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Introducing a New Multi-Wavelet Function Suitable for sEMG Signal to Identify Hand Motion Commands

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Abstract— **In recent years, electromyogram signal (EMG) feature selection, based on wavelet transform, has received considerable attention. This study introduces a new multi-wavelet function for surface EMG (sEMG) signal intended for tasks that involve hand movement recognition. To create the new wavelet function, several types of well known mother wavelet were exploited and through their integration the proposed mother wavelet was generated. The proposed wavelet function closely reproduced the characteristics of the EMG signal, while increasing the recognition accuracy of hand movements. We used eight unique classes of hand motions and considered the ability of various mother wavelets and the proposed multi-wavelet to recognize these movements. Furthermore, we used local extrema and zero crossing (ZC) as DWT features. The results demonstrate that the proposed multi-wavelet function provides 87% recognition mark compared to 78%, the best performance that any other mother wavelet was able to achieve.**

Keywords— **wavelet function, multi-wavelet, EMG signal, prosthesis, pattern recognition.**

I. Introduction

The EMG signal represents electrical currents generated in muscles during its contraction, depicting neuromuscular activities. Surface EMG signal is non-invasively collected on the surface of the skin. The signal is used for diverse applications, such as clinical diagnosis of muscle malfunction and as a reference signal for control assistive device intended for prosthesis hand. Specifically, EMG activation signal for prosthesis hand has received considerable attention during past decade for amputees and congenitally deficient upper limb patients [1]. Available EMG based systems for prosthesis arms are generally simplistic as the type and number of hand movements to control the arm is limited. This matter has reduced the ability of such devices in comparison with the true functionality of human hands. To design the more resembling devices one needs to extract useful information from EMG signal in order to generate enough discrimination among hand movements. Furthermore, Current systems for this application extract EMG information based on an estimate of the amplitude or rate of changes [1]. This information is not sufficient for designing multifunctional prosthesis hand that can emulate human hands closely. In an attempt to increase the information extracted from EMG signal, investigators have proposed various EMG features and classifiers. In addition, some schemes also used multiple channel electrodes to measure EMG signals. Hudgins et al proposed that there is a significant temporal structure in transient EMG bursts and these structures generate required information for pattern recognition [1], [2]. Some of the temporal features that are generally utilized by researchers are signal amplitude, zero crossing, frequency characteristics of the EMG signal, mean absolute value (MAV), slope sign changes (SSC), signal length and coefficients of EMG autoregressive (AR) model.

Yet researchers tried to improve the accuracy of EMG pattern recognition system by using different type of classifiers such as Fuzzy inference system (FIS), adaptive neuro-fuzzy inference system (ANFIS) and other EMG features [3], [4] and [5]. However, the results show that although classifiers may have obvious improvements in system classification rate but ultimately, it is the actual EMG signal representation that has the most effect on the system classification performance. Recently, it was proposed to use time-frequency representation (TFRs) for EMG features extraction, since EMG signal patterns have characteristics in both time and frequency domains [6]. Time-frequency representation can localize the energy of signal in time and in frequency and therefore provides a more accurate description of EMG signal. Englehart et al used three types of TFRs, namely short time Fourier transform (STFT), wavelet transform (WT), and wavelet packet transform (WPT). He showed that time-frequency features increase the accuracy of EMG pattern recognition system and demonstrated that by representing signal in suitable manner the linear classifier exceeds the performance of other classifiers. For constructing a feature set by WT, one needs to determine the parameters that may affect it. These parameters are wavelet function (Mother wavelet) and depth of decomposition.

Guglielminotti and Merletti theorized that if the wavelet function is chosen so as to match the shape of the motor unit action potentials (MUAP), the resulting WT yields the best possible energy localization in the time-frequency plane [7]. Laterza and Olmo found out that WT is an alternative to other time frequency representations with the advantage of being linear, yielding a multi-resolution representation and not being affected by cross terms, particularly when dealing with multi-component signals [8]. Under certain conditions, the EMG signal can be considered as the sum of scaled delayed versions of a single prototype.

Based on Guglielminotti's theory, Laterza and Olmo [8] used wavelet analysis to match the shape of the MUAP. For

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a unipolar recorded signal and under certain hypotheses presented by Gabor [9], the typical MUAP shape can be approximated as the second-order derivative of a Gaussian distribution and hence the well-known Mexican hat wavelet may be utilized. An extension of this approach may be exploited towards designing an appropriate mother wavelet representation in the hand movement recognition application. In this work we propose a new mother wavelet that is able to most appropriately model sEMG signal. The sEMG is a noninvasive but complex signal which is a great candidate for the TFR analysis. In order to generate such mother wavelet we consider the effect of various mother wavelet types in sEMG pattern recognition and attempt to find the best suitable mother wavelet. Next by using the proposed mother wavelet, the new wavelet function is extracted and implement on sEMG signal to construct appropriate feature sets in the hand movement recognition application. Such sEMG features set may constitute an effective set to control sEMG based prosthesis hands.

II. Signal Conditioning And Preprocessing of sEMG

The sEMG signal is a complex bio-signal influenced primarily by factors such as physiological and anatomical properties and characteristics of instrumentation. Suitable instrumentation preparation and sEMG signal acquisition are prerequisites for an appropriate signal processing scheme. Since hand motions result from contraction of the muscles in the forearm, we use the surface electrodes for measuring sEMG signal from the extensor digitorum, the extensor carpi radialis, the palmaris longus and the flexor carpi ulnaris, which are the muscles concerned with hand movements.

The instrumentation was conducted by placing two differential electrodes [1] on the forearm under the elbow and positioning the reference electrode on the wrist. Upon the sEMG registration, it was filtered using a band-pass filter of 20 to 500 Hz to minimize motion artifacts and noise, and amplified by a high gain and CMRR amplifier [10]. Next to eliminate the power line noise a notch filter at 50 Hz was applied. The acquired sEMG signal was then sampled at 2 KHz and converted into a digital stream of data.

Four healthy subjects participated for collecting sEMG signals. Eight movements of hands were considered and sEMG signal for each movement was extracted. These movements were hand opening and closing, pinch, thumb flexion, wrist radial flexion and extension and wrist flexion and extension. For each class of movements 100 signals were collected, 25 signals from each subject. We divided our acquired signals into two categories. First category was utilized as a training set data and second was employed as a test set, in the manner that each of them included 50 signals.

III. Feature Selection Based on WT for EMG Signals

Time-frequency domain representations (TFRs) combine time and frequency features in order to extract more information of signal. TFRs have received considerable attention for biological signal pattern recognition cases, and recently in EMG pattern recognition [6].

The major incentive for using these representations as a feature for the application of sEMG pattern recognition is the need to gain more information about the signal. This selection may result in a better discrimination among various hand movements. Wavelet transform, a viable candidate, is utilized to split a signal into shifted and scaled versions of the mother wavelet. The WT overcomes the main drawback of the STFT by appropriately varying time and frequency resolution producing a good time resolution at high frequency and a good frequency resolution in long windows (low frequency) [12]-[16]. The continuous wavelet transform is defined as:

$$CWT_x(\tau,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-\tau}{a}\right)dt \qquad (1)$$

where $\psi(t)$ is the mother wavelet. The analysis determines the correlation of the signal with shifted (by τ) and scaled (by a) versions of the mother wavelet. In its discrete form, namely discrete wavelet transform (DWT), $a = 2^j$ و $\tau = n.2^j$ where $n, j \in \mathbb{Z}$. To utilize WT as a select feature for the sEMG signal pattern recognition, two specific characteristics namely the choice of mother wavelet and depth of decomposition, has to be considered. Next the effectiveness of this selection may be evaluated through an error check which improves the parameter selection. However there is a fundamental drawback to the DWT, namely the lack of shift invariance. If the signal to be analyzed is shifted, the coefficients of wavelet transform vary in a complex manner.

To overcome this problem, we can use shift invariant features of DWT such as local extrema or zero crossing (ZC) [17], [18]. The DWT decomposition can be terminated prior to a full decomposition. If the signal has a length of N samples then the maximum depth of decomposition will be $J = \log_2^N$. The sEMG signal in this study had 512 samples thus the maximum depth of decomposition was 9. Thus for effective sEMG pattern recognition, the combined effects of these two parameters were considered and the accuracy of the system was evaluated at each stage and the best mother wavelet for EMG pattern recognition was determined empirically.

Figure 1 represents the procedures for choosing the WT mother wavelet. Initially to reduce the complexity of the analysis, three types of hand motions were used. These were hand closing, thumb flexion and thumb movements, resulting from a collective activation of rather high number of contributing forearm muscles. To implement, initially the depth of decomposition effect on system accuracy was chosen. In this study the best accuracy of system was obtained by using 9 levels of decomposition.

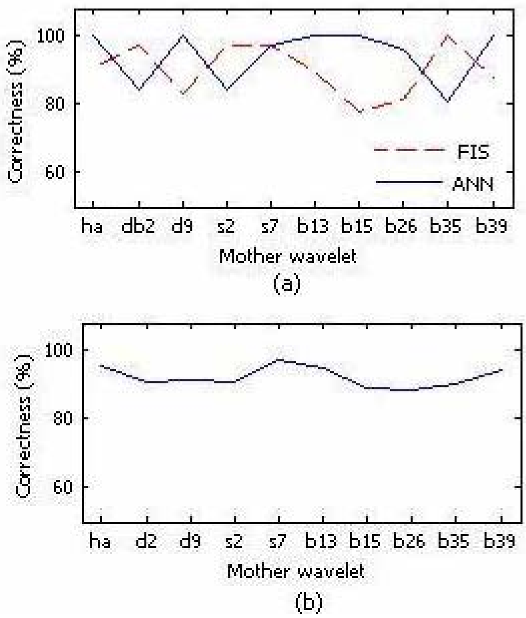

Fig.1. Selections of WT Mother Wavelet in the task of EMG Pattern recognition for three types of hand movements (a) by using two intelligent classifiers and (b) average results of these classifiers.

To obtain the accuracy of EMG pattern recognition system, all 9 levels of decomposition were used and local maxima and ZC were extracted as their noted features.

Next the effect of mother wavelet type was considered and the best mother wavelet for the task of sEMG pattern recognition was selected. In this study we used two intelligent classifiers, namely artificial neural network (ANN) and fuzzy inference system (FIS) to decrease the effect of classification technique on system accuracy. Subsequently the best mother wavelet was selected. In our study, we evaluated a multitude of mother wavelets such as haar (ha), daubechies (db), coiflet (c), symlet (s) and biorthogonal (b). All of the presented wavelets in Figure 1 had an appropriate performance in the EMG pattern recognition task. Figure 1(b) shows the average results by using two types of classifiers. The results depicted in Figure 1(b) shows that symlet7, haar, biorthogonal 1.3; biorthogonal 3.9 and daubechies9 have the best performance in both classifiers. Next the proposed multi-wavelet which integrates the combined effects of above selected wavelets may be ultimately applied for sEMG pattern recognition task.

IV. CREATING THE NEW WAVELET FUNCTION ADAPTED FOR EMG PATTERN RECOGNITION

Our interpretation of WT for the task of sEMG pattern recognition was based on the inner product or cross correlation of the signal $x(t)$ with the scaled and time shifted wavelet $\psi(t-\tau/a)$. This cross correlation function is a measure of the similarity between signal and the wavelet. In our application, the best mother wavelet is selected such that a maximum correlation with sEMG signal is achieved. Therefore mother wavelet plays a basic role in our work.

In this work we used decomposition and reconstruction low-pass and high-pass filters of selected wavelets and designed new wavelet by combining the selected filters. For this purpose we used linear combination of selected filters and updated the coefficient of the combined relation to attain the optimal coefficients that have the best performance in the EMG pattern recognition algorithm. The next step was to introduce the new mother wavelet by solving the above equations. The created filters do not possess the QMF (Quadratic Mirror Function) property. This property is described as follows:

$$h[n] = (-1)^n \, l[L-1-n] \text{ For n=0, 1... L-1} \qquad (2)$$

where L is the filter length, and h[n] and l[n] are the high-pass and low-pass filters respectively. To overcome this problem the energy of each filter is calculated and the filter with higher energy is selected. Next we constructed the other filters that have QMF property. By implementing this process, we observed that the two types of filters have the same energy value. For this purpose we selected decomposition low-pass filter and created high-pass filter with QMF property. Figure 2 depicts the proposed wavelet filters.

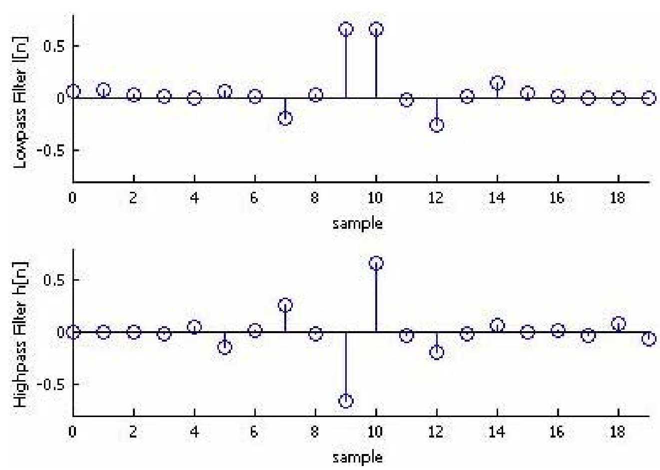

Fig.2. Designed low-pass and high-pass filters for the proposed sEMG wavelet

After creating the filters, the proposed wavelet function and new scaling function were created. The computation process for wavelet generation based on the created filters description was as follows. The descriptive equations are defined as:

$$\psi(x) = \sqrt{2}\sum_{k=0}^{L-1} l[k]\varphi[2x-k] \qquad (3)$$

$$\varphi(x) = \sqrt{2}\sum_{k=0}^{L-1} h[k]\varphi[2x-k] \qquad (4)$$

Figure 3 shows the resulted wavelet function and scaling function.

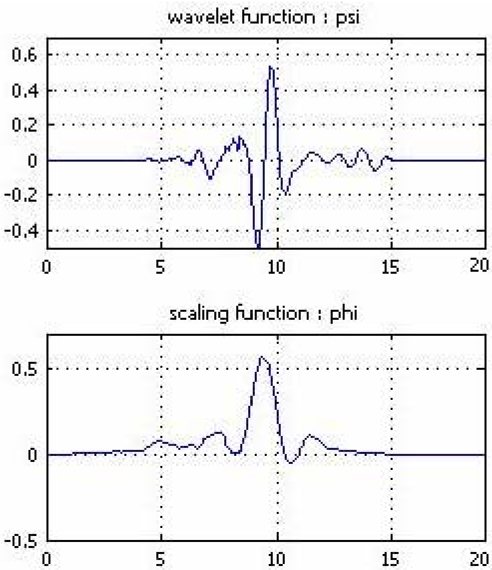

Fig.3. Proposed wavelet and scaling function for EMG signal

V. APPLICATION OF SEMG WAVELET FUNCTION IN PATTERN RECOGNITION

After creating the sEMG wavelet function, we need to consider the application of this wavelet for usage in the task of recognition prosthesis hand motion commands. For this purpose our EMG signals are decomposed with a high level of decomposition, namely 9 levels. We used eight classes of hand movements and tested the ability of this wavelet to recognize hand movements. Also in order to overcome the problem of shift invariant property of wavelet function, local maxima and zero crossing of wavelet coefficients have been used as WT selected features. Table I compares the acquired results of the proposed multi-wavelet function with the known mother wavelets that have a suitable result in the task of EMG pattern recognition. Table I depicts the average accuracy of EMG pattern recognition system through selected and proposed wavelets for distinction among eight hand movements. The results show that our proposed new wavelet function provides the best results for the hand movements' recognize. Based on these results we realized that this new wavelet may also assist us to model the EMG signal in a suitable manner and have a high degree of correlation with EMG signal. The results illustrated that the proposed multi-wavelet function attained 87% recognition mark compared to 78% which belongs to Symlet7 and offers the best performance among previously introduced mother wavelets.

TABLE I

COMPARING THE AVERAGE ACCURACY OF EMG PATTERN RECOGNITION SYSTEM BY USING WAVELETS AND PROPOSED WAVELET TO IDENTUFY 8 HAND MOTION COMMANDS (%)

Mother wavelet types					
Sym7	Haar	db9	Bior1.3	Bior3.9	Proposed wavelet
78	74	70	70	67	87

VI. CONCLUSION

In this study a new multi-wavelet function for sEMG signals is introduced. Our approach to create this wavelet was to utilize original mother wavelets and select an appropriate collection of them to construct proposed sEMG wavelet intended for pattern recognition of distinctive hand motion commands. Upon selection of candidate mother wavelets, based on consolidation of filter banks, an appropriate multi-wavelet function resembling sEMG signal was proposed. This new wavelet was successfully evaluated through a pattern recognition scheme while it proved superior to the original mother wavelets of interest by increasing the recognition accuracy of hand motion commands.

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