Processing of myoelectric signals in a microcomputer for identification of movements intention and the cost reduction in the purchase of prosthesis in Peru

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Abstract. In the present document a processing technique is applied to identify the intention of movement in the myoelectric signals, by means of algorithms entered in a microcomputer with a software of free programming that presents a great speed when executing the instructions, with the necessary resources, to replace the PC and thus achieve low costs while maintaining the high quality standard, making the system accessible and reliable for people with low economic resources, while generating greater portability compared to the current prostheses that are handled in Peru, that are mostly made abroad, which increases the cost.

1. Introduction

Electromyographic signals are biomedical signals [1] used to generate equipment that implies greater independence for people with functional diversity, which will lead to great physical and psychological improvements for patients [2]. In Peru, according to the INEI, 5.2% of the total population has some kind of functional diversity; among the most frequent is the motorboat, with 59.2% of the total of disabled[3].

Myoelectric control systems have been used to control assistive and rehabilitive devices for many years by performing classified patterns of Surface electromyography signals (EMG) [4]. Surface electromyography (EMG) can be used for telehealth [5] and for the control for the prosthesis [6]. The presence of noise [7], [8] such as measurement noise [9], [10], power line interference, quantization noise, ECG and movement artifact [7], [11] they obscure the information content of the signal and reduce its usefulness for the prosthetic control base on the recognition of patterns, causing a reduction in the classification of the gesture of precision [12].

For this reason, there is an evolution in the processing technique, from the spectral analysis by means of the Fourier transform until arriving at the multiresolution spectral analysis by means of the "wavelet transform" [13], to provide a safe platform to perform daily tasks [14], we must choose an appropriate classification algorithm for a problematic task, which in particular requires practice: each algorithm has its own peculiarities and is based on certain assumptions [15]. With the technological advance, every time it is possible to improve the construction of prosthesis systems as extensions of some member of the body [13]. This advance has allowed the reduction in size of electronic equipment, something that is currently allowing replacing computers that depend on a PC (Personal Computer) to perform the processing of signals by embedded systems or microcomputers.
These embedded systems are of a small size, have a very low cost and have the computational resources to perform tasks of high demand. [2] Taking into account the architecture of the embedded system, there is a noticeable decrease in energy consumption compared to high performance computers. Consequently, there would be a decrease in the size of the source, giving it greater autonomy and sustainability [16]. In this study we will apply the method based on the optimization of the representation space in combination with a robust classifier (support vector machine, SVM), in the case of multichannel signals [17] inside a microcomputer with which the tests will be carried out corresponding between the prosthesis of the arm and the algorithms inserted by means of programming using free software [18]. The tests must take into account factors such as machine performance, percentages of classification and temporal analysis [15]. The success of the classification depends almost entirely on the selection of characteristics of EMG signals [19], [20] to prove its feasibility and make our research work once it is accessible to people with limited resources, since 25.0% of the population with some functional diversity is poor, 2.3 percentage points more than the total population 22.7% people as we see in figure 1. [3].

![Disability ratio and poverty level.](image1)

**Figure 1.** Disability ratio and poverty level.

What would affect the improvement of quality of life of people with functional diversity [2] and because the most advanced myoelectric hand prostheses are capable of performing any action that a human hand would develop, but the great disadvantage is its high cost, a prosthesis with the mentioned characteristics would be costing approximately 60 thousand American dollars [14].

2. Developing

2.1. Structure design

The stage of acquisition, conditioning, digitization and processing is seen in figure 2.

![System of control of a robotic prosthesis.](image2)

**Figure 2.** System of control of a robotic prosthesis.

2.2. Analysis
Pre-processing: prior to the extraction of features is done using different techniques to reduce noise and highlight the signal for analysis.

Processing: The Wavelet Transform (Wavelet Transform, WT) is a useful method to extract information from specific bands. Once we know the bandwidth (BW), we apply the wavelet transform to find the level of decomposition required [2]. Its channel goes from 20 Hz to 500 Hz [6], [13]; therefore, we proceed to divide the bandwidth successively until we find the level of decomposition that contains the desired range [2].

These signals are used to calculate the energy in each desired band: cD3 and cD4 for the wave’s μ and β and cA4 to know the energies of the main component with respect to the total. The calculation of the energy of cD3 and cD4 is derived from:

\[
E(cD3) = (cD3)(cD3)^T
\]

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\]

The relative energy of the main component cA4 with respect to the total energy is obtained from:

\[
E(cA4) = \frac{1}{\frac{1}{2}} \int (cA4)(cA4)^T (cDi)(cDi)^T
\]

With these three values for each of the N channels, we obtain the vector of characteristics \( f(v) \) composed of 3N values [2]. So that \( f(v) \) is equal to:

\[
f(v) = \left[ E1(cD3), E(cD4), E1(cA4), E2(cD3), E2(cD4), E2(cA4), \ldots EN(cD3), EN(cD4), EN(cA4) \right]
\]

The normalized feature vector \( F \) is:

\[
F = \frac{f(v) - \mu}{\sigma}
\]

Another method of extracting characteristics is the MAV. Different window lengths are analyzed and related for classification accuracy [1], with equation 6 we obtain these characteristics.

\[
\overline{X_m} = \frac{1}{L} \sum_{k=1}^{L} |X_k|
\]

We optimize the mother wavelet using an estimate of the probability of classification error. A regularized estimate of this probability is calculated from the learning set using the cross-validation procedure (CV) [1], as we can see in figure 3.

![Figure 3. k-fold validación cruzada con k=4.](image)

Each of the subsets is used as a training set and all other subsets as a sample set [17]. The general probability of classification error is the average value of the n_e probabilities \( P_e^\theta \):

\[
P_e^\theta = \frac{1}{n_e} \sum_{i=1}^{n_e} P_e^\theta (\omega_i)
\]
Then, the optimal parameter will be called $\theta$. The final classification rule corresponding to the optimal Wavelet is derived from all learning sets [17]. Now we will analyse the SVM. The SVM has decision limits with large margins that tend to have a minor generalization error [15]. SVM takes the input data as an n-dimensional feature space. Then a dimensional hyperplane (n-1) appears that separates the space into two parts, as shown in figure 4.

The n-dimensional input data at $x_i$ ($i = 1, 2 \ldots l$) is labelled, and $i = 1$ for class 1 and as $y_i = -1$ for class 2 by the matrix $y_i$. The hyperplane is defined for linearly separable data [1].

$$f(x) = w \cdot x + b = \sum_{i=1}^{n} w(i) \cdot x(i) + b$$

(Sgn (f (x))) is the decision function. In equation (8), $x$ is an n-dimensional vector and $b$ is a scalar. These determine the position of the hyperplane that completely separates the space has to obey the limits.

$$y_i(x_i \cdot w + b) - 1 \geq 0 \iff \begin{cases} \{ f(x_i) = y_i w + b \geq 1 \\ f(x_i) = y_i w + b \leq 1 \} & y_i = +1 \\ \{ y_i = -1 \} & y_i = -1 \end{cases}$$

(9)

En la ecuación siguiente, $\xi_i$ es la variable independent and $C$ is the error penalty. The minimized hyperplane solution is as follows:

$$\phi(w, \xi) = \frac{1}{2 \cdot (w \cdot w)} + C \cdot \sum_{i=1}^{n} \xi(i)$$

(10)

Depending on:

$$y_i[(x_i \cdot w) + b] \geq 1 - \xi(i), \quad i = 1, 2, \ldots, l$$

(11)

3. Results

Software:

Matlab is one of the most used programs for processing, in this work ot will be taken into account for the comparison with Python.

In Python, the time it took to execute the algorithms was shorten when performing EMG signal processing as we can see in figure 5.

Figure 4. Separation with the support vector.

Figure 5. Comparison in execution times.
Matlab had a better accuracy in the classification percentage than Python when performing the cross validation, this being a little noticeable difference as we can see in figure 6.

![Figure 6. Percentage of classification Python vs Matlab.](image)

**Figure 6.** Percentage of classification Python vs Matlab.

Hardware:
A comparison chart is shown comparing the processing time of a raspberry pi 3 B and a laptop as we can see in figure 7.

![Figure 7. Time of a laptop Vs Raspberry](image)

**Figure 7.** Time of a laptop Vs Raspberry

4. Conclusions
Python is a software that allows a greater speed of execution when performing the processing. Due to the speed of execution, it ignores some data, which makes it imprecise when making the classification, however, this margin of error is small.
The raspberry embedded system meets all the requirements for correct signal processing, as well as being a portable element that will allow a better mobilization of people with functional diversity.

5. Observations
We noticed that at the beginning of the tests there was a variation in the values that depended on the characteristics of the PC.

6. Recommendations
In order to carry out a comparative analysis in time of execution of different programs it is necessary that the tests are carried out in a same computer, this so that the processing speed does not affect the measurement of time.

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