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The Use of the Wavelet Transform in EMG M-Wave Pattern Classification

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Abstract - **A system was previously designed to obtain estimates of the number of motor units (MUNE) in a superficial muscle and hence number of functioning motor neurons to that muscle. This method uses incremental stimulation of a motor nerve and subsequent recognition and classification of the elicited M-waves. In this earlier work we used the Fourier power coefficients as pattern classifiers. The presented work compares the Fourier transform classifier results with those obtained using a wavelet transform classifier. Data to test the two approaches were obtained from the thenar muscles of ten normal subjects. The results show that the wavelet transform is superior to the Fourier in classifying M-waves with significantly improved inter and intra-class variances.**

Key words – motor unit number estimation, MUNE, electromyography, Fourier analysis, wavelet analysis, motor unit action potentials

I. INTRODUCTION

Estimation of the number of motor units (MU) in a skeletal muscle is a valuable technique in the diagnosis and monitoring of neuromuscular diseases. It is still an ongoing area of research and a number of different approaches have been presented [e.g. 2]. In the past we have developed an automated method [1] based on the incremental manual method where the motor nerve is incrementally stimulated to give a family of unique M-waves as in Figure 2. If the procedure is done carefully each successively larger M-wave can be assumed to be the addition of one more motor unit action potential (MUAP). This family of responses together with the maximum obtainable M-wave can then be used to estimate the total number of MUs in the muscle. Since the motor nerve consists of tightly packed bundles of nerve fibers, a single stimulus amplitude may excite different combinations of nerve fibers and hence elicit different M-waves, a process known as alternation. As each M-wave is recorded, the Fourier transform is calculated in real time and the power spectral coefficients used to classify it as a new response class or as a member of a previously obtained class. Errors in classification lead to poor estimates of the number of motor units in a muscle. Wavelets, because they are applicable to non-stationary data have been used to classify MUAPs [3,4] or decompose electromyographic signals [5] to estimate the presence of muscle fatigue. Since M-waves (e.g. Fig. 2) are summations of MUAPs, the wavelet transform may be a more applicable classifier than the Fourier transform. Unfortunately M-waves become more similar in shape as the number of contributing MUAPs increases, with increases in amplitude being the only significant difference. To our knowledge, classification of M-waves using the wavelet transform is a novel approach and presents unique challenges not encountered in MUAP classification. In this paper we determine the suitability of the wavelet transform for classifying the M-waves obtained from sub-maximal stimulation of the motor nerve. Both Fourier and wavelet transforms are tested using data obtained from the human thenar muscle.

II. WAVELET DECOMPOSITION

Historically, the Fourier transform has been used for the analysis of signals found in engineering applications. However, many biomedical electrical signals such as those found in EMG are non-stationary and exhibit transient characteristics. Fourier analysis, because it represents the signal by a sum of continuous sinusoids is not the most efficient transform for transient data such as the MUAP recorded in EMG. The Short-Time Fourier Transform introduced by Gabor (1946), retains time information by applying the traditional Fourier transform through a fixed-size time window. Wavelet theory furthers this idea by introducing variable-sized windowing to achieve high time-frequency resolution.

Wavelet analysis represents a signal as a weighted sum of shifted and scaled versions of a characteristic wave-like function. The class of wavelet functions have key features such as a finite number of oscillations, a finite duration and no DC component. Moreover, wavelets are often irregular and asymmetric and enable better representation of signals composed of fast changes.

The wavelet transform is defined mathematically as:

$$\left\langle f,\psi_{a,b}\right\rangle = \frac{1}{\sqrt{a}}\int f(t)\psi\left(\frac{t-b}{a}\right)dt$$

Here, $\psi(t)$ is the mother wavelet, which is scaled by factor a and delayed by time b and $f(t)$ is the signal for analysis. It is evident that when the signal matches the wavelet, the coefficient will be large.

Wavelet decomposition can be implemented by a bank of quadrature mirror filters that perform a series of high and low-pass filter operations followed by down-sampling. This form of analysis is known as the Discrete Wavelet Transform (DWT). The filter structure is determined by the particular wavelet family used for the analysis. The outputs of the low and high pass filters are known as the approximation and detail respectively. The decomposition process is iterative with the approximations at each level being successively decomposed into further approximation and detail. The decomposition generates a set of vectors which contain signal information at different frequency bands as determined by the filter bank frequency response. At any level the original signal can be reconstructed from the approximation and detail at that level and the detail signals from all previous levels.

III. METHODOLOGY

Electrode Placement The recording electrodes were 27mm by 11mm (Sentry Medical Products, Irvine, CA) with the stigmatic electrode placed over the thenar eminence to cross the first metacarpal bone perpendicularly at the junction of its proximal and middle thirds as shown in Figure 1. The reference electrode was attached to the proximal phalanx of the thumb. A ground electrode was located on the dorsum of the hand.

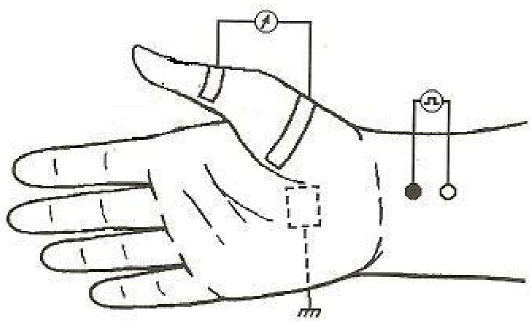

Figure 1: Electrode placement.

Data acquisition A stimulating electrode bar with 0.5 cm electrodes 2.5 cm apart was strapped proximal to the subject's wrist over the median nerve and the arm was supported in a comfortable position to reduce motion artifact. A 0.05 ms current pulse delivered by a Digitimer DS7A was used to stimulate the median nerve. The resulting EMG signals were filtered from 10 Hz to 1 kHz and amplified appropriately. All signals were sampled at 4 kHz and collected through a National Instruments data acquisition board.

A Labview program was developed to trigger the stimulator, collect and display 50 ms of pre-stimulus and 50 ms of post-stimulus data, and perform signal processing and pattern classification of the acquired M-waves. Additionally, the program provides ongoing real-time displays of automatically identified class templates and the number of M-wave members in each. The program then uses the template set and the maximum M-wave to estimate the number of motor units in the muscle. A goodness of fit between the largest template and the maximum M-wave is also calculated to indicate the validity of the assumption that the sample of motor units contributing to the template set is representative of the population of motor units in the muscle (e.g. 20 vs. a population of 200 in the thenar). The program also rank orders the templates according to amplitude and successively subtracts them to derive the surface MUAPs. Only the M-wave classification component of this process is presented in this paper.

To begin, the maximum M-wave and sub-threshold responses were collected and stored. The nerve was subsequently stimulated at 1Hz while the stimulus amplitude was controlled manually and gradually increased. Each collected response was subject to a variance check of the pre-stimulus, a 60 Hz periodic noise reduction based on coherent detection and the removal of the stimulus artifact. Finally, the response was band-limited to 20 to 500Hz.

Once the raw-data were processed, the responses were stored but also classified into unique templates based on one of two pattern recognition schemes. The first pattern recognition scheme employed the Fast Fourier Transform to obtain the power spectral coefficients of each M-wave response. The sum of the Euclidean distances between the first 40 power spectral coefficients of the current M-wave and the already established templates was then calculated and compared to a discriminator or threshold value to either create a new template or allocate the M-wave to an existing one. The discriminator value was chosen empirically for each subject so that the first 4 to 5 visually inspected unique M-waves were correctly classified. The template was then updated to be the average of all M-waves assigned to it. The alternative pattern recognition scheme involved a 3-level wavelet decomposition using the Daubechies 5 wavelet. This particular wavelet was chosen because it is similar in shape to the typical M-wave responses. The M-wave classification scheme was the same as for the Fourier approach except that the third level approximation wavelet coefficients were used as the classification vector. Alternation was addressed by requiring that each template must have at least 3 members and that these must have been obtained within a limited number of stimuli. This program allowed us to collect a sequence of M-waves over a range of stimulus amplitudes that could be tentatively classified in up to 20 classes. The raw M-waves were later analysed using Matlab programs to compare classification results for the two transform methods and determine sensitivity to changes in discriminator value.

IV. RESULTS

Ten male and female subjects, age range 22 to 60, with no known neuromuscular problems, gave informed consent and participated in the study which was approved by the REB of Hamilton Health Sciences, Hamilton, ON, Canada. Typically, 20 M-wave response templates were collected for each subject. Extensive motor unit alternation at higher stimulus amplitudes prevented the collection of higher numbers of templates for most subjects being tested. Figure 2 shows the smallest 5 M-wave (for clarity) templates generated through wavelet pattern recognition for one subject during a special study to obtain up to 25 M-waves for each class. The waveforms were recorded from the left thenar of a 60 year old male subject. One hundred to 150 stimuli were typically required to generate a 20 template set resulting in a test time under 3 minutes. Spontaneous motor unit firings at all stimulus levels for some subjects and excessive alternation at higher levels increased the number of required stimuli. Spontaneous background EMG was detected by calculating the variance of the pre-stimulus data and comparing it to a threshold value.

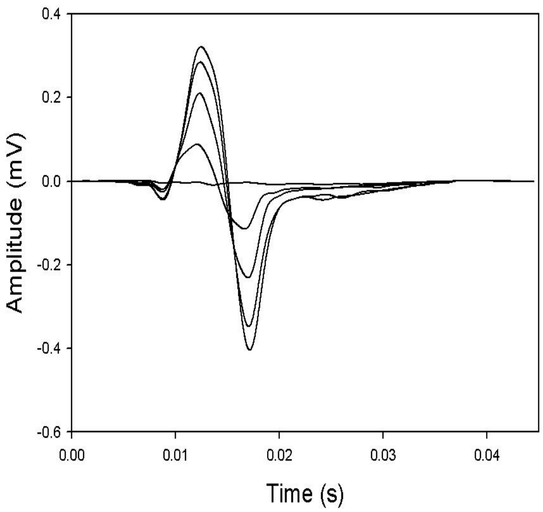

Figure 2: The smallest 5 M-Wave templates recorded from a thenar muscle using wavelet pattern recognition.

As a measure of how well wavelet pattern recognition separates M-waves into templates, statistical analyses were performed on the Euclidean distance measures. All M-waves recorded for a session were analysed visually and assigned to different classes. Fourier or wavelet feature sets were calculated for each M-wave in each class. Intra and inter-class distances were then obtained for each class of M-waves using Euclidean distance measures. Inter-class distances were calculated by taking the Euclidean distance between the feature set of each M-wave assigned to a class with the mean template set for the two nearest neighbour classes. Figure 3 shows the intra-class and inter-class distances for both Fourier and wavelet approaches for the M-waves used for Fig. 2

In these figures the left 6 data points, BB to 55, show the means and standard deviations of the intra-class distances for the 5 M-wave templates and the baseline. The right most 5 data points show the inter-class distances between nearest neighbour classes. It can be seen in these figures that although the mean intra and inter-class distances for both methods are comparable, the standard deviations in the Fourier transform approach for both intra and inter are larger. For the 5 M-wave templates recorded from the thenar muscle it was found that the wavelet pattern recognition technique misclassified 2 of 112 recorded waveforms while the spectral power coefficients pattern recognition technique misclassified 10 of 112 recorded waveforms.

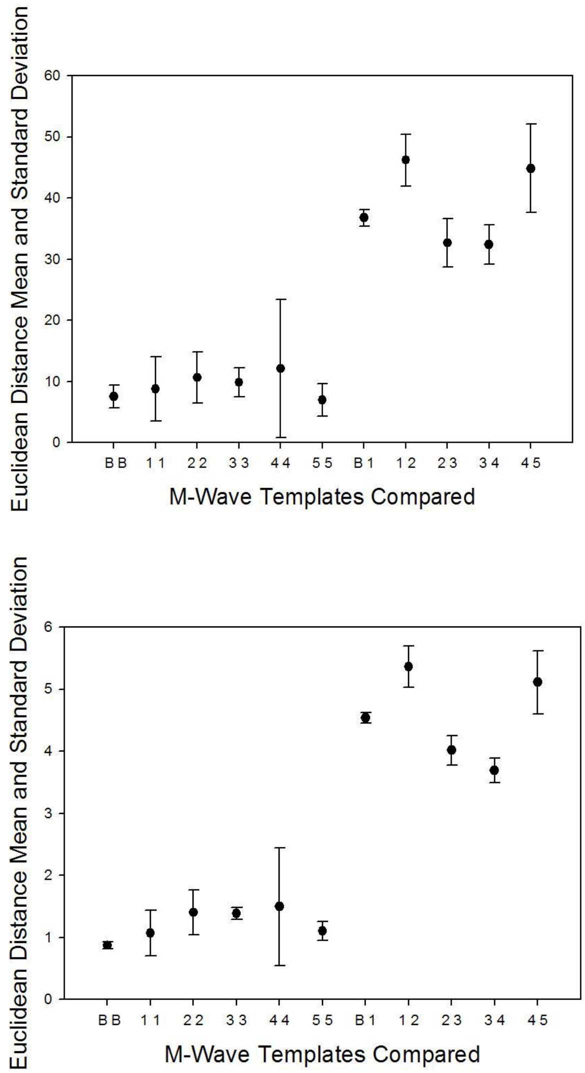

Figure 3: Intra-class and Inter-class Euclidean distances for the smallest 5 M-wave templates using spectral coefficients (upper) and wavelet analysis (lower).

Although many different distance measures can be used in pattern classification, we decided to only use the common Euclidean distance measure. For clinical applications such as the incremental motor unit counting technique, it is desirable that the Euclidean threshold value be subject independent. The previously recorded M-waves for all subjects were reclassified using a range of threshold values for both spectral and wavelet approaches. Since threshold values around 1.5 and .15 were found to be useful during data collection with Fourier and wavelet transforms respectively, the thresholds were changed by 7% increments of these values to give equal relative ranges. Figure 4 shows the resulting number of unique M-waves identified for three different subjects as the threshold value changes. The numbers of M-waves classified were 164, 103 and 182 for subjects 1, 2 and 3 respectively. Subject 1 had the least amount of alternation and acceptable spontaneous background EMG resulting in a higher number of distinct M-waves. Subjects 2 and 3 had higher levels of either the background EMG noise or alternation at higher levels of stimulation and the achievable number of distinct M-waves was lower. As can be seen, small threshold values result in higher numbers of templates in two subjects while larger values underestimate the number because additions of small MUAPs are ignored. Very small threshold values result in small numbers of identifiable M-waves because our system requires at least 3 members for a template to be accepted. This figure also shows that the wavelet approach is generally less sensitive to changes in threshold value than the spectral approach. Figure 5 shows the template set for subject 1 using the spectral approach and a threshold of 1.5. In the incremental motor unit number estimation technique, the estimate is calculated by dividing the maximum M-wave by the average MUAP contribution as determined by the largest M-wave template in the set (e.g. Fig 5) divided by the number in the set. Using wavelets and a common threshold will result in a more reliable estimate when testing patients in the clinic.

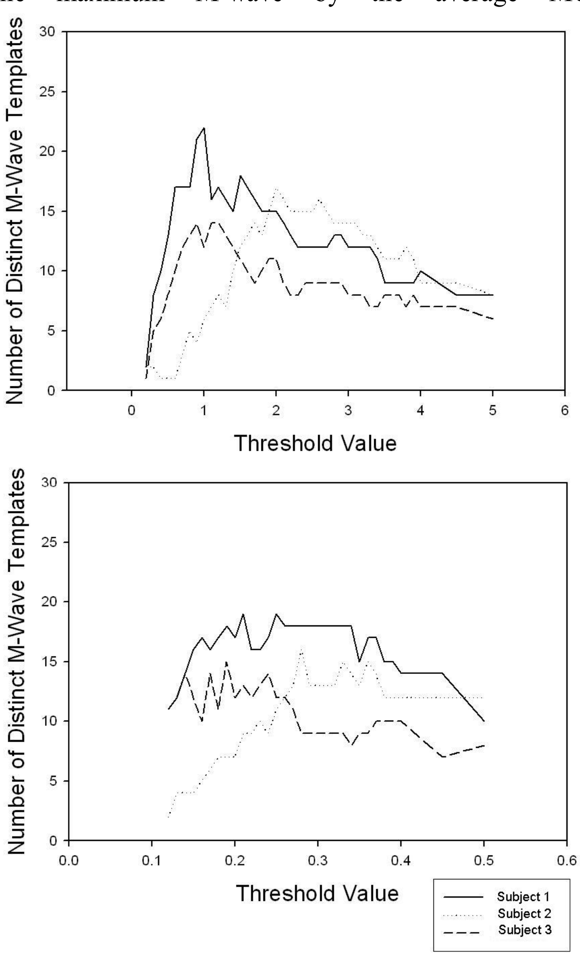

Figure 4: Number of M-waves classified using spectral coefficients (upper) and wavelet analysis (lower).

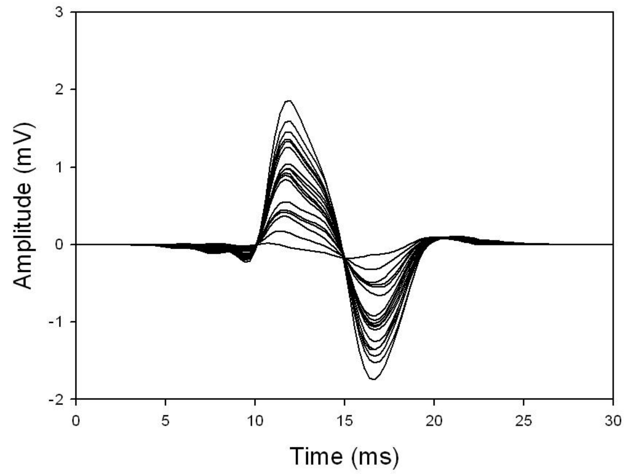

Figure 5: Template set for subject 1 using spectral coefficients and threshold value 1.5

V. DISCUSSION and CONCLUSIONS

The automated program developed, allows rapid acquisition of the maximum M-wave and a set of up to 20 templates of sub maximal M-waves. Overall the wavelet features are more applicable to the classification of M-waves than the power spectral coefficients. At present other wavelet transforms are also being tested including a time invariant transform. Myopathic and neuropathic patients are also being tested since their MUAPs have different statistical properties.

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