Proceedings of the 26th Annual International Conference of the IEEE EMBS
San Francisco, CA, USA • September 1-5, 2004

Wavelet Analysis of Surface Electromyography Signals

J. Kilby, H. Gholam Hosseini

Electrotechnology Department, Auckland University of Technology, Private Bag 92006, Auckland 1020, New Zealand

Abstract—**A number of Digital Signal Processing (DSP) techniques are being applied to Surface Electromyography (SEMG) signals to extract detailed features of the signal. Fast Fourier Transform (FFT) is one of the most common methods for analyzing the signal whether it is filtered or not. Another DSP technique is referred to as Wavelet analysis, a method that is gaining more use in analyzing SEMG signals. This research focuses on using the Discrete Wavelet Transform (DWT) and the Wavelet Package Transform (WPT). Both DWT and WPT use analytical wavelets called "mother wavelet," which comes in different sets or "families." Wavelet analysis has the advantage over FFT as it provides the frequency contents of the signal over the time period that is being analyzed.**

SEMG signals were collected from a muscle under sustained contractions for 4 seconds with different loads. The raw signals were analyzed using FFT, DWT and WPT in LabVIEW® using its Signal Processing Toolset. Using Wavelet analysis the SEMG signal was decomposed into its frequency content form and then was reconstructed.

In this paper the results are presented to show that certain families of mother wavelets of Wavelet analysis are more suitable than others for analyzing SEMG signals.

Keywords—**Discrete Wavelet Transform, Electromyography Analysis, Surface Electromyography, Wavelet Package Transform**

I. Introduction

Surface electromyography (SEMG) signals are collection of electrical activities obtained at the surface of the skin which represent the neuromuscular activities of the examined muscle they originate from [1]. The amplitude characteristics of SEMG have a random behavior with no periodic form in the wave pattern as there is in the electrocardiography (ECG) signals [2]. The amplitudes of these signals can range from 0 to 10 mV_{pp} or 0 to 1.5 mV_{rms}. The usable frequency range of the signal is between 0 to 500 Hz [3].

A number of digital signal processing methods have been applied to the SEMG signals but the more popular methods include Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT) and Wavelet Package Transform (WPT).

By using FFT, the frequency spectrum of any signals, including SEMG, are clarified and recognized by breaking down the signal into its corresponding sinusoidal of different frequencies.

When analyzing non-stationary signals such as the SEMG, there is a drawback with using FFT as it is unable to determine when a particular frequency content of the signal takes place in time [1, 4]. Wavelet analysis is becoming more common in digital signal processing method for analyzing SEMG signals.

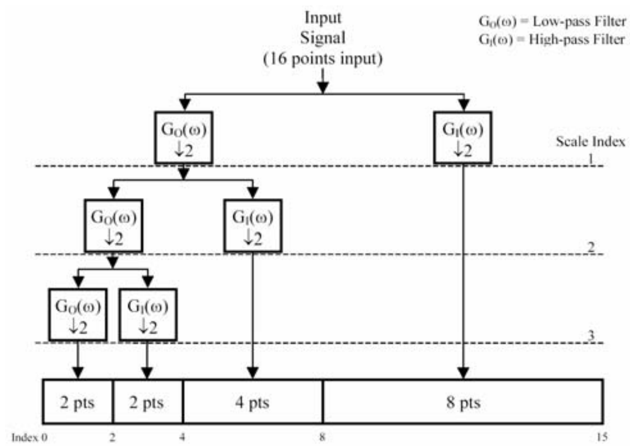

Fig. 1. Path structure of digital signal processing by the DWT analysis to scale index 3.

The level of decomposition or analysis to show the frequency content of a signal by both DWT and WPT is referred to as "scale index."

The DWT acts as a bank of low-pass $G_O(\omega)$ and high-pass $G_I(\omega)$ filters that decompose a signal into multiple signal bands. It separates and retains the signal features in one or a few sub-bands as shown in Fig. 1. The level of decomposition shown in Fig. 1 is to scale index 3 and shows the sub-banding obtained from a discrete signal that has 16 samples. This sub-banding of the DWT is variable, which means the feature of band varies such that the frequency resolution is proportional to the center frequency. This sub-banding has been shown to be more appropriate for many physical signals, but the partition is still fixed.

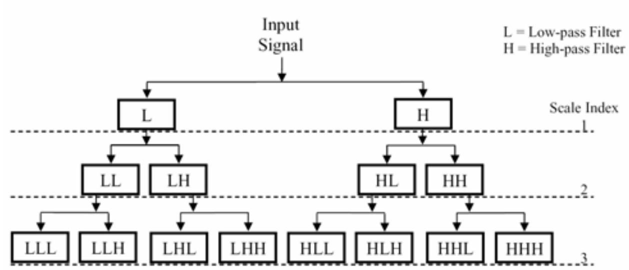

Fig. 2. Tree-like structure of digital signal processing by the WPT analysis to scale index 3.

The WPT provides a selective sub-banding which is the best for a given part of signals selected as shown in Fig. 2. The selective banding in WPT is determined by the order of low-pass and high-pass filtering from a tree-like structure using these filters [5]. For example, at scale index 3 the box labeled LHL shows the order of filtering that was used to obtain the output. In this case the signal would have been analyzed, firstly using the low-pass filter, secondly the high pass filter and finally analyzed using the low-pass filter to obtain the final output.

One of the biggest advantages of using DWT and WPT is that signal features can be easily extracted. In many cases, both DWT and WPT outperform the conventional FFT when it comes to extraction feature and noise reduction. The DWT and WPT have also many applications in data compression, pattern recognition, speech recognition, texture analysis and image compression.

Using both DWT and WPT give the ability to determine certain frequency contents in the time domain and also perform local analysis of a larger signal, reveal the trends, breakdown points and discontinuities of the signals.

Compared to FFT that gives the frequency spectrum of the signal, the DWT and WPT give frequency contents of the signal in the time domain by applying a shorter window to the higher frequency contents of the signal.

II. METHODOLGY

The raw signals were collected from a healthy subject by placing the surface electrodes on the skin over the biceps brachii muscle. This muscle was placed under sustained isometric contractions for four seconds with different loads ranging from 5 kg, 10 kg, 15 kg to a maximum load the subject can withstand. The data was collected using a Grass P511 AC amplifier. The obtained SEMG signals were band-pass filtered (5 to 500 Hz) and amplified by a gain factor of 1000 and then sampled at a sampling frequency of f_s= 1024 Hz with 12-digitizing bits. These signals are then analyzed using LabVIEW® software with the add-on signal processing toolset feature. Virtual instruments (VIs) were built using the graphical programming language G within LabVIEW® version 6.1 [6] to process and analyze these signals using FFT, DWT and WPT.

The Wavelet analysis performs by a function called analytical wavelet or "mother wavelet." There are five families or sets of mother wavelets in LabVIEW® which differ in their mathematical principles named as Daubechies (db02 to db14), Biorthogonal (various), Coiflets (coif1 to 5), Haar and Symmlets (sym2 to 8).

Both DWT and WPT were employed up to a scale index of 5 and only the low-pass filter path of WPT were considered for analyzing of the signal as shown in Fig. 2.

Each mother wavelets available within LabVIEW® were used to decompose the SEMG signals and reconstruct them back by the inverse Wavelet analysis. The reconstructed signals were then subtracted from the original signals to obtain errors in order to perform statistical analysis of the results.

III. RESULTS

The results shown in Fig. 3 to Fig. 5 and Fig. 8 were obtained by designing a number of different VIs in LabVIEW®.

Fig. 3 shows the raw SEMG signal of 5 kg load and its frequency spectrum using the FFT analysis. Although the SEMG signal collected for analysis was filtered before being digitally processed by LabVIEW® at 5 to 500 Hz, the FFT still showed some frequencies below 5 Hz. This is due to the external electronic circuits not being able to filter out the low frequencies of the signal perfectly.

Fig. 4 shows the SEMG signal of the 5 kg load and the DWT output analysis obtained. The wavelet analysis was set at scale index 4 using Daubechies db02 mother wavelet and the sub-banding of the output is shown by the dotted lines.

Fig. 5 shows the WPT output wavelet analysis using Daubechies db02 mother wavelet of the 5 kg load SEMG

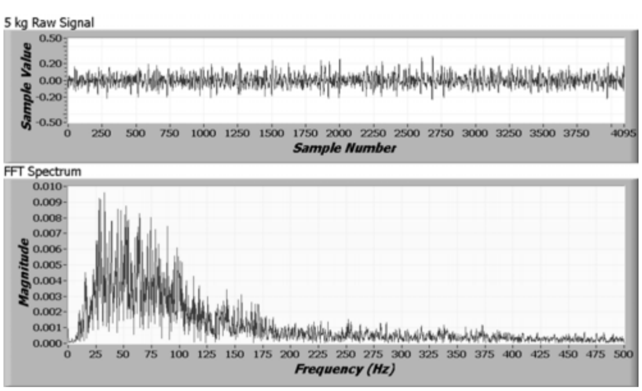

Fig. 3. Raw signal of the 5 kg load (top).
Frequency spectrum by FFT of the 5 kg load (bottom).

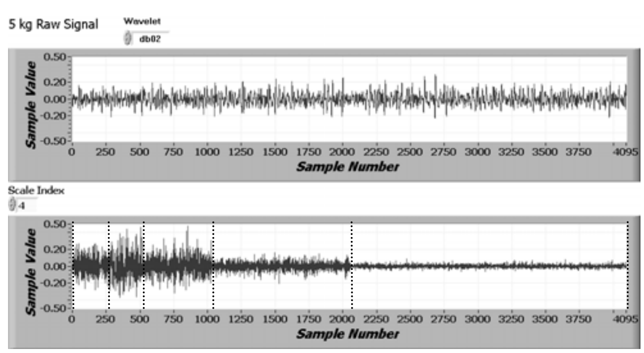

Fig. 4. Raw signal of 5 kg load (top).
The DWT set at scale index set at 4 using Daubechies db02 mother wavelet of the 5 kg load (bottom). The sub-banding of the output is shown by the dotted lines

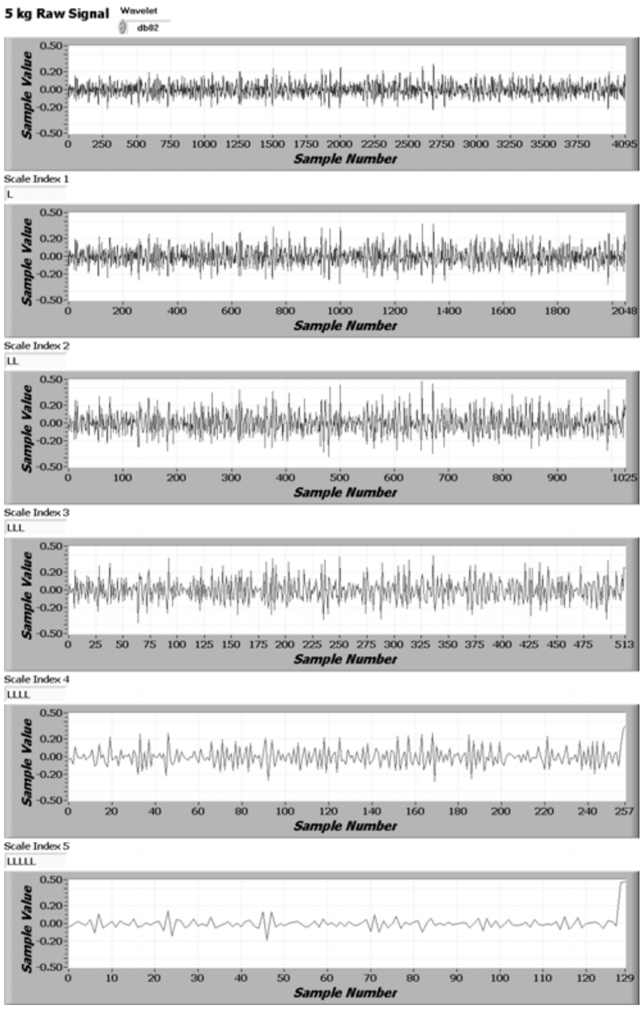

Fig. 5. Raw signal of 5 kg load (top).
The WPT output wavelet analysis using Daubechies db02 mother wavelet of the 5 kg load from scale index 1 to 5 using the low-pass filter path only (second from the top to bottom).

TABLE I.
THE VARIANCE OF ERROR VALUES FOR THE VARIOUS WAVELET FAMILIES

Daubechies		Biorthogonal		Haar		Coiflet		Symmlet	
	Variance		Variance		Variance		Variance		Variance
db02	1.73E-09	bior1_3	1.59E-09	Haar	1.76E-09	coif1	1.68E-09	sym2	1.73E-09
db03	1.74E-09	bior1_5	1.84E-09			coif2	1.65E-09	sym3	1.74E-09
db04	1.72E-09	bior2_2	2.15E-09			coif3	1.69E-09	sym4	1.71E-09
db05	1.64E-09	bior2_4	1.92E-09			coif4	1.70E-09	sym5	1.76E-09
db06	1.77E-09	bior2_6	1.97E-09			coif5	2.06E-09	sym6	1.72E-09
db07	1.67E-09	bior2_8	2.02E-09					sym7	1.66E-09
db08	1.76E-09	bior3_1	5.71E-09					sym8	1.68E-09
db09	1.69E-09	bior3_3	3.71E-09						
db10	1.71E-09	bior3_5	2.84E-09						
db11	1.75E-09	bior3_7	2.63E-09						
db12	1.72E-09	bior3_9	2.69E-09						
db13	1.77E-09								
db14	1.76E-09								

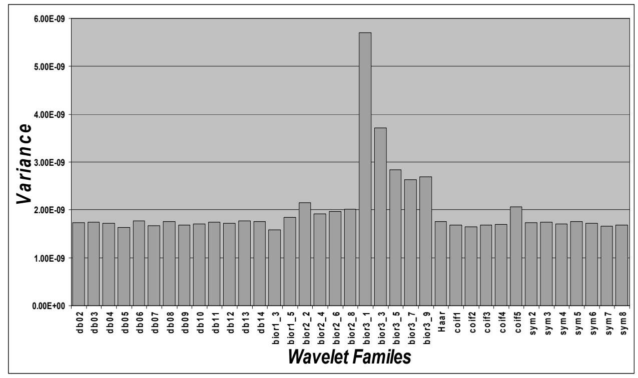

Fig. 6. Bar chart showing the variance of the errors for the various families of mother wavelets using the 5 kg load signal.

signal at scale indexes 1 to 5 using the low-pass filter path only.

The variance of the errors of the various families of mother wavelets for the statistical analysis are shown in the Table I. Fig. 6 shows a bar chart of these error variances. Findings from the statistical results indicated that Daubechies db05 is the most suitable mother wavelet for analyzing SEMG signals. Fig. 7 shows the original, the reconstructed and the errors between the two signals for the 5 kg load. It was found that the scale index of 5 does not contain useful information. Therefore, the scale index was set at 4 with mother wavelet Daubechies db05.

Fig. 8 shows the WPT analysis of 5 kg, 10 kg, 15 kg and maximum load signals at scale index 4 of the low pass filter analysis using Daubechies db05.

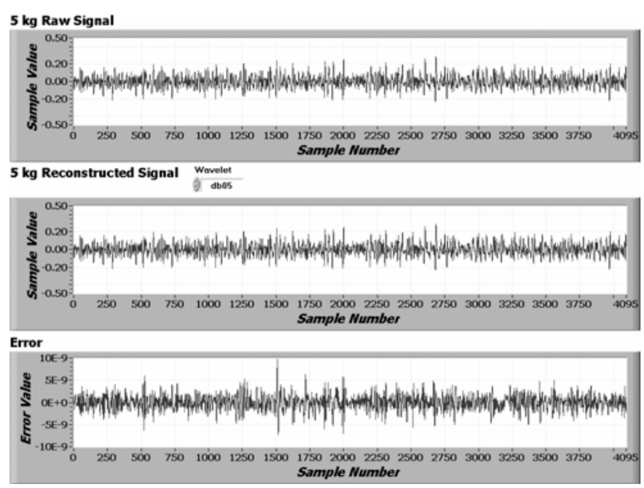

Fig. 7. Raw signal of 5 kg load (top).
Reconstructed signal from scale index 4 using Daubechies db05 using the low-pass filter path only (middle)
Error between original and reconstructed signals (bottom).

IV. DISCUSSION

Comparing the variance of errors from the five different wavelet families readily available within LabVIEW®, Daubechies and Symmlet wavelets present the most consistent level of errors. The variance of errors using Coiflet wavelet was consistent for coif1 to coif4, but was extreme for coif5. The variance of errors varied greatly from wavelet to wavelet within the Biorthogonal family. As for the Haar, there was only one Wavelet to employ for the signal analysis.

Therefore the ones that can be used for future analysis of SEMG signals could be Daubechies, Symmlet or Coiflet (coif1 to coif4) families.

We performed WPT decomposition of the SEMG signals for the 5 kg, 10 kg, 15 kg and the maximum load using db05 Wavelet. It was found that the most useful data for characterizing the SEMG signals could be obtained at the scale index of up to 4 and using the low- pass filter path only. Any greater scale indexes of decomposition did not produce any meaningful information for this purpose. Comparing all four decomposed signals as shown in Fig. 8, it may be possible to characterize regions within the signals that are similar in pattern but different in amplitude. These regions may be of importance to determine what the muscle is doing at a particular moment in time.

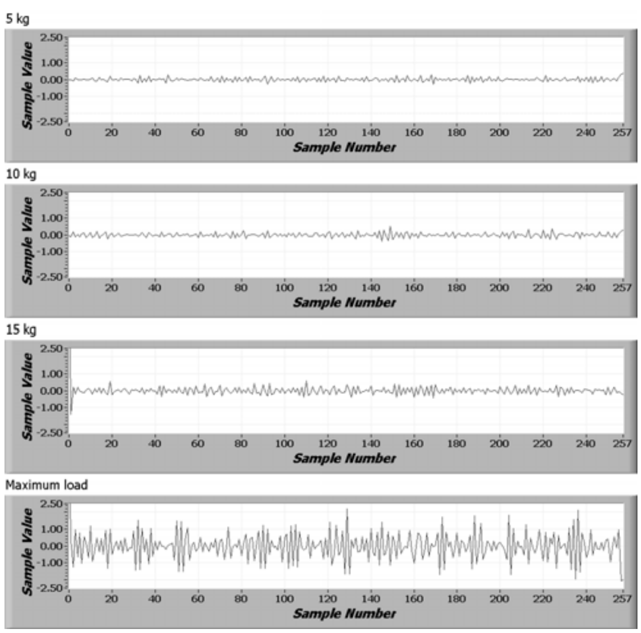

Fig. 8. The WPT of the 5 kg, 10 kg, 15 kg and maximum load signals set at scale index 4 using Daubechies db05 mother wavelet and the low-pass filter path only.

V. CONCLUSION

Digital processing of SEMG signals is a complex process. The FFT gives a picture of the frequency content of the signal but it is not related to time, while the DWT and WPT provide more detailed information by applying a shorter window to the higher frequency contents of the signal. Thus the Wavelet analysis of the SEMG signals can be performed at certain scale index to study the activity of muscles within the time window. The future work in utilizing these results will be such as building further reference or database for muscle responses under different loads using Artificial Neural Network techniques. There are other mother wavelets such as Morlet, Mexican Hat and Meyer, which have not been considered in this study, as they are not available within the LabVIEW® signal processing toolset. These wavelets can be used for further investigation once they are programmed or incorporated within the software.

ACKNOWLEDGMENT

The authors acknowledge the assistance given by Professor Peter McNair and Grant Mawston from the Physical Rehabilitation Research Centre, School of Physiotherapy at Auckland University of Technology for supplying the SEMG signals used in this paper.

REFERENCES

[1] R. Constable and R. J. Thornbill, “Using the Discrete Wavelet Transform for Time-Frequency Analysis of the Surface EMG Signal,” *ISA, vol. 16*, pp. 121-127, 1993.

[2] J. A. Crowe, N. M. Gibson, M. S. Woolfson, and M. G. Somekh, “Wavelet Transform as a Potential Tool for ECG Analysis and Compression,” *Journal of Biomedical Engineering,* vol. 14, pp. 268-273, 1992.

[3] C. J. De Luca, “The Use of Surface Electromyography in Biomechanics,” *Journal of Applied Biomechanics,* vol. 13, pp. 135-163, 1997.

[4] S. Karlsson and B. Gerdle, “Mean frequency and signal amplitude of the surface EMG of the quadriceps muscles increase with increasing torque - a study using the continuous wavelet transform,” *Journal of Electromyography and Kinesiology*, vol. 11, pp. 131-140, 2001.

[5] P. J. Sparto, J. M. Jagadeesh, and M. Parnianpour, “Wavelet Analysis of Electromyography for Back Muscle Fatigue Detection During Dynamic Constant-Torque Exertions,” *ISA, vol. 15,* pp. 82-87, 1997.

[6] *Signal Processing Toolset User Manual*. Austin, Texas: National Instruments Corporation, 2002. pp 11-1-11-20.