Evidence of cognitive activity in functional near infrared spectroscopy signal

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Abstract: We show that functional near infrared spectroscopy signals can monitor task-related cerebral hemodynamic response. We detect periodicities in the near infared spectroscopy signals and show that the estimated periods are consistent across multiple detectors and subjects, despite the jittered periodicity of the stimuli sequence that is used in a target categorization experiment.

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1. Introduction

Functional near infrared spectroscopy (fNIRS) has been proposed as a novel, non-invasive and rapid technique to monitor the brain hemodynamics during cognitive tasks [5]. In fact it is known that the neuronal responses are reflected in the signal patterns of the deoxyhemoglobin (deoxy-Hb) measured through near infrared spectroscopy. One advantage of fNIRS over competitor functional monitors is the fact that the increase in the oxyhemoglobin (oxy-Hb) concentration and concomitant decrease in the deoxy-Hb concentration, when located over the area with the maximal blood level oxygenation dependent (BOLD) signal, can be tracked on a millisecond basis using multi-wavelength illumination. Researchers have observed that oscillatory activity can occur independently of any cognitive task; though, the background activity and the cognitive activity exhibit different spectral behavior [3]. Furthermore, there exist spectral bands that are uncorrelated with involuntary physiological activities, such as breathing, heart beat, etc., while others are affected by psychological or pathological conditions, such as fatigue that leads also to performance degradation [1]. Although there do not exist strict mathematical models for these conjectures, impulse response models have been proposed to describe the brain hemodynamic response to various stimuli [4, 5, 6].

In this proof-of-concept study, we aim to validate the responsiveness of the fNIRS signal to cognitive activities in the brain. The strongest evidence, if any, of the cognitive activity in the fNIRS signal is the presence of measured periodicities, correlated with the target presentation protocol. Hence, we search for evidence of periodicity in the fNIRS signals in the subbands most likely to reflect such cognitive activity [2], and evaluate the likelihood that these artifacts are not resulting from the background activity of the brain.

2. Data, method and results

Functional NIRS data are collected at BITLab of Drexel University, by a system developed at Dr. Britton Chance's laboratory at University of Pennsylvania. Measurements are taken from four quadruples of photodetectors, i.e., sixteen in total, which are equidistantly placed on the forehead during a cognitive task (target categorization). At the center of every quadruple, there is a source that emits light at three different wavelengths of 730 nm, 805 nm and 850 nm. The data was obtained from oxyhemoglobin measurements, which resulted from the application of the modified Beer-Lambert law at these wavelengths.

The cognitive protocol consists of a target categorization task, in which subjects are presented in the center of the screen with two classes of stimuli in a Bernoulli sequence. The subjects are asked to press the left button on a mouse when they see "OOOOO" and right button when they see the target "XXXXX". We have the following specifications for target stimuli: (i) during the course of a given experiment, there are 64 target stimuli that follow a block periodic temporal pattern, where in every block there are 8 stimuli with randomly jittered locations, and the same pattern is repeated in every one of the eight blocks; (ii) inter-target interval is a random variable uniformly distributed on the (30, 50) samples or (18,29) seconds interval; (iii) for a given experiment, there exist 8 sessions with identical inter-target interval (ITI) sequences. Duration of stimuli, of both context and target types, is 500 ms and in between the stimuli there are blank intervals of 1 second. Recording is done at a sampling rate of 1.7 Hz, so that the Nyquist bandwidth is 850 mHz. Five male subjects with an age range of 22-50 are recruited for the preliminary test. Although given the spatial arrangement of photodetectors one should have a total of 5×16 = 80 signals, we observed that some of the detector outputs were not usable, due to either severe motion artifacts or occasional defects of the sensor. After eliminating the improper measurements, we ended up in a collection of 72 fNIRS-HbO_2 time series. These approximately 2700-sample long signals were detrended, and effectively the very low frequency components below 3 mHz is removed.

Since the cognitive stimuli are quasi-periodic, with inter-target intervals uniformly distributed between 18-29 seconds, we can expect some sort of periodic behavior in the signal portions that are related to cognitive activity. The cognitive activity waveforms, if any, will be in general immersed in some baseline activity waveforms. In fact, experiments show that cognitive activity responses are very difficult to discern by observing the waveforms in the full-band signals. The periodicity detection algorithm we adopted is based on a pitch period estimation method for speech signals, namely the least-squares periodicity detection algorithm (LSPE) [7]. The idea is based on the minimization of the weighted mean-squared error (MSE) between the observed signal $x(t)$ and an estimated signal $x_0(t)$ that in turn satisfies a periodic relation: $x_0(t) = x_0(t + kP_0)$, t = 1,2..,T and k=1,…,K. It has been shown that P_0 that minimizes the weighted MSE is equivalently the one that maximizes

$$J_1(P_0) = \frac{I_0 - I_1}{E - I_1} \qquad (1)$$

where I_0 stands for the weighted energy of the estimate $x_0(t)$ and E for the weighted energy of the original signal $x(t)$. In addition, the term I_1 is a bias correcting term defined as $I_1(P_0) = \sum_t \frac{x^2(t)w^2(t)}{\sum_k w(t + kP_0)}$, where $w(t)$ is a weight sequence. In (1), we search for the value of $\hat{P}_0$ that maximizes the $J_1(P_0)$ functional, which is taken as the dominant period in the signal, provided the periodicity index $J_1(P_0)$ is sufficiently high. In fact, the index function can be interpreted as a confidence score that attains the value 1 only for a truly periodic signal. Since some maximizing value of $\hat{P}_0$ can always be found, for this estimate to correspond to a genuine periodicity, the confidence score should exceed a threshold. In our case, we allow $\hat{P}_0$ to take values between P_{min} = 20 and P_{max} = 60 in the units of samples and compute corresponding score $J_1(\hat{P}_0)$. Let's note that, since the cognitive stimuli are not exactly periodic and since furthermore the cognitive activity signals are heavily embedded in baseline signals, we do not expect the $J_1(\hat{P}_0)$ scores to be too high. A second source of jitter may be due to the randomly delayed firing of cognitive activity, which may not follow immediately the target onset. Given all these sources of disturbance, we decided to eliminate the outliers from the estimated periodicities. We consider a periodicity estimate as admissible if it falls within the 30-to-50 interval.

In a concomitant study [8], we have demonstrated that fNIRS signals in different frequency bands each of which is associated with one or more particular physiological activity. We have observed that the 30-250 mHz band is the most convenient in terms of cognitive activity, since the 0-30 mHz low frequency band consists mostly of the fNIRS baseline, and the higher frequencies (>250 mhz) are weak in energy and consist of random fluctuations in addition to the heart beat signal. We therefore prefilter all NIRS signals to the 30-250 mHz band. In Fig. 1, we provide periodicity scores for two different fNIRS signal portions.

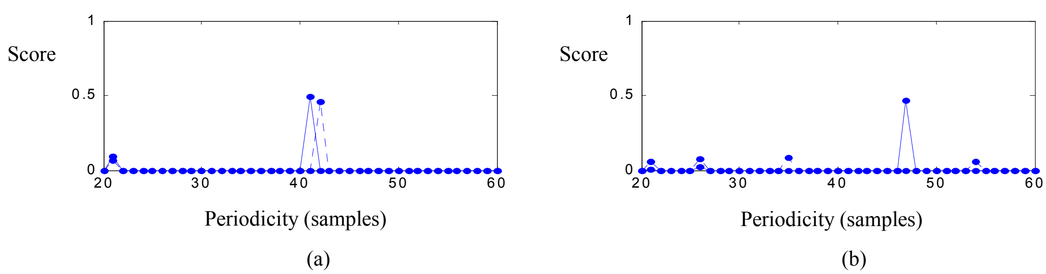

Fig. 1. (a) Periodicity index profiles of a fNIRS session with (solid line) and without (dotted line) prefiltering: prefiltering improves the confidence attributed to the detected periodicity, (b) Periodicity index profiles of another fNIRS session with prefiltering (solid line) and without (dotted line): in this case, a high-confidence periodicity score emerges within the expected range of (30,50) samples for the prefiltered case, while the unfiltered case totally fails.

Given that the experimental protocol consists of eight identical sessions in succession, we run the LSPE algorithm session by session on the fNIRS-HbO_2 data collection. That is, we consider each of the eight time segments of the prefiltered signal separately and let the algorithm return eight candidate periodicities per detector per subject. This yields several (up to eight) periodicity estimates per detector on any one subject. In order to investigate intersubject and interdetector variability of periodicity estimates, we compute two quantities: (i) the mean period, averaged over admissible estimates, averaged over all subjects, for a given photodetector, denoted as $\overline{P}_{detector}(k), k = 1,...,16$, (ii) the mean period, averaged over all admissible estimates from all detectors of a given subject, denoted as $\overline{P}_{subject}(l), l = 1,...,5$.

The plots of these quantities with interquartile bars are displayed in Fig. 2.

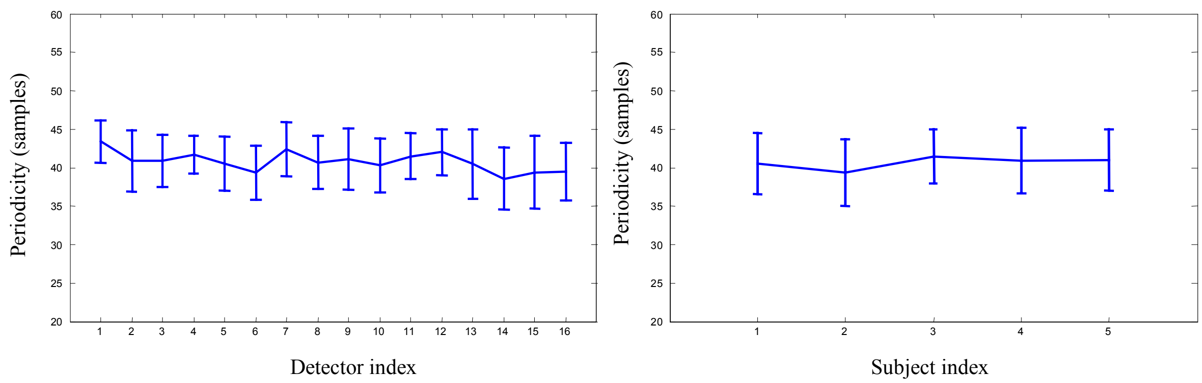

Fig. 2. Plots of $\overline{P}_{detector}$ (left) and $\overline{P}_{subject}$ (right). The bars indicate the inter-quartile range of data.

3. Discussion and conclusion

We have proven the conjecture that the cognitive activity in the brain can be monitored via the functional near infrared spectroscopy. Most experimental protocols involve quasi-repetitive tasks and this quasi-periodicity seems to be well reflected in the measurements. In fact the estimated periodicities are in the same range of the target presentation intervals, namely 35-45 samples or 20.5-26.5 seconds. These estimates are consistent across detectors and subjects, provided the inadmissible estimates are pruned out. Notice that not all detectors can be expected for all subjects to reflect to the same degree of accuracy the brain hemodynamic reaction to cognitive tasks, because the optodes (photodetectors) are deployed over a large area of the brain while the response could be more localized; for example, the reading from an optode in the vicinity of an arteriole would be more reliable and distinct. The occurrence of inadmissible estimates, which vary from optode to optode and from subject to subject, could indicate that we are monitoring solely the background activity of the brain at that location for a given subject. Fig 2.(left) provides a validation that all the optodes actually measure task-related cerebral hemodynamic activity. This evidence is captured by the periodicity that is consistenly observed over all detectors (averaged over subjects) or all subjects (averaged over detectors).

5. References

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