A New Technique for the Classification and Decomposition of EMG Signals

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ABSTRACT

The shapes and firing rates of motor unit action potentials (MUAPs) in an electromyographic (EMG) signal provide an important source of information for the diagnosis of neuromuscular disorders. In order to extract this information from EMG signals recorded at force levels up to 20% of maximum voluntary contraction (MVC) it is required: i) To identify the MUAPs composing the EMG signal, ii) To classify MUAPs with similar shape and iii) To decompose the superimposed MUAP waveforms into their constituent MUAPs. For the classification of MUAPs two different pattern recognition techniques are presented: i) An artificial neural network (ANN) technique based on unsupervised learning, using the self-organizing feature maps (SOFM) algorithm and learning vector quantization (LVQ) and ii) A statistical pattern recognition technique based on the euclidian distance. The success rate on real data for the ANN technique is about 96% and for the statistical one about 94%. For the decomposition of the superimposed waveforms the following technique is used: i) Crosscorrelation of each of the unique MUAP waveforms, obtained by the classification process, with the superimposed waveforms in order to find the best matching point and ii) A combination of euclidian distance and area measures in order to classify the components of the decomposed waveform. The success rate for the decomposition procedure is about 90%.

1. Introduction

Electromyography is the study of the electrical activity of the muscle and provides useful information for the assessment of neuromuscular disorders. EMG signals recorded at low force levels (less than 20% MVC) are composed of MUAPs generated by different motor units (MU). The MU is the smallest functional unit of the muscle that can be voluntarily activated. It consists of a group of muscle fibres all innervated from the same motor nerve. The MUAP shape reflects the MU architecture. With increasing muscle force the EMG signal shows an increase in the number of activated MUAPs recruited at increasing firing rates. This makes it difficult for the neurophysiologist to distinguish the individual MUAP waveforms. The EMG signal decomposition and MUAP classification into groups of similar shapes provide important information for a correct diagnosis.

A number of researchers have been working in the field during the last few decades. LeFever and DeLuca [5] used a special three channel recording electrode, template matching and firing statistics for classification. Their decomposition method required operator intervention. Haas and Meyer [1] in their system called ARTMUP used potential features like duration, area, amplitude and number of turns as input to a hierarchical clustering technique for classification, followed by a two stage decomposition. McGill et al. [8] developed the ADEMG system that used template matching and a specific alignment algorithm for classification. Loudon et al. [7] used eight potential features as input to a statistical pattern recognition technique for classification. The decomposition of superimposed waveforms used a combination of procedural and knowledge-based methods. Hassoun et al. [2] in their system called NNERVE used time domain features as input to a three layer ANN with a 'pseudo-unsupervised' learning algorithm for classification.

In this work an unsupervised learning ANN using the Kohonen self-organizing feature maps in conjunction with learning vector quantization and a statistical pattern recognition technique based on euclidian distance were developed to classify MUAPs. The objective is to develop an accurate, simple, fast and reliable system which can perform well even with a limited amount of data. Furthermore an algorithm for decomposition of superimposed waveforms using crosscorrelation for MUAPs alignment, and a combination of euclidian distance and area measures in order to classify the decomposed waveforms is presented.

2. Method

2.1. Data acquisition and preprocessing

The EMG signal was recorded from the biceps brachii muscle at low force level, for 5 seconds, using the concentric needle electrode. The signal was analogue bandpass filtered at 3 Hz to 10 KHz, and sampled at 20 KHz with 12 bits resolution. The EMG signal was then lowpass filtered at 8 KHz and downsampled by a factor of two at 10 KHz.

2.2. Segmentation

The next step is to cut the EMG signal in segments of possible MUAP waveforms and eliminate areas of low

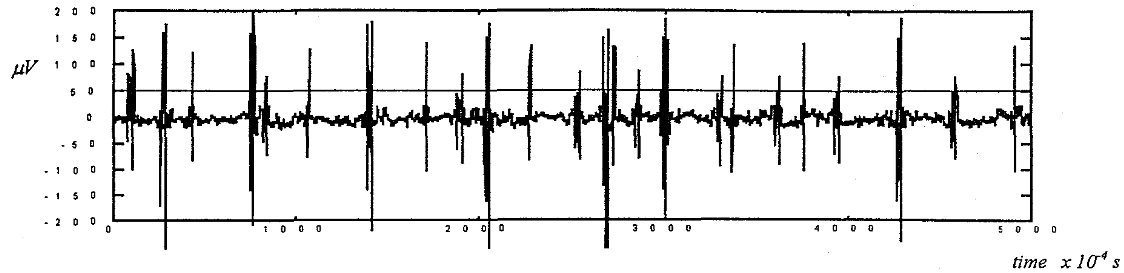

Fig.1. Raw EMG signal. Peaks over threshold are considered as candidate MUAPs

activity (Fig. 1 and Fig. 2). The segmentation algorithm calculates a threshold, depending on the maximum and mean value of the whole EMG signal. Peaks over the calculated threshold are considered as candidate MUAPs. A window with a constant width of 100 points (i.e. 10 ms at 10 KHz) is applied centred at the identified peak. If a greater peak is found in the window, the window is centred at the greater peak otherwise the 100 points are saved as a candidate MUAP waveform . The threshold is calculated as follows:

- *If* maximum(emg) > 30 * mean(abs(emg))
  then threshold = 5 * mean(abs(emg));
  else threshold = maximum(emg) / 5.
- The threshold is allowed to take values from 50 to 150 μV.

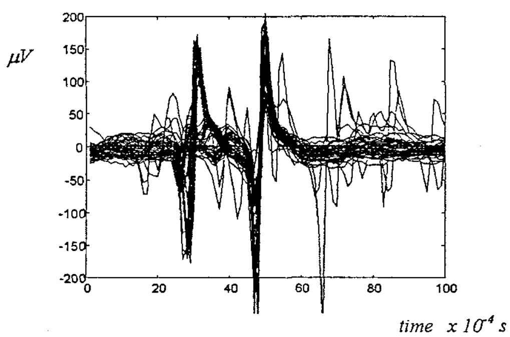

Fig. 2 . Segmented EMG signal

2.3. Classification

MUAP waveforms are processed in order to identify groups of similar MUAPs, all transmitted from the same MU, and separate superimposed waveforms. In this work two different methods for MUAP classification are presented, a neural network based pattern recognition technique using unsupervised learning and a statistical one using the euclidian distance.

2.3.1. Neural network pattern recognition technique

A single-layer neural network is presented for the identification and grouping of similar MUAPs and separation of superimposed waveforms. The developed ANN is a feedforward network composed from 100 input nodes and 8 output nodes. The selected number of 8 output nodes is considered satisfactory since the maximum number of active motor units at low force is at most 5-6. The classification procedure is implemented in three phases: In the first phase unsupervised learning is applied based on one dimensional self-organizing feature map (Kohonen) and competitive learning, in the second phase, in order to improve classification performance, a (self) supervised learning technique, the learning vector quantization (LVQ2 by Kohonen) is applied and in the third phase the actual classification takes place.

A. Self-Organizing Feature Map (SOFM) - Learning Phase 1

The objective of this phase is to provide a first 'approximate' quantization of the input space (Voronoi vectors) by adapting the weight vectors of the neurons in the feature map [3], [4], [6]. The implementation steps are:

Step 1: Initialise weights at small random values.

Step 2: Calculate distances between input vector x_i and weight vectors w_{ik} for each output node k:

$$d_k = \sum_{i=1}^{N} (x_i - w_{ik})^2 \quad \text{where } k=1..8 \text{ and } N=100.$$

The output node with minimum distance is the winner.

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

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

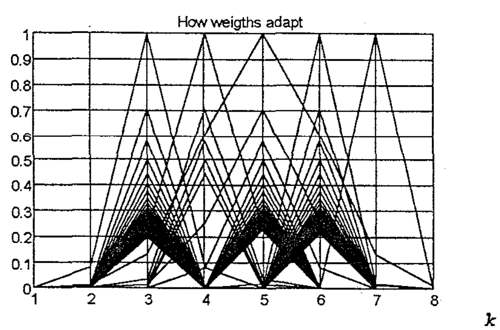

Fig.3. Learning rate h_k (with g =1) getting narrower within time and smaller as often an output node k is selected winner

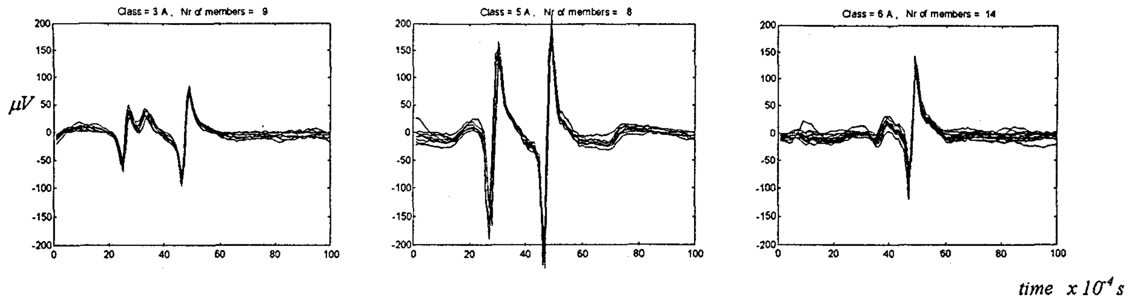

Fig. 4. MUAPs with similar shapes classified into three different classes

The learning rate h_k is a Gaussian function that gets narrower within time (neighbourhood) (Fig. 3). The learning rate is also frequency sensitive, which means it gets smaller the more often a neuron is selected winner:

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

where $0 < g \leq 1$, kw is the winner node, t is the number of iterations and t_{kw} is the number of times the specific node is selected winner.

Step 4: Go to step 2 for all segmented inputs.

After all inputs are presented to the network, the first adaptation of weights is completed and the system proceeds to the second learning phase.

B. Learning Vector Quantizer (LVQ) - Learning Phase 2

The task of this phase is to adapt the weight vectors slightly (move Voronoi vectors) in order to improve the classification quality [3]. LVQ is actually a supervised learning technique, i.e. demands forehand knowledge of correctly labelled (classified) inputs. Since such a knowledge is not available it is assumed that the adaptation carried out during the first phase is correct enough and thus the segmented inputs coming in will be correctly classified. Weights adaptation and winner selection is again on-going. The implementation steps are:

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

Step 2: Present inputs and calculate distances d_k between input vector x_i and weight vectors w_{ik} for each output node k as in step 2 of learning phase 1. The output node with minimum distance d_{k1} is the first winner $k1$ and the output node with the second best minimum distance d_{k2} is the second winner $k2$.

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

$$w_{ik1}(t + 1) = w_{ik1}(t) + h_{k1} * (x_i - w_{ik1}(t))$$

and for the second winner $k2$

$$w_{ik2}(t + 1) = w_{ik2}(t) - 0.1 * (d_{k1} / d_{k2}) * h_{k1} * (x_i - w_{ik2}(t)) .$$

The learning rate h_{k1} begins from 0.2 and decreases linearly with the number of times t_{k1w} the specific node $k1$ is selected as first winner:

$$h_{k1} = 0.2 - 0.01 * t_{k1w} \; .$$

The factor d_{k1}/d_{k2} is used so as to move the second winner far away if the classification boundaries are close enough or little if the classification boundaries are far away. In other words the weight vector with the correct label is moved towards the input while the incorrect label is moved away from it.

Step 4: Go to step 2 for all segmented inputs.

After all inputs are presented to the network, the network is trained and the actual classification process starts.

C. Classification phase

In this phase all the input vectors will be classified to one of the output nodes and superimposed waveforms will be separated. The implementation steps are the following:

Step 1: Calculate distances d_k between input vector x_i and weight vectors w_{ik} as in step 2 of the learning phase 1. The output node kw with minimum distance d_{kw} is the winner.

Step 2: In order to separate the superimposed waveforms from simple, non overlapping MUAP waveforms the length of weights vector of the winner node kw is calculated as the sum of squares of its vector values

$$l_{kw} = \sum_{i=1}^{N} w_{ikw}^{\;2}$$

If $d_{kw} / l_{kw} < 0.2$ *then* the input is classified;
else the input is considered as a superimposed waveform.

Step 3: Go to step 2 for all segmented inputs.

Step 4: If the number of members in a class is three or more then their average is calculated and a MUAP class is identified (Fig. 4). Otherwise they are saved with the superimposed waveforms for decomposition.

2.3.2. Statistical pattern recognition technique

In this technique the euclidian distance is used in order to identify and group similar waveforms. The group average is continuously calculated and used as a comparative measure for MUAPs classification applying a constant threshold technique. The implementation steps are the following:

Step 1: The system starts with the first waveform x as input and calculates its vector length and the distance between it and all the other waveforms y as

$$l_x = \sum_{i=1}^{N} x_i^2 \quad \text{and} \quad d_{xy} = \sum_{i=1}^{N} (x_i - y_i)^2 \quad .$$

Step 2: Find the waveform y with the minimum distance which is the one with the greatest similarity with x and remove it from the input data.

Step 3: Sliding and baseline correction. Firstly slide the waveform y with minimum distance up to 2 points backwards and up to 2 points forwards in order to find the best alignment point. Recalculate the distance d_{xy} for each case and assign the smallest as $d_{\min}$. Then calculate baseline correction bc as

$$bc = \left(\sum_{i=1}^{10} y_i + \sum_{i=91}^{100} y_i - \sum_{i=1}^{10} x_i - \sum_{i=91}^{100} x_i\right) / 20 \quad .$$

Subtract bc from waveform y and recalculate distance with x. If it is smaller than $d_{\min}$ assign it as $d_{\min}$.

Step 4:

If $d_{\min}/l_x < 0.125$

then group, calculate group average and go to step 1 with group average as input;

else if number of group members > 2

then form a new class;

else waveform is superimposed;

go to step 1 with y as input.

If the minimum distance divided by the vector length of the first waveform is less than a constant threshold set to 0.125, then the two waveforms form a group. Then the group average is calculated and the procedure is repeated (go to step 1 with the group average as input) comparing the group average now with all the rest in order to find the next waveform with the minimum Euclidian distance. If the above condition is satisfied then a new waveform is added in the group and a new group average is calculated and so on. If not the process stops, and if the group members are more than three then a class is formed and its averaged waveform is saved. If they are less than three they are considered as superimposed waveforms. The process continues where it stopped comparing the last encountered waveform with all the remaining until all waveforms are processed. Threshold values were chosen after extensive testing. The averaged class waveforms are again the unique MUAP waveforms composing the EMG signal.

2.4. Decomposition of superimposed waveforms

The EMG signal obtained by the use of a concentric needle electrode contain, even at low force, overlapping potentials. It is important for a correct firing rate analysis to identify as much MUAPs as possible through decomposition of the superimposed waveforms into its constituent MUAPs. It is assumed that the correct unique MUAP waveforms composing the superimposed ones are known through one of the previous classification processes (Fig. 5). The decomposition steps are the following:

Step 1: Extract the main part of the MUAP. Reduce the unique MUAPs durations by dropping the beginning and ending points of the waveform that are less than 1/15 of the amplitude (minimum to maximum). This is necessary in order to crosscorrelate the most important part of the MUAP only.

Step 2: Crosscorrelate each reduced MUAP with a superimposed waveform and find the best matching point as the point where the crosscorrelation coefficient takes its maximum value.

Step 3: For each matching pair calculate the normalised euclidian distance, the area difference and a variable threshold.

The normalised euclidian distance (*Nd*) is the sum of squares of the values obtained by the subtraction of the reduced MUAP from the superimposed waveform for the reduced MUAP duration, divided by the sum of the squares of the reduced MUAP vector values:

$$Nd = \sum_{i=1}^{M} (x_i - c_i)^2 \Big/ \sum_{i=1}^{M} c_i^2$$

where M is the number of points of the reduced MUAP waveform c, and x is the superimposed waveform. The average area difference (*Ad*) is the average of the absolute values obtained by the subtraction of the reduced MUAP from the superimposed waveform for the reduced MUAP duration:

$$Ad = \sum_{i=1}^{M} |x_i - c_i| / M \quad .$$

The variable area threshold (*Th*) is defined as:

$$Th = 4 + 0.5 * \sum_{i=1}^{M} |c_i| / M \quad .$$

Step 4: The best matching MUAP is identified as the one with minimum($Nd * Ad / Th / M$) and is classified as belonging to the reduced MUAP class if

$$Nd < 0.2 \text{ or } (Ad < Th \text{ and } Nd < 0.5) \quad .$$

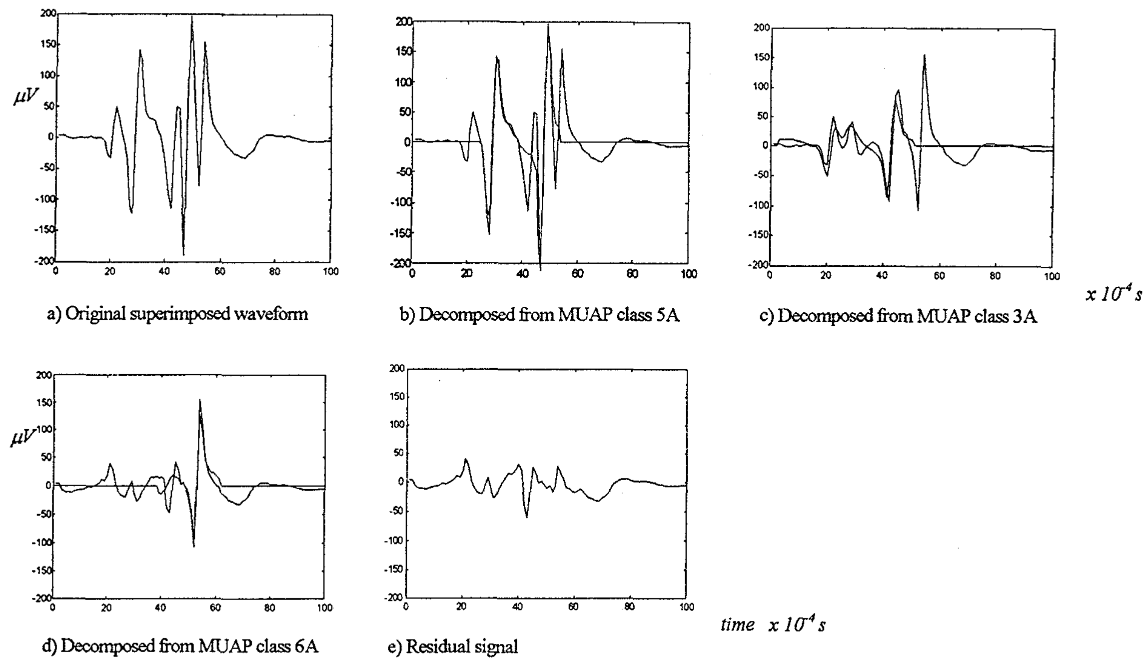

Fig. 5. Decomposition of a superimposed waveform into its three constituent MUAPs

Step 5: The best matching MUAP, if classified, is subtracted from the superimposed waveform. The so obtained new waveform is fed in (go to step 2) for a next cycle until no other MUAP is identified or the maximum waveform value is less than 50 μV. Otherwise, if not classified, the next superimposed waveform is fed in.
Go to step 2 for all superimposed waveforms.
Step 6: Complete firing rate table with the newly identified MUAPs.

3. Results and Discussion

EMG data collected from 24 subjects were analysed using the pattern recognition techniques described above. Data were recorded from 8 normal (NOR) subjects, 8 subjects suffering with motor neuron disease (MND) and 8 subjects suffering from myopathy (MYO). Table 1 tabulates the classification success rate on 811 MUAPs, obtained from 463 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. The average success rate for the SOFM with the LVQ algorithm was 96%, for the SOFM algorithm alone 93%, and for the statistical pattern recognition technique 94%. The ANN technique also yielded good results without the LVQ learning phase. In general, where the algorithms failed to identify a class it was because of inadequate number of class members and waveform variability. The success rate for the decomposition of the superimposed waveforms was about 90%.

MATLAB was used for implementing the above algorithms. The processing time on a PC 486DX2 66 MHz for a 5 sec epoch EMG signal with 50 waveforms was about 4 sec for the segmentation and about 8 sec for the classification with SOFM with LVQ, 6 sec for SOFM and 10 sec for the statistical technique. The processing time for the decomposition of 12 superimposed waveforms with 3 classes was about 20 sec.

Both pattern recognition techniques described are quite simple in their conception and the success rate high enough. Classification and decomposition of real EMG data into their constituent Motor Unit Action Potentials is often a difficult task because of MUAPs waveform variability, jitter of single fiber potentials and MUAPs superpositions. Artificial Neural Networks appear attractive for the solution of such a problem because of their ability to adapt and to create complex classification boundaries. The statistical technique has the disadvantage of using a constant threshold for classification that makes it less flexible since what looks similar in shape has not necessarily a small euclidian distance. Also the computational time increases geometrically with the amount of processed data. On the other hand the use of slide and baseline correction improved the classification success rate by about 5%. It was also observed in both techniques that often, due to waveform variability, MUAP classes coming from the same MU, although they looked similar, were not grouped together. Merging of these classes can be achieved by using the firing statistics after the decomposition process or by using the statistical pattern

Table 1: Classification success rate (in brackets the number of identified classes to total number of classes).

	SOFM with LVQ	SOFM	Statistical
NOR	(277/293) 95%	(273/293) 93%	(275/293) 94%
MND	(251/266) 94%	(239/266) 90%	(251/266) 94%
MYO	(248/252) 98%	(241/252) 96%	(238/252) 94%
TOTAL:	**(776/811) 96%**	**(753/811) 93%**	**(764/811) 94%**

recognition technique with a greater constant threshold (=0.3) and the averaged class waveforms as input.

Several new ideas were introduced in this work in order to improve the algorithms performance: i) The use in the SOFM of a learning rate that gets narrower within time (neighbourhood) and that is also frequency sensitive. ii) The use of the LVQ in a self-supervised manner with the factor d_{k1}/d_{k2} to optimise the second winner weights adaptation. iii) In the classification phase the use of a threshold technique in order to separate the superimposed waveforms. iv) The use of the group average in the statistical pattern recognition technique as a comparative measure. v) In the decomposition of the superimposed waveforms the combination of euclidian distance and area measures in order to classify the decomposed waveform.

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 to a hybrid diagnostic system for neuromuscular diseases based on ANN where clinical data, EMG, muscle biopsy, biochemical and molecular genetic findings will be combined to provide a diagnosis.

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