A two-stage method for MUAP classification based on EMG decomposition

Christos D. Katsis\textsuperscript{a,b}, Themis P. Exarchos\textsuperscript{a,b}, Costas Papaloukas\textsuperscript{c}, Yorgos Goletsis\textsuperscript{d}, Dimitrios I. Fotiadis\textsuperscript{e,f,*,} Ioannis Sarmas\textsuperscript{g}

\textsuperscript{a}Department of Medical Physics, Medical School, University of Ioannina, GR 451 10 Ioannina, Greece
\textsuperscript{b}Unit of Medical Technology and Intelligent Information Systems, Department of Computer Science, University of Ioannina, P.O. Box 1186, GR 451 10 Ioannina, Greece
\textsuperscript{c}Department of Biological Applications and Technology, University of Ioannina, GR 451 10 Ioannina, Greece
\textsuperscript{d}Department of Economics, University of Ioannina, GR 451 10 Ioannina, Greece
\textsuperscript{e}Unit of Medical Technology and Intelligent Information Systems, Department of Computer Science, University of Ioannina, P.O. Box 1186, GR 451 10 Ioannina, Greece
\textsuperscript{f}Biomedical Research Institute—FORTH, GR 451 10 Ioannina, Greece
\textsuperscript{g}Department of Neurosurgery, Medical School, University of Ioannina, GR 451 10, Ioannina, Greece

Received 9 January 2006; accepted 6 November 2006

Abstract

A method for the extraction and classification of individual motor unit action potentials (MUAPs) from needle electromyographic signals is presented. The proposed method automatically decomposes MUAPs and classifies them into normal, neuropathic or myopathic using a two-stage feature-based classifier. The method consists of four steps: (i) preprocessing of EMG recordings, (ii) MUAP clustering and detection of superimposed MUAPs, (iii) feature extraction and (iv) MUAP classification using a two-stage classifier. The proposed method employs Radial Basis Function Artificial Neural Networks and decision trees. It requires minimal use of tuned parameters and is able to provide interpretation for the classification decisions. The approach has been validated on real EMG recordings and an annotated collection of MUAPs. The success rate for MUAP clustering is 96%, while the accuracy for MUAP classification is about 89%.

© 2006 Elsevier Ltd. All rights reserved.

Keywords: Quantitative electromyography; Electromyogram decomposition; MUAP detection and classification; Radial basis function network; Decision trees

1. Introduction

Electromyography (EMG) is the study of the electrical activity of the muscle and is a valuable tool in the assessment of neuromuscular disorders. Computer-aided EMG has become an indispensable tool in the daily activities of neurophysiology laboratories in facilitating quantitative analysis and decision making in clinical neurophysiology, rehabilitation, sport medicine and human physiology. EMG findings are used to detect and describe different disease processes affecting the Motor Unit (MU), which is the smallest functional unit of the muscle. At slight voluntary muscle contraction a motor unit action potential (MUAP) is recorded, reflecting the electrical activity of a single anatomical MU\textsuperscript{[1]}. MUAPs from different MUs tend to have different shapes, which remain almost the same for each discharge. Thus, MUAPs can be identified and tracked using pattern recognition techniques. The resulting information can be used to determine the origin of the disease, i.e. neuropathy or myopathy [2–4].

When a patient maintains a low level of muscle contraction, individual MUAPs can be easily recognized, since only a few MUs are active. As contraction intensity increases, more MUs are recruited; different MUAPs overlap, causing an interference pattern (i.e. superimposed MUAPs) in which the neurophysiologist cannot always detect individual MUAP shapes reliably. The changes brought about by a particular disease alter the functionality of the muscle and nerve cells, causing characteristic changes in the MUAPs. Usually, in clinical EMG, neurophysiologists assess MUAPs from their shape using an oscilloscope and listening to their audio characteristics. Using these
Therefore, these ambiguous cases require quantitative analysis, as the measurement of the MUAP parameters of interest [9] is time-consuming and liable to variable errors due to the subjective assessment of the MUAP parameters of interest [9]. LeFever and DeLuca [10] used a special three channel recording electrode and a visual—computer decomposition scheme based on template matching and firing statistics for MUAP identification. Stulberg et al. [11] in their original system used waveform template matching, whereas more recently [12] they used different shape parameters as input to a template matching technique. Andreassen [13] followed the manual method developed by Buchthal et al. [8], where MUAPs were recorded photographically and then analyzed heuristically. Manual methods, although important at the time, were time consuming and liable to variable errors due to the subjective measurement of the MUAP parameters of interest [9].

Quantitative needle EMG analysis consists of two major processes: EMG decomposition and MUAP classification. Both of them have attracted researchers’ interest. One of the earliest methods for quantitative EMG decomposition was developed by Buchthal et al. [8], where MUAPs were recorded photographically and then analyzed heuristically. Manual methods, although important at the time, were time consuming and liable to variable errors due to the subjective measurement of the MUAP parameters of interest [9].

In this work, we present a method for the classification of MUAPs, even superimposed, extracted from a needle EMG recording, into normal (NOR), myopathic (MYO) and neuropathic (NEU). The method is based on a procedure introduced in [26] to automatically decompose EMG without the use of tuning parameters such as the number of MUAP clusters. Then, a two-stage classifier is employed, which is based on an RBF neural network and a decision tree, to classify the resulting MUAP clusters.

The proposed method introduces several novel features: (a) it is able to provide interpretation for the classification results, (b) it requires a small training set, (c) the employment of decision rules offers the potential of discovering new knowledge (in the form of rules), while the rule-based nature makes the decision-making process transparent, (d) it is fully automated, and (e) the evaluation results are superior compared to other methodologies proposed in the literature.

2. Materials and methods

The proposed method consists of four steps (Fig. 1): In the first step, the EMG signal is preprocessed to automatically detect areas of low activity and candidate MUAPs. In the second step, similar MUAPs are grouped (clustered) and a representative MUAP (template) is computed. The number and shape of template MUAPs are automatically determined. Furthermore, superimposed MUAPs are identified and decomposed into their constituents. In the third step template MUAP features (Amplitude, Duration, Rise Time, Area and Number of Phases) are extracted, while in the fourth step, the MUAP is classified as NOR, MYO, or NEU using a two-stage classifier. The classifier consists of an RBF ANN for the classification of MUAPs into normal and pathological, and a decision tree for the classification of pathological MUAPs into neuropathic and myopathic.

2.1. EMG preprocessing

Initially, signal preprocessing and candidate MUAP detection takes place. Since EMG is contaminated by noise (due to non-targeted muscles recorded activity and electrode movement), a bandpass filter (3 Hz–8 KHz) is applied. In order to detect the MUAPs comprising the EMG, the signal is segmented to generate possible MUAP waveforms (candidate MUAPs). Using a data-driven threshold \( T \) we identify areas of interest in the signal [27]. The computed threshold ranges from 30 to 100 \( \mu \)V, which is within the limits used in other works [12,13,27,28]. Also a sliding window with a constant length of 121 sampling points (i.e. \( \sim \) 6 ms at 20 kHz sam-
pling rate, in order to fit the main part of each MUAP) is centred at the identified peak. If a larger peak is found in the window, the window is centred at this peak; otherwise the 121 signal points are considered as a candidate MUAP waveform.

2.2. EMG decomposition

The second step consists of two stages: extraction of template MUAPs and detection and decomposition of superimposed MUAPs (Fig. 2).

Initially, an averaging process is realized in order to define a representative for each MUAP waveform, namely a MUAP template. The candidate MUAPs are grouped using a clustering procedure as it is described below.

MUAP clusters are automatically detected and for each cluster the average shape (MUAP template) is determined. The procedure for the detection of the number of clusters in EMG data is based on the minimization of a regularized cost function (details can be found in [24]), with respect to the distance of the candidate MUAPs from the cluster centres and the distance of the cluster centres from each other.

Once the number of clusters $k$ is detected and in order to obtain the template MUAP’s shape, the fuzzy $k$-means algorithm is used. Fuzzy $k$ means offers the ability to quantify the degree of membership of each candidate MUAP in every cluster. In order to extract MUAP’s features, each MUAP is expanded from 6 to 25 ms on the original EMG signal (where the position of the identified MUAP peak was marked during detection), since in most of the cases the MUAP duration does not exceed 18 ms [29]. Due to superpositions in the expanded window, in order to eliminate discrepancies from the class average, the standard deviation (STD) for each sampling point of all MUAPs in a class is calculated. Points with values beyond $\pm 1.5$ STD from the average are excluded from the computation of the cluster average.

Having the template MUAPs extracted, detection and decomposition of the superimposed MUAPs takes place. EMG signals contain superimposed potentials produced by the overlapping of different MUAPs. Candidate MUAPs with a degree of membership smaller than a predefined threshold are considered as superimposed. In our approach the threshold value was set to 0.8 after extensive testing in collaboration with a medical expert. According to the proposed decomposition routine (see Fig. 3), first the crosscorrelation between the superimposed waveform and the template MUAP with the largest degree of membership of each candidate MUAP in every cluster. In order to extract MUAP’s features, each MUAP is expanded from 6 to 25 ms on the original EMG signal (where the position of the identified MUAP peak was marked during detection), since in most of the cases the MUAP duration does not exceed 18 ms [29]. Due to superpositions in the expanded window, in order to eliminate discrepancies from the class average, the standard deviation (STD) for each sampling point of all MUAPs in a class is calculated. Points with values beyond $\pm 1.5$ STD from the average are excluded from the computation of the cluster average.

Having the template MUAPs extracted, detection and decomposition of the superimposed MUAPs takes place. EMG signals contain superimposed potentials produced by the overlapping of different MUAPs. Candidate MUAPs with a degree of membership smaller than a predefined threshold are considered as superimposed. In our approach the threshold value was set to 0.8 after extensive testing in collaboration with a medical expert. According to the proposed decomposition routine (see Fig. 3), first the crosscorrelation between the superimposed waveform and the template MUAP with the largest degree of membership is computed. This MUAP is time shifted as many sampling points as they are impaired by the crosscorrelation and subtracted from the superimposed waveform. Similarly, a crosscorrelation is carried out between the residual waveform and the template MUAP with the next highest degree of membership. The process is repeated until the maximum waveform
2.3. Feature extraction

Several measurable features of the EMG have been used in the computational diagnosis of neuromuscular diseases. MUAP amplitude, duration, rise time, area, and number of phases are most commonly considered, in order to annotate them as NOR, MYO or NEU [30,31]. Thus, having extracted the template MUAPs, the following features are calculated (Fig. 4):

- **Amplitude**: It is the difference between the maximum negative and positive peak.
- **Duration**: It is the time interval between MUAP onset and offset points. To define the onset of the MUAP waveform, we identify the first point where the signal is greater than a threshold equal to 1/10 of the amplitude. Starting from this point and moving backward to the beginning of the waveform, a sliding window of 1 ms is applied. The point in the window closer to the baseline is the MUAP onset point. The MUAP offset point is calculated in a similar way.
- **Rise time**: It is the time between the maximum negative peak and subsequent maximum positive peak within the duration of each MUAP.
- **Area**: It is defined between the MUAP waveform and the baseline for the calculated duration.
- **Number of phases**: They are counted within each MUAP. A phase is a section of a MUAP that falls between two baseline crossings and reaches an absolute value of amplitude larger than 0.02 mV.

All five features constitute the feature vector $v = \{\text{feature1}, \ldots, \text{feature5}\}$ for each MUAP.

2.4. MUAP classification

In order to classify the template MUAPs into NOR, MYO and NEU, a two-stage classifier is employed. First, an RBF ANN [32] is used to classify the template MUAPs into normal...
and pathological (MYO and NEU). Then, pathological MUAPs are classified using a decision tree [30] into MYO and NEU. It should be noted that ANNs that employ RBFs usually require a larger architecture (more neurons) than standard feed-forward ANNs for the same classification task. However, their main advantage is that they are trained much faster and easier and in the same time with a smaller training set [32]. Decision trees on the other hand, have been employed since they offer the ability for decision interpretation, especially with respect to the construction of decision rules. Decision rules can be constructed from a decision tree simply by traversing any given path from the root node to any leaf.

2.4.1. First stage: normal/pathological MUAP classification

In an RBF ANN the nodes in the hidden layer utilize a transfer function:

\[ f(x) = e^{-||x||^2}. \]  

The input to the transfer function of each neuron is the vector distance (Euclidean) between a weight vector \( w \) (estimated during training) and the input vector \( v \) (EMG features), multiplied by a bias \( b \).

According to this schema, a RBF has a maximum 1 when the input (distance) is 0, thus as the distance between \( w \) and \( v \) decreases, the corresponding output increases. Consequently, a radial basis neuron acts as a detector that produces 1 whenever the input \( v \) is identical to its weight vector \( w \). This is the goal which must be achieved during the training process using the training patterns. The bias \( b \), allows the sensitivity of the radial basis neuron to be properly adjusted. We can understand that after training and during testing, when a feature vector is introduced to the network, each neuron in the hidden layer will produce an output value which reflects how close the input vector is to each neuron’s weight vector. Thus, radial basis neurons with weight vectors quite different from the input vector \( v \) have outputs near zero. On the other hand, a radial basis neuron with a weight vector close to the input vector produces a value near 1.

We have employed Probabilistic Neural Networks (PNNs) [33,34] which is a class of RBF ANNs. The first hidden layer at such ANNs operates similarly with that of RBFs described above. PNNs have an additional hidden layer which sums the outputs of the nodes from the previous layer in order to produce a vector of classification probabilities. A compete transfer function is applied in the final layer to produce the final output. This transfer function identifies the maximum probability, and produces 1 for the corresponding class and 0 for the other classes.

In order to train the PNN, a training set of already annotated template MUAPs was used. Their feature vectors \( v \) were introduced to the network, which produces the final classification in one of the two categories: normal or pathological. Since the classification performance of the PNN highly depends on the selected training set, a boosting procedure [35] was followed in order to generate an appropriate set of training patterns in order to select a small number of patterns that represent adequately our MUAP database. We selected heuristically the training vec-

2.4.2. Second stage: myopathic/neuropathic MUAP classification

The construction of the decision tree is implemented using the C4.5 inductive algorithm [33]. The essence of the algorithm is to construct a decision tree from the training data. Each internal node of the tree corresponds to a principal component, while each outgoing branch corresponds to a possible range of that component. The leaf nodes represent the class to be assigned to a sample. The C4.5 algorithm applies to a set of data and generates a decision-tree, which minimizes the expected value of the number of tests for the classification of the data. Moreover, the C4.5 algorithm can solve the overfitting problem using a post-pruning method.

The most important feature in the C4.5 algorithm is its ability to automatically select the feature which is appropriate at each node. The feature of each node is selected in order to divide input samples effectively. Information gain is used as a measure of effectiveness. In order to define the information gain, we first define a measure called entropy, which is the degree of complexity about input samples. In the case of existing \( c \) classes in a set \( S \), the entropy of \( S \), \( H(S) \), is defined as

\[ H(S) = \sum_{i=1}^{c} p_i \log_2 p_i, \]  

where \( p_i \) is the ratio of the class \( i \) in the set \( S \). We can now define the information gain, which is the reduction of entropy. Information gain for a feature \( A \), \( \text{Gain}(S, A) \), is obtained as

\[ \text{Gain}(S, A) = H(S) - \sum_{u \in \text{Values}(A)} \frac{|S_u|}{|S|} H(S_u), \]  

where \( \text{Values}(A) \) represents the range of feature \( A \) and \( S_u \) is a subset of \( S \) having \( u \) as a result of feature \( A \).

In our case, the five features which describe the template MUAPs are continuous valued. Continuous-valued features can be incorporated into the decision tree by dynamically defining new discrete-valued features which partition the continuous feature value into a discrete set of intervals. More precisely, for a feature \( A \) that is continuous valued, the algorithm can dynamically create a new Boolean feature \( A_t \) that is true if \( A \leq t \) and false otherwise (first two branches of the decision tree shown in Fig. 5). The major problem is how we select the best value for the threshold \( t \). Clearly, we have to pick a threshold \( t \) which produces the greatest information gain. By sorting the training instances according to the continuous feature \( A \) and then identifying adjacent examples that differ in their target classification, we can generate a set of candidate thresholds midway between the corresponding values of \( A \). These candidate thresholds can then be evaluated by computing the information gain associated with each one. The information gain is computed for each of the candidate features, and the one with the highest information gain is selected.
After the induction of the decision tree, we apply a post-pruning method [33] and more specifically the pessimistic pruning, in order to avoid overfitting. This method prescribes that if the predicted error for a root node in a subtree is less than the predicted error for the subtree, then a subtree will be replaced with its root node, which becomes a new leaf in a pruned tree.

Decision trees offer interpretability of classification by constructing decision rules. Decision rules come in the form if $<\text{antecedent}>$, then $<\text{consequent}>$. The antecedent consists of the feature values from the branches taken by the particular path through the tree, while the consequent consists of the classification value for the target variable given by the particular leaf node.

In order to train the decision tree, we used the subset of the pathological MUAPs employed for the training of the RBF network (72 template MUAPs). In the testing phase, the inputs to the decision tree were the test MUAPs (120 template MUAPs) that were recognized as pathological from the previous stage of the classifier (RBF ANN). Thus, the decision tree categorized the pathological MUAPs into MYO and NEU.

2.5. Dataset

Our dataset contains needle EMG signals from 62 subjects. All EMG recordings were acquired from biceps brachii following the same protocol [25]. From the 62 subjects 20 had no history or physical evidence of neuromuscular disease, 20 suffer from myopathy, and 22 suffer from motor neuron disease. The annotation in each group was based on the patient history and muscle biopsy. It should be mentioned that only subjects with no history or signs of neuromuscular disorders were considered as normal. EMG recordings were acquired under constant isometric conditions and up to 30% of the Maximum Voluntary Contraction (MVC) level. Each subject was asked to produce an elbow flexion at the aforementioned MVC level and to sustain it for 2 s. An experienced neurophysiologist was asked to characterize every template MUAP produced from the second step of the proposed method. The resulting MUAP library consists of 365 template MUAPs. 173 were characterized as normal, 73 as myopathic and 119 as neuropathic.

3. Results

The preprocessing of the EMG recordings resulted in 9919 candidate MUAPs. Following the preprocessing step the MUAPs are decomposed (if superimposed) and template MUAPs are extracted. To measure the performance of the proposed method we use the success rate which is defined as

$$\text{success rate} = \left(1 - \frac{\sum |\text{mismatches}|}{\sum \text{clusters detected by neurophysiologist}}\right) \times 100\%.$$  \hspace{1cm} (4)

The extraction of the template MUAPs reported high success rate, 96%, while the detection of the superimposed MUAPs identified correctly the 94% of them.

Sensitivity, specificity and accuracy are computed for the classification step. The above for the RBF ANN classifier, as well as the performance in terms of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are shown in Table 1. These, concern the classification of the template MUAPs into normal and pathological. In Table 2 the classification results of the decision tree, into myopathic or neuropathic are shown. These results were obtained without taking into consideration the false classifications (false positives and false negatives) of the RBF ANN classifier. Finally, the confusion matrix for the two-stage classifier is presented in Table 3, while the classification results are shown in Table 4.

<table>
<thead>
<tr>
<th>RBF ANN</th>
<th>Classified as pathological</th>
<th>Classified as normal</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pathological</td>
<td>111</td>
<td>9</td>
<td>Sensitivity: 92.50%</td>
</tr>
<tr>
<td>Normal</td>
<td>9</td>
<td>93</td>
<td>Specificity: 91.18%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Accuracy: 91.89%</td>
</tr>
</tbody>
</table>

Please cite this article as: C.D. Katsis, et al., A two-stage method for MUAP classification based on EMG decomposition, Comp. Biol. Med. (2006), doi: 10.1016/j.compbiomed.2006.11.010

Fig. 5. Example of a decision tree created with the C4.5 algorithm. The tree classifies unknown cases in one class among X, Y, Z, W classes, using the features A, B, C and the threshold values $t$, $l$, $k$ respectively.
Table 2
The results of the second stage of the classifier (decision tree) into myopathic or neuropathic MUAPs (the false classifications of the first stage of the classifier were not taken into account)

<table>
<thead>
<tr>
<th>Class</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MYO</td>
<td>85.71</td>
</tr>
<tr>
<td>NEU</td>
<td>98.72</td>
</tr>
<tr>
<td>Overall (MYO and NEU)</td>
<td>94.17</td>
</tr>
</tbody>
</table>

Table 3
Confusion matrix for the two-stage classifier

<table>
<thead>
<tr>
<th>Classified as NOR</th>
<th>Classified as MYO</th>
<th>Classified as NEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOR</td>
<td>93</td>
<td>3</td>
</tr>
<tr>
<td>MYO</td>
<td>9</td>
<td>27</td>
</tr>
<tr>
<td>NEU</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4
Overall classification results of the two-stage classifier

<table>
<thead>
<tr>
<th>NOR</th>
<th>MYO</th>
<th>NEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity (%)</td>
<td>91.18</td>
<td>64.29</td>
</tr>
<tr>
<td>Specificity (%)</td>
<td>92.50</td>
<td>97.78</td>
</tr>
<tr>
<td>Accuracy (%)</td>
<td>88.7</td>
<td></td>
</tr>
</tbody>
</table>

Some indicative rules extracted from the decision tree are shown below:

... If Amplitude > 0.353 mV AND Area > 0.5226 mV²ms
Then MUAP is Neuropathic.
If Amplitude <= 0.353 mV AND Area > 0.7306 mV²ms
Then MUAP is Myopathic.
If Amplitude <= 0.618 mV AND Area > 0.7306 mV²ms and Area <= 0.5226 mV²ms
Then MUAP is Myopathic.
...

It should be mentioned that several experiments were conducted, before employing the specified two-stage classifier. The C4.5 algorithm was employed for the 3-class problem (NOR, MYO, NEU) and for the 2-class problem (NOR, PATH) but reported lower overall accuracy (approximately 78% and 77%, respectively). The two-stage system which consists of an RBF ANN and a decision tree provided the highest classification results.

4. Discussion

A novel method has been presented that automatically decomposes EMG recordings and classifies template MUAPs as normal myopathic or neuropathic. Initially the candidate MUAPs are detected. Then, the number of clusters in EMG data is computed and the shape of the template MUAPs is identified. An RBF ANN classifies the extracted template MUAPs into normal and pathological and finally a decision tree classifies the pathological template MUAPs into neuropathic and myopathic. Our method provides high results, along with the interpretation, in an automated way eliminating the need for parameter tuning. The two-stage approach allows our method to be trained with a small dataset, yet to perform well.

According to the literature, only a few works in needle EMG have been reported concerning MUAP classification [20–26]. Our approach, as opposed to previous EMG analysis schemes, performs both EMG decomposition and MUAP classification. It is characterized by automated mode of operation and minimal use of tuned parameters. Data-driven determination of thresholds is also considered as a significant advantage since it enhances method’s adaptability to different EMG signals. Moreover, the number of template MUAP clusters is automatically calculated [26]. Finally, the use of RBF ANNs requires a small training set while the employment of decision trees provides the appropriate interpretation for the classification decisions. In medical applications, the ability to explain the reason for a decision is of great value for the domain experts [36] and can assist them to reach a diagnosis faster and safer.

The overall classification accuracy achieved was higher than previous studies (Table 5). More specifically, our method performs better than other feature-based methods by over 10% in classification accuracy. However, the comparison should take into consideration that different EMG analysis methods may focus on different MVC levels or different muscles. For this reason only qualitative comparisons and conclusions can be drawn. The main disadvantage of the rest of the methods reported in Table 5 is their inability to provide explanations for their classification decisions. On the contrary, our method satisfies this important requirement and is able to provide for each template MUAP, the reason leading to each decision (for myopathic and neuropathic template MUAPs) while at the same time reports high accuracy. An in-depth look on the results reveals that the two-stage classifier performs very well for normal MUAPs as well as neuropathic ones, but its sensitivity deteriorates for myopathic MUAP classification. This is due to the fact that pathological MUAPs that were falsely classified as normal from the RBF network were myopathic ones.
The proposed approach can provide a valuable tool to neurophysiologists for MUAP detection and classification. Using the proposed method, when an EMG signal is processed its constituent MUAPs are identified, their features are automatically extracted and the MUAPs can be classified according to their pathology. The extracted information is valuable for the patient diagnosis. The proposed method can be easily integrated into EMG analysis software packages due to its near real-time performance and its automated nature, which makes it user friendly to a non-expert.

It should be mentioned that the results produced are based only on features extracted from the EMG recordings. In clinical practice, neurophysiologists make considerable use of patient’s clinical data while performing diagnosis. For this reason, further research is needed on the effect of such clinical data on the classification outcome. Finally, the performance of our method was high, however further clinical assessment might be considered in order to be fully evaluated.

5. Conclusions

A novel method for EMG analysis has been proposed that employs a two-stage classifier for MUAP classification. The superimposed MUAPs are automatically detected, decomposed into their constituents and classified according to their pathology using an RBF ANN and a decision tree. The method combines high performance, interpretability of results, automated mode of operation and small training set needs. It is therefore highly suitable for a clinical decision support system, providing a valuable tool to neurophysiologists both for MUAP detection and classification.

6. Summary

Electromyography (EMG) findings are used to detect and describe different disease processes, affecting the MU. At slight voluntary muscle contraction a motor unit action potential (MUAP) is recorded; reflecting the electrical activity of a single anatomical MU. As contraction intensity increases, more MUs are recruited; different MUAPs overlap, causing an interference pattern (i.e. superimposed MUAPs) in which the neurophysiologist cannot always detect individual MUAP shapes reliably. As a result, quantitative analysis in clinical can offer a more standardized sensitive and specific evaluation of the neurophysiological findings.

Reported techniques address either the problem of EMG decomposition or the classification of MUAP into normal and pathological classes. Furthermore, MUAP classification is performed using pattern recognition techniques, thus no explanations for the decisions made are provided. In this work, we present a method for the classification of MUAPs, even superimposed, extracted from a needle EMG recording, into normal, myopathic and neuropathic. The method automatically decomposes EMG signals without the use of tuning parameters such as the number of MUAP clusters. Then, a two-stage classifier is employed, which is based on a RBF neural network and a decision tree, to classify the resulting MUAP clusters. The two-stage classification approach followed introduces significant advantages: (a) the classifier offers interpretation for the classification results, which can easily be used by the doctor, (b) the evaluation results are superior compared to other methodologies proposed in the literature, (c) the training set is relatively small which makes the method more attractive and (d) the method is characterized by automated mode of operation and minimal use of tuned parameters.

In more detail, the proposed method consists of four steps: in the first step, EMG signal is preprocessed using an algorithm that automatically detects areas of low activity and candidate MUAPs. In the second step, the number and shape of template MUAP clusters are determined. Furthermore, superimposed MUAPs are automatically identified and decomposed into their constituents. In the third step MUAP features (Amplitude, Duration, Rise Time, Area and Number of Phases) are extracted, while in the fourth step, an unknown MUAP is classified as normal, myopathic, or neuropathic using the two-stage classifier. The classifier consists of an RBF artificial neural network for the classification of MUAPs into normal and pathological, and a decision tree for the successive classification of pathological MUAPs into neuropathic and myopathic.

Our approach has been validated on real EMG recordings and an annotated collection of MUAPs. The success rate for MUAP clustering is 96%. Approximately 94% of the superimposed MUAPs are correctly identified. The obtained accuracy for MUAP classification is about 89% which is higher than previous studies. Even more, our method over performs other feature-based methods by over 10% in classification accuracy.

Our method combines high performance, interpretability of results, automated mode of operation and small training set requirements. It is therefore highly suitable for a clinical decision support system, providing a valuable tool to neurophysiologists for both MUAP detection and classification.

Acknowledgements

The authors would like to thank Prof. C. S. Pattichis, University of Cyprus, Cyprus for the provision of EMG data and his helpful comments. The work is partially funded by the EU (AUBADE project: IST-2002-507605).

References


Please cite this article as: C.D. Katsis et al., A two-stage method for MUAP classification based on EMG decomposition, Comp. Biol. Med. (2006), doi: 10.1016/j.compbiomed.2006.11.010


[18] Themis P. Exarchos

[19] Christos Katsis

[20] Costas Papaloukas

[21] Yorgos Goletis

[22] Dimitrios I. Fotiadis

Please cite this article as: C.D. Katsis et al., A two-stage method for MUAP classification based on EMG decomposition, Comp. Biol. Med. (2006), doi: 10.1016/j.compbio.2006.11.010