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Extracting Effective Features of SEMG Using Continuous Wavelet Transform

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Abstract—**To date various signal processing techniques have been applied to Surface Electromyography (SEMG) for feature extraction and signal classification. Compared with traditional analysis methods which have been used in previous application, Continuous Wavelet Transform (CWT) enhances the SEMG features more effectively. This paper presents methods of analysing SEMG signals using CWT and LabVIEW for extracting accurate patterns of the SEMG signals. We used the scalogram and frequency-time based spectrum to plot the power of the wavelet transform and enhance the diagnosis features of the signal. As a result, clinical interpretation of SEMG can be improved by extracting time-based information as well as scales, which can be converted to frequencies. Using the extracted features of the dominant frequencies of the wavelet transform and the related scales, we were able to train and validate an Artificial Neural Network (ANN) for SEMG classification.**

I. Introduction

An accurate and computationally efficient means of classifying surface electromyography signal patterns have been the subject of considerable research efforts in recent years where having effective signal features is crucial for reliable classification [1]. Numerous research and studies have concentrated on feature extraction and pattern recognition in the field of bio-medical signal or bio-signal processing and achieved tremendous contribution to the facilities developed for the signal analysis in the clinical field today.

Recently, a simple method based on wavelet packet transform has been proposed to extract the features of SEMG named relative wavelet packet energy. These features are evaluated from several selected frequency bands of the signal. Wavelet transform represents different patterns of SEMG signal more accurately and improves the accuracy of signal classification [2].

With computers and software becoming more and more powerful tools to process complex algorithms on numerous data at high speed, the advancement in digital signal processing applied to bio-signals is an inevitable one and ongoing. Software such as MATLAB and LabVIEW are well known for their use in mathematical processing and virtual instrumentation for laboratory requirements. They are commercially available where both have built-in functions or tools for signal processing.

In signal processing, determining the frequency content of a signal by FFT is one of the main aspects in feature extraction and understanding the characteristics of a signal. However, obtaining the frequency content alone is not sufficient for analysing bio-signals due their non-stationary in nature [3]. FFT loses the time information after transforming time-based signal to frequency-based signal.

It is an essential and in the interest of analysing a bio-signal to obtain 'time-based' information of when a particular frequency content occurs [3], [4]. Short Time Fourier Transform (STFT) is a method capable of achieving this so called the time-frequency content or the time-frequency based representation. However CWT allows more detailed analysis and better time-frequency resolution of the SEMG signals.

II. Experimental Setup

A. Subjects

Thirty-four healthy volunteers with no previous history of knee or severe musculoskeletal injury (30 males and 4 females, age 18-35 years) participated in this study. The data collection was approved by the Auckland University of Technology Ethics Committee (AUTEC) and was performed after each subject had given their written consent.

B. Methods

After a general warm-up, the subject was seated on the Biodex System 3 Pro dynamometer (Biodex Medical, Shirley, NY, USA) with the upright chair set at 110 degrees and one of their knees bent to 90 degrees. The load cell lever arm was attached to the chair that measured voluntary isometric force of the quadriceps (Fig. 1).

The subject then performed a specific warm-up and familiarisation of the experimental setup. The subject was then rested for 3 minutes before the actual maximal strength test to obtain Maximum Voluntary Isometric Contraction (MVIC) of the quadriceps.

The MVIC force or 100% maximal force of the leg quadriceps was executed by having the subject to push against the load cell lever in the direction shown by the arrow in Fig. 1. Three MVICs were measured and recorded for a 10 second period. There was a two-minute rest period between each MVIC test and the highest MVIC was selected for analysis. Following the maximal strength tests, participants performed the sustained force production test.

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Fig. 1: A subject executing strength test to obtain Maximum Voluntary Isometric Contraction (MVIC) of the quadriceps.

This test was executed by having the subject push the load cell lever for 25%, 50%, and 75% of their maximum or MVIC force.

The subject was required to perform and sustain the isometric contraction of the quadriceps for a given force level for a period of 10 seconds. A two-minute rest period was given between each of the force levels.

EMG signals were obtained from the vastus lateralis and the vastus medialis muscles of both legs. The signals were recorded by a bipolar isolated amplifier using a Grass P511 AC amplifier (Grass Instruments Co. MA, USA) with a CMMR > 90 dB, input noise < 4 μV peak to peak. The electrodes were placed according to the set of recommendations published by Surface Electromyography for Non-invasive Assessment of Muscle (SENIAM) [5]. The reference electrode was attached to an area with no muscle tissue below the knee.

Signals from the EMG amplifier and the dynamometer were acquired simultaneously by a multifunction data acquisition board NI PCI-6024E (National Instruments Corporation, Austin, Texas, USA) with LabVIEW software (National Instruments Corporation, Austin, Texas, USA) for raw data acquisition on a host personal computer. Recorded signals were converted by an analogue-to-digital converter with 12 bit accuracy in the ± 5 V range and sampled at 2048 Hz. Before sampling, the signals were filtered using a bandpass filter between 1 Hz and 3 kHz.

III. Signal Processing and Analysis

Processing of the SEMG signals was performed off-line using newly developed virtual instruments (VI) in LabVIEW version 6.1 using its Signal Processing Toolset. The signals were digitally filtered using a Butterworth band pass filter (5 to 500 Hz, 4th order) before performing CWT analysis.

In contrast to traditional time-frequency methods such as STFT, the CWT is a time-scale representation rather than a time-frequency.

Given the input signal x(t), the CWT is defined in equation (1).

$$CWT_x(a,\tau) = \int_{-\infty}^{\infty} x(t)\psi^*_{a,\tau}(t)dt \tag{1}$$

where $a \in \Re^+$ represents the scale parameter, $\tau \in \Re$ represents the translation diameter of time shifting and the basis function $\psi^*_{a,\tau}$ is obtained by scaling the mother wavelet $\psi(t)$ at time τ and scale a. The asterisk indicates that the complex conjugate of the wavelet function is used in the transform.

The mathematical expression of a wavelet family which consists of members or daughter wavelets, $\psi a,\tau$ is obtained by scaling and time shifting of the mother wavelet $\psi(t)$ defined in equation (2) [6].

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right) \tag{2}$$

when a becomes large, the basis function $\psi_{a,\tau}$ becomes a stretched version of the prototype, which emphasises the low-frequency components. A small a contracts the basis function $\psi_{a,\tau}$ and stresses the high-frequency components. However, the shape of the basis function will always remain unchanged [6].

Since $\psi^*_{a,\tau}$ is defined in equation (2) hence equation (1) also can be written as equation (3) [7].

$$CWT_x(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-\tau}{a}\right)dt \tag{3}$$

The CWT coefficient plots are precisely the time-scale view of the signal as referred earlier. It is a different view of the signal from the time-frequency view, but they are still related to each other.

The plot of squared magnitude or power of the wavelet transform is called 'scalogram'. Equation 4 defines the calculation formula for the scalogram [7], [8].

$$\left|CWT_x(a,\tau)\right|^2 = \left\|\frac{1}{\sqrt{a}}\right|\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-\tau}{a}\right)dt\right|^2 \tag{4}$$

Scalogram can be represented as images in which intensity are expressed by different shades of grey.

It is also important to understand the nature of scales and the fact that wavelet analysis does not produce a time-frequency view of a signal. This feature is not considered as a weakness, but it is a strength of the transform [9]. Not only that time-scale is a different way to view data, it is a very natural way to view data deriving from a great number of natural phenomena. However, in this case there is an essential need to convert or connect scales to frequencies where information can be of relevance. The relationship between scale and frequency can only be given in a broad sense. This frequency is called the 'pseudo-frequency' corresponding to a scale. To convert from scales to frequencies it is required to compute the centre frequency F_c of the wavelet and to use the relationship as expressed in equation (5).

$$F_a = \frac{\Delta . F_c}{a} \tag{5}$$

where a is the scale number, Δ is the sampling number

which is the number of samples taken per second, F_c is the centre frequency of a wavelet in Hz, and F_a is the pseudo-frequency in Hz corresponding to the scale a.

The centre frequency F_c is originated from the frequency maximising the FFT of the wavelet modulus [9]. By processing the mother wavelet using FFT, the centre frequency F_c is obtained from the dominant frequency appearing in the frequency spectrum.

For the feature extraction process, a part of the raw SEMG signals was selected. The selected region is a four-second interval after the first peak signal activation. The first two seconds were not processed and analysed to allow changes in the muscle tension at the beginning of the muscle contraction. The next two seconds was the region to be processed and analysed [10], [11]. There was no muscle fatigue present in this region and was assumed to be quasi-stationary, which is stationary during short time intervals. Under this assumption spectral analysis for feature extraction can be applied [10], [11].

Power spectrum was obtained from every 1024 samples or 0.5 seconds interval with an overlap of 50% to create a total of seven 0.5 second intervals. The average of the power spectrum was formed from these 0.5 second intervals by averaging all of the spectra lying within the region. This method was used to reduce the variance in the spectrum estimates and create the characteristic values of the power distribution [11]. From this, the average of the spectrum, the mean and median frequencies were calculated. This process was executed for each of the selected scales to determine the RMS values of the signal, mean and median frequencies from the average power spectrum.

IV. RESULTS

The raw SEMG data collected from the EMG amplifier and the dynamometer simultaneously by a multifunction data acquisition board NI using LabVIEW.

Fig. 2 shows the force trace (top plot) and SEMG signal (bottom plot) from a newly developed LabVIEW-based virtual instrument (VI) for vastus lateralis muscle of the right leg of a male subject exerting 75% MVIC.

Fig. 3 shows the two second interval of the signal between cursors 1 and 2 (left hand plot) of Fig. 2 to be analysed using CWT. This signal was processed using a newly developed VI by LabVIEW to produce the overall averaged power spectrum (right hand plot), scalogram and its corresponding time-frequency based spectrum plot.

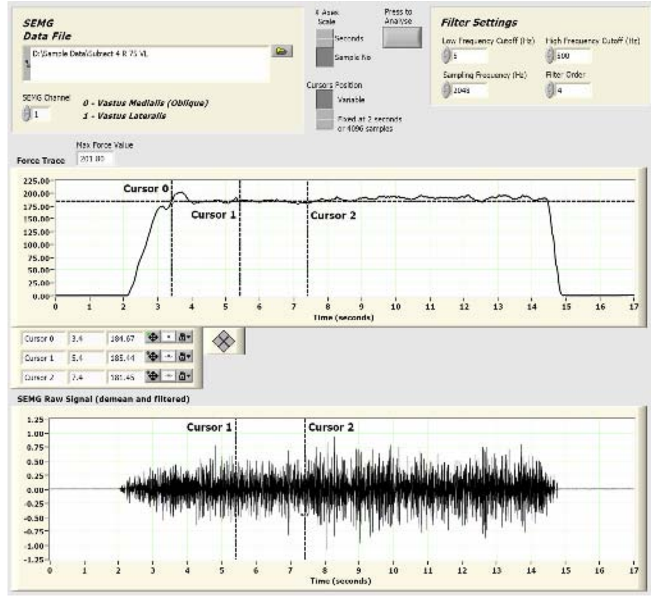

Fig. 2: Force trace (top plot) and SEMG signal (bottom plot) of 75% of MVIC from right leg's vastus lateralis of a male subject.

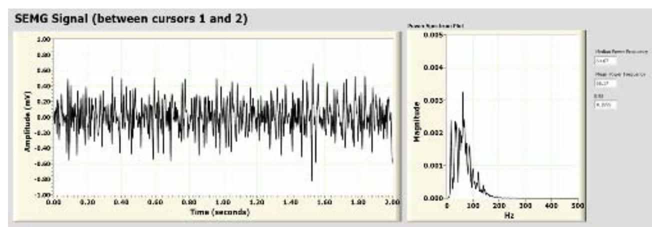

Fig. 3: Shows the two second interval of the signal analysed between cursors 1 and 2 (left hand plot) as shown in Fig. 2 with the averaged power spectrum plot (right hand plot).

Table 1 gives the extracted feature values for a selected two-second period, the mean and median frequencies of the average power spectrum, and the RMS values at scale indexes of 8, 16, 32, 64 and 128 of the CWT using the Morlet wavelet, which has a centre frequency F_c value of 0.8125 Hz.

TABLE 1
EXTRACTED FEATURES FROM THE RIGHT LEG'S VASTUS LATERALIS FROM A MALE SUBJECT AT 75% OF MVIC AS SHOWN IN FIG. 2 AND FIG. 3.

Scale No	Mean frequencies (Hz)	Median frequencies (Hz)	RMS (mV)
8	168.83	167.12	0.0839
16	95.47	94.21	0.3886
32	51.70	50.59	0.6281
64	26.77	26.25	0.4095
128	14.93	13.89	0.3265

Figure 4 shows the scalogram (top plot) and its corresponding time-frequency based spectrum plot (bottom plot) for the two second interval signal shown in Fig 3.

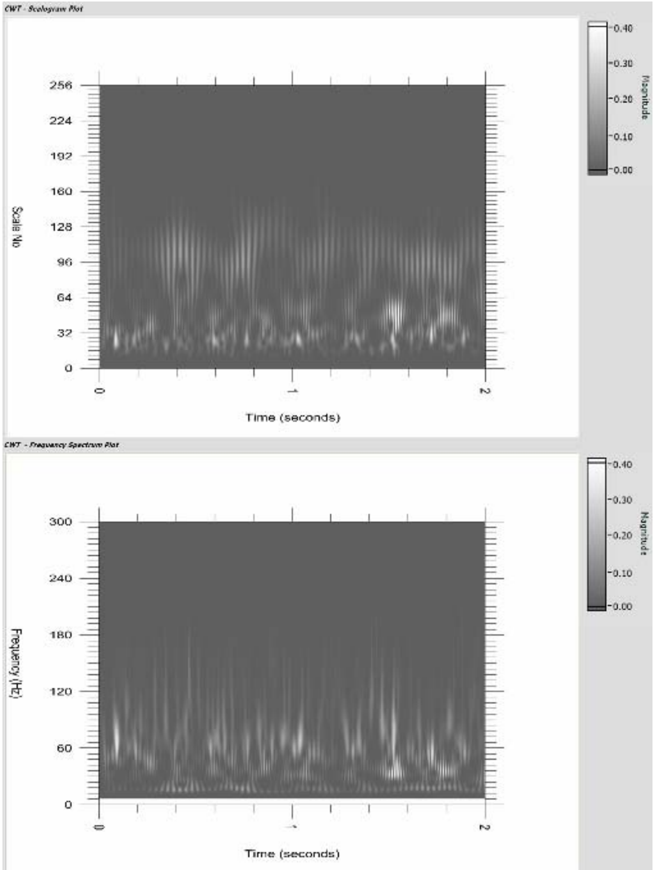

Fig. 4: Shows the scalogram (top plot) with corresponding frequency-time based spectrum plot (bottom plot) of the analysed signal shown in Fig. 3.

V. Discussion and Conclusion

The main objective of this research was to analyse SEMG signals using CWT and the developed VI's in LabVIEW, in order to extract signal features that can be used for classification.

The CWT-based approach produces a dyadic decomposition structure which is constant for all signals [12]. Correspondingly, the CWT provides 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 and gain very fine features.

The results showed that by using the scalogram and the frequency-time based spectrum plot shown in Fig. 4, the extracted features of the dominant frequencies and the related scales of the CWT analysis can be used to train and validate a signal classifier based on an ANN.

Moreover, signal processing tools for feature extraction of the SEMG signals were found to be more flexible in LabVIEW. The reason for this claim is the versatility of controlling of the signal segments to be analysed from the front display panel of the VI's without going into the core programming block chart, hence minimising programming error.

Future work is to collect and analyse SEMG signals for abnormal muscles with various pathological conditions for the vastus lateralis and the vastus medialis. These signals can be used for testing and validating the existing ANN, and for building a substantial database to develop an intelligent signal classifier for clinical application in muscle diagnostics.

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