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AUTOMATIC DISCOVERY OF THE NUMBER OF MUAP CLUSTERS AND SUPERIMPOSED MUAP DECOMPOSITION IN ELECTROMYOGRAMS

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Abstract- **A novel data driven method for needle EMG decomposition is presented. The method is capable of automatically detecting the number of MUAPs. Superimposed MUAPs are detected and decomposed automatically into their constituents. No *a priori* knowledge of the number of MUAPs is required. The method is evaluated using a dataset consisting of 8 normal, 8 suffering from myopathy and 7 suffering from neuropathy subjects. The success rate on finding the correct number of clusters was 95%, 89% and 80%, respectively.**

Keywords **- EMG signal decomposition; MUAP clustering; Quantitative MUAP analysis.**

I. INTRODUCTION

Traditionally in clinical electromyography, neurophysiologists assess MUAPs shape using the oscilloscope and their audio characteristics. On this way an experienced electrophysiologist can detect abnormalities with reasonable accuracy. Subjective MUAP assessment although satisfactory for the detection of unequivocal abnormalities may not be sufficient to delineate less obvious deviations or mixed patterns of abnormalities.

EMG signals detected using needle electrodes at low voluntary force levels can be decomposed into their constituent Motor Unit Action Potential Trains (MUAPTs). Different motor units generate these MUAPTs. The motor unit is the smallest functional unit of the muscle that can be voluntarily activated. It consists of a group of muscle fibers all innervated from the same motor nerve. The MUAPTs that contribute to an EMG signal provide information on the temporal behavior and morphological layout of motor units, which are active during muscle contraction. Such information can assist in the diagnosis of various neuromuscular disorders and in the development of a better understanding of healthy or pathological neuromuscular systems.

Increasing the voluntary contraction results in an increase of activated MUAPs recruited at increasing firing rates, making it difficult even for an expert neurophysiologist to distinguish the individual MUAP waveforms. Therefore, quantitative EMG decomposition is vital in order to minimize observer bias and for a more precise interpretation of the results. Lately, many EMG decomposition algorithms have been developed but none of them has gained great acceptance for clinical use. One widely used method for identifying MUAP discharges is template matching. In this method templates are formed for each frequently occurring discharge and then new discharges are classified according to the templates they match more closely [1-3]. A difficulty arises, however, when two or more discharges overlap, to produce a superposition that does not match any of the templates. Resolving superpositions has been a stumbling block in EMG decomposition [4]. Le Fever [5] used a special three channel recording electrode and a hybrid visual decomposition scheme. Christodoulou and Pattichis [6] developed methods based on artificial neural networks. In this paper we present an unsupervised method for EMG decomposition based on an extension [7] of the K-means clustering algorithm that does not require a *priori* specification of the number of MUAP clusters. In addition, the superimposed MUAPs are automatically detected and decomposed into their constituents.

II. METHODOLOGY

The proposed method consists of the following stages: (a) data acquisition and signal preprocessing, (b) MUAP identification, (c) MUAP clustering, (d) detection of superimposed MUAPs, (e) decomposition of superimposed MUAPs and (f) MUAP features computation.

(a) Data acquisition and signal preprocessing

The electromyographic signals were recorded from the biceps brachii at low to moderate force levels up to 30% of maximum voluntary contraction (MVC) under isometric conditions. The subjects were sitting comfortably at a desk on which the brace was fixed. Every subject was asked to produce an elbow flexion at the aforementioned MVC level and sustain it for two seconds. An UWE HS-30K digital dynamometer was used to verify the contraction level. EMG signal was collected using monopolar electrodes and amplified by a Sierra Cadwell II electromyograph. The signals are digitally recorded and stored in a database. Each EMG signal was bandpass filtered at 3-10 kHz. A National Instrument's DAT card was used to digitize it with sampling rate 20 KHz and 12-bit resolution. Finally, the signal was low pass filtered at 8 kHz.

(b) MUAP identification

The EMG signal is segmented into intervals of possible MUAPs. The segmentation algorithm used is data driven.

First, a threshold depending on the maximum value $\max\{x_i\}$ and the mean absolute value (1/L) $\sum_{i=1}^{L}|x_i|$ of the whole EMG signal is calculated, where x_i represents the discrete input values and L is the number of samples. Peaks over the calculated threshold are considered as candidate MUAPs. A window with a constant length of 120 sampling points is applied centered at the identified peak. If a greater peak is found in the window, the window is centered at this peak; otherwise the 120 signal points are considered as a candidate MUAP waveform. The MUAP detection algorithm is described in detail in [6].

(c) MUAP clustering

In this stage the number of active motor units and for each active motor unit its average or prototype MUAP shape are accurately determined [8]. The procedure employed for the detection of the number of clusters in EMG data is based on the minimization of the regularized cost function [7]:

$$J=\sum_{\mu=1}^{p}\sum_{v=1}^{k} I(y^{(v)} \mid x^{(\mu)}) \| x^{(\mu)}-y^{(v)} \|^2 + \\ +\sum_{\mu=1}^{p}\sum_{v=1}^{k} \tilde{\lambda}_v \tilde{I}(y^{(v)} \mid x^{(\mu)}) \| y^{(v)}-y^{(w)} \|^2 , \quad (1)$$

where $I(y^{(v)} \mid x^{(\mu)})$ is an indicator function which is 1 if v=argmin$_l$ $\| x^{(\mu)}-y^{(l)} \|^2$ and 0 otherwise. $\tilde{I}(y^{(v)} \mid x^{(\mu)})$ is an indicator function equal to 1 if $y^{(v)} \in \mathrm{N}_{y^{(w)}}$, w= argmin$_l$$\| x^{(\mu)}-y^{(l)} \|^2$, $N_{y^{(w)}}$ is the neighborhood of the cluster center $y^{(w)}$ and $x^{(\mu)} \in \Re^n$ and p is the number of patterns, $\{x^{(\mu)}: \mu=1,2,...,\mathrm{p}\}$. The cost function itself consists of two parts. The first part is related to the distribution of the cluster centers to minimize the sum of squared distance from each input pattern to the nearest cluster center. The regularization (second) term of the cost function further requires that the sum of squared distances from a cluster to its nearby clusters is minimum [7]. At the end of each clustering epoch, cluster centers in the same neighborhood are combined, while clusters with small number of MUAPs are removed. We obtain the number of clusters at a given "neighborhood scale" and the corresponding plot is generated as it is shown in Fig.1. As appropriate number of clusters k, is selected the number of clusters which persists over the largest range of neighborhood. Details concerning the method can be found in [7]. In order to develop the typical MUAP template the fuzzy K-means algorithm was used. The fuzzy K-means algorithm is based on the minimization of the following objective function (with respect to a fuzzy K-partition (U) and a set of k prototypes ($y^{(v)}$)):

$$J_q=(U,y^{(v)})=\sum_{\mu=1}^{p}\sum_{v=1}^{k}(\mathrm{u}_{v\mu})^q d^2(x^{(\mu)},y^{(v)}), k \le p , \quad (2)$$

where, $x^{(\mu)}$ is the μth n-dimensional feature vector, $y^{(v)}$ is the centroid of the vth cluster, $u_{v\mu}$ is the degree of membership of $\mathrm{x}^{(\mu)}$ in the vth cluster, $d^2(x^{(\mu)},y^{(v)})$ is any inner product metric (distance between $x^{(\mu)}$ and $y^{(v)}$), p is the number of data points and k is the number of clusters. The parameter q (any real number >1), is the weighting exponent for $u_{v\mu}$ which controls the "fuzziness" of the resulting clusters.

(d) Detection of superimposed MUAPs

Candidate MUAPs with degree of membership <0.8 are considered as superimposed. The threshold value was chosen heuristically after extensive testing.

(e) Superimposed MUAPs decomposition

The needle EMG signal recorded even at low to moderate levels contains superimposed potentials. The following decomposition approach is used. First, the prototype MUAP that has the greatest degree of membership (Fig.2) is subtracted from the superimposed waveform (Fig.3). Then a crosscorrelation is carried out between the residual waveform (Fig.4), and the prototype MUAP that has the second in order degree of membership (Fig.5). This MUAP is time shifted, as many sampling points are impaired from the crosscorrelation and subtracted from the residual waveform (Fig.6). Finally if the maximum waveform value of the residual signal is greater than 30 μV, it is assumed that the superimposed waveform contains another prototype MUAP and a new crosscorrelation is carried out between the residual waveform and the third in order degree of membership prototype MUAP. The above procedure is repeated again and a new residual waveform arises. It is assumed that the correct number of clusters, the prototype MUAPs and the superimposed waveforms are known.

(f) Computation of MUAP features

The last stage in our EMG analysis system is the computation of MUAP features. To perform this computation it is necessary (using the original EMG signal) to expand of MUAP to 25msec since in most of the cases the MUAP duration does not exceed 18 msec. The measured MUAP parameters (phases, turns, duration, rise time and amplitude) and the corresponding measuring algorithms are described in detail in [6].

III. Results

The proposed method is evaluated for a dataset that contains three groups of patients: 8 Normal subjects (nor), 7 subjects suffering from motor neuron disease (neu) and 8 subjects suffering from myopathy (myo). The diagnosis in every group is based on the patient profile, muscle biopsy and biochemical data. The success indicator was defined as:

$$1-\frac{\sum |\text{mismatches}|}{\sum \text{clusters detected by neurophysiologist}} \qquad (3)$$

The obtained results are presented in Table 1. The performance of the method is very satisfactory. It is noted that the method is less effective in the case of neuropathies. This is due to the fact that in neuropathies the MUAP shape does not remain the same for the whole signal duration because of premature motor nerve terminals. Therefore, it is possible to produce more clusters.

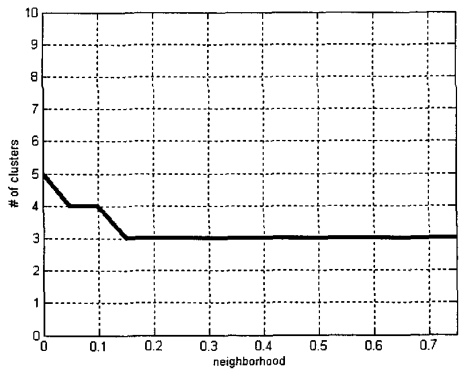

Fig.1 The number of clusters obtained as the scale parameter is varied for an EMG signal. It may be observed from this plot that three cluster solution persists over the largest range of neighborhood.

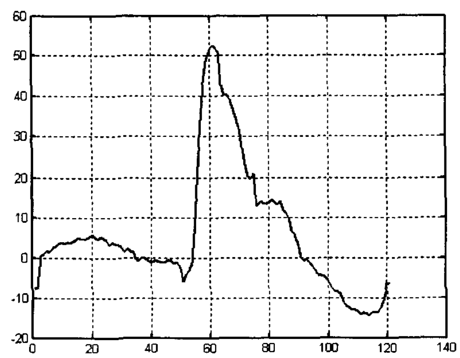

Fig.2. Prototype MUAP with the largest degree of membership.

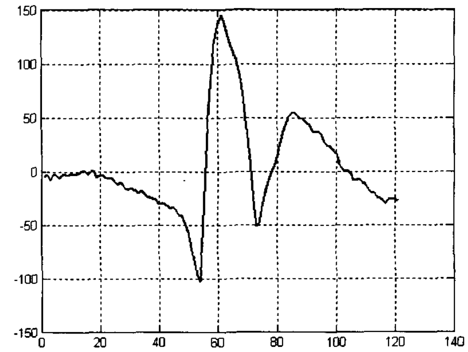

Fig. 3. Superimposed MUAP produced superimposing Fig.2 and 5.

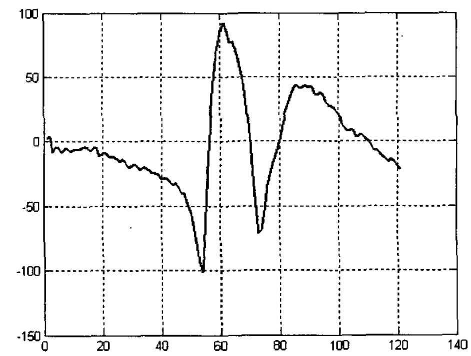

Fig.4. Residual waveform obtained subtracting Fig.3 and 2.

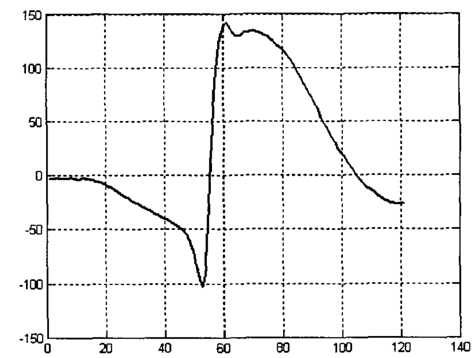

Fig. 5. Second in order degree of membership prototype MUAP.

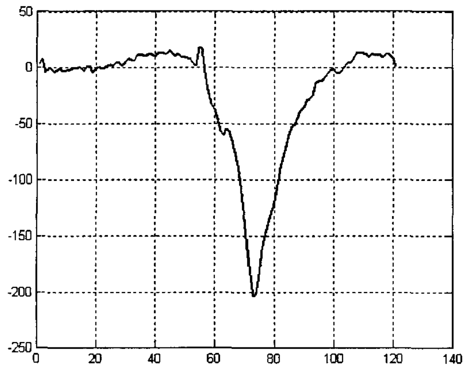

Fig. 6. Residual waveform obtained subtracting Fig.4 from 5.

Table 1
Number of clusters detected by the proposed method and by an experienced neurophysiologist.

Signal	# clusters by our method	# clusters detected by neurophysiologist
Nor_1	2	2
Nor_2	3	3
Nor_3	2	2
Nor_4	3	3
Nor_5	3	3
Nor_6	2	2
Nor_7	3	3
Nor_8	2	3
Total (nor)	**20**	**21**
Classification rate nor: **95%**		
Myo_1	2	2
Myo_2	3	3
Myo_3	1	2
Myo_4	3	3
Myo_5	2	2
Myo_6	3	3
Myo_7	2	2
Myo_8	1	2
Total (myo)	**17**	**19**
Classification rate myo: **89%**		
Neu_1	2	2
Neu_2	2	2
Neu_3	2	2
Neu_4	4	3
Neu_5	2	2
Neu_6	3	2
Neu_7	3	2
Total (neu)	**18**	**15**
Classification rate neu: **80%**		

IV. Discussion

The measurement of EMG signals during isometric contractions which is performed at a prescribed fraction of the maximal voluntary contraction (MVC) level provides information of considerable interest. Decomposition of the EMG signal is a difficult task because no *a priori* knowledge about the number of MUAPs or their shape is available. Furthermore, MUAPs from different motor units may be developed simultaneously creating superimposed waveforms. Our method detects initially the number of clusters using an extension of K-means clustering algorithm. The fuzzy K-means algorithm identifies the superimposed MUAPs. Those are decomposed into their constituents.

V. Conclusions

The decomposition of real EMG signals into their constituent MUAPs and their classification into groups of similar shapes is a typical case of a pattern recognition problem. A method for MUAP clustering is presented. The technique is the first that addressed the automatically detection of the number of MUAP clusters. The superimposed MUAPs are automatically detected and decomposed into their constituents. The success rate of the method varied from 95 % (nor) to 80 % (neu). The proposed technique is fast and reliable and can be a valuable tool to assist the neurophysiologist in clinical practice. It also possesses the following desirable attributes:
(1) Accuracy and completeness of classification.
(2) Robust performance for a variety of EMG signals.
(3) Minimal use of arbitrary thresholds.
(4) Ability to perform well in the presence of background noise.

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