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Brain-Computer Interfaces Based on Attention and Complex Mental Tasks

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Abstract Brain-Computer Interface (BCI) technology is widely used in rehabilitation field. There are two main applications of BCI systems in assistive technology: regain the movements or communications for people with motor disability and neurofeedback for training the subject to emit a specific brain activity. In this study, we introduce two typical applications of BCI systems in our lab. For the first case, the BCI system based on mental tasks classification for people with motor disability is described. An effective features extraction and classification methods of EEG signals were proposed. In this study, the average classification accuracy over 140 task-pairs is up to 99.4% and an information transfer rate of 56.8 bits/minutes was achieved. For the second case, a neurofeedback (NFB) system was established, which utilized Virtual Reality (VR) to create appropriate feedback information which is more interesting, imaginative and interactive than traditional graphical presentations. Visual & auditory (IVA)-continuous performance test (CPT) results show that it can provide an effective therapy for treating attention deficit hyperactivity disorder (ADHD) children.

Keywords: brain-computer interface, mental tasks, neurofeedback, ADHD rehabilitation

1 Introduction

Brain-computer interface (BCI) has been identified to function as an extra channel between brain and external environment to transmit information bypassing the spinal and peripheral neuromuscular systems [1, 2] and has also found applications in rehabilitation, neuroscience and cognitive psychology. Existing research in applications of BCI is composed of two main areas. For assistive technology, BCI makes it possible for people with motor disabilities to regain the interactions with external environment in

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order to improve the quality of their lives [2, 3, 4, 5]. The second area aims at training the subject to emit a specific brain activity [6]. In this application, BCI is called as Neurofeedback (NFB), it becomes a therapy tool which helps subjects recover their cognitive function by consciously altering some features of their electroencephalographic (EEG) signals in order to stay in certain brain state. These features can be used to activate a certain action, including visual/auditory representations. By continuous neurofeedback training humans can learn how to change their brain electrical activity in a desired direction. It can assist individuals with a variety of conditions and disabilities in which the brain is not working as well as it might be. Neurofeedback has been used widely to treat certain kinds of disorders and diseases such as Attention Deficit Hyperactivity Disorder (ADHD) In general, a BCI system based on mental tasks classification will find very useful application in rehabilitations, especially in the areas of motor function restoration and the rehabilitation training for people with full loss of movement capability. It can be used to restore communication such as speech capabilities. A BCI system interfaced with virtual reality (VR) can be used as environmental controls such as thermostats, television and even smart home controls. This application will provide safe environments for "locked-in" patients. It can restore the function of peripheral nerves or sent control command to maneuver wheelchairs so as to make it possible for people with motor disabilities to accomplish simple motion by themselves. Finally a BCI system can be valuable in neuron-rehabilitation of disabled people by reinforcing use of damaged or diseased neural pathways.

The objective of this study is to introduce the two typical applications of BCI in our lab. For the first case, complex mental tasks classification was analyzed. Effective features extraction and visualizing methods of EEG signals were proposed for further offline analysis and online application for restoring the movements and communication. For the second case, a neurofeedback system was established, which utilized Virtual Reality (VR) to create appropriate feedback information. Compared to traditional graphical presentations, more interesting, imaginative and interactive treatment for attention deficit hyperactivity disorder (ADHD) was achieved.

2 A BCI system based on mental tasks classification

Currently, in order to restore the movements and communication for people with motor disabilities, the input signal of BCI systems is composed of evoked potentials (EP), slow cortical potentials (SCPs), event related potentials (ERP) and spontaneous EEG related to motor imagery tasks or different mental tasks [7]. And the features representing EEG patterns can be obtained using either frequency [8, 9] or non-frequency [10, 11] domain information of EEG signals. Frequency domain information is more widely used in BCI systems, e.g., Keirn has performed complex mental tasks by using asymmetry ratios and power values at four frequency bands: delta, theta, alpha, and beta [12]. Current methods extract energy information mainly from the whole EEG segments of specific length. However, while mental tasks were performed, EEG segments of any length started from a specific time point are related to different kinds of brain activity information. A convenient way is to use a phase space of different dimensions to represent the mental tasks. In our study, we used energy information of phase-space as features to perform mental tasks classification with Fisher's Linear discriminant as the classifier.

Phase-space energy decomposition is a feature extraction method with two steps: reconstruction of the phase space from EEG signals, followed by performing energy decomposition in frequency domain from each vector in the reconstructed phase-space. Features obtained by this method can describe the variations of EEG signals in more details and have good resolution in time domain. In addition the study found that phase-space energy decomposition method can show the features more accurately representing the mental tasks and their consistent variations along time axis, and further improves the accuracy of classification. This study also analyzed the effects of each 10Hz energy between 0 and 100Hz of EEG signals on mental tasks classification.

Classification method based on linear discriminant is desirable in BCI research due to its characteristics of being simple, fast, and easy to implement. Fisher's linear discriminant was used as classifiers for dimension reduction of the input patterns. Since Fisher's criterion focuses on the separation of different classes, it can produce low-dimensional output patterns appropriate for classification. It is also appropriate for online application.

Seven male subjects (ages from 22 to 26) participated in the experiment. Five mental tasks, including baseline, multiplication, letter composing, geometric figure rotation and visual counting were performed by each subject. An EEG recording of seventy seconds constituted a trial. A session comprised five such trials. The middle sixty EEG signals of each trial are used for analyses. Subjects performed one session in one day for each task, and different sessions were recorded on separate weeks.

The EEG signals were recorded from eight channels (F3, F4, C3, C4, P3, P4, O1 and O2) which are referenced to electrically-linked mastoids according to the 10-20 electrode system. A separate channel was used to detect eye blinks using two electrodes placed below and above the subjects left eye. The signals were band pass faltered at 0.1-100Hz and sampled at 1000Hz. There are 140 mental tasks in all for analysis.

Task-pair classification was performed using eighty features that were extracted from frequency bands of 0 to 100 Hz and 8 EEG channels. Table 1 presents the averaged classification accuracy across all fifty task pairs for each subject. The average classification accuracy over 140 task-pairs is up to 99.4%. The information transfer rate, given in bits per trial, is used as an evaluation measurement in a brain-computer interface [13]. The information transfer rate (derived from [14]) in bits per trial was calculated by

$$B = \log_2 N + P \log_2 N + (1 - P) \log_2 \frac{1 - P}{N - 1} \tag{1}$$

N is the number of different types of mental tasks and P the accuracy of classification. In this study, an information transfer rate of 56.8 bits/minutes was achieved. These results imply the good potential use of mental tasks classification in online BCI system.

	s1	s2	s3	s4	s5	s6	s7
b vs. m	100±0	99.8±0.3	98.2±0.7	99.1±0.5	99.6±0.4	99.3±0.5	98.5±0.5
b vs. l	93.6±1.1	100±0	99.9±0.2	100±0	99.5±0.4	100±0	100±0.1
b vs. r	100±0	100±0	99.2±0.4	100±0	99.5±0.4	100±0	99.6±0.3
b vs. c	93.9±1	100±0.1	100±0	100±0	100±0	100±0.1	99.7±0.4
m vs. l	100±0	100±0	99.8±0.2	99.4±0.5	99.6±0.3	99.9±0.4	100±0.1
m vs. r	100±0	99.9±0.2	99.7±0.3	98±0.6	97±1	95.6±1	99.7±0.4
m vs. c	100±0	99.8±0.3	100±0	100±0	99.9±0.2	98.6±0.6	99.9±0.2
l vs. r	100±0.1	100±0	99.4±0.4	99.5±0.5	99.3±0.5	100±0	99.8±0.3
l vs. c	98±0.8	100±0	100±0	100±0	97.8±0.8	100±0	100±0
r vs. c	100±0.1	100±0.1	100±0	100±0	99.7±0.3	99.3±0.4	100±0.1

Table 1: averaged classification accuracy across all fifty task pairs for each subject

3 A BCI-NFB-VR system for ADHD treatment

Currently NFB technology has been mainly used in behavioral medicine as an adjunct to psychotherapy [15, 16, 17, 18]. VR is a human-computer interface in which users can move their viewpoint freely in real time [19, 20]. Its purpose is to be constructed a virtual environment (VE), bring about a natural interactivity and make a live-sensation from multimodality.

In this study, a system based on NFB and VR technology for ADHD treatment is established. The NFB utilizes operative conditioning principles selectively enhancing or suppressing EEG waves within preset frequency bands, hence subjects can maintain their brain state in a specific state so as to gradually recover their cognitive function [17, 21]. It is a painless, non-invasive treatment and allows the individual to gain information about his or her EEG wave activity, to use computerized biofeedback system to change their EEG activities.

This ADHD training system utilizes VR to create appropriate feedback, which is more interesting, imaginative and interactive than traditional graphical presentations. During the whole process, the feedback modalities continuously represent brain activity with a minimum constant delay. In this paper we discuss the technical and experimental basis of the proposed NFB system.

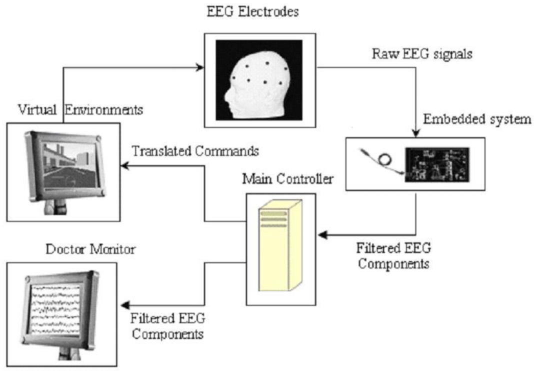


Figure 1: Structure model of the system. First, raw EEG signals are sampled; then the EEG data are translated into "commands" by signal processing module; lastly virtual environments feedback is presented to subject.

The structure of the proposed BCI-NFB-VR system is presented in Fig. 1. The three main components of the system are: (1) a signal collection component to record EEG data at a particular scalp location; (2) a signal processing component to convert EEG data to computer commands; (3) a VR driver component to provide VE dynamically co-varying with the commands.

The first module is a multi-channels, high input impedance EEG electrodes set. Three electrodes (Cz, Fp1 and Fp2) which are located on the scalp according to the standard "10-20 system" placement are used to collect EEG signals. The electrodes are connected to an embedded system for EEG signals collection and pre-processing. The embedded system has three functions: 1) Convert the analog EEG signals into digital EEG data. In this conversion, High signal-to-noise ratio amplifier is embedded in the circuit and the EEG signal is sampled 256 times per second with 12 bits of accuracy; 2) Convert raw EEG data into different EEG components and remove the EEG artifacts (such as EOG, ECG, etc.). A set of filters is used to remove artifact and only keep the frequencies of interest. Since only 0-30Hz signals in EEG are interested, the low-pass filters are set to 30 Hz; 3) Transfer EEG components to the main controller by USB port [22].

A novel method based on wavelet packet analysis is proposed to effectively remove electrooculogram (EOG) - the most intricate artifact from EEG signals in real time. In the process, the EEG signal is decomposed subtly in the frequency domain using wavelet packet decomposition, and then EOG, typically the low-frequency wavelet components, is detected and eliminated with the threshold decided according to statistical principles. EEG signal is reconstructed, taking its most correlative signal from

Fp1 channel as a reference so as to avoid introducing new artifacts by the algorithm itself.

The second module is the main controller, a personal computer, which transfers the filtered EEG components to "commands" signal. The process consists of three parts: Firstly, the EEG signal is decomposed into different frequency bands (Theta: 4-7Hz, SMR: 12-15 Hz, Beta: 15-18Hz) based on wavelet packet analysis method. Secondly, the corresponding power of each sub-band is calculated. The parameters such as θ/β can be calculated form that power information. Finally, the "commands" can be obtained by using the simple fusion rule. If both θ/β and SMR power go beyond a predefined threshold, the "command" is an inspiriting signal; otherwise the "command" is a stop signal.

The "command" signal obtained from the main controller is fed to the third module, the visual environment (VE) games and becomes a parameter affecting the behaviors of the VE games. Values of the "command" correspond to the changes in position, appearance, and size of VE objects or in the subject's viewpoint of the VE scene. In the process of learning to "control" their brain waves, the subjects will gradually recover their cognitive function. An example of VE feedback game is showed in Fig.2. Three airships are flying in outer space. Two of them are controlled by computer. One (the middle one) is controlled by the subject's "brain wave". If the "command" signal is inspiriting signal, the airship controlled by the subject will speed up. Otherwise it will keep unchanged. And The VE scene will change automatically. Before each training session, the subject was instructed to do a forepart session so that the operator can measure the baseline of EEG. This is because the baseline could be varied according to different emotional or physical conditions. At the start of the session, the subject is presented with the training task in the form of the VE scene; try to "control" it. The monitor is placed a few feet away, directly in front of the subject. It provides the virtual environments feedback to the subject. There is another therapist computer that is usually positioned behind the patient. This enables the therapist to monitor the subject's EEG during the session without disturbing the biofeedback. The therapist can stop the training when the EEG is invalidated or the subject can not finish the task in preconcerted time. In all of the training scenarios, the frame rate was over 30/s, which is responsive enough to give the subject a sense of direct control.

Two ADHD subjects (an 8 years old male and an 11 years old female) are recruited for this experiment. All the subjects were diagnosed clinically with an attention deficit/hyperactivity disorder. During the training, all the subjects were evaluated by an Integrated Visual & Auditory (IVA) - Continuous Performance Test (CPT) [23]. Scores for the six primary scales of the IVA-CPT are obtained for both visual and auditory performance. There are two major quotients derived from these six scales. Prudence (Pru), Consistency (Con), and Stamina (Sta) comprise a full scale Response Control Quotient (RCQ), while Vigilance (Vig), Focus

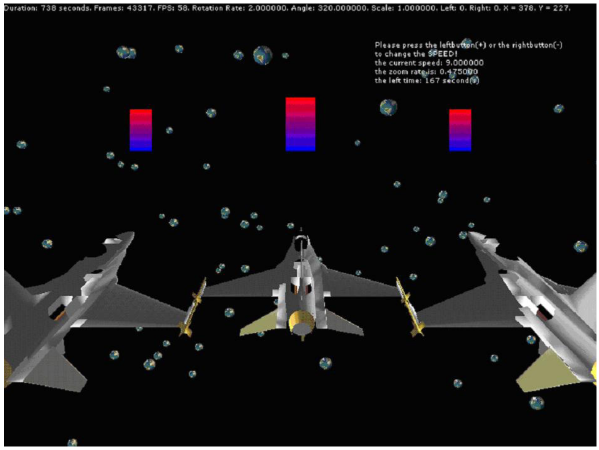


Figure 2: The interface of the VR environment.

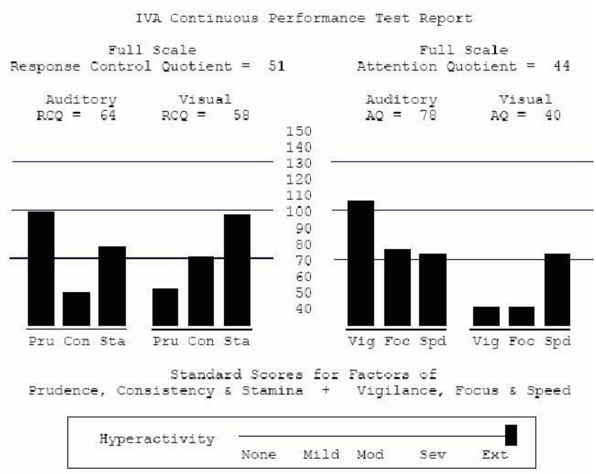
(Foc), and Speed (Spd) comprise a full scale Attention Control Quotient (ACQ). The RCQ measures impulsivity, while the ACQ measures inattentiveness. These two global measurements of impulsivity and inattentiveness are further broken down into visual and auditory responses. These global composite quotient scales allow efficient summary and evaluation of the test results. Figure. 3 illustrates an example, the results of pre- and post-treatment IVA/CPT for subject 1.

Table 2 presents subjects' RCQ and ACQ from pretest to posttest. The RCQ yielded significant pre-treatment to post-treatment differences. It shows significant gains in the RCQ. Increases in ACQ are also found to be significant. After one month of use, the treatment proved to be effective. It can be concluded that this BCI-NFB-VR system can be used to improve the attention of children and adolescents suffering from ADHD.

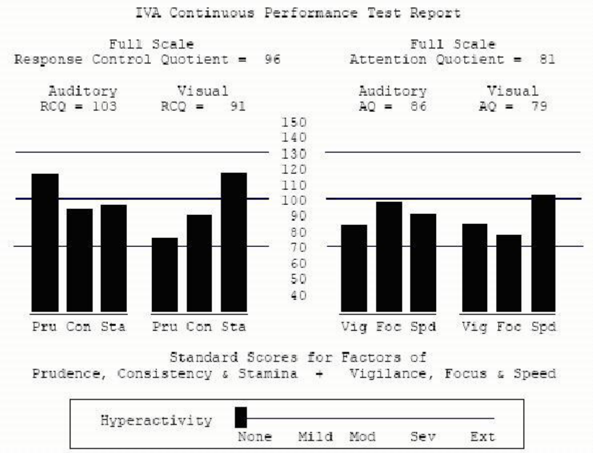
Subject	Response Control Quotient (RCQ)		Attention Control Quotient (ACQ)	
	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment
1	51	86	44	81
2	67	110	81	113

Table 2: Subjects' RCQ and ACQ from pretest to posttest by IVA-CPT

In this study, the NFB-VR system was also regarded as a NFB framework, because all signal processing methods and Visual Environment feedback game are encapsulated in the dynamic link library (DLL). This system can be used to assist the preparation of the application for different rehabilitation training if we select different EEG components and correlative Visual Environment feedback games. So this system will be utilized as an adjunct to other psychotherapy such as anxiety, Depressive disorder and stroke.



(a) Pre-treatment Test Report



(b) Post-treatment Test Report

Figure 3: IVA-CPT report of pre- and post- treatment

4 Conclusion

The BCI method of phase-space energy decomposition was found to reflect more accurately the variation of energy of EEG signal. Using this method, higher classification accuracy can be achieved. This implies that mental tasks classification has good potential to be used in online BCI system for restoring the movements and communications for people with motor disabilities. We developed a NFB system which provides virtual environments to treat ADHD children. Two subjects tested clearly benefited from the treatment. The system is non-invasive and relatively easy for the therapist and the children to use. It can provide an effective therapy tool for treating ADHD children.

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