Denoising of EMG Signals Based on Wavelet Transform

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***Abstract*— 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. In this paper, Wavelet transform (WT) has been applied for removing noise from the surface EMG. To fully understand the concept of WT, Matlab Simulation was used for sEMG data was collected from a forearm muscle.**

Keywords: sEMG; wavelet transform; denoising; Daubechies; 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.

II. EMG: ANATOMICAL AND PHYSIOLOGICAL BACKGROUND

The development of EMG started with Francesco Redi's documentation in 1666. The document informs that highly specialized muscle of the electric ray fish generates electricity [3]. By 1773, Walsh had been able to demonstrate that Eel fish's muscle tissue could generate a spark of electricity. In 1792, a publication entitled "De Viribus Electricitatis in Motu Musculari Commentarius" appeared, written by A. Galvani, where the author showed that electricity could initiate muscle contractions [4]. Six decades later, in 1849, Dubios-Raymond discovered that it was also possible to record electrical activity during a voluntary muscle contraction. The first recording of this activity was made by Marey in 1890, who also introduced the term electromyography [5]. In 1922, Gasser and Erlanger used an oscilloscope to show the electrical signals from muscles. Because of the stochastic nature of the myoelectric signal, only rough information could be obtained from its observation. The capability of detecting electromyographic signals improved steadily from the 1930s through the 1950s and researchers began to use improved electrodes more widely for the study of muscles [1]. Clinical use of surface EMG for the treatment of more specific disorders began in the 1960s. Hardyck and his researchers were the first (1966) practitioners to use sEMG [5]. In the early 1980s, Cram and Steger introduced a clinical method for scanning a variety of muscles using an EMG sensing device [5]. It is not until the middle of the 1980s that integration techniques in electrodes had sufficiently advanced to allow batch production of the required small and lightweight instrumentation and amplifiers. At present a number of suitable amplifiers are commercially available. In the early 1980s, cables became available which produce artifacts in the desired microvolt range. During the past 15 years, research has resulted in a better understanding of the properties of surface EMG recording. In recent years, surface electromyography is increasingly used for recording from superficial muscles in clinical protocols, where intramuscular electrodes are used for deep muscle only [2][4].

Electromyography (EMG) signals can be employed for clinical and biomedical applications. At present, there are three common applications of the EMG signal, first, determining the activation timing of the muscle; that is, when the excitation to the muscle begins and ends; second, estimating the force produced by the muscle; third, obtaining an index of the rate at which a muscle fatigues through the analysis of the frequency spectrum of the signal.

Muscle contraction and other activities in the human body are processed in the brain. Then, the brain will dictate to spinal cord. The motor neurons in the spinal cord will divide to a number of axonal which is called axonal terminals. Axonal terminals are attached to a number of muscle fiber. The electrical signal propagates in the muscle fibers. Muscle fibers are innervated by neurons whose cell bodies are located in spinal cord. The nerve fibers, or axons, of these motor neurons leave the spinal cord and are distributed to the motor nerves. As mentioned above, each motor axon branches several times and innervates many muscle fibers. A single motor neuron and all innervated muscle fibers are named a motor unit. The distributed signal in one motor unit is synchronized and equal for all innervated muscle fibers. The resulting signal is called the muscle fiber action potential. The combination of the muscle fiber action potentials from all the muscle fibers of a single motor unit is the motor unit action potential (MUAP). MUAP in EMG signals provide an important source of information for the diagnosis of neuromuscular disorders. When a motor unit fires, all of the innervated muscle fibers in a motor unit are fired. When a motor unit is recurrent firing, the motor unit will create a train of impulses known as the motor unit action potential train (MUAPT). The combination of electrical activity created by each active motor unit is the myoelectrical signal (ME) [6].

To acquire surface EMG (sEMG) signal, electrodes are placed on the skin overlying the muscle. Alternatively, wire or needle electrodes are used and these can be placed directly in the muscle. When EMG is acquired from electrodes mounted directly on the skin, the signal is a composite of all the muscle fiber action potentials occurring in the muscle or muscles underlying the skin. 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. The EMG signal may be either positive or negative voltage as shown in Fig. 1.

This premise was necessary to illustrate the EMG signal how it is produced and also to understand the complexity of this signal whereas, as aforementioned, the recording usually done by mounting the electrodes on the skin overlying thousands of muscle fibers. Moreover, there are a variety of layers of connective tissue (tissue which connects other tissues and organs) and skin. Therefore, EMG signal will be vastly greater complex signal while traveling through different layers; in consequence of acquiring noise coming from the crosstalk between lots of surface acquired signals those propagate in the same time in different motor units in different layers.

Figure 1. Surface raw EMG signal

III. 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 [7].

IV. SHORT-TERM FOURIER TRANSFORM: THE SPECTROGRAM

The first time–frequency methods were based on the straightforward approach of slicing the waveform of interest into a number of short segments and performing the analysis on each of these segments, usually using the standard Fourier transform. A window function is applied to a segment of data, effectively isolating that segment from the overall waveform, and the Fourier transform is applied to that segment. This is termed the spectrogram or "short-term Fourier transform" (STFT) since the Fourier Transform is applied to a segment of data that is shorter, often much shorter, than the overall waveform. Since abbreviated data segments are used, selecting the most appropriate window length can be critical. This method has been successfully applied in a number of biomedical applications.

There are two main problems with the spectrogram: (1) selecting an optimal window length for data segments that contain several different features may not be possible, and (2) the time–frequency tradeoff: shortening the data length, N, to improve time resolution will reduce frequency resolution which is approximately 1/(NTs). Shortening the data segment could also result in the loss of low frequencies that are no longer fully included in the data segment. Hence, if the window is made smaller to improve the time resolution, then the frequency resolution is degraded and vice versa.

A number of approaches have been developed to overcome some of the shortcomings of the spectrogram. The first of these was the *Wigner-Ville distribution* which is also one of the most studied and best understood of the many time–frequency methods. The approach was actually developed by Wigner for use in physics, but later applied to signal processing by Ville, hence the dual name. The Wigner-Ville distribution is a special case of a wide variety of similar transformations known under the heading of *Cohen's class of distributions*. The Wigner-Ville distributions, and others of Cohen's class, use an approach that harkens back to the early use of the autocorrelation function for calculating the power spectrum. The classic method for determining the power spectrum was to take the Fourier transform of the autocorrelation function. To construct the autocorrelation function, the waveform is compared with itself for all possible relative shifts, or lags. The equations are written in both continuous and discreet forms:

$$r_{xx}(\tau) = \int_{-\infty}^{\infty} x(t)x(t+\tau)dt \qquad (1)$$

and

$$r_{xx}(n) = \sum_{k=1}^{M} x(k)x(k+n) \qquad (2)$$

where τ and n are the shift of the waveform with respect to itself.

In the standard autocorrelation function, time is integrated (or summed) out of the result, and this result, $r_{xx}(\tau)$, is only a function of the lag, or shift, τ. The Wigner-Ville, and in fact all of Cohen's class of distributions, use a variation of the autocorrelation function where time remains in the result. This is achieved by comparing the waveform with itself for all possible lags, but instead of integrating over time, the comparison is done for all possible values of time. This comparison gives rise to the defining equation of the so-called *instantaneous autocorrelation* function:

$$R_{xx}(t,\tau) = x\left(t+\frac{\tau}{2}\right)x*(t-\tau/2) \qquad (3)$$

$$R_{xx}(n,k) = x(k+n)x*(k-n) \qquad (4)$$

where τ and n are the time lags as in autocorrelation, and * represents the complex conjugate of the signal, x.

As mentioned above, the classic method of computing the power spectrum was to take the Fourier transform of the standard autocorrelation function. The Wigner-Ville distribution echoes this approach by taking the Fourier transform of the instantaneous autocorrelation function, but only along the τ (i.e., lag) dimension. The result is a function of both frequency and time. When the one dimensional power spectrum was computed using the autocorrelation function, it was common to filter the autocorrelation function before taking the Fourier transform to improve features of the resulting power spectrum. While no such filtering is done in constructing the Wigner-Ville distribution, all of the other approaches apply a filter (in this case a two-dimensional filter) to the instantaneous autocorrelation function before taking the Fourier transform. In fact, the primary difference between many of the distributions in Cohen's class is simply the type of filter that is used.

The Wigner-Ville has several advantages over the STFT, but also has a number of shortcomings. However, the Wigner-Ville distribution has a number of shortcomings. Most serious of these is the production of cross products: the demonstration of energies at time–frequency values where they do not exist. These phantom energies have been the prime motivator for the development of other distributions that apply various filters to the instantaneous autocorrelation function to mitigate the damage done by the cross products. In addition, the Wigner-Ville distribution can have negative regions that have no meaning. The Wigner-Ville distribution also has poor noise properties. Essentially the noise is distributed across all time and frequency including cross products of the noise, although in some cases, the cross products and noise influences can be reduced by using a window. In such cases, the desired window function is applied to the lag dimension of the instantaneous autocorrelation function (Eq.4).

In the Fourier transform, the waveform was compared to a sine function - in fact, a whole family of sine functions at harmonically related frequencies. This comparison was carried out by multiplying the waveform with the sinusoidal functions, then averaging (using either integration in the continuous domain, or summation in the discrete domain):

$$X(\omega_m) = \int_{-\infty}^{\infty} x(t)e^{-j\omega_m t}dt \qquad (5)$$

where Eq. (5) is in the continuous form.

Almost any family of functions could be used to probe the characteristics of a waveform, but sinusoidal functions are particularly popular because of their unique frequency characteristics: they contain energy at only one specific frequency. Naturally, this feature makes them ideal for probing the frequency makeup of a waveform, i.e., its frequency spectrum. Other probing functions can be used, functions chosen to evaluate some particular behavior or characteristic of the waveform. If the probing function is of finite duration, it would be appropriate to translate, or slide, the function over the waveform, $x(t)$, as is done in the short-term Fourier transform (STFT):

$$STFT(t,f) = \int_{-\infty}^{\infty} x(\tau)(w(t-\tau)e^{-2\pi f\tau})d\tau \qquad (6)$$

where f, the frequency, also serves as an indication of family member, and $w(t-\tau)$ is some sliding window function where t acts to translate the window over x. More generally, a translated probing function can be written as:

$$X(t,m) = \int_{-\infty}^{\infty} x(\tau)f(t-\tau)_m d\tau \qquad (7)$$

where $f(t)_m$ is some family of functions, with m specifying the family number.

If the family of functions, $f(t)_m$, is sufficiently large, then it should be able to represent all aspects the waveform $x(t)$. This would then allow $x(t)$ to be reconstructed from $X(t,m)$ making this transform *bilateral.* Often the family of basis functions is so large that $X(t,m)$ forms a redundant set of descriptions, more than sufficient to recover $x(t)$. This redundancy can sometimes be useful, serving to reduce noise or acting as a control, but may be simply unnecessary. Note that while the Fourier transform is not redundant, most transforms represented by Eq. (7) (including the STFT and all the distributions discussed before) would be, since they map a variable of one dimension (t) into a variable of two dimensions (t,m).

V. THE CONTOUNUS WAVELET TRANSFORM

The wavelet transform introduces an intriguing twist to the basic concept defined by Eq. (7). In wavelet analysis, a variety of different probing functions may be used, but the family always consists of enlarged or compressed versions of the basic function, as well as translations. This concept leads to the defining equation for the continuous wavelet transform (CWT):

$$W(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|a|}}\psi*(\frac{t-b}{a})dt \qquad (8)$$

where b acts to translate the function across $x(t)$ just as t does in the equations above, and the variable a acts to vary the time scale of the probing function, Ψ. If a is greater than one, the wavelet function, Ψ, is stretched along the time axis, and if it is less than one (but still positive) it contacts the function. Negative values of a simply flip the probing function on the time axis. While the probing function Ψ could be any of a number of different functions, it always takes on an oscillatory form, hence the term "wavelet." The * indicates the operation of complex conjugation, and the normalizing factor $1/\sqrt{a}$ ensures that the energy is the same for all values of a (all values of b as well, since translations do not alter wavelet energy). If $b = 0$, and $a = 1$, then the wavelet is in its natural form, which is termed the *mother* wavelet;* that is, $\Psi_{1,0}(t) \equiv \Psi(t)$. A mother wavelet along with some of its family members produces by dilation and contraction. The wavelet shown is the popular *Morlet* wavelet, named after a pioneer of wavelet analysis, and is defined by the equation:

$$\psi(t) = e^{-t^2}\cos(\pi\sqrt{\frac{2}{\ln(2)}}\ t) \qquad (9)$$

The wavelet coefficients, $W(a,b)$, describe the correlation between the waveform and the wavelet at various translations and scales: the similarity between the waveform and the wavelet at a given combination of scale and position, a, b.
If the wavelet function, $\psi(t)$, is appropriately chosen, then it is possible to reconstruct the original waveform from the wavelet coefficients just as in the Fourier transform. Since the CWT decomposes the waveform into coefficients of two variables, a and b, a double summation (or integration) is required to recover the original signal from the coefficients:

$$X(t) = \frac{1}{C}\int_{a=-\infty}^{\infty}\int_{b=-\infty}^{\infty} W(a,b)\psi_{a,b}(t)da\ db \qquad (10)$$

Where

$$C = \int_{-\infty}^{\infty}\frac{|\psi(\omega)|^2}{|\omega|}d\omega$$

and $0 < C < \infty$ (the so-called *admissibility condition*) for recovery using Eq. (10).

In fact, reconstruction of the original waveform is rarely performed using the CWT coefficients because of the redundancy in the transform. When recovery of the original waveform is desired, the more parsimonious discrete wavelet transform is used.

VI. THE DISCRETE WAVELET TRANSFORM

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. The basic analytical expressions for the DWT will be presented here; however, the transform is easier to understand, and easier to implement using filter banks. The DWT is often introduced in terms of its recovery transform:

$$x(t) = \sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} d(k,l)2^{-\frac{k}{2}}\psi(2^{-k}t - l) \quad (11)$$

Here k is related to a as: $a = 2^k$; b is related to l as $b = 2^k\ l$; and $d(k,l)$ is a sampling of $W(a,b)$ at discrete points k and l.

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*. The definition of the scaling function uses a dilation or a *two-scale difference equation*:

$$\Phi(t) = \sum_{n=-\infty}^{\infty}\sqrt{2}c(n)\Phi(2t-n) \qquad (12)$$

where $c(n)$ is a series of scalars that defines the specific scaling function. This equation involves two time scales (t and $2t$) and can be quite difficult to solve.

In the DWT, the wavelet itself can be defined from the scaling function:

$$\psi(t) = \sum_{n=-\infty}^{\infty}\sqrt{2}d(n)\Phi(2t-n) \qquad (13)$$

where $d(n)$ is a series of scalars that are related to the waveform $x(t)$ (Eq. (11)) and that define the discrete wavelet in terms of the scaling function. While the DWT can be implemented using the above equations, it is usually implemented using filter bank techniques.

VII. WAVELET DENOISING

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.

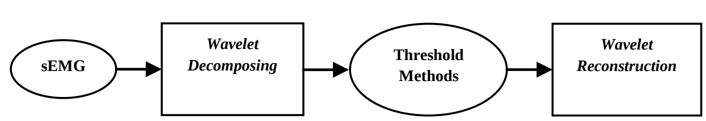

Figure 2: Wavelet based denoising of sEMG signals

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.

1. Wavelet Decomposition

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 upsampling and downsampling operations. The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal.

2. Threshold Method

Suppose the following equation represents a simple model of the EMG signal,

$$f(t) = s(t) + n(t) \tag{13}$$

where, $s(t)$, $n(t)$ denotes EMG signals and White Gaussian Noise $N(0,\sigma^2)$, respectively.

The energy of the original signal s(t) is effectively captured, to a high percentage, by transform values whose magnitude are all greater than a threshold, T*s* >0. The noise signal's transform values all have the magnitudes while lie below a noise threshold T*n* satisfy T*n* < T*s*. Then, the noise in *f(t)* can be removed by thresholding its transform. All values of its transform whose magnitude lies below the noise threshold T_n are set equal to 0.

VIII. SIMULATIONS AND RESULTS

The raw sEMG data was downloaded from [8]. Data in this file was obtained using a bipolar surface EMG sensor (emgPLUX sensor from bioPLUX) placed at a forearm muscle. The sampling rate and test time are 1000Hz and 5 second, respectively.

Any of the WFs (db2, db6, db8, and dmey) are effective for noise removal in the case of sEMG based on [9, 10]. In this experiment WF db6 is chosen and found to be effective for noise removal. This work was done by using wavemenu (Wavelet Toolbox Main Menu) in Matlab® Software. Different ways to denoise the sEMG signal was performed as depicted and illustrated below.

In Fig. 3 illustrates a sample raw sEMG signal and its coefficients by using db6 with 4 levels of decomposition. Moreover, wavelet tree for db6 of level 4 is shown in Fig. 4.

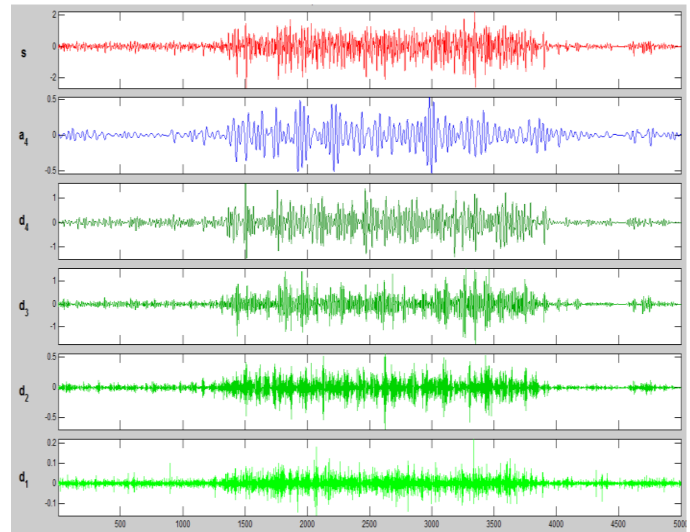

Figure 3: Decomposition at level 4: s=a4+d4+d3+d2+d1 (before applying denoising)

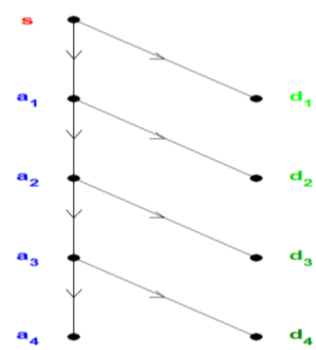

Figure 4: Show the Wavelet Tree for db6 of level 4

By using manual Soft *Minmax* Thresholding Method, the denoised signal was advanced after the residuals signal was removed. For each level, the threshold was manually selected as depicts in Figs. 5, 6, and 7, whereas un-scaled white noise structure was selected.

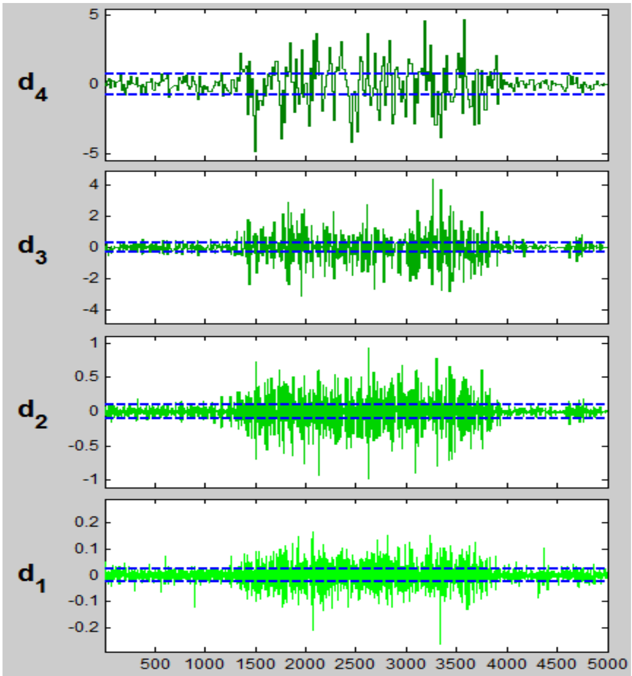

Figure 5: Original details coefficients and their threshold levels.

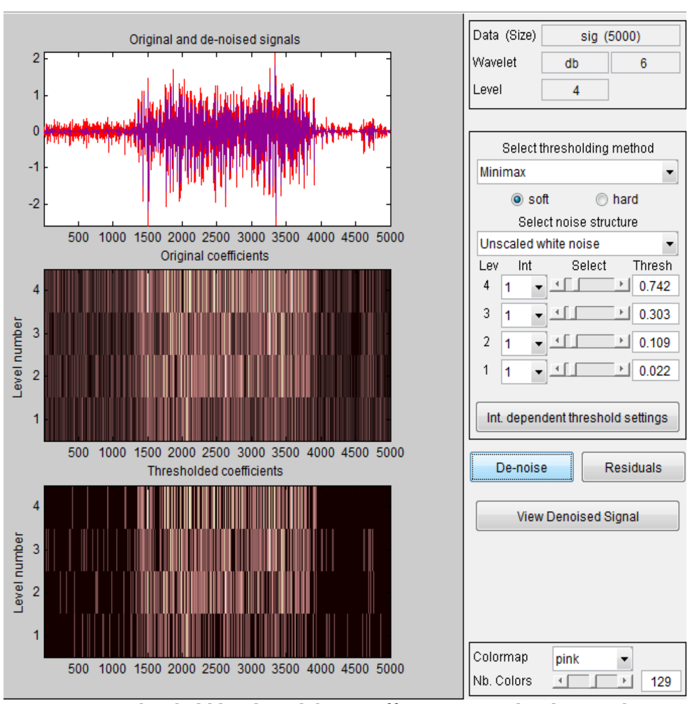

Figure 6: Threshold levels and their coefficients. From level 1 to 4 the thresholding are 0.022, 0.109, 0.303 and 0.742 respectively.

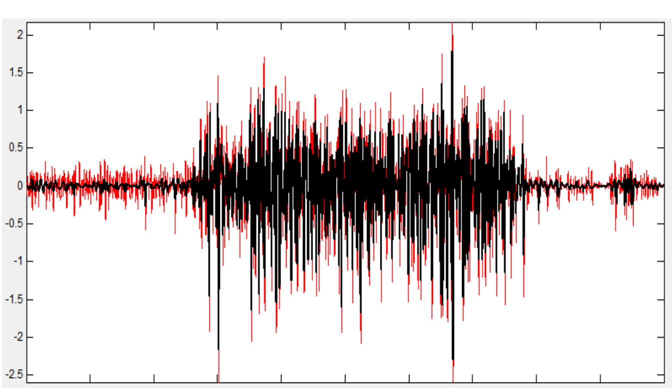

Figure 7: The black signal is the denoised signal and the red one is the original signal.

In another hand, another way for choosing the threshold method, the *Compression* was used to see the electrical consumption signal is redisplayed in red with the compressed version superimposed in black as shown in Fig. 8.

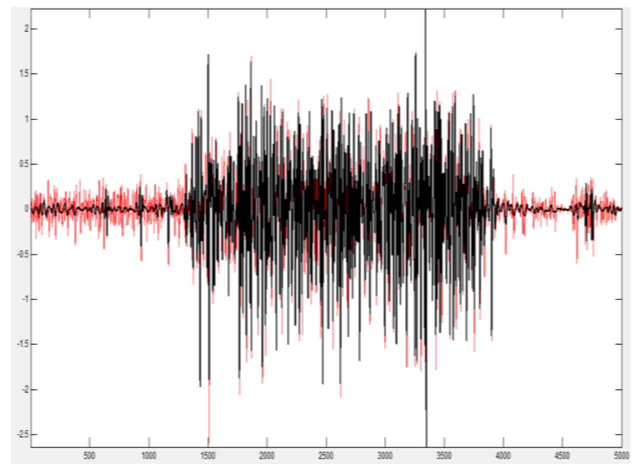

Figure 8: The original and compressed signals are colored red and black, respectively.

You can see that the compression process removed most of the noise, but preserved 88.28% of the energy of the signal. The automatic thresholding was very efficient, zeroing out all but 11.76% of the wavelet coefficients. The residuals signal is shown in Fig. 9.

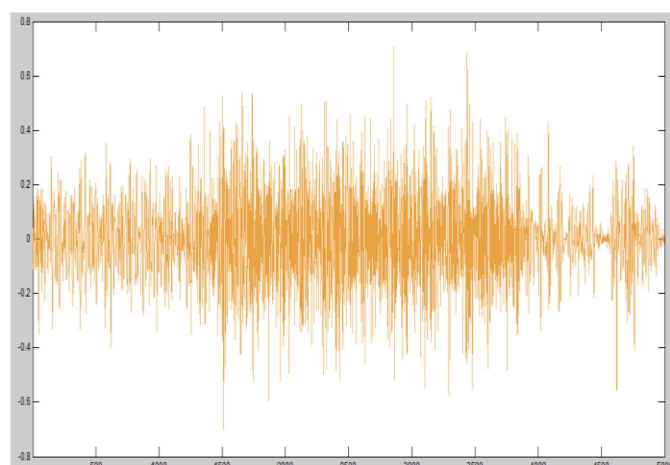

Figure 9: The residuals signal.

IX. CONCLUSION

This paper provides a brief introduction of the wavelet transform in EMG signals processing. 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. The future study will construct feature vectors that are entered into a BP neural network classifier and nearest neighbor classifier, respectively, to add completeness to this ongoing study.

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