ABSTRACT

Near infrared spectroscopy (NIRS) is an effective technique for examining functional brain activity during cognitive tasks by enabling the measurement of the concentration changes of oxy-hemoglobin and deoxy-hemoglobin. In NIRS data analysis, accurate estimation of the hemodynamic response function (HRF) is still under investigation. Most existing methods assume that the shape of the HRF to be known. This assumption may not be appropriate because the HRF may vary from subject to subject and/or from region to region. In this paper, a deconvolution algorithm to estimate the HRF is presented. The advantage of this method is no prior hypothesis about the shape of the HRF is required. In addition, in order to increase the sensitivity of NIRS to functional brain activity, an adaptive filter is designed to remove physiological noises from the noisy NIRS data. The effectiveness of the proposed methods was verified by numerical simulations, the results of which are provided herein.

KEY WORDS

Hemodynamic response function, physiological noise removal, adaptive filtering, deconvolution algorithm.

1. Introduction

Near infrared spectroscopy (NIRS) is an optical spectroscopy technique which enables to measure changes in cerebral hemodynamic associated with functional brain activity. Over the last few decades, NIRS has attached very considerable interest and attention in the study of cognitive processes in human [1-3]. Primary reasons are found in its ability of noninvasive measurement, good spatial resolution, high temporal resolution [4-5], and its portability and low cost. Typically, an optical apparatus consists of sources and detectors which are placed (affixed) on the surface of the head (using a cap), the sources emit near infrared light between 650 nm and 950 nm [1] and the detectors at different distances from the sources, receive light after it has traveled through the living tissue. Light that travels through tissue is attenuated due to absorption and scattering. Within the near infrared range of light, two primary absorbing chromophores in biological tissue are oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR). During a cognitive activity, changes in concentration of HbO and HbR will provide information about brain functions. By measuring optical density changes at two wavelengths, concentration changes of HbO and HbR can be obtained by using modified Beer-Lambert law [6].

The primary goal of NIRS research is to use information provided by the hemoglobin signal (i.e., concentration change of HbO and HbR) to infer conclusions about the underlying unobserved neuronal activation in the brain. Most studies in NIRS data analysis have been shown that hemodynamic system in human brain can be treated as a linear time-invariant (LTI) system [6-7], in which the brain hemodynamic response (output) to a stimulus (input) is approximately equal to the convolution of the input paradigm with a hemodynamic response function (HRF). Therefore, the knowledge of HRF is an essential key for a better understanding of cerebral activations. The HRF can be modeled as the gamma-variate function [8], the Gaussian function [9] or the Glover function [10]. However, many experiments have been shown that the HRF differs from subject to subject [11] and from region to region [4].

In this paper, we introduce the use of a deconvolution method to estimate the HRF from NIRS data. The advantage of this method is no prior hypothesis about the shape of the HRF is required. However, NIRS measurements are often sensitive to the physiological noises arising from the superficial layers (such as scalp and skull) and inside brain tissue itself, due to factors such as heart activity, respiration, and blood pressure changes (Mayer wave). In order to reduce these unwanted signals, frequency-based methods such as low pass filtering, band pass filtering have been used with some successes [12-14]. However, this approach can also remove functional hemodynamic response, because the frequency bands of functional hemodynamic response and physiological noises are highly overlapping. To overcome this problem, we introduce the use of an adaptive filter to remove physiological noises. The advantage of adaptive filtering includes its capability of preserving the functional hemodynamic response, its simple implementation and low computational overhead. In order to implement this method, it requires the use of a pulse oximetry [15] or an
additional measurement using short source-detector separation [16] to support the reference signal. In this paper, however, the reference signal for the adaptive filter is generated as a linear combination of sinusoids at specific estimated frequencies of the cardiac, respiratory and Mayer waves.

The layout of this paper is organized as follows: Section 2 introduces the linear model of NIRS time series. Section 3 proposes the use of an adaptive filter to remove physiological noises. The deconvolution method to estimate the HRF is presented in Section 4. Section 5 presents the simulation results and some discussions. Finally, some conclusions are given in Section 6.

2. Linear Model of NIRS Time Series

Typically, an NIRS time series includes: a functional hemodynamic response \( y_{\text{signal}}(t) \) which is due to brain activation; physiological noises \( y_{\text{phy}}(t) \) which may arise from the superficial layers (such as scalp and skull) and inside brain tissue itself due to factors such as heart activity, respiration and changes in blood pressure (Mayer wave); a trend signal \( y_{\text{trend}}(t) \) which may cause as the result of subject motion, bad securing of the optical probe to the head, long-term physiological change or/and instrumental instability. If the linearity holds for the hemodynamic system, then an NIRS time series \( y(t) \) can be expressed as follows:

\[
y(t) = y_{\text{signal}}(t) + y_{\text{phy}}(t) + y_{\text{trend}}(t) + \varepsilon(t),
\]

(1)

where \( \varepsilon(t) \) is an additive noise which is assumed to be a Gaussian white noise, \( \varepsilon \sim (0, \sigma^2) \). The functional hemodynamic response \( y_{\text{signal}}(t) \) is described as a convolution between a time series of the stimulus describing an experimental paradigm \( u(t) \) and an impulse response function \( h(t) \)

\[
y_{\text{signal}}(t) = u(t) \ast h(t).
\]

(2)

From the viewpoint of NIRS, \( h(t) \) is the HRF. To account for the physiological noise specific to the NIRS data, a time-varying model developed by Prince et al. (2003) [17] is used

\[
y_{\text{phy}}(t) = \sum_i \left( a_i \cos 2\pi f_i t + b_i \sin 2\pi f_i t \right), \quad i \in \{ c, r, m \},
\]

(3)

where \( a_i \) and \( b_i \) are the coefficients representing the actual amplitude of physiological noises, \( f_i \) are the physiological frequencies (i.e., the cardiac \( f_c \), respiratory

\[
y_{\text{trend}}(t) = \sum_{m=0}^{M} \alpha_m t^m + \varepsilon(t),
\]

(4)

where \( M \) is the degree of the polynomial and \( \alpha_m \) are the constant weights.

Substituting (2)-(4) into (1), the overall linear model of the measureable NIRS time series is then rewritten as follows

\[
y(t) = u(t) \ast h(t) + \sum_i \left( a_i \cos 2\pi f_i t + b_i \sin 2\pi f_i t \right) + \sum_{m=0}^{M} \alpha_m t^m + \varepsilon(t),
\]

(5)

The linear model of the hemodynamic response system is depicted in Figure 1.

3. Adaptive Filtering Based Removal of Physiological Noises

The structure of the proposed method to remove physiological noises is shown in Figure 2. Here, an adaptive filter with a finite impulse response (FIR) and transversal structure is used [20]. The NIRS time series (i.e., concentration changes of HbO and HbR) \( y(n) \) serves as the primary signal of the adaptive filter, while reference signal \( y_{\text{phy.ref}}(n) \), which is correlated with physiological noises contained in the primary signal, is employed as the input of the adaptive filter. In this paper, the reference signal is generated as a linear combination of sinusoids at the estimated cardiac, respiratory, and Mayer wave frequencies.

3.1 Generation of the reference signal

In order to estimate the frequencies of physiological noise, we first calculate the power spectrum of the NIRS signal...
Then the estimated frequencies of the cardiac $\hat{f}_c$, respiratory $\hat{f}_r$, and Mayer wave $\hat{f}_m$ are taken at the locations of the largest spectral peak in the frequency bands of the cardiac, respiratory and Mayer wave, respectively. Here, the cardiac frequency band is chosen from 0.8 to 1.2 Hz, corresponding to the heart rates varying from 48 to 72 beats/min; the respiratory frequency band is chosen from 0.2 to 0.4 Hz, corresponding to the respiration rates varying from 12 to 24 cycles/min; and the frequency band of Mayer wave is chosen from 0.05 to 0.15 Hz.

Finally, the reference signal is generated as follows

$$y_{\text{phy\_ref}}(t) = \sum_{i} \left[ a_i^0 \cos 2\pi f_i^0 t + b_i^0 \sin 2\pi f_i^0 t \right],$$

where $a_i^0$ and $b_i^0$ are the initial coefficients representing the initial amplitude of physiological noises. The actual amplitude will be adjusted through the optimization method of the adaptive filter.

### 3.2 Adaptive filter algorithm

As shown in Figure 2, the reference signal is weighted by $P$ adjustable filter coefficients $\theta_1(n), \theta_2(n), \ldots, \theta_P(n)$ to produce the output $\hat{y}_{\text{phy\_est}}(n)$, i.e.

$$\hat{y}_{\text{phy\_est}}(n) = \sum_{p=1}^{P} \theta_p(n)y_{\text{phy\_ref}}(n-p+1),$$

where the subscript $p$ is the filter coefficient index, $n$ is the index of the time point, and $P$ denotes the order of the filter. The filter output error $e(n)$ is then derived as

$$e(n) = y(n) - \hat{y}_{\text{phy\_est}}(n)$$

$$= y(n) - \sum_{p=1}^{P} \theta_p(n)y_{\text{phy\_ref}}(n-p+1).$$

The coefficients of the adaptive filter $\theta_p(n)$ are adjusted for every sample with the aim of minimizing the mean-square error. By using the Widrow-Hoff least mean square algorithm (LMS) [20], the adaptation law for the filter coefficients is given by

$$\theta_p(n) = \theta_p(n-1) + 2\mu e(n)y_{\text{phy\_ref}}(n-p),$$

where $\mu$ is the step-size which controls the stability and the convergence rate of the algorithm. In order to increase the convergence rate of the LMS algorithm, the time series of $y(n)$ and $y_{\text{phy\_ref}}(n)$ were normalized by their respective mean values (subtract the mean value from every sample and then divide the result by the mean value).

### 4. Estimation of the HRF

After removing the physiological noise, the filtered signal $y'(t)$ can be rewritten in a discrete form as follows

$$y'(n) = \sum_{k=1}^{K} u(n-k+1)h(k) + \sum_{m=0}^{M} a_m n^m + \varepsilon_n,$$

where the first term is the discrete expression of $u(t) \otimes h(t)$, the second term is the discrete expression of the trend signal, $K$ – dimensional vector $h = [h(k)]^T$ represents the unknown HRF to be estimated, $N$ is the number of data points of the NIRS time series, and $(N-K+1)$ is the actual amount of data used in calculation. In matrix form, (12) is boiled down as follows

$$Y' = X\beta + \varepsilon,$$

where

$$Y' = [y'(K) \ y'(K+1) \ \ldots \ y'(N)]^T,$$

$$X = \begin{bmatrix} u(K) & u(K+1) & \ldots & u(N) \end{bmatrix}.$$
In this paper, a linear model of the hemodynamic system for NIRS data was proposed. To account for the physiological noise and the trend specific to the measurement NIRS data, the time-varying models were developed. In order to increase the sensitivity of NIRS to the functional brain activity, an adaptive filtering based removal of the physiological noise was designed. Finally, a deconvolution algorithm was used to estimate the HRF as well as the trend. The efficiency of the proposed methods was validated by simulation study.

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Figure 3. Simulated NIRS signal: The signal was compounded the functional hemodynamic response from the physiological noises, trend, and white noise.

Figure 4. The NIRS signal after removing the physiological noises by using the adaptive filter (solid line) was compared with the simulated signal (dashed line).

Figure 5. Estimation of the trend by using the deconvolution method: The functional hemodynamic response was contaminated by the trend (dashed line); the estimated trend (solid line).

Figure 6. The comparison between the estimated HRF (circled line) and the simulated Glover HRF (solid line).

References


