Using Brain-Computer Interfaces for Implicit Input

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ABSTRACT
Passive brain-computer interfaces, in which implicit input is derived from a user's changing brain activity without conscious effort from the user, may be one of the most promising applications of brain-computer interfaces because they can improve user performance without additional effort on the user's part. I seek to use physiological signals that correlate to particular brain states in order to adapt an interface while the user behaves normally. My research aims to develop strategies to adapt the interface to the user and the user's cognitive state using functional near-infrared spectroscopy (fNIRS), a non-invasive, lightweight brain-sensing technique. While passive brain-computer interfaces are currently being developed and researchers have shown their utility, there has been little effort to develop a framework or hierarchy for adaptation strategies.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION
I propose a framework and taxonomy to consider implicit interfaces, which use brain data as input to interactive systems, along with the design principles and patterns I have developed from my previous work with them. I discuss considerations specific to designing implicit user interfaces based on functional near-infrared spectroscopy (fNIRS) brain data. Based on these considerations, I present an overview of examples of brain-based adaptive systems that we have built and studied, which illustrate these principles and patterns, and demonstrate effective use of brain data in human-computer interaction. My research focuses specifically on signals coming from the brain, but these principles and strategies can be applied broadly to other physiological sensor data, and this work has applications in many domains of data analysis involving multitasking or varying cognitive workload.

Using brain, body, behavioral, and environmental sensors, it is possible to capture subtle changes in the user's cognitive state in real time. This opens new doors in human-computer interaction research. This information can be used as continuous input to interactive visualization systems, making the systems more in sync with the user, providing appropriate help and support when needed. However, brain, body, and other sensor data are different from most existing input modalities. To achieve this goal, the interactive system must be carefully designed to take advantage of this more subtle new class of input, leading to *implicit interfaces*. Implicit inputs are user actions or situational contexts that the system understands as input, but that were not actively chosen by the user to interact with the system. For interfaces that incorporate these, the properties of the sensor data must be considered as well as the user states that can be classified successfully from the data. While the design principles and strategies are generalizable and could apply to any type of physiological sensor, I propose that fNIRS is especially useful for implicit input because it is lightweight and non-invasive, and allows users to interact with a system in a natural manner without influencing the signal.

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BACKGROUND

Implicit Input
Most human-computer interaction techniques use explicit input, in which the user consciously manipulates a device (e.g., mouse or keyboard) to indicate a desired command or action in the system. In contrast, passive brain-computer interfaces (BCIs) are based on "reactive states of the user's cognition automatically induced while interacting in the surrounding system" [16]. Passive inputs assess user state and use that to help control interaction without direct or intentional effort from the user. These systems supplement direct input with implicit input, typically derived from physiological sensors attached to the user, in order to adjust application parameters based on user state. Driven by more efficient monitors and the computational power and algorithms to process large quantities of data in real time, modern technology can more affordably integrate passive systems and has spawned research into passive biocybernetic adaptation [5]. Such implicit input is fundamental to the fields of ubiquitous computing and context-aware systems, but mainly focuses on situational and environmental context, and not on cognitive state as context. Interactive visualizations can be improved by using the state of the user as an input to the system, and adapting subtle aspects of the interface appropriately.

Adaptations triggered by passive input face two primary challenges: to accurately model the user's cognitive state and to sensibly adjust the system based on this model. BCI helps solve the first challenge of passive systems by providing user models that more directly tap into the source of user state. Cutrell and Tan suggest that the implicit commands inferred from a user's changing brain activity may be the most promising, universal application of BCI [4]. Explicit brain-issued commands suffer disproportionally from errors and have a limited range of input, whereas implicit commands offer purely additional information without the user's deliberate attention, and the user does not see misclassifactions, nor have to spend additional cognitive resources recovering from these errors.

fNIRS and Prefrontal Cortex

fNIRS uses near-infrared light to detect levels of oxygenated and deoxygenated hemoglobin on the surface of the prefrontal cortex. Light at this wavelength penetrates biological tissue and bone but is absorbed by hemoglobin in the bloodstream, and has similar vascular sensitivity to fMRI [10]. Since neural activity is accompanied by increased oxygen demands in order to metabolize glucose, much like fMRI, fNIRS can detect activation at localized areas of the brain. For a more in depth validation of fNIRS signals in comparison to fMRI, we refer to Strangman et al. [15]. fNIRS detects slow trends of hemodynamic changes, and is thus more appropriate to detect overall state rather than event-related responses.

Recently, fNIRS has increasingly been leveraged to research users because it is considered to be safe, comfortable, relatively robust to movement artifacts, and can be designed for portability. In addition, it is resilient to head movement, facial movement, ambient noise, heartbeat, and muscle movement [7, 13]. This is critical for complex environments where the user must be able to function freely and normally.

Predictive models have been used to differentiate the fNIRS signal between levels of workload [12], verbal and spatial working memory [9], and to determine periods of cognitive multitasking [14] and levels of expertise [3].

DESIGN PRINCIPLES

Regardless the type of sensor, implicit user interfaces that utilize brain and body sensor data share important characteristics, and together define a new class of user interfaces. First, by definition, implicit input is passively obtained from the user. In addition, sensor data is often noisy, is constantly changing, and is continuous, unlike a discrete menu selection or mouse click. Further, the machine learning classification algorithms only provide estimates of cognitive state, with some inherent level of uncertainty. The nature of this input requires careful consideration to ensure successful user interface design. I outline high level principles that can guide development of interfaces that can take advantage of implicit input channels such as those coming from brain and body sensors. Many of these principles could also apply to other similar input channels.

For non-disabled users, passive channels of input are most useful when augmenting other input devices and providing a supplemental channel that indicates user state, instead of being the primary source of input in a system. In addition, because physiological data can be noisy, the adaptations must be resilient to misclassifications. One way to help prevent this is to provide a confidence value for predictions, in order to influence the interface only when the system is certain of state. Because the prediction might not always be correct, a visualization designer should avoid irreversible or mission-critical adaptations. Instead, the adaptations must be used in a paradigm where the benefits outweigh the costs, and where a high number of correct adaptations can improve performance more than the damages from incorrect classifications.

The adaptation should make subtle, helpful changes to the interface that would not be too disruptive if the user's state is misinterpreted. For example, cognitive state information may be used to change future interactions rather than to make prominent changes directly to the current display. Other potential types of interfaces would be those with multiple views or with limited screen real estate. The brain data could be used to make tradeoffs based on the user's cognitive state. Interface adaptations, which run the risk of causing confusion and adding to the user's workload, must be designed carefully to avoid performance decrements. In particular, care must be taken to avoid surprising or confusing the user by making unexpected changes to the interface.

ADAPTIVE STRATEGIES

I propose a novel taxonomy, still in progress, in which adaptations are categorized by their target functional level and immediacy. Specifically, adaptations can affect the semantic or syntactic levels of a system [6], and can be implemented as either immediate or future changes. From combining these levels and timing, I propose a 2x2 model of four different adaptive strategies.

The semantic level of a system refers to the functions performed and the system's internal values and parameters, while the syntactic level of a system refers to the sequence of inputs and outputs, but not the values of these operations [6, 11]. Thus, we can think of the semantic changes as ones that affect the behavior of the system and the goals and actions of a user, whereas syntactic changes are based on the user interface and do not modify the content of the application.

These system changes can be adjusted in two different levels of immediacy. Immediate changes affect the elements currently on screen or being interacted with, while future changes adjust variables and elements that have not yet appeared. Immediate adjustments have the advantage of mapping directly to the user's experience and having a direct effect. However, they need to be done subtly in order to not disrupt user experience. Future changes can be effective because stronger changes to the system may occur without surprising the user. However, future changes to the state of the system may be difficult to implement and evaluate.

I propose that these strategies can be implemented in conjunction with each other to produce four distinct adaptive strategies for interactive systems: immediate semantic adaptations, future semantic adaptations, immediate syntactic adaptations, and future syntactic adaptations. Below, I outline how each of these adaptations affects a system and then illustrate these principles through descriptions of several systems that I have either built or am currently building.

In **immediate semantic adaptations**, the main display stays consistent; however, actions triggered by interaction with on-screen elements change according to implicit cognitive state input. The system may take control of elements such as timing, or actions of elements that are currently displayed, change the effects of input devices, or even adapt autonomy levels.

As in the previous category, in **future semantic adaptations** the display does not change, but over time the underlying functionality may change based on the implicit cognitive state input. An example of this might be search results, where information can vary in content. Physiological sensors could monitor user state during interaction with the information, and map visual designs with metrics such as engagement or preference. Over time, an intelligent system could compare the user's state across different information delivery mechanisms, and slowly gravitate towards personalized interfaces that elicit better performance and cognitive measures.

In **immediate syntactic adaptations**, information on-screen is modified, filtered, or emphasized according to a user's cognitive state. This can be done via methods such as changing the peripheral data or layering of information on a display, and may aid the focus of the user by making critical information more salient at critical moments. Constant updates across the entire interface or changes in the display format may be jarring and unsettling for users, and disrupt their ability to form cohesive mental models of the system. Instead, subtle modifications to inactive elements on screen may clarify the display for the user. Here, we can leverage the high temporal resolution of physiological sensors. Rather than evaluating the entire interface as one cohesive entity, we can evaluate individual interface elements and personalize them in a way that they might best serve the user.

In **future syntactic adaptations**, we change the upcoming layout of a system based on cognitive state. Combining user state with predictions of how the user will react to user interface elements, the system can decide how to appropriately present information to the user. We can modify the type of visualization or stimuli, level of detail, number of options initially visible in a menu, or size of visual elements to provide what might be most suitable for the user.

IMPLEMENTATION AND USER STUDIES

Real-Time Classification

To explore these interactions, I use and built upon a platform to study brain-based adaptive, implicit user interfaces. It focuses on capturing brain activity from functional near-infrared spectroscopy sensors, but the main components can be used for other brain and body sensors as well. This platform expands the functionality of our Online fNIRS Analysis and Classification (OFAC) system [7] and Brainput system [14]. The system learns to identify brain activity patterns occurring as a user experiences various cognitive states. It provides a continuous, supplemental input stream to an interactive system, which uses this information to modify its behavior to provide better support for the user. Thus, I can use non-invasive methods to detect signals coming from the brain that users naturally and effortlessly generate while using a computer system.

The main principle of the system is that I calibrate a user model based on a validated cognitive task known to induce specific cognitive states (e.g., high workload vs. low workload or multitasking vs. non-multitasking). By performing these known tasks repeatedly, we generate a dataset of labeled data. This data set is used in the modeling phase to build a machine learning model that finds specific patterns in this data that indicate one cognitive state or another in future, unlabeled data. I have implemented feature detection, which decreased the computational complexity of the system, and improved the runtime and accuracy of the model (as measured by cross-validation accuracy) using better models and parameter searching. One of my other additions to the system is that it also returns confidence values of the classification, so that we can assess the certainty of the model's predictions and only make adaptations when we have high levels of confidence.

UAV Operation

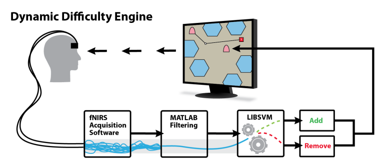

Figure 1. Diagram of our closed-loop dynamic difficulty adaptation engine for UAV adaptation. Raw signals acquired the fNIRS device are filtered, then used to classify user workload. When we are confident that the user is in a suboptimal state, we appropriately add or remove UAVs in order to provide the right amount of work.

I provide an example of *immediate syntactic adaptation*, where we directly add or remove work for the user, in a system for unmanned aerial vehicle (UAV) path planning. We [1] hypothesized that avoiding extended periods of too low or too high workload in this task may lead to flow, a state of immersion and increased engagement. To demonstrate this idea, we ran a laboratory study in which participants performed path planning for multiple UAVs in a simulation. We calibrated a machine learning model on their signals of low and high workload and then varied the difficulty of the task by adding or removing UAVs when we deemed it appropriate. We found that we were able to decrease errors by 35% over a baseline condition of random additions and removals. Our results show that we can use fNIRS brain sensing to detect task difficulty in real time and construct an interface that improves user performance through dynamic difficulty adjustment.

Brain-Based Target Expansion

To show an *immediate syntactic adaptation*, in which physiological signals change how the user interacts with elements on screen, I introduce a brain-based target expansion system [2]. This system improves the efficacy of bubble cursor [8] by increasing the expansion of high importance targets at the optimal time based on brain measurements correlated to a particular type of multitasking. We demonstrate through controlled experiments that brain-based target expansion can deliver a graded and continuous level of assistance to a user according to their cognitive state, thereby improving task and speed-accuracy metrics, even without explicit visual changes to the system. Participants performed a primary audio task (audio recall n-back) while also performing a visual search task with targets of high and low priority. Participants performed best on both tasks, earning the most points, and clicked on targets faster when using a dynamic expansion that reacted to brain input compared to no expansion or static (always full) expansion. Such an adaptation is ideal for use in complex systems to steer users toward higher priority goals during times of increased demand.

Future Research: Phylter for Google Glass

As wearable computing becomes more mainstream, it holds the promise of delivering timely, relevant data to the user. However, these devices can potentially inundate the user, distracting them at the wrong times and providing the wrong amount of information. This can disrupt work or social interactions, and exacerbate the very problems that wearables such as Google Glass might solve. Can we use this for future semantic changes, in which we change the information that we show the user, or future syntactic changes, in which we only change the visual form of graphics or data shown to the user?

To solve this, I am building a system *Phylter* that uses physiological sensing to modulate notifications to the user. Phylter receives streaming data about a user's cognitive state (in the form of machine learning classifications), and receives potential information for the user. It then bases its decision on whether to deliver the message on the message's specified importance and prediction about the user's interruptibility. The current software is calibrated to receive physiological input from the fNIRS-based classification system but is generalizable to other input and output devices. It displays and logs when it receives notifications so that when a system utilizes the service it knows whether or not the user has received a message.

I am currently exploring how to best use this system. In a proof-of-concept pilot, I demonstrated that the software indeed sends the notifications at the right time. I am in the process of conducting an experiment that proves the system modifications can be meaningful, as well as developing additional features.

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