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WAVELET ENERGIES AS A FEATURE AND THEIR IMPACT ON CLASSIFYING MOVEMENTS BASED ON sEMG

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ABSTRACT
Surface Electromyography signal processing and classification is an issue that concerns a large number of research groups, demanding more accurate, simple and sophisticated feature extraction schemes in order to accomplish better performance in different applications, with a solid subject being the control of prosthetics since decades ago with early signs of satisfying accuracy. In this research, we investigate the effect of efficient feature extraction on the wavelet domain using the discrete Wavelet transformation (DWT), on NINAPPRO, a database of 27 subjects performing different sets of movements, which is available for researchers worldwide. Energy measures estimated on the wavelet domain is the novel set of features introduced in the sEMG signal analysis community is implemented and compared to already simple features of the time domain. The experimental results show the use of wavelet energies on the wavelet domain can significantly improve the classification challenge.

KEY WORDS
Classification, sEMG, feature extraction, wavelet energies, NINAPRO, gesture classification.

1. Introduction

Biomedical signals are of great importance for clinical evaluation of the patients. The variety of such signals according to the body sources that these are acquired from as well as the combination of the different biomedical signals provide an advanced diagnostic tool to the clinician. The biomedical signals usually measure the electrical currents during the activity of human organs, tissues, muscles etc. and this response is transferred to relevant equipment for recording, viewing, monitoring or processing purposes. Such signals that emanate from contracting muscles representing neuromuscular activities are referred as electromyography signals (EMG). The EMG signal is a biomedical signal that measures electrical currents generated in muscle during its contraction. It is acquired directly from the skin's surface using such electrodes, capable to record Motor Unit Action Potentials (MUAP) from which the muscle tissue is composed. The EMG signal appears with amplitude that increases as the rate of the firing muscle response increases. These pulses are recorded as functions of time with a non-Gaussian form [1]-[3].

The shape, morphology and distribution in EMG signals produced by the corresponding firing rates of Motor Unit Action Potentials (MUAPs) is key information for diagnosis and can be used for clinical evaluation of the patients with kinesiological and neuromuscular disorders. During the last decade a lot of research can be found in the area of prosthetic hand based on the analysis of EMG signal. In addition to this a lot of research has been completed to the location of patterns on such signal that can then be explained or used by the experts.

Many mathematical models have been developed for the extraction of the important characteristics of EMG signals in order to process and recognize structures of the EMG. More specifically, hand motion recognition has been used in research work and a common collusion to the recognition / classification of motions using features of EMG can create more accurate results. In recent efforts / projects, researchers work with groups of subjects with predefined scenarios executed with standard patterns. To this direction, the introduction of the NINAPRO database, which is a database of sEMG and kinematic data gathered from 27 intact subjects while performing 52 movements of interest brought a standard procedure for the assessment of the gesture recognition techniques developed to the related scientific society [12].

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Various signal processing transformations along with corresponding measures estimated over the corresponding domain have been proposed [9] either on the time domain or on the frequency domain after the application of the Fourier on the sEMG signal. In addition, the discrete wavelet transform (DWT) was elaborated and has shown better performance because of its multilevel decomposition since it combines time and frequency resolution of the signal. Since the analysis of the EMG signal and the recognition of patterns within these signals is in common use for joint prosthetic hands, the wavelet analysis seems to be a valuable tool for extracting more information from the input signals [6]. Feature extraction aims to locate information through the construction of feature sets consisted of feature vectors chosen to preserve class separability. Classification accuracy is affected more by the choice of feature set than by the choice of classifier. Classification algorithms that have been used in similar application to the classification of EMG signals, include Bayesian classifiers [9], artificial neural networks , Gaussian mixture models, hidden Markov models, fuzzy logic and genetic algorithms [5]-[8].

In this paper, we used a widely known signal transformation, the wavelet transform, which combines frequency and spatial signal information and transforms the signal into the relevant wavelet domain. The input signal which in our case is the sEMG signal is decomposed in a number of levels applying filtering, downsampling procedures. Consequently energy measures for each different decomposition level in the wavelet domain are estimated constituting the corresponding feature vector. These feature / energy based vectors formed in this way are then used for the recognition of each movement from the set of 52 movements and the 27 users that exist in the NINAPRO database [12]. From the experiments, which are shown in the following paragraphs, we concluded that the use of energy values in the wavelet domain brings a significant improvement to the classification performance. This improvement was obvious compared to the performance of other features, usually estimated in time domain, on the same EMG data. It is worth to be noted that a reasonable improvement achieved in the accuracy of which gesture a user is performing, even without training for that user.

The paper is structured as follows. In the second paragraph is presented a short description of the architecture of the NINAPRO database. The third paragraph contains the description of the wavelet decomposition approach as well as the estimation of the energy features on the wavelet domain of the EMG signal. Results and discussion on the application of the energy vectors are presented to the fourth paragraph and the conclusions along with the future trends of this work are described in the fifth paragraph.

2. Architecture and Data Description

NINAPRO [12], the database used in our research consists of measurements of 27 male and female subjects, performing repetitions of 52 movements, which were introduced to them using a video. During measurements, each subject followed the instructions on the video, on when he/she should perform each movement and when to rest. The experimental setup consisted of a 22-senror Cyberglove II dataglove to gather the finger positions. The glove has 22 strain gauges sewn, and it represents 22 joint angles as 8-bit values, for an average of resolution of less than one degree. A standard commercial 2-axis inclinometer is fixed onto the subject's wrist and used to collect the wrist orientation. Activity of the muscles was gathered using ten active double-differential OttoBock MyoBock 13E200 surface EMG electrodes, which provide an amplified, bandpass filtered and rectified signal, with a bandwidth of 0-25 Hz. As for the electrodes placement, the targeted placement is not necessary as pattern recognition techniques can function properly, sometimes can even take advantage of muscle cross-talk. Eight uniformly spaced electrodes are placed beneath the elbow, while two more are placed on the flexor and extensor muscles.

In our research, we only used the data from the electrodes in order to recognize different movements only based on sEMG, a project quite challenging for such size of data. The movements were divided in four main classes:

12 basic movements of the fingers,

8 isometric, isotonic hand configurations,

9 basic movements of the wrist and

23 functional movements using everyday objects in order to mimic a daily-life action.

The purpose of our work is to investigate the correlation between same movements from different subjects and the classification, or generalization of a move among different people.

We focused on classifying same movements without choosing standard patients. In other words, the training and the testing of the system were inter subject, and without using the same patients data for each phase. In other similar works in literature with high accuracy results [9]-[11], the high percentage of classification success was achieved as the best result of all the trials, or a mean value of the trials. In [11], the results were not higher than 80%, in all the well-known combinations for feature extraction and classification in sEMG signals. The idea behind the classification method we used is to use random movements from the 4 different sets of movements, and to develop a system capable of defining in which set the move belongs to with the highest possible accuracy without knowing who executed the exercise. That leads to a system capable of recognizing a movement from its shape, using the features that have similar properties from each signal and using them for creating a patter for moves, not moves from a person.

3. Wavelet Energies in sEMG signals

Fast Fourier Transformation (FFT) has been used as a valuable tool for signal analysis based on the frequency spectrum. Since FFT represents a global frequency analysis it is proven weak in location of more dynamic movements that happen to the input signal. In this case is needed a time information of the signal along with the frequency analysis of the FFT. A tool that could be used is the Wavelet transformation of the signal which, by definition, combines the information from signal components, frequency and time.

Recent studies have come to the conclusion that a spatial/frequency representation, which preserves both global and local information, is adequate for the characterization of signal. The wavelet transform offers a tool for spatial/frequency representation by decomposing the original signal to the corresponding scales / levels. When decomposition level decreases in the spatial domain, it increases in the frequency domain providing zooming capabilities and local characterization of the signal characteristics. Wavelets offer the advantage is the time-frequency localization which is a necessary characteristic in signal analysis. The energy of the wavelet is expected within a finite time interval revealing frequency localization at low frequencies and time localization at high frequencies.

We have chosen to use Discrete Wavelet Transform (DWT) for the decomposition of the frequency domain of the signal for the representation of the signal which offers a representation of the frequency domain since they have appear with robustness in the presence of noise, can be sparser, and can have greater flexibility in representing the structure of the input signal. The 2D DWT transformation is implemented by applying a separable filterbank [14].

In the area of biomedical signals analysis wavelets offer a valuable tool for signals that are nonstationary and time varying in nature like the EMG signals. Multi resolution analysis used in the wavelet transformation provides characteristics that come from the different frequency components and the time simultaneously. The wavelet decomposition is utilized with the application of basis functions, translations and dilations of a function called mother wavelet [14]. In the proposed approach each EMG signal is transformed to its wavelet domain using the Discrete Wavelet Transform (DWT),

$$f(t) = \sum_i c_{k_0}(i)\varphi_{k_0,i}(t) + \sum_i \sum_{k=k_0}^{K} d_k(i)\psi_{k,i}(t) \tag{1}$$

where k0 $\in$ Z, Z is the set of integers, K is the total number of wavelet decomposition levels, φ is the scaling function, ψ is the mother wavelet, $c_{k_0}(i) = < g, \varphi_{k_0,i}(t) >$ and $d_k(i) = < g, \psi_{k,i}(t) >$. Daubechies wavelet bases were used due to their orthonormal property, which is important for the preservation of the signal characteristics along the different scales of the transform [13]. The above equations provide a recursive way for calculating the DWT coefficients. In practice, it is assumed that a discrete signal in its original resolution is equivalent to the approximation coefficients.

By definition energy measures are calculated as the sum of square of the signal's values. In the case of a transformed signal the corresponding energy measures are calculated accordingly to the definition but also taking into consideration the specific properties of the transformation. Having applied the wavelet transformation on the input EMG signal, the energy measures that are to be calculated are in correspondence with the decomposition level the wavelet is applied as well as the output of the filter banks produced by the decomposition procedure. The estimated local energy measures of wavelet coefficients are varying over different scales and are estimated by summing the squares of all coefficients:

$$E^{B_j(k)} = \sum_i b^{j,k}(i)^2 \qquad (2)$$

with $b^{j,k}$: the wavelet coefficients of the signal decomposition level $B_j(k)$, $j = 0, 1, 2, 3 \ldots$. Since the first level, for $j = 0$, of the decomposition usually called the approximation level, its coefficients contains significant signal information and as it is expected more energy appear in this scale compared to other coefficients at the same level. Another major advantage for the use of local energy measures is that the energy features are the statistical measures of the whole band without considering the time variance problem, they may not effectively distinguish some kinds local signal characteristics. Considering the concept of local energy values of frequency bands this overcomes the inclusion of the local signal features varying in time [13].

4. Results and Discussion

The experimental study of this paper outlines the series of the conducted experiments and the obtained results in order to evaluate the novel feature extraction methodology based on the energy values of the wavelet transformation of the sEMG input signal. The aim of the experimentation presented in this paragraph is the determination of significance of the contribution to a better classification of the movements using the local wavelet energy values of the signal.

As it has already been documented in the previous paragraph, the wavelet transformation locates and underlines signal characteristics from both time and frequency domains of the signal. In addition the use of energies on the wavelet domain encodes energy signal components from both domains bringing out the local properties of each examined signal window.

The experimentation setup developed in this work, uses the whole data from the NINApro database meaning that we didn't exclude any of the 27 subjects and the 52 movements of each subject. As for the experimenting procedure we randomly choose sets of 3 or 4 movements using various sizes of windows. Each signal window contains a part of the signal of a limited duration. Window sizes chosen are of size 100ms to 500ms. Following this, the window is then decomposed into 2 levels using the Daubechies-4 mother wavelet as a basis function. The variety of mother wavelets that could be used instead of Daubechies-4 as well as the various wavelet transformation algorithms is rather wide but this is not within the scope of this paper. For simplicity reasons we finally chosen the 2-d discrete wavelet decomposition using the Daubechies-4 basis function.

The decomposition of the initial sEMG signal is completed in two levels according to equation (1) and for each level we estimate the signal's energy value according to the equation (2). The feature vector consists of the corresponding energies on different levels, consisted of the horizontal, vertical and diagonal directions at i-th level which are defined as :

$$E_i^h = \sum_{x=1}^{M}\sum_{y=1}^{N}\left(H_i(x,y)\right)^2,$$
$$E_i^v = \sum_{x=1}^{M}\sum_{y=1}^{N}\left(V_i(x,y)\right)^2,$$
$$E_i^d = \sum_{x=1}^{M}\sum_{y=1}^{N}\left(D_i(x,y)\right)^2 \qquad (3)$$

For the two level wavelet decomposition according to the above equation (3) we obtain a set of 7 local energy values which are the components of the corresponding feature vector. Using such vectors, a 7-dimensional feature space is created. This space contains all the vectors of the different values that are examined and the next step is the application of a classifier to the data in order to classify each vector to one of the 52 movements. The proposed classifiers, in the literature constitutes an extended set which can be categorized into two main categories, supervised or unsupervised algorithms depending on the need or not of training samples that represent each class.

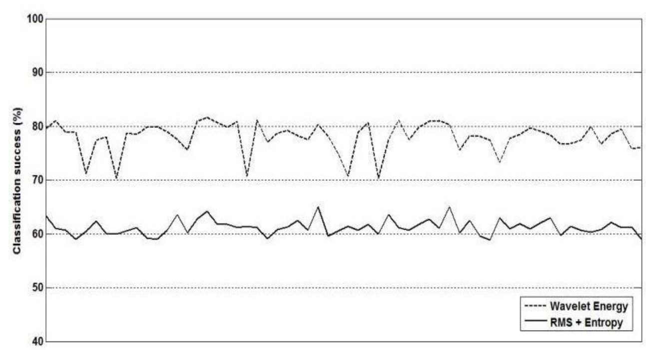

Figure 1. Classification accuracy using RMS and Entropy versus Wavelet Energies for three movements

In our experimentation and mainly for simplicity reasons we adopted a supervised classifier, the k-NN. Since it is a supervised algorithm we separate the input sEMG data form the NINAPRO database into two set, one for the training set and the rest for the test set with a small percentage of training and a larger set of testing data. In similar research works in literature, the size of the two set usually was chosen of the same size by dividing the whole set of data by two.

Summarizing all the above we would like to highlight the influence of the different parameters involved in the proposed classification scheme:

a) Scenarios developed include two and three movements with 30% training. We tried an increase to 50% for the training set. (Fig.2a)
b) The comparison was implemented between similar simple features for sEMG found in literature, like Root Mean Square (RMS) and Entropy, and wavelet energies.
c) All the features are extracted using window sizes of 100ms, 250ms and 500ms. The windows were overlapped.(Figure 2b)

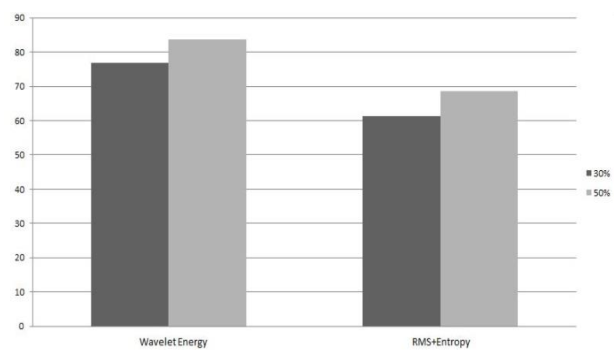

Figure 2a. Impact of change in training percentage

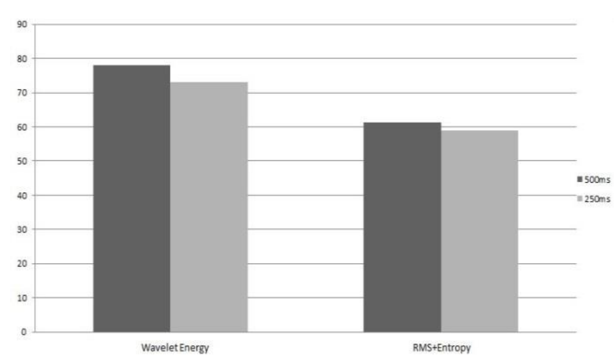

Figure 2b. Changes caused by reducing the time window

Combining all the above, we came to the conclusion, that the use of the wavelet energy values estimated on the sEMG signals, from the NINAPRO database, results a) to a significant improvement to the classification rate of movements include within the NINPRO database and b) a reasonable accuracy which movement a user is performing, even without a training phase for that user. This is more obvious in the next Figures 3a and 3b in which the line that corresponds to the performance achieved by the use of the wavelet energies is at a higher level independently to the parameter values that are chosen (30%-50% for the training set and 250-500ms for the window size)

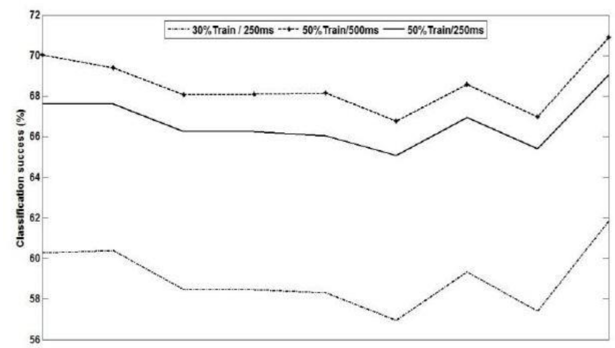

Figure 3a. The overall performance of RMS and Entropy for different settings

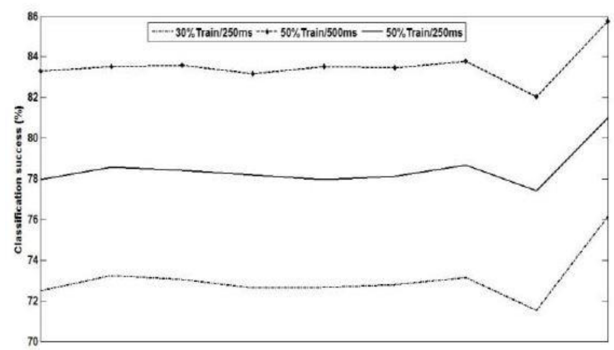

Figure 3b. Performance of Wavelet energy for the same input values

In Table 1 the standard deviations along with the experimental results for the mean value of sets of two and three movements classification are presented, all with a time window 500ms and training set- testing set ratio approximately equal to 1/3 (30% for training, 100% for testing). Although the standard deviation is fairly low and does not show an unstable system, in future work methods for more linearity will be applied, in order to secure a versatile system in different sets of data. The results look promising, and the system will be tested with different datasets of surface Electromyography data in order to validate its true efficiency.

	Two movements		Three movements	
	Rms+Entropy	Wavelet Energy	Rms+Entropy	Wavelet Energy
Standard deviation	± 1,8877	±4.7447	±1.4002	±2.7501
Accuracy (%)	72.92	85.23	61.22	77.94

Table 1. Comparison between standard deviations and classification accuracy

The trials were repeated 50 times each, each time with different movements picked up randomly, without interruption. The effect of increasing the movements tested has an interesting conclusion to give. Although as it was natural, increasing the movements decreases the classifiers performance, there seems to be a stabilized overall accuracy over the samples used. In Figure 4, the performance for two and three movements is presented, both when using RMS and signal Entropy as features, and when using Wavelet Energy.

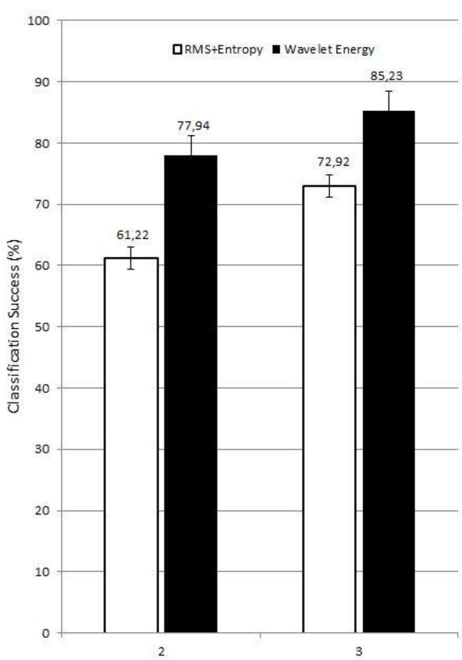

Figure 4. Mean values of 50 experiments for two and three movements

5. Conclusion

The use of simple in implementation of sEMG signal measures, energies, on the wavelet domain improves the movement classification performance significantly. We tested the proposed approach on sEMG signals included in the standard, for bio-robotics application, NINAPRO database. Based on the nature of the energy values on the time / frequency decomposition of the sEMG signal and the above described experimentation scheme we came to the conclusion that these values can contribute in the increase of the movement recognition in a number of important application like, robotics, prosthetics etc. The wavelet energies can significantly contribute along or not with other features to higher movement classification rate even in cases that the system is not trained for a specific user.

From this point of research there are a number of relevant topics that can be investigated in order to set-up a simple mathematical framework for such applications of movement classification. Some of these attractive future research trends can be the comparison of the already proposed feature sets but estimated on the time / frequency domain, the comparison of the results with other supervised classifiers that can possibly bring better results than the k-NN. Finally, since the proposed framework is a simple one, its hardware implementation is a feasible task and especially useful either for use by clinicians or by humans that are affected.

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