

Functional Near-Infrared Spectroscopy for Adaptive Human Computer Interfaces

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ABSTRACT

We present a brain-computer interface (BCI) that detects, analyzes and responds to user cognitive state in real-time using machine learning classifications of functional near-infrared spectroscopy (fNIRS) data. Our work is aimed at increasing the narrow communication bandwidth between the human and computer by implicitly measuring users' cognitive state without any additional effort on the part of the user. Traditionally, BCIs have been designed to explicitly send signals as the primary input. However, such systems are usually designed for people with severe motor disabilities and are too slow and inaccurate for the general population. In this paper, we demonstrate with previous work¹ that a BCI that implicitly measures cognitive workload can improve user performance and awareness compared to a control condition by adapting to user cognitive state in real-time. We also discuss some of the other applications we have used in this field to measure and respond to cognitive states such as cognitive workload, multitasking, and user preference.

Keywords: brain-computer interface, fNIRS, functional near-infrared spectroscopy, adaptive interfaces, workload

1. INTRODUCTION

The communication channel between the human and the computer has long been a limited one, whereby the human can press keys and click a mouse, while the computer can display pixels on a two-dimensional screen. However, both the human and computer are complex machines, capable of sophisticated functions. Their power is limited by the bottleneck of communication between them. The computer cannot detect the full spectrum of information that humans can convey, including user cognitive state.

Physiological computing can increase this limited bandwidth by creating “an additional channel of communication from the user to the computer, albeit a largely unconscious one”.² Detecting these signals in real-time and adapting the user interface to them can improve this narrow of channel of communication with no additional effort on the part of the user.³

Detecting user cognitive state has been explored with a number of measures such as interaction with the computer (such as keyboard or mouse activity)⁴ or environmental context.⁵ Physiological measures have also been used⁶ such as indirect and direct physiological input.⁷ Brain sensing techniques seem to have the most direct access to cognitive state by looking at changes in brain activity using electroencephalography (EEG)⁸ and functional near-infrared spectroscopy (fNIRS).⁹

We have been investigating the use of implicit brain-computer interfaces (BCIs) to passively obtain information about user cognitive state.^{1,10,11} Traditionally, BCIs have been used to explicitly send signals as the primary input.¹² A classic example is the P300 Speller¹³ which is 6x6 matrix of characters where the P300 signal is used to select letters in order to spell out a word. Another frequently used signal is motor imagery¹⁴ where the user imagines moving their right or left hand in order to control some aspect of the interface such as moving left or right.¹⁵ Such systems are designed for people with severe motor disabilities, which, while invaluable to

them, are too slow and too inaccurate for the general population. Recently, there have been several explicit BCI systems designed for able-bodied people such as with games¹⁶ or a multitouch table.¹⁷

In contrast to focusing on intentional brain activity, implicit BCIs do not require any additional effort on the part of the user. The system implicitly gathers information about user cognitive state as the user carries out their task. Cutrell and Tan (2008)³ suggested that implicit brain data could be the most promising, universal application of BCIs. Systems have been developed that take advantage of implicit brain sensing^{18,19} including those with fNIRS.^{20,21}

In this paper, we present an implicit BCI that detects, evaluates and adapts to user cognitive workload in real-time by using machine learning classifications. In order to respond to cognitive workload in real-time, we built a machine learning model of each user's cognitive states of high and low workload. We did this by using a *calibration task* that elicited high and low workload and analyzed users' brain data in each state. Once the model was built, we used it to classify cognitive workload in real-time during an *experimental task* with new fNIRS brain data. The system was then able to adapt the user interface to the user's cognitive workload in the experimental task.

We demonstrate, with an example application, that user performance and awareness is improved with an adaptive BCI that responds to user cognitive state in comparison to a control condition.

2. CALIBRATION TASK

In order to build a machine learning model that distinguished between fNIRS data elicited from high and low cognitive workload, users first carried out a calibration task. We used the n-back task as the calibration task because it has been demonstrated to incite increasing levels of activation in the prefrontal task as n increases in both fMRI^{22,23} and fNIRS^{24,25} studies.

2.1 Equipment

Two probes from an Imagent fNIRS device from ISS Inc. (Champaign, IL) were placed on participants' forehead to measure data from the prefrontal cortex (Figure 1). Each probe contained four light sources, each emitting near-infrared light at two wavelengths (690 and 830 nm) and one detector; thus we had sixteen data channels (2 probes x 4 source-detector pairs x 2 wavelengths). The signals were filtered for heart rate, respiration, and movement artifacts using a third-degree polynomial filter and low-pass elliptical filter.



Figure 1. Each fNIRS probe had 4 sources (five are shown but four were used) and one detector which were placed on the forehead to take measurements from the prefrontal cortex.²⁶

2.2 N-Back Task

Users were shown varying squares on a screen for 500ms at a time and were asked to indicate whether the current stimulus was the same as a stimulus n squares back. There were 2 conditions: a 1-back condition to elicit low cognitive workload and a 3-back to induce high cognitive workload (Figure 2). Users carried out 15 trials of each condition with 10 stimuli in each trial. Each trial totalled 25 seconds and was followed by a 15 second break.

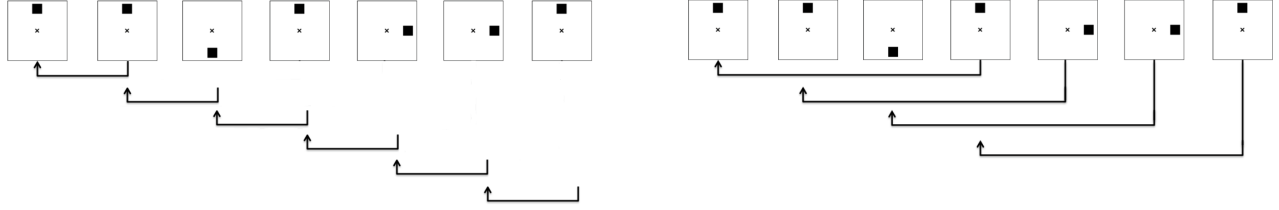


Figure 2. N-back task: Each square was flashed on the screen one at a time. Left: 1-back elicits significantly lower cognitive workload than Right: 3-back which requires holding more information in the short-term memory.

2.3 Modeling Cognitive Workload

During the n-back task, raw fNIRS data was collected by Boxy (fNIRS acquisition software from ISS, Inc.) and sent to a specialized analysis system which was built in-lab using MATLAB. There, the system calculated the time series of change in light intensity compared to an initial baseline period of 30 seconds for each of our 16 information channels (2 probes x 4 light sources x 2 wavelengths).

Previous work had demonstrated that mean and linear regression slope of users' fNIRS data had acted as good features of differences in cognitive workload.²⁷ Thus we used these features for classifying cognitive workload during the n-back task. For each n-back trial, we constructed an example of 32 features (16 information channels x 2 descriptive features) in order to build our model of user difficulty. We then fed each of these examples into LIBSVM, a machine learning library for support vector classification,²⁸ where we used a linear kernel to prevent overfitting the data.²⁴ In addition, we did a parameter search for the C and γ , the cost and gamma parameters for the machine learning model, in order to find the best model for each individual user. This technique uses the training data to build a support vector machine in order to classify new input and give a probability estimate. Finally, after building the model, we used 10-fold cross-validation to ensure that the model was accurate.

2.4 Results

The study included twelve participants (five male) between the ages of 18 and 26. Results showed clear differences in brain data between the conditions eliciting high and low cognitive workload. Figure 3 shows the changes in relative optical intensity from one individual as an example. All trials (each 25 seconds in length) are averaged across all 16 channels. Figure 3 also shows which channels the machine learning algorithm picked to classify this individual's brain data. For other individuals, the algorithm picked other channels. This individual's data is typical of the general trend we saw as participants completed 1-back and 3-back trials.

3. EXPERIMENTAL TASK

The LIBSVM model built from the calibration task can now be applied to the experimental task to classify new fNIRS data in real-time. We will demonstrate the system with the unmanned aerial vehicle (UAV) simulation task from previous work.¹

3.1 UAV Simulation Task

We used a single-operator multiple-UAV system designed by the Human and Automation Lab at MIT.²⁹ Participants (or operators) were shown an overhead view of a map with UAVs (Figure 4) and instructed to guide the UAVs to a sequence of targets as quickly as possible while avoiding obstacles. Participants controlled between three and seven UAVs. Operators were instructed that obstacles, shown as teal octagons, were no-fly zones, and that while UAVs could fly through them, there would be a large penalty for doing so. If entered, obstacles should be exited as soon as possible. Leaving UAVs idle for a long period of time would also result in a penalty, so participants were motivated to balance performing the task quickly and without collisions.

Participants were told that they were part of a team of UAV operators and that vehicles would be passed off from their control to other operators, and other operators vehicles would be passed to them. Intermittently,

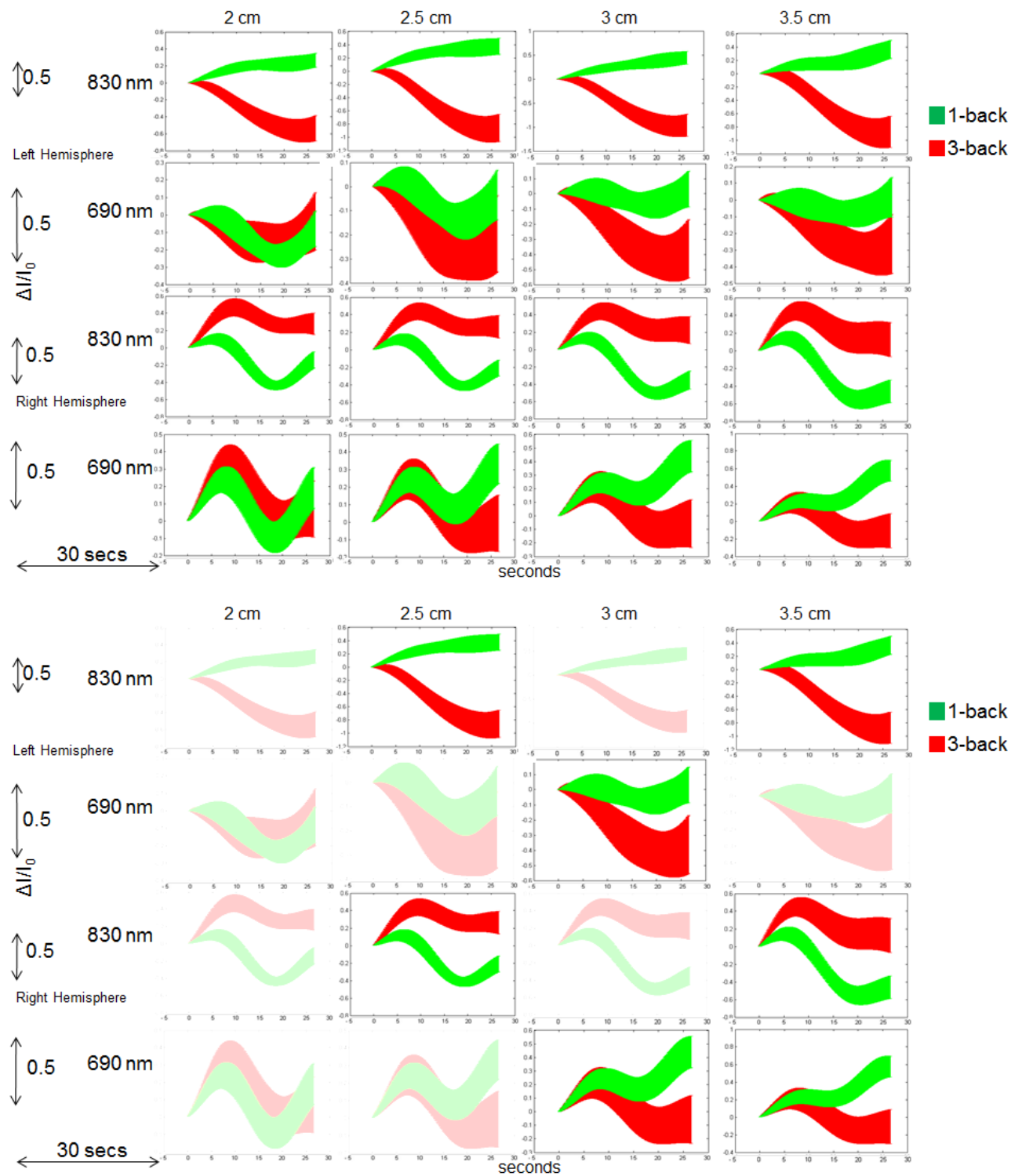


Figure 3. Top: Relative change in optical intensity of one individual averaged across 30 trials for 25 seconds per trial across all 16 channels. Bottom: The highlighted channels are the ones used to pick features by the machine learning algorithm. The algorithm picked different channels for different individuals.

UAVs were added or removed to modify the operators current challenge level. A pilot study determined that only UAVs with no current obstacles were removed in order to avoid distraction of users' cognitive resources.

In addition, obstacles were added or removed, sometimes appearing in current UAVs' flight paths, causing participants to divert their flight paths. All scenarios were designed to cause consistency in obstacle density and path distance.

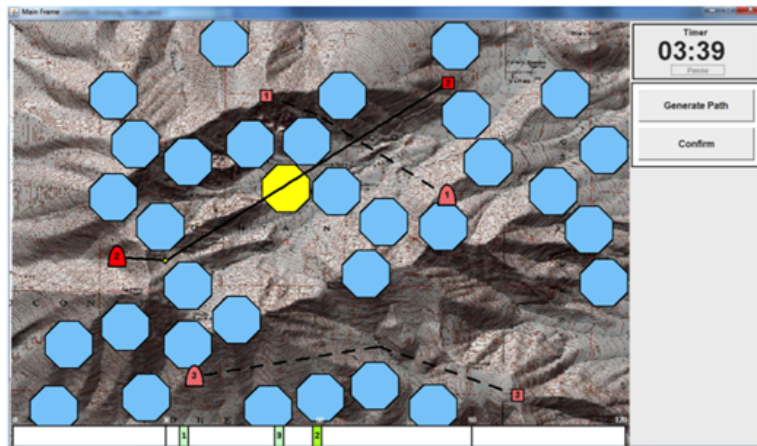


Figure 4. Unmanned Aerial Vehicle (UAV) Simulation Task. Participants were instructed to guide UAVs to their numbered targets without passing through obstacles (octagons).¹

3.2 Classification of fNIRS Data in Real-Time

To predict user state in real time, we analyzed the last 25 seconds of brain data as this was the same length of each trial in the calibration task. For each sliding window of time, the system provided a prediction and confidence value every 500 ms. We used the same mean and linear regression slope features as described in the calibration task. We calculated overall system confidence averages of cognitive state by averaging the last 8 seconds of predictions. This period of time was determined by pilot studies to be an accurate representation of changes in cognitive workload.

When average confidence values were above 80% for low or high cognitive workloads, the system added or removed a UAV, respectively. The confidence average used was determined by pilot studies and ensured that adaptations only occurred if the system was confident that the user was displaying extreme cognitive workload.

3.3 Experimental Design

In order to compare our adaptive BCI system against a control we gave participants two conditions:

- *Adaptive Condition:* UAVs were added when user cognitive workload was low and were removed when user cognitive workload was high.
- *Control Condition:* UAVs were added and removed at random intervals of 20-40 seconds, determined by a series of pilot studies to emulate the timings of the adaptive condition as closely as possible.

3.4 Results

In order to evaluate the success of the system, we carried out paired t-tests in the following categories:

Successes: the number of UAVs that reached the target without entering an obstacle.

Failures: the number of UAVs that entered at least one obstacle on the way to the target.

Obstacles entered: the total number of obstacles that planes entered during operation. This metric differs from failures because a UAV can enter multiple obstacles in a single flight.

Distance in obstacles: the total distance (in pixels) that UAVs travelled in obstacles during operation. This measure helps us understand how quickly users were able to recover from these mistakes.

Average neglected UAVs: a neglected UAV is idle waiting for a route or having an obstacle in its route and needing redirection. This metric refers to the average number of neglected UAVs at any given moment during an operation.

Results showed that users controlled the same number of UAVs (mean of 4.41 in adaptive and 4.69 in control) in both conditions.

There were no significant differences in the number of successes. However we did see a significant difference in user *performance* with significantly higher failure rates ($t(11) = 3.17, p < 0.01, \text{Cohen's } d = 0.92$) and number of obstacles entered ($t(11) = 4.14, p < 0.01, \text{Cohen's } d = 1.2$) in the control condition.

We also noticed a significant difference in user *awareness* with significantly higher distances travelled in obstacles ($t(11) = 2.84, p < 0.05, \text{Cohen's } d = 0.82$) and average number of neglected UAVs ($t(11) = 2.78, p < 0.05, \text{Cohen's } d = 0.80$) in the control condition.

The results can be seen in Figure 5 where the upward sloping lines demonstrate better user performance in the adaptive BCI condition compared to the control condition.

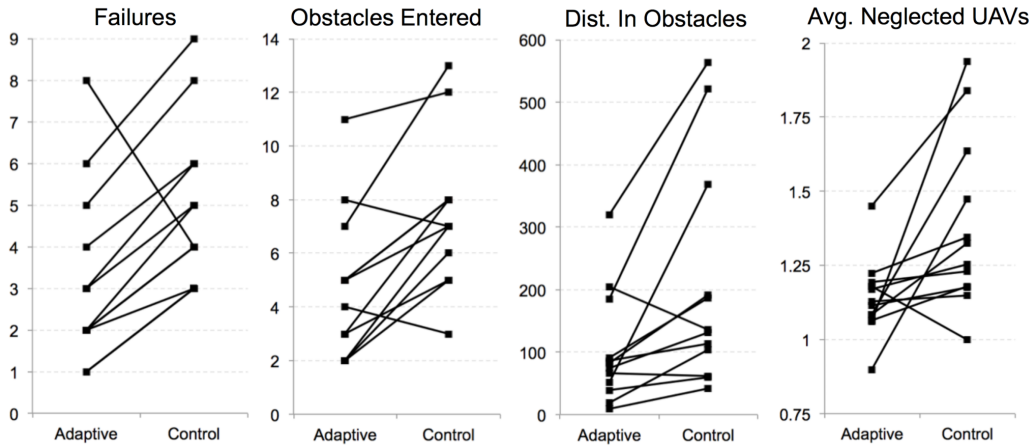


Figure 5. Slopegraphs of results within each category. Upward sloping lines demonstrate better user performance in the adaptive BCI condition compared to the control condition. At least 10 out of 12 participants performed better within each category.¹

4. DISCUSSION

These results suggest that we were able to model user cognitive workload accurately enough to improve user performance and awareness. Participants in the adaptive condition had fewer failures and entered fewer obstacles, suggesting that the system was able to prevent them from cognitively overloading. Participants also travelled for lesser distances within obstacles and neglected fewer UAVs in the adaptive condition suggesting that they were more aware of their mistakes and responded more quickly to fixing them. Yet, participants handled the same number of UAVs in both conditions, suggesting that the adaptive BCI system knew when to add and remove UAVs at the correct moments (in response to their cognitive workload).¹

This is an example application of how the computer can be given more information about the user implicitly, without disturbing the user's task, and respond to the user, increasing their performance and awareness. This provides measurable benefits at no extra cost to the user. This system has advantages over systems where users

have to explicitly self-indicate when they are starting to cognitively overload, because they may not have the extra cognitive resources to indicate overload, or may be unable to accurately and objectively assess their own cognitive levels. In fact, just the added task of having to monitor one's own cognitive workload can take up too much of already limited cognitive resources.

We have also carried out a wide range of applications in systems that respond to user cognitive workload in real-time. Solovey et al. (2012)¹⁰ built an implicit BCI based on the cognitive multi-tasking state which was verified initially by fMRI work.³⁰ The calibration task was based on the same method used in the fMRI study³⁰ to elicit multi-tasking states in participants. This built a machine learning model that could differentiate branching (a subset of multi-tasking where the user must hold a task in memory while carrying out another task) and non-branching cognitive states. This model of branching was then used in an experimental task where participants were asked to remotely supervise two robots in a virtual environment to collect information and return back to the control center. The autonomy of one of the robots was controlled by the adaptive BCI system. In the adaptive condition the robot would become autonomous when participants' fNIRS data indicated that the participant was in a state of branching. In a maladaptive condition this was reversed. In the control condition the robot was never autonomous. All eleven participants took part in all three conditions. Results showed that the lowest task completion rates occurred within the maladaptive condition while task completion was the highest in the adaptive condition when robot autonomy switched on when users' cognitive resources were the most scarce, aiding them in the task when they needed it the most. Participants also indicated in questionnaires that the robot in the maladaptive condition was more annoying and less cooperative, suggesting that the adaptive BCI system was more able to work alongside users' cognitive state than the maladaptive condition.

Another example of our work with implicit BCIs that adapt to user cognitive state is that of Peck et al. (2013)³¹ who worked with building a movie recommendation system based on fNIRS data indicating user preference. Users were first shown images of their most liked and disliked movies during the calibration task, after which, they looked at images of movies they had not yet seen during the experimental task. The users' recommendation ratings were then compared with the adaptive system's ratings for that user and a control condition. Recommendations from the BCI adaptive system were found to improve with time, suggesting that the preference model was gradually learning about the user. Compared with user ratings, the system skewed towards classifying movies as low preference, except when it noted high preference, in which case it would often agree with user ratings.

Taken together, these studies are all building towards implicit, adaptive BCIs that can respond to changing user cognitive state in real-time. Findings demonstrate measurable benefits that can be seen by performances in the adaptive systems compared to control conditions. We hope that this paper demonstrates some of the ways that fNIRS can be used to increase the communication bandwidth between the human and computer to build a new generation of BCIs for the general population.

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