Adaptive Brain-Computer Interface

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Abstract
Passive brain-computer interfaces are designed to use brain activity as an additional input, allowing the adaptation of the interface in real time according to the user's mental state. While most current brain computer interface research (BCI) is designed for direct use with disabled users, I focus my research on passive BCIs for healthy users. The goal of my dissertation is to employ functional near-infrared spectroscopy (fNIRS), a non-invasive brain measurement device, to augment an interface so it uses brain activity measures as an additional input channel. I have measured and classified brain signals that are interesting in HCI context, such as mental workload and difficulty level of a task. My future work will focus on creating an interface that responds to one of those measures by adapting the interface. By combining brain signal measured with an adaptive interface I expect to contribute a functional passive brain-computer interface that measures and adapts to the user's brain signal.

Keywords
Brain-Computer Interface, human cognition, functional near-infrared spectroscopy, fNIRS, task classification

ACM Classification Keywords
H. 5. 2 User Interfaces: Input devices and strategies;
B. 4. 2 Input/Output Devices: Channels and controllers;

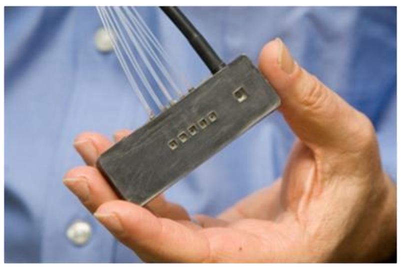

Figure 1. A picture of the right probe. A probe includes a detector (larger square) and four light sources (smaller squares).

Introduction

A brain-computer interface (BCI) can be loosely defined as an interface controlled directly or indirectly by brain activity of the user. While most BCI research is designed for direct use with disabled users, we instead focus on passive BCIs [1] for healthy users. Passive BCIs are interfaces that use brain measurements as an additional input, in addition to standard devices such as keyboards and mice.

Electroencephalography (EEG) is the most common brain measurement tool in BCI. However, we use functional near-infrared spectroscopy (fNIRS), an emerging technology with the advantage of being both non-invasive and portable (see Figure 1). By measuring the reflection of near-infrared light sent into the brain, we can extrapolate a measure of brain activity. This tool has been used in medical and biomedical contexts, but little has been done to take advantage of it in a human-computer interaction (HCI) context.

My research goal is to create interfaces that "pay attention" to the user, to allow them to increase their performance, efficiency, and/or overall experience. Understanding when the user is overloaded, for example, can provide useful information to the interface, which can be adapted to fit the user's mental state.

My dissertation includes: measuring and classifying meaningful brain signals, creating an interface that adapts to one of those measures, and combining brain signal measure with an adaptive interface to complete a functional brain-computer interface that measures and adapts to the user's brain signal.

Exploring brain signals measured with fNIRS

The first step when creating a brain-computer interface system is to determine an interesting brain signal using the device of choice. Each tool and probe allows for a particular area of the brain to be examined, which indicates a need to explore the brain signals.

fNIRS calculates change in hemoglobin concentrations [7] (see Figure 1). Our probes measure the brain area called the anterior prefrontal cortex located under the forehead, an active region that deals with high-level processing [5]: working memory, planning, problem solving, memory retrieval and attention. While Matthews et al. note that the "motor cortex activation is the most common mental strategy for fNIRS-BCI control" [4], I believe in the potential of using higher cognitive function in a passive BCI. Because of this rich area, I have investigated different signals with HCI potential, including difficulty level [2], mental workload [3], reading/memorization, and interest. I observed promising results when assessing the signal of those experiments.

Feasibility Study: Mental Workload

In an experiment that asked subjects to count the number of sides of each colors on a rotating cube, we attempted to measure different levels of mental workload [3]. We could distinguish between them, with between 56% and 72% accuracy when classifying two levels of mental workload, using machine learning classification. We used a sliding windows method with multilayered perception. The results are promising, making this a successful feasibility study.

Difficulty levels during video game play
Distinguishing difficulty levels could prove to be an interesting input signal, on which to adapt the interface. The experiment presented the user with two levels of difficulty of an arcade game (Pacman) [2]. Data from nine participants shows we can discriminate well between the subject playing or resting (94% accuracy, with chance at 50%), as well as discriminate between two difficulty levels and rest periods (77% accuracy, with chance at 33%), which shows potential for use in an adaptive interface. I investigated the data using both statistical analysis and machine learning classification.

Reading/Memorizing words with different interest levels
I also ran an experiment that asked subjects to passively view, or memorize words of different interest level to them. A preliminary statistical analysis shows a significant difference in the brain signal between both the view type (reading or encoding), and two interest levels. Results from this brain signal could be applied in a learning software, such as giving feedback about the user's last attempt at memorizing a piece of information. Browsing software could also use these results as a measure of how hard a user is working on a particular text or webpage: encoding might lead to more mental workload. It could be used in web searches to select pages of previously high mental workload. The interest level measure could also provide extra information in a browsing situation, as a gage of interest of the current document.

What's next?
I am currently choosing a major application for the second part of the research. I need to select the brain signal with the most possibility, and combine it with an interface that will have interesting adaptation potential.

Creating a passively adaptive lightweight interface
Using one of the signals explored previously as a proof of concept, the objective in this part of the thesis is to create a lightweight, adaptive interface that will that assumes fNIRS reading, and will change according to such signal (by using simulated results, for example). One possible interface measures degrees of workload or interest when reading a webpage and uses that to sort the webpages, in order to better search for and find them. Another could use cognitive load assessment to control information pace of peripheral communication.

Part of the research will include testing the adapting interface. Because we will be using simulated data to feed the interface, the best evaluation method might be a Wizard-of-Oz experiment. This type of evaluation consists on having the experimenter pretend to be the computer and react to the user's input. In this case, one would pretend to be the brain measuring device, and would feed the interface with a visual evaluation of the user's state.

Evaluation will provide valuable information about this system. One possible evaluation method is to compare adapting and non-adapting periods. Comparing adaptation from brain signal and random adaptation would also be of interest. We could compare heuristics of performance, enjoyment, awareness of adaptation.

Creating a complete adaptive BCI
When the previous parts have been successfully completed, it would prove interesting to combine the adap-

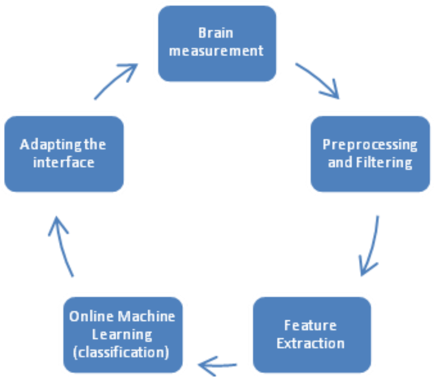

Figure 2. Basic steps in a brain-computer interface.

tive interface with real brain-computer data: a specific brain signal will be measured with fNIRS, classified, and this information will be passed on the interface to react accordingly, as illustrated in Figure 2. Although [6] has conceptualized a BCI system using fNIRS, I would like to create the first working BCI with fNIRS technology.

In addition to the evaluation techniques applied in the previous part, we will explore the value of the adaptive system given better brain inputs, as those will improve over time.

Long Term Vision

I believe we can create passive BCIs with many contexts and types of applications. I am currently using fNIRS, but I am interested in this and technologies like it that can provide more information about the user. The use of additional inputs such as psychophysiological signals can lead to better HCI.

Conclusion

Measuring brain signals related to interfaces can lead to applications such as interface evaluation and adaptation. My thesis explores brain signals measured with fNIRS, use them to adapt the interface and close the loop by connecting brain signals to the adaptable interface. I am really enthusiastic about the potential for fNIRS and similar techniques to greatly enhance how people interact with computers. The creation of a brain-computer interface will open opportunities for adaptation on different brain signals, with a device that is portable, non-invasive and safe.

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