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A Method for Detecting and Editing MUPTs Contaminated by False Classification Errors during EMG Signal Decomposition

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***Abstract*— A robust method for detecting motor unit potential trains (MUPTs) contaminated with false classification errors (FCEs) during EMG signal decomposition and then removing the FCEs from a contaminated train is presented. Using motor unit (MU) firing pattern information provided by each MUPT, the developed algorithm first determines whether a given train is contaminated by high number of FCEs and needs to be edited. For contaminated MUPTs, the method uses both MU firing pattern and motor unit potential (MUP) shape information to detect MUPs that were erroneously assigned to the train (i.e., represent FCEs). For the simulated data used in this study contaminated MUPTs could be detected with 88.7% accuracy. For a given contaminated MUPT, the algorithm on average correctly detected 83.4% of the FCEs and left 93.4% of the correctly assigned MUPs. The accuracy of the MUPs classified to a MUPT was estimated to be 92.1% on average.**

List of Symbols and Abbreviations

EMG	Electromyographic
FCE	False–classification errors
FDA	Fisher linear discriminate analysis
IDI	Inter–Discharge Interval
MCE	Missed classification errors
MU	Motor unit
MUP	Motor unit potential
MUPT	Motor unit potential train
PSI	Percentage of shape inconsistency
SCC	Single–contaminated classifier
m	Number of effective time samples representing the MUPs of a MUPT
μ	The mean of IDIs of a MUPT
σ	The standard deviation of the IDIs of a MUPT

I. Introduction

An electromyographic (EMG) signal detected by an electrode during muscle contraction, is the superposition of background noise and the motor unit potential trains (MUPTs) created by the active motor units (MUs). The firing patterns of these active MUs along with their motor unit potentials (MUPs) contain valuable information regarding the state of health as well as the anatomical and physiological features of the muscle under study. One effective way of extracting such information is via EMG signal decomposition.

EMG signal decomposition is the process of resolving a EMG signal into several MUPTs each of which represents the activity of a MU that was active during signal detection and which contributed significant MUPs to the detected signal. This process is completed using digital signal processing and pattern recognition techniques in three or four steps: signal preprocessing, signal segmentation (MUP detection), and then clustering and possibly supervised classification of the detected MUPs [1]–[3]. The purpose of EMG signal decomposition is to provide an estimate of the MU firing patterns and MUP templates of active MUs. Such information can assist with the diagnosis of neuromuscular disorders [4]–[6], the understanding of motor control [7], and the characterization of MU architecture [8]. A recent comprehensive review of the algorithms developed for the decomposition of indwelling EMG signals can be found in [1].

As with other pattern recognition problems, errors may occur during the decomposition of an EMG signal. Some MUPs of a MUPT may be missed or some MUPs of other trains may be mistakenly assigned to the wrong train. Consequently, a MUPT may be contaminated by two types of errors: missed classification errors (MCEs) and false classification errors (FCEs).

Missed classification errors, also known as false negative errors, represent those MUPs of a MUPT that were missed during MUP detection, clustering or supervised classification. Due to MCEs, long intervals occur between consecutive MUPs and hence the inter–discharge interval (IDI) distribution is skewed to the right. MUPTs with a high MCE rate are called incomplete trains. Because of possibly small samples sizes, the estimation of MU firing pattern statistics and the MUP template of a MUPT can be unreliable for incomplete trains.

False classification errors (FCEs), also known as false positive errors, in a MUPT represent the MUPs that were incorrectly assigned to this train. In general, FCEs are due to the similarity of the MUPs created by different MUs along with insufficient knowledge about the exact MU firing patterns, MU firing pattern statistics, and the MUP templates of the active MUs. FCEs cause MUP shape inconsistency and/or IDI inconsistency in a MUPT. A MUPT that has a high number of FCEs is called a contaminated train. Contaminated MUPTs have IDI distributions that are skewed to the left and their MU firing pattern statistics are often underestimated (due to the increased number of shortened IDIs). In addition, the instantaneous MU firing rate versus time plots for contaminated trains provide a

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confused representation of the firing rates of the corresponding MU. Such invalid information may contribute to either clinical or scientific misstatements when used clinically or for physiological investigation.

Identifying contaminated MUPTs and then editing them to remove the FCEs during EMG signal decomposition can improve decomposition accuracy. At the end of each pass during decomposition, contaminated MUPTs are identified and then have their FCEs removed. Such editing can help with assigning more MUPs to the extracted trains in the next iterations of decomposition, and can improve estimation of the MUP templates and MU firing pattern statistics of the extracted MUPTs. Ultimately, the editing process can improve decomposition accuracy.

To date, editing MUPTs extracted by a decomposition algorithm is conducted manually by an expert operator. The FCE in each MUPT is identified by assessing its instantaneous MU firing rate plot and a raster plot of its assigned MUPs. The accuracy of such editing, as with other methods that need human operator supervision, depends on operator experience and skill. In addition, such a process is time consuming and cannot be practically completed in a busy clinical environment. More importantly, the process cannot be executed during automatic decomposition of an EMG signal. In this paper, an algorithm that can detect contaminated MUPTs and automatically edit its FCEs is presented. Details of the method are given below.

II. Methods

Contaminated MUPTs are first detected using the single–contaminated classifier (SCC) developed earlier [9]. For each contaminated MUPT the algorithm then attempts to detect and remove FCEs. Following is a description of each step.

A. Detecting Contaminated MUPTs

MUPs erroneously assigned to a MUPT generally cause MUP shape and/or IDI inconsistencies. The IDI distribution of a contaminated MUPT is skewed to the left and the variability in its instantaneous MU firing patterns is increased. In this work, such information was employed to determine whether a given MUPT is a contaminated MUPT or not. Considering this two–class problem (contaminated MUPT and non-contaminated MUPT), the SCC was developed to determine the class label of a given MUPT. The SCC used is a Fisher linear discriminate analysis (FDA) classifier [10] that uses ten features extracted from the IDIs and MU firing pattern of the given MUPT.

The features used by the SCC are listed in Table 1; definitions and calculation details for these features are presented elsewhere [9]. In short, the majority of these features target the left side of the IDI distribution of the given MUPT, where short IDIs (i.e., the errors of interest) are reflected. The identification rate targets the right side of the IDI distribution to measure the level of MCE in the MUPT. The firing rate mean consecutive difference measures the variation in the instantaneous firing rate. The instantaneous firing rate at each MUP occurrence in a MUPT is defined as the inverse of a local IDI that is obtained by applying a normalized Hamming filter to the 5 IDIs before and after the current MUP.

Table 1. Firing pattern features used for developing the single–contaminated classifier. The output of these features can indicate whether a given MUPT is contaminated by a high number of FCEs or not.

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
ID– rate	Identification rate
FR–MCD	Firing rate mean consecutive difference
IDI–MCD	IDI mean consecutive difference

The FDA–based SCC classifier was used because it is robust and computationally efficient to implement. In addition, as shown in [9] the FDA–based SCC outperformed SCCs developed based on support vector machine and pattern discovery concepts in correctly classifying contaminated MUPTs.

B. Detecting FCEs in a Contaminated MUPT

The FCE detection algorithm employs both MU firing pattern and MUP shape information to classify the MUPs of a MUPT as being either a FCE or a correct MUP assignment. Initially, erroneously assigned MUPs (i.e, FCEs) are detected using shape information. The goal is to detect those MUPs whose shape is inconsistent with the shapes of the majority of the MUPs in the MUPT. With the information provided by the EMG decomposition algorithm used, each MUP in the given MUPT is represented by a window of 80 sample points (representing an interval of 2.56 ms at a sampling rate of 31.25 kHz) within the EMG signal band–pass filtered using a low–pass differencing filter [11]. Among these 80 samples, the m samples for which the N MUPs of the contaminated MUPT significantly differ from each other are used to detect FCEs using only MUP shape information.

Let $x_i[n]$ n=1,2,…,80 represent the 80 filtered time samples of the ith MUP in the MUPT. For each n, the gap values g[n] which are the largest change in the sorted $x_i[n]$ values are determined and then the m values with the largest g[n] that are also at least 8 samples (0.26 ms) apart are used as effective features to represent the MUPs assigned to the

MUPT under study.

Let $y_i[k]$ k=1,2,…,m denote the m effective time samples representing the ith MUP in the given contaminated MUPT; S[k] represents the m corresponding samples of the MUP template of the given MUPT; and ε denote the root mean square value of the noise contaminating the MUPs. For each MUP, the percentage of shape inconsistency (PSI) and its distance from the MUP template are calculated as:

$$PSI_i = \frac{1}{m}\sum_{k=1}^{m}\{U(y_i[k] - S[k] - 3\varepsilon) + U(-y_i[k] + S[k] - 3\varepsilon)\} \quad (1)$$

$$d_i = \frac{1}{\varepsilon^2}\sum_{n=1}^{m}(|y_i[n] - S[n]|)^2 \quad (2)$$

where U(t) is the unit step function.

Based on the calculated values for PSI_i and d_i and using χ^2 statistics, MUPs are classified into three classes based on their shape: 1) *definitely* a FCE if $d_i > \chi^2(m,\alpha)$ AND PSI_i > 0.8; 2) *potentially* a FCE if $d_i > \chi^2(m,\beta)$; and 3) a correctly assigned MUP.

In the second step of detecting FCEs, erroneously assigned MUPs are detected using MU firing pattern information. MUPs that cause IDI inconsistencies are detected and classified into three categories based on their firing pattern: 1) *Semi-definitely* a FCE if $IDI_i < \mu$-3σ; 2) *potentially* a FCE if $IDI_i < \mu$-2σ; and 3) *do not know* if $IDI_i > 2\mu$. Where μ and σ are the mean and standard deviation of the IDIs of the given train estimated using the error–filtered estimation algorithm that provides accurate estimaties of these IDI statistics of a MUPT even when contaminated by a high MCE rate [12].

In the third step, a MUP is classified as a FCE if it was assigned into either: 1) the *definitely* a FCE based on shape class; or 2) the *potentially* a FCE based on shape class AND the *do not know* based on firing pattern class; or 3) the *potentially* a FCE based on shape class AND the *potentially* a FCE based on firing pattern class. In addition, a MUP is labeled as a FCE if it is assigned into the *Semi-definitely* based on IDI class and its PSI > 0.4. Otherwise it is classified as a correctly assigned MUP.

III. Results and Discussion

Each part of the developed method was tested using simulated data. Specifically, 535 MUPTs extracted from 43 EMG signals each of 10s length with different levels of intensity, ranging from 24 to 193 pps, with jitter values ranging from 50 to 150μs, and with IDI variability (i.e., coefficient of variation) ranging from 0.10 to 0.45 generated using an EMG signal simulator developed by Hamilton-Wright and Stashuk [13] were used. These data allowed us to study the performance of the developed method in relation to various degrees of MUP shape and IDI variability. The generated signals were decomposed using DQEMG software [14]. MUPs were added to each train extracted from an EMG signal at random points in time until the FCE rate of the train was between 5% and 20% (with 5% intervals). The added MUPs were selected randomly from the remaining MUPTs extracted from the same EMG signal.

Table 2. The performance of the FCE detection algorithm obtained using 535 MUPTs obtained from the decomposition of 43 simulated EMG signals.

Sensitivity (%)	Specificity (%)	Accuracy(%)
84.4±0.7	93.4±0.1	92.1±1.0

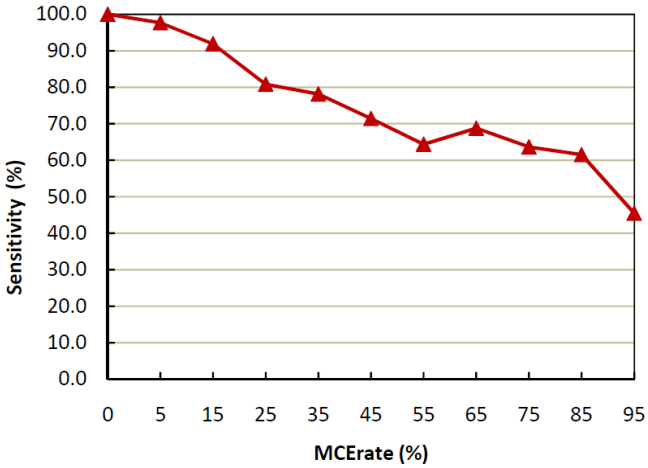

Figure 1. Sensitivity of the SCC classifier in detecting a contaminated MUPT versus the MCE rate in the train.

The FDA–based SCC, configured based on previous simulated training data [9], had a sensitivity (i.e. the ability to detect a contaminated train) of 88.7% and a specificity (i.e., the ability to detect a non-contaminated train) of 95.5% and an overall accuracy of 90.1% when applied to the simulated data of this work. The accuracy of the FDA–based SCC in detecting contaminated MUPTs decreases as their MCE rates increase. As shown in Figure 1, the FDA–based SCC correctly detected approximately only 65% of the contaminated MUPTs having MCE rates between 55% and 85%.

The calculated means and standard deviations across the MUPTs studied for the sensitivity, specificity and accuracy of the FCE detection algorithm with $m = 5$, $\alpha = 0.01$, and $\beta = 0.05$ are presented in Table 2. These settings were empirically found to perform better based on experimentation with several MUPTs.

As shown, the FCE detection algorithm can detect the majority of the added FCE errors and was also able to correctly classify most of the correctly assigned MUPs. However, the sensitivity decreases as the MCE rate in the contaminated MUPTs increases (see Figure 2). As shown, the sensitivity of the algorithm for contaminated MUPTs having MCE rate between 25% and 85% was approximately 80%. One reason for the drop in performance of both the SCC and the FCE detection algorithm with increased MCE

is that the accuracy of estimating the IDI statistics, especially the standard deviation, decreases as the train becomes more sparse [12].

Figure 3 illustrates the estimated values for the sensitivity of the FCE detection algorithm versus the similarity between the MUP template of the contaminated MUPT and an erroneously assigned MUP measured using the pseudocorrelation [15]. As shown, the sensitivity of the algorithm decreases as the similarity between the incorrectly assigned MUP (i.e., the FCE) and the MUP template of the contaminated MUPT increases such that in the worse case (pseudocorrelation = 0.8) the algorithm failed to detect around 78% of the FCEs created by MUPs that are very similar to the MUP template. Sensitivity for such cases can be improved by increasing α or classifying at least one of the two MUPs creating an IDI < μ-3σ as an FCE, but such an adjustment may cause specificity to decrease. Nevertheless, the performance of the algorithm on average is promising in terms of detecting and removing FCEs from contaminated MUPTs.

IV. Conclusion

A robust method for detecting MUPTs contaminated by a high number of false classification errors and then detecting the erroneously assigned MUPs was presented. Evaluation based on simulated data shows that the FDA–based SCC developed for discriminating between contaminated and non-contaminated MUPTs correctly detected around 88.7% of the contaminated trains. The results also revealed that the FCE detection algorithm can on average detect 84.4% of the FCEs in a given MUPT. However, the accuracy of both the SCC and the FCE detection method decreases as the percentage of MCEs in a MUPT increases. In addition, the sensitivity of the FCE detection algorithm in detecting an MUP erroneously assigned decreases as the similarity between the MUP and the MUP template of the MUPT increases. Nevertheless, the overall accuracy of the method (92.1%) is encouraging and suggests using the method during EMG signal decomposition to improve the results or to facilitate editing extracted MUPTs.

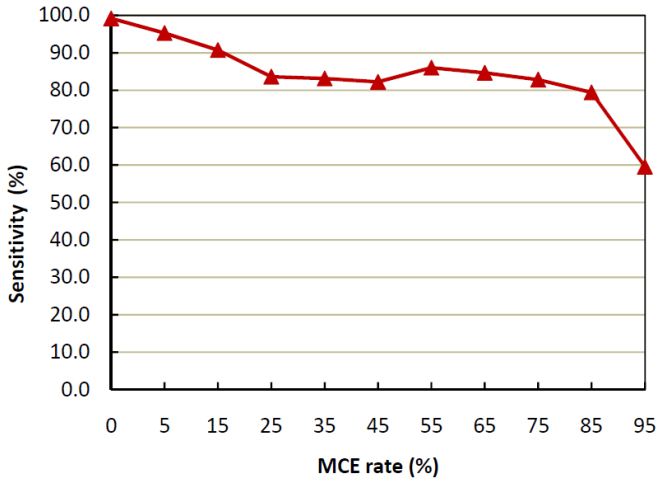

Figure 2. Sensitivity of the FCE detection algorithm in correctly detecting FCEs in a contaminated MUPT versus the MCE rate of the train.

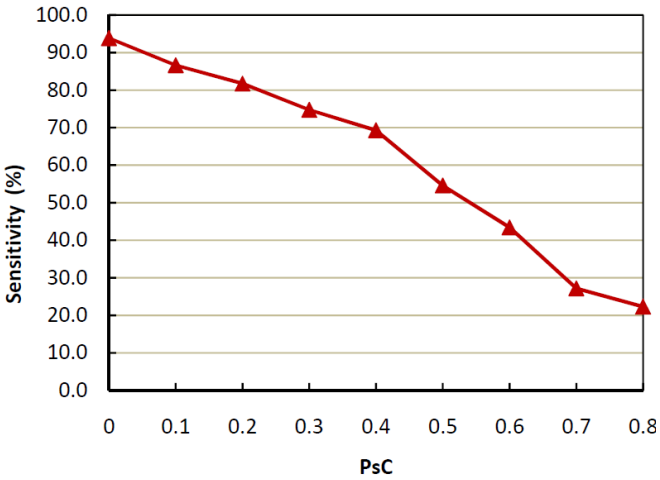

Figure 3. Sensitivity of the FCE detection algorithm in correctly detecting of a MUP erroneously assigned to a contaminated MUPT versus the pseudocorrelation (PsC) between the MUP and the template of the MUPT.

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