Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

A Novel Approach to Recognize Hand Movements Via sEMG Patterns

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Abstract—**Electromyogram signal (EMG) is an electrical manifestation of contractions of muscles. Surface EMG (sEMG) signal collected form surface of the skin has been used in diverse applications. One of its usages is exploiting it in a pattern recognition system which evaluates and synthesizes hand prosthesis movements. The ability of current prosthesis has been limited in simple opening and closing that decreases the efficacy of these devices in contrary to natural hand. In order to extend the ability and accuracy of prosthesis arm movements and performance, a novel approach for sEMG pattern recognizing system is proposed. In order to have a relevant comparison, present and recent research for designing similar systems was re-evaluated. In this study, we investigate time domain, time-frequency domain and combination of these as a representation of sEMG signal feature for accessing signal information. For pattern recognition of sEMG signals for various hand movements, two intelligent classifiers, namely artificial neural network (ANN) and fuzzy inference system (FIS) were utilized. The results indicate that using compound features with principle component analysis (PCA), dimensionality reduction technique and fuzzy technique for classifier produces the best performance for sEMG pattern recognition system.**

I. Introduction

Electromyogram signal (EMG) collected on the surface of the skin can be used in various applications. An important application is in the area of rehabilitation prosthesis hand motion control. Most of the proposed sEMG based systems utilized to distinguish hand movement are limited to 4 movements [1]-[3]. Many investigators have exploited time domain features of signal including amplitude, zero crossing (ZC) and EMG autoregressive model (AR) [1],[4]. Most work in the EMG signal classification assumes steady state characteristics, collected through and during a constant force and maintained contractions [2]. Hudgins et al was the first to consider the information of the transient bursts of EMG signal that accompanies the onset of contractions [1]. He used time domain features and ANN classifier for discriminating among four motion commands. Englehart et al applied time-frequency domain features and showed that these representations that fuse time and frequency information simultaneously are more appropriate for EMG patterns recognition[2], [3]. For classification purposes, investigators utilized techniques based on linear discriminate functions, neural networks, and fuzzy systems.

In this work, three types of features, namely, time, time-frequency representations and combination of these have been used. Figure 1 provides a brief overview of the techniques that are implemented for the proposed system. The instrumentation of this study utilizes eight differentiating movements. The approach in this work is determining the best parameters of each feature extraction method with minimum number of hand (three) movements. Next is to fuse these features evaluated at their optimum state. Finally these methods are applied to all eight hand motions for evaluation of and comparison of their accuracy and effectiveness.

II. The Overall Scheme of sEMG Pattern Recognition System

The overall scheme of sEMG pattern recognition system that is utilized in this work is depicted in Figure 1. We consider four major parts including, sEMG pre-processing and conditioning (not shown in Figure 1), feature extraction, Dimensionality reduction and classification.

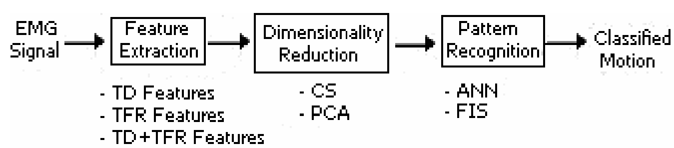

Fig.1. Conventional Scheme for hand prosthesis control

The goal of pre-processing step is to appropriately prepare and amplify the sEMG signal for the next analytical steps. Also in this module, artifact noise is eliminated. During the feature extraction step sEMG signal is processed with respect to three types of feature representations, namely time domain, time-frequency domain and their combination. Next a dimensionality reduction technique is applied to simplify the task of the classifier. This segment exploits two approaches, namely class separability (CS) and principle component analysis (PCA). The last compartment of this system determines the type of motion commands necessary to control prosthesis hand. There, classifiers are applied through artificial neural networks [1]-[3] and fuzzy inference system [6]-[9] and the overall results are evaluated for their accuracy to choose best approach.

III. sEMG Acquisition and Preprocessing

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

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1-4244-0788-5/07/$20.00

extensor carpi radialis, the palmaris longus and the flexor carpi ulnaris, depicted in Figure 2. Differential electrodes were placed on the forearm under the elbow and the reference electrode was situated on the wrist. After the acquisition, sEMG signal was filtered using a band-pass filter consisting of a high-pass filter with 500 Hz cut off frequency to reduce motion artifacts and a low- pass Filter with 20 Hz cut off frequency to reduce noise and amplified by an amplifier with high gain and CMRR [5]. Also a notch filter was exerted at 50 Hz to eliminate power line noise.

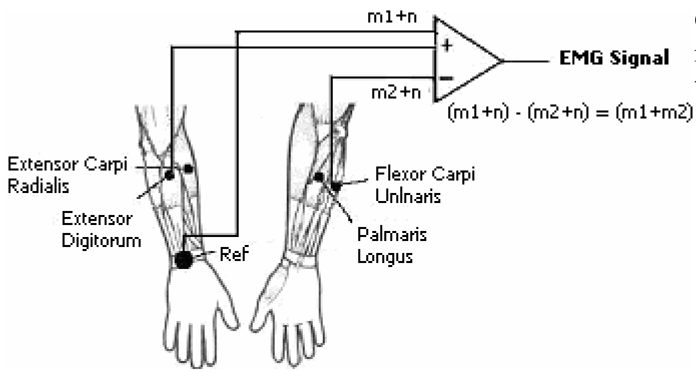

Fig.2. Surface electrode placement on forearm muscles

Afterward signal was sampled with 1 KHz and converted into a digital stream of data. A roster of four healthy subjects participated for collecting sEMG signals. Eight hand movements were considered and sEMG signal for each movement were extracted. These movements, shown in Figure 3, were hand opening and closing, pinch, thumb flexion, wrist radial flexion and extension and wrist flexion and extension. For each class of movement 100 signals were collected, 25 signals from each subject. The data base was divided into two halves of training and test data sets.

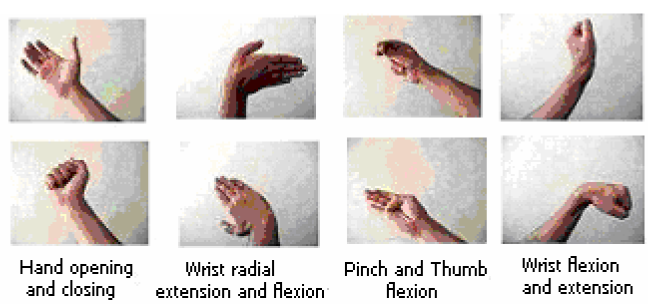

Fig.3. the eight classes of motion used in the two channel experiment

IV. Using Time Domain Features to Design sEMG Pattern Recognition System

The sEMG signal was segmented and appropriate features were extracted from each segment. Design parameters relevant to time domain feature extraction, namely sEMG length and segmentations were utilized. A length of 200ms was implemented for the sEMG signal and it was further divided into lengths of 10 to 50ms with step size of 10ms. The three initial movements were hand closing, pinch and thumb flexion. Furthermore, best features had to be selected to create the feature set. In the sEMG feature set, five features that had the best results were chosen. These features were, mean absolute value (MAV), zero crossing (ZC), Wilson amplitude (WAMP), slope sign changes (SSC) and coefficients of autoregressive model (AR) [1].

Next the number of movements was increased to eight and the results were evaluated. Table I indicates the comparative results for various types of analytical methods as the number of hand motions considered are increased from three to eight. The results demonstrate that the pair of CS, as the dimensionality reduction technique, and the neural network, as classifier recognition approach, provides the best accuracy for all eighth movements combined.

TABLE I
COMPARATIVE RESULTS FOR TECHNIQUES AS NUMBER OF HAND MOTIONS ARE INCREASED FROM THREE TO EIGHT

Number of movements	Classifier and dimensionality reduction			
	FIS		*ANN*	
	PCA	*CS*	*PCA*	*CS*
3	100	100	100	100
4	100	91	100	97
5	95	89	92	92
6	95	80	87	89
7	78	84	82	85
8	67	60	57	78

V. Using Time-Frequency Domain Features to Design sEMG Pattern Recognition System

In recent years TFR has received considerable attention in the application of sEMG pattern recognition. Among these representations, this study focuses on the linear types, such as short time Fourier transform (STFT), wavelets transform (WT), and wavelet packets transform (WPT).The fundamental difference between these representations is in the manner in which they partition the time-frequency plane[2],[3].

A. *Using STFT to construct sEMG Features Set*

EMG and sEMG are non-stationary signals. In STFT, the signal is divided into small enough segments, where these segments of the signal can be assumed to be stationary.

For this purpose, a window function “w” is chosen. The width of this window must be equal to the segment of the signal where its stationary character is valid,

$$STFT\,(k\,,m\,) = \sum_{i=0}^{L-1} x\,[i\,]w\,[i\,-k\,]e^{-2j\pi im\,/L} \qquad (1)$$

In this equation, L is the length of window function, T_s is sampling period, and $F = 1/LT_s$ is the frequency sampling steps size. The resolution in time and frequency is lower bounded by time-bandwidth uncertainty principle or Heisenberg inequality ($\Delta t.\Delta f \geq 1/4\pi$).

The main constrain is that each cell in the time-frequency plane must have identical shape which may not be suitable for physical signal. For the case of sEMG patterns recognition, the feature sets were created by using STFT coefficients. For this purpose the effective parameters, namely window size, window overlap, and window type, were considered. In order to improve the recognition process, the effect of each parameter was considered.

Initially the effect of window size was considered by using Gaussian window and setting the overlap size equal to zero. Next the best window overlap was chosen by applying the best method from previous step and the Gaussian window. These steps were then repeated for other window types. Hence by performing these procedures the best parameters for STFT were obtained. Table II presents the summarized results obtained for the parameters of STFT. For this purpose the parameters that have the best performance for both FIS and ANN classifier were considered. Next these parameters were utilized in construction of feature set to increase the number of movements. In general, the goal is to enhance the accuracy of system and hence increase degree of freedom for hand prosthesis.

TABLE II
SELECTION GUIDE FOR STFT PARAMETERS

STFT parameters	Results	
	PCA	CS
Window size	125 (ms)	250 (ms)
Overlap size	0	w/4=62.5
Window type	Kaiser	Gaussian

B. Using WT to construct sEMG Features Set

The WT overcomes the main drawback of the STFT by varying time and frequency resolution. The continuous wavelet transform is defined as:

$$CWT_x(\tau, a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-\tau}{a}\right) dt \qquad (2)$$

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, a and τ are set as $a = 2^j$ and $\tau = n.2^j$ where $n, j \in \mathbb{Z}$. This form is called discrete wavelet. Transform (DWT). A common preference is to set $a_0 = 2$ (dyadic wavelet basis), which allows greater computational efficiency. The wavelet coefficients can constitute a very effective feature set [2], [10] but there is a fundamental drawback to the DWT that is. If the signal to be analyzed is shifted, the coefficients of wavelet transform vary in complex manner. This matter presents significant problem in the performance of pattern recognition.

To overcome lack of shift invariance, one can use shift invariant features of DWT such as local extrema or zero crossing (ZC) [2],[3]. In this work we used local extrema as a DWT feature because the amplitude of extrema conveys more information. For WT two parameters were determined, namely choice of mother wavelet and depth of decomposition, where the best mother wavelet is determined empirically. The sEMG signal in this study had 512 samples thus the maximum depth of decomposition ($J = \log_2^N$) was 9. These results were obtained by initially selecting the level of decomposition and using Haar as mother wavelet. Results showed that at high level of decomposition, the best performance of system was obtained. Next, we used 9 level of decomposition with different types of mother wavelets for choosing the best mother wavelet. In this study, we considered different types of mother wavelet such as Haar (ha), Daubechies (d), Coiflet (c), Symlet (s) and Biorthogonal (b) and their all associated order. Table III summarizes the results of the above mentioned procedure. As the selected depth level of decomposition can be either, 7, 8, or 9, the best classification performance was chosen with a full depth of decomposition.

TABLE III
SELECTION GUIDE FOR WT PARAMETERS

WT parameters	Determined Results	
	PCA	CS
Mother wavelet	Symlet 7 Bior1.1	Coiflet3 Daubechies7
Depth of decomposition	7, 8 and 9	7, 8 and 9

C. Using WPT to Construct sEMG Features Set

The wavelet packet transform (WPT) is a generalized version of the WT that offers a richer range of possibilities for signal analysis. In order to determine the feature set for the classification problem an additional parameter should be chosen, namely best basis selection. For this purpose local discriminate basis (LDB) algorithm was used based on three cost functions, namely entropy, relative entropy and Euclidean distance criterion and accuracy of system for sEMG pattern classification was determined. For each LDB the performance cost function of each mother wavelet was determined resulting in the selection of nine level entropy criterion based decomposition. Table IV depicts the selection guide for WPT.

TABLE IV
SELECTION GUIDE FOR WPT PARAMETERS

WPT parameters	Determined Results	
	PCA	CS
Entropy	Coiflet 2, Symlet 7 Daubechies5	Bior 1.3
Relative entropy	Coiflet 2, Symlet 8	Bior 3.9, Bior2.2 Bior4.4
Euclidean distance	Coiflet 5	Bior 2.2

VI. Using Compound Features to Design sEMG Pattern Recognition System

After determining the best parameters for each of the features in the respected TFR method, to reach further improvements, an integration scheme was imposed towards optimizing the pattern recognition system that performs with the maximum number of hand movements. Two approaches were chosen for this purpose. These were the combination of all three TFR features, namely STFT, WT, and WPT, and combination of three TFR features plus the time domain features. The reason for using these types of features was to emphasize on temporal structure of EMG signal joint fused with the advantages of TFRs for the task of pattern recognition of maximum number of hand movements.

VII. Performance Evaluation of Signal and Combined Features

In order to attain the best approach for designing sEMG pattern recognition system for hand movement, the accuracy of the proposed system was evaluated, using previously mentioned features of sEMG signal. For this purpose, initially the accuracy of each and the combined feature sets of time domain and TFR were evaluated and compared for the maximum number of hand movements, distinctly for PCA and CS dimensionality reduction techniques and FIS and ANN classifiers. Figure 4 depicts the results of this comparative study where the combined features with PCA dimensionality reduction and FIS as classifier provide the best results.

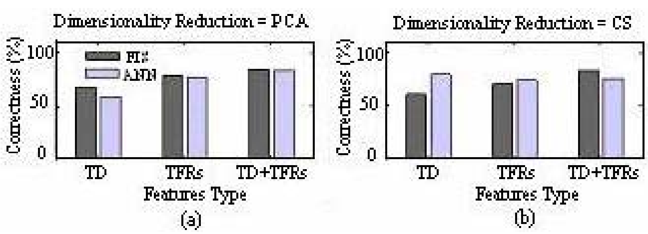

Fig.4. Comparing the accuracy of sEMG pattern recognition system using different types of features for eight hand movements (a) PCA and (b) CS.

Also noting from this Figure, PCA has a better general performance than CS. Table V depicts the summarized results for this analysis. The results show that ANN performs better with time domain features and CS whereas FIS response is improved for TFR and PCA. In this table, also we see that EMG features have the most effect on the accuracy of pattern recognition system despite the changes in dimensionality reduction and classifiers techniques.

TABLE V
SELECTION SUMMARY FOR THE BEST COMBINATION TO DESIGN sEMG PATTERN RECOGNITION SYSTEM

Rank	Combination for designing sEMG Pattern recognition	Average accuracy for 8 Movements
1	TFRs+TD+PCA+FIS	83%
2	TFRs+TD+PCA+ANN	82%
3	TFRs+TD+CS+FIS	82%
4	TFRs+PCA+FIS	78%
5	TD+CS+ANN	78%

Finally to evaluate the accuracy and discrimination ability of the sEMG pattern recognition system versus number of hand movements and different feature sets, a three dimensional presentation of % of correctness versus types of feature sets and number (type) of hand movements is depicted in Figure 5. The results demonstrate that FIS classifier along with PCA dimensionality reduction and combined features of time domain and TFR provide the best results for designing sEMG pattern recognition system.

VIII. Conclusion and Future Work

This investigation provides an exploratory and comparative study to propose a novel approach for designing sEMG pattern recognition system. In this study three types of sEMG feature sets, namely time domain, time frequency domain and their combination were utilized. The analysis utilized PCA and CS as dimensionality reduction technique and fuzzy inference system and artificial neural network as classifiers. Eight hand movements were considered and sEMG pattern recognition system was designed for recognizing these movements.

Results demonstrate that using the combined feature sets along with PCA as dimensionality reduction technique and FIS as classifier, best performance was achieved. The outcome of this research can be exploited to improve degree of freedom and performance of the hand prosthesis systems.

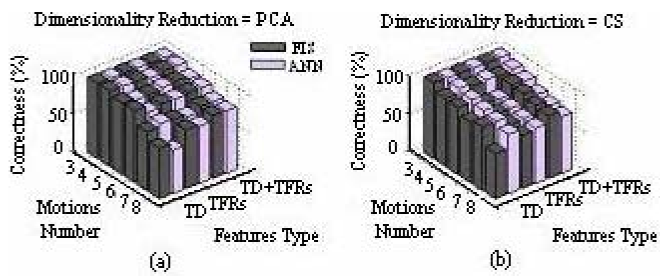

Fig.5. Representations the accuracy of sEMG pattern recognition system versus movement's number and features type in 3D Using PCA and CS.

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