On the classification of EEG/HEG-based attention levels via time-frequency selective multilayer perceptron for BCI-based neurofeedback system

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Abstract—**Attention Deficit/Hyperactivity Disorder (ADHD) is a neurobehavioral disorder which leads to the difficulty on focusing, paying attention and controlling normal behavior. Globally, the prevalence of ADHD is estimated to be 6.5%. Medicine has been widely used for the treatment of ADHD symptoms, but the patient may have a chance to suffer from the side effects of drug, such as vomit, rash, urticarial, cardiac arrthymia and insomnia. In this paper, we propose the alternative medicine system based on the brain-computer interface (BCI) technology called neurofeedback. The proposed neurofeedback system simultaneously employs two important signals, i.e. electroencephalogram (EEG) and hemoencephalogram (HEG), which can quickly reveal the brain functional network. The treatment criteria are that, for EEG signals, the patient needs to maintain the beta activities (13-30 Hz) while reducing the alpha activities (7-13 Hz). Simultaneously, HEG signals need to be maintained continuously increasing to some setting thresholds of the brain blood oxygenation levels. Time-frequency selective multilayer perceptron (MLP) is employed to capture the mentioned phenomena in real-time. The experimental results show that the proposed system yields the sensitivity of 98.16% and the specificity of 95.57%. Furthermore, from the resulting weights of the proposed MLP, we can also conclude that HEG signals yield the most impact to our neurofeedback treatment followed by the alpha, beta, and theta activities, respectively.**

I. INTRODUCTION

Attention Deficit/Hyperactivity Disorder (ADHD) is a neurobehavioral disorder which causes its sufferers to have extreme difficulty focusing, paying attention and controlling their behaviors. It affects both children and adults but more prevalently diagnosed in children. It has been described as one of the most common problem in school children. In Thailand, the prevalence of ADHD was estimated to be 6.5% [1]. Hence, it currently becomes a public health concern. Medicine has been widely use to cure the ADHD symptoms. Methylphenidate and Monoamine Oxidase Inhibitor are drugs that generally prescribed. Taking the drug can immediately make the children be able to concentrate for a couple of hours, but the children that are dosed may have some side effects, such as vomit, rash, urticaria, cardiac arrthymia and insomnia [10].

Neurofeedback is one of the alternative methods for treating ADHD [2-5]. Brain signals and the video games are concurrently employed in this method. Patients have to control the video games by their attention. Computer processes the bio-signals of patients as the attention level and give the feedback to the patients in real-time via the selected action in the video game.

There are a lot of techniques used to capture the attention features in neurofeedback, for example, frequency analysis [10], time-domain analysis [11], joint time-frequency analysis (JTFA) and live z-score with normative database [12]. In this paper, the method of artificial neuron network (ANN) is applied. Multilayer perceptron is the method of ANN that used for classifying the data. This neurofeedback system consists of the steps of 1) signal acquisition, 2) signal processing and 3) feedback controlling device. Multilayer perceptron is applied for classifying data into two classes in the step of signal processing (attention/inattention). The patient should be in the attention class and try to maintain it as long as possible by using the video game as the feedback.

In this work, two bio-signals, i.e. electroencephalogram (EEG) and hemoencephalogram (HEG), are simultaneously employed to reveal the brain function. The EEG represents the voltage difference between two brain positions while the HEG illustrates the brain blood oxygenation that increases when the brain performs a high activity and high metabolism. The treatment criteria are that, for EEG signals, the patient needs to maintain the beta activities (13-30 Hz) while reducing the alpha activities (7-13 Hz), i.e. the attention stage. Simultaneously, HEG signals need to be maintained continuously increasing to some setting thresholds of the brain blood oxygenation levels. Therefore, in this paper, time-frequency selective multilayer perceptron (MLP) is employed to efficiently capture the mentioned phenomena in real-time.

II. DATA ACQUISITIONS

In this work, we acquire two bio-signal for our proposed neurofeedback system. The first acquired signal is the electroencephalogram (EEG) or the brain wave. It is the recording of brain activities that shows electrical signals from the neural synapse. Another one is the hemoencephalogram (HEG) or brain blood oxygenation. It is the quantities that can reveal the brain metabolism which is directly vary with the brain oxygen usage. The data used in this study is acquired from five healthy subjects, five men and one woman. Ages of volunteers are in the range between 22 to 26 years old. We simultaneously collect their EEG data and HEG data. Each subject will perform 200 trials of the attention/inattention tasks. It is equally divided into relaxation tasks (inattention) and attention tasks. For inattention tasks, the subjects are asked to relax with eye opening. For attention tasks, the subjects are asked to play game. Guitar heroes game is selected since it requires high attention to play according to the psychiatrist recommendation.

A. EEG Acquisition

EEG data were obtained from the BIOPAC^{TM} MP100 with the Ag/AgCl electrodes placed according to the 10–20 international electrode placement system (Fig.1). The sampling rate is set to 480 Hz and band-pass filtering between 1 to 50 Hz. The positions that we choose for placing the electrodes are T3 (+ or -), T4 (+ or -) and Cz (ground) so that the signals which are synchronized with the sound stimulation can be observed.

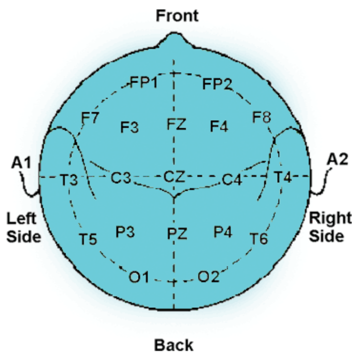

Fig. 1 The 10–20 international electrode placements [12].

B. HEG Acquisition

HEG data were obtained from HEG the headband that designed by Hershel Toomim [8]. The near infrared (nIR) headband contains an optical transmitter and receiver (Fig. 2). It utilizes the fact that more highly oxygenated blood is redder in color. It sends pulses of red and infrared light through the skull to the cortex beneath. We measure the level of oxygen in blood by comparing the intensity of red light and infrared light. The red LED and infrared LED are alternately sent the light with the sampling rate of 480 Hz.

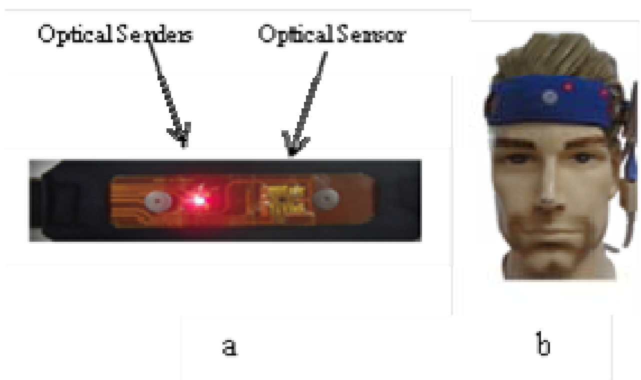

Fig. 2(a) nIR HEG Headband (b) the appearance when fasten the headband around the head

III. FEATURE EXTRACTION

Since raw data of the EEG and HEG are of large dimension. We have to reduce the size of data for reducing the computational load by the methods below:

A. Feature Extraction of EEG

Since the input EEG is acquired at the rate of 480 sample/second, the dimension is too large for the real-time computation every one second. The power spectral density (PSD) is the selected method used in this step. PSD shows the strength of the variations (power) as a function of frequency. The unit of PSD is power per frequency. Computation of the PSD is done directly by computing the autocorrelation function of the input signal and then transforming it via the fast Fourier transform (FFT).

Since attention level has the close relation with the frequencies of the EEG. The appropriate selected feature is to transform this time-domain nonstationary EEG signal into the frequency domain by the PSD. The selected features can be reduced by summing the power of each frequency level into three frequency bands, i.e. theta band (3-7 Hz), alpha band (8-13 Hz) and beta band (14-30 Hz).

B. Feature Extraction of HEG

For the HEG feature, it is the intensity of the signals at the receiver calculated by comparing the intensities of the reflected red light with the reflected infrared light.

Hence, after finishing these feature extraction steps, we will have only four dimensional input to our system, i.e. theta band power, alpha band power, beta band power and HEG level. All of these are the inputs to the classification process.

IV. CLASSIFICATION OF THE SELECTED FEATURES

This section is divided into two main topics. The first topic provides the brief background to our previous method proposed in [13]. The second topic is our proposed method in this paper.

A. Previous Work using Linear Classifier

In this previous work, linear classifier is employed separately on EEG and HEG. Features of EEG are calculated in time domain (as shown in Fig. 3) to get the beta/alpha ratio.

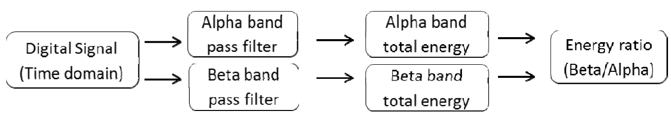

Fig. 3 Analysis in time domain via total energy in Time-domain

According to Fig. 3, to further emphasize on the aspect of digital signal processing, digital signals are filtered into two frequency bands, i.e. alpha band and beta band, by the 9th order Butterworth IIR filter. If the ratio is more than the setting threshold, digital output will be 1. This case implies that the patient is in the attention stage. Similarly, if the ratio is less than the threshold, digital output will be 0. This case implies that the user is in an inattention stage. The setting threshold can be calculated via the linear classification. Similarly, HEG level is compared to setting threshold, if the HEG level is more than the setting threshold, the digital output will be 1. If the HEG level is less than the threshold, digital output will be 0. The setting threshold can be calculated separately via the linear classification

B. Classification via Multilayer Perceptron (MLP)

A multilayer perceptron (MLP) is the supervised learning method which can be designed to have multiple hidden layers. The backpropagation algorithm consists of two passes. For the forward pass, the activations are propagated from the input to the output layer. For the backward pass, the error between the actual output and the desired output in the output layer is propagated backwards in order to update the weights and the bias values.

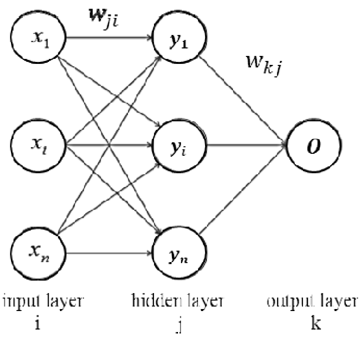

Fig.4 The general structure of MLP with a hidden layer.

The backpropagation algorithm employs a gradient descent method. Once the momentum term is added, the algorithm gives the weight change of a connection between neurons *i* and *j* as follows

$$\Delta w_{ji}(k) = \eta\delta_j x_i + \alpha\Delta w_{ji}(k-1) \ , \quad (1)$$

where η is a learning rate parameter, α is the momentum coefficient, and δ_j is a factor depending on whether neuron j is an output neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)(y_j^{(k)} - y_j) \ , \quad (2)$$

where $net_j \equiv \sum x_i w_{ji}$ and $y_j^{(k)}$ is the desired output for neuron j. Here represents sigmoidal function. For hidden layers and output layer,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\sum_q w_{qj}\delta_q \ , \quad (3)$$

As there are no desired outputs for hidden neurons in Eq. (3), the difference between the desired and actual output of a hidden neuron j is replaced by the weighted sum of the δ_q terms already obtained for neurons q connected to the output j. Thus, iteratively, beginning with the output layer, the δ term is computed for neurons in all layers and weight updates for all connections according to Eq. (1).

C. The Implementation of Multilayer Perceptron

In this work, the MLP is trained several times using different number of hidden neurons until getting the best performance. The MLP architecture of this work is show as in Fig. 5.

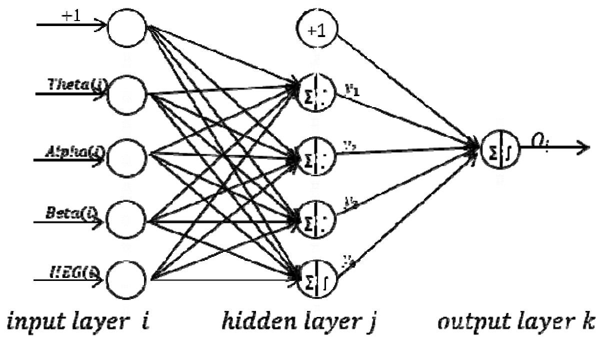

Fig. 5 Architecture of MLP

The steps of implementations of this work are described as follows (Fig. 6):

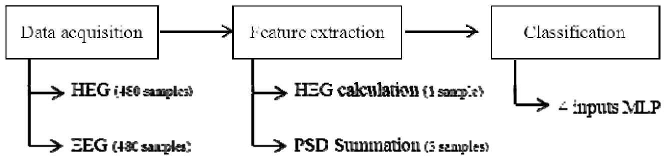

Fig. 6 Attention level classification implementation by using EEG and HEG

According to Fig.6, for implementing real-time neurofeedback system, the system needs to process the decision every second. This makes the raw EEG data have 480 samples as well as the HEG. According to Section III, EEG can be reduced into power of three frequency bands and HEG can be reduced into one HEG value. Therefore, the number of input dimension to the MLP is four.

V. RESULTS

In this section, we compare the proposed MLP classification of our proposed hybrid EEG-HEG neurofeedback with our three previous works, i.e. using only EEG with linear classification, using only HEG with linear classification, and using hybrid EEG-HEG with designed logic conditions.

For each subject, EEG and HEG thresholds are obtained via linear classifier on the training session as well as the MLP parameters. The training session includes 1) paying attention to play the video game and 2) having a relaxed sitting with eye opening. The performances of each method are shown in term of specificity (the percentage of attention that correctly identified as not having the condition) and sensitivity (the percentage of inattention that correctly identified as having condition). For hybrid EEG-HEG neurofeedback using MLP, we find the best architecture by the method of cross validation and also show the performance in term of specificity and sensitivity. The performances of each method are shown in Table I.

TABLE I
PERFORMANCE OF EACH METHOD

Method	Sensitivity	Specificity
EEG neurofeedback using linear classification	90	70
HEG neurofeedback using linear classification	29	94
Hybrid EEG-HEG neurofeedback using logic conditions	90	82
Hybrid EEG-HEG neurofeedback using MLP	98	95

In Table I, EEG neurofeedback gives high sensitivity of 90% but gives quite low specificity of 70%. HEG neurofeedback yields good performance for specificity of 94%, but yields the lowest sensitivity of 29%. By combining the two signals as the hybrid system with the logic (or) condition, 90% of sensitivity and 82% of specificity can be achieved. To further improve these previous works, the hybrid EEG-HEG neurofeedback using MLP gives the best performance of 98% sensitivity and 95% specificity. The best structure of multilayer perceptron consists of 3 layers including 4 hidden nodes with the binary sigmoidal function.

VI. CONCLUSIONS

In this work, we have improved the performance of the hybrid EEG-HEG neurofeedback via MLP and compared its performance with the previous methods. Moreover, by using the MLP, we can observe the level of significant for each of our 4 inputs by the resulting weights of the proposed MLP. That is, we can also conclude that HEG signal yields the most impact to our neurofeedback treatment followed by the alpha, beta, and theta activities, respectively.

In future work, statistical analysis, e.g. z-score, should be included in our hybrid system.

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