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ORIGINAL ARTICLE

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MUAP extraction and classification based on wavelet transform and ICA for EMG decomposition

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Abstract We have developed an effective technique for extracting and classifying motor unit action potentials (MUAPs) for electromyography (EMG) signal decomposition. This technique is based on single-channel and short period's real recordings from normal subjects and artificially generated recordings. This EMG signal decomposition technique has several distinctive characteristics compared with the former decomposition methods: (1) it bandpass filters the EMG signal through wavelet filter and utilizes threshold estimation calculated in wavelet transform for noise reduction in EMG signals to detect MUAPs before amplitude single threshold filtering; (2) it removes the power interference component from EMG recordings by combining independent component analysis (ICA) and wavelet filtering method together; (3) the similarity measure for MUAP clustering is based on the variance of the error normalized with the sum of RMS values for segments; (4) it finally uses ICA method to subtract all accurately classified MUAP spikes from original EMG signals. The technique of our EMG signal decomposition is fast and robust, which has been evaluated through synthetic EMG signals and real EMG signals.

Keywords Motor unit action potentials (MUAPs) · EMG signal decomposition · Wavelet filtering · Independent component analysis (ICA) · Minimum spanning tree (MST)

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1 Introduction

The electromyography (EMG) signal, detected with micro electrodes such as concentric needle electrodes, is the summation of the motor unit action potential trains (MUAPTs) of all recruited motor units and noises including background and instrumental noise. A motor unit (MU) is an independent functional unit of the neuromuscular system and will generate motor unit action potential (MUAP) during muscle contraction. A motor unit action potential train (MUAPT) is generated by one MU during its repeated firing. EMG signal decomposition is the process of detecting the MUAPs generated by motor units (MUs) active during EMG acquisition and with fibers close to the detection surface, and classifying all these MUAPs into their constituent MUAPTs. Because the shape of the MUAP was largely depended on some factors including the configuration of the needle electrode, its position relative to the muscle fibers, the level of contraction and the clinical state of a subject's neuromuscular system, it is a difficult task to implement EMG signal decomposition. However, we can get the information related with the MUAP waveshapes and MU firing pattern from the results of the EMG signal decomposition. All information has proven to be of major importance for the diagnosis of neuropathies and myopathies [18, 20] as well as the investigation of the neuromuscular control loop [25].

In the middle of 1950s, Buchthal and Rosenfalck [1] introduced quantitative motor unit potentials (MUPs) analysis with manual identification and measurement method. Quantitative MUPs analysis upgraded to be half-automated with the application of computer through computer-assisted EMG decomposition procedure. The matched filter utilized the information of the waveform to recognize a MU potential [12]. A lot of experts have practiced template-matching method, which is the improvement for the matched filter technique. LeFever and DeLuca [13] developed an EMG decomposition algorithm based on the maximum a posteriori decision algorithm. McGill et al. [15], Stashuk and Qu [22], and Stålberg et al. [20] all ever applied this method for EMG signal decomposition. However, their methods are generally interactive, requiring the operator to manually adjust parameters, to decide whether to accept or reject candidate MUAPs, or to specify if the assignment template should be updated. Template matching methods can only track slowly varying waveforms, but it may be unable to track irregularly varying waveforms. Furthermore, any programs that rely on firing pattern information will have considerable difficulty in performing accurate motor unit extraction in the case of an irregular firing pattern.

Recently with the invention of the new pattern recognition and time-frequency analysis methods, automated quantitative EMG analysis is increasingly becoming feasible. Hassoun et al. [9] proposed an adaptive artificial neural network (ANN) classification system. Christodoulou and Pattichis [2] developed an unsupervised learning ANN using a modified version of the Kohonen self-organizing feature maps (SOFM) algorithm in conjunction with learning vector quantization (LVQ). ANN appears to be attractive because of their properties of adaptability or learning. However, the advantage of ANN technique may unnecessarily be superior to that of the template matching technique while the information about MUAP is not completely unknown. Moreover, the ANN technique is usually very time-consuming. Fang et al. [4] developed an identification algorithm based on spectrum matching in the wavelet domain calculating wavelet coefficients in the time-frequency domain. This technique classified spikes based on the nearest neighboring algorithm, which is less sensitive to waveform variation. Zennaro et al. [25] developed a software package of EMG LODEC (Electromyogram long-term decomposition). The decomposition program specially designed for multichannel long-term recordings of signals of slight muscle movements. In the method hierarchical cluster analysis based on wavelet transform is applied for clustering and the minimum distance classifier based on discriminant wavelet coefficients was applied for classification. Otherwise, Gazzoni et al. [8] described an automatic system for the detection and classification of MUAPs from multi-channel surface EMG signals. The algorithm proposed by Gazzoni et al. [8] is able to identify a MU sample representative of the muscle. Nakamura et al. [16] examined whether the application of independent component analysis (ICA) is useful for separation of MUAPTs from the multi-channel surface EMG signals. Their results illustrated that ICA could separate groups of similar MUAP waveforms of the surface EMG signals into each independent component.

The method proposed by Fang et al. [4] can make better performance compared with the former decomposition methods. At the same time, the software package developed by Zennaro et al. [24, 25] is an automatic decomposition technique. Nevertheless, this technique of multi-channel surface EMG detection designed by Gazzoni et al. [8] and Nakamura et al. [16] needs elaborate arrangement of electrodes array.

The wavelet coefficients from lower frequency bands are preferred to be chosen as the feature space for clustering and classification purpose [4; 25]. Spectrum-matching technique can also improve the performance of decomposition process because feature space with wavelet coefficients representation may always decrease the dimension of feature set. Moreover, ICA method has been proven to be more effective in removing power noise and white noise in EMG signals [19] and could separate groups of similar MUAP waveforms of the surface EMG signals into each independent component [16]. Otherwise, the single-linkage nearest-neighbor cluster method is more suitable for EMG clustering [23] because the method is less sensitive to waveform variation. Accordingly, we attempt to remove potential noises from the EMG signals using wavelet filtering and ICA method along with threshold estimation calculated in wavelet transform, to extract MUAPs by single amplitude threshold filtering, to cluster MUAPs based on minimum spanning tree and spectrum-matching technique in wavelet domain, and to classify MUAPs to their constituent MUAPTs based on minimum distance classifier.

2 Methods

2.1 Data acquisition

In this study, real EMG recordings were acquired from subjects during routine EMG examination through standard concentric needle electrodes. The analog amplification was provided by a standard EMG instrument, the amplifier filters were set to 2–10 kHz and the amplifier's gain was selected at 100. EMG signals were collected from the biceps brachii of subjects at slight to moderate contraction force level. Five seconds of continuous signal was recorded from subjects including ten representative normal individuals whose ages ranging from 21 to 32 years (eight males and two females). Seven recordings were chosen for data analysis from these signals and three recordings were subtracted because they included too much interference patterns. All subjects, who have been informed in advance about our data acquisition intention, were volunteered to participate in our data collecting. During recordings, each subject laid in the examination bed and was instructed to perform a sustained isometric contraction. All of our data were detected in Shanghai Huashan Hospital of Fudan University. The signals were sampled at 30 kHz with a standard 12-bit analog-to-digital converter and stored in binary format on a hard disk for analysis.

2.2 The artificial generation of the EMG signal

The artificially generated EMG signals can usually be regarded as a reference to test the performance of EMG decomposition algorithm. A complete model not only can provide a priori knowledge about exact firing position and waveform features of all MUAPs in the signal, but also is the only way to test the algorithms with signals having selected characteristics in order to test the sensitivity to different parameters [5]. Farina et al. [6] proposed a model for the generation of one or more channels of normal intramuscular EMG signals to test decomposition algorithm. This model started with a library of real MUAPs represented in a 16-dimensional space using their Associated Hermite (AH) expansion. In this study Farina's modeling method was used to create artificial intramuscular EMG signals. All of our artificial recordings generated using this model were 5 s long and corrupted with random white noise at a different signal to noise ratio (SNR). The random noise was generated by bandpass filtering Gaussian white noise. All signals were single channel recordings sampled at 30 kHz.

The MUAP library includes 25 MUAP waveforms artificially extracted from real EMG recordings. Each MUAP waveform is expanded by the AH function which has already been proven to show a good compact support description including the shape and the time evolution of nonstationary signal. This expansion requires the appropriate choice of the truncation order and the estimate of the scalar parameter λ [3]. We set the values of the truncation order n and the scalar parameter λ by many experiments as follows:

$$n \doteq 15, \quad \lambda = \text{round}(25 + \text{length}/10)$$

in which ''round'' denotes the operation of taking integer and ''length'' is the length of the relative MUAP. The random and trend shape variability and the random and trend time scale variability are introduced by respectively changing randomly or linearly the AH coefficients and the scalar parameter of the expansion. The values of all parameters including v_{w1}, v_{w2}, v_{s1} and v_{s2}, which respectively simulate and quantify the variability of random shape, trend shape, random time scale and trend time scale, are all set to 0.02. The random and trend shape variability is the variability of the MUAPs shape belonging to the same MU respectively in a random and progressive way during time. In the same way, the random and trend time scale affect the MUAP width respectively in a random and progressive way during time. The generation of firing pattern is based on three statistical characteristics: regular firing, double discharge firing and random firing. Regular firing pattern was introduced by the mean interpulse interval (IPI), which follows size principle. For the EMG data of short interval under constant force contractions, the regular firing behaviour of a MU can be modeled as a stationary renewal point process. The positions of all double firing and random firing spikes, which were determined by uniform random variables, embody double and random firing pattern. A set of six simulated EMG signals has been generated with the aforementioned model program (Table 1).

2.3 EMG signal decomposition

The presented algorithm to extract and classify MUAPs includes the following steps. The flow chart of the whole signal decomposition process is illustrated in Fig. 1.

2.3.1 Step 1: Remove white and background noises through wavelet filtering and thresholding estimation calculated in wavelet transform

We assume that the noisy signal can be formulated by $x(t) = s(t) + w(t)$, where $x(t)$ is the recorded EMG signal, which is the linear summation of noise-free signal $s(t)$ and noise $w(t)$ with variance of σ^2. The de-noising objective is to suppress the noise part of the signal $x(t)$ and to recover the noise-free signal $s(t)$. The wavelet coefficients are evaluated:

$$X_\varphi(a,\tau) = S_\varphi(a,\tau) + W_\varphi(a,\tau) \tag{1}$$

where $X_\varphi\,(a,\tau)$, $S_\varphi\,(a,\tau)$ and $W_\varphi\,(a,\tau)$ are respectively the wavelet coefficients of $x(t)$, $s(t)$ and $w(t)$ at scale index a and time index τ. $[\varphi_m \mid m \in z]$

is the orthogonal wavelet base. In this study we used the compactly supported biorthogonal wavelet base that is Daubechies compactly supported wavelet with five vanishing moments or db5.

The interference of white noise, which affects the entire spectrum in the Fourier transform, can be easily denoised with the thresholding estimate calculated in wavelet transform. Due to the impossibility to compute the optimal Bayes or minimax estimator that minimizes the risk among all possible operators [14], we choose thresholding estimator that has a risk close to this lower bound. Hard threshold is the simplest thresholding estimator in wavelet bases $[\varphi_m \mid m \in z]$. A diagonal estimator of $S_\varphi\,(a,\,\tau)$ can be written as follows:

$$\tilde{S} = DX = \sum_{m=0}^{N-1} d_m(X_\varphi(a,\tau))\varphi_m. \tag{2}$$

A hard thresholding estimator is implemented with:

$$d_m(x) = \rho_T(x) = \begin{cases} x & \text{if} \quad |x| > T \\ 0 & \text{if} \quad |x| \le T \end{cases}. \tag{3}$$

The operator D in (2) is a non-linear projector in the basis $[\varphi_m \mid m \in z]$. According to the relation of energy conservation between time and wavelet domain we can set the value of T in (3) by $T = \lambda \cdot \sigma$, and the value of the parameter λ is set to be between 8 and 15 by the user according to the SNR. Here σ is the noise energy estimated from the following expression in time domain [24]:

$$\sigma_i^2 = \frac{1}{L_R} \sum_{k=i}^{i+L_R-1} s_{\mathrm{EMG}}^2[k] \tag{4}$$

where L_R is the length of a window ($L_R \in Z$), $s_{\mathrm{EMG}}\,[k]$ are the discrete EMG signals. The minimum $\sigma^2{}_n$ of $\sigma^2{}_i$ can

Table 1 Characteristic features of the artificial generated EMG signals

EMG number	M [number of motor units (MUs)]	Total number of motor unit action potentials (MUAPs)	Firing frequencies of M MUs	Signal to noise ratio (SNR)
1	4	160	7, 9, 10, 25	16
2	5	143	5, 6, 10, 13, 15	32
3	6	166	9, 9, 10, 12, 12, 14	19
4	7	169	7, 10, 10, 11, 13, 14, 15	20
5	7	157	5, 8, 9, 9, 11, 12, 15	20
6	8	159	6, 8, 9, 9, 11, 12, 12, 13	16

be estimated as the noise power according to the following equation [24]:

$$\hat{\sigma}_n^2 = \min \sigma_i^2. \tag{5}$$

In this paper, we firstly bandpass filtered the original EMG signal by wavelet filter rather than traditional digital filter which would usually cause time delay. Accordingly, we filtered the signal by setting relative wavelet coefficients to zeros. For example, we could put low-frequency coefficient a_9 to zero. This coefficient was obtained by wavelet transform at ninth level and may include some components during the frequency bank among 0–30 Hz. Likewise we could put some high-frequency details, which do not include useful MUAP components to zeros. Then we removed the background noise and white noise included in EMG signals by wavelet threshold estimation method.

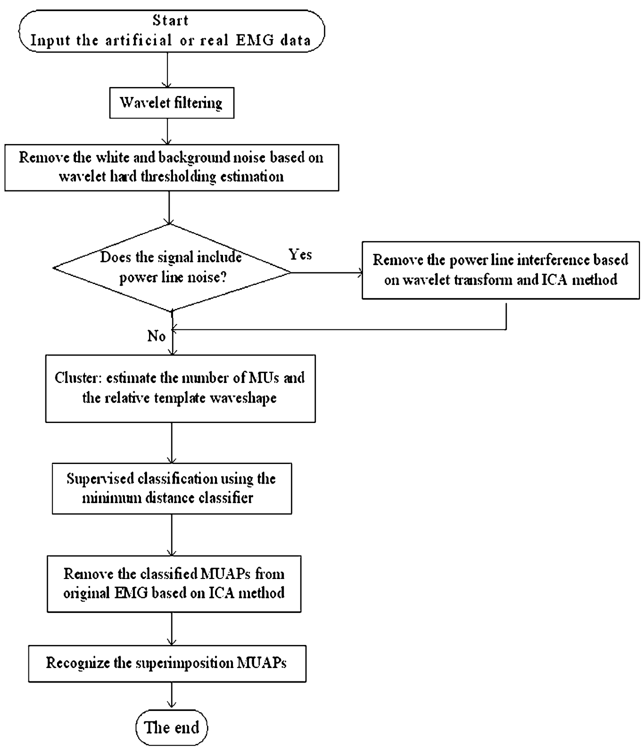

Fig. 1 Flow chart of the process of electromyography (EMG) signal decomposition

2.3.2 Step 2: Remove the power noise based on wavelet transform and the ICA algorithm

Independent component analysis (ICA) is a new method that aims to find a linear representation of several source signals so that the components are statistically independent, or as independent as possible. We assumed the following ICA signal model introduced by Hyvärinen and Oja [11]:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{6}$$

where observed signals $\mathbf{x}(t)$ is a zero-mean m-dimensional vector, source signals $\mathbf{s}(t)$ is a n-dimensional random vector whose components are assumed mutually independent, and $\mathbf{A}$ is full-rank $N \times M$ scalar linearly mixing matrix to be estimated. According to the comment of Hyvärinen and Oja [11], because the independent component must have non-Gaussian distributions, the key of estimating the ICA model is to find an effective non-Gaussianity measure. For obtaining the solution of ICA, we consider a linear transformation as $y = \mathbf{w}^{\mathrm{T}}\mathbf{x}(\mathbf{t}) = \mathbf{w}^{\mathrm{T}}\mathbf{A}\mathbf{s}(\mathbf{t}) = \mathbf{z}^{\mathrm{T}}\mathbf{s}$, where $\mathbf{z} = \mathbf{A}^{\mathrm{T}}\mathbf{w}$, $\mathbf{w}$ is an estimator of a row of the matrix $\mathbf{A}^{-1}$ and could be considered as a vector that maximizes the non-Gaussianity of $\mathbf{w}^{\mathrm{T}}\mathbf{x}$, which means $\mathbf{w}^{\mathrm{T}}\mathbf{x} = \mathbf{z}^{\mathrm{T}}\mathbf{s}$ equals one of the independent components. A quantitative measure of non-Gaussianity of random variable y is negentropy that is a very important measure of non-Gaussianity based on the information theory. Negentropy J is defined as: $J(y) = H(y_{\mathrm{gauss}}) - H(y)$, where $H(y)$ is the entropy of a discrete random variable and entropy is the basic concept of information theory. Negentropy is always non-negative, and it is zero if and only if y has a Gaussian distribution. In this study, we use the new approximations to estimate negentropy developed by Hyvärinen and Oja [11] and the fast and stabilized fixed-point algorithm for estimating negentropy (fast ICA) developed by Hyvärinen [10].

After bandpass filtering and removing the white and background noises, we combined wavelet filtering and ICA algorithm together to remove power line interference that was mixed in one channel EMG signal. For this point, the EMG data was firstly divided into several equal segments that would be regarded as input matrix to ICA decomposition program. After ICA decomposition we could distinguish the power ICs from other ICs. These power components may include useful

MUAP components. So we utilized wavelet filter to remove the ICs coming from power noise and hold the useful components. Finally the EMG signal could be reconstructed with the ICs after power components have been removed. Whereas, the process of removing power noise is sometimes unnecessary because under normal circumstances this kind of noise could be removed through a notch-filter.

2.3.3 Step 3: MUAPs extraction based on the amplitude single threshold filtering (EMG signal segmentation)

The purpose of MUAPs extraction is to detect all active segments, being either one single MUAP or superposition spike of several MUAPs, and inactive segments from the denoised EMG signals. The method we applied is based on amplitude single threshold filtering. After denoising, the noise power σ^2_n of the inactive segments is estimated automatically according to (4) and (5). The beginning and ending points of active segments are detected by thresholding based on the estimated noise power. With the estimated noise power and the EMG signal samples, the active segments can be determined. If the amplitude of the signal is above or below a certain threshold ($\pm\lambda_1\sigma_n$), an active segment is detected. The beginning and end of a segment is reached when the signal samples lay at least 1 ms between the two threshold ($-\lambda_2\sigma_n$ and $\lambda_2\sigma_n$) before the beginning point and after the ending point. Typical values for the parameter λ_1 and λ_2 are set respectively between seven and nine and between three and five by the user [24].

Here it should be emphasized that any extracted active segments which have only one phase or whose duration is shorter than 2 ms should be excluded from the set of active segments. Then the extraction results were subsequently combined together. Moreover, all detected active segments should be aligned with their peak at the center, and stored in a matrix. The position of beginning point of every active segment was also assembled together in a separated one-dimensional (1-D) array.

2.3.4 Step 4: MUAP clustering based on the nearest-neighbour concept

Now an active segment is either a single MUAP or superposition spike of several MUAPs. The purpose of this section is to distinguish all single MUAPs from superimposed MUAPs and arrange these single MUAPs to their constituent MUAPTs based on the single-linkage hierarchical clustering algorithm. In this paper, we take the wavelet coefficients at third to sixth level after wavelet transform at sixth level as feature space. One important point for clustering algorithm is the definition of the distance measure. We have investigated two similarity measures, which are respectively the Euclidean distance (7) and the distance measure based on the variance of the error normalized with the sum of the RMS values for the segments [17] (8). Their denotation in formula is as follows:

$$d(\boldsymbol{X}_i, \boldsymbol{X}_k) = (X_i - X_k)^{\mathrm{T}}(X_i - X_k) \tag{7}$$

$$d(s_1, s_2) = \frac{E(e^2(n)) - E^2(e(n))}{\sqrt{E(s_1^2(n))} + \sqrt{E(s_2^2(n))}} \tag{8}$$

in Eq. 7, X_i denotes the ith N-dimensional feature vector of MUAP; in Eq. 8, s_1 (n) and s_2 (n) are two active segments to be compared and $e(n)$ is their error signal. In this study, the distance measure defined by (8) was used as similarity measure for clustering. The distance measure defined by (7) was used as similarity measure in the minimum distance classifier.

Now the single-linkage hierarchical clustering algorithm was used to recognize which segments originate from their corresponding motor units (MUs) and which segments are compound. This algorithm permits a simple graph-theoretical interpretation, namely the minimum spanning tree (MST) method. In the MST, the nodes are the active segments represented by feature space and the edges are the distances between two nearest-neighbour segments in the feature space. Therefore, the MST has the smallest sum of distance among all possible trees. By removing those edges in the MST with values greater than a given threshold, the MST is divided into subtrees and each subtree represents a cluster. The MST method is able to cluster the MUAPs of slowly variation from one occurrence to the next and does not depend on the presentation order of the samples. This method is therefore best suited for EMG clustering. The results of clustering are very sensitive to the value of discriminatory threshold for cutting these edges. In this technique, we do not choose the threshold but to select an appropriate number of clusters for cutting these edges. For example, we may set the number of cluster equal to half of the total of all active segments when the force level is about 50% of maximal voluntary contraction (MVC), or we set the number of clusters equal to 20% of the total of all active segments when the force level is light or below 20% of MVC.

Finally any cluster, which contains at least five segments, was chosen as a potential MUAP class. MUAP template is the mean of all waveshapes in their constituent MUAP class.

2.3.5 Step 5: MUAP classification based on the minimum distance classifier and removing the classified MUAPs through ICA method

In this section the purpose is to classify non-overlapping but un-classified active segments by clustering and to track MUAP shape variation. The supervised classifier we used is based on the minimum distance classifier. The classification program is based on the most discriminant wavelet coefficients and the clustering results. The choice of threshold is critical, and we set its value equal to the minimum among all the mean values of all inter-class distances. Due to signal non-stationarity and electrode movement, the MUAP shapes vary from discharge to discharge. We utilized the weighted averaging techniques applied by Zennaro et al. [25] to adapt the MUAP class template.

Finally all MUAPs that have been accurately clustered and classified should be removed from original EMG signals by ICA decomposition technique. To this aim we firstly arranged all classified MUAPs waveforms to generate a time series, then combined the time series and original EMG signal together to make a two-dimension input matrix as ICA decomposition process. The result of ICA decomposition is a two-dimension matrix that respectively represents the difference signal by subtracting previously classified MUAPs from the original EMG signal, and the signal composed of all classified MUAPs. By analysis the difference signal is composed of superimposed MUAP spikes. So the superimposed spikes are therefore detected.

3 Results

We utilized artificially generated EMG signals and real EMG recordings at different voluntary contraction levels to evaluate the performance of this proposed algorithm.

3.1 Evaluation using artificially generated EMG signals

Figure 2a denotes a synthetic intramuscular EMG signal whose SNR is 21. Fig. 2b denotes the denoised signal by wavelet filtering and thresholding estimation calculated in wavelet transform. Figs. 2c and d represent respectively a detail of the synthetic EMG signal shown in Fig. 2a and b. It is unnecessary to remove power noise from the generated EMG signal because this signal does not include this kind of noise.

After removing noise from the synthetic EMG signal, all active segments were detected based on the amplitude single thresholding filtering technique introduced in Sect. 2.3.3. Then all these active segments detected should be clustered and classified based on MST and a supervised classifier. The results of clustering and classification based on a generated EMG signal are shown in Fig. 3, which reported the firing pattern and the waveforms of the six MUAPs that have been identified.

Finally, the classified MUAPs were subtracted from the original EMG signal by ICA decomposition method in order to obtain the difference signal. Figure 4 shows the process of removing classified MUAP components from an original synthetic EMG signal. In Fig. 4a, the upper figure is the original denoised signal, and the lower figure is the signal by arranging all classified MUAPs waveforms. When we used the signal denoted by the lower figure in Fig. 4a as the template signal, the result of ICA decomposition algorithm is shown in

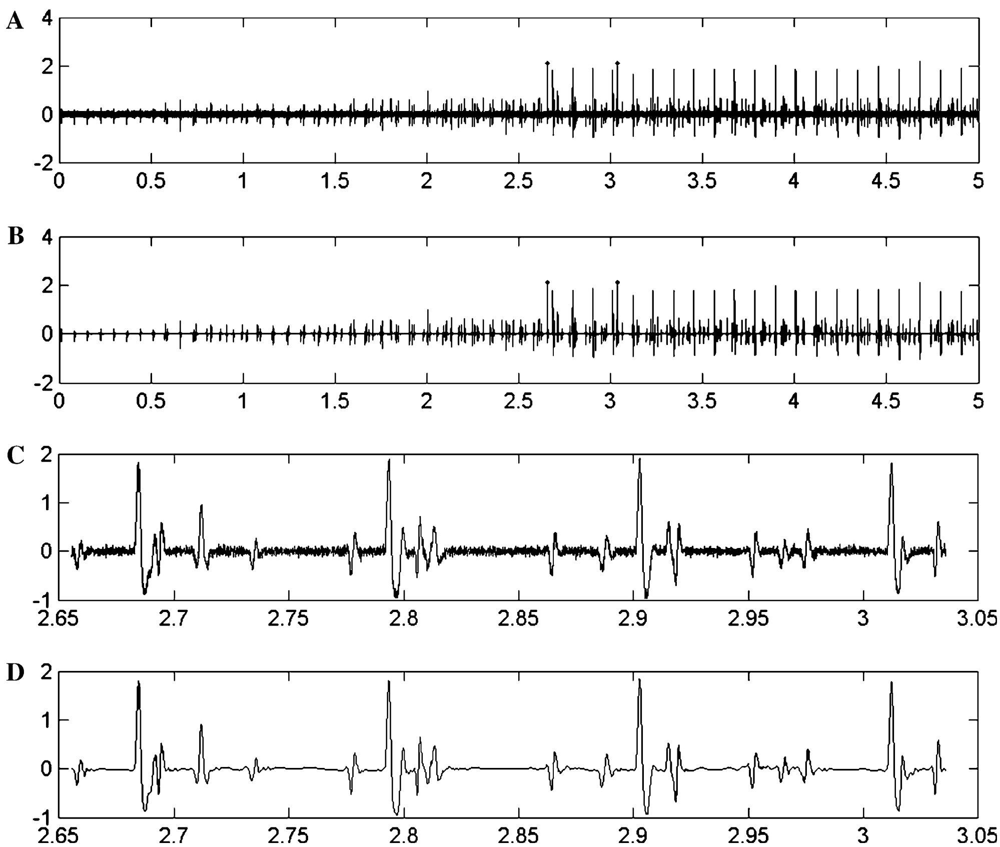

Fig. 2 An example of denoising process based on the wavelet filtering and thresholding estimation. **a** A synthetic EMG signal. **b** The denoised version of (**a**). **c**, **d** Details of a section of signals denoted in (**a**) and (**b**)

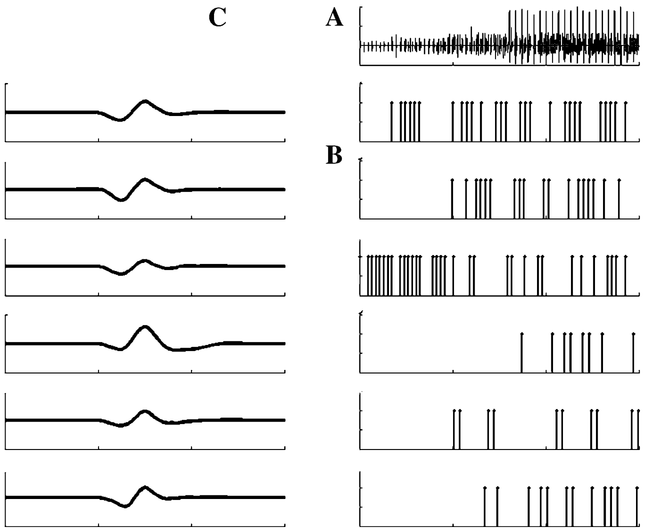

Fig. 3 An example of decomposition based on a synthetic EMG signal. **a** The denoised signal based on a synthetic EMG signal. **b** The resulting motor unit (MU) firing patterns for each MU classes identified by clustering and supervised classifier. **c** The motor unit action potential (MUAP) waveforms decomposed from the signal in (**a**)

Fig. 4b. It is clear that the upper figure of Fig. 4b is the difference signal by subtracting previously classified MUAPs waveforms from the original EMG signal through ICA method. This difference signal is composed of all superimposed MUAP spikes and a little non-classified single MUAP spikes.

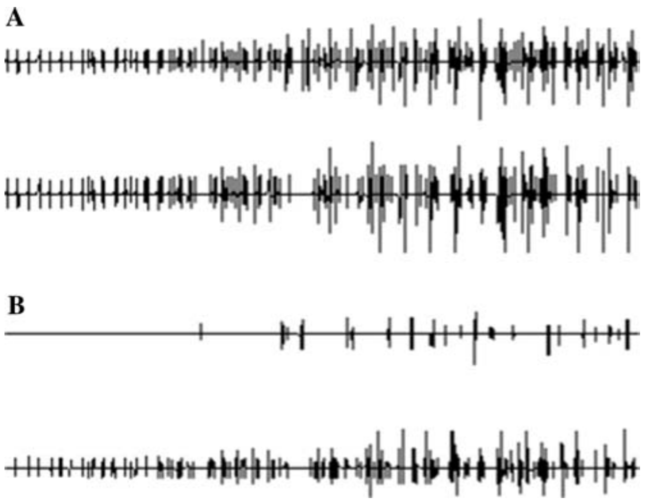

Fig. 4 An example of removing identified MUAP components from the original EMG signal showed in Fig. 2. **a** The original synthetic EMG signal and the signal composed of the previously classified MUAPs waveforms. In (**a**), the *upper figure* is the original denoised signal, and the *lower figure* is the signal composed of all classified MUAPs waveforms. **b** The output result of independent component analysis (ICA) decomposition for the input signals shown in (**a**). In (**b**), the *upper figure* is the difference signal subtracted identified MUAPs waveforms from the original synthetic EMG signal based on ICA algorithm. The *lower figure* is the same signal as the one shown in the *lower figure* of (**a**), but the sign was inverted

3.2 Report of the result based on real EMG signals

The evaluation of EMG decomposition algorithm of real measured signals is usually very important because many physiological aspects related to MU firing statistics are completely disregarded in the phenomenological EMG model such as the common drive and the synchronization of MU firing. Moreover, the way to model shape variability is simple and easy to quantify. Finally, linear variation of shape or firing frequencies is another strong simplification compared with real signals. All these simplifications have been done in order to reduce the number of parameters necessary to describe the random process. Therefore, the decomposition method based on the evaluation of the model EMG signal should further decompose the real EMG signals. Figure 5 is an example of removing white and background noises from a real EMG recording. Figure 5a and b show respectively a real EMG recording detected from a normal subject that includes power line interference and the denoised signal based on wavelet filter and hard thresholding estimation in wavelet domain. Figure 5c and d show respectively the enlarged part of a section of signals shown in Fig. 5a and b.

Figure 6 shows an example of removing power interference from the real EMG signal showed in Fig. 5 through ICA and wavelet filtering. The EMG signal was firstly divided into three equal segments that formed the input matrix of ICA decomposition. Figure 6a shows the results of ICA decomposition. It is clear that the first IC does not include power line components but the other two ICs include. Then these two ICs were filtered in order to remove the power interference components by wavelet filter. Finally the denoised signal was reconstructed by the inverse transform of ICA. Figure 6b shows the reconstructed signal after the power noise was removed from the signal shown in Fig. 5.

The candidate signals after removing noises were segmented by the method suggested in Sect. 2.3.3. Each segment may be one active MUAP or superimposed spike of several MUAPs. These segments were then clustered and classified by the two above-mentioned classifiers. One example of the results of clustering and classification is shown in Fig. 7.

3.3 Statistical analysis of the results

Table 2 shows the decomposition results of the artificial EMG signals listed in Table 1. The decomposition results were compared to the known information of the EMG model. The results listed in Table 3 are related to

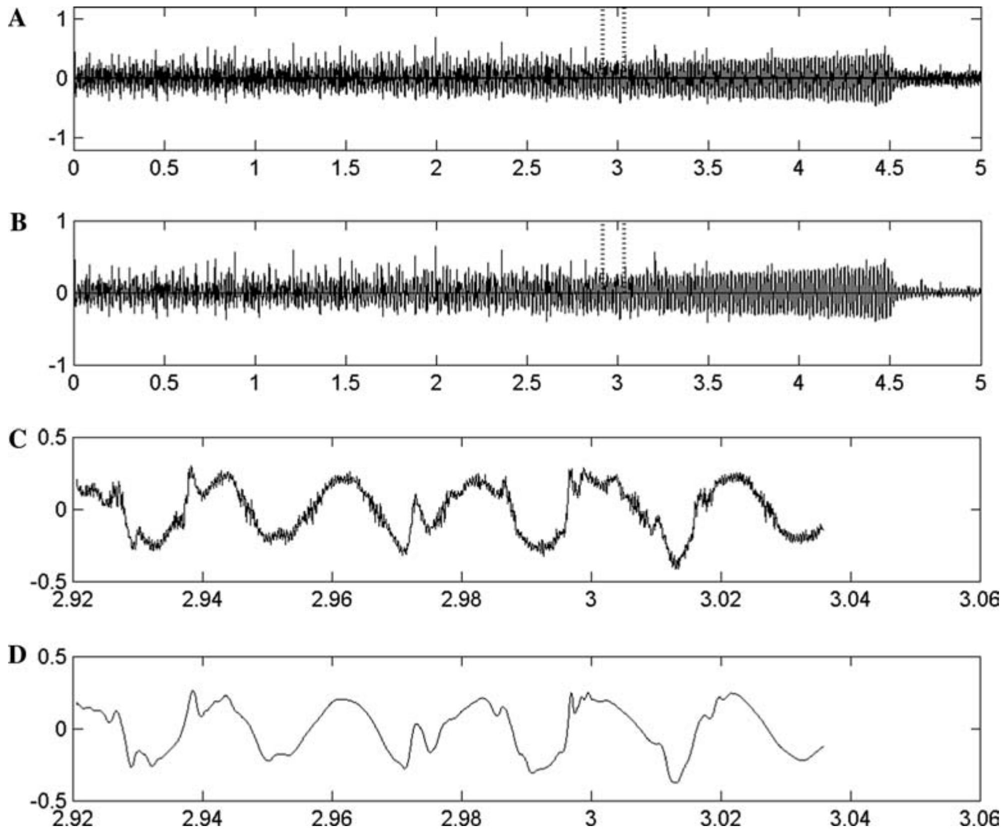

Fig. 5 An example of removing white and background noises from real EMG recordings. **a** A real EMG signal detected from normal person. **b** The denoised signal based wavelet firing and threshold estimation calculated in wavelet transform. **c**, **d** Details of a section of signals denoted in (**a**) and (**b**), respectively marked by the two *vertical discontinuous lines*

the real EMG recordings. These results were compared to the gold standard obtained by manually decomposition of the real EMG signals. A skilled operator who has 2 years of EMG investigation experience performed the manual decomposition process. Moreover, several veteran EMG doctors advised and verified the results of manual decomposition.

In Tables 2 and 3, the detected MUAPs include all single MUAP spikes and superimposed MUAP spikes. Among the detected MUAP spikes, only single MUAP spikes were classified and the superimposed MUAP spikes were detected but not classified. At the same time, among all single MUAP spikes some non-classified MUAPs made the percentage of non-classified MUAPs. Among all classified MUAPs some wrongly classified MUAPs made the percentage of wrongly classified MUAPs, and the others made the percentage of correctly classified MUAPs. The average decomposition ratio of artificial EMG signals was about 94.95% according to Table 2. The average percentage of correctly classified MUAPs was higher than 99%. The average percentage of non-classified MUAPs was only 5.05%. According to Table 3, the average decomposition ratio of real EMG signals was about 92.97%. The average percentage of correctly classified MUAPs was higher than 92%. The average percentage of non-classified MUAPs was only 7.03%.

It is worth noting that the whole decomposition time is all below 170 s referring to Tables 2 and 3. Moreover, we attempted to execute amplitude single threshold filtering to the original EMG signal, which was the traditional MUAPs detection method [4, 25]. The MUAP extraction times based on the traditional method and the proposed method are respectively shown in Tables 2 and 3. All run times listed in Tables 2 and 3 were measured by time functions in matlab programs.

4 Discussion

In this paper, we proposed an automatic EMG signal decomposition procedure and evaluated the performance of the method by the artificial and real EMG signals. The entire decomposition process is basically conducted in matlab language. The time of analyzing either generated or real EMG signals of 5-s periods required by our decomposition algorithm in an 800-MHz Pentium desktop computer is all below 170 s. In this paper, we firstly utilized the wavelet hard threshold estimation technique to attenuate white and background noises, and then applied wavelet filtering and ICA to remove power interference. Unlike the traditional method it amplitude filtered the original EMG signal, this technique used amplitude single threshold filtering to detect active segments based on denoised signal. We can see from Tables 2 and 3 that the MUAP extraction time through the proposed method is consistently

A

B

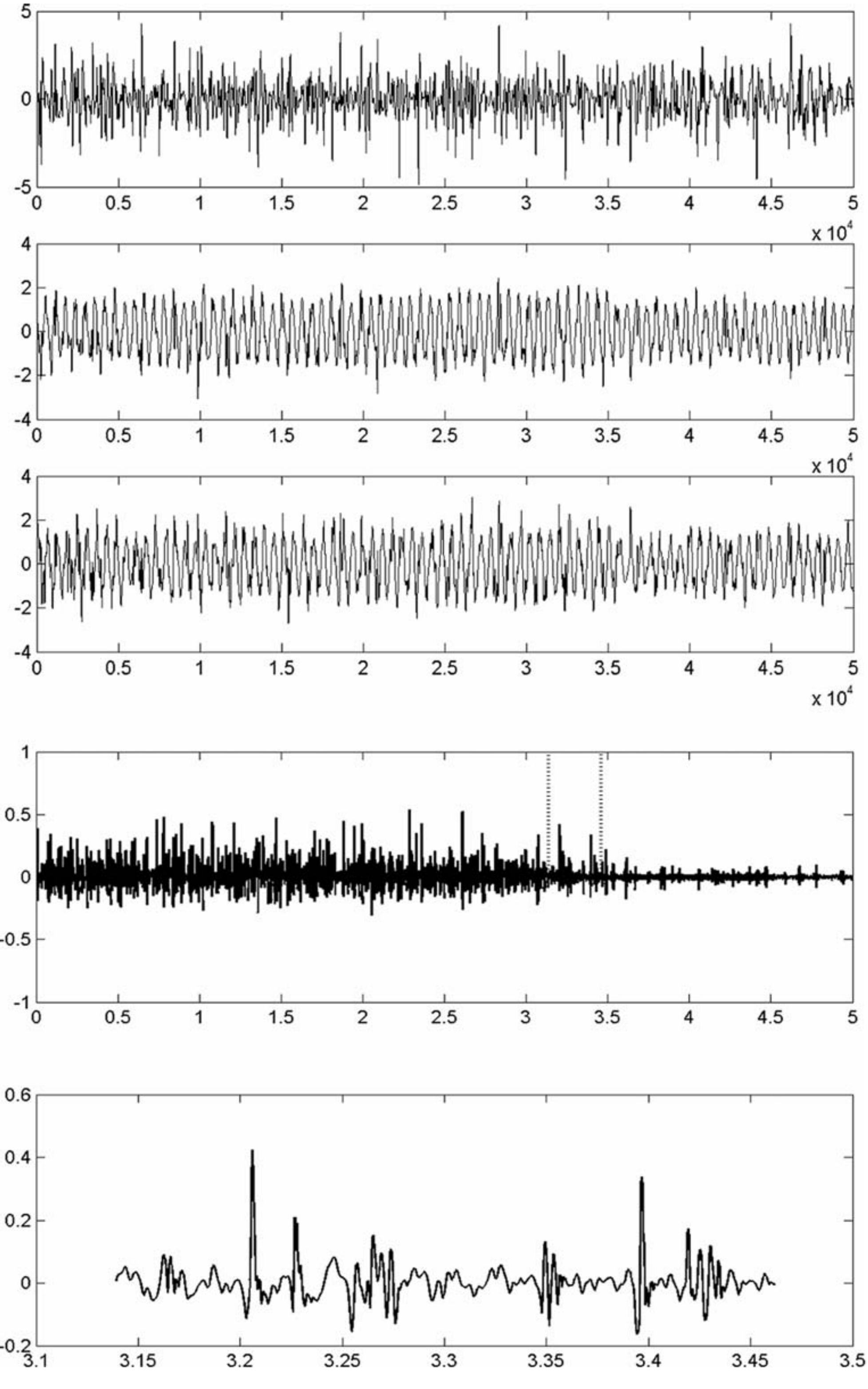

Fig. 6 An example of remove power interference based on the wavelet filtering and ICA. **a** Independent components obtained from the signal showed in Fig. 5b based on ICA. **b** The denoised version of the signal denoted by Fig. 5. In (**b**), the *lower part* is the detail of a section of the signal showed in the upper part marked by the two *vertical discontinuous lines*

shorter than the time through the traditional method. Therefore the speed of our decomposition technique can be greatly improved. At the same time, the decomposition technique is robust because our denoising procedure can effectively remove potential noises from EMG recordings.

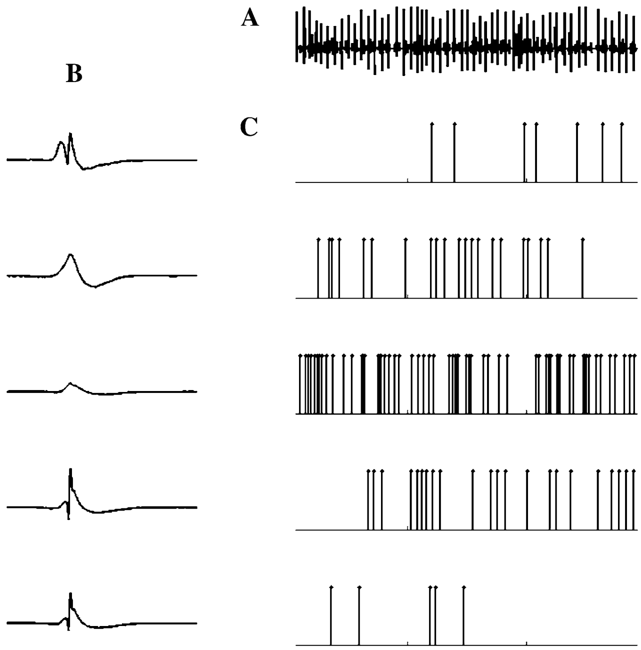

Fig. 7 An example of decomposition based on a real EMG signal. **a** The denoised signal based on a real EMG signal. **b** All MUAP waveforms decomposed from the signal showed in (**a**). **c** The relative MU firing patterns for each MU classes identified by clustering and supervised classifier

The performance of our method based on artificially generated signals was very effective and the results were consistently accurate. However, because simulated signals usually did not take into account or even disregarded some aspects of muscles, our algorithm should be further evaluated through real EMG recordings. From Fig. 7 we can see that the recruitment rule of MUs essentially follow size principle, i.e., large MUs recruit at higher recruitment threshold and fire with lower rate than small ones.

The variability of the MUAP waveform within a MUAPT and the similarity of MUAPs from different trains are two major factors that affect the results of EMG decomposition algorithm. It is also the two factors that bring on non-classified and wrongly classified MUAP spikes. Otherwise, the percentage of the classified MUAPs will decrease with the introduction of more superimposed MUAP spikes. Therefore, we observed from Tables 2 and 3 that the percentage of the classified MUAPs is increased when the superimposed MUAPs decreased. In this paper we take a preliminary study on the unsupervised and supervised identification of MUAPs and the technique of subtracting all identified MUAPs from original EMG signals with ICA decomposition method. The experiments using artificial and real data showed that our technique is accurate and effective. Moreover, it can

Table 2 Achieved decomposition result with artificial generated EMG signals listed in Table 1

EMG signal	1	2	3	4	5	6	Mean
Percentage of classified MUAPs	83.75	70.63	65.07	62.14	63.06	56.60	66.875
Percentage of correctly classified MUAPs	99.25	99.01	100.00	99.05	100.00	98.89	99.37
Percentage of wrongly classified MUAPs	0.75	0.99	0.00	0.95	0.00	1.11	0.63
Percentage of non-classified MUAPs	1.87	0.00	10.23	1.77	7.00	9.44	5.05
Percentage of superimposed MUAPs	14.38	29.37	24.70	36.09	29.94	33.96	28.07
The whole decomposition time (MUAP extraction time) based on the proposed method (s)	109.9566 (86.8280)	116.5634 (90.4220)	128.5143 (101.5780)	160.1091 (128.3590)	144.4136 (113.3590)	133.0940 (105.5470)	
MUAP extraction time based on the traditional method (s)	89.9530	92.7500	125.5790	143.4070	128.5000	123.7180	

Table 3 Achieved decomposition result with real EMG recordings of normal subjects

EMG signal	1	2	3	4	5	6	7	Mean
Number of detected MUAPs	174	216	228	240	241	171	178	
Number of identified MUs	4	3	4	5	4	3	2	
Percentage of classified MUAPs	67.24	62.04	44.74	78.75	56.02	68.42	80.90	
Percentage of correctly classified MUAPs	93.17	91.04	97.56	94.77	90.37	88.89	93.06	92.69
Percentage of wrongly classified MUAPs	6.83	8.96	2.44	5.23	9.63	11.11	6.94	7.31
Percentage of superimposed MUAPs	21.26	37.96	50.44	19.58	41.08	27.49	16.85	
Percentage of non-classified MUAPs	17.09	0.00	10.78	7.41	5.19	5.98	2.78	7.03
The whole decomposition time (MUAP extraction time) based on the proposed method (s)	122.0930 (82.0940)	137.3900 (121.6720)	146.3600 (121.7340)	143.6392 (130.6250)	166.1270 (131.1560)	150.4830 (135.9380)	151.3580 (139.3484)	
MUAP extraction time based on the traditional method (s)	182.2820	189.8750	210.1250	165.2650	235.4820	186.5310	172.5000	

be observed that the decomposition results of artificial generated EMG signal are better than the results of real EMG. This is probably because real signal includes more superimposed MUAP spikes, more complex shape variability and more stochastic firing statistics.

However, we should point out that fastICA can effectively separate power line components from EMG, but it may not be suitable for EMG decomposition. This is because the fluctuations in the performance of ICA for each source EMG signal were big and some components obtained by ICA decomposition were inverted according to the results of Garcia et al. [7], which could become a problem when trying to automatically decompose EMG signal.

5 Conclusion

The technique of the EMG signal decomposition is fast and robust. The whole decomposition time of either artificial or real 5 s-periods EMG recording is all below 180 s. The MUAP extraction time through the proposed method is consistently shorter than the time through the traditional method. This is because we did not utilize amplitude threshold filtering for the original EMG signal but for denoised signal. After denoising we executed amplitude threshold filtering for MUAPs extraction. Because the speed of our EMG decomposition program was improved greatly and the performance of our method is very robust our technique may be suitable for on-line analysis. However, according to the comments of Stashuk [21], the accuracy of clustering and classifying results is more important than the task that all detected MUAPs are assigned. Therefore, our decomposition technique only clustered and classified single MUAPs. Certainly, the decomposition results are incomplete because of the restriction of time and the limitation of our data collection. Currently, in order to finish the complete EMG decomposition, we're going to do the further research and investigation related to new EMG signal decomposition method. The next study will include but nor limited points as follows: (1) extracting new effective MUAP features such as non-linear feature parameters; (2) trying to finish complete EMG signal decomposition through resolving superimposed action potentials.

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