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Techniques for Feature Extraction from EMG Signal

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***Abstract*—The myoelectric signal (MES) is one of the biosignals utilized in helping humans to control equipments. For this we required to recognize the hand movement. In this direction the first step is feature extraction. The optimal feature is important for the achievement in EMG analysis and control. By this extracted feature we reduce the computational cost of a multifunction myoelectric control system. The goal of this paper is to define the methods and approaches which are most suited for extracting the features from EMG signal. The techniques discussed here are spectral approaches like STFT, Thompson transform etc, wavelet based analysis, fuzzy based feature extracter and temporal approaches.**

Keywords: Feature Extraction, STFT, Wavelet, Thompson Transform.

I. Introduction

The Electromyography (EMG) signal, also referred to as the myoelectric signal (MES), acquired from the forearm skin surface provides valuable information about neuromuscular activities. Electromyography (EMG) signals have the properties of non-stationary, nonlinear, complexity, and large variation. These lead to difficulty in analyzing EMG signals. To make a system based on the EMG first we need to extract the features of the acquired EMG signal based on which it can be further classified for various hand movements. This technique is also called as pattern classification. In case of EMG signal a pattern is represented by the temporal signal given in fig. 1. Normally the temporal signals are of limited (shorter) duration and are sampled and converted into digital format. In such situation it is more appropriate to represent a pattern as a finite time sequence $s[0], s[1],..., s[N-1]$. Presenting this sequence directly to a classifier is impractical due to the large number of inputs and due to the randomness of the signal. Therefore, the sequence $s[n]$ must be mapped into a smaller-dimension vector $X = (x_1, x_2, ..., x_D), D << N$, called *feature vector*, which best characterizes the pattern.

The MES is a complicated signal controlled by the central nervous system (CNS). It is affected by anatomical and physiological properties of muscles, the control scheme of the peripheral nervous system, and the characteristics of the instrumentation used to detect and measure the signal[1-2].

There is a wide area of research in the development of the control system based on pattern recognition of EMG signals. One of the control strategies being extensively researched is known as myoelectric control strategy. In this prosthetic arm is controlled by utilizing pattern recognition to classify the EMG patterns. The limitations on these control system is the huge amount of data extracted from the myoelectric signal required to be processed. This limitation can be removed by utilizing the feature extraction techniques which converts the large amount of data into smaller dimension data.

The aim of this paper is present various techniques [3-6] which can be used to extract the features from the recorded EMG signal. All approaches have been used in classification of EMG patterns.

There are various approaches and methods[7-9] for feature extraction. All approaches have been used in classification of EMG patterns. The goal of this work is to present methods some of existing and successful feature extraction methods.

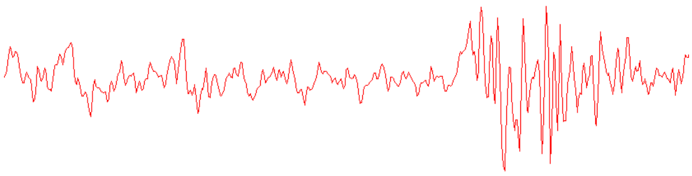

Fig.1. Recorded Row EMG signal

II. Feature Extraction Methods

There are various methods which can be used to extract the features from the acquired EMG data. These methods are different from the classical approaches like spectral analysis of the EMG signal.

A. *Wavelet Analysis*

Wavelet Transform (WT) is a time-frequency analysis method that is successful in the analysis of non-stationary signals including the EMG signal. However, the WT yields a high-dimensional feature vector [10]. But high dimensionality of a feature vector causes an increase in the learning parameters of a classifier [11]. This leads to the requirement of dimensionality reduction method which can increase the speed as well as the accuracy of the classifier [11-13]. For this reason, in wavelet analysis, selection of an optimal dimensionality reduction method is essential before applying the feature vector to a classifier. Feature projection, Principal component analysis are some famous techniques for dimension reduction. The main benefit of the WT is generation of the useful subset of the frequency components or scales of the interested signal.

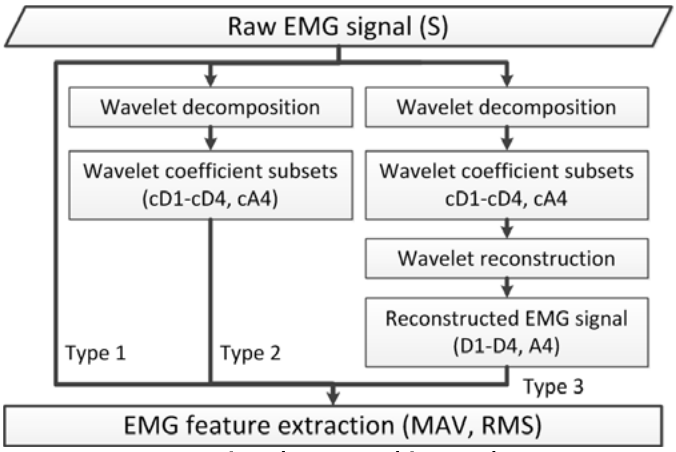

Fig.2: Procedure of extraction of the EMG features

Wavelet transform method is divided into two types: discrete wavelets transform (DWT) and continuous Wavelet transform (CWT). Generally DWT is used for the analysis of discretised EMG data [14-15]. The DWT transforms the EMG signal with a suitable wavelet basis function (WF). In this the original EMG signal is passed through a low-pass filter and a high-pass filter (coefficients of filters depend on WF type) to obtain an approximation coefficient subset (CA1) and a detail coefficient subset (CD1) at the first level. In order to obtain the multiple-resolution subsets, repetitious transformation is done. This process is repeated until the desired final level is obtained. In the EMG analysis, four levels of wavelet decomposition show better performance [16-18]. These coefficients works as the features of the EMG signal. However some good wavelet functions that are suitable for EMG signal analysis are shown in paper [18].

B. *Auto Regressive Analysis*

The Auto Regressive modelling has been used effectively in order to process the EMG signal and to get the feature vector out of it. The AR parameter a, reflection coefficient k can be used as the feature vector for the classification of the EMG signal.

In the AR model (also called linear prediction model), each sample x(n) of the SEMG is described as a linear combination of previous samples plus an error term e(n) which is independent of past samples[]

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n)$$

Where

- x(n) Samples of the modelled signal.
- a_k AR coefficients
- e(n) Residual of error sequence
- p Model's order

The model can be interpreted as a linear system with e(n) as its input and x(n) its output. e(n) is white noise and x(n) is the SMEG. The transfer function of the system is given by:

$$H(z) = \frac{X(z)}{E(z)} = \frac{1}{1 + \sum_{k=1}^{p} a_k z^{-k}}$$

represents the AR filter. H(z) contains poles only. Thus, the model can work only for signals with a well-defined peaky spectrum like speech [19] and EEG [20], and can be fitted also to SEMG, as will be shown below. The spectrum off the sequence x(n) can be estimated from the model.

$$\hat{S}_p^1(\omega) = \left|X(\omega)\right|^2 = \frac{1}{\left|1 + \sum_{k=1}^{p} a_k e^{-j\omega k}\right|^2}.$$

It was assumed that the spectrum of e(n) satisfies |E(w)| =1, i.e., for the appropriate p it approaches a white noise sequence.

The AR coefficients (a_i) are calculated by an algorithm [] that minimizes the residual energy $\sum_n e2(n)$.

From the 256 samples in each block, the following parameters are calculated:

A_i, i= 1,2,…..p The AR coefficients.
K_i, i=1,2,…...p The reflection coefficients [21]
P_i, i=1,2,…..P The poles of the AR filter H(z).

These parameter of the AR analysis are than used the feature vector for the SEMG signal and can be further used for analysis e.g. classification.

III. Frequency Domain Approaches

There are various techniques in the frequency domain by which we can extract the feature from EMG signals

A. *Power Spectral Density*

This is the very easy and traditional way to characterize the spectral properties of a time sequence. Power Spectral Density (PSD) can be obtained from the signal by the formula given below.

$$\hat{P}(f) = \frac{1}{N}\left|\hat{S}(f)\right|^2 = \frac{1}{N}\left|\sum_{n=0}^{N-1} s[n] e^{-j2\pi fn}\right|^2$$

In order to decrease the spectral leakage caused by truncation, the sequence is multiplied by the sometime windowing function, e.g. Hamming window, Black Mann window etc.

B. *Spectral Magnitude Averages*

Spectral Magnitude Averages is defined as the some averaged values of power spectral density. It is given by the following equation:

$$\hat{P}_m = \frac{1}{f_m - f_{m-1}} \int_{f_{m-1}}^{f_m} \hat{P}(f)df, \quad m = 1, 2, \ldots, L.$$

These averages help to reduce the effect of a considerable variance of power spectral density.

C. *Thompson Transform*

For the short time sequences the PDF becomes ineffective due to increased bias and variance. The discrete Fourier transform of the truncated sequence can be written as:

$$\hat{S}(f)=\sum_{n=0}^{N-1}s[n]e^{-j2\pi fn}=\int_{-1/2}^{1/2}\sum_{n=0}^{N-1}e^{j2\pi(u-f)}dZ(u).$$

The sum of the right hand side is known as Dirichlet kernel function.

$$\mathcal{D}_N(x)=\sum_{n=0}^{N-1}e^{-j2\pi nx}=e^{-j\pi x(N-1)}\frac{\sin(N\pi x)}{\sin(\pi x)}$$

By substitution we can get:

$$\hat{S}(f)=\int_{-1/2}^{1/2}D_N(f-u)dZ(u)\,.$$

This equation shows that the estimated spectrum is convoluted version of the true spectrum due to truncation of the time sequence. In order to make best estimate of the true spectrum, the integral, the integral equation has to be solved, which is an ill-posed inversion problem.

Thompson has offered a solution which is based on the spectral decomposition of the Dirichlet Kernel function. The Thompson estimator of PSD can be summarized as follows:

$$\hat{P}(f)=\frac{\sum_{k=0}^{K-1}\lambda_k\hat{P}_k(f)}{\sum_{k=0}^{K-1}\lambda_k},\quad \hat{P}_k(f)=\left|\sum_{n=0}^{N-1}s[n]v_k[n]e^{-j2\pi fn}\right|^2$$

Where λ_k and v_k [22] are eigenvalues and associated orthonormal eigenvectors of the Dirichlet-Toeplitz D with elements:

$$d_{ij}=\frac{\sin(2\pi(i-j))}{\pi(i-j)}.$$

The sequences v_k are called discrete prolate spheroidal sequences (DPSS). Both v_k and λ_k depend on parameters N and W.

D. *Short Time Fourier Transform*

The short time Fourier transform has been used by Hanaford etal [23] to study the rapid head and wrist movement, and to show that the spectrum changes with time. by using a windowing function STFT can be expressed as:

$$S(f,t)=\sum_{n=0}^{N-1}s[n]w[n-t]e^{-j2\pi ft}.$$

Often phase unwrapping is employed along either or both the time axis T and frequency axis, w, to surpress any jump discontinuity of the phase result of the STFT.

The time Index T is normally considered to be 'slow' time and usually not expressed in as high resolution as time t.

IV. CONCLUSION

The goal of this paper was to present the various methods like wavelet approaches, auto regressive methods in the field of feature extraction of EMG signals. This paper also presented the various spectral approaches that can be used in order to extract the feature vector from the surface EMG signals. There are also various spatial or time domain approaches which can also be used for the feature extraction from EMG signals. There is lot of work done in spatial domain by using zero crossing and methods based on amplitude of the EMG signal. In the future there can be various algorithms which will use fuzzy logic, neural networks in order to extract the features from EMG signals.

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