



Identification and Classification of Electroencephalogram Signals Based on Independent Component Analysis

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ABSTRACT

This paper aims to develop a desirable EEG-based classification algorithm. For this purpose, the discrete wavelet transform was applied to denoise the EEG signals. Then, the brain's left and right hand movement features were extracted from the denoised signals by the independent component analysis (ICA). Finally, the support vector machine (SVM) classifier was adopted to recognize and classify the movement of the left and right hand actions. The experimental results show that our method achieves the recognition accuracy of 89.5% and 90.6% respectively. The research findings provide a valuable reference for the future research into the BCI system.

Key Words: Electroencephalogram (EEG), Brain Computer Interface (BCI), Independent Component Analysis (ICA), Support Vector Machine (SVM)

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Introduction

For a long time, humans have been longing to unravel the mystery of brain activities. Since the 20th century, the electroencephalogram (EEG) has opened up a new angle into brain research, thanks to the development of electronics, computer, biomedicine and cognitive psychology (Wang, 2017). In recent years, the EEG-based brain-computer interface (BCI) became a research hotspot in rehabilitation and biomedical engineering. (Ma *et al.*, 2007) The BCI establishes a direct communication channel between human brain and the external environment, without relying on the nerves and muscles around normal output channels. Considering the dependence of BCI performance on the classification of EEG data, it is very meaningful to develop a desirable EEG-based classification algorithm.

BCI system

The structure of the BCI system is shown in Figure 1. In general, the BCI system consists of three main parts: the EEG data acquisition module, the signal processing module, and the equipment control module. The EEG data acquisition module, as the input of the BCI system, is formed of the amplifier circuit, the filter, and the D/A conversion circuit. This module is responsible for collecting neural signals. The signal processing module extracts, recognizes and classifies the EEG signals from the electrical activities in the brain, using feature extraction and pattern recognition algorithms. This module is essential to the BCI system, and was selected as the focal point in this research. The equipment control module classifies the control commands in light of the external environment, and thus

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controls the external devices like wheelchairs and electric fans. Overall, the BCI is a novel interactive system that offers a direct channel between human brain and the external electronic devices, with brain signals as information carrier (Liu, 2017). The system does not rely on the normal output channels of the brain. (Cui *et al.*, 2004) The centerpiece of EEG-based BCI is the feature extraction. The selection of proper features and related operations are the difficult technical points.

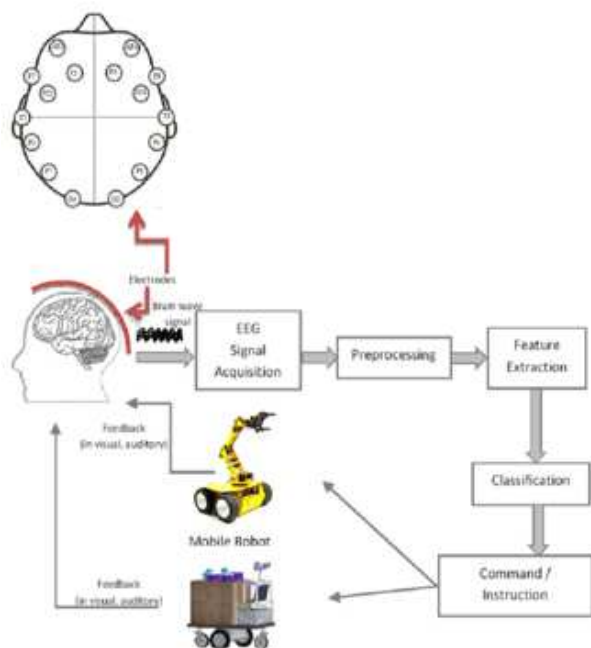


Figure 1. Brain-computer interface system

EEG

The brain electrical signals are important bioelectric signals generated in the spontaneous electrical activities of the central nervous system. The human brain is an extremely complex organ, involving hundreds of billions of neurons. In cerebral cortex alone, there are nearly 140 billion neurons. The most widely accepted theory on the generation of brain electrical signals is the postsynaptic potential theory. The theory holds that the signals are resulted from the combined effect of postsynaptic potentials of numerous cerebral cortex neurons. Neuron is the basic unit of the nervous system. (Ji *et al.*, 2012) The electrical signal of a single neuron cannot be measured by the scalp electrodes, it is mixed thoroughly with the signals from all the other neurons connected to the neuron. When the sum of these signals exceeds a threshold, the neurons

will produce a nerve impulse, forming the EEG signals.

Therefore, the cortical surface potential reflects the total effect of the activities of many neurons. One of the common methods to capture the EEG signals from the spontaneous electrical activities of brain neurons is to place scalp electrodes in different positions of the head. The electrode spacing is set to the voltage of EEG signals, and the potential difference with the reference electrode (Meng and Quyang, 1997). The variation in electrical activities is plotted as the electroencephalogram (EEG), with time series being the x-axis and the time points corresponding to the potentials being the y-axis (Guo, 2017). The EEG wave can be approximated as a sine wave, and the signals can be described with cycle (frequency), amplitude and equivalent parameters. The spontaneous rhythmic electrical activity can be divided into four bands: Delta wave (0.5~3Hz), Theta wave (4~8Hz), Alpha wave (8~13Hz), Beta wave (14~30Hz).

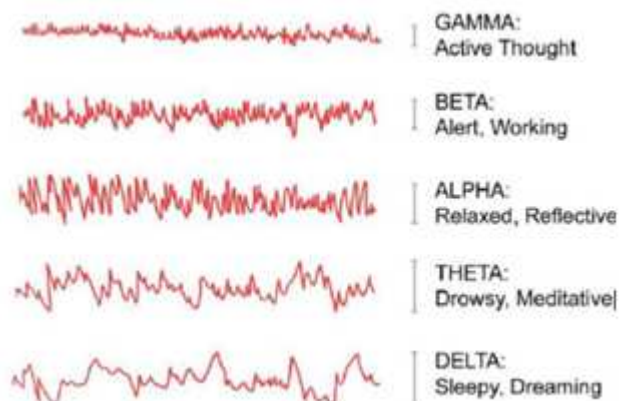


Figure 2. EEG Signals

EEG signal acquisition

The P300 (P3) wave is an event related potential (ERP) component elicited in the cognition process. The ERP, discovered by Sutton *et al.* (1965) refers to any stereotyped electrophysiological response to a stimulus. The P3 wave concentrates in the central cortex area, and peaks at around 300ms after the events. The significance of the wave is negatively correlated with the probability of the relevant events. Since the P3 is an endogenous response, the user of a P3-based BCI system should be trained. Figure 3 lists the data sequences used to stimulate P3 signals. On the screen, a 6x6 matrix of numbers and letters is highlighted randomly by row or by column again and again, aiming to stimulate the



required P3 signals. In the experiment, the subjects need to first think of a letter or number; then, his/her brain will produce the corresponding neural activities when the relevant letter or number is highlighted on the screen. At this moment, the computer will record the time and the intensity of neural activities. In this way, it is possible to know the thoughts of subjects by searching for the highlighted row or column at the excitation of the P3 wave. In light of the above, the potentials that stimulate P3 were adopted as the stimuli for EEG signals (Kemy, 2002).

Before the signal acquisition, it is necessary to upload the facial images of the subjects into the test system. Here, the uploading procedure is realized in the following steps. First, double click Face Reader 6 to open the interface in Figure 2. Then, import different facial images into the software, or take a photo with the camera and make various expressions in 50 seconds. The software can identify the expressions rapidly at an accuracy of 95%. Finally, export the identified expressions in plain text or other data formats, and reserve these data for subsequent facial feature extraction. Figure 3 is the results of facial recognition.



Figure 3. P300 stimulation sequence screen

EEG Denoising

The EEG signals contain useful signals and many noises, such as power frequency interference. This is because brain electrical signals are highly nonstationary and prone to the effects of the external environment. Thus, it is important to filter out the noises without hurting the useful signals. In view of this, the popular wavelet filtering method was employed for EEG denoising. By definition, discrete wavelet transform determines a signal $f(t)$ determined in different sub-bands: j adjusts the signal location in frequency domain, while k adjusts signal

location in time domain. If j has a wide field of vision and low frequency, the transform can output the general information of the signal; if j has a narrow vision and high frequency, the transform can output the details of the signal. In practice, the useful signals and noises can be determined by the scope of bandwidth by wavelet transform formula (1).

$$C_{j+1,m} = \sum \bar{h}(k-2m)C_{j,k}, d_{j+1,m} = \sum \bar{g}(k-2m)C_{j,k} \quad (1)$$

First, the original EEG signals were decomposed into different frequency ranges. Then, the noises were removed according to formula (2).

$$C_{j+1} = HC_j, d_{j+1} = GC_j \quad (2)$$

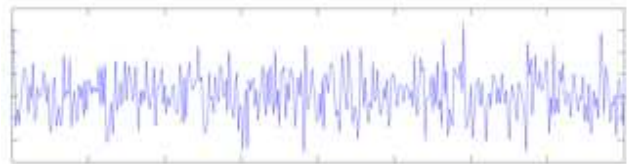


Figure 4. EEG signals the raw data

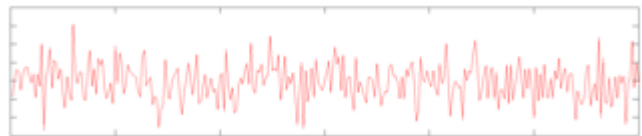


Figure 5. Brain electrical signal denoising

Figure 4 shows the raw EEG data, and Figure 5 presents the denoised signals.

Comparing the two figures, it is clear that the discrete wavelet transform has a good noise.

Independent Component Analysis (ICA)

Let $x(x_1, \dots, x_n)$ be n linear mixed signals, each of which is a mixture of independent random variables $s(s_1, \dots, s_n)$. Then, the mixing matrix can be expressed as formula (3) below.

$$x = As \quad (3)$$

The ICA model is a generative model. It describes the observed data based on the handling of the mixed data S_i . The independent components are hidden variables that cannot be directly observed, and the mixing matrix is unknown. Thus, only the random vector x is observable. The vector should be minimized before estimating A and S under assumed conditions.



In the ICA analysis, the S_i is assumed to be statistically independent and obey non-Gaussian distribution, and the mixing matrix A is assumed to be square. After estimating the mixing matrix A , the independent component of inverse matrix W can be obtained by the following formula:

$$s=Wx \tag{4}$$

After obtaining the independent component, the linear combination x_i can be obtained as:

$$y=W^T x = \sum w_i x_i \tag{5}$$

Thus, there is a backlog of vector W . If W is an inverse matrix, then the linear combination must be an independent component. Since matrix A is unknown, it is impossible to determine the definite value of A , but it is possible to make approximate estimates. If $z=A^T W$, we have:

$$y=W^T x = W^T W^T A = z^T s \tag{6}$$

Where y is the linear combination of S_i , and its weight is assigned by Z_i . Since two random variables are closer to Gaussian distribution, $Z^T S$ is closer to Gaussian distribution than any other S_i . In this case, it is clear that Z_i is the only zero element. Hence, the maximum W can be taken as a vector $W^T X$ of non-Gaussian distribution. Such a vector corresponds to z . Then, $W^T X = z^T s$ is equal to one of the independent component. It is possible to get an independent component using the non-Gaussian maximum $W^T X$.

In this paper, the ICA analysis of the EEG signals is performed on the Matlab. Figure 6 shows the results at the sampling frequency of 250Hz. It can be seen that each sample EEG signal has a certain ability of anti-interference. The second to seventh layers on the right are the decomposed power spectrums of the signals in the first to sixth layers on the left.

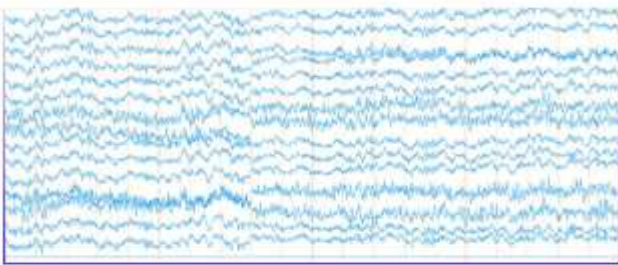


Figure 6. Brain waves in the ICA analysis diagram 6 brain wave shape analysis of ICA

In Figure 7, the red dotted line stands for right hand movement, and the blue line represents left hand movement. It is observed that the EEG signals of different tasks have different rhythms. Compared to Figures 4 and 5, Figure 7 reflects the effect of the ICA analysis on the EEG power spectrum.

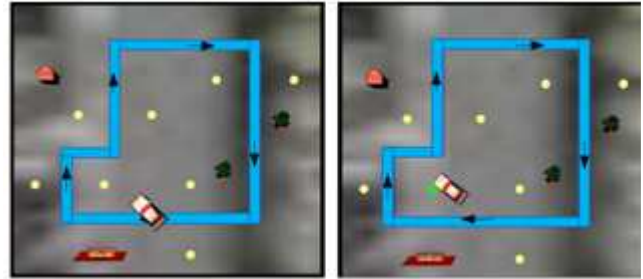


Figure 7. Collision detection scene graph

Support Vector Machine (SVM) Classification

The SVM is an ideal tool to tackle small sample, nonlinear pattern recognition problems. By this method, the optimal classification plane (i.e. the optimal classification lines) can be derived from linear separable samples. To minimize empirical and real risks, it is necessary to pursue zero training error and maximum classification interval.

In the high-dimensional space, the optimal classification lines become the optimal classification plane. The plane consist of linear separable samples $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n), x \in R^d, y \in \{+1, -1\}$. Then, the general form of the linear discriminant function in d dimension can be expressed as:

$$g(x) = w(x) + b \tag{7}$$

So, the classification surface can be expressed as:

$$w(x) + b = 0 \tag{8}$$

Then, the discriminant function was normalized, such that the two classes of all samples satisfy $|g(x)| \geq 1$. For the closest classification surface $|g(x)| = 1$, the classification interval is $2/\|w\|^2$. Thus, the optimal classification plane must satisfy the following conditions:

$$y_i \geq [wx_i + b] - 1 > 0, i = 1, 2, \dots, n \tag{9}$$



Therefore, the optimal classification plane was established as $\|w\|^2$. The minimum surface satisfies the $y_i[(wx_i)+b]-1=0$ condition of the training sample is called a support vector.

$$\nabla_w = w - \sum a_i y_i x_i = 0 \quad (10)$$

Solution of the optimal classification: check if the optimal classification plane satisfies the conditions for minimum Lagrange multiplier:

For a_i , the optimal classification function can be solved as:

$$f(x) = \text{sgn}\{w^*x + b\} = \text{sgn}\{\sum a_i y_i (x_i x) + b^*\} \quad (11)$$

Classification results

The C3 and C4 channels of the double-modal EEG signal data were split into eight segments. Each segment has 512 pieces of data. The 6-order AR parameters were processed by the SVM classification algorithm for 35d. The data were categorized by two kinds of actions: left hand movement and right hand movement. Figures 8 and 9 show the classification results of the two kinds of actions, respectively.

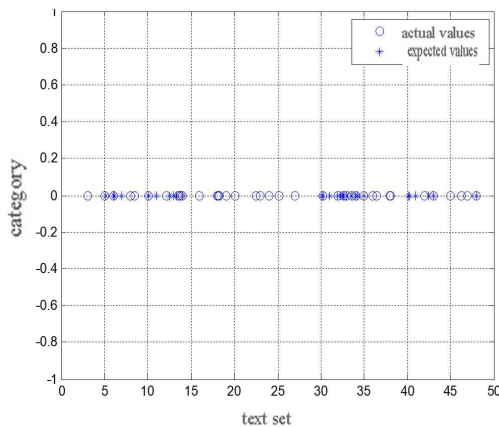


Figure 8. C3 channel classification figure actual and forecast

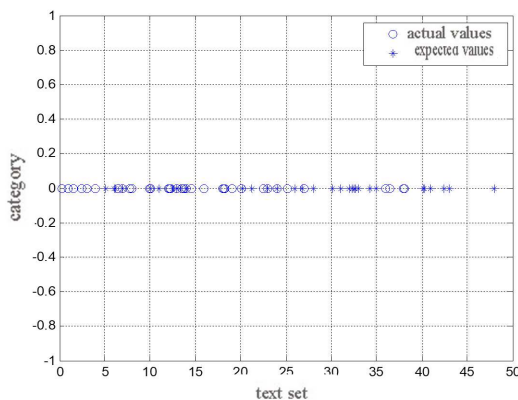


Figure 9. C4 channel classification figure actual and forecast

After feature extraction, the SVM algorithm was adopted to improve the classification results. The data results show that the recognition rate of C3 channel reached 89.5% and that of C4 channel reached 90.6%.

Multimodal EEG processing

The EEG acquisition system was grounded on the interface of LabWindows™/CVI. The functions include data acquisition, waveform display, data storage, and report generation. The system can display and store data in real time, and store data for a specified period (Ogura *et al.*, 1996).

During the experiment, several electrodes were attached on the head of each subject to capture the dynamic EEG signals. The captured signals were then amplified and processed on the software platform using LabWindows™/CVI, Matlab and SVM.

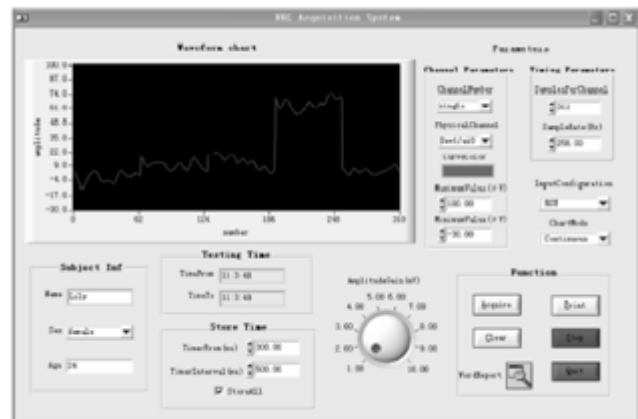


Figure 10. Signal acquisition system software interface

The BCI system also adopts the feedback technology. Based on the visual or audio feedbacks, the subjects can consciously adjust the EEG signals, making them easier to interpret. The purpose is to produce the optimal EEG signals through thought training. In the BCI system, the introduction of the feedback technology has the following advantages:

- (1) Continuous excitation of signals: the subjects can constantly see their thoughts on the screen rather than the wrong judgements. The movement of vertical cursor towards the destination is undoubtedly a powerful incentive.
- (2) Attraction of attention: the subjects are unlikely to get distracted due to the constant progress.
- (3) Enhancement of performance: the feedbacks to the signal processing module enhance the stability and accuracy of the system.



Some common feedback methods were adopted in our BCI system, including scroll bar, virtual navigation, cursor, spot, and virtual reality (VR). However, it is difficult to get visual feedback with the first four methods. Thus, the VR was employed to create an interactive, immersive, real-time training environment, in which more visual feedbacks are provided to stimulate the subjects' EEG signals (Mikhailova, 2012). Besides, the subjects could adjust their EEG signals through comparison between the virtual actions and their own imaginary actions, thereby enhancing the "brain fitness" of the machine.

The EEG is a faint low-frequency bioelectrical signal, with peak voltage of 0.5~100 μ V, effective frequency of 0.5~30Hz, and signal-to-noise ratio of 1:5. It is easily submerged by noise and interference. Hence, the amplifier circuit must have high input impedance, high common mode rejection ratio, high gain, low noise, low drift, no linearity, strong anti-interference ability, and suitable frequency and dynamic range. Therefore, the Mipower amplifier, a high precision bioelectrical signal amplifier developed by Tsinghua University, was selected for this research. The amplifier boasts complete functions, eliminating the need for additional data acquisition card (Figure 11). The effective connection of all electrodes is guaranteed through impedance monitoring and real-time impedance display. Coupled with USB, the amplifier can collect data every 40ms via TCP/IP according to the fixed format. The packet loss is very rare, and interfaces are reserved for follow-up processes.



Figure 11. Mipower amplifier hardware diagram

Implementation BCI feedback system

Three steps are needed to build a complete VR feedback system: creating a 3DMax role model, setting up action libraries, and fine-tuning the VR scenes.

In the VR feedback platform, three roles were modeled: female, male and child. The first

thing is to create lifelike virtual humans in 3DMax geometric model. The model is a hybrid model of the curved surface and the skeleton. The appearance is displayed in the curved surface layer, and the movements are reflected in the skeleton layer.

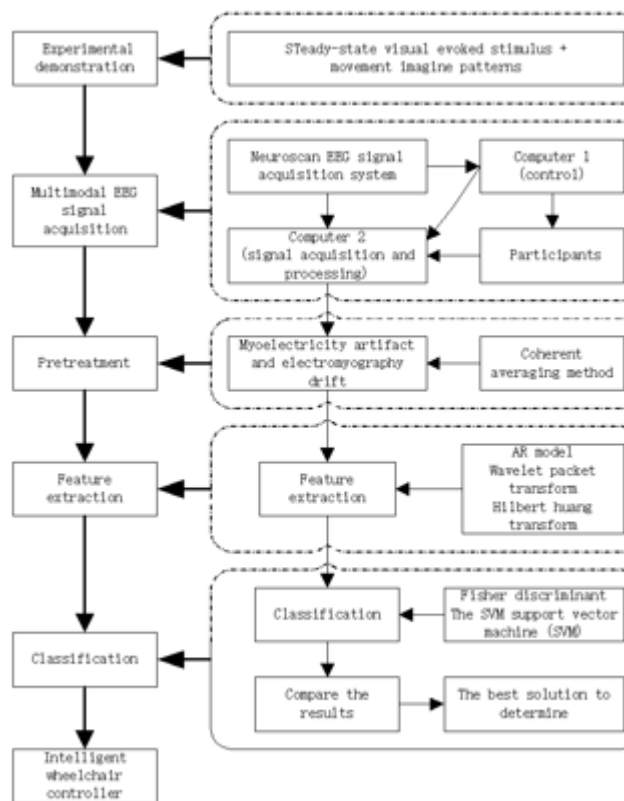


Figure 12. Multimodal brain electrical signal processing system

Conclusions

First, the discrete wavelet transform was applied to denoise the EEG signals. Then, the brain's left and right hand movement features were extracted from the denoised signals by the ICA. Finally, the SVM classifier was adopted to recognize and classify the movement of the left and right hand actions (Shagass, 1985). The experimental results show that our method achieves the recognition accuracy of 89.5% and 90.6% respectively. The research findings provide a valuable reference for the future research into the BCI system.

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References

- Cui JG, Wang X, Zi XB, Zhang DQ. EEG signals of the latest research methods. *Journal of Shenyang Institute of Aviation Industry* 2004; 21(2): 64-66.
- Guo W. On the functional recovery mechanism of the cerebral nervous system in diabetic state under the combination effect of exercise and medication. *NeuroQuantology* 2017; 16(1): 63-70.
- Ji Z, Qin SR, Peng LL. Modern analysis method of brain electric signal. *Journal of Chongqing University* 2012; 25(9): 108-12.
- Kermy TM. Fundamentals of polysomnography and sleep disorders. *New Hope. Intellisleep Technology and Consulting* 2002; 10(30): 197-215.
- Liu C. Design and Implementation of Real-time Brain-computer Interface System Based on LabVIEW. *NeuroQuantology* 2017; 16(3): 97-104.
- Ma YY, Zhang D, Zhou WJ. Brain electrical signal processing methods. *Beijing Biomedical Engineering* 2007; 26(1): 99-102.
- Meng X, Ouyang J. EEG signals of several nonlinear dynamics analysis methods. *Journal of Beijing Biomedical Engineering* 1997; (3): 135-40.
- Mikhailova E.S. EEG Mapping of Three Alpha Subbands in Healthy and DePressive Subjects under Music Test. *Proceedings of the 13th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE* 2012; 13: 12010-18.
- Ogura C. Toward the promotion of clinical application of event-related potentials. *Recent Advances in Event-Related Brain Potential Research* 1996:1085-88.
- Shagass C, Roemer RA, Straumanis JJ, Josiassen RC. Combinations of evoked potential amplitude measurements in relation to psychiatric diagnosis. *Biological Psychiatry* 1985; 20(7):701-22.
- Wang Q. Study of emotional changes based on neural management and electroencephalogram experiments on low-carbon consumption behavior. *NeuroQuantology* 2017; 16(2): 25-31.

