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Control Engineering

Elixir Control Engg. 50 (2012) 10320-10324

ISSN: 2229-712X

Wavelet analysis based feature extraction for pattern classification from Single channel acquired EMG signal

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ARTICLE INFO

Article history:

Received: 5 July 2012;

Received in revised form:

16 August 2012;

Accepted: 4 September 2012;

Keywords

Feature Vector;

Wavelet; RMS feature vector;

Biopac MP36;

EMG Signal;

Daubechies wavelet family.

ABSTRACT

Wavelet analysis is one of the most powerful and latest tool in the field of signal processing. It provides the better resolution in time and frequency domain simultaneously. Because of these properties of the wavelet it can be effectively used in EMG signal processing in order to determine the certain changes in amplitude at certain frequencies. At different levels of various mother wavelets we can get the useful resolution component from the EMG signal. In this paper, a single-channel electromyogram acquisition system Biopac MP36 was used to obtain the surface electromyogram signal. Single pair of surface electrodes was used to measure and record the EMG signal on forearm muscles. Then different levels of Daubechies Wavelet family were performed to analyze the EMG signal. We have used root mean square (rms) value of the EMG signal at different level of wavelet coefficients and reconstructed wave. The experimental results shows that rms feature vector provides very good performance for the classification of patterns.

Introduction

The Electromyography (EMG) signal, also referred to as the myoelectric signal (MES), acquired from the forearm skin surface provides valuable information about neuromuscular activities. Electromyography (EMG) signals have the properties of non-stationary, nonlinear, complexity, and large variation. These lead to difficulty in analyzing EMG signals. To make a system based on the EMG first we need to extract the features of the acquired EMG signal based on which it can be further classified for various hand movements. This technique is also called as pattern classification. Wavelet transform (WT) has emerged as an effective tool to extract the useful information from EMG and as well as various other biomedical signals [1]. There is a vast collection of literature which has focused on the evaluation and investigation of an optimal feature extraction obtained from wavelet coefficients [2-6]. Most of these research works have paid more attention to identifying hand motion commands. Hence, in this paper we have investigated the same for some hand movements from one useful forearm muscle as a representative EMG signal.

WT is a time-frequency analysis method that is successful in the analysis of non-stationary signals including the EMG signal. The main advantage of wavelet transform is that the selection of dimensions of feature vector is very flexible and it provides approximately same results for various dimensions of feature vector.

In our previous work [7-8] towards active prosthesis machines for disabled persons, we have made the real time machine which can classify two hand motions effectively. In this work, as the further development in the real time prosthesis machines, our aim is to classify more than two hand motions. In this paper, we used two popular and successful EMG features in both clinical and engineering applications, root mean square (RMS) and mean absolute value (MAV) [9], as the representative features.

Introduction to Wavelet Analysis

In a basic course of signal processing [10], we assume that the signals last forever. For example, while calculating the Fourier transform, we represent any signal in terms of basis functions and these basis functions last from $t = -1$ to $t = +1$, where t denotes time. However, no signal in this world can last forever. Thus, we should deal with signals in finite domains.

In the basic course of signal and systems we deal with Fourier transforms and they deal with sine waves. Sine waves have many nice properties. They occur naturally, most analytic and smoothest possible periodic functions. Moreover they can form a very good basis for representing other waveforms. Addition, differentiation, subtraction or Integration of sine wave gives sine wave itself. Any linear combination of all these operations on a sine wave results in a sine wave of the same frequency. But the biggest drawback of sine waves is that they need to last forever. If the sine wave is truncated (a one sided sine wave, for example), the response to this signal by a system, in general, is different from the response which would be obtained if the signal would be a sine wave from $t = -1$ to $t = +1$. There would be transients which are not periodic. All the properties mentioned above, are no longer valid. So, to be realistic in our demand we deal with wavelets. Wavelets are waves that last for a finite time, or more appropriately, they are waves that are not predominant forever. They may be significant in a certain region of time and insignificant elsewhere or they might exist only for finite time duration. For example, a sine wave that exists only between $t = 0$ and $t = 1$ msec is, in principle, a wavelet (though not a very good one), a wave that doesn't last forever.

Wavelet analysis was developed from Fourier analysis which was performed in short time period [11]. The size of window can be modified by using the real time frequency analysis. Consequently, the signal analysis can be performed at

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the high signal frequency leading to the same results with the analysis at the low frequency.

Combination of wavelet can be used to describe the signal characteristics. Each wavelet is based on the same function called "mother wavelet". These wavelets are the subset of mother wavelet operated with scaling and translation as shown in equation 1. From the equation, the scaling and translation are represented as *a* and *b*, respectively. The scaling is compressing or dilation of mother wavelet resulting from the variation in its frequency. The scaled wavelet is normalized by $1/\sqrt{a}$ to maintain its energy to be equal to the energy of mother wavelet. Therefore, if the $\varphi\ (t)$ is the function of mother wavelet, a general term of wavelet with the position of *a* and *b* can be written as following by equation (1).

$$\varphi_{b,a}(t)= \frac{1}{\sqrt{a}}\ \varphi\left[\frac{t-b}{a}\right]=\varphi(\text{scale, position, t}) \qquad (1)$$

The useful signal is included in the part of low frequency and the noise is included in the part of high frequency. By using wavelet analysis we separate the low frequency component and high frequency component from the signal (S), The resulting signals termed as approximate values (Ca) and detailed values (Cd) respectively. This process of getting these values is called decomposition of the signal, as shown in Fig. 1. From the figure, one-dimensional wavelet is used to decompose an original signal into three levels [3] that can be represented in equation (2).

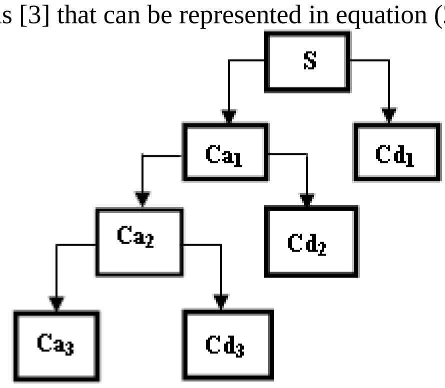


Fig. 1: Multilevel Decomposition of the Signal (level 3)

$$S=Ca_3+Cd_3+Cd_2+Cd_1 \qquad (2)$$

Wavelet transform method is divided into two types: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). DWT was selected in this study because of the concentration in real-time engineering applications [12-14]. There are various families of wavelet functions which gives the improved results in time and frequency domain. In this paper we have used Daubechies family with db3 wavelet function. Figure 2 shows the waveform of db3 wavelet function.

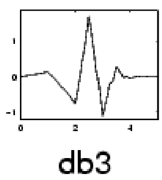


Fig. 2: db3 wavelet function

Methods for Feature Extraction

The temporal or time domain signals are of limited (shorter) duration and are sampled and converted into digital format. In such situation it is more appropriate to represent a pattern as a finite time sequence *s*[0], *s*[1],..., *s*[*N* -1] . Presenting this sequence directly to a classifier is impractical due to the large number of inputs and due to the randomness of the signal. Therefore, the sequence *s*[*n*] must be mapped into a smaller-dimension vector $X = (x_1, x_2, ..., x_D)$, $D << N$, called *feature vector*, which best characterizes the pattern [6].

After applying the wavelet transform, the wavelet coefficient subsets (Cd_1-Cd_3, Ca_3) and the reconstructed EMG signals (D_1-D_3, A_3) were extracted. We can select any two signal either Cd_3 and Ca_3 pair or D_3 and A_3 pair, in order to made a 2-D feature vector from single channel EMG signal. In this study we have used Cd_3 and Ca_3 pair for feature extraction. In this study the popular and successful features called MAV and RMS are selected.

Mean Absolute Value

Mean values of the signal consisting of N no. of samples is given by the following formula.

$$MAV= \frac{1}{N}\sum_{n=1}^{N}|x_n| \qquad (3)$$

Where x_n represents the n^{th} sample of the EMG signal (S) or the wavelet coefficients subsets (Cd_1-Cd_3, Ca_3) or the reconstructed EMG signals (D_1-D_3, A_3) in a window segment and *N* denotes the length of EMG signal window-segment. In this paper we have used 256 samples values.

RMS and logRMS

RMS value of the sequence consisting of N no. of values is given by:

$$X_{RMS}= \sqrt{\frac{1}{N}\sum_{n=1}^{N}|x_n|^2} \qquad (4)$$

Where x_n represents the n^{th} sample of the EMG signal (S) or the wavelet coefficients subsets (Cd_1-Cd_3, Ca_3) or the reconstructed EMG signals (D_1-D_3, A_3) in a window segment and *N* denotes the length of EMG signal window-segment.

The log-transformed feature space, demonstrates a more uniform scattering of points compared to the untransformed RMS features of an able-bodied participant. The log transform is given by:

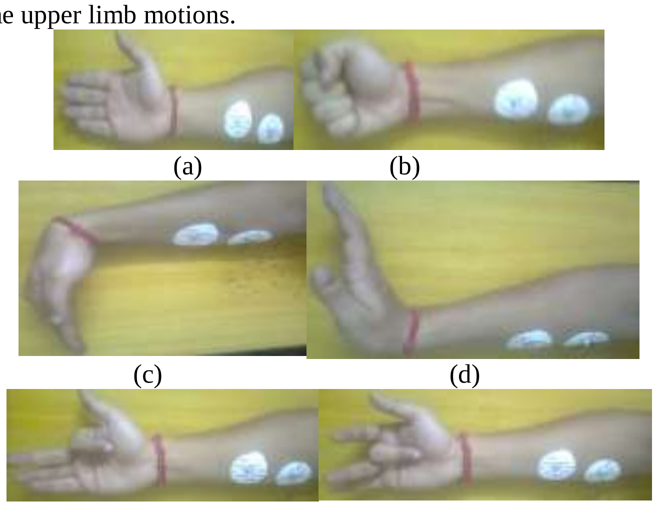
$$X_{RMS}= \log(x_{RMS}) \qquad (5)$$

Single Channel EMG Acquisition and Electrode Placement Location

In this section, we describe the experimental procedure for EMG signal acquisition and electrode placement location in order to get good EMG from single muscle. To acquire and display the EMG signal we need a biomedical signal acquisition and display system. In our study we used BIOPAC MP36 machine to acquire the EMG signal and acknowledge software to display the EMG signal. One can use its own hardware and software in order to acquire and display the signal. Biopac is a company which makes biomedical signal acquisition system. MP36 [16] is also one of them and this machine can be used for acquiring various types of signal like EMG, ECG, EEG, Respiration signal etc. This machine comes up with software named Acknowledge, which is used to display the acquired signal on the computer screen in real time. This software also provides the facility to implement various types of signal processing tools like filters, FFT, PSD and many others. These tools can be operated on the signal one signal is recorded. Figure 3 shows the biopac MP36 machine.

Fig. 3: Biopac MP36 biomedical data acquisition machine

In order to get the best EMG signal for single muscle (one channel) electrodes must be placed very carefully at proper place. There are mainly two forearm muscles which respond to most of the hand movements. We can target any one of those muscles. We target right forearm flexor carpi radialis muscle for some upper limb motions.



(a) (b)

(c) (d)

(e) (f)

Fig. 4: Electrode position and various hand movements (a) Electrode placement location for single channel EMG recording (b) Hand close movement (c) Wrist flexion (d) Wrist extension (e) First finger closed (f) Middle finger closed.

Figure 4 shows the electrode placement location and five hand movements, which are as follows: (b) hand close (c) wrist flexion (d) wrist extension (e) first finger closed (f) middle finger closed. For these five postures, we extract the feature vector using wavelet and results are really encouraging in terms of classifying these movements.

Experimental Procedure

In this study, we used one pair of single-channel surface electrodes to measure and record EMG signal of a 24 year old healthy man. Both electrode of AgCl were placed on a forearm flexor carpi radialis muscle.

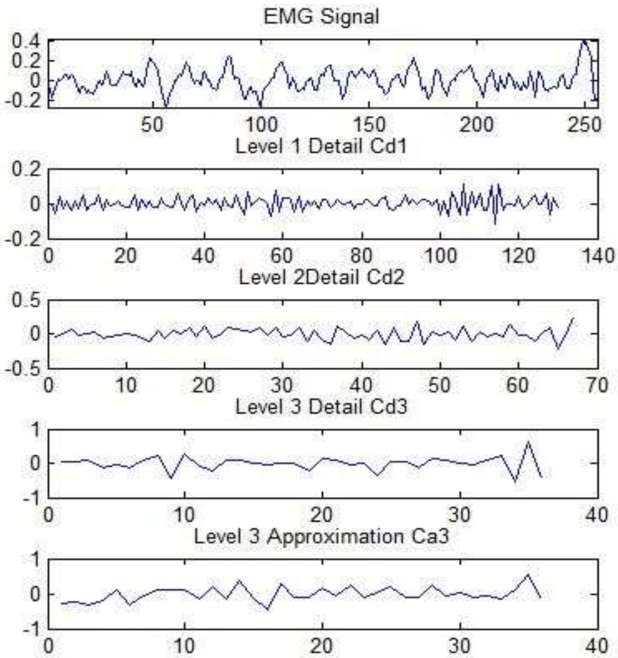
First, we applied the different Daubechies wavelet functions, ranging from db3 to db7, from Daubechies wavelet family to analyze the EMG signal. We found that for 256 data sample window, size of EMG signal reduced significantly for Daubechies function above db3. So, we finalized db3 wavelet function for the analysis of EMG signal.

Second, the feature extraction was accomplished by using MAV and RMS both. We took the MAV and RMS of Ca_3 to make the one dimension of feature vector and that of Cd_3 to make the other dimension of feature vector. By doing so we made 2-dimensional feature vector which can be fed to neural network of SVM for further classification.

Results and Discussion

EMG signals were recorded from the forearm muscle for various hand movements, which were described in previous section, and they were subjected to the db3 Daubechies wavelet function. Figure 5(a) shows the EMG signal and its detailed and approximate coefficients and different levels of db3 wavelet function and figure 5(b) shows the reconstructed EMG signal at different levels from coefficients counterparts. It is shown that in most types of natural signals, the most important part of the signal is low frequency components [17] i.e. Ca_3, Cd_3 and D_3 and A_3 are important in terms of signal characteristics. Hence, they can be used as the identity of its original signal, whereas high frequency components (i.e. Cd_1-Cd_2 and D_1-D_2) can be assumed as noises.

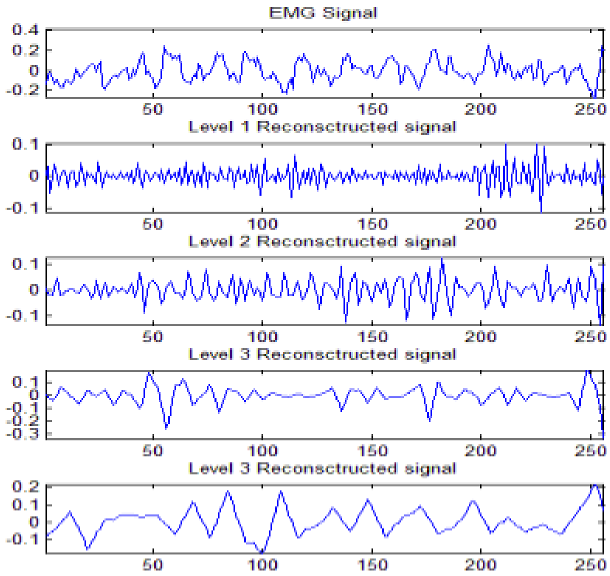
If we take a look at the figure 5, then it is clear that low frequency component (Ca_3 and A_3) have indirect correspondence and contains the irrelevant low resolution background; whereas first two level higher frequency components (Cd_1-Cd_2 and D_1-D_2) are somewhat similar to the original signal (S). So, we can say that Cd_1 and Cd_2 or higher frequency components remain the trend (appropriate to the low frequency contents) of the EMG information and removes the fluctuation (i.e. unwanted high frequency components) of interference. So, the signals (Cd_1-Cd_2 and D_1-D_2) are the effective EMG information parts.



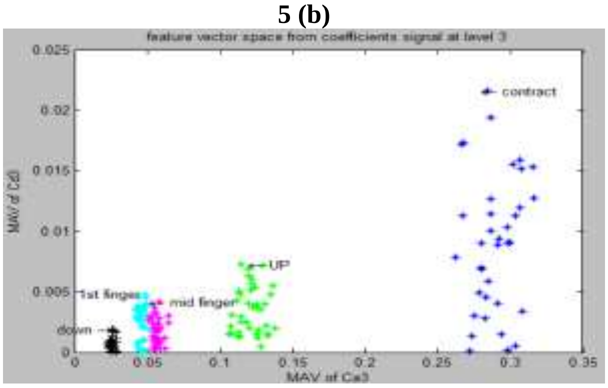
5 (a)

Fig. 5: Example of the EMG signal using wavelet multi-resolution analysis (a) with db3 wavelet and 3 levels decomposition (b) Reconstructed EMG signal from its coefficients at different levels

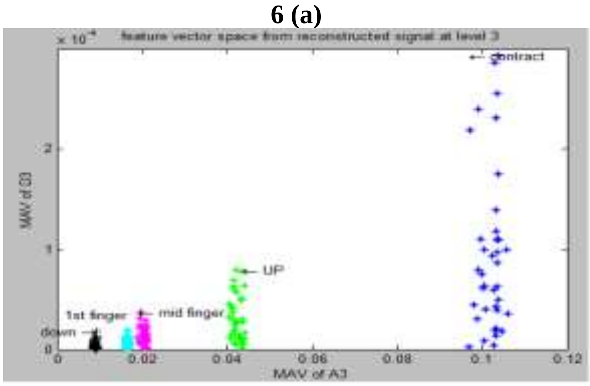
Figure 6 (a) shows the feature vector space of MAV from the coefficients of wavelet decomposition at level 3 and figure 6(b) shows the feature vector space of MAV from the reconstructed wave from it's coefficients at level 3. From the figure it is clear that features extracted from the reconstructed signal have an edge over their counterpart that was extracted from the coefficients of wavelet decomposition.



5 (b)



6 (a)

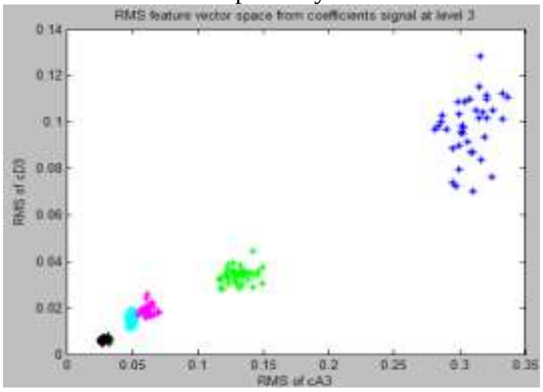


6 (b)

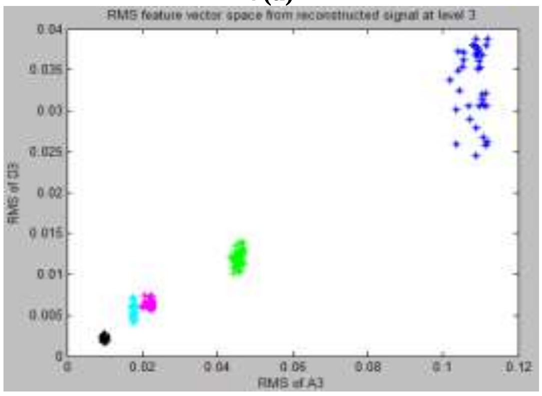
Fig. 6: The scatter plots of MAV feature, (a) MAV feature extracted from approximate and detailed coefficients of wavelet decomposition at level 3 (b) MAV feature extracted from reconstructed EMG signal at level 3 decomposition from there coefficients, for different hand movements

Figure 7(a) shows the feature vector space of RMS from the coefficients of wavelet decomposition at level 3 and figure 7(b) shows the feature vector space of RMS from the reconstructed wave from it's coefficients at level 3. This also have the nearly same results as that was for the MAV.

From these two figures 6 and 7, it is clear that whatever feature vector we use the classification accuracy is nearly same but at the same time they are making nearly ideal classes for the classifiers which show the supremacy of the wavelet transform.



7(a)



7(b)

Fig. 7: The scatter plot of RMS feature space (a) RMS feature extracted from approximate and detailed coefficients of wavelet decomposition at level 3 (b) RMS feature extracted from reconstructed EMG signal at level 3 decomposition from there coefficients, for different hand movements (colors have same significance as of in fig. 6)

Conclusion

In this paper we have shown the usefulness of multiple level wavelet transform decomposition for EMG feature extraction. The results shown here proves that it provides better class separability and can be used for machine learning algorithms. In future we will try to incorporate this analysis into real time machine learning and classification algorithms. This will help us to make the better and cost effective prosthesis device for disabled persons.

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