Identification of EMG activity with machine learning in patients with amputation of upper limbs for the development of mechanical prostheses

J N Zuleta¹, M Ferro¹, C Murillo¹, R A Franco-Luna¹,²
¹Tecnoacademia Risaralda, Servicio Nacional de Aprendizaje SENA, Carrera 21 con 73 bis, Dosquebradas, Colombia
²Facultad de Ingeniería, Universidad Tecnológica de Pereira, Carrera 27 # 10-02, Pereira, Colombia
rfranco@sena.edu.co

Abstract. A study of electromyographic signals (EMG) in subjects with partial hand amputation using machine learning techniques (ML) is presented in this document. The EMG were analyzed for five hand poses. We used the Fast Fourier Transform (FFT), and Wavelet transform as descriptors for the feature extraction, the identification and classification system was implemented based on Vector Support Machines (VSM). Percentages of accuracy greater than 90% were obtained in the cases of close hand, left hand, right hand and relax hand, while open hand obtained an acceptable performance with accuracy percentages lower than 90%.

1. Introduction
The use of EMG applied to the automatic identification of muscle activity is increasing. In medicine are essential in clinical diagnosis of neuromuscular and neurological disorders patients [1], in the field of biomedical instrumentation are important for the development of robotic prostheses, wheelchairs and devices physical rehabilitation as exoskeletons [2]. EMGs show electrical potentials associated with the level of muscle activity generated during contraction and relaxation. The potentials can be detected by means of intramuscular devices (iEMG) and superficial devices (sEMG) located on the muscle, this work considers only sEMG.

Different EMG features extraction techniques have been used, in 1975, Graupe and Cline classified EMG with a success rate of more than 75% using Mean Absolute Value (MAV), this approach was taken up in several works, among which stands out Bingken and Shiyou in 2016 [3], Khushaba et. to the. in the same year [4] and Bhattacharya and Sarkar in 2017 [5]. In 1995, W. Kang used Mel-Frequency Cepstral Coefficients (MFCC), obtaining an accuracy of 85% [6], a method adopted by Lee and Kim in 1996 [7] and recently by several authors [8,9,10]. The Fourier transform and its variations - fast Fourier transform (FFT) and fast short pulse Fourier transform (STFFT), are widely used in the characterization of EMG [11,12]. Techniques based on time-frequency combinations have also been used, such as the Wavelets transform [13,14], obtaining accuracies greater than 90%.

In this work we analyzed the EMG for five hand poses: close hand, open hand, left hand, right hand and relax hand. FFT and wavelet transform were used as descriptors for the features extraction. Vector
support machines (VSM) were implemented as a machine learning technique (ML) for the identification and classification system.

2. **Materials and methods**

2.1. **Subjects**
Ten subjects aged between 15 and 48 years participated in this investigation. All subjects completed a document on consent to participate. There was also psychological accompaniment considering details related to the emergence of his disabling condition, life story collected based on precise clinical interview guidelines and the help of projective measuring instruments, this to assess the feasibility of work with the subject and possible risks of generating considerable levels of anxiety due to the expectation of a possible corrective intervention in later phases of the investigation.

2.2. **Acquisition of EMG**
The myo armband from Thalmic was used, it has eight Medical Grade Stainless Steel EMG sensors, highly sensitive nine-axis IMU containing three-axis gyroscope, three-axis accelerometer, three-axis magnetometer, and sampling frequency of 200Hz. Software was designed in Matlab to capture, visualize and store the EMG.

2.3. **Hand poses**
The myo armband sensor was located on the forearm. Five hand poses were analyzed: close hand, open hand, left hand, right hand and relax hand. Subjects repeated ten times each pose. Figure 1 shows the five hand poses.

![Figure 1. Hand poses: a) close hand, b) open hand, c) left hand, d) right hand, e) relax hand.](image)

3. **Data analysis**
For the development of this document a pattern of three stages worked: the initial step is the detection signal, followed by the step of feature extraction and finally the classification stage. No dimensionality reduction is applied, since the aim is to identify the performance of the ML system based on raw data and compare two signal characterization methods: FFT and Wavelets.

![Figure 2. Scheme of 3 stages for ML implementation](image)
3.1. Detection and adaptation of EMG.
After the configuration of the Myo Armband bracelet, the programming of a data acquisition system using the SDK of the development company and Matlab mathematical analysis software was carried out. A script was developed that allows collecting and organizing the information as shown in figure 3.

![Data Base Diagram]

- This element contain all structure of database
- This variable contains all the names of the people that the signals were captured
- Here we can find all of the movement purposed for detect with de EMG signals, this signals are, Close Hand, Open Hand, Left Hand, Right hand and Relax hand.
- In that point, we can find the signals of the all sensor. The Myo Armband has an eight EMG sensor distributed around of the arm.

**Figure 3.** Sequential outline of the data structure.

3.2. Feature extraction
For the initial development and validation of the database, the mathematical methods to be compared are FFT and the transformed Wavelet haar. The equation (1) shows the discrete Fourier transform.

\[
X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \quad k = 0,1,\ldots,N-1
\]  

(1)

From the FFT implementation, the frequency coefficients are obtained, which will be used as a descriptor of the signal. Figure 4 shows a set of 5 captures of the experiment for the pose close hand where the behavior of the signals in the time of the 8 sensors can be observed, and in Figure 5 the FFT corresponding to each sensor is observed.

![Pose close hand on the eight sensors]

**Figure 4.** Pose close hand on the eight sensors
Another technique widely used in signal analysis is the Wavelet transform with a "haar" mother signal, for the implementation a decomposition of order 6 was used and a vector was constructed with the detail and approximation coefficients of the Wavelet haar transform, the descriptor obtained with the application of the wavelet transform can be seen in figure 6 (left).

In the experimental development a third descriptor was implemented from the Wavelet signal (WL-2), each of the groups of approximation and detail coefficients can be seen as a modal decomposition process. Each group was implemented a set of statistical moments composed of the average, standard deviation, kurtosis, median mean and autocorrelation, this descriptor is shown in Figure 6 (right).
3.3. Training and classification

After having built the database of the five poses to be identified, each pose composed of a set of signals from the 8 EMG sensors of the bracelet, the features extractors based on FFT, Wavelets haar and their statistics were applied. A one-to-one structure was implemented for each hand pose and the configuration of a binary SVM.

For the training the database was randomly divided 70% training and 30% validation in each iteration of Monte Carlo to guarantee statistical relevance. Figure 7 shows the structure of data processing for training using Monte Carlo iterations. Two experiments were performed with 1000 and 100 iterations of Monte Carlo with an approximate computation time of 95 minutes and 13 minutes respectively, the deviation between both experiments was less than 1%.

![Figure 7. Structure of data processing for training using Monte Carlo iterations.](image)

4. Results and discussion

After training, the performances of SVM for identifying poses with the use of the proposed descriptors were evaluated. Table 1 shows the percentage of accuracy and deviations obtained by the descriptors FFT, WLhaar and WL^-2.

| Pose         | Accuracy (%) | Deviation (%) |
|--------------|--------------|---------------|
|              | FFT          | WLhaar        | WL^-2         | FFT  | WLhaar | WL^-2 |
| close hand   | 97.33        | 94.38         | 95.04         | 0.85 | 1.39   | 1.16  |
| open hand    | 87.50        | 79.56         | 84.30         | 2.19 | 2.88   | 2.40  |
| left hand    | 94.64        | 91.97         | 94.44         | 1.22 | 1.54   | 1.37  |
| right hand   | 92.75        | 88.55         | 93.68         | 1.40 | 1.89   | 1.44  |
| relax hand   | 84.47        | 92.97         | 89.33         | 2.40 | 1.52   | 1.86  |

The FFT descriptor presented an outstanding performance in three of the poses (close hand, left hand and right hand), with accuracies over 92%, reaching 97.33% in close hand, this shows great separability in its frequency spectra. The lowest performances using FFT were obtained in open hand
and relax hand with accuracies of 87.50% and 84.47% respectively, which are considered acceptable for the identification process.

Moreover, the descriptor WLHarr presented an outstanding performance in the poses close hand, left hand and hand relax with accuracies above 90%. In the right hand and open hand poses the performance was lower with success percentages of 88.55% and 79.56% respectively. In turn, the descriptor WL-2 presented accuracies greater than 93% in the poses close hand, left hand and right hand, in addition, 89.33% and 84.30% in relax hand and open hand respectively.

Analyzing the performance by hand pose, the results of the FFT descriptor showed a greater accuracy in the poses close hand, open hand and left hand. The descriptor WLhaar classified with greater accuracy the pose relax hand while WL-2 did it in right hand. Additionally, open hand was the pose with the lowest percentage of acerts, being lower than 90% in the three descriptors, a percentage that is comparable with results obtained in other works [2,5,10]. In contrast, close hand and left hand were classified with accuracies greater than 90% by the three descriptors.

5. Conclusions
An identification and classification structure was obtained for the five proposed poses with accuracies higher to 90% in the cases close hand, left hand, right hand and relax hand, while open hand obtained an acceptable performance with accuracies less than 90%.

The performance results of the descriptors suggest that some hand poses present combinations of muscle activities that could be confused by the identification system and be classified erroneously, especially in the open hand and relax hand cases. The implementation of techniques for eliminating redundant components such as PCA could improve the performance of the classifier.

The variations in the results of the three descriptors allowed to identify the importance of these in the performance of the classifier. It is concluded that the implementation of additional descriptors and the fusion of methodologies could allow a broader spectral separation and consequently better performances of the classifier.

6. References
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