A SHIFT-INVARIANT WAVELET IN MUNE PATTERN RECOGNITION

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Abstract *– A system was designed to estimate the number of motor units (MUNE) in a superficial muscle using incremental stimulation of a motor nerve followed by classification of the collected M-waves. In earlier work we used the Fourier power coefficients as pattern classifiers. The work presented examines the shift-invariant wavelet transform as an alternative M-wave classifier. The shift-invariant wavelet transform pattern classifier is compared to classification with the traditional wavelet transform vectors. Data to test the two approaches was obtained from the thenar muscles of six healthy subjects. The results show that the shift-invariant wavelet transform compensates for latency shifting and is superior to the traditional wavelet transform in classifying M-waves with smaller intra-class variances.*

Key words – motor unit number estimation, MUNE, electromyography, wavelet analysis, shift-invariant wavelet, motor unit action potentials

I. INTRODUCTION

In the study of neuromuscular disease, the number of functional motor units (MUs) in a muscle provides quantitative information to assess the severity of and to determine the course and responsiveness to treatment for the disorder. Several motor unit number estimate (MUNE) techniques exist [e.g. 2] but there is still room for improvement in both the sensitivity and reliability of the estimates. Previously we developed an automated system [1] based on the incremental manual method proposed by McComas et. al. [3]. In this technique the motor nerve is incrementally stimulated to give a family of unique M-waves known as the composite response (CR) shown in Figure 3. The technique assumes that each successively larger M-wave results from the recruitment of one additional motor unit action potential (MUAP). Alternation, the phenomenon of a single stimulus amplitude eliciting different combinations of M-waves, limits the number of unique M-wave templates comprising the CR. The MUNE is obtained by dividing the maximal obtainable M-wave by the size of the mean MUAP contribution as determined by the CR. Thus, errors in the CR due to misclassification of M-waves lead to poor estimates of the number of motor units in the muscle. In the original work, the CR was created using a standard pattern recognition scheme to class identical M-waves that differed solely due to additive noise. The Fourier transform was applied to each recorded M-wave 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. In a more recent attempt [4], wavelets, because they are applicable to non-stationary data, were used to classify the M-waves, with the results showing improvement over the power spectral coefficient classification scheme. Unfortunately, due to latency shifting, for repetitive stimuli the collected M-wave responses may be time-shifted versions of each other. One inherent drawback of the wavelet transform is its sensitivity to translation and the classification scheme in [4] was found to misclassify M-waves when latency shifts were present. In this paper we investigate the improvement a shift-invariant wavelet algorithm lends to classifying the M-waves obtained from sub-maximal stimulation of the motor nerve. The results are compared to those obtained with the traditional wavelet transform using data collected from the human thenar muscle.

II. SHIFT-INVARIANT WAVELET

In biomedical applications such as EMG, signals are non-stationary and exhibit transient characteristics. As the Fourier transform contains only frequency characteristics and does not retain time information of the original signal it is not the ideal decomposition tool for such data. Contrarily, wavelet decomposition achieves high time-frequency resolution and is well-suited for transient signals such as the M-wave. In wavelet analysis, the signal is decomposed into a series of scaled and shifted versions of a mother wavelet. The transform results in a series of wavelet coefficients that are dependent on the scale and position of the mother wavelet. The wavelet transform effectively acts as a correlator between the shifted, scaled mother wavelet and segments of the signal. In practice, the discrete wavelet transform is efficiently implemented with a two-channel sub-band coder using quadrature mirror filters [6]. In this implementation the signal is passed through high and low pass filters to produce two new signals which are subsequently down-sampled to correct for doubling in the data. The decomposition process is iterative with each successive level decomposing the low frequency components of the signal into smaller frequency bands. Unfortunately, the wavelet transform is sensitive to translation and the wavelet coefficients of two signals may differ greatly even when the two signals are merely time shifted versions of each other. This complicates pattern recognition when the signals are to be classed based on shape and amplitude, as in M-wave pattern recognition, and not on time delays.

Several shift-invariant wavelet algorithms serve to correct this problem. The multi-scale wavelet representation (MSWAR) [5] produces shift invariance by a modification of the Mallat algorithm as shown in Figure 1. For each level of decomposition the signal is passed through the quadrature mirror filters. Additionally, the original signal undergoes a circular shift by 1 and this shifted version is passed through the same filters. The resulting outputs are down-sampled and combined to produce the wavelet coefficient vectors at each level. These vectors contain information from both the original signal decomposition and the decomposition of a circularly shifted version of the original signal. The process is repeated for all levels of decomposition. Though this algorithm is computationally more involved than the traditional wavelet transform it is invaluable for the pattern recognition of translated signals.

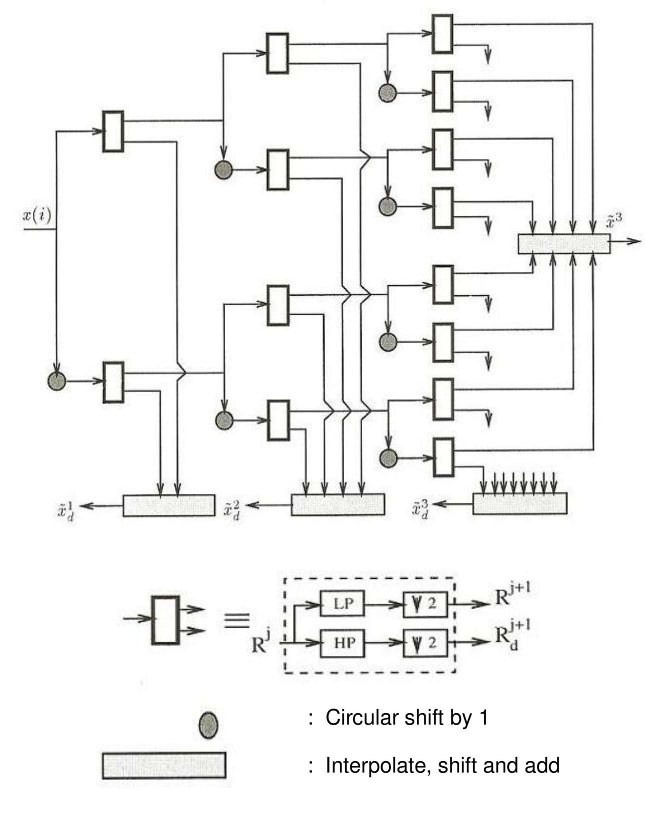

Figure 1: A 3-level shift-invariant MSWAR [5].

III. METHODOLOGY

Subject Set-up: The recording electrodes were made from disposable self-adhesive ECG electrodes (Tyco Healthcare Group, Mansfield, MA). The recording electrode was constructed by cutting the 25mm by 23mm electrode longitudinally. The halves were placed end to end over the thenar eminence to cross the first metacarpal bone perpendicularly at the junction of its proximal and middle thirds as shown in Figure 2. An additional half of an ECG electrode, used for reference, was attached to the proximal phalanx of the thumb. A ground electrode was located at the dorsum of the hand. Moreover, the stigmatic and reference electrodes were connected to the amplifier via a shielded cable to reduce the effect of external noise.

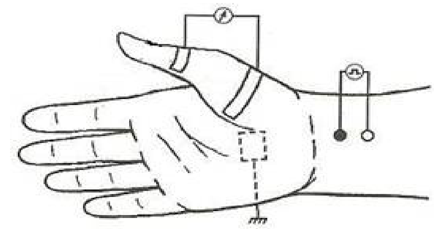

Figure 2: Electrode placement.

Data acquisition: The stimulator used for this system was a Digitimer DS7 (AM Systems, Sequim, WA) constant current isolated stimulator. A trigger pulse was invoked by the software through one of the digital outputs on the data acquisition board at a rate of 1 Hz. The stimulating pulse width was set to 100 microseconds to minimize patient discomfort. The stimuli were delivered through 6 mm diameter stainless steel electrodes mounted 1.8 cm apart on a plastic bar. The plastic bar was strapped over the median nerve proximal to the wrist. The bar position was moved slightly on initial set-up to find the optimal placement. This was the position where there was little lumbrical co-stimulation. The stimulus amplitude level was manually controlled during this experiment. All recorded signals were amplified and band-passed filtered using an A-M Systems 1700 differential amplifier (A-M Systems, Sequim, WA) with high-pass and low-pass settings at 10 Hz and 500 Hz respectively. The gain of the amplifier was set at 1000 for all subject collections. All signals were sampled at 4 kHz and collected through a National Instruments data acquisition board.

Data acquisition was facilitated by a Labview program which controlled the stimulator trigger, the collection and display of 50 ms of pre-stimulus and 50 ms of post-stimulus data, and the signal processing and pattern classification of the recorded M-waves. The program was developed to provide ongoing real-time displays of the automatically identified templates and the number of M-wave members in each. This information aided the operator in selecting the stimulator amplitude as this parameter was under manual control. Additionally, the program used the template set and the maximum M-wave to estimate the number of motor units in the muscle. The work presented here is primarily concerned with the M-wave classification component of this process and the details of the MUNE will be omitted.

For each subject, the experiment began by recording the maximum M-wave. Subsequently, the sub-threshold responses were collected by stimulating the nerve at 1 Hz while the stimulus amplitude was gradually increased by a trained operator. For each collection, a variance check of the pre-stimulus, a 60 Hz periodic noise reduction based on coherent detection and the removal of the stimulus artifact were performed. The response was then band-limited to 20 to 500 Hz and classed into a previously defined template or into a new template class.

The classification was performed based on one of two pattern recognition schemes, selectable on the Labview front panel at the onset of the experiment. The first pattern recognition scheme used, as a feature set, the coefficients generated by a 3-level wavelet decomposition of each M-wave response. The Daubechies 5 wavelet was chosen because it is similar in shape to the typical M-wave responses. The sum of the Euclidean distances between the 3rd level approximation vector and all 3 detail vectors of the wavelet decomposition of the current M-wave and the already established templates was then calculated. This distance was compared to a discriminatory threshold to either create a new template or allocate the M-wave to an already defined one. If the M-wave was allocated to a previously existing template, the template was updated to be the average of all M-waves assigned to it. The alternative pattern recognition scheme used the 3-level shift-invariant wavelet algorithm shown in Figure 1. The M-wave classification scheme was the same as for the traditional wavelet approach. The effects of alternation were limited by requiring a minimum of 3 M-wave members to a class before considering that class a unique M-wave template. For the experiment, the discriminatory threshold was kept constant across all subjects at a value found optimal in previous work [4].

IV. RESULTS

A study was conducted using the left and right thenar muscles of 2 healthy males and 4 healthy females, age ranging from 21 to 60. The subjects were not known to have any neuromuscular problems and gave informed consent for the study which was approved by the REB of Hamilton Health Sciences, Hamilton, ON, Canada. For each subject, 20 M-wave response templates were collected. The collection of additional templates was hindered by motor unit alternation at the higher stimulus amplitudes. Figure 3 shows the first 12 M-wave templates in a typical CR for one subject generated using the traditional wavelet transform pattern recognition scheme.

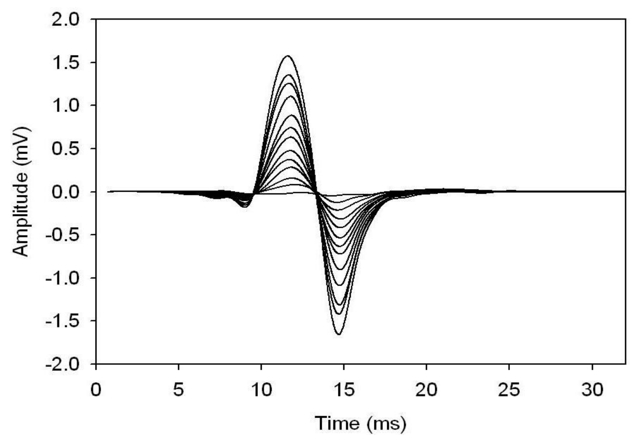

Figure 3: The CR of M-wave templates recorded from a thenar muscle using wavelet pattern recognition.

To determine how well the traditional wavelet pattern recognition scheme performs in comparison to the shift-invariant wavelet transform a measure of intra-class distance within M-wave templates was calculated. It was decided that this was an adequate measure because two identical but time-shifted M-waves have different wavelet coefficients due to the traditional wavelet transform's inherent translational sensitivity. Thus, the Euclidean distance calculated between these two M-waves during the pattern recognition scheme will be close to the threshold value and will be largely different from either the intra-class or inter-class averages. Thus, the standard deviation for both intra-class and inter-class distances will be larger. The shift-invariant wavelet does not generate largely different coefficients for translated M-waves. The resulting Euclidean distance between two such recordings will be minimal and translated M-waves will be classed together. It is expected then, that the standard deviation in the intra-class distance measure for the M-wave templates created using shift-invariant wavelet pattern recognition will be smaller than those created using traditional wavelet pattern recognition. Figure 4 shows the average intra-class Euclidean distance for each subject with both pattern recognition schemes. The Euclidean distance calculations were

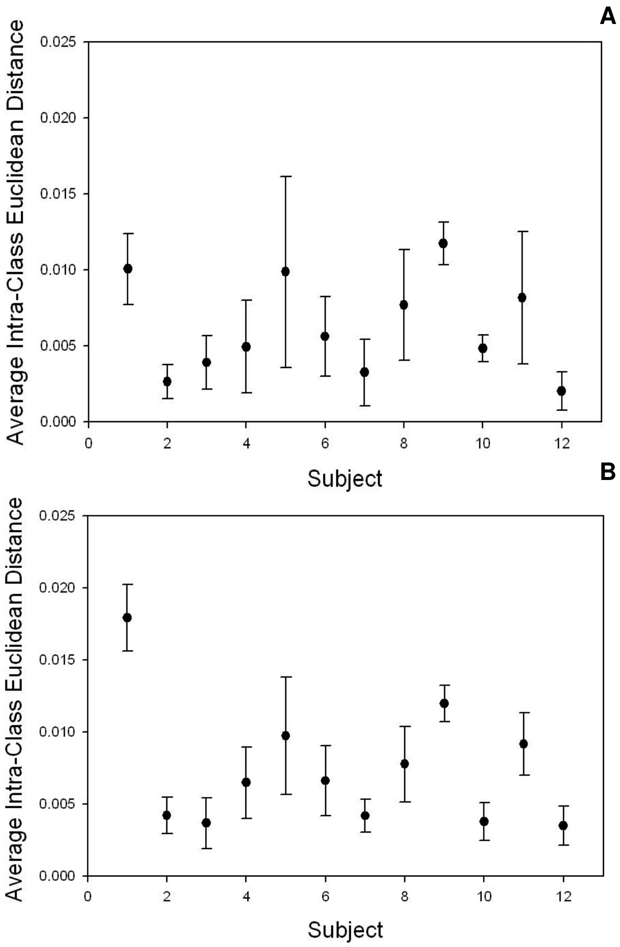

Figure 4: Average intra-class normalized Euclidean distances over all recognized templates found using (A) traditional wavelet transform or (B) shift-invariant wavelet transform for each subject.

normalized so that comparisons between subjects and between pattern recognition techniques are meaningful. It is evident that the intra-class distances for shift-invariant wavelet pattern recognition exhibit less variance. This is particularly apparent for subjects 4, 5, 7, 8 and 11. The improvement is not seen across all subjects, as latency shifting is not always present in the recorded data. When the electrical stimulus is applied to elicit an evoked response in a muscle, action potential generation is dependent on the voltage field in the tissues under the stimulating electrode and is most likely to occur at the nodes of Ranvier. Latency shifting occurs when the most distal node near the cathode is hovering around the activation threshold, causing action potential generation to alternate between this node and the adjacent node closer to the cathode on successive stimulations. Thus, latency shifting is associated with the number of repetitive stimuli. Table 1, shows the number of administered stimuli per subject. The highest numbers of stimuli correspond to subjects 4, 5, 7, 8 and 11. The results are as expected with these subjects experiencing the greatest reduction in variance with shift-invariant pattern recognition.

Table 1: Number of administered stimuli per subject

Subject	**1**	**2**	**3**	**4**	**5**	**6**
No. Stimuli	75	166	189	255	249	188
Subject	**7**	**8**	**9**	**10**	**11**	**12**
No. Stimuli	257	371	127	220	212	166

V. CONCLUSIONS

The real-time LabVIEW system developed for this work provides a practical and reliable approach for collecting and recognizing evoked M-wave responses. The shift-invariant wavelet features appropriately class latency shifts and are more applicable to the classification of M-waves than the traditional wavelet transform coefficients. At present a more robust alternation detection algorithm is being developed. This algorithm will be implemented in a modified system to test patients with motor-neural diseases.

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