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Hand movement classification by time domain feature extraction in EMG signals

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Abstract— **Prosthetic hands empower amputees by automating control through surface electromyography signals, which are electrical recordings of muscle activity during contraction and relaxation, applying statistical feature analysis, are of great importance in biomedical research and related areas. The aim of this study was to classify six electromyography signals representing different hand movements by extracting statistical features in the time domain. The importance of key steps such as filtering, rectification and segmentation was emphasized to obtain an adequate representation of the data. Through feature extraction, the classification of hand opening and closing states was achieved. This highlights the need for careful feature selection in the classification process.**

Keywords—emg signal, signal processing, feature extraction, prothesis, classification.

I. Introduction

Electromyographic (EMG) signals are the recording of electrical activity generated in muscle tissue, produced during the process of muscle contraction and relaxation [1]. The signals generated by motor neurons when activating body muscles exhibit a stochastic character, the EMG voltages measured typically range from 0 to 100 mV. These signals have frequencies ranging from 20 to 500 Hz, the components with the highest signal amplitude tend to be in the mid-range of 50-150 Hz. [2].

Applying statistical feature analysis for processing and classification is of great importance in EMG signal research and related areas in biomedical engineering. [3]. Feature extraction is an important step in the electromyographic signal classification process. The features of EMG signals are typically categorized into three groups: time domain, frequency domain, and time-frequency domain. Research has demonstrated that features extracted from the time domain and time-frequency domain tend to yield superior outcomes for EMG signal analysis compared to only examining frequency domain features [4]. Therefore, the appropriate choice of a method that allows extracting relevant information from the processed EMG signals is essential, to improve the accuracy in the classification of such EMG signals [5]. As described in this study [6], EMG signals contaminated with ECG noise to different degrees were simulated to investigate the variations in the features of the EMG signal where 13 time domain and 4 frequency domain features of the EMG signals were calculated [7], related to the extraction of features of electromyographic signals, the Fourier Transform has been used for the extraction of features in the frequency domain. In recent years, the use of different processing techniques for the extraction of relevant features of electromyographic signals have been investigated. One of these techniques is the wavelet transform, which has proven to be effective in extracting information in both the time domain and the frequency domain [8]; this study utilizes the tunable Q-factor wavelet transform (TQWT) feature extraction with bagging and boosting ensemble classifiers for hand movement recognition; . In addition, in the study presented in [9] , the authors proposed to extract the features of the electromyographic signals in the time domain, such as the maximum amplitude and the average maximum amplitude, and have been used to recognize and classify the muscular activity associated with the movement of the fingers, thus feature extraction analysis in time domain requires little computational processing [10]. Finally, the research [11] develops a method for classifying hand movements through the analysis of electromyographic signals and the extraction of features in time domain.

The novel contribution of this work lies in the classification of EMG signals through statistical features extracted solely in time domain: RMS, kurtosis, absolute mean, and skewness. The aim was to classify six EMG signals representing six different hand movements: the opening and closing of each finger. The rationale for selecting these specific time domain features was their ability to capture key aspects of EMG signal morphology - namely amplitude, shape, and symmetry. By carefully selecting these relevant time domain features, and extracting them from the raw EMG signals, successful classification of hand opening and closing states was achieved. This demonstrates that careful feature selection in the time domain alone can enable accurate EMG classification, without requiring more complex frequency or time-frequency representations. The proposed time domain feature set provides a computationally simple yet powerful approach for EMG pattern recognition.

II. Methodology

The proposed methodology for EMG signal classification utilizes a four-stage process: acquisition, preprocessing, feature extraction and classification. Raw EMG signals are first acquired in the acquisition stage. These raw signals then undergo preprocessing to improve signal quality and enable robust estimation of temporal features. Relevant feature properties are then extracted from the preprocessed signals during the feature extraction stage. Specifically, statistical time domain features including RMS, kurtosis, mean absolute value and skewness are extracted to capture key amplitude, shape, and symmetry aspects. Finally, in the classification stage, the extracted time domain features are used as inputs to categorize and recognize the EMG signals corresponding to different hand movements. As depicted in Fig. 1, preprocessing and classification are implemented in MATLAB

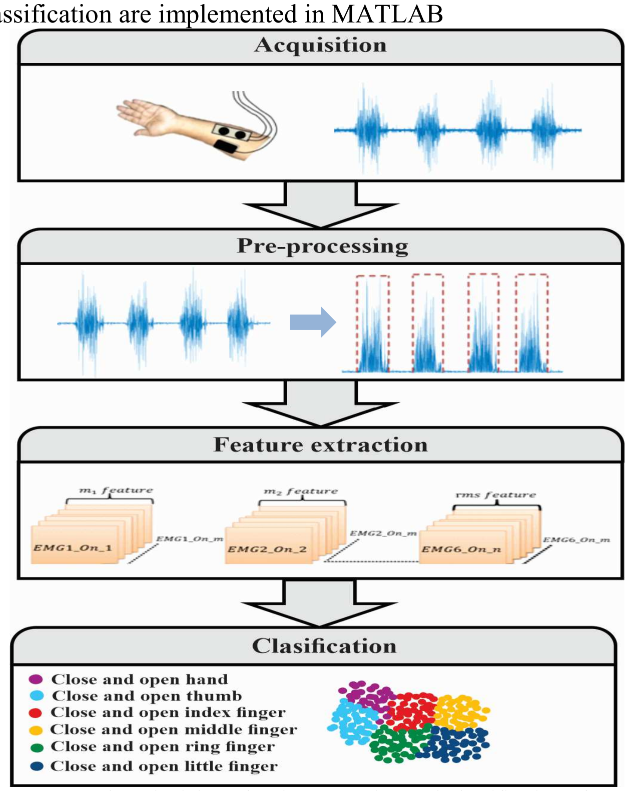

Fig. 1 Proposed methodology for the processing and classification of EMG signals; in the classification stage, the colored labels are merely representative.

A. Experiment and data acquisition

This study proposes to identify the opening (relaxation) and closing (contraction) of both the entire hand and each finger individually. The experimental setup shown in Fig. 2 presents the hand in a state of relaxation and contraction. The acquisition of electromyographic (EMG) signals was carried out with Ag/AgCl electrodes, which do not polarize and generate a high impedance upon contact with the skin. Its placement was carried out as described in [12]. The MyoWare 2.0 sensor was used, which has the Ad8619 instrumentation amplifier, low power consumption and a high signal-to-noise ratio (SNR). In addition, it has a first-order low-pass analog filter with a cut-off frequency of 20.8 Hz and a first-order high-pass filter with a cut-off at 498.4 Hz. The STM32f407VG card was used for signal acquisition due to its portability. High resolution ADC converter and flexible programming interface.

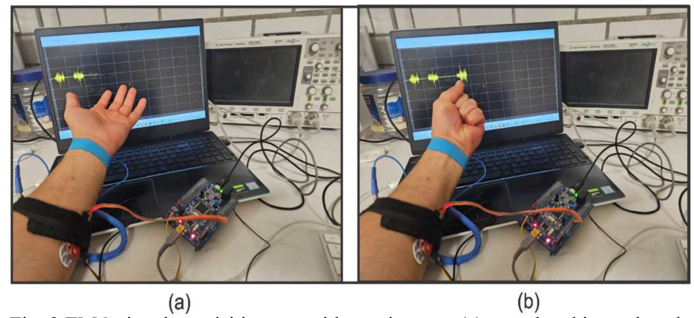

Fig. 2 EMG signal acquisition set, with two images: (a) open hand in a relaxed muscle state and (b) closed hand in a contracted muscle state. These representations capture changes in muscle electrical activity during different states of contraction.

The signals obtained for each specific event are presented in Figure 3. For the event 'Open and close the hand', it was named EMG_1, with sensors located in the flexor carpi radialis muscle. In the 'Open and Close Thumb' event, it was called EMG_2 and was acquired with sensors in the brachioradialis muscle. Similarly, the event 'Open and close index finger' was associated with EMG_3 with sensors in the flexor carpi radialis, while 'Open and close middle finger' and 'Open and close ring finger' were characterized by EMG_4 and EMG_5, respectively, with sensors in the palmaris longus muscle. Finally, the event 'Open and close little finger' produced EMG_6, recorded by sensors in the flexor retinaculum muscle. The sampling frequency for each test was 5 KHz and was repeated 15 times to ensure the reliability and repeatability of the experiment.

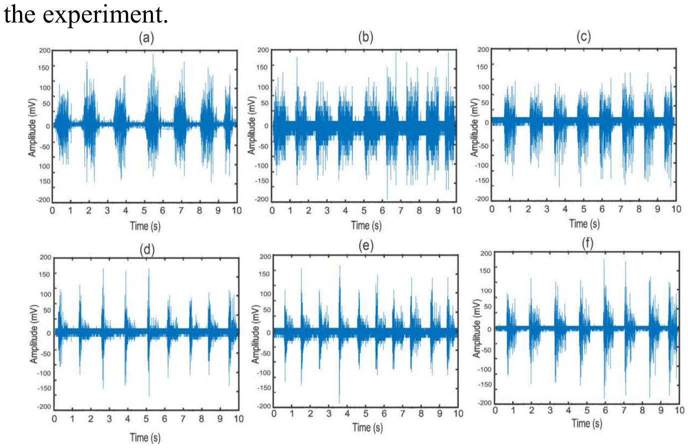

Fig. 3 Six EMG signals were obtained for each event which (a) corresponds to opening and closing the hand; (b) Open and close thumb; (c) Open and close little finger; (d) Open and close index finger; (e) Open and close middle finger; (f) Open and close ring finger.

B. Pre-procesing

The raw signal conditioner is made in the pre-processing stage and requires three steps filtering, rectification, and time windows. The first step is to eliminate the signal noise to be able to extract relevant information; the processing is realized by FIR filter using a Kaiser window, due to its easy design and implementation, as well as its low computational cost [13]. The Kaiser window has a good stopband attenuation and a smooth transition between the passband and stopband. The Kaiser window is defined as in Equation (1):

$$\omega_{kais}(n) = \omega_{kais}(-n) = \frac{I_o\left[\beta\sqrt{1-\left(\frac{2n}{M}\right)^2}\right]}{I_o(\beta)} \quad (1)$$

where, I_o is the modified Bessel function of the first type of zero order and the parameter β is a non-negative real parameter that determines the shape of the window [14]. Then, the improvement of the signal-to-noise ratio (SNR) of the EMG signal is made in the second step and it consists of signal rectification to facilitate the extraction of significant information from the signals.

For this study, a full wave rectification was applied. And the last step is the time window to segment the signal into smaller parts. Each segment represents a specific section of the EMG signal to facilitate the analysis, extraction of features and the application of signal processing algorithms. For this study, segments of the signal corresponding to muscle contraction were taken; Therefore, each test described in the previous stage was segmented into active (muscle contraction) and passive (muscle relaxation) parts.

C. Feature extraction

Now, in this stage, the feature extraction was carried out using specific techniques in the time domain, with the aim of capturing relevant information about the movements of opening and closing the hand, as well as the individual movements of each finger. In this stage a set of features was calculated for each segment of all the signals, generating vectors for the corresponding values. For every segment, the time domain features of Table 1 are calculated. Where x_i is a signal time series where $i = 1,2, \dots n$ are the number of data points, and $\bar{\bar{x}} = \frac{1}{n}\sum_{i=1}^{n}|x_i|$. As can be seen, the time domain features are easy to calculate and improve the classification process.

TABLE 1 STATISTICAL FEATURES IN THE TIME DOMAIN

Feature	***Symbol***	***Expression***
Skewness	*Skew*	$\dfrac{\frac{1}{n}\sum(x_i-\bar{x})^3}{\left(\sqrt{\frac{1}{n}\sum(x_i-\bar{x})^2}\right)^3}$
Kurtosis	*Kurt*	$\dfrac{\frac{1}{n}\sum(x_i-\bar{x})^4}{\left(\sqrt{\frac{1}{n}\sum(x_i-\bar{x})^2}\right)^4}$
Absolute mean	*AM*	$\lvert\bar{\bar{x}}\rvert$
Root Mean Square	*RMS*	$\sqrt{\frac{1}{n}\sum_{n=0}^{n-1}(x_i-\bar{\bar{x}})^2}$

C. Classification

To perform classification using only time domain features, feature vectors were constructed for each EMG signal specifically, the statistical features of RMS, kurtosis, mean absolute value, and skewness coefficient were calculated. along segments of each signal, resulting in a 4-dimensional feature vector representing each signal.

In this way, a feature vector was formed for each EMG signal, which will serve as input for the classification stage. To visualize the separation between each signal based solely on these features, the probability density distributions of each feature were plotted for the entire data set. Gaussian kernel density estimation was used to estimate the underlying probability density functions of each feature.

Overlapping distributions would indicate poor separability between each signal corresponding to a certain motion for a given feature, while clearly separated distributions or bells would indicate good classification. These visualizations show the classification approach implementing only these time domain features.

III. RESULTS

Raw signal for the event of closing and opening the hand is presented in Fig. 4 (a) which is a noisy signal. The filtering process considerably removed unwanted noise and reduced present interference in the raw signal. This resulted in a smoother and more defined filtered signal, which in turn allowed a more precise and reliable identification of the features of interest, observed in the comparison shown in Fig. 4 (b). On the other hand, Fig. 4 (c) presents a graphical representation of the rectified and segmented signal, where there are two types of signal rectification: half wave, which eliminates the negative values and considers only the positive ones, and full wave, which obtains the absolute value of both positive and negative values. Full wave rectification is preferred for further analysis.

The windows or segments in the rectified signal indicate the periods of muscular activity, characterized by an increase in signal amplitude. The size of the window or segment reflects the duration of the muscular activity. The results obtained from the analysis of the features extracted from the opening and closing signal of the hand show a clear and different discrimination between both states, but only for the absolute mean in Fig. 5 (a) and for the RMS in Fig. 5 (b). However, both kurtosis in Fig. 5 (c) and for skewness Fig. 5 (d), the Gaussians overlap, gives a degree of greater complexity to be able to distinguish between a state of contraction and the relaxed state of the muscle.

The plots show the probability distribution using absolute mean, RMS, kurtosis, and skewness features for the states of closing and opening the hand. In the representation, the red Gaussian plot corresponds to the probability distribution associated with the state of closing the hand, while the blue Gaussian plot represents the probability values related to the state of open hand. However, when performing the skewness and kurtosis feature analysis, a significant overlap of the probability distributions corresponding to the states of opening and closing the hand is observed. Therefore, it is concluded that these features are not useful to effectively classify between the two states.

To conclude this study, the task of differentiating between the closed state of each finger and the closed state of the hand based on feature extraction presents a considerable challenge in terms of separating Gaussian probability distributions. Despite applying specific features, such as RMS Fig. 6 (a) the probability distribution from event “close the little finger” is slightly separated from the distribution of the event “close middle finger”, showing an overlap mainly in their tails. This overlap suggests a similarity in certain aspects of the analyzed features, this is because the movements of the fingers are interconnected by muscular and neural proximity, so that the voluntary movement of one finger tends to slightly involve the adjacent fingers.

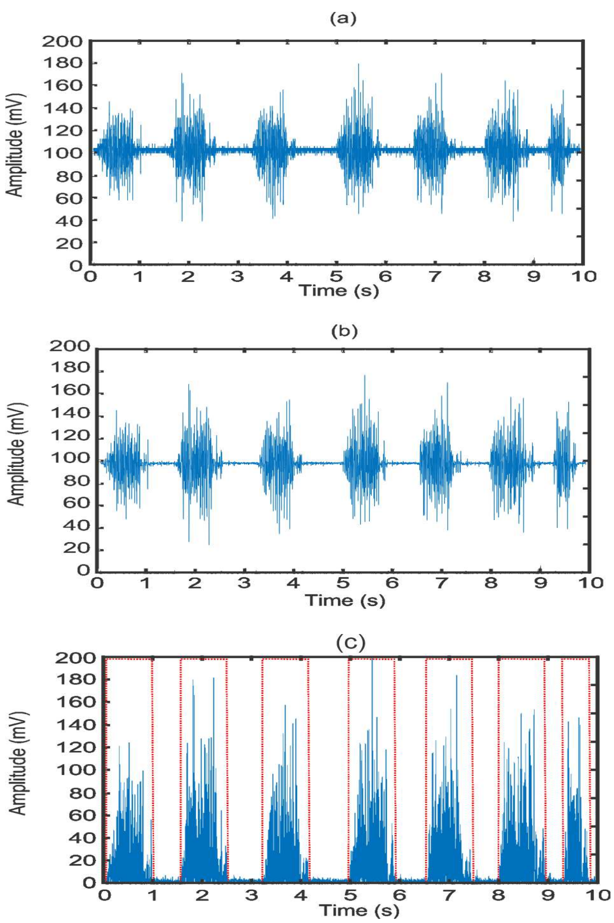

Fig. 4. Signals of the pre-processing stage (a) Raw signal, (b) Filtered signal and, (c) Rectified EMG signal and the segments corresponding to muscle contraction.

While using the AM characteristic, Fig. 6 (b), a clear differentiation is observed in the probability distributions for the events "close middle finger" and "close index finger" compared to individual events such as "close thumb", "close ring finger" and "close hand". The separation between the Gaussians is evident, especially with respect to the "close little finger" event, where an almost perfect separation is achieved. Despite this good separation with respect to other events, it is important to note that the "close middle finger" events and "close index finger" have some degree of overlap with each other. This overlap indicates similarities in some features, which can present a challenge in the precise classification of these events. Kurtosis Fig. 6 (c) and skewness Fig. 6 (d) also show a separation between certain events, however there is no clear differentiation between the relaxed and contracted states of the muscle when applying these features and therefore they would not be useful for classification purposes. Therefore, there is a limitation in the ability to separate these distributions; however, they can be useful to be able to classify between a maximum of 3 signals from one another.

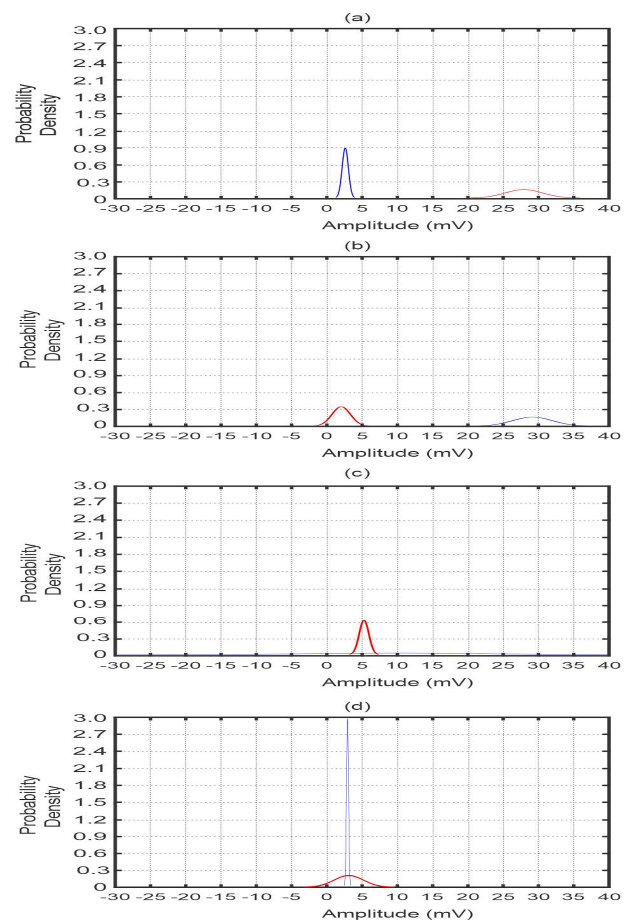

Fig. 5. Probability distribution for the classification of opening (blue gaussian) and closing (red gaussian) of the hand with the features (a) of the absolute mean; (b) RMS; (c) kurtosis; (d) skewness; The dotted red line indicates the mean of each Gaussian with ±3 standard deviations.

Given this limitation, it is necessary to consider the application of more robust classification methods to improve the accuracy and the ability to separate the distributions. For future studies, it is intended to investigate the use of Gaussian mixture models (GMM) and neural networks. With this, more accurate and robust classification of different hand states is expected to be achieved. These approaches could help to overcome the limitations observed in the separation of Gaussian distributions using only features.

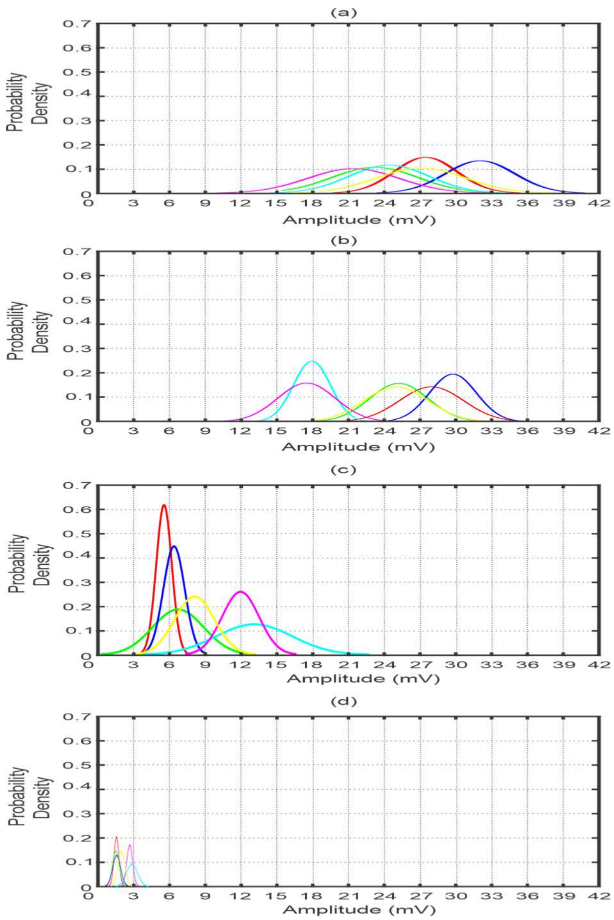

Fig. 6. Probability distribution for the classification of opening and closing of the hand and each with the features; the red color is for the event close hand; green for close thumb; blue for close little finger; yellow for close ring finger; cyan for close index finger; purple for close middle finger. The dotted red line indicates the mean of each Gaussian with ±3 standard deviations.

IV. CONCLUSIONS

In this proposal the digital processing of EMG signals as been addressed with the aim of classifying the different hand states, such as opening and closing the hand, as well as each finger individually. This methodology required: acquisition, preprocessing, feature extraction, and classification.

Throughout the study, the importance of key steps such as filtering, rectification and segmentation of EMG signals has been highlighted to obtain an adequate representation of the data and facilitate their subsequent analysis. By extracting features in the time domain, using measures such as RMS, MA, it was possible to obtain a classification of the opening and closing states of the hand, which is essential in applications such as prosthesis control or EMG-based user interfaces. It was also observed that some features, such as kurtosis and asymmetry, have not provided a clear and effective separation between the different states of the hand, however, they show an evident classification only in the contracted state of the muscle This indicates the importance of a careful selection of the features used in the classification process. However, to make a more complex classification such as discriminating between all the EMG signals using the statistical features, in this case, applying the four features mentioned above did not achieve a satisfactory result, this indicates the need to explore more robust and advanced classification methods in future research.

It is proposed to investigate approaches such as the use of more complex machine learning algorithms, such as the Gaussian Mixture Model (GMM) algorithm or deep neural networks, which can capture more intricate patterns and learn more sophisticated feature representations.

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