Pattern Recognition of Human Grasping Operations Based on EEG

Xiao Dong Zhang and Hyouk Ryeol Choi*

Abstract: The pattern recognition of the complicated grasping operation based on electroencephalography (simply named as EEG) is very helpful on realtime control of the robotic hand. In the paper, a new spectral feature analysis method based on Band Pass Filter (simply named as BPF) and Power Spectral Analysis (simply named as PSA) is presented for discriminating the complicated grasping operations. By analyzing the spectral features of grasping operations with the use of the two-channel EEG measurement system and the pattern recognition of the BP neural network, the degree of recognition by the traditional spectral feature method based on FFT and the new spectral features method based on BPF and PSA could be compared. The results show that the proposed method provides highly improved performance than the traditional one because the new method has two obvious advantages such as high recognition capability and the fast learning speed.

Keywords: Band pass filter, electroencephalography, grasping manipulation, pattern recognition, power spectral analysis.

1. INTRODUCTION

In the last decades, a number of methods for feature extraction and pattern recognition using EEG have been presented. Almost all have to do with diagnosis of the human brain or neural system, or the pattern recognition of simple mental tasks. However, the pattern recognition of complicated grasping operations based on EEG has never been reported.

Recently, Richard *et al.* proposed a conceptual schema on the control system of neuro-prosthesis using EEG measurement signal [1]. The new system indicates that there is a relation between human hand movements and the EEG signals related. Christoph *et al.* discussed the rapid prototyping of an EEG-based Brain-computer Interface (BCI), which could discern the imagined task, either left or right hand movement using an adaptive autoregressive model and linear discrimination analysis [2]. Ramoser *et al.* presented an approach on optimal spatial filtering of a single trial EEG during an imagined hand movement [3], and Bianchi *et al.* investigated the time frequency analysis and spatial filtering questions in the evaluation of the event related synchronization in the beta rhythm corresponding to finger movements [4]. Erfanian and Gerivany discussed that EEG signals and an enhanced resource-allocating neural network could be used to detect the voluntary hand movements [5]. Mahmoudi and Erfanian presented a new research question on a single-channel EEG-based prosthetic hand grasp control for amputee subjects [6]. Kurillo *et al.* analyzed electroencephalographic correlation during Grip-force Tracking, and suggested different correlation analysis results between grasping and relaxation [7].

To apply EEG signals in the realtime control of the robot hand, we propose a new approach based on spectral feature analysis and artificial neural network, which has successfully finished the EEG-based classification of hand movements and the other usual accompanying mental tasks, such as blinking eyes, watching red color, and listening music [8,9]. The spectral feature analysis of the proposed approach is concerned with the traditional spectral features of five segments including frequency components δ, θ, α, β, and γ. And it is very effective for the pattern recognition of the different mental tasks mentioned above. However, the spectral feature analysis and its recognition model are difficult to apply to the pattern recognition of complicated grasping operations because these operations produce the similar EEG signals of the spectral features.

Millan *et al.* reported a new approach on Noninvasive Brain-Actuated Control of a Mobile Robot by Human EEG in recent reports [10]. Because

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δ wave of EEG signal is primarily associated with deep sleep, and Θ wave appears as consciousness slips toward drowsiness, they suggested that the δ wave and Θ wave of the EEG signal should be cancelled during the pattern recognition of the mobile robot movement, and applied the concept to realize the classification of the complicated mental tasks including "Left turn", "Right turn", and "Forward movement".

Similarly, human grasping operations are also a more complicated mental tasks like upper mobile robot movements and thus, we present a new spectral feature analysis method based on BPF and PSA. Because it actively deletes the δ wave and Θ wave of the EEG signal by the band pass filter with 8-40Hz, and only provides clearer spectral features with 3 segments by power spectral analysis, the new spectral feature analysis method is better than the traditional spectral feature analysis method.

This paper is organized as follows. In Section 2, the traditional spectral feature method based on FFT is described in details. Based on this method, a new spectral feature method based on BPF and PSA are discussed for the pattern recognition of complicated grasping operations. In Section 3, a two channel EEG measurement system is established for collecting the EEG signals of the operation tasks and completing their pattern recognition. In Section 4, the four basic hand operations are discussed as the objective of recognition. In Section 5, the three typical grasping manipulations are discussed as the objective of recognition, and the results are discussed. Finally, the conclusions of our investigation are presented in Section 6.

2. SPECTRAL FEATURE ANALYSIS METHODS

2.1. Traditional spectral feature based on FFT

As well known, the discrete Fourier Transform algorithm is written as follows.

$$X(n\Delta f) = \sum_{k=0}^{N-1} x(k\Delta t) e^{-j2\pi kn/N}, \tag{1}$$

where N is the total number of the signal discrete points. k, n are the variables of the discrete point, and k, n =0, 1, ..., N-1. Δt and Δf denote the time interval size and the frequency interval size of the discrete signal, respectively. $x(k\Delta t)$ and $X(n\Delta f)$ represent the discrete value of the signal at the kth point in the time-domain and the nth point in the frequency-domain, respectively.

With the fast development of digital signal processing technology, the Fast Fourier Transform algorithm (FFT) is usually used to realize the transform from $x(k\Delta t)$ to $X(n\Delta f)$ above.

According to the general feature of the EEG signal, the wave more than 40 Hz is thought as a noise from EMG, and there are five basic frequency components for the valuable wave less than 40 Hz, which are usually defined as follows.

(1) δ - delta wave with 0.5~4 Hz
(2) θ - theta wave with 4~8 Hz
(3) α - alpha wave with 8~14 Hz
(4) β - beta wave with 14~30 Hz
(5) γ - gamma wave with 30~40 Hz

So we can divide the frequency domain into the five effective frequency segments for the traditional spectral feature analysis method. With the following definitions,

$$n_0\Delta f \triangleq 0.5,\ n_1\Delta f \triangleq 4,\ n_2\Delta f \triangleq 8,\ n_3\Delta f \triangleq 14,\ n_4\Delta f \triangleq 30, \tag{2}$$

then the maximum amplitude x_1^*, x_2^*, x_3^*, x_4^* and x_5^* in these segments can be defined as follows.

$$x_1^* = \underset{n=n_0}{\overset{n=n_1}{Max}}\{X(n\Delta f)\}, \tag{3}$$

$$x_2^* = \underset{n=n_1+1}{\overset{n=n_2}{Max}}\{X(n\Delta f)\}, \tag{4}$$

$$x_3^* = \underset{n=n_2+1}{\overset{n=n_3}{Max}}\{X(n\Delta f)\}, \tag{5}$$

$$x_4^* = \underset{n=n_3+1}{\overset{n=n_4}{Max}}\{X(n\Delta f)\}, \tag{6}$$

$$x_5^* = \underset{n=n_4+1}{\overset{n=N-1}{Max}}\{X(n\Delta f)\}. \tag{7}$$

In order to generalize the power distribution of these maximum spectral features above, variables are defined as follows.

$$x_T \triangleq x_1^* + x_2^* + x_3^* + x_4^* + x_5^*, \tag{8}$$

$$x_1 \triangleq x_1^* / x_T, \tag{9}$$

$$x_2 \triangleq x_2^* / x_T, \tag{10}$$

$$x_3 \triangleq x_3^* / x_T, \tag{11}$$

$$x_4 \triangleq x_4^* / x_T, \tag{12}$$

$$x_5 \triangleq x_5^* / x_T, \tag{13}$$

and then the spectral feature vector **X** is also obtained as

$$\mathbf{X} = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5]^T. \tag{14}$$

According to the variable definition and the equation deduction above, x_1, x_2, x_3, x_4, and x_5 denote the percentage of the frequency components δ, θ, α, β, and γ in all the spectrum of the EEG signal, respectively. So the spectral feature vector **X** represents the distribution rule about the spectral features of the EEG signal.

2.2. New spectral feature based on BPF and PSA

The traditional spectral features with 5 segments above can be successfully applied to the pattern recognition of the hand movements, but it is very difficult to apply the features realizing the pattern recognition of the complicated grasping operations. So, the new spectral feature analysis method was investigated as follows.

2.2.1 Band pass filter

The Band Pass Filter with pass band domain $[f_i, f_j]$ using FFT algorithm may be designed as follows.

The first step is the FFT transform of the signal *x(t)* as (1) above. According to the pass band domain $[f_i, f_j]$, the results of the FFT transform should be set, respectively. For the following definitions,

$$n_i\Delta f \triangleq f_i,\ \ n_j\Delta f \triangleq f_j, \tag{15}$$

when $n = n_i, \cdots, n_j$, the following equation is obtained.

$$X^*(n\Delta f) = X(n\Delta f). \tag{16}$$

Otherwise, when $n = 0, \cdots, n_{i-1}$ and $n = n_{j+1}, \cdots, N-1$, its value is 0 as follows.

$$X^*(n\Delta f) = 0. \tag{17}$$

The last step is to use Inverse Fast Fourier Transform (IFFT) such as

$$x^*(k\Delta t) = \frac{1}{N}\sum_{n=0}^{N-1} X^*(n\Delta f)e^{j2\pi kn/N}. \tag{18}$$

2.2.2 Power spectral analysis

Based on Fast Fourier Transform and its Inverse Fast Fourier Transform, the following (19) is derived by obtaining absolute values of both-sides Power Spectrum.

$$\begin{aligned}\text{Total Power} &= \frac{1}{N^2}\sum_{n=0}^{N-1}\left|X(n\Delta f)\right|^2 \\ &= \sum_{k=0}^{N-1}\left|x(k\Delta t)\right|^2.\end{aligned} \tag{19}$$

From (19), the sum of the square of the original signals is identical to the square of the spectral signals passed by the Fourier Transform, called Total Power. In other words, the total power of the signals is all the same in time domain and frequency domain according to Parseval theorem [11]. One-side Power Spectrum satisfying this theorem can be defined as follows.

$$\begin{aligned}P(0) &= \frac{1}{N^2}\left|X(0)\right|^2, \\ P(n\Delta f) &= \frac{1}{N^2}\left[\ \left|X(n\Delta f)\right|^2 + \left|X(N\Delta f - n\Delta f)\right|^2\ \right], \\ P(\frac{N}{2}\Delta f) &= \frac{1}{N^2}\left|X(\frac{N}{2}\Delta f)\right|^2,\end{aligned} \tag{20}$$

where n=1, 2, ···, (N/2-1).

2.2.3 New spectral feature

Based on the analysis of many experimental results, we find there are similar distribution rules of the spectral feature for the complicated grasping operations. Moreover, their low frequency components including the δ wave and Θ wave are bigger in the EEG signal. So a new spectral feature analysis method based on BPF and PSA is presented as shown in Fig. 1.

At first, a Band Pass Filter is adopted after the EEG signal is collected by the measurement system, which passes the 8-40Hz specified band domain signal using FFT algorithm, and the other frequency component signals including the δ wave and Θ wave of the EEG signal, and the noise signal more than 40Hz are actively deleted, respectively. And then, the Power Spectral Analysis is adopted for the signal from the BPF. Lastly, the new spectral feature is output for the pattern recognition by Artificial Neural Network.

According to the traditional spectral feature analysis method, and the introduction of BPF and PSA above, for the following definition,

$$n_5\Delta f = 40, \tag{21}$$

the new spectral feature can be gained as follows.

$$x_1^* = \sum_{n=n_2+1}^{n=n_3} P(n\Delta f), \tag{22}$$

$$x_2^* = \sum_{n=n_3+1}^{n=n_4} P(n\Delta f), \tag{23}$$

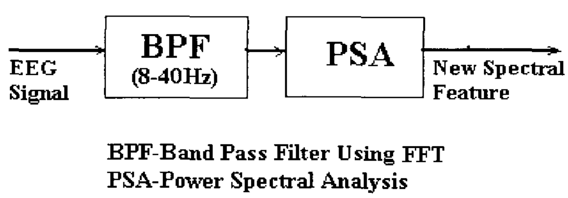


Fig. 1. New spectral feature analysis method based on BPF and PSA.

$$x_3^* = \sum_{n=n_4+1}^{n=n_5} P(n\Delta f). \tag{24}$$

In order to generalize the power distribution of these power spectral features, variables are defined as follows.

$$x_T = x_1^* + x_2^* + x_3^*, \tag{25}$$

$$x_1 = x_1^* / x_T, \tag{26}$$

$$x_2 = x_2^* / x_T, \tag{27}$$

$$x_3 = x_3^* / x_T, \tag{28}$$

and then the new spectral feature vector **X** is also obtained as follows.

$$\mathbf{X} = [x_1 \quad x_2 \quad x_3]^T. \tag{29}$$

According to the variable definition and the equation deduction above, x_1, x_2, and x_3 denote the power spectral percentages of the frequency components α, β, and γ in the EEG signal, respectively.

3. RECOGNITION SYSTEM AND MODEL

3.1. Recognition system

In order to achieve the pattern recognition of some human grasping operations, a two-channel EEG measuring and recognition system is set up in our laboratory. Fig. 2 shows the system, in which a subject is doing the basic hand operation named as relaxation. The schematic of this system is shown as Fig. 3, which clearly depicts that this system mainly includes disk electrode×4, LXEJ102 junction box, QEEG-2 device and a Pentium PC.

On the other hand, the system collects the EEG signal according to the principle of the mono-polar electrode, and the two signal electrodes are actually led out at P3 and P4 from the scalp of the human brain according to the international 10/20 system, and the other two electrodes, called as the reference electrode and the ground one, respectively, are also led out from the two earlobes of the subject.

According to the preliminary experiments, the sampling frequency was set as 256Hz, and the gain was set as 204.2μv during the entire experiment.

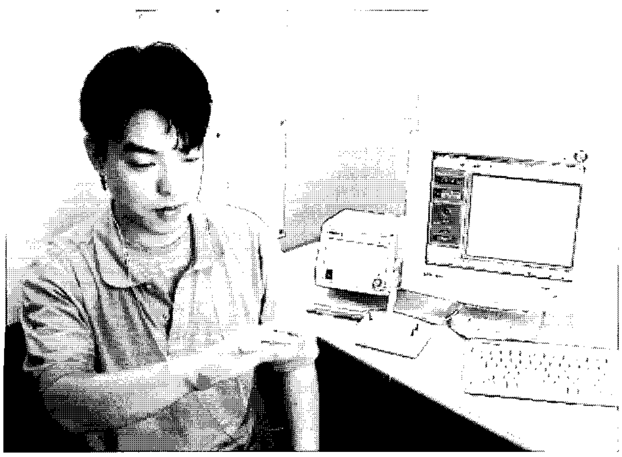


Fig. 2. Recognition scene with a subject.

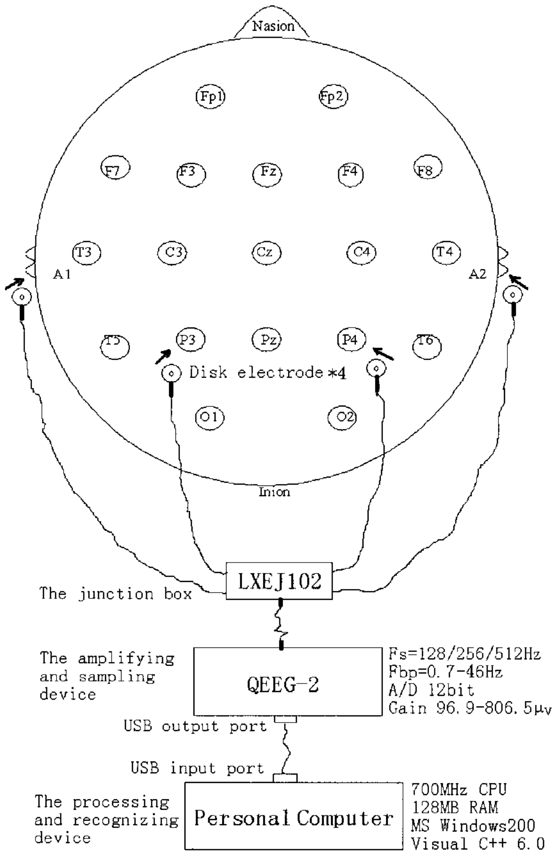


Fig. 3. The schematic of the two channel EEG measurement system.

3.2. Recognition model

A three-layer BP network was selected for the pattern recognition of the complicated grasping operations in this paper, as shown in Fig. 4, and the layers were called the input layer, hidden layer and output layer, respectively.

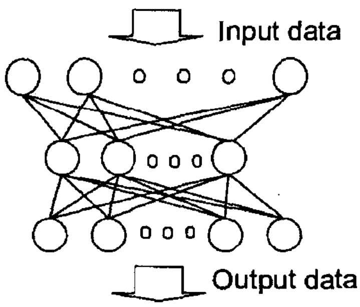


Fig. 4. The typical BP network structure.

The upper layer is the linear input layer with K neurons, and its input data are the traditional spectral features described in (14) or the new spectral features described in (29).

The bottom layer is the non-linear output layer, and its output data should be a vector, which can represent the classified result of the complicated grasping operations. If we define the vector as $\mathbf{Y}$, and there are M mental tasks, then the vector can be described as follows.

$$\mathbf{Y}=[y_1 \quad y_2 \quad \dots \quad y_M]^T, \tag{30}$$

where $y_1, y_2 \cdots, y_M$ denotes the possibilities of the complicate grasping operations, respectively.

The middle layer is the non-linear hidden layer, whose neuron number L is determined by the neuron numbers of the other two near layers as follows.

$$L = \sqrt{K \times M}. \tag{31}$$

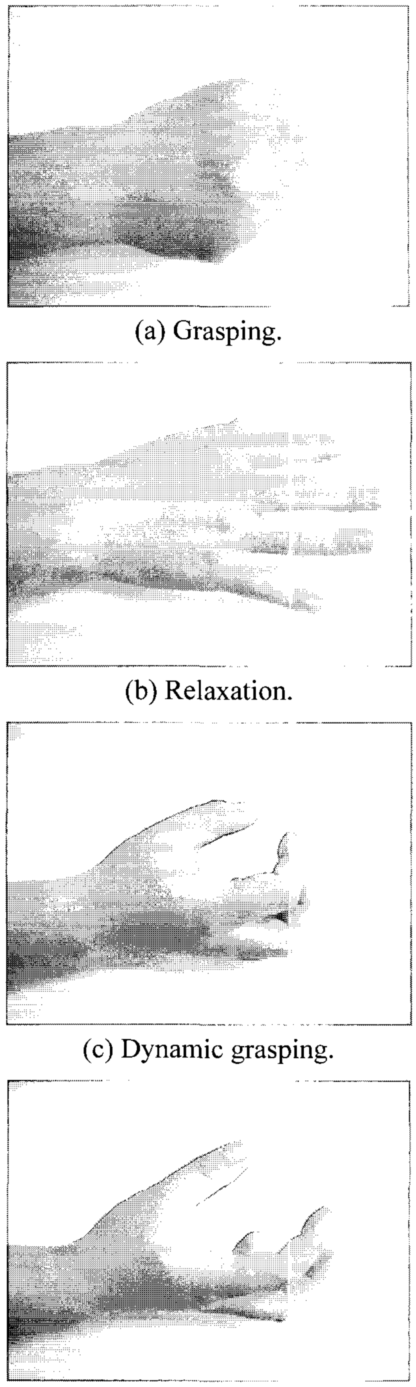
4. RECOGNITION OF FOUR BASIC HAND OPERATIONS

4.1. Feature extraction and learning samples set

For pattern recognition of the complicated grasping operations, the four subjects were at first asked to perform the four basic hand operations as shown in Fig. 5, which include grasping, relaxation, dynamic grasping and dynamic loosing.

Through many experimental tests using the two channel EEG measurement system above, the traditional spectral features and the new spectral features of the four basic hand operations were collected. The learning samples of the BP network for the pattern recognition of these mental tasks were set in Table 1 and Table 2 according to 0/1 fuzzy rule, whose columns on the left side express the spectral features of every basic hand operation, and those on the other side express the possibilities 1 or 0 of every basic hand operation with regard to the four basic hand operations in order, respectively.

For example, there are eight learning samples of the four basic hand operations in Table 1, and for some learning sample such as No.1, its left side shows that five spectral features of grasping operation are 0.740, 0.120, 0.074, 0.051, 0.016, and its right side presents the recognition pattern of the grasping, namely 1, 0, 0, 0. The first is with regard to grasping operation only as 1, and the other three elements are not with regard to the grasping as 0. Furthermore, the other samples in Table1 and Table2 have the similar meaning.



(a) Grasping.

(b) Relaxation.

(c) Dynamic grasping.

(d) Dynamic loosing.

Fig. 5. The four basic hand operations.

4.2. BP network and its sample training

According to the introduction of the recognition model above, while the traditional spectral features based on FFT are used for the pattern recognition of the four basic hand operations, the input layer, the hidden layer and the output layer of the BP network have 5, 4 and 4 neurons, respectively. When the new spectral features based on BPF and PSA are used, the input layer, the hidden layer and the output layer of the BP network have 3, 4 and 4 neurons, respectively.

We applied the learning samples described in Table 1 and Table 2 to the BP network for sample training. According to the experience, the training parameters are selected in Table 3.

Table 1. The learning samples of the four basic hand operations using the traditional spectral features based on FFT.

Input X						Output Y			
Grasping	0.740	0.120	0.074	0.051	0.016	1	0	0	0
Grasping	0.765	0.106	0.069	0.046	0.012	1	0	0	0
Relaxation	0.695	0.120	0.096	0.061	0.028	0	1	0	0
Relaxation	0.818	0.076	0.059	0.033	0.014	0	1	0	0
Dynamic grasping	0.405	0.132	0.065	0.230	0.167	0	0	1	0
Dynamic grasping	0.558	0.118	0.045	0.166	0.112	0	0	1	0
Dynamic loosing	0.440	0.112	0.158	0.177	0.113	0	0	0	1
Dynamic loosing	0.534	0.111	0.117	0.181	0.058	0	0	0	1

Table 2. The learning samples of the four basic hand operations using the new spectral features based on BPF and PSA.

Input X				Output Y			
Grasping	0.526	0.382	0.091	1	0	0	0
Grasping	0.549	0.377	0.073	1	0	0	0
Relaxation	0.563	0.326	0.105	0	1	0	0
Relaxation	0.600	0.308	0.088	0	1	0	0
Dynamic grasping	0.186	0.562	0.251	0	0	1	0
Dynamic grasping	0.189	0.575	0.235	0	0	1	0
Dynamic loosing	0.308	0.430	0.185	0	0	0	1
Dynamic loosing	0.374	0.501	0.109	0	0	0	1

Table 3. The training parameters of the BP network.

THE MOMENTUM RATE	THE LEARNING RATE	THE MAX TOTAL ERROR	THE INDIVIDUAL ERROR	THE MAX NUMBER OF ITERATION
η	α	E	e	N
0.9	0.7	0.01	0.001	10000

Based on the training parameters in Table 3, the training procedure of the BP network for the four basic hand operations are shown in Fig. 6. Through the comparing analysis of the training processes, for the new spectral features based on BPF and PSA, when the iteration number reached 588, the training procedure was completed with the total error of 0.009997602. On the other hand, for the traditional spectral features based on FFT, when the iteration number reached 3681, the training procedure was completed with the total error of 0.009969781. The result showed that as the learning samples of the BP network, the new spectral feature gave 6 times higher training speed than the traditional spectral feature.

4.3. Recognition results

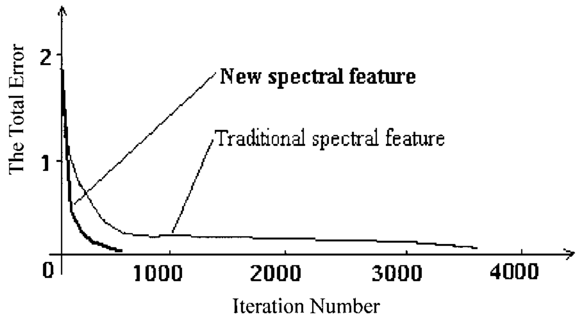


Fig. 6. The training process of BP network for the four basic hand operations.

Table 4. The recognition results of the four basic hand operations.

Feature Kind	Grasping	Relaxation	Dynamic Grasping	Dynamic Loosing
New Spectral Feature	80%	80%	90%	90%
Traditional Spectral Feature	50%	50%	60%	60%

where the recognition possibilities is based on 10 samples to be recognized, in the meantime, for every sample, we think the recognition result is right if the biggest element is more than 0.75 and it matches the operation task to be recognized; otherwise, it is wrong.

After the sample training was over, we still collected the 10 new spectral features and the 10 traditional spectral features for every basic hand operation, and input them into the BP network, respectively. The recognition results of the BP network are shown in Table 4.

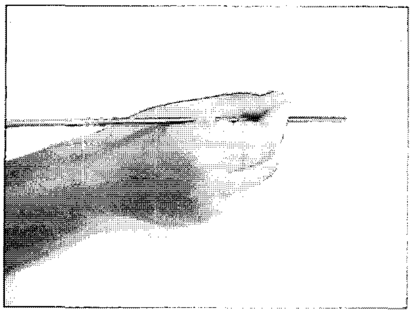
Table 4 shows that as recognition features, the new spectral features gave higher recognition possibilities than the traditional spectral features did, and the recognition possibility was improved from 50%, 50%, 60%, and 60% to 80%, 80%, 90%, and 90% for grasping, relaxation, dynamic grasping, and dynamic loosing of the basic hand operations, respectively.

5. RECOGNITION OF THREE TYPICAL GRASPING MANIPULATIONS

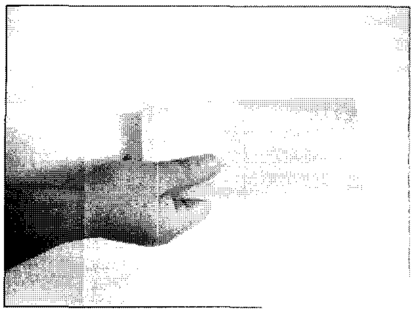
5.1. Feature extraction and learning samples set

On the basis of the recognition above, the four subjects were also asked to perform three typical grasping manipulations as shown in Fig. 7, which include grasping a small bar, a hard paper, and a baseball.

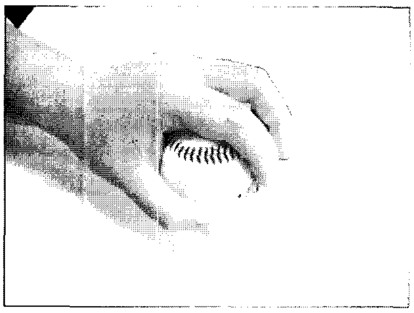
Using the same approach above, the traditional spectral features and the new spectral features of the three typical grasping manipulations were collected, and their learning samples were set in Table 5 and Table 6 according to 0/1 fuzzy rule, respectively.



(a) Grasping a small bar.



(b) Grasping a hard paper.



(c) Grasping a baseball.

Fig. 7. The three typical grasping manipulations.

Table 5. The learning samples of the three typical grasping manipulations using the traditional spectral features based on FFT.

Input X						Output Y		
A small bar	0.808	0.095	0.050	0.031	0.016	1	0	0
A small bar	0.855	0.055	0.057	0.022	0.011	1	0	0
A hard paper	0.679	0.079	0.176	0.048	0.018	0	1	0
A hard paper	0.707	0.071	0.159	0.046	0.017	0	1	0
A baseball	0.855	0.086	0.030	0.023	0.007	0	0	1
A baseball	0.861	0.078	0.029	0.024	0.007	0	0	1

5.2. BP network and its sample training

If the traditional spectral features based on FFT were used for the pattern recognition of the three typical grasping manipulations, the input layer, the hidden layer and the output layer of the BP network had 5, 4 and 3 neurons, respectively. However, when the new spectral features based on BPF and PSA were used, the input layer, the hidden layer and the output layer of the BP network had 3, 3, and 3 neurons, respectively.

Using the same training parameters as the pattern recognition of the four basic hand operations in Table 3, the training procedure of the BP network for the three typical grasping manipulations are shown in Fig. 8. The training effects were similar to those of the four basic hand operations. For the new spectral features, when the iteration number reached 583, the training procedure was completed with the total error of 0.009998503. On the other hand, for the traditional spectral features, when the iteration number reached 1330, the training procedure was completed with the total error of 0.009947825. The result showed that as the learning sample of the BP network, the new spectral feature gave two times higher training speed than the traditional spectral feature did.

Table 6. The learning samples of the three typical grasping manipulations using the new spectral features based on BPF and PSA.

Input X				Output Y		
A small bar	0.528	0.359	0.106	1	0	0
A small bar	0.613	0.301	0.076	1	0	0
A hard paper	0.733	0.200	0.052	0	1	0
A hard paper	0.732	0.211	0.049	0	1	0
A baseball	0.495	0.421	0.083	0	0	1
A baseball	0.469	0.432	0.098	0	0	1

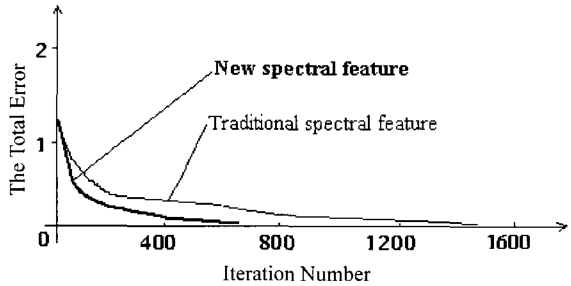


Fig. 8. The training process of BP network for the three grasping manipulations.

Table 7. The recognition results of the three typical grasping manipulations.

Feature Kind	Grasping a small bar	Grasping a hard paper	Grasping a baseball
New Spectral Feature	80%	80%	80%
Traditional Spectral Feature	40%	50%	40%

The definition of the recognition possibilities is the same as that in Table 4.

5.3. Recognition results

As the same situation, we also collected 10 new spectral features and 10 traditional spectral features for every grasping manipulation, and input them into the BP network, respectively. The recognition results of the BP network are shown in Table 7.

Table 7 shows that as the recognition features, the new spectral features gave higher recognition possibilities than the traditional spectral features did, and the recognition possibility improved from 40%, 50%, and 40% to 80%, 80%, and 80% for grasping a small bar, grasping a hard paper, and grasping a baseball, respectively.

6. CONCLUSIONS

From the analysis method of the traditional spectral feature based on FFT, a new spectral feature analysis method based on BPF and PSA was presented for the pattern recognition of the complicate grasping operations. The two types of spectral features were tested by using the two channel EEG measurement system and input to the BP network for the recognition analysis. The results showed that the new spectral feature was better than the traditional spectral feature not only for the pattern recognition of the four basic hand operations including grasping, relaxation, dynamic grasping and dynamic loosing, but also for the pattern recognition of the three typical grasping manipulations including grasping a small bar, a hard paper and a baseball.

The new spectral feature has advantages over the traditional spectral feature: higher learning speed during the sample training, and higher recognition possibility for the complicated grasping operations. However, the recognition possibility of both the four basic hand operations and the three typical grasping manipulations by the new spectral feature was only about 80% because of the inherent shortcoming of the analysis method and the unstable measurement of EEG signal. These shortcomings must be overcome by other approaches in the future time so that the EEG signal can be fully applied in the realtime control of the robot hand.

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