A BCI to Control Serial-link Manipulators Using EEG Signals

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***Abstract*—Over last years Brain Computer Interfaces (BCI) have been investigated to facilitate the communication between humans and machines. This paper introduces a framework to control different serial-link manipulators with electroencephalographic (EEG) signals in real time. Different features such as MAV, ZC, kurtosis, variance, band power, maximum-minimum distance and wavelets were calculated to test the performance of two different supervised machine learning algorithms, Artificial Neural Networks and Support Vector Machines with cubic polynomial kernel. A classification accuracy of 91.10% was obtained with ANN and five time domain features. Three robotic devices were developed: the UR5, the R17 and the Puma 560 with their respective soft joint trajectories to be activated by the interface. The Graphical User Interface (GUI) was developed to be intuitive and user friendly, it shows in real time the signals captured, features extracted, classification results and robot commands. It also allows the user to control the robot in automatic or manual mode.**

***Index Terms*—BCI, EEG, ANN, SVM, GUI, Serial-link Manipulator**

I. Introduction

Human beings are developing new technologies trying to improve people's life. One example of these new technologies is the Brain Computer Interface (BCI). Research on BCIs began in 1973 when Jacques Vidal from the California University began to research in methods for data processing. The first tests with noninvasive BCIs were made in the 90s trying to understand in a better way the cerebral activity [1].

These researches depend significantly of the type of data that is used, and this data depends directly from the type of device that is used to measure the signals. The medical and professional devices measure high fidelity signals but have the disadvantage of their high cost. That's why researchers choose to use the low fidelity noninvasive devices as in [1], [2], [3] & [4]. The reason why to use this low fidelity but functional devices is the accessibility for everyone worldwide.

In the last decade the researchers have focused in signal processing and different methods to extract features from them. First, they thought that electroencephalographic (EEG) signals were random values, but they found different mathematic models in time, frequency or time-frequency domain that allows to recognize patterns in signals and classify them [3] & [5]. Signal processing is fundamental to control robots like in [6] where they control a robot or in [2] & [7] where they control a prosthesis.

During this research we develop a first phase of a BCI to control robots from the department of Electronics, Mechatronics and Biomedical engineer of the Universidad del Valle de Guatemala. The following sections present a proposed framework to control serial-link manipulator using EEG signals.

The rest of the paper is organized as follows: Background is presented in Section II. Section III shows the Proposed Framework. Details of the Classifier Validation and GUI Design are given in Section IV. In Section V, Discussion and Conclusions are presented. Future work is suggested in Section VI.

II. Background

A. Electroencephalogram

The electroencephalogram is a study that measures the electrophysiologic activity and records the electric activity of the brain. This has a direct relationship with the neural activity inside the brain. The signals that the electroencephalogram records are known as EEG and they are voltage fluctuations from the ionic current between brain's neurons in a period of time [5].

Recording EEG signals is considered complex because they are considered stochastic signals that presents variations depending on different factors such as: cranial structure of the patient, mental state of the patient, concentration level, muscle movements, involuntary movements and the position given to the electrodes [5].

EEG signals have been used in different researchs trying to control robots or prosthesis, like in [2] and [4]. Both researchs use low fidelity EEG sensors like in this research.

B. Pattern Recognition in EEG Signals

Feature extraction is a process that transforms the input space onto a low-dimensional subspace that preserves most of the relevant information [3]. In this paper we used features in time and time-frequency domain, such as: mean absolute value (MAV), zero crossing (ZC), variance (v), kurtosis (k), band power (bp), maximum-minimum distance (MMD), and wavelets.

Machine Learning is an application of Artificial Intelligence that builds mathematic models from training data to make predictions or took decisions. It is when machines are capable to learn and improve from experience without being explicitly programmed [8]. In this research we use two types of supervised machine learning algorithms that are Support Vector Machines (SVM) and Artificial Neural Network (ANN), these algorithms were also used in [9], [10] and [11].

Support Vector Machine is a supervised algorithm that builds model of classification from training data previously classified, it tries to find the best line, plane o hyperplane depending on the dimension of the problem that can divide correctly de data [12].

Artificial Neural Network is a supervised algorithm guided by backpropagation that tries to minimize the loss function. It simulates the way human brain analyzes and processes information, it has a hierarchical organization by layers [3].

C. Brain Computer Interface

A Brain Computer Interface (BCI) is a system capable of measure the cerebral activity and translate it to process it in a computer. They are commonly used to study the cerebral activity in different scenarios. The cerebral activity is presented like EEG signals and their quality depends of the type of BCI [5]. There are three principal types of BCIs that are invasive, parcially invasive and non invasive. The signals of better quality are obtained from the invasive BCI, but it needs neuro surgerys. That is the main reason why researches prefer the non invasive BCI, despite the quality of the signal is not as good as in invasive methods [5].

Different types of BCIs are implemented like in [7] that they used them for clinic purposes and in [13] that they propose a general purpose BCI.

D. Serial-link Manipulator

A serial link-manipulator is a chain of rigid links and joints. Each joint has one degree of freedom that can be translational if it is a prismatic joint or rotational if it is a revolute joint. Motion of the joint changes the relative pose of the links that it connects. The base of the chain is generally fixed, and the other end is free to move and its generally name as end effector [14].

In this work we used three types of serial-link manipulators. The models used were R17, UR5 and the Puma 560. The R17 is a model from ST Robotics [15] that has 5 revolute joints and one prismatic. The UR5 is a model from Universal Robots [16] and has 6 revolute joints. The Puma 560 is a model from Unimation [17] that has 6 revolute joints. All models were developed with the help of Peter Corke Library [14] and ARTE Library [18].

Serial-link manipulators can be controlled with bioelectric signals, like in [11] that they control a industrial robot with EMG signals or in [4] that they control a scale manipulator with EEG signals.

III. Proposed Framework

The proposed framework is illustrated in Figure 1. The EEG signals are processed to denoise them, next the different features are extracted, then the supervised machine learning algorithm is applied to classify, finally the robot executes different commands depending the result of the classification.

While all the process is happening, in the interface there will be the graphics of the different signals, the features extracted, the classification result and the robot command, all in real time. This will be shown in a Guide User Interface developed to organize better the information and allow user to have all things in one window.

A. Signal Capture

This stage of the system uses noninvasive electrodes equipment to acquire EEG signals in real time. The data is sent to the computer.

B. Signal Processing

The next stage consists of processing the signals. The term processing refers to filtering the signal and eliminate background noise and artifact rejection. Different type of filters should be selected depending on the application, the most common filters applied are the notch and the bandpass filter.

C. Feature Extraction

In this stage the processed signals have a dimensionality reduction preserving their relevant information. Different features are selected depending of the type of signal being analyzed, these features can be in the time, frequency, or time-frequency domain.

D. Classification

The features vectors are fed to the classifier previously trained with a training dataset. The classification algorithm is expected to be fast, robust, and accurate in the real time classification.

E. Robot Control

This stage sends a command to the type of robot selected, depending on the classification result received. The classification result and the trajectories are shown in a Graphical User Interface developed to be user friendly and see the signals, classifier and robot control in real time. The commands sent to the robot should consider the time and space restrictions of each model.

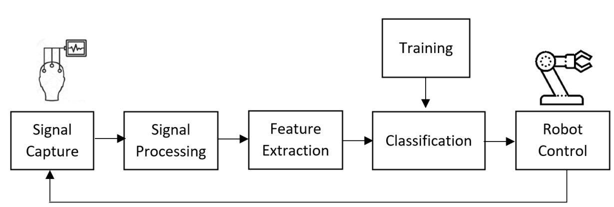

Fig. 1. BCI Proposed Framework.

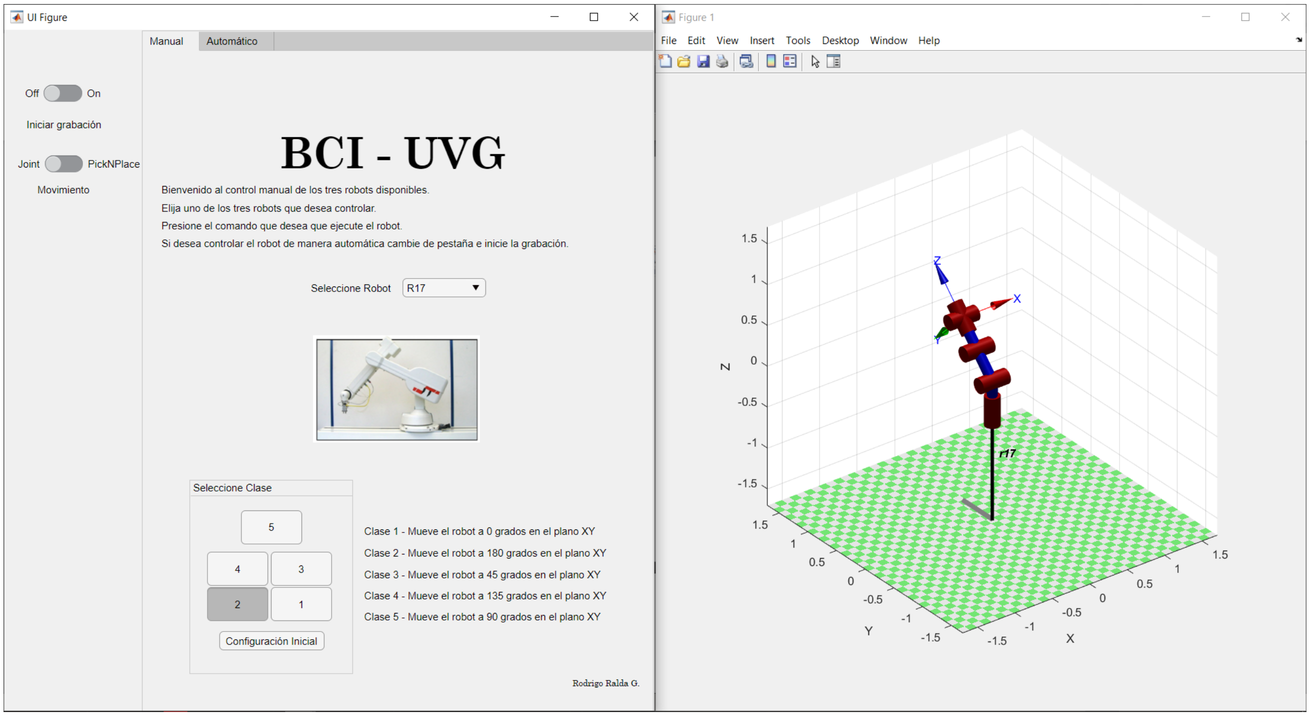

Fig. 2. Manual control per joint for R17.

IV. Experiments and Results

To validate the proposed framework, we have made some experiments trying to simulate a first approximation of what the BCI will look like. To validate the correct classification, we tested different supervised machine learning algorithms, SVM and ANN. Both algorithms were tested with different features, trying to find the best classification performance.

A. Classifier Validation

To validate the classifier, we used a Sleep Database from Physionet [19] & [20]. The database files contain labels identifying the sleep stages with epochs of 30 seconds. The signals used were EEG from channels Fpz-Cz and Pz-Oz, horizontal EOG and submental EMG. The database labels are wake up, stages 1, 2, 3 and REM. This data was analyzed with three different combinations of features as seen in Table I.

The first experiment features calculated were Mean Absolute Value, Zero Crossing, Band power, Kurtosis and Variance. The second experiment features were Mean Absolute Value, Zero Crossing, Band power, Kurtosis and Maximun-Minimun Distance. Unlike the last two experiments where time doain features were used, the third experiment used features in the time-frequency domain, specifically wavelets.

Each experiment was tested with two different classification algorithms, as seen in Table I the ANN present better results than SVM in all cases.

B. Robot Control

For the Robot Control stage, two different routines of movements were developed. The first routine of movements includes five soft trajectories whose final joint configurations are shown in Tables III and II for Puma 560 and R17, respectively. Each trajectory lasts 0.25 seconds. The same procedure was made for the UR5.

The second routine of movements it's a control per joint individually, it only moves one joint at a time. Depending on the classifier result, it only moves one joint at a time 45 °.

C. Graphical User Interface (GUI)

In the GUI there are two main tabs, one for the manual control as shown in Figure 2 and other for the automatic

TABLE I
Classifer Accuracy Results with Three Different Experiments and Two Algorithms.

Features	SVM	ANN
MAV, ZC, bp, k & v	78.80%	90.60%
MAV, ZC, bp, k & MMD	78%	91.10%
Wavelets	84.70%	84.80%

TABLE II
Joint configuration for every class with R17.

Junta/Clase	0	1	2	3	4	5
J1 (m)	0	0	0	0.473	0.473	0.473
J2 (rad)	0	$\pi/2$	$-\pi/2$	$\pi/2$	$-\pi/2$	0
J2 (rad)	0	$\pi/4$	$\pi/4$	$\pi/4$	$\pi/4$	$\pi/4$
J4 (rad)	0	$\pi/4$	$\pi/4$	$\pi/4$	$\pi/4$	$\pi/4$
J5 (rad)	0	0	0	0	0	0
J6 (rad)	0	0	0	0	0	0

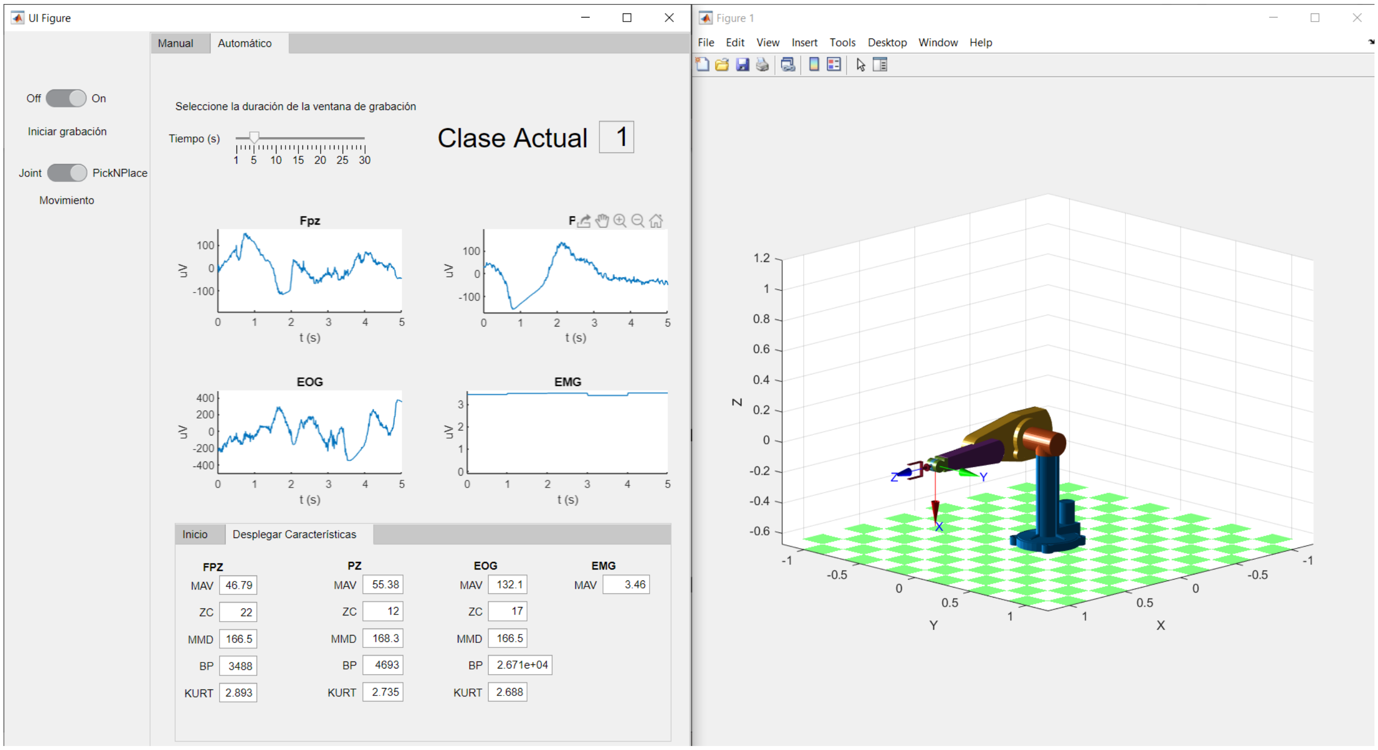

Fig. 3. Automatic control for Puma 560.

control as shown in Figure 3. In the manual tab is possible to manually control the two routines mentioned before. In the GUI there is a button to select if the robot will be controlled automatically or manually. In the manually control the user can get familiar with the types of robots available and the movement that the robot will make depending the result of the classification.

In the automatic control the robot make different movements depending the model and routine selected in the manual tab and the result of the classification. In the automatic tab are shown the signals captured in real time, the features calculated and the result of the classifier. It is possible to select the time length of the capture window in the slider as shown in Figure 3.

V. Discussion and Conclusions

The proposed framework is a first step towards an automated system for controlling Serial-link manipulators with EEG signals in real time. All stages functionality was validated with the data from the public database.

The purpose of this research was to show the possibility of controlling robots with EEG signals based on the proposed framework. The classification accuracy is crucial for the system to work well, so we choose commonly used classifiers with simple features to validate this module. As shown in table I we obtained accuracies of 91.10% with ANN for five time domain features. These features are easy to calculate and implement, so the real time implementation was not affected.

For the robot control module, we made three different models of robots to show the compatibility of the system with different serial-link manipulators. We have also implemented two types of movement routines for every model, to show that the complexity of the trajectories effectuates by the robot depends on the type of application. Its important to remember that the robots have space and time limitations that must be respected.

In the proposed GUI design, they are shown the robots movement, the signals in real time and the classification result. It also allows the user to interact with the robot models in manual mode. This design can be modified or adapted to be more user intuitive. We envision a system based on the proposed framework that helps people in rehabilitation centers and also implemented as assistive robots.

TABLE III
Joint configuration for every class with Puma 560.

Joint/Class	0	1	2	3	4	5
J1 (rad)	0	0	0	$\pi/4$	$3\pi/4$	$\pi/2$
J2 (rad)	$\pi/2$	0	π	0	0	0
J2 (rad)	$-\pi/2$	$-\pi/2$	$-\pi/2$	$-\pi/2$	$-\pi/2$	$-\pi/2$
J4 (rad)	0	0	0	0	0	0
J5 (rad)	0	0	0	0	0	0
J6 (rad)	0	0	0	0	0	0

VI. Future Work

We invite to continue with the next stages of what this research has started and implement the next recommendations.

We recommend for future works to implement the proposed framework with own EEG recordings, the classifiers and features used in this research must be evaluated again with that new data obtained. We also recommend evaluating different features for the classifier like in frequency domain, trying to obtain better accuracy percentages. We also recommend evaluating the intuitiveness of the GUI with different users of different ages, trying to develop a system easy to use for every person who needs it.

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