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Improving EMG based Classification of basic hand movements using EMD

Christos Sapsanis, George Georgoulas, Anthony Tzes, and Dimitrios Lymberopoulos

Abstract—**This paper presents a pattern recognition approach for the identification of basic hand movements using surface electromyographic (EMG) data. The EMG signal is decomposed using Empirical Mode Decomposition (EMD) into Intrinsic Mode Functions (IMFs) and subsequently a feature extraction stage takes place. Various combinations of feature subsets are tested using a simple linear classifier for the detection task. Our results suggest that the use of EMD can increase the discrimination ability of the conventional feature sets extracted from the raw EMG signal.**

Index Terms—**Biomedical signal analysis, Empirical Mode Decomposition (EMD), pattern classification, electromyography (EMG).**

I. Introduction

Controlling a robotic exoskeleton hand is a problem that should be faced in order to construct an autonomous system for a hand amputee. The utilization of electromyogram (EMG) signals seems to be a viable solution since every movement has a distinct signature on the produced signal. The EMG signal classification can be quite accurate leading to efficient control strategies of a robotic hand [1] with the advances in Biosensors, Pattern Recognition and Biosignal processing [2], [3]. Moreover, it is more comfortable for a hand amputee to wear a glove that includes the EMG electrodes than using the rather promising electroencephalography (EEG) electrodes in the area of the head [4]. This issue is of significant importance for using such a system in a daily basis.

Several approaches to solve the motion command identification problem using EMG signals have been suggested, achieving in some cases low classification error, using not necessarily typical daily hand's movements and a large number of electrodes (in most of the cases more than 4) [5]. This is an issue that can have a negative impact in the expenditure for the construction of a system that consists of sensors and electrodes and it may not be so comfortable and acceptable from a hand amputee. Therefore, it would be desirable, for a dexterous prosthesis, to let the amputee command a grasp posture and force, just by performing the corresponding action with the exoskeleton prosthetic hand. Also, a way to finely modulate the force involved in a grasp is paramount in daily life activities, for example to hold a credit card, a glass of water, a pencil, a ball without breaking it or to grasp a hammer without letting it slip [6].

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This paper presents a pattern recognition approach for the identification of basic hand movements using surface EMGs acquired using two electrodes attached on two specific muscles of the hand. The novelty of our approach resided on the use of only two electrodes and the application of Empirical Mode Decomposition (EMD) for the extraction of additional features. Our results show that the information carried by the EMD extracted features can increase the classification accuracy leading eventually to more effective control of a robotic hand.

The rest of this paper is structured as follows. Section II describes the experimental set up along with a short description of all the involved technologies. Section III presents the experimental results and Section IV concludes the paper providing some hints for future research.

II. EMD-based EMG-Data Hand Movement Classification

The pattern recognition approach consists of few discrete stages. First a number of EMG recordings were collected as described in the next subsection. Then a preprocessing stage was involved to exclude the non-contracting portions at the beginning of each movement. Following the muscle contraction detection, segmentation of the rest of the signal takes place using overlapping windows. The classification stage focuses on the classification of each one of these basic window segments into six distinct categories, after the extraction of an appropriate feature set using both the raw EMG signal as well the Intrinsic Mode Functions (IMFs) that are produced by the application of the EMD. The rest of this section provides a short description of each one of the aforementioned stages.

A. EMG Data Collection

The experiments consisted of freely and repeatedly grasping of different items which were essential to conduct the hand movements. The speed and force were intentionally left to the subject's will. There were two forearm surface EMG electrodes Flexor Capri Ulnaris and Extensor Capri Radialis, Longus and Brevis [7]) held in place by elastic bands and the reference electrode in the middle, in order to gather information about the muscle activation.

For the data collection five healthy subjects (two males and three females) of the same age approximately (20 to 22-year-old) were asked to repeat the following six movements, which can be considered as basic hand movements [8] (Figure 1):

a) Spherical: for holding spherical tools
b) Tip: for holding small tools
c) Palmar: for grasping with palm facing the object
d) Lateral: for holding thin, flat objects

e) Cylindrical: for holding cylindrical tools
f) Hook: for supporting a heavy load

For each movement the subject was asked to perform it for six seconds and the whole procedure was repeated 30 times for each basic movement. Therefore for each subject a total of 180 6-second long 2-channel EMG signals were recorded.

The data were collected at a sampling rate of 500 Hz, using as a programming kernel the National Instrument's (NI) Labview [9]. The signals were band-pass filtered using a Butterworth Band Pass filter with low and high cutoff at 15Hz and 500Hz respectively and a notch filter at 50Hz to eliminate line interference artifacts.

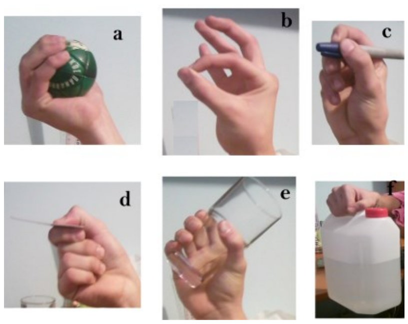

Figure 1. Illustration of the hand gestures.

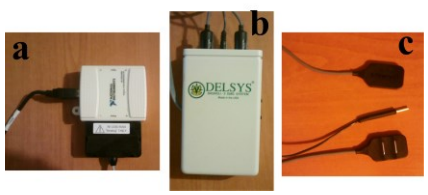

Figure 2. The experimental setup: a) National Instruments analog/digital conversion card NI USB-6009. b) 2-channel EMG system. c) 2 Differential and 1 reference EMG Sensor.

The hardware that was used (Figure 2) was an NI analog/digital conversion card NI USB-6009, mounted on a PC. The signal was taken from two Differential EMG Sensors and the signals were transmitted to a 2-channel EMG system by Delsys Bagnoli™ Handheld EMG Systems [10].

C. Preprocessing

In order to focus only on segments where the muscle is contracted, we applied the sliding window approach proposed in [11]. Within a sliding window of 40 msecs the average IEMG value (see section II.F) was calculated. Once that value exceeded a predefined threshold we considered that the muscle was no longer in a resting phase and we started processing the rest of the recording.

There are two major techniques in data windowing: adjacent windowing and overlapping windowing [11]. In this work we selected the overlapping approach with time windows of 300 msecs (150 data points) and an overlap of 270 msecs (or a time leap of 30 msecs) (Figure 3). On each of these segments we applied EMD for the extraction of IMFs.

D. Empirical Mode Decomposition

Most real life processes are inherently non-linear and non-stationary. As a result, using algorithms that assume linearity and stationarity can be problematic. EMD [12] provides a novel adaptive method for analyzing non-linear and/or non-stationary signals that are encountered in most, real life applications.

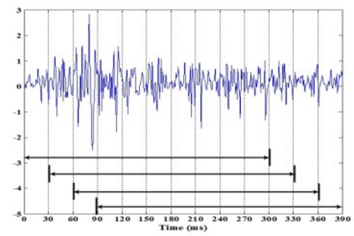

Figure 3. 300 msec long overlaping windows

EMD acts as an adaptive non-linear filter, decomposing the signal into a number of IMFs, where an IMF represents a simple oscillatory function satisfying two conditions:

1. The number of zero crossings and the number of local extrema are either equal or differ by one.
2. The local average (defined by the average of local maximum and local minimum envelops) is equal to zero.

These two conditions guarantee that all the maxima of an IMF are positive and all its minima are negative.

Given a signal $x(t)$ the EMD algorithm can be summarized as follows:

1. Identify all local minima and local maxima of the given signal ($x(t)$). Create an upper ($e_{max}(t)$) and a lower ($e_{min}(t)$) envelope interpolating between successive local maxima and local minima respectively (usually via cubic interpolation)
2. Calculate the running mean $m(t) = \frac{e_{\min}(t) + e_{\max}(t)}{2}$
3. Subtract the mean from the signal to extract the detail $d(t)=x(t)-m(t)$.
4. Repeat the whole process replacing $x(t)$ with $m(t)$ until the final residual is a monotonic function (or a user specific number of IMFs has been extracted – application dependant).

In practice, step 4 may not produce a valid IMF. As a result, shifting needs to take place, which implies the iteration of steps 1 to 4 on the detail $d(t)$ until a specific criterion is met [12], [13]. Therefore, the original signal $x(t)$ is eventually decomposed into a sum of IMFs plus a residual term: $x(t) = \sum_i IMF_i(t) + r(t)$.

Figures 4 and 5 depict one of the two EMG signals along with the corresponding first three IMFs for the case of: a) Lateral movement and b) Cylindrical movement.

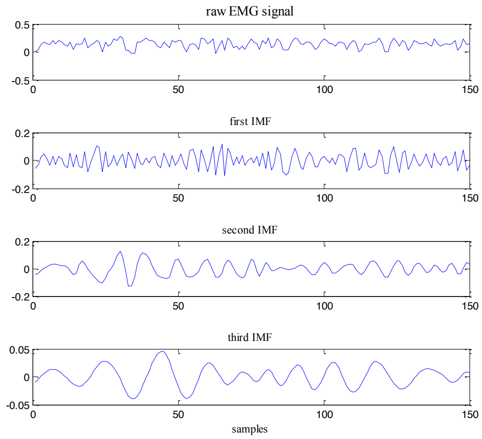

Figure 4. Raw EMG signal along with the first three IMFs for the case of the Lateral movement

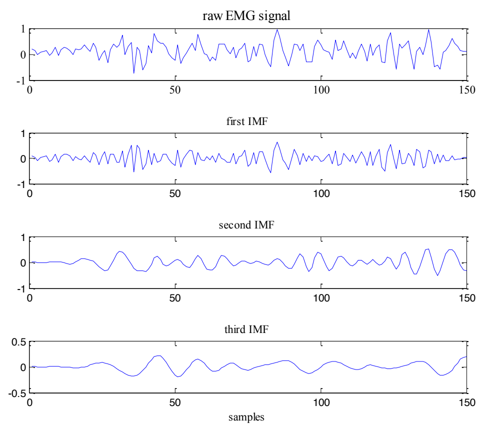

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Figure 5. Raw EMG signal along with the first three IMFs for the case of the Cylindrical movement

E. Feature extraction

As in almost all pattern recognition applications involving biomedical signals, a feature extraction stage is necessary in order to condense the relevant information and also alleviate the problem with the curse of dimensionality. The features should be selected in such a way as to maximally separate the desired output classes. In practice, the feature selection is regarded by some researches as being more of an art than a science [14].

In our case eight popular features [15] were extracted, this time not only from the original EMG signals but from the three IMFs that were produced after processing the EMG signals with the help of EMD toolbox [16] as well as from the residual. The eight features are the following

1) Integrated Electromyogram (IEMG):

This feature is an average value of the absolute values of EMG, defined as $IEMG = \frac{1}{N}\sum_{k=1}^{N}|x_k|$,

where x_k is the k^{th} sample data out of N samples of EMG raw data.

2) Zero Crossing (ZC):

ZC counts the number of times that the signal crosses zero. A threshold needs to be introduced to reduce the noise induced at zero crossing. Given two contiguous EMG signals x_k and x_{k+1}, the ZC can he calculated as:

$$ZC = \sum f(x), \text{ where}$$

$$f(x) = \begin{cases} 1, & \text{if, } (x_k > 0 \; AND \; x_{k+1} < 0) \\ & \text{OR } (x_k < 0 \; AND \; x_{k+1} > 0 \\ 0, & \text{otherwise} \end{cases}$$

for $k = 1, 2, 3, \ldots N\text{-}1$

3) Variance (VAR):

VAR is a measure of the power density of the EMG signal given by:

$$VAR = \frac{1}{N-1}\sum_{k=1}^{N}(x_k - \mu)^2$$

where μ is the average.

4) Slope Sign Changes (SSC):

SSC counts the number of times the slope of the signal changes sign. Given three contiguous EMG signals x_{k-1}, x_k and x_{k+1} the number of slope sign changes can be calculated by $SSC = \sum f(x)$ where

$$f(x) = \begin{cases} 1, & \text{if, } (x_k < x_{k+1} \; AND \; x_k < x_{k-1}) \\ & \text{OR } (x_k > x_{k+1} \; AND \; x_k > x_{k-1}) \\ 0, & \text{otherwise} \end{cases}$$

for $k = 1, 2, 3, \ldots. (N\text{-}1)$

5) Waveform Length (WL)

WL is a cumulative variation of the EMG that can indicate the degree of variation about the EMG signal. It is given by $WL = \sum_{k=1}^{N-1}(|x_{k+1} - x_k|)$

6) Willison Amplitude (WAMP)

WAMP is the number of counts for each change of the EMG signal amplitude that exceeds a defined threshold. It can indicate the muscle contraction level as given by

$$WAMP = \sum_{k=1}^{N-1} f(|x_{k+1} - x_k|)$$

$$f(x) = \begin{cases} 1, & \text{if } x > \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

7) Kurtosis:

The kurtosis of a distribution is defined as $k = \frac{E(x-\mu)^4}{\sigma^4}$

8) Skewness

The skewness of a distribution is defined as $s = \frac{E(x-\mu)^3}{\sigma^3}$

where μ is the mean of x, σ is the standard deviation of x, and $E(t)$ represents the expected value of the quantity t.

The kurtosis and skewness variables compute a sample version of this population value.

Therefore a total of 40 (8 features from the EMG, 24 (3x8) from the three IMFs and 8 features from the residual) features were extracted for each segment.

F. Classification

Since our intention was to check whether the inclusion of the EMD based extracted features can increase the performance of a classification system the emphasis was not set on the optimal selection of the classifier. We therefore selected a simple linear classifier (a classifier that creates decision boundaries between compartments in the feature space that are linear (hyper)planes), since as it was pointed out in [17] for most real life data, "a simple linear surface can do surprisingly well as an estimate of the true decision surface". In other words each feature vector $\mathbf{x}$ is assigned to class for which the value of the corresponding discriminant function is maximum:

$$i = \arg\max_{i} \left\{ 2\ln P(\omega_i) - (\mathbf{x} - \boldsymbol{\mu}_i)^T \mathbf{C}^{-1} (\mathbf{x} - \boldsymbol{\mu}_i) \right\}$$

where $\boldsymbol{\mu}_i$ is the mean of class i, $P(\omega_i)$ is the prior probability of class i, and $\mathbf{C}$ is the estimated covariance matrix assumed common for all classes (even though this assumption does not hold in many practical applications, the classifier still performs surprisingly well). One other advantage of the selection of the specific classifier is that it does not require the tuning of any parameters, which is one of the major issues in machine learning [18].

III. Experimental Studies

In this work we used each subject "at its own control", meaning that the data coming from each subject were not mixed with data coming from any other subject. In order to estimate the performance we used the 5 x 2CV (cross-validation) approach [19]. In other words each time we randomly selected 15 of the recordings for training and the rest 15 for testing for each one of the six movements that were described in Section II and are depicted in Figure 1. Then we swapped the two sets (the training set was becoming the testing set and vice versa) and the whole process was repeated five times. The averaged results for each one of the five subjects (total number (all six movements included) of correct segments for each subject over the five trials divided by the total number of segments for each subject over the five trials) are depicted in Table I. We tested the performance of the algorithm using; a) only features coming from the raw EMG signals, b) features coming from the first IMF and c) all extracted features. We do not show the results for the features coming from the rest of the IMFs since the classification performance deteriorates.

IV. Conclusions

In this work we presented a preliminary study regarding the use of EMD for the extraction of additional features for the task of hand movement classification using EMG signals. As seen from Table I, even though individually the features extracted by the raw EMG signals perform better than the features sets extracted by the IMFs, the ensemble of features performs the best.

Therefore even though we have not performed a systematic feature selection stage the inclusion of the information coming from the IMFs seems to have a positive impact on the classification accuracy. In future work we will focus both on extracting the most relevant of the involved features as well as on testing more powerful classification schemes which will be tested on a larger database that we are forming involving more subjects.

TABLE I. Classification Performance for the 5 Subjects

subject	Classification accuracy (average)		
	Raw EMG extracted features	***First IMF extracted features***	***All extracted features***
Male 1	86,92	78,03	90,42
Male 2	92,38	84,97	94,80
Female 1	85,24	83,32	87,25
Female 2	83,88	78,94	88,05
Female 3	84,82	77,68	85,53

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