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Review of EMG Signal Classification for Diagnosis of Neuromuscular Disorders

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Abstract— Electromyographic (EMG) signal provide a significant source of information for diagnosis, treatment and management of neuromuscular disorders.Neuromuscular diseases changes, the shape and characteristics of the motor unit action potentials (MUAPs). The MUAPs detected from myopathic patients are characterized by high frequency contents, low peak-to-peak amplitude and MUAPs neuropathic patients are poly-phasic, low frequency, high peak-to-peak amplitude than the normal MUAPs. This paper gives a review of different techniques used for decomposition of EMG signal, extraction of time domain and time-frequency domain features of motor unit action potentials (MUAPs) . Different classification strategies including single classifier, multi-classifier fusion classifier trainable and non-trainable are investigated. The performance of Support Vector Machine (SVM), Distance weighted K-nearest neighborhood (DWKNN) classifier and neural network are meticulously studied. The essence of this paper is to review the most recent developments and research studies related to the issues mentioned above.

Keywords— Support Vector Machine, EMG; Discrete wavelet Transform; K-nearest neighborhood (KNN).

I. INTRODUCTION

Electromyographic (EMG) signal analysis plays a major role in the diagnosis of neuromuscular diseases, such as amyotrophic lateral sclerosis (ALS) and myopathy. Neuromuscular diseases changes, the shape and characteristics of the motor unit action potentials (MUAPs) and firing patterns of the motor unit (MU) are affected. MUAPs detected from myopathic patients are characterized by high frequency contents, low peak-to-peak amplitude and MUAPs neuropathic patients are poly-phasic, low frequency, high peak-to-peak amplitude than the normal MUAPs. [1], [2]. The amplitude and time and frequency domain properties of the surface EMG signal are dependent on the timing and intensity of muscle contraction. When a patient maintains low level of muscle contraction, individual MUAPs can be easily recognized. As contraction intensity increases, more motor units are Different MUAPs will overlap, causing an interference pattern in which the neurophysiologist cannot detect individual MUAP shapes reliably [3]. The methods reported in [1], [11] used wavelet-domain features extracted through multi-level decomposition using a filter bank structure consisting of only the analysis bank with Daubechies 4 wavelet filters, and several time domain features are used, such as zero crossing rate, turns-amplitude ratio, root-mean-square (RMS) value and autoregressive (AR) coefficients [13],[14]. Several classification methods such as fusion classifier, multi-classifier, an SVM that provides such probabilities for each class is reported in [1], [16]. Existing EMG signal decomposition methods can successfully decompose EMG signals extracting MUAPs by dominant MUAP selection method or thresholding active and non-active region [24],[26] . The motor unit potential trains (MUPTs) is assumed to have MUP shape validity, if motor unit MU discharges corresponding to a valid MUPT occur at regular intervals and in general, have a Gaussian-shaped inter-discharge interval (IDI) histogram [16] , [27] , [28].

This paper is divided into three section, first section discusses various methods of EMG decomposition and their limitation. Second section consist study of time and time frequency domain feature extraction and optimization. The last section related to analysis of Classifier such as single, multi-classifier, fusion based classifier. Finally, experimental results are compared for performance and sensitivity analysis.

II. EMG SIGNAL DECOMPOSITION

EMG signal is contain so-called *inactive* segments with low activity and *active* segments containing MUAPs. The Empirical mode decomposition (EMD) and Independent component analysis (ICA) reported in [31]. Empirical mode decomposition (EMD) is a kind of self-adapting signal processing method and it is very suitable for dealing with nonlinear and non-stationary signals. ICA algorithms, fixed-point algorithm is widely used in signal processing with its fast convergence, good separation. The algorithm can estimate the original signal mutually statistically independent and mixed by unknown factors from the observed signal. FastICA algorithm is based on negative entropy criterion of the fixed point iterative algorithm. After EMD decomposition, each IMF contains a vibration mode, and IMF is the different frequency band components from high-frequency to low-frequency of signal. While the main EMG action information are concentrated in the 20-500Hz frequency band of Active segment, so after decomposition, the main information of action signal are concentrated almost in the first two IMF. Since EMG is mainly in the 20-5000Hz, the first two IMFs with main information signal are used to build AR Model. Gurmanik Kaur et al. [3], segment signal to eliminate areas of low activity by segmentation algorithm it calculates a threshold depending on the maximum value and the mean absolute value of the whole EMG signal, another approach reported [32] used the onset and offset times of each active segment were manually determined and applied to all the channels. Ideally, an automatic amplitude-based thresholding algorithm would be used to segment the data. EMG further segmented into a series of overlapping analysis windows (window length: 256 ms, overlapping step: 128 ms).

III. TIME AND TIME-FREQUENCY FEATURE EXTRACTION AND SELECTION

A. Time Domain Features Extraction.

Time domain features are morphological features of the MUAPs which are used for visual assessment. MUAPs myopathic patients are characterized by high frequency contents, low peak-to-peak amplitude. Neuropathic patients are poly-phasic, low frequency, high peak-to-peak amplitude than the normal MUAPs. The following morphological features were extracted from MUAP is reported in [1], [20], [21].

1). Rise Time: The time between the initial positive to the next negative peak within the main spike.
2) Ratio of Peak to Peak magnitude to RMSvalue
3) Spike Duration: The time between the first to the last positive peak.
4) Ratio of ascending slope to descending slope positive spike of MUAP.
5) Ratio Area of positive to Area of negative spike MUAP
6) Phases: The number of baseline crossings where amplitude exceeds ±25 μV, plus one.
7) Thickness: The ratio of the area to the peak-to-peak amplitude.
8) Peak-to-Peak Samples Number: Total number of samples between the minimum positive and the maximum negative peak.

The important observation reported in [25] that RMS values corresponding to the ALS patients fluctuate abruptly in the initial and final frames but exhibit a stable range of values in the middle portion but for normal and myopathy data RMS value remain steady. Methods proposed in [33] utilize a set of morphological features (duration, amplitude, area, number of phases and number of turns).

B. Time-frequency Feature Extraction Scheme

The DWT is a multi-resolution technique that offers localization both in time and frequency. Hence, the DWT is chosen to extract features from the EMG signal. DWT coefficients roughly represent the magnitude of the signal at that time point, which corresponds to the peak of the wavelet function. The observation reported in [25] detail DWT coefficients represent successively higher frequency information that is absent from the approximation, but specific information high frequency component (detail coefficient) related to each class and level of decomposition is to be searched. DWT coefficients with higher values are proposed in [25] to be utilized, arranging the DWT coefficients in descending order the first M coefficients are used as features. Statistical parameters, such as the mean and maximum of DWT coefficients are also separately considered as features. TaherehKamali et al. [1] presented genetic algorithm method to search for the best discriminative frequency band, then statistical technique to reduced feature set by calculating Mean power, Standard deviation, Average power of the absolute values of the coefficients in each sub band [19]. Saara M. Rissanen et al. [10] extracted feature as Recurrence rate of EMG, Coherence, and Correlation dimension of EMG, Root-mean-square amplitude of acceleration signal features from EMG and acceleration measurements of both sides of the body Recurrence rate of EMG.

C. Mother Wavelet Selection

Wavelet decomposition of signal is carried to find most discriminative feature for each class and suitable mother wavelet selection. Mother wavelet selection is reported in [17],the best mother wavelet was determined experimentally using cross validation technique .The choice of mother wavelet can be based on it can be selected based on correlation γ between the signal of interest and the wavelet-denoised signal . It determines estimation of the original signal, but also affect the frequency spectrum of the denoised signal

$$\gamma = \sum \frac{(X-\bar{X})(Y-\bar{Y})}{(X-\bar{X})^2(Y-\bar{Y})^2} \qquad \text{....1}$$

Where $\bar{X}$ and $\bar{Y}$ are mean value of set X and Y, respectively.The family of five mother wavelets consisting of Symlet , Daubechies , Morlet , Coiflet and Haar were studied .Symlet4 and Daubechies4 provided the most discriminative frequency band for three groups (myopathic, neuropathic, and normal).

IV. CLASSIFICATION STRATEGIES

The proposed hybrid aggregation module reported in [11] is a combination of two stages of aggregation: the first,aggregator is based on the abstract level and the second is based on the measurement level. Both aggregators may be data independent or the first aggregator may be data independent and the second data dependent. We used as the first aggregator, the majority voting scheme behaving as a data independent aggregator, while, as second aggregator either the average combination rule behaving as a data independent aggregator .TaherehKamaliet al.[1] proposed, single , multi classifier multi feature , multi classifier majority voting method .Support Vector Machine (SVM) as base classifier with classification strategies one against one (OAO) and one against all (OAA) used to predict class label The selected SVM has Gaussian radial basis function (RBF) kernel which is expressed as follows

$$K(x,x') = e^{-\gamma/|x-x'|^2} \qquad ....2$$

Where x the input feature vector to the SVM, x' is the center of the support vector and γ is the width of the kernel [1]. SVM was first trained as a standard SVM and then a sigmoid function was trained which maps the SVM outputs to the posterior probabilities. The conditional probabilities of the two classes for given input vector x is given by

$$\mathrm{P1(x)} = \frac{1}{1+\exp(\beta 1 . f(x) + \beta 2)} \qquad ....3$$

$$\mathrm{P2(x)} = 1 - \mathrm{P1(x)} \qquad .....4$$

f(x) is the output standard SVM, where β1 and β2 are parameter of sigmoid function, these parameters are derived from maximum likelihood estimation during training phase.SVM kernels and dimension reduction techniques provide the best classification performance.

A. Majority Voting

The group with more votes is selected as the ultimate decision. The votes of base classifier trying classify other than its group label are inverted for majority voting method to be used However, in the case of equal number of votes between two groups ,then decision is based two top priority classifier within the group. Classifier with priority P1 is highest and P3 is lowest.

B. Distance weighted k-Nearest Neighborhood (WKNN)

K-nearest neighborhave an identical weight in decision making, and neglects that closer nearest neighbor contribute more to classification. Dudani proposed the weight the distance weighted k-Nearest Neighbor (KNN) rule (WKNN) in which votes of the different members of the one of the K neighbors set are computed by the function of their distance to the query [31].

In this scheme, the i-th weight of the corresponding nearest neighbour is given as

$$\mathrm{W_i} = \begin{cases} \dfrac{(\mathrm{d_K^{NN}} - \mathrm{d_i^{NN}})}{(\mathrm{d_K^{NN}} - \mathrm{d_1^{NN}})}, \text{if } \mathrm{d_K^{NN}} \neq \mathrm{d_1^{NN}} \\ 1, \text{ if} \mathrm{d_K^{NN}} = \mathrm{d_1^{NN}} \end{cases} \qquad ....5$$

Where $\mathrm{d_i^{NN}}$ is the distance to the query of the i-th nearest neighbord_1^{NN} is the distance the nearest neighbor and d_K^{NN} is the distance of the K-furthest neighbor.

Then, the query is assigned the majority weighted voting class label y_{jmax} using the following rule

$$y_{jmax} = \arg max_{yi} \sum_{(x_i, y_i) \varepsilon T} W_i \times I(y = y_i^{NN}) \qquad ....6$$

Algorithm for DWKNN can be state as

1. Compute the distances of nearest neighbors of the query $\bar{x}$.
2. Sort the distances in an ascending order.
3. Calculate the dual weights of k nearest neighbors,$W = \{\overline{W_1}, \overline{W_2} \dots \dots \overline{W_K}\}$ from equation 5.
4. Assign a majority weighted voting class labely_{jmax} to the query $\bar{x}$

C. Clustering of Segments

Miki Nikolic et al. [33] reported algorithm which is a modified nearest-neighbor clustering algorithm which, based on a minimum spanning tree (MST), successively forms clusters of similar looking segments, using heuristically determined tree cutting thresholds. To determine if two segments are similar in shape, distance measure d ($s1$, $s2$) uses the variance of the residual after the two segments are aligned and subtracted, normalized with the sum of the rms values for the segments. s_1 and s_2 are the two segments to be compared and e is the residual signal when they are subtracted.

$$d(s_1, s_2) = \frac{VAR(e)}{RMS(s_1) + RMS(s_2)} \qquad ....7$$

VAR is the variance and RMS is the root mean square.

Hossein Parsaei et al [2] reported adaptive certainty-based classification algorithm combines both MUP shape and MU firing pattern information to calculate the confidence of assigning a candidate MUP to a MUPT. These two trains are found by calculating the Euclidian distance between the candidate MUP and the MUP template of each MUPT. MUP shape certainty includes normalized absolute shape certainty (C_{ND}) and relative shape certainty C_{RD} .

$$C_{NDi}^{j} = \max\left\{1 - \frac{r_i}{||s_i||^2}, 0\right\}; i = 1,2 \qquad ......8$$

$$C_{RDi}^{j} = 2 + (-1)^{i}\frac{r_1}{2r_2}\ ; i = 1,2 \qquad \text{.......9}$$

Where S_1 and S_2 respectively represent the feature vectors of the closest and the next closest MUP template to MUPj , m_j represents the feature vector $MUP_j$of the being classified, r_i is the Euclidean squared distance betweenS_j and m_j.

E. Performance Evaluation Parameter of Classifier

Following performance parameters will be used:

1) Specificity): Ratio of number of correctly classified normal subjects to number of total normal subjects.
2) Sensitivity: Ratio of number of correctly classified subjects suffering from a particular disease (ALS or myopathy) to number of total subjects suffering from that particular disease (ALS or myopathy).
3) Total classification accuracy:Ratio of number of correctly classified subjects to number [34]

Table 1 Review of different approach for decomposition and classification of EMG signal

S.No	Author/Reference No	Methodology	Percentage accuracy
1	HoosienParsaei et al [1]	Multi-classifier methods proposed that uses multiple features sets and a combination of both trainable and nontrainable fusion techniques to aggregate base classifiers	97%
2	Gurmanik Kaur et al.[3]	Time domain and autoregressive (AR) features Neural network (NN) classifier is used for classification	75.06%
3	Sarbast Rasheed et al[7]	Pool of base classifiers consists of different kinds of classifiers: the adaptive certainty-based,the adaptive fuzzy *k*-NN, and the adaptive matched template filter classifiers	93.5%
4	PaulitoPalmes et al [4]	SVM, ANN, regularized discriminant analysis Bayes classifier and Gaussian processes for classification	91.5%
5	Hossein Parsaei et al. [14]	Classifier fusion technique, *K*-means clustering, support vector machine, firing pattern validity classifier, shape validity classifier	98.8%
6	SHANG Xiaojing et al [5].	Independent component analysis, Empirical mode decomposition, AR model.	93.3%
7	Daniel Zennaro et al[22].	Long-term Decomposition , univariate criterion, Parseval theorem, Euclidean distances	96.1%

V. DISCUSSION AND CONCLUSION

The goal of this paper was to present the various feature extraction methods Time domain and wavelet approaches, Template matching methods in the field of feature extraction of EMG signals. This paper also presented the various base classifier used. Also gives review recent approaches applied in field of EMG classification. From the table 1. Hossein Parsaei et al [14]. Proposed multi classifier techniques whichestimate the overall Validity of a train by fusing the MU firing pattern and MUP shape validity of a given MUPT, determined separately by two distinct SVMs**,** combined to predict class label achieved accuracy 98.8%. In another approach, multi -classifier outperform where pool of base classifier used which include both trainable and non-trainable fusion technique with multiple feature set, majority voting method is used to predict class label. Support vector machine is used as base classifier then sigmoid function was trained which maps the SVM outputs to the posterior probabilities achieved accuracy 97% [1]. Designing an optimal classifier for a given problem involves Model selection is critical because, if the chosen model is not inherently capable of solving the problem, parameter optimization. Unfortunately, there are no general working principles in selecting the most appropriate model for a given problem. The second step involves finding the best set of values of the chosen model's parameters employ either or a combination of theoretical analysis, trial and error, or a systematic way of searching for the best parameters using numerical computation. An ensembleis composed of several SVMs cooperatively working together to have optimal solution of the given problem. It is composed of SVMs with the bestperformance in one of the classes. It also includes an SVM with the best overall classification accuracy in all classes. Combining their expertise, classification can be optimized by finding the best set of weights that controls the degree of contribution of each classifier in the decision making. it is concluded that multi-classifier, fusion or hybrid classifier outperform than base classifier. Wavelet decomposition.

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