

## Transient State Analysis of the Multichannel EMG Signal Using Hjorth's Parameters for Identification of Hand Movements

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**Abstract**—Most myoelectric controlled systems are based on the common assumption that there is no information in the instantaneous value of the myoelectric signal and therefore, analysis is made on the steady state of the muscle contraction. However, this control scheme faces two main drawbacks: users need to be trained in order to produce the sustained contractions, and the control signal can only be generated until the steady state is reached. Prosthetic devices with long actuating delays often result in users' frustration and eventually, in the abandonment of the devices. As a proposed solution, analysis of the transient state of the electromyography (EMG) signal would allow classifying movements during the dynamic part of the muscle contractions reducing the time required to generate control commands. This paper proposes a novel method for transient EMG classification based on the use of Hjorth's parameters. Surface multichannel EMG signals were recorded from 10 normally limbed subjects for both the transient and steady EMG states while performing six different hand motions. Comparatively high classification accuracy was obtained from the transient state analysis of the signals suggesting the existence of deterministic information in this part of the muscle contraction and the fact that Hjorth's parameters seem to adapt well enough to the nature of myoelectric signals as to allow extracting highly representative information from them.

**Keywords**-EMG steady state; EMG transient state; Hjorth's parameters; multichannel EMG; normalized slope descriptors

### I. INTRODUCTION

Research on the use of electromyography (EMG) for upper limb prostheses control has been conducted since the 1940's [1]. In the following years, remarkable progress in myoelectric controlled devices has been achieved; however, still numerous challenges remain in signal processing in order to replicate as close as possible the functions of the human limb. Development on this area must be closely related to the understanding of the psychological complexities that the amputee faces [2] due to the fact that the prosthetic device becomes an extension of the patient's body.

High abandonment rates reported for upper limb prosthesis [3] make evident the need to improve myoelectric control. The performance of a myoelectric controlled system is evaluated with regards to three important aspects of

controllability [4]: the accuracy of movement selection, the intuitiveness of the actuating control, and the response time of the control system. A 200 to 300 ms interval is a clinically recognized maximum delay that users find acceptable before they get frustrated with the response time of the prosthesis [4]-[6]. Hence, the motivation to analyze the transient state of the EMG signal arises in order to identify movements while the muscle contraction is being generated and not until it reaches a steady state.

The EMG signal is a non-stationary, non-linear, and stochastic process produced as a result of the summation of several motor unit action potential trains (MUAPTs) [1],[7]-[9]. However, two main states can be recognized during the muscle contraction. The transient state is described as the bursts of myoelectric activity that accompany sudden muscular effort while executing the movement. It is related with the beginning of the activation of the motor units (MUs) that will be involved in the muscle contraction. The steady state corresponds to the part of the contraction when almost every MU that will be involved in the movement is already activated. It will be considered as the muscular effort during a sustained contraction when the movement's final position is reached, and the muscle length is no longer modified, i.e., the myoelectric signal produced by a stable muscle contraction [10],[11].

The aim of this work is to propose a novel method for transient state analysis of the multichannel EMG signal by using normalized slope descriptors (NSDs) as features for classification. The main objectives are proving that Hjorth's parameters are suitable for EMG analysis, and demonstrating the possibility of identifying movements from the beginning of the muscle contraction in order to reduce the delay obtained when waiting until the steady state is reached to generate the control signal.

In the following sections, this paper provides an overview of the state of the art in the use of the transient EMG state for movement identification followed by an introduction to Hjorth's parameters and their use in biomedical applications. Subsequently, it explains the method that was followed, including the data acquisition protocol and the signal processing method, as well as the results obtained from the analysis of both the transient and steady EMG signals recorded from 10 normally limbed

subjects in order to identify a set of hand and wrist movements. Results are discussed and compared to previously reported methods. Finally, the last section presents conclusions and some ideas on the future work that can be done.

## II. STATE OF THE ART IN THE USE OF THE TRANSIENT EMG STATE FOR MYOELECTRIC CONTROL

EMG classification has been most often based on the steady state analysis of the muscle contraction. This has greatly simplified commercial myoelectric controlled systems that usually rely on the premise of the accepted myoelectric signal generation models. However, the steady state contains a short temporal structure of the active modification of recruitment and firing patterns involved in the contraction and that can be found within the transient state [1],[5],[6],[10]. In 1993, Hudgins *et al.* [5] were the first to consider the structure in the myoelectric signal (MES) during the onset of the contraction to develop a new control strategy based on the analysis of the transient EMG state. They were able to discriminate between four movements with roughly 90% accuracy. Only a few studies, such as [12]-[15], have reported the use of the transient state to classify EMG signals. Englehart *et al.* [6] introduced the use of Wavelet Transform (WT) and Wavelet Packet Transform (WPT) for classification of transient EMG signals. They classified more accurately the steady state than the transient data. However, Hangrove *et al.* [16] showed that including transient data along with steady state data while training the classifier increases the classification error, but it also increases real-time performance and system usability, which should be considered when evaluating the system.

The use of multichannel EMG provides a better representation of the real muscle activity in the collected signal [17]-[19]. The increase in classification performance while increasing the number of channels was investigated in [20]. Moreover, with multichannel EMG, the positions of the electrodes become less critical [21], making it a promising technique. However, when extrapolating the system to amputees, an excessive number of electrode sites could be hard or even not possible to locate.

Interference and muscle crosstalk introduce non-linearity into the EMG signal. The combination of muscle tissue, adipose tissue, skin, and the skin-electrode interface behaves like a non-linear low pass filter that attenuates and distorts the surface EMG signal; nevertheless, methods for non-linear time series analysis have not been widely applied to EMG [7].

## III. HJORTH'S PARAMETERS

Hjorth introduced, in 1970, three parameters based on time domain properties [22]-[25]. They were intended as a clinically useful tool capable of describing quantitatively the graphical characteristics of an electroencephalography (EEG) trace in terms of amplitude, slope, and slope spread, so that they receive the name of normalized slope descriptors (NSDs). These parameters are named "activity", "mobility", and "complexity".

*Activity* measures the variance of the amplitude of the signal as shown in (1). In the frequency domain, it can be conceived as the envelope of the power spectrum.

*Mobility* measures the ratio between the standard deviation of the slope and the standard deviation of the amplitude given per time unit; hence, it represents dominant frequency. This ratio depends on the curve shape in such a way that it measures the relative average slope. Its mathematical definition is presented in (2).

*Complexity* is a dimensionless parameter that quantifies any deviation from the sine shape as an increase from unit. It is calculated as shown in (3). It can be interpreted as a measure of the signal's bandwidth.

$$Activity = m_0 = \sigma_0^2, \quad (1)$$

$$Mobility = \sqrt{m_2/m_0} = \sigma_1/\sigma_0, \quad (2)$$

$$Complexity = \sqrt{(m_4/m_2) - (m_2/m_0)} = \frac{\sigma_2/\sigma_1}{\sigma_1/\sigma_0}, \quad (3)$$

where  $m_n$  is the spectral moment at order  $n$ ,  $\sigma_0^2$  is the variance from the analyzed segment of the non-linear time series  $f(t)$ , and  $\sigma_1$  and  $\sigma_2$  are the standard deviations of the first and second derivatives of  $f(t)$ , respectively. It has been shown that the spectral moment of order  $2n$  corresponds to the variance  $\sigma_n^2$  of the derivative of order  $n$  [24], so that:

$$m_0 = \sigma_0^2, m_2 = \sigma_1^2, m_4 = \sigma_2^2, m_6 = \sigma_3^2 \dots m_{2n} = \sigma_n^2$$

The spectral moment  $m_n$  can also be calculated in terms of its frequency as shown in (4).

$$m_n = \int_{-\infty}^{+\infty} \omega^n \cdot S(\omega) d\omega \quad (4)$$

$S(\omega)$  corresponds to the power density spectrum, and it is obtained from the multiplication of the Fourier Transform,  $F(\omega)$ , by its conjugate,  $F^*(\omega)$ , which causes the phase to be excluded. As the frequency description from the Fourier transform is always symmetrical with respect to zero frequency, in a statistical approach to the shape of the frequency distribution, all odd moments will become zero, and the information will be contained in the even moments.

Hjorth's parameters serve as a bridge between a physical time domain interpretation and the conventional frequency domain description [23]. The transformation between both domains is based on the energy equality within the actual epoch and can be calculated by the time-frequency relationship shown in (5)-(7).

$$m_0 = \int_{-\infty}^{+\infty} S(\omega) d\omega = \frac{1}{T} \int_{t-T}^t f^2(t) dt = \sigma_0^2 \quad (5)$$

$$m_2 = \int_{-\infty}^{+\infty} \omega^2 S(\omega) d\omega = \frac{1}{T} \int_{t-T}^t \left( \frac{df(t)}{dt} \right)^2 dt = \sigma_1^2 \quad (6)$$

$$m_4 = \int_{-\infty}^{+\infty} \omega^4 S(\omega) d\omega = \frac{1}{T} \int_{t-T}^t \left( \frac{d^2 f(t)}{dt^2} \right)^2 dt = \sigma_2^2 \quad (7)$$

Hjorth's parameters were originally formulated for EEG analysis and description and have been widely used in sleep EEG processing for data reduction and discrimination of sleep stages [26]-[28]. Other studies related with EEG signal analysis have reported the use of Hjorth's parameters for applications such as psychotropic drug research [26],[27], assessment of postalcoholic diseases [29], temporal lobe seizures lateralization [25], classification of facial movement artifacts in the EEG signal [30], monitoring changes in EEG signals of patients with renal failure before and after hemodialysis [31], creating ink topographic displays for visual monitoring of changes in EEG signals [32], evaluation of performance in channel reduction for EEG classification in emotion assessment [33], among others. Mouz -Amady and Horwat [34] applied NSDs to EMG signals and concluded that they could be used to describe the spectral content of surface EMG during repetitive movements due to their results of high correlation coefficients (ranging from 0.81 to 0.93) between Hjorth's mobility and the FFT mean frequency. Hjorth's parameters have also been applied successfully in non-biomedical fields [22].

#### IV. METHOD

##### A. Data Acquisition Protocol

The surface EMG signals used for this study were those recorded in [35] using 8 differential channels (Ag-AgCl surface electrodes model VERMED NeuroPlus A10043 with an inter-electrode distance of 1.5 cm) placed on the dominant forearm of 10 normally limbed subjects, aged between 23 and 50, and with no register of neuromuscular disorders. The electrode disposition is shown in Fig. 1. To ensure the positioning of the electrodes over the muscles of interest, each participant was asked to repeatedly close and open the hand in order to identify the muscles mentioned in table I.

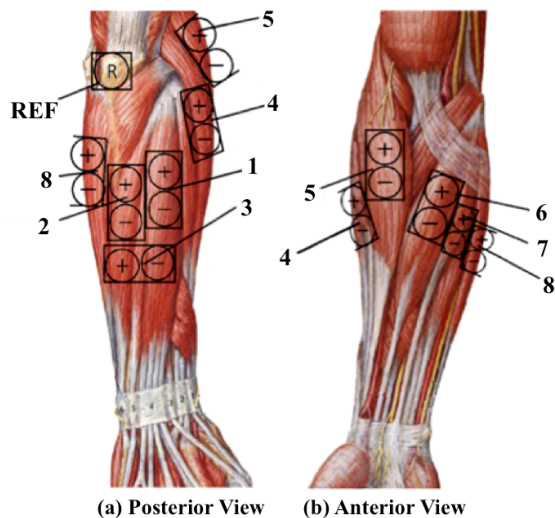


Figure 1. Posterior (a) and anterior (b) views of electrode placement for EMG signal recording. Corresponding muscles are identified in Table I.

TABLE I. FOREARM MUSCLES RECORDED BY EACH EMG DIFFERENTIAL CHANNEL

EMG Channel	Forearm Muscle
1	Extensor digitorum communis
2	Extensor carpi ulnaris
3	Differential measure between extensor digitorum communis and extensor carpi ulnaris
4	Extensor carpi radialis longus
5	Brachioradial
6	Flexor carpi radialis
7	Palmaris longus
8	Flexor carpi ulnaris

The skin was carefully cleaned before electrode placement, and the reference electrode was located on the elbow. Each subject was asked to execute six different hand motions, namely hand opening/closing, wrist pronation/supination, and wrist flexion/extension. The series of movements were repeated five times with a one-minute rest between them in order to avoid muscle fatigue. Each recording was 20 seconds long, starting with the forearm in an inactive position, followed by the dynamic part of the contraction, and finished by sustaining the contraction, once the final position was reached, until the end of the recording.

Written consent was obtained from every subject before starting the study. In a previous session, the protocol was explained to each of the participants and the amplification gain of the eight differential EMG channels was calibrated according to the amplitude of the contraction for each subject.

In order to reduce unwanted variability, every participant was asked to perform the study in a standing position with the dominant arm extended to the front and the hand relaxed.

The acquisition system consisted of 8 differential channels with adjustable amplification gain and a first order analog band-pass filter with a low cut-off frequency of 20 Hz and a high cut-off frequency of 400 Hz. Each analog output was connected to a National Instruments acquisition card (model DAQ-Card 6024WE) for 12-bit A/D conversion. EMG signals were recorded with a sampling rate of 1024 Hz.

##### B. Data Processing

The multichannel EMG signals were processed and analyzed using MATLAB® (version R2012b). Each recording was divided by supervision in transient and steady states. The transient state was extracted from the part of the EMG recording that corresponded to the dynamic part of the movement. The steady state consisted of the section in the recording where the final position was reached and the muscle contraction was sustained. A Hamming window was applied to segment the signal for feature extraction. Classification performance was tested with two window lengths, 256 and 128 ms, both with 50% sample overlap.

A wavelet shrinkage method at third level of decomposition and based on Stein's unbiased risk estimate

(SURE) was applied to each windowed segment for de-noising purposes and to narrow the signal’s frequency band. The decomposition level was chosen considering that the main concentration of energy in the surface EMG signal is located within the band of 50-150 Hz. The de-noised signals were rescaled using a noise level dependent estimation.

Once the window length was selected, Hjorth’s parameters were calculated per channel for each of the segments using (1)-(3). This was made for every movement. Each of these parameters constituted an independent input; they were arranged in rows in order to build the feature matrix. Four different input matrices were tested to evaluate which one yielded the best performance. The first one contained as inputs the three parameters for each of the channels. The other three consisted of just two independent inputs per channel excluding one of the parameters in each case, i.e., the first one excluded complexity, the second one excluded mobility, and the third one excluded activity.

C. Artificial Neural Network’s Parameters

For classification of the EMG signals, an artificial neural network (ANN) model was trained using the aforementioned feature matrices as inputs, containing 24 independent inputs when using the three parameters and 16 in the cases where two parameters were used. A Bayesian regulation backpropagation algorithm was used to train the model. The final ANN’s architecture depended on the available feature matrix dimension; however, the model consisted of only one hidden layer with 9 neurons in it. This number of neurons was defined based on experimental testing. For classification purposes, the network output was binary codified, i.e., a unique 3-digit combination of zeros and ones was used to identify each of the movements.

In order to evaluate the network’s performance, a k-fold cross-validation process (k=5) was carried out.

V. RESULTS

A. Window Length Selection

Two Hamming windows of different size were tested over the whole transient data set. The first one had a length of 256 ms and the second one of 128 ms. Both windows were applied with a 50% sample overlap. Table II and Fig. 2 show the classification percentage obtained for each window length.

TABLE II. MEAN CLASSIFICATION PERCENTAGE AND STANDARD DEVIATION ACCORDING TO WINDOW LENGTH

Movement Type	Window Length [ms]	
	256 ms	128 ms
Closing	97.71±2.95%	98.71±1.25%
Opening	97.43±2.11%	96.86±1.48%
Pronation	96.86±2.50%	94.86±3.03%
Supination	97.71±3.51%	96.43±3.03%
Flexion	100.00±0.00%	99.71±0.60%
Extension	99.14±1.38%	98.14±1.66%
Mean	98.14±0.99%	97.45±1.10%

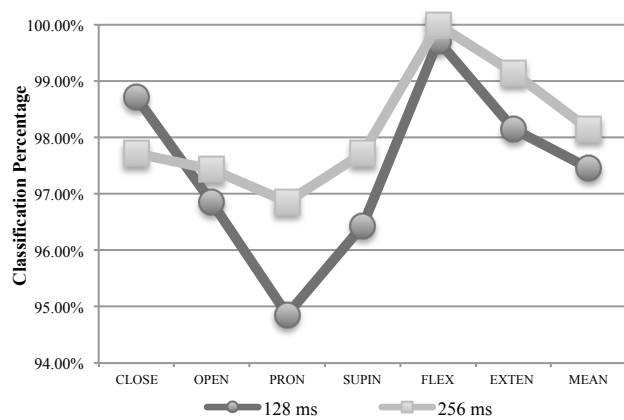


Figure 2. Comparison in classification percentage of the transient EMG state for each movement type using different window lengths.

Classification percentage did not decrease dramatically when using the 128 ms window length as compared to the 256 ms window; therefore, the smaller window size was used for the following tests considering that decreasing processing delays was one of the objectives.

B. Hjorth’s Parameters Selection

Classification performance was evaluated with four different feature matrices in order to select which of Hjorth’s parameters allowed extracting the most representative information from the signals. Each matrix consisted of a different set of Hjorth’s parameters as previously explained in section IV.

The test was applied on the transient state of the EMG signals. The obtained results are shown in Table III. The column labeled ‘A, M, and C’ contains the classification percentages for each movement type using the three Hjorth’s parameters. The three following columns denote the classification percentages obtained when using just two of the parameters.

The mean classification error percentage obtained from using each feature matrix was calculated and is presented in Fig. 3. These percentages consider the mean classification for the whole test population including every movement type.

TABLE III. MEAN CLASSIFICATION PERCENTAGE ACCORDING TO THE COMBINATION OF HJORTH’S PARAMETERS USED IN THE FEATURE MATRIX

Movement Type	Hjorth’s Parameters			
	A, M, and C	A and M	A and C	M and C
Closing	98.14%	96.57%	97.14%	98.71%
Opening	96.86%	95.43%	96.14%	96.86%
Pronation	94.00%	94.43%	93.00%	94.86%
Supination	95.57%	94.29%	93.29%	96.43%
Flexion	99.86%	99.57%	97.87%	99.71%
Extension	97.86%	98.29%	96.71%	98.14%
Mean	97.05%	96.43%	95.69%	97.45%
SD	2.95%	3.57%	4.31%	2.55%

A stands for ‘Activity’, M for ‘Mobility’, and C for ‘Complexity’

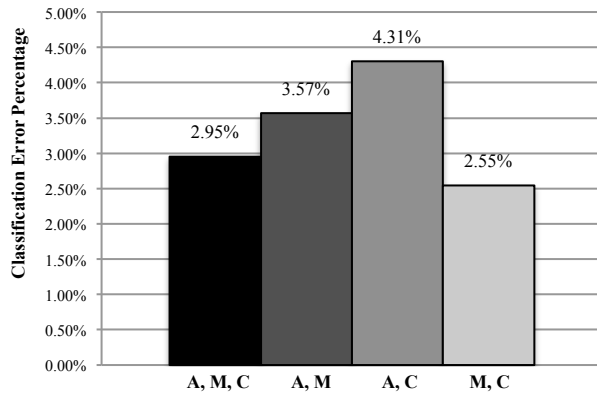


Figure 3. Mean classification error percentage obtained by using different combinations of Hjorth's parameters as features for classification.

As the lowest classification error was obtained from using mobility and complexity as input features, the following comparison between classification performance using the transient and steady EMG states was made with this selected feature matrix.

The parameter 'activity' was no longer considered for the analysis.

### C. Comparison in Classification Accuracy of the Transient and Steady EMG States

Previous studies such as [6], have reported higher classification accuracy when using the steady state of the EMG signal as compared to the transient state; therefore, the proposed method was evaluated for both EMG states. The mean classification percentages obtained for each of the subjects are presented in Table IV. The comparison in mean classification accuracy per movement type is illustrated in Fig. 4.

TABLE IV. TABLE TYPE STYLES

Subject	EMG State	
	Transient	Steady
1	97.38%	97.62%
2	99.05%	99.29%
3	97.62%	97.14%
4	95.71%	96.67%
5	97.86%	99.76%
6	96.67%	97.14%
7	98.33%	99.05%
8	96.19%	96.67%
9	96.90%	98.10%
10	98.81%	97.86%
<b>Mean ± SD</b>	<b>97.45±1.10%</b>	<b>97.93±1.11%</b>

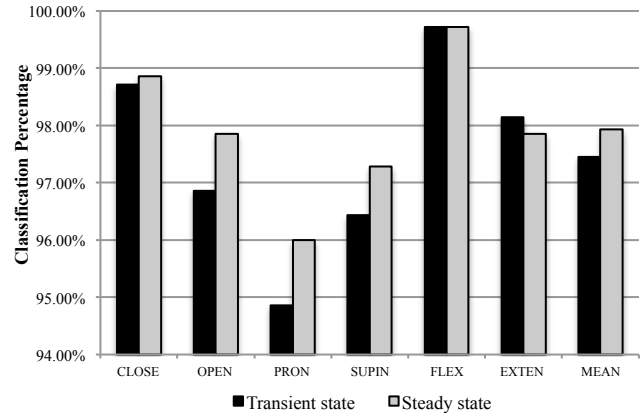


Figure 4. Mean classification percentage per movement type for the transient and steady EMG states.

The black bars in Fig. 4 represent the mean classification percentage of the transient state for each of the movements. The gray bars represent the mean classification of the steady state. These results are discussed in the following section.

## VI. DISCUSSION

The proposed method departs from the use of features originally intended for EEG description. The EEG signal is formed by the superposition of characteristic responses; in a similar way, the EMG signal is the superposition of MUAPs, which seems to make Hjorth's parameters also suitable for their analysis due to the nature of myoelectric sources.

The parameters' values, except for activity, referring to a single response, are also valid for a superposition of responses [23], which can justify that classification error increases when including this parameter, as shown in Fig. 3. For non-periodic phenomena with a limited complexity, as it is the case of the EMG signal, the basic information is essentially contained in the first few polynomial coefficients; therefore, the number of required (non-redundant) parameters correspond to the complexity of the system under observation [24]. Several studies [25],[26],[28],[31] have reported to find significant information in EEG traces using just two of Hjorth's parameters; furthermore, three of them reported to find them in mobility and complexity as it was the case in the present study.

Hjorth explained in [24] the way in which Hjorth's parameters describe first and second order responses of a system. The response of a first order system is an exponentially decaying impulse ( $e^{-\alpha t}$ ), where  $\alpha$  is the inverse time constant of the system. When Hjorth's parameters are computed for this response, mobility is identical to  $\alpha$  and hence describes the system. The response of a second order system is modeled as a decaying sinusoid ( $e^{-\alpha t} \cdot \sin(\beta \cdot t)$ ). The relationship between Hjorth's parameters and the constants of the system are given in (8). By making some algebraic manipulations, the constants can be expressed as a function of Hjorth's parameters as in (9).

$$\begin{cases} M(\text{mobility}) = (\alpha^2 + \beta^2)^{\frac{1}{2}} \\ C(\text{complexity}) = 2\alpha \end{cases} \quad (8)$$

$$\begin{cases} \alpha = C/2 \\ \beta = M \cdot (1 - C^2/4M^2)^{\frac{1}{2}} \end{cases} \quad (9)$$

Based on the previous assumptions, the system is completely determined by mobility and complexity. The number of required descriptors to obtain the basic information of the system corresponds to the system's order. The muscle contraction can be modeled as a second order system, which would justify the performance achieved by using these two parameters.

The mean classification percentage obtained from the steady EMG signals was just slightly higher than the one reported for the transient state (refer to Fig. 4). This suggests that similar classification accuracy can be obtained from both EMG states using Hjorth's parameters as compared to previous reported methods [6].

The lowest classification percentages using both the transient and steady states corresponded to pronation and supination movements. This indicates that the muscles recorded by the EMG channels, which are mainly flexors and extensors, had less participation in these two movement types. Classification accuracy did not suffer a significant decrease when using a window length of 128 ms as compared to one of 256 ms, which could allow obtaining a faster response for control purposes and would make it more suitable for on-line applications.

## VII. CONCLUSIONS AND FUTURE WORK

It has been widely discussed whether or not the transient state of the muscle contraction contains enough relevant information as to accurately discriminate between different types of motions; however, Hjorth's parameters seem to adapt well enough to the transient MES as to extract highly representative information from it. Most myoelectric controlled devices have been based on the assumption that there is no information in the instantaneous value of the MES; therefore, it is necessary to wait until a sustained stable contraction is reached in order to generate the control signal and start actuating the device, which is not desirable in clinical applications. The present study reaffirms the existence of deterministic components within the onset part of the muscle contraction as initially proposed by Hudgins *et al.* [5], and the fact that the information is relevant enough as to discriminate between the proposed movements. Using the transient EMG state for myoelectric control would allow generating a control signal since the beginning of the muscle contraction, which would also resemble more to the natural movement of the human limb and would allow diminishing the actuating delay of the devices. Even if classification is slightly higher when using the steady state, including transient MES information can lead to more robust usability and performance. If the system is capable of identifying the transient EMG state, the subject is simply prompted to perform a contraction in a natural manner instead of needing long training periods to learn how to make the sustained contractions.

Hjorth's parameters allow characterizing signals in both the time and frequency domains. Although they are based on

spectral moments, they can be calculated using time variances, which implies simpler processing and makes it more suitable for continuous on-line calculations as compared to frequency-domain analysis that normally requires complex transformations.

The analyzed data proved to contain significant information within the first 128 ms of the onset of the contraction. Classification was more accurate when using a 256 ms window for feature extraction; however, this value gets really close to the clinically recognized maximum delay for real-time applications (200 to 300 ms), and the total system's delay has yet to be considered. Thus, a 128 ms window seems to provide a good compromise between system's accuracy and response time.

Using multichannel EMG signals allows recording information from several muscle sites, which allows analyzing the participation of corresponding muscles on a certain movement; however, when using a great number of electrodes, extrapolating the system to an amputee patient becomes very complex and sometimes not feasible.

As future work, we propose to use a greater number of subjects to test the algorithm's performance; to develop a reliable method to automatically identify the onset of the contraction regardless of the noise affecting the system, which would allow automatically initiating feature extraction in order to generate the control signal; to increase the number of movements to identify; and to extrapolate the system to amputee subjects.

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