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Enhancing Classification Accuracy of Wrist Movement by Denoising sEMG signals

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***Abstract*— This paper presents identification of 4 different wrist movements by analyzing fore-arm surface Electromyogram (sEMG) signals. In order to reduce noise picked up during the recording, wavelet based denoising is applied using Daubechies mother wavelet. Spectral features along with Wilson's amplitude were extracted and given to a linear classifier. The experimental result shows better recognition performance using the given features when denoising is applied. The maximum accuracy for identification of four wrist movement was 97.5% which is quite significant as compared to the previous researches.**

I. Introduction

Surface Electromyogram (sEMG) is a commonly used simple technique for acquisition of signal from muscles. While travelling through different body tissues, the EMG signal acquires noise which results into poor SNR of the recorded signal. Since in sEMG the signal is collected from the skin surface, it may contain interactions with other motor units as well [1]. Other types of noise artefacts present in the sEMG signal can be due to line frequency (50 Hz), muscle fatigue [2] and force [3], broad band noise from the electronic instrument [4] etc. Further, EMG signals are non-stationary signals and are subject dependent [5]. Due to these reasons, identification and classification of different wrist movements from sEMG is a challenging task [3, 6-7].

From the literature, a fuzzy-based decision-making system was presented aimed at accurate identification of motion by evidence accumulation method based on artificial intelligence with multiple features [8]. , Identification of four discrete elbow and forearm movements using 4 EMG signals was reported [9] using Fourier and wavelet packet transform with an accuracy of 93.5%. In another approach, a combination of wavelet packet and principal component analysis with a classification error of less than 4% was achieved [10]. Englehart and Hudgins (2003) developed a real time control scheme for myoelectric control with a classification accuracy of as high as 94%. Also, an ANN-based intelligent system to classify seven hand movements for limited subjects was proposed in [11]. There are also evaluations about the effect of noise with EMG features with minimum MSE average is 0.001392 at SNR value of 20 dB and 0.072319 at SNR value of 0 dB [12].

This paper proposes the use of a wavelet based pre-processing for denoising the sEMG of four wrist movements i.e. flexion, extension, radial deviation and ulnar deviation taken from the fore-arm of a human body. Wilson's amplitude and energy based features are extracted and given to a linear discriminant function based classifier. Comparative recognition accuracy was evaluated with and without denoising preceding the feature extraction stage. A maximum increase of about 4% was observed in the recognition accuracy and a maximum classification accuracy of 97.5% was achieved for the four wrist movement identification problem.

Muscle activity is recorded from Flexor carpi radialis muscle (CH.A), Extensor carpi radialis longus muscle (CH.B) , Radialis brachi (CH.C) and Extensor carpi ulnaris muscle (CH.D) by a myoelectrode has amplitude in the range of 50μV – 100mV. The data set consists of EMG signal recording sampled at 1000 samples/sec. Three subjects were asked to perform four wrist movements (shown in Figure 1) each having 15 trials. In order reduce the effect of muscles fatigue on the EMG signal; each movement of approximately 10 second duration was followed by 2 seconds of the relaxed state. The EMG recording was carried out in the signal processing laboratory of Electronics Engineering Department, AMU Aligarh, India. Data was recorded using DATA LOG MWX8. Four channels of EMG data were recorded with four surface electrodes positioned according to the standard system. The four movements have been performed were wrist flexion, wrist extension, wrist radial and wrist ulnar as shown in Figure 1.

The signal processing steps applied in this research is shown in Figure 2. An additional step of denoising at the preprocessing stage is proposed in order to reduce the effect of noise in the recorded sEMG signal. The success of this process for EMG pattern recognition depends on the selection of the features that represent raw EMG signal.

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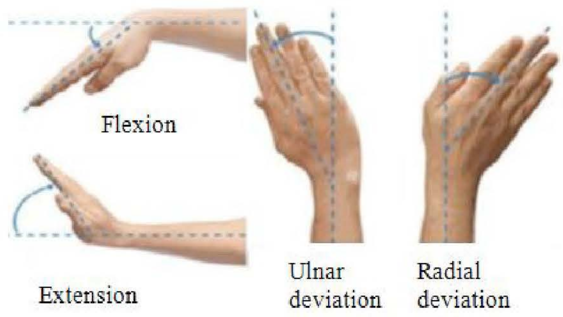

Figure 1: Four different wrist movements

II. Methodology

A muscle activity that is recorded by a myoelectrode is firstly applied with some pre-processing techniques before the chosen features are extracted from the recorded data sets. Then, the feature data will be weighted in a classifier before running through some possible post-processing applications like prosthesis control. Three key elements viz. preprocessing, feature extraction and motion classification in Figure 2 illustrate how such a system may be achieved. In this research, we have recorded data sets and analyze what features and classifier to be used for the given process..

Most of the pre-processing (such as selecting the proper muscle locations, using latest and calibrated device for recording sEMG signals) is already taken care of, but it may be refined by using a notch filter in order to reduce the effect of line frequency (50 Hz). Now we need to extract features and try to find a suitable subset that will contain information for a classifier to identify the four writ movement the test subject performs.

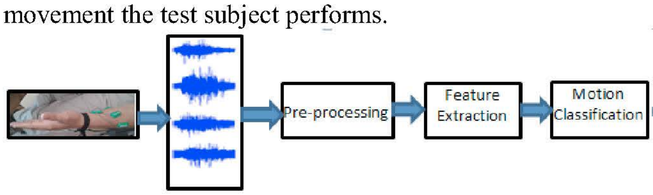

Figure 2: A simple flow diagram showing key elements of a prosthesis control system from EMG acquisition to motion classification.

The aim of this study is to smoothen out the signal by reducing the amount of noise present in the recorded EMG signal by using wavelet based denoising algorithm. Subsequently, the features from the EMG signal actually responsible for the movement are extracted and given to a classifier. Here, wavelet based denoising is carried out using Daubechies wavelet of second order using soft thresholding, which performs better reconstruction and performs better analysis as compared to other mother wavelets [12]. A level dependent threshold estimation method using global positive threshold was used for denoising.

The discrete wavelet transform (DWT) uses high pass filter to separate high frequency components known as details (D) and low frequency components as approximations (A).. Decomposing the signal up to second level showed improved performance in reducing the amount of noise as reported in [12]. Secondly, wavelet denoising is performed on the wavelet coefficients by selecting the universal threshold estimation method [13] described below;

$$Thr = \sqrt{2\log(N)} \quad (1)$$

where, N is the total length of the samples for the time domain signal. After the threshold value is calculated thresholding can be done using hard or soft transformations as explained below,

Hard Thresholding: This transformation can be described as the usual process of zeroing all detail coefficients whose absolute values are lower than the threshold, which can be expressed as;

$$X = \begin{cases} 0, & X < Thr \\ X, & X \geq Thr \end{cases} \quad (2)$$

Soft Thresholding: This transformation is an extension of hard thresholding, first zeroing all detail coefficients whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards zero, which can be expressed as;

$$X = \begin{cases} 0 & , \quad X < Thr \\ sgn(X)(X - Thr), & X \geq Thr \end{cases} \quad (3)$$

Figure 3 shows a sEMG signal along with its denoised version for second level of decomposition using Daubechies wavelet applied with universal thresholding for soft transformation.

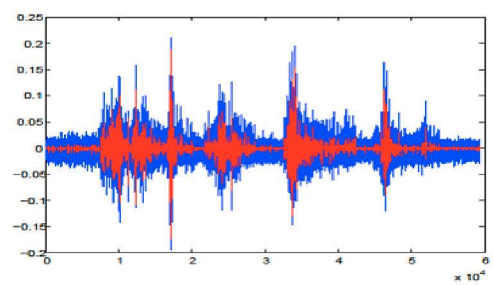

Figure 3: Raw EMG signal and its Denoised version

The features used in this research are Wilson's Amplitude, energy, entropy, spectralmoment1 and spectralmoment2 which are further explained below,

A. Wilson's Amplitude: Wilson amplitude (WAMP) is the sum of the number of times the difference between denoised sEMG signal amplitude among two adjacent signal exceeds a predefined threshold.

$$WAMP = \sum_{i=1}^{N} f(|x_i - x_{i-1}|) \quad (4)$$

$$f(x) = \begin{cases} 0, & x < threshold \\ 1, & x \geq threshold \end{cases} \quad (5)$$

where, x_i is the ith signal and N are the total no. of sample values. Typically a threshold value of 10mV has been selected.

B. Spectralmoment1 and Spectralmoment2: Spectral moment is an alternative statistical analysis way to extract features from the EMG power spectrum. The first two moments (SM1–SM2) are the most important spectral moments [14]. The definitions of their equations can be expressed as follows:

$$SM1 = \sum_{i=1}^{N} P_i f_i \quad (6)$$

$$SM2 = \sum_{i=1}^{N} P_i f_i^2 \quad (7)$$

where f_i is the frequency and P_i is the power spectrum at the ith frequency.

III. RESULTS AND DISCUSSION

The processed data from a list of 3 subjects for 4 different movements each providing 15 trials i.e. a total of 3x4x15=180 trials was fed into a linear classifier for pattern recognition. The main objective of this research is to investigate the advantage of using wavelet based denoising algorithm in pre-processing for sEMG signal classification. Figure 3 shows a sEMG signal along with its denoised version for second level of decomposition using Daubechies wavelet applied with universal thresholding for soft transformation.

From the literature, we find that the basic model of prosthetic control with unscaled noise or non-white noise showed different results [12] which were due to the denoising procedures. The best results were obtained using a combination of universal thresholding, soft transformation and threshold rescaling with non-white noise. Table I shows the classification accuracies for different features both with and without wavelet denoising.

TABLE I. THE EVALUATION OF FEATURES FROM THE CLASSIFICATION POINT OF VIEW FOR BOTH WITH AND WITHOUT WAVELET DENOISING

Feature used	**Classification Accuracies**	
	Without wavelet Denoising	***With wavelet Denoising***
Wilson's Amplitude	91.667%	95.833%
Spectralmoment 1	96.420%	96.420%
Spectralmoment 2	90.000%	96.428%
Energy	95.000%	96.428%
Entropy	95.000%	92.500%
SM 1 + SM 2	95.000%	95.000%
Energy + Entropy	95.000%	97.500%
WAMP + Energy	97.250%	97.500%

IV. CONCLUSION

Results calculated from the above processing showed significant improvement with respect to signal classification and noise tolerance from the optimum and effective features viewpoints. A total of five features were calculated in order to identify the four wrist movements. The results presented here have also important implications to other applications controlled by EMG such as robotics or neuroprosthetic devices.

The results indicate that a combination of WAMP and energy along with the denoising algorithm leads to the best results.

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