Analysis of EMG Signals Based on Wavelet Transform-A Review

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Analysis of EMG Signals Based on Wavelet Transform – A Review

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Abstract— ***Wavelet-based signal processing has become commonplace in the signal processing community over the past decade.Wavelet analysis is often very effective because it provides a simple approach for dealing with local aspects of a signal. Electromyography (EMG) signals can be used for clinical/biomedical applications, Evolvable Hardware Chip (EHW) development, and modern human computer interaction. EMG signals acquired from muscles require advanced methods for detection, decomposition, processing, and classification. One of the most important applications of wavelets is removal of noise from signals called denoising accomplished by thresholding wavelet coefficients in order to separate signal from noise. The purpose of this paper is to highlight the use of Wavelet transform (WT) for EMG signal analysis. A comparison study is also given to show performance of various EMG signal analysis methods over wavelet. This paper provides researchers a good understanding of EMG signal and its analysis procedures.***

Keywords— **sEMG, wavelet transform, STFT, Fourier analysis, denoising, decomposition.**

I. INTRODUCTION

Biomedical signal means a collective electrical signal acquired from any organ that represents a physical variable of interest. This signal is normally a function of time and is describable in terms of its amplitude, frequency and phase. The EMG signal is a biomedical signal that measures electrical currents generated in muscles during its contraction representing neuromuscular activities. The nervous system always controls the muscle activity (contraction/relaxation). Hence, the EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. EMG signal acquires noise while traveling through different tissues. Moreover, the EMG detector, particularly if it is at the surface of the skin, collects signals from different motor units at a time which may generate interaction of different signals. Detection of EMG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering. The main reason for the interest in EMG signal analysis is in clinical diagnosis and biomedical applications. The shapes and firing rates of Motor Unit Action Potentials (MUAPs) in EMG signals provide an important source of information for the diagnosis of neuromuscular disorders. Once appropriate algorithms and methods for EMG signal analysis are readily available, the nature and characteristics of the signal can be properly understood and hardware implementations can be made for various EMG signal related applications. So far, research and extensive efforts have been made in the area, developing better algorithms, upgrading existing methodologies, improving detection techniques to reduce noise, and to acquire accurate EMG signals. Few hardware implementations have been done for prosthetic hand control, grasp recognition, and human machine interaction. It is quite important to carry out an investigation to classify the actual problems of EMG signals analysis and justify the accepted measures.

The technology of EMG recording is relatively new. There are still limitations in detection and characterization of existing nonlinearities in the surface electromyography (sEMG, a special technique for studying muscle signals) signal, estimation of the phase, acquiring exact information due to derivation from normality [1][2] Traditional system reconstruction algorithms have various limitations and considerable computational complexity and many show high variance [1]. Recent advances in technologies of signal processing and mathematical models have made it practical to develop advanced EMG detection and analysis techniques. Various mathematical techniques and Artificial Intelligence (AI) have received extensive attraction. Mathematical models include wavelet transform, time-frequency approaches, Fourier transform, Wigner-Ville Distribution (WVD), statistical measures, and higher-order statistics.

The use of Fourier analysis to study biological signals such as EMG recordings is not the most efficient method for transient data analysis. However, the time frequency analysis based on the wavelet transform is better suited to handle the non-stationary characteristics of the EMG signals. The technology of EMG recording is relatively new. There are still limitations in detection and characterization of existing nonlinearities in the surface electromyography (sEMG, a special technique for studying muscle signals) signal, estimation of the phase, acquiring exact information due to derivation from normality.

Wavelet transform is well suited to non-stationary signals like EMG. Time-frequency approach using Wavelet in hardware could allow for a real-time instrument that can be used for specific motor unit training in biofeedback situations.

This paper firstly gives a brief review about analysis of EMG signal using wavelet transform along with its advantages. This is followed by highlighting the up-to-date detection, decomposition, processing, and classification methods of EMG signal. Finally, the advantages of wavelet over other methods have been discussed.

II. WAVELET ANALYSIS

A transform can be thought of as a remapping of a signal that provides more information than the original. The Fourier transform fits this definition quite well because the frequency information it provides often leads to new insights about the original signal. Fourier analysis provides a good description of the frequencies in a waveform, but not their timing. However, the inability of the Fourier transform to describe both time and frequency characteristics of the waveform led to a number of different approaches. None of these approaches was able to completely solve the time–frequency problem. Timing information is often of primary interest in many biomedical signals. A wide range of approaches have been developed to try to extract both time and frequency information from a waveform. Basically they can be divided into two groups: time–frequency methods and time–scale methods. The wavelet transform can be used as yet another way to describe the properties of a waveform that changes over time, but in this case the waveform is divided not into sections of time, but segments of scale [3].

The CWT has one serious problem: it is highly redundant (In its continuous form, it is actually infinitely redundant). The CWT provides an oversampling of the original waveform: many more coefficients are generated than are actually needed to uniquely specify the signal. This redundancy is usually not a problem in analysis applications such as described above, but will be costly if the application calls for recovery of the original signal. For recovery, all of the coefficients will be required and the computational effort could be excessive. In applications that require bilateral transformations, we would prefer a transform that produces the minimum number of coefficients required to recover accurately the original signal. The *discrete wavelet transform* (DWT) achieves this parsimony by restricting the variation in translation and scale, usually to powers of 2. In the DWT, a new concept is introduced termed the *scaling function*, a function that facilitates computation of the DWT. To implement the DWT efficiently, the finest resolution is computed first. The computation then proceeds to coarser resolutions, but rather than start over on the original waveform, the computation uses a smoothed version of the fine resolution waveform. This smoothed version is obtained with the help of the scaling function. In fact, the scaling function is sometimes referred to as the *smoothing function*.

III. EMG SIGNAL PROCESSING USING WAVELET

Raw EMG offers us valuable information in a particularly useless form. This information is useful only if it can be quantified. Then the signal-processing methods are applied on raw EMG to achieve the accurate and actual EMG signal.

Both the time and frequency domain approaches have been attempted in the past. The wavelet transform (WT) is an efficient mathematical tool for local analysis of nonstationary and fast transient signals. One of the main properties of WT is that it can be implemented by means of a discrete time filter bank. The Fourier transforms of the wavelets are referred as WT filters. The WT represents a very suitable method for the classification of EMG signals.

Guglielminotti and Merletti [4] theorized that if the wavelet analysis is chosen so as to match the shape of the MUAP, the resulting WT yields the best possible energy localization in the time-scale plane [4]. In 1997, Laterza and Olmo [5] found out that WT is an alternative to other time frequency representations with the advantage of being linear, yielding a multiresolution representation and not being affected by cross terms; this is particularly relevant when dealing with multicomponent signals. 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 [5] have used wavelet analysis to match the shape of the MUAP. For a unipolar recorded signal and under certain hypotheses presented by Gabor in 1946 [6], the typical MUAP shape can be approximated as the second-order derivative of a Gaussian distribution. The result suggested using the well-known Mexican hat wavelet, which is indeed the second-order derivative of a Gaussian distribution. Based on the research, Laterza and Olmo concluded that the WT is particularly useful for MUAP detection in the presence of additive white noise. In this situation, the noise contributions are spread over the entire time scale plane, independently of the wavelet used. The disadvantage of this proposal [5] was that the Mexican hat wavelet is not perfectly matched to the MUAP shape. Therefore, the obtained results are likely to be subject to further improvement if a perfect matching is performed. In 1998, Ismail and Asfour [7] came with a theory saying that, the most common method used to determine the frequency spectrum of EMG are the fast and short term Fourier transforms (FFT and SFT). But they also concluded that the major drawback of these transformation methods is that they assume that the signal is stationary.

In 1999, Pattichis and Pattichis [8] discovered that the WT can also be used to analyze signals at different resolution levels. According to the theory, the process of analyzing signals at different resolution level is known as multiresolution analysis. They analyzed the relationship between wavelet coefficients and the time-frequency plane. The WT algorithm consists of the decomposition phase and reconstruction phases. Pattichis and Pattichis briefly outline how coefficients from each stage of the WT can be used to construct functional approximation to the original signal. Given signal samples $x0$, $x1$, $x2$...... the corresponding continuous time signal is given by equation 1:

$$f^{o}(t) = \sum_{k} x_k \phi(t-k)$$

where $\varphi(t-k)$ is called a scaling function. This assumes that the signal samples are weighted averages of the continuous signal.

Again in 2003, Kumar *et al*. [9] came with a similar kind of proposal saying that the WT decomposes signal into several multiresolution components according to a basis function called "wavelet function" (WF). The WF is both dilated and translated in the time undertaking a two-dimensional cross correlation with the time domain sEMG signal. This method can be seen as a mathematical microscope that provides a tool to detect and characterize a short time component within a nonstationary signal. It is the technique that provides information related to the time-frequency variation of the signal. Kumar *et al*. also concluded that the Short Fourier Transform (SFT) with the relatively short time windows can attempt to track spectral variation with time, but does not adopt an optimal time or frequency resolution for the nonstationary signal. In [10], sEMG has been decomposed using WT with various WF and the output of the power transform domain is calculated and used as the deciding parameter in choosing the WF that provides the best contrast between sEMG cases. As a result of their research activity, it can be said that using sEMG and wavelet transforms, it is possible to determine the muscle fatigue (muscle failure) status simply by determining the Sym4 or Sym5 wavelet decomposition of the signal at level 8 and 9 (out of 10 levels). Figure 1 shows the experimental procedure.

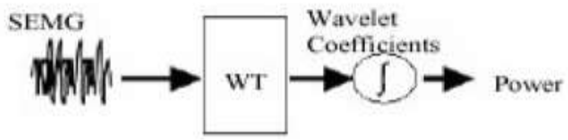

Fig. 1 Block diagram of experiment procedure

The Surface EMG (sEMG) signals was denoised using discrete wavelet transform (DWT) and a threshold method. The DWT and threshold based denoising was implemented using MATLAB Wavelet toolbox. The figure below shows the flow of the algorithm.

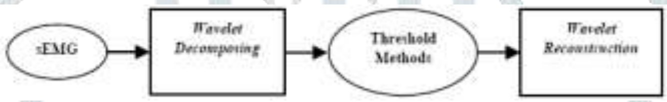

Fig. 2 Wavelet based denoising of sEMG signals

Wavelets commonly used for denoising biomedical signals include the Daubechies (db2, db8, and db6) wavelets and orthogonal Meyer wavelet.

The wavelets are generally chosen whose shapes are similar to those of the MUAP. The WT decomposes a signal into several multi-resolution components according to a basic function which is wavelet function. As discussed before, filters are one of the most widely used signal processing functions. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling operations. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal.

A. Comparison with other time-frequency methods

Fourier Transform is the most prominent method used for frequency analysis of time domain signal. It is suitable for stationary signal where all frequency components present at all time. Conversely, there is also a type of signal having various components of frequency in different instant of time. In other words, the frequency components vary with time. This type of signal is called non-stationary signal. SEMG signal is a non-stationary type signal. Evaluation for non-stationary signal is better done with methods used for time-frequency analysis. The time-frequency approach on SEMG signal had been studied and applied by researcher with implementation of various methods such as Short Time Fourier Transform (STFT) [11,12], Wigner-Ville Distribution (WVD) [13-15], Choi-Williams Distribution (CWD) [16] and Wavelet Transform (WT) [17-20].

Comparison between different methods of time-frequency approach on SEMG signal had been studied and reported in several literatures. Canal [21] had compared WT with STFT and found that WT had good resolution and high performance for visualization of neuropathy and myopathy activity. A much wider comparison study had been done by Karlsson et al. [22]. Four methods had been used which are STFT, Running Windowed Exponential Distribution (RWED), pseudo Wigner-Ville distribution (PWVD) and continuous Wavelet transform (CWT). According to this literature, analysis using STFT, RWED and PWVD might results in difficulty to achieve a good time and frequency resolution. As for CWT, it has been found that it is very reliable in analysis of bioelectrical signals in general and shows better statistical performance than other methods.

Much earlier comparison study was done by Davies & Riesman [23] when they implemented the time-frequency analysis on SEMG during muscle fatigue. STFT, WVD and CWD had been chosen. In its discussion, Davies & Riesman [24] found that WVD is not a precise representation of the changing of frequency components with fatigue. STFT shows clearly the spectrum compression as muscle fatigues but CWD is said to most accurately show the frequency compression.

IV. CONCLUSIONS

This paper provides a brief introduction of the wavelet transform in EMG signals processing.For EMG signal processing; the WT is an alternative to other to other time frequency representations. WT has the advantage of being linear, yielding a multiresolution representation. Crossterms do not affect WT when dealing with multicomponent signals. We see that a major drawback of SFT is that stationary signal is assumed. The Electrocardiogram signal is a good example of a weak biosignal since its amplitude is commonly under a microvolt, and it is commonly contaminated by noise with amplitude on the order of millivolts. Conventional Wavelet Denoising (WD) has been demonstrated to be an effective algorithm for a wide range of signal processing, when the signal-to-noise ratio (SNR) of the signal being denoised is relatively high. Thus, Wavelet denoising methods is expected to offer a powerful compliment to conventional filtering techniques like notch filters and frequency domain filtering methods, which will be very efficient for sEMG signal analysis. Finally, we conclude that wavelet is a powerful tool that is used for the frequency analysis of the EMG signals.

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