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Classification of MUAP's by using ANN Pattern Recognition Technique

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ABSTRACT

The shapes and firing rates of MUAP's (motor unit action potentials) in an EMG (electromyography) signal provide an important source of information for the diagnosis of neuromuscular disorders. In order to extract this information from EMG signals recorded at low to moderate force levels, it is required: i) to identify the MUAP's composing the EMG signal, ii) to classify MUAP's with similar shape. For the classification of MUAP's a pattern recognition techniques is present which is an artificial neural network (ANN) technique based on unsupervised learning, using a modified version of the self-organizing feature maps (SOFM) algorithm and learning vector quantization (LVQ). A total of 521 MUAP's obtained from 2 normal subjects, 4 subjects suffering from myopathy, and 5 subjects suffering from motor neuron disease were analyzed. The success rate for the ANN technique was 97.6%.

Keywords: *Artificial Neural Network, Electromyography, learning vector quantization, Motor unit Action Potentials, Self-organizing feature maps.*

I. INTRODUCTION

There are more than 100 neuromuscular disorders that affect the brain and spinal cord, nerves, or muscles. Many of these diseases are hereditary and life expectancy of many sufferers is considerably reduced. Early detection and diagnosis of these diseases by clinical examination and Laboratory tests are essential for their management as well as their prevention. EMG (Electromyography) examination studies the electrical activity of the muscle and forms a valuable neurophysiologic test for the assessment of neuromuscular disorders. EMG signals recorded at low to moderate force levels are composed of motor unit action potentials (MUAP's) generated by different motor units. The motor unit is the smallest functional unit of the muscle that can be voluntarily activated. The MUAP shape reflects the structural organization of the motor unit. MUAP classification into groups of similar shapes provides important information for the assessment of neuromuscular pathology. In previous work the classification was done by only the SOFM technique. The objective of this work is to introduce a new pattern recognition technique which will consist of the SOFM technique along with LVQ technique to get the correctly classified o EMG signals.

Recent advances in computer technology have made automated EMG analysis feasible. Although a number of computer-based quantitative EMG analysis algorithms have been developed, some of them are commercially available. Most importantly, there is no uniform international criterion neither for pattern recognition of similar MUAP's nor for MUAP features extraction [1], [2]. A brief survey of quantitative EMG studies carried out during the last two decades follows. LeFever and DeLuca [3][4] used a special three-channel recording electrode and a hybrid visual-computer decomposition scheme based on template matching and firing statistics for MUAP identification. The more recently in their system called multiple motor unit potentials (multi- MUP), they used different shape parameters as input to a template matching technique [5]. Guiheneuc *et al.* [6], classified MUAP's at low levels of voluntary contraction through comparison of shape parameters.

In this work, a pattern recognition techniques were developed to classify MUAP's is an unsupervised learning ANN using a modified version of the Kohonen self organizing feature maps (SOFM) algorithm in conjunction with learning vector quantization (LVQ) [11]. The additional use of the LVQ aims to improve the classification performance by slight adaptation of the classification boundaries. The proposed techniques were successfully applied in the classification of EMG signals

recorded from normal (NOR) subjects and subjects suffering from motor neuron disease (MND) and myopathy (MYO).

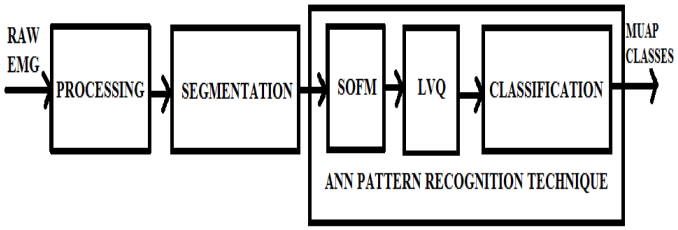

Fig.1 Flow chart of classification

II. METHOD

The proposed system consists of the following modules: Data acquisition and Preprocessing, Segmentation, and Classification. Fig 1 illustrates the system flowchart. And the next section will contain the procedure for the classification of EMG signal.

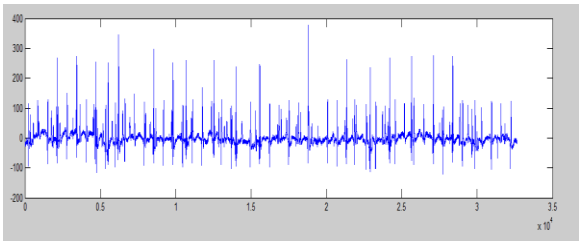

Fig. 2 raw EMG signal

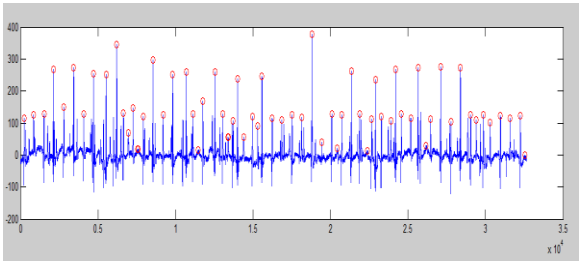

Fig. 3 Classified MUAP's of the EMG Signal

2.1 *Data acquisition and preprocessing*

The EMG signal was recorded from the muscle at low to moderate force levels up to 30% of maximum voluntary contraction (MVC) under isometric conditions. The signal was acquired for 5 s, using the concentric needle electrode. The signal was analogue band-pass filtered at 3–10 kHz, and sampled at 20 kHz with 12-b resolution. The EMG signal was then low-pass filtered at 8 kHz.

2.2 *Segmentation*

The next step is to cut the EMG signal into segments of possible MUAP waveforms and eliminate areas of low activity. The segmentation algorithm calculates a threshold depending on the maximum value $\max_i \{x_i\}$ and the mean absolute value (1/L) $\sum_{i=1}^{L}(x_i)$ of the whole EMG signal. Peaks over the calculated threshold '***T***' are considered as candidate MUAP's.

The threshold T is calculated as follows:

$$\text{if } \max_i \{x_i\} > \frac{30}{L}\sum_{i=1}^{L}(x_i),$$

$$\text{then } T = \frac{5}{L}\sum_{i=1}^{L}(x_i),$$

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

Where x_i = discrete input values

L = number of samples in the 5 s EMG signal

The threshold ***T*** is allowed between 30 and 100 µV. It is noted that there is no standardized procedure to estimate the threshold level: Dorfman and McGill [2] mentioned an amplitude threshold of 20–50 V,Stalberg *et al.* [5] used a 30-V threshold, whereas Andreassen[7] used an amplitude threshold in excess of 50 V.

2.3 *Classification*

The segmented EMG signals are processed in order to identify groups of similar MUAP's. In this work a method for MUAP classification is presented: a neural-network-based pattern recognition technique.

Neural-Network Pattern Recognition Technique

A single layer neural network is used for the identification and grouping of similar MUAP's and separation of superimposed waveforms. The ANN architecture the classification procedure is implemented in three phases. In the first phase SOFM (self-organizing feature map) (Kohonen) [11] is used. In the second phase, in order to improve classification performance, the learning vector quantization method (LVQ2 by Kohonen) [11], is applied. In the third phase, the actual classification takes place. It should be noted that in each learning phase the input is presented to the network only once, for only

one learning epoch. This makes the algorithm fast and suitable for real-time applications.

2.3.1 *Self-organizing feature map (SOFM)-Learning phase 1*

The objective of this phase is to provide a first "approximate" quantization of the input space by adapting the weight vectors of the neurons in the feature map [9]–[11], [12]. A problem with SOFM when the weights are initialized at small random values is that such initialization may give different results at different runs. This is undesired when trying to evaluate and optimize the performance of the algorithm or when the physician wants to review the classification results. In order to avoid this problem, the weights of the output nodes should not initialized at small random values but at 0.0001.

The implementation steps are as follow:

Step 1: Initialize weights at 0.0001.

Step 2: Calculate distances between the input vector x_i and weight vectors for each output node k.

$d_k = \sum_{i=1}^{N}(x_i - w_{ik})^2$ Where k = 1,2,----8 and N=120 ……(1)

The output node with minimum distance is the winner.

Step 3: Adapt the weights. The weights for each output node k and for each i are adapted with

$$w_{ik}(t+1) = w_{ik}(t) + h_k\,(x_i - w_{ik}(t)). \quad .....(2)$$

Where h_k = learning rate and it is a Gaussian function.

It can be given as:

$h_k = g\exp(-(k - k_w)^2 t/2)\sqrt{(t_{kw})}$ ....(3)

Where,

Value of g can be $0 < g \leq 1$,

k_w is the winner node,

t is the number of iterations,

t_{kw} is the number of times the specific node is selected as the winner.

For the initialization $g = 1$ and for the first winner $t_{kw} = 1$ and $k = k_w$, then $h_k = 1$.

If calculated $h_k < 0.005$, then the weights of the specific node are not adapted, since the change in the weights vector will be minimum. This is implemented in order to save computation time.

Step 4: Go to Step 2 and repeat for all segmented inputs. After all inputs are presented to the network, the first adaptation of the weights vector is completed and the system proceeds to the second learning phase.

2.3.2 *Learning vector quantization (LVQ)- Learning phase 2*

The task of this phase is to adapt the weights vectors slightly in order to improve the classification performance [9], [11]. LVQ demands knowledge of correctly classified inputs. It is assumed that the adaptation carried out during the first learning phase is correct and thus the segmented inputs will be correctly classified Weight adaptation and winner selection is again on-going as described in learning phase 1.

Fig. 4 Classes of MUAP's

In the modified version of LVQ2 the implementation steps are as follow:

Step 1: Use the values of the weight vectors as obtained from learning phase 1.

Step 2: Present input and calculate distances d_k between the input vector x_i and weight vectors w_{ik} for each output node as in equation (1). The output node with the minimum distance d_{k1} is the first winner $k1$ and the output node with the minimum distance d_{k2} is the second winner $k2$.

Step 3: Adapt weights. The weights for the first winner output node $k1$ is adapted with

$$w_{ik1}(t+1) = w_{ik1}(t) + h_{k1}\,(x_i - w_{ik1}(t)) \quad ....(4)$$

And for the second winner $k2$ with the weight

$$w_{ik2}(t+1) = w_{ik2}(t) - 0.1(d_{k1}/d_{k2})h_{k1}\,(x_i - w_{ik1}(t)) \quad ....(5)$$

The learning rate h_{k1} is initialized to 0.2 and decreases linearly with the number of times t_{kw1} the specific node $k1$ is selected as the first winner

$$h_{k1} = 0.2 - 0.01t_{k1w} \quad \ldots.(6)$$

Here

w_{ik1} is weight vector with the correct label (first winner),

w_{ik2} is the weight vector with the incorrect label (second winner),

The factor d_{k1}/d_{k2} is used to control the adaptation of the second winner.

Step 4: Go to Step 2 and repeat for all segmented inputs. After it the actual classification process starts.

2.3.3. Classification phase

In this phase all the input vectors are classified to one of the output nodes.

The implementation steps are the following:

Step 1: Calculate distances d_k between the input vector x_i and the weight vectors w_{ik} as in equation (1).

Step 2: The length l_{kw} of the weight vector of the winner node kw is calculated as the sum of the squares of its vector values

$$l_{kw} = \sum_{i=1}^{N} w^2{}_{ik} \quad \ldots.(7)$$

If d_{kw}/l_{kw} <0.2, then the input is assigned to the MUAP class of the winner node.

The physical meaning of d_{kw}/l_{kw} is that the greater its value, the greater the dissimilarity between the waveforms.

Step 3: Go to Step 2 and repeat for all segmented inputs.

Step 4: If the number of members in a class is three or more, then a valid MUAP class is identified. Fig. 3 illustrates the classification of MUAP's of the raw EMG signal given in fig. 2.

III. RESULT

EMG data collected from 11 subjects were analyzed using the pattern recognition techniques described in Section ii. Data were recorded from 2 normal (NOR) subjects, 4 subjects suffering from myopathy (MYO) and 5 subjects suffering from motor neuron disease (MND). MATLAB was used for implementing the above algorithms. The processing time on a PC Pentium 233 MHz for a 5-s epoch was about 0.5 s for the segmentation and about 0.6 s for the classification with SOFM and LVQ. Since MATLAB is an interpreter, all the timings may be significantly improved by the use of a compiled version of the algorithms.

IV. CONCLUSION

In conclusion, the pattern recognition techniques as described in this work make possible the development of a fully automated EMG signal analysis system which is accurate, simple, fast, and reliable enough to be used in routine clinical environment. Future work will evaluate the algorithms developed in this study on EMG data recorded from more muscles and more subjects. In addition, this system may be integrated into a hybrid diagnostic system for neuromuscular diseases based on ANN where EMG [8], muscle biopsy, biochemical and molecular genetics findings, and clinical data may be combined to provide a diagnosis [26].

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