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Surface Electromyogram Signal Estimation Based on Wavelet Thresholding Technique

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Abstract— **Surface Electromyogram signal collected from the surface of skin is a biopotential signal that may be influenced by different types of noise. This is a considerable drawback in the processing of the sEMG signals. To acquire the clean sEMG that contains useful information, we need to detect and eliminate these unwanted parts of signal. In this work, a new method based on wavelet thresholding technique is presented which provides an acceptable purified sEMG signal. sEMG signals for this study are extracted for various hand movements. We use three hand movements to calculate the near optimal estimation parameters. In this work two types of thresholding techniques, namely Stein unbiased risk (SURE) estimator and adaptive Bayes estimator are utilized coupled with selected types of mother wavelets with different levels of decomposition. After designing the estimation technique, for evaluating the efficacy of method, the formed signals are sent to a pattern recognition system in order to discriminate among eight hand movements. The acquired results indicate that the wavelet based estimation technique using SURE thresholding approach is an appropriate method for producing sEMG signals without noise that may result in considerable improvement in the application of hand movement recognition.**

I. INTRODUCTION

Electromyography is the study of muscle function through the inquiry of the electrical signals the muscles emanate. Surface EMG an extracted signal from the surface of the skin, represents neuromuscular activities of a specific region of interest. It is a complicated signal, affected by the anatomical and physiological properties of muscles, the control scheme of the peripheral nervous system, as well as the instrumentation used for its detection and recording.

EMG signal is influenced by various types of noise. [1] The signal noise components can alter the characteristic of signal. Due to importance of sEMG in clinical diagnostic and rehabilitation applications, analysis of the effect of noise is very crucial.

Following collection of the sEMG signal, the first step for analysis is the noise reduction where one estimates the desired signal from the noisy one. There are several estimation techniques for this purpose based on statistical estimation methods, such as maximum likelihood technique. [2].

In this work, we propose a wavelet based estimation technique to generate the clean sEMG signals. In our approach, a multi-step process is utilized, where initially appropriate criteria for selection of the mother wavelet and numbers of levels of decomposition are implemented and next the thresholding technique is applied. After estimating the signals, to evaluate our proposed method, the signals are fed to a pattern recognition system to recognize hand movements. In this study, eight number of hand movements were utilized and the clean sEMG signals for each class were estimated.

II. METHODOLOGY

A. The overall sEMG processing and estimation system

The sEMG signal can be used in different application, for example, numerous neuromuscular disorders present with aberrant EMG signals while performing functional tasks such as posture and locomotion, the precise control of the muscular-skeletal system for complex human movements and association of the EMG data with biomechanical parameters. [3-6] in all of these applications, EMG processing system requires the clean signals since the noisy ones may drastically affect the signal processing procedures. In this work we apply the EMG processing system to a recognition system of appropriate hand movements. This has further application in designing and controlling EMG based hand prosthesis.

The utilized system in this study has two major parts, the first section deals with conditioning and purifying the sEMG signals and the second is associated to an application of interest, namely the hand movement recognition system.

Due to non-stationary and biological nature of EMG signal, a good acquisition of sEMG signal is a prerequisite for good signal processing. Since hand motions result from contraction of the muscles in the forearm section, we used surface electrodes for measuring sEMG signal from the extensor digitorum, the extensor carpi radialis, the palmaris longus and the flexor carpi ulnaris. In this work we use two channels of differential surface electrodes for collecting sEMG signal.

After the extraction of sEMG signals, they are prepared for the next processing steps by using amplification and filtering techniques [1],[6],[12]. A roster of four healthy subjects participated for collecting sEMG signals. Eight hand movements were considered and sEMG signals for each were extracted. These motions were hand opening (op) and closing (cl), pinch (pi), thumb flexion (th), wrist flexion (w-fl) and extension (w-ex), wrist radial flexion (wr-fl) and extension (wr_ex). For each class of movement, 100 signals were collected. We divided the acquired signals into two categories. First category was utilized as a training data set and the second was employed as a test set, in the manner that

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each of them included 50 signals. To increase the ability of our system to recognize hand movements, we utilized several signals in each class of movement as a validation set and therefore the test set actually incorporated both the test and validation sets.

A. SEMG Signal Estimation Using Wavelet Thresholding Technique.

Wavelets have been used in different signal processing applications, one being in the field of signal analysis and estimation. For EMG signals collected from surface of the skin, this matter is of major importance. The basic representation for a noisy signal is given as,

$$x = s + n \qquad (1)$$

where x, s and n are the collected sEMG signals, desired (clean) signal and additive noise modeled as a simple white Gaussian noise.

The signal estimation objective is to suppress the noise part of the signal '*x*' and to recover and estimate 's' as closely as possible in terms of mean square error (MSE) criterion. The signal estimation technique based on wavelets is implemented in three major steps namely, decomposition, thresholding wavelet's detailed coefficients and reconstruction [7]. In decomposition a mother wavelet and a level of decomposition J are chosen and the wavelet decomposition of signal x is computed at the defined level. If $W_J(.)$ is a forward wavelet operation at level J, we will have:

$$\underline{X} = W_J(s) + W_J(n) = \underline{S} + \underline{N} \qquad (2)$$

Then For each level of 1 through J, a threshold technique is selected and is applied to the detailed coefficients. This technique comes in two flavors, namely soft and hard. In this work we are using the soft thresholding technique as follows.

$$\mu_t(k) = \begin{cases} \operatorname{sgn}(k)\left(|k| - t\right) & |k| \ge t \\ 0 & elsewhere \end{cases} \qquad (3)$$

Finally wavelet reconstruction is performed based on the original approximation coefficients of J level and the modified detailed coefficients of levels 1 through J.

To perform and optimize the above procedures, three main issues must be addressed, namely selection of the suitable mother wavelet, level of decomposition and lastly, the thresholding technique that may be considered as soft or hard. To provide the best mother wavelet and depth of decomposition, we considered three basic movements namely, hand closing, pinch and thumb flexion and applied different type of well-known mother wavelet for choosing the best parameters.

B. Wavelet Thresholding Techniques

There are various types of thresholding techniques that could be used for signal estimation application. In this study, we consider two effective techniques namely Stein Unbiased Risk Estimator (SURE) and Bayes Shrink Adaptive Wavelet Thresholding (BSAT), presented as follows.

- ***SURE Method:***

In this Thresholding technique, a separate threshold is computed for each subband. Dohono et al [8-9] showed that the SURE technique could be used as the unbiased estimate of the MSE for the soft thresholding scheme. For an input $x = x_i|_{i=1}^{N}$ and threshold T, the estimate is given as,

$$\hat{U}(x,T) = \hat{\sigma}N + \sum_{i=1}^{N}\left\{\min(x_i^2, T^2) - 2\hat{\sigma}^2 I(x_i \le T)\right\} \qquad (4)$$

where $\hat{\sigma}^2$ is the variance of the noise and I is the indicator function . Here $I(.) = 1$ if $|x_i| \le T$ and $I(.) = 0$ if $|x_i| > T$. Hence SURE threshold is defined as,

$$T_{SURE} = \arg\min_{0 \le T \le \hat{\sigma}\sqrt{2\log N}} \hat{U}(x,T) \qquad (5)$$

It can be shown that that if the signal components dominate, the SURE thresholding technique performs better and when the noise dominates the general thresholding ($T = \hat{\sigma}\sqrt{2\log N}$) is more suitable. [9] For this reason and due to the extreme sparsity of the wavelet coefficients we use a heuristic or hybrid thresholding approach. This can be described by following equation:

$$T = \begin{cases} \hat{\sigma}\sqrt{2\log N} & s_d^2 \le \gamma_d \\ T_{SURE} & s_d^2 > \gamma_d \end{cases} \qquad (6)$$

where here $s_d^2 = \frac{1}{N}\sum_{i=1}^{N} x_i^2 - \sigma^2$ and $\gamma_d = \frac{\sigma(\log_2^N)^{1.5}}{\sqrt{N}}$. [10].

- ***Bayes Shrink wavelet Threshold:***

In this method similar to the SURE approach, a subband based thresholding is utilized. The subband adaptive threshold Bayes Shrink technique was proposed for 2-D signals with detailed subband coefficients having a generalized Gaussian (GG) distribution. While this method only slightly increases the computational complexity of the estimation process, it has been shown to provide significant improvements in estimation process. [11] Each subband can be thought of as a random vector with elements that are independent identically distributed GG random variables. The probability density function of a GG random variable is defined as:

$$f_{\alpha,\beta}(x) = \frac{\beta}{2\alpha\Gamma(1/\beta)} e^{-(\frac{|x|}{\alpha})^{\beta}} \qquad (7)$$

where $\Gamma(.)$ is a gamma function and α, β are associated with the GG density and responsible for controlling the overall form of GG possibly varying from subband to subband. The optimal soft threshold

τ_B for a given detail subband is well approximated by a soft threshold proportional to the standard deviation of the wavelet-domain coefficients. Specifically,

$$\tau_B = \frac{\hat{\sigma}^2}{\sigma_s} \tag{8}$$

Here again $\hat{\sigma}^2$ is the noise variance and σ_s is given as $\sigma_s = \sqrt{\max(\hat{\sigma}_j^2) - \hat{\sigma}^2}$ where $\hat{\sigma}_j^2$ is the standard deviation of the wavelet coefficients in the subband of interest for the signal.

Since each detailed subband can have a different GG distribution and therefore a different variance, a separate threshold is calculated for each. using only the data from that subband and the noise variance, which is constant across all subbands.

In both methods, for level dependant thresholding, the noise variance for level j can be obtained by median absolute deviation, where 0.6745 is a normalization factor. The operator "AbsMedian" selects the median of the absolute values of all the wavelet coefficients $c_{j,k}$ at resolution level j.

$$\hat{\sigma}_j = \frac{AbsMedian(c_{j,k})}{0.6745} \tag{9}$$

III. Near Optimal Selection of Wavelet Parameters and Thresholding Technique:

For optimizing the parameters selection process and matching the parameters with sEMG signals, we consider a multi step process.

In this work we use sEMG signal estimation in the application of hand movements' recognition. The criteria for deciding on parameters are mean square error (MSE) and signal to noise ratio (SNR).

In this study we extracted sEMG signals for eight number of hand movements. For selection the estimation process parameters three specific movements namely, hand closing, pinch and thumb flexion were considered. The corresponding signals were fed to wavelet based estimation system. We implemented the procedures by considering different types of mother wavelets and level of decomposition versus thresholding techniques. It has been shown that if the signal has N samples, the maximum depth of decomposition will be $J = \log_2^N$ [4-5]. The mother wavelets that we studied in this work are Coiflet, Symlet, Biorthogonal, and Daubechies. For each wavelet family, various orders were considered as well. Hence first the signals are decomposed by using different types of mother wavelets and level of decompositions. Next through application of the thresholding technique, the detail coefficients i.e. high frequency component of signals, are modified and finally the signals are reconstructed by applying the modified wavelet coefficients. Figure 1 shows the estimated sEMG signals in three basic hand movements by using mother wavelet 'symlet2' with a depth of decomposition of 6 and two thresholding techniques.

To choose the parameters, first we examined the effect of level of decomposition by using different types of mother wavelet and thresholding techniques.

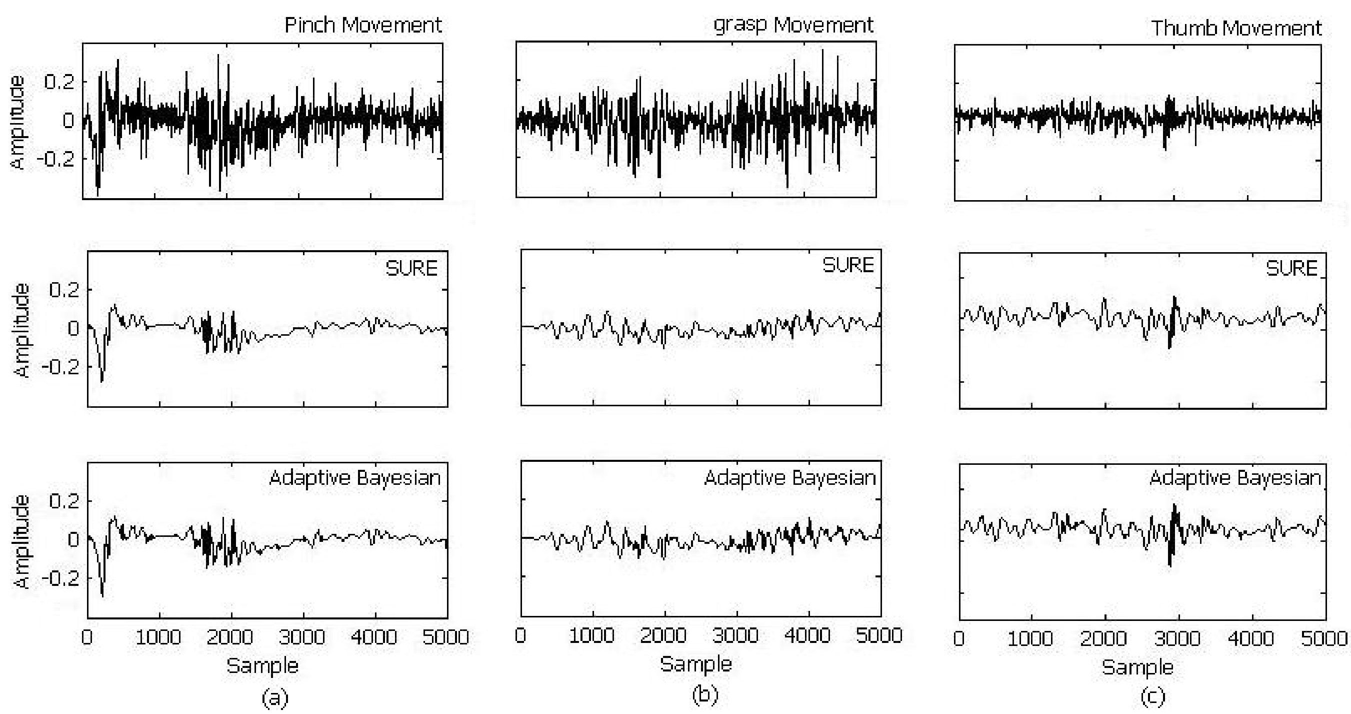

Fig 1: Estimated sEMG signals using SURE and Adaptive Bayesian Thresholding methods for three basic movements

Where a level of decomposition of six provided the best result. Next we examined all relevant types of mother wavelets combined with two Thresholding techniques. In this step we selected the best wavelets and Thresholding technique. Table 1 presents the obtained results.

Table 1.Summary of mother wavelet selection for sEMG estimation Based on wavelet Thresholding

SURE		**AdaptBayes**	
Mother wavelet	SNR	Mother wavelet	SNR
Bior1.5	0.5999	Bior3.3	0.5032
Bior6.8	0.5868	Bior3.5	0.4555
Coif5	0.5790	Bior1.5	0.4334
Coif3	0.5723	Bior3.9	0.4302

As shown in Table 1, the Biorthogonal 1.5 has the best result in the estimation of sEMG signals combined with the SURE thresholding method. Now that the required parameters are determined, we can design sEMG pattern recognition system for identifying hand motions.

IV. Hand Movements Recognition Based on Estimated sEMG Signals

Following the estimation of sEMG signals through wavelet thresholding approach and specified required parameters, the efficacy of estimation process is evaluated through the application of a recognition system based on selected hand movements. For this purpose the previously mentioned eight hand movements were considered.

After estimation of the sEMG signals, they are fed to the pattern recognition system. This sEMG pattern recognition system has a similar scheme to that which was introduced in our previous studies [6]. The system has three main parts, namely sEMG feature extraction, dimensionality reduction and classifier.

In this study we used the combined feature technique, namely time and time-frequency features (TFRs). [12] Here mean absolute value (MAV) and slope sign changes (SSC) are selected as Time features and the number of zero crossing and local maxima of STFT and Wavelet transform are depicted as TFRs. To increase the performance of system and elimination the unwanted information, principle component analysis (PCA) was used as the dimensionality reduction technique.

After creating sEMG features, they are exerted into a classifier to identify hand movements. In this study, an adaptive neuro-fuzzy system (ANFIS) is utilized as a classifier. The overall sEMG pattern recognition system is similar to that we introduced previously except that the sEMG signals are now desired (estimated) signals whose noise levels are decreased significantly. [6],[12]

The acquired results of sEMG pattern recognition system are summarized in Table 2. The overall average accuracy of this system is 94% which is improved compared to previously reported results [6]. Furthermore, these results are superior in comparison with averaged non-estimated signals of 87.6%. These results emphasize the importance of sEMG signal denoising preparation.

Table2. The acquired results for identifying hand movements By using wavelet based estimated signals

Movement	op	cl	Pi	Th	w-fl	w-ex	wr-fl	wr-ex	average
Average Results	98	100	94	93	92	92	92	91	94

V. Conclusion

In this work, we used wavelet thresholding technique for estimating sEMG signals. Initially parameters of wavelet estimation were selected by using three basic of hand movements. Next the SURE Thresholding method with biorthogonal wavelet and six levels of decomposition were chosen as the suitable parameters. After the selection and designing the sEMG estimation system based on wavelet thresholding, the efficacy of the system was evaluated in a hand motion recognition system. The acquired results provided a drastic improvement for identifying eight hand motions with an average accuracy of 94%.

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