Feature Selection Based on Modified Genetic Algorithm for Optimization of Functional Near-Infrared Spectroscopy (fNIRS) Signals for BCI

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***Abstract*— One of the pivotal issues which must be tackled when an effective brain-computer interface (BCI) is to be designed, is to reduce the enormous space of features extracted from fNIRS signals. BCI researchers often use genetic algorithms (GA) as the technique to extract features. The classic genetic algorithm obtains a feature set with the high classification accuracy; however, it is unable to create a reliable classifier due to the large dimensionality of this set. Herein, we propose a refined version of the genetic algorithm, which chooses a small number of features and determines the optimal feature combination for classification of fNIRS signals for a BCI system.**

***Keywords*— Functional near-infrared spectroscopy; Genetic algorithm; Feature selection; Brain-computer interface; Support vector machines**

I. Introduction

"A brain-computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles" [1]. Such frameworks can be used as methods for communication and recovery of motor functions for persons with the motor issues, such as amyotrophic lateral sclerosis and spinal cord injury [2-4].

For acquiring brain signals both invasive and non-invasive methods are used. The invasive methods [5] are not preferred because of the electrodes are directly implant into the grey matter. Numerous non-invasive modalities have been used for brain signal acquisition, which includes functional magnetic resonance imaging (fMRI), (electroencephalography) EEG, functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG), and positron emission tomography (PET).

fNIRS and EEG are portable systems and suitable modalities for BCI. Coyle et al. (2007) used a custom-built fNIRS system (named Mindswitch) to test on-off control to control the output of fNIRS based BCI [6]. Sitaram et al. (2007) showed that fNIRS signal patterns during execution movement and imagery [7]. We use fNIRS to acquire data from brain because of its easy wearability and higher spatial resolution. It has been in use for cerebral hemodynamic study since 1977 [8]. A detailed review on fNIRS-based BCI studies is provided in Naseer and Hong, 2015 [9]. The main challenge for BCI system is to reduce the high dimensionality of the extracted features. Genetic algorithms (GA) can be applied in BCI for feature selection [10-14]. Their main advantage is that they are not very inclined to get stuck at local minima.

In this research, we propose a novel technique for optimal feature selection from fNIRS signals using a modified GA [10] to decrease the time of classification and improve accuracy. The average classification accuracy of the combination of 2 features was found 97.37% using the support vector machine which is significantly higher than the previous results [15].

II. Materials and Methods

A. Signal Acquisition

fNIRS detects the hemodynamic changes in the blood flow because of neuronal activation. When an activity is performed, the neurons fire and, therefore, require oxygen to become active. This oxygen is provided by the oxygenated hemoglobin (HbO). The blood oxygenation level flow to that area increases, because of that increase there is a rise in HbO and decrease in deoxygenated hemoglobin. It measures the changes in the concentration of HbO and deoxygenated hemoglobin (HbR) that result from neuronal activation.

An incident of the photon on the brain scatters unlike the x-rays and penetrate 3 cm into the human brain tissues. To detect the cortical activities in the brain, around 3 cm source to detector distance is considered as the optimal path, 80% of the detected photons follow the banana shape. The depth increases with the source-detector distance, and it depends on the optical properties of the tissue.

Once the light penetrate into the human brain, it detects the hemodynamic response i.e. changes in the concentration of oxygenated hemoglobin ($\Delta c_{\mathrm{HbO}}(t)$) and deoxygenated hemoglobin ($\Delta c_{\mathrm{HbR}}(t)$) in the blood along the photon path using the modified Beer-Lambert Law as:

$$\begin{bmatrix}\Delta c_{\mathrm{HbO}}(t)\\ \Delta c_{\mathrm{HbR}}(t)\end{bmatrix} = \frac{1}{l \times d}\begin{bmatrix}\alpha_{\mathrm{HbO}}(\lambda_1) & \alpha_{\mathrm{HbR}}(\lambda_1)\\ \alpha_{\mathrm{HbO}}(\lambda_2) & \alpha_{\mathrm{HbR}}(\lambda_2\end{bmatrix}^{-1}\begin{bmatrix}\Delta A(t,\lambda_1)\\ \Delta A(t,\lambda_2)\end{bmatrix} \quad (1)$$

where $\Delta A(t;\lambda_j)$ (j =1, 2) is the absorbance (optical density) measured at two points of wavelength λ_j,$a_{\mathrm{HbX}}(\lambda_j)$ is the extinction coefficient of HbX in $\mu M^{-1}mm^{-1}$, d is the differential path length factor (DPF), and l is the emitter-detector distance (in millimeters).

A multichannel continuous wave system (DYNOT: DYnamic Near-infrared Optical Tomography; two wavelengths: 760 and 830 nm) obtained from NIRx Medical Technologies, was used for the detection of brain activity at a sampling rate of 1.81 Hz. The near infrared (NIR) light is transmitted on the scalp from the source at the above-mentioned wavelength, that scattered through the cortical area of the cerebrum where chromophores of HbO and HbR are present, a portion of NIR light is absorbed by the HbO and HbR and the remaining light is detected by the detectors.

B. Subjects

Seven healthy subjects were recruited for the experiment. Each one of them had normal vision and none of them had any history of any visual or psychological disorder. After explaining the details of the whole experiment, the verbal consent was taken from all of the subjects. The experiment was conducted in accordance with the latest Declaration of Helsinki.

C. Channel Configuration and Optodes Placement

The situating of optodes in the NIR experiment is of vital significance to ensure that the photons travel through the region activated by brain activity. The distance between an emitter and a detector is very important, as it influences the signal quality and penetration depth. The maximum penetration depth is considered at the midpoint between the emitter and the detector.

A total of 4 emitters and 10 detectors were used for the detection of mental arithmetic versus rest signals from the prefrontal cortex, which configuration included 16 channels. In fNIRS-based BCI systems, the prefrontal cortex is the brain region which is most widely used because it involves fewer motion artifacts and signal attenuation due to the slippage in hair. The distance between the detector and the emitter plays an imperative role to acquire fine-quality signals and the obtainment of maximum information therefrom [16]. Usually, in fNIRS-based BCI systems, the emitter-to-detector distance is 3~4 cm; in this research, the distance was set to 2.8 cm [16], as shown in Fig. 1.

D. Experimental Paradigm

The subjects were seated in a quiet room on a comfortable chair in front of a computer monitor at the distance of 70 cm. They were asked to restrict their motor motions and relax before the start of the experimental paradigm to settle down the hemodynamic response to the baseline. The subjects were asked to rest and then to perform a mental arithmetic task, as shown in Fig. 2, then he/she performed a mental arithmetic task for 44 s. The total length of the experiment was 440 s for each subject with total five trials in each experiment section. In the mental arithmetic task, the subjects did calculation consisting of the subtraction of a two-digit number from a three-digit number with the successive subtraction of another two-digit number from the result of the initial subtraction [15,17] (e.g. 300 - 14, 286 - 11, 275 - 16, etc.).

E. Signal Processing

To calculate the changes in the concentration of HbO and HbR ($\Delta c_{\text{HbO}}(t)$ and $\Delta c_{\text{HbR}}(t)$) in the micro vessels of the cortex, modified Beer-Lambert law (MBLL). The signals contain physiological noises. Butterworth 4th-order filter was used to remove the noise. The signals were low-pass filtered with the cut-off frequency 0.3 Hz to remove the high-frequency physiological noises due to respiration (0.4Hz for adults) and heartbeat (1-1.5Hz). Then, a high-pass filter with the cut-off frequency of 0.1 Hz was used to minimize the effect of low-frequency oscillations (Mayer waves). Finally $\Delta c_{\text{HbO}}(t)$ and $\Delta c_{\text{HbR}}(t)$ were then calculated using equation (1).

F. Classification

Support vector machine (SVM) has been widely used classification modality in fNIRS based BCI systems because of its high classification performance. It scales relatively well to high dimensional data and errors can be controlled explicitly. The main idea of SVM is to create the hyperplanes that maximize the margins between the classes in order to acquire maximum classification accuracies. SVM has good generalization proficiency because a regularization parameter is presented in it which can permit or penalize classification errors on the training sets [18].

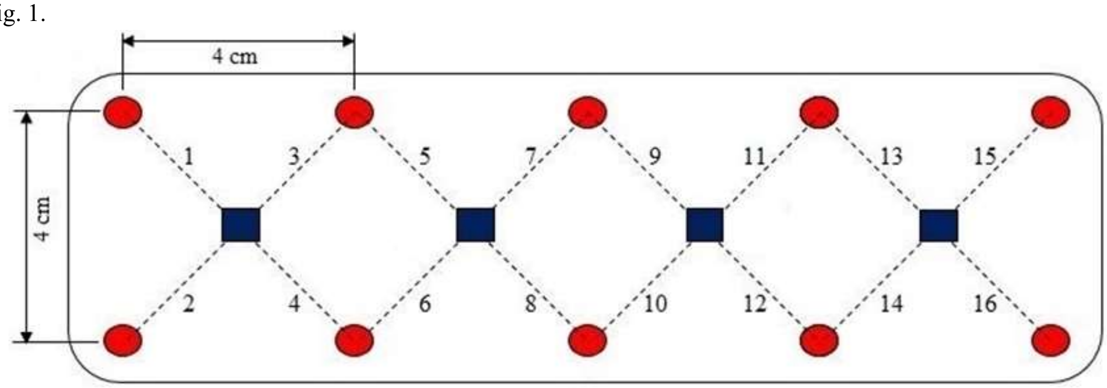

Fig. 1. Optodes placement: The red circles represent the detectors and the blue filled squares represent the emitter.

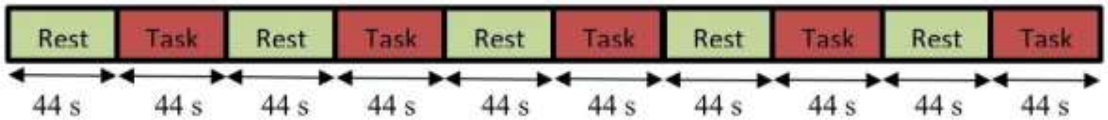

Fig 2. Schematic of the experimental paradigm: The green blocks represent the 44 s rest periods at the beginning and at the end; the second, red block represents the 44 s mental arithmetic task.

III. Results and Discussion

For evolutionary optimization with GA, a binary string considered the genetic information of an individual. Initially, a whole population consisting of several individuals are randomly initialized. Each classification performance was evaluated by 10-fold cross-validation followed by SVM classifier over the course of 10 runs. The two-dimensional feature spaces for subjects 4 is shown in Fig. 3, respectively. It can be seen from Fig. 3 that the feature vectors corresponding to mental versus rest task responses are distinguishable. The classification accuracies achieved for mental vs rest tasks are listed in Table I. The average accuracy across all subjects was found to be 97.96%. Total 10 trails were taken for better results. Fig. 4 shows the ΔHbO response for the 4th participant for arithmetic mental and rest tasks. In this paper, we successfully achieve higher classification accuracies from the brain using prefrontal activities.

Previous fNIRS-based BCI studies have mostly emphasized advanced signal-processing techniques and improved algorithms to improve classification accuracy and, thereby, enhanced BCI performance [19]. Another study was to detect four different classes of the signal for generation of control commands for movement estimation suitable for BCI purposes. A hybrid EEG-fNIRS based BCI was used to get better results [20-21]. For the generation of dual movement control command using prefrontal cortex, maximum classification accuracy was 79% [22]. In our previous study [15], mental arithmetic versus rest tasks signals was classified using linear discriminate analysis (LDA) as the classifiers. The classification accuracies achieved were 93%. In this paper, the classification accuracies were improved to 97.96% using modified version of genetic algorithm along with SVM. Khan and Hong, (2015)'s study was based on a passive driving-task BCI, whereas this study dealt with an active, arithmetic-task BCI [23]. Technical breakthroughs in the future are expected through the detection of initial dips [24].

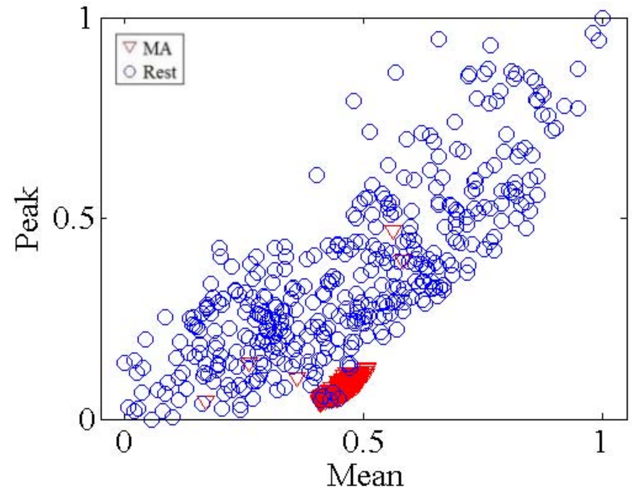

Fig.3. 2-dimensional feature space for Subject 4: The triangles/circles indicate the mental/rest tasks.

TABLE I. SVM Classification Accuracies

Subject	Classification accuracy
1	97.93 %
2	98.28 %
3	97.36 %
4	98.23 %
5	97.56 %
6	98.30 %
7	98.07 %
Average	97.96 %

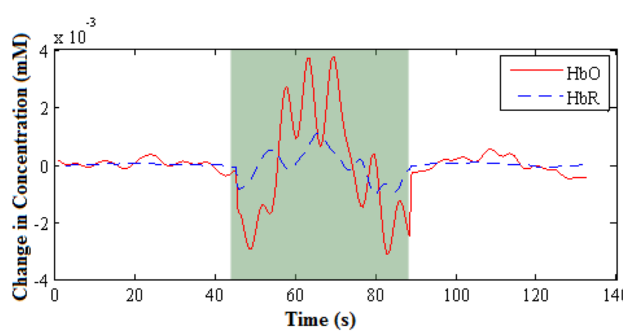

Fig. 4. Average ΔHbO signals of 4th participant for the mental verses rest task

IV. CONCLUSIONS

In this study, we proposed a technique to improve the classification accuracies by using the modified genetic algorithm along with support vector machine for mental versus rest tasks by using signal mean and signal slope values of oxygenated hemoglobin as features. The average classification accuracy across all the subjects was exceeding 97 % in all 10 iterations. The proposed method successfully proved that hybrid genetic algorithm is suitable to reduce the dimensionality of the higher dimensional features.

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