Exploring Brain-Computer Interfaces (BCIs) and their use for Human Learning Activities

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Abstract

This research review will explore the advances in Brain-Computer Interfaces, also known as BCI. Brain-Computer Interface technology transforms brain activity into data that can be analyzed digitally, thus serving as input for interactive systems. Advances in brain imaging and cognitive neuroscience are now allowing us to interface with the brain directly. Principles and design patterns that enable us to take advantage of brain data can now be utilized to build systems that are more efficient. There is a growing number of resources on the feasibility of using brain and body sensors to monitor brain activity/user engagement and leverage this information for advanced computing and learning. This research review explores the basics of BCI, the relationship between BCI and Human-Computer Interaction (HCI) and the role of BCI in human learning activities such as reading.

HCI practitioners are studying ways to use as many neural networks yielded by BCI as possible. The study of BCI is just another advancement in the field of Human-Computer Interaction and the objective to build systems that cater to the cognitive, physiology, and environmental processes of the user.

Introduction

For generations, humanity has fantasized about just uploading a book to the brain. Like Neo of the movie *The Matrix*, on a Saturday morning, you upload to your brain a book on how to fix your broken car transmission. Unfortunately, there is no such technology. And humanity has not dreamed of this for generations (especially considering the Matrix was only release in 1999). However, we cannot say that this technology will never be available.

Each moment, technology advances and enhances the ability for humans to interact and communicate with the machines and systems used daily. These very same advances have led to the need to absorb more and more information from various sources to perform numerous tasks. During interactions with these systems, humans generate cognitive states and sensory data that can either be used as direct input into the system or passive data that shows the user's experience while performing a task. To take advantage of this valuable data, the ability to interface with the human brain must be necessary. It is only recently that advances in cognitive neuroscience and brain imaging have started to allow for the opportunity to interface with the brain. The ability to absorb and use this information is now made possible using Brain-Computer Interfaces (BCI).

The use of BCI becomes a powerful communications tool by using the advances in neuroscience and brain imaging technology. It creates opportunities for innovation in the human-computer interaction space. HCI researchers can now collect stronger data around the user's cognitive state and intent by observing their physiology, behavior, environment and now brain activity. Using this data, they can now develop systems that adapt to and support the user's task. Learning activities such as reading can significantly benefit from the use of BCI and HCI together.

Literature Review

Understanding Brain-Computer Interfaces

Brain-Computer Interfaces (BCI) are communication systems that do not require the use of your motor skills but instead allow you to use the signals from your brain to control computers or communication devices.

The creation of brain-computer interfaces has primarily been driven by the need to aid and assist individuals with physical disabilities and those lacking auditory communication abilities. Often time people suffering from devastating neuromuscular injuries and neurodegenerative diseases such as amyotrophic lateral sclerosis (ALS), will eventually lose control of all voluntary muscular activity; however cognitive functions will still be intact. Advances in neurological imaging technologies have allowed us to collect sensory data from the brain via brain-computer interfaces. The promising future predicted for BCI has encouraged the research community to study the involvement of BCI in the life of non-paralyzed humans.

Brain-Computer Interfaces consist of two paradigms – active BCI and passive BCI. Active BCI is the study of how BCI can be used as an input for users on different machines. Passive BCI studies the user's state while performing a particular task.

It is often great to think of the brain as a computer with a fast central processor; however, this is not quite the case. The brain happens to be a complex set of sub-systems, with each system highly specialized for its task. The brain can roughly be divided into two systems: the cerebral cortex and sub-cortical regions. The cerebral cortex is the largest and most complex part of the brain, supporting most sensory and motor processing skills. The cerebral cortex also supports reasoning, planning, language and pattern recognition. As a result, BCI has mostly focused on this area of the brain.

According to Tan and Nijolt (2010), there are two general classes of brain imaging technologies: invasive technologies, in which sensors are implanted directly on or in the brain, and non-invasive technologies, which measure brain activity using external sensors. Invasive brain technologies are embedded directly in the brain and involve surgical procedures. They can lead to medical complications, rejection by the body and further complications. As a result, they are usually not the focus of BCI research. Many researchers focus on non-invasive technologies, though not as accurate, they are much safer and can even be taken advantage of for human-computer interaction development activities. BCI researchers utilize many non-invasive technologies, but there are two most predominate - Electroencephalography (EEG) and Functional Near Infrared Spectroscopy (fNIRS).

Electroencephalography (EEG): Unlike some neuroimaging tools, electroencephalography (EEG) provides a more direct measure of neuronal activity by recording electrical signals on the scalp generated by neurons firing in the brain. EEG measurements have excellent temporal resolution with delays in the tens of milliseconds, but spatial resolution tends to be poor. According to Tan and Nijolt (2010), two centimeters on the cerebral cortex could be the difference between inferring that the user is listening to music when they are in fact moving their hands. Because EEG data is more portable, less expensive and less intrusive, it remains one of the most useful and feasible data sources in BCI research.

Functional Near Infrared Spectroscopy (fNIRS): Functional Near Infrared Spectroscopy (fNIRS) is also a primary source of brain data collection in BCI. The fNIRS technology works by projecting near-infrared light into the brain from the surface of the scalp and measuring optical changes at various wavelengths as the light is reflected out (for a detailed discussion of fNIRS, see Coyle et al. 2004). fNIRS technology is often used to build functional maps of brain activity.

Both technologies, EEG and fNIRS, are highly sophisticated neuroimaging technology that are useful in their own ways. While neither of these technologies is perfect for observing cognitive activities in the brain, they are nicely complementary, and researchers can carefully select the right tool depending on the research.

Brain-Computer Interaction (BCI) and Human-Computer Interaction (HCI).

Now that we have broadly explored what BCIs are, the parts of the brain that they focus on and the tools used to collect the sensory data, we will look at how BCI can be leveraged in human-computer interaction development. As computing systems become increasingly complex and intelligent, the role and expectations of the human in the computer system change as well (Solovey, E., Afergan, D., Peck, E., Hincks, S., Jacob, R., (2015). BCIs are established enough that HCI practitioners can add them to their tool belt when designing computer interactions.

Brain-computer interfaces now present several major opportunities for the human-computer interaction community:

- The BCI community and its experiments have mainly focused on the complicated mechanics of obtaining data from the brain. This presents HCI researchers with the opportunity to make the most of the data collected and design experiences that take advantage of a user's intentions and cognitive states. Also, the cognitive states identified in these experiments have direct significance to many HCI scenarios, particularly when a user is multitasking.

A study conductions by Solovey, E., Afergan, D., Peck, E., Hincks, S., Jacob, R., (2015) found that the possibility exists for the following:

> Automatically recognizing that the user is experiencing one of these states provides an opportunity to build adaptive systems that support multitasking. For example, by recognizing that most interruptions are quickly ignored, as in the delay condition, the system could limit these types of interruptions or reduce their salience as appropriate. … Finally, distinguishing between predictive and random scenarios could trigger the system to increase support when the user's tasks become unpredictable. (p.35:8)

- Theoretically, using fNIRS, brain activity data can be utilized as a continuous input source to an interactive system, making the system more in sync with the user and providing help and support when needed. This type of neural input provides the HCI community with the opportunity to develop systems that provided recommendations based on the data streamed from the brain. Like Netflix or Facebook, information and help can now be presented to the user based on brain activity rather than the usual physiological actions performed on the computer/device (moving the mouse, using the keyboard to type and search).
- Research has also shown that the HCI community has become particularly successful at exploring and creating new applications by leveraging BCI feedback. This has led to thinking about the uses of technology to not only solve existing pain points or aid those with disabilities but also to address the needs of non-disabled individuals. BCI and HCI efforts are now being utilized to develop technology for the alleviation of stress,

advanced computing, efficiency at work and human learning activities. Essentially, the goal has become to develop technologies that can enhance everyday life.

Uses of BCI in Human Learning Activities

Research is now being conducted on augmenting human learning by using BCI coupled with core human-computer interaction principles and patterns. Recognizing and summarizing a person's activities have proved to be an efficient way to becoming self-aware and improving habits. Specifically, reading has been known to have a high impact on learning ability and has been known to improve language skills.

Research shows that reading and retention is heavily influenced by the reader's level of engagement. Users may retain information more readily by incrementing their reading engagement physiology. Learning materials that may be considered uninteresting are then more easily retained. According to Andujar, M., Gilbert, J. (2013), the physiological reading method is an innovative reading approach that may change the reader's learning experience by identifying the user's engagement and displaying engaging videos related to the reading when the engagement drops under an established baseline.

Most reading engagement research utilizes frontal lobe EEG sensors to monitor a person's engagement in real-time as they are reading. Documented below are four major studies related to reading and engagement:

- LET'S LEARN is an EEG-augmented reading system using content-related videos grabbed from YouTube to improve users' engagement.
- FOCUS is an EEG-augmented reading system. Its hardware contains three main parts: a physical book, a commercial BCI device (Emotiv1) and a pico- projector.

- PAY ATTENTION designs an embodied story-telling agent, which uses a modulated spoken volume and gestures to attract users' attention when their engagement level drops.
- BRAVO continually analyzes users' brain activity, estimates their attention and meditation levels, and presents users with learning material that only results in high engagement.

These studies, for the most part, have revealed that it is feasible to determine reading activities and measure levels of engagement using BCI systems. Users have also been more engaged while performing the EEG reading. Further studies in this area will focus on gaining more accurate brain activity data, developing wearable devices that are more appropriate for collecting brain activity and ways to introduce this technology as an educational tool.

Discussion/Future Directions

Like any technology, BCI is moving through the various phases of development. In some respects, it is still very theoretical and experimental. However, BCI is moving quickly towards the phase of maturity where its intricacies can be understood and used to build new, unique experiences. While some researchers think that these interfaces will get good enough to improve the lives of incapacitated users vastly, not all are confident that brain-computer interfaces will eventually be good enough to replace motor movement even for non-disabled users completely. In fact, many researchers have mixed feelings about whether this is useful or advisable in many situations.

A study conducted by Solovey, E., Afergan, D., Peck, E., Hincks, S., Jacob, R., (2015) found that "implicit, passive brain-computer interfaces show promise to increase the bandwidth between the user and the computing system without additional work or conscious thought on the part of the user. This is an early step toward computers that can interpret the user's cognitive state and adapt accordingly. The ability to capture subtle changes in the user's cognitive state in real time opens new doors for human-computer interaction research."

Should the technology continue to develop, there could be many uses for it. For example, BCIs could be utilized as a secondary option for computer users suffering from carpel tunnel syndrome. It could also be used for workplace tasks where response times are critical, such as safety mechanisms on airplanes or spacecraft interfaces. Lastly, it could be used for gaming and entertainment purposes. Even now some consumer devices claim the use of some form of EEG control.

Conclusion

We are far from having the ability to upload books directly to the brain. While BCI has its potential, it also faces many challenges. Some of these difficulties include:

- Brain complexity. The brain is very complex, and there exists no one-for-one brain mapping to neural response. The brain can often respond to multiple influences at once. This can often impact the data collected.

- Usability. Despite its expected success, BCI faces usability challenges and the reluctance of users to use the technology.

- Training process. There is often a lengthy training process involved with using BCIs.

- Technical constraints. The technology used today, while advanced, still needs further improvement to better target specific user activities.

In this research review, we only begin to touch on the complexities of the brain, BCI and its influence on HCI and human learning activities. Because it is an emerging technology, there is plenty of room for growth and innovation. The fact remains that we are now able to take the information provided via brain-computer interfaces and begin to create systems that are more adaptive and responsive. Brain activity data can be used to increase the accuracy of the HCI systems, resulting in BCI contribution in various fields such as industry, educational, advertising, entertainment, and transportation.

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