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An online BCI game based on the decoding of users' attention to color stimulus

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Abstract—**Studies have shown that statistically there are differences in theta, alpha and beta band powers when people look at blue and red colors. In this paper, a game has been developed to test whether these statistical differences are good enough for online Brain Computer Interface (BCI) application. We implemented a two-choice BCI game in which the subject makes the choice by looking at a color option and our system decodes the subject's intention by analyzing the EEG signal. In our system, band power features of the EEG data were used to train a support vector machine (SVM) classification model. An online mechanism was adopted to update the classification model during the training stage to account for individual differences. Our results showed that an accuracy of 70%-80% could be achieved and it provided evidence for the possibility in applying color stimuli to BCI applications.**

I. Introduction

Brain Computer Interfaces (BCIs) is an alternative communication interface between brain and external world without using the brain's normal output pathways of peripheral nerves and muscles. One important motivation of BCI is to help improve the quality of life for people whose normal neural pathways that control muscles or the muscles themselves are impaired, such as amyotrophic lateral sclerosis, brainstem stroke, spinal cord injury and cerebral palsy [1][2]. The ultimate goal of BCI research is to enable paralyzed patients to communicate with the external world, such as expressing will, operating some programs and controlling a prosthesis [3].

Electroencephalography (EEG) signals, which are recorded from the scalp, are widely studied in human BCI application since they are noninvasive and have high temporal resolution [4]. Three components of EEG have been studied in human to control BCI systems: 1) Slow cortical potentials (SCPs) can offer basic communication capability for people with some severe neurological diseases [5], but the communication process is very slow (e.g., one minute per letter [6]); 2) Sensorimotor rhythms have been proved to be suitable for BCI communication for changes in μ and ß rhythms that are associated with movement and motor imagery; 3) The well-studied P300 [7] potential is another major BCI control signal sensitive to the low probability target items which are mixed with high probability non-target items.

Stimuli arousing previous three components of EEG belong to particular kinds, i.e. oddball paradigm, motor movement or motor imagery, which may limit the range of BCI application. Patients may have disability at different parts of the body and are only sensitive to certain stimulus, so a single or a limited number of components cannot satisfy the people's needs in all cases. Various styles of stimulus should be investigated in BCI application to suit different people's needs.

Color is a fundamental aspect of human perception and could be natural for human to be used in BCI control. Some researchers have studied the impact of different colors on brain activity. Increased beta and decreased alpha power were observed when human were exposed to red and blue light than dark [8]. The comparison between red and blue color stimulus was made in [9][10] in which powers of theta, alpha and beta brainwave were reported to be larger for red than blue stimulus. The above work was focused on offline analysis to identify the differences between different color stimuli in a statistical way. Based on these statistical differences, the powers of different brainwave frequencies responding to color stimulus can be analyzed to identify potential BCI control signals.

In this paper, an arithmetic game of choice questions was developed, in which a BCI is implemented to decode users' attention to color stimulus and determine their intended choice. The focus of this paper is to test the accuracy and speed of EEG signal to separate blue and red color stimuli, and to further evaluate the possibility to apply different color stimuli in real-time BCI control.

II. Methods

A. Experimental setup

During the BCI game, a volunteer sat comfortably on a chair which was 0.5 meter in front of a 23-inch LCD monitor. Scalp EEG was recorded using a 16-channel electrode system developed by Emotiv Systems Inc. [11], including 14 scalp electrodes and 2 reference electrodes located behind both ears. Based on the international 10-20 system, the locations for these 14 electrodes are AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1 and O2. All 14 channel data were sampled at 128Hz, with a band-pass filter at 0.2-45Hz and a notch filter at 40Hz to remove the linear interference. The setup of our BCI game is illustrated in Fig.1.

Five healthy volunteers (25± 2years old, one female) with normal or corrected normal vision participated in this study. Only one male subject had some experience in BCI and the remaining subjects had never used a BCI before this study. Moreover, no one was color blind which is an important requirement as our BCI is developed based on color stimuli. The subjects were required to calculate the answer of each question and selected it through our BCI application. Each subject was asked to complete a training stage consisted of two phases and a testing stage consisted of three rounds of the game.

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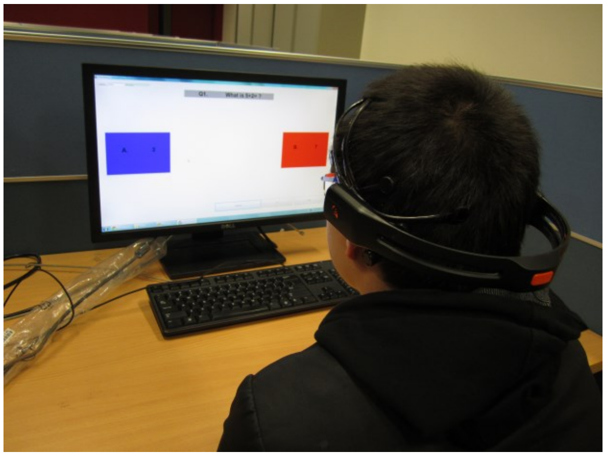
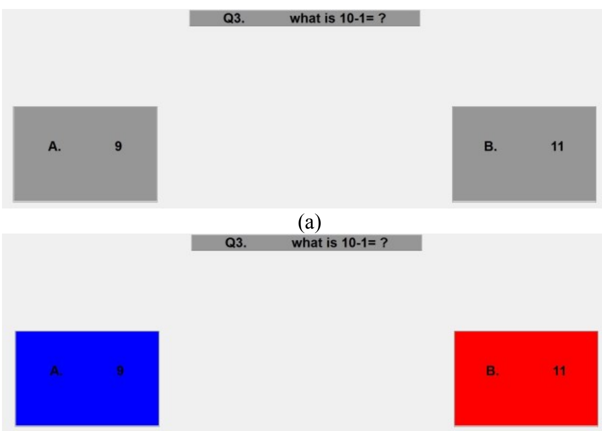


Figure 1 Setup of the BCI System

B. BCI Protocol

The task of the subjects is to answer some simple questions where each question only involved simple addition and subtraction of 2 two-digit numbers. When a new choice question was presented to the subject, three rectangles appeared on the screen at the same time. A 1.5cm×20cm rectangle filled with gray color was arranged in the upper part of the screen for the presentation of each question. Each of the two options was inside a 12cm×8cm rectangle appeared at the bottom left and bottom right of the screen. These two rectangles with options were initially filled with gray color (Fig.2 (a)) for three seconds to promote the new question and leave time for the subject to calculate the answer so that they can choose an option rectangle to focus on. Then the option rectangles were filled with blue and red colors respectively (Fig.2 (b)). Right answers were balanced in two rectangles using a uniform discrete distribution. The subject was required to stare at the told right option in the training stage or the selected option calculated by the subject in the testing stage until the next new question was presented or a decision was made by the system. To ensure that the color options were seen clearly, the font size of the text was set relatively small (yet legible) compared to the size of the color option rectangles to minimize any impact of the text stimulus in the classification, if any. In addition, the distance between the two option rectangles was set as far as possible to lower the inference from the alternate color.



(b)

Figure 2 Interface of the question and options shown to the subject (a) initially; and (b) after three seconds when the options are filled with blue and red colors.

C. Feature Extraction

Three seconds after a new question was presented to the subject, the ongoing EEG data during training and testing stages were first divided into one second segments, which were then processed to remove the baseline where a common average reference [1] was subtracted from the signals of each electrode and passed to a band pass filter of 1-30Hz. Based on the previous study on the relationship between colors and brain activity [8][9][10], band powers of theta (4-8Hz) band in electrodes AF3 and AF4, alpha (8-13Hz) band in electrodes AF3, AF4,F3, F4, F7 and F8, and beta (13-30Hz) band in electrodes O1 and O2 [12] were selected as the discriminate features. Each band power was computed using fast Fourier transform from the one second of EEG data and the powers in the corresponding frequency range were added for each of the 8 selected electrodes described above. This results in a feature vector of 8 elements for each one second of EEG data.

D. Classification Model

Support vector machine (SVM) [13] with radial basis function (RBF) is used due to its speed and accuracy. SVM maps the data into a high dimensional feature space in which a hyperplane $\boldsymbol{\omega}^T + b = 0$ that maximizes the margin between the nearest points to the hyperplane is constructed. SVM with the RBF kernel has achieved good classification results in BCI applications [14][15] under a fewer hyperparameters to be adjusted [16]. A Gaussian RBF SVM was implemented with LIBSVM toolbox [17] in our BCI game. The penalty factor C in the SVM and the parameter γ in the Gaussian RBF kernel function were selected by grid-search using ten-fold cross-validation.

E. Online Analysis Procedure

The Training stage has 2 phases in which the first phase is to build an initial classification model and the second phase is to update the classification model by adding more training data from the subject until a consistent and accurate classification result has been achieved. Subjects were informed about the correct answers in advance and were required to stare at the right option when each question was shown in both training phases.

After a new question was shown to the subject, the option rectangles were displayed with gray color as described in Section II.B. After three seconds, the colors of the two option rectangles were changed to blue and red. A feature vector was then extracted from each one second of EEG data. During the first training phase, four feature vectors extracted from the subsequent four seconds, which was determined by an offline analysis considering both accuracy and time, of EEG data were added to the training vector matrix. Meanwhile the correct option of the current question was added to the label vector. After recording the data from all questions in the first training phase, a classification model was trained using Gaussian RBF SVM introduced in Section II.D. In this paper, the number of questions in the first training phase was set to be the same for all subjects, i.e., 20 questions.

The motivation of the second training phase (Fig.3 (b)) is to update the classification model according to individual subject's input data until a consistent and accurate result has been achieved for that particular subject. After a new question was shown and the blue and red colors were displayed in the option rectangles, four feature vectors were extracted with each feature vector coming from the subsequent one-second blocks of EEG data, which was the same process as in the first phase described above. Each of the four feature vectors was applied to the previous trained classification model to obtain four classification results. If more than two classification results (thus majority) belonged to the same class, one option would be chosen (Fig. 3(a)). Otherwise a new feature vector from the next additional one second of EEG data would be extracted to derive a new classification result. This process was repeated until the majority of the latest four classification results belonged to one class. Then the classification result was compared to the correct answer. The feature vectors from the current question as well as the correct answer were added to the training feature matrix and label vector respectively to train a new classification model. The subject would be shown an additional question until the classification result and the correct answer agreed for five consecutive questions.

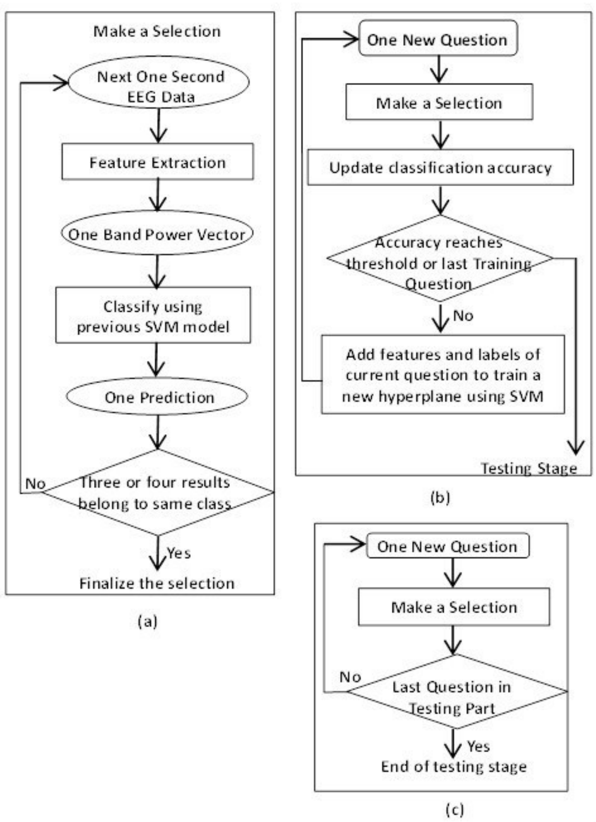


Figure 3 (a) Process for making a selection, (b) the second phase of training stage and (c) testing stage.

During the testing stage (Fig.3(c)), a subject would not be told about the correct answer and he/she had to calculate the answer and then looked at the blue/red color rectangle that corresponded to the subject's choice. The feature vectors would be extracted from the EEG data and the classification was made based on the trained SVM model in the same way as the training stage. This means that the majority of (more than two) classification results from four consecutive seconds of EEG data had to belong to the same class before a final decision was reached for that question. As the questions were easy enough for normal adults, it can be assumed that the accuracy of the classification model heavily depends on the decoding ability of the BCI. In this paper, each subject was presented with 10 questions in one round and then was given a two-minute break before the next round during the testing stage.

III. Experiment Results

Some experiments were conducted to evaluate the performance of the proposed BCI game in terms of time involvement and accuracy.

A. *Training Stage*

EEG data from 20 questions were captured for each subject to extract features for training an initial classification model. The correct answers for the 20 questions used in the first phase of the training stage were balanced, meaning that 10 correct answers were from option A (blue) and the other 10 correct answers were from option B (red). As described in Section II.E, the classification model was updated in the second phase of the training stage by adding more training data until a consistent and accurate classification accuracy was achieved. As a result, the number of questions required to train a proper classification model in the second phase of the training stage would be subject dependent.

TABLE I. Number of Questions Used in the Two Phases of the Training Stage

Subject	Number of questions in the first phase of the training stage	Number of questions in the second phase of the training stage	Total number of questions in the training stage
#1	20	12	32
#2	20	12	32
#3	20	15	35
#4	20	18	38
#5	20	17	37

TABLE II. Time Spent in the Two Phases of the Training Stage

Subject	First Phase		Second Phase		Total Time in Training Stage (s)
	Total Time (s)	*Average time per question (s)*	*Total Time (s)*	*Average time per question (s)*	
#1	160	8	181.9	15.2	341.9
#2	159.1	8	162.2	13.5	321.8
#3	159	8	198.6	13.2	350.5
#4	160	8	280.8	15.6	440.8
#5	159.7	8	245.1	14.5	406.4

Table I shows the number of questions used in the first phase and second phase of the training stage for each subject. Table II shows the time spent on each question in the first phase and second phase of the training stage for each subject. It can be observed in Table I and Table II that the required number of training questions and the time spent have individual differences among the subjects. To obtain a good classification model, subject #1 and #2 only needed 32 questions while 38 questions were required for subject #4. In terms of the time spent for the questions, subject #3 had to spend a total of 440.8s in the training stage while subject #2 required the shortest amount of training time (321.8s). Moreover, even subject #1 and #2 had the same number of questions for the training, the average time required for the questions differed because it took a longer time on average for subject #1 to come up with the majority in the classification results during the second phase of the training stage thus the total training time may also differ despite the same number of training questions.

B. Testing Stage

Table III shows the results in terms of the classification accuracy and time spent during the testing stage for each subject. During the testing stage, each subject had to answer 10 questions in one round and then was given a break of 2 minutes before starting the next round. A total of 3 rounds were conducted for each subject during the testing stage. The average accuracy was calculated by taking the mean of the percentages of the correct classification by our proposed system among three rounds.

Table III shows that most of the subjects can use our BCI to select the intended option within 15 seconds and at an accuracy range of 70%-80%. Similar to the second phase of the training stage, individual differences can also be observed in the accuracy and testing time. Subject #3 performed the best with an accuracy of 83% while subject #4 performed the worst but still reached an accuracy of 70%. In addition, subject #1 and #5 could use our BCI to select an answer to a question almost 3 seconds faster than subject #3 and #4 on average.

TABLE III. CLASSIFICATION ACCURACY AND TIME SPENT IN THE TESTING STAGE

Subject	Average accuracy (%)	Total Testing Time (s)	Average Time for Each Question (s)
#1	80%	113	11.3
#2	73.3%	136	13.6
#3	83.3%	142	14.2
#4	70%	149	14.9
#5	73.3%	117	11.7

IV. CONCLUSIONS AND FUTURE WORK

In this paper, a choice game using the blue and red color stimuli was implemented to examine how well color stimuli can be incorporated into BCI applications. Band powers of theta, alpha and beta from different electrodes were used as features. SVM with Gaussian RBF was used as the classifier due to its speed and accuracy. By taking individual differences in consideration, the number of training data was adjusted in a subject dependent manner until a consistent and accurate classification model was obtained. It has been shown that our BCI could help users to make a selection from two options with an accuracy of 70%-80%. This illustrates a promising result for applying color stimuli to online BCI applications.

One major objective of BCI research is to improve quality of life for disabled persons. Patients may have different kinds of problems such that they may only respond to certain stimulus. As a result, more patients will benefit from the BCI research that explores various kinds of stimuli. Our proposed work provided evidence for applying color stimuli to BCI applications. Band powers, especially in theta, alpha and beta band, of EEG signal can form an alternative feature set under blue and red color stimuli.

There are still plenty of research issues to be explored in BCI applications. More colors can be tested to identify the best color combination or offer additional options in BCI applications. Moreover, the size of each color rectangle as well as the distance between them can be studied to optimize the performance. Finally the combination between color stimulus and other visual stimulus can be examined to further improve the accuracy and practicality of BCI applications.

REFERENCES

[1] J. N. Mak, and J. R. Wolpaw, “Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects,” *IEEE Reviews in Biomedical Engineering*, vol. 2, pp. 187-199, Dec 2009

[2] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller and T. M. Vaughan, “Brain-computer interfaces for communication and control,” *Clinical Neurophysiology*, vol. 113, pp. 767-791, March 2002

[3] J. J. Daly and J. R. Wolpaw, “Brain – computer interfaces in neurological rehabilitation,” *The Lancet Neurology,* vol.7, pp.1032-1043, Nov 2008

[4] R. F. Chai, S. H. Ling, G. P. Hunter and H. T. Nguyen, “Mental Task Classifications using Prefrontal Cortex Electroencephalograph Signals,” *34st Annual International Conference of the IEEE EMBS*, pp.1831-1834, San Diego, USA, 2012

[5] A. Kubler and N. Birbaumer, “Brain-computer interfaces and communication in paralysis: Extinction of goal directed thinking in completely paralysed patients?,” *Clinical Neurophysiology*, vol. 119, no. 11, pp. 2659-2666, Nov. 2008

[6] N. Birbaumer, “Breaking the silence: Brain Computer Interfaces (BCI) for communication and motor control,” *Psychophysiology*, vol. 43, no. 6, pp. 517-532, Nov. 2006

[7] S. Kanoh, K. Miyamoto and T. Yoshinobu “A P300-based BCI System for Controlling Computer Cursor Movement,” *33rd Annual International Conference of the IEEE EMBS*, pp.6405-6408, Boston, Massachusetts USA, 2011

[8] M. G. Figueiro, A. Bierman, B. Plitnick and M. S. Rea, “Preliminary evidence that both blue and red light can induce alertness at night,” *BMC Neuroscience,* vol.10, article.105, Aug 2009

[9] A. Yoto, T. Katsuura, K. Iwanaga and Y. Shimomura, “Effects of Object Color Stimuli on Human Brain Activities in Perception and Attention Referred to EEG Alpha Band Response”, *J. Physiological Anthropology,* vol.26, pp. 373-379, 2007

[10] H. Zhang, and Z. Tang, “To judge what color the subject watched by color effect on brain activity,” *IJCSNS International Journal of Computer Science and Network Security*,vol.11,no.2,pp.80-83, 2011

[11] H. Ekanayake, “P300 and Emotiv EPOC: Does Emotiv EPOC capture real EEG?”, http://neurofeedback.visaduma.info/emotivresearch.htm, Oct. 7, 2011

[12] D. P. Subha, P.K. Joseph, U. R. Acharya and C. M. Lim, “EEG signal Analysis: A Survey,” *Journal of Medical Systems*, vol.34, pp.195-212, April 2010

[13] C. Cortes and V. N. Vapnik, “Support-Vector networks”, *Machine Learning* , vol.20, pp.273-297, Sep.1995.

[14] D. Garrett, D. A. Peterson, C. W. Anderson, and M. H. Thaut, “Comparison of Linear, Nonlinear, and Feature Selection Methods for EEG Signal Classification,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, no. 2, pp. 141-144, June 2003

[15] M. A. Oskoei, J. Q. Gan and H. Hu, “Adaptive Schemes Applied to Online SVM for BCI Data Classification,” *31st Annual International Conference of the IEEE EMBS*, pp.2600-2603, Minnesota, USA, 2009

[16] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche and B. Arnaldi, “A review of classification algorithms for EEG-based brain-computer interfaces,” *Journal of Neural Engineering*, vol.4, pp.R1-R13 Jan. 2007

[17] C. C. Chang and C. J. Lin, “LIBSVM: a library for support vector machines,” *ACM Transactions on Intelligent Systems and Technology,* vol. 2, pp. 1-27, 2011.