EMG-BASED SYSTEM FOR BASIC HAND MOVEMENT RECOGNITION

SISTEMA DE RECONOCIMIENTO DE MOVIMIENTOS BÁSICOS DE LA MANO CON BASE EN SEÑALES EMG

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ABSTRACT: This paper presents a system for the automatic identification of six basic hand movements in healthy subjects based on a steady-state of electromyographic signals. The following basic hand motions were detected: opening, closing, flexion, extension, pronation, and supination, as well as the rest condition. A modular approach of pattern recognition with discrete wavelet transform, principal component analysis, and support vector machines was used to discriminate each movement. Identification was completed off-line every 256 ms with a hardware-software interface composed of a signal acquisition system with two electromyographic differential channels using Matlab® and LabVIEW® software. The system was trained and tested using five subjects of different gender, age, and physical complexion, with identification rates of up to 99.25 %.

KEY WORDS: Electromyography, hand-prosthesis, pattern recognition, principal component analysis, discrete wavelet transform, support vector machines

RESUMEN: Este artículo presenta un sistema que permite identificar de forma automática, en sujetos sanos, y haciendo uso de señales electromiográficas superficiales en estado estable, los siguientes movimientos básicos de la mano: apertura, cierre, flexión, extensión, pronación y supinación, incluyendo la condición de reposo. La discriminación de los diferentes movimientos se realiza a partir de una metodología modular de reconocimiento de patrones que incluye el uso de la transformada wavelet discreta, análisis de componentes principales y máquinas de soporte vectorial. La identificación fue realizada off-line cada 256 ms mediante una interfaz hardware–software conformada por un sistema de adquisición de señales de dos canales diferenciales y algoritmos programados en Matlab® y LabVIEW®. El sistema fue entrenado y evaluado para cinco sujetos de diferente género, edad y complexión física, obteniendo tasas de acierto de hasta el 99.25 %.

PALABRAS CLAVE: Electromiógrafo, prótesis de mano, reconocimiento de patrones, análisis de componentes principales, transformada wavelet discreta, máquinas de soporte vectorial

1. INTRODUCTION

Upper limb prosthesis has evolved from simple mechanical devices with aesthetical purposes to complex devices using surface electromyographic (sEMG) signals [1]. The sEMG signals enable practical and natural movements for handicapped persons using less effort and a quick learning rate, which promotes an easy and painless transmission [1–9].

Englehart et al. provided the first approach using sEMG signals as a method of control in 2001 [3]. The approach utilized a system of six types of movement identification (hand closed, hand open, wrist flexion, wrist extension, ulnar deviation, and radial deviation) with four sensing channels. Englehart also used the wavelet packet transform (WPT), principal components analysis (PCA), and neural networks as the main processing components. Recently, Oskoei and Hu [4] demonstrated the use of support vector machines (SVMs) as a classifier for obtaining optimal results compared with other commonly used techniques. To reduce computational time, Güle and Koçer [5] applied the discrete wavelet transform (DWT) in contrast to previous work [6–8] where the WPT was implemented. Integrating a methodology on the basis of pattern recognition without PCA, Lucas et al. [9] obtained good results; however, they used eight sensing channels to recognize six movements which imply an associated complex instrumentation.

The aim of this work was to recognize seven basic hand movements (Fig. 1, including the rest condition), using sEMG signals generated by forearm muscle activity with only two sensing channels.

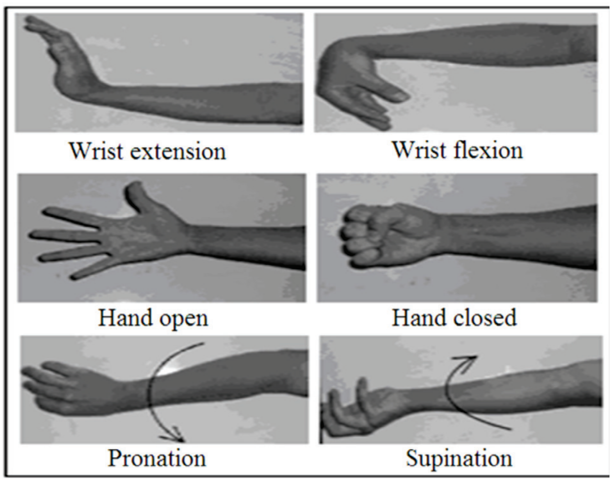

Figure 1. Movements for classification

2. SYSTEM DESIGN

The identification process was completed by using the four sequential modules that are commonly used in pattern recognition [2–3]:

- sEMG signal acquisition and conditioning
- feature extraction
- dimensionality reduction
- movement identification

The entire movement identification system based on sEMG signaling is summarized in Fig. 2 and consists of two principal modules. The first module is related to signal acquisition and conditioning, and the second is related to computerized digital processing. Each block is described in the following sections.

2.1 semg signal acquisition and conditioning

This module is designed to process the analog sEMG signals to reduce electromagnetic noise, filter the desired frequency components, amplify its magnitude, and finally, to digitalize the signals. Afterwards, the signal is processed on a PC to determine which movement was made.

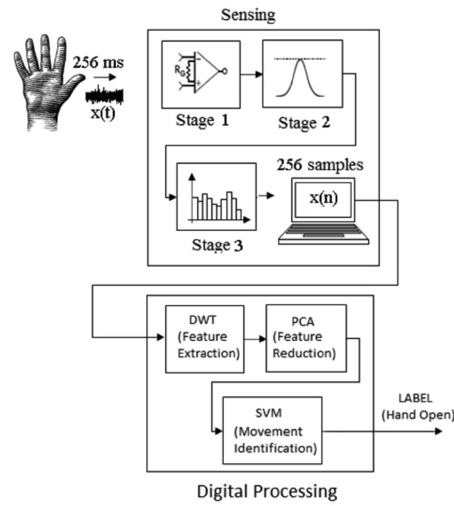

Figure 2. Movement identification system

2.1.1 Electrode type

The silver/silver chloride (Ag/AgCl) electrode is a transducer that is commonly used to convert ionic currents on the skin produced by muscular activity [10–12].

The surface electromyography for the non-invasive assessment of muscles (SENIAM) group [11] recommends an electrolytic gel application to optimize conductivity and skin adherence with the electrodes and to take advantage of their characteristics. Following the SENIAM guidelines, several characteristics were selected for the sEMG signal acquisition:
Electrode form: circular
Electrode size: 10 mm diameter
Electrode material: Ag/AgCl
Skin preparation: cleaned with alcohol, free from hair
Sensor location: longitudinal, parallel to the muscular fibers; see Figs. 3 and 4
Distance between electrodes: approximately 20 mm

2.1.2 Electrode location

Electrodes were placed between two motion points and through the longitudinal midline. The longitudinal axis corresponds to the muscle fiber direction (Fig. 3) [11–13].

Figure 3. Muscle longitudinal axis

Two bipolar channels were used (see Fig. 4), to reduce computing time, storage requirements, and the needed instrumentation.

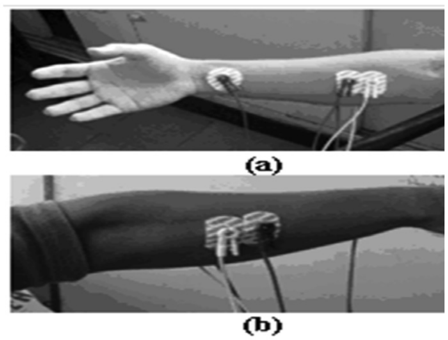

Figure 4. (a) Anterior forearm region and (b) posterior forearm region

For sEMG signal acquisition, two phases notably influenced the processing: the *transient state* and the *stationary state* [2–3].

The transient state is related to the initial phase of movement that is observed during instantaneous sudden myoelectric activity. The stationary state is related to the myoelectric activity during a sustained movement.

In this study, the sEMG signal was addressed in the stationary state. This method does not require threshold identification to capture the signal when the movement occurs.

2.1.3 Acquisition board

For data registration and sEMG signal storage, a hardware-software interface was implemented. This layout for signal conditioning was based on an electrocardiograph schematic [10], with adaptations of amplification characteristics and bandwidth for obtaining the desired signals.

The nature of a sEMG signal is defined by the following characteristics:

- The typical sEMG signal amplitude is 0–6 mV.
- A useful signal energy is found in the 0–500 Hz range, with the main components located in the 50–150 Hz range.

Given these characteristics, the acquisition module has three stages:

Stage 1

The input stage is composed of op-amps AD620 and OP97. It is designed for signal acquisition in a differential mode by eliminating electromagnetic noise interference and common mode signals, thus improving the signal-to-noise ratio (SNR) [10,13]. Total gain is 2000 V/V [8] and is distributed in two circuits to avoid output saturation in the initial stage. Small differences in the measured signal amplitude are often produced due to skin conditions or static biopotential. Therefore, a variable gain amplifier is needed for amplitude adjustment.

Stage 2

The second stage is the filtering stage, which is necessary in order to reject signals that have undesired frequency ranges. Three filters were designed with the Sallen-key architecture [10].

The first filter is a second order high-pass filter with a unitary gain, and a cut frequency of 20 Hz. This filter eliminates the offset produced by the movement of the electrode contact with the skin and by the cable movement [13].

The second filter is a second order low-pass filter with 40 dB/dec attenuation, unitary gain, and a 500 Hz cut frequency. This filter is proposed to accommodate for weakened high frequency amplitudes where the sEMG signal energy is low [10].

A 60 Hz noise cancellation was made with a first order notch filter. This filter has a quality factor of 10, unitary gain, and 23 dB of rejecting [13].

For sEMG signal amplification, a non-inverter circuit with a 100 V/V gain was implemented at the notch filter output; Fig. 5 shows a prototype.

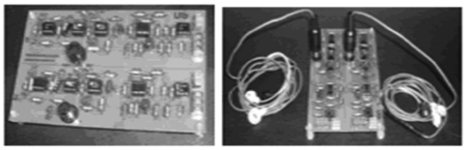

Figure 5. Signal conditioning hardware

Stage 3

In this stage, the sEMG signal was digitalized, as it was previously filtered and amplified. An acquisition board LAB PCI 1200 was used with ±5 V, 12-bit differential resolution, and a sampling frequency of 1000 Hz [10–12].

The visualization and storage stage was completed using LabVIEW®. The front panel, where acquisition and register parameters are configured, is shown in Fig. 6. These parameters include storage time, sampling frequency, number of acquisition channels, storage files, and devices used [14].

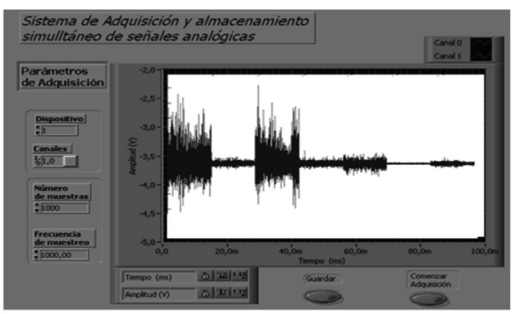

Figure 6. Electromyograph front panel

The sEMG signal sensing is executed during 256 ms per channel.

2.2 Feature extraction

This module processes the sEMG signal features in the time-frequency domain producing an "initial features set".

Most approaches based on feature sets obtained from frequency analysis show better results than approaches based on time domain analysis [3].

2.2.1 Discrete Wavelet Transform

The discrete wavelet transform (DWT) is the representation of a function by wavelets. The wavelets are scaled, and the translated copies of a finite-length or fast-decaying oscillating waveform are known as the mother wavelet. Wavelets can be combined using a shift, multiply, and sum technique called convolution. Portions of sEMG signals are used to extract information [15].

The DWT has advantages over traditional techniques for representing functions with discontinuities and sharp peaks. In addition, accurate deconstruction and reconstruction of finite, non-periodic, and non-stationary signals can be obtained by applying a multiresolution analysis.

The results obtained from a DWT provide the scale and detail coefficients, which represent time and frequency data packs [15].

The feature vector is formed by statistics calculated on the detail coefficient packets and approximation coefficients obtained on each resolution level of the wavelet analysis (descriptors). In this stage, the corresponding pattern of each movement is formed by the feature vector of the anterior channel signal followed by the feature vector of the posterior channel [14].

The statistics calculated for this stage are: root mean square (RMS), variance, standard deviation, correlation, covariance, median, mean, maximum value, minimal value, and wavelet energy. The statistics calculated over the wavelet coefficients provide information regarding the tendencies, abnormalities, and energy of the sEMG signal.

2.2.2 Wavelet parameters

In this study, parameters such as minimum computing time, similarity to the sEMG signal based on correlation coefficient, and better representation of frequency content of the sEMG signal (see Table 1), were used to decide which wavelet signal will be tested. Hence, a preliminary test was carried out over several mother wavelets to discriminate which wavelets were best suited [14].

In this work, mother wavelets used in previous pattern recognition studies [16–17] were used to evaluate previous criteria.

The preselected mother wavelets were: *daubechies3*, *daubechies4*, *daubechies5*, *daubechies6*, *coiflet3*, *coiflet4*, *coiflet5*, *coiflet6*, *symlet4*, *symlet5*, and *symlet6*.

To define the decomposition level, each level was related to their analyzed frequency range (see Table 1). According to [12], the dominant energy is located at 50–150 Hz, matching mainly to the third level of decomposition.

On the other hand, according to previous research [3], identification degrades quickly along the segment of longitudinal decrement. However, 256 samples had a good performance without affecting the real time restrictions that are imposed by a hand prosthesis, where the control system must take action within 300 ms (300 samples with a sampling frequency Fs = 1 KHz) according to international standards [2–3].

Table 1. Resolution level and corresponding frequency range of sEMG signal

Resolution Level	Frequency range in Hz
1st Level	250 to 500
2nd Level	125 to 250
3rd Level	62.5 to 125
4th Level	31.25 to 62.5

Based on previous studies, the original signal was analyzed with the wavelet transform process by sectioning it with disjointed and adjacent windows formed by 256 samples.

Several tests were performed on healthy subjects. The order of the movements was as follows: hand closed, hand open, wrist flexion, wrist extension, pronation, resting and supination. The execution time of each movement was ten seconds.

The process performed in this feature extraction module is summarized in Fig. 7.

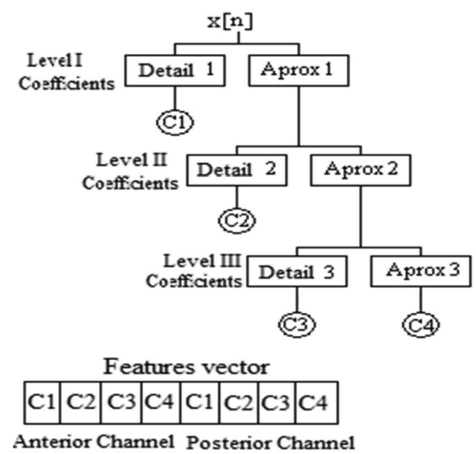

Figure 7. Scheme of feature extraction

The digital sEMG signal x[n] is decomposed in three resolution levels. The coefficients represent the degree of correlation between the original signal x[n] and the displaced and scaled versions of the mother wavelet. Descriptors C1, C2, C3, and C4 correspond to the statistics that are calculated with these coefficients.

2.3 Feature reduction

There is a drawback when the feature vector is used as a direct input for the artificial intelligence algorithms. Feature vectors are, mostly, high dimensionality vectors with no information order. For this reason, it is necessary to reduce the vector size with techniques that preserve and organize the most relevant information. These techniques reduce the processing time and improve the results of the artificial intelligence algorithm [18–19].

Dimensionality reduction can be executed using characteristic projection methods, such as principal component analysis (PCA) [20]. The objective of PCA is to detect redundant information and to reorganize it for an easier interpretation.

The PCA analysis preserves a new set of features, with minimum square error, which are ordered from maximum to minimum variance.

New features are obtained using the Eigen-vectors of the covariance matrix or the correlation matrix. When the correlation matrix is used, the analysis is not affected by amplitude variations in the feature vector. This phenomenon is known as normalized analysis [20].

According to the Kaiser Criterion [21], only the new features with a variance higher than the mean are required. When this criterion is evaluated using the correlation matrix, it is called the *normalized Kaiser*.

For this work, another criterion based on sEMG signal was adapted to exclude the new features with small variance values [20]. Hence, preliminary tests were executed using data from the sEMG signals, and only the new features with variance greater than 2 % of the maximum value were included. This criterion was called *percentage*.

The dimensionality reduction module was then applied as shown in Fig. 8. The feature vector was reduced by PCA.

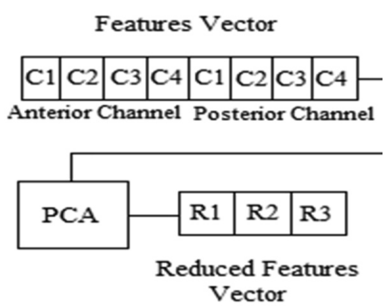

Figure 8. Dimensionality reduction

The new features (R1, R2, and R3) were linear combinations of the initial ones (C1… C4).

2.4 Movement identification

Support vector machines (SVMs) were used for movement identification. Contrasting with the Bayesian method, these machines do not require any hypothesis regarding the probability density function of the data. In comparison with neural networks, they can reduce the number of parameters that must be introduced by the user [22–23].

Intuitively, given a group of samples distributed into two classes, a linear SVM searches for a hyper plane to locate the maximum number of samples on the same side, while the distance from the classes to the hyper plane is maximized. If the hyper plane exists, the data are linearly detachable [22–23].

If data are not linearly detachable, the hyper plane search lacks relevance. Nonlinear SVMs trough kernel functions are then used as an alternative. If there are more than two classes, a parallel arrangement of biclassificator SVMs is implemented along with an interpreter element [14,24].

In this stage, the software tool MSVToolBox10 [25], developed at Universidad Industrial de Santander, was used to find the optimal defining parameters through cross-validation and a grid search [14,25]. The main parameters defined are: kernel, penalty constant, slack variables, the optimization method, and the decomposition method [26].

The implementation of this movement identification module is shown in Figure 9.

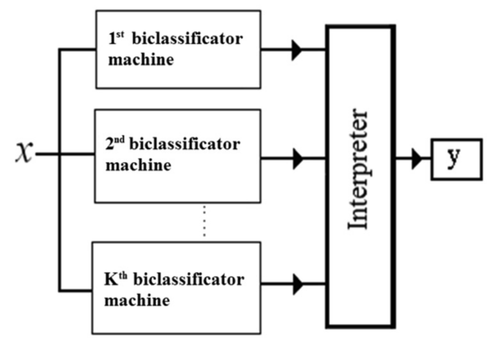

Figure 9. Movement identification

The reduced feature vector is labeled according to the executed movement by the interpreter element based on partial decisions of biclassificator machines (multiclass SVMs). These machines can discriminate between two specific movements (*ovo*) or between one movement and the rest (*ovr*).

3. TESTS EXECUTED

Data from each subject was divided into two sets with 50 % designated for training and 50 % for validation. The identification system was implemented using a five-fold cross-validation over the training data. Two preliminary tests were performed on the data from one subject to determine the optimal parameters of DWT, PCA, and SVMs, and these parameters were then applied to all five subjects.

3.1 First preliminary tests

Two initial pilot tests were performed to observe the effects and changes produced by the mother wavelet, resolution level, and variations in descriptors.

During both pilot tests, PCA parameters (normalized Kaiser), and SVMs parameters (polynomial kernel, *ovo* decomposition, penalty constant with value 100, optimization method *smo*, interpreter element based on voting schemes, and Gaussian membership probability functions) were fixed.

These SVMs parameters were used following a preliminary test with a classification ratio of 70 %. The SVMs variations in Table 2 were evaluated by cross-validation and a grid search. Using criteria presented in Section 2, the RMS value as statistic in the feature extraction stage (descriptor), mother wavelet *daubechies4*, third resolution level, and normalized Kaiser Criterion were used.

Table 2. SVMs parameters

Parameter	Options
Kernel	Polynomial, Sigmoidal, Radial base
Decomposition	ovo, ovr
Interpreter	Gaussian membership probability functions, and Voting methods
Optimization	Irwls and smo
Penalty constant	[0-1000]

The first pilot test was executed using the mother wavelets preselected in Section 2.2.2. This pilot test was completed under fixed resolution level and descriptors. The mother wavelets that presented a classification ratio over 80 % were: *coiflet3*, *coiflet4*, *symlet4*, *symlet6*, *daubechies4*, *and daubechies5*.

In the second pilot test, the objective was to determine which of the statistics proposed in Section 2.2.1 provide relevant information for the classifier. The descriptors were varied while the resolution level and mother wavelet *daubechies4* were kept fixed (the best wavelet in first pilot test).

The statistics that presented a classification ratio over 80 % were: RMS value, variance, mean value, and standard deviation.

To find the adequate alternative to calculate the PCA with 'percentage' criteria associated, a final pilot test was performed using fixed parameters from the previous pilot tests.

3.2 Second preliminary tests

Two resolutions levels (third and fourth) were taken into account because these coefficients concentrate the dominant frequency ranges into sEMG signals, as can be seen in Table 1.

Two groups were formed for the statistical tests, one that took into account only the RMS value and another that took into account all the values obtained from first preliminary tests.

As result, 16 test combinations (variations) were obtained to evaluate each particular mother wavelet. Each combination was performed with all possible variations from Table 2.

4. RESULTS

The best combination, (see Table 3), obtained an error of 0.75 % for the classification.

Table 3. Optimal performance combination

Parameter	Description
Mother Wavelet	Daubechies 4
Resolution level	4
Calculated statistic	RMS value
PCA analysis	Normalized Standard

With respect to the classification of feature vectors using SVMs, the parameters with the best performance were: polynomial kernel, decomposition method *ovo*, interpreter element based on voting functions, Gaussian membership probability functions, and the optimization method *smo.* The decomposition method *ovr* did not guarantee good results, and the optimization method *irwls* did not converge in most tests.

Finally, an extrapolation test was performed to check the validity of this result in other subjects. During this test, the parameters shown in Table 3 were used, and sEMG signals from five subjects with different characteristics were analyzed. The results of each classification of error of movements per subject are shown in Table 4.

Table 4. Error rate (%) per movement in tests for 5 subjects using the best performance combination of preliminary tests

H. Open	H. Closed	Extension	Flexion	Pronation	Rest	Supination	Total
5.3	0	36.84	0	0	0	10.52	7.51
0	5.3	0	0	0	0	0	0.75
0	0	0	31.57	0	0	10.52	6.01
0	0	0	0	0	0	15.78	2.25
0	0	0	0	0	0	31.57	4.51

Table 4 shows the identification error in different movements using data related to men/women, between 18 and 38 years old. The results demonstrate some error for most of the data related to forearm supination. It is also noted that the smallest amount of recognition error corresponds to remaining movements with some exceptions.

5. DISCUSSION

The convergence ratio in training was very fast because cross-validation and SVMs do not have local minimums and require few parameters. The use of fewer sensing channels also reduces computational costs.

The proposed hand movement identification system in this work can be used to build practical upper limb prosthesis similar to the work of Huang et al. [27]. Because of the few instrumentation requirements of this system (only two sensing channels) and the relative easy implementation of this signal processing into embedded systems, it is expected that the economic costs can be reduced as compared with previous systems.

Off-line processing is sufficient for 256 ms of sEMG signal applying DWT, PCA, and SVMs to obtain good results, but testing with other window widths is required to verify on-line systems.

The RMS value is the only statistic required to generate the proper feature vector by applying DWT with the mother wavelet *daubechies4* and the fourth resolution level.

The PCA analysis allows better classification results under the normalized ‘percentage’ criterion, reducing the feature vector roughly 50 %.

6. CONCLUSION

The most influential parameters on the success rate of movement identification are related to the correct acquisition of the sEMG signals. Therefore, the implementation of a notch filter is mandatory to filter the 60 Hz signal. All wires should be shielded, and the gain must be adapted by taking into account the static biopotential variations of each subject. Without these considerations, it is not possible to recognize sEMG patterns of hand movements, because signal quality is not guaranteed.

Using only two acquisition channels, each one with a sampling frequency of 1 KHz, it is possible to obtain success rates over 90 % in six basic hand movement identifications in healthy subjects with different ages, genders, and physiques.

To control a hand prosthesis or robotic arm, the next step is to implement the proposed approach on an embedded system. It is also necessary to assess the movement identification system using sEMG signals obtained from handicapped persons to verify the performance of the system.

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