

Recovery of evoked hemodynamic response in fNIRS using protocol constraint and wavelet transform decomposition

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Abstract: The functional hemodynamic response is mainly affected by physiological interference which occurs in superficial layers of brain tissue. This makes the hemodynamic response estimation a challenging task. Recent studies have mostly tried to use the information content of the near and far source detectors of fNIRS systems to remove the systemic interference. In this study, we develop a constrained adaptive estimation procedure using wavelet transform decomposition to determine the share of physiological interference in brain hemodynamic response. In our proposed method, we decompose the near channel signal by wavelet transform into several components and then estimate the proper weights for each component adaptively by RLS, LMS and Kalman filter. The performance of the proposed algorithm is quantified by MSE and Pearson's correlation coefficient (R^2) criteria. We also compare our algorithm with previous methods which have used adaptive filtering based on Empirical Model Decomposition (EMD) and Ensembled-EMD. Our method turned out to outperform past works concerned with estimating Evoked Hemodynamic Response signals.

Keywords: *Evoked Hemodynamic Response, functional Near Infrared Spectroscopy, Adaptive Filter, Kalman Filter, Wavelet Transform.*

I. INTRODUCTION

Neurological activation results in releasing of vasoactive mediators leading to dilation of the surrounding arterioles and capillaries [1]. This dilation changes the regional blood flow and is closely related to the neural activity changes which can be detected as a positive blood oxygenation level-dependent (BOLD) in functional MRI (fMRI) signal. This is due to the fact that neural activity increases the oxygen consumption of the blood flow within a specific area of brain where is mostly responsible for that activity. An fMRI system is expensive and bulky machinery that makes it impossible to be used during normal every day activities. Furthermore, fMRI has poor temporal resolution and its recordings are affected badly by head movements. Therefore, it is crucial to develop a real-time portable low cost modality to monitor the brain activity. The modality that has all these characteristics is the functional near-infrared spectroscopy (fNIRS) [2]. fNIRS is a neuroimaging technique that has been used over past 20 years for noninvasive

monitoring of the brain hemodynamic changes. The main underlying principle of fNIRS is measuring the hemodynamic response during a mental activity by monitoring the intensity changes of the received light passing through the brain tissue. The light photons within infrared range (650-950 nm) are mainly either absorbed or scattered by oxy-Hb and deoxy-Hb blood chromophores. The changes in the concentration of these chromophores can be calculated by modified Beer Lambert Law (MBLL) [3]. Hence, fNIRS non-invasively monitors the hemodynamic changes during a neural activity within corresponding brain regions [2]. Despite aforementioned advantages, the hemodynamic response of mental activities is contaminated with physiological hemodynamic inferences arising from heart rate, breathing, and other homeostatic processes. These interferences are called systemic or global interference that occur both in superficial layer of brain and in brain tissue itself. Several methods have been developed to remove these interferences. The most widely used method is low pass or band pass filtering [4]. Unluckily, since the frequency content of hemodynamic response overlaps the systemic interference, these methods are partially ineffective. The other common method is Block Averaging (BA) which requires more than 50 trials of fNIRS recordings to estimate EHR satisfactorily [5]. In [4] the subtraction of brain active region of interest (ROI) from the non-activated region is proposed. More practical version of this method is the use of a dual channel fNIRS system [6-8]. In [6] Saager et al. take the short distance source detector (<1cm) as systemic interference and cancel it from far distance source detector by linear minimum mean square (LMMSE). Other studies [7-9] have used adaptive filters to reduce physiological interferences. In [8] Zhang et. al considered empirical mode decomposition (EMD) to decompose the near channel into its intrinsic mode functions (IMFs). Then, proper weights for each IMF are determined by a kind of adaptive filter to estimate the weight of the physiological interference in far channel signal. Mode mixing problem is identified as a main drawback of EMD [10]. In an effort to relieve this drawback, Ensembled EMD is developed in [11]. In [9] an adaptive algorithm based on EEMD technique is applied on dual channel fNIRS system in order to improve the estimation of physiological interference.

Similarly, in [12], Gagnon et al. used an algorithm based on Kalman filter to estimate the EHR. Many previous studies have defined a protocol for collecting data. This protocol can be applied on an adaptive filter as a constraint to avoid unsuitable weights for regressors. In addition, wavelet transform decomposes a signal into orthogonal components which is by itself a suitable property of signals when fed into an adaptive filter. Hence, in this study, we propose two main ideas to improve EHR estimation: 1) decomposing near channel signal into its constituents by wavelet transform, 2) applying a protocol constraint to the adaptive filter. To compare the effectiveness of our proposed algorithm with other discussed methods, mean square error (MSE) and Pearson's correlation (R^2) were calculated as quantitative criteria. The details of our algorithm are described in section 2. The results of our proposed method for the data we have collected over 8 healthy subjects are presented in Section 3. Finally, Section 4 discusses the results and concludes the paper.

II. MATERIALS & METHODS

A schematic of the configuration of a dual channel fNIRS probe along with the block diagram of our proposed method is shown in Figure 1. As seen, the light source (S) transmits light photons and two detectors (D₁ and D₂) collect those photons which travel the banana-shaped pathways through the brain tissue.

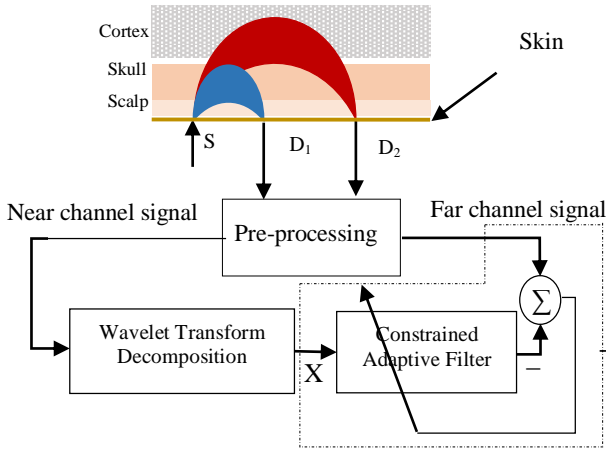


Figure 1. Schematic of the configuration of a dual channel fNIRS probe and its output to the block diagram of our proposed method.

Since every source-detector pair forms a channel, there are two channels here: near and far. Previous studies have stated that the penetration depth of light photons is about half of S-D₁ distance [13]. Therefore, the near channel contains information of hemodynamic changes of skin and scalp that comprises heart rate, breathing, Mayer, and low oscillation frequencies (also called Y_{near}). The far channel has functional hemodynamic changes with a pinch of near channel information that contaminate hemodynamic response of mental activities arising from cortex (Y_{far}). This can be stated mathematically as

$$Y_{far} = W * Y_{near} + EHR + N,$$

where N is the noise of measurement and W is the weight vector to be adjusted by the constrained adaptive filter.

By a minor rearrangement we have

$$EHR = Y_{far} - W * Y_{near} - N,$$

which emphasizes the fact that EHR is derived by subtracting the estimated physiological interference from the far channel measurements.

a. Preprocessing

In this step, the intensity of far and near channel signals are converted to HbR and HbO₂ concentration by using Modified Beer-Lambert Law. Then the motion artifact is removed by the Scholmann's algorithm [14], and the signal trend is canceled by means of wavelet transform [15]. Finally both signals are normalized whose concentration is shown in Figure 2.

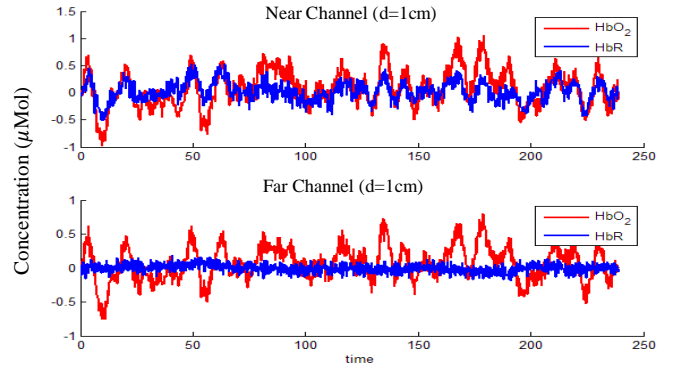


Figure 2. Pre-processed signals of HbR and HbO₂ concentration.

b. Wavelet transform decomposition

As mentioned before, the near channel contains physiological information that can be decomposed into its components by signal processing techniques such as EMD [8], EEMD [9] and wavelet transform [15]. In this study, *Daubechies* wavelet ($N=4$) is employed to decompose the HbO₂ concentration of near channel. The influence weights of the decomposed components are estimated by the constrained adaptive filter of the block diagram in Figure 1. This block is shown in more details in Figure 3.

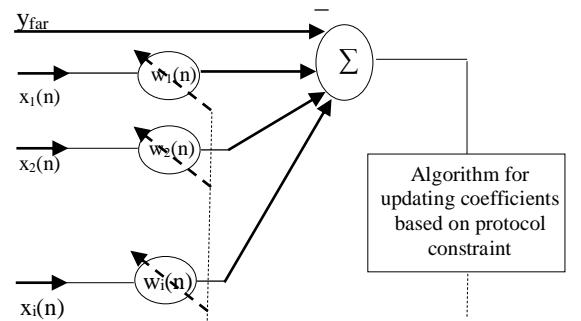


Figure 3. The dashed part of Figure 1 in more details

As seen, the near channel signal is decomposed by the wavelet transform block whose output makes up signals x_1 to x_i . These signals as well as the far channel signal sum up to

make the input of the estimation block. RLS, LMS, and Kalman Filter algorithms are used as the estimation block in this study. This block is supposed to tune the summing weights for signals x_1 to x_i .

c. Constrained LMS, RLS and Kalman filter

Acquisition of fNIRS data is always carried out based on a predefined protocol that consists of several tasks and rest intervals. The estimation of functional hemodynamic response in task intervals has been the aim of many previous studies. In these studies the influence of rest and task intervals are considered the same. The rest intervals have no functional activity; therefore, the signals of the near and far channels only contain physiological interference. On the other hand, the mutual information between near and far channels become more dissimilar in task intervals which is caused by the occurrence of a mental activity. This dissimilarity, if quantified, can be used as a parameter to update the weights of the defined filters. This procedure can be enumerated as follows: 1) In the rest intervals, after hemodynamic signal is damped within 8-10 seconds, an extra coefficient whose maximum value is unity is included in the aforementioned filters. In case there is a task interval preceding the rest, this coefficient is increased exponentially. 2) In the task intervals, the functional signal ascends and then descends exponentially by the outset of the rest interval. This causes the extra coefficient to be descending then ascending which is opposed to the functional signal. In other words, this coefficient tries to reduce the difference between near and far channels, which is called error, in the rest interval and allow larger difference in the interval where there is some mental activity. The trend of the protocol coefficient described just before is depicted in Figure 4.

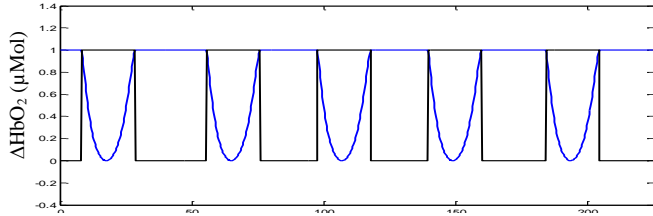


Figure 4. The trend of protocol coefficient value

In rest intervals, the weight updating strategy of the constrained RLS (CRLS), constrained LMS (CLMS), and constrained Kalman (CKalman) filter are adopted from [9, 16] and can be mathematically formalized as

$$\begin{aligned} w(n+1) &= w(n) + 2\mu(n)e(n)x(n), \\ w(n) &= w(n-1) - e(n)Q(n)x(k), \\ w(n|N_t) &= w(n|n) + p(n|n)p(n+1|n)^{-1}w(n+1|N_t) - w(n+1|n), \\ e(n) &= y_{HbO2far} - w(n)x(n). \end{aligned}$$

However, in the task intervals, the weight updating strategies CRLS, CLMS and CKalman filter should be modified as

$$\begin{aligned} w(n+1) &= w(n) + 2\alpha(n)\mu(n)e(n)x(n), \\ w(n) &= w(n-1) - e(n)\alpha(n)Q(n)x(k), \\ w(n|N_t) &= w(n|n) + p(n|n)p(n+1|n)^{-1}\alpha(n)w(n+1|N_t) - w(n+1|n). \end{aligned}$$

where α is the protocol coefficient.

d. Subjects and data acquisition

In this work 12 healthy subjects (age mean \pm standard deviation: 26 ± 8 years) were chosen for data acquisition. Each subject completed a questionnaire to provide demographic information, drug use history, and physical status. An fNIRS system with dual channel probe that is developed and evaluated by our team in University of Tehran [9, 17] was placed on the participants' prefrontal cortex and affixed by a band. During data acquisition procedure, the participants were asked to sit back relaxed in a dark silent room and have a 4-minute rest. Finally, the data acquired from 8 out of 12 subjects was labeled as valid and used for this paper. These subjects confirmed that they had been relaxed during the experiment and their mind had not been occupied by daily stress.

III. RESULTS

a. Synthetic EHR data generation

To evaluate and compare the performance of our proposed method with existing algorithms, simulated hemodynamic response function was generated by means of the gamma function $h(t) = t^b \exp(-t/d)$ [8] with $d=0.56$ and value of b within $[0.5, 1.3]$. The EHR inter stimulus intervals (the intervals with zero concentration value in Figure 5 between each two EHRs) were taken from a uniform distribution over $[8, 20]$ seconds. An example of a train of simulated EHRs is shown in Figure 5.

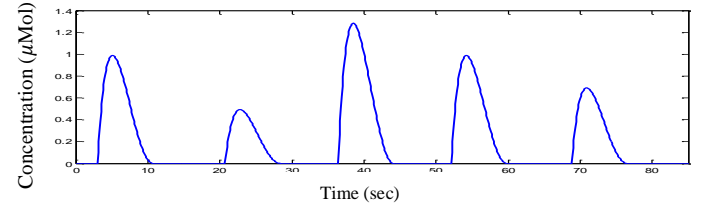


Figure 5. An example of stimulated EHR

b. Set up the dataset and Comparing the methods

In this step, the train EHR signal generated in the previous section is added to the pre-processed signal of HbO₂ concentration from far channel (Section II.a) in order to obtain a signal for far channel which we call *semi-simulated* (because this signal has both synthetic and real-world shares) signal for each subject ($Y_{far-sim}$). Then about 70% of Y_{near} and $Y_{far-sim}$ is set apart for training and the rest is dedicated to test our algorithms. In next step, both train and test portion of Y_{near} decomposed into their components by wavelet transform, EMD and EEMD. We set the number of wavelet decomposition levels to 4, for we assume 4 sources of interferences as explained in Section. II. The number of decomposition levels for EMD and EEMD is set by their intrinsic criterion to 9. Then only the decomposed train data of Y_{near} and $Y_{far-sim}$ are used for updating the weights of CLMS, CKalman and CRLS filters. Then the calculated weights by each algorithm are applied on test data and the estimated EHR is measured. To smoothen the result, we use Savitzky-Golay filter [18]. The estimated EHR by each of these algorithms is calculated and averaged over the specific intervals of the trial. These specific

intervals are chosen in a way so that each one encloses one EHR period as depicted in Figure 6.

To make the evaluation and comparison of our proposed method with previous works more concrete, both MSE and R^2 measures between simulated and estimated EHR over all subjects are shown as two bar graphs in Figure 7.a and Figure 7.b the MSE and correlation between the mentioned adaptive filters with protocol constraint and without it are compared respectively. These bars represent the mean and the error bars symbolize the standard deviation.

IV. DISSCUSION & CONCLUSION

fNIRS can be effectively employed to provide useful information for the study of cerebral activity. Unfortunately, the hemodynamic response of cerebral activity is highly degraded by physiological interference. The estimation of EHR from fNIRS signals is a challenging problem due to its small amplitude with respect to physiological components.

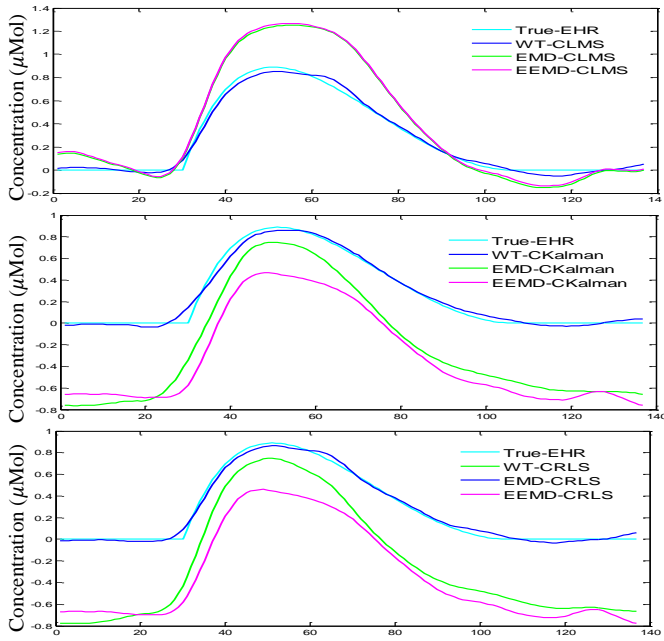


Figure 6. The block averaging of estimated EHRs by the mentioned algorithms

In the present study, an effective method to improve the recovery of EHR from fNIRS signals is presented. In summary, we distinct EHR from physiological interference by means of dual channel fNIRS. First the preprocessed signal of the near channel is decomposed by Wavelet Transform (WT); then, the weight of each component with distinct frequency content is adjusted by constrained adaptive filters to extract an estimate for physiological interferences. As it is shown in Figure 7.a, b the constrained adaptive filters which uses wavelet transform performs better than the other unconstrained adaptive filters.

The superiority of this performance can be accorded to both the type of the employed transform and the method for estimation the weights of its components. As can be clearly seen in Figure 7, among estimation methods for the weights of

the wavelet components, CLMS outperforms the other estimation methods and results in the least mean square error. We believe this is the consequence of involving protocol constraint into the estimation procedure which avoids the algorithm from falling into local optimums and extracts the estimated EHR quite similar to its simulated counterpart. Our method also produces the largest centered correlation between the recovered and simulated hemodynamic signals. This correlation delineates how well our method estimates the simulated signal details. We guess the reason that makes the wavelet transform stand apart from the other tested transforms is its multi resolution nature. The constituents which make up the near channel signal ranges over multiple resolutions due to their sources. These components range from B-Waves, M-Waves, Respiration which belong to low frequency section, up to Heart beat which is treated as the high frequency component. Because Wavelet transform considers resolution of the signals in its decomposition procedure, it is more likely to decompose the near channel signal into components which are close to these real world signals.

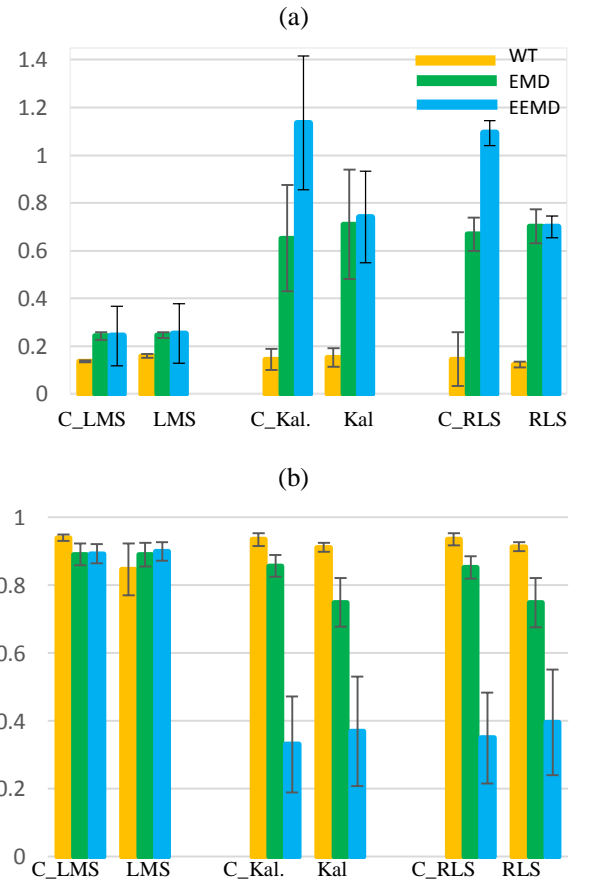


Figure 7. a) mean squared errors (MSE) b) pearson R^2 coefficients, between simulated and recovered evoked hemodynamic response. The bars represent the mean and the error bars symbolize the standard deviation over all subjects.

Our method also produces lower variance in multiple runs of the algorithm which makes its results more reliable than competing methods. We believe that this desired property arises from the fact that we have employed the transform and

estimation methods which makes it more probable to extract signals with meaningful real world counterparts. We also use an adaptive procedure in a hope to capture the non-stationary characteristics of the physiological components of the fNIRS signals. This makes our algorithm capable of estimating the time varying weights for wavelet components which can be thought of time-varying parameters of the underlying model for the signals. This joint with the fact that we impose no assumption on the amplitude, shape, and duration of the EHR signals make the whole algorithm robust against multiple sources of variations.

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