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Stimulus Level Estimation using functional Near-Infra-Red data and Neural Network

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Abstract— **In this paper we applied a well-tested neural network, so-called Supervised Fuzzy Adaptive Resonance (SF), to investigate the potential of functional Near-Infra-Red (fNIR) spectroscopy for automated assessment of physical stimulus intensity. To induce mild, moderate and severe physical stimuli, we asked the participants to keep their left hand in the ice water for gradually increased durations. Initial tests with fNIR data from 6 healthy participants (36 trials) indicated that SF is a reliable automated method to estimate the intensity of the induced stimuli with a high accuracy.**

I. Introduction

Monitoring changes in the oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) levels in the brain had been a very hot research topic over the past decade. Current studies using functional Magnetic Resonance Imaging (fMRI) showed that there is a direct relation between the cortical neuronal activity and blood oxygenation in the brain [1, 2]. These studies are based on the premise that "the magnetic signal characteristics of hemoglobin is blood oxygenation level dependant (BOLD)" [3]. Recent fMRI studies and pre-frontal cortex analyses confirmed that physical stimulus causes modulation of cortical activity in sensory, and cognitive processing regions [3, 4]. However, fMRI technology has limitations such as cost, size, and lack of portability, to name only few. Other technologies such as functional near-infrared spectroscopy (fNIRS), as shown in figure 1, provide a portable, cheap and more user-friendly tool for daily use. Recent studies demonstrated that FNIRs is a reliable optical imaging technique to non-invasively monitor changes in the level of oxygenated and deoxygenated hemoglobin in the brain [1, 2]. Currently, application of this technology is limited to assess various cognitive-type stimuli such as attention, working memory, problem solving and there is no study on the physical stimuli [1-3].

In order to check the possibility of using fNIRS to monitor effects of the physical stimuli on the cortical cerebral blood oxygenation, in this novel study, we used well-tested Supervised Fuzzy Adaptive Resonance (SF) neural network [10] to process fNIR data and estimate

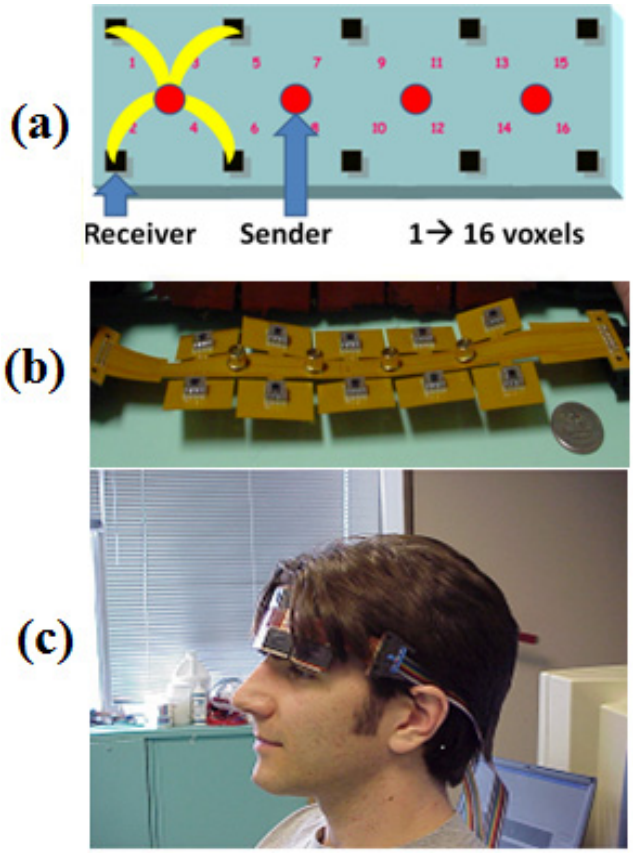

Figure 1. The fNIR system modified by Brain Optical Monitoring group of Drexel University: a) route between optical senders and receivers (banana pattern). There are 10 receivers and 4 senders, which in total returns 16 voxel data; b) optical sender/receivers located in a headband which includes 4 senders and 16 receivers; c) headband attached to subject's frond head.

stimulus intensity. Such an objective quantification of stimuli may contribute significantly to the use of drug therapy for pain disorders. As there is a very wide range for physical stimuli, in this paper, we only tested the fNIR technology and SF with a simplest physical stimuli (cold pressor test: keeping subject's hand in ICE water for few seconds). On the other hand, this paper just aims to show the ability of fNIRS for ice-stimuli level assessment of six right handed healthy participants. Based on findings for these healthy cases, further investigations are necessary to find mechanism behind hemodynamic response of the brain to physical stimuli in both healthy and unhealthy participants (including patients with chronic pain).

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II. METHODS

A. fNIR Recording Device

To record fNIR data, a portable continuous wave fNIR system was used. As can be seen in figure 1, our recording consists of three main components: a) the senders/receives headband (S/R-H) that covers the entire forehead as shown in Figure 1. The S/R-H included 4 light sources which contain 3 built in LEDs having peak wavelengths at 730, 805, 850 nm and 10 detectors designed to image cortical areas underlying dorsolateral and inferior frontal cortices. With a fixed source-detector separation of 2.5 cm, it results in a total of 16 voxel data (see figure 1a); b) a data acquisition (amplifier and A/D) and c) a computer for the data analysis software [5-9]. The sampling rate was 1.6Hz. Figure 2 shows a typical fNIR data recorded from a participant who was seated comfortably in a chair in a client room.

B. Participants and data recording protocol

In this study 6 subjects who had no history of neurological disorders nor pain participated. Before experiments, we explained the recording protocol to the participants and asked them to carefully read and sign the consent form approved by the institutional review board at Drexel University. In all tests, participants were seated comfortably in a chair in a client room. We tried to provide a comfortable and relaxing environment for the participants and asked them to focus on the experiment as much as possible and avoid any kind of mind distraction. All recordings were monitored by a neurologist to ensure that there would be no problems for the participants during and after the stimuli.

Each subject was asked to take part in three tests, each test with different duration of stimulus. So at the end we gathered 36 trails from participants. The protocol we used to induce mild, moderate and severe stimuli consists of following steps: 1) baseline recording (pre-stimulus): for 30 seconds fNIR data was recorded; 2) stimulus-start: subject put his/her hand in the ice water (~ -0.8°C) for N seconds, where N was 4, 8 and 12, respectively for mild, moderate and severe stimuli; 3) stimulus-end: subject takes his hand out of the water; 4) post-stimulus: subject informs operator whenever he feels the stimulus effects are gone; 5) recovery time: recording will be continued for 3 minutes (see figure 3).

C. fNIR Data Processing

After recording fNIR data based on above-mentioned protocol, we processed all of 16 channel data in two steps. In first step (Pre-processing), the raw intensity measurements were filtered using a law-pass filter with a cut-off frequency of 0.14Hz to eliminate heart pulsation and respiration signals [6]. In the next step (post-processing), we subtracted the raw intensity measurements recorded at two wavelengths (S=S_850-S_730) to cancel common signal (motion artifact) and improve common mode rejection ratio (CMRR). Referring to Beer-Lambert law, S is an estimation of relative changes of oxy-Hb (ΔoxyHB):

$$\Delta OxyHB = \alpha_1 . \log_{10}(S_{850}) - \alpha_2 . \log_{10}(S_{730}) + c_o$$

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As physical stimulus and hand movements could

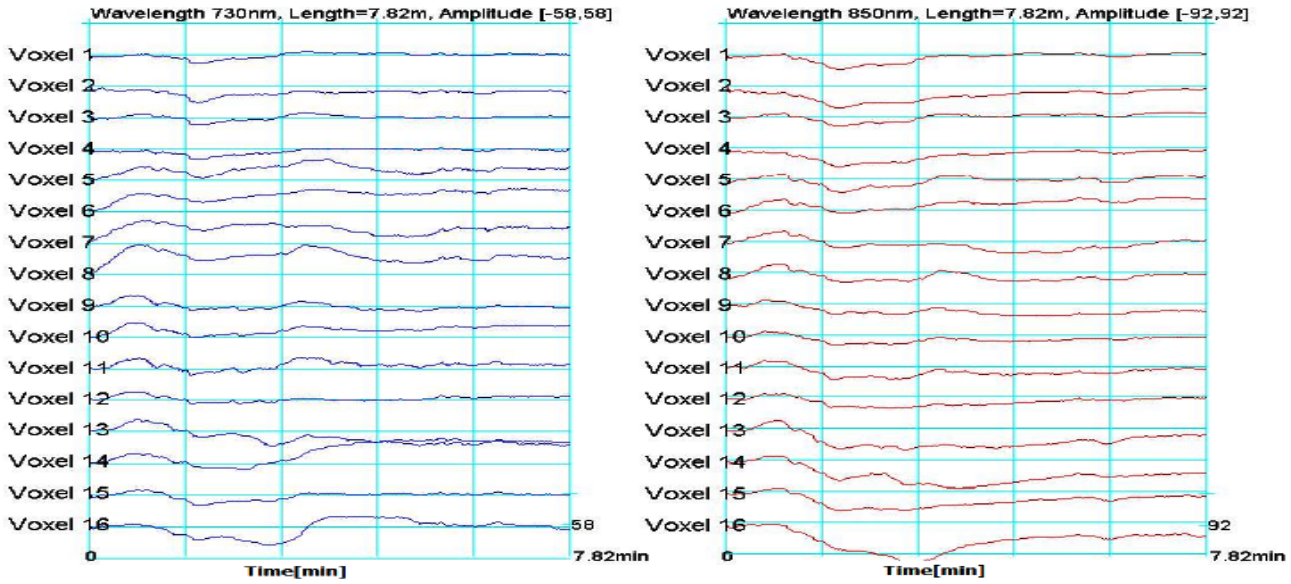

Figure 2. Typical fNIR data recorded from a participant who was seated comfortably in a chair in a client room.

generate higher intensity for raw measurements, we didn't use Beer-Lambert formula which employs a logarithmic process to estimate oxy-HB and deoxy-HB and we just subtracted raw measurements at 850 and 730nm wavelengths to perform post-processing.

For each physical stimuli (mild, moderate, or severe), the S data were first segmented into a prestimulus segment of 30s, stimulus-poststimulus segment of N+ K seconds, and recovery segment of 5 minutes. N was 4, 8 or 12, respectively for mild, moderate, and severe stimulus. K was time difference between time that subject reports stimulus effect is gone and time that subject takes hand out (see figure 2). Then data matrices P, S and R were formed using prestimulus, stimulus-poststimulus and recovery segments for 16 voxels. Since each of 6 subjects participated in 3 trials, we had 36 P, S and R matrices to be used in feature extraction and data classification analysis.

D. Feature Extraction

Before applying SF neural network to classify fNIR data to mild, moderate and severe classes, we need to extract essential information from matrices P, S and R and eliminate redundant information. As mentioned before, the physical stimulus causes modulation of cortical activity in sensory, and cognitive processing regions. To detect this amplitude modulation from fNIR data and track changes, for each voxel, we computed correlation coefficients (CCt) between prestimulus (*p*), stimulus-poststimulus (*s*) and recovery (*r*) segments as a measure of similarity:

$$CCt = \left[CC_i(p,s) \quad CC_i(p,r) \quad CC_i(s,r)\right]$$

$$for \quad i = 1:16$$

$$CCL = average\{CCt\}_{voxels(1->8)}$$

$$CCR = average\{CCt\}_{voxels(9->16)}$$

Where, CCL and CCR mean average of CCt values for voxels respectively located in the left side and right side of the forehead. The same procedure was repeated for all 36 trials recorded from 6 subjects.

Figure 4 shows correlation coefficients of left and right side-forehead for three typical trials. As can be seen right-side-forehead patterns are random whilst left-side-forehead patterns change based on intensity of the induced stimuli. As physical stimuli induced to the left-hand of the subjects, subject's response appears only in CCL. Therefore, CCLs were only used to train and test SF neural network. As can be seen by comparing CC(p,s) and CC(p,r), subject's response to the moderate and severe stimuli recovered faster in terms of signal intensity. In the mild stimulus case, as it was the first

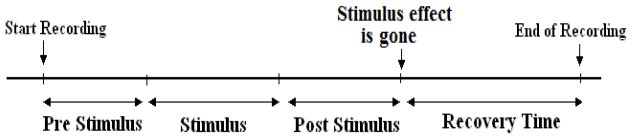

Figure 3. Recording protocol to record fNIR data in response to physical stimulus.

stimulus, subject's brain showed longer duration response. It can be seen that when we induced second and third stimuli, subject's response to mild stimulus was not recovered yet as time gap between stimuli was 10min. we observed this phenomena in other trials as well. As extracted features (CCL) are almost complex, we need to hire a neural network based classifier to map these features to higher space within hidden layer to be able to linearly separate classes in output layer.

E. Neural network classifiers

To classify data features extracted based on correlation coefficients, in this study we used a recently developed supervised neural network called Supervised Fuzzy Adaptive Resonance Theory (SF). It performs classification on two levels: At first level, pre-classifier which is self-organized (unsupervised) Fuzzy ART [10, 11] tuned for fast learning (η=1 & $\rho \to 1$) classifies the input data roughly to arbitrary (M) classes. At the second level, post-classification level, a special array called Affine Look-up Table (ALT) with M elements stores the labels of corresponding input samples in the address equal to the index of fuzzy ART winner. It is shown that SF has high learning speed, low computational load and high accuracy, and easy to use (no need to tune any parameter) for pattern classification (See [10] to find more about SF and its characteristics).

III. Results and Discussion

Our practical experiences showed that the most important features of the mild, moderate and severe stimuli epochs of fNIR data were saved at CCLs, decreasing the features (CCL) dimension to 3 data points. These three points for each epoch were then normalized to [−1, 1], and finally saved randomly into a unique data matrix. The resulted data matrix with dimension of 36x3 were then used to classify epochs to mild, moderate and severe classes (3 classes/outputs) using the SF neural network which has fixed structure .

As in this study we just had 36 trials, to train and test the SF, we used leave-one-out cross-validation which uses one data sample as the validation (testing) data, and the remaining sample pairs as the training data. This routine should be repeated (36 times as we have 36 data samples) in such a way that each data sample in the

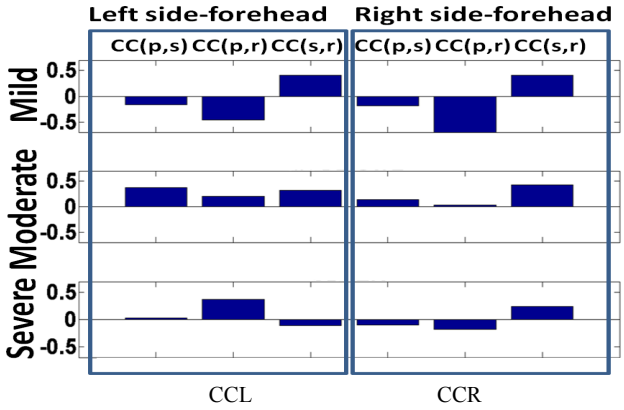

Figure 4. Correlation coefficients (CCs) for three typical trials of a healthy subject. CCL and CCR respectively mean CCs for the left-side-forehead and right-side-forehead. As physical stimuli induced to the left-hand of the subjects, subject's response appears only in CCL.CCLs are used to train and test SF neural network.

dataset is used once as the validation data. Table 1 shows the performance of the classifiers under test. All tests were done on the Centrino Duo computer.

It can be seen from these preliminary results that the performance of SF classifier is high and learnt very fast. Training time for learning in SF was just few milliseconds (three learning cycles) for convergence. Another factor that affects the learning speed is computational load. SF doesn't need high computational load since in its first stage (ART) computational load is very low and its second stage is only a set of simple memory cells [12].

One interesting benefit of SF can be its incremental learning capability when new data become available (on-line learning) [12]. Our future aim is to test the reliability, stability and performance of SF using a larger subject pool for on-line learning. In order to extend the system into a complete, "fNIR data analyzer" more involved tests should be carried out in the future. First, a representative fNIR data set of healthy subjects of both sexes and all adult age groups together with a representative data set from clinical patient groups needs to be collected. Then the neural network should be trained using all these data sets. Finally, the system has to be validated with an independent set of healthy controls and clinical patients before any clinical use to estimate intensity of induced physical stimuli.

TABLE 1: Performance of SF classifier to categorize fNIR data to mild, moderate and severe classes

CS	SF
OP%	91.6
CI%	10.26
NLC	3
LT	3.4ms

CS means 'Classifier'; SF mean SF neural network; O.P means 'overall performance (averaged)' after (15 times) leave-one-out cross-validation tests; NLC, CI and LT mean 'number of learning cycles for training', 'confidence interval (95%) on performance' and 'Learning time', respectively.

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