COMPARISON OF THE TECHNIQUES USED FOR SEGMENTATION OF EMG SIGNALS

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Abstract: - The shapes of motor unit action potentials (MUAPs) in an electromyographic (EMG) signal provide an important source of information for the diagnosis of neuromuscular disorders. In order to extract this information from the EMG signals recorded at low to moderate force levels, segmentation is required to identify the MUAPs composed by the EMG signal. In this work, three techniques for segmentation of EMG signal are presented: i). Segmentation by identifying the peaks of the MUAPs, ii). by finding the beginning extraction point (BEP) and ending extraction point (EEP) of MUAPs and iii) by using discrete wavelet transform (DWT). A total of 12 EMG signals obtained from 3 normal (NOR) subjects, 5 myopathic (MYO) subjects and 4 motor neuron diseased (MND) subjects were analyzed. The success rate for the technique used peaks to extract MUAPs was 95.90%, for the technique used BEPs and EEPs was 75.39% and for the technique used DWT was 66.64%.

Key-Words: - Electromyography, motor unit action potentials, segmentation.

1 Introduction

Electrical potentials measured from a skeletal muscle result from the summed resting membrane potentials and the action potentials which occur when its muscle fibers are stimulated. Skeletal muscle fiber action potentials are generated by the integrated neural motor output of the central nervous system. Each single motor nerve fiber stimulates several muscle fibers to produce muscle action potentials. The spatial and temporal summation of the potentials arising from the activity of a single motor nerve is referred to as a single motor unit action potential (MUAP). The superposition of all MUAPs within the vicinity of the electrode constitutes the electromyogram (EMG) signal.

Observation of a patient's EMG signal is a key initial step taken by a physician for the assessment of neuromuscular disorders. The shapes of MUAPs composing the EMG signal provide useful information in this context. The process of identification of individual MUAPs in the EMG signal is referred to as EMG signal segmentation into the constituent MUAPs. The changes brought about by a particular neuromuscular disorder alter the properties of the muscle and nerve cells, causing characteristic changes in the MUAPs. Distinct MUAPs can be seen only during weak contractions when few motor units are active. When a patient maintains low level of muscle contraction, individual MUAPs can be easily recognized. As contraction intensity increases, more motor units are recruited. Different MUAPs will overlap, causing an interference pattern in which the neurophysiologist cannot detect individual MUAP shapes reliably. Traditionally, in clinical electromyography, neurophysiologists assess MUAPs from their shape using an oscilloscope and listening to their audio characteristics. On this way, an experienced neurophysiologist can detect abnormalities with reasonable accuracy. Subjective MUAP assessment, although satisfactory for the detection of unequivocal abnormalities, may not be sufficient to delineate less obvious deviations or mixed patterns of abnormalities. These ambiguous cases call for quantitative MUAP analysis. With the aid of computer technology, today it is possible to analyze EMG signal quantitatively that helps in saving time and standardizes the measurements. Several methods have been implemented in the past for single motor unit action potential (MUAP) recognition. Richard Gut et al used a sliding time window for segmentation. If the mean slope within this window exceeds a certain threshold, the beginning of an active segment is postulated. The end of a segment is reached when the total variation of the EMG within the window falls below another threshold [1]. E. Chauvet et al used an amplitude detection scheme where the threshold value is set at each iteration. For a given iteration, the threshold is determined by lowering its precedent value. This principle allows the detection of a reduced number of MUAPs, thus facilitating the identification of a MUAPT [2]. Later on, E Chauvet et al detected MUAP spikes when their amplitudes were higher than a detection threshold value. At the first iteration, the detection threshold was initialized at the maximum amplitude of the signal segment under study. After thresholding, the number of detected spikes was counted, if this number did not reach at least 5 spikes per second, the threshold level was lowered to 90% of its previous value [3]. C.D. Katsis et al used a threshold T to identify peaks in the EMG signal and a window with a constant length[4], [5], [6]. Constantinos S Pattichis et al identified the BEP and EEP of the of the MUAPs by sliding a window of length 3 ms and width ±40 µV throughout the EMG signal [7]. Jianjun Fang et al set a horizontal cursor at a level to distinguish spike potentials from background noise. Upon detection of a spike, a segment of spike waveform with its peak aligned at the center is collected [8]. Guglielminotti and Merletti theorized that if the wavelet analysis is chosen so as to match the shape of the MUAP, the resulting WT yields the best possible energy localization in the time-scale plane [9]. Laterza and Olmo found out that WT is an alternative to other time frequency representations with the advantage of being linear, yielding a multiresolution representation and not being affected by crossterms; this is particularly relevant when dealing with multicomponent signals. Under certain conditions, the EMG signal can be considered as the sum of scaled delayed versions of a single prototype. Based on Guglielminotti's theory, Laterza and Olmo have used wavelet analysis to match the shape of the MUAP [10]. For a unipolar recorded signal and under certain hypotheses presented by Gabor [11], the typical MUAP shape can be approximated as the second-order derivative of a Gaussian distribution. The result suggested using the well-known Mexican hat wavelet, which is indeed the second-order derivative of a Gaussian distribution. Based on the research, Laterza and Olmo concluded that the WT is particularly useful for MUAP detection in the presence of additive white noise. In this situation, the noise contributions are spread over the entire time scale plane, independently of the wavelet used The disadvantage of this proposal was that the Mexican hat wavelet is not perfectly matched to the MUAP shape [10]. Therefore, the obtained results are likely to be subject to further improvement if a perfect matching is performed. Ismail and Asfour came with a theory saying that, the most common method used to determine the frequency spectrum of EMG are the fast and short term Fourier transforms. But they also concluded that the major drawback of these transformation methods is that they assume that the signal is stationary [12]. However, EMG signals are nonstationary. Pattichis and Pattichis discovered that the wavelet transform can also be used to analyze signals at different resolution levels. The wavelet transform algorithm consists of the decomposition phase and reconstruction phases. They briefly outlines how coefficients from each stage of the WT can be used to construct functional approximation to the original signal [13].

To contribute to the quantification of the routine needle EMG examination, we have evaluated three segmentation techniques for detection of MUAPs. In the first technique, the EMG signal is segmented using an algorithm that detects areas of low activity and candidate MUAPs.Second technique, identified the BEPs and EEPs of the possible MUAPs by sliding a window throughout the signal.And in the third technique, EMG signal is decomposed with the help of daubechies4 (db4) wavelet to detect MUAPs.

2 Material and Methodology

2.1 Data acquisition and pre - processing

Our data contain real time EMG signal obtained from the Department of Computer Science, University of Cyprus, Cyprus. All the EMG signals were acquired from the biceps brochii muscle at upto 30% of the maximum voluntary contraction (MVC) level under isometric conditions. The signals were acquired for 5 seconds, using the standard concentric needle electrode, from NOR, MYO and MND subjects. The typical EMG recordings are given in Fig.1, Fig.2 and Fig.3. The EMG signals were analogue band pass filtered at 3-10 KHz, sampled at 20 KHz with 12-bit resolution and then low pass filtered at 8 KHz.

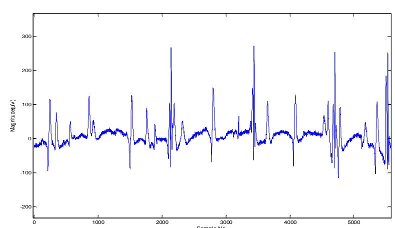

Fig.1 Raw EMG signal of a NOR subject.

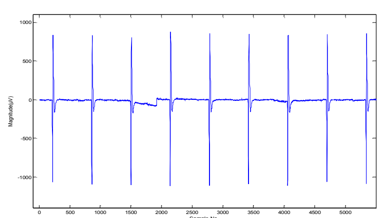

Fig.2 Raw EMG signal of a MYO subject.

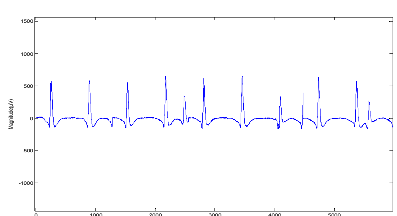

Fig.3 Raw EMG signal of a MND subject.

2.2 Segmentation

EMG signal is the superposition of the electrical activities of the several motor units. The segmentation of EMG signal is necessary to understand the mechanisms related to muscle and nerve control. Three techniques are discussed with regards to segmentation of EMG signal.

2.2.1 Segmentation by identifying the peaks of the MUAPs

This segmentation algorithm calculates a threshold depending on the maximum value $\max_i \{x_i\}$ and the mean absolute value $(1/L)\sum_{i=1}^{L}|x_i|$ of the whole EMG signal, where x_i are the discrete input values and L is the number of samples in the EMG signal. The threshold (T) is calculated as follows:

$$\text{If } \max_i\{x_i\} > \frac{30}{L}\sum_{i=1}^{L}|x_i|\text{, then } T = \frac{5}{L}\sum_{i=1}^{L}|x_i|$$

$$\text{else } T = \max_i\{x_i\}/5$$

Peaks over the calculated threshold are considered as candidate MUAP's. Then a window of 120 sampling points (i.e., 6 ms at 20 kHz) is centered at the identified peak. If a greater peak is found in the window, the window is centered at the greater peak; otherwise the 120 points are saved as MUAP waveform. This algorithm is described in detail in [14]. The segmented EMG signals of normal, myopathic and motor neuron diseased subjects in segments of 6ms and centered at the maximum peak, are shown in Fig.4, Fig.5 and Fig.6 respectively.

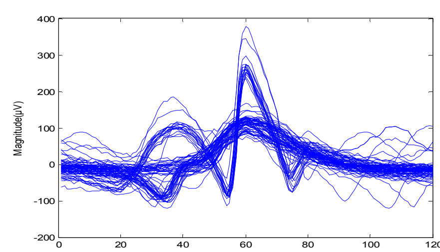

Fig.4 Segmented EMG signal of a NOR subject in segments of 6ms and centered at the maximum peak.

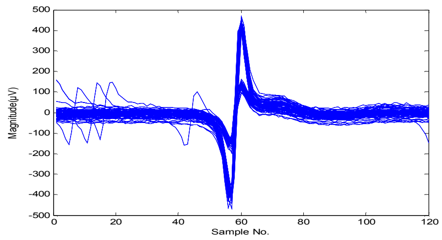

Fig.5. Segmented EMG signal of MYO subject in segments of 6ms and centered at the maximum peak.

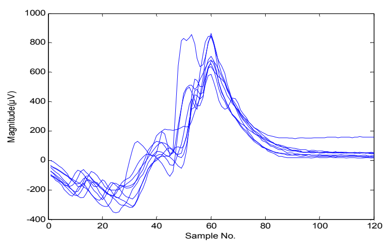

Fig.6 Segmented EMG signal of a MND subject in segments of 6ms and centered at the maximum peak.

2.2.2 Segmentation by identifying the BEPs and EEPs of the MUAPs

The EMG signal is high-pass filtered at 250 Hz and the BEPs and EEPs are identified by sliding an extraction window of length 3 ms and width ±40 µV. BEP is the first point that satisfies the criterion searching to the left of the EMG waveform, the signal to the left of BEP remains within ± 40 µV for 3ms. EEP is the point to the right of which signal remains within the range of ±40 µV for 3ms. These extraction points are then mapped to the original signal [7].

Fig.7, Fig.8 and Fig.9 shows a portion of the extracted MUAPs. In these figures triangular marks indicate the peaks and circle marks indicate the BEPs and EEPs.

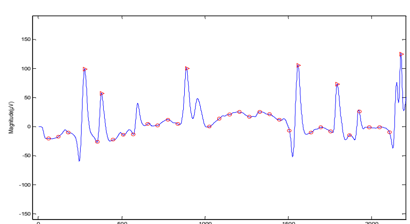

Fig.7 A portion of the extracted MUAPs by finding BEPs and EEPs of the MUAPs in case of a NOR subject.

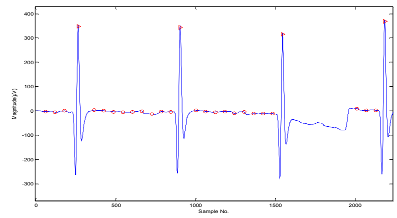

Fig.8 A portion of the extracted MUAPs by finding BEPs and EEPs of the MUAPs in case of a MYO subject.

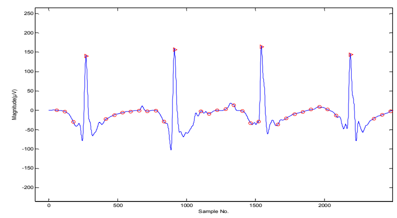

Fig.9 A portion of the extracted MUAPs by finding BEPs and EEPs of the MUAPs in case of a MND subject.

2.2.3 Segmentation by using DWT

DWT is a transformation of the original temporal signal into a wavelet basis space. The time-frequency wavelet representation is performed by repeatedly filtering the EMG signal with a pair of filters that cut the frequency domain in the middle. Specifically, the DWT decomposes a signal into an approximation signal and a detail signal. The approximation signal is subsequently divided into new approximation and detail signals. This process is carried out iteratively producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal[13]. In our work, we used db4 discrete wavelet to find the location of MUAP peaks on the time axis. We decomposed the signal up to 4th level and used a threshold of 50 µV to find the peaks of the MUAPs and then scaled the index of MUAP peaks to the original signal. A portion of the extracted MUAPs by using db4 wavelet in case of NOR, MYO and MND subjects, is shown in Fig.10, Fig.11 and Fig.12 respectively. In these figures circle marks indicate the peaks of the identified MUAPs and star marks indicate 40 points around each peak.

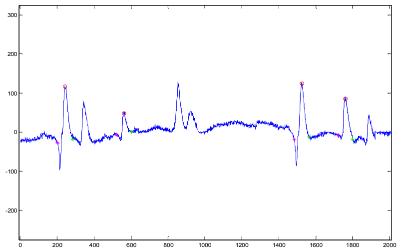

Figure10. A portion of the extracted MUAPs by using db4 wavelet in case of a NOR subject.

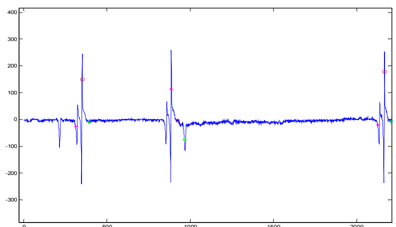

Figure11. A portion of the extracted MUAPs by using db4 wavelet in case of a myopathic subject.

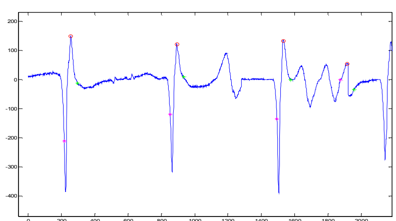

Figure12. A portion of the extracted MUAPs by using db4 wavelet in case of a motor neuron diseased subject.

3 Results

EMG data collected from 12 subjects were analyzed using the segmentation techniques described in Section 2.2. Data were recorded from 3 NOR subjects, 5 MYO subjects and 4 MND subjects. Only subjects with no history or signs of neuromuscular disorders were considered as normal. MATLAB was used for implementing the segmentation algorithms.

Table1 tabulates the comparison of the results of three segmentation techniques. The technique used for the extraction of MUAPs by identifying their peaks, yielded best results when compared with the manually observed true MUAPs. Table2 tabulates the success rates of three segmentation techniques. The success rate is the percentage ratio of the correctly identified MUAPs by the segmentation algorithm and the number of true MUAPs identified by manual observation. The success rate for the technique using peaks to extract MUAPs is 95.90%, for the technique using BEPS and EEPs, is 75.39% and for the technique using DWT, is 66.64%. Examining the success rate for each class, the highest success rate(96.07%) was obtained for the NOR group. The success rate for other classes is attributed to the more complex and variable waveform shapes.

Table 1- Comparison of the Results of Segmentation Techniques

Subjects	Total No. of MUAPs identified			
	By identifying the peaks of MUAPs	By using DWT	By identifying the BEPs and EEPs of the MUAPs	By manual observation
NOR(3)	196	107	196	204
MYO(5)	278	243	124	290
MND(4)	182	121	166	190
Total(12)	656	471	486	684

Table 2- Success Rate of the Segmentation techniques.

Segmentation Technique	Success Rate (%)			Total Success Rate (%)
	NOR	MYO	MND	
By detecting the peaks of the MUAPs	96.07%	95.86%	95.78%	95.90%
By identifying BEPs and EEPs of the MUAPs	96.07%	42.75%	87.36%	75.39%
By using DWT	52.45%	83.79%	63.68%	66.64%

4 Conclusion

In conclusion, the extraction of MUAPs by identifying the peaks, as described in this work, is accurate, simple, fast, and reliable. Data driven calculation of thresholds is another advantage since it enhances method's adaptability to different EMG signals. The most important issue in this technique is the selection of the length of the segmentation window. In our work, a 6 ms window was chosen as covering the main MUAP spike duration in most of the disease cases. A shorter window will fail to contain the main MUAP spike in the case of motor neuron diseases where MUAPs usually have larger duration. This could break a long MUAP into two artificial potentials. A shorter segmentation window will result in the identification of more potential occurrences in the case of normal or myopathic signals, since only the main spike will be included. The extracted MUAPs can be clustered and classified into NOR, MYO and MND classes by using pattern recognition techniques. In this way, valuable information can be provided to the medical expert in order to facilitate EMG diagnosis. The proposed approach can easily be integrated in existing software packages, while its fully automated nature ensures that it can be easily used by non-IT expert.

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