Overview of EMG signal preprocessing and classification for Bionic hand control.

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***Abstract*—This paper deals with the field of Biological Signal especially one of the most used signals in the field of prosthetic devices, which is the EMG signal. After introducing this kind of signal, we will talk about different techniques used for preprocessing it in order to prepare it for classification tasks. We Will then overview different noises that affect those sensible type of signals, different techniques applied for filtering them and the useful envelope detection methods that can be applied on EMG. The next part of this paper will look at some famous feature extraction and classification techniques that proved themselves useful when dealing with classification tasks of biological signals. Finally, we will present the mechanical design of a multiarticulate multifunctional prosthetic hand, the promising classification results that can gives 98.3% and our perspectives.**

***Keywords*—EMG, Filters, Envelope detection, Prosthetic hand, classification, SVM, LDA**

I. Introduction

Whatever the reason, problems with blood circulation, atherosclerosis, diabetes, injuries, traffic accidents, military combat, cancers or birth defects, the impact of limb losses is reparable and deeply affects the daily life of any amputee. Recovering from limb loss can be hard and using artificial limb is some time not an option because even with prosthesis, there is always a different aspect that should be treated to effectively integrate the amputee in the society again. Also, the different levels of amputation need different aspect of treatment because the hand loss which is one of the most used tools of the human body in order to interact with others is very different from a lower limb loss [1].

This paper will take the loss of upper limb as subject and treat it in three main parts. The first part will introduce EMG signals, different noises that can affect them, different filtering and preprocessing techniques, including envelope detection, that can be used to prepare those signals for the feature extraction and classification tasks. The second part will explain the different type of feature extraction techniques and group them into three main domains, the time domain, the frequency domain and the time frequency domain. Keeping the normal flow of machine learning problems, after extracting features comes the classification task using supervised classifiers like support vectors machine (SVM) and linear discriminant analysis (LDA). The final and the third main part before concluding will discuss the achieved results, compare different feature extraction technique, different envelope detection technique, different classifiers and presents a 3D design of a multiarticulate multifunctional very esthetic prosthetic hand.

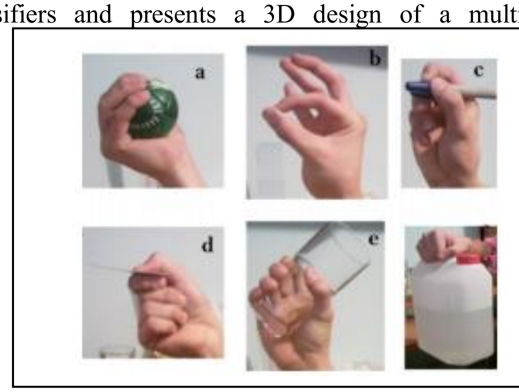

Fig. 1. The six hand gesture used for the classification. The hook gesture used for heavy loads, the cylindrical gesture used to hold cylindrical objects, the lateral gesture used to hold thin objects, the palmar gesture used to hold object with the palm in face of them, the spherical gesture for spherical objects and the tip gesture to hold tiny objects [2]

Signals are collected using two forearm surface electrodes held under the flexor capri radialis and the extensor capri radialis, longus and brevis which are classified as a superficial muscle responsible for hand flexion and abduction.

The signals used in this study correspond to gesture shown in the figure 1 which contain six hand gesture, the hook used for holding heavy loads, the cylindrical used for holding cylindrical objects, the lateral used for holding thin objects, the palmar where the hand palm facing the object, spherical for holding spherical object and tip for piking tiny objects. For each movement, a six second signal was recorded 30 time from Delsys Bagnoli™ two channels EMG system. The data were collected with a sampling frequency of 500 Hz and filtered using a Butterworth band pass filter with low and high cutoff frequency of 15 Hz and 500 Hz respectively and 50 Hz notch filter for line interference artifact elimination [2].

II. EMG Signal preprocessing

A. Most encountered EMG signal noise categories

There are many types of noise that can harmfully affect EMG signals. The First type of noise to mention is the electrical noise from power lines and external sources [3]. The second type of noise is motion artifact caused by relative movements of the electrodes with respect to the skin under the target muscle [4]. The third type of noise is the crosstalk which is a phenomenon in which the signal from one muscle interfere with that of another [5]. The fourth type of noise known as Clipping phenomenon which describes the fact that the electrode become saturated due to the excessive EMG amplitude [6]. The fifth type of signal is physiological noise which designate all other biological signals generated by the human body like EEG or EKG signals. This is why the preprocessing stage is the most important stage of the EMG signal classification process hence the importance of filtering and cleaning the signal.

B. Different EMG signal filtering and denoising techniques

Before talking about filtering of EMG signals, we should know more about noises that can affect them. Five principle noise can be described:

Electrical noise from power line and external sources like electromagnetic fields and electronic components. This noise can be removed by notch filtering or high-quality equipment. Motion artifacts caused by unwanted movements of electrodes with respects to the skin. Cross-talk contamination which is the phenomena of interference between signal of one muscle with neighbor muscle signal. Clipping describe the saturation of electrode due to the excessive EMG signal amplitude. Physiological noise are noises resulting from the other body signal.

Many filters are used with EMG signal and each one of them have a special goal and an application purpose. The most used filters are Butterworth, Chebyshev, inverse Chebyshev, Bessel, Elliptic and Equi-Ripple filters with four classes the Low pass filter, high pass filter, band stop filter and band pass filter.

It is generally assumed that EMG signals should be high pass filtered with a cutoff frequency of 10-30 Hz in order to remove motion artifacts to accurately estimate muscle force. High pass filtering can also be used for electrocardiographic (ECG) contamination removal from EMG signal, decreasing the amplitude and smoothing the signal with an optimal cutoff frequency of 30 Hz.

Low pass filters are used to inhibit frequency components in a signal above a cut-off or stop band frequency and allows signal below cut-off or band pass frequency to pass with minimum amount of distortion. This filter is generally used before the analog to digital conversion stage to avoid sampling anti-aliasing or removing resonance from systems. Low pass filtering is also used after signal rectification to extract the signal envelope [7].

Bandpass filter and notch filter are combination of the high pass and low pass filter.

Band pass filter remove low and high frequencies from the signal. Baseline drift associated with motion artifacts and DC offset can be removed by the low frequency cutoff of the band pass filter with a typical value of 5 to 20 Hz. A typical value of 200 – 1000 Hz High frequency cutoff of the band pass filter remove high frequency noises and prevents aliasing.

Notch filter is used to remove a narrow band of frequency components below and above a notch frequency. It can be used for removing power line frequency (50 or 60 Hz) or removing resonance from systems [8].

The filtering is a step toward signal feature extraction and classification. But some more steps can be useful before reaching this stage. One of the most used method is the envelope detection.

C. Preprocessing Envelope detection methods

Many envelope detection techniques are applied to EMG signal to enhance the interpretability and classification results. From this technique we can mention Hilbert Transform, peak detection, RMS calculation and linear envelope [9].

The RMS envelope is detected by calculating the rms value of the signal using a sliding window. The linear envelope is calculated by rectifying the signal the applying a low pass filter. The peak based envelope detection uses an interpolation between local maxima of the signal to generate the envelope. The Hilbert envelope of the signal is determined by calculating the magnitude of the complex analytical signal [10].

III. Features extraction and classifcation techniques

Feature extraction is an art of choosing the best characteristics that describes an object and extracting useful information from any kind of signal. Many feature extraction techniques are used in literature in main three domains: the time domain, the frequency domain and the time frequency domain.

A. Time domain features extraction techniques

The table below describes the most used time domain feature extraction and their interpretation [11]:

TABLE I. Time domain features

Feature	*Equation*
Integrated EMG (IEMG)	$IEMG_K = \sum_{i=1}^{N} \lvert x_i \rvert$
Mean Absolute Value (MAV)	$MAV_K = \frac{IEMG_K}{N} = \frac{\sum_{i=0}^{N} \lvert x_i \rvert}{N}$

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Feature	*Equation*
Modified Mean Absolute Value 1 (MMAV1)	$\text{MMAV1}_k = \frac{1}{N}\sum_{i=1}^{N} w_i\lvert x_i\rvert$ $w(i) = \begin{cases} 1, & 0.25\,N \le i \le 0.75\,N \\ 0.5, & otherwise \end{cases}$
Modified Mean Absolute Value 2 (MMAV2)	$\text{MMAV2}_k = \frac{1}{N}\sum_{i=1}^{N} w_i\lvert x_i\rvert$ $\text{w(i)} = \begin{cases} 1, & 0.25\,N \le i \le 0.75\,N \\ \frac{4i}{N}, & 0.25\,N > i \\ \frac{4(i-N)}{N}, & 0.75\,N < i \end{cases}$
Mean Absolute Value Slope (MAVS)	$\text{MAVS}_k = \text{MAV}_{k+1} - \text{MAV}_k$
Root Mean Square (RMS)	$\text{RMS}_k = \sqrt{\frac{\sum_{i=1}^{N}\lvert x_i\rvert^2}{N}}$
Variance (VAR)	$\text{VAR}_k = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$
Waveform Length (WL)	$\text{WL}_k = \sum_{i=1}^{N-1}\lvert x_{i+1} - x_i\rvert$
Zero Crossing (ZC)	$\{x_i > 0 \; and \; x_{i+1} < 0\} or$ $\{x_i < 0 \; and \; x_{i+1} > 0\} \; and$ $\lvert x_i - x_{i+1}\rvert \ge \epsilon$
Slope Sign Change (SSC)	$\{x_i > x_{i-1} \; and \; x_i > x_{i+1}\} \; or$ $\{x_i < x_{i-1} \; and \; x_i < x_{i+1}\}$ and $\lvert x_i - x_{i+1}\rvert \ge \epsilon \; or \; \lvert x_i - x_{i-1}\rvert \ge \epsilon$
Willson Amplitude (WAMP)	$WAMP_K = \sum_{i=1}^{N-1} f(\lvert x_i - x_{i+1}\rvert)$ $f(x) = \begin{cases} 1, & x > \epsilon \\ 0, & otherwise \end{cases}$
Simple Square Integral (SSI)	$\text{SSI}_k = \sum_{i=1}^{N}(x_i{}^2)$
Auto-Regressive Coefficient (AR)	$x_k = -\sum_{i=1}^{N} a_i x_{k-1} + e_k$

Every feature is used for a special purpose, for example the IEMG is usually used to determine the On-Set of EMG signal, MAV is the mean of the IEMG, the MMAV 1 is a linear weighted MAV, the MMAV 2 is a non-linear weighted MAV, RMS is used to estimate the power of a contraction in a non-fatiguing situation, the VAR is used to estimate the deviation of a series of EMG values from the mean, ZC used to determine the number of times the signal change sign by crossing the zero, and so on.

B. Frequency domain features extraction techniques

The table below describes the most used frequency domain feature extraction and their interpretation:

TABLE II. FREQUENCY DOMAIN FEATURES

Feature	*Equation*
Frequency Median (FMD)	$F_{MD} = \frac{1}{2}\sum_{i=1}^{M} PSD_i$
Frequency Mean (FMN)	$F_{MN} = \frac{\sum_{i=1}^{M} f_i PSD_i}{\sum_{i=1}^{M} PSD_i}$
Modified Frequency Median (MFMD)	$\text{MFMD} = \frac{1}{2}\sum_{i=1}^{M} A_i$
Modified Frequency Mean (MFMN)	$MFMN = \frac{\sum_{i=1}^{M} f_i A_i}{\sum_{i=1}^{M} A_i}$

C. Time-Frequency domain features extraction techniques

The table below describes the most used time-frequency domain feature extraction and their interpretation [12]:

TABLE III. TIME-FREQUENCY DOMAIN FEATURES

Feature	*Equation*
Short Time Fourrier Transform (STFT)	$STFT_x(t,w) = \int W^*(\tau - t)x(\tau)e^{-jw\tau}d\tau$
Wavelet Transform (WT)	$W_x(a,b) = \int x(t)\left(\frac{1}{\sqrt{a}}\right)\psi^*\left(\frac{t-b}{a}\right)dt$
Wavelet Packet Transform (WPT)	Wavelet packet transform is considered as an improvement for the wavelet transform

Due to the fast calculation and minimum resources consumption, time domain features will be used to extract useful information from EMG signals.

Five time-domain features were selected due to their wide usage in literature which are RMS, MAV, MMAV1, MMAV2 and WL. After calculating the correlation matrix table IV which illustrate a high correlation and making a boxplot to look at the distribution of the features data figure-2 which demonstrate a high variability we decided to keep all the five features because of their dependency and close distribution values.

TABLE IV. CORRELATION MATRIX

1	0.96	0.99	0.99	0.99
0.96	1	0.96	0.96	0.96
0.99	0.96	1	0.99	0.99
0.99	0.96	0.99	1	1.00
0.99	0.96	0.99	1.00	1

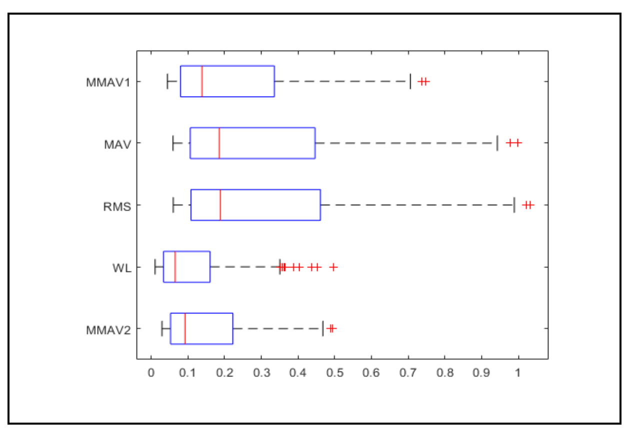

Fig. 2. Boxplot of five feature distribution (RMS, MAV, MMAV1, MMAV2, WL)

D. EMG signal supervised classification techniques

Three types of classification techniques can be used to deal with EMG signal, the supervised learning in which the data set for training is labeled. Unsupervised learning in which no labeling is provided and the aim of this technique is to bring out data with similarity and cluster them. Semi-supervised learning in which labeled and unlabeled data are used for the classification [13].

Supervised learning class is widely used with small datasets that can be easily labeled like our case. Supervised learning has a very promising result.

Support vector machine (SVM) is powerful supervised discriminative classifier who uses hyperplanes which are decision boundaries to separate classes. Given a set of labeled data, the SVM try to find the optimal hyperplane that separates the data. The optimal hyperplane is determined using margins which are built based on support vectors, which refers to data points close to the hyperplane, to calculate distance between dataset and hyperplanes. By maximizing margins, we obtain hyperplanes that best separate classes. So, we ensure that future data can be classified correctly with some confidence. Figure below gives an example of good and bad margin. Sometimes, the separation is linearly impossible so SVM can use kernels to pass to a high dimensional space in which classification is better.

By default, the SVM is a binary classifier but there is many strategies that can improve the capability of this technique to become a multiclass classifier, the one used here is the One-vs-One strategy which takes a pair of class from a set of n class and develop a binary classifier for each pair. During the classification, a majority vote technique is applied in which a binary classifier predicts one class and the class with the highest probability is selected. Because of the nonlinear aspect of this classification task and the overlapping data, a radial basis function kernel (RBF) is used to transform the two-dimensional classification to a higher dimensional space where different classes can be separated easily.

Linear discriminant analysis (LDA) is a supervised multi-class classification algorithm that can be also used as a dimensionality reduction technique helping in pre-processing data to avoid overfitting. Linear Discriminant analysis is based on the estimation of the means and covariance matrix of input variables.

IV. RESULTS, DISCUSSION AND PERSPECTIVES

This section will gather all information and methods used to obtain a good classification result. It will also argument our previous choices and prove them.

This section will also talk about the perspectives and future work which is the finale stage of designing the multiarticulate multifunctional prosthetic hand. We will discuss the components of the system step by step beginning with EMG acquisition system, the electronic or control parts, the mechanical design and finally the manufacturing method.

A. Results and discussion

The first stage was the envelope detection of the band pass filtered EMG signal of the used dataset. As shown in figure 2, linear envelope gives the best shape of the original signal. This is improved by the results of the classification in table IV which shows that the linear envelope gives the best classification results with the SVM and LDA.

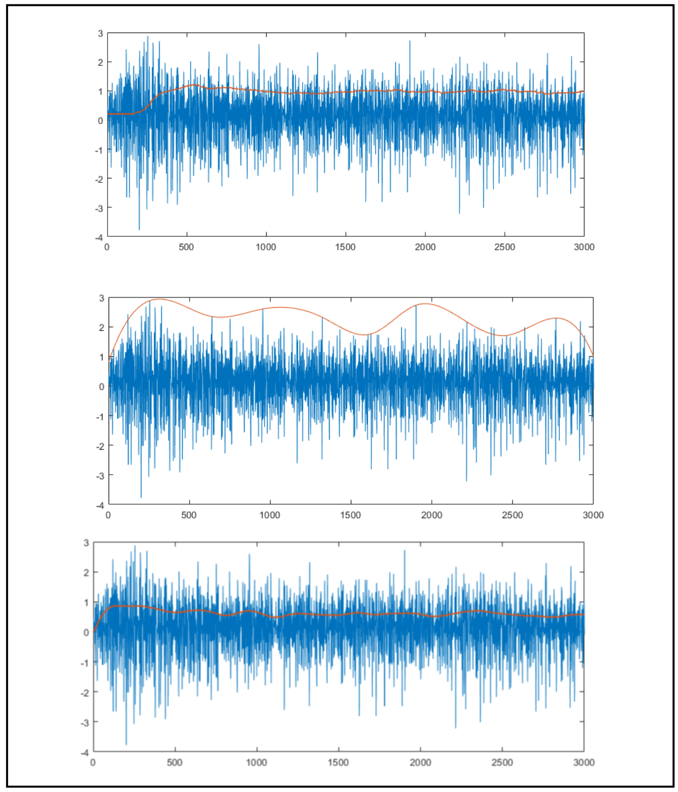

Fig. 3. envelope shapes obtained using different techniques, the first image is the shape obtained using RMS envelope technique, the second image is the shape extracted using the peak envelope technique and the las image describes the shape extracted using the linear envelope detection technique.

The next stage in the classification process is feature extraction. Because of the friendly resource consumption and the good time calculation response, time domain features where chosen for this task.

TABLE V. CLASSIFICATION RESULTS

Classifier	Individus	Peak Envelope	RMS Envelope	Linear Envelope
SVM (one-vs-one)	Male1:	93.6%	98.05%	97.5%
	Male2:	78.8%	96.9%	95.0%
	Female1:	91.9%	45.5%	97.5%
	Female2:	93.3%	70.27%	98.3%
	Female3:	96,1%	59.16%	97.7%

LDA	Male1:	85,5%	82.2%	98.05%
	Male2:	89,4%	75.27%	97.2%
	Female1:	90.27%	74.16%	96.1%
	Female2:	81.6%	81,1%	94.4%
	Female3:	86,1%	74,7%	95.27%

As shown by the table IV, the linear envelope gives the best classification results, next come the peak envelope and the last one is the RMS envelope. This is due to the smooth envelope of the linear method compared with the two other methods [15].

B. Perspectives

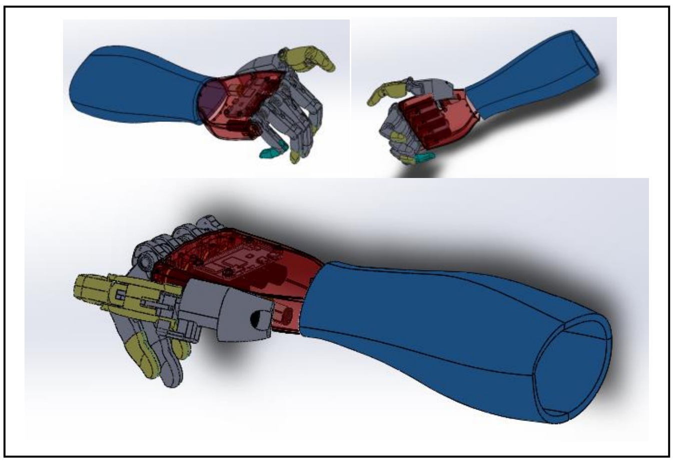

Fig. 4. Prosthetic Hand Design Using SolidWorks

Many revolutionary designs of prosthetic hand devices are achieved during the last decade, most of the are so basic and simple that are unable to achieve more than two movements of opening and closing hand. Other designs like BeBionic Hand of Ottobock, iLimb hand of Touch Bionic and some other manufacturer provide a very realistic human hand-like features. This new generation of prosthetic hand is able to mimic an acceptable number of hand gesture with a very advanced esthetic look. The only drawback is the high price of this kind of prosthetic devices. Those prosthetic hand was an inspiration for us to build our prosthetic hand with a very low cost, a very esthetic look and a high number of gestures.

The first step is designing an esthetic prosthetic hand with a good look that can be accepted by amputees and society. By searching for already existing designs, updating and adjusting functionality and characteristics, we come out with a good base for our prosthetic device.

The second step is choosing a good and an available tool for mechanical design. SolidWorks was selected for the 3D design of the prosthetic hand due to the large feature available on it, the existence of student editions and his large community which can provide us with necessary help and advices.

The third step is the 3D printing of the model of the designed prosthetic hand using the generated .stl files from SolidWorks.

Because 3D printing becomes more and more used even in manufacturing process, the prototype of the prosthetic hand is designed using ABS which is a hard material and resistant to temperature [16] and an Ultimaker 3D printer in figure 5 [17].

Fig. 5. Ultimaker 3D printer

The next step after validating the 3D design and 3D printing is the implementation of the algorithms described below in an embedded system capable of handling the amount of calculation and processing of the classification process. The system should respond in less than 300 ms including the acquisition of the EMG signal, the filtering and envelope detection, feature extraction and the application of the classifier. Raspberry pi zero w with 1 GHz single core CPU, a 512 MB RAM and a 40 general purpose input-output was selected for doing the task of the classification process. Because of these characteristics and the small dimensions of this minicomputer, the raspberry pi zero w is a very good choice for prototyping the embedded part.

Fig. 6. Raspberry Pi Zero W [18]

In addition to the embedded part responsible for the classification process, an STM32F103C8T6 mini board with 72 MHz max CPU frequency, a 64 KB flash, a 20 KB SRAM, a 12-bit ADC with 10 channels, four timers and many communication protocols is used for controlling motors and drivers and analog to digital conversion.

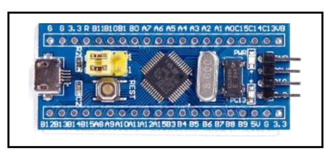

Fig. 7. STM32F103C8T6 mini board [19]

CONCLUSION

EMG signals are widely used in many fields especially prosthetic devices and rehabilitation. Those signals can be easily affected by the noisy environment and loose significant and important information. This why filtering the signal is a very important stage to obtain useful information from the signal. After filtering, many envelope detection techniques were applied to obtain the shape of the signal and decrease the effect of any other noise that the filtering stage wasn't able to eliminate it. The feature extraction came after this to extract useful information from the signal to prepare it for the classification. Supervised techniques are used in this stage to classify EMG signals like the SVM and LDA.

Future work will concentrate on applying the deep learning techniques to classify EMG signal and testing the prosthetic hand in real world application.

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