mV. With frequencies between 0 to 500 Hz, highlighting the signals of greater intensity in the range of 50 to 150 Hz [4].

B. Related Works

The study of bioelectric signals has contributed to the development of different projects that aim to improve human well-being. In particular, surface electromyographic signals (sEMG) represent a very important and widely used tool because they can be easily obtained non-invasively and without medical supervision.

The main objective to study these signals is the development of methodologies that allow the control of rehabilitation devices, as in [1] and [5], where a hand prosthesis whose movements are controlled by EMG signals is implemented. As well as the development of pattern recognition algorithms in real-time applications, as in [6] where, through pattern

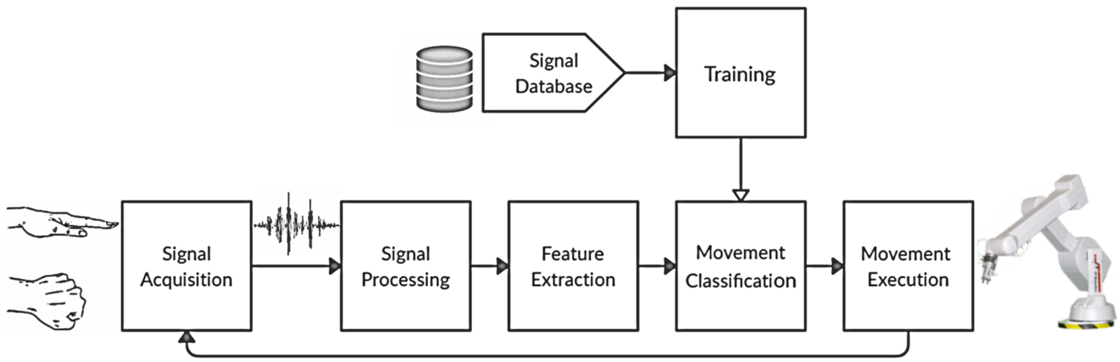

Fig. 1. Proposed Framework.

recognition in EMG signals, six types of hand movements were identified.

In other studies such as the one done in [2] a system based on neural networks (NN) is proposed for the identification of patterns. After having made a comparison among neural networks (NN) and support vector machines (SVM) to evaluate which one presented better results in the proposed application.

The studies shown in [2] and [7] detail experiments aimed at determining which features are most relevant and effective for pattern recognition. Demonstrating that extracting time-domain features from the sEMG signal involves less processing time than extracting features in frequency and time-frequency domains.

III. Proposed Framework

Figure 1 illustrates the proposed method in which the real-time movement of a robotic device is controlled through the acquisition, processing and classification of sEMG signals. The command executed by the robotic device is determined by the movement/gesture detected.

A. Signal Acquisition

The first stage uses surface electrodes and biomedical equipment to acquire surface electromyographic signals in real time. This information is subsequently sent to the computer for future analysis and processing.

B. Signal Processing

Given the nature of electromyographic signals and that they are obtained using surface electrodes, an additional filtering process is required to the acquired data. According to investigations such as [4] and [8], it was determined that EMG signals present frequencies ranging from 0 to 500 Hz, presenting greater activity in the range of 50 to 150 Hz.

Therefore, a filtering stage is proposed to extract this range of more prominent activity and to eliminate the effect of unwanted frequencies and noise from artifacts.

C. Feature Extraction

The feature extraction stage consists mainly of selecting a series of representative values for a given data set. In order to represent the signals by feature vectors, which will be used in the classification stage.

The number and type (time/frequency domain) of features to extract depend on the problem, the nature of the signal and the amount of data available.

D. Training

This stage must be done before running the final system. In this step, the classifier is trained with previously acquired signals, properly labeled and stored in a database.

E. Movement Classification

In this stage, the feature vectors are used as input to the classifier, in order to determine which movement/gesture was executed by the user. This classification algorithm is expected to be as robust, fast, and accurate as possible.

F. Simulation/Interface

In this final stage, the system translates the results of the classifier into commands that are sent to a robotic system, which executes the movement established according to the class predicted by the classifier.

IV. Experiments and Results

In order to validate the proposed method, two series of main experiments were carried out. First, feature extraction tests and classifier training tests were carried out using recordings of different grip types from a public database. Finally, experiments were carried out using signals acquired from a test subject to validate the algorithms for acquisition, processing and classification of surface electromyographic signals in real time.

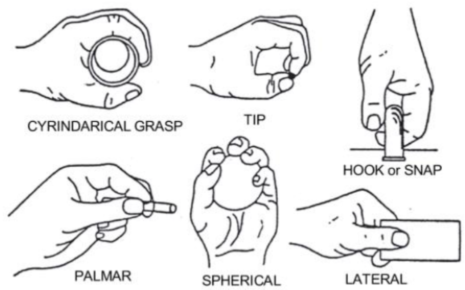

Fig. 2. Different classes contained in the database [9].

A. Experiments Using Basic Hand Movements Signals from a Public Database

The database used in these experiments is available in [9] and includes surface electromyographic signals from 6 hand movements. The data were collected at a sampling rate of 500 Hz, using as a programming kernel the National Instruments (NI) Labview. The signals were band-pass filtered using a butterworth band pass filter with low and high cutoff at 15 Hz and 500 Hz respectively and a notch filter at 50 Hz to eliminate line interference artifacts.The subjects were two men and three women aged between 20 and 22 who carried out 6 grasps 30 times each in a time interval of 6 seconds. The signals were taken from two differential EMG sensors and transmitted to a 2-channel EMG system.

Two types of classifiers were evaluated and compared: a multi-class Support Vector Machine (SVM) and a Neuronal Network (NN). For the SVM, two types of kernel were tested: linear and polynomial. Performing 5-fold cross validation on each run. On the other hand, for the NN a model with 10 neurons in the hidden layer was implemented, using 80% of the data for training and 20% for validation and testing. These classifiers were selected since they are common, simple and do not require high computational power.

Three time-domain features were extracted to represent the signals: Mean Absolute Value (MAV), Zero Crossings (ZC) and the Waveform Length (WL). Only time-domain features were used since they can be calculated easily and quickly. Furthermore, previous research such as [2] report satisfactory results using temporal features in real-time applications. To evaluate the performance of the classifiers and the set of features, each classifier was trained and evaluated ten times for each subject. According to the data from the database, six classes were considered, which are shown in Figure 2. The average classification results are shown in Table I.

TABLE I
AVERAGE CLASSIFICATION ACCURACIES FOR EXPERIMENTS USING A PUBLIC DATABASE.

Test Subject	Avg. Acurracy (%)		
	Linear SVM	Polynomial SVM	NN
1	88.3	88.3	95.6
2	95.0	92.2	97.8
3	87.8	88.3	96.1
4	95.6	96.7	98.9
5	93.9	93.3	98.9

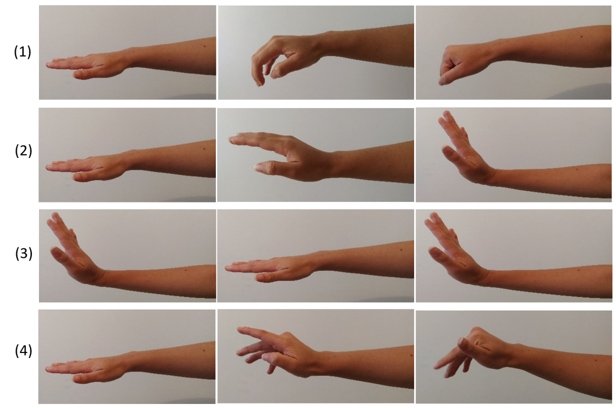

Fig. 3. Hand gestures considered: 1) clench, 2) up, 3) up-up, and 4) tap.

B. Experiments Using Signals Acquired in Real Time

1) Data Acquisition and Processing: A Bitalino and an Arduino were used for the real-time signal acquisition stage. The Bitalino has four channels, two of which can sample EMG signals. For these tests and for the final simulation in real time signals are acquired by two channels at a sample rate of 1kHz. In the processing stage, two IIR Butterworth digital filters were applied to the sEMG signals. These types of filters were used because they present a smooth frequency response, are fast to execute, and require little computational power. The first filter consists of a band-pass with cut-off frequencies at 20 and 450 Hz. In order to extract the range of frequencies with the greatest muscle activity and to delimit the noise from the equipment. The second filter was a band-reject filter with cut-off frequencies at 58 and 62 Hz, to eliminate possible noise from the electrical network.

2) Data Collection: A database with a collection of 160 sEMG signals was generated. 40 repetitions for each gesture shown in Figure 3. Each gesture was performed with the same level of effort and rested between takes. The sEMG signals associated with each gesture, are those generated during the transition from a resting position to the actual hand gesture and back to the resting position. The sEMG signals stored in this database are properly labeled according to the gesture performed for classifier training purposes.

On the other hand, 3 records were made where each movement shown in Figure 3 was made 5 times, this in order to have new information to validate the previously trained classifier.

3) Training and Classification: Based on the results shown in Table I, the classifier with neural networks presented higher performance than the SVM one. Therefore, for the following tests only neural networks were used.

Two techniques were used to train the classifier. The first was the same as the one used with the public database, where features are extracted from the raw signal. The next technique

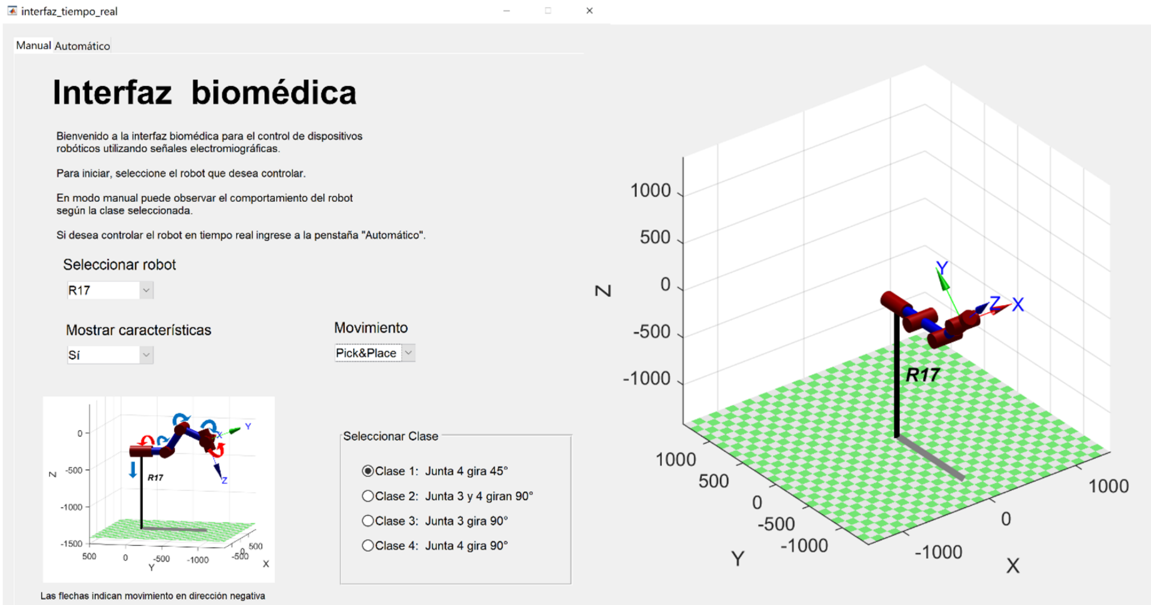

Fig. 4. Manual control for the R17 robot.

divides the sEMG signal into two segments of equal length to capture the structural information of the signal. For each segment of the signal, the following features were extracted: Mean Absolute Value (MAV), Zero Crossings (ZC), Root Mean Square (RMS) and the Waveform Length (WL).

TABLE II
AVERAGE CLASSIFICATION ACCURACIES FOR TEST AND VALIDATION RECORDINGS.

Recording	Avg. Acurracy (%)			
	MAV-ZC-WL		MAV-ZC-WL-RMS	
	Method 1	Method 2	Method 1	Method 2
1	83.0	88.5	87.0	91.5
2	94.5	95.0	97.5	96.0
3	91.8	92.8	88.9	92.1

Table II shows the average results of evaluating the neural network ten times for both techniques with two different sets of features. According to these results, the technique that divides the sEMG signals into segments presents better results. Likewise, the four-feature set is better in performance and accuracy.

4) Robotic Interface: For this stage, a graphical user interface (GUI) was used. The interface is divided into two main tabs: Manual and Automatic. The first tab allows the user to control the robotic system manually as shown in Figure 4. Letting the user familiarize himself with the robotic device models available and observe the movement that will be executed by the robot according to the classification results. In addition, the user can choose between two forms of movement. One, based on Pick-and-Place applications, where the robot executes a trajectory. Starting from the origin and ending in the configurations shown in Table III. The second movement option, executes a control per joint, where one joint is moved at a time individually based on the classification results.

TABLE III
JOINT CONFIGURATION ACCORDING TO EACH CLASS FOR THE R17 ROBOT.

No. Class	Joint (rad)					
	J1	J2	J3	J4	J5	J6
1	0	0	0	$\pi/4$	0	0
2	0	0	$\pi/2$	$\pi/2$	0	0
3	0	0	$\pi/2$	0	0	0
4	0	0	0	$\pi/2$	0	0

The second tab runs an automatic control of the robotic system as shown in Figure 5. This tab continuously shows the sEMG signal acquired in real time, the features extracted and the class number predicted by the classifier.

V. DISCUSSION AND CONCLUSIONS

The purpose of this research was to demonstrate that the proposed framework allows the development of a system capable of controlling robotic devices using sEMG signals. To implement and validate the different stages of the framework, data from a public database and data from a database created with signals acquired in real time were used.

For the first set of experiments, we evaluated commonly used classifiers and simple features. The classification results were good with accuracies in the range of 80% to 98% as shown in Table I. With these results it was concluded that it is better to use neural networks than support vector machines to carry out the classification in the final system, since NN present better performance. These tests also demonstrate that using time-domain features is enough to obtain accurate re-

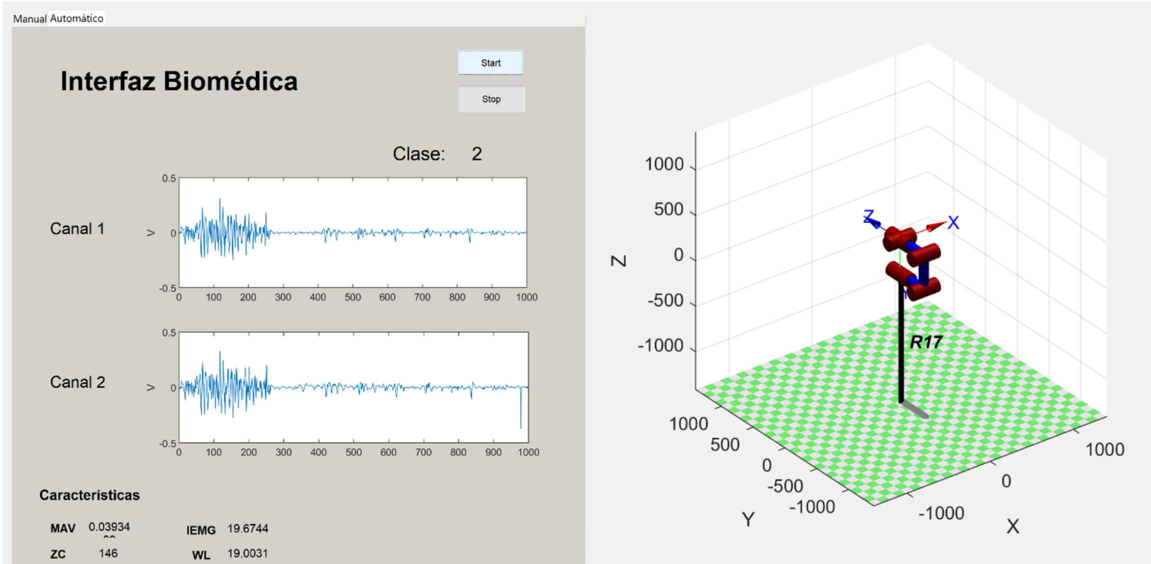

Fig. 5. Automatic control for the R17 robot.

sults. Besides being easy to calculate and implement in real time applications.

For the second set of experiments, we evaluated the segmentation of sEMG signals before extracting the features in each segment. The results of Table II show that for the proposed framework it's better to use this technique to obtain higher accuracies. Therefore, for the final system a classifier with neural networks was used, the division of sEMG signals into segments of equal size after their acquisition was implemented and the following features were calculated: MAV, ZC, WL and RMS.

Finally, the functionality of the final system was demonstrated using the data obtained in real time, a previously trained classifier and a graphic user interface (GUI). Proving that the proposed framework achieves the ultimate goal of controlling robotic devices by acquiring and processing sEMG signals in real time and implementing classification methods based on pattern recognition.

In the future, we envision that the proposed framework will contribute to the scientific community and to the development of medical assistance devices controlled by bioelectric signals such as surface electromyographic signals.

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