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Feature Extraction and Classification of sEMG Signals Applied to a Virtual Hand Prosthesis

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Abstract— **This paper presents the classification of motor tasks, using surface electromyography (sEMG) to control a virtual prosthetic hand for rehabilitation of amputees. Two types of classifiers are compared: k-Nearest Neighbor (k-NN) and Bayesian (Discriminant Analysis). Motor tasks are divided into four groups correlated. The volunteers were people without amputation and several analyzes of each of the signals were conducted. The online simulations use the sliding window technique and for feature extraction RMS (Root Mean Square), VAR (Variance) and WL (Waveform Length) values were used. A model is proposed for reclassification using cross-validation in order to validate the classification, and a visualization in Sammon Maps is provided in order to observe the separation of the classes for each set of motor tasks. Finally, the proposed method can be implemented in a computer interface providing a visual feedback through an virtual hand prosthetic developed in Visual C++ and MATLAB commands.**

I. INTRODUCTION

sEMG has been the focus of attention of researchers for many years, and many of these studies on the identification of the sEMG signal have been carried out [1]. Nowadays, it can be said that sEMG is the most powerful source of control signal to develop myoelectric prosthetic arms/hands [2]. The success of myoelectric control depends greatly on classification accuracy, and effective feature extraction and classification methods are crucial to achieve high classification performance in pattern recognition [3].

Applications of pattern recognition for myoelectric control schemes were first introduced in 1960's-1970's [4] and elementary pattern recognition technique such as linear discriminant analysis was used for the identification of sEMG signals [5], [6]. However, due to limited acquisition instruments and computing capacity at that time, real-time control was not feasible. A literature review is available in [7], and parameters like accuracy, number of electrodes, classifier and features were evaluated. The number of electrodes was taken as reference in order to perform comparative analysis. Fifteen kinds of hand motions are identified using four channel of sEMG signals on the forearm, and using feature temporal to control a prosthetic hand.

In our work, in order to analyze the sEMG signals with nonstationary properties, we first make use of sliding windows. Subsequently, we extract three features: RMS, VAR and WL of each window. Then, the features are subjected to cross-validation process with the aim of creating random partitions and then process them through the developed classifiers (Bayesian and k-NN), and finally to analyze the performance. Results showed a margin around 98% of accuracy in some cases, which represents a high success rate according to the literature. According to the average results for the case of the Bayesian classifier was obtained 94% and for the k-NN about 95%.

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A. Previous work

This work is based on our previous works [8], [9], which deals with a methodology of procedures protocol for acquisition of sEMG signal in different types of tasks. Fig. 1 shows the steps of the experimental evaluation of the Bayesian – k-NN based classification system here developed.

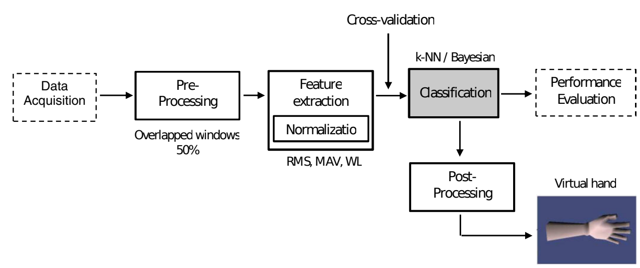


Fig. 1. Steps of the experimental evaluation of the Bayesian – k-NN based classification system.

We try to recognize fifteen kinds of hand motion, separated into four groups: Set 1 (Flexion of single fingers), Set 2 (Flexion of combinated fingers), Set 3 (Wrist actions), and Set 4 (Combined fingers); all with reference to the rest position or Class 1. Table I shows these motor tasks, and Fig. 2 shows the tasks.

B. sEMG Acquisition

Data were captured with an sEMG signal acquisition system connected to a laptop (Core 2 duo, 2 GHz, 3 GB RAM) with battery. The sEMG signals produced by the contraction of muscles are presented to the inputs of an Instrumentation (differential) amplifier with high CMRR. The acquisition system uses an active surface electrodes (Touch Bionics), and the output signals pass through a notch filter at 60Hz to attenuate mains-born interferences. The output signals then pass through a bandpass filter with a 3db cut-off set @ 500 Hz.

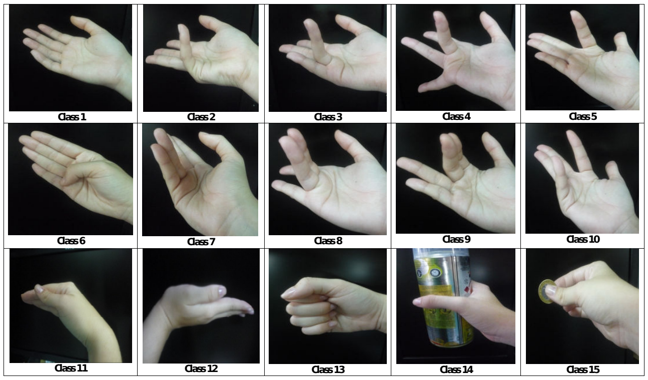


Fig. 2. Motor tasks performed by the subject.

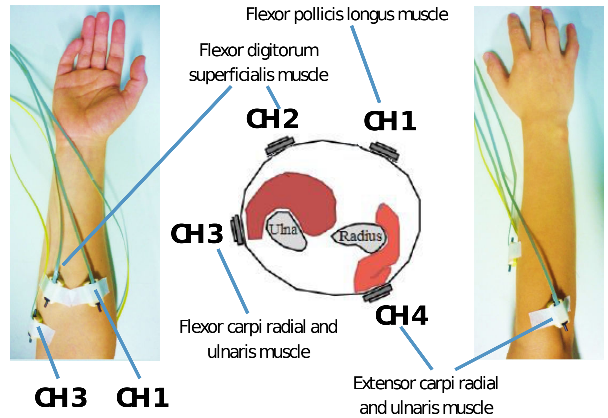


Fig. 3. Real position of the electrodes and transradial cutting of the muscles involved.

The sEMG signals were digitized by an ADC board (NI USB-6009 of National Instruments), and the sampling frequency was 1000 Hz. The signal acquisition circuit has two LM358N ICs, each of them has two operational amplifiers for four channels. In this stage, cut off of the low pass filter is 309 Hz and 5 Hz for the high pass filter. The digitized sEMG signals are then processed to get features for the pattern recognition. We use four surface electrodes to measure sEMG signals, CH1: Flexor pollicis longus muscle, CH2: Flexor digitorum superficialis muscle, CH3: Flexor carpi radial and ulnaris muscle; CH4: Extensor carpi radial and ulnaris muscle, which are the muscles related to hand motions (Fig. 3).

II. Feature extraction

The first step in the analysis of the data was to compute the following features of sEMG signals that have been proposed by the literature: Root Mean Square (RMS), Variance (VAR), Waveform Lenght (WL).

TABLE I
SETS OF MOTOR TASKS.

Set	Class	Task Motion
Set 1	Class 1	Absolutely relaxed
	Class 2	Little finger movement
	Class 3	Ring Finger movement
	Class 4	Middle Finger movement
	Class 5	Index finger movement
	Class 6	Thumb finger movement
Set 2	Class 7	Little and Ring fingers movement together
	Class 8	Ring and middle fingers movement together
	Class 9	Index and Middle fingers movement together
	Class10	Little and Index fingers movement together
Set 3	Class 1	Absolutely relaxed
	Class11	Wrist flexion
	Class12	Wrist extension
Set 4	Class 1	Absolutely relaxed
	Class13	All fingers movement
	Class14	Hand grasp
	Class15	Pinch grip

III. Experimental Results

Four subject participated to the experiments, carrying out motor tasks in three different days, with fifteen hand motions including relaxation for a period of about ten seconds. The mean age of the subjects is 29 years old; three volunteers are right-handed (*Subject 1, Subject 2, Subject 3*) and the last subject is a left-handed person (*Subject 4*).

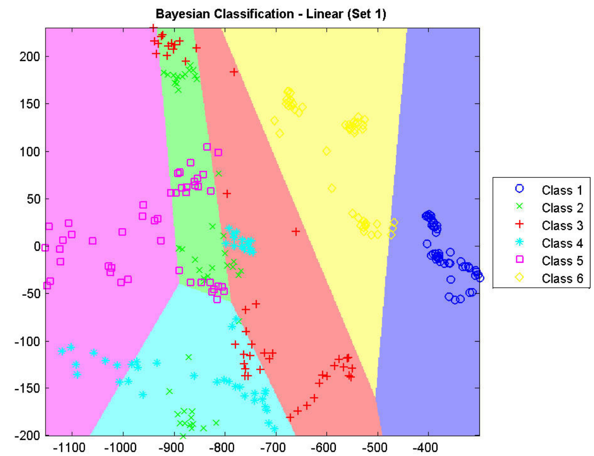
A fifth volunteer (*Subject 5*) was evaluated, which carried out ten days of testing motor performing the same tasks, being a right-handed person. All volunteers were male. Data were analyzed using independent classifiers and classifying according to the following sets of tasks: Flexion of single fingers (Set 1), Flexion of single fingers and Flexion of combinated fingers (Set 1 and Set 2, i.e. Set 1-2), Wrist actions (Set 3), and Combined fingers (Set 4).

The cross-validation strategy used in this work involves splitting a set of samples that can be analyzed in two disjoint sets of data. The most common way of applying the technique of cross-validation is to leave 10% of the samples for the evaluation and train the remaining 90%. When the set of samples is separated into blocks and the number of these is 10, a 10-fold cross-validation is determined. Cross-Validation is a technique considered reliable which provides results in real time [10]. The pattern repeats ten times the training process and the resulting success rate is used as a measure of goodness of the algorithm evaluated [11].

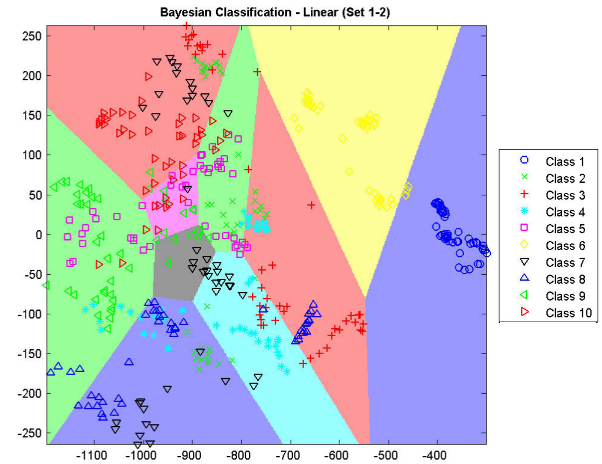
We used two variants of the Bayesian classifier to analyze the data: Linear and Quadratic, obtaining the best results in most cases with the quadratic type, as shown in Table II. Table II show the accuracy for classifiers Bayesian and k-NN.

According to the results, wrist actions (in Linear and Quadratic Bayesian) provide a very good separability which can be also, observed in the Sammon Map as shown in Figure 5-8.

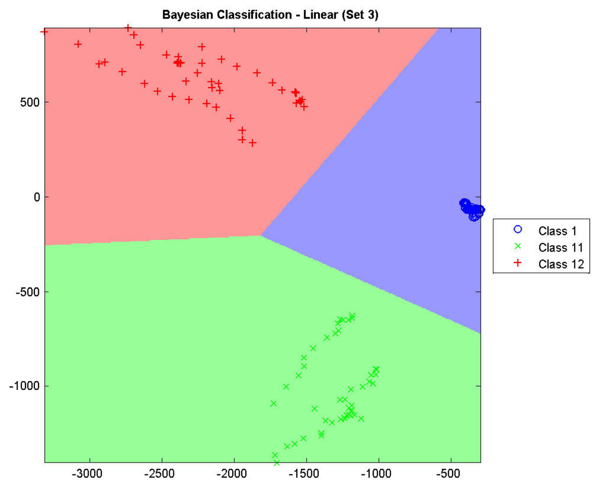
For the case of k-NN classifier, a cross-validation process compares it to thirty Nearest Neighbors specifying a *Euclidean* distance, following the rule *"nearest"* (majority rule with nearest point tie-break).



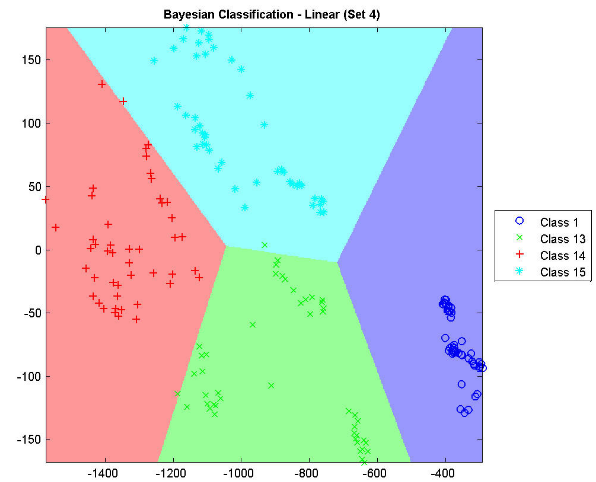
(a) First set (Set 1) of motor tasks.



(b) First (Set 1) and second (Set 2) set, i.e. (Set 1-2), of motor tasks.



(c) Third set (Set 3) of motor tasks.



(d) Fourth set (Set 4) of motor tasks.

Fig. 4. Grouped scatter plot of Linear Bayesian classificacion.

After analyzing with different number of k-folds obtained a slight improvement in the classification for the case of k = 10, i.e, 10-fold, as was proposed in the hypothesis approach for classification.

IV. Virtual Hand Modeling

The virtual hand was designed using free development tools, such as software development and DirectX Blender. Blender is used as modeling tool and has features animation set to the movement of the object model in 3-dimensions and relationship between each joint. The model is composed of various objects with a parent-child relationship where one or more child objects can move independently with restrictions. The encoding of the virtual hand was developed in C ++ in 100 frames per second (fps), fully adjustable.

Human joints have a particular set of movements. In the system of virtual hand, the number of joints defined in relation to the number of angles of the object, and 18 (six Objects: palm, thumb, index finger, middle finger, ring finger and little finger; multiplied by three angles). It is possible to move independently each finger and also the structure of the palm. For example, the thumb can rotate separately, without the wrist joint, however, if the palm rotates the wrist joint, the thumb must rotate with it.

The online system was developed using two channels for handling the tasks of pronation and supination (CH3 and CH4) but using all steps before commented on the development platform. The control panel of the online system is shown in Figure 5.

Two tasks were developed to try to model the human motion to close or open a hand. Tests were performed for approximately 60 seconds and with a sampling rate of 200 ms.

Figure 6 shows a volunteer participant moving the virtual hand with the developed system.

V. Conclusions and Future Works

It is possible to see that in the classification of the Set 1-2, the accuracy rate decreases in both classifiers, due to the fact that similar tasks contain another group of classes,

TABLE II
ACCURACY RATE OF CLASSIFIERS VS DIFFERENT SETS OF MOTOR TASKS.

Subjects	Set Tasks	Accuracy% Bayesian Linear	Accuracy% Bayesian Quadratic	Accuracy% k-NN Average
Subject 1	Set 1	93.01	99.37	96.52
	Set 1-2	77.98	98.42	91.80
	Set 3	100	100	100
	Set 4	100	100	99.62
Subject 2	Set 1	84.26	97.88	90.71
	Set 1-2	77.42	98.68	88.15
	Set 3	100	100	99.85
	Set 4	100	99.58	99.34
Subject 3	Set 1	84.60	97	91.04
	Set 1-2	82.69	94.51	89.73
	Set 3	100	100	99.90
	Set 4	97.03	98.96	96.75
Subject 4	Set 1	82.50	97.17	91.65
	Set 1-2	79.12	96.36	88.10
	Set 3	100	100	99.97
	Set 4	100	100	98.32
Subject 5	Set 1	73.82	94.46	94.73
	Set 1-2	51.06	82.19	89.19
	Set 3	99.82	100	100
	Set 4	90.26	98.59	96.11

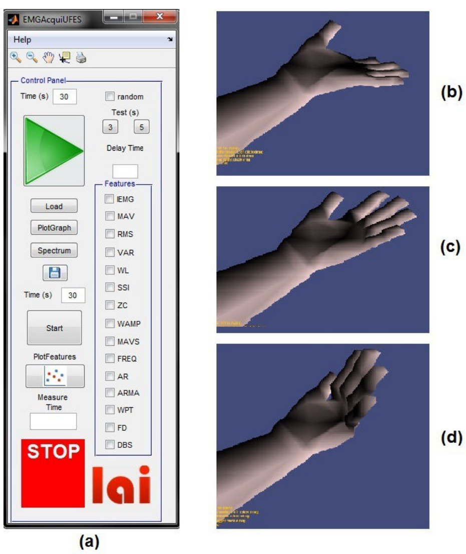


Fig. 5. (a) Control Panel System Online: (b) Virtual hand in the open position; (c) Virtual hand position relaxation; (d) Virtual hand in the closed position.

nevertheless we obtain hit rates of over 98% as is the case of quadratic Bayesian classifier. The wrist movement tasks have scored best hits coming in both cases a 100% of hit rate and high separability in the diagrams Sammon Maps.

The lowest success rate was obtained in recognition of the ten motor tasks (Set 1 and Set 2) in the case of Linear Bayesian classifier (51.06%) as show in Table II.

According to the results of classification performance, analyzing the sensitivity and sensitivity, it is concluded that the best classifier is the Bayesian quadratic type.

In the case of the implementation of the online system, it provided high response speed (200 ms) for changes in hand movements. With the development of this work, it was possible to obtain a biofeedback tool for an amputee which has the ability to get around according to a preset and adaptable system here proposed.

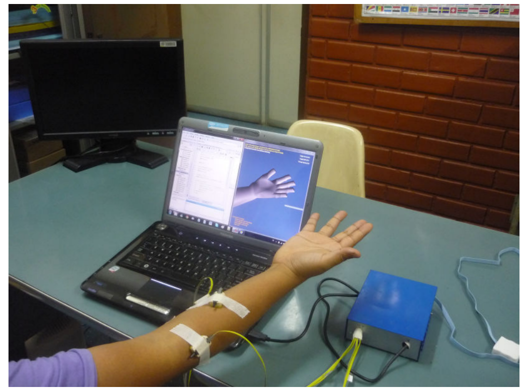


Fig. 6. A voluntary controlling a virtual hand.

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