2014 5th IEEE RAS & EMBS International Conference on
Biomedical Robotics and Biomechatronics (BioRob)
August 12-15, 2014. São Paulo, Brazil

Electromyographic signals processing for robotic assistance tools in the rural population

Andrés A. Ramírez D[1], Mario Jiménez[2] and Miguel F. Arevalo[3]

***Abstract*— This paper presents an algorithm to process the electromyography signal (EMG). It requires low computational power which allows it to be implemented in embedded, low cost platforms. The proposed algorithm uses the Short-Time Fourier Transform (STFT) and the feature extraction methods, namely, modified mean frequency, and the first spectral moment (SM1). This algorithms is able to identify four different movements of one upper limb, allowing to control a robotic assistance tool with four degrees of freedom. Thanks to the properties of this algorithm, rural populations can have access to this type of technologies.**

I. INTRODUCTION

Landmines are considered a lethal weapon all around the world. Worldwide, the number of victims increases by about 200000 a year [1]. From these large number of victims, 30 % are amputees of upper limbs, and most of them belong to the working-age population. Unfortunately, Colombia does not escape from this reality. According to the International Committee of the Red Cross (ICR), four rehabilitation centers were supported in 2012. In these centers, more than 34000 victims were attended, and they were remitted after an armed conflict or after general accidents [2]. Hundreds of these victims received physiotherapy, prosthesis, and/or orthosis, until complete recovery.

The presidential program for the integral action against landmines of Colombia, reported a total of 10628 landmine victims during the period between 1990 and January 2014. These victims were in a large percent 61 % members of military forces, and 39 % were civil population, mostly inhabitants of rural areas [3].

The role of technological fields like bioengineering is crucial for the recovery and the improvement of the quality of life of victims of landmines. For example, the development of robotic tools that can support rehabilitation, may increase the possibilities of amputees to find a job again, and perform regular activities in much better conditions. However, the implementation of such tools is very limited in rural areas due to the elevated costs that they represent.

Nowadays, different types of prosthesis that can be coupled to the human body exist. Some prosthesis consist mainly of mechanic systems, while others use signals recorded from the human body to control different movements and positions [4]. One of these recorded signals is the surface Electromyography (sEMG), which is analyzed to achieve autonomous movements of the prosthesis. Different techniques have been used to progress in the development of advanced robotic prosthesis. In [5], a set of methods to analyze frequency and time domain features was presented. These methods include the mean amplitude of the sEMG signal, zero-crossing rate, histograms, autoregressive coefficients, Fourier transform, amongst others [6]. More advanced methods like time-frequency representations have been explored in [7], [8], and they correspond to short-time Fourier transform (STFT) [9], wavelet transform (WT) [10], [11], and wavelet packet transform (WPT) [12]. The latter has received a considerable amount of attention on the analysis of EMG signals. Some studies have used different channels and different muscles to record EMG signals, in order to improve the accuracy and quality of the algorithms [13], [14]. Once several features are extracted from the signals, different algorithms have been used to classify the events. These algorithms include Bayesian classifier [15], [16], Markov methods [17], multilayer perceptron [18], [19], and fuzzy classifier [20].

This paper aims to develop an algorithm that identifies four different movements of an upper limb, by means of an acquisition and processing system based on sEMG. This algorithm should be easy to implement on a low cost platform, hence, it can be easily offered to populations in rural areas of Colombia. The acquisition and classification of movements would allow to assist landmine victims with robotic, controlled and affordable technologies, which at the end, will improve the quality of life of this affected population.

II. METHOD

II-A. *sEMG data acquisition*

The first step of the project, consisted of the acquisition of electromyographic signals. These were taken using a single channel in the *extensor carpi radialis* of healthy subjects. Four movements were characterized, namely, hand opening and closing, wrist pronation and supination. In total, 12 subjects were included in the study, and they were asked to perform 25 repetitions of each movement.

The acquisition system consists of three surface electrodes (3M red dot 25mm foam solid gel). The sEMG signals were digitized at $1000Hz$, using the sound card of a personal computer. Furthermore, a bandpass filter with cutoff frequencies at $10Hz$ and $300Hz$ was implemented.

[1]Facultad de Ingeniería, Ingeniería en Automatización, Universidad de la Salle, Bogotá, Colombia. aaramirez@unisalle.edu.co
[2]Facultad de Ingeniería, Programa Bioingeniería, Universidad El Bosque, Bogotá, Colombia. mjimenezh@unbosque.edu.co
[3]Facultad de Ingeniería, Ingeniería en Automatización, Universidad de la Salle, Bogotá, Colombia. pipe.213@hotmail.com

978-1-4799-3127-9/6/14/$31.00 ©2014 IEEE

In addition, a digital notch filter at $60Hz$ was used to remove power line interferences. In order to guarantee real-time processing, the digitalization was done on windows of $320ms$ each.

II-B. sEMG pattern recognition

Taking into account the requirements of the system, namely, low cost and reduced computational resources, the proposed algorithm aims to achieve maximum performance with simple processing techniques. It is well known [10] that analysis based on time-frequency representations achieve better performance than methods based on one of the two. For example, in [12], it was shown that wavelet package transform (WPT) provides better recognition performance of multiple movement gestures. However, the computational costs of WPT-based applications are very high, which limits its implementation on a high-level computating platform [4]. The short time Fourier transform (STFT) also allows the analysis in the time-frequency domain with a lower computational cost. For the specific purpose of this project, the STFT was chosen, due to its low computational cost and performance compared to that of WPT.

II-B.1. Short time Fourier transform: Hannaford studied the sEMG spectrum of rapid movements by means of short time Fourier transform analysis of electromyographic signals [9]. First, the signals were divided into segments using a time window, then Hannaford applied the discrete Fourier transform to each segment, and their frequency content was then analyzed. The used of this transformation allowed Hannaford to study the time-frequency dependencies of the sEMG signals.

The short time Fourier transform can be expressed as:

$$STFT(t, f) = \int x(\tau)w(\tau - t)e^{-2\pi jf\tau}d\tau \qquad (1)$$

Where $x(\tau)$ is the raw signal, and $w(t)$ is the Hamming window. The window size defines the number of segments in which the time domain is divided, at the same time, the resolution of the time-frequency domain is defined.

For each movement, we apply the short time Fourier transform (STFT) with a Hamming window of $160ms$ and a shift of $80ms$, this generates 50 % of overlapping samples and split the sEMG into 31 segments (i.e. $i = 31$).

The procedure begins with the STFT application to each sEMG. The result of the STFT can be displayed in two ways, through a spectrograma or through individual representation of the discrete Fourier transform of each segment.

II-B.2. Feature extraction: Four different methods were implemented to perform feature extraction. Each of these methods is applied to the short time Fourier transform of all segments that compose the sEMG, and they are described as follows.

1. Modified mean frequency $(MMNF)$:

$$MMNF_i = \frac{\sum_{j=1}^{M} f_{ij}A_{ij}}{\sum_{j=1}^{M} A_{ij}} \qquad (2)$$

   Where $MMNF_i$ is the modified mean frequency in the segment i, f_{ij} is the value of frequency sample j for the segment i and A_{ij} is the frequency spectrum amplitude in the frequency f_{ij}.
2. 1st Spectral moment SM_1

$$SM_{1i} = \sum_{j=1}^{M} f_{ij}P_{ij} \qquad (3)$$

3. 2nd Spectral moment SM_2

$$SM_{2i} = \sum_{j=1}^{M} f_{ij}^2 P_{ij} \qquad (4)$$

4. 3rd Spectral moment SM_3

$$SM_{3i} = \sum_{j=1}^{M} f_{ij}^3 P_{ij} \qquad (5)$$

   For the spectral moments $SM_{1,2,3}$, P_{ij} is the power spectral amplitude of sEMG in the frequency f_{ij} of segment i.

In this way, four features characterize each segment (range in time) of the signal. Thus, for each movement repetition we obtain a matrix of four features by $i = 31$ segments. Also, we compared each of the combinations between the four features to expand features space and remove lower performance combinations.

II-B.3. Feature projection and Classification: The time-frequency transformations generate a high number of features which on their turn generate a high dimensional feature space. In addition, the STFT generates decompositions of 31 segments, for which four features are calculated. Therefore, it is necessary to apply dimensionality reduction in order to find a tractable feature vector for the clustering algorithm.

Different methods exist to perform dimensionality reduction, for example, principal component analysis (PCA) and linear discriminant analysis (LDA). There are other techniques that combine the last two, such as Self-Organizing Feature Map (SOFM) [12]. In this study, the feature selection (i.e. dimensionality reduction) was performed by means of the mean and standard deviation of each feature over time.

The pattern recognition algorithm was then completed using a fuzzy c-means clustering algorithm. The latter aims to minimize the classical objective function c-means defined as:

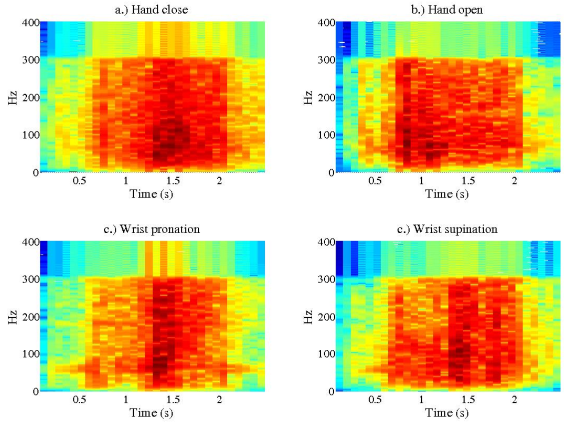

Fig. 1. sEMG power spectrum for each movement

$$J(Z;U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m \left\| z_k - v_i \right\|_A^2$$

where

$$U = [\mu_{ik}] \in M_{fc}$$

is a fuzzy partition matrix of Z, m is a parameter which determines the fuzzines of clusters,

$$V = [v_1, v_2, \cdots, v_c],\ v_i \in \Re^n$$

is a vector of centers. The dissimilarity measure $\left\| z_k - v_i \right\|_A^2$, is a squared inner-product distance norm [21].

The fuzzy clustering algorithms have the following advantages, are insensitive to overtraining, are robust to data uncertainty and are easy to implement on embedded systems based on the lookup table method.

III. Results and Discussion

The sEmg spectrogram is shown in figure 1. The four movements exhibit a high frequency concentration around $100Hz$ in the movement middle time.

The signal Time-dependent behavior is shown in figure 1 (b). Notes a primary response at time $t \approx 0{,}8s$ which has the largest frequency component. However, at time $t \approx 1{,}2s$ a secondary response is observed with a considerable frequency concentration.

Figure 2 shows a bar graph for representing the feature extraction for the sEMG of hand close movement. This figure shows an array of four features for each of the 31 segments composing a single signal. Figure 2 shows how each feature has a distribution along the time axis, which can be easily represented by its statistical moments.

Figure 3 shows the movements distribution in the (MMNF) feature space. The points in red represent repetitions of the hand closing movement, points in blue represent hand opening movement, the green points represent wrist pronation and cyan points represent repetitions for wrist supination. In figure 3, the separation for pronation movement is observed, however, the remaining three movements overlap in MMNF feature space. This makes the use of an expanded feature space. The feature combinations that exhibits the best performance correspond to $(MMNF, SM1)$ and $(MMNF, SM3)$.

Figure 4 shows the first features pair (MMNF,SM_1). Signals are projected in the feature space from the mean value and standard deviation between SM_1 and MMNF, offering a better separation index.

The figure 5 shows the second feature pair (MMNF,SM_3). Although, to discriminate the signals in the feature space, the separation between movements is less effective than in the case of Figure 4. This is due to the behavior of spectral moment SM_1, which weighted with equal proportion the power spectrum amplitude and the frequency value in all segments. On the other hand, the spectral moment SM_3 weights the power spectral amplitude with frequency to the power three, decreasing the effect of the amplitude spectrum..

Finally, after searching the best combination in the feature space, the last step in the implementation of the system was the fuzzy classifier. Figure 6 shows the results of the fuzzy algorithm using the whole dataset. It is shown that the shapes of the clusters are irregular, as well as their centroids, and their density distributions. Each cluster was then characterized by its most repetitive label, namely the most common movement. Figure 6 (c-d) shows the results for the identification of four different movements of an upper limb. The hand open and hand close movements provide the best performance. The wrist supination and wrist pronation show superposition and wrong classification in the bordering cluster, however, this might be due to the noise at the

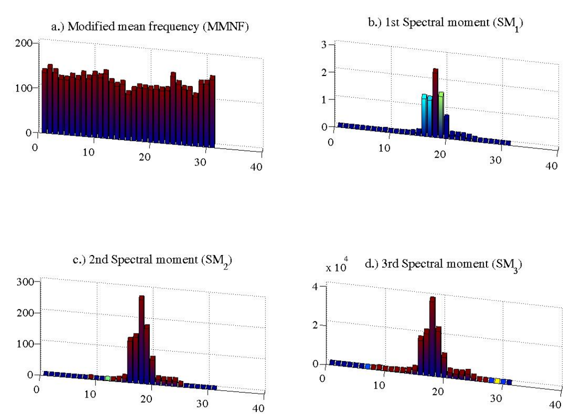

Fig. 2. Feature extraction matrix in a bar graph

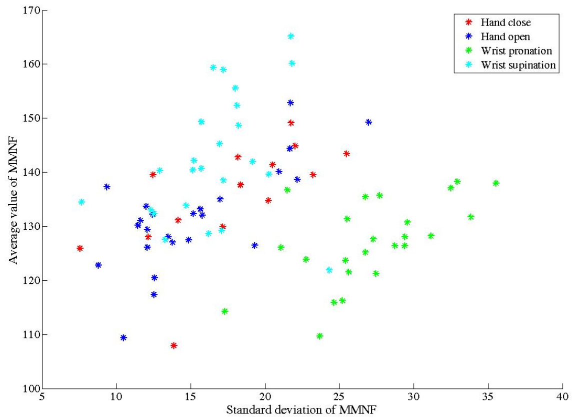

Fig. 3. Movement representation in (MMNF) feature space

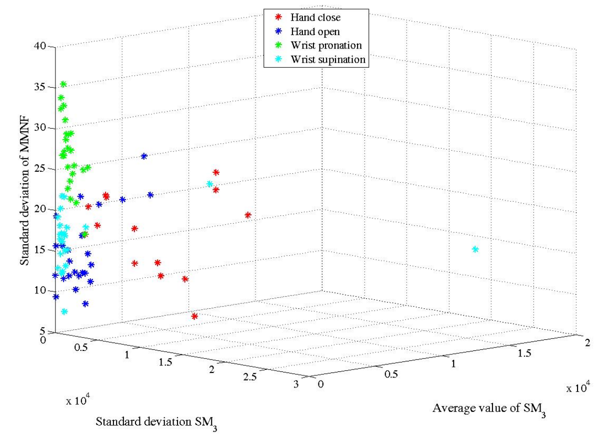

Fig. 5. Movement representation in $MMNF \times SM_3$ features space

acquisition moment and to some extremes values of the features that were used to train the fuzzy algorithm.

IV. Conclusion

The application of an algorithm based on short time Fourier transform and a discriminating using, modified mean frequency (MMNF) and 1st spectral moment SM_1 show the viability of implementing algorithms of less complexity and less computational consumption on low processing and low cost platforms. This opens the way for developing inexpensive devices that can contribute in building robotic assistance tools for the rural population.

References

[1] F. H. A. Salem, K. S. Mohamed, S. B. K. Mohamed, and A. A. E. Gehani, "The development of body-powered prosthetic hand controlled by emg signals using dsp processor with virtual prosthesis implementation," *Hindawi Publishing Corporation Conference Papers in Engineering*, vol. 2013, p. 8, 2013.

[2] C. I. de la Cruz roja, *Situacion Humanitaria informe de actividades Colombia 2012*, J. Raich, Ed. Pro-Offset Editorial S.A., 2013.

[3] P. de Colombia. Programa presidencial para la accion integral contra minas antipersonal. Consultado en marzo de 2014. [Online]. Available: http://www.accioncontraminas.gov.co/Paginas/victimas.aspx

[4] W. Xiao, H. Huang, Y. Sun, and Q. Yang, "Promise of embedded system with gpu in artificial leg control: Enabling time-frequency feature extraction from electromyography," *Conference Proceeding IEEE Engineering Medicine Biology Society*, vol. 6926, p. 4, 2009.

[5] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "A novel feature extraction for robust emg pattern recognition," *Journal of computing*, vol. 1, pp. 71–80, 2009.

[6] J.-U. Chu, I. Moon, Y.-J. Lee, S.-K. Kim, and M.-S. Mun, "A supervised feature-projection-based real-time emg pattern recognition for multifunction myoelectric hand control," *IEEE/ASME Transactions on mechatronics VOL. 12, NO. 3, JUNE 2007*, vol. 12, pp. 282–290, 2007.

[7] K. Englehart, B. Hudgins, P. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Special Issue of Medical Engineering and Physicson Intelligent Data Analysis in Electromyography and Electroneurography.*, vol. 1, p. 13, 1999.

[8] M. Hamedi, S.-H. Salleh, A. M. Noor, T. T. Swee, and I. K. Afizam, "Comparison of different time-domain feature extraction methods on facial gestures' emgs," *Progress In Electromagnetics Research Symposium Proceedings*, vol. 1, pp. 1897–1900, 2012.

[9] B. Hannaford and S. Lehman, "Short time fourier analysis of the electromyogram: Fast movements and constant contraction," *IEEE Transactions on biomedical engineering*, vol. BME-33, pp. 1173–1181, 1986.

[10] A. Phinyomark, A. Nuidod, P. Phukpattaranont, and C. Limsakul, "Feature extraction and reduction ofwavelet transform coefficients for

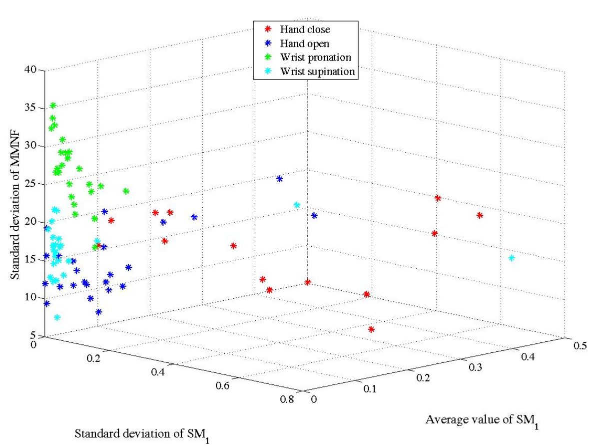

Fig. 4. Movement representation in $MMNF \times SM_1$ features space

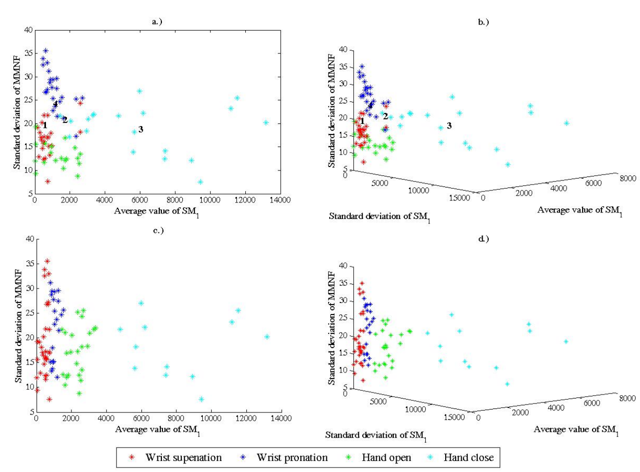

Fig. 6. Center cluster representation and clustering result

emg pattern classification," *Electronics and electrical engineering*, vol. 6 (122), pp. 27–32, 2012.

[11] F. A. Mahdavi, S. A. Ahmad, M. H. Marhaban, and M.-R. Akbarzadeh-T, "Surface electromyography feature extraction based on wavelet transform," *International Journal of Integrated Engineering*, vol. 4, pp. 1–7, 2012.

[12] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. A. A. Bakar, K. Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques," *Sensors*, vol. 13, pp. 12 431–12 466, 2013.

[13] R. Boostani and M. H. Moradi, "Evaluation of the forearm emg signal features for the control of a prosthetic hand," *Physiological Measurement*, vol. 24, pp. 309–319, 2003.

[14] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "Application of wavelet analysis in emg feature extraction for pattern classification," *Measurement science review*, vol. 11, pp. 45–52, 2011.

[15] M. Zardoshti-Kermani, B. C. Wheeler, K. Badie, and R. M. Hashemi, "Emg feature evaluation for movement control of upper extremity prostheses," *IEEE Transactions on Rehabilitation Engineering*, vol. 3, pp. 324–333, 1995.

[16] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for emg signal classification," *Expert Systems with Applications*, vol. 39, pp. 7420–7431, 2012.

[17] S. Adee, "Dean kamen's, luke arm prosthesis readies for clinical trials," *IEEE Spectrum*, 2008.

[18] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of emg signal analysis: detection, processing, classification and applications," *Biological Procedures Online*, vol. 8, pp. 11–35, 2006.

[19] Q. He, C. Peng, B. Wu, and H. Wang, "Detectionofsurfaceemg signal using active electrode," *Sheng Wu Yi Xue Gong Cheng Xue Za Zhi*, vol. 20, pp. 488–490, 2003.

[20] D. Joshi, S. Atreya, A. S. Arora, and S. Anand, "Trends in emg based prosthetich and development: a review," *Indian Journal of Biomechanics*, pp. 228–232, 2009.

[21] R. Babuska, *Fuzzy modeling for control*. Springer Netherlands, 2012.