Expert committee classifier for hand motions recognition from EMG signals

Clasificador comité de expertos para el reconocimiento de movimientos de la mano usando señales EMG

David A. Reyes López^{1*} Humberto Loaiza Correa²
Mauricio Arias López³ Jorge E. Duarte Sánchez⁴

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ABSTRACT

This paper presents the design and implementation of a novel technique for the recognition of four hand motions for real time response (flexion (FL), extension (EX), opening (OP) and closure (CL)) from electromyographic (EMG) signals generated from two forearm muscles: palmaris longus and extensor digitorum. The development of the work had two main stages: the low cost hardware for acquisition and conditioning of the EMG analog signals and the processing system for the identification and classification of the movement performed for real time response; the entire system was integrated in a hardware-software application using MATLAB and processing techniques for the discriminant analysis were performed. Three methods were evaluated for pattern recognition getting 98% recognition rates with the method proposed which had the best performance.

Keywords: Neural networks and support vector machines, EMG signals, discriminant function, real time response.

RESUMEN

Este trabajo presenta el diseño e implementación de una nueva técnica para el reconocimiento de cuatro movimientos de la mano (flexión (FL), extensión (EX), apertura (OP) y cierre (CL)) para respuesta en tiempo real a partir de señales electromiográficas EMG generadas desde dos músculos del antebrazo: palmaris longus y extensor digitorum. El trabajo se desarrolló en dos principales etapas: el hardware de bajo costo para la adquisición y adecuación analógica de las señales EMG; el sistema de procesamiento para la identificación y clasificación de los movimientos capturados para respuesta en tiempo real. El sistema fue integrado mediante una aplicación hardware-software usando MATLAB y se usaron técnicas de procesamiento para el análisis discriminante. Tres métodos fueron evaluados para el reconocimiento de patrones obteniendo tasas de reconocimiento del 98% con el nuevo método propuesto.

Palabras clave: Redes neuronales y máquina de vectores de soporte, señales EMG, función discriminante, respuesta en tiempo real.

¹ Grupo de Investigación Percepción y Sistemas Inteligentes. Escuela de Ingeniería Eléctrica y Electrónica. Universidad del Valle. Cali, Colombia. E-mail: david.reyes@correounivalle.edu.co

² Grupo de Investigación Percepción y Sistemas Inteligentes. Escuela de Ingeniería Eléctrica y Electrónica. Universidad del Valle. Cali, Colombia. E-mail: humberto.loaiza@correounivalle.edu.co

³ Grupo de Investigación Bionanoelectrónica. Escuela de Ingeniería Eléctrica y Electrónica. Universidad del Valle. Cali, Colombia. E-mail: mauricio.arias.lopez@correounivalle.edu.co

⁴ Grupo de Investigación Percepción y Sistemas Inteligentes. Escuela de Ingeniería Eléctrica y Electrónica. Universidad del Valle. Cali, Colombia. E-mail: jorge.enrique.duarte@correounivalle.edu.co

* Autor de correspondencia. E-mail: david.reyes@correounivalle.edu.co

INTRODUCTION

Human machine interfaces are based on the use of biopotentials as a control signal for external devices including intelligent prostheses, which can assist people who have lost their limbs whether is caused by car accidents, industrial accidents, diabetes or as evidenced in a study by the Colombia's Management for Comprehensive Action against Anti-personnel Mines [1] that in Colombia another cause of amputation is related to anti-personnel mines injuries. To address these challenges there are several commercial prosthetic devices, developed in other countries, such as Otto Bock hand [2], the i-Limb [3] or SmartHand [4] that allow these people to recreate some of the human hand movements [5].

Several research results show that the most commonly biopotential used to control this type of prosthetics devices are the electromyographic EMG signals, which record the electrical activity generated in muscle tissue, produced during contraction and relaxation of muscles [6, 7, 8, 9, 10]. These signals give an idea of the neuromuscular activity associated with a contraction, but does not necessarily indicates the force developed by the muscle, instead it gives the information of which muscle was activated by the central nervous system and which muscle provides indirectly a more leading role in a function or movement particularly [6]. EMG signals are used in the medical field for diagnosing muscle diseases such as myopathy, neuropathy [11] or Parkinson's disease [12] and, thanks to technological advances these signals are also used as control signals for electronic systems.

Today many studies address the treatment of EMG signals and are used in several fields, for example, assistive devices for disabled people [13] prosthetic hands [14, 15] or control signals for electric wheelchairs [16], however most works tends to be laborious and expensive equipment are used [17]. Some problems have been detected in the development of an EMG system:

- A. Proper selection of muscles and the position of the electrodes to acquire the EMG signal.
- B. Construction of a discriminant function.

In conventional systems, the greatest interest is to obtain a high recognition rate with B. Many methods

are used as discriminant functions to recognize EMG signals regardless of the subject. For better identification, it has had to choose the muscles that are activated directly by the movement [18].

The proposed system was developed in two stages of work, which were divided into phases; the first stage is divided into three phases: analog acquisition-conditioning, transmission and analog to digital conversion of EMG signals. The second stage is the design of the discriminant function in software using processing and pattern recognition techniques, which main objective was to identify the movement made from the EMG signals captured. Figure 1 shows the diagram block implemented for the development of the myoelectric integral system.

Figure 1. Diagram block of the process implemented in the development of this work.

ANALOG EMG SIGNAL ACQUISITION AND CONDITIONING

As in [19] this work implemented a low cost two channel hardware system to acquire EMG signals superficially, so the signal acquisition can be performed with minimal risk to the patient [20]. The signal captured by the electrodes is connected to an analog and conditioning block which amplifies and filters the signal. For the Analog to Digital (AD) conversion computer's stereo sound card was configured so the EMG analog signals was conditioned to the voltage range that the card allows.

A. EMG signal acquisition

In works such as [21, 22] and [23] forearm muscles were used to capture hand movements producing enough useful information for the task, according

to that extensor digitorum and palmaris longus muscles were selected in this work. The selected muscles are extensors and flexors muscles of the wrist joint having antagonistic participation in some hand movements [24]. For each muscle two cardiography monopolar electrodes were used. The location of the electrodes is of great significance because locating them wrong could cause unwished results in the system. Electrodes are properly placed to acquire the EMG signals in this work as shown in Figure 2, reference electrode were positioned on the opposite forearm.

Figure 2. Electrodes properly placed to acquire the EMG signals in this work.

B. Analog EMG signal conditioning

For the conditioning of the analog EMG signal it was designed and implemented an analog circuit described by the characteristics in Table 1. Is worth mentioning that in a similar manner in works such as [25, 26, 27, 28], the interference of 60 Hz was not filtered due it is within the useful frequency range of the EMG signals.

Table 1. Parameters for analog conditioning of the EMG signal.

EMG signal adequacy	
Stage	Description
Acquisition	Two channel
Differential	Instrumentation amplifiers fixed gain: 1000
Filtering	2nd order lowpass butterworth filter $F_c = 600$ Hz
Amplification	Adjustable gain = 2
Circuit powersupply	9V battery

Once the stage of the conditioning of analog EMG signal, movements are captured and viewed on an oscilloscope to test the operation of the analog system.

EMG SIGNAL PROCESSING

For the development of the processing system a computer application was designed using the experimental platform MATLAB under educational license. The laptop computer was a DELL Latitude with an Intel i5 @2.67 GHz processor and 2 GB Ram. Once the EMG signal is captured by the designed hardware it proceeds to perform a pre-processing stage that consists of several sub-stages:

A. Analog to digital conversion

To convert the EMG signal from analog to digital the sound card stereo input of the computer was configured using the minimum sampling frequency (8 kHz), much higher than the bandwidth of interest (500Hz). Data Acquisition Toolbox was used to gather data. In Figure 3 a captured EMG signal with the hardware implemented and converted into digital is shown.

Figure 3. Two channel EMG signal gathered in MATLAB with the hardware designed (Blue: Extensor digitorum muscle - Green: Palmaris longus muscle).

B. Preprocessing stage

Processing techniques were implemented such as: Resampling, filtering, EMG signal detection, segmentation and normalization. Table 2 shows the parameters of this stage.

For the EMG signal detection several threshold values were evaluated because in the literature a fixed value is not specified for this. In [29] mention that using a single threshold value for different intensities of exercises or different muscle groups can cause misleading results. Thus, researchers may need to use different strategies to establish a threshold value. As a result, they not recommend any defined threshold value due to the highly variable nature of the selection process. In this work the

Table 2. Parameters for the preprocessing stage.

Digital emg signal Pre-processing	
Stage	Description
Resample	8 kHz to 1 kHz
Filtering	160 order bandpass fir filter $f_c = [20-600]$ Hz
EMG signal normalization	EMG signal maximum detection
EMG signal detection	Threshold detection = 400 mV
Segmentation	256 samples of each emg signal

best performing threshold for detection of EMG signals was 400 mV.

For the analysis of EMG signals, the most common is to obtain the records into segments of length 256 samples and apply the techniques of feature extraction for each segment [29]. Meanwhile, [23] and [30] use the length of segments 256, 128, 64 and 32 samples in each assay and, as in other works [31], use of rectangular windows 200 and 400 ms with results equally satisfactory but with the notation that greater lengths imply more processing time and greater delay in the response. In this case segmentation of 256 samples was done.

C. Gathering the EMG Data

Through voluntary participation, 11 subjects, men and women without disabilities between 11 and 60 years old were selected. A protocol for acquiring movements to classify, wrist extension, wrist flexion, opening and closing the hand, as shown on Figure 4, was done consisting in performing 10 repetitions of each movement in periods of 2s, obtaining thus a total of 110 samples per movement. To avoid fatigue as in [23] subjects were allowed to rest for 1-5 min. The parameters to make the dataset were the same as described previously. To have information of steady and transient states, the EMG signal was gathered for the entire movement, from the beginning of it til the reach of rest state.

D. Features extraction and dimensional reduction

With the dataset of the EMG signal obtained, to identify the movements made, several computational techniques processing were performed. In [5] mention works that have used several methods in both time

Figure 4. Motions performed in the system. A) Hand or wrist flexion. B) Hand or wrist extension. C) Hand closure. D) Hand opening.

and frequency domain getting good results in the EMG pattern recognition. In this paper statistical analysis methods such as mean, variance, energy, maximum value and relations between features were used in the time and frequency processing techniques for each channel or muscle. The Fast Fourier Transform (FFT) was implemented to obtain the signal in the frequency domain. A total of 34 variables were calculated as described in Table 3.

Due to the large number of variables calculated, the resulting features vector is large which reflects in a very high computational cost if it is used as inputs for the recognition system. Two techniques for the analysis and feature extractions were applied to address the problem and achieve a reduction in the dimensionality of the vector: Covariance matrix (MC) between features were performed and Principal Component Analysis (PCA) which in [5] had good performance in the results obtained. Figure 5 shows the results of the covariance matrices calculated in (a) for the 4 movements to classify, in (b) for two movements (flexion and extension of the wrist) and (c) for both remaining motions (opening and closing the hand). The matrix have a tendency in colors scales where green means that the covariance between features are small or close to 0, the red colors are those whose covariance are close to 1. Comparisons with the features with covariances close to 0 and covariances close to 1 were performed, as shown in Figure 5 there are several features with covariances tending to 1, which gives information

Table 3. Extracted features in EMG signals.

Temporal space	Number of variables	Frequency space (FFT)	Number of variables
Mean per muscle	2	Mean per muscle	2
Var per muscle	2	Var per muscle	2
Energy per muscle	2	Maximun per muscle	2
Maximum per muscle	2	Frequency of maximum per muscle	2
Mean Difference	1	Mean Difference	1
Var Difference	1	Var Difference	1
Energy Difference	1	Maximum difference	1
Maximum difference	1	Mean Division	1
Mean Division	1	Var Division	1
Var Division	1	Maximum Division	1
Energy Division	1	Var ÷ Mean;	2
Maximum Division	1	Maximum ÷ Mean difference	2
Total	16		18

of dependency between features. After the MC analysis a PCA were done to the features with best performance in the discriminant issue obtaining that with the first 4 principal components it can get up to 94.5% variance of the total data.

Figure 5. Covariance matrices calculated in the features extraction process.

After a series of evaluations, finally features which performed the best on the discrimination of movements captured by the EMG system, were selected. Table 4 shows the features that were implemented as an entry for the classification system.

Table 4. Features selected after the dimension reduction stage.

Feature
Var FFT – Channel 2
Energy – Channel 1
Maximum FFT – Channel 2
Mean FFT – Channel 1

Figure 6 shows the representation of the four movements in a 2D view for display purposes. The influences of selected muscles that have antagonistic activity to identify movements, such as extension and flexion of the hand, have a clear discrimination between them. On the other hand, it also noted that for the movements that have synergistic activity, as opening and closing the hand, one muscle group participates more actively than the other, that is, to close the hand, contributes more to the movement the flexor muscles than the extensor ones and in an opposite case with hand opening.

Figure 6. 2D view of the four motions to classify.

E. Identification of the motions from EMG signals

For the identification phase computational techniques were implemented for pattern classification, dividing the dataset by 50% for training and 50% for validation

and testing. Three classification techniques were implemented for the recognition of motions from the EMG signals captured. The first technique was implemented with a feedforward artificial neural network (ANN) Multilayer Perceptron (MLP) type with 4 classes in its output, each corresponding to each movement. The second, a neural network with Radial Basis Function (RBF) also with 4 classes in its output layer. The results were satisfactory for both networks with different types of architectures in the training stage with a success averaged of 90%. Table 5 shows the confusion matrix for both classifiers.

Table 5. A) Confusion Matrix for the MLP ANN trained. B) Confusion Matrix for the RBF ANN trained.

A)	CL	EX	FL	OP
CL	66	1	3	11
EX	1	71	0	4
FL	3	0	79	1
OP	8	3	0	69

B)	CL	EX	FL	OP
CL	76	1	11	12
EX	1	95	0	4
FL	3	0	97	0
OP	13	8	0	79

After analyzing the results obtained with the implemented classifiers it is proposed to improve the rate of classification because good results were obtained with the relevant classes, flexion and extension movements, but between opening and closing low recognition rate was evident.

The proposal was implemented by dividing the problem into three categories consisting to unify, into a single class, the opening and closing movements of the hand and together with the remaining 2 classes (flexion and extension) to implement an Expert Committee (EC). This EC is composed with two classifiers: one that discriminates the new unified class from the other two, and the second, a robust one, that allows the discrimination between the patterns with low recognition. For this, the first classifier a feedforward MLP neural network was trained, this time with 3 classes at its output and the second classifier, the 'expert', by implementing Support Vector Machines (SVM) which had good performance in several works [9, 31, 32, 33] for the discrimination between two classes. Different SVM kernel functions were evaluated, obtaining a better performance for the linear function. An

improvement was obtained in the recognition rate for the movements with greater confusion (opening and closing). Table 6 shows the results in the training stage for the EC proposal implemented to improve classification rates.

Table 6. Confusion Matrix for the EC proposal implemented. A) The MLP feedforward ANN Confusion Matrix. B) SVM Confusion Matrix.

A)	CL-OP	EX	FL
CL-OP	191	6	3
EX	5	95	0
FL	4	0	96

B)	CL	OP
CL	76	20
OP	13	81

VALIDATION AND TESTS RESULTS

Testing was conducted for real time response of the myoelectric implemented system with 7 subjects without disabilities, men and women in the range between 20-40 years old, who voluntarily participated in the exercise. Needless to say, these people were not part of the data collected in the dataset obtained for the training phase of the classifiers. Tests were done for both forearms (right and left). Each subject received an introduction of the methodology to follow for using the EMG application, which was:

- Palpation of muscles selected for the correct electrode positioning.
- Preparation of the forearm muscles with conductivity gel.
- A mimic response for the motion to made which had a duration time of 1s.
- A visualization of the motion made was done using a Graphical User Interface (GUI) which gives the user an incentive when the system recognized a motion.

After obtaining the outputs of the classifiers a threshold called threshold decision is evaluated to get more accuracy in the classification results. A new class is introduced into the test parameters called "No Classify (NC)", which is activated when none output of the classifier exceeds the threshold decision. Several values of threshold decision were evaluated for each classification

technique selecting the one with best performance in the recognition task.

Figure 7 shows how the variation of the threshold decision affects the success of class recognition.

Figure 7. Threshold decision variation for each classification technique. A) MLP ANN B) RBF ANN C) Experts Committee.

After selecting the threshold with best performance, each technique was tested where it showed that

the recognition rate increased for each evaluated method as shown in the tests confusion matrices.

Table 7. Test results. A) feedforward MLP ANN. B) RBF ANN. C) Expert Committee – ANN+SVM.

A						
CL	11	47	0	2	0	96%
EX	5	0	50	0	5	91%
FL	1	0	0	59	0	100%
OP	11	11	0	0	38	78%
NC=12%						
Threshold decision:		% Success:			92%	
0.65		% Rejection:			12%	
B						
CL	9	35	0	5	1	85%
EX	6	0	44	0	0	100%
FL	0	0	0	50	0	100%
OP	5	11	0	0	34	76%
NC=10%						
Threshold decision:		% Success:			91%	
0.55		% Rejection:			10%	
C						
CL-OP	16	103	0	1		99%
EX	16	3	41	0		93%
FL	2	0	0	58		100%
NC=14%						
% Success:		98%				
% Rejection:		14%				
SVM						
CL	42	2				95%
OP	5	53				91%
% Success:		93%				
Threshold decision: 0.5						

DISCUSSION AND CONCLUSIONS

It was designed and implemented a system that captures the EMG signals from forearm muscles for real-time identification of 4 hand movements (flexion, extension, opening and closing of the hand) comparing 3 types of classification techniques in the identification stage and getting results >91% in the recognition rate for each classifier implemented and improving the rate to 98% with the implementation of a novel Expert Committee type Classifier.

It is shown an improvement on classification results performed for real time response after dividing the problem of classification by implementing the new technique, Expert Committee and by evaluating the threshold decision for each of the classification techniques implemented. It was also observed that the “No Classify” class helps to improve the recognition rates.

The location of the electrodes is an important factor for the proper functioning of the system during the entire process (from training to testing), because if you mistakenly make it, the results produced by the system may not be as expected. It is therefore recommended to train movements to identify with people who will test the system even with the people who will be part of the dataset for the training phase, thus achieving improved recognition rate.

FUTURE WORK

In order to assess a muscle-computer interface, besides the generalization tests for the classifiers, a Controllability Test can be conducted as well (Target Achievement Control Test, [34]). So it can evaluate the performance of the system for kinetic and intrinsic geometric parameters in processes of prosthesis control by biosignals, such as EMG signals.

Although the system is trained and tested with forearm muscles in future works it can also have the same results capturing movements from other muscle groups, with the same characteristic of flexors and extensors, for example: biceps and triceps. This is because the movements identified in this work have an antagonistic participation.

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