Automated Decomposition of needle EMG Signal Using STFT and Wavelet Transforms

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***Abstract*—We present an automated method for decomposing EMG signals into their components, motor-unit action-potential (MUAP) trains based on short time Fourier transform STFT and wavelet transform. Since the number of MUAP classes composing the EMG signal, the number of MUAP's per class, their firing pattern, and the expected shape of the MUAP waveforms are unknown, the decomposition of real EMG signals into their constituent MUAP's and their classification into groups of similar shapes is a typical case of an unsupervised learning pattern recognition problem. The method is able to handle single- or multi-channel signals, recorded by concentric needle electrodes during low and moderate levels of muscular contraction. The method uses empirical features in STFT transform, shape and template of MU and CWT in order to decompose the signal to its original MUAP. Also the discrete wavelet transform has been acquired in early steps in order to eliminate the level of low amplitude noise in signal. We compare the output of the automated algorithm with manual decomposition and results seems quiet acceptable. The average success rate for the FCM with wavelet coefficients as features was 91.01 %.**

Keywords- motor unit action potential, wavelet transform, spectrogram , segmentation, FCM clustering, MU decomposition

I. INTRODUCTION

The electromyographic (EMG) signal, recorded by a needle or fine-wire electrode is made up of trains of motor unit potentials (MUPs), and thus includes a potentially rich source of information about motoneuron discharge behavior and motor-unit (MU) organization. To obtain this information, it is essential to sort out the activity of multiple simultaneously active MUs, a process known as decomposition. Before the advent of computers, simple EMG signals were sometimes decomposed manually by identifying distinctively shaped MUPs on traces photographed at high-sweep speed. Computer methods have now been developed to automate various aspects of this process. However, some degree of human oversight is still necessary to decompose moderately complex EMG signals completely and with consistent reliability. The goal of full decomposition is to detect all the MUs that are active in a signal and to identify every one of their discharges.

In reality, most EMG signals contain a continuum of activity, ranging from large MUPs that can be clearly distinguished to small ones that blend into and help constitute the background noise. Thus, the number of MUP trains that can be fully identified depends to some extent on the amount of effort one is willing to expend. Most EMG signals also contain frequent superimpositions. These occur when two or more MUs discharge at nearly the same time and their MUPs overlap.

$$EMG(\mathrm{t}) = \sum_{m=1}^{N_m} MUPT_m(\mathrm{t}) + n(\mathrm{t}) \qquad (1)$$

In (1) a comprehensive models the system by electrical signal components is shown [1]. The recorded signal is the superimposition of motor unit action potentials which involved in contraction plus some noise. The motor neurons send Dirac pulses to trig the motor units and if the trigger pulse is more than threshold the motor unit will fire.

The decomposition of real EMG signals into their constituent MUAP's and their classification into groups of similar shapes is a typical case of an unsupervised learning pattern recognition problem. The number of MUAP classes composing the EMG signal, the number of MUAP's per class, their firing pattern, and the expected shape of the MUAP waveforms are unknown. The problem gets even more difficult because of MUAP waveform variability, jitter of single fiber potentials, and MUAP superpositions. Any automated method for EMG analysis should require no operator intervention; should be fast, robust and reliable; and achieve high success rate in order to be of clinical use. Most of the previous methods briefly described in Section I used mainly template matching which requires a predetermination of the classification boundaries and may fail to detect classes with insufficient frequency of MUAP repetitions and MUAP's with high shape variability [2]. The location of a MU's motor endplate and muscle tendon junction can be estimated from the latencies of the onset and terminal wave of the MUP waveform. These features tend to be quite small, and signal averaging is needed to detect them reliably. Full decomposition makes it possible to average the MUP waveforms of multiple MUs from a single signal. Full decomposition is also useful for studying discharge irregularities such as those associated with doubly innervated muscle fibers (Lateva et al., 2002). Full decomposition makes it possible to detect such irregularities even in busy signals by subtracting out the activity of the other MUPs that are not of interest [3].

Clinically, EMG signal analysis, in the form of EMG signal decomposition and MUP classification into groups of similar shapes, is used to assist in the diagnosis of neuromuscular disorders, to analyze the neuromuscular system, and in biofeedback training. The characteristics of an EMG signal are largely affected by anatomical and physiological properties of the muscle. For example, as the force of contraction increases, the number of motor units active and the rate at which they are active increases. The EMG signal therefore becomes more complex with increasing force of contraction. Furthermore, the fundamental structure of a muscle such as the size, distribution and number of motor units and how they are controlled can also be reflected in the characteristics of an EMG signal. For these reasons, many researchers are interested in devising techniques for the quantitative analysis of EMG signals [2].

II. METHODS

A framework was designed that requires a needle EMG data as input and provides segmented and clustered of the individual MUAP as output. The individual components of our framework are outlined In Figure1.

A. Data acquisition

In this paper NRSIGN 5000Q EMG/NCV/EP machine has been used to record the signal. The sample rate of signal is 40 K sample/Sec, High pass 0.16Hz and Low pass 5 KHz. The resolution of A/D is 16bit. During experiment our signal can be varied from 20uV to 800uV. The noise level of amplifier in (with grounded input) is from 10uV to 15uV, but during experiment the noise level can be increase to more than 20uV(environment EMI impact).In this experiment we used concentric needle electrode. Concentric needle electrode consists of two parts:

1. G1: A very fine electrode in the center
2. G2: the body of needle (stainless steel cannula).

This electrode type has several advantages: (1) its ability to record EMG activity with a minimum of interference from surrounding muscles, (2) its fixed-size recording surface, (3) the absence of a separate reference electrode, and (4) the extensively defined quantitation of the sizes of normal MUAPs for various ages and muscles.

Because the recording electrode is very near to source of signal, the noise level of signal can be low enough and we have the minimum distortion of signal at the same time. The body of needle electrode is reference electrode and the central part of electrode is active or plosive electrode.

Our dataset consist of 80 trace (60 Sec) of Needle EMG signal from Biceps and Deltoid in five experiments from 8 different people .

The EMG signal acquired in low and medium contraction (not in full contraction) in order to have not more than 10 to 15 motor unit active. In full contraction the decomposition can be a very hard job. So assumed that the motor unit action potentials that come from the muscle and have similar shape are belonged to one active motor unit. This assumption is not far from reality since every motor unit has its own physical characteristic and location.

B. Preprocessing

In preprocessing, hardware and software notch filter have been applied on data, and as signal had some low frequency noise regarding the needle movement inside the tissue a simple high pass filter has been used.

Because in Needle EMG signal, there is high frequency noise, which may come from other motor unit's activity or electromagnetic radiation noise, a low pass filter should be applied on signal. After applying the low pass the distortion of signal can be very high. In the other word the high frequency component of the signal has been eliminated by low pass filtering in furrier domain. So DWT has been proposed to reduce the noise in high frequency.

By thresholding signal with Daubechies D4 in d1 and d2 (fine coefficients) the noise level has been decreased, however there was not much signal distortion in motor units. In this way the energy of motor unit has been preserved (see fig2). This energy is one of the most important features that have been used in segmentation.

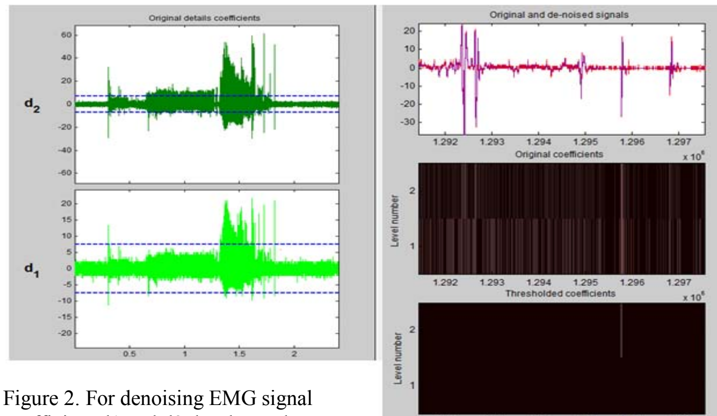


Figure 2. For denoising EMG signal coefficient d1 and d2 has been chosen for thresholding. The mother function is Daubechies D4. The distortion of MUAPs after filtering was less than FT linear approximation

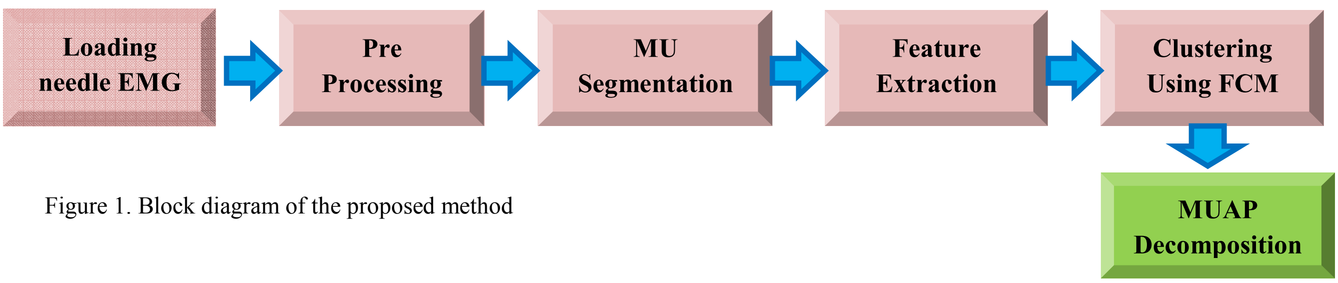


Figure 1. Block diagram of the proposed method

C. MUAP Segmentation

Segmentation of motor unit action potentials is one the most important part of automotive decomposition algorithm. In segmentation we need to find the MUAPs in time domain and specify the starting and end points of each MUAP. Since many MUAPs can be overlapped in time domain the algorithm should be smart enough to segment them. Usually signal is contaminated with a random noise so algorithm shouldn't be sensitive to random noise. In segmentation, method was based on STFT. Segmentation based on spectrogram analyzes was helpful enough and when, compare the results with manual segmentation the results was satisfactory (more than 98% accuracy).

Segmentation by STFT: For segmentation on STFT domain Kaiser Window has been used, the window has been swept over the signal and during the shifting, the frequency component of signal has been extracted by FT. By sweeping Kaiser Window the FT is focused on central components in the window and avoids the uncertainty in borders. So for every point t_n in time domain, we have a STFT curve. The STFT of the trace may be displayed by a spectrum. In this spectrum the light colors are related to low frequencies and dark colors are related to high frequencies. (see fig.3)

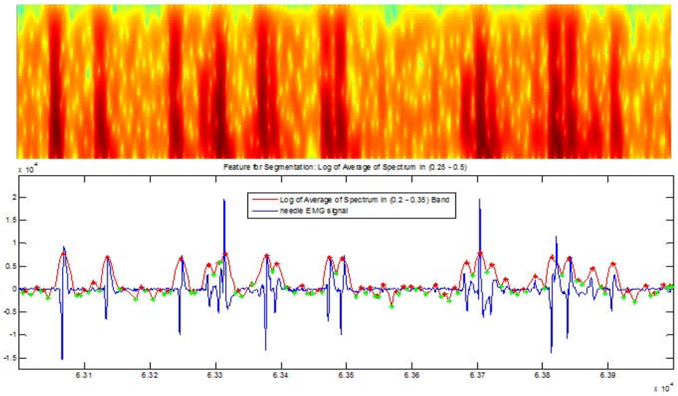


Figure 3. For every point in time domain we have curve which related to STFT of signal. In this Spectrum light color are refer to high frequency and dark colors are refer to low frequencies. It can be seen that the energy of Spec jumps up at MUAPs positions.

In this spectrum the vertical axis is related to the frequency (0,π) and the horizontal axis is time. The blue signal is the EMG signal in time domain. In order to segment MUAP the logarithm of power average over band λ_L=0.2π to λ_H=0.35π can be computed.

$$P_{seg}[n] = \log\left(\frac{1}{\lambda_H - \lambda_L} \sum_{\lambda=\lambda_L}^{\lambda_H} X[n,\lambda]^2 \right) \qquad (2)$$

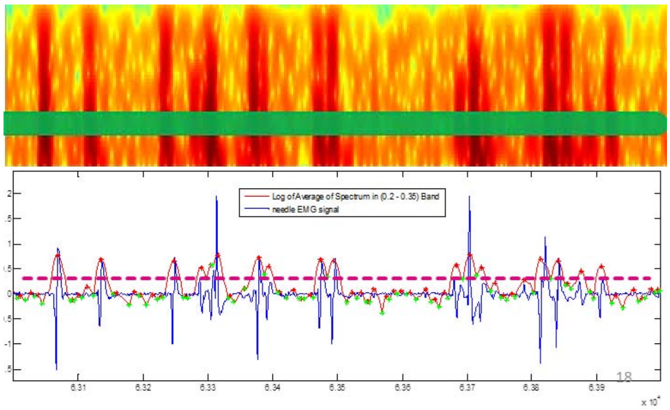


Figure 4. In order to decrease the computation time a limited range between 0.2π to 0.35π in frequency band has been chosen for computing average power curve. We can define a threshold and start decomposition with more dominant motor units in trace.

For every MUAP in time domain (individual MUAPs) one local maximum can be detected in logarithmic average of power. For segments that consist of two or three complex shapes (MUAPs) more than one maximum pick might be detected. And practically it can be seen that for every maximum pick more than a specific threshold one motor unit can be segmented in trace. Local minimums before and after the MUAP have been used to define the start and end points of segment.

For the first step, the threshold assumed that a fixed line for logarithmic average of power curve (green curve) and segment the MUAPs, contains power upper than this fixed threshold. (see fig.4). The better way can be start with a high threshold and segment the MUAPs that their energy is upper than this high value threshold (giant MUAPs). In this way the segmentation starts by segmenting the MUAPs that contains high energy and after segmenting the giant MUAPs the threshold can be decreased to segment MUAPs, which contain lower energy. For validation of automated segmentation results, the results have been compared with the result of manual

D. Feature Extraction

In practice for manual decomposition the shape and sound of signal can be very helpful. In many cases physicians can recognize the patterns without even take a look at signal and just by listening to the sound of signal. As ears mechanism are based on measuring the power of sound at different audio frequencies. This fact leads us to choose STFT as a first choice.

In Feature extraction, we need to extract some dominant information's that can explain and specify MUAPs in the best way. In recent methods time event information like onset, positive peak, negative peak, number of phases considered as features. However these features are very specific and easy to find (low computational time), they are sensitive to noise. In addition in cases that there are more than one MUAP in one segment finding these features are not convenient.

In this paper STFT and CWT has been proposed for feature extraction. 29 features in STFT method were considered, in CWT 10 or 10 first coefficients (high frequency coefficients) were considered as feature.

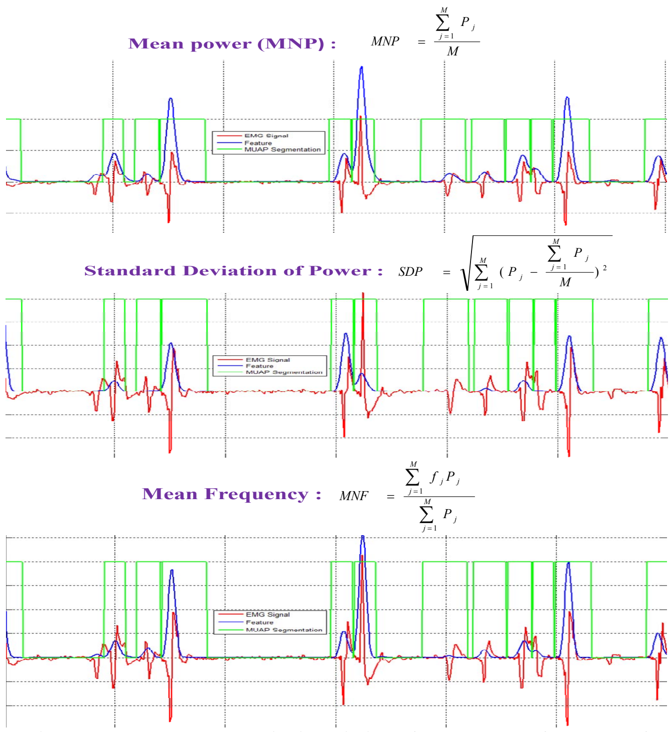


Figure 5. Mean power, Standard Deviation of power, Mean frequency of segmented part of spectrogram are three of most important features (blue color) extracted from signal (red color) and segmented part (green color), There are 26 more features that has been extracted.

More number of features in feature space, means more computation cost. In the other hand, more Number features means having more accuracy and precision. So it is essential to find a tradeoff between number of features, computation time and accuracy of method [4]. For solving this problem we can assume the problem, solved. At first a set of manually decomposed signal can be chosen. By taking a look at these segmented signals, we can find many features that can specify the MUAPs. Many features need to be examined and empirically effective set of features can be chosen. (see fig.6)

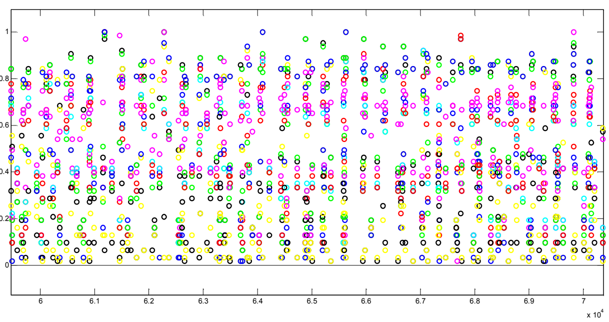


Figure 6. Every column in this diagram is related to one MUAP and the color small circles are features. This data is related to 8 Seconds of data and includes 100 MUAPs, 28 features have been considered in this decomposition and their values have been normalized.

Three types of features have been chosen in this project, firstly the features that are related to the power of MUAPs, secondly the features that are related to the shape and morphology of signal and finally CWT high resolution coefficient of the signal.

After defining features set, features should be computed for every segment. For every segment there is a feature vector that consist of the set of computed features, the elements of vectors should be normalized and the feature space matrix can be defined.

Feature extraction by Wavelet Transform: CWT has been proposed for this step. In CTW the number of elements of every coefficient is equal to the number of elements of signal. Because Daubechies D4 mother function is very similar to general form of MUAP, This mother function has been chosen [5].

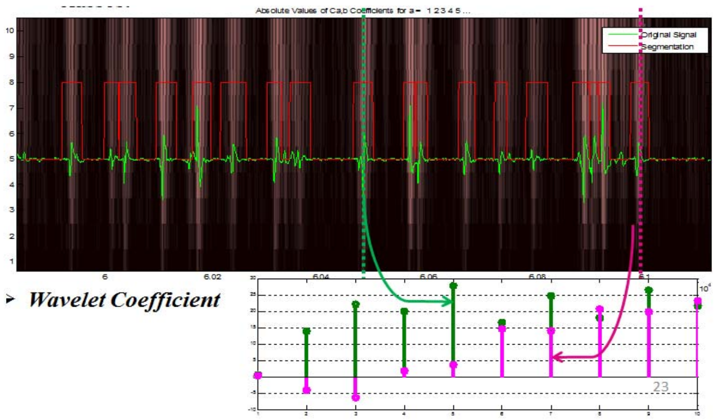


Figure 7 . CWT has been computed for first 10 coefficients. In low order coefficients (1, 2, 3, 4 ,5) the difference among different motor units are clear, however for higher coefficients (6 to 10) the differences cannot be seen visually. Practically first 5 coefficient is enough for decomposition.

E. *Clustering and Classification*

The decomposition of EMG signals into their constituent MUAP's and their classification into groups of similar shapes is a typical case of an unsupervised learning pattern recognition problem. Clustering schemes can play their roles for this question. In this study, we realized this clustering process with method Fuzzy C-means Clustering (FCM). [6], [7]

Eventually we come up with limited no of classes. Each class defines a motor unit that generates the signal. Technically no of classes are equal to the number of Motor units that are located in the area of interest and generating action potential. In final stage, we just go over the averaging on each class, in this way we can have the signal shape of the specific class which is like signature of this MU.

III. RESULTS

In this study we have developed a method to classify surface EMG signals into multiple classes. Our target is to reach a high quality of the classification. Results obtained suggest that our proposed algorithm detects and classifies MU of each muscle's fiber very efficiently.

The result of method can be seen in figure 8(a)(b). For single MUAP segments the result is completely satisfactory, but we have error when two or three MUAPs have been overlapped. However in segmentation almost all the overlapped MUAPs has been segmented properly in decomposition phase we couldn't extract them from the signal properly. Result of algorithm is illustrated in figure8(c).

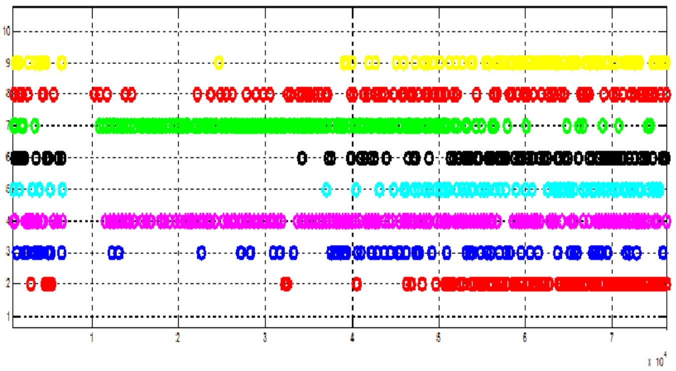


Figure 8 (a) . Vertical axis is related the MUAPs that have been found in trace The color circles are related to defines the class of MUAPs in specific time.(every row is for one fiber MUAPs).

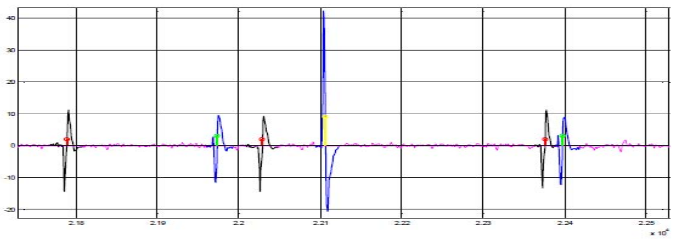


Figure 8 (b). Decomposition of MUAPs.

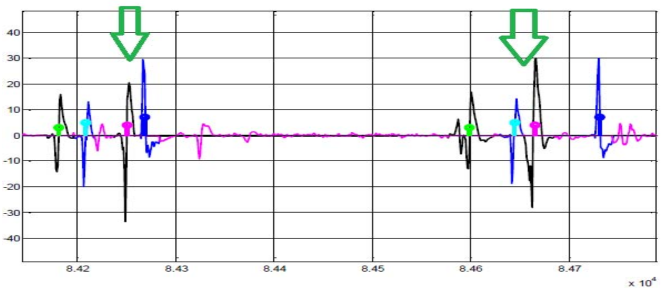


Figure 8 (c). Decomposition of MUAPs. Compound MUAPs have been decomposed (Green Arrows).

Measured EMG signals from 8 healthy subjects during different computer tasks, such as tapping, tracking, and number inputting were used. Each task had duration of 60 second. In this algorithm, first we employed the spectrogram to perform the segmentation. The length of the used time window in STFT that produced the best results for MU segmentation is 5ms. These interferences are more appeared during high contraction of muscles. Table 1 shows results of segmentation in comparison to manual method in terms of TP, FP, and FN.

The proposed method is applied subject, data set. We observe an error in classifier outcomes in 1150 MU among more than 30300 MUAPs. So, the accuracy of the algorithm is 94.20%. We compared the outcomes of the automatic algorithm with the manual results obtained under specialized supervision.

The main goal of the segmentation algorithms is to capture as accurate as possible the structures of interest. For the assessment of their performances, the segmentation results are compared with manually segmented ground truth using several quality measures. Further on the chosen evaluation metrics are described.

Accuracy is related to the rate of correct results with respect to the whole domain and precision is the percentage of the accurately identified positives with respect to all positive results. As well, in the case of these measures, higher percentages refer to higher performances of the assessed segmentation algorithm.

The similarity between the ground truth and the segmentation results can be also computed using the Dice coefficient and is defined as shown in below equation.

$$Dice\,coefficient = \frac{2TP}{(TP+FP)+(TP+FN)} \tag{3}$$

A low value for the Dice coefficient would suggest that there is low similarity between the ground truth and the outcome of the segmentation algorithm, while a unity coefficient would denote a perfect segmentation.

Table 1: Quality measures for the MUAP segmentation

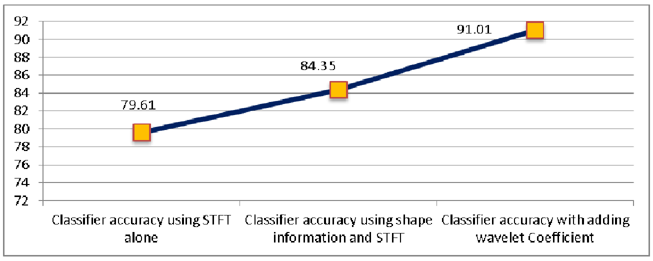
Quality measures	Sensitivity	Accuracy	Dice coefficient
MU segmentation	96.49 %	96.20 %	98 .06 %

In classification, each fiber's MU is detected by applying FCM method to feature space. Feature space consists of 32 feature vectors for each MU. We derived the feature space based on: features extracted from spectrogram spectrum analysis, features corresponding to information extracted from MU's shape, and wavelet coefficients. We normalized the feature space prior to apply it to the classifier. We also improved distinguishing different MUs features by applying histogram equalization to feature vectors with a limited histogram or in another word feature vectors which had a low contrast.

Classification results show that by adding wavelet coefficient to the feature space, the classifier better distinguishes each fiber's MU. By investigating the shape and type of the wavelet window we concluded that a db4 window had better performance in comparison to other windows. This improvement lies in independence of different MU classes in feature space.

Table 2 shows the classification success rate on more than 30000 MUAP's, obtained from surface EMG recordings. The classification success rate was defined as the percentage ratio of the correctly identified MUAP classes by the algorithm and the number of true MUAP classes present in the signal as identified by an experienced person. The average success rate for the FCM with wavelet coefficients as features was 91.01 %, for the STFT and template waveform algorithm alone 84.35%, and for the spectrogram analysis only features 79.61%.

Table 2: The clustering success rate



Segmentation Result			
Needle EMG	Correctly detected (TP)	Incorrect Detected(FP)	Non Detected(FN)
	95%	1.5%	3.5%
Decomposition Result			
Needle EMG	Correctly detected (TP)	Incorrect Detected(FP)	Non Detected(FN)
	84%	11%	5%

Also, by improving decomposition approach through an iterative procedure in which the threshold and consequently decomposed MU is reduced in each iteration, we can increase the classification accuracy.

Our algorithm needed 26.84sec to classify a 25sec-surface EMG signal which contained nearly 1100 MUs from 8 classes. We used a core i7, 2GHz computer and MATLAB programming environment to process the data. We also decreased sampling rate from 40 KHz to 4 KHz in segmentation to reduce the process time. This decrease, significantly reduces the process time while having no effect on segmentation accuracy.

IV. CONCLUSION

In this paper we proposed a fully automatic algorithm for decomposition of MUs based on STFT and wavelet transform. All subjects obtained ethical approval before aqcuisition needle EMG data. The implemented decomposition algorithm comprises several stages for the successful accomplishment of the task. The first step takes into account the pre-processing of the signal to be analysed for reducing the noise and enhancing the features of interest for the subsequent segmentation and decompositoin algorithms. the next section discusses segmentation techniques. Next, feature extraction methods are introduced. Feature used in this study comprises spectrogram analysis, shape and template of MUs and wavelet coeeficients. Finally FCM clustering method are used for decomposition of MUs. The clustering of MUAPs was relatively fast and no user inputs were needed over a wide range of signals [8]. We applied the algorithm to the 8 healthy subjects during different computer tasks, such as tapping, tracking, and number inputting were used and the average success rate for the FCM with wavelet coefficients as features was 91.01 %.

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