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Evaluation of EEG features during Overt Visual Attention during Neurofeedback Game

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***Abstract*—Brain-Computer Interface (BCI) is an emerging modality for direct communication between brain and computer, bypassing brain's conventional communication pathway of the nerves and muscles. Though BCI investigations have been targeting on the development of assistive devices for paralyzed patients initially, recent BCI research exploits the possibilities of BCI in entertainment and cognitive-skill enhancement through neurofeedback games also. Neurofeedback is an effective tool for boosting cognitive skills of both healthy and attention-deficit people based on real-time feedback and self-regulation of brain signals. This paper investigates the feasibility of employing EEG features related to sustained attention and overt visual attention-shift towards left or right visual periphery from a fixation point in the context of a neurofeedback game. Three healthy subjects have successfully played the proposed neurofeedback game by selecting the targets solely by EEG features related to overt visual attention, offering an average accuracy of 72.22%.**

Keywords—Electroencephalogram (EEG), Brain-Computer Interface (BCI), Neurofeedback and Overt attention.

I. Introduction

Brain-Computer Interface (BCI) is relatively a new approach to communication between man and machine, which translates brain activity into commands for communication and control [1]. As BCI is capable of detecting human intentions it is a promising communication tool for paralyzed patients for communicating with external world [2]. Most of the current BCI systems employ Electroencephalogram (EEG), one of the widely used non-invasive brain activity recording technique. EEG is an easier and cheaper technique than the other non-invasive methods such as functional Magnetic Resonance Imaging (fMRI), functional Near-infrared Spectroscopy (fNIRS) and Magneto-encephalography (MEG) [3]. EEG-based BCI has been focusing on the development of assistive technologies for the disabled during the last four decades of its research, on account of its ability to interpret human intentions. Recently BCI based neurofeedback games have attained much attention in research because of its great potential for enhancing brain's cognitive skills [4]. Neurofeedback allows an individual to self-regulate his brain signal in response to its real-time visual or auditory feedback. Training the brain has the capability to rewire the underlying neural circuits based on its plasticity, and to improve brain functions [5-7].

The therapeutic effects of neurofeedback training and its capabilities for the enhancement of cognitive skills have been widely discussed in literature [7-9]. Based on its great potential, neurofeedback has been considered as an alternate treatment modality for individuals with Attention-deficit Hyperactive Disorder (ADHD). ADHD is characterized by three behavioral symptoms: inattention, hyperactivity and impulsivity [10, 11]. Although these symptoms decline with age, up to half of the children continue to meet clinical diagnostic criteria in adulthood, especially for those with the combined and inattentive subtypes. The primary symptoms of inattention are that either the children fail to give close attention easily or they have difficulty in sustaining and orienting their attention. It has been argued that visual orienting (the ability to shift attention from one location to another) is problematic for individuals with ADHD [12]. Investigations in [13] found that children meeting the diagnostic criteria for ADHD responded significantly more slowly to stimuli appearing in the periphery than non-ADHD children. Compared to non-ADHD individuals, persons with ADHD often have insufficient alerting states [14].

The incidence of ADHD is a significant challenge on medical, financial and educational resources. It leads to many negative outcomes including academic underachievement, low self-esteem, work difficulty, social rejection, driving accidents, substance misuse and criminality, making it an important public health problem with high economic burden [12, 15, 16]. The main treatment modalities for ADHD include medication and behavioral treatments [16]. It has been reported that only between 70-80% of ADHD children respond favorably to psychostimulants. Medication has been found to have no effect on 25–40% of children with this disorder [17]. Besides, stimulant medications often cause significant side effects including poor appetite and physical growth suppression, and non-adherence rate as high as 25%. Behavior modification is another widely used treatment for ADHD. This type of treatment usually needs dedicated involvement of both parents and teachers. Utilizing behavior modification with stimulant medication creates a more comprehensive approach to treatment. However, substantial number of children does not respond to this type of treatment. None of the available intervention strategies have proven to be sufficiently effective, especially in terms of generalization and long-term effects. Hence, in the search for additional or alternative treatment

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option for children with ADHD, neurofeedback has emerged as one of the most promising options [16]. It is a neurobehavioural treatment aimed at acquiring self-control over certain brain activity patterns and implementing these skills in daily-life situations.

Based on the specific ability of neurofeedback to re-organize brain's neural circuits and empower specific brain functions, we have proposed an EEG based neurofeedback game in [17]. The proposed neurofeedback game required the player to memorize a set of elements in a 3 x 3 matrix and re-fill them correctly using his attention-related brain signals. The game in [17] was designed such that player is allowed to select the answer using keyboard input if his attention level estimated from EEG exceeds a certain subject-specific threshold value. In current work, we aim towards replacing the keyboard usage for answer selection in [17] solely by EEG features. Selection of elements of our visual environment for prioritized processing can be achieved overtly, with eye movements, or covertly, i.e. without eye movements. We propose to employ the player's overt visuospatial attention based EEG oscillations in the target selection process of the neurofeedback game. Overt visuospatial attention represents the ability to focus attention at one point in apace with overt eye movements.

A number of BCI applications depending on Event-related potential (ERP) occurs doing covert and overt attention are found in literature [18]. Many ERP-based BCI applications such as visual speller have been successfully employed, even in the case of amyotrophic lateral sclerosis (ALS) patients [18]. For ALS patients, oculomotor control can deteriorate in progressed stages of the disease and therefore such applications rely on covert attention only. Covert visuo spatial attention refers to the ability to focus attention at one point in space without overt eye movements. Topographically-specific modulations of alpha-band (~8–14 Hz) power have been consistently correlated with anticipatory states during tasks requiring covert attention shifts [19-22]. Alpha rhythm represents the dominant rhythm in the attentive and awake human. Its amplitudes are pronounced during the absence of visual stimulation and decrease during cognitive activity [21]. In visual spatial attention tasks, it has been shown that parietal alpha power decreases over contralateral sites preceding target presentation when attention is selectively directed to one visual hemi field. Study in [22] reports that when attention is shifted away from fixation, alpha band activity over parietal regions ipsilateral to the attended hemi field is enhanced relative to the control condition.

ERP studies have demonstrated overlapping links between overt and covert control mechanisms [18-21]. Temporal dynamics of oscillatory alpha-band activity is considered as a common mechanism across both overt and covert attentional deployments [19]. In the context of BCI based neurofeedback applications, overt visual attention is a feasible candidate that can be exploited because the target population is not having restricted oculomotor control as in ALS patients. Nevertheless they need to improve capabilities for sustaining attention or promptly shifting attention from location to another. Motivated by these facts, a neurofeedback game equipped with training elements on fixating or shifting player's attention orientation is presented in this paper, which can possibly enhance brain's specific skills and related daily-life activities. In the proposed neurofeedback game, we employ sample entropy based EEG features for detecting sustained attention, and power changes in alpha band of EEG for identifying the attention-shift. The game is designed such that it motivates player to achieve good control over his sustained attention and selective attention.

The rest of this paper is organized as follows. Section II provides the framework of the proposed BCI-based neurofeedback game. Section III presents the experiments performed and Section IV analyses the results of the experiments. Section V concludes our paper.

II. Proposed Methodology

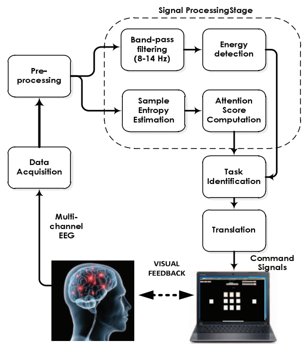

Fig. 1 Proposed BCI framework.

Fig.1 shows the schematic of the proposed BCI framework. In the proposed framework, (i) brain signals are captured using EEG recording device, (ii) pre-processed to remove baseline artifacts, (iii) relevant entropy and energy features are extracted in the signal processing stage, (iv) intentions of user are detected/classified and finally they are translated into game control commands. A brief explanation of different modules is provided in this section.

A. Data Acquistion

Data acquisition module consists of a wireless headset named as Emotiv Epoc Neuroheadset for recording EEG and a software package for the preliminary processing of data. This module is responsible for measuring EEG signal from scalp using electrodes, passing the signals to the computer software, preliminary filtering (notch filtering at 50 Hz and bandpass filtering of 0.2-45 Hz), and analog to digital conversion of captured signals. The sampling frequency of signals is fixed as 128 Hz [17, 23].

B. Pre-processing stage

The pre-processing stage is responsible for fine tuning the raw signal obtained from the headset for further processing. For every EEG channel recorded, the baseline correction of the incoming data is done by subtracting the mean of the signal just prior to the onset of any active attention tasks. This is to nullify the effect of possible time-domain shifts of EEG from zero line over time due to various noise resources, and to ensure that an observed effect is not already present in the signal before the stimuli were actually present.

C. Signal processing Stage

EEG signal from the pre-processing unit then undergoes the energy detection stage for estimating overt visual attention-shift, and entropy estimation stage for attention level detection.

*1) **Features for overt visual attention-shift:*** Shifting of attention is associated with specific changes in alpha band of EEG over brain regions that process the attended hemifield. Based on this fact, we utilize this topographic alpha band activity for finding out the location where the player is focusing on the game's Graphical User Interface (GUI). Energy of alpha band in ipsilateral brain sites increases whereas it decreases in contralateral brain regions, if an individual shifts attention from fixation towards a point in his left/right visual periphery. Hence, at first, EEG signals during the time period when player shifts his attentional orientation from a central fixation point towards a target in right/left visual hemifield are bandpass filtered using Infinite Impulse Response (IIR) bandpass filter of range 8-14 Hz. Energy of the filtered EEG from p^{th} channel: α^p is computed using the equation (1) as:

$$\alpha^p = \sum_{i=1}^{N} \log(X^p(i)^2) \qquad (1)$$

where $X^p(i)$ denotes the i^{th} sample of EEG signal of length N samples, from p^{th} channel. Then, an alpha band energy metric named as δ^{ALPHA} in eqn. (2) is computed to predict the orientation of overt attention.

$$\delta^{ALPHA} = \left[\sum_{p=1}^{P/2} \alpha^p - \sum_{p=P/2}^{P} \alpha^p\right] \Bigg/ \left[\sum_{p=1}^{P/2} \alpha^p\right] \times 100 \qquad (2)$$

For computing δ^{ALPHA}, the set of selected '*P*' EEG channels are symmetrically arranged in such a way that the first *P/2* channels are from left hemisphere whereas the rest *P/2* are from right hemisphere. As eqn. (2) implies δ^{ALPHA} is the normalized percentage deviation α^p of left hemisphere channels with respect to the right hemisphere. As the ipsilateral alpha band energy is expected to be higher compared to the contralateral during attention-shift, the metric δ^{ALPHA} presented in eqn. (2) is more negative if the player shifts attention from fixation to right, and more positive if the player shifts attention from fixation to left. From each hemisphere, the frontal, parietal and occipital areas are chosen for δ^{ALPHA} computation as those brain regions are considered to be important in selective attention [21].

*2) **Features for sustained attention**:* EEG activity during sustained attention is slightly more complex than that in inattention task. Hence, we employ entropy features, a measure of complexity of signal which increases with the degree of disorder present in signal, to assess the attention level. Entropy of EEG signal during attention tasks is found to be greater than inattention tasks [17]. This work uses an extension of simple entropy, termed as Sample Entropy (*SampEn*) given by Eqn. (3). It is the negative natural algorithm of the conditional probability that two sequences similar for m points in a time series of N samples remain similar at the next point, where self matches are not included in calculating the probability.

$$SampEn(m,r,N) = -\ln\left[A^{m+1}(r) \big/ B^m(r)\right] \qquad (3)$$

where m is the embedding dimension and r is the tolerance for accepting matches. B^m is the probability that two sequences will match for m points, whereas A^{m+1} is the probability that 2 sequences will match for $m+1$ points. The values of m and r adopted in this work are 2 and 0.25σ respectively where σ is the standard deviation of the signal [17]. After estimating the *SampEn* features of all EEG channels, the attention score is taken as the highest among the *SampEn* values obtained from all the selected channels.

D. Task Identification

The two specific tasks employed in the proposed system are focused visual attention and attention-shift towards left/right visual periphery. For sustained attention detection, attention level is classified as high if the attention score estimated from entropy value is greater than a subject-specific threshold. For identifying overt attention orientation, if the δ^{ALPHA} computed according to eqn. (2) is less than a particular threshold, it is considered as right orientation whereas it is considered as left orientation, if δ^{ALPHA} is greater than the threshold. These two threshold values regarding attention score and δ^{ALPHA} have to be determined for every subject prior to the game play.

E. Translation of Tasks and Gaming Interface

The identified tasks are translated into game commands for controlling the gaming interface. The gaming interface, control parameters and mapping of mental tasks into command signals are briefly explained here.

1) Gaming Interface: The gaming interface is similar to the GUI employed in [4, 17] except a few minor changes in the presentation of matrix display. The flowchart of game control is as shown in Figure 2. The GUI protocol is designed such that player has to focus on a set of numbers displayed in the form of a 3 x 3 matrix textbox, memorize them and correctly re-fill the matrix. The subject is able to refill the matrix correctly only if his attention level exceeds a specific threshold. This attention level is continuously provided in the form of a progress bar in the GUI. This feedback information continuously helps the user to regulate his concentration value above the pre-defined threshold level.

After the display period of 3 sec, the textboxes will turn blank for a period of 4 sec. At the end of the 4-sec blank display period, the system highlights the previously displayed textboxes one by one for duration of 3 seconds. This stage requires active concentration of subject for which he is requested to focus on the central text box. If the subject is able to raise the attention above a subject-specific threshold value (which is computed during training phase before playing the game) within 4 sec, answers will be displayed in the textboxes on the right and left side of the GUI ('4' and '5' respectively for the example shown in Fig. 2).

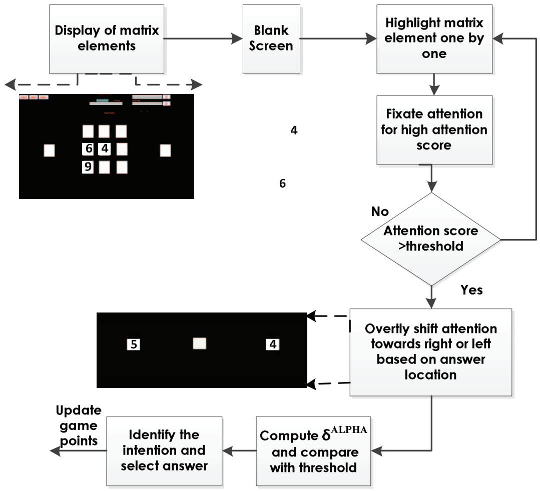

Fig. 2 Flowchart of gaming control.

One of the text boxes will display correct answer (right-side text box which displays '4') whereas wrong answer is placed on the other (left-side text box which displays '5'). The location of answer placement is randomly chosen. Player is required to rapidly shift his attention from central textbox to the answer textbox on the right or left side of the main matrix panel to select the answer. If δ^{ALPHA} is less than threshold, it is assumed that player intends to select element in the right textbox and vice versa. If the subject selects correct answer, a smiley appears on the textbox where the answer was placed. Then, the subject has to move the smiley by concentrating on the smiley or a specific point on screen, to the highlighted textbox. The game is designed such that speed of smiley is directly proportional to the attention of subject. If the attention level of the subject is below the threshold, the answer options would not appear on the screen, and the subject will not be able to do the answer selection using overt attention. Subsequently the GUI will highlight the location of next element. During one game session, subject has to fill a total of 6 matrices and player is presented with the final game score at the end of the 6^{th} matrix. The final game score mainly consists of the number of correctly filled elements and number of fully filled matrices.

III. EXPERIMENTS

All the neurofeedback experiments have been done in a silent room so that no other distractions are allowed while playing the game. Three healthy subjects have volunteered to play the game. During the experiments, the subject has been sitting in armchair, facing the computer monitor at about 60 cm apart. Twelve EEG channels have been recorded from the scalp to compute the EEG features and they are *AF3*, *F7*, *F3*, *FC5*, *P7*, *O1*, *O2*, *P8*, *FC6*, *F4*, *F8* and *AF4* using Emotiv Epoc neuroheadset, according to 10-20 international system of EEG electrode placement. The experiment consists of two major sessions named as calibration and gaming sessions.

During calibration, every subject has to undergo 2 training sessions for computing 2 subject-specific threshold values for assessing sustained attention level and attention-shift respectively. Threshold for sustained attention is computed based on entropy values of EEG signal obtained from 10 trials during which the subject performs repeated active concentration and relaxation tasks. The average entropy value of 10 trials during the concentration period has been taken as the subject-specific threshold. The threshold for attention-shift is determined based on EEG signals recorded from 60 trials out of which 30 trials belong to left shift and 30 trails belong to right shift. Respective cues will be provided on the training interface for which the player has to overtly shift his attention orientation from a central fixation point towards a target point present in the right or left visual periphery of the computer screen. Average values of δ^{ALPHA} for 30 right shift trials and 30 left shift trials have been computed. Median of this value is taken as threshold termed as $\delta^{ALPHA\text{-}threshold}$ for attention-shift detection. If the computed δ^{ALPHA} is greater than $\delta^{ALPHA\text{-}threshold}$, it is left shift whereas it is right shift if δ^{ALPHA} is less than the threshold.

After estimating these two subject-specific threshold values, the gaming session is conducted in real time. Every subject has to play a single game session of difficulty Level-1 during gaming session where the highest number of correctly filled matrices is 6 and correctly filled matrix elements is 18.

IV. RESULTS

Three subjects, named as S_1, S_2 and S_3 in the sequel, have played the game successfully and their game performance in terms of attention score, accuracy in answer selection based on overt attention-shift and the percentage of correctly filled matrix elements are discussed here.

A. Attention Score Values

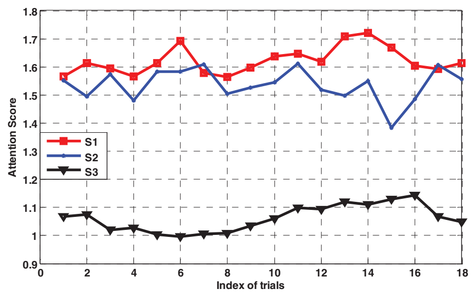

Fig. 3 Attention scores obtained during game play for 3 subjects.

For subjects S_1, S_2 *and* S_3, the calibrated subject-specific threshold value for attention level detection are 1.5, 1.4 and 1 respectively. Fig. 3 represents the attention scores obtained for subjects S_1, S_2 *and* S_3 for the 18 trials of matrix filling operation during game. For S_1, the attention scores are higher than the pre-defined threshold for every trials whereas for S_2, 15^{th} trial shows lower attention score. For S_3, 6^{th} trial gives less attention score than subject-specific threshold value. However, it can be found that all the players are able to maintain their attention levels above the selected threshold for most of the trials.

B. Detectionof Attention-shift

Shift of attention towards left or right show distinguishable α^p features between left hemisphere channels and right hemisphere channels. Fig. 4 represents the scatter plots for alpha band energy measure α^p obtained during left and right shift tasks during calibration. Fig.4 (a) shows scatter plot of α^p values between the 2 classes obtained during calibration from channels *F7* and *F8*.

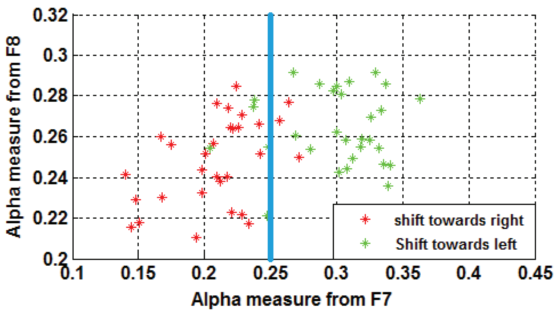

Fig. 4 (a) Scatter plot showing α^p from *F7* and *F8* during calibration.

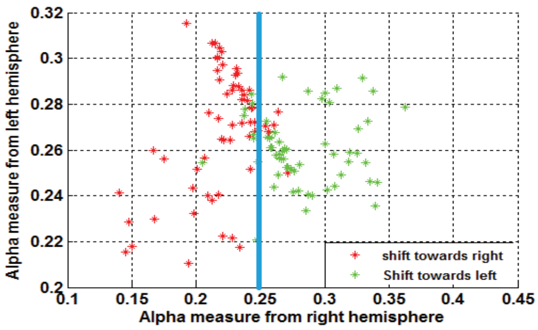

Fig. 4 (b) Scatter plot showing average of α^p features.

In order to better visualize the discrimination of these alpha energy features in the left and right hemisphere during attention-shift tasks, the average α^p values of selected 6 channels from left hemisphere (*AF3*, *F7*, *F3*, *FC5*, *P7*, *O1*) and of the 6 channels from right hemisphere (*O2*, *P8*, *FC6*, *F4*, *F8* and *AF4*) are plotted in Fig. 4(b). Offline analysis clearly shows the separability of the 2 tasks using the proposed alpha band metric.

Based on the training data, values of $\delta^{ALPHA\text{-}threshold}$ for subjects S_1, S_2 and S_3 are estimated. Based on this pre-selected threshold, 12, 14 and 13 attention-shift trials out of 18 have been successfully identified during online game for subjects S_1, S_2 and S_3 respectively.

C. Overall Game Performance

The overall game performance can be assessed by the points won by each subject at the end of the game in terms of the number of correctly filled matrices and matrix elements. Table I shows the game performance offered by each subject.

Table I Game performance evaluation

Subjects	Correctly filled matrix elements	Percentage Accuracy of matrix filling	Fully correct matrices
S_1	12	66.67%	1
S_2	14	77.78%	2
S_3	13	72.22%	1
Average	**13**	**72.22%**	**1.33**

It can be found that average accuracy in matrix filling operation is 72% during the real time game performance for all the 3 subjects. The proposed framework employs sample entropy and only a simple threshold based method for attention-shift detection. In order to enhance the accuracy in task identification and game performance in future, more efficacious signal processing and machine learning techniques have to be developed and integrated in the game.

V. CONCLUSION

Neurofeedback games exploit the possibility of replacing conventional game control inputs by brain signals. They put forward a promising candidate for boosting the cognitive skills of healthy as well as the attention-deficit. This paper presents an attention-based neurofeedback game which employs only player's sustained attention and selective attention based EEG features for controlling the game and achieving game points. Attention levels of all the players have been identified with sample entropy features whereas shifting/orientation of attention is successfully detected based on an alpha metric proposed in this paper. Among the 3 subjects, average accuracy of answer selection during the game is 72 % using the proposed alpha metric. In future, it is essential to develop more robust and stable feature extraction algorithms to improve game performance. The study has also to be extended including more number of healthy as well as attention-deficit subjects to investigate the generalization and exact utility of the proposed method.

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