

## Wavelet Denoising and Surface Electromyography Analysis

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**Abstract:** In this research, Surface Electromyography (SEMG) signal analysis from the right rectus femoris muscle is performed during walk. Wavelet Transform (WT) has been applied for removing noise from the surface SEMG. Gaussianity tests are conducted to understand changes in muscle contraction and to quantify the effectiveness of the noise removal process. Results show that the proposed method can effectively remove noise from the raw SEMG signals for further analysis.

**Keywords:** Denoising, gaussianity, SEMG, wavelet transform

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### INTRODUCTION

Electromyography (EMG) signal represents the electrical activity of muscles. A muscle is composed of Many Motor Units (MUs). EMG signals detected directly from the muscle or from the skin by using surface electrodes, respectfully, show a train of Motor Unit Action Potentials (MUAP) plus noise (Basmajian and De Luca, 1985; Hussain *et al.*, 2009). With increasing muscle force, the raw EMG signal shows an increase in the number of MUAP recruited at increasing firing rates, resulting in the Interference Pattern (IP). The firing pulses are normally considered a random function of time, which is non-Gaussian in nature (Kaplanis *et al.*, 2000; Reaz *et al.*, 2006). Quantitative analysis of the IP is useful in the diagnosis of neuromuscular disorders. In the past years, several computer-aided techniques for IP analysis have been proposed such as turns amplitude analysis, decomposition methods and power spectrum analysis. It is difficult to obtain high-quality electrical signals from EMG sources because the signals typically have low amplitude (in range of mV) and are easily corrupted by noise. The simplest way method of removing narrow bandwidth interference from recorded signal is to use a linear, recursive digital notch filter. But the disadvantage of the notch filter is that, it distorts the signal (Mewette *et al.*, 2001).

Wavelet-based noise removal is performed in this research for the EMG signal analysis. Wavelet denoising (noise removal) has already been used in denoising a number of physiological signals and other kind of signals (Carre *et al.*, 1998; Reaz *et al.*, 2007; Akter *et al.*, 2008; Reaz and Wei, 2004; Hasan *et al.*, 2009). This method is preferred over signal frequency domain filtering because it can maintain signal characteristics even while reducing noise. This is because a number of threshold strategies are

available, allowing reconstruction based on selected coefficients. Wavelet Functions (WFs) Daubechies (db) 6 is used for the WT.

In this research, bispectrum analysis, a particular form of Higher-Order Statistics (HOS), is introduced for analyzing SEMG signals. The Gaussianity test shows the changes in muscle contraction during walk and also determines the effectiveness of the wavelet based denoising method.

Results in this study also show that, SEMG becomes less Gaussian with increase of MVC. The wavelet based noise removal technique is also able to remove noise effectively from raw SEMG signals. The signal after denoising is free from random noise (random noise with a mean value of zero), which enhances the bispectrum analysis.

### DESIGN METHODOLOGY

For this experiment, 5 separate EMG data files were used. The sample raw EMG signals of a subject from University Kebangsaan Malaysia are used for the simulation of the algorithm. SEMG was recorded from the right "rectus femoris" muscle of a normal subject aged 22. All analog channels are recorded at 1000 samples per sec. SEMG signal was captured during the subjects walking trial where the subject increased the walking speed/force with time.

These SEMG signals were denoised using Discrete Wavelet Transform (DWT) and a threshold method. The DWT and threshold based denoising was implemented using MATLAB Wavelet toolbox. Bispectrum was estimated to estimate the muscle contraction at various muscle contraction stages. Figure 1 shows the flow of the algorithm.



Fig. 1: Wavelet based denoising and bispectrum analysis 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 (Mewette *et al.*, 2001; Mark, 2000).

**Wavelet decomposition:** The WT decomposes a signal into several multi-resolution components according to a basic function called the wavelet function. 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 (subsampling) operations. The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal.

**Threshold method:** Suppose that the contaminated signal  $f$  equals the SEMG signal  $s$  plus the noise signal  $n$ . The threshold method is applied as followed:

- The energy of the original signal  $s$  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  $f$  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.

**Signal reconstruction:** An inverse transform is performed, providing a good approximation of  $f$ . The reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain and the original signal.

**Bispectrum analysis:** The two-dimensional discrete-time Fourier transform of the 3<sup>rd</sup> order cumulant gives the Bispectrum. Knowing the frequency components,  $X(k)$ , of the output signal  $x(k)$ , the bispectrum,  $B_x(k, l)$ , can be estimated using Eq. (1):

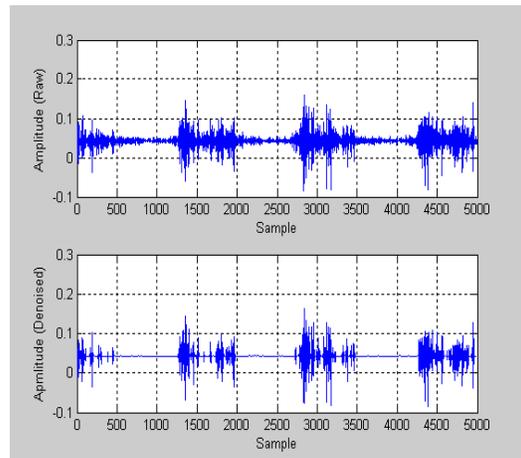


Fig. 2: Noisy raw SEMG from “rectus femoris” muscle (top) and result of wavelet denoising performed using the ‘db6’ wavelet with 4 levels of decomposition (bottom)

$$B_x(k, l) = E\{X(k)X(l)X^*(k+l)\} \tag{1}$$

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

To quantify the non-Gaussianity of a random process, the normalized bispectrum gives the bicoherence. The Gaussianity test basically involves whether or not the estimated bicoherence is zero. Equation (2) gives the bicoherence:

$$B_n(k, l) = \frac{B(k, l)}{\sqrt{P(k)P(l)P(k+l)}} \tag{2}$$

where,  $P(.)$  is the power spectrum.

The Gaussianity test,  $S_g$  (actually zero-skewness test) basically involves deciding whether or not the estimated bicoherence is zero. The bispectrum analysis was performed with MATLAB 6.5 (Mathworks Inc). A window of 256 point and 0.51 smoothening was used for the bispectrum analysis. The analysis for the Gaussianity test was accepted if the probability false alarm was less than 5%.

## RESULTS AND DISCUSSION

Any of the WFs (db2, db6, db8 and dmey) are effective for noise removal in the case of SEMG based on

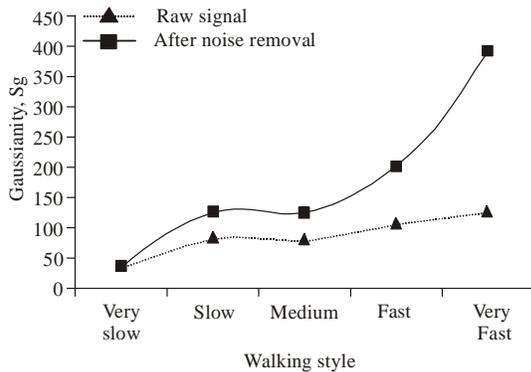


Fig. 3: Change of Gaussianity,  $S_g$  during walk with increasing force

(Mewette *et al.*, 2001; Mark, 2000). In this experiment WF db6 is chosen and found to be effective for noise removal. Figure 2 illustrates a sample raw SEMG signal and the signal after denoising using db6 with 4 levels of decomposition.

Kaplanis *et al.* (2000) also used Bispectrum analysis for analyzing the “Biceps Brachii” muscle (Kaplanis *et al.*, 2000). It is reported that SEMG becomes less Gaussian on increasing Mean Voluntary Contraction (MVC). Other research works using HOS showed that MUAP waveform increased according to increase in load weight where there is no involvement of Motor Units (MUs) in the resting muscle (Yana *et al.*, 1995).

Results contained by this research shows that the signal becomes less Gaussian with increased force as in (Basmajian and De Luca, 1985). The results obtained by the Gaussianity tests for the raw SEMG signals and denoised signals are illustrated in Fig. 3. The dotted line in the figure represents the change of Gaussianity for the raw signals and the solid line demonstrated the Gaussianity for the signal after noise removal. The raw and denoised signal show similar results where both SEMG signals become less Gaussian with from the “very slow” walking style to “very fast”. In the walking trial the shape of the MUAP increased because of the increasing walk force as in (Yana *et al.*, 1995). The important thing to notice from the figure is that, the signals after noise removal is more non-Gaussian than the raw SEMG signals. This indicates that the denoising method effectively removed unwanted noise from the signals.

HOS can suppress Gaussian noise from the SEMG signals. The shape of the MUAP can be also be estimated through HOS based reconstruction algorithm. To characterize the behavior of MUAP the denoising method will be effective since it can remove random noise before the bispectrum analysis.

### CONCLUSION

Wavelet denoising methods have already been successfully used in other biomedical signal processing.

It is expected to provide a powerful compliment to conventional noise-removal techniques like notch filters and frequency domain filtering methods, which will be very effective for bispectrum analysis and MUAP shape estimation.

### REFERENCES

- Akter, M., M.B.I. Reaz, F. Mohd-Yasin and F. Choong, 2008. Hardware implementations of an image compressor for mobile communications. *J. Commun. Technol. E+*, 53(8): 899-910.
- Basmajian, J.V. and C.J. De Luca, 1985. *Muscles Alive-The Functions Revealed by Electromyography*. The Williams and Wilkins Com., Baltimore.
- Carre, P., H. Leman, C. Fernandez and C. Marque, 1998. Denoising of the uterine EHG by an undecimated wavelet transform. *IEEE T. Biomed. Signal Process.*, 45(9): 1104-1114.
- Hasan, M.A., M.B.I. Reaz, M.I. Ibrahimy, M.S. Hussain and J. Uddin, 2009. Detection and processing techniques of FECG signal for fetal monitoring. *Biol. Proced. Online*, 11(1): 263-295.
- Hussain, M.S., M.B.I. Reaz, F. Mohd-Yasin and M.I. Ibrahimy, 2009. Electromyography signal analysis using wavelet transform and higher order statistics to determine muscle contraction. *Expert Syst.*, 26(1): 35-48.
- Kaplanis, P.A., C.S. Pattichis, L.J. Hadjileontiadis and S.M. Panas, 2000. Bispectral analysis of surface EMG. 10th Mediterranean Electrotechnical Conference, Cyprus, 2: 770-773.
- Mark, P.W., 2000. Wavelet-based noise removal for biomechanical signals: A comparative study. *IEEE T. Biomed. Eng.*, 47(3): 360-368.
- Mewette, T.D., N. Homer and J.R. Karen, 2001. Removing Power Line Noise from Recorded EMG. *Proceedings of the 23<sup>rd</sup> Annual International Conference, Istanbul, Turkey*, 3: 2190-2193.
- Reaz, M.B.I. and L.S. Wei, 2004. Adaptive Linear Neural Network Filter for Fetal ECG Extraction. *Proceedings of International Conference on Intelligent Sensing and Information Processing, ICISIP 2004*, pp: 321-324.
- Reaz, M.B.I., M.S. Hussain and F. Mohd-Yasin, 2006. Techniques of EMG signal analysis: Detection, processing, classification and applications. *Biol. Proced. Online*, 8(1): 11-35.
- Reaz, M.B.I., F. Choong, M.S. Sulaiman and F. Mohd-Yasin, 2007. Prototyping of wavelet transform, artificial neural network and fuzzy logic for power quality disturbance classifier. *Elect. Pow. Components Syst.*, 35(1): 1-17.
- Yana, K., H. Mizuta and R. Kajiyama, 1995. Surface electromyogram recruitment analysis using higher order spectrum. *IEEE 17th Annual Conference on Engineering in Medicine and Biology Society, Montreal, Canada*, 2: 1345-1346.