

# Decomposition of Surface Electromyographic Signal Using Hidden Markov Model

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**Abstract:** The detection of physiological signals from the motor system (electromyographic signals) is being utilized in the practice clinic to guide the therapist in a more precise and accurate diagnosis of motor disorders. In this context, the process of decomposition of EMG (electromyographic) signals that includes the identification and classification of MUAP (Motor Unit Action Potential) of a EMG signal, is very important to help the therapist in the evaluation of motor disorders. The EMG decomposition is a complex task due to EMG features depend on the electrode type (needle or surface), its placement related to the muscle, the contraction level and the health of the Neuromuscular System. To date, the majority of researches on EMG decomposition utilize EMG signals acquired by needle electrodes, due to their advantages in processing this type of signal. However, relatively few researches have been conducted using surface EMG signals. Thus, this article aims to contribute to the clinical practice by presenting a technique that permit the decomposition of surface EMG signal; (2) presentation of the morphological patterns of MUAPs in the EMG signal; (3) identification of the firing sequence of the Motor Units. The model proposed in this work is an advance in the research area of decomposition of surface EMG signals.

Key words: Decomposition of EMG signal, hidden markov models, differential evolution, spectral clustering.

# 1. Introduction

Talking, walking and writring are examples of some actions taken by the neuromotor system of the human body. The movement is orchestrated by the coordinated action of peripheral regions, spinal cord, brainstem and cerebral [1].

Detection and analysis of physiological signals from the Neuromotor System have been present in several studies, from basic science to clinical diagnostics [2, 3]. Electromyography is an analytical method for the study of physiology, biomechanics and Neuromotor System fundamentals of human body [4]. Understand the EMG (electromyographic) signal implies understanding the functioning of muscles and how bioelectrical signals are generated [3, 5].

The EMG signal is derived from the sum of several MUAP (Motor Unit Action Potentials) from the muscle fibers, leading to muscle contraction [1]. In this way, the decomposition of the EMG signal results in the set of the various MUAPs that make up the EMG signal [6, 7].

MUAPs information, such as morphology, duration, rate of occurrence and trigger time, is very used to diagnose neuromuscular disorders [8, 9]. And also, the morphology of MUAPs contains information about health and anatomy of muscle fibers [10].

Thus, the analysis of MUAPs helps the professional to assess if there is any motor disorder and what is its origin: (1) motor neuron axon injury (neuropathy); (2) the injury or muscle fiber atrophy (myopathy) [11-14].

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The MUAPs presenting a myopathic disorder generally have short duration and low amplitude. And the MUAPs which present high amplitudes have characteristic of neuropathic disorders.

Nevertheless, understand normal or abnormal behavior control of Motor Units is essential in the decision of the need of a pharmacological or surgical intervention. And also, another important application of EMG signal decomposition is in the area of ageing and ergonomics, where it is interesting to understand when the motor control is changed as a result of aging, exercise, fatigue or excessive and prolonged power production [15].

However, the process of EMG signal decomposition is a complex task. The features of an EMG signal depend on the type of electrode used (intramuscular or surface), positioning relative to the muscle, the contraction level and the clinical status of the neuromuscular system of the patient [16].

In this context, some surveys have already been initiated to study the decomposition of EMG signals collected from surface electrodes, in order of the disadvantages described earlier. However, despite the interesting results already achieved, researches are recent and are still in the early stage of development [10]. So, there is a need for investigation of techniques for decomposition of EMG signals collected from surface electrodes, what would contribute to the proposal for a new path for the research in the area of surface electromyography.

Taking as inspiration the graphical probabilistic models used in researches with surface electroencephalographic signals in recent decades [17-20], and considering the fruitful results presented the authors of those by researches. probabilistic-graphical models can be an interesting technique to use with surface EMG signals. The use of probabilistic-graphical models can be a new way to implement a system of surface EMG signal decomposition, able to make the classification of MUAPs and calculate the probability of Motor Units firing at a given time. With a tool that uses probabilistic models for classifying MUAPs, it will be possible to perform the estimation of the firing sequence of Motor Units that composes the EMG signal. A technique with this feature is very important as a help in evaluating the operating mechanism of the neuromuscular system and much needed for the biofeedback therapies focusing on muscular rehabilitation.

Thus, the purpose of this work is to use the probabilistic graphical hidden markov model, in the process of decomposition of a surface EMG signal.

# 2. Materials and Methods

To develop the proposed system, initially it was necessary to project a framework for the system to be able to perform the EMG processing (noise elimination and detection of MUAPs) and perform the decomposition of surface EMG signal.

For the pre-processing step of EMG signal, that includes the application of filter for elimination of possible noise and MUAPs detection, the EMG decomposition system BR was used [8]. Thus, this system already provides the MUAPs present in EMG signal. Then, it was used the Hidden Markov Model for the MUAP clustering according to the morphological similarity between them. And so, whereas a Motor Unit generates a unique morphological pattern of MUAP, it is possible to determine how many Motor Units are active in EMG signal and also to present the morphological pattern of the MUAPs generated by them.

Fig. 1 presents the diagram with the system structure of surface EMG signal decomposition that was developed, containing the whole process and the techniques that were used in the decomposition of the EMG signal, as well the responses that are presented by the system.

## 2.1 MUAP Clustering

After the MUAPs detection stage, the next step developed by the proposed system is the MUAP clustering. This stage has the following functions:



Fig. 1 Block diagram of the structure of proposed system.

(1) Clustering of MUAPs that exhibit similar characteristics in its morphology;

(2) Identify the amount of active Motor Units in EMG signal that is being analyzed;

(3) Present the standard MUAP morphology that is generated by each active Motor Unit,

To this end, the process of MUAP clustering is accomplished by executing the following sequence:

(1) Feature extraction of MUAPs

In this step, selected features of MUAPs were detected in EMG signal. The process of extracting features of MUAPs was inspired by the work of the researchers Kanar et al. [21, 22]. They developed an algorithm based on Hidden Markov Model for pattern recognition. The main difference between the classical algorithms for pattern recognition and Hidden Markov Models is the process of extracting features. In the case of Hidden Markov Models, a uni-dimensional data can be divided into a sequence of segments, and from this sequence is extracted a vector of characteristics.

On the problem of recognition of dynamic behavior studied by the researchers [21], a dynamic signal was represented by a sequence y(k), k = 1, 2, ..., K, where Kis the amount of points. The procedure of feature extraction is started with the division of the sequence y(k) in T segments with L of length. Each segment is represented by  $y_t(1)$  (Eq. (1)).

$$y_t(l) = y[(t-1)L+1]$$
 (1)

where, l = 1, 2, ..., L and t = 1, 2, ..., T.

The next step is the extraction of characteristics of each segment. The dynamic patterns in general are characterized by successive segments increasing and decreasing. Thus, the information of angulation and curvature of each segment are components of the vector of characteristics. These characteristics can be obtained through polynomial approximations on each segment. The angulation of the first-order polynomial provides information about the behavior, that is, increasing, decreasing or constant. And the second-order polynomial can be used to get the second derivative, which will provide information about the curvature of the segment. And the third information that will compose the vector of characteristics is the average of the segment.

Thus, the vector of characteristics of each segment will consist of:

Angle

The first-order polynomial approximate to the sequence of points in a segment, can be expressed as Eq. (2):

$$f_t(x) = \phi_{t1}x + \phi_{t0} \tag{2}$$

where, t=1, 2, ..., T and x is a continuous variable.

Curvature

The second order polynomial is defined according to Eq. (3):

$$g_t(x) = \gamma_{t2}x^2 + \gamma_{t1}x + \gamma_{t0} \tag{3}$$

The equation can be used to compute the second derivative (Eq. (4)):

$$ct(x) = \frac{\frac{d^2g_t}{d^2x}}{(1+(dg_t/dx)^2)^{3/2}}$$
(4)

For this feature, the curvature is calculated at the midpoint of the segment  $(k_t)$ . Thus, the second feature will be  $c_t(k_t)$ .

Average

The average of the points of the segment also provides important information regarding signal level (Eq. (5)):

$$\mu_t = \frac{\sum r_t(l)}{L} \tag{5}$$

Thus, for each segment *t*, where t = 1, 2, ..., T, the authors will have a vector of characteristics  $O_t$ , according to Eq. (6):

$$O_t = \begin{pmatrix} \varphi_{t1} \\ c_t(k_t) \\ \mu_t \end{pmatrix} \tag{6}$$

Then, in accordance with Kanar et al. [21], a dynamic signal can be segmented into L segments and

each segment can be represented by a vector of characteristics O (Eq. (7)):

$$0 = \{o_1, o_2, o_3, \dots, o_T\}$$
(7)

MUAPs features extraction using the method of Kanar et al.

Whereas a MUAP morphology is similar to a dynamic signal, that is, can be represented by a sequence of increasing segments, decreasing or constant, it is possible to apply the set of features proposed by Kanar et al. [21], in the process of extracting features of MUAPs.

Thus, a Motor Unit Action Potential can be divided in *L* segments, and each segment will have a set of features  $O_t$  (Fig. 2). After the stage of feature extraction of MUAPs, the next step is to generate the Hidden Markov Model, as shown below.

(2) Hidden Markov Model

The next step is to generate a Hidden Markov Model that represents each MUAP detected in EMG signal. The aim of creating a template for each MUAP is explained by the need to build a Matrix of Similarity between MUAPs patterns that is necessary for the application of spectral clustering algorithm.

According to Kanar et al. [21], each set of features extracted from a determined data can be considered as being the observation that is observed in a state S. So, if considering each segment and defining in the previous section as a state, there will be a total of T states ( $S_i$ ). And also, the transition of these states is always from



Fig. 2 Example of a MUAP represented by left-right topology of a Hidden Markov Model with T states, and each state S represents a segment t.

left to right, considering the dynamics of the evolution of the EMG signal in time. Thus, the MUAP can be represented by a Hidden Markov Model of T states, with the left-right topology.

Thus, each MUAP detected on EMG signal, will be extracted a set of features  $O_t$ , t = 1, 2, ..., T, where *T* is the amount of segments of the MUAP. After performed this step, it will be created a Hidden Markov Model, left-right topology, with *T* states. Thus, each MUAP will be represented by a  $H\lambda$  (Fig. 2).

For this topology of Hidden Markov Model, the state transition matrix (*A*), will be represented by Eq. (8):

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ \vdots & \ddots & & 0 & \vdots \\ 0 & \cdots & 0 & 1 & 0 \\ 0 & \dots & 0 & 0 & 1 \end{pmatrix}$$
(8)

Each MUAP *i* that is presented in the EMG signal, was created a Hidden Markov Model  $\lambda_i$ , using the set of features  $O_i$ . Thus, the maximum likelihood produced by model  $\lambda_i$  is that generated by the set of observations  $O_i$ . It is important to highlight the fact that observations with close values will necessarily, generate likelihood with close values. And this case will happen when there are MUAPs with similar morphologies. And, MUAPs with similar morphologies will generate observations with nearby values. Consequently, the likelihoods will have close values. And also, considering that, these will be happened generally:

A Motor Unit produces a single morphological pattern of MUAP;

Different Motor Units generate distinct morphological patterns of MUAPs.

Then it can be concluded that if generating a Matrix of distance/dissimilarity between all MUAPs i and using the likelihood generated by  $p(O_i|\lambda_i)$ , it is possible to find out what are the MUAPs that have similar morphologies, that is, what are the MUAPs that were generated by the same Motor Unit. In this way, how many distinct morphological patterns exist in the EMG signal will be found, and therefore, the amount of Motor Unit active in the EMG signal can be inferred.

Thus, in possession of the models  $\lambda_i$  and the set of observations  $O_i$ , it is possible to construct a dissimilarity matrix required to perform spectral clustering algorithm.

(3) Spectral clustering

After the construction of the Hidden Markov Model for each one of MUAPs present in EMG signal and with the models  $\lambda_i$  and the set of observations  $O_i$ , the generation of the Dissimilarity Matrix is as follows: the cell (i, j) in the Distance Matrix corresponds to  $p(O_i|\lambda_i)$ , that is, corresponds to the likelihoods of the observations sequences  $O_i$ , generated by the  $\lambda_j$ . Thus, the Distance Matrix will be generated as Eq. (9):

$$\begin{pmatrix} P(O_1|\lambda_1) & P(O_1|\lambda_2) & \cdots & P(O_1|\lambda_N) \\ P(O_2|\lambda_1) & P(O_2|\lambda_2) & \dots & P(O_2|\lambda_N) \\ \vdots & \dots & \ddots & \vdots \\ P(O_N|\lambda_1) & P(O_N|\lambda_2) & \cdots & P(O_N|\lambda_N) \end{pmatrix}$$
(9)

With the distance matrix, the spectral clustering algorithm will be executed. As a result, the following amounts will be obtained:

The amount of existing groups:

The spectral clustering algorithm will provide the amount of existing groups between N likelihoods provided in the matrix of distances. As a consequence, the following amounts will be inferred:

The amount of morphological patterns of MUAPs;

The amount of active Motor Units in EMG signal.

The classification of each set of observations in a given group:

After estimating the amount of groups, the spectral clustering algorithm sorts each likelihood, through the information was provided by the matrix of distance, in one of the groups estimated. So, considering that each group represents, in the work, an active Motor Unit, the author will have as a result:

How many MUAPs were generated by each Motor Unit;

What are the MUAPs generated by each Motor Unit; What is the standard MUAP morphology generated

by each Motor Unit.

# **3. Results**

To validate the methodology and the results of the system, two data types are used: real and synthetic EMG signals.

(1) Synthetic EMG signals

For the validation process of the proposed system, it was used a synthetic EMG Signal Generator, developed by Ref. [8]. In this simulator, to generate the EMG signal, the inter-pulses characteristics of MUAPs resulting from investigations of the first dorsal interosseous muscle are considered.

This simulator of EMG signals allows the user to simulate the hardware and generate synthetic EMG signals according to the configuration of the following parameters: (1) number of active Motor Units; (2) the EMG signal simulation time in milliseconds; (3) sampling frequency; (4) signal-to-noise ratio.

The advantage of using this simulator is due to the fact that it is possible to evaluate the output of the developed system, by using EMG signals with known characteristics (the number of active Motor Units and its firing sequence).

(2) Real EMG signals

The database of real EMG signals that was used for the validation of the proposed project was provided by Ref. [8]. The data were collected from 15 volunteers who have run six different types of muscular contraction. In total, 900 s is stored in this database EMG signal.

Signals were obtained through experimental data, sampled at 10 kHz and collected using reference electrodes (TECA NCS2000, Oxford Instrument Medical, Ag/AgCl), array of surface electrodes (MedTech Systems Ltd., Ag/AgCl) and invasive electrodes (TECA X53153, Oxford Instruments Medical) and needle electrode, which were placed in first dorsal interosseous muscle of volunteers.

The advantage of using this database in the process of validation of the proposed system is due to the use of the array of electrodes. This array is composed of two electrodes, differential double, and each one of them has a catchment area of 1 mm in diameter and 3 mm distant from the other electrode (centre to centre). In this way, it has 2 surface electrodes close enough to capture the same EMG signal and two EMG channels storing these signals. Thus, the EMG signal picked up by these two electrodes will be very similar due to the proximity of the electrodes. This context is conducive to the process of validation of the proposed system, because it is possible to evaluate the system response in the two channels and check the consistency between the results provided.

#### 3.1 Synthetic EMG Signals

The validation process using synthetic EMG signals is presented in the following two tests with EMG signals with different number of active Motor Units.

3.1.1 Test 1

For this validation test, it was raised a synthetic EMG signal with the following characteristics: (1) simulation time: 1,000 ms; (2) sampling frequency: 10,000 Hz; (3) number of Motor Units: 3; (4) signal-to-noise ratio: 20 dB.

Fig. 3 presents the MUAPs detected by the software EMG decomposition system. The dashed lines and continuous indicate, respectively, the beginning and end of each MUAP.

After the step of MUAPs detection, the next step is accomplished by the proposed system: MUAPs clustering.

The step of MUAPs clustering, using Hidden Markov Model and Spectral Clustering, resulted in three morphologically distinct groups of MUAPs (Fig. 4). This means that the system has detected 3 active Motor Units in the EMG signal analyzed.

After the clustering stage, it is necessary to evaluate the quality of the clusters detected. It is necessary to evaluate the morphological cohesion between MUAPs belonging to a same group.

For the evaluation of quality of MUAPs groups, the algorithm to DE (differential evolution) has been used [23]. This algorithm is designed to assess the quality of the MUAPs groups held by Hidden Markov Model and



Fig. 3 MUAPs detected in synthetic EMG signal, delimited by the dashed lines and vertical solid.



Fig. 4 MUAPs groups detected in step of clustering: (a) group of MUAPs with standard waveform of type 1; (b) group of MUAPs with standard waveform of type 2; (c) group of MUAPs with standard waveform of type 3.

Spectral Clustering. In other words, the DE will check if all MUAPs of a specific group really have the same morphological pattern.

## (1) MUAPs of Group 1

Fig. 5 presents the result of evaluating the quality of MUAPs of Group 1, using the DE algorithm. After



Fig. 5 Quality evaluation of MUAPs of Group 1 using differential evolution algorithm.

running the DE, 100% of MUAPs converged to a single morphological pattern, indicating that the MUAPs of Group 1 is cohesive.

#### (2) MUAPs of Group 2

Fig. 6 presents the result of evaluating the quality of MUAPs of Group 2, using the DE algorithm. After running the DE, 100% of MUAPs converged to a single morphological pattern, indicating that the MUAPs of Group 2 is also cohesive.

# (3) MUAPs of Group 3

Fig. 7 presents the result of evaluating the quality of MUAPs of Group 3, using the DE algorithm. After



Fig. 6 Quality evaluation of MUAPs of Group 2 using differential evolution algorithm.



Fig. 7 Quality evaluation of MUAPs of Group 2 using differential evolution algorithm.

running the DE, 100% of MUAPs converged to a single morphological pattern, indicating that the MUAPs of Group 3 is also cohesive.

After the clustering stage, the authors have the amount of Motor Units active in the EMG signal and

they also know the MUAPs that were generated by a particular Motor Unit. That way, it is possible to return to the EMG signal and determine the firing sequence of Motor Units (Fig. 8).

Analyzing the correlation between firing sequence of Motor Units of the synthetic EMG signal with that generated through the proposed system, it was evaluated the correlation between these sequences and found to  $\rho = 0.99$ .

3.1.2 Test 2

For this validation test, there was raised a synthetic EMG signal with the following characteristics: (a) simulation time: 8,000 ms; (b) sampling frequency: 10,000 Hz; (c) number of Motor Units: 5; (d) signal-to-noise ratio: 20 dB (Fig. 9).

Initially, it was held the MUAPs detection of the EMG signal. After that, the step of MUAPs clustering, using Hidden Markov Model and Spectral Clustering, resulted in 5 groups of MUAPs, morphologically distinct (Fig. 10).

In each one of the five groups of MUAPs, it was found that DE algorithm was able to validate the quality of the groups, it is, managed to detect only one morphological pattern in each group. In groups 2 and 3, DE achieved the convergence of 98% and 99% of the population of MUAPs, respectively. In the remaining groups, it was reached 100% of convergence with MUAPs that belonged to a single pattern.

In this way, it is possible to infer that the Hidden Markov Model and Spectral Clustering algorithm reached a good quality in MUAPs clustering, as they showed a strong similarity of pattern between the members of all the groups analyzed.

And also, the system provided the firing sequence of the Motor Units present in the EMG signal analysis. To assess the correctness of this sequence, it was calculated the correlation between it and the original sequence that generated the synthetic signal, and was obtained a correlation coefficient  $\rho = 0.98$ , which indicates a high correlation between the two sequences.



Firing sequence of Motor Units





Fig. 9 Synthetic EMG signal with five Motor Units actives.

### 3.2 Real EMG Signals

In the validation process with real EMG signals, tests were conducted with the signals of the database avaliable by Ref. [10], using the two channels collected at array of electrodes.

For the validation of the results, the correlations of system responses between the signals from the two array of electrodes were observed. Table 1 presents a summary of the application of the system in the EMG signals collected from 15 volunteers. For each volunteer, the following variables are presented: (1) The amount of Motor Units detected in EMG signal collected from the electrode 1;

(2) The amount of Motor Units detected in EMG signal collected from the electrode 2;

(3) The correlation coefficient  $\rho$  between the firing sequence of the Motor Units of the two EMG signals collected by the two electrodes;

(4) The average correlation coefficient  $\rho$  between morphological patterns of MUAPs detected between the two EMG signals, collected by the two electrodes. This average was calculated on the basis of the correlation coefficient between all groups of morphological patterns



Fig. 10 MUAPs groups detected in step of clustering: (a) group of MUAPs with standard waveform of type 1; (b) group of MUAPs with standard waveform of type 2; (c) group of MUAPs with standard waveform of type 3; (d) group of MUAPs with standard waveform of type 4; (e) group of MUAPs with standard waveform of type 5.

of MUAPs detected in the two EMG signals.

The results obtained with the real EMG signals are consistent with those that were expected for the validation of the proposed system. The choice of this database of EMG signals is due mostly to the fact of having available signals collected by EMG electrodes very close of each other (array of electrodes). This setup was a necessary condition in order to validate the

Table 1Summary of the application of the proposedsystem in the real EMG signals.

Volunteer	Motor Units Electrode 1	Motor Units Electrode 2	$\rho$ sequences	ρ MUAPS
1	2	2	0.88	0.91
2	3	3	0.92	0.89
3	3	3	0.89	0.91
4	2	2	0.90	0.75
5	3	3	0.93	0.79
6	2	2	0.86	0.87
7	2	2	0.92	0.96
8	3	3	0.88	0.93
9	3	3	0.88	0.91
10	2	2	0.82	0.77
11	2	2	0.88	0.91
12	3	3	0.90	0.94
13	2	2	0.70	0.84
14	4	4	0.71	0.83
15	3	3	0.88	0.94

proposed system for real EMG signals, because, due to the proximity of the electrodes, the decomposition of EMG signals detected by them should be consistent. Thus, the consistency between the results obtained from these two channels EMG, denotes the correctness of developed system.

## 4. Discussion

In both types of tests conducted with synthetic and real EMG signals, the system provided the following results on the decomposition of surface EMG signal:

(1) Amount of actives Motor Units;

(2) Morphological pattern of the MUAP generated by each Motor Unit;

(3) Firing sequence of the Motor Units.

In tests conducted with synthetic EMG signals, the system has detected correctly the amount of active Motor Units and presented, also, a strong correlation between the firing sequence of Motor Units generated by the proposed system and by the synthetic signal-whose characteristics is already known.

The detection of the firing sequence of the Motor Units was noted in Table 1, by examining the correlation coefficient  $\rho$ , there was a strong correlation between all Motor Units firing sequences analyzed. This result demonstrates that the developed system detected the correct sequence of firing of Motor Units, because there was consistency in the correlation between the two Motor Units firing sequences detected by EMG signal collected by the two array of electrodes. And also, in the analysis of synthetic signal, the system showed a high correlation coefficient between the firing sequence of the Motor Units detected by EMG signal analysis and synthetic string that, that in fact generated this signal EMG.

And also, when comparing the morphologic pattern generated by the system for each EMG signal analyzed of the array of electrode, the system also obtained a strong correlation in all cases analyzed. To the two electrodes, the system detected morphological patterns of MUAPs similar, that is, detected the same amount of active Motor Units and the same pattern of morphological MUAP generated by each one of them. In that way, it can be inferred that the system provided answers consistent with those that were proposed.

It is important to note the use of DE algorithm for the quality evaluation of a group of MUAPs and, also, in the presentation of the morphological pattern of a certain group of MUAPs: The final result of the application of DE algorithm is exactly the morphological pattern of the MUAP generated by the Motor Unit. In all tests, it was obtained a convergence of 100% of the MUAPs population for a single morphological when considered pattern, the neighborhood next to the pattern detected. This result reflects very well the good functioning of the probabilistic selection implemented in DE algorithm, because it shows that the population, in no one of the cases analyzed, became stuck in a great local and prevented from reaching the great global.

It was possible to verify that the optimization of the parameters of the Hidden Markov Model with DE algorithm also proved to be effective, whereas in all cases analyzed, HMM was raised so that the likelihood between the HMM of MUAPs of EMG signal presented the proximity necessary to be accomplished the clustering, using the Spectral Algorithm, and thus the amount of active Motor Units could be detected. If HMM had not been raised correctly, this condition would have been reflected in the clustering stage, because it would not be possible to correctly identify the amount of active Motor Units and the group cohesion of MUAPs would not be detected successfully when evaluated with DE.

Nevertheless, other existing systems of decomposition of surface EMG signals use predefined patterns of MUAPs to accomplish the grouping of MUAPs and, thus, detect the amount of active Motor Units. However, the proposed system does not need to know a priori which is a pattern of MUAP, it will be created a Hidden Markov Model for each MUAP detected and, through the spectral clustering, they are clustered in groups appropriate. Thus, the non-use of predefined patterns of MUAPs is also a differential technique implemented in this project.

The representation of each MUAP by a HMM, using the technique of extraction of characteristics is a scientific advance in the research area of decomposition of surface EMG signal, since it is not necessary to make the supervised clustering of MUAPs, i.e., it is not necessary to know a priori the possible MUAPs patterns that should be found in the EMG signal.

It is therefore possible to conclude that the probabilistic graphic Hidden Markov Model, spectral clustering technique and the differential evolution have potential applicability in the decomposition of surface EMG signals. And also, these tools presented coherent and cohesive results across all validation tests carried out. Thus, this set of tools is promising and may be a new direction for the research in the area of decomposition of surface EMG signal.

# 5. Conclusions

Through the results obtained it is possible to infer that the proposed system of decomposition of surface EMG signal presented a functioning consistent with the expected results. Thus, it is possible to affirm that the developed system presented coherent results in terms of:

(1) Identification of the amount of active Motor Units in EMG signal;

(2) Presentation of morphological patterns of MUAPs presented in EMG signal;

(3) Identification of the firing sequence of Motor Units in EMG signal.

It is important to emphasize the potentiality of the Hidden Markov Model and Spectral Clustering for the process of MUAP clustering of the surface EMG signal. And also, the DE algorithm proved to be a good tool for the process of internal quality assessment of MUAPs groups. These tools presented in this article, which had not been used in other researches in the area of decomposition of EMG signals, provided excellent results for surface EMG signal processing.

The developed system is not intended to solve all problems concerning the decomposition of surface EMG signals, but he presents a new approach and new techniques which produce useful results to clinical practice and Biofeedback therapies. The architecture of the proposed model constitutes a breakthrough in the research of decomposition of surface electromyography.

Despite the innovations of the techniques proposed in the developed system and of the satisfactory results, the proposed system has some limitations:

(1) The validation of the system was carried out only for the First Interosseous Dorsal muscle I;

(2) The system does not treat the phenomenon cross-talk and the superposition of MUAPs;

(3) The system does not consider the case of two or more Motor Units generate the same morphological pattern of MUAP, that is, it is considered that each Motor Unit generates a morphological pattern of MUAP distinguished;

(4) The system considers that a Motor Unit always generates a same pattern of MUAP.

From the developed work, other studies may be performed to improve the results and the application of

the proposed system:

(1) Investigation of the use of this system in Biofeedback techniques;

(2) Validation, application and analysis of the developed system in EMG signals from other muscle groups;

(3) Investigation of the use of this system in clinical practice;

(4) Calculating the probability of firing of Motor Units.

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