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Decomposition of Intramuscular EMG Signals Using a Knowledge –based Certainty Classifier Algorithm

H. Parsaei, D. W. Stashuk, and T. M. Adel

Abstract—**An automated system for resolving an intramuscular electromyographic (EMG) signal into its constituent motor unit potential trains (MUPTs) is presented. The system is intended mainly for clinical applications where several physiological parameters for each motor unit (MU), such as the motor unit potential (MUP) template and mean firing rate, are required. The system decomposes an EMG signal off–line by filtering the signal, detecting MUPs, and then grouping the detected MUPs using a clustering and a supervised classification algorithm. Both the clustering and supervised classification algorithms use MUP shape and MU firing pattern information to group MUPs into several MUPTs. Clustering is partially based on the K–means clustering algorithm. Supervised classification is implemented using a certainty–based classifier technique that employs a knowledge–based system to merge trains, detect and correct invalid trains, as well as adjust the assignment threshold for each train. The accuracy (93.2%±5.5%), assignment rate (93.9%±2.6%), and error in estimating the number of MUPTs (0.3±0.5) achieved for 10 simulated EMG signals comprised of 3–11 MUPTs are encouraging for using the system for decomposing various EMG signals.**

I. Introduction

Electromyographic (EMG) signal decomposition is the process of resolving an EMG signal into its constituent motor unit potential trains (MUPTs). The intention of decomposing an EMG signal is to provide an estimate of the firing pattern and motor unit potential (MUP) template of each active motor unit (MU) that contributed significantly to the EMG signal. The extracted MU firing patterns and MUP shapes can assist with the diagnosis of neuromuscular disorders [1], the characterizing of MU architecture [2], and the acquisition of a better understanding of the neural control of movement [3].

Several automatic and semi–automatic EMG signal decomposition techniques have been developed using various MUP features, clustering and supervised classification algorithms. A group of the existing decomposition algorithms provide full decomposition and attempt to detect all of the MUPTs comprising an EMG signal. Some, however, attempt to extract only the MUPTs of the MUs that significantly contributed significant to the EMG signal. A recent comprehensive review of the algorithms developed for the decomposition of intramuscular EMG signals is provided in [4].

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*H. Parsaei was with the Dept. of Systems Design Eng., University of Waterloo, Waterloo, ON, N2L 3G1, Canada. He is now with the Technical & Eng. College of Shiraz, Vocational & Technical University, Iran,(e–mail: hparsaei@uwaterloo.ca)

D.W.Stashuk and T. M. Adel are with the Dept. of Systems Design Eng., University of Waterloo, Waterloo, ON, N2L 3G1, Canada, (e–mail:{Stashuk, thesham}@uwaterloo.ca).

Existing decomposition methods have been shown to be able to successfully decompose various simulated and real EMG signals at different contraction levels, but the obtained performance still depends on several factors such as the parameters used by the algorithms, the decomposability of the signal, and the stationarity and variability of MUP shape and MU firing pattern over the entire signal. Depending on the complexity of the signal being decomposed as well as the parameters and criteria used during clustering and classification, to either assign a MUP to a train or to merge or split trains, different decomposition results may being obtained. In this work, starting with algorithms developed for a decomposition– based quantitative EMG (DQEMG) system [5], a knowledge–based system has been used to develop a knowledge–based EMG decomposition (KBEMGD) system for addressing some of these issues.

DQEMG uses a certainty–based classifier (CBC) algorithm [6] for classifying MUPs and several heuristic criteria to merge MUPTs. The accuracy of the DQEMG system in estimating the number of constituent MUPTs of an EMG signal is related to the heuristic criteria and parameters used to merge MUPTs; highly conservative criteria may result in overestimation of the number of MUPTs and vice versa for less conservative criteria. In addition, the rate of false–classification errors (FCEs) and missed–classification errors (MCEs) of the obtained MUPTs are related to a user–defined certainty assignment threshold (C_{AT}). If the C_{AT} value is set at a high value (>0.5), the obtained MUPTs will have high MCE rates but low FCE rates (high classification accuracy). On the other hand, when the C_{AT} value is set at a low value (<0.01), the MCE rate will be low but the FCE rate will be high [6]. Unfortunately, there is not a fixed value for the C_{AT} which is appropriate for all EMG signals. This parameter has to be "tuned" by the user to get the desired level of decomposition performance. Moreover, it can be shown both practically and conceptually that a better performance will be achieved when a C_{AT} value is defined and then tuned for each MUPT individually, instead of using one C_{AT} for all trains. Manually tuning the C_{AT} value for each train during decomposition is infeasible. The KBEMGD system presented in this paper employs a knowledge–based system —instead of heuristic, user defined criteria used previously— to merge, split, and individually adjust the C_{AT} value for each MUPT based on the given signal to obtain the optimum decomposition results. Following is a brief discussion of the main steps of this EMG decomposition system. Detailed discussions are given in [7].

II. Clinical EMG Decomposition System

The KBEMGD system decomposes a detected EMG signal off-line. The system consists of five major steps (Fig.1): signal preprocessing, MUP detection, clustering and supervised classification of detected MUPs, and MUP template and MU firing pattern estimation. Signal preprocessing, MUP detection, and clustering of detected MUPs are implemented using methods similar to that in DQEMG [5]. The main contribution of this work is in the classification step where the heuristic criteria and user -defined parameters of the DQEMG system are replaced by several supervised classifiers and signal dependent parameters determined by a knowledge–based system.

An acquired EMG signal is band pass filtered using a 1st-order low pass difference filter to decrease MUP temporal overlap, to accentuate the differences between MUPs created by different MUs, and to increase the separation between MUPs and the background noise. The positions of suitable MUPs in the filtered signal are detected using a threshold crossing technique in which the prefiltered EMG signal is scanned for the peaks that satisfy several criteria[5].

Assuming N MUPs are detected in the EMG signal being decomposed, the rest of the decomposition process is a pattern recognition problem; the MUPs are represented by a vector of feature values and then are sorted into several MUPTs. For feature extraction, each MUP is represented by 2.56 ms of filtered data (i.e., 80 samples at a 31250 Hz sampling rate), centered about the position of its peak. The samples are used for clustering and classification. In the remainder of this paper, the j^{th} detected MUP is denoted by MUP_j, j=1,2,…,N.

Detected MUPs are grouped into several MUPTs using a clustering and then a supervised classification algorithm. The objectives are to achieve: a) an association of one to one correspondence between the resulting MUPTs and the MUs that contributed significantly to the signal being decomposed; b) low FCE and MCE rates in the extracted MUPTs.

Clustering is mainly used for estimating the number of MUPTs, their prototypical MUP shapes (or templates), and their MU firing pattern statistics which are required for supervised classification. Here, MUP clustering is conducted using a shape and temporal–based clustering (STBC) algorithm[8] which is partially based on the K–means clustering algorithm. The STBC algorithm employs MUP shape information to group MUPs (MUPs are clustered based on MUP shape similarity), but the firing pattern information is used to test the validity of the assignments. To speed up the decomposition process, the STBC algorithm is only applied to the MUPs detected in a 5 second interval (with the highest number of detected MUPs) of the EMG signal. Details of the STBC used can be found in [8].

Using the information obtained regarding possible MUPTs constituting the EMG signal being decomposed, the remaining unclassified MUPs are assigned to the extracted MUPTs via a an adaptive certainty–based classification (ACBC) algorithm which is partially based on the CBC algorithm previously developed for MUP classification [1],[6]. With the ACBC (or CBC) algorithm , a candidate MUP (let's say MUP_j) is assigned to the MUPT with which the time of occurrence and shape of this MUP are more consistent than to the firing pattern and MUP shape of the other MUPTs. For this purpose, both MUP shape and MU firing pattern information are used to calculate the certainty (confidence) of assigning MUP_j to the extracted MUPTs. Having the certainties calculated, the candidate MUP is assigned to the MUPT which has the greatest certainty value, if this value is > C_{AT}. Otherwise, the MUP is left unassigned.

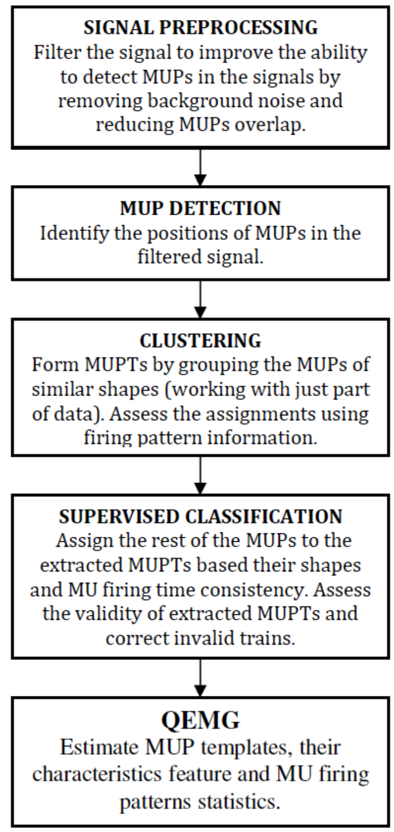

Figure 1. Major steps of a decomposition system and their objectives.

The certainties for assigning MUP_j are evaluated for only two trains: the MUPTs with the most and the next most similar MUP templates to MUP_j where the similarity measure used is the Euclidian distance between MUP_j and the MUP template of each MUPT. Having these two trains identified, the certainties of assigning MUP_j to one of these two MUPTs are calculated by combining MUP shape and MU firing pattern certainties. Details are given in [7] but in short MUP shape certainty includes normalized absolute shape certainty (C_{ND}) and relative shape certainty (C_{RD}). The first represents the distance from MUPj to the template of a train, normalized by the energy of the template. The second represents the distance from MUP_j to the most similar MUP template relative to the distance of MUP_j to the next most similar MUP template. Firing pattern certainty, C_{FC}, measures the consistency of the occurrence time of MUP_j relative to the established MU firing pattern of a MUPT. Having calculated the values of the shape certainties and the firing pattern certainty, the overall certainties for assigning MUP_j to one of the two selected MUPTs are estimated as

$$C_i^j = C_{ND\ i}^j \times C_{RD\ i}^j \times C_{FC\ i}^j;\ i = 1,2 \qquad (1)$$

where C_i^j is the overall certainty of assigning MUP_j to $MUPT_i$ which is one of the two closest MUPTs to MUP_j. Finally, MUP_j is assigned to the MUPT that has the greatest certainty value, if this value is greater than the C_{AT} value. Otherwise, the MUP is left unassigned.

The C_{AT} parameter has a high impact on MCE and FCE rates in the resulting MUPTs. Unfortunately, there is no fixed value for C_{AT} which is appropriate for all EMG signals.

Moreover, it can be shown both practically and conceptually that a better performance will be achieved when a C_{AT} value is defined and then tuned for each MUPT individually, instead of using one C_{AT} value for all trains. Manually tuning the best C_{AT} value for each train during decomposition is infeasible. In addition to having to tune the C_{AT} value, one of the challenges in EMG decomposition is that the number of MUPTs comprising a signal is not known in advance. To estimate this parameter, DQEMG (or the CBC) merges MUPTs based on several heretically defined criteria during MUP classification [6] . The accuracy in estimating the number of MUPTs depends on the validity of these empirically defined criteria. In the KBEMGD system this tuning is performed automatically rather than having to be done by the system user. During classification, the KBEMGD system for example updates a measure of how well MUP classification was conducted in the previous pass and determines how the C_{AT} value for each MUPT should be adjusted to decrease the MCE and FCE rates of each train. Several methods proposed for estimating MUPT validity [9], and MUPT MCE and FCE rates [10], [11] and for editing and correcting invalid trains [12] are incorporated so that the system can efficiently merge, split, and edit trains such that each MU that significantly contributed MUPs to the EMG signal being decomposed has only one corresponding MUPT in the decomposition results. Specifically, once each classification pass through the set of detected MUPs is completed and before the next supervised classification pass starts:

1. The validity of each extracted MUPT is assessed using a MUPT–validation system [9]. Invalid trains are detected, corrected and have their C_{AT} values adjusted. Merged MUPTs are split into valid trains using the K–means clustering algorithm; contaminated MUPTs have their FCEs corrected using an automated MUPT editing algorithm [12].
2. The C_{AT} value for each MUPT is adjusted based on its validity; $C_{AT} \in [\,0.005, 0.990]$. For invalid MUPTs, the C_{AT} values are increased by a step of Δ while for valid MUPTs the C_{AT} values are decreased. The rate of decrease is adjusted based on the similarity of MUPT MUP templates [7].
3. Pairs of MUPTs that have similar MUP templates are merged if the resulting train is valid determined by the MUPT–validation system [9].

Finally, the MU firing pattern statistics and MUP templates for each MUPT are updated as in [6]. The MUP assignment and MUPT splitting, editing, and merging steps are repeated until either, the maximum number of iterations is exceeded or the MUPTs are stable. If trains are merged or split at least one more supervised classification pass will be completed.

After the initial MUP classification process is performed, a final inspection is made on the MUPs that were either left unassigned or assigned to MUPTs with certainty <0.5. In this “updating” phase the dimensionality of the feature space (i.e., 80) is first reduced using a linear discriminant analysis method and then certainties for each of these MUPs in this new feature space are recalculated as above, but here the Mahalanobis distance (instead of the Euclidian distance) is used to find the two closest MUPTs to the MUP and to calculate its C_{ND} and C_{RD} values. The MUP will be moved from its current MUPT to the MUPT that has the greatest new certainty value, if the new certainty value is greater than both C_{AT} and the current certainty value.

Once decomposition is completed, the MUP template and MU firing pattern statistics for each extracted MUPT are estimated for future analysis, such as for QEMG. A MUP template for each MU is estimated using the median trimmed mean averaging technique [13] and MU firing pattern statistics are estimated using an error filtered algorithm[14].

III. Results and Discussion

The performance of the KBDEMG system and the original decomposition algorithms of the DQEMG system were evaluated and compared using 10 simulated EMG signal composed of 3–11 MUPTs. The characteristics of these signals are given in columns 2 to 5 of Table 1. The following four performance measure indices were used to evaluate these two systems.

$$\mathrm{A_r}\% = \frac{Number\ of\ MUPs\ assigned}{Total\ number\ of\ MUPs\ detected} \times 100 \tag{2}$$

$$\mathrm{A_c}\% = \frac{Number\ of\ MUPs\ correctly\ classified}{Total\ number\ of\ MUPs\ assigned} \times 100 \tag{3}$$

$$\mathrm{CC_r}\% = \frac{Number\ of\ MUPs\ correctly\ classified}{Total\ number\ of\ MUPs\ detected} \times 100 \tag{4}$$

$$\mathrm{E_{NMUPTs}} = Number\ of\ extracted\ MUPTs\ \text{-}\ Number\ of\ expected\ MUPTs \tag{5}$$

The two indices A_r and A_c in fact ,respectively, express the completeness and accuracy of the MUPTs provided by the systems.

The results for both KBEMGD and DQEMG system applied to the 10 signals used are summarized in Table 1. These results were produced using these two experimentally defined parameters: C_{AT}=0.02 for the DQEMG system and $\Delta = 0.005$ for the KBEMGD system. The overall mean and standard deviation (STD) for each performance index used are also provided. Statistical comparisons of the average values were conducted using paired t-tests (α= 0.05), comparisons of the STD values were conducted using F-tests (α= 0.05).

Based on the results presented in Table 1, the overall performance of KBDEMG system was significantly better than that of the DQEMG system (p<0.005). Besides the higher average accuracy, the performance of the KBEMGD system over the 10 EMG signals used was less variable than that of the DQEMG system, which shows that the KBEMGD system has better overall and less variable performance.

An interesting and significant improvement in the KBEMGD system relative to the DQEMG system is its ability to more accurately estimate the number of MUPTs comprising the EMG signals used. As shown, for most EMG signals the KBEMGD system correctly estimated the number of trains in the signals; however, the DQEMG system extracted 4 to 5 extra MUPTs for some signals.

The higher A_r and A_c values for the KBEMGD system indicates that the MUPTs obtained by KBEMGD system are more complete and accurate than those obtained by the DQEMG system. Such improvements can lead to better

TABLE I. PERFORMANCE OF THE DQEMG COMPARED TO THAT OF THE KBEMGD

Signal	Intensity (pps)	No. of MUPTs	Jitter (ms)	IDI_CV	DQEMG A_r (%)	DQEMG Ac (%)	DQEMG CCr (%)	DQEMG E_{NMUPTs}	KBEMGD A_r (%)	KBEMGD Acc (%)	KBEMGD CCr (%)	KBEMGD E_{NMUPTs}
1	30.5	3	100	0.15	92.1	97.2	89.5	0	99.3	98.7	98.0	0
2	62.6	6	150	0.10	70.7	74.4	52.6	4	91.7	93.9	86.1	0
3	70.7	7	100	0.15	73.3	96.9	71.0	0	97.3	98.7	94.4	0
4	79.3	8	25	0.15	91.0	82.3	74.9	0	95.5	98.7	94.3	0
5	85.2	9	50	0.15	89.3	87.3	78.0	0	94.6	96.9	91.4	0
6	95.6	9	75	0.30	77.3	85.9	66.4	4	94.8	85.0	80.6	1
7	94.6	9	150	0.15	78.8	85.4	67.3	3	91.3	93.2	85.1	0
8	96.0	9	150	0.30	75.7	72.0	54.5	5	92.0	84.2	76.6	1
9	134.5	10	50	0.30	76.8	89.5	68.8	5	91.4	89.8	82.1	1
10	127.5	11	50	0.15	81.6	83.7	68.3	4	92.9	94.4	87.7	0
		Mean			80.7	85.5	69.1	2.5	94.1	93.4	87.9	0.3
		STD			7.6	8.2	10.7	2.2	2.7	5.4	6.9	0.5

estimation of the MUP templates and MU firing patterns of the MUs because the accuracy of the error filtered estimation algorithm[14] in estimating MU firing pattern statistics increases when the MCE rate in the train decreases. The relative improvement in the decomposition results for the KBEMGD system increases with the complexity of the signal. Comparing the results presented in Table 1 for signal#1 to those shown for signal #10 supports this statement. The improvement in CC_r (for example) for signal #1 is 8.5=% while that for signal # 10 is 19.4%.

A challenge in decomposing clinical EMG signals is that MUP shape variability or MU firing pattern variability might be higher than those in simulated EMG signals or even than those in real EMG signals acquired for research purposes using more controlled activation protocols. Such variability could be due to needle movement or disease. The KBEMGD system performed well in decomposing real clinical EMG signals when it was applied to several such signals. The numerical results were not provided because true decomposition results for the clinical EMG signals used were not available, but qualitative assessment of the extracted MUPTs [4] showed that KBEMGD system performed well and better than the DQEMG system in decomposing clinical EMG signals.

A main drawback of the KBEMGD system is that it is more computational complex and therefore slower than the DQEMG system. Estimating MUPT validity during classification and also calculating the covariance matrix of the MUP features and its inverse in the "updating" phase of this step takes time. Nevertheless, the system is still fast enough to be used in clinical environments.

IV. CONCLUSION

The KBEMGD system described in this paper is a clinical system for the decomposition of intramuscular EMG signals acquired during isometric contractions. The system is an extension of the DQEMG system. Quantitative evaluation using 10 simulated EMG signals and qualitative assessment using several clinical signals reveal that the KBEMG system represents a substantial improvement in performance over the DQEMG system. Such improvements in decomposition results, especially in estimating the number of MUPTs, along with the confidence that the extracted MUPTs are valid encourage the use of the KBEMGD system for decomposing intramuscular EMG signals for clinical applications.

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