Analysis of Surface Electromyography Signals Using Discrete Fourier Transform Sliding Window Technique

J. Kilby and K. Prasad

Abstract—**An optimum frequency resolution is useful for extracting features of any signals for further analysis. The purpose of this research was to determine the best frequency resolution of Surface Electromyography (sEMG) signals by using a sliding window with Discrete Fourier Transform to produce spectrogram plots. The process was carried out in two stages of investigations.**

The first investigation was to hold the sampling frequency constant at 8192 Hz and to use a new algorithm with sliding window sizes ranging from 16 to 512 samples through the signal. The results showed that the spectrogram that produced the best visual frequency resolution was with a window size of 64 samples. The calculated time period of sampling frequency of 8192 Hz with window size of 64 samples is hence 1/128 seconds.

The second investigation was to use the time period of 1/128 seconds found in the investigation one. This time period of 1/128 second is held constant in order to determine window sizes that passed through different sampling frequencies which were set at 1024 Hz, 2048 Hz and 4096 Hz. Hence the calculated window sizes sample values are 8, 16 and 32 respectively. The spectrogram was plotted for each window sizes and it was found that a window size of 32 samples with the sampling frequency at 2048 Hz gave the best visual frequency resolution for the analysis of sEMG signals.

Index Terms—**Fourier, spectrogram, electromyography, signal Processing.**

I. Introduction

Surface electromyography (sEMG) signals is the study of muscle activity obtained in the form of electrical signals [1]. The sEMG signals obtained by electrodes placed on the skin surface overlying the muscle are then sent to a computer. The sEMG signals are collected in data files for subsequent processing and analysed using relevant mathematical procedures to determine mean and median frequencies.

The amplitude characteristics of sEMG signals have a random or stochastic behaviour with no periodic form [2]. The amplitudes of these signals can range from 0 to 10 mV (peak to peak) or 0 to 1.5 mV (RMS) [2]. The useable frequency range of the signal is from 0 to 500 Hz, with dominance being in the 50 to 150 Hz range [2]. Signals at frequencies above 500 Hz are considered noise, and have little information, so they need to be filtered out by a low pass filter [2].

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 extraction is crucial for reliable classification [3]. 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 [2].

With computers and software becoming more and more powerful tools which are able 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.

The Fourier Transform (FT) of input signal $x(t)$ is defined as the following notation in equation (1), where ω is the angular frequency and $\omega = 2\pi f$ with f as the input frequency, $x(t)$ is the time domain signal. Then $F(\omega)$ is its FT represented in frequency domain, which is the sum over all time of the signal $x(t)$ multiplied by complex exponential [4].

$$F(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt \tag{1}$$

FT allows the frequencies within the sEMG signal to be broken down. These extracted frequencies can be used to relate to force production, muscle fatigue and deficits in the musculoskeletal system [2].

Since a digital computer only works with discrete data, a technique called Discrete Fourier Transform (DFT) is used [5]. Fast Fourier Transform (FFT) is the practical application name used for the DFT that maps discrete-time sequences into discrete-frequency representation as in equation (2), where $x[n]$ is the input sequence, $F(k)$ is the DFT, $2\pi k$ is the angular frequency of input sequence frequency k and N is the number of samples in both discrete-time and the discrete-frequency domains.

$$F(k) = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kt/N} \tag{2}$$

In signal processing, determining the frequency content of a signal by DFT is one of the main aspects in feature extraction and understanding the characteristics of a signal. However, obtaining the frequency of the overall signal content alone is not sufficient for analyzing bio- the time information after transforming time-based signal to

Manuscript received October 14, 2012; revised November 21, 2012.

This work was supported in part by the AUT University School of Engineering Research Grant with AUT Ethics Approval.

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DOI: 10.7763/IJCTE.2013.V5.702

frequency-based signal. By using *Sliding Window Technique* in DFT, time information is regained and therefore frequency resolutions can be seen through its spectrogram plot [4].

II. Methodology

A. Subjects

Thirty healthy volunteers with no previous history of knee or severe musculoskeletal injury (18 males and 12 females, age 18-35 years) participated in this study. This study was approved by the Auckland University of Technology Ethics Committee (AUTEC) and was performed after each subject had given written consent.

B. Experimental Setup

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

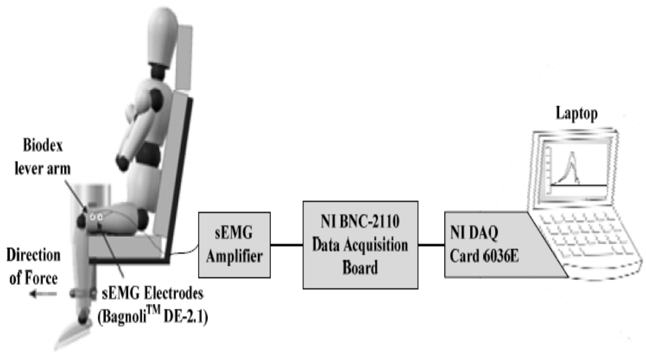


Fig. 1. Schematic of the components used for data acquisition of sEMG signals from a subject performing set value of their MVIC

The subject then performed a specific warm-up and familiarisation of the experimental setup. The subject was then rested for 3 minutes before performing the maximal strength test to obtain Maximum Voluntary Isometric Contraction (MVIC) of the quadriceps. The MVIC force (100% maximal force) of the leg quadriceps was executed by the subject pushing 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, the subject performed a sustained force production test. This test was executed by having the subject push against the load cell lever with 10%, 20%, 30%, 40% and 50% of MVIC force. The subject was required to perform and sustain the isometric contraction of the quadriceps at the given force levels for a period of 10 seconds.

C. sEMG Electrode Placement

The sEMG signal was obtained from the vastus lateralis muscle of the leg. Before the data collection, the subject's leg was shaved around the area of the muscles being tested. It was gently abraded with skin preparation cleanser, then cleansed with a 70% alcoholic swab and left to dry before attaching adhesive Ag (99.9%) electrodes Bagnoli™ DE-2.1 (Delsys Inc., USA) with 10 mm inter-electrode spacing. sEMG signals were recorded by a single differential amplifier with a CMRR > 92 dB, input noise < 1.2 μV (RMS). The electrode was placed according to the set of recommendations published by Surface Electromyography for Non-invasive Assessment of Muscle (SENIAM) [6] see Fig. 2 for details. The reference electrode was attached to an area with no muscle tissue below the knee.

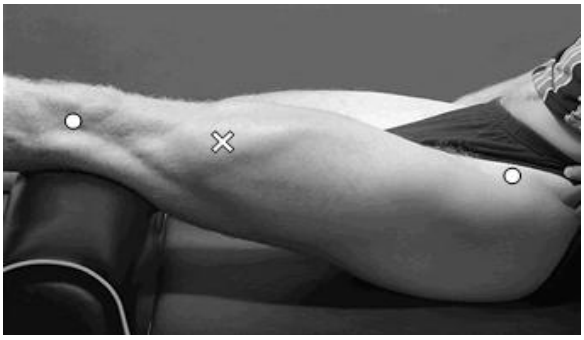


Fig. 2. Placement of electrode on the vastus lateralis muscle marked as a white cross between the two reference points marked as white dots.

D. Data Acquisition of sEMG Signals

Signals from the sEMG amplifier were acquired by a multifunction data acquisition board NI BNC-2110 plus NI DAQCard_6036E (National Instruments Corporation, USA) with LabVIEW 2011 software (National Instruments Corporation, USA) for raw data acquisition on a host laptop computer. The signals were analogue-to-digital converted with 16 bit resolution in the ± 5 V range and sampled using different sampling frequencies. Before sampling, the raw signals were amplified with a gain of 1000.

E. Signal Processing of sEMG Signals

Knowing the minimum acceptable sampling frequency is of critical importance in order to correctly reproduce the original analogue information. The rule for this is known as Nyquist Theorem where sampling frequency has to be at no less than twice the frequency of the original sampled signal. When sampling frequency is too low, the Nyquist Theorem is violated. This leads to an incorrect reconstruction of the signal, typically referred to as aliasing. Aliasing occurs when the original signal is under sampled as not enough points have been gathered to capture all the information correctly. As the usable frequency range of sEMG signals between 0 to 500 Hz, hence the minimum sampling frequency used to collect the sEMG signals was set at 1024 Hz. The other sampling frequencies used were 2048 Hz, 4096 Hz and 8192 Hz.

The recorded sEMG signals were subsequently analysed off-line using a newly developed code for performing signal processing analysis of the sEMG signals using MATLAB 2010 (MathWorks Inc, USA). Any direct current (DC) component that may exist in the signals was removed before the analysis. The signals were subsequently digitally filtered using a 4th order Butterworth band-pass filter with a pass-band from 5 to 500 Hz.

A new algorithm was written in MATLAB to produce a spectrogram by sliding a window through the sEMG signal over a 1 second period at a known percentage value of MVIC as shown in Fig. 3.

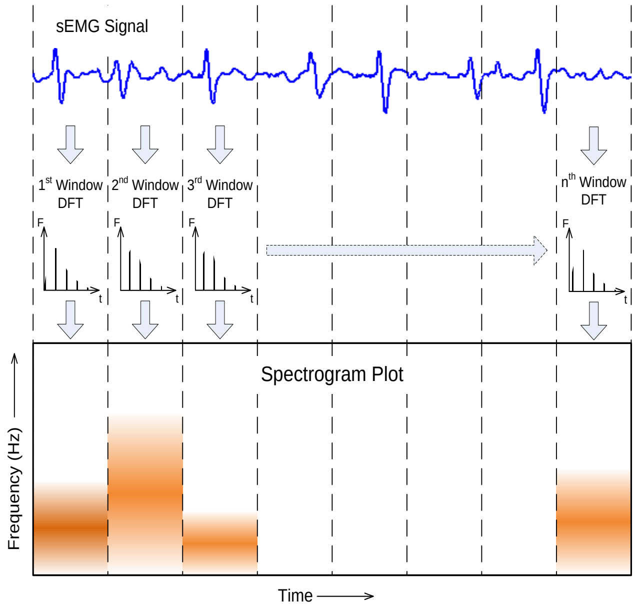


Fig. 3. The top plot shows a 1 second period of a sEMG signal to be analysed using the sliding window technique using DFT. The bottom plot shows a Spectrogram Plot produced by sliding a known fixed window length through the signal. DFT analysis was performed at each window shown graphically in the figure between the sEMG signal and the Spectrogram plot.

A window value was first set in terms of sample values of the signal and passing it through the signal. The algorithm takes the first sliding window of the signal and performing a DFT spectrum of the signal and stores the values in a matrix. This is continued until the final n^{th} window. Once the values of signal data was analyzed a spectrogram plot is produced showing the frequency content of each window against time. A Hanning window was used in the processing of the DFT frequency spectrum to obtain smoothness of the output frequency spectrum avoiding spectral leakages and outliers.

To find the optimum window size along with the sampling frequency for analysis of sEMG signals, two stages of investigations were carried out.

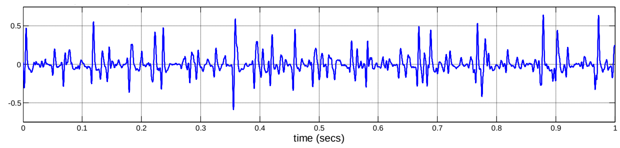
The first investigation was to use a fixed sampling frequency and then altering the window size through the same signal. This required only one signal to be collected at the highest sampling frequency of 8192 Hz and analyzing with different window sizes of using sample values of 16, 32, 64, 128, 256 and 512.

The second investigation was to use the window size from the first investigation that gave the best frequency resolution extracted from the signal. Using this window size, time period was determined and used to further calculate the sample values of window sizes over a range of different sampling frequencies. These selected sampling frequencies are 1024 Hz, 2048 Hz, 4096 Hz and 8192 Hz. Therefore there are more than one signal was collected at different sampling frequencies.

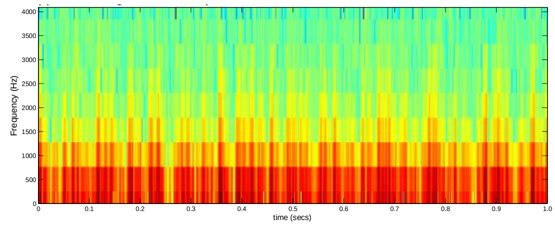
III. Results and Discussion

The results of the first investigation in determining a suitable window size analysis using single sEMG sampled at 8192 Hz and altering the sliding window sizes of DFT spectrum analysis is shown in Fig. 4.

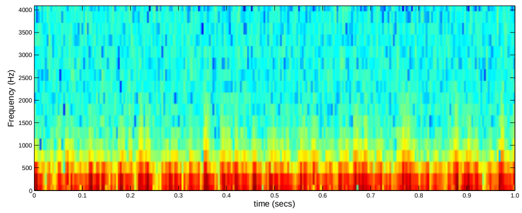
sEMG Signal Sampled at 8192 Hz



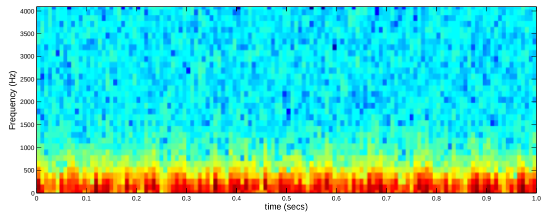
(a) Window Length Set at 16 Samples



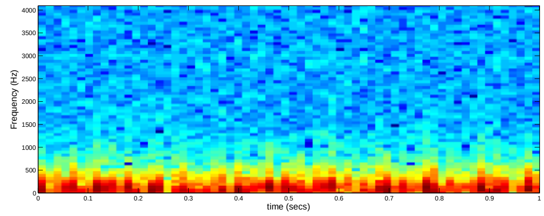
(b) Window Length Set at 32 Samples



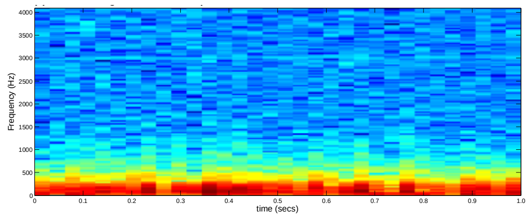
(c) Window Length Set at 64 Samples



(d) Window Length Set at 128 Samples



(e) Window Length Set at 256 Samples



(f) Window Length Set at 512 Samples

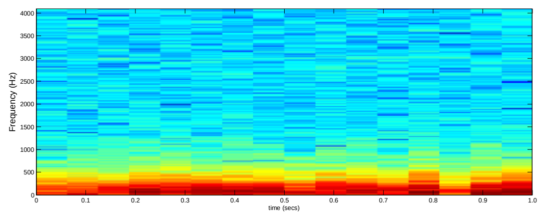


Fig. 4. The top plot shows a 1 second period of a sEMG signal sampled at 8192 Hz over that was used to produce the following Spectrogram plots. Plot (a) window length of 16 samples, plot (b) window length of 32 samples, plot (c) window length of 64 samples, plot (d) window length of 128 samples, plot (e) window length of 256 samples, and plot (f) window length of 512 samples.

The top plot shows a 1 second period of a sEMG signal that was collected at 20% MVIC from the vastus lateralis muscle of the quadriceps used for this investigation. The following plots below from (a) to (f) are the spectrograms plotted at various window sizes from 16 to 512 samples.

By increasing the window size from 16 to 512 samples, the best resolution is seen to be produced in plot (c) of Fig. 4 which was achieved at 64 samples. The frequency resolution in plot (c) is more refined than any of the other plots. The 'hard threshold' of the frequencies is just above the 500 Hz value at approximately 650 Hz. This frequency may vary due the level of contraction of the muscle and is due to the physiology of the muscle fibres [2].

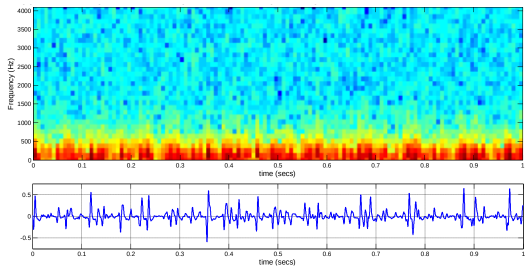
The second investigation was to use the window size of 64 samples with sampling rate at 8192 Hz from the first investigation which yields the time period of 1/128 seconds.

This time period was kept constant for subsequent selected different sampling frequencies and hence a new window sample size was determined for each of the different sampling frequencies as shown in Table 1.

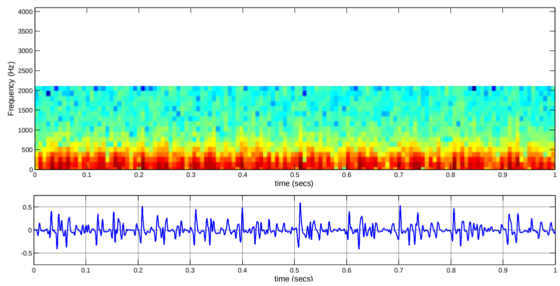
TABLE I: WINDOW SIZES AT VARIOUS SAMPLING FREQUENCIES

Sampling Frequency	Window Size
8192 Hz	64 samples (=time period 1/128 seconds)
4096 Hz	32 samples (=time period 1/128 seconds)
2048 Hz	16 samples (=time period 1/128 seconds)
1024 Hz	8 samples (=time period 1/128 seconds)

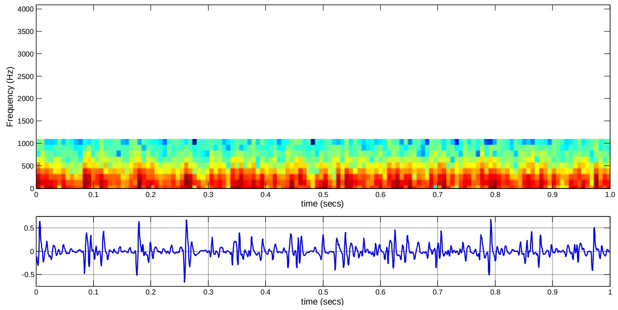
The spectrograms for each window size determined in Table I along with the corresponding sampling frequencies have a maximum frequency value of half of the sampling frequency which is due to the Nyquist Theorem. By examining the spectrogram plots, it can be seen visually that a sampling frequency of 4096 Hz and window size of 32 samples in plot (b) shown in Fig. 5 produced the best frequency resolution.



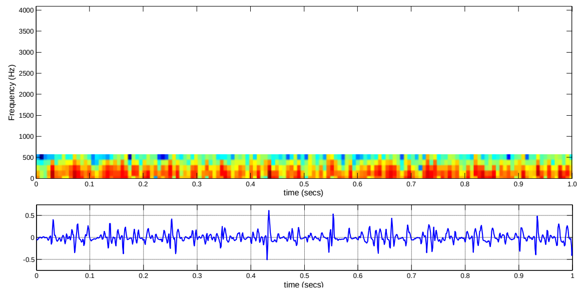
(a) Window Length set at 64 Samples and sEMG Signal Sampled at 8192 Hz



(b) Window Length set at 32 Samples and sEMG Signal Sampled at 4096 Hz



(c) Window Length set at 16 Samples and sEMG Signal Sampled at 2048 Hz



(d) Window Length set at 8 Samples and sEMG Signal Sampled at 1024 Hz

Fig.5. Spectrogram plots and sEMG Signals from the second investigation. Plot (a) window length set at 64 samples and sEMG signal sampled at 8192 Hz. Plot (b) window length set at 32 samples and sEMG signal sampled at 4096 Hz. Plot (c) window length of set at 16 samples and sEMG signal sampled at 2048 Hz. Plot (d) window length set at 8 samples and SEMG signal at 1024 Hz.

IV. CONCLUSION

The results of both investigations showed that performing a sliding window technique along with DFT and producing a spectrogram plot is a useful way for analysing sEMG signals which have no periodic form.

Overall, the results show that for a constant sampling frequency in the first investigation, having a wide window size of 512 samples gave a poor frequency resolution. This improved when the window size was made narrower to a size of 64 samples.

The second investigation showed that by using the best window size from the first investigation, time period can be determined and fixed for finding window sizes of different sampling frequencies. In this case, the best frequency resolution seen from the spectrogram was the one with a sampling frequency of 4096 Hz and a window size of 32 samples.

From this research the next step is to look at the other levels of MVIC and see if the above values of sampling frequency and window size give similar results in terms of frequency resolution. Once this has been determined, the next step will be to extract typical features such the mean and median frequency values from each of the DFT windows along with the RMS value for classification purposes.

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