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The Verification of Physiological Model of SEMG Based on Wavelet Decomposition

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Abstract

The decomposition methods of surface electromyogram (SEMG) signals are mainly based on independent component analysis, blind source separation and the neural network. Because actual signals are the decomposition faced to single-guide signals, so the neural network decomposition method has more advantage. In this paper, we improve the composition of neural network based on the generation principle and decomposition significance of SEMG, and use this network to decompose the signal and to obtain a higher accuracy through the experimental data above. Beside, under medium-low shrinkage level the decomposition algorithm can successfully extract the dissemination information of motor unit action potentials in SEMG.

Keywords: *SEMG signal, Wavelet Decomposition, Neural network*

1. Introduction

EMG is bioelectric signals produced by the neuromuscular system during activities, and its essence is formed by motor unit action potentials sequence and noise superposition of collecting electrode. The SEMG decomposition restores the constitution to its main motor unit action sequences (MUAPS), according to the skin surface collecting signals. This process is able to calculate the muscle motor unit recruitment (MU), the firing rate changes and other control information so that we can better research physiological characteristics of the MU, moreover, it has a remarkable significance for diagnosis of diseases and coordination process of muscle movement [1].

We have never stopped to explore the field of EMG decomposition for the past many years. Piper used a metal disc to detect SEMG in 1912, but it is still relatively difficult to extract the activities information of individual MU. Subsequently, A. Gerber, *et al.*, started to decompose EMG, which is considered to be a good start. In 1984, De Luca, *et al.*, gave evaluation method of the EMG decomposition algorithm for the first time on the basis of previous. In 1990s, D. Stashuk [2] began working EMG feature extraction, template clustering and other researches, making signal decomposition practical forward push a big step. Then, Qiang Li [3] decomposed signals of low shrinkage force based on continuous wavelet testing. On this basis, Chunxiang Tan [4] summarized information maximization fast algorithm, having a remarkable achievement. Jihai Yang did a comparison test for Simulation EMG and real EMG, and its recognition rate may eventually reach 90 percent, so it could better solve automatically decomposition of signals and separation of superimposed waveforms.

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With the development of analysis and research, the main ways of decomposition are needle electrode electromyogram (NEMG) signals decomposition and SEMG signals decomposition. Compared with NEMG signal, SEMG signal has non-invasive, fast, coordinated and other characteristics, becoming the mainstream in recent years in many areas. Because of its MUAP and more superimposed waveform, signal to noise ratio(SNR) less and more complex waveforms , SEMG decomposition is still the problem of EMG research, and its stability and accuracy are to be further improved. Therefore, in decomposition research, we lead into improved Artificial Neural Network to decompose completeness and accuracy for purpose, which is more suitable for clinical study of a single block of muscle [5]. For researching the above factors of influence decomposition results, firstly, we improve SNR of the SEMG signal and reduce the impact of ambient noise and other interference factors by wavelet noise reduction method. Secondly, using high-low frequency wavelet coefficients goes to characterize the active segment, such that the extracted feature value can contain more information related to the active segment. At last, in order to achieve the integrity of SEMG signal decomposition work, we will do secondary cluster for superimposed waveform.

2. EMG Generation Principle

SEMG signal is generated by a series of MUAP and noise of actual measurement the merge. Multiple MUAP's collection produce MUAPT, and they are also superposition generated by single fiber action potentials (SFAP) of all muscle fibers of the same MU in the detection [6]. So its formation mechanism is inseparable with muscle contraction, organizational variation and nervous system control, yet understanding the relationship between them is the basic premise of SEMG of our analysis and decomposition.

Physiological layer EMG model [7] is to use mathematical functions to describe the above generating process of SEMG signal, diagram of Physiological layer SEMG model as shown in Figure 1.

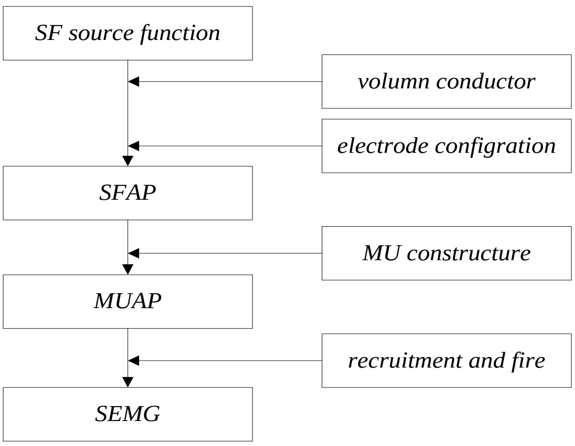

Figure 1. Principle Diagram of Physiological Layer SEMG Model

Where the source function refers to the intracellular action potential (IAP) and transmembrane current, In the EMG model, General using Airspace mathematical functions, which is proposed by Rosen falck, describe IAPs waveform of muscle fibers along the Z axis:

$$V_m(z) = \begin{cases} Az^3e^{-z} - B, z > 0 \\ 0, z \le 0 \end{cases} \tag{1}$$

Muscle can cause single motor neuron excitability in motion, leading to excitation-contraction of related muscle fibers. Therefore, the basic functional unit of muscle fibers involved in muscle movement composed is defined as MU. And the generated potential spatially superimposed, as shown in Figure 2.

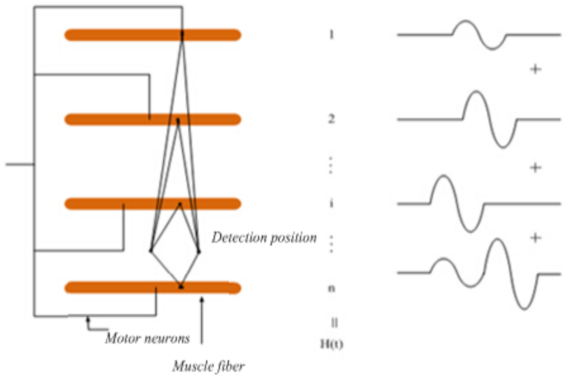

Figure 2. MUAP Generation Principle Diagram

Where 1 to n are the muscle fibers of the close proximity, h(t) stands for MUAP, when Muscle excitation-contraction produces SEMG signal, MUAP of all the excitement muscle fibers show superposition results in the detection[8]. Therefore, the basic components of SEMG are MUAP. In different MU, the excitement is almost synchronous, but is independent each other, composed as shown in Figure 3.

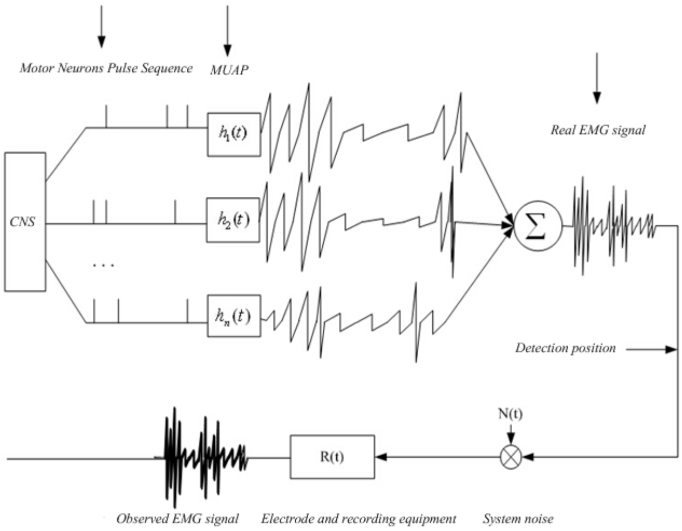

Figure 3. SEMG Generation

3. EMG Signal Processing

3.1. Pretreatment of EMG Signal

SEMG is a weak bioelectric signal, and its acquisition process is susceptible to interference from ambient noise. In order to improve SNR with little destroy the MUAP waveform, we remove frequency interference of the data, high-frequency noise and baseline drift part. In the paper, using wavelet transform does wavelet decomposition for signals. According to the different performance of wavelet spectrum, we remove spectral components generated by the noise, preserving a small spectrum of the original signal, and then reconstruct the original signal to obtain signal after reducing noise [9, 10].

SEMG frequency probably concentrates in 6 to 500Hz, so we select db5 wavelet as wavelet function. If f(i) is sampling signal. e(i) stands for white Gaussian noise or high-frequency signal, s(i) is Useful signal, we can get Formula(2):

$$s(i) = f(i) + e(i), i = 0,1,2...,n-1 \tag{2}$$

s(i) signals is decomposed into three layer, obtaining the decomposition process shown in Figure 4 .

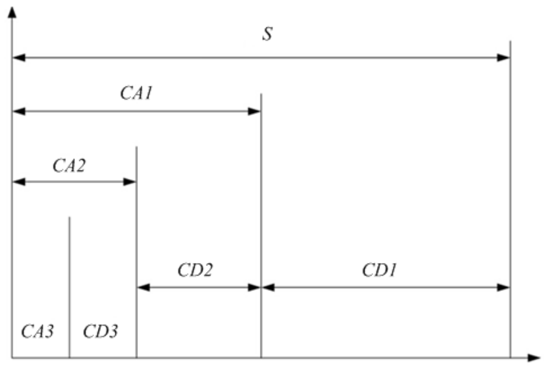

Figure 4. Three Layers Decomposition Process of Wavelet

Due to the high frequency signal, decomposition is not completely useless. Therefore, selecting a threshold value for each layer of high frequency coefficients execute threshold quantization. In the paper, in order to avoid shock, we use soft threshold value to deal with it, which is selected for a given threshold, as shown in the following equation:

$$\begin{cases} \mathrm{y} = \mathrm{sign(x)}(|\mathrm{x}| - \Delta\mathrm{x}), |\mathrm{x}| > \Delta\mathrm{x} \\ 0, \mathrm{e}lse \end{cases} \tag{3}$$

According to the low-frequency coefficients of the N layer of wavelet decomposition and high-frequency coefficients of the N layer after the quantization process, we execute one-dimensional signal wavelet reconstruction to achieve the purpose of de-noising, waveform reconstructed as follows Formula(4):

$$\mathrm{c}_{\mathrm{k+1,n}} = \sum_{1} (p_{\mathrm{n-21}} c_{k,1} + \mathrm{q}_{\mathrm{n-21}}\, d_{k,1}) \tag{4}$$

Where $c_{k,n}$ is the low frequency signal of the k layer, and $d_{k,n}$ is the high frequency signal of the k layer.

3.2. Activities Segment Extraction

Activities segment contains at least signal fragment of one MUAP, while the remaining portions, which are the noise and the background signal, are not considered by us. The purpose of extraction is to obtain the most effective data in the shortest time and excessive signal, which can get more accurate extraction. In this section, signal amplitude is set a threshold value, and we select greater than the threshold value as the active segment [11]. Amplitude and mean square value are judged simultaneously by this process, it not only clips signal segment only containing noise, but also determine the signal segment only containing baseline drift. Sliding window is shown below.

$$\begin{cases} V_{pi} = Max(X_{ij}) - Min(X_{ij}) \\ V_{di} = \dfrac{1}{m}\sum_{j=1}^{m}(X_{ij} - \overline{X_i})^2 \end{cases} \tag{5}$$

Where X_{ij} is the waveform sampling point value within the window, $\overline{X_i}$ stands for the average value of the signal within the window, m stands for the data point within the window. Each movement 10 points by command sliding window detect the collected signals, if the signal of two consecutive windows satisfies the following formula (6), the collected signal will contain MUAP.

$$\begin{cases} V_{pi} > V_{p\max} / Th_{pi} \\ V_{di} > V_{d\max} / Th_{di} \end{cases} \tag{6}$$

Maximum T_{med} near the window is set as the center, the two sides take 10ms as a preselecting active segment, and this segment of the signal is align processed so that we can further interception ,which determines the desired activity segments, avoiding variability of the SEMG itself.

$$T_{med} = \begin{cases} T_{a\max}, V_{a\max} > Th_{mn} \cdot V_{a\min} \\ T_{a\min}, V_{a\min} > Th_{mn} \cdot V_{a\max} \\ (T_{a\max} + T_{a\min})/2, else \end{cases} \tag{7}$$

3.3. Feature Extraction

The active segments need to feature extraction before clustering and the different scales wavelet coefficient is filtrated. The original signal is replaced by wavelet coefficient responding the characteristics of signals, which slows down the intensity of operation and enhances computational efficiency and decomposition accuracy. In the paper, wavelet transform based on the time-frequency analysis. The db5 wavelet is chosen to make a decomposing of three layers on multichannel active segments, which is described in Formula (8) then coefficient of low frequency is extracted as new eigenvector.

$$WT_s(c,b) = \frac{1}{\sqrt{c}}\int_{-\infty}^{+\infty} s(t)\psi\left(\frac{t-b}{c}\right)dt, c > 0 \tag{8}$$

Where $\psi(t)$ stands for wavelet basis function, b is time displacement and c is Scale expansion. Feature extraction includes the decomposition and reconstitution of wavelet, which is similar to pretreatment. The collection of subspace coefficient described as $\{x_i, i = 1,2,...,n\}$ in different scales is attained after wavelet transform. In order to gain the local information of time-frequency for original signal, the vector quantity is filtrated based on the character of least energy through smoothness signals and detail signals in various scale space. Finally, the energy of wavelet coefficient optimized is chosen as feature value, which is described as follows:

$$F = [\log(\frac{1}{N_i}\sum_{j=1}^{N_i}|S_i(j)|^2)], \quad \mathrm{i} = 1,...,\mathrm{n}+1 \tag{9}$$

Where N_i is the length of frequency band for wavelet coefficient described as S_i .

3.4. The Training of Neural Network

The model of neural network composed of many mathematicization nerve cell is a classifier with self-learning ability and adaptively. The model is widely applied in the areas of classification and identification for signals. The neural network includes ART network, Hopfield network, self-organizing network and BP neural network. The structure chart of BP neural network applied the most widely is shown in Figure 5. The input layer is the initial information imported in the network, the hidden layer is determined by the input layer and its linked weights and the output layer is determined by the hidden layer and the linked weights of the output layer. The route of transmission is clearly visible.

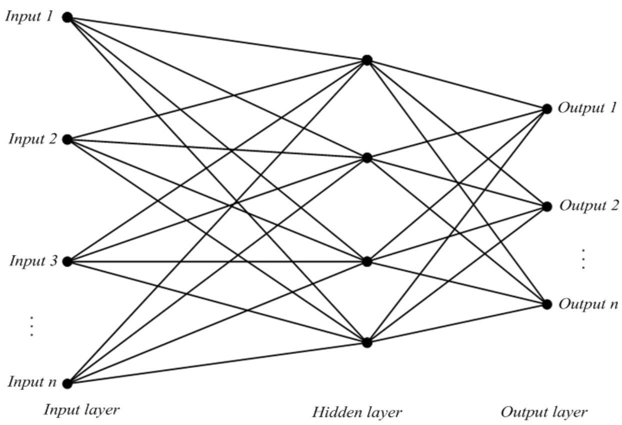

Figure 5. The Structure of Neural Network

The transmission function of BP neuron, whose learning algorithm includes unsupervised learning and supervised learning, is nonlinearity. The supervised learning, the operation of network training of which is complex but valid, is shown in Figure 6. In the paper, the decomposing of SEMG is based on the neural network of the supervised learning.

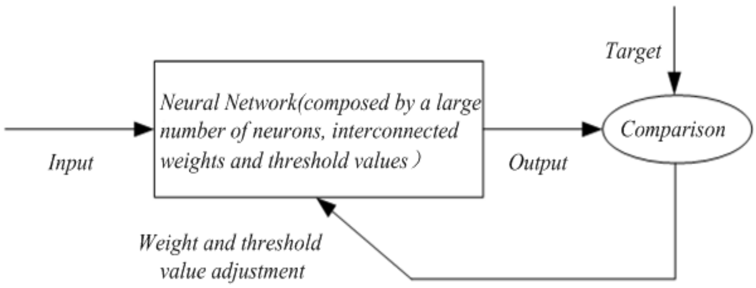

Figure 6. Principle Diagram of Supervised Learning

It is trained to achieve the learning and correction of threshold value and weight after the structured is determined, which is described as follows:

(1)Firstly, the linking weight belonging the section of (-1, 1) is assumed as random number and e is the sign of error function. Then we can calculate the accuracy value described as ε and the maximum of learning number described as M.

(2)Calculate the expected output described as $x(k)$ and $d_0(k)$ of the kth input samples, and the input and output of various neurons between the hidden layer and the output layer, which is described as follows:

$$hi_h(k) = \sum_{i=1}^{n} w_{ih} x(k) - b_h, h = 1,2,..., p \tag{10}$$

$$ho_h(k) = f(hi_h(k)), h = 1,2,..., p \tag{11}$$

$$yi_o(k)=\sum_{h=1}^{p}w_{ho}ho_h(k)-b_o, o=1,2,...,q \quad (12)$$

$$yo_o(k)=f(yi_o(k)), o=1,2,...,q \quad (13)$$

(3)The partial derivative of the hidden layer described as $\delta_h(k)$ is calculated by the partial derivative of the output layer described as $\delta_o(k)$. The linking weight described as $w_{ho}(k)$ is revised, which is described in Formula (14).

$$w_{ho}^{N+1}=w_{ho}^{N}+\eta\delta_o(k)ho_h(k) \quad (14)$$

(4)So the global error is described in Formula (15).

$$E=\frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}(d_o(k)-y_o(k))^2 \quad (15)$$

(5)If the error reaches to the given precision range or it is greater than the maximum of learning number, the calculation is stopped. If the above-mentioned condition doesn't exist, the next new sample is trained.

3.5. The Combination of Template and the Classification of Active Segments

Most of templates are classified after the clustering classification [12], but individual signals are divided into more than two MUAPTs by a MUAPT, because the center of clustering is greater than original number of MUAPT. MUAPTs need to be combined to avoid the error. The paper adopts the Euclidean distance between templates. The algorithm is widely applied the combined of signals, the similarity degree lies in acceptable range. The effect of the algorithm is decided by the choosing of threshold value, which means that it is decided by the corresponding relation of the least Euclidean distance between the active segments and remaining templates. Tm1 is assumed as Relative threshold and Tm2 is assumed as absolute threshold. The interaction between two thresholds avoids the erroneous judgment.

The sectional active segments still didn't find their classifications after the templates are combined. So it is necessary to classify the active segments. In the paper, the recognition algorithm with supervision order is adopted to recognize the active segments without classifications, which is described as follows:

(1)The mean of needing to be classified described as TM_k and the used templates described as T_k is calculated by giving moment, which is shown in Formula (16) and Formula (17).

$$T_k=(1-k_t)\times T_{ok}+k_t\times TM \quad (16)$$

$$TM_k=mean\{Acs_j, i\in T\phi_{kt}\} \quad (17)$$

Where k is tracking coefficient, TM is the mean of active segment wave, and $mean\{\cdot\}$ stands for the average calculating operation, $T\phi_{kt}$ stands for N_r elements closed to t_0 among ϕ_k , k_t is the sign of tracking sensitivity for templates, N_T is the sign of smoothness degree of noise and N_T is positive integer greater than one.

(2)The Euclidean distance described as d_{1k} and the area difference described as d_{2k} of the active segments and the corresponding template described as T_k is calculated. The comparability measurement described as ξ is calculated by the active segments and the corresponding template described as T_k, then the minimum value described as ξ_j and the second minimum value described as ξ_i can be found.

(3)When the active segments satisfy the conditions of $\xi_j < sThr1$ and $\xi_j < sThr2 * \xi$, it is the jth template. The giving moment described as $\phi_k = \{t_{k1}, t_{k2}, ..., t_{kS_k}\}$ of te active segments and the number described as $T\phi_k$ are adjusted. The template after adjusting is T_{nk}.

(4)The four steps mentioned above are calculated repeatedly and the classification of the active segments is over after all signals are calculated. Then the MUAP classification of signals decomposed approximately is gained.

It is certain to include missing and issuing of identify the raise in the residual signal after the template is combined. Therefore, the classification of the active segments is called the second cluster in practical operational.

4. The Results and the Analyses

SEMG is collected according to EMG collection equipment called JE-TB, whose system is stable, reliable, scientific and flexible. The equipment is widely applied in many areas, such as clinical rehabilitation, the collection and analysis of EMG signal, sports research and so on. SEMG comes from the bicipital muscle of the upper arm for male tester without the history of muscle disease. A length of SEMG of tester in the condition of maintaining medium-low level contractility and SEMG after reducing noise are shown in the right side of Figure 7. From the figure, we can find the SEMG after reducing noise, whose SNR is 13.57dB, is similar to original one, but it becomes clearer.

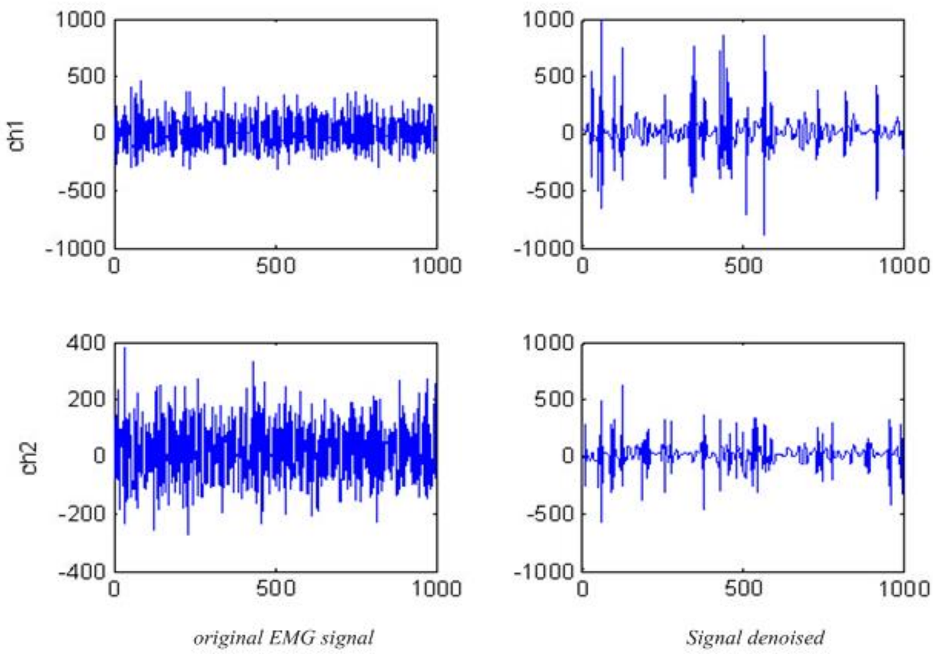

Figure 7. SEMG after Reducing Noise

Then we can calculate that the threshold value of range for SEMG is 0.1158 and that of length is 20ms. 60 active segments are cut from the SEMG undergoing pretreatment, which is shown in Figure 8.

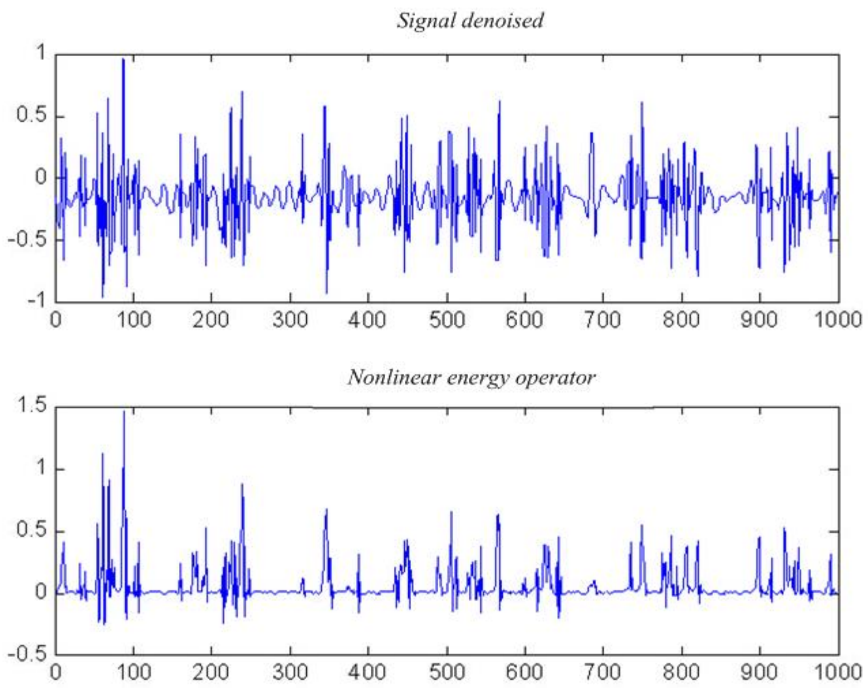

Figure 8. The Active Segments Extraction of SEMG

The characteristic value of wavelet coefficients collected and is classified according to wavelet neural network. Seven MUAP waves are attained. From the Figure 9, we can find that the same category MUAP waves are relatively similar and the otherness is existed among the different ones, which explains the correctness of the algorithm while resolving low contractility SEMG.

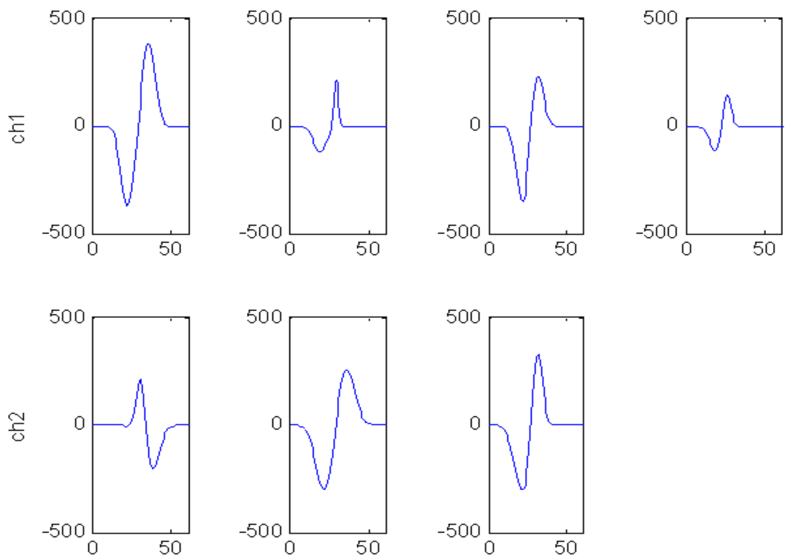

Figure 9. SEMG Cluster Centers

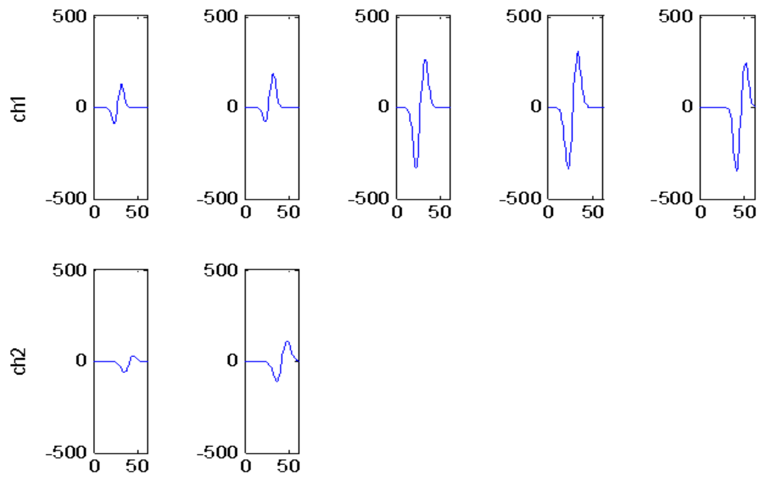

Figure 10. Compared by SEMG the Two Cluster Centers

Table 1. Two-channel Decomposition Results

Recognition MU	MU1	MU2	MU3	MU4
Correct rate	0.86	0.92	0.94	0.91

The final result of SEMG decomposition is shown in Figure 10. Some samples belong to the overlapped waves after the active segments are classified, which has a little influence on the total signals. So two clustering analysis are the final result of decomposition for single-guide SEMG. The statistic analysis of decomposition result is shown in Table 1 in order to obtain the relationship of two-channel decomposing, which indicates the superior correctness of decomposition.

5. Conclusion

In the paper, two-channel SEMG are studied. The way of decomposing SEMG based artificial neural network is discussed completely and the application of SEMG are also mentioned. The paper made a preliminary study on the composing process of SEMG, the optimization of BP algorithm and the other problems. The work is aimed at increasing accuracy rate and instantaneity of decomposition template. The experimental result indicates that the way gained upper accuracy rate and is appropriate for the decomposition of SEMG with medium- low level contractility.

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