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MUP Shape-based Validation of a Motor Unit Potential Train

Hossein Parsaei and Daniel W. Stashuk

***Abstract*—A method using the gap statistic is proposed to evaluate the validity of a motor unit potential train (MUPT) in terms of motor unit potential (MUP) shape consistency. This algorithm determines whether the MUPs of a given MUPT are homogeneous in terms of their shapes or not. It also checks if there are gaps in the inter-discharge interval (IDI) train of the given MUPT. If the MUPs are not homogeneous or if there is a temporal gap in the MUPT, the given MUPT is split into valid trains. To overcome MUP shape variability caused by jitter or needle movement during signal detection, similar MUPTs are merged if the resulting merged train is a valid train. Experimental results using simulated EMG signals show that the accuracy of the developed method in determining valid MUPTs and invalid MUPTs correctly is 97.58% and 99.33% on average, respectively. This performance encourages the use of this method for automated validation of MUPTs.**

I. INTRODUCTION

QUANTITATIVE analysis of information extracted by decomposing needle-detected electromyographic (EMG) signals can provide valuable information for the diagnosis and treatment of neuromuscular diseases[1],[2]. For example, the shape and stability characteristics of needle-detected MUPs can be used to aid in the diagnosis of some neuromuscular disorders such as myopathic and neuropathic diseases [3]-[5]. But this is only true when this information is valid; before using decomposition results, the fact that the extracted MUPTs are representative of the activity of single motor units (MUs) needs to be confirmed.

A composite EMG signal can be resolved into its constituent MUPTs using a process known as EMG signal decomposition [6]. This is implemented by employing digital signal processing and pattern recognition techniques. Many EMG signal decomposition methods have been developed, but evaluation of the developed methods has not been investigated in detail. Up to now, three methods have been proposed to estimate the accuracy of an EMG signal decomposition system [7]-[9].

In the first method, simulated signals of known composition are decomposed using the considered algorithm and the results are then compared to those expected. Results of this evaluation method may not accurately represent performance on real data, because all the factors that affect decomposition accuracy cannot be included in the simulated signals. Therefore, an EMG signal decomposition algorithm may perform well when using simulated EMG signals and have poor performance when using real signals.

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The authors are with the Systems Design Engineering Department, University of Waterloo, ON, Canada. (519-888-4567 Ext.32982; fax: 519-746-4791; hparsaei@engmail.uwaterloo.ca , stashuk@pami.uwaterloo.ca).

The second method is analogous to the first one, but here the reference is provided from real EMG signals decomposed manually. This technique is more practical than the first one, but it can only be executed for EMG signals detected during low level contractions and containing up to 5 or 6 MUPTs. An algorithm may successfully decompose such simple EMG signals, but fail to perform as well on more complex signals [7]. Moreover, the resulting MUPTs provided by manual decomposition depend on the operator's skill in decomposing EMG signals. Different patterns may be created by the same or different operators, especially if the MUs fire irregularly or the MUPs of different MUs are similar.

The last technique also known as cross-checking [9] is the best current method for evaluating the accuracy of an EMG signal decomposition algorithm. Two needle electrodes are placed lengthwise along the muscle fibers so that they detect the activity of the same pool of MUs (as much as possible). Each detected signal is decomposed individually, and the results are then compared. Usually the occurrence times of all the MUPs of each MUPT common to both signals are compared. This approach is more realistic than the two others, but it needs a special electrode or a special instrument with at least two channels of data acquisition. The position of the electrodes, if two electrodes are used, is also another issue. If one electrode is positioned far away from the other, it is obvious that the detected signals will not represent the activity of the same MUs. Moreover, the important issue for this method and the other two methods discussed is that they cannot evaluate the obtained MUPTs automatically and online (i.e. once the decomposition process in completed and the MUPTs are obtained).

Here, a method is proposed to automatically validate MUPTs. The proposed method is designed to assess the validity of the extracted MUPTs during or after the decomposition process.

II. VALIDATING A MUPT

Validation of a MUPT can be split into two parts (Figure 1): MU firing pattern validation, and MUP shape validation. For MU firing pattern validation, the given MUPT is evaluated using the times of occurrence of the MUPs assigned to it. The goal is to assess whether a MUPT represents the firings of a single MU or the merged activity of more than one MU, and if is a single train whether the estimated levels of missed and false classification errors in the MUPT are acceptable. For MUP shape validation, the given train is assessed based on the shapes of the MUPs assigned to it. A train is considered as valid train if it passes both tests. Here, the details of a method for MUP shape

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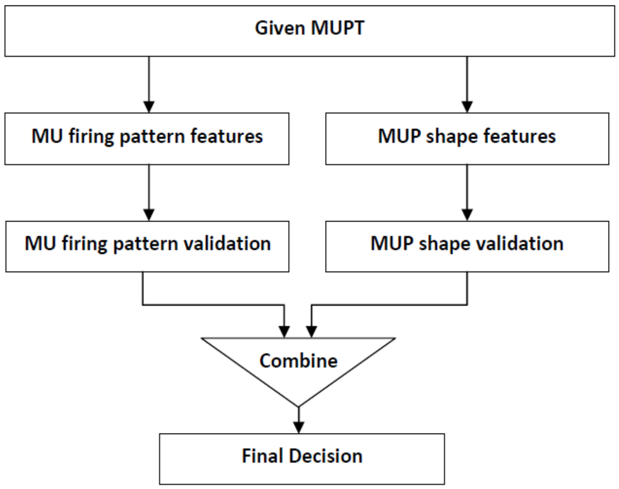

Fig.1. MUPT validation procedure.

validation are presented. MU firing pattern validation is discussed elsewhere [10].

A. Shape –based Validation of a MUPT

Here the goal is to assess whether a decomposition-created MUPT represents the MUPs of a single MU.

On the whole, the process of EMG signal decomposition can be considered as a clustering problem because neither the number of MUPTs (i.e. clusters) nor the labels of the MUPs are known in advance. During EMG signal decomposition, detected MUPs are clustered into groups called MUPTs. Therefore, shape-based validation of a MUPT can be considered as cluster validation and the issue at hand is to assess whether a MUPT represents one cluster in terms of the shapes of the assigned MUPs. In this work, an algorithm based on the gap statistic method [11] is proposed for this task. The features used were the 80 sample points of the first-order difference filtered MUPs assigned to a considered MUPT. These 80 samples are centered on the position of the peak of the MUPs.

The gap statistic method estimates the number of clusters (K) by comparing the change in within-cluster dispersion to that expected under an appropriate null reference distribution of the given data set. This method is based on the following idea: for a given data set the within-cluster dispersion, W_k, decreases monotonically as the value of K increases, but beyond some value of K the decreasing slope of W_k gets close to zero and W_k flattens. W_k is usually given by:

$$W_k = \sum_{r=1}^{k} \frac{1}{2n_r} D_r \qquad (1)$$

Where D_r is the sum of the pairwise distances for all points (x's) in cluster r and is defined as:

$$D_r = \sum_{i \in C_r} \sum_{j \in C_r} \left\| x_i - x_j \right\|^2 \qquad (2)$$

The appropriate number of clusters is the value of K at which this "elbow" occurs [12]. Finding the location of the elbow is difficult. Moreover, this technique cannot be used for testing one cluster versus more than one. The gap statistic overcomes these issues by providing a reference for W_k, generally for $\log(W_k)$. This reference is the expected value for $\log(W_k)$ under the assumption that the data is a single cluster and is found using Monte Carlo sampling. The graph of $\log(W_k)$ for k=1,2,..,K is compared to its expectation and the null hypothesis of a single cluster is rejected in favor of more than one cluster if there is strong evidence for this based on the gap statistic. Their estimate for the number of groups is the minimum value of k where $\log(W_k)$ is the furthest below this reference curve.

Here, the goal is to assess whether a MUPT represents one cluster in terms of the assigned MUP shapes. So the above algorithm needs to be run for k=1 and 2. Therefore, if the maximum gap occurs at k=1, then the MUPT under question consists of the MUPs of a single MU and based on shape can be considered as a valid train.

There are two challenges in using this technique for validating MUPTs. First, it makes wrong conclusions for MUPTs that have variable-shaped MUPs (i.e. false positive error). MUP shape variability is caused by electrode movement, by interfering contributions from the MUPs of other active MUs (i.e. superposition), or by jitter. Jitter is the variability in the time required at the neuromuscular junctions of a MU to depolarize its muscle fiber membranes. This variability results in variable arrival times of the constituent muscle fibre potentials of a MUP at the electrode and causes the shape of the MUP to vary from MU discharge to discharge [6]. If the electrode is moved during signal detection, the amplitude or shape of the MUPs may change because this changes the position of the electrode relative to the fibers of the active MUs. For such trains, the gap statistic method concludes that the train under question is invalid and includes the MUPs of more than one MUs while it does not. The other challenge is that sometimes the algorithm fails to determine invalid trains (i.e. false negative error). This may be because the clusters are highly overlapped. To overcome these issues and make the algorithm robust, an algorithm has been proposed which merges MUPTs with similarly shaped MUPs, splits invalid trains, and also checks if there is a gap in the IDI train of a given MUPT. Following are the details of these steps.

In assessing a train under question, it is flagged as invalid train if either the gap statistic algorithm concludes it is not a single train or there exists gap-IDIs in the IDI train of the given MUPT. The gap-IDI is determined based on the mean (μ) of the IDI train estimated using the EFE algorithm [13] and the similarity of the MUPs. The similarity of two MUPs is measured using pseudocorrelation which is defined as [14]:

$$\mathrm{PsC}(x,y) = \max\left\{\frac{\sum_{i=1}^{N}\left(x_i y_{j+i} - |x_i - y_{j+i}| \max\{|x_i|, |y_{j+i}|\}\right)}{\sum_{i=1}^{N} \max\{|x_i|, |y_{j+i}|\}}\right\} \qquad (3)$$

where x_i and y_i are the samples of the two MUPs x and y, receptively. In calculating the PsC , j is changed until PsC is maximized. PsC is "1" for two perfectly matched templates and is "0" for dissimilar templates.

A gap-IDI in a train is defined as following:

Case 1. μ of the IDI train is available .
The two consecutive MUPs cause a gap-IDI if their IDI is greater than 5μ and their pseudocorrelation is less than 0.5.

Case 2. μ is not available (train is sparse).
The two consecutive MUPs cause a gap-IDI if their IDI is greater than 600 ms and their pseudocorrelation is less than 0.6.

An invalid train is split into K trains using the K-means algorithm, where the parameter K is set equal to the number of gap-IDIs or inconsistent IDIs or 4, based on the following conditions:

1. If there exist gap-IDIs, K is set equal to the number of gap-IDIs.
2. Else if there are inconsistent IDIs, K is set equal to the number of inconsistent IDIs.
3. Else set K=4.

In the third case one can use the gap statistics algorithm to estimate k, but our experience showed that most of the invalid MUPTs consist of up to 4 trains. So to make the algorithm fast, K is set to 4 in this case.

Two trains are merged if their templates are close (their PsC is above a threshold, e.g. 0.7) and the IDI train of the merged train is valid. In the final step, trains with less than 5 MUPs are deleted.

Throughout this process not only is the given MUPT evaluated but its errors are also removed when it is not a valid train. As a result invalid trains are turned into valid trains (see Fig.3 as an example).

III. RESULTS AND DISCUSSION

The effectiveness of the method proposed for validating MUPTs was studied using simulated data. Simulated EMG signals were generated using an EMG signal simulator [15]. The simulator enables us to generate EMG signals with different complexities, such as different numbers of MUs, different values for IDI parameters (mean and standard deviation), and different values for MUP shape variability.

The generated signals were decomposed using the DQEMG software [16].The resulting MUPTs were assessed visually and valid MUPTs and invalid trains were determined. To generate more invalid trains from the selected MUPTs, up to four MUPTs, were merged as well. In total 1000 MUPTs (500 valid and 500 invalid trains) were generated. This data set was divided into 10 subsets of 50 valid and 50 invalid trains. For each subset, the accuracy of the developed method in labeling the given MUPTs was measured. The results are summarized in Table 1. In this table Valid as Valid stands for the valid MUPTs classified as valid trains, and Invalid as Invalid represents the invalid trains recognized as invalid MUPTs. The average accuracy of the developed method in determining valid MUPTs and invalid MUPTs is 97.58% and 99.33%, respectively. Most of

Table 1. Mean and standard deviations of the accuracy of the shape-base MUPT validation method applied to simulated MUPTs.

Term	*Valid as Valid*	*Invalid as Invalid*	*Overall*
Accuracy(%)	97.6±0.2	99.3±0.2	98.5±0.1

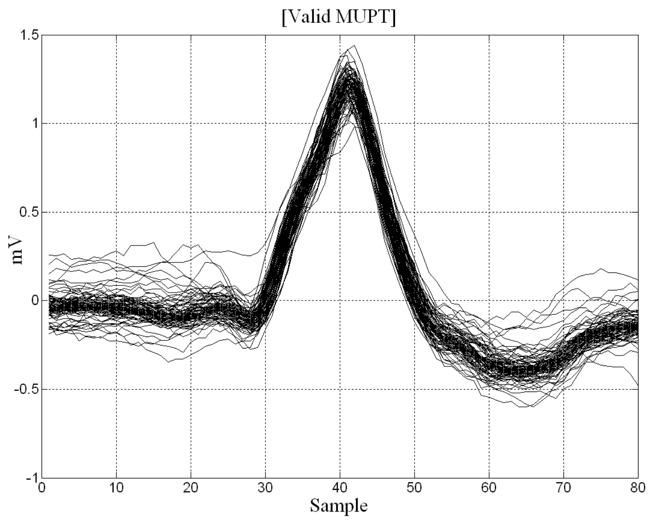

Fig.2. A valid MUPT labeled as valid train.

the valid trains recognized as invalid are trains with highly variable MUP shapes caused by either high numbers of superimpositions or high jitter. So, the accuracy of this method in determining valid MUPTs will be higher for trains provided by EMG decomposition algorithms that resolve superimposed MUPS. The accuracy of this method in determining invalid MUPTs is very encouraging; it can detect an invalid train with probability 0.99. It is obvious that for diagnostic proposes misclassifying an invalid MUPT as a valid train is more costly than doing the inverse classification. Therefore this performance encourages us to use this method to facilitate the process of validating a MUPT and to improve decomposition accuracy.

The developed method was also tested using real data. "Nikolic M, Rigshospitalet" EMG signals [17] which were detected from normal, myopathic and neuropathic individuals using a standard concentric needle electrode during constant low level voluntary contractions[1]were used for this purpose. The results were similar to those obtained using the simulated data described here.

Figure 2 shows an example of a valid train labeled as a valid train. Visually inspecting the shape of the MUPs assigned to this train confirms that they are homogeneous and hence theses MUPs were generated by a single MU (i.e. it is a valid train).

Figure 3 shows an example of an invalid train recognized as an invalid train and then split it into two valid trains. As shown, it is hard to recognize that this MUPT is an invalid train by assessing this shimmer plot, but the developed algorithm was be able to detect this invalid train.

[1] These signals and more information about them are available from : http://emglab.net/emglab/Signals/N2001/index.html

IV. Conclusion and Future Works

An algorithm for automatic validation of MUPTs extracted by an EMG signal decomposition algorithm based on MUP shape was proposed. This algorithm is based on the gap statistic method and evaluates a given MUPT in terms of MUP shape consistency and assesses whether the MUPs of a considered MUPT are homogeneous in terms of their shapes. The experimental results using both simulated data and real data show that the ability of the algorithm to correctly label a MUPT is encouraging. This accuracy was %98 on average.

In future work, the goal is to develop a method to measure the confidence in the validity/invalidity of the given MUPT. Having that, one can then estimate the accuracy obtained by an EMG decomposition algorithm in decomposing a specific EMG signal.

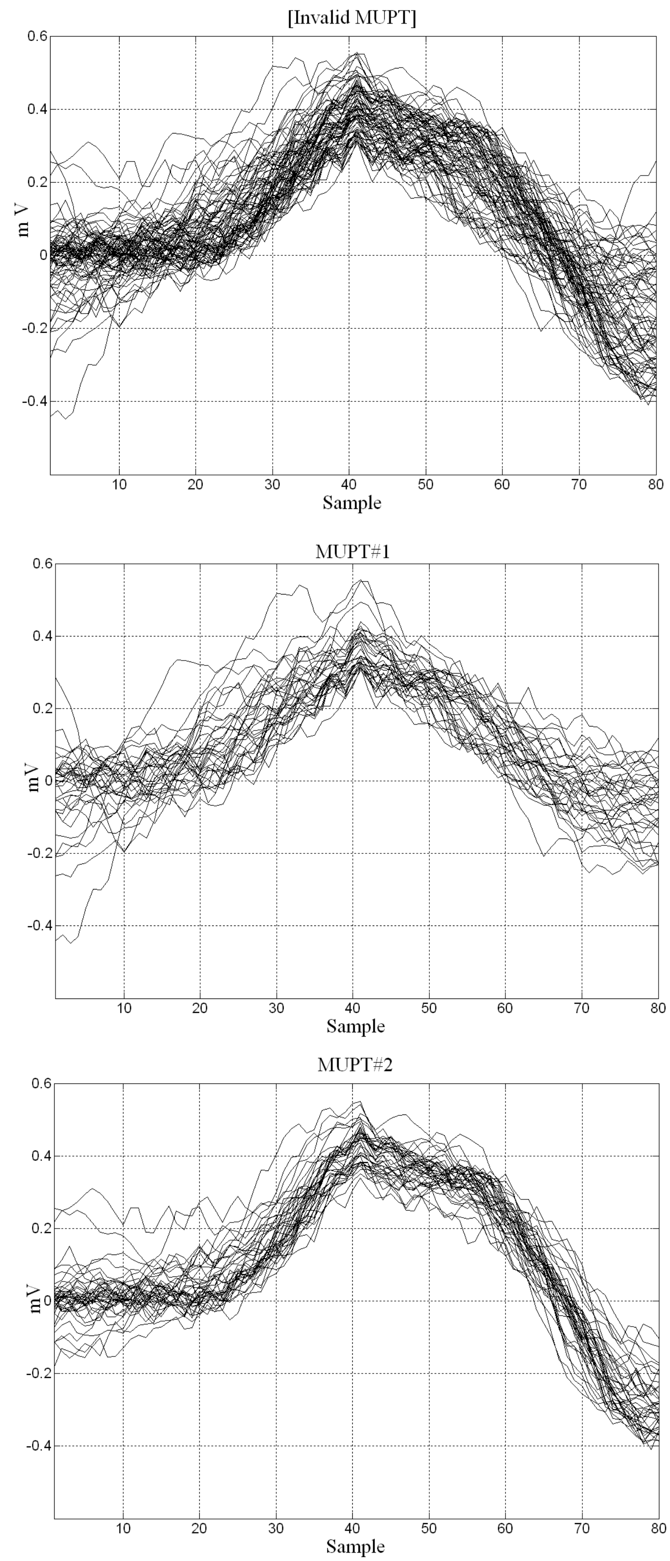

Fig.3. An invalid MUPT (top) flagged as invalid train and was split into two valid trains (middle and bottom).

References

[1] A. Fuglsang-Frederiksen, "The role of different EMG methods in evaluating myopathy," *Clin. Neurophysiology*, vol.117, pp.1173–1189, 2006.

[2] E. Stålberg, B. Flack, M. Sonoo, S. Stålberg, and M. Åström, "Multi-MUP EMG analysis – a two year experience in daily clinical work," *Electroencephalography & Clin. Neurophysiology*, vol.97, pp.145-154, 1995.

[3] L. J. Pino, D. W. Stashuk, S. G. Boe, and T. J. Doherty, " Motor unit potential characterization using ‘‘pattern discovery”," *Med. Eng.& Phys.*, vol.30, pp. 563–73, 2008.

[4] L. J. Pino, D. W. Stashuk, S. Podnar, "Bayesian characterization of external anal sphincter muscles using quantitative Electromyography," *Clin. Neurophysiol*. vol.6, no.17, 2008.

[5] A. Hamilton-Wright, D. W. Stashuk, "Clinical characterization of electromyographic data using computational tool," in *Proc. of CIBCB/IEEE*. Toronto, Sept 2006, pp.1-7.

[6] D.W. Stashuk, "EMG signal decomposition: how can it be accomplished and used?" *J. of Electromyography and Kinesiology*, Vol.11, pp.151-173, 2001.

[7] C. J. De Luca, *Reflections on EMG signal decomposition*. In: Desmedt JE, editor. Computer-aided electromyography and expert system. Elsevier Pub, pp. 33–37, 1989.

[8] D. Farina, R. Colombo, R. Merletti, and H. B. Olsen," Evaluation of intra-muscular EMG signal decomposition algorithms," *J. of Electromyography and Kinesiology*, vol.11, pp.175–187, 2001.

[9] K .C. McGill, Z. C. Lateva, and M. E. Johanson "Validation of a computer-aided EMG decomposition method," in *Proc. 26th Annual Int. Conf. IEEE EMBS* , San Francisco, USA, September, 2004, pp.4744-4747.

[10] H. Parsaei, F. Jahanmiri Nezhad, D. W. Stashuk, and A. Hamilton-Wright , "Validation of motor unit potential trains using motor unit firing pattern information," in 31st Annu. Int. Conf. of IEEE EMBS Minnesota, USA, Sept. 2009.

[11] R. Tibshirani, G. Walther, and T. Hastie," Estimating the number of clusters in a data set via the gap statistic," *J. of the Royal Statistical Society*, vol.63, no.2, pp.411–423, 2000.

[12] C. A. Sugar, "Techniques for Clustering and Classification with Applications to Medical Problems,” Stanford University, PhD Thesis, 1998.

[13] D. W. Stashuk, and Y.Qu," Robust method for estimating motor unit firing-pattern statistics," *Medical & Biological Eng. & Computing,* vol.34, no.1, pp.50-57, 1996.

[14] J. R. Florestal, P. A. Mathieu, A. Malanda, "Automated decomposition of intramuscular electromyographic signals*," IEEE Trans. Biomed. Eng.* Vol.53, no.5, pp.832-839, 2006.

[15] A. Hamilton-Wright, D.W. Stashuk, "Physiologically based simulation of clinical EMG signals," *IEEE Trans. Biomed. Eng*., vol.52, no.2, pp. 171-183, 2005.

[16] D. W. Stashuk, "Decomposition and quantitative analysis of clinical electromyographic signals," *Medical Eng. & Physics*, vol.21, pp.389-404, 1999.

[17] M.Nikolic," Detailed Analysis of Clinical Electromyography Signals EMG Decomposition, Findings and Firing Pattern Analysis in Controls and Patients with Myopathy and Amytrophic Lateral Sclerosis," PhD Thesis, Faculty of Health Science, University of Copenhage, 2001.