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Validation of Motor Unit Potential Trains Using Motor Unit Firing Pattern Information

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Abstract—**A robust and fast method to assess the validity of a motor unit potential train (MUPT) obtained by decomposing a needle-detected EMG signal is proposed. This method determines whether a MUPT represents the firings of a single motor unit (MU) or the merged activity of more than one MU, and if is a single train it identifies whether the estimated levels of missed and false classification errors in the MUPT are acceptable. Two supervised classifiers, the Single/Merged classifier (SMC) and the Error Rate classifier (ERC), and a linear model for estimating the level of missed classification error have been developed for this objective. Experimental results using simulated data show that the accuracy of the SMC and the ERC in correctly categorizing a train is 99% and %84 respectively**.

I. Introduction

INFORMATION regarding motor unit potential (MUP) waveforms and motor unit (MU) firing patterns during muscle contractions is very useful for clinical examination as well as physiological investigation. Specifically, such information can assist with the diagnosis of neuromuscular disorders [1]-[3] and the understanding of motor control [4]. 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 [5], [6]. An effective way of obtaining MUPT information is via EMG signal decomposition.

EMG signal decomposition is the process of resolving a composite EMG signal into its constituent motor unit potential trains (MUPTs). In general, this process is done in four steps: signal preprocessing, signal segmentation and MUP detection, clustering of detected MUPs, and supervised classification of detected MUPs [7].

The goals of automatic decomposition techniques are to extract a template MUP waveform and MU firing pattern for each MU that contributed significant MUPs to the original composite signal. Diagnosis is then facilitated by decomposing a needle-detected EMG signal, measuring the features of the detected MUPTs and finally analyzing the measured features [8].

Although quantitative analysis of the extracted information from decomposed EMG signals can facilitate the diagnosis and treatment of neuromuscular diseases, this is can only happen when this information is valid. Therefore, before using decomposition results (i.e. MUP shape and MU firing pattern information) for either clinical or research purposes the fact that the extracted MUPTs, obtained using either a manual or automatic EMG signal decomposition process, are representative of the occurrence times of single MUs and have low numbers of false classification errors (FCEs) needs to be confirmed. Although many methods have been developed to decompose EMG signals, automatic validation of the obtained MUPTs have not been studied in detail.

Assessing the validity of a MUPT can be split into two tests: a test of MUP shape validation, and a test of MU firing pattern validation. For the MUP shape validation test, a given train is assessed based on the shapes of the MUPs assigned to it. The goal is to assess whether the shapes of the MUPs in a decomposition-created MUPT represents the MUPs of a single MU or not. For the MU firing pattern validation test, a given MUPT is evaluated considering the times of occurrence of the MUPs assigned to it. A train is considered valid if it passes both tests. In this work, details of the MU firing pattern validation test are presented. A system to facilitate temporal validation of MUPTs is developed. The system validates a given MUPT using firing pattern information extracted from the MUPT. A MUP shape validation test is discussed elsewhere [9].

II. Methodology

A. MU Firing Pattern

MU firing patterns are usually represented by the intervals between two consecutive MU firings in a MUPT, which are called inter-discharge intervals (IDIs). During short, constant-force (or slowly-changing force) low-level contractions, IDIs follow a Gaussian distribution with a mean related to the inverse of the mean firing rate of the MU and a standard deviation of 10%–25% of the mean [10]-[12]. The IDI distribution of an invalid MUPT, however, does not look like a Gaussian distribution. Depending on the type of errors present, the IDI distribution is skewed to the left or to right [10], [13], and [14]. In this section, we describe three types of invalid trains and their IDI distributions that may result from the decomposition of an EMG signal.

A **merged** train is created when the shapes of MUPs

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created by two or more different MUs are very similar to each other such that a decomposition algorithm erroneously considers these MUPs as being created by one MU and thus places them in one MUPT. However, the IDIs extracted from a merged train do not have the characteristics of a typical MU firing pattern. The IDI distributions of merged trains are less like a Gaussian distribution, presenting much wider ranges of variation with no central peaks relative to the IDI histogram of a single train.

An **incomplete** train is a MUPT for which all MUPs generated by a MU are not assigned to this train. Missed classification errors (MCEs) stand for those MUPs of this MUPT that were missed during the MUP detection, clustering or classification steps. Incomplete trains are created due to unresolved superimposed MUPs, insufficient knowledge about the exact shape of the template MUP of a MUPT and its MU firing pattern statistics. Due to missing MUPs, long intervals occur between consecutive MUPs and hence the IDI distribution is skewed to the right. High levels of MCE make the measurement of MU firing pattern statistics and the prototypical MUP for each active MU unreliable, because the sample size is small.

A **contaminated** train is a MUPT that includes some mistakenly assigned MUPs. These mistakenly assigned MUPs are called false classification errors (FCEs). As with MCEs, FCEs are due to the fact that the exact shape of the template of a MUPT and MU firing pattern statistics are not known. Therefore, when MUPs created by two or more MUs are very similar they may assigned to the wrong MUPTs. FCEs cause the number of shortened IDIs in a single train to increase. Therefore the IDI distribution of a single train with high FCE skews to the left and the MU firing pattern statistics of this train are underestimated. Finding invalid trains caused by these three types of errors can improve the robustness of an EMG decomposition algorithm and can also improve the accuracy of conclusions made based on information extracted from the results of a decomposition algorithm.

B. Validating a MU Firing Pattern

The overall procedure of the developed MU firing pattern validation algorithm is shown in Fig.1. This method is based on the fact that the IDI characteristics of single/valid trains differ from those of merged MUPTs and trains with large numbers of MCEs or FCEs. As shown, 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 determine whether the estimated level of MCE and FCE in the MUPT is acceptable. These three conditions are tested using two supervised classifiers, the Single/Merged classifier (SMC) and the Error Rate classifier (ERC), and a first order linear model. The SMC classifier determines whether a given train is a single train. The ERC classifier determines whether the estimated level of FCE in the given MUPT is acceptable. The linear model estimates the level of MCE in the considered train.

A train will be labeled as valid if it is labeled as a single

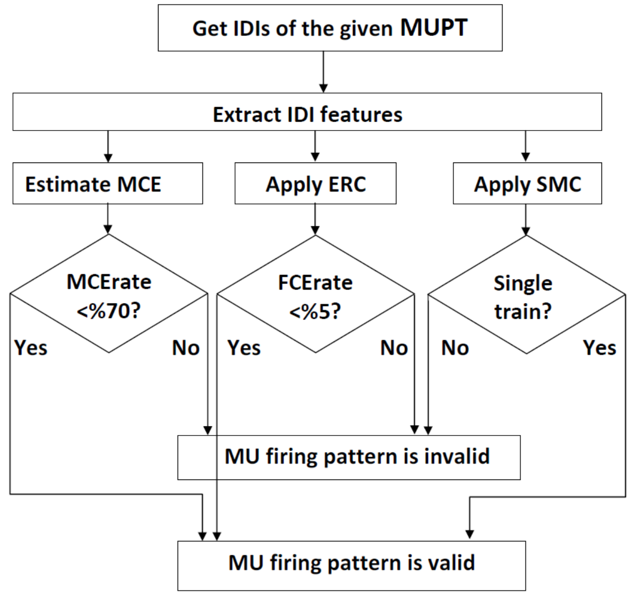

Fig.1.Procedure for validating MU firing pattern

train, by the SMC, if the estimated level of FCE is acceptable, as determined by the ERC and the level of MCE in the train is acceptable, as determined by the linear model. In this work the acceptable levels for FCE and MCE were set to 5% and 70% respectively. The detailed composition of this method including feature extraction, classifier and linear model development is presented below.

C. Discriminative Features

As discussed above, certain firing pattern characteristics of a single train are not similar to those of a merged, contaminated or incomplete train. We therefore used these different characteristics as features for the classification task. Here, in addition to their general discriminate ability, the features should also be sufficiently discriminative even for trains with high values of MCE, which usually happens during the initial steps of a decomposition process. The features used in this work are listed in Table 1. Except for IDrate which targets the right side of the IDI distribution to measure the level of MCE in the MUPT, these features target the left side of an IDI distribution, where short IDIs or, in other words, the errors of interest are reflected. See [14] for detailed feature definitions.

To calculate the features used, the mean (μ) and standard deviation (σ) of the IDIs of a MUPT must be known. These two parameters were estimated using the error-filtering algorithm (EFE) presented by Stashuk and Qu [10].

D. The SMC and ERC Supervised Classifiers

To determine the best implementation for the SMC and the ERC, three classification methods were examined; Fisher linear discriminate analysis (FDA), Support Vector Machine (SVM) and Pattern Discovery (PD).

FDA was considered because it is a very simple and powerful linear classifier. Also it is very easy and computationally cheap to implement, especially after training [15].

Table 1. Firing Pattern Features

Feature	Description
CV	Coefficient of Variation
CV_L	Lower Coefficient of Variation
CV_L/CV_U	The ratio of lower and Upper CV
PI	Percentage of inconsistent IDIs
$LIDI_R$	Lower IDI ratio
1stSCorr	First Coefficient of Serial Correlation
Skewness	A measure of symmetry of the IDI histogram
IDrate	MUP Identification rate
FR-MCD	Firing Rate mean consecutive difference
IDI-MCD	IDI mean consecutive difference

A SVM was evaluated because it minimizes an upper bound on the generalization error, which has been shown to be superior to conventional learning algorithms (e.g. neural networks) that minimize the error on the training data [16]. A Gaussian radial basis function was used as kernel function. In training the SVM, the parameters of the kennel function and also the regularization parameter were determined experimentally via cross-validation. For the SVM implementation, the MATLAB toolbox provided by Canu and his-coworkers [17] was used.

PD [18], an associative rule-based classifier, was considered because of its ability to deal with nonlinear class distributions. Patterns discovered in training data and present in a feature vector to be classified are combined using information theory metrics for classification. A detailed description of how this methodology can be used as a classifier is provided by Hamilton-Wright and his co-workers in [19].

E. Estimating the Level of MCE

MCE rate is inversely related to the identification rate (ID rate). As MCE increases the IDrate decreases and vice versa. IDrate is defined as:

$$IDrate = \frac{Number\ of\ Extracted\ MUPs}{Expected\ Number\ of\ MUPs} \qquad (1)$$

Experimental results show that the MCE level is highly correlated to the IDrate with a correlation coefficient of -0.96. Hence, the MCE level can be modeled by applying linear regression techniques to a set of data that represents the level of MCE in MUPTs versus their IDrate. The following 1st order linear model was extracted using simulated data.

$$MCElevel = -1.086 \times IDrate + 1.024 \qquad (2)$$

$$R^2 = 0.9403$$

Having this model, the MCE level of a MUPT can be estimated if its IDrate is available.

III. RESULTS AND DISCUSSION

Each part of the developed method was trained and tested using simulated MU firing patterns. The simulated MU firing patterns were created using a wide variety of parameters. Trains of 75 IDIs, which on average correspond to EMG signals of 7.5s duration, were initially and independently generated using Gaussian distributions with mean IDIs of 80, 90, 100, 110, or 120 ms and coefficient of variations (CVs) ranging from 10% to 30%. There are 20 replicates for each (mean and CV) set of values. For development of the SMC, up to 5% FCE and from 0% to 70% MCE was added to the true trains. Each possible pair of the generated trains (different mean, STD, false and misclassification rate) was then merged. On the whole, 90,000 single trains and 90,000 merged trains were generated. For development of the ERC, the FCE went from 0 to 15%, including both acceptable and unacceptable values. The CV and MCE variations were the same as for the SMC training data set. There were 30 replicates for each (mean and CV) set of values, resulting in 35,000 valid trains (with acceptable FCE) and 35,000 invalid trains.

The average accuracy (and standard deviation) of the three classifiers considered for the SMC is summarized in Table 2. Each row describes the confusion matrix of each classifier. In this Table, SasS stands for single trains classified as a single train and MasM stands for merged trains classified as a merged train. The first column in each misclassification error rate category shows the mean and standard deviation of the accuracy of the three classifiers for single MUPTs and the next column shows the mean and standard deviation of the accuracy of the three classifiers for merged MUPTs. These numbers were calculated by testing each classifier on ten different data sets. For each MCE rate, the best classifier(s) based on the t-test at the 5% significant level are indicated by '*'. As this table shows, the SVM classifier has the highest accuracy.

Table 3 shows the results for the three ERCs considered. In this table, AasA stands for trains with acceptable FCE rate classified as a train with acceptable FCE rate and UasU stands for trains with unacceptable FCE rate classified as a train with unacceptable FCE rate. The first column in each MCE rate category shows the mean and standard deviation of the accuracy of the three classifiers for MUPTs with acceptable FCE rate and the next column show the mean and standard deviation of the accuracy of the three classifiers for MUPTs with unacceptable FCE rate. The accuracy of the classifiers was estimated by testing each classifier on ten different data sets. For each MCE rate, the best classifier(s) based on the t-test at the 5% significant level are indicated by '*'. As Table 3 shows, the SVM performs better than the FDA and PD classifiers in classifying AasA. On the other hand, the FDA classifier is the best at classifying MUPTs with unacceptable FCE rate correctly. On the whole, the FDA classifier is better than the SVM and PD classifiers for error rate classification, because of the following three reasons. First, in total the accuracy of the FDA classifier is

Table2. Mean and standard deviations of the accuracy of the three studied classifiers applied to simulated single or merged MUPTs (SasS: Single train classified as Single train, MasM: Merged train classified as Merged train).

Misclassification Error Rate				
	0% to 70%		60% to 70%	
Accuracy(%)	SasS	MasM	SasS	MasM
FDA	98.8±0.1	99.2±0.1	98.0±0.2	93.9±0.4
PD	99.3±0.1	99.1±0.1	99.3±0.1	99.7±0.3
SVM	*99.5±0.1	*99.5±0.1	*99.4±0.1	*95.7±0.2

Table3.Mean and standard deviations of the accuracy of the three studied classifiers applied to simulated MUPTs having acceptable and unacceptable FCE rate (AasA: train with acceptable FCE rate classified as train with acceptable FCE rate, UasU: train with unacceptable FCE rate classified as train with unacceptable FCE rate).

Misclassification Error Rate				
	0% to 50%		60% to 70%	
Accuracy(%)	AasA	UasU	AasA	UasU
FDA	80.7±0.6	*87.3±0.5	71.9±2.1	*71.0±1.3
PD	79.6±0.8	85.8±0.5	76.0±3.0	66.3±1.8
SVM	*82.7±0.6	85.5±0.6	*76.1±1.8	68.1±1.5

greater than that of the SVM and PD classifiers. For the data with 0% to 70% MCE rate, which is the general case, the FDA classifier has an average accuracy of 81.72%, while the SVM and PD classifiers had accuracy of 80.96, and PD 80.20, respectively. Second, the FDA classifier is faster than the SVM and PD classifiers. Third, the FDA classifier has the best performance in correctly classifying MUPTs with unacceptable FCE rate. It is clear that misclassifying an invalid MUPT as a valid train is more important than the inverse classification; the FDA classifier is therefore the best choice for error rate classification.

The linear model developed for estimating the MCE level of a MUPT has been evaluated using simulated data described above. But here only the IDIs of single trains have been used. This data set was split into 10 subsets each containing 9000 single trains. The mean square error (MSE) between the true MCE level and that given by the model was calculated over each subset. The average of the resulting 10 MSEs is considered as an estimation of the MSE. The model has an average MSE (and standard deviation) of 0.0036 (1.8E-4), which is close to zero and shows that the model performs well in estimating the level of MCE in a MUPT.

The high performance of the developed classifiers and the linear model in determining invalid trains encourages the use these methods for validating a MUPT. These methods can also be used during the decomposition of an EMG signal to make more accurate decisions when assigning detected MUPs and hence improving decomposition accuracy.

IV. Conclusion

A system consisting of two supervised classifier and a linear model has been presented for automated validation of a MUPT using its MU firing pattern information. The MU firing patterns of the given MUPT are represented by the characteristics of the IDI histogram of the MUPT. One of the developed classifiers, the SMC, determines whether a MUPT represents the firings of a single MU or the merged activity of more than one MU. The second classifier, the ERC, determines whether the level of FCE errors in a MUPT is acceptable or not. The linear model estimates the level of MCE in a MUPT to see whether it is acceptable or not. The results are encouraging and suggest that using these methods can improve EMG signal decomposition results, and can facilitate automatic validation of a MUPT, extracted from either a manually or automatically decomposed EMG signal.

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