Cross Comparison of Motor Unit Potential Features Used in EMG Signal Decomposition

Mohsen Ghofrani Jahromi, Hossein Parsaei, Ali Zamani, and Daniel W. Stashuk

***Abstract*—Feature extraction is an important step of resolving an electromyographic (EMG) signal into its component motor unit potential trains, commonly known as EMG decomposition. Until now, different features have been used to represent motor unit potentials (MUPs) and improve decomposition processing time and accuracy, but a major limitation is that no systematic comparison of these features exists. In an EMG decomposition system, like any pattern recognition system, the features used for representing MUPs play an important role in the overall performance of the system. A cross comparison of the feature extraction methods used in EMG signal decomposition can assist in choosing the best features for representing MUPs and ultimately may improve EMG decomposition results. This paper presents a survey and cross comparison of these feature extraction methods. Decomposability index, classification accuracy of a *k*-nearest neighbors classifier, and class-feature mutual information were employed for evaluating the discriminative power of various feature extraction techniques commonly used in the literature including time domain, morphological, frequency domain, and discrete wavelets. In terms of data, 45 simulated and 82 real EMG signals were used. Results showed that among time domain features, the first derivative of time samples exhibit the best separability. For morphological features, slope analysis provided the most discriminative power. Discrete Fourier transform coefficients offered the best separability among frequency domain features. However, neither morphological nor frequency domain techniques outperformed time domain features. The *detail* 4 coefficients in a discrete wavelets decomposition exceeded in evaluation measures when compared with other feature extraction techniques. Using principal component analysis slightly improved the results, but it is time consuming. Overall, considering computation time and discriminative ability, the first derivative of time samples might be efficient in representing MUPs in EMG decomposition and there is no need for sophisticated feature extraction methods.**

***Index Terms*—Classification accuracy, decomposability index, EMG decomposition, feature extraction, machine learning, mutual information, separability measures.**

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I. Introduction

ANALYZING electromyographic (EMG) signals, detected during a muscle contraction, provides information that can be used in physiological investigations and clinical examinations for either the study of motor control or the diagnosis of neuromuscular disorders. The technique of detecting, evaluating and analyzing EMG signals is known as electromyography. During a conventional EMG examination, a clinician manually assesses the characteristics of needle-detected EMG signals across a number of distinct needle positions and forms an overall impression of the condition of the muscle. Such a subjective assessment is highly dependent on the skills and level of experience of the clinician, and is prone to a high error rate and operator bias. To overcome these issues, quantitative methods (QEMG) have been developed. QEMG methods, in general, characterize motor unit potential (MUP) waveforms using statistical and probabilistic techniques that allow greater objectivity and reproducibility in supporting the diagnostic process [1]. A key step in QEMG is EMG decomposition which is the process of resolving an EMG signal into its constituent motor unit potential trains (MUPTs).

An automatic intramuscular EMG signal decomposition process, in general, includes six steps: signal preprocessing, signal segmentation and MUP detection, feature extraction, clustering and supervised classification of detected MUPs, resolving superimposed MUPs, and estimating MU firing pattern statistics and MUP templates. Signal preprocessing which is involved with filtering the signal is mainly to highlight the informative contents of the signal by removing contaminating instrumentation noise and artifacts, to sharpen MUPs, to increase the differences between MUPs and the background noise, and to accentuate the differences between MUPs created by different MUs. Signal segmentation divides an EMG signal into segments containing possible MUPs that were generated by active MUs. In general, MUPs are detected using threshold crossing techniques. Scanning the signal for peaks that exceed a threshold provides a set of peaks that show candidate MUP positions. A window centered at each identified peak is then applied to the signal and the data points that fall in the window are stored as a MUP. A feature vector that contains a set of features characterizing the MUP, represents each detected MUP. In the clustering and classification stage, the MUPs are sorted into several trains. If a full or complete decomposition is required, superimposed MUPs are resolved into their constituent MUPs in another step. In the final step

TABLE I
SUMMARY OF EMG SIGNAL DECOMPOSITION ALGORITHMS REGARDING THE FEATURES USED

Features used	Previous Work
Time domain	Lefever and De Luca (PD-I) [2], [3] Stashuk (DQEMG) [4] Hassoun et al. (NNERVE) [5], [6] Nikolic and Krarup (EMGPAD [7], EMGTools [8]) Christodoulou and Pattichis [9], [10] Haas and Meyer (ARTMUP) [11], [12] Gut and Moschytz [13] Koch and Loeliger [14] Katsis et al. [15] Nawab and De Luca (PD-II) [16], [17] Erim and Lin [18] Parsaei and Stashuk (VBEMGD) [19]
Morphological	Nandedkar et al. (MMA) [20] Katsis et al. [21] Gerber et al. [22] Loudon et al. [23] Stalberg et al. [24], [25] Florestal et al. (MTLEMG) [26]
Frequency domain	McGill et al. (ADEMG) [27] Stashuk and De Bruin [28] McGill et al. (EMGLAB) [29]
Wavelet domain	Zennaro [30] and Wellig [31] (EMG-LODEC) [32] *(Lower bands coefficients)* Yamada et al. [33] *(Principal Components of the coefficients)* Ren et al. [34] *(Optimal Wavelet packets features)* Rasheed et al. [35] *(detail coefficients at levels 4-6 in a 6-level decomposition)*

of decomposition, the MUP templates and MU firing pattern statistics for each extracted MUPT are estimated for future analysis (especially for QEMG).

Several decomposition systems and algorithms have been developed through time each proposing innovative techniques for the aforementioned steps. [2]–[35]. A thorough survey in this regard has been conducted by Parsaei *et al.* [36]. Feature extraction is a crucial part for clustering and classification tasks which might have a significant impact on the precision and speed of the whole system. Diverse methods and domains of MUP feature extraction have been introduced to date. As shown in Table I, feature extraction methods in the wavelet domain, for instance, are divergent and inconsistent; some researchers used the wavelet coefficients from only four frequency bands 2 to 5 [30]–[32], while others employed all coefficients [33], or detail coefficient at levels 4 to 6 [35]. Consequently, a cross comparison of the feature extraction methods used in EMG signal decomposition is required to assist researchers in using the best features for improving EMG decomposition results. In this work, our objective was to address this issue. Different feature extraction methods that have been used in intramuscular EMG decomposition were reviewed and compared to provide a guideline for choosing the most effective and informative features for representing MUPs during EMG signal decomposition.

II. FEATURE EXTRACTION PARADIGMS

Normally, in a pattern recognition system each sample is represented by a set of features called a feature vector.

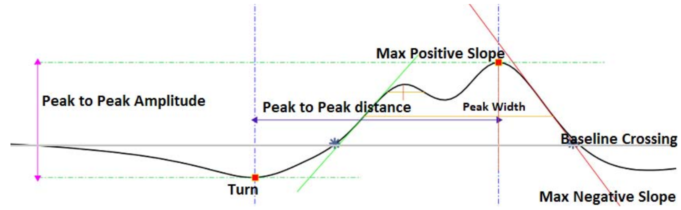

Fig. 1. Schematic View of Morphological Features.

A detected MUP with n samples can be represented by vector $x_{n\times 1}$ in the time domain.

$$\mathbf{x} = [x_1, x_2, \ldots, x_n]^T \tag{1}$$

where $x_i, i = 1, 2, \ldots, n$ represents time samples of the MUP.

Feature extraction is the process of transforming input patterns using a linear or non-linear transformation into a set of features [37]. Each MUP with n number of samples is reduced into a point $\hat{\mathbf{x}}$ in a $d - dimensional$ space:

$$\hat{\mathbf{x}} = F(\mathbf{x}) = [\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_d]^T, (d \leq n) \tag{2}$$

where F is the employed transformation function. It is essential for a feature vector to be easily computed. It should contain the least redundancies; i.e. the feature values must be as uncorrelated as possible. Furthermore, it must be able to be effectively used to distinguish MUPs generated by different MUs and be robust to MUPs variability in a single MUPT [38].

Until now, various features have been used to represent MUPs during EMG signal decomposition. They mainly include the time samples themselves, first or second derivative of time samples, features regarding the morphology of the MUPs, Fourier transform or power spectrum coefficients, and Wavelet coefficients [2]–[35]. Table I summarizes the features used in previous works.

A. Time Domain Features

Each detected MUP is represented as a digitized waveform segment that constructs the vector $x_{n\times 1}$ (Eq.1). Raw time samples are, in fact, the discrete time sample of a detected MUP without a succeeding transformation or filtering of either the MUPs or the EMG signal. In other words, the vector x, as defined in Eq. 1, is used to represent a MUP in an $n - dimensional$ feature space. The first and second difference of the MUP samples may also be considered. For the sake of comparison, the first and second order "low-pass differentiators (LPD)" proposed by McGill *et al.* [27] are also evaluated in this work. It is worth mentioning that "low-pass differentiators" act as band-pass filters [39].

B. Morphological Features

Concise but valuable information about each MUP can be acquired by using its morphology. Morphological features have the benefit of conveying a structural and physiological interpretation for physicians. Following is a description of several morphological features. These features are graphically illustrated in Fig. 1.

1) Slopes: The maximum and minimum values of the first difference of the samples of a MUP are considered the highest positive and negative slopes, respectively.

2) Area: The area under the curve of the rectified MUP and also the area of the rectified 1^{st} difference of the MUP.

3) Peak Analysis Parameters: Values and locations of the peaks of a MUP might contain discriminative information. Primarily, for each detected MUP, the highest and lowest peaks are derived. Peak to peak amplitude is the difference between the highest and the lowest peaks. The time at which a peak occurs is of interest as well. The width of a peak (peak width) is computed as the distance between the points to the left and right of the peak where a MUP intercepts a horizontal reference line whose height is equal to one-half of the peak height. Duration is defined by the time from the first to the last peak or valley of a MUP [26], [40].

4) Number of Phases and Turns: Each change in the direction of a portion of a MUP is called a turn while phase is the departure from and return to the baseline, respectively. The number of phases equals to the number of zero-crossings plus one. The number of turns equals the number of all peaks and valleys in a MUP [25].

5) Thickness: Thickness is the ratio of area to peak-to-peak amplitude [20].

Correctly estimating morphological features in MUPs with low signal-to-noise ratio (SNR) is difficult because these features are highly sensitive to high-frequency noise. Applying a simple moving average filter to the MUP waveforms can significantly enhance estimation of these features [41]. A moving average filter of length 0.3 ms was used in our experiments.

C. Frequency Domain Features

1) Discrete Fourier Transform Coefficients: The discrete Fourier transform (DFT) of vector x with length N, represented by $[X_k]^T$, can be used as a feature vector. An estimation of the power of the signal at each frequency component estimated by $[X_k X_k^*]^T$ can also be used to represent a MUP in the feature space. The DFT can be seen as a filtering process in which each X_k reveals the amount of frequency content of the signal.

2) Power Spectral Density: The power spectral density (PSD) shows how the power contained in a signal is distributed in the frequency domain. The PSD of a stochastic signal equals to the Fourier transform of its auto-correlation function. For a finite-length signal, PSD estimation techniques include non-parametric methods such as the Periodogram and Welch's method and parametric methods such as the Yule-Walker and Burg approach. In this work, PSD is estimated using the Periodogram, Welch, Multitaper, Yule-Walker, Burg, Covariance, and Modified Covariance methods.

D. Wavelet Domain Features

The discrete wavelet transform (DWT) of a signal is an efficient method for simultaneously representing both time and frequency domain information of the signal under study. In fact, the DWT of a signal provides a two-dimensional time-frequency representation which incorporates both time and frequency domain information about a signal. In general, wavelet coefficients of a given signal are computed by successively passing the signal through a series of low-pass and high-pass filters. Passing the samples through a low pass filter results in approximation coefficients, and filtering the signal with a high pass filter provides detail coefficients. Fig. 2 shows how the coefficients are computed using a set of successive low-pass and high-pass filters. At each level, the high-pass filter gives detail wavelet coefficients and the low-pass filter gives approximation wavelet coefficients. The input signal can be represented by the approximation coefficients of level i together with detail coefficients of level i and upper levels. Choosing the number of levels in a DWT and the selected mother wavelet has a vital impact on the output feature vector. A companion work was dedicated to a detailed survey on obtaining the mother wavelets with the highest separability measures [42].

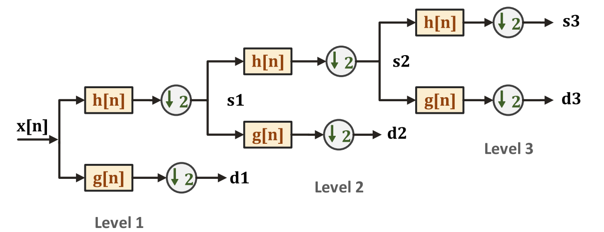

Fig. 2. Wavelet decomposition with a 3-level filter bank.

E. Principal Components of Features

The possibility of reducing the dimensionality of the MUP feature vector along with having uncorrelated features is explored in this work. The feature vector representing a MUP is transformed to a new coordinate system using principal component analysis (PCA). The PCA method [43] is an unsupervised dimensionality reduction technique that tries to seek a set of new orthogonal variables each of which is a linear combination of the original variables. The criterion of orthogonality ensures that there is the chance of attaining new components with the least amount of redundant information [44]. One can expect that after applying PCA on a set of MUPs and choosing those components that possess a specific percentage (usually 95%) of the total variance, a new space of features is obtained in which MUPs can be separated with less difficulty.

III. Separability Measurement

Three measures were used to evaluate the discriminative power of the features studied. These measures are described in this section.

A. Decomposability Index (DI)

DI is a metric introduced in [19] to quantify the reliability with which MUPs can be correctly assigned to the corresponding MUPTs comprising an EMG signal being decomposed. Motivated by Fisher's criterion used to estimate the separability between two clusters, for each MUPT a separability index was defined and used:

$$J_i = \min_{j=1,2,..,M, j\neq i} \left\{ \frac{SB_{i,j}}{SW_{i,j}} \right\} \tag{3}$$

where M is the number of MUPTs comprising a given EMG signal, $SB_{i,j}$ is the between-train variance of the i^{th} and j^{th} MUPTs, and $SW_{i,j}$ is the within-train variance of these two trains. The two parameters $SB_{i,j}$ and $SW_{i,j}$ are estimated as ($\|.\|$ denotes Euclidean distance):

$$SB_{i,j} = \|\bar{\mathbf{x}_i} - \bar{\mathbf{x}}\|^2 + \|\bar{\mathbf{x}_j} - \bar{\mathbf{x}}\|^2 \tag{4}$$

where $\bar{\mathbf{x}_i}$ is the mean of the n_i MUPs in the i^{th} MUPT; $\bar{\mathbf{x}_j}$ is the mean of the n_j MUPs in the j^{th} MUPT and $\bar{\mathbf{x}}$ is the mean of $\bar{\mathbf{x}_i}$ and $\bar{\mathbf{x}_j}$.

$$SW_{i,j} = \frac{1}{n_i - 1}\sum_{k=1}^{n_i}\|\mathbf{x}_{i,k} - \bar{\mathbf{x}_i}\|^2 + \frac{1}{n_j - 1}\sum_{l=1}^{n_j}\|\mathbf{x}_{j,l} - \bar{\mathbf{x}_j}\|^2 \tag{5}$$

with $\mathbf{x}_{i,k}$ being the k^{th} MUP in the i^{th} MUPT. The J_i value in fact quantifies the discriminability of the MUPs of a particular MU (MU_i) from those of other MUs in an EMG signal.

Ultimately, the DI value for a given EMG signal is estimated by finding the median of the J_i values:

$$DI = median\{J_1, J_2, \ldots, J_M\} \tag{6}$$

It should be noted that for each EMG signal a single DI value is calculated.

B. Classification Accuracy

Accuracy of a classifier is a common criterion to evaluate the quality of features used to represent patterns. A k-nearest neighbors (kNN) classifier is employed in this work. The value of k was set to 5 which was determined experimentally using cross validation technique. We chose this classifier because it is generally known as a robust baseline classifier. This index and classifier have previously been used for studying various feature extraction methods for EEG-based mental task discrimination [45].

C. Class-Feature Mutual Information

Sheikholeslami and Stashuk [46] used mutual information to evaluate a set of features in the process of MUP optimal feature selection. If we consider the observed feature as a continuous random variable X and its corresponding MUPT class as a discrete random variable C, their average mutual information is defined by:

$$I(X;C) \triangleq \sum_{c\in C}\int_x P(x,c)I(x;c)dx \tag{7}$$

where the pointwise mutual information is:

$$I(x;c) \triangleq log\frac{P(x|c)}{P(x)} = log\frac{P(c|x)}{P(c)} \tag{8}$$

Suppose we have observed a MUP with feature vector x and we want to assign it to a MUPT to which we think it belongs. If x is represented by an informative feature, its label can be easily guessed. The index $I(x;c)$ measures the amount of information about the corresponding class we obtain when a sample x belonging to MUPT c is observed.

TABLE II

Real Data Used for Validation of the Experiments

Contributor	Contraction	Muscle	Electrode
Florestal JR. [48]	isometric	brachioradialis	Fine-wire
McGill KC. [49]	isometric	brachial biceps	Monopolar
Doherty, Stashuk [50]	isometric	biceps	Concentric
McGill KC. [51]	isometric	brachial biceps	Monopolar

If the input feature and the output class are totally independent, we have $P(c|x) = P(c)$; therefore $I(x;c) = 0$ which means that x gives no information about the output class. On the other hand, if by observing x, one can confidently deduce that the output class is c; then $P(c|x) = 1$ and the mutual information equals the self-information of c, i.e. $log\frac{1}{P(c)}$.

$P(x)$, the probability density function of the random variable x and its conditional form $P(x|c)$, are estimated from the histogram of x. $P(c)$, the probability distribution function of random variable c is calculated by dividing the number of samples in each class by the total number of samples: $P(c_i) = \frac{n_i}{n}$

IV. Data

To conduct an experiment comparing features discussed in Section II, we used both simulated and real EMG signals. For simulated data, 45 EMG signals with intensities ranging from 20 to 200 MUPs or simply pulses per second (pps) were generated using a physiologically-based EMG simulator [47]. The sample rate was 31.25 KHz. For real data, several real EMG signals listed in Table II were employed. For the sake of brevity, we only put key information regarding the employed real signals in this table, complimentary information can be found in the reference provided for each signal in the table. The employed multi-channel signals provided in [48] were recorded simultaneously using three or four pairs of fine wire electrodes; in our experiment the signals detected by each electrode were considered as single-channel EMG signals. To keep the frequency characteristics of the feature extraction methods and the dimensionality of the corresponding feature space consistent for both simulated and real data, we re-sampled the real data. The signals were up-sampled using a cubic spline interpolation and then down sampled to 31.25 kHz. For each EMG signal (simulated/real), the MU discharge patterns provided either by the EMG signal simulator or by a human expert operator were used as reference. Given that the firing pattern of each MU in each signal provided, the corresponding MUPs was extracted by placing a window on the signal at each occurrence of MU firing. A window with a width of 161 *samples* (corresponding to 5.152 *ms*) was used to extract MUPs. Shimmer plots of the MUPs for one of the real signals used is shown in Fig. 3. It is worth mentioning that no preprocessing (filtering) was applied to the signals before feature extraction.

V. Results and Discussion

Figs. 4 – 9 show the results of separability measurements on the simulated data. A smoothing spline is fitted to the results for a better illustration.

Time-domain analyses (Figs. 4 and 5) showed that taking the first difference of the raw time samples (band-pass filtering

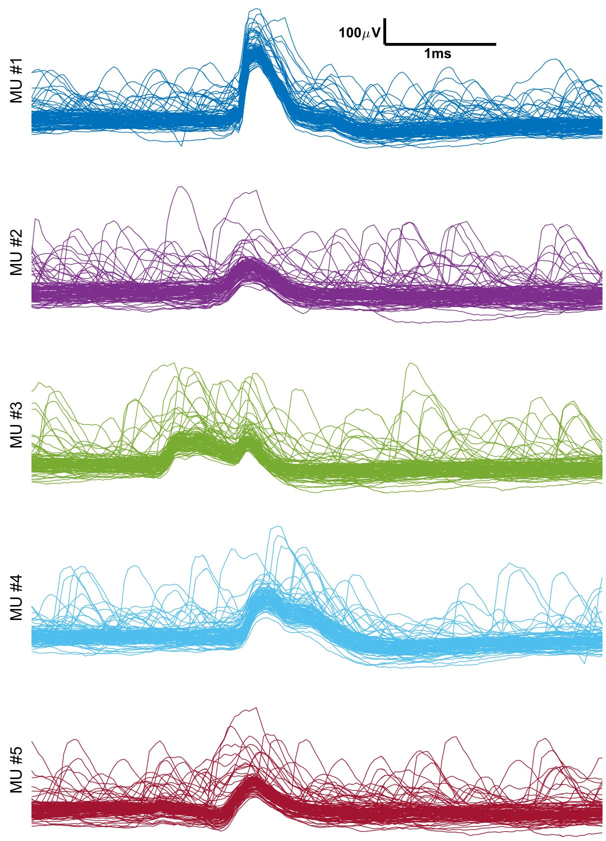

Fig. 3. Shimmer plots of a real EMG signal [48].

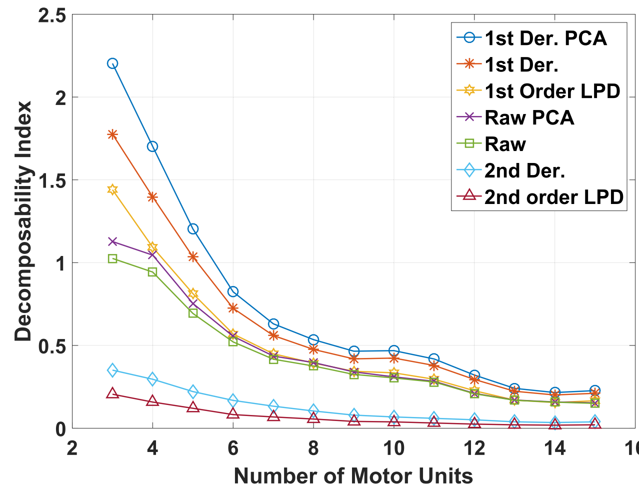

Fig. 4. Decomposability Index obtained from time domain features.

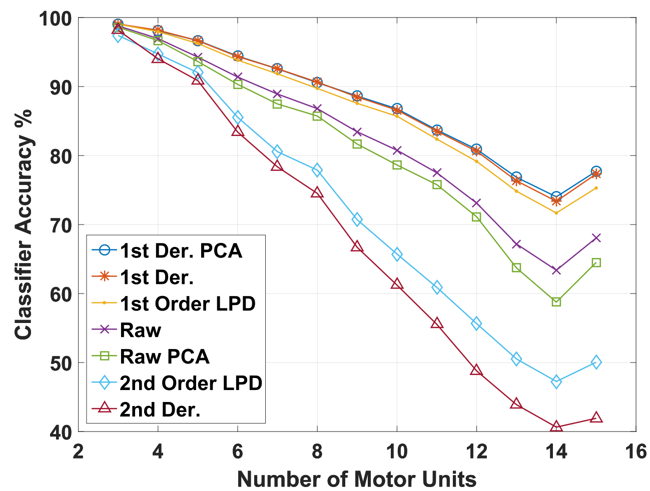

Fig. 5. Classifier Accuracy using time domain features.

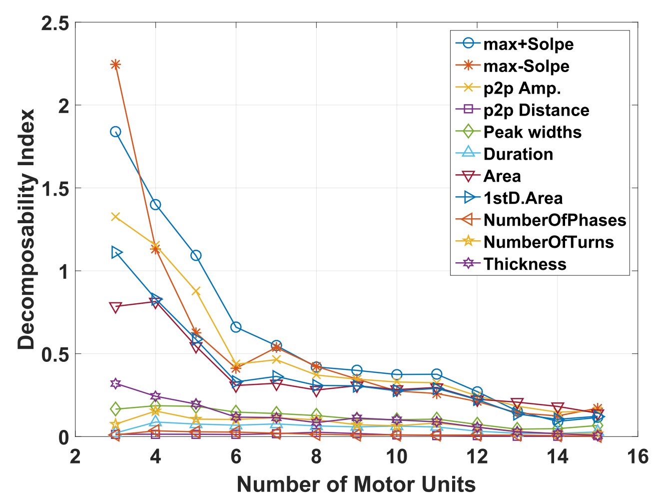

Fig. 6. Decomposability Index obtained from morphological features.

of the MUPs) or applying PCA can enhance the discrimination of MUPs. It was seen that the combination of these two techniques (principal components of the first difference) brings the best separability in the time domain.

The results for morphological domain analysis are summarized in Figs. 6 to 8. According to these results the four features maximum positive and negative slope, peak to peak amplitude, and area of the first difference were the most informative features. However, compared to time domain features, morphological features are less discriminative. In addition, estimating morphological features, especially features that are related to the peak of a MUP, is sensitive to the SNR of MUP and is difficult for those MUPs contaminated by superposition. Consequently, features from the peak analysis are not contributive unless the problem of superimposed MUPs is handled.

The results for the frequency domain features are summarized in Figs. 9 and 10. It can be inferred from Fig. 9 that discrete Fourier coefficients convey better separability than features derived from the power spectral density. Welch's method and the multi-taper approach have shown the best performance among the PSD estimators.

Fig. 10 presents a comparison between the coefficients of $bior2.2$ wavelets before and after imposing principal components analysis. It should be noted that we studied different mother wavelets in this experiment; in this figure only the best results are presented. A detailed and comprehensive review of MUP feature extraction using various mother wavelets is given in a companion work [42].

Fig. 11 compares the studied domains regarding their best features. For all techniques, the decomposability index reduces as the number of active motor units increases. This is consistent with the fact that the decomposition complexity of the signal increases with the number of active MUs. The reason is

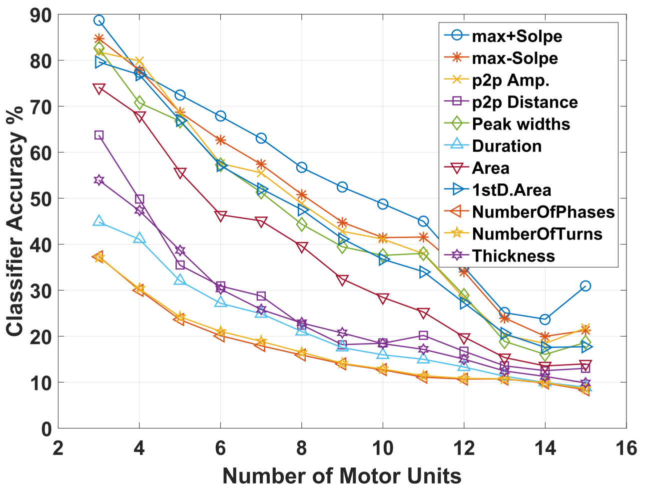

Fig. 7. Classification Accuracy of a kNN classifier using morphological features.

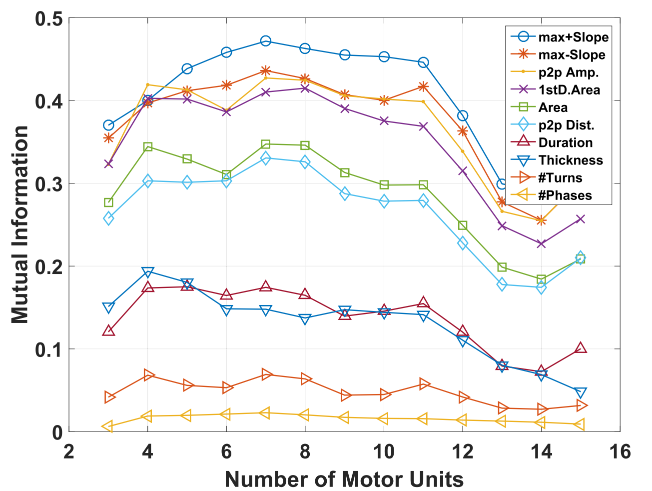

Fig. 8. Mutual information analysis of morphological features.

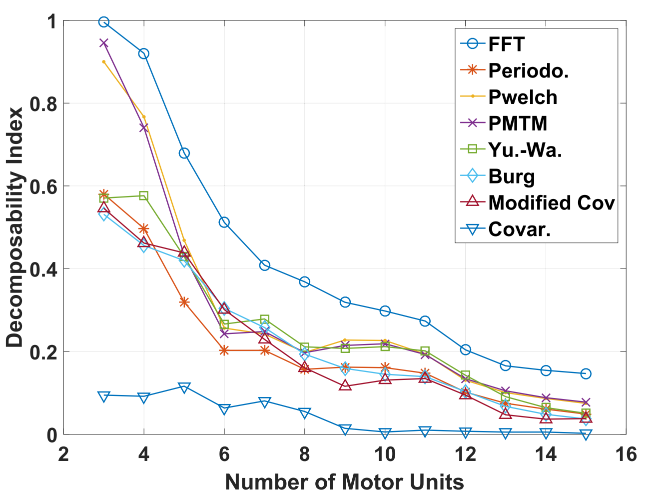

Fig. 9. Decomposability Index obtained from frequency domain features.

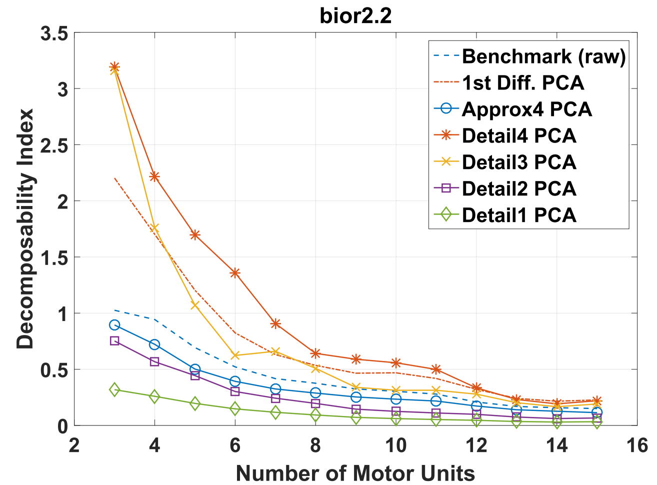

Fig. 10. Decomposability Index after applying PCA to wavelet coefficients (bior 2.2 filters in a 4-level decomposition).

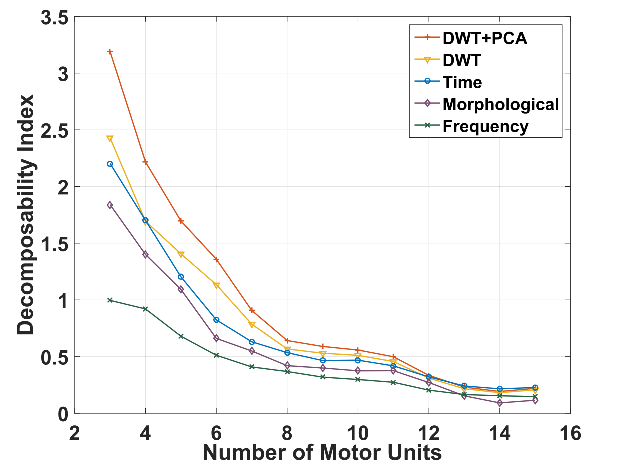

Fig. 11. Decomposability Index obtained from the best features in each domain.

mainly because of increasing number of superimposed MUPs and ultimately the variability of the MUP samples in each class (i.e., MUPT). Likewise, the effectiveness of the feature extraction methods studied in discriminating MUPs reduces. For such difficult signals, in fact, there are not any practical advantages in using one set of features over another set. Supervised feature extraction techniques may result in better discrimination between MUPs of different MUs as it is shown in [52]; nevertheless, supervised methods need training data that may not be available during the EMG signal decomposition process. For such hard-to-decompose signals that may include similar MUPs created by two or more different MUs, firing pattern information should be used for discriminating the MUPs [4], [8], [19], [28], [29], [35], [53].

Figs. 11 and 12 compare the best features from each domain. In Fig. 12, each bar represents a range of DI values across the 45 simulated EMG signals used. Remember that for each EMG signal a single DI value is calculated. Therefore, this plot in fact illustrates the consistency of the performance of each feature extraction method over the data set used in this work. A feature vector used to represent MUPs for EMG signal decomposition should use a low number of uncorrelated and computationally cheap-to-compute features, have high discrimination ability, and be minimally sensitive to the shape variability of the MUPs created by an MU. Obviously, we seek a feature extraction method that is least sensitive to signal complexity. In other words, its effectiveness for hard-to-decompose signals is comparable to that for easy-to-decompose signals. Therefore, a low variability over different

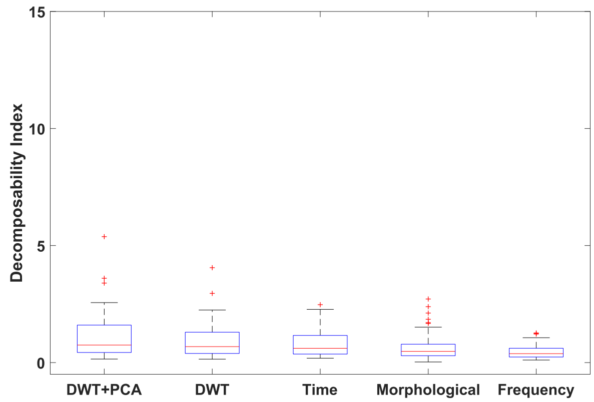

Fig. 12. Comparing feature extraction techniques regarding the best method in each domain for simulated EMG signals.

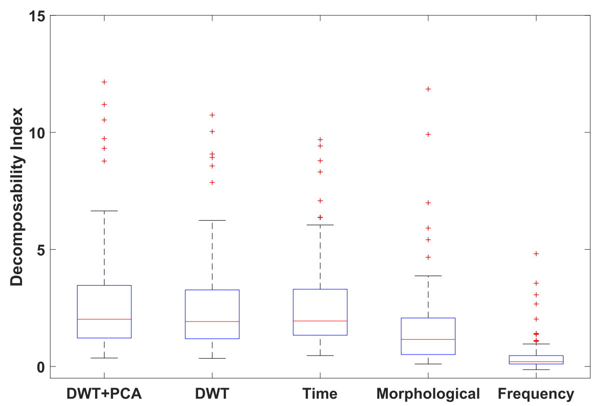

Fig. 13. Comparing feature extraction techniques regarding the best method in each domain for real EMG signals.

signals is desired. In this regard, the frequency domain features are preferred as they provided the lowest variability. The DWT features have the highest variability. However, frequency domain features provided the lowest DI values. In short, considering computation time and the fact that the DI values provided by the various feature extraction methods studied in this work are not statistically nor practically different, the time-domain features (the first derivative of the time samples) are the most efficient for representing MUPs for EMG signal decomposition. Using PCA may slightly improve the decomposability and ultimately may lead to a better correct classification rate for an EMG decomposition system. The main reason is that MUP time samples (filtered or non-filtered) that are used as a feature vector are correlated and redundant, therefore, PCA assists with finding effective dimensions for the feature space [54]; however, one must take into consideration the computational complexity of PCA and its requirement of larger amounts of available data samples for proper calculations.

In general, the results obtained using the real data are consistent with those obtained using the simulated data. Fig. 13 compares the best features from each domain for the real data used in this work. As shown, the DWT provided the best features and PCA slightly improved the discrimination of the MUPs. The DI values obtained for real data are slightly higher than DI values obtained on the simulated data set. One possible reason is that the MUP shape variability in the real signals are lower than that in the simulated signals. The other possible reason is the higher decomposability of MUPTs in the real data relative to those in the simulated data as most of the real signals used were recorded using fine-wire electrodes that are more selective than concentric electrodes involved in the EMG simulator used to generate simulated data. Nevertheless, the results obtained using real data followed almost an identical trend as the results of simulated data; the DWT provided the best features and PCA slightly improved DI values.

The first difference in the time domain is essentially high-pass filtering of the raw signal, so in many algorithms this is part of the preprocessing. We explored the effectiveness of combining first differences in the time domain and wavelet feature extraction (as the best method). Wavelet-domain features are extracted from the first differences in the time-domain. The improvement obtained in DI values using this filtering- then-feature extraction method was not significant. Considering the fact that the first differences in the time domain are related to calculating the detail part of the first stage of the discrete Haar-wavelet transform, one can say that the first difference in the time domain is in some sort a DWT feature extraction. Here we combined the best feature extractor with first differences in the time domain which may not be the best possible combination, a compelling question that could be addressed in future work is finding the best combination of preprocessing and feature extraction or even investigating whether certain types of features work better together than by themselves.

It should be noted that there are several other factors such as the types of electrodes used to detect the signals, amplifier filter settings during signal recording, MU firing pattern, MUP shape variability and SNR of the signal/MUP that affect the decomposability of a given EMG signal. Here we did not investigate the performance of the feature extraction methods for each of these parameters individually. Nevertheless, the DI used in this work considers MUP shape variability, similarity between MUPs of different MUs and SNR implicitly. Moreover, it is worth noting that the results about feature discriminability presented in Figs. 4-12 are based on signals with the characteristics of conventionally recorded clinical EMG signals. It should not be assumed that they necessarily apply to signals with other characteristics. In particular, it should not be assumed that the feature paradigms recommended here would necessarily have provided better decomposition results in all the investigations listed in Table I, which involved signals with a variety of different characteristics due to differences in electrode type, amplifier filter settings, and digital preprocessing. Nevertheless, the results obtained in this work suggest that investigating different feature extraction methods during EMG decomposition is worthwhile and may assist with improving the decomposition results.

VI. Conclusion

Feature extraction is a key step in the EMG signal decomposition process. As with any other pattern recognition system, feature extraction has a significant impact on the performance (both accuracy and computation time) of a decomposition system. In this work, an experimental evaluation of MUP feature extraction techniques used for intramuscular EMG decomposition was performed. Decomposability index and classification accuracy were employed to measure the discriminative power of different feature vectors. Mutual information analysis was also used for morphological features. 45 simulated and 82 real signals were used to search for the most informative features. Results showed that principal components of the 4th detail coefficients in a discrete wavelet transform brings the most separability. Applying the first derivative and PCA improved the separability of raw time samples. Maximum positive slope was the most discriminative feature in the morphological domain. The discrete Fourier transform showed the best results among frequency domain features. Considering computation time and discriminative ability criteria, among the feature extraction methods studied in this work, time-domain features (the first derivative of the time samples which is essentially high-pass filtering of the raw signal) are the most efficient for representing MUPs for EMG signal decomposition. However, care should be taken not to generalize these results to every EMG signal as these results were obtained using several signals with the characteristics of conventionally recorded clinical EMG signals.

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