Optimizing the Individual Differences of EEG Signals through BP Neural Network Algorithm for a BCI Dialing System

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Abstract. Brain-computer interface (BCI) establishes an additional pathway between brain and the external environment. With BCIs, paraplegic patients or the elderly people can communicate with others conveniently and finish some simple tasks individually. In this paper, we build an online brain computer interface system. The system consists of three main modules: electroencephalography (EEG) acquisition module, signal processing module and dialing system on the Android Platform. The system has several advantages, such as non-invasive, real-time, without training and the adaptability to different users by using backpropagation (BP) neural network. Experimental results show that by using BP neural network, the accuracy of the dialing system is improved.

Keywords: brain-computer interface (BCI), Android Platform, Bluetooth communication, backpropagation (BP) neural network.

1 Introduction

According to the U.S. Census Bureau reports, the problem of global population aging is more and more serious [1]. It is predicted that in 2040, 65 years old or older population will reach 14% of the total population. In recent years, the number of paraplegic patients caused by traffic accidents or natural disasters is increasing year by year. Taking care of the old people of action inconvenience and paraplegic patients needs a lot of human and material resources.

Brain-computer interface is a new communication channel that bypasses the normal motor outflow from the brain [2]. By brain-computer interface, the disabled can do some simple tasks in an unattended situation. With the development of machine learning and signal processing method, BCIs can be utilized across a wide range of clinical or daily life settings.

A variety of invasive electrophysiological methods for monitoring brain activity may serve as a brain computer interface, including magnetoencephalography (MEG),

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positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and so on [3]. However, since sensors of invasive method can last only a limited time before they lose signal, electrodes have to be implanted into users' brains once again, which causes great harm to the health of users [4]. What's more, MEG, PET, and fMRI are expensive, demanding and usually tied to laboratories, which cannot be popularly used by common people.

These years, the event-related potentials (ERPs) for example P300 and steady-state visually potential (SSVEP) have received increasing amounts of attention as a BCI control signal [5]. BCIs on the basis of visually evoked potentials do not require self-regulation of the EEG signals, but they require uninterrupted gaze on the target for a considerable amount of time, users may feel rather uncomfortable [6].

Taking the advantages but mediating the disadvantages of the above brain-computer interfaces, this study is aimed to develop a convenient and noninvasive BCI system without long time training. Considering the individual differences of EEG signals, this paper employs BP neural network algorithm to improve the stability of the BCI system. Taking a BCI dialing system on an Android Platform as a case study, the effect of the proposed method is investigated.

The remainder paper is organized as follows: Section 2 presents the system configuration and the EEG signals acquisition procedure. Section 3 introduces the adaptive threshold selection by using BP neural network. Performance of the developed system is evaluated in Section 4. Finally, the conclusions and future work are presented in Section 5.

2 System Configuration and EEG Signals Acquisition

2.1 System Configuration

This system is an online brain-computer interface system based on EEG signals. It is divided into three independent modules, namely, EEG signals acquisition module, EEG signals processing module and the command execution module on the Android Platform.

The configuration of the entire BCI dialing system is illustrated in Fig.1. The equipment of the system including: Emotiv, computer and the Android smart phone. The Emotiv neuroheadset captures the user's real-time brainwave (EEG) signals, and the EEG data are wirelessly transmitted to the computer through the USB receiver after the AD conversion process. The computer is responsible for receiving and storing EEG data sent by the Emotiv neuroheadset, processing the data online, adaptively selecting threshold by using neural network, and sending the control command to the Android Platform via Bluetooth. The Android Platform receives the control command and makes a call to the designated person.

Figure 2 presents the working process of the developed BCI dialing system on the Android Platform.

2.2 EEG Signals Acquisition

This system uses a wireless Emotiv neuroheadset with 14 channels to obtain the raw EEG data, whose sample rate is 128 Hz. Electrodes of the neuroheadset are positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (the international 10-20 system) [7]. Figure 3 shows the map of EEG electrodes.

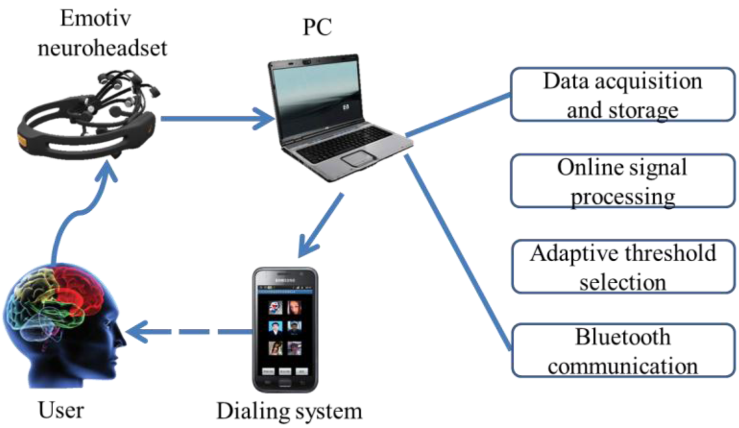


Fig. 1. System configuration

(a) (b) (c)

Fig. 2. Working process of the developed BCI dialing system: (a) Subject watches the Android Platform while his EEG signals are measured by Emotiv; (b) Subject laughs when he wants to dial a phone; (c) Subject dials with the corresponding number successfully.

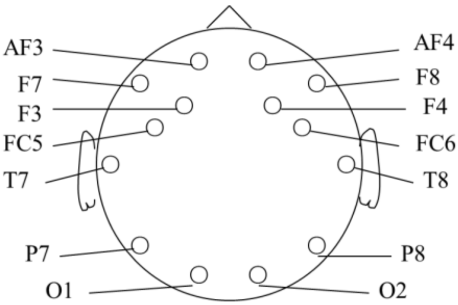
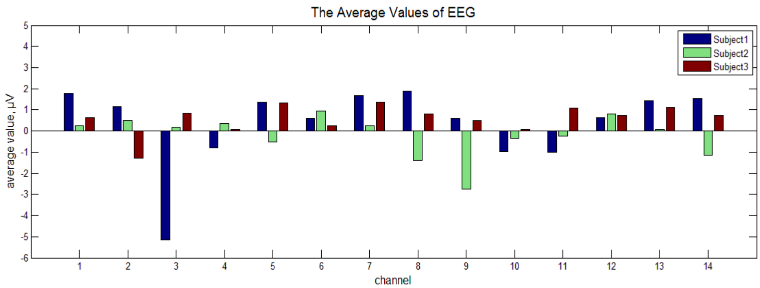


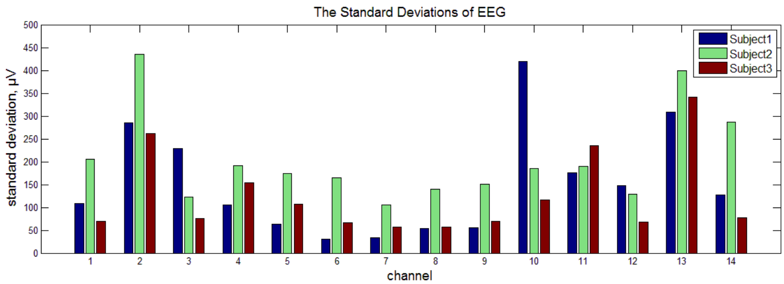
Fig. 3. Map of EEG electrodes for 14 channels

We select the EEG signals generated by the expression of laugh as the valid input. Real-time EEG signals are received and processed by the computer that connected with the neuroheadset wirelessly.

Through experiments, we found that the EEG signals of different subjects generated by laugh were quite different. We recorded the EEG data of three subjects within 500 [s]. During the 500 [s], each subject laughed 20 times, the interval of each time of laugh is 20 [s]. By calculating the mean values and the standard deviations of the 14-channel EEG data of the three subjects, we obtained the following results map, as shown in Fig.4. According to Fig.4, the mean values of 14-channel EEG data and the standard deviations are significantly different, which indicates that the degree of EEG fluctuations of a subject is quite different with others.



(a)



(b)

Fig. 4. (a) Mean values of 14-channel EEG data; (b) Standard deviations of 14-channel EEG data

3 Adaptive Threshold Selection

3.1 Introduction to BP Neural Network

In this BCI dialing system, the threshold is an important parameter. If the detected magnitude of laugh is larger than the threshold that we have set, a control command will be sent to the Android Platform from the computer to execute the dialing task; otherwise do nothing. Figure 5 illustrates how the EEG signals are processed into control command.

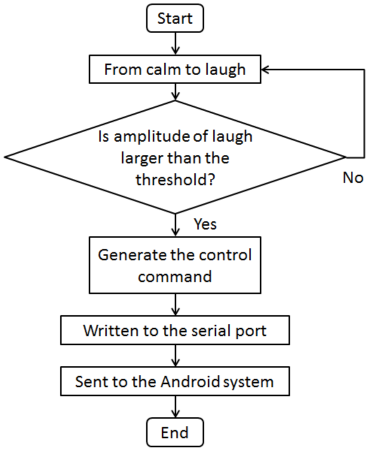


Fig. 5. The flowchart of the control command generated from EEG signals

The program determines the values of users' laugh magnitude based on the changes of their brainwaves, which are different with each other. Thus, a uniform threshold may not be suited to all users. In order to let the proposed BCI dialing system fits for different users, it is necessary to adjust the threshold according to different users' EEG characteristics.

In this paper, we use the neural network and its BP algorithm to realize the adaptive threshold selection process. BP networks is the most widely used multi-layered feed-forward networks. BP network structure is generally divided into input layer, hidden layers and output layer [8]. The fundamental idea of the BP algorithm is to calculate the influence of each weight in the network with respect to an arbitrary *E* by applying the chain rule repeatedly.

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial s_i}\frac{\partial s_i}{\partial net_i}\frac{\partial net_i}{\partial w_{ij}} \tag{1}$$

Where w_{ij} is the weight from neuron j to neuron i, net_i is the weighted sum of the inputs of neuron i, and s_i is the output. If the partial derivative for each weight is known, the aim of minimizing the error function is achieved by performing a simple gradient descent.

$$w_{ij}(\mathrm{t}+1) = w_{ij}(\mathrm{t}) - \delta\frac{\partial E}{\partial w_{ij}}(\mathrm{t}) \tag{2}$$

Where δ is the learning rate that scales the derivative [9].

This paper uses the Matlab neural network toolbox to build the BP neural network to meet our requirements. According to the related studies, the number of nodes in the hidden layer is twice as many as the number of nodes in the input layer. Figure 6 shows the structure of the neural network.

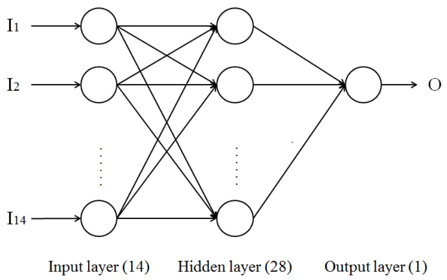


Fig. 6. Neural network structure

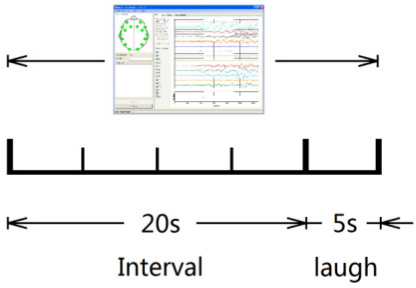


Fig. 7. The experiment paradigm

3.2 Training for BP Neural Network

Experiment Design. The EEG data were taken from three healthy subjects (three males, 21-25 years old). The subjects were required to laugh twenty times in 500 [s], each time of laugh continued 5 [s], and the laugh interval was 20 [s].

The Acquisition of Training Samples for Neural Network. Training samples consist of two parts: the first part is the 14-channel EEG data of each sampling point during 500 [s]; the second part is the thresholds that are set manually. During the experiment, the values of the subject's EEG data as well as the magnitude of laugh at each sample point were recorded. According to the subject's facial expressions and the magnitude of laugh at each sampling point, the thresholds are selected manually. If the subject was laughing, the value of the threshold is the recorded laugh magnitude plus 0.2; otherwise, the value of threshold is the recorded laugh magnitude minus 0.2.

Training Results. As far as the BP neural network algorithm is concerned, the input of neural network is the 14-channel EEG data, and the output is adaptive threshold. The entire network has one hidden layer (with 28 nodes), one output layer (with 14 nodes). There are about 3000 training samples of each subject, and the range of the output value is [-0.2, 1.2]. We set the expected error limit as 0.1, and the neural network training epochs as 50. The greater the threshold is, the more the EEG sensitivity of the subject is. The mean value of the output of the trained neural network is taken as the threshold of each subject. The obtained thresholds of three subjects are 0.49, 0.41 and 0.12 respectively, and the corresponding convergence error curves of the three subjects are shown in Fig.8 to Fig. 10 respectively.

4 Applications on Android Platform

4.1 Introduction to the Dialing System

Consistent with the initial impetus of brain-computer interface technology, our design aims at improving the living quality of the disabled and the elderly people, and

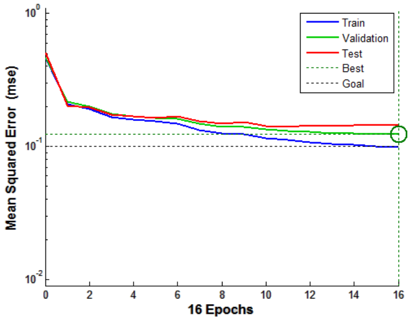


Fig. 8. Convergence error curve of subject 1

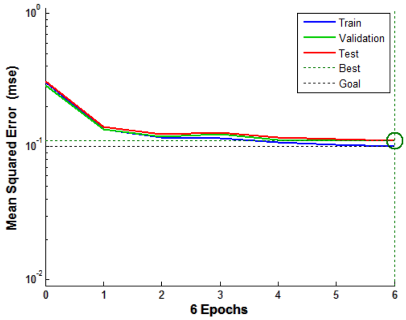


Fig. 9. Convergence error curve of subject 2

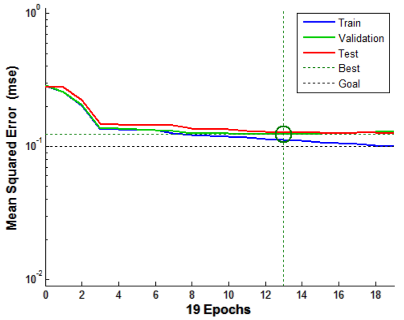


Fig. 10. Convergence error curve of subject 3

assisting them to some simple activities. In this paper, the EEG signals generated by laugh are used to realize the dialing function of the Android Platform.

After processing the EEG signals measured by the Emotiv neuroheadset, the computer generates the control command and sends it to the Android Platform via Bluetooth to execute the dialing task. The reason to select Bluetooth communication is that Bluetooth is a kind of low-power consumption, low-cost, stable and flexible wireless communication. In order to achieve Bluetooth communication, a connection between the computer and the Android Platform should be established first.

When the Android Platform connects with the computer successfully, subjects are required to enter the dial control interface, and the system will be ready to receive the control command from the computer. The phone numbers of six persons are stored in the system, as shown in Fig.11 (a), and these numbers can be edited mutually. After saving the six phone numbers, subjects can enter the dialing interface, shown in Fig.11 (b). Each image represents a phone number, and after clicking start twinkling button, the six images will twinkle in random order, the twinkle time of each image is 2 [s]. If the user laughs during the period of one of the six images twinkling, and the magnitude of laugh exceeds the threshold, the Android Platform will receive the control command from the computer that connected with the Emotiv neuroheadset wirelessly. Thus, the system can make a call to the designated person.

Fig. 11. (a) Save contacts' phone numbers; (b) Dial control interface; (c) Make call to the designated person.

4.2 Experimental Results

Experimental Design. To test the thresholds adaptively selected by the neural network, we carried out experiments on the same three subjects separately.

The subjects were required to make a call to one of the six persons whose images were shown on the interface. The subject laughed during the twinkling period of the designated image, and when the magnitude of laugh exceeded the threshold, a dialing task can be executed. Each subject executed the dialing trial ten times. If the subject called to the designated person, the trial was successful. Otherwise, if the subject did not dial or called to another person, the trial was failed. According to the training results of the neural network, the thresholds of the three subjects are: 0.49, 0.41 and 0.12 respectively.

Results. By recording and analyzing each trial of the three subjects, we obtain the following results. Table 1 shows the success rates of three subjects.

Discussion. The success rate of each subject is more than 80%, which indicates that the adaptive thresholds selected by the neural network are reasonable and feasible. However, there are several factors that may influence the success rates:

- The electrodes on the Emotiv neuroheadset may touch on the different scalp areas of different subjects.
- Even for the same subject, the positions of the electrodes may be different at different trials.
- In addition, the BCI dialing system prompts the user by the twinkling images. The reaction time of a normal adult is 0.15 [s] to 0.4 [s]. Although the delay caused by the reaction time may affects the success rate of the BCI dialing system, since the twinkling time of each image is 2 [s], this factor may not influence the success rate greatly.

Table 1. Success rates of three subjects

Subject number	Threshold	Success rate
1	0.49	0.8
2	0.41	1.0
3	0.12	0.8

5 Conclusions and Future Work

This work aims to realize an online BCI dialing system. The system has the following features:

- Noninvasive and convenient
  Using noninvasive method does not cause any harm to human body. The EEG signals can be easily acquired from the Emotiv neuroheadset.
- Need no training
  In this paper, we use the EEG signals generated by the expression of laugh to control the dialing system. There is no need for training the subjects, nor do the subjects feel discomfort.
- Solving the problem of individual differences
  Considering the facts that the EEG signals of different subjects generated by laugh are quite different, we use the BP neural network algorithm to adaptively select the threshold for each user.

Experimental results indicate that the developed BCI dialing system can be used by common people, and the proposed BP neural network can select the threshold of the EEG signals for each user successfully. In this way, the individual differences of EEG signals can be optimized. There are also some enhancements need to be investigated in the future:

- More experiments need to be carried to verify the effect of the factors mentioned above that may influence the success rate of the dialing system.
- In addition, in order to improve the success rates, other algorithms will be adopted to improve the selection process of the adaptive thresholds.
- The BCI dialing system based on Android Platform is a common control interface, the control signals can also be sent to robots via Bluetooth to achieve control of robots.

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