Reduction of physiological effects in fNIRS waveforms for efficient brain-state decoding

M. Ahmad Kamran a,1, Keum-Shik Hong a, b, ∗

a Department of Cogno-Mechatronics Engineering, Pusan National University, 2 Busandaehak-ro, Geumjeong-gu, Busan 609-735, Republic of Korea
b School of Mechanical Engineering, Pusan National University, 2 Busandaehak-ro, Geumjeong-gu, Busan 609-735, Republic of Korea

HIGHLIGHTS

• Dynamics of the HR has been modeled as ARMA reflecting the past influence of stimuli.
• Physiological signals are added to the model as exogenous signals resulting in ARMAX.
• In contrast to existing studies, temporal variation has been incorporated to HR model.

ARTICLE INFO

Article history:
Received 17 April 2014
Received in revised form 20 July 2014
Accepted 31 July 2014
Available online 8 August 2014

Keywords:
Functional near-infrared spectroscopy
Homodynamics
Auto regressive moving average model
with exogenous signals
Recursive least squares estimate

ABSTRACT

This paper presents a methodology for online estimation of brain activities with reduction in the effects of physiological noises in functional near-infrared spectroscopy signals. The input-output characteristics of a hemodynamic response are modeled as an autoregressive moving average model together with exogenous physical signals (i.e., ARMAX). In contrast to the fixed design matrix in the conventional general linear model, the proposed model incorporates the temporal variations in the experimental paradigm as well as in the hemodynamics. The performance of the proposed method has been tested by using box-car type functions followed by individual tapping tasks. The results and their significance were verified using t-statistics indicating that ARMAX seems to be better able to track/reveal the hemodynamic response. Also, online brain-activation maps were generated for localizing brain activities. Experimental results are compared with those of the existing conventional GLM-based method.

© 2014 Elsevier Ireland Ltd. All rights reserved.

1. Introduction

Functional near-infrared spectroscopy (fNIRS) is a non-invasive neuro-imaging technique to measure hemodynamics changes in the brain [1–15,20–25], which indirectly indicate neural spiking activities. The hemodynamic signal obtained by fNIRS is an amalgam of the brain-activation-related component known as the hemodynamic response function (HRF), some physiological noises (e.g., cardiac- and respiratory-related interference and low-frequency Mayer waves), and others [5]. While considering motion-related noises, fNIRS has the great advantage of not being affected by (small) movements [4]. With regard to the physiological noises, identification of their spatial and temporal effects constitutes a challenge. In the interests of noise reduction and, thereby, for better estimation of brain-activation signals from observed fNIRS time series, several other methods have been proposed: the Kalman estimator [8], independent component analysis (ICA) [2,11,20], a wavelet-based algorithm [12], principal component analysis (PCA) [22], the conventional general linear model (GLM) [3,21], low-pass filtering [13], as well as most commonly used conventional averaging techniques [6,15,19].

Physiological processes are known to produce, in NIRS data, temporal correlations that might lead to inflated t-values and, thus, an incorrect estimation of brain activity [8]. The analysis of NIRS data time series using an autoregressive moving-average with exogenous signals (ARMAX) model, therefore, can facilitate brain-activation estimation. In this paper, we propose an online brain-activation estimation methodology that reduces the effects of physiological noises, specifically low-frequency fluctuations, cardiac and respiratory interferences. Since the measured fNIRS signal is not consistent in the trials repeated over time, it will
be advantageous to include the prior knowledge on the hemodynamic response (HR) in the estimation model of the HR. Thus, an ARMAX model-based approach incorporating physiological signals as exogenous signals was used to predict brain states during a particular cognitive task. The fNIRS time series at a particular channel is supposed to be a linear combination of various components. The components include the dynamical characteristics of the oxy- (HbO) and deoxy-hemoglobin (HbR) changes in a specific brain region, the influence from the previous stimuli, the physiological signals that prevail at all time, base line and other noises.
The influence from the previous stimuli is represented by the convolution of the canonical hemodynamic response function (cHRF) and the given stimuli. The physiological signals include the cardiac signal, the respiratory signal, and the low-frequency fluctuation, which were generated using the method in [1]. The coefficients in the linear combination, indicating the activity strength, are known as activity-strength parameters. The estimation of activity-strength parameters is carried out using the RLSE algorithm due to its low computation cost and rapid convergence. Most of the relevant previous studies have performed offline and/or have pre-processed fNIRS data.

The advantages of our proposed methodology are (i) the dynamics of the HR has been incorporated into an ARMA model reflecting the past influence of the stimuli; (ii) by adding the physiological signals as exogenous signals into the ARMA model (i.e., ARMAX), the estimation accuracy has been enhanced; (iii) as the estimation is conducted online, its real-time implementation has been possible; and finally the performance of the proposed methodology has been compared with the previous GLM-based adaptive framework [3] to show its effectiveness. The significance of results was verified using t-statistics. Furthermore, an online brain-activation map was generated for localizing the brain activity using t-values. A schematic view of the proposed methodology is provided in Fig. 1.

2. Materials and methods

2.1. Hemodynamic response function

The proper selection of parameters that impart shape and scale to the waveform to be used as impulse response is very important. The canonical hemodynamic response function (cHRF), which is composed of two Gamma functions, is commonly used as a symbol of cortical activity. For example, in [21], the cHRF as a function of time was generated, as a linear combination of two Gamma variant functions, as

\[ h(k) = \alpha_1 \{ \Gamma(k, \tau_1, \phi_1) - \alpha_2 \Gamma(k, \tau_2, \phi_2) \} . \]  

(1)

where \( h \) is the cHRF, \( k \) is the discrete time, \( \alpha_1 \) is the amplitude, \( \tau_1 \) and \( \phi_i (i = 1, 2) \) tune the shape and scale, respectively, and \( \alpha_2 \) is the ratio of the response to undershoot. The predicted hemodynamic response function (pHRF), \( u(k) \), is defined as the convolution of the cHRF in Eq. (1) and the stimulus \( s(k) \) as follows.

\[ u(k) = k_1 \{ h(k) \times s(k) \} , \]  

(2)

![Fig. 4. HRs upon Fig. 2(c): The top panel shows the pHRF (dotted) and the estimated HR (solid), the middle one indicates \( \hat{b}_1 \), and the bottom one displays the t-value of \( \hat{b}_1 \).](image-url)
where \( k_1 \) is the scaling parameter and \( s(k) \) is defined as
\[
s(k) = \begin{cases} 
0, & \text{if } k \in \text{rest} \\
1, & \text{if } k \in \text{task} 
\end{cases}
\]

In Eq. (3), rest and task stand for the rest- and the task-period, respectively. The specific frequencies of cardiac pulsation, the respiratory process, and the Mayer wave are \(-1\) Hz, \(-0.2-0.3\) Hz, and \(-0.05-0.11\) Hz [1]. These signals can be modeled mathematically as
\[
v_i = q_i \sin \left( 2 \pi f_i k + \theta_i \right); \quad i = 1, 2, 3,
\]
where \( v_i \) (i=1, 2, 3) refer to the cardiac, respiratory, and Mayer waves of frequencies \( f_1, f_2, \text{and } f_3 \), respectively, \( q_i \) represent the respective scaling parameters, and \( \theta_i \) are the initial phases that range from 0 to \( 2\pi \).

### 2.2. Brain-activity model

In this section, a linear model for localization and estimation of the brain activation prompted by a particular cortical task is introduced. GLM was most frequently used methodology in past [16], but it still needs modification in design matrix for the analysis of optical signal [14]. The mathematical form of the discrete brain-activation model is defined as
\[
y_i(k) = \sum_{n=1}^{n_0} a_{i,n} y(k-n) + \sum_{m=1}^{m_0} b_{i,m} u(k-m) \\
\quad + \sum_{j=1}^{3} q_{i,j} \sin \left( 2 \pi f_{i,j} + \theta_{i,j} \right) + q_{i,0} y_0 + e_i(k),
\]
where \( y \) is the measured time series; \( i \) represents the channel; \( u \) is the pHRF; \( y_0 \) is the baseline term; \( e_i(k) \) is zero mean Gaussian noise at channel \( i \); and \( a_{i,n} \) \( (n = 1, 2, \ldots, n_0) \), \( b_{i,m} \) \( (m = 1, 2, \ldots, m_0) \), \( q_{i,j} \) \( (j = 1, 2, 3) \), and \( q_0 \) are the unknown coefficients that have to be updated using a recursive algorithm for estimation, where \( n_0 \) and \( m_0 \) are the order of system and input time series, respectively. Eq. (5) can be simplified as the vector form
\[
y_i(k) = \mathbf{x}_i^T(k) \mathbf{\beta}_i(k) + e_i(k),
\]
where \( \mathbf{x}_i(k) \in \mathbb{R}^{(n+m+4)\times1} \) is the regression vector. For further simplification, let us define
\[
\mathbf{y}_c(k) = [y(k-1) \quad y(k-2) \cdots y(k-n_0)]^T
\]
\[
\mathbf{u}(k) = [u(k-1) \quad u(k-2) \cdots u(k-m_0)]^T
\]
\[
\mathbf{y}_p(k) = [v_1 \quad v_2 \quad v_3]^T,
\]
where \( \mathbf{y}_c \) represents the temporal correlation of the output, \( \mathbf{u} \) is taken from the pHRF, and \( \mathbf{y}_p \) denotes the physiological signals. Thus, Eqs. (7)–(9) can be combined as
\[
\mathbf{x}_i^T(k) = \begin{bmatrix} \mathbf{y}_c(k) & \mathbf{u}(k) & \mathbf{y}_p(k) & y_0 \end{bmatrix}.
\]

Also, we define the parameter vector as follows.
\[
\mathbf{\beta}_i(k) = [a_{i,1} \quad a_{i,2} \quad a_{i,0} \quad b_{i,1} \quad b_{i,2} \cdots b_{i,0} \quad q_{i,1} \quad q_{i,2} \quad q_{i,3} \quad q_0]
\]
\[
\text{Remark: The proposed model can be expressed in following matrix form using the measured fNIRS time series of a particular channel } i \text{ at } N \text{ consecutive time steps.}
\]
\[
\mathbf{y} = \mathbf{X}\mathbf{\beta} + \mathbf{e}
\]
where \( \mathbf{y} \in \mathbb{R}^{N\times1} \) is the chromophors (HbO or HbR) concentration changes at N-steps, \( \mathbf{X} \in \mathbb{R}^{N\times(n+m+4)} \) is the design matrix in the conventional GLM method, and \( \mathbf{e} \in \mathbb{R}^{N\times1} \) is the zero mean Gaussian noise. It is noted that Eq. (12) is not used in this work, but Eqs. (10) and (11) are used for online implementation. Additionally, the physiological frequencies need to be estimated/measured if change too much or coupling occurs, otherwise model will breakdown or results could be misleading.

### 2.3. NIRS data acquisition

The concentration changes of HbO and HbR indirectly represent brain activation by directly representing changes in the blood supply. They can be computed mathematically using the modified Beer–Lambert law [8, 14] as
\[
\begin{bmatrix} \Delta \phi_{\text{HbO}}^j(k) \\ \Delta \phi_{\text{HbR}}^j(k) \end{bmatrix} = \begin{bmatrix} a_{\text{HbO}}(\lambda_1) & a_{\text{HbR}}(\lambda_1) \\ a_{\text{HbO}}(\lambda_2) & a_{\text{HbR}}(\lambda_2) \end{bmatrix}^{-1} \begin{bmatrix} \Delta \phi(k, \lambda_1) \\ \Delta \phi(k, \lambda_2) \end{bmatrix},
\]
and
\[
D = \text{diag} \begin{bmatrix} DPF(\lambda_1) & DPF(\lambda_2) \end{bmatrix},
\]
where superscript \( i \) denotes the \( i \)th measuring channel of emitter-detector pair, \( \Delta \phi(k, \lambda_j) \) are concentration changes of optical densities at particular wavelengths \( \lambda_j \) (with \( j = 1, 2 \) representing 760 nm and 830 nm, respectively), \( \Delta \phi_{\text{HbO}}^j \) and \( \Delta \phi_{\text{HbR}}^j \) are the concentration changes of HbO and HbR, respectively, in the \( i \)th channel, and \( a_{\text{HbO}}(\lambda_j) \) and \( a_{\text{HbR}}(\lambda_j) \) \( (j = 1, 2) \) are the molar extinction coefficients of HbO and HbR, respectively, at wavelength \( \lambda_j \).

**Fig. 5.** Activation maps of six subjects at \( k = 18, 180, \text{and } 290.**
The extinction coefficients corresponding to 760 nm are 1.486 (for HbO) and 3.843 (for HbR) and those corresponding to 830 nm are 2.231 (for HbO) and 1.791 (for HbR). The differential path length factor (DPF) is a unit-less quantity, and is corrected by application of the age-dependent factors [7] in the equations given below.

\[
\text{DPF}_1 = 5.13 + 0.07 \times (A^{0.81}),
\]

\[
\text{DPF}_2 = 4.67 + 0.062 \times (A^{0.877}),
\]

where \(A\) represents the age of the subject.

2.4. NIRS measurement system and optodes placement

The experiments were performed with the continuous-wave NIRS system (DYNOT: dynamic near-infrared optical tomography; NIRx Medical Technologies, Brooklyn, NY) at a sampling rate of 1.81 Hz. The data were acquired from the left motor cortex at sixteen different emitter-detector-pair locations. The distance between each emitter-detector pair was 2.2–3.2 cm. Fig. 2(a) shows the channel configuration.

2.5. Experimental paradigm

Six right-handed healthy volunteers (all males, aged 25–35 years) participated in the experiment. Two experimental paradigms were considered: Fig. 2(b) shows four box-car functions during 170 s and Fig. 2(c) depicts four box-car functions followed by four event-related functions (individual taps) for generating a task-switching environment [6]. Each subject in the present case was instructed to perform tapping of the right index finger during the task session. The first half of Fig. 2(c) consisted of a typical box-car function (i.e., rest–task–rest) and the second half including four different event-related task sessions was separated by a 30 s rest session. These four event-related task sessions consisted of one-, three-, five- and ten-finger taps, respectively.

3. Processing methodology

An ARMAX model was used with a regression vector consisting of \((n + m + 4)\) components. Let \(\hat{\beta}(k)\) and \(\hat{\beta}(k - 1)\) be the weight vectors at two adjacent time steps. Then, the objective is to minimize the difference, mathematically, as

\[
\delta \hat{\beta}(k) = \hat{\beta}(k) - \hat{\beta}(k - 1),
\]

(17)
subject to $N$ constraints

$$y(k+j) = x^T(k+j) \hat{\beta}(k+j) + \varepsilon(k+j), \quad j = 1, 2, \ldots, N. \quad (18)$$

The optimization problem presented in [17,18] can be solved by using the RLSE method by minimizing the cost function defined below.

$$J(\hat{\beta}, k) = e^T(k)e(k), \quad (19)$$

$$e(k) = y(k) - X(k)\hat{\beta}(k-1), \quad (20)$$

Finally, the update equation is derived as follows.

$$\hat{\beta}(k) = \hat{\beta}(k-1) + k(k)e(k), \quad (21)$$

$$k(k) = (I - k(k)x^T(k))^{-1}, \quad (22)$$

where $\hat{\beta}(k) \in \mathbb{R}^{m+4} \times 1$ is the unknown vector, $k(k)$ is the weighting vector, and $P(k)$ is the recursive inverse of the input covariance matrix at the $k$th sample time.

The brain-activation maps were based on $t$-statistics under the null hypothesis $\mathcal{H}_0: \hat{\beta} = 0$, where $c$ is the vector of contrast; the corresponding $t$-values were calculated as follows [14]:

$$t = \frac{c^T\hat{\beta}}{\text{SD}(c^T\hat{\beta})}, \quad (24)$$

where $\text{SD}$, denoting the standard deviation, is calculated as

$$\text{SD}(c^T\hat{\beta}) = \sqrt{\sigma^2 c^T(x^T\varepsilon)^{-1}c}, \quad (25)$$

where $V$ is the auto correlation matrix for the time series, and $\sigma$ is the variance that can be estimated by

$$\hat{\sigma} = \frac{e^T e}{\text{Trace}(RV)}, \quad (26)$$

where $R$ is the residual forming matrix defined mathematically as

$$R = \left[(I - x^T(x^T)x)^{-1}x^T\right]. \quad (27)$$

4. Results

Fig. 3 displays the HRs upon Fig. 2(b). The red dotted curve indicates the pHRF, the blue solid curve shows the estimated HR, and $\hat{b}_1$ denotes the estimated value of $b_1$ that is the activity strength parameter associated with the pHRF. Fig. 4 depicts the HRs upon Fig. 2(c). The objective of the second part in Fig. 2(c) is to find out whether individual finger taps can be identified with the proposed method or not. Fig. 5 provides the online brain-activation maps ($t$-statistics maps) for all of the subjects. The comparison of the proposed methodology with the existing conventional GLM based methodology is shown in Fig. 6. The estimates of activity strength parameters (for all the subjects and channels) corresponding to the canonical HRF (i.e., $\hat{b}_1$) are presented in Fig. 7.

5. Discussion

In the present work, an ARMAX model was devised and utilized for online brain-activation mapping. The system and input orders in the model were selected as $m_0 = 3$ and $m_0 = 4$, respectively (how to determine the optimum orders is under research). The results of the proposed methodology have been compared with the existing conventional GLM based approach with the adaptive algorithm in [3], in which the activity strength parameters were found by using
the RLSE algorithm. In [3], the regressor vector consisted of four components. That is, the model in their framework was represented as follows.

$$\mathbf{x}(k) = [x_1(k) \ x_2(k) \ x_3(k) \ x_4(k)],$$  

(28)

where $x_1(k)$ is the pHRF, $x_2(k)$ and $x_3(k)$ are two time derivatives of $x_1(k)$, and $x_4(k)$ is the base line correction term. Several studies reported in the past have used the GLM with a modified version of the design matrix (i.e., different regressors have been used). In a similar work [8], the regression vector is supposed to be a combination of five components: $x_1(k), x_2(k)$ and remaining three forms a set of high pass filter with cut-off frequency 0.0006 Hz.

Abdelnour and Huppert [1] reported the results for handedness (left or right) classification on the basis of GLM methodology with the design matrix composed of the form

$$\mathbf{x}(k) = [x_1(k) \ y_p(k) \ x_4(k)],$$  

(29)

where $y_p$ is the set of three sinusoidal signals for physiological processes defined in Eq. (9). Additionally, several physiological processes are known to produce temporal correlation in NIRS data [8]. The used design matrix in these studies was fixed. Therefore, it cannot reflect the variation of the signals once the experiment has started. Thus, if the variation in the signal can be added as a part of the model, it could be beneficial. Having consideration of findings in [1,8], it shall be advantageous to add effect of temporal correlation with pHRF, physiological noises and baseline in HR estimation model while estimating cortical activity at particular region of brain.

The comparison of results of the proposed methodology with the existing GLM-based framework has shown a significant improvement. The close look of Fig. 6 shows that the activity strength parameter corresponding to HRF has been improved compared over the conventional GLM-based methodology. Furthermore, it is also evident from Fig. 6 that the estimation error by the proposed methodology is lesser than the conventional GLM-based methodology. To present all the estimation results for all the channels/subjects, Fig. 7 has been added.

6. Conclusions

This paper presents a recursive online brain-activation mapping framework. An ARMAX model-based approach incorporating physiological signals as exogenous input was used to predict brain states. The results of the proposed scheme have been compared with the existing conventional GLM-based scheme. Furthermore, the proposed scheme has been verified in task switching environment as well, which depicts its applicability to real-time scenario.

Acknowledgments

This work was supported for two years by Pusan National University Research Grant.

References


