BCI for passive input in HCI

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ABSTRACT

Much of BCI research to date has focused on the direct control of computer interfaces (e.g., mouse cursors or text input systems) by sensing brain states. While using brain activity as a replacement for motor movement is an astonishing and worth-while endeavor, we believe that brain-computer interfaces used in this capacity will remain limited to a fairly small group of users with limited motor abilities. We think there is a potential to use brain sensing in a more passive context, looking beyond direct system control to make BCI useful to the general population in a wide range of scenarios. Here we present some potential applications and considerations for using brain sensing as a supplementary input in HCI contexts. What are the differences from using BCI for direct interaction? How do we deal with the noise associated with typical users' environments and usage? How do we make BCI systems cheap enough to be used by any computer user?

Author Keywords

BCI, brain-computer interfaces, machine learning.

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

In many ways a brain-computer interface is the holy grail of HCI research. The idea of direct neural control of computational systems goes to the heart of what HCI researchers and designers are all about: creating usable and useful systems that are intuitive and "just work" like a user wants them to. One definition of HCI is to improve the "impedance match" between computer systems and the people that use them, and BCIs are the epitome of that goal. Science fiction versions of this are common and compelling. Unfortunately, reality is a bit more sobering; we are a long way away from *The Matrix*.

Nevertheless, as our understanding of neuroscience improves and the tools for brain imaging and sensing evolve, great strides are being made in creating computer interfaces based on the sensing of brain states. Tools that use electromagnetic information such as EEG, MEG, ECoG, and depth recordings and hemodynamic information using fMRI and FNIR have all been used for BCIs. In humans, this research has largely been aimed at users with severe motor impairments, enabling them to interact with computers by inputting text and selecting objects for interaction. This work is incredibly valuable, providing such users a lifeline and an amazing potential for improving their lives. However, such interfaces are also very limited. First, the bandwidth of information gleaned from them is extremely constrained, making them a poor substitute for direct interaction for anyone with normal abilities. In addition, the sensing systems themselves are expensive and extremely sensitive to environmental noise. Finally, some techniques, such as ECoG, require brain surgery which is obviously unacceptable for users who have any alternatives.

In contrast to this work on the direct control of computer systems, we believe there are a number of other applications for BCIs that are not as hampered by these problems and may be useful to healthy users and to HCI researchers and designers.

DETECTING AND CLASSIFYING COGNITIVE STATE

We believe that one of the greatest promises of brain sensing is the ability open a window into cognitive and affective states of users that are not normally available to systems or casual observers. Access to these states may allow us to derive direct measures of phenomena such as task engagement, cognitive workload, working modality, anxiety, surprise, pleasure, or frustration. These measures could open new avenues for researchers and designers in evaluating systems and interfaces. In addition, adaptive systems could use information about the state of the user combined with a wide range of other information about a user's context to adapt themselves to support the current state of the user.

BCI as a tool for evaluation in HCI

Thus far, research in HCI has relied on purely observable behavior to evaluate systems and tools. For this, we have profitably used performance metrics (such as task completion times and error rates) and qualitative tools (e.g., questionnaires, interviews, usability observations). We have also used various behavioral and physiological measures to infer cognitive processes, such as mouse movement and eye gaze as a measure of attention, or heart rate and galvanic skin response as measures of arousal and fatigue. However, many cognitive processes are hard to measure externally. For these, we typically resort to clever experimental design or subjective questionnaires which give us indirect metrics for specific cognitive phenomena. It is very difficult to get direct information into users' cognitive workloads (e.g., how hard it is to perform a certain task), particular cognitive strategies used (such as verbal versus spatial memory encoding). As others have noted, such information could be extremely helpful for HCI research [4].

Similarly, information into users' affective state is critical for a good evaluation of their experience when interacting with the systems. An estimation of affect is of paramount importance for recreational systems such as games—the whole point is to have fun and be engaged. Successful games carefully balance frustration, accomplishment, delight, pleasure, etc. to deliver "fun." Direct measures of affect that do not interrupt the "flow" of games would be extraordinarily useful. Similarly, the importance of affect in the evaluation of productivity software should not be minimized. While managing a database application may not be as engaging as World of Warcraft, direct measures of frustration, irritation and pleasure would be welcomed by any usability professional.

In our work, we want to explore brain imaging as a measure that more directly quantifies the cognitive utility of our interfaces. While the idea of using these technologies in HCI research is not new, there has been little work exploring their use in actual HCI settings. We wish to understand how such techniques can be used with normal users in realistic settings for HCI research.

BCI in adaptive systems

Brain sensing for system evaluation seems a clear first step. HCI laboratories are less sensitive to the cost of systems (though this is still a serious constraint), and researchers have far more control over the environment that the systems will be deployed in. However, an obvious next step is to integrate information about users' cognitive and emotional states directly into systems that they interact with [1, 5, 6].

Even a primitive knowledge of a user's cognitive load or activity state could be of enormous utility to system designers. We believe that the main utility of such information will be to use it in combination with other contextual information (e.g., current task, information from sources such as cameras and microphones, and a user's history). The idea is that while individual contextual elements may be inadequate for determining state (e.g., attentional load for gating interruptions), the summative information provided by all the different sensors and system status will allow systems to make sophisticated and reliable judgements about a user's current cognitive or emotional state.

Obstacles and important areas of research

For both of the above scenarios, there are two obstacles we see as limiting research and the potential widespread use of BCI in HCI. First, the cost of brain-sensing systems that are commonly used in BCI research is currently far too high for most HCI researchers to consider working with them. Even relatively inexpensive systems (as neuroimaging systems go) such as EEG are still prohibitively expensive for most HCI labs. Part of the problem is that EEG signals are faint and noisy. While one can purchase a low-cost EEG system for as little as US$1500, the resolution is low (2 channels) and the noise is high.

The second problem is the sensitivity of such systems to noise (electrical noise, movement artifacts, EMG noise, etc.). If brain imaging systems are to be commonly used by HCI researchers, we must be able to use them in normal (or close-to-normal) environments. If good BCI results are only achieved in an isolated Faraday cage with immobile users, we have a very long way to go.

By combining research in machine learning and classification with an exploration into inexpensive sensors and noisy environments, our lab is exploring the feasibility and pragmatics of using brain sensing technologies to detect and classify state. For example, in [5], Lee and Tan used one of these inexpensive off-the-shelf EEG systems to classify the state (task) of a user while playing the game "Halo." They were able to classify Solo vs. Interactive Play with ~90% accuracy. While the classifier took about 15 minutes of processing to generate, subsequent classification using the system was nearly instantaneous. The classifier could then be updated in the background with new training data.

In more recent work, we have taken a slightly different tack, using EEG to estimate or classify working memory load. In this work, we are attempting to tackle two main issues. First is to extend foundational work in detecting and classifying cognitive state and depth of processing as an estimate of cognitive workload, a goal related to the work of Gevins and colleagues [2, 3]. Second, in this work, we wish to explore issues related to the cost and quality of sensing systems, task generalizability and training issues. The idea is to use a state of the art EEG system (Biosemi ActiveTwo 32 channel EEG) for recording information from participants engaged in a variety of tasks designed to measure cognitive load. However, we do nothing to attempt to shield the users from ambient electrical noise (e.g., 60 Hz hum, noise from computers, etc). Using this data, we develop classifiers for different tasks and workload. We then work with these classifiers to investigate the size of training windows, the amount of training data required, and the number of channels necessary for adequate classification.

The goal is to begin to quantify the trade-offs associated with the amount of training data and number of channels used for classification in (close to) real-world environments. In addition, much more foundational work remains to be done in understanding the basic correlates of cognitive load and how well they transfer between different tasks.

SUMMARY

To recap, we believe that a great deal of promise lies in research into brain sensing for passive or background access into cognitive and affective state. In HCI, such information will be used in the evaluation and research into basic human-computer systems, as well as great promise in adaptive systems that use information about the state of the user combined with a wide range of other information to support a wide range of activities.

However, several serious obstacles must be overcome to see the full fruit of BCI in HCI research. We must reduce the cost of brain sensing systems, and simultaneously deal with the many issues of noise and uncertainty that give current systems so many problems. In addition, there remain many issues related to the validity and cross-task relevance of measures that must be understood. We believe that the future for BCIs is bright, but much work lies ahead!

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