Chapter 1
Brain-Computer Interfaces and Human-Computer Interaction

Desney Tan and Anton Nijholt

Abstract Advances in cognitive neuroscience and brain imaging technologies have started to provide us with the ability to interface directly with the human brain. This ability is made possible through the use of sensors that can monitor some of the physical processes that occur within the brain that correspond with certain forms of thought. Researchers have used these technologies to build brain-computer interfaces (BCIs), communication systems that do not depend on the brain's normal output pathways of peripheral nerves and muscles. In these systems, users explicitly manipulate their brain activity instead of using motor movements to produce signals that can be used to control computers or communication devices.

Human-Computer Interaction (HCI) researchers explore possibilities that allow computers to use as many sensory channels as possible. Additionally, researchers have started to consider implicit forms of input, that is, input that is not explicitly performed to direct a computer to do something. Researchers attempt to infer information about user state and intent by observing their physiology, behavior, or the environment in which they operate. Using this information, systems can dynamically adapt themselves in order to support the user in the task at hand.

BCIs are now mature enough that HCI researchers must add them to their tool belt when designing novel input techniques. In this introductory chapter to the book we present the novice reader with an overview of relevant aspects of BCI and HCI, so that hopefully they are inspired by the opportunities that remain.

D. Tan (✉)
Microsoft Research, One Microsoft Way, Redmond, WA 98052, USA
e-mail: desney@microsoft.com

A. Nijholt
University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands
e-mail: anijholt@ewi.utwente.nl

D.S. Tan, A. Nijholt (eds.), *Brain-Computer Interfaces,*
Human-Computer Interaction Series,
DOI 10.1007/978-1-84996-272-8_1,

Book ID: 210720_1_En, Date: 2010-05-13, Proof No: 1, UNCORRECTED PROOF

1.1 Introduction

For generations, humans have fantasized about the ability to communicate and interact with machines through thought alone or to create devices that can peer into person's mind and thoughts. These ideas have captured the imagination of humankind in the form of ancient myths and modern science fiction stories. However, it is only recently that advances in cognitive neuroscience and brain imaging technologies have started to provide us with the ability to interface directly with the human brain. This ability is made possible through the use of sensors that can monitor some of the physical processes that occur within the brain that correspond with certain forms of thought.

Primarily driven by growing societal recognition for the needs of people with physical disabilities, researchers have used these technologies to build brain-computer interfaces (BCIs), communication systems that do not depend on the brain's normal output pathways of peripheral nerves and muscles. In these systems, users explicitly manipulate their brain activity instead of using motor movements to produce signals that can be used to control computers or communication devices. The impact of this work is extremely high, especially to those who suffer from devastating neuromuscular injuries and neurodegenerative diseases such as amyotrophic lateral sclerosis, which eventually strips individuals of voluntary muscular activity while leaving cognitive function intact.

Meanwhile, and largely independent of these efforts, Human-Computer Interaction (HCI) researchers continually work to increase the communication bandwidth and quality between humans and computers. They have explored visualizations and multimodal presentations so that computers may use as many sensory channels as possible to send information to a human. Similarly, they have devised hardware and software innovations to increase the information a human can quickly input into the computer. Since we have traditionally interacted with the external world only through our physical bodies, these input mechanisms have mostly required performing some form of motor activity, be it moving a mouse, hitting buttons, using hand gestures, or speaking.

Additionally, these researchers have started to consider implicit forms of input, that is, input that is not explicitly performed to direct a computer to do something. In an area of exploration referred to by names such as perceptual computing or contextual computing, researchers attempt to infer information about user state and intent by observing their physiology, behavior, or even the environment in which they operate. Using this information, systems can dynamically adapt themselves in useful ways in order to better support the user in the task at hand.

We believe that there exists a large opportunity to bridge the burgeoning research in Brain-Computer Interfaces and Human Computer Interaction, and this book attempts to do just that. We believe that BCI researchers would benefit greatly from the body of expertise built in the HCI field as they construct systems that rely solely on interfacing with the brain as the control mechanism. Likewise, BCIs are now mature enough that HCI researchers must add them to our tool belt when designing novel input techniques (especially in environments with constraints on normal motor movement), when measuring traditionally elusive cognitive or emotional phenomena in evaluating our interfaces, or when trying to infer user state to build adaptive systems. Each chapter in this book was selected to present the novice reader with an overview of some aspect of BCI or HCI, and in many cases the union of the two, so that they not only get a flavor of work that currently exists, but are hopefully inspired by the opportunities that remain.

1.1.1 The Evolution of BCIs and the Bridge with Human Computer Interaction

The evolution of any technology can generally be broken into three phases. The initial phase, or proof-of-concept, demonstrates the basic functionality of a technology. In this phase, even trivially functional systems are impressive and stimulate imagination. They are also sometimes misunderstood and doubted. As an example, when moving pictures were first developed, people were amazed by simple footage shot with stationary cameras of flowers blowing in the wind or waves crashing on the beach. Similarly, when the computer mouse was first invented, people were intrigued by the ability to move a physical device small distances on a tabletop in order to control a pointer in two dimensions on a computer screen. In brain sensing work, this represents the ability to extract any bit of information directly from the brain without utilizing normal muscular channels.

In the second phase, or emulation, the technology is used to mimic existing technologies. The first movies were simply recorded stage plays, and computer mice were used to select from lists of items much as they would have been with the numeric pad on a keyboard. Similarly, early brain-computer interfaces have aimed to emulate functionality of mice and keyboards, with very few fundamental changes to the interfaces on which they operated. It is in this phase that the technology starts to be driven less by its novelty and starts to interest a wider audience interested by the science of understanding and developing it more deeply.

Finally, the technology hits the third phase, in which it attains maturity in its own right. In this phase, designers understand and exploit the intricacies of the new technology to build unique experiences that provide us with capabilities never before available. For example, the flashback and crosscut, as well as "bullet-time" introduced more recently by the movie the Matrix have become well-acknowledged idioms of the medium of film. Similarly, the mouse has become so well integrated into our notions of computing that it is extremely hard to imagine using current interfaces without such a device attached. It should be noted that in both these cases, more than forty years passed between the introduction of the technology and the widespread development and usage of these methods.

We believe that brain-computer interface work is just now coming out of its infancy, and that the opportunity exists to move it from the proof-of-concept and emulation stages into maturity. However, to do this, we will have not only have to continue the discovery and invention within the domain itself, but also start to build bridges and leverage researchers and work in other fields. Meanwhile, the human computer interaction field continues to work toward expanding the effective information bandwidth between human and machine, and more importantly to design technologies that integrate seamlessly into our everyday tasks. Specifically, we believe there are several opportunities, though we believe our views are necessarily constrained and hope that this book inspires further crossover and discussion. For example:

- While the BCI community has largely focused on the very difficult mechanics of acquiring data from the brain, HCI researchers could add experience designing interfaces that make the most out of the scanty bits of information they have about the user and their intent. They also bring in a slightly different viewpoint which may result in interesting innovation on the existing applications of interest. For example, while BCI researchers maintain admirable focus on providing patients who have lost muscular control an alternate input device, HCI researchers might complement the efforts by considering the entire locked-in experience, including such factors as preparation, communication, isolation, and awareness, etc.
- Beyond the traditional definition of Brain-Computer Interfaces, HCI researchers have already started to push the boundaries of what we can do if we can peer into the user's brain, if even ever so roughly. Considering how these devices apply to healthy users in addition to the physically disabled, and how adaptive system may take advantage of them could push analysis methods as well as application areas.
- The HCI community has also been particularly successful at systematically exploring and creating whole new application areas. In addition to thinking about using technology to fix existing pain points, or to alleviate difficult work, this community has sought scenarios in which technology can augment everyday human life in some way. We believe that we have only begun to scratch the surface of the set of applications that brain sensing technologies open, and hope that this book stimulates a much wider audience to being considering these scenarios.

The specific goals of this book are three-fold. First, we would like to provide background for researchers that have little (or no) expertise in neuroscience or brain sensing so that they gain appreciation for the domain, and are equipped not only to read and understand articles, but also ideally to engage in work. Second, we will present a broad survey of representative work within the domain, written by key researchers. Third, because the intersection of HCI/BCI is relatively new, we use the book to articulate some of the challenges and opportunities for using brain sensing in HCI work, as well as applying HCI solutions to brain sensing work. We provide a quick overview and outline in the remainder of this introductory chapter.

1.2 Brain Imaging Primer

1.2.1 Architecture of the Brain

Contrary to popular simplifications, the brain is not a general-purpose computer with a unified central processor. Rather, it is a complex assemblage of competing sub-systems, each highly specialized for particular tasks (Carey 2002). By studying the effects of brain injuries and, more recently, by using new brain imaging technologies, neuroscientists have built detailed topographical maps associating different parts of the physical brain with distinct cognitive functions.

The brain can be roughly divided into two main parts: the cerebral cortex and sub-cortical regions. Sub-cortical regions are phylogenetically older and include a areas associated with controlling basic functions including vital functions such as respiration, heart rate, and temperature regulation, basic emotional and instinctive responses such as fear and reward, reflexes, as well as learning and memory. The cerebral cortex is evolutionarily much newer. Since this is the largest and most complex part of the brain in the human, this is usually the part of the brain people notice in pictures. The cortex supports most sensory and motor processing as well as "higher" level functions including reasoning, planning, language processing, and pattern recognition. This is the region that current BCI work has largely focused on.

1.2.2 Geography of Thought

The cerebral cortex is split into two hemispheres that often have very different functions. For instance, most language functions lie primarily in the left hemisphere, while the right hemisphere controls many abstract and spatial reasoning skills. Also, most motor and sensory signals to and from the brain cross hemispheres, meaning that the right brain senses and controls the left side of the body and vice versa. The brain can be further divided into separate regions specialized for different functions. For example, occipital regions at the very back of the head are largely devoted to processing of visual information. Areas in the temporal regions, roughly along the sides and lower areas of the cortex, are involved in memory, pattern matching, language processing, and auditory processing. Still other areas of the cortex are devoted to diverse functions such as spatial representation and processing, attention orienting, arithmetic, voluntary muscle movement, planning, reasoning and even enigmatic aspects of human behavior such as moral sense and ambition.

We should emphasize that our understanding of brain structure and activity is still fairly shallow. These topographical maps are not definitive assignments of location to function. In fact, some areas process multiple functions, and many functions are processed in more than one area.

1.2.3 Measuring Thought with Brain Imaging

Regardless of function, each part of the brain is made up of nerve cells called neurons. As a whole, the brain is a dense network consisting of about 100 billion neurons. Each of these neurons communicates with thousands of others in order to regulate physical processes and to produce thought. Neurons communicate either by sending electrical signals to other neurons through physical connections or by exchanging chemicals called neurotransmitters. When they communicate, neurons need more oxygen and glucose to function and cause an increase in blood flow to active regions of the brain.

Advances in brain imaging technologies enable us to observe the electric, chemical, or blood flow changes as the brain processes information or responds to various stimuli. Using these techniques we can produce remarkable images of brain structure and activity. By inspecting these images, we can infer specific cognitive processes occurring in the brain at any given time.

Again, we should emphasize that with our current understanding, brain imaging allows us only to sense general cognitive processes and not the full semantics of our thoughts. Brain imaging is, in general, not mind reading. For example, although we can probably tell if a user is processing language, we cannot easily determine the semantics of the content. We hope that the resolution at which we are able to decipher thoughts grows as we increase our understanding of the human brain and abstract thought, but none of the work in this book is predicated on these improvements happening.

1.2.4 Brain Imaging Technologies

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. Although invasive technologies provide high temporal and spatial resolution, they usually cover only very small regions of the brain. Additionally, these techniques require surgical procedures that often lead to medical complications as the body adapts, or does not adapt, to the implants. Furthermore, once implanted, these technologies cannot be moved to measure different regions of the brain. While many researchers are experimenting with such implants (e.g. Lal et al. 2004), we will not review this research in detail as we believe these techniques are unsuitable for human-computer interaction work and general consumer use.

We summarize and compare the many non-invasive technologies that use only external sensors in Fig. 1.1 (see the Appendix of this Chapter). While the list may seem lengthy, only Electroencephalography (EEG) and Functional Near Infrared Spectroscopy (fNIRS) present the opportunity for inexpensive, portable, and safe devices, properties we believe are important for brain-computer interface applications in HCI work.

1.2.4.1 Electroencephalography (EEG)

EEG uses electrodes placed directly on the scalp to measure the weak (5–100 μV) electrical potentials generated by activity in the brain (for a detailed discussion of EEG, see Smith 2004). Because of the fluid, bone, and skin that separate the electrodes from the actual electrical activity, signals tend to be smoothed and rather noisy. Hence, while EEG measurements have good temporal resolution with delays in the tens of milliseconds, spatial resolution tends to be poor, ranging about 2–3 cm accuracy at best, but usually worse. 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. We should note that this is the predominant technology in BCI work, as well as work described in this book.

1.2.4.2 Functional Near Infrared Spectroscopy (fNIRS)

fNIRS technology, on the other hand, 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 back out (for a detailed discussion of fNIRS, see Coyle et al. 2004). The NIR response of the brain measures cerebral hemodynamics and detects localized blood volume and oxygenation changes (Chance et al. 1998).

Since changes in tissue oxygenation associated with brain activity modulate the absorption and scattering of the near infrared light photons to varying amounts, fNIRS can be used to build functional maps of brain activity. This generates images similar to those produced by traditional Functional Magnetic Resonance Imaging (fMRI) measurement. Much like fMRI, images have relatively high spatial resolution (<1 cm) at the expense of lower temporal resolution (>2–5 seconds), limited by the time required for blood to flow into the region.

In brain-computer interface research aimed at directly controlling computers, temporal resolution is of utmost importance, since users have to adapt their brain activity based on immediate feedback provided by the system. For instance, it would be difficult to control a cursor without having interactive input rates. Hence, even though the low spatial resolution of these devices leads to low information transfer rate and poor localization of brain activity, most researchers currently adopt EEG because of the high temporal resolution it offers. However, in more recent attempts to use brain sensing technologies to passively measure user state, good functional localization is crucial for modeling the users' cognitive activities as accurately as possible. The two technologies are nicely complementary and researchers must carefully select the right tool for their particular work. We also believe that there are opportunities for combining various modalities, though this is currently underexplored.

1.3 Brain Imaging to Directly Control Devices

1.3.1 Bypassing Physical Movement to Specify Intent

Most current brain-computer interface work has grown out of the neuroscience and medical fields, and satisfying patient needs has been a prime motivating force. Much of this work aims to improve the lives of patients with severe neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), also popularly known as Lou Gerig's disease, brainstem stroke, or spinal cord injury. In the latter stages of these disorders, many patients lose all control of their physical bodies, including simple functions such as eye-gaze. Some even need help with vital functions such as breathing. However, many of these patients retain full control of their higher level cognitive abilities.

While medical technologies that augment vital bodily functions have drastically extended the lifespan of these patients, these technologies do not alleviate the mental frustration or social isolation caused by having no way to communicate with the external world. Providing these patients with brain-computer interfaces that allow them to control computers directly with their brain signals could dramatically increase their quality of life. The complexity of this control ranges from simple binary decisions, to moving a cursor on the screen, to more ambitious control of mechanical prosthetic devices.

Most current brain-computer interface research has been a logical extension of assistive methods in which one input modality is substituted for another (for detailed reviews of this work, see Coyle et al. 2003; Vaughan 2003). When users lose the use of their arms, they typically move to eye or head tracking, or even speech, to control their computers. However, when they lose control of their physical movement, the physiological function they have the most and sometimes only control over is their brain activity.

1.3.2 Learning to Control Brain Signals

To successfully use current direct control brain-computer interfaces, users have to learn to intentionally manipulate their brain signals. To date, there have been two approaches for training users to control their brain signals (Curran and Stokes 2003). In the first, users are given specific cognitive tasks such as motor imagery to generate measurable brain activity. Using this technique the user can send a binary signal to the computer, for example, by imagining sequences of rest and physical activity such as moving their arms or doing high kicks. The second approach, called operant conditioning, provides users with continuous feedback as they try to control the interface. Users may think about anything (or nothing) so long as they achieve the desired outcome. Over many sessions, users acquire control of the interface without being consciously aware of how they are performing the task. Unfortunately, many users find this technique hard to master.

Other researchers have designed interfaces that exploit the specific affordances of brain control. One such interface presents a grid of keys, each representing a letter or command (Sutter 1992). Each row or column of the grid flashes in rapid succession, and the user is asked to count the number of flashes that occur over the desired key. The system determines the row and column of interest by detecting an event-related signal called the P300 response, which occurs in the parietal cortex about 300 milliseconds after the onset of a significant stimulus.

We believe that there remains much work to be done in designing interfaces that exploit our understanding of cognitive neuroscience and that provide the maximum amount of control using the lowest possible bit rate (for discussion of this and other research challenges in this area, see Wolpaw et al. 2002). We believe that expertise in human-computer interaction can be leveraged to design novel interfaces that may be generally applicable to brain-computer interfaces and low bit rate interactions.

1.3.3 Evaluation of Potential Impact

We are still at a very early stage in brain-computer interface research. Because current systems require so much cognitive effort and produce such small amounts of control information (the best systems now get 25 bits/minute), they remain useful mainly in carefully controlled scenarios and only to users who have no motor alternatives. Much work has to be done before we are able to successfully replace motor movement with brain signals, even in the simplest of scenarios.

While researchers believe that these interfaces will get good enough to vastly improve the lives of disabled users, not all are certain that brain-computer interfaces will eventually be good enough to completely replace motor movement even for able-bodied users. In fact, many researchers have mixed feelings on whether or not this is useful or advisable in many situations. However, we do foresee niche applications in which brain-computer interfaces might be useful for able-bodied people.

For example, since these interfaces could potentially bypass the lag in mentally generating and executing motor movements, they would work well in applications for which response times are crucial. Additionally, they could be useful in scenarios where it is physically difficult to move. Safety mechanisms on airplanes or spacecraft could benefit from such interfaces. In these scenarios, pilots experiencing large physical forces do not have much time to react to impending disasters, and even with limited bandwidth brain control could be valuable. Also, since brain control is intrinsically less observable than physical movement, brain-computer interfaces may be useful for covert operation, such as in command and control or surveillance applications for military personnel.

Brain-computer interfaces could also be successful in games and entertainment applications. In fact, researchers have already begun to explore this lucrative area to exploit the novelty of such an input device in this large and growing market. One interesting example of such a game is Brainball, developed at the Interactive Studio in Sweden (Hjelm and Browall 2000). In this game, two players equipped with EEG are seated on opposite sides of a table. Players score simply by moving a ball on the table into the opponent's goal. The unusual twist to this game is that users move the ball by relaxing. The more relaxed the EEG senses the user to be, the more the ball moves. Hence, rather than strategic thoughts and intense actions, the successful player must learn to achieve calmness and inactivity. At the time this book was written, various game companies (such as Mattel) have already released consumer devices (toys) that claim some form of EEG control, with multiple others pending release.

1.4 Brain Imaging as an Indirect Communication Channel

1.4.1 Exploring Brain Imaging for End-User Applications

As HCI researchers, we are in the unique position to think about the opportunities offered by widespread adoption of brain-computer interfaces. While it is a remarkable endeavor to use brain activity as a novel replacement for motor movement, we think that brain-computer interfaces used in this capacity will probably remain tethered to a fairly niche market. Hence, in this book, we look beyond current research approaches for the potential to make brain imaging useful to the general end-user population in a wide range of scenarios.

These considerations have led to very different approaches in using brain imaging and brain-computer interfaces. Rather than building systems in which users intentionally generate brain signals to directly control computers, researchers have also sought to passively sense and model some notion of the user's internal cognitive state as they perform useful tasks in the real world. This approach is similar to efforts aimed at measuring emotional state with physiological sensors (e.g. Picard and Klein 2002). Like emotional state, cognitive state is a signal that we would never want the user to intentionally control, either because it would distract them from performing their tasks or because they are not able to articulate the information.

People are notoriously good at modeling the approximate cognitive state of other people using only external cues. For example, most people have little trouble determining that someone is deep in thought simply by looking at them. This ability mediates our social interactions and communication, and is something that is notably lacking in our interactions with computers. While we have attempted to build computer systems that make similar inferences, current models and sensors are not sensitive enough to pick up on subtle external cues that represent internal cognitive state. With brain imaging, we can now directly measure what is going on in a user's brain, presumably making it easier for a computer to model this state.

Researchers have been using this information either as feedback to the user, as awareness information for other users, or as supplementary input to the computer so that it can mediate its interactions accordingly. In the following subsections, we describe threads that run through the various chapters, consisting of understanding human cognition in the real world, using cognitive state as an evaluation metric for interface design, as well as building interfaces that adapt based on cognitive state. We think that this exploration will allow brain imaging, even in its current state, to fundamentally change the richness of our interactions with computers. In fact, much like the mouse and keyboard were pivotal in the development of direct manipulation interfaces, brain imaging could revolutionize our next generation contextually aware computing interfaces.

1.4.2 Understanding Cognition in the Real World

Early neuroscience and cognitive psychology research was largely built upon case studies of neurological syndromes that damaged small parts of the brain. By studying the selective loss of cognitive functions caused by the damage, researchers were able to understand how specific parts of the brain mediated different functions. More recently, with improvements in brain imaging technologies, researchers have used controlled experiments to observe specific brain activations that happen as a result of particular cognitive activities. In both these approaches, the cognitive activities tested are carefully constructed and studied in an isolated manner.

While isolating cognitive activities has its merits, we believe that measuring brain activity as the user operates in the real world could lead to new insights. Researchers are already building wearable brain imaging systems that are suitable for use outside of the laboratory. These systems can be coupled with existing sensors that measure external context so that we can correlate brain activity with the tasks that elicit this activity. While the brain imaging device can be seen as a powerful sensor that informs existing context sensing systems, context sensing systems can also be viewed as an important augmentation to brain imaging devices.

Again, we believe that there are opportunities here that are currently underexplored. Using this approach, we are able not only to measure cognitive activity in more complex scenarios than we can construct in the laboratory, but also to study processes that take long periods of time. This is useful in tasks for which the brain adapts slowly or for tasks that cannot be performed on demand in sterile laboratory environments, such as idea generation or the storage of contextual memory cues as information is learned. Also, while neuroscience studies have focused on the dichotomy between neurologically disabled and normal patients, we now have the opportunity to study other individual differences, perhaps due to factors such as gender, expertise on a given task, or traditional assessment levels of cognitive ability. Finally, we believe that there exists the opportunity to study people as they interact with one another. This can be used to explore the neural basis of social dynamics, or to attempt to perform dynamic workload distribution between people collaborating on a project. Furthermore, having data from multiple people operating in the real world over long periods of time might allow us to find patterns and build robust cognitive models that bridge the gap between current cognitive science and neuroscience theory.

1.4.3 Cognitive State as an Evaluation Metric

In a more controlled and applied setting, the cognitive state derived from brain imaging could be used as an evaluation metric for either the user or for computer systems. Since we can measure the intensity of cognitive activity as a user performs certain tasks, we could potentially use brain imaging to assess cognitive aptitude based on how hard someone has to work on a particular set of tasks. With proper task and cognitive models, we might use these results to generalize performance predictions in a much broader range of scenarios.

For example, using current testing methods, a user who spends a huge amount of cognitive effort working on test problems may rate similarly to someone who spent half the test time daydreaming so long as they ended up with the same number of correct answers. However, it might be useful to know that the second user might perform better if the test got harder or if the testing scenario got more stressful. In entertainment scenarios such as games, it may be possible to quantify a user's immersion and attentional load. Some of the work in this book is aimed at validating brain imaging as a cognitive evaluation method and examine how it can be used to augment traditional methods.

Rather than evaluating the human, a large part of human-computer interaction research is centered on the ability to evaluate computer hardware or software interfaces. This allows us not only to measure the effectiveness of these interfaces, but more importantly to understand how users and computers interact so that we can improve our computing systems. Thus far, researchers have been only partially successful in learning from performance metrics such as task completion times and error rates. They have also used 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, there remain many cognitive processes that are hard to measure externally. For these, they typically resort to clever experimental design or subjective questionnaires which give them indirect metrics for specific cognitive phenomena. For example, it is still extremely difficult to accurately ascertain cognitive workloads or particular cognitive strategies used, such as verbal versus spatial memory encoding.

Brain sensing provides the promise of a measure that more directly quantifies the cognitive utility of our interfaces. This could potentially provide powerful measures that either corroborate external measures, or more interestingly, shed light on the interactions that we would have never derived from external measures alone. Various researchers are working to generalize these techniques and provide a suite of cognitive measures that brain imaging provides.

1.4.4 Adaptive Interfaces Based on Cognitive State

If we take this idea to the limit and tighten the iteration between measurement, evaluation, and redesign, we could design interfaces that automatically adapt depending on the cognitive state of the user. Interfaces that adapt themselves to available resources in order to provide pleasant and optimal user experiences are not a new concept. In fact, researchers have put quite a bit of thought into dynamically adapting interfaces to best utilize such things as display space, available input mechanisms, device processing capabilities, and even user task or context.

For example, web mechanisms such as hypertext markup language (HTML) and cascading style sheets (CSS) were implemented such that authors would specify content, but leave specific layout to the browsers. This allows the content to reflow and re-layout based on the affordances of the client application. As another example, researchers have built systems that model the user, their surroundings, and their tasks using machine learning techniques in order to determine how and when to best interrupt them with important notifications (Horvitz et al. 1998). In their work, they aim to exploit the computing environment in a manner that best supports user action.

Adapting to users' limited cognitive resources is at least as important as adapting to specific computing affordances. One simple way in which interfaces may adapt based on cognitive state is to adjust information flow. For example, verbal and spatial tasks are processed by different areas of the brain, and cognitive psychologists have shown that processing capabilities in each of these areas is largely independent (Baddeley 1986). Hence, even though a person may be verbally overloaded and not able to attend to any more verbal information, their spatial modules might be capable of processing more data. Sensory processes such as hearing and seeing, have similar loosely independent capabilities. Using brain imaging, the system knows approximately how the user's attentional and cognitive resources are allocated, and could tailor information presentation to attain the largest communication bandwidth possible. For example, if the user is verbally overloaded, additional information could be transformed and presented in a spatial modality, and vice versa. Alternatively, if the user is completely cognitively overloaded while they work on a task or tasks, the system could present less information until the user has free brain cycles to better deal with the details.

Another way interfaces might adapt is to manage interruptions based on the user's cognitive state. Researchers have shown that interruptions disrupt thought processes and can lead to frustration and significantly degraded task performance (Cutrell et al. 2001). For example, if a user is thinking really hard, the system could detect this and manage pending interruptions such as e-mail alerts and phone calls accordingly. This is true even if the user is staring blankly at the wall and there are no external cues that allow the system to easily differentiate between deep thought and no thought. The system could also act to minimize distractions, which include secondary tasks or background noise. For example, a system sensing a user getting verbally overloaded could attempt to turn down the music, since musical lyrics get subconsciously processed and consume valuable verbal resources. Or perhaps the cell phone could alert the remote speaker and pause the phone call if the driver has to suddenly focus on the road.

Finally, if we can sense higher level cognitive events like confusion and frustration or satisfaction and realization (the "aha" moment), we could tailor interfaces that provide feedback or guidance on task focus and strategy usage in training scenarios. This could lead to interfaces that drastically increase information understanding and retention.

1.5 The Rest of the Book

The chapters in this book are divided into four sections, which loosely parallel the goals of the book:

Part I, Overview and Techniques.

Chapter 2 (Neural Control Interfaces) opens the book by outlining some of the unique challenges and opportunities for designing BCI control interfaces. It presents a loose taxonomy of different factors that should be considered and provides a nice framework for pursuing work in this space. Chapter 3 (Could Anyone Use a BCI?) explores the phenomenon of "BCI illiteracy", the observation that most BCI systems do not typically work for all users. It uses this as grounding for discussion around standardized lingo and measurement metrics to facilitate discussions and comparisons across systems. Chapter 4 (Using Rest Class and Control Paradigms for Brain Computer Interfacing) addresses one specific technical challenge in BCI work, the Midas Touch problem. This is a classic HCI problem in which the control system must distinguish between intended commands and everyday actions, in this case thoughts. Chapter 5 (EEG-Based Navigation from a Human Factors Perspective) presents the analogy between designing BCIs and navigation devices, which include components of planning (cognition), steering (perception), and control (sensation). This provides an interesting way of considering the integration between human factors and BCI work.

Part II, Applications.

Chapter 6 (Applications for Brain-Computer Interfaces) presents a broad survey of applications for BCI systems and characterizes the range of possibilities for neural control. Among these are applications for assistive technologies, recreation, cognitive diagnostics and augmented cognition, as well as rehabilitation and prosthetics. Chapter 7 (Direct Neural Control of Anatomically Correct Robotic Hands) describes the potential to achieve dexterous control of prosthetic hands using BCIs. The chapter describes both the requirements for the BCI, as well as the match with a fully anthropomorphic robot hand that the authors have developed. Chapter 8 (Functional Near-Infrared Sensing and Environmental Control Applications) describes the relatively young fNIRS technology, as well as potential benefits in environmental-control BCIs. Chapter 9 (Cortically-Coupled Computer Vision) complements standard control work with a novel paradigm that extracts useful information processing using brain sensing technologies. Specifically, authors present visual search and image retrieval applications that use EEG to automatically decode whether an image is relevant or grabs a user's attention. Chapter 10 (Brain-Computer Interfaces and Games) surveys the state of the art of BCI in games and discusses factors such as learnability, memorability, efficiency, as well as user experience and satisfaction in this context.

Part III, Brain-Sensing in Adaptive User Interfaces.

Chapter 11 (Brain-based Indices for User System Symbiosis) introduces the concept of operator models and the usefulness of brain-based indices in creating computer systems that respond more symbiotically to human needs. Chapter 12 (Enhancing Human-Computer Interaction with Input from Active and Passive Brain-Computer Interfaces) describes the transition from direct control BCIs that provide explicit commands to passive BCIs that implicitly model user state as secondary input to adaptive systems. Chapter 13 (From Brain Signals to Adaptive Interfaces: Using fNIRS in HCI) ties several of the previous chapters together (e.g. Chapter 8 and 10) and describes details of fNIRS technology that are critical in considering the design of BCI-based adaptive systems.

Part IV, Tools.

Chapter 14 (Matlab-Based Tools for BCI Research) reviews freely available standalone Matlab-based software, and drills into BCI-Lab as well as the Fieldtrip and Datasuite environments. Chapter 15 (Using BCI2000 for HCI-Centered BCI Research) rounds the book up with an overview of the BCI2000 system, a popular framework for implementing general-purpose BCIs and one that HCI researchers getting into the field could benefit from.

Appendix

Technique	Physical Property	Measurement Mechanism	Advantages	Disadvantages
Electro-encephelograph (EEG)	Electrical potential	Electrodes are placed carefully on the scalp in order to measure the weak (5-100 μV) electrical potentials generated by neural activity in the brain	• Portable, wearable • High temporal resolution (tens or hundreds of milliseconds)	• Low spatial resolution (at best 1-2 cm, usually more) due to noise added when signals move through fluid, bone, and skin. • Requires careful placement of electrodes directly on scalp
Magneto-encephelograph (MEG)	Magnetic potential	Measures magnetic fields generated by the electrical activity of the brain	• MEG enables much deeper imaging and is much more sensitive than EEG, since skull is almost completely transparent to magnetic waves	• Bulky and expensive equipment due to necessity for superconductivity
Positron Emission Tomography (PET)	Blood flow	Detects chemical activity of injected radioactive tracers by measuring gamma ray emissions		• Bulky and expensive equipment • Unsuitable for sustained use due to need to inject radioactive substances
Single Photon Emission Computed Tomography (SPECT)	Blood flow	Works like PET except that uses photomultiplier tubes to measure photons generated by gamma rays	• Slightly less expensive than PET	• Lower temporal and spatial resolution than PET • Bulky and expensive equipment • Unsuitable for sustained use due to need to inject radioactive substances
Functional Magnetic Resonance Imaging (fMRI)	Blood flow	Measures magnetic properties of blood to determine the decrease in deoxyhemoglobin to active brain regions (increased blood flow to these regions is not accompanied by proportional increase in oxygen consumption)	• High spatial resolution (~1mm-1cm)	• Low temporal resolution (5-8 seconds) because inflow of blood is not an immediate phenomenon • Bulky and expensive equipment due to need for superconducting magnets
Functional Near Infrared (fNIR)	Blood flow, Changes in cortical tissue	Measures the absorption and scattering of near infrared light directed into the brain to determine changes in tissue oxygenation (slow response) as well as changes in neuronal membranes during neuron firing (fast event related response)	• High spatial resolution (<1cm) • Similarity to fMRI allows transfer of knowledge • Inexpensive equipment • Portable, wearable • Does not require large amount of expertise to set up • Non-ionizing light safe for extended use	• Low temporal resolution (5-8 seconds) when using slow response measurements

Fig. 1.1 Overview of current functional brain imaging technologies

References

Baddeley AD (1986) Working Memory. Oxford University Press, New York

Carey J (ed) (2002) Brain Facts: A Primer on the Brain and Nervous System, 4th edn. Society for Neuroscience, Washington DC, USA

Chance B, Anday E, Nioka S, Zhou S, Hong L, Worden K, Li C, Murray T, Overtsky Y, Pidikiti D, Thomas R (1998) A novel method for fast imaging of brain function, non-invasively, with light. Opt Express 2(10):411–423

Coyle S, Ward T, Markham C (2003) Brain-computer interfaces: A review. Interdiscip Sci Rev 28(2):112–118

Coyle S, Ward T, Markham C, McDarby G (2004) On the suitability of near-infrared (NIR) systems for next-generation brain-computer interfaces. Physiol Meas 25:815–822

Curran E, Stokes MJ (2003) Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems. Brain Cogn 51:326–336

Cutrell E, Czerwinski M, Horvitz E (2001) Notification, disruption and memory: Effects of messaging interruptions on memory and performance. In: Hi-rose M (ed) Human-Computer Interaction–Interact '01. IOS Press, Amsterdam, pp 263–269

Hjelm SI, Browall C (2000) Brainball—Using brain activity for cool competition. In: Proceedings of NordiCHI 2000

Horvitz E, Breese J, Heckerman D, Hovel D, Rommelse K (1998) The Lumiere project: Bayesian user modeling for inferring the goals and needs of software users. In: Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence

Lal TN, Hinterberger T, Widman G, Schröder M, Hill NJ, Rosenstiel E, Elger CE, Schölkopf B, Birbaumer N (2004) Methods towards invasive human brain computer interfaces. In: Conference on Neural Information Processing Systems

Picard RW, Klein J (2002) Computers that recognize and respond to user emotion: Theoretical and practical implications. Interact Comput 14(2):141–169

Smith RC (2004) Electroencephalograph based brain computer interfaces. Thesis for Master of Engineering Science, University College Dublin

Sutter EE (1992) The brain response interface: Communication through visually induced electrical brain responses. J Microcomput Appl 15(1):31–45

Vaughan TM (2003) Guest editorial brain-computer interface technology: A review of the second inter-national meeting. IEEE Trans Neural Syst Rehabil Eng 11(2):94–109

Wolpaw JR, Birbaumer N, Mcfarland DJ, Pfurtscheller G, Vaughan TM (2002) Brain-computer interfaces for communication and control. Clin Neurophysiol 113:767–791