Fuzzy Clustering and Feature Selection Analysis Toward Improved Identification of MUAP in Needle EMG Signal

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***Abstract*— Decomposing the EMG signal and determining fiber's motor units is a challenging work in this area. The high amounts of resident noise and artifacts distort the signal. But, the decomposition gets more complicated, when we have motor unit action potential MUAP, interference during one channel recording. Considering this distortion, recognition and separation of motor units from each other, and determining the degree of their membership to each fiber gives valuable information. In this paper. First, motor units are determined and separated according to a set of filters similar to Gabor filters, then by extracting some different time-frequency and morphology features, the feature space will be determined. In the next step, the number of clusters which are the number of fibers will be determined. The clustering method used for this purpose is FCM clustering method. One of the innovations of the proposed method in this study is using an algorithm which improves the accuracy of the decomposition. This algorithm employs the membership information of each motor unit in fuzzy clustering along with the feature selection using mutual information of each motor unit. The results indicate 7.3% improvement while decreasing computational costs.**

Keywords- *motor unit action potential, wavelet coefficient, Gabor bank filter, FCM clustering, genetic algorithm*

I. INTRODUCTION

Recent advances in computer technology, signal processing, and pattern recognition techniques have led to the development of new techniques for extracting valuable information from the EMG signals detected from a muscle. Therefore, electromyography now plays a major role in physiological investigations and clinical examinations for either the study of motor control or the diagnosis of neuromuscular disorders. One such technique is EMG signal decomposition [1]. In actuality, most EMG signals contain a continuum of activity, ranging from large MUs that can be clearly distinguished to small ones that blend into and help constitute the background noise. Thus, the number of MUAP 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 MUAPs overlap.

$$EMG(t) = \sum_{m=1}^{N_m} MUAP_m(t) + n(t) \quad (1)$$

In (1) 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 [1][2][3]. Unfortunately, the MUAP template shapes and MU firing patterns of invalid MUAPs cannot be easily distinguished from those of valid trains. Often, the MUAP template shape of an invalid train looks similar to that of a valid train; nevertheless, the train does not represent the MUAPs of a single MU. As such, the variability of MUAP shapes and possibly the MU firing pattern are greater for invalid trains compared to valid trains. If such inaccurate information is not detected and excluded from further analysis, it could improperly suggest an abnormal muscle when interpreted clinically or it may contribute to scientific misstatements [4]. Full decomposition is also useful for studying discharge irregularities such as those associated with doubly innervated muscle fibers. Full decomposition makes it possible to detect such irregularities even in busy signals by subtracting out the activity of the other MUAPs that are not of interest [5]. Usually automated EMG signal decomposition includes the following steps; (1) preprocessing (2) MUAP segmentation (3) feature extraction (4) MUAP clustering and classification.

The preprocessing steps are performed for eliminating the background noise and low frequency information. Also, filtering, reduces MUP durations, decreases the, MUP temporal overlap, sharpens MUPs, and increases the differences between MUPs and the background noise. Filtering highlights the dissimilarities between MUPs which are created by different MUs; So, filtering enhances MUP identification and classification. Usually, band-pass filters or low-pass difference, LPD, filters are employed [6] [7]. Implementation of LPD filters is easy and can be done in a fast way. Therefore, LPDs are appropriate for real-time and clinical purposes. But, these filters are not ideal and contain high frequency noise components.

In segmentation step, the main goal is detecting all MUAPs produced through active MUs. But, MUs which don't have muscle fibers near the electrode's detection surface will contribute low amplitude MUPs in practice. Furthermore, These

MUAPs contain low frequency components and their shapes are very similar. Hence, assigning these MUAPs to their correct fibers is very hard, and only MUPs which have the possibility of being correctly assigned should be detected. Usually, this step will be performed through a threshold crossing approach [8],[9].[10] The main features for determining the detection threshold value are consist of root mean square (RMS) value, mean absolute value, and maximum absolute value ,of the signal. The maximum absolute value decreases the probability of small MUAPs being lost in larger MUAPs, and creates a likely bias against minor MUAPs. The length of the applied window in choosing MUAPs can be variable [11], [12]. A MUAP starts when its sample values surpass a threshold and finishes when they occur below this threshold. When a fixed-length window is selected, the length of the window should be set for including a fixed duration, usually 2.5 ms [13] or 6 ms [14]. Longer windows enhance MUP depiction, but increase decomposition time as well. Employing a short fixed window creates multiple detections of complex or long-duration MUPs.

For extracted features, usually large number of features improves the accuracy of classification, but creates the curse of dimensionality too. Typically, a proper set of features which have the high discriminant properties among the different classes is desired. So far, different features have been employed for representing the detected MUAPs. Raw-data (time samples) and first or second-derivative of time samples [15], [16]. Fourier transform coefficients and power spectrum [17] and principal components of wavelet coefficients [18] are some examples of features used in representing and assigning fibers to MUAPs. Yamda et al [18] applied the principal component analysis (PCA) to all wavelet coefficients for extracting best discriminating features.

II. METHODE

In This study we try to improve the specification of decomposing and classifying MUAPs in an EMG signal using selected high discriminant features and fuzzy methods. Fig 1 shows different steps of the method used in this paper. The proposed method is described using the block diagram shown in fig 1. First, noise and artifact are removed from the signal using discrete wavelet transform DWT method. In the next step, a reliable segmentation method should be applied. The most challenging work in this step is separation of MUAPs which are interfered with others. Then, adequate features for each muscle fiber EMG signal and the number of proper fibrs should be estimated. The feature space includes morphology of Action Potential, AP, continues wavelet coefficients, CWT, Gabor energy bank filter and short time Fourier transform, STFT. Here the clustering method is unsupervised, and number of muscle fibers (i.e. number of clusters) is unknown. So, a Gap-Statistics algorithm is used to estimate the number of clusters by employing aforementioned features. In the next step, by using genetic algorithm, GA, the dimension of the feature space will be reduced. After that, each MUAP is assigned to one fiber using the FCM clustering method. The FCM has some undesired effects, but in our proposed method, the undesired effects will be reduced.

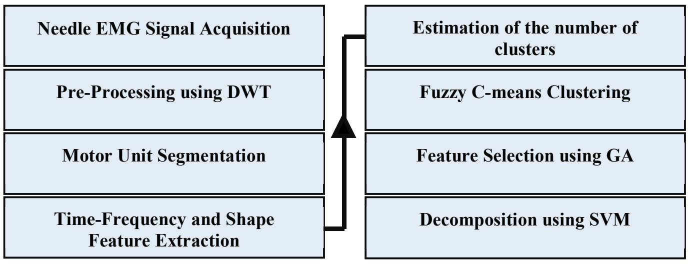


Figure 1. Block diagram of the proposed method.

In this method, 50% of Motor units with highest probability in each FCM cluster are selected as training data, then all segmented MUAPs are decomposed using SVM classification method. The applied method is explained in more details in the following sections. The results are presented in section III.

A. Data acquisition

In this research, NRSIGN 5000Q EMG/NCV/EP machine was used for record the signal. The sample rate of signal is 8 K sample/Sec, High pass filter cut-off frequency is 0.16Hz and Low pass filter cut-off frequency is 2 KHz. The resolution of A/D is 16 bits. The recorded signal is varied between 20uV and 800uV. The amount of amplifier’s input noise (with grounded input) varies between 10uV and 15uV, but during experiment the noise can be increased to more than 20uV (environment EMI impact). In this experiment we used concentric needle electrode. The body of needle electrode is reference electrode and the central part of electrode is the active (or plosive) electrode.

Our dataset consist of 80 trace (60 Sec) of needle EMG signal from Biceps and Deltoid muscles in 10 experiments from 8 different people. The EMG signal acquired in low and medium contraction (not in full contraction) for not having more than 10 to 15 active motor units. In full contraction, the decomposition can be very hard to perform. The applied method is based on the assumption that motor unit action potentials with similar shape belong to one active motor unit. This is a good assumption, since every motor unit has its own physical characteristic and location.

B. Preprocessing

In preprocessing, hardware and software notch filter was applied on data, and as signal had some low frequency noise due to needle movement inside the tissue, a simple LPD filter was used [19].

As in needle EMG signal, we have high frequency noise which might come from other motor units’ activities or electromagnetic radiation noises, a low pass filter should be applied to signal. The low passed signal can be much distorted. In another word, the high frequency component of the signal will be eliminated by low pass filtering in furrier domain. So DWT was employed to reduce the high frequency noise. By thresholding signal with Daubechies D4 in d1 and d2 (fine coefficients) the noise level was reduced; however, there was not much signal distortion in motor units. Therefore, the energy of motor unit is preserved. This energy is one of the most important features which is used in segmentation.

C. MUAP Segmentation

Segmentation of MUAP is one of the most important parts of automotive decomposition algorithm. In segmentation, we should detect 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, as the signal is contaminated with a random noise, the algorithm shouldn't be sensitive to noise [19]. Different AP morphology in each fiber, and the interference of motor units are the main difficulties in thresholding method which make it inappropriate for segmenting MUAPS [9]. To overcome this difficulty, we use a set of filters similar to Gabor filters. By analyzing the frequency spectrum of MUAPs, we can see that the spectrum is more centered near the 400 to 800 HZ frequencies.

$$B(t,\lambda,\sigma) = S(t,\lambda) \times N(t,\sigma) \tag{2}$$

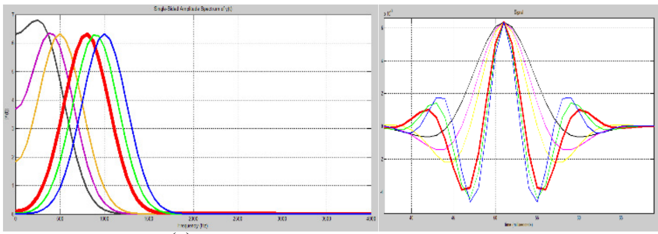
$$G_{abs}(t) = \left| EMG(t) * B(t,\lambda,\sigma) \right| \tag{3}$$

$$S_{segment}(t) = \log(G_{abs}(t) * W_{hanning}(t,\xi)) \tag{4}$$

Considering this fact, a sinusoid signal multiplied with a Gaussian window is used as the appropriate kernel for convolution. AS shown in Eq.(2), the selected kernel is convolved with main signal, and like Eq(4) the absolute value of the output signal is convolved with a Hanning window of 5 ms length. The resulted signal is used in the segmentation process. In Eq(2), the filter is defined as the multiplication of a complex sinusoidal and a Gaussian kernel, in which *S(.)* and *N(.)* are sinusoidal and Gaussian function components respectively. The sinusoid frequency λ, and variance of the Gaussian window σ, are two main parameters that control the band-pass filter. These parameters, i.e. λ and σ are related to the central frequency and the band width of the band-pass filter respectively. Figure 2 shows the impact of these parameters on the shape of the band-pass filter and employed kernel. Considering the spectrum of EMG signal, λ=600 Hz and σ=5 were selected to obtain the best segmentation results. Output signal of Eq.4 is shown in figure 3. To smooth the signal, the absolute value of the produced signal is convolved with a Hanning window of 5 millisecond length. To reduce the amplitude scale of the signal, the logarithm of output was used. Finally, by threshoding the acquired signal, the process of MUAP clustering will be completed. In this process, the signals with a peak value higher than selected threshold are recognized as MUAPs, and local minimums before and after them are considered as the starting and ending points of the MUAP respectively (see figure 3,bottom).

D. Feature Extraction

After segmentation, we should assign each MUAP to its muscle fiber activity group. On the other hand, the number of muscle fibers in the target region in which the needle is inserted is unknown. So, feature extraction in this step is very important. The 10 number of morphology of each MUAP (see table 1), the first 20 coefficients of CWT with db4 window, the 50 features extracted from Gabor bank filter include 5 different variance and 10 central frequency and 15 features from different bands of STFT coefficient are extracted as feature space. By investigating the shape and type of the wavelet window, we concluded that a db4 window had better performance in comparison to other windows [19]. The computation cost is increased when we employ more features; however, usually more features improves the accuracy. So, it is essential to find a tradeoff between the number features, computation time and accuracy of method [20]. Since for each interval we should assign a value as its feature value, first, feature signals are smoothed through convolving them with a Hanning window. The area under the convolved signal is used as the feature value.



(a) (b)

Figure 2. Filter bank which resulted from Eq(2). λ=300Hz to 1K Hz with 100Hz steps and σ = 5 (a) Frequency domain (b) Time domain.

Table 1. Selected mathematical definition of shape feature extraction

Feature Extraction	Mathematical definition
Difference Absolute Standard Deviation value	$DASD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N-1}(x_{n+1}-x_n)^2}$
Integrated EMG	$IEMG = \sum_{n=1}^{N} \lvert x_n \rvert$
Simple Square Integral	$SSI = \sum_{n=1}^{N} \lvert x_n \rvert^2$
Average Amplitude Change :	$AAC = \frac{1}{N}\sum_{n=1}^{N-1} \lvert x_{n+1}-x_n \rvert$
Zero Crossing	$ZC = \sum_{n=1}^{N-1}\left[\mathrm{sgn}(x_n \times x_{n+1}) \cap \lvert x_n - x_{n+1} \rvert \geq 0\right]$
Max Positive peak Max Negative peak	$MPP = \max(x_n)$, $MNP = \max(-x_n)$
Waveform length	$WL = \sum_{n=1}^{N-1} \lvert x_{n+1}-x_n \rvert$
Root Mean Square	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$
Modified Mean Absolute Value	$MMAV = \frac{1}{N}\sum_{n=1}^{N} w_n \lvert x_n \rvert$ $w_n = \begin{cases} \alpha & if \ \frac{N}{2}-\delta \leq n \leq \frac{N}{2}+\delta \\ \beta & otherwise \end{cases}$

E. Estimation of the number of clusters

Decomposing EMG signals into their constituent MUAP's, and classifying into groups of similar shapes can be achieved through an unsupervised pattern recognition Method. Clustering approaches are typical methods used for this purpose [20]. In this study, we realized this clustering process through a FCM approach. Finally, we came up with limited number of classes. Each motor unit which generates the signal constitutes a class. Technically, the number of classes are equal to the number of Motor units that are located in the area of interest and generating action potential. A typical graphical method to cluster evaluation contains plotting an error measurement versus several proposed numbers of clusters, and locating the "elbow" of this plot. The "elbow" occurs at the most dramatic decrease in error measurement. To formalize this method, the gap criterion is used. This criterion estimates the "elbow" location as the number of clusters with largest gap value. So, under this criterion, the optimal number of clusters occurs at the solution with the largest global or local gap value within a tolerance range. The gap value is defined as:

$$G_{p_n}(k) = -E_n^*\{\log(W_k)\} - \log(W_k) \tag{5}$$

In which n is the sample size, k is the number of evaluated clusters, and W_k is within-cluster dispersion measurement

$$W_k = \sum_{r=1}^{k} \frac{1}{2n_r} D_r \tag{6}$$

In which n_r is the number of data points in cluster r, and D_r is the sum of the pairwise distances for all points in cluster r. The $log(W_k)$ is computed using the sample data, and the expected value expected value $E{*}n\{log(W_k)\}$ is obtained through Monte Carlo sampling from a reference distribution. The gap value is defined even for clustering solutions with only one cluster. This value can be used with any distance metric. But, as the clustering algorithm should be applied to the reference data for each proposed clustering solution [20].

F. Fuzzy C-means Clustering (FCM)

After determining the number of clusters, the probability of belonging to one of the clusters is determined using the FCM algorithm. The objective function is selected as Eq.7

$$J = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m d_{ik}^2 = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m \left\|x_k - v_i\right\|^2 \tag{7}$$

In Eq.7 m is a number larger than 1. x_k is the k_{th} sample and V_i is the center of i_{th} cluster. U_{ik} is the membership level of the i_{th} sample to the k_{th} cluster. The sign ‖.‖ is the level of similarity of a sample with the center of a cluster. Using U_{ik} , a matrix, U, will be derived that has c rows and n columns and its components can have a number between the range of 0 and 1. If all the components of matrix U are in the range of *0-1,* then the algorithm is similar to classic c-mean clustering. The sum of all components in one column should be equal to 1 in matrix U (Eq.8).

$$\sum_{i=1}^{c} u_{ik} = 1, \qquad \forall k = 1,...n \tag{8}$$

This criterion means that the sum of membership level of each sample to cluster c should be equal to 1. Using the above criterion and minimizing the objective function, the following equations can be derived.

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \qquad v_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \tag{9}$$

The required steps of the algorithm are as follows:

1) Initial value for c, m and U^0; initial clusters are estimated.
2) The center of each cluster is determined (V_i)
3) Calculating the membership matrix from the clusters in 2.
4) If $||U_{l+1}-U_l||\leq\varepsilon$ the algorithm is over, otherwise go to step 2.

By choosing the maximum membership probability, the decomposition process will be completed.

G. Features Analysis

Employing all features might be useful to overcome some problems, but in many situations subspace of features summarize the data in a good way. So, it is better to reduce the dimension of the feature space. Mutual information (MI) can be estimated through statistical parameters. As Eq.10 shown asymmetric dependency coefficient (ADC) can achieved from relation of MI and entropy of C, classes and f, features by using Shannon formula (Eq.11)

$$ADC(C,f) = \frac{MI(C,f)}{H(C)} \tag{10}$$

$$H(C) = -\sum_{i=1}^{K} p(C_i)\lg_2 p(C_i) \tag{11}$$

$$H(f) = -\sum_{x} p(f=x)\lg_2 p(f=x) \tag{12}$$

$$MI(C,f) = -H(C,f) + H(C) + H(f) \tag{13}$$

As the total number of MUAPs in the whole data set is very much, and manual clustering is practically impossible, the fuzzy clustering should be first done with all feature space including shape and time-frequency features. Then, we consider half of the MUAPs of each class with highest dependence as the train data and perform the feature analysis on these data.

H. Feature Selection using Genetic Algorithm

In the following by using the genetic algorithm optimization method with MI criterion feature selection is performed.

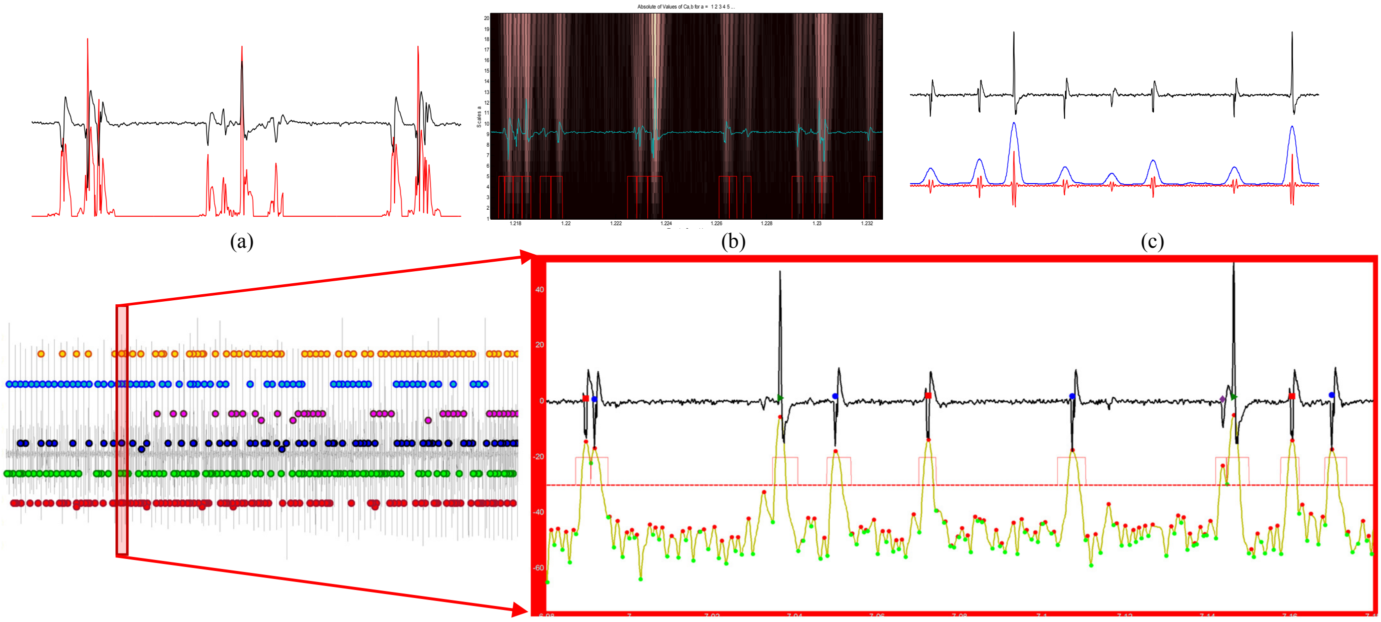


Figure 3. **Top** (a) original EMG signal (black) and RMS shape feature, (b) 20 coefficient wavelet, (c) Gabor bank filter with F_c=500 Hz and σ = 5 (red) and convolved by Hanning smoothing window (blue). **Bottom**, firing rate patterns of MUAPs (6 class) and signal extracted for segmentation analysis (yellow

Genetic algorithm as a computational optimization algorithm considers a collection of points in answer space in each iteration, and searches the answer space areas in an efficient way. In this section the genetic algorithm optimization with MI criterion was explained. The details of applied method are explained in the following. Using the GA, first, for each of 5 subjects, 12 features which create the most discrepancy among the prominent data will be selected. Note that these features create the discrepancy based on the dependence of these data to their classes. GA has a better performance in finding features in large data sets. If we select less than 5 features, the classifier's accuracy will be decreased, and using more than 12 features doesn't create a significant improvement in classifier's accuracy, and even using more than 20 features decreases the classifier's accuracy; so, here we used 12 features. As we explained in previous section we used mutual information for selecting features.

III. Experimental Results

In this study, we developed a method to classify needle EMG signals into multiple classes. Obtained results suggest that our proposed algorithm is very efficient in detecting and classifying MU of each muscle's fiber. The result are shown in figure 3. Although in segmentation step almost all the overlapped MUAPs were segmented properly. Measured EMG signals from 8 healthy subjects during different computer tasks, such as tapping, tracking, and number inputting were used. Each task lasted 60 seconds. The results of the automatic algorithm were compared to the manual results obtained under specialized supervision and the accuracy of the algorithm is 95.1%. In classification, each fiber's MU is detected by applying FCM method to feature space. We can see that among 12 selected features from each subject, 7 features are common in each of them (see table 2). So, by using these features we can improve the classifier's performance while reducing the computational cost noticeably. Results indicate that when we use these 7 features in 3 other subjects, the classifier's performance has a 7.3% improvement. We normalized the feature space prior to applying it to the classifier.

Table 2. seven selected features using mutual information by GA

DASD shape feature (see table 1)	Power spectrum band using proposed Gabor (F_c=500 and σ=3)
MMAV shape feature (see table 1)	Power spectrum band using proposed Gabor (F_c=400 and σ=5)
5^{th} coefficient db4 wavelet	Power spectrum band using proposed Gabor (F_c=700 and σ=5)
8^{th} coefficient db4 wavelet	

To investigate the performance of automated decomposition method, 4000 MUAPs which have been classified manually by a specialist were compared to the results of our proposed method. Manually classified MUAPs contain all low and intermediate contraction steps and resting condition. To compare the accuracy of our proposed method with other approaches, considering the large number of MUAPs, classifier's results were compared to the GUI results of McGill which is the most comprehensive work in this field [1], [2]. We referred to a specialist to find more about MUAPs which were different with those of the GUI's results. Table 3 shows the on more than 30300 MUAP's, obtained from needle EMG recordings. The average success rate for decomposition with all

Table 3 classification success rate

Needle EMG	All Features	After PCA Algorithm	Using Feature Selected Analysis
Decomposition	83.6%	87.8%	**95.1%**

features was 83.6 %, by using PCA algorithm 87.8%, and for the feature selected analysis 95.1%. Our algorithm needed 106 sec to classify a 60sec-needle EMG signal for 87 features which contained more than 4000 MUs from 8 classes, but for 7 features selected, the time consuming reduced to 23 sec. We used a core i7, 2GHz computer and MATLAB programming environment to process the data.

IV. CONCLUSION

In this paper a fully automatic algorithm was proposed for decomposition of Mus. This study concentrates on automatic validation of a given MUAP using both its MU shape and MU firing pattern information. The motivation for developing automated methods to estimate the validity of MUAPs are to facilitate the use of EMG signal decomposition results for clinical applications of quantitative electromyography by providing the overall validity of MUAPs and excluding or highlighting invalid MUAPs. Also this method improves the accuracy and completeness of decomposition results. The implemented decomposition algorithm comprises several stages for the successful accomplishment of the task based on a combination of feature extraction, cluster validation techniques, and supervised classification algorithms. The goal was to develop a fast and accurate MUAP validation system which can be used both during the decomposition process and after decomposition. All subjects obtained ethical approval before aqcuisition needle EMG data. We applied the algorithm to 8 healthy subjects during different computer tasks, such as tapping, tracking. By improving decomposition approach through a proposed procedure in which the 7 most distinguish capability features selecting and fuzzy clustering information employed, we could increase the classification accuracy. The average success rate for the SVM classifier was 95.1 % and the results show a 7.3% improvement.

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