A Hybrid Classifier for Characterizing Motor Unit Action Potentials in Diagnosing Neuromuscular Disorders

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ABSTRACT

Background: The time and frequency features of motor unit action potentials (MUAPs) extracted from electromyographic (EMG) signal provide discriminative information for diagnosis and treatment of neuromuscular disorders. However, the results of conventional automatic diagnosis methods using MUAP features is not convincing yet.

Objective: The main goal in designing a MUAP characterization system is obtaining high classification accuracy to be used in clinical decision system. For this aim, in this study, a robust classifier is proposed to improve MUAP classification performance in estimating the class label (myopathic, neuropathic and normal) of a given MUAP.

Method: The proposed scheme employs both time and time–frequency features of a MUAP along with an ensemble of support vector machines (SVMs) classifiers in hybrid serial/parallel architecture. Time domain features includes phase, turn, peak to peak amplitude, area, and duration of the MUAP. Time–frequency features are discrete wavelet transform coefficients of the MUAP.

Results: Evaluation results of the developed system using EMG signals of 23 subjects (7 with myopathic, 8 with neuropathic and 8 with no diseases) showed that the system estimated the class label of MUAPs extracted from these signals with average of accuracy of 91% which is at least 5% higher than the accuracy of two previously presented methods.

Conclusion: Using different optimized subsets of features along with the presented hybrid classifier results in a classification accuracy that is encouraging to be used in clinical applications for MUAP characterization.

Keywords
EMG,Hybrid classifier design, MUAP characterization, Mutual information, Wavelet

Introduction

Electromyographic (EMG) signals demonstrate the electrical activity of muscles during voluntary contraction. Each muscle consists of many muscle fibers which are organized into groups for the control of muscle force with each muscle fiber of a group being connected to a motor neuron. Each muscle fiber of a group is activated concurrently by the motor neuron to which they are connected. Each muscle consists of small muscle fibers which are controlled by different α-motoneurons via the connected axons. A motor neuron, its axon and the set of connected muscle fibers are called a motor unit (MU) [1].

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The summation of the muscle fiber potentials created by the spatially and temporally dispersed depolarization and repolarization of all of the excited fibers of a single MU is known as motor unit action potential (MAUP). During a muscle contraction, several MUs may be activated each of which fire repetitively to maintain the force of the muscle contraction. Therefore, each activated MU generated a train of MUAP known motor unit action potential train (MUAPT). EMG signal acquired from a contracted muscle is the summation of MUAPTs and background noise [1].

EMG can be detected using either needle electrodes or surface electrodes each of which has its own advantages, disadvantages and usages. Surface electrodes record the summation of activities from many motor units and even the activity of adjacent muscles. On the other hand, needle electrodes permit recording of individual motor unit potentials and provide much information about deep muscles. For diagnostic applications it is desired to get detailed temporal and spatial information about the muscle fibers of a MU; therefore EMG signals detected directly from the muscles by needle electrodes are used for clinical use [2].

Neuromuscular diseases alter the morphology and physiology of MUs and ultimately their firing patterns and MUAP shapes. Neuromuscular disorders, in general, are grouped in two principal categories: myopathic and neuropathic. Myopathic disorders are caused by death or atrophy of muscle fibers and neuropathic disorders are caused by the death or damage of motor neurons. MUAPs detected from myopathic patients usually have high frequency contents, short peak to peak amplitude, short duration and consequently are smaller and more complex than normal cases. MUAPs detected from neuropathic patients are polyphasic (number of baseline crossings are increased), have long peak to peak amplitude, long duration and consequently are larger and more complex than normal cases. Consequently, analyzing MUAPs created by the MUs of a contracting muscle can assist with identifying its state of health [3].

In traditional clinical practice, neurologists assess individual MUAPs visually and auditory to diagnose disorders. In visually assessment of MUAPs, neurologists analyze isolated MUAP morphology and MU firing patterns. These features demonstrate MUAP shape and MU firing patterns which are representative for the underlying diseases. In auditory assessment neurologists investigate frequency and amplitude of the clicks and crackles made by amplified EMG signals. In general, both visual and auditory assessments of MUAP are performed simultaneously and the one with better discriminative information is considered as a reference for decision. MU firing pattern are considered as a supplementary source of information. Although such a qualitative analysis can assist with diagnosing neuromuscular disorders, there are several limitations with these techniques [4].

Qualitative EMG analysis results depend on expert skills and may prone to errors and misinterpretations. Both subjective visually and auditory assessment of MUAPs may crude with poor sensitivity and specificity. In addition, qualitative EMG analyzing cannot provide quantitative data for comparison purposes and measuring disease severity and improvement. Therefore, computer based quantitative EMG algorithms have been developed to overcome these shortcomings [5].

The literature describes different sets of extracted features and classification schemes for automatic diagnosing of neuromuscular

disorders. Pattichis *et al.* [6] used MUAP parameters as input to a sequential parametric pattern recognition classifier. Pattichis and Pattichis [7] have analyzed the effectiveness of the wavelet transform (WT) for describing MUAP morphology and three different neural networks for classification. Pattichis and Elia [8] used autoregressive, cepstral and time domain analysis in classification of EMG signals. Subasi *et al.* [9] investigated the usefulness of using an autoregressive model and wavelet neural network to extract discriminative features from EMG. Katsis *et al.* used SVM [10], RBFN and Decision Tree (DT) [11] for MUAP classification. Pino *et al.* [12] used Naïve Bayesian (NB), DT and pattern discovery (PD) classifiers for MUAP classification and characterization. Dobrowolski *et al.* [13] used MUAPs decomposition using wavelet and SVM for the classification of neuromuscular disorders. Recently, Subasi [14] used ANFIS with AR and discrete wavelet transforms (DWT) features to automatically diagnose neuromuscular disorders. The principal shortcoming of all these works is absence of high classification accuracy which is critical for clinical decision support systems.

In this research, we proposed a novel classification scheme that uses the combination of time and time-frequency features for characterizing MUAPs detected from a given EMG signal. The objective was to develop a robust MUAP characterization system to be used in clinical decision system. In the next sections, details of the employed features, proposed classification scheme, evaluation mechanism and obtained results are presented.

Material And Methods

Extracting MUAPs from EMG signal

To extract features and analyze electrical activities of muscles, two main approaches are exist: MUAP analysis [15] and inference pattern (IP) [16] analysis. In the first approach, features are extracted from individual MUAPs whereas in the second approach features are elicited from composite EMG signal. MUAP analysis provides more comprehensive and informative set of features compared to IP method because in this method features are elicited from MUAPs directly. Therefore, in this study MUAP analysis technique is employed to study neuromuscular disorders. To extract MUAPs, templates of motor unit action potential trains (MUAPTs) are estimated via decomposing a given EMG signal into its component MUAPTs using validity–based EMG decomposition (VBEMGD) system. The VBEMGD system is an extension of decomposition–based quantitative EMG (DQEMG) system [16-18] and is an algorithm for decomposing intramuscular EMG signals acquired during isometric contractions. The VBEMGD system decomposes an EMG signal off–line by band–pass filtering the signal, identifying the position of MUAPs in the filtered signal by a threshold crossing technique, and then grouping the detected MUAPs using a clustering and a knowledge–based supervised classification algorithm. For more information, please refer to [19].

Feature Extraction and Selection

Successful MUAP characterization system is highly dependent on the discriminate ability of feature set used to represent each MUAP. In other words, distribution of the elicited features for different MUAP classes should not overlap with that of the other classes. As far as physicians make a decision about a MUAP via assessment of its parameters, it is desirable to project MUAP infor-

Table 1: MUAP morphological features and their definition.

Feature	Definition
Rise Time	The time between the initial positive to the next negative peak within the main spike.
Duration	The time between start and end point of a MUAP.
Spike Duration	The time between the first to the last positive peak.
Area	Rectified MUAPs integrated over the calculated duration.
Phases	The number of baseline crossings where amplitude exceeds ±25µV, plus one.
Thickness	The ratio of the area to the peak to peak amplitude.

Table 2: Relationship between MUAP abnormalities and anatomical consequences.

MUAP Abnormality	Anatomical Consequences	Predicted MUAP Type
Reduced duration	Loss or atrophy of muscle fibers	Myopathic
Increased duration	Increased number of muscle fibers	Neuropathic
Reduced amplitude	Loss or atrophy of muscle fibers	Myopathic
Increased amplitude	Regeneration, reinnervation or splitting of muscle fibers	Neuropathic
Increased number of phases	Regeneration, reinnervation or splitting of muscle fibers	Neuropathic-Myopathic

mation from different aspects. Due to variability of time and frequency based features, no single feature are sufficiently discriminative to be used; consequently, various features should be used to represent MUAPs. In this work, time domain and discrete wavelet transforms (DWT) features were employed for this purpose. Details of feature extraction and reduction used in this study are given in the following two sub–sections.

Time Domain Features

The six time–domain parameters listed in table 1 are used to represent each MUAP [20-21]. Time domain features play an important role in clinical decision system since they are transparent and interpretable by clinicians.

To select appropriate time domain features, first, we need to investigate the relationship between neuromuscular disorders and the resulting MUAP shape. Table 2 lists anatomical correlations between abnormalities in MUAPs and the corresponding changes in the muscles.

Time domain feature selection is performed in two steps. In the first step, based on neurophysiologic effects of myopathic and neuropathic disorders, a group of features are selected for discriminating each MUAP class from others. As an example, neurophysiologic features for separating myopathic type from other (normal and neuropathic) are selected. In the second step, between the features of each group, sequential forward floating selection algorithm (SFFS) [22] is performed and for each class, final candidate features are selected.

DWT Coefficients Extraction

Wavelet transform has been introduced by Daubechies [23] and can be used to describe

time and frequency characteristics of a signal simultaneously. One of the main properties of the wavelet transform is its capability in handling non stationary signals such as bio-medical signals (e.g EMG). To extract DWT features, first an appropriate mother wavelet (MW) should be selected. This selection is performed based on the experiments. In this study, DB4 MW provides the highest similarity to the structure of employed MUAPs and therefore is selected for this application. To reduce dimension of DWT coefficients, the following three statistical indexes are used [24]:

1)   Mean of the absolute values of the coefficients in each sub-band.
2)   Average power of the wavelet coefficients in each sub-band.
3)   Standard deviation of the coefficients in each sub-band.

To select features from the extracted DWT coefficients, mutual information (MI) criterion is used. MI is a measure of interdependence between random variables [25]. Let X and Y be two random variables, the mutual information $I(X;Y)$ is defined as follows:

$$I(X;Y)=H(X)+H(Y)-H(X,Y) \qquad (1)$$

Where $H(.)$ is the entropy of a random

variable and determines the associated uncertainty. Suppose that the random variable X is continuous, $H(X)$ is defined as

$$H(X)=-\int p(x)\log_2 p(x)dx \qquad (2)$$

In case of discrete value for random variable X, $H(X)$ is defined as follows:

$$H(X)=-\sum p(X)\log_2 p(X) \qquad (3)$$

In Eqs. (2) and (3), $p(X)$ represents the marginal probability distribution of random variable X. According to the Bayes rule on conditional probability, Eq. (1) can be re-written as:

$$I(X;Y)=H(X)-H(X|Y)=H(Y)-H(Y|X) \qquad (4)$$

In Eq. (4), there is no assumption about the relationship between random variables; therefore, it is quite general and often considered as the generalization of the linear correlation coefficient. However, if X and Y are Gaussian random variables, their mutual information is a simple transformation of their linear correlation coefficient ρ [26]:

$$I(X;Y)=-\frac{1}{2}\log(1-\rho^2) \qquad (5)$$

Mutual information can be easily expanded to include more than two random variables. According to the chain rule [25], the joint mutual information among a set of features $(X_1, X_2, ..., X_n)$ and the outcome Y is

$$I(X_1,X_2,...,X_n;Y)=\sum_{i=1}^{N}I(X_i;Y|X_{i-1},X_{i-2},...,X_1) \qquad (6)$$

JMI represents how much the information provided by the feature vector $(X_1, X_2,..., X_n)$ decreases the uncertainty about the random variable X. When we have a large feature space, we expect that some of features may be dependent to each other. By employing JMI as the feature selection criterion, an optimal feature space can be achieved which contains not only the most relevant, but also contains the least redundant features.

To select the time-frequency domain features based on MI and JMI, a stepwise algorithm was employed so that each new selected feature has the highest individual MI with the output and lowest possible JMI with the preselected features. This procedure is as follows in the first step, single feature X_i

which has highest MI with the output variable Y, is selected. It should be noted that in each selection step, the candidate feature X_j should be selected if it maximizes the following weighted difference:

$$I(X;Y) - \beta \sum I(X_k;X_j) \qquad (7)$$

Where *k* represents preselected features and *j* represents the candidate features [27]. The parameter value β is determined empirically between 0.5 and 1.0

Classification Scheme

Recently, multi-classifier scheme becomes so popular due to the basic idea that classifiers using different architectures or different features can complete each other to enhance the classification performance. This has led to a belief that by simultaneously using features and classifiers of different types, classification accuracy can be improved such that the performance of the combination is not worse than the average of the individual classifiers, but not necessarily better than the
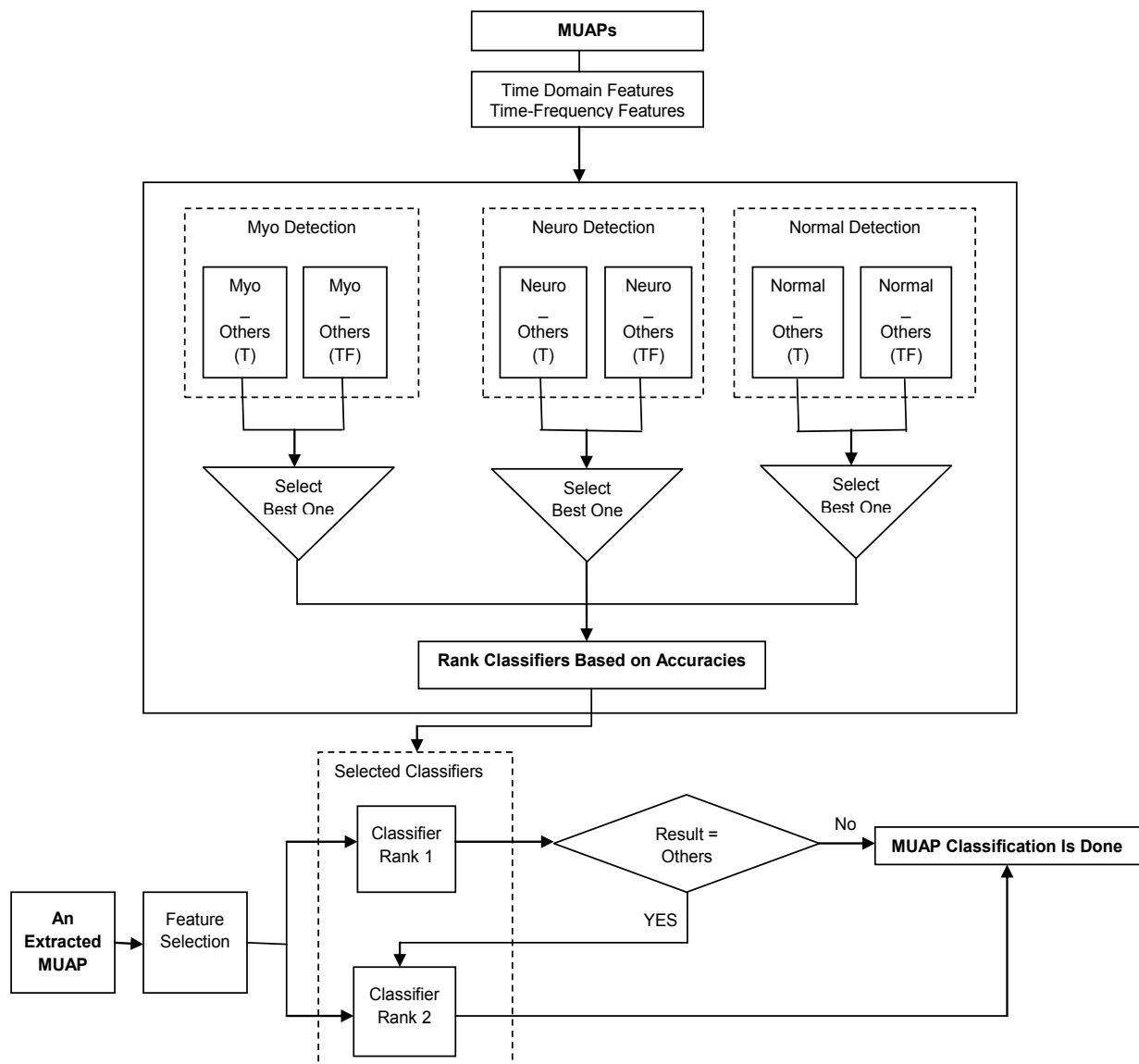

Figure 1: Roadmap of developed classification scheme

best classifier [28]. Based on this idea, we have used different classifiers with various feature sets to increase overall MUAP classification accuracy.

An important step in developing our hybrid structure was selecting the type of classifier. In this study, support vector machine (SVM) introduced by Vapnik [29] with Gaussian radial basis function (RBF) kernel is selected to focus on finding the marginal samples (support vectors), in addition to guarantee controlling the expected errors. The selected SVM has the following kernel function:

$$K\left(x,x^{'}\right)=e^{-\gamma|x-x^{'}|^{2}} \tag{8}$$

Where x is the input feature vector to the SVM, $x^{'}$ is the center of the support vector, and γ is the width of the kernel. In this paper, parameters including C (penalty factor) and γ were found experimentally through the cross validation.

Figure 1 shows the roadmap of the proposed classification scheme. As shown, the proposed structure does not follow the conventional serial or parallel topology and is structured in a hybrid manner. Three classification modules are defined: myopathic detection, neuropathic detection and normal detection. In each module, two base classifiers are existed: one is fed with the selected time domain features and the other one is fed with the selected time-frequency domain features. In the training phase, among the base classifiers used in each module, the most accurate one is selected as the candidate base classifier for this module. Therefore, three base classifiers out of six are selected and ranked based on their accuracies. In the test phase, the two first best classifiers selected in the training phase corporate in voting and estimate the class label of a given MUAP.

Dataset and Classifier Evaluation

The proposed method in this study was tested using the real dataset provided by Dr. Miki Nikolic [30]. This dataset consists of real single-channel EMG signals recorded in Rigshospitalet in Copenhagen, Denmark and were detected from normal, myopathic and neuropathic muscles using a standard concentric needle electrode during low and constant level of contractions. The signals were decomposed using the VBEMGD system [19] and the MUAPs for each MU are estimated. The resulting MUAPs were assessed and labeled by an expert. The classification completed by the expert is considered as the gold standard data. Seven performance indicators were defined to evaluate the suggested method: an accuracy measurement, three sensitivity and three specificity measurements.

$$\mathbf{Spc_{Myo}} = \frac{TN(myo)}{(TN+FP)myo}\times 100 \tag{9}$$

$$\mathbf{Spc_{Neuro}} = \frac{TN(Neuro)}{(TN+FP)Neuro}\times 100 \tag{10}$$

$$\mathbf{Spc_{Normal}} = \frac{TN(Normal)}{(TN+FP)Normal}\times 100 \tag{11}$$

$$\mathbf{Sen_{Myo}} = \frac{TP(myo)}{(TP+FN)myo}\times 100 \tag{12}$$

$$\mathbf{Sen_{Neuro}} = \frac{TP(Neuro)}{(TP+FN)Neuro}\times 100 \tag{13}$$

$$\mathbf{Sen_{Normal}} = \frac{TP(Normal)}{(TP+FN)Normal}\times 100 \tag{14}$$

$$\mathbf{A_{Tot}\%} = \frac{Number\ of\ MUAPs\ correctly\ classified}{Total\ number\ of\ MUAPs}\times 100 \tag{15}$$

Table 3: Obtained performance indices by running proposed multi-classifier scheme on Rigshospitalet real EMG signals datasets.

Specificity			Sensitivity			Total Accuracy
Myo	**Neuro**	**Normal**	**Myo**	**Neuro**	**Normal**	
88.6	82.0	94.0	86.0	100	80	90.01.5

Table 4: Comparison between two famous reported works and our work.

Work	Classification Accuracy	Approach Type	Features Used
Pattichis [7]	79.5	MUAP analysis	Time, frequency and time-frequency domains
Katis [11]	86.0	MUAP analysis	Time domain
This work	91.0	MUAP analysis	Time and time-frequency domains

Results and Discussion

Classification performance of the developed MUAP characterization system is summarized in table 3. The numbers provided in this table was obtained by running 10 fold cross validation on the dataset introduced in subsection "Dataset and Classifier Evaluation". The results show that how well the proposed method can classify myopathic, neuropathic and normal cases.

For comparison purpose, we have implemented two of most famous reported works for MUAP characterization on our dataset: Katis [11] and Pattichis [7] and present obtained accuracy calculated with leave one out method in table 4. As results show, our algorithm can discriminate myopathic, neuropathic and normal classes with higher rate of accuracy. The strength of our algorithm is due to cooperating both time and time-frequency features in addition to selecting optimized set of features for each class type. We also employ multi classifier scheme which help to enhance overall classification accuracy compared with the case of single classifier scheme.

Conclusion

The main goal in MUAP characterization system is preserving acceptable classification accuracy. In this study, a novel classification scheme is proposed which consists of six base classifiers implemented by SVM base learners. Each base classifier is fed with different set of time or time-frequency domain features. The developed classification scheme consists of two stages and in each stage best classifiers are selected based on accuracy and finally the first two best classifiers are corporate to produce the final results. The achieved results show that multi classifier scheme can significantly enhance the classification results and provide acceptable classification accuracy to be used in clinical support system. In compare to two MUAP characterization systems presented in literature [7,11], the developed classifier system showed better accuracy and increased the classification accuracy of MUAP by at least

5%. The achieved results are promising and show that the developed system can assist with diagnosing, managing, and treatment of neuromuscular disorders.

Acknowledgment

Conflict of Interest

None

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