# Exploring Calibration Techniques for Functional Near-Infrared Imaging (fNIR) Controlled Brain-Computer Interfaces

Peter Wubbels[1], Erin Nishimura[1], Evan Rapoport[1], Benjamin Darling[2], Dennis Proffitt[2], Traci Downs[1], and J. Hunter Downs, III[1]

[1] Archinoetics, LLC. 700 Bishop St. Ste 2000. Honolulu, HI 96813
[2] Proffitt Perception Lab. University of Virginia. 102 Gilmer Hall, Box 400400. Charlottesville, VA 22904

**Abstract.** Functional near-infrared sensing (fNIR) enables real-time, non-invasive monitoring of cognitive activity by measuring the brain's hemodynamic and metabolic responses. We have demonstrated the ability for non-vocal and non-physical communications through detecting directed changes in cognitive tasks. Building upon past research, this paper reports methods that allow the calibration of the fNIR oxygenation signal to better be used in more complex communicative and selection tasks. This work is then discussed in the context of a faster, continuous fNIR brain-computer interface framework.

**Keywords:** Functional Near-Infrared Imagining, Brain-Computer Interface, fNIR, BCI.

## 1 Introduction

Near-infrared technology uses optical imaging in the near-infrared spectrum to monitor relative changes in oxy- and deoxy-hemoglobin in human tissue based on the scattering response of light in these wavelengths [1]. Functional near-infrared (fNIR) sensing monitors relative oxygenation in the tissue of specific brain regions during cognitive activity. Lagging several seconds after the onset of neuronal activity, a hemodynamic and metabolic response leads to increases in blood flow and an increase in the concentration of oxy-hemoglobin in the area of the brain required for that activity. These regional rises in oxygenation can be detected as activations through fNIR sensing in that area, and then used to control software applications, such as brain-computer interfaces [5].

State of the art fNIR brain-computer interfaces (BCIs) use binary selection, or the process of choosing between two options, to control an interface or communicate. While researchers have shown that this method can be up to 95 percent accurate, it is slow, requiring upwards of two minutes to select an item from a list of eight possibilities [7].

D.D. Schmorrow, L.M. Reeves (Eds.): Augmented Cognition, HCII 2007, LNAI 4565, pp. 23–29, 2007.

In an attempt to address this speed bottleneck, researchers are exploring the feasibility of more complex selection schemes. This study specifically looked at the controllability of gradient selection interface with an fNIR system. A gradient selection can be understood as analogous to moving a cursor in one-dimension over a series of "bins" or choices. Eventually, a user will stop their cursor over a particular "bin," signalling the selection of the option it represents. However, using fNIR to control this new type of interface is not trivial or straightforward. Whereas in current systems selection blocks are post-processed, to truly take advantage of gradient selection interfaces, a user will need to control the system in real-time. This goal and the fact that the selection algorithm is no longer limited to a single yes or no distinction, point to a need for a new framework for calibration, thresholding and interface control. The algorithms used for post-processed binary selection need to be updated and applied in a new, more adaptable and dynamic manner.

This paper aims to address the first step in bringing more continuous selection methods to fNIR controlled BCIs by testing three calibration methods used to transform relative oxygenation data into a more meaningful and immediately controllable signal. This initial calibration stage is vitally important to an fNIR controlled BCI because the physiological process being measured can vary drastically from trial to trial, and even on an hourly basis. Calibration thus serves to provide not only a more useful derived signal, but also a current range for operation. Among other things, the current range can also function as an indicator of signal quality, or even a user's level of control. Once research into the calibration of the fNIR signal for gradient interfaces matures, the results can be used to significantly improve fNIR BCI speed and selection rate.

## 2 Methods

The OTIS system, developed by Archinoetics, LLC, is a continuous-wave fNIR system that was used in this study to monitor regional oxygenation changes due to cognitive activity. This system, shown below in Figure 1, is a portable device with up to two sensors that allow for sensing over areas of the scalp with hair, a distinct feature of this fNIR sensing system. The system uses three wavelengths of NIR light and has a sampling frequency of 34.8Hz [4].


**Fig. 1.** The OTIS system with a two-channel sensor

## 2.1 Study Design

For this study, three calibration techniques (explained below) for transforming relative oxygenation data derived from an fNIR system into a gradient interface control signal were tested. All techniques were themselves initialized through the analysis of two, ten second periods of data. In the first period, the test subject was asked to generate an active response, whereas in the second, the subject was asked to relax. Since the fNIR sensor was placed over Broca's area, the designated active task was subvocal counting and the inactive task was nonsense syllable repetition; these tasks were selected because the former task strongly activates Broca's area whereas the latter task does not. The two blocks were designed to give a realistic expected range of values for the particular technique and they were recorded separately before each of the three trials. A ten second recording period was chosen based on previous analysis of two trials, each with the same subject and each containing an active and rest task. These data showed all calibration techniques stabilized at or around six seconds (Figure 2).

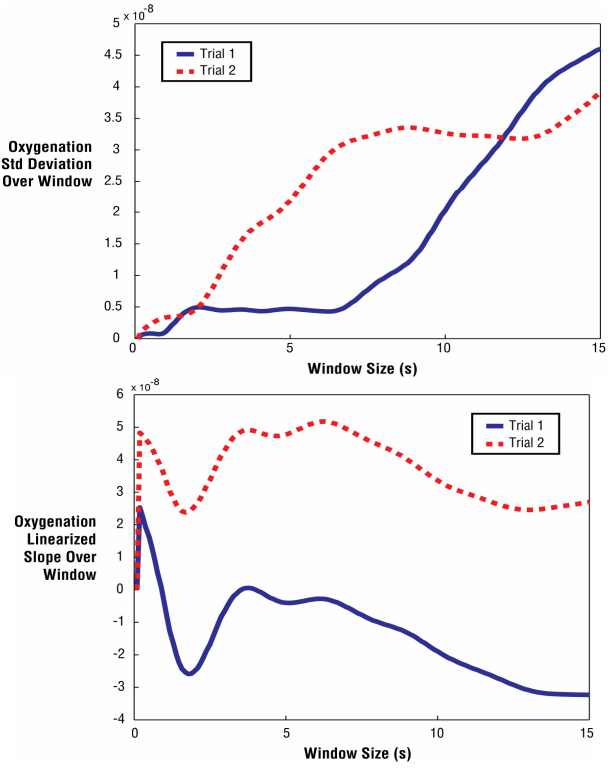


**Fig. 2.** Window size versus value derived from calibration technique over two trials. *Technique 2 (Standard Dev.)* is shown on the top, while *Technique 3 (Best Fit Line Slope)* is shown at bottom. The graph for *Technique 1 (Simple Max/Min)* is not provided because it requires no stabilization time.

After the initialization was completed, one of three calibration techniques was used to establish an expected range for subsequent data. The range was calculated in the following manner:

- *Technique 1(Simple Max/Min):* Global maximum and minimum oxygenation values were pulled from the initialization data. These specify the limits for subsequent data points.
- *Technique 2 (Standard Dev.):* Using a moving window of six seconds (192 data points), the standard deviation was calculated for the windowed data. The maximum and minimum observed values were recorded and used as the range for later data.
- *Technique 3 (Best Fit Line Slope):* Using a moving window of six seconds (192 data points), the best fit line was calculated using the least squares method for the windowed data. The maximum and minimum observed slope for this line were recorded and used as the range for subsequent data.

Once the range was calculated, testing proceeded with a series of activation trials. A user was shown a graph of their current data, as calculated by one of the three techniques, and then asked to make the signal move to either the upper or lower half of the screen by the end of a ten second period. Responses were classified into one of four groups: 1) Above the upper bound of the range. 2) Below the lower bound of the range. 3) Within the range and in the correct half of the screen. 4) Within the range, but in the incorrect half of the screen. An illustration of the graph is provided in Figure 3. Ten selection tasks were performed for each technique, and the targeted selection half was not known to the subject before the trial.

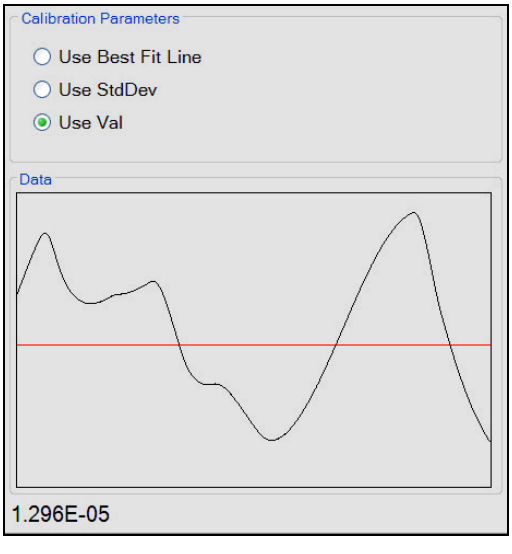


**Fig. 3.** The calibration screen. Currently, *Technique 1 (Simple Max/Min)* is being used. The horizontal line on the graph denotes the division between the upper and lower halves used in the trials. The value in the bottom left corner is the current data point as calculated by the calibration technique. For *Technique 1*, the value is a representation of the relative oxygenation values in the blood.

### 2.2 Data Analysis

The data gathered was logged in raw optical form with timestamps and state information. Relative oxy-hemoglobin concentrations were calculated using a modified Beer-Lambert equation. This oxygenation signal was then ideally filtered with zero phase distortion using a low-pass filter to remove higher frequency noise and normalized to the mean and standard deviation of the filtered signal over each trial. This derived data stream was then used as the source for all calibration techniques. Finally, the output of each calibration technique was graphed in the interface for the subject to monitor.

### 2.3 Subjects and Environment

For this case study we used one male subject with experience using an fNIR system. The subject was seated in a comfortable chair in a dark, quiet room with only the light from the computer monitor. The subject's eyes were closed throughout the initialization periods, but open during the testing phase to allow feedback. Each selection task was performed over ten seconds, followed by a five second rest period.

## 3 Results

Ten trials per technique, each conducted with the same subject, had accuracy rates of 10%, 80% and 90% for *Techniques 1, 2,* and *3* respectively. A detailed chart of the trial results is presented in Table 1.

**Table 1.** Trial Results. Accuracy for each response target (upper or lower half) is provided, as well as data addressing "nearly correct" responses. These include responses that were out of range, but adjacent to the target half.

| **Accuracy** | ***Technique 1 (Simple Max/Min)*** | ***Technique 2 (Standard Dev.)*** | ***Technique 3 (Best Fit Slope)*** |
|---|---|---|---|
| **Total** | **10%** | **80%** | **90%** |
| Lower Half | 20% | 80% | 80% |
| Upper Half | 0% | 80% | 100% |
| **Out of Range** | **90%** | **10%** | **10%** |
| Correct Half | 40% | 10% | 10% |
| Adj. Total | 50% | 90% | 100% |

Researchers noticed that the trials run for *Technique 1* were affected by a downwards trend that overwhelmed any activations. In this case, the range initially set was too limited, and the values fell below the lower bound soon after the first trial was run. To make this technique more robust, a new range would need to be

recalculated every few minutes. This would assure the current values would stay within range and be usable as a control signal for a BCI.

Also of note is the final row in Figure 4. This row specifies the number of trials during which the user managed to move the oxygenation values towards the correct half, but ended with a value outside of the preset range. This can be understood as slightly overshooting a target, and still indicates a "nearly correct" response for that trial. If these trials are counted as correct responses, then *Technique 2* and *Technique 3* would have accuracy levels of 90% and 100% respectively.

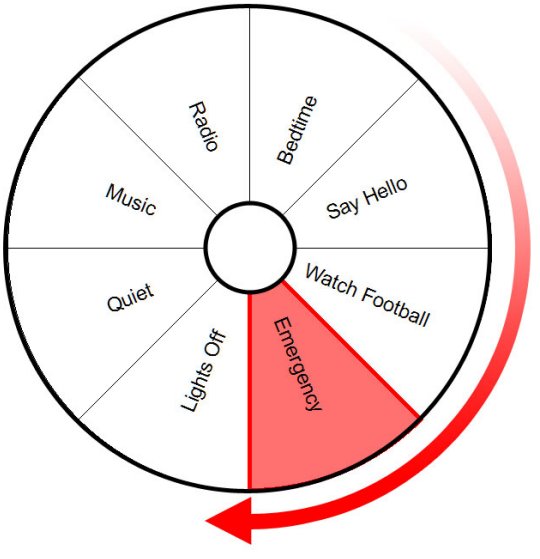


**Fig. 4.** A wheel interface. Each division of the circle represents a different idea or action that can be communicated or enacted by a user of the BCI. The highlighted section travels around the circle in the direction indicated by the arrow as a user increases their activation level. When it stops, the action designated in the highlighted section is executed.

## 4 Discussion

This exploratory study was designed to evaluate the feasibility of three different calibration methods by examining their real-time controllability. This work serves to validate both *Technique 2* and *Technique 3* as potential calibration options for an fNIR BCI. This is the vital first step in creating a continuously controlled BCI framework for assistive or augmentative purposes.

To further develop this calibration stage, more will be done on fine-tuning the parameters of each calibration algorithm. *Technique 1* in particular could benefit significantly from a more dynamic approach to the maximum and minimum value calculation.

As the calibration process for continuous and gradient BCIs advances, work can begin to proceed on the next steps in the BCI pipeline. In the meantime, however, because this new continuous control signal is available, more complex interfaces with many more choices can be presented to a user. This will significantly increase the speed and bit-rate of a BCI. These new interfaces will also be more intuitive, allowing direct selection of an item, rather than a binary narrowing down of a list.

The authors have already prototyped a number of ideas for more continuous BCIs, including a wheel interface that consists of a circle, divided into many "slices" that a user can select. The interface translates the fNIR control signal into "force" that spins the wheel until it rests on a selection (see Figure 4). Small increases in the control signal cause small rotations of the wheel, while a larger increase can lead to a full revolution.

Once perfected, these interfaces will open up a new world of possibilities for both disabled and able-bodied users. For the severely disabled, such as those suffering from amyotrophic lateral sclerosis (ALS), or Lou Gehrig's disease, a BCI offers a means of communication after all other physical means have failed. ALS patients, in the later stages of their illness, often lose all motor control and a BCI is one of their only options for continued linguistic interaction [2], [3]. For able-bodied users, a faster and more robust BCI offers a different kind of benefit. It allows for non-verbal communication, monitoring of cognitive load and perhaps even control of a remote or wearable system [7].

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