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Signal Acquisition by Functional Near Infrared Spectroscopy and Data Analysis for Mental Aptitude Tasks

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***Abstract*— General Linear Model is a statistical approach to enable an accurate analysis of NIRS signal. In this study. the fNIRS data are regressed using a linear combination of task-related regressors plus an error term. The mental tasks related regressors are obtained by convolving boxcar functions, that correspond to our experimental design with HRF. Experimentally the signal was acquired from a functional NIRS system during the brain activation from the participant while visual stimulation task. The block design for data acquisition consists of 40s rest and 60s task in repetition. From the measured data, oxy-hemoglobin was estimated and considered for parametric analysis. We observed a statistical significance of p<0.9 from our analysis.**

Keywords*— *Functional NIRS, General Linear Model, Hemodynamic Response Function, Cerebral Hemodynamic Changes, Mental task

I. Introduction

The worldwide energy reserves are running down to the alarming rate, which is a major international concern at economic, ecological, manufacturing and society levels [1]. And with the concern is escalating over global climate changes, policy makers are advancing the renewable energy sources (RESs) as a means of meeting emissions reduction goals. A gridable vehicle (GV) is a modified version of the plug-in hybrid electric vehicle or an electric vehicle (EV) that can bring about a revolution in the energy and transportation sectors. To be economical, and have environmental and societal impacts, next generation vehicles (gridable vehicles) should have capability to charge and discharge from the grid in an intelligent manner that maximizes the utilization of RESs. Furthermore, a major portion of global emission represented in the power and energy consumption in the industrial sector, in which 40% of the global CO_2 production occurs. Transportation sector is responsible for 24% [2]. The projected costs of an escalating climate change are to the extent that 20% of the global domestic product (GDP). Nevertheless, these costs could be restricted to just about 1% of GDP by taking the proper measurements [3]. In Addition, Climate is also changing due greenhouse gas emission. And it is now extensively acknowledged as a real condition that has likely serious effects for human society. Therefore, it is essential for industries to put this factor into their concerns as well as their strategic plans [4]. Therefore, environment friendly modern planning is essential. And the new energy plan encourages us to deploy the electric vehicles on the road. Not mentioning the huge electric vehicles are charged from present electric grid randomly, the peak load will be very high. Thus it will result economically and environmentally expensive especially if thermal power plants remain the major source of electric energy. PHEV and EV researchers have mainly concentrated on interconnection of energy storage of vehicles and grid [5-11]. Their goals are to educate about the environmental and economic benefits of PHEV and EV, and to enhance the product market. However, power system reliability consists of system security and adequacy. A smart power system is adequate if there is a sufficient power supply to meet customer needs with minimum cost and emission. PHEVs, by themselves, cannot solve the emission problem completely, because they need electric power which is one of the main sources of emission. Therefore, success of practical application of PHEVs and EVs greatly depends on the maximum utilization of renewable energy so that the goal of cost-emission reduction is achievable. However, the integration of GVs with RESs in a smart grid with the appropriate control technology has the potential for cost-emission reduction.

Therefore, by using the smart grid it maximizes the utilization of renewable energy; improves reliability and security; and provides sufficient customer choice and affordability as seen in figure 1. Where A,B,C, E: RESs; D: Emissions proportional to energy taken from thermal power plants; F: GV as a small portable power plant (SP3), load or energy storage; G: Smart parking lot (SmartPark) as a virtual power plant (VPP), bulk load or bulk energy storage; H: An information and communication device (ICD) in a GV to interact with a distribution center. Distribution center carrying out real-time dynamic stochastic optimization for cost and emission reduction A true smart grid with GVs and RESs will be a complex system in a dynamic environment. Traditional static optimization methods cannot meet the requirements of a smart grid in real-time. Such a smart grid calls for dynamic stochastic optimization techniques to achieve in real time cost and emission reductio.

II. Material and Methodology

2.1 General Linear Model (GLM)

GLM is a statistical approach to enable an accurate analysis for NIRS signal. The model describes the data as a linear combination of functions plus an error term. The model is mathematically expressed as:

$$Y(t) = \beta.X(t) + \varepsilon \quad (1)$$

Where, Y(t) is the fNIRS data and X(t) is the regressor matrix which consists of vectors of regressor functions. The regressor matrix was consisted of a block-design model function derived by hemodynamic response function [9], baseline offset and baseline drift components. The coefficient for the block-design model in β can be determined as the beta value representing the intensity of the fNIRS signal which changes with the given task. In our experiment, we focused only on oxy-Hb concentration for the GLM approach. Eq. (1) can be re-written in terms of oxy-Hb concentration which is explained in following steps.

Let $y_{oxyHb}^{(i)} \in R^N$ and $\epsilon_{oxyHb}^{(i)} \in R^N$ denote the time-series of the oxy-Hb signal and noise at the *i*-th channel at the location r_i given by

$$\boldsymbol{y}_{oxyHb}^{(i)} = [y_{oxyHb}(r_i, t_1) \cdots y_{oxyHb}(r_i, t_N)]^T \quad (2)$$

$$\boldsymbol{\epsilon}_{oxyHb}^{(i)} = [\epsilon_{oxyHb}(r_i, t_1) \cdots y_{oxyHb}(r_i, t_N)]^T \quad (3)$$

Then the corresponding GLM model is given by

$$y_{oxyHb}^{(i)} = \boldsymbol{X}_{oxyHb}\, \beta_{oxyHb}^{(i)} + \epsilon_{oxyHb}^{(i)} \quad (4)$$

Where $\boldsymbol{X}_{oxyHb} \in R^{N \times M}$ denotes the design matrices for oxy-Hb, and $\beta_{oxyHb}^{(i)} \in R^{M \times 1}$ is the corresponding response signal strength at the *i*-th channel respectively.

The least-squares estimation of β is given by

$$\boldsymbol{\beta = X^{*}Y} \quad (5)$$

Where **X*** is the pseudo-inverse matrix of **X** and is given by

$$\boldsymbol{X^{*}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T \quad (6)$$

The regression coefficient β and the residual error ϵ are tested with the one sample t-statistics test. The t values are calculated by

$$C = \frac{\boldsymbol{c}^T\boldsymbol{\beta}}{\sqrt{\varepsilon^2 \boldsymbol{c}^T(\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{c}}} \quad (7)$$

Where ***c*** is the contrast vector, which determines the array elements of the regression coefficient β .

2.2 Hemodynamic Response Function (HRF)

Any kind of neuron activation in the brain will be responded by consumption of oxygen and increased blood flow in the surrounding area which can be considered as hemodynamic response. Functional MRI studies explored the measurement of blood oxygen level dependent (BOLD) contrast to investigate the functional activation of the brain. In the literature, Boynton, et al [10]; Friston, et al [11]; suggested a model for linear relationship between a stimulus and the BOLD signal based on linear time invariant (LTI) system. Their goal was to use information from the BOLD signal in making important conclusions about the neuronal activation. From the shape analysis of hemodynamic response function (HRF), information about the brain stimulation intensity, the latency and its duration can be extracted from the values of amplitude, delay and the duration respectively. However, the interpretability becomes more complex at higher statistical powers as the HRF is a non-linearity and complex function. A number of shape fitting models are available that potentially simplifies the characterization of HRF. Poisson function [11], Gamma function [12][13] and Gaussian functions [14][15] are available in the literature for modeling the HRF. After an elaborate investigation, the double Gamma function [16] is now being used in many of the studies.

Since both fMRI and fNIRS methods have the common goal of recovering the hemodynamic response, the well established regression approach in fMRI studies have been extended to fNIRS measurements [17]. In our model based study, for analyzing fnirs time series data, we applied the GLM and used Gamma function as the HRF. In this study, fNIRS data are regressed using a linear combination of task related regressors plus an error term. The task related regressors are obtained by convolving boxcar functions, that corresponds to our experimental design with HRF. The starting and end of each event is coded by the boxcar function shape. The design matrix is comprised of task related regressor plus a constant term which models the expected hemodynamic response of the assigned task. Broadly, two types of studies are carried out with fNIRS method and they are, task-related and non-task relate. In the non-task related studies, which is also known as resting state fNIRS, the brain activation of the participants are analyzed during the participants are performing the given tasks that is out of scope in this paper. In our study, participant is allowed for a specific task and the design of the experiment is shown in Fig. (1). It has been designed as the participant allowed consecutively for rest and task over a time period of 40 second and 60 second respectively. In the figure only two blocks are shown which are repetitive. The brain stimulating events during the tasks are convolved with the hrf and the design matrices are produced. For demonstrating the design model, random signal was generated which was then compared with convolved result to get the output signal. All these steps were executed in MATLAB (The MathWorks Inc., MA, USA) software platform.

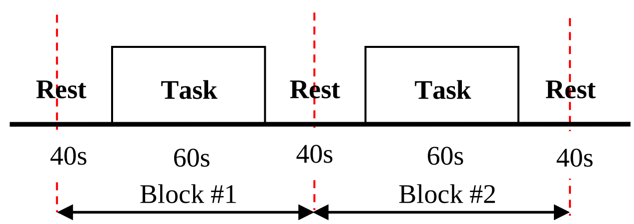
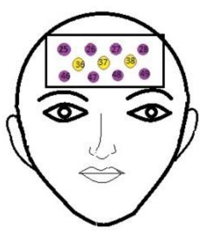


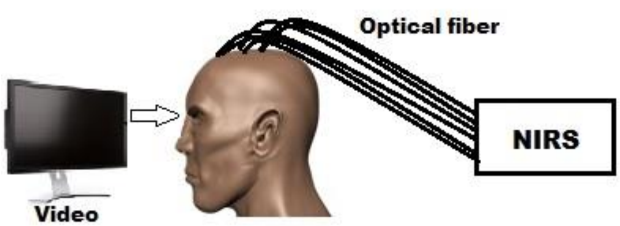
Figure 1. Block design of time sequence

2.3 Experimental Paradigm

In our experiment, we asked volunteers to watch a video clip which was played on the desktop computer. Before the commencement of the task. He was allowed to take rest by closing eyes and staying calm. We used fNIRS data were collected from a 22 channels fNIRS topography system (LABNIRS, Shimadzu, Co., Japan) to measure the brain activation of the volunteer during the task. The system utilizes three wavelengths of the light at 780nm, 805nm and 830nm that are passed through optical fiber bundle. One end of each fiber are coupled with the respective wavelength and another end terminate in a special textile made head cap. The cap is configured for optical source fibers and the photo-detector fibers keeping a gap of 3 cm between each pair of source and detector. These optodes are arranged in a standard 10-20 electrode system. To acquire the data from the prefrontal segment of the brain, we used only 12 channels of the electrode positions which occupies the frontal part of the head when the cap is positioned on the head of the participant. The positions of electrodes are shown in Figure 2a. We collected the data from the designed experimental procedure (Figure 2b) and processed in MATLAB Software system.



(a)



(b)

Figure 2. Experimental setup. (a) shows the placement of optode housed in a head cap (b) Data acquisition procedure from a participant on visual stimulation for brain activation.

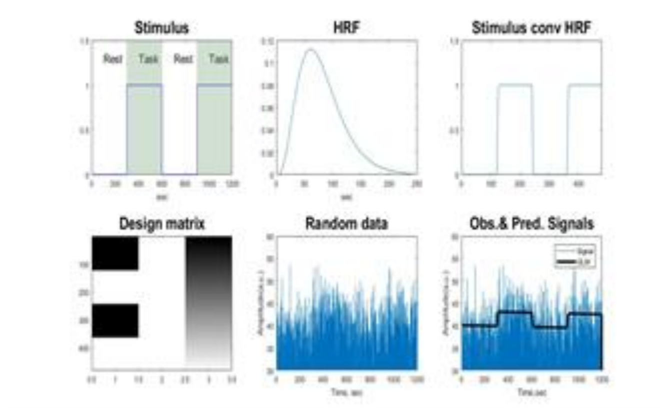


Figure 3. Simulation results of the GLM

III. Results and Discussion

As explained in above paragraphs, we developed a linear model to analyze the time series data obtained from fNIRS. In the GLM model, we incorporated the boxcar function corresponding the task which is shown in above figure. Then it was convolved with HRF which was modeled as double Gamma function. The model was initially tested by random signal. The signal with GLM model as output is shown in Figure 3.

We measured oxygenated hemoglobin, deoxygenated hemoglobin and total hemoglobin data from the fNIRS system during the participant's prefrontal brain activation. To observe theses changes hence to analyze the response of the brain activation, we considered the video clip as stimulating signal in the frontal cortex of the brain. For the GLM analysis, the data was loaded in an open source NIRS-SPM software which is accessible to the users. Output of the result is shown in Figure 4.

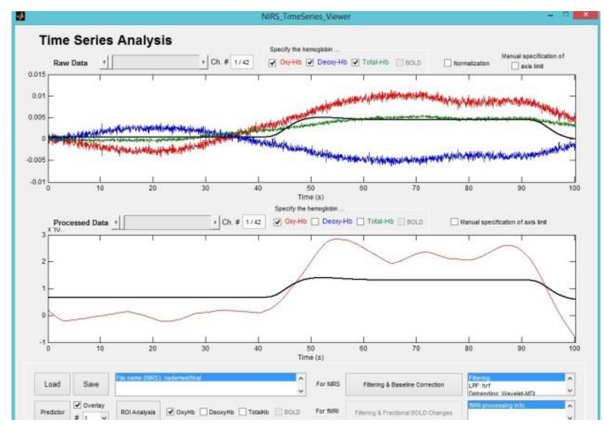


Figure 4. Processed data from NIRS-SPM software

In the figure, upper part of the figure window shows the raw data of oxy-Hb, deoxy-Hb and total-Hb quantities. The figure is captured over a region-of-interest during one block of the task. The bottom part of the same figure shows the processed and analyzed data. It has been shown that only oxy-Hb is selected as parametric analysis in the NIRS-SPM software. The black colored data line shows the GLM output for the selected ROI. It is clear from the result that the response from the video clip appeared from the 40s. to 100s as the starting and end points of the neuronal stimulating signal. However, it can be seen that there is onset latency on either ends of the stimulus.

IV. Conclusion

In this work, we developed a model on the basis of linear time invariant system to analyze the fNIRS time series data. The model describes the data as a linear combination of functions plus an error term. In the statistical based general linear model (GLM) the simulation result obtained by convolving the boxcar function with hemodynamic response function. Then, we collected experimental data from the fNIRS system with the subject watching a video clip for activating the brain during that task. The fNIRS signal was then analyzed from GLM in NIRS-SPM open source software. From the statistical analysis of the real signal the statistical significance of $p<0.9$ was observed. This shows that the model analysis and from experimental analysis, the t-score values are comparable. From the acceptable correlation study, it is hence demonstrated that the changes in hemoglobin concentration can be observed in the prefrontal cortex by functional near infrared spectroscopy method

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