Using Your Brain for Human-Computer Interaction

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ABSTRACT
To further increase the bandwidth from humans to computers, I am investigating methods for sensing signals that users naturally give off while using a computer system. I plan to use this data to augment the explicit input that the user provides through standard input devices. Using a relatively new brain imaging tool called functional near-infrared spectroscopy, along with a more established brain sensing tool called electroencephalography (EEG), we can detect signals within the brain that indicate various cognitive states. These devices provide data on brain activity while remaining portable and non-invasive. If used with care, this additional information can lead to interfaces that adapt appropriately to changes in the user's cognitive state. The focus of my research is to investigate the impact that these input modalities can have on HCI research.

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General terms: Design, Human Factors

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INTRODUCTION

As human-computer interaction (HCI) researchers, we strive to improve user experience and user performance when using interactive computer systems. Over the past fifty years, computers have gained power and efficiency, and can now process massive amounts of information at high speeds. Humans, on the other hand, have not witnessed such dramatic improvements. Thus, we develop interaction techniques to make humans more effective when they interact with computer systems. Early systems used punch cards, and later, command line interfaces. Today, the mouse and keyboard are ubiquitous input devices, while graphical displays on monitors are used for transmitting information from the system to the user. However, these techniques still are not able to capture the richness of the user's thoughts and intentions when interacting with a computer system.

To further increase the bandwidth from humans to computers, I am investigating methods for sensing signals that users naturally give off while using a computer system. I plan to use this data to augment the explicit input that the user provides through standard input devices. Using a relatively new brain imaging tool called functional near-infrared spectroscopy (fNIRS) [1, 16], along with a more established brain sensing tool called electroencephalography (EEG), we can detect signals within the brain that indicate various cognitive states. These devices provide data on brain activity while remaining portable and non-invasive. If used with care, this additional information can lead to interfaces that adapt appropriately to changes in the user's cognitive state. My research aims to identify the best use of this cognitive state information in user interfaces.

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BRAIN IMAGING FOR HCI

Advances in non-invasive brain imaging techniques have allowed us to learn a great deal about the way that the brain works. However, most brain imaging devices were designed for use in clinical or laboratory settings, and often require restrictions on the patient or study participant. Most of these restrictions are not reasonable for realistic HCI settings.

Functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and magnetoencephalography are effective non-invasive tools (i.e. they do not require surgery), but they still are not ideal for HCI research. Besides being expensive, they require subjects to sit or lay down in unnatural positions and remain essentially motionless [10]. In addition, PET requires ingestion of hazardous material and fMRI exposes subjects to loud noises that may interfere with the study [7] and the powerful magnetic field prevents computer usage. These factors make it impractical to use these techniques in a realistic interactive situation.

Figure 1. fNIRS (left) and EEG (right) provide useful cognitive and affective state information while remaining non-invasive and practical for HCI settings.

Because it is less invasive, electroencephalograph (EEG) has seen wide use in BCI research (e.g. [3, 8, 10, 14, 17]), although there are some drawbacks. It has a significant setup time, requires gel to be applied to the scalp and electronic devices in the room can interfere with the signal. It has limited spatial resolution, but good temporal resolution.

My research uses fNIRS and EEG (Figure 1), along with novel machine learning techniques to detect cognitive state information to augment any explicit input the user provides. FNIRS is an emerging tool that detects changes in blood oxygen levels, while remaining safe, portable and non-invasive. When applied to the brain, these metabolic and hemodynamic changes can reveal changes in cognitive state. It is simple to use, has an easy setup (no gel), and has no interference from electronic devices. In addition, because it measures hemodynamic changes instead of electrical activity, it could complement signals from EEG to improve accuracy of BCI systems. However, like EEG, the data can be noisy and less reliable than the more invasive techniques, requiring machine learning algorithms that can handle this type of data. Although EEG and fNIRS are less reliable than the more intrusive methods, they open new doors for HCI research since they are safe, non-invasive, and portable, yet still provide cognitive state information. In my research, I plan to primarily use fNIRS, but also will take advantage of the complementary information provided by EEG and fNIRS together.

FNIRS AND EEG BACKGROUND

Because brain sensing is not commonly used in HCI research, it is useful to explain how the two devices work.

Figure 2. One fNIRS probe. In a typical setup, two probes placed on the forehead. The thin clear fibers are attached to the LEDs and the black, thicker fiber is attached to the light detector. A headband holds the probes in place.

Functional near-infrared spectroscopy

Functional near-infrared spectroscopy is an emerging technique for brain sensing. The system is made up of two probes (Figure 2) with LEDs that send light at two wavelengths in the near-infrared range (690nm and 830nm). Biological tissues are relatively transparent to light at this wavelength. The main absorbers of the light are the oxygenated hemoglobin and deoxygenated hemoglobin in the blood. These act as relevant markers of hemodynamic and metabolic changes associated with neural activity in the brain. The reflected light is then picked up by the detectors on the device. Depending on the amount of light that is reflected, we can get a measure of brain activity in that area of the brain. Since our probes were designed for use on the forehead, we primarily get data on the prefrontal cortex.

Like most brain imaging techniques, fNIRS was designed primarily for laboratory and clinical settings. However, it avoids many of the restrictions of other techniques, and therefore we feel it has promise for HCI research [15]. My dissertation work investigates how we can take advantage of this new technology to advance HCI research.

Electroencephalography

EEG measures electrical activity produced by the brain as neurons fire. A typical setup consists of numerous electrodes placed on the scalp that measure the voltage at that location, relative to a reference point. EEG has a temporal resolution of 1ms, but is subject to noise from fluid, bone, skin, and nearby electronic devices. Often EEG data is interpreted by looking at several frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma (>30 Hz). We plan to use EEG along with fNIRS.

BRAIN-COMPUTER INTERFACE BACKGROUND

Progress in brain imaging has opened the door for research on brain-computer interaction (BCI). For example, users without motor control or speech can currently use a virtual keyboard [9] and navigate in their environment [11] using mental motor imagery. Most systems are designed with brain activity as the primary, and often only, input to the system. Users concentrate on a certain type of thought (such as imagined hand movement) in order to control the system. This requires concentration, effort, and training, and often seems unnatural. Some require implanted electrodes in the skull [9, 12, 13] or long training periods with limited bandwidth [11]. While these systems are valuable to paralyzed and locked in patients, they do not provide sufficient gains to healthy users to make the effort required worthwhile to the healthy users.

Lee and Tan [10] describe two approaches to brain-computer interfaces: operant conditioning and pattern recognition. With operant conditioning, the user is trained to control his or her brain signal using feedback from the system. This approach is often used as explicit input to the system as in the examples above. It is most useful when the user is invested in the system, as is the case with disabled users. In the pattern recognition approach, the user does not go through extensive training. Instead, the system uses signal processing and machine learning techniques to learn patterns associated with various cognitive states. This method is most likely used as implicit input to the system, and may be more practical for most HCI settings.

Following the pattern recognition approach, I plan to make use of brain activity as an additional input channel, providing hard-to-detect information such affective and cognitive states of the user. I want to develop strategies for real-time utilization of this information to enhance, not disrupt, the user experience. The systems will sense natural signals without requiring any additional effort from the user.

BRAIN SENSING AND ADAPTIVE USER INTERFACES

To create an adaptive interface that uses passive brain input, there are several steps required as shown in Figure 3. As the user performs various tasks, a signal is generated by the brain activity and detected using brain sensors such as

EEG and fNIRS. This signal is preprocessed to remove known sources of noise before being classified using machine learning. Once the user's cognitive state information has been classified, this information can be interpreted and used as input to an adaptive interface.

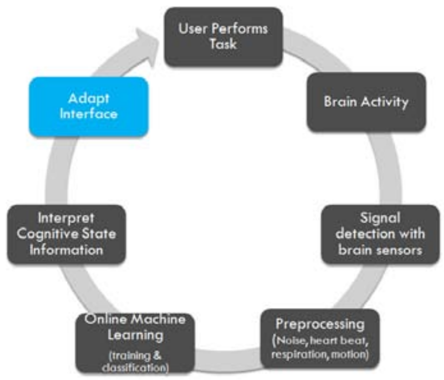

Figure 3. Adaptive UI utilizing brain sensors.

Systems that adapt to brain signals are still in their infancy and there is much work to be done in each of the steps in Figure 3. This interdisciplinary work spans the fields of machine learning, signal processing, brain-computer interfaces, biomedical engineering, as well as HCI.

HCI CONSIDERATIONS FOR BRAIN INPUT

There are still many challenges in the signal acquisition, signal processing, and machine learning areas, and I have been working on these areas. However, my goal is to focus on the human-computer interaction and interface challenges. If we assume that many of the other challenges will be met eventually, and that cognitive state classification will continue to improve in accuracy, then we can start thinking about what this means for user interfaces. This step is not straight-forward and there are many considerations to take into account. It can be investigated even before the fNIRS and EEG work is perfect, thus working on the problem from both ends.

The signals generated from the brain sensors have characteristics that make them challenging to use as input to an interactive system. With these characteristics, can we still build user interfaces? How should they be designed? What domains could use this type of input? These are some of the questions that I hope to address in my research. By understanding the unique properties of the brain input, new paradigms for interaction can be developed.

Implications for Design

Because the brain input is implicit (unlike a mouse or keyboard that the user explicitly uses for input), we do not want to surprise or confuse the user by making unexpected changes to the interface. In addition, the data is often noisy, and is constantly changing. Plus, the machine learning classification algorithms are unlikely to be perfect, leading to unreliable, imperfect cognitive state classification. Therefore, the adaptive interfaces should make subtle, helpful changes to the interface that ideally would not be too disruptive if the user's state was misinterpreted. For example, the cognitive state information may be used to change future interactions, to pre-choose defaults, or to change the effect of a click. In addition, the brain signal offers a continuous measure of various cognitive states (i.e. varying level of workload). This is different from discrete input such as a menu selection or mouse click. Interfaces should take advantage of the continuous nature of the brain signal.

Applications of brain-adaptive interfaces

Another important task is to identify applications and domains in which this type of input would be useful. Because we have had good results measuring cognitive workload [2, 4-6], I plan to build interfaces for tasks that have varying levels of cognitive workload. More specifically, we have been able to distinguish between cognitive resources [6], so these systems may be useful in interfaces that involve both spatial and verbal working memory. In addition, since we can measure cognitive state in real time, it would likely be useful in situations with streaming data. Other potential types of interfaces would be those with multiple views or with limited screen real estate. The brain data could be use to make tradeoffs based on the user's cognitive state. These paradigms may be useful for other situations with implicit, noisy input, in addition to brain-adaptive interfaces.

RESULTS AND CONTRIBUTIONS

To date, our research group at Tufts has taken steps toward building an adaptive BCI using fNIRS. Since fNIRS is new, there are not established methods for analyzing the data from the device. Thus, we have had to develop algorithms that can be used to better understand the data coming from the machine. To classify cognitive states from fNIRS data alone, we developed noise reduction and machine learning classification algorithms. These have been developed to work in real time, as data is collected, in order to adapt the system in real time. These techniques will improve analysis of any new fNIRS data. In addition, the methods could be applied to pattern recognition in other datasets with noisy time series data. This work is ongoing as I continue improving the classification accuracy.

In addition, we have conducted studies to determine the feasibility of recognizing various cognitive states, such as mental workload level [2, 4-6], with the fNIRS device. From these studies, we have shown the viability of distinguishing various cognitive workload levels, game difficulty levels, and specific cognitive resources (i.e. verbal working memory). I am now experimenting with interfaces that can appropriately take advantage of this information to improve the user experience, without confusing or frustrating the user with unexpected behavior.

ONGOING WORK

Now that we have taken steps to obtain cognitive state information using fNIRS and EEG, I am working on understanding how best to use this information in user interfaces. While I have some hypotheses about what will work best with this type of data (as described above), I would like to empirically investigate this. To do this, I will build interfaces with different adaptive behaviors. Through user evaluations, I will learn what aspects of adaptive interfaces work best with the cognitive state data that we are measuring with fNIRS and EEG.

CONCLUSION

Portable, non-invasive brain sensing devices are becoming realistic tools for HCI researchers, giving us a better understanding of the user's cognitive and affective state. This knowledge can have a big impact on user interfaces, but it must be used appropriately. Since this input has unique characteristics that set it apart from most standard input techniques, I have been exploring the effective use of the device in human-computer interaction. This is an early step towards computers that can interpret the user's state and adapt accordingly.

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REFERENCES

1. Chance, B., Anday, E., Nioka, S., Zhou, S., Hong, L., Worden, K., Li, C., Murray, T., Ovetsky, Y. and Thomas, R. A novel method for fast imaging of brain function, non-invasively, with light. Optics Express, 10 (2). 411-423.

2. Girouard, A., Solovey, E.T., Hirshfield, L.M., Chauncey, K., Sassaroli, A., Fantini, S. and Jacob, R.J.K., Distinguishing Difficulty Levels with Non-invasive Brain Activity Measurements. in INTERACT 2009, (Uppsala, Sweden, 2009), Springer.

3. Grimes, D., Tan, D.S., Hudson, S., Shenoy, P. and Rao, R., Feasibility and Pragmatics of Classifying Working Memory Load with an Electroencephalograph. In CHI 2008 Conference on Human Factors in Computing Systems, (Florence, Italy, 2008).

4. Hirshfield, L.M., Chauncey, K., Gulotta, R., Girouard, A., Solovey, E.T., Jacob, R.J.K., Sassaroli, A. and Fantini, S., Combining Electroencephalograph and Near Infrared Spectroscopy to Explore Users' Instantaneous and Continuous Mental Workload States. In HCI International 2009, (2009).

5. Hirshfield, L.M., Girouard, A., Solovey, E.T., Jacob, R.J.K., Sassaroli, A., Tong, Y. and Fantini, S., Human-Computer Interaction and Brain Measurement Using Functional Near-Infrared Spectroscopy Poster Paper. In ACM UIST 2007 Symposium on User Interface Software and Technology, (2007), ACM Press.

6. Hirshfield, L.M., Solovey, E.T., Girouard, A., Kebinger, J., Sassaroli, A., Tong, Y., Fantini, S. and Jacob, R.J.K., Brain Measurement for Usability Testing and Adaptive Interfaces: An Example of Uncovering Syntactic Workload with Functional Near Infrared Spectroscopy. In Proceedings of CHI'09 Conference on Human Factors in Computing Systems, (2009).

7. Izzetoglu, M., Izzetoglu, K., Bunce, S., Onaral, B. and Pourrezaei, K. Functional Near-Infrared Neuroimaging. IEEE Trans. on Neural Systems and Rehabilitation Engineering, 13 (2). 153-159.

8. Keirn, Z.A. and Aunon, J.I. A new mode of communication between man and his surroundings. Biomedical Engineering, IEEE Transactions on, 37 (12). 1209.

9. Kennedy, P.R., Bakay, R.A.E., Moore, M.M., Adams, K. and Goldwaithe, J. Direct control of a computer from the human central nervous system. Rehabilitation Engineering, IEEE Transactions on [see also IEEE Trans. on Neural Systems and Rehabilitation], 8 (2). 198.

10. Lee, J.C. and Tan, D.S. Using a low-cost electroencephalograph for task classification in HCI research Proc. of UIST, ACM Press, 2006.

11. Millán, J.d.R., Renkens, F., Mouriño, J. and Gerstner, W. Brain-actuated interaction. Artif. Intell., 159 (1-2). 241-259.

12. Moore, M., Kennedy, P., Mynatt, E. and Mankoff, J. Nudge and Shove: Frequency Thresholding for Navigation in Direct Brain-computer Interfaces Proc. ACM CHI 2001 Human Factors in Computing Systems Conference Extended Abstracts, ACM Press, 2001, 361-362.

13. Moore, M.M. and Kennedy, P.R. Human factors issues in the neural signals direct brain-computer interfaces Proceedings of the fourth international ACM conference on Assistive technologies, ACM, Arlington, Virginia, United States, 2000.

14. Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N. and Wolpaw, J.R. BCI2000: a general-purpose brain-computer interface (BCI) system. Biomedical Engineering, IEEE Transactions on, 51 (6). 1034.

15. Solovey, E.T., Girouard, A., Chauncey, K., Hirshfield, L.M., Sassaroli, A., Zheng, F., Fantini, S. and Jacob, R.J.K. Using fNIRS Brain Sensing in Realistic HCI Settings: Experiments and Guidelines ACM UIST 2009 Symposium on User Interface Software and Technology, ACM Press, 2009.

16. Villringer, A., Planck, J., Hock, C., Schleinkofer, L. and Dirnagl, U. Near Infrared Spectroscopy (NIRS): A New Tool to Study Hemodynamic Changes During Activation of Brain Function in Human Adults. Neurosci. Lett., 154. 101-104.

17. Wolpaw, J.R., McFarland, D.J., Neat, G.W. and Forneris, C.A. An EEG-based brain-computer interface for cursor control. Electroencephalography and Clinical Neurophysiology, 78 (3). 252.