SEMG Signal Processing and Analysis Using Wavelet Transform and Higher Order Statistics to Characterize Muscle Force

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Abstract: - An algorithm is proposed for processing and analyzing surface electromyography (SEMG) signals using wavelet transform and Higher Order Statistics (HOS). EMG signal acquires noise while travelling though different media. Wavelet denoising is performed in this research for initial EMG signal processing. With the appropriate choice of the Wavelet Function (WF), it is possible to remove interference noise effectively. Root Mean Square (RMS) difference and Signal to Noise Ratio (SNR) values are calculated to determine the most suitable WF. Results show that WF db2 performs denoising best among the other wavelets. Power spectrum analysis is performed to the denoised SEMG to indicate changes in muscle contraction. Furthermore, HOS method is applied for further efficient processing due to the unique properties of HOS applied to random time series. Gaussianity and linearity tests are conducted as part of HOS which shows that SEMG signal becomes less gaussian and more linear with increased force.

Key-Words: -SEMG, wavelet transform, denoising, mean power frequency, HOS, bispectrum.

1 Introduction

The electromyography (EMG) signal gives an electrical representation of neuromuscular activation associated with a contracting muscle. A muscle is composed of many Motor Units (MUs). The technique of studying muscle function by using a surface electrode is normally known as Surface Electromyography (SEMG). EMG signals detected directly from the muscle or from the skin by using surface electrodes show a train of motor unit action potentials (MUAP) and noises. Wavelet-based based noise removal is performed in this research prior to signal processing and analysis. Wavelet denoising (noise removal) has been found effective in denoising a number of physiological signals [1, 2, 3, 4]. It is preferred over notch filters and signal frequency domain filtering because it tends to preserve signal characteristics even while minimizing noise. In this research, daubechies, symmlet and orthogonal Meyer Wavelet Functions (WFs) are used for the Wavelet transform (WT). The best suitable WF is determined by finding the Root Mean Square (RMS) difference and Signal to Noise Ratio (SNR) values.

SEMG signals can be characterized by a power spectrum density function because the signal is stochastically modelled as a zero mean coloured noise. The amplitude of the signal increases due to recruitment of MUs with increased muscle force [4, 5]. SEMG signal analysis can also provide the measurement from a muscle through out a sustained fatiguing contraction. In this research, mean power frequency is considered for the SEMG power spectrum analysis during load test to understand muscle contraction and determine fatigue.

Furthermore, this study exploits the use of Higher Order Statistics (HOS) in further efficient SEMG signal processing and analysis. HOS method is also applied for suppressing gaussian white noise within the signal. A fundamental means by which the probability theory can describe a random process is by means of the different order moments and cumulants. The first order moment or cumulant of any process indicates the mean of that process. The second order moment of that process indicates the autocorrelation, while its second order cumulant indicates the variance of that process. HOS starts from the 3^{rd} order to n^{th} order moment [6]. Along with other HOS measures, the bispectrum, a frequency-domain measure of third-order cumulants has been used in this research for the signal analysis to provide information about the signals' gaussianity and linearity. The Gaussianity test and linearity test of the normalized bispectrum shows changes in muscle contraction. The analysis also determines the effectiveness of the wavelet based denoising method.

Results in this study show that, wavelet based noise removal technique using WF db2 works best to remove interference noise from SEMG signals. The effectiveness was observed more clearly while analyzing the power spectrum properties of the SEMG signals. The bispectrum analysis also shows that SEMG becomes less gaussian and more linear with increased walking speed/force (increase in mean voluntary contraction). Moreover, this research proves that the power spectrum of EMG shows a shift to lower frequencies during fatigue.

2 Methodology

2.1 Experimental Setup

Two sets of different SEMG data files were considered for the experiment. The first set of SEMG signal was recorded from the left "biceps brachii" and the second set was recorded from the right "rectus femoris" muscle. The sample raw SEMG signals were collected from three normal subjects aged 22 to 40 at University Kebangsaan Malaysia (UKM). All analog channels were recorded at 1000 samples per second without any filter.

2.2 Algorithm Design

The two main algorithms applied in this research for the EMG signal processing and characterization are the WT and HOS.

2.1.1 Wavelet Denoising

Wavelets generally used for denoising biomedical signals include the Daubechies 'db2', 'db4' 'db5' 'db6' and 'db8' wavelets and orthogonal Meyer wavelet. In the case of SEMG, the wavelets are generally chosen whose shapes are similar to those of the MUAP [3, 7, 8].

Wavelet decomposition: The DWT is computed by successive low-pass and high-pass filtering in the discrete-time domain. The DWT of a signal x[n] is calculated by passing it through a series of filters. The outputs give the detail coefficients (from the high-pass filter, yhigh[n]) and the approximation coefficients (from the low-pass, ylow[n]). The filter outputs are then down-sampled as given by

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k].g[2n-k] \quad (1)$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k].h[2n-k] \quad (2)$$

respectively. For this research WFs Daubechies (db2, db4, db5, db6, db8), Symmlet (sym4, sym5), and orthogonal Meyer (dmey) are used for the decomposition. Four levels of decomposition is considered for the SEMG signals in this experiment

Threshold method: A threshold is determined for the raw EMG signal which is applied on the wavelet decomposition. The thresholding process of the wavelet coefficients is illustrated in Fig. 1.

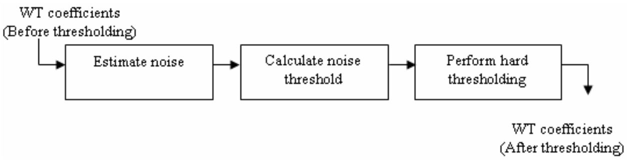

Fig. 1: Thresholding process on wavelet coefficients

Considering that the contaminated signal *f* equals the raw SEMG signal *s* plus the noise signal *n,* i.e. $f=s+n$. The thresholding is performed in following steps, where T_s is the signal threshold and T_n is the noise threshold [9]:

1. The energy of the original signal *s* is effectively captured, to a high percentage, by transform values whose magnitude are all greater than some threshold $T_s > 0$.
2. The noise signal's transform values all have the magnitudes which lie below some noise threshold T_n satisfying $T_n < T_s$.

Then the noise in *f* can be removed by thresholding its transform where all values of the transform whose magnitude lies below the noise threshold T_n are set equal to 0. This way of thresholding is called hard thresholding.

Wavelet reconstruction: An inverse transform is performed on the coefficients after thresholding, providing a good approximation of the EMG signal. The reconstruction is the reverse process of wavelet decomposition. For this research, four levels of wavelet decomposition/reconstruction is applied as mentioned earlier.

2.1.2 RMS Difference Calculation

The RMS difference, R of the contaminated signal *f[n]* compared with the denoised signal *s[n]* is defined by

$$R = \sqrt{\frac{(f_{[1]} - s_{[1]})^2 + .. + (f_{[N]} - s_{[N]})^2}{N}} \quad (3)$$

where *f* is the raw SEMG signal and *s* is the signal after denoising. *N* is the total number of samples (length of data). According to equation 3, the higher the RMS difference, the better the denoising performance of the WF.

2.1.3 SNR Calculation

The SNR is calculated by equation 4.

$$\mathrm{SNR} = 10\log_{10}(\mathrm{Xn/Xs}) \quad (4)$$

where, X_n is the variance for the noisy signal, and X_s is the variance for the denoised signal. According to equation 4, higher the value of (–db), the better the performance of the WF.

2.1.4 Higher Order Statistics

Bispectrum is obtained by the two-dimensional discrete Fourier transform of the 3rd order cumulant. Knowing the frequency components *X(k)* and *X(l)* of the output signal *x(k)*, the bispectrum $B_x(k,l)$ can be estimated by

$$B_x(k,l) = E\{X(k)X(l)X^*(k+l)\} \quad (5)$$

where *E{.}* donates the statistical expression, *k,l* are the discrete frequency components and * denotes the complex conjugate.

Bispectrum Estimation Process: Given a set of real observations (here the SEMG signal) {*x(n)*} for *n = 0, 1, 2, …. ,N-1,* where it is assumed that the data set is stationary [10,11, 12]. The algorithm for the bispectrum estimation is given in details in fig. 2.

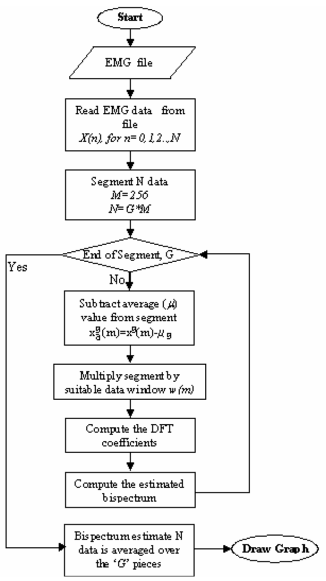

Fig. 2: Flow chart of bispectrum estimation

A common problem in signal processing is that the observed signal consists of a non-gaussian stationary signal in additive gaussian noise. Let us consider a mixture process which is the sum of two processes (gaussian and non-gaussian), as equation 6,

$$x(n) = e(n) + w(n) \quad (6)$$

where, *e(n)* is non-gaussian zero mean and *w(n)* is the gaussian white noise. Equation 6 can be represented in terms of power spectrum, $P^x(k)$ and bispectrum, $B^x(k)$ through equation 7 and 8 respectively.

$$P^x(k) = P^e(k) + P^w(k) \quad (7)$$

$$B^x(k,l) = B^e(k,l) + B^w(k,l) = B^e(k,l) = \gamma_3^e \quad (8)$$

where k and l are the frequency components. It is noted that bispectrum of a gaussian signal is zero and the resulting bispectrum of the modeled mixer signal gives the skewness (γ_3^e) value only. Therefore, additive noise has been suppressed in the output signal. Therefore, the bispectrum offers robustness to additive gaussian white noise.

Gaussianity and Linearity Tests: The normalized bispectrum gives the bicoherence. Bicoherence is the mixed function of the second and third order statistics and it is used to quantify the non-Gaussianity of a random process. Bicoherence, $B_n(k,l)$ is estimated by

$$B_n(k,l) = \frac{B_x(k,l)}{\sqrt{P(k)P(l)P(k+l)}} \quad (9)$$

where $B_x(k,l)$ is the bispectrum and *P(…)* is the power spectrum. The test of Gaussianity, S_g is based on the mean bicoherence power defined by

$$S_g = \sum |B_n(k,l)| \quad (10)$$

The Gaussianity test is mainly the zero-skewness test which determines whether or not the estimated bicoherence is zero. The linearity test determines whether or not the estimated bicoherence is constant in the bi- frequency (*k, l*) domain. It is the measurement of the difference (*dR*) between a theoretical and an estimated inter-quartile range *R* [13].

Power Spectrum Analysis: The power spectrum is obtained by fast Fourier transform (FFT) given in equation 12 during the bispectrum estimation process. Hanning window is used with a 256 point FFT. The mean power frequency pf is obtained by equation 11.

$$pf_{mean} = \frac{\int fPS(f)df}{\int PS(f)df} \quad (11)$$

where f is the denoised signal and PS is the power spectrum.

3 Result and Discussion

Wavelet denoising method is applied to SEMG signal at various muscle contraction/force stages (rest, light contraction, strong contraction and contraction with load for biceps brachii muscle) and at various walk styles/force (slow walking style, medium walking style, fast walking style, and very fast walking style for rectus femoris muscle). The mean power frequency and bispectrum was used to analyze the EMG signal to understand the muscle force and fatigue.

Kumar et. al [14] demonstrated that using wavelets, the differences between the EMG corresponding to fatigue muscle and non-fatigue muscles is highlighted in the power of the wavelet coefficients when using WFs symmlet4 (sym4) and symmlet5 (sym5). Ren et. al [8] used WF db5 to denoise EMG signal in their research. In this experiment the appropriate WF for EMG is chosen based on the calculated RMS difference and SNR values. The raw EMG signals were taken to calculate the RMS difference and SNR for the all WFs suitable for biomedical signal processing (db2, db4, db5, db6, db8, and dmey) including sym4, sym5, and db45 with four levels of decomposition. Table 1 and table 2 gives the results of the average RMS difference of the chosen WFs for the three subjects from the *"rectus femoris"* muscle at various contraction levels.

Table 1 **:** Average RMS differences of various WFs

WF/ Force	***Slow***	***Medium***	***Fast***	***V. Fast***	***Avg***
db2	0.023394	0.025761	0.036118	0.035513	0.03019
db4	0.023216	0.025692	0.035767	0.034624	0.02982
db5	0.023209	0.025558	0.035648	0.033597	0.02950
db6	0.023029	0.025532	0.035666	0.033161	0.02934
db8	0.023024	0.025156	0.036438	0.035398	0.03000
sym4	0.022986	0.025331	0.03521	0.032953	0.0291
sym5	0.022983	0.025398	0.033601	0.032748	0.02868
dmey	0.022282	0.024669	0.033562	0.03215	0.02816

Table 2 – Average SNR values of various WFs

WF/ Force	Slow	Medium	Fast	V. Fast	Avg
db2	-3.8504	-2.3722	-1.2662	-1.7506	-2.3098
db4	-3.2413	-2.3739	-1.288	-1.6904	-2.1484
db5	-3.7259	-2.3608	-1.2791	-1.5977	-2.2408
db6	-3.6403	-2.3506	-1.2792	-1.6004	-2.2176
db8	-3.6132	-2.2804	-1.359	-1.7989	-2.2629
sym4	-3.6201	-2.302	-1.233	-1.5662	-2.1803
sym5	-3.6075	-2.2977	-1.1191	-1.5075	-2.1329
dmey	-3.2128	-2.174	-1.1185	-1.5312	-2.0091

According to the results in Table 1, the considered WFs show similar kind of performance; however the daubechies WFs have higher RMS difference compared to WF sym4, sym5, and dmey. This means that daubechies (especially db2 from the average column in Table 1) WF's are capable of denoising SEMG signals better than other wavelet families; symmlet and orthogonal meyer. According to Table 2, the SNR values show a similar kind of results where the Daubechies WFs show better performance compared to the other WFs. But from the SNR values it is also observable that WFs db2 gives the best result.

Since WF db2 shows better performance from the results, therefore, it is considered for the SEMG signal denoising process.

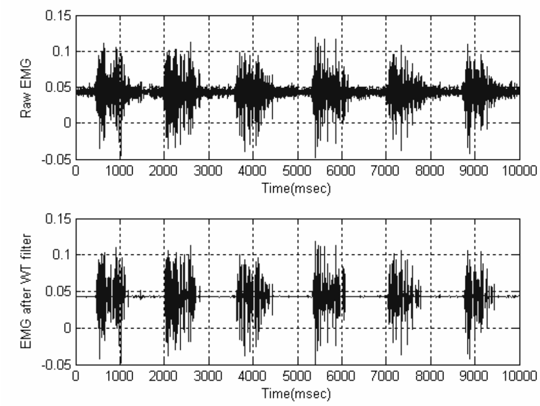

Fig. 3 gives the sample raw SEMG signal and its denoised signal. Figure 3 – Raw SEMG signal and denoised SEMG signal at WF db2 at four level of decomposition

According to the study by Hagberg and Ericson, mean power frequency is lower at low contraction levels when compared with high contraction levels [15]. Moritani et al. also obtained similar results where significant increase in SEMG amplitude and mean power frequency were found with increasing force [16]. It is also shown that during muscle fatigue, the power spectrum of SEMG shows a shift to lower frequencies [3, 17]. Mean/median frequency is used to quantify this shift. Fig. 4 shows the mean power frequency of SEMG signal for the three subjects at the various muscle contraction stages using WF db2. Results obtained by this research that there was significant increase in the mean power frequency with increase of muscle force as in [15, 16]. Fatigue was also noticed by observing a shift to lower frequencies in the power spectrum as in [17].

For this experiment, SEMG signal was captured from "rectus femoris" muscle at the following force levels/walking styles: slow walk, medium walk, fast walk, and very fast walk. Results for a subject at the mentioned force level are presented in this paper using bispectrum analysis for two cases; a. SEMG signal with wavelet denoising, b. without wavelet denoising. The results are obtained from the Gaussianity tests of the raw signal using only bispectrum, and the signal using bispectrum after the noise removal technique. The results for the Gaussianity tests are given in Fig. 5 for a subject during the walking trial.

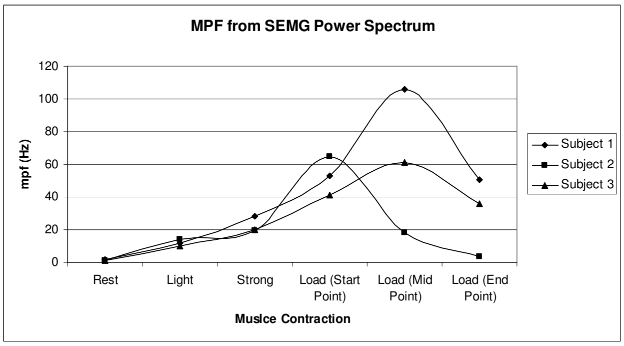

Figure 4 – Mean power frequency of SEMG signal for the three subjects at the various muscle contraction stages using WF db2 (biceps brachii)

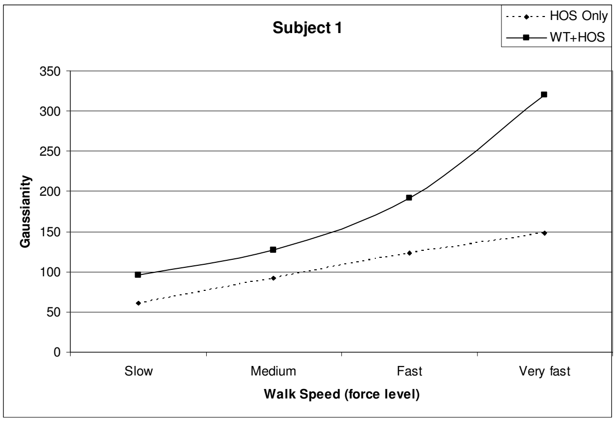

Figure 5 – Gaussianity tests of a subject during walking trail using HOS only and WT plus HOS

Bispectrum analysis was also used by Kaplanis and Pattichis [13] for analyzing the “Biceps Brachii” muscle. It is reported that SEMG becomes less Gaussian and more linear on increasing mean voluntary contraction (MVC). Other research using HOS also showed similar results where SEMG becomes less gaussian with increased muscle contraction due to load [4, 11, 12]. The results for the linearity test for the three subjects are given in Fig. 10.

According to Fig. 6, it is demonstrated that the signals become more linear with increased walk speed/muscle force. The linearity tests show same pattern as the Gaussianity tests which is the reverse pattern for the trial. Results obtained by this research explain that the signal becomes less gaussian as in [11, 12, 13] and more linear as in [12, 13] with increased force. The dotted lines in Fig. 5 represents the change of gaussianity for the raw signals applying HOS only and the solid lines demonstrated the gaussianity for the signal after noise removal applying WT and HOS. The raw signal and denoised signal show similar characteristics where both SEMG signals become less gaussian from “slow” walking style to “very fast” walking style. The important thing to notice from the Fig. 5 is that, the signals after denoising is less gaussian compared to the other signal using only HOS. This indicates that the wavelet based denoising method using WF db2 effectively filtered interference noise. Furthermore, additive noise (Gaussian white noise) present in the EMG signal is suppressed in the bispectrum of the output signal. MUAPs have been estimated in Fig. 7 for “rectus femoris” muscle for a subject.

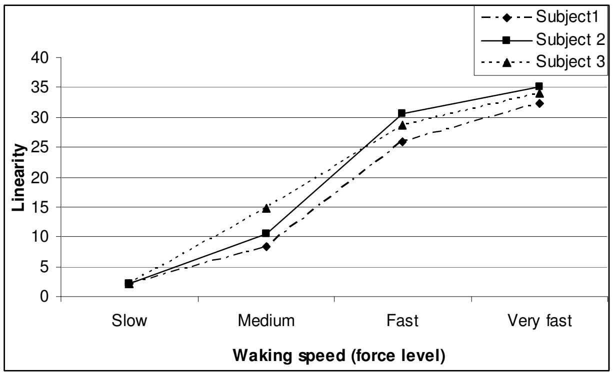

Figure 6 – Linearity tests for three subjects during walking trail using WT and HOS

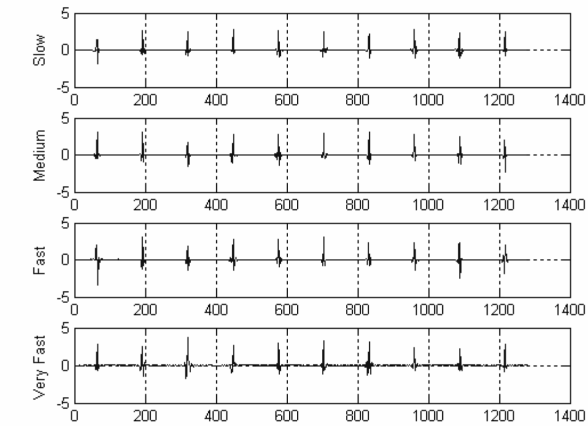

Figure 7 – Output signal of “rectus femoris” during walk for a subject using bispectrum

4 Conclusion

In this research, WT is successfully applied for denoising SEMG signal and HOS is also able to suppress Gaussian white noise. So, both the techniques were suitable for SEMG signal processing, which filtered recording noise (denoise) and remove Gaussian noise effectively. Results show that WF db2 can denoise EMG signal most effectively among the other WFs. The study also shows that increase in the muscle contraction level (from low contraction level to high contraction level) provides significant increase in SEMG mean power frequency demonstrating changes in the MUs recruitment. Moreover, power spectrum of SEMG shows a shift to lower frequencies during fatigue. Bispectrum analysis shows that the signal becomes less Gaussian and more linear with increasing muscle force.

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