Extracting Temporal and Spectral Parameters from Surface Electromyography Signals during a Fatigue Contraction

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Abstract—**This paper presents findings from a study of five healthy subjects performing 50% maximum voluntary contraction until complete fatigue of the muscle. An overlapping window technique was used to find the values for mean frequency (MNF), median frequency (MDF) of the power spectrum, root mean square (RMS) and muscle fibre conduction velocity (MFCV). The surface electromyography signal (sEMG) was collected from the vastus lateralis muscle using a three channel Laplacian electrode. The results show the MNF and MDF values showed a consistent trend with each other where they remained at steady values between 20-30% and 75-80% of the signal after which they fell 15-30% of this value. The RMS showed a linear increase in value. The MFCV showed a similar trend to that found in the MNF and MDF values.**

Index Terms—**MNF, MDF, RMS and MFCV**

I. Introduction

Fatigue is a factor that affects all individuals on a daily basis. Its definition is very complex, not unique and controversial. There are two basic types of fatigue (a) whole body physical fatigue and (b) localized muscle fatigue [1], [2]. If muscles are exercised strenuously for a long period of time, muscle fatigue occurs. A muscle is fatigued when it is unable to contract even though it is still being stimulated. Without rest, an active or working muscle begins to tire and contracts more weakly until it finally ceases to react and stops contracting [3].

Temporal and spectral parameters are used as feature extraction and pattern recognition in the processing and analysis of bio-medical signals [4], [5]. The use of the signal analysis is apparent in the field of research and clinical health for diagnosing health related problems and rehabilitation using bio-medical signals such as surface Electromyography (sEMG) signals. sEMG signals is the study of striated muscle activity obtained in the form of electrical signals [1]. The sEMG signals are obtained by electrodes placed on the skin surface overlying the muscle which are then sent to a computer.

In signal processing, determining the frequency content of a signal by Fourier transform is one of the main aspects in feature extraction and understanding the characteristics of a signal.

The Fourier transform $F(\omega)$ of a time domain input signal $x(t)$ represented in the frequency domain is the sum of the signal $x(t)$ multiplied by a complex exponential as given in equation (1), where ω is the angular frequency and $\omega = 2\pi f$ with f is the input frequency [6], [7].

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

Since a digital computer only works with discrete data, a technique called Discrete Fourier Transform (DFT) is used [6]. Fast Fourier Transform (FFT) is the practical application name used for the DFT that maps discrete-time sequences into discrete-frequency representation as given 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 [6, 7].

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

A common technique in signal processing of sEMG signals is to consider the squared of the values of the FFT coefficients as given in equation (3) producing a resultant plot that is referred to as a power spectrum [7].

$$P(\omega) = |F(\omega)|^2 = \left| \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt \right|^2 \tag{3}$$

Aspects of a signal such as the mean and the median frequency of the power spectrum and the root mean square (RMS) value of signal's electrical potential also play important roles in the whole task of features extraction for signal characterization. The ultimate aim of this exercise is to develop a system with the ability for signal classification by features, which is a powerful and promising tool for diagnosing problems.

The mean frequency (MNF) is the average of all frequencies of the power spectrum and can be expressed as given in equation (4) where $P(\omega)$ is the power spectrum of the signal [4].

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$$MNF = \frac{\int_0^{\infty} \omega P(\omega)\, d\omega}{\int_0^{\infty} P(\omega)\, d\omega} \quad (4)$$

The median frequency (MDF) is the frequency having 50% of the distribution on each side of the power spectrum as given in equation (5) [4].

$$\int_0^{MDF} P(\omega)\, d\omega = \int_{MDF}^{\infty} P(\omega)\, d\omega \quad (5)$$

The RMS value of a signal *x(t)* over a time interval *0-T* is determined by computing the equation as given in (6) [4].

$$RMS = \sqrt{\frac{1}{T}\int_0^T x^2(t)dt} \quad (6)$$

The collection of the sEMG signals from the surface of the skin to the data being stored involves a number of different stages, starting from a continuous analogue signal and ending with a discrete or digital signal [8]. These stages include amplification, analogue-to-digital conversion and signal conditioning.

Laplacian surface electrodes use spatial filters in sEMG recording and are represented by the Laplace filters. This is a class of high-pass spatial filters which approximate the second spatial derivative of the surface potential. Longitudinal and transversal Laplace filters can be combined to become the normal double differential (NDD) filter, which is a very selective spatial filter that enhances single motor unit (MU) activity from the interference signals, even at maximal contraction levels. The weights of the NDD filter, its filter mask can be written as in (7) [9, 10].

$$A_i = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (7)$$

The NDD configuration can be obtained by means of five cross-wised electrodes and is frequently used for two-dimensional sEMG recordings. This and other two-dimensional spatial filter configurations have been applied to extract single MU information from surface recordings [10-13].

The muscle fibre conduction velocity (MFVC) was obtained by performing a cross-correlation between two corresponding sEMG signals [14]. The cross-correlation is performed using the recorded data offline and was via the Fourier transform. The resulting cross-correlation function $R_{xy}(\tau)$ as given by (8).

$$R_{xy}(\tau) = \frac{x(t-\tau)y(t)dt}{k} \quad (8)$$

where *x(t)* and *y(t)* are two different sEMG signals, with τ is the time difference between them and *k* a constant to normalise the cross-correlation plot between -1 and +1. The peak in the cross-correlation plot was displaced by time ΔT from time zero, which was used to calculate the MFCV as given in (9).

$$MFCV = \frac{d}{\Delta T} \quad (9)$$

where *d* is the inter-electrode distance between the two sEMG signals.

II. Methodology

A. Subjects

Five healthy volunteers with no previous history of knee or severe musculoskeletal injuries (5 males, 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

Subjects were seated in a purpose built upright chair set at 110° with their knee flexed to 90° see Fig. 1. The chair was adjusted to ensure that the back of the knee rested comfortably against the edge of the seat. Once comfortable, the subject was secured to the chair using a lap and chest strap. The lower leg, minus socks or other clothing, was strapped to a metal attachment in series with a strain gauge at the ankle level, just proximal to the lateral malleolus. Comfort was ensured by using a heat-moulded thermoplastic brace to secure the leg. This experimental setup was similar to that used by Maïsetti, O., *et al* [15].

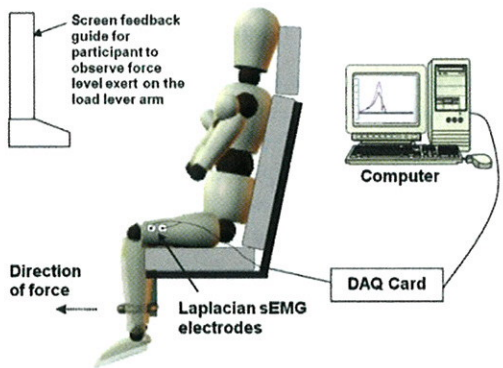

Figure 1. Schematic diagram showing the equipment setup for data acquisition of sEMG signals.

Force measurements: a PST model, 250 kg-maximum strain gauge (Precision Transducers Ltd, New Zealand) was used to measure the maximum voluntary contraction (MVC), and to provide a measurement of 50 % of MVC during endurance test. Force readings were in Newtons (N), and were collected from the strain gauge via a custom made amplifier by an Apple G4 personal computer sampling at 2 kHz. A real-time force trace was displayed on a computer monitor using a customized software program (Superscope LL 5.0 GW Instruments, USA). This provided visual feedback of the force being generated by the subjects.

C. sEMG Electrode Placement

Skin preparation: The procedure recommended by De Luca [16] was followed to ensure skin impedance was below 10kΩ. First, the electrode sites were shaved. The shaved area was then rubbed with an abrasive paste (Omni-Prep®, D.O. Weaver & Co., USA) and the skin was then cleansed with 70% alcohol wipes and left to dry before attaching the electrodes. Finally, a small amount of conductive gel was wiped onto the shaved area. This was shown during testing to improve the quality of the signal from the Laplacian electrode. Electrodes used are (a) mono-polar silver/silver-chloride (Ag/AgCl) passive electrodes (Red Dot, 3M Health Care, USA) for grounding purposes and (b) for data collection of sEMG signals was via an eleven-pin (4 mm diameter) two-dimensional high-spatial resolution three channels Laplacian electrode (Université de Technologie, Compiegne, France) with an inter-electrode distance of 10 mm see Fig. 2.

D. Data Acquisition of sEMG Signals

Signals were collected and filtered by NND using the mask as given in equation (7) for each channel by the Laplacian sEMG electrodes with a gain of 100. Each sEMG channel was then further amplified with a gain of 1000 and filtered using a band-pass filter between 3 Hz and 1 kHz Grass model P511 amplifier (Grass Instruments Company, USA). The analogue signals were acquired by a multifunction data acquisition board NI PCI-6024E (National Instruments Corporation, USA) with LabVIEW 2010 software (National Instruments Corporation, USA) for raw data acquisition on a host desktop computer. The signals were analogue-to-digital converted with 16 bit resolution in the ± 5 V range and sampled at 10 kHz.

Figure 2. Three channel Laplacian electrode (right) and amplifier (left) used for data collection of sEMG signals from the vastus medialis muscle of the quadriceps. Supplied by Université de Technologie, Compiegne, France.

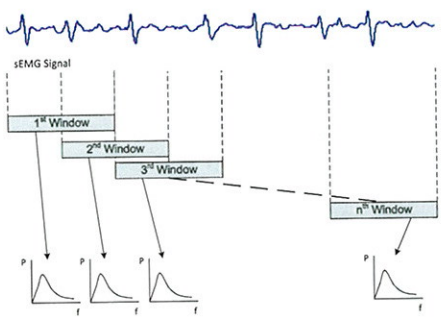

Figure 3. The top plot shows a single channel sEMG signal to be analysed using a 1 second window size with a 0.5 second overlap. Power Spectrum is used to calculate the MNF and MDF plus the RMS value of the windowed signal.

E. Signal Processing of sEMG Signals

Each of the three separate channel sEMG signals recorded 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). The sEMG signals were demeaned removing any direct current (DC) component that may exist in the signals 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 allow for each channel to be analysed at the same time see Fig 3 [6], [17]. The algorithm takes a 1 second window size of data from which a power spectrum was produced and analysed to calculate the MDF, and MNF values along with the RMS value. By taking a 1 second window size it is assumed to be quasi-stationary that is stationary during short time intervals. Under this assumption spectral analysis for feature extraction can be applied [18], [19].

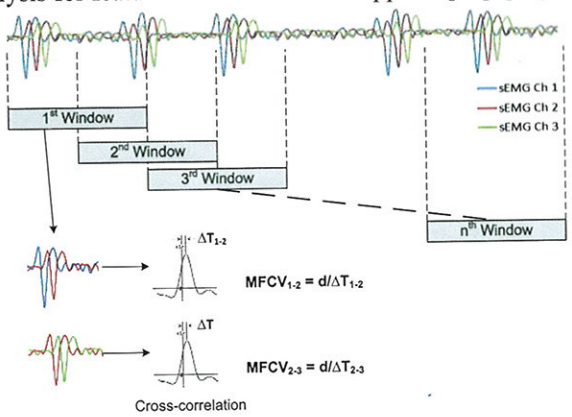

Figure 4. The top plot shows all 3 sEMG signals to be analysed using a 1 second window size with a 0.5 second overlap. Cross-correlation is used to obtain the MFCV between to channels 1-2 and channels 2-3.

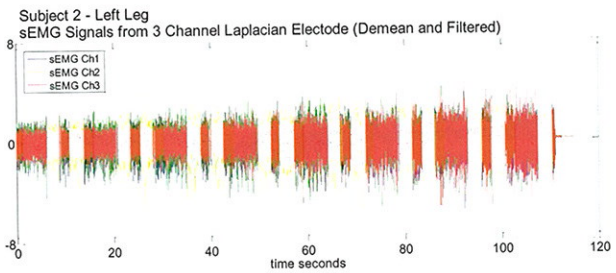

Figure 5. Demean and filtered sEMG signals collected from the three channel Laplacian electrode.

A Hanning window was used for the power spectrum to obtain smoothness of the output frequency spectrum avoiding spectral leakages and outliers. Each window size extracted was overlapped by 0.5 seconds to give a more detailed view of how the MNF, MDF and RMS vary over time through the sEMG signal. The values for MNF, MDF, and RMS were stored in a matrix; this was continued until the final nth window. Once all three signals were analysed, a separate plot for each value against time was produced.

The MFCV was calculated separately from a new algorithm using the cross-correlation function available in MATLAB see Fig. 4. This required taking channels 1 and 2 of the sEMG data to find the MCVF for a 1 second window and then proceeding to overlap each window by 0.5 seconds. The same method was performed using channels 2 and 3. The values for MFCV for each window were stored in a separate matrix, until the final n^{th} window. Once all the signals were analysed a separate plot for each value against time was produced.

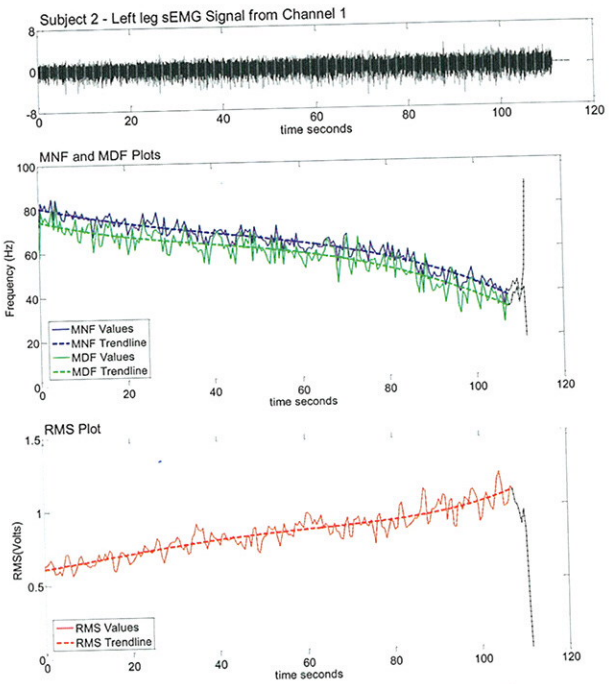

Figure 6. Show the sEMG signal for channel 1 (top plot) with the combined values for MNF, MDF (middle plot) and RMS values (bottom plot).

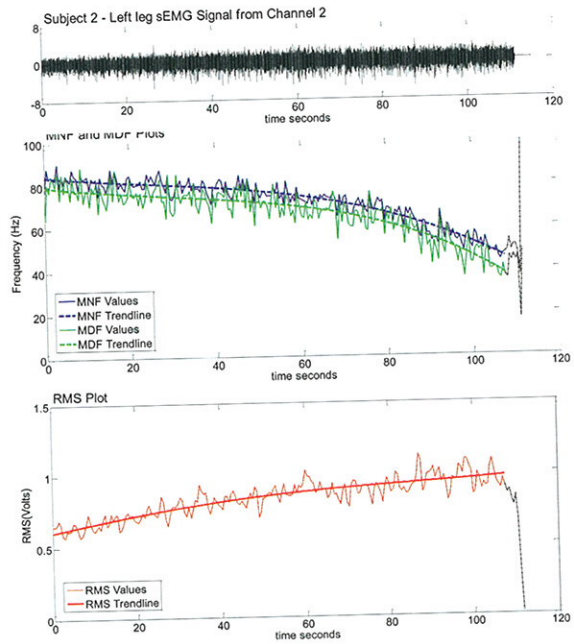

Figure 7. Shows the sEMG signal for channel 2 (top plot) with the combined values for MNF, MDF (middle plot) and RMS values (bottom plot).

III. Results and Discussions

Fig. 5 shows all three sEMG s collected from the left leg of subject 2 from this study of five subjects. These signals have been demeaned to remove any dc voltage component that may exist in the signals and further digitally filtered using a 4^{th} order Butterworth band pass filter between 5 Hz and 1 kHz.

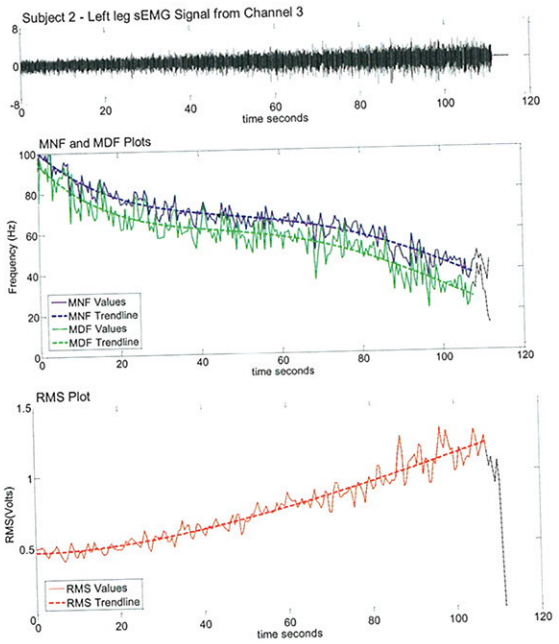

Figure 8. Shows the sEMG signal for channel 3 (top plot) with the combined values for MNF, MDF (middle plot) and RMS values (bottom plot).

The new algorithm using Fourier Power spectrum in Fig. 3 was used to find the MNF, MDF and RMS values for a set overlapping window size of 0.5 seconds was passed through each signal from the beginning until the end of the fatiguing. The results for each separate signal were plotted and are shown in Figs 6-8.

For analysis purposes, the last 4 seconds of the sEMG signal just before the subject completely fatigued were ignored in the overall analysis of the results. This is shown by the dotted black lines in Figs 6-8 for the MNF, MDF and RMS values. It clearly shows that the last 4 seconds are meaningless to the overall picture of the data presented.

Trendlines were added to the MNF, MDF and RMS plots using the *'polyval'* function in MatLAB. The 4^{th} order polynomial gave the best trendline in order to determine visually what was happening to these values throughout the signal.

By examining the results in Figs 6-8 the trendlines for MNF and MDF values follow same the trend, with MDF lower in value than the MNF. This indicates that the power spectrum for each window is skewed to the left i.e. the lower frequencies are dominant in the signal. Looking at the values for MNF and MDF frequencies it can be seen that all three signals have different trends during the first 20 seconds after which they follow a similar pattern. The values remain steady from 20 to

70 seconds after which they drop to about 20% in value until complete fatigue in the subject. The RMS values obtained show a doubling in a linear fashion throughout the signal for all three signals.

Once the analysis to find the MNF, MDF and RMS values were completed, a new algorithm was used to determine MFCV, see Fig. 4. To determine the MFCV, signals from channel 1 and channel 2 with the inter-electrode distance of 10 mm are required. The same was done to find the MFCV between channel 2 and channel 3. The results were plotted as a combined plot shown in Fig. 9.

For analysis purposes of MFCV, the last 2 seconds of the sEMG signal just before the subject completely fatigued was ignored in the overall analysis of the results. This is shown in as a black dotted line in in Fig. 9. It clearly shows that the last 2 seconds are meaningless to the overall picture of the data presented.

The MFCV results presented show the first values between channel 1 and 2 are greater than that for channel 2 and 3, but after about 20 seconds they follow the same trend. The MFCV remains at steady value between 20 seconds until 70 seconds after which it drops by 20-25% in value where after that complete fatigue occurred in the subject.

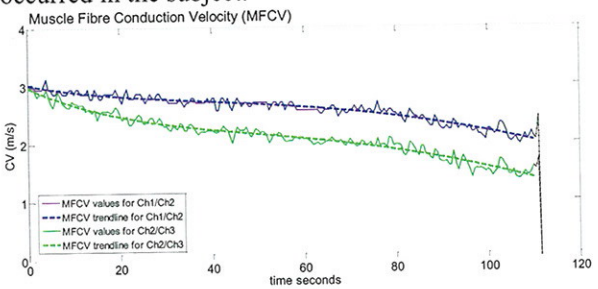

Figure 9. Shows a combined plot for MFCV values and trendlines between Ch1/Ch2 and Ch2/Ch3.

IV. Conclusion

All results using the first algorithm obtained for all subjects in this study have given similar results. That is for MNF and MDF values all follow the same trend throughout the sEMG signal. Therefore only one of these features need be selected for analysis purposes. The most beneficial one to use would be the MDF values as this shows a frequency value where the power spectrum splits the distribution in half. By visually examining the MNF and MDF trendlines, there was always a levelling off in these values between the 20-30% to the 75-80% of the muscle contraction. After this point these values dropped anywhere between 15-30% until the subject fatigues completely.

The RMS values in all cases showed a linear increase from the start of the muscle when it contracts until the subjects fatigued. However there was no other noticeable trend in the RMS values obtained from the analysis carried out.

The MFCV values in all cases showed a similar trend to that found in the MNF and MDF values. This indicates that these features are linked together in terms of the muscle behaviour through the contraction from start to finish. This can potentially be done as further investigation in terms of linking these features together.

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