WAVELET BASED FEATURE EXTRACTION OF ELECTROMYOGRAM SIGNAL FOR DENOISING

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ABSTRACT

Electrical signals recorded from muscles require processing before its use, so the modeling of these bioelectric signals is necessary. Wavelets are used for the processing of signals that are non-stationary and time varying. The surface Electromyogram signals were estimated with following steps, first, the obtained signal was decomposed using wavelet transform; then, decomposed coefficients were analyzed by threshold methods. With the appropriate choice of wavelet, it is possible to remove interference noise effectively in order to analyze the signal. This paper presents a comparative study of different Daubechies wavelets (db2-db14) family for analysis of arm motions. From the analyzed results, it was inferred that wavelet db4 performs denoising best among the wavelets and is suitable for accurate classification of surface Electromyogram signal. Because of the wavelet denoising, accurate observation of activity that is not possible with conventional filtering, becomes possible.

Keywords: Electromyography, wavelet denoising, voluntary contractions, surface electrodes.

INTRODUCTION

The recording and analysis of bioelectric signals are of interest for many clinical diagnoses. In all cases detection and measurement with analysis will be investigated within the framework of conceptual models. In Surface electromyography, signal is generated by motor unit action potentials. Decomposition of motor unit potentials from Electromyogram is the process of isolation of individual waveform from the continuous signal, and for accurate analysis several decompositions have been proposed [1]. Once appropriate algorithms is available then the characteristics of the signal can be understood very easily [2]. So far, research and extensive efforts have been made to acquire and process surface Electromyogram signal using better algorithms and improved detection techniques to reduce noise etc. During the last two decades, many extraction techniques have made it practical to develop advanced surface Electromyogram detection and analysis procedures. Wavelet denoising in analysis of surface Electromyogram signal is being studied since last decade and is the most recent technique for processing signals with time varying spectra, because of its energy compaction capabilities and relative bandwidth rather than absolute bandwidth facilitating multiresolution analysis. The present study is motivated by the fact that there is no universal mother wavelet which is applicable to all types of signals. The choice of right wavelet function becomes important to achieve the optimal performance [3].

The objective of this present investigation was to develop a system to assess effect of different voluntary contractions on muscle activities for the design of above elbow prosthetic arm. For this, we have investigated usefulness of surface Electromyogram features being extracted. The general wavelet based denoising procedures are composed of three steps: decomposition, determination of denoising wavelet's detail coefficients, and reconstruction. Different levels of various mother wavelets were used to obtain the useful resolution components from the signal. The result shows that the wavelet based noise removal technique using wavelet function db4 works best to remove noise from the surface Electromyogram signals.

The paper is organized as follows: section 2 presents signal acquisition and wavelet analysis subdivided into wavelet denoising and feature extraction. In section 3, experimental results based on DWT is presented and finally, discussion and conclusion is given in section 4.

MATERIALS AND METHODS

In order to understand the surface Electromyogram signal's characteristics, the signals were recorded from the biceps brachii and triceps brachii muscles at low, medium and high voluntary contractions under isometric conditions. The whole process of the recording and analysis of signal is shown in the block diagram (Figure 1).

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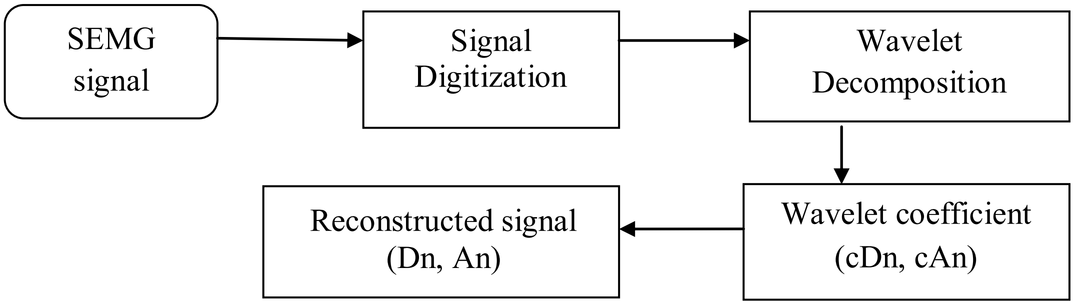

Fig. 1 Block diagram for wavelet analysis of surface Electromyogram signal

2.1 Denoising using wavelet analysis

The principle of wavelet denoising [4-6] consists of decomposing the signal by performing wavelet transform, followed by applying suitable thresholds to the detail coefficients, zeroing all coefficients below their associated thresholds, and finally reconstructing the denoised signal based on the modified detail coefficients. The underlying model for the surface Electromyogram signal, f(n), is the superposition of the signal, s(n), and noise, e(n),

$$f(n) = s(n) + e(n) \qquad (1)$$

Once the signal is through wavelet decomposition, a threshold needs to be selected for estimation of the signal of interest, s(n), from f(n) by discarding the corrupting noise e(n).

2.2 Basis Selection:

The criterion for the selection of best basis for DWT includes [7]:

- ✓ Speedy computation of inner product with basis function;
- ✓ Regularity in frequency localization for identifying signal oscillations;
- ✓ Signal with large contribution in spectrum should be localized;
- ✓ Superposition of basis function for keeping reconstruction speedy.

2.3 Feature Extraction

As the surface Electromyogram signal is time and force dependent signals whose amplitude varies at random above and below the zero values, so signal analysis becomes important in a way to define characteristic properties of signal. A wide variety of features have been considered individually and in group [8-10] representing both surface Electromyogram amplitude and spectral content. The calculation of some of the extracted parameters is as follows:

1) *Root mean square (RMS)*: The root mean square is a statistical measure of the magnitude of a varying quantity. It is especially useful when variants are both positive and negative. RMS value is used to quantify ac variables. Signals with higher energy have higher RMS values. It is defined as:

$$V_{rms} = \sqrt{\frac{(x_1^2 + x_2^2 + x_3^2 + \ldots\ldots + x_n^2)}{n}} \qquad (1)$$

2) *Energy (E)*: It is also defined as simple square integral (SSI). It is the summation of square values of the amplitude of sEMG signal samples and is given by the equation:

$$E = \sum_{n=1}^{N} |\, x(n) \,|^2 \qquad (2)$$

3) *Power Spectrum (PS)*: For a given signal, the power spectrum gives a plot of the portion of a signal's power (energy per unit time) falling within given frequency limits. Power spectrum of a signal gives peaks at the fundamental harmonics. Quasi periodic signals give peaks at linear combinations of two or more irrationally related frequencies (often giving the appearance of a main sequence and sidebands) and chaotic dynamics gives broad band components to the spectrum.

RESULTS

In first part, the raw signal for different muscle voluntary contractions was acquired with processing done using classical filters and wavelet transform approach. The processing of signal includes the following steps:

(a) Filtering the signal with a band-pass filter (10 Hz and 500 Hz) updating the waveform graph cursors to represent the current values of the upper and lower cut-off frequency.

(b) Dual channel spectral measurement to determine the frequency response of the filter.

(c) Determination of different features like root mean square, energy of signal, power spectrum. Block panel of the system is presented in Figure 2.

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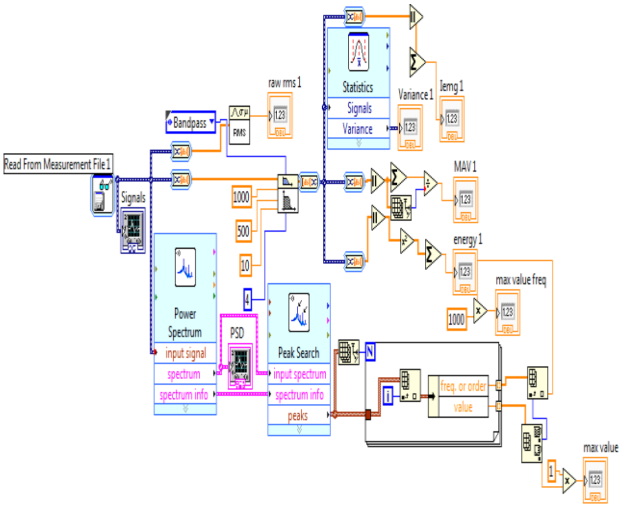

Fig. 2 Front panel showing extracted features

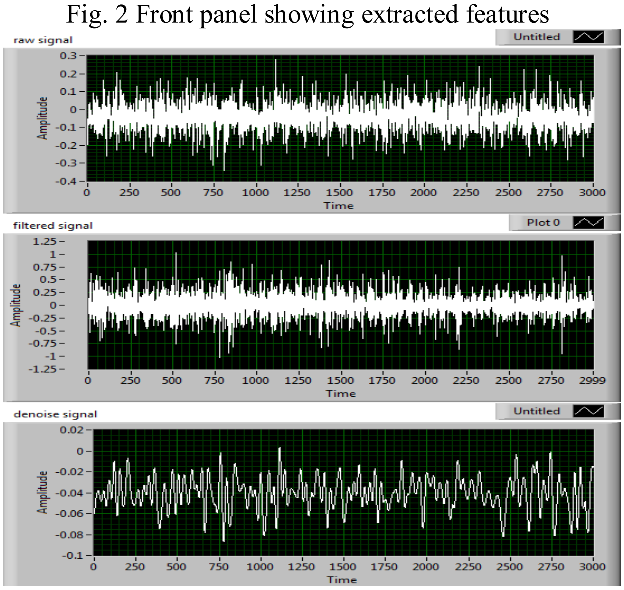

Fig. 3 Raw Surface Electromyogram signals after Band pass filter and DWT denoising

In second part, band pass filtering and Discrete Wavelet transform (DWT) denoising of surface Electromyogram signal was done, as shown in Figure 3. Here, different Daubechies (db2 to db14) wavelet functions were utilized for the extraction of different decomposition coefficients and for reconstruction of signal. A comparative data of raw surface Electromyogram signals for three subjects with extracted features for different muscular contraction force is presented in Table 1. To describe the results of these wavelet features, various representatives for denoised RMS are discussed in Table 2.

Table 1- Feature sets for different movement from biceps position

Feature Name	Voluntary contraction (Force)								
	Low			Medium			High		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
RMS	0.08	0.10	0.14	0.32	0.28	0.31	0.59	0.54	0.47
VAR	0.004	0.007	0.018	0.09	0.07	0.09	0.34	0.27	0.21
PSUM	0.008	0.014	0.013	0.147	0.116	0.141	0.607	0.426	0.257

Table 2 - Average RMS of Db family (three subjects)

Feature Name	RMS			
	Low	Medium	High	Average
Db2	0.03622	0.06743	0.09985	0.06783
Db3	0.04923	0.06598	0.10166	0.07229
Db4	0.05026	0.06647	0.10081	**0.07251**
Db5	0.04916	0.06645	0.10000	0.04187
Db6	0.04914	0.06656	0.09808	0.07153

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Db7	0.0491	0.06602	0.09871	0.07127
Db8	0.04912	0.0.0656	0.09998	0.07160
Db9	0.04986	0.06612	0.09970	0.07189
Db10	0.04922	0.06660	0.09856	0.07146
Db11	0.04915	0.06633	0.09828	0.07125
Db12	0.04907	0.06579	0.09911	0.07132
Db13	0.04917	0.06587	0.09960	0.07155
Db14	0.04924	0.06636	0.09912	0.07157

The raw surface Electromyogram signals were used to calculate the RMS values for all the wavelet functions suitable for biomedical signal processing with four levels of decomposition. Table 2 gives the results of the average RMS value. According to the results in Table 2, the wavelet functions from the Daubechies family show better performance; however, the wavelet function db4 shows better performance value than the other wavelet functions. This means that wavelet function db4 (from the average column in Table 2) is capable of denoising surface Electromyogram signals better than the other wavelet functions of same family.

The mean square error of surface Electromyogram signals has been calculated to evaluate the quality of robustness function:

$$\text{MSE} = \frac{\sum_{i=1}^{n}(s - s_e)^2}{N} \qquad (3)$$

Where N denotes the length of the signal, s represents the wavelet coefficients of the original signal and s_e are the wavelet coefficients of the denoising signal. The performance of algorithms is the best when mean square error has the smallest value. The average smallest mean square error after denoising is 0.0033, 0.033 and 0.0866 respectively in contrast to conventional filter technique where mean square error (MSE) value is 0.0166, 0.1433, and 0.4533 for low, medium and high signal respectively which means that the useful information in the surface Electromyogram signal is retained and undesirable part of the signals are removed.

DISCUSSION AND CONCLUSION

Noise contaminating the surface Electromyogram signals has its frequency components falling in the energy band of the signal and this creates major problems. Band pass filter of range (10 Hz and 500 Hz) was used to remove noise. However, some other types of noise still affect feature extraction of the signal. The noise may be complex stochastic processes within a wideband, and it cannot be removed by using traditional digital filters. To remove the wideband noise and for full fledged reconstruction of original signal, wavelet transform approach utilizing multiresolution analysis was used.. In order to define the decomposition level [11] each level was related to its analyzed frequency range. The dominant energy is located in 50-150 Hz range, matching mainly to the third level of decomposition. So, we selected wavelet functions to decompose the original surface Electromyogram signals to 4^{th} level.

Results suggest that wavelet method has slightly less mean square error than the classical method. The assessment of muscle force relation with surface Electromyogram signals can be applied to a wide class of daily used applications.

Finally it was concluded that for any signal occurring under aforesaid conditions and spectrum, the designed amplifier is capable to amplify signal up to an enhanced level, so that it could be analyzed easily and wavelet db4 performs denoising best and is suitable for accurate classification of signal. One way repeated analysis helps to ensure class separability relationship for proving data to be significant for design of prosthetic devices.

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