

# Improving HCI with Brain Input: Review, Trends, and Outlook

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## ABSTRACT

In the field of HCI, researchers from diverse backgrounds have taken a broad view of application domains that could benefit from brain signals, both by applying HCI methods to improve interfaces using brain signals (e.g., human-centered design and evaluation of brain-based user interfaces), as well as integrating brain signals into HCI methods (e.g., using brain metrics in user experience evaluation). Recent advances in brain sensing technologies, new analysis methods, and hardware improvements have opened the door for such research, which will accelerate with the increased commercialization of wearable technology containing brain sensors. In this monograph, we examine brain signals from an HCI perspective, focusing on work that makes an HCI-related contribution. We pursue three main goals. First, we give a primer for HCI researchers on the necessary technology, the possibilities, and limitations for using brain signals in user interfaces. Second, we systematically map out the research field by constructing a taxonomy of applications, input paradigms, and interface designs. For this purpose, we reviewed more than 100 publications in major HCI conferences and journals. Finally, we identify gaps and areas of emerging work to lay a foundation for future research on HCI for and with brain signals.

# 1

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## Introduction

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Emerging research is providing more practical brain measurement tools as well as greater understanding of brain function. This process will continue through international investments in brain research as well as the commercialization of wearable technology containing brain sensors. These developments open up many research directions that until recently seemed unachievable, but that could soon drastically change our relationship with technology and with each other.

People have been imagining this future for decades. As long as there have been computers, there has been a desire to integrate one's thoughts directly with them. This integration promises improvements in numerous facets of life (e.g., communication, memory, mobility, learning, entertainment, etc.).

As the technology progressively comes into contact with human users, new challenges and opportunities arise that are central to human-computer interaction (HCI). Available brain sensing technology allows us to draw conclusions about a person's cognitive states and processes, for example by providing non-invasive access to the electrical activity measured through sensors on the skull. Thus, brain sensing offers a

window into the user's internal cognitive processes that could inform the design of interactive systems.

In this review, we use the term *brain input* to refer to the use of brain signals as input to an interactive system (to be differentiated from input going into the brain). Continuous brain signals can augment interface evaluation metrics such as task completion time, error rate and subjective feedback to provide a fuller picture of the dynamic state of an individual during HCI. They can also be used in real-time as input to an interactive system, but have characteristics that are fundamentally different from conventional input devices. New input paradigms and interaction techniques are needed for effective and worthwhile use of brain signals that also preserve user values such as privacy, security and safety. These important design considerations will play a key role in future adoption of brain sensing for solving real-world problems and for use by a wider audience.

Consequently, since 2008, brain-related publications have had a stable presence at the ACM CHI conference and in the broader set of primary HCI conferences and journals. To date, over 100 articles employing brain sensor data have been published in HCI-focused venues, tackling HCI questions related to brain sensing and brain interfaces. These papers are diverse in goals, methods, analysis, and reporting practices, due to the interdisciplinary nature of HCI research and the fact that the use of brain signals as computer input is still in its infancy.

Despite this, there is insight to be gained by looking back at the path this research has taken thus far and to identify areas where the studies share common ground. Of particular interest is how these papers build on, but collectively differ, from the more established field of traditional brain-computer interfaces (BCIs), which have historically focused on technical aspects, such as signal processing and machine learning, to provide a communication channel for patients unable to communicate otherwise. As HCI work expands and broadens the reach of brain signals to new application areas, it is a good time to identify common practices and themes that have emerged in this work and that will drive the future research paths in HCI.

In existing HCI work on using brain signals, there are clusters of frequent application domains, control paradigms, and neural processes

used, as well as unique examples that stand out. An underlying challenge is that such investigations require knowledge about recording and processing neural signals, real-time processing and classification of the data, integration into a non-trivial application, as well as experimental paradigms to train and test the systems under realistic conditions. Accordingly, a considerable number of publications concentrate only on parts of this chain, such as the mental state assessment, but leave out others, such as the actual testing of a quantifiable usability improvement. Surprisingly, while many groups are working on similar aspects of this research, there are still only limited shared resources, such as executable paradigms, data sets, and processing pipelines.

The goal of this review is to bring together resources and insights about this evolving field from an HCI perspective. Because its foundations come from diverse disciplines (neuroscience, biomedical engineering, machine learning, traditional BCIs, as well as human–computer interaction), it can be difficult to find resources all in one place for gaining necessary background, or for discovering the state-of-the-art. We aim to provide an entry point on the diverse approaches and methods, and to synthesize the body of existing work to identify trends and emerging research questions that would be of interest to HCI researchers and students. Over the course of this review, we will outline the fundamentals of designing, building and evaluating interactive systems using brain signals. We will discuss steps to improve methods of re-using and reproducing existing results to unlock new and more complex designs for brain input paradigms. Where applicable, we will provide pointers to work that thoroughly covers relevant topics and will give more attention to areas where such resources do not yet exist.

In particular, with the rise of research on brain signals in computing, other recent reviews have covered related areas. Because the field is complex and heterogeneous, these unsurprisingly focus on different areas than this review. Ramadan and Vasilakos (2017) concentrate on using brain input for active control, mostly for the support of disabled individuals. Similarly, Rezeika *et al.* (2018) focus on active control interfaces for text entry. In contrast, Aricò *et al.* (2018) review systems which focus on user state monitoring in the wild. The Brain–Computer Interfaces Handbook (Nam *et al.*, 2018) is a comprehensive textbook

that brings together many aspects of real-time brain input for active control and passive user state monitoring. All of these books and reviews are written from the perspective of the traditional BCI community. Early steps to connect the BCI research to HCI were taken in Tan and Nijholt (2010), but much work has emerged in the ten years since that was written. Our monograph will refer the reader to relevant sections of these related surveys and reviews, instead of providing redundant resources.

The rest of the monograph is organized as follows. Sections 2–4 review and characterize existing literature on the foundations and broader context of using brain signals, discussing different HCI application domains that use these methods, and finally presenting definitions and examples of the main paradigms used in HCI for brain input. Section 5 explains many of the cognitive processes measured and used in HCI research. Sections 6 and 7 are technology-centered and introduce different architectures and development tools to design applications which use brain signals. They also present the fundamentals of the most important brain sensing technologies. Section 8 introduces HCI-centered evaluation methods, as well as generalizability and reproducibility considerations of using brain signals in a scientifically sound and sustainable way. Sections 9 and 10 then discuss future research directions and the strengths and limitations of brain signals as input with currently available technology.

# 2

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## Foundations and Broader Context

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### 2.1 Origins of BCIs

While books and movies have long envisioned concepts similar to brain-computer interfaces, the realization of these visions has only begun in recent years due to technology breaking through some barriers that were slowing progress. These barriers included the need for hardware that is safe and capable of measuring brain waves reliably, the need for real-time signal processing and analysis that can convert raw signals into meaningful signals, the need for deep and broad understanding of brain function, the need for suitable datasets for developing models and tools for brain-computer interfaces, and the difficulty of studying the brain signals coming from human subjects, among many other challenges.

Early work that opened the door for brain-computer interfaces focused on clinical uses of electroencephalography (EEG) (see Section 6.1 for background on the technology). Wolpaw *et al.* (2002) provides a review of this work and how it provided a foundation for early BCIs, focusing on EEG-based BCIs involving visual evoked potentials, slow cortical potentials, P300 evoked potentials, sensorimotor cortical activity, and cortical neurons. Coyle *et al.* (2004) discussed the feasibility of using functional near-infrared spectroscopy (fNIRS) for brain-computer

interfaces (see Section 6.2). The majority of work in this area has been motivated by the long-term objective of direct control and communication for disabled users, either in a hospital or at home. However, this goal has still been difficult to achieve and much of the work has not yet included disabled end-users in the research.

In the last 20 years, we have seen an increase in research examining aspects of brain-computer interfaces. Originally, most of this continued developing the direct control approach, with a focus on disabled individuals. In particular, *BCI spellers* have been a large focus of work, as they could provide the opportunity for communication to those unable to communicate otherwise. Thus, BCI spellers are one of the most mature applications for BCI. A great deal of work has gone into both back end and front end improvements to increase the bandwidth of such systems. Rezeika *et al.* (2018) reviews 75 papers published between 2010 and 2019 focused on the user interface design of BCI spellers, providing a taxonomy of features found in these systems, as well as the approaches that have been taken to make these applications “faster, more accurate, more user friendly, and most of all, able to compete with traditional communication methods” (Rezeika *et al.*, 2018). Examining some of the challenges and design decisions that have evolved specific to using brain input for communication in these BCI spellers can inform other brain input applications, beyond spellers. Interestingly, Rezeika *et al.* (2018) notes that some of the major gaps still today in BCI spellers, despite 20 years of work, include the need for more emphasis on user interface design to satisfy the needs of end-users along with the fact that only five systems out of 75 that they surveyed were tested with the targeted users with motor impairments. Thus, the field of HCI could undoubtedly enrich traditional BCI work by addressing these gaps.

## 2.2 Lessons from “Traditional” BCI Work

Because the traditional BCI field has now existed for several decades, it has matured to have standard methods and practices that could be translated into related areas of human–computer interaction research. In particular, there are clear expectations for validation of results through analysis of raw data, interpretation of features, and addressing artifacts.

Despite our focus on the emerging area of HCI research with brain signals, there is much to learn from traditional BCI research. These will be discussed in later sections.

### 2.3 Our Focus on Human–Computer Interaction

The focus of this monograph is on existing research and areas of future work that has an HCI focus. To do this, we have created a corpus of publications that use brain signals along with HCI methods. This often falls into two categories:

1. the application of HCI methods to systems employing brain signals (e.g., usability evaluation of a brain-based adaptive system), and
2. the use of brain signals to create or enhance HCI methods (e.g., using brain signals to evaluate workload induced by a user interface).

To identify such publications, we systematically examined contributions from the main proceedings (full papers) of the following conferences: ACM CHI, ACM UIST, ACM IUI, ACM ICMI, NordiCHI, ACM CSCW, and ACM UbiComp. Additionally, we considered publications in the following journals: *ACM Transactions on Computer-Human Interaction (TOCHI)*, *International Journal of Human–Computer Studies (IJHCS)*, *Interacting with Computers* and *Frontiers on Human-Media Interaction*. We made this decision to ensure that the authors themselves considered HCI to be the central contribution in their work. As these conferences and journals employ HCI experts as reviewers and editors, we can assume that the accepted manuscripts indeed have a focus on HCI. It is clear that many other publications beyond this selection are related to HCI, for example in the fields of multimodal interaction and affective computing, or in more specialized venues, for example focusing on human–robot interaction or virtual reality. With the defined selection criteria, we ensure that the authors self-identified, through their choice of publication outlet, as being HCI-centric. This reduces the number of “false positives” of papers that mention HCI only tangentially and helps to keep the selection of works relatively homogeneous. Another



field with potentially relevant publications is *neuroergonomics*, which has the goal of “understanding the brain in everyday activities” (Ayaz and Dehais, 2018; Parasuraman and Rizzo, 2008). In that way, it often utilizes methods and concepts similar to the ones discussed here, but with a less specific focus on improving HCI, which we want to target in this overview. Throughout the monograph, we do also include related papers outside of these, but mainly to fill in details about advances outside of HCI research. Therefore, this monograph should not be seen as a complete list of everything that has been accomplished in the use of brain signals for HCI; instead, it is a digestible sample tailored towards researchers from an HCI background looking for an overview of what is possible in this field.

In this corpus, the earliest work that discusses brain signals in HCI was published at CHI 1996 (Velichkovsky and Hansen, 1996). This paper, titled “New technological windows into mind: there is more in eyes and brains for human–computer interaction,” notes that while neuroimaging techniques such as PET and MRI provide in-depth information about physiological states and process, they are not practical for HCI research. However, at the time of publication, new approaches to EEG analysis were beginning to emerge making EEG a promising tool for creating “a new generation of flexible, learnable and, perhaps, emotionally responsive interfaces.” That article also envisioned brain signals and eye tracking information being combined with autonomous artificial agents and eye tracking.

Five years later, at CHI 2001, Doherty *et al.* (2001) described studies of brain-injured users with locked-in syndrome as they used a commercial system called *Cyberlink* that contains an EEG channel along with EOG and EMG and that had been originally designed for military use. This work demonstrated successful use of this system for assistive technology and offered design considerations and research methods to move this type of research forward. More details of this work are described in other work (Doherty *et al.*, 1999, 2000).

Another five years later, at UIST 2006, Lee and Tan (2006) demonstrated the feasibility of using a low-cost, off-the-shelf electroencephalograph (EEG) system to provide signals that are relevant to HCI research.

This built on an earlier workshop paper (Tan, 2006) that outlined potential uses and methods of EEG in HCI research, as both an evaluation metric and as input to an adaptive system. These papers opened the door to HCI researchers, showing that the technology was now within reach to researchers out of clinical settings.

From there, a continuous stream of publications has appeared in HCI venues. Some of this includes direct improvements on earlier “traditional” BCI work, such as the BCI speller paradigms. Other HCI work has taken new directions, branching out into diverse areas and approaches for utilizing brain input.

A large category of this work falls under what Fairclough (2009) describes, as “physiological computing systems that employ real-time measures of psychophysiology to communicate the psychological state of the user to an adaptive system.” While physiological computing can instead rely on non-brain physiological signals (e.g., eye movement, heart rate, etc.), there are many examples of brain-based systems that fit the description.

Jacucci *et al.* (2015) categorized physiological computing systems into two categories: *body schema extensions* and *mental status determinations*. Most traditional BCI work would fall into the category of body schema extensions, as they involve volitional and intentional thought. The category of mental status determination is distinct from traditional BCI work, in the way that it focuses more on measuring a particular psychological state or mood that changes spontaneously and unintentionally. This information is often used to supplement any other input, enabling the interactive system to be more supportive of the user’s changing cognitive state, building on the idea of the *bio-cybernetic loop* (Pope *et al.*, 1995). These types of systems are also referred to as *implicit*, *context-aware*, *passive* (Zander and Kothe, 2011), or *non-command* brain-computer interfaces.

Fairclough’s review article (Fairclough, 2009) builds a foundation for this area of research by providing background and describing six fundamental issues that physiological computing research must address:

1. *Psychophysiological inference* and the complexity of the relationship between physiological measures and a particular user state.

In particular, it is rare that there is a one-to-one mapping between a physiological measure and a psychological state, and so careful considerations need to be made when the relationship is actually many-to-one, one-to-many and many-to-many (Cacioppo and Tassinary, 1990; Cacioppo *et al.*, 2000). In addition, the relationships might be context-specific (e.g., inside a lab vs. in the field, or only during one particular task).

2. *Psychophysiological validity* of the measure across different environments and individuals,
3. *Representing the psychological state of the user* as a one-dimensional continuum, or a classification of one or more distinct categories of state, to multidimensional measures of state, and combining measures with other information sources such as task performance.
4. *Interaction design* for explicit and implicit system interventions and handling perceptions of system error.
5. Defining the *biocybernetic loop* that controls system adaptation.
6. *Ethical implications*, particularly privacy and user autonomy.

Despite being written over 10 years ago, these six issues still are active research areas today and require deeper investigation. Thus they remain highly relevant to the future of brain signal research in HCI.

# 3

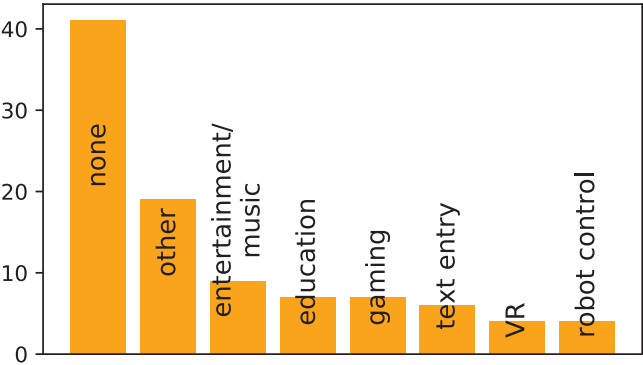
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## Human–Computer Interaction Application Domains

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Most HCI research using brain signals is tied to an area of application to motivate the presented developments and experiments. Some works directly refer to a domain, i.e., a field in which the research can be applied to improve effectiveness, efficiency, or other user experience aspects of people active in this field. Other work ties the brain signal to a specific type of non-brain user interface that can be improved or replaced through brain input. If we exclude abstract allusions of applicability for a concrete use case, however, much research is de-coupled from an application but focuses on a methodological contribution, e.g., to propose algorithmic improvements or novel forms of brain-based interaction. Figure 3.1 shows the relative frequency of domains and applications in the studied literature corpus.

The analysis shows us that brain signals show up across diverse contexts. Some domains only appear once but demonstrate the breadth of usage scenarios for brain signals as input: “programming” (Crk *et al.*, 2015), “security warnings” (Anderson *et al.*, 2015), and “geoscientific image analysis” (Sivarajah *et al.*, 2014). Still, there are domains that appear frequently. The first and third most frequent domains are “entertainment/music” and “gaming”. These two domains have in common



**Figure 3.1:** Frequency of specific domains in HCI literature on brain signals.

that they can integrate brain input with relatively low risk, as they are not safety-critical or error-sensitive, compared to others. These domains also leverage the novelty aspect of integrating brain input. For example, Morgan *et al.* (2015) used a number of different physiological sensors, including EEG, as frequency markers for certain characteristics of a musician during a session. They found that beta band power correlates to positivity and leadership. In games, Burns and Fairclough (2015) use irrelevant acoustic probes during a computer game to measure the degree of immersion during a game by analyzing the neural responses to these probes. They could show that the neural responses to these probes differed based on the degree of immersion, modulated through the challenge level of the game.

Another recurring domain using brain signals is “education”, where it can support learners to better focus on the material. For example, Szafrir and Mutlu (2012) used an EEG-based model to detect diminishing levels of attention in learning situations and counter that through verbal and non-verbal cues of an artificial educational agent to re-establish attention. They show that such attention-adaptive behavior helped to improve post-experiment recall substantially. Similarly, Huang *et al.* (2014) monitored engagement from EEG signals of children reading and could show that context-dependent BCI training interventions at times of decreasing engagement improves teachers’ assessment of resulting reading quality.

Finally, with “text entry” (e.g., Putze *et al.*, 2017), “virtual reality” (e.g., Kober and Neuper, 2012), and “robot control” (e.g., Lampe *et al.*, 2014), we see a number of recurring general-purpose interface elements which are combined with brain signals. These elements are not tied to specific domains but are an integral part of many different applications. Adding brain signals as a novel aspect of such an established functionality to improve their usability therefore has the potential of impacting many domains at once.

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## Brain Input Paradigms in HCI

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Across the application domains in HCI research, we see diverse approaches taken when integrating brain signals into interactive systems and these approaches lead to different types of user interactions and experiences. We use the term *brain input paradigm* to refer to these ways that brain signals are used as input to a computer or machine. For example, some HCI papers present paradigms using the signals in *real time*, while others have *offline* use cases of brain signals. The online ones are then further differentiated by how the brain signal is exploited. In particular, some systems use *explicit* or *direct* control and others use *implicit* or *passive* (Cutrell and Tan, 2008; Solovey *et al.*, 2015; Zander and Kothe, 2011; Zander *et al.*, 2014).

Below, we discuss several key categories in more depth and provide examples from the literature that highlight the types of HCI contributions made.

### 4.1 Explicit Control

In *explicit control* paradigms, which are also referred to as *direct control*, mental commands are given by the user and these are mapped directly to user interface operations. This requires robust detection of particular

brain signals that a user can learn to control. For example, a particular brain signal pattern could be detected and directly connected to left cursor motion, while another brain signal pattern could be directly connected to right cursor motion. Thus, this paradigm involves explicit use of brain activity in order to directly manipulate an aspect of the user interface.

Explicit control paradigms make up the majority of traditional brain-computer interface research, and could provide valuable tools for individuals who are unable to utilize other modalities due to disability, injury or situational context. Within HCI, as seen in the examples below, research on explicit control BCIs often builds on traditional BCI applications, but focuses on novel application areas or innovative ways to improve usability, efficiency, or user experience, where HCI researchers have expertise.

As seen below, explicit control paradigms have been further categorized into *active control* and *reactive control* paradigms (Zander *et al.*, 2010), depending on whether brain activity is controlled independent of any external stimuli or in response to external stimuli.

#### 4.1.1 Active Control with Motor Imagery

A common signal that is used as a conscious mental command is the signal created from imagining motor movements, such as moving a hand, foot or finger. This type of control would be considered *active* since it does not rely on any external stimuli and the user can simply create the control signal. For example, Hex-o-Spell (Williamson *et al.*, 2009) is a spelling application that classifies two imagined motor movements and maps them to either clockwise or counter-clockwise movement along a hexagon that contain letters. In other work, an intelligent robot was controlled through EEG signals generated when an individual imagined left and right finger tapping, which was mapped to left and right robot motion, as well as toe motion that was mapped to downward robot motion, and relaxation, which was mapped to upwards robot movement (Lampe *et al.*, 2014). Other work explored the classification of four motor movements, including left hand, right hand, both hands, and both feet (D'albis *et al.*, 2012), which was then integrated into a communication



application that enables letter selection and other related commands that are laid out in three or four locations on the screen. Each of the locations is associated with one of the four mental commands.

#### 4.1.2 **Reactive Control with P300 Event Related Potential**

A signal that is often used in explicit control paradigms is called the P300 event related potential. This signal is specific to EEG measurements (see Section 6.1). With EEG, a positive spike in the brain signal can be detected 300 milliseconds after a target is presented. This relatively robust signal has been integrated into spelling applications such that the presentation or highlighting of a desired letter produces the P300 signal that can be used to select the letter.

This *reactive* paradigm has led to successful communication and much work has been done on improving the accuracy and efficiency of this type of system in the BCI community. Moving out of lab and clinical settings, researchers have also studied home users, their caregivers and their therapists over a 6-week period (Miralles *et al.*, 2015) and even more than a year (Wolpaw *et al.*, 2018) to understand the ability of end-users to independently use a BCI system at home as well as the challenges faced.

While many papers focus on improving classification accuracy, some HCI work has explored improvements to the interface itself. For example, researchers have explored adjusting the order of flashes to optimize letter selection speed (Park *et al.*, 2010). Other work has proposed a “zigzag” layout instead of the standard grid to address issues with adjacency, crowding, and user fatigue. Sauvan *et al.* (2009) proposed a model to predict the time and number of flashes required using different P300-based selection techniques based on Markov theory.

Building on the success of P300 spellers, researchers have explored the use of the P300 paradigm for other user interface selection tasks. For example, Poli *et al.* (2013) mapped the P300 response to different directions for pointer control instead of letters. Yuksel *et al.* (2010) integrated a P300 selection paradigm into a multi-touch tabletop that can highlight real-world items on the table, in the same way that letters have been highlighted in P300 spellers. The P300 paradigm

has also been integrated into games (see Kaplan *et al.*, 2013 for a review). These examples demonstrate how the P300 reactive paradigm can be used in situations beyond spelling on a computer display. Rapid serial visual presentation-based brain-computer interfaces have been developed that use the P300 paradigm (Lees *et al.*, 2018). In these cases, the P300 paradigm is used, not so much as explicit control, but as a passive method for capturing the immediate brain response to images or words, to be used for surveillance applications, data categorization, face recognition and medical image analysis.

#### **4.1.3 Reactive Control with Steady-State Visually Evoked Potential (SSVEP)**

A third signal that had been used for active control interfaces is the steady state visually evoked potential (SSVEP). This *reactive* paradigm takes advantage of the fact that brain signals will modulate at a similar frequency to visual stimuli. Thus, areas of a screen can flash at different intervals, with a unique flashing pattern located near each available command or interactive component on a display. Based on the brain modulation, the system can determine which area of the display the user is focused on, and make a selection or execute command. Motivated to use SSVEP as an input modality for virtual reality, researchers combined SSVEP interfaces with eye tracking and demonstrated spelling performance of 10 words per minute, which was higher than with either SSVEP or eye tracking alone (Ma *et al.*, 2018).

#### **4.1.4 Improving Explicit Control Paradigms**

Learning to control brain activity to use an explicit brain-computer interface can be challenging and time consuming, and researchers have explored ways to make this more efficient and effective. With an operant conditioning approach, which was the primary method for many years, users learn to create particular brain signals by receiving feedback from the system. With machine learning approaches, systems can learn and model brain data and take some of the burden off the user to reduce the training time significantly. Kosmyna *et al.* (2015a) demonstrated that enabling two-way learning where the user provides feedback to the

machine learning system and the system provides feedback to the user can lead to successful training of BCI systems.

In much of the work on spelling and communication applications, language models are integrated to enable letter prediction, which informs the letter placement in the interface, as well as word prediction which enable shortcuts if the desired word is predicted. These both lead to more efficient communication (D'albis *et al.*, 2012; Williamson *et al.*, 2009), similar to the way that auto-complete functions improve efficiency when writing messages or entering text input in a traditional user interface.

HCI contributions in active control BCI research have also centered on the exploration of user interface layout to enable increased speed and accuracy. The Hex-O-Spell (Williamson *et al.*, 2009) application described earlier took a design that had been introduced to address uncertainty in gesture interaction in mobile interaction (Williamson and Murray-Smith, 2005) to overcome similar challenges that BCI users face. Other HCI research has focused on making the development process more efficient through simulation (Quek *et al.*, 2011).

## 4.2 Implicit Input

With *implicit input*, which is also referred to as *passive input*, the brain data that occurs naturally is detected passively in real-time, with no special effort from the user. Unlike most explicit control systems, which often utilize brain data as the primary system input, implicit input paradigms frequently integrate brain data as a secondary input channel to interactive systems.

Such systems build on and have similarities to *context-aware systems* (Dey *et al.*, 2001), or implicit input (Schmidt, 2000) used in ubiquitous computing (Weiser, 1991), as well as and *non-command interfaces* (Jacob, 1993). The internal cognitive state of the user can be viewed as context for the interaction, and the system responds without waiting for a user's explicit command.

For example, several systems have been created to infer aspects of user workload and then automatically adapt behavior to improve task performance. Solovey *et al.* (2012) used fNIRS brain signals to infer a user's multitasking state, and continually provide context for

a human–robot task, in which the robot adapted its autonomy level, without any explicit command from the user. Afergan *et al.* (2014a) demonstrated a dynamic difficulty engine in which the user’s dynamic working memory load is used as context to adjust the task difficulty level. Yuksel *et al.* (2016) trained a system to differentiate when an individual was playing easy or difficult piano pieces, and then automatically advanced a music training task based on the brain activity context, demonstrating increased speed and accuracy of learning.

In such systems, Putze and Schultz (2014) found a tradeoff between a user’s satisfaction with the system and the overall performance, that depended on the intrusiveness of the system’s support, where more intrusive support strategies increased performance, but decreased user satisfaction.

Other systems have adapted an experience in real-time, using the inferred user engagement state as context. Szafr and Mutlu (2012) created a system that monitored attention levels with EEG and used this to trigger learning interventions when user engagement dropped. In other work, the engagement level of an audience was continually monitored and used to trigger changes in a simulated theatrical performance such as lighting or sound cues (Yan *et al.*, 2016).

Afergan *et al.* (2014b) integrated fNIRS data into the bubble cursor paradigm, a target expansion technique where the target size increases based on some measure of importance. Here, brain data was used as an indicator of multitasking states where target expansion could improve performance.

### 4.3 Neurofeedback and Visualization

*Neurofeedback* shows representations of raw or processed neural data to the user in real-time, enabling them to self-regulate their own brain activity consciously (Sitaram *et al.*, 2017). While neurofeedback historically has been used for clinical purposes, to treat patients with various psychological and neurological health issues, its use in human–computer interaction has broader use cases and also explores particular user populations. For example, Antle *et al.* (2018) explored the design space of neurofeedback interfaces for children. Aranyi *et al.* (2015) created an

anger-based neurofeedback system in which a character faded from a scenario as the user expressed anger. Techniques similar to neurofeedback have been used to visualize brain activity for educational purposes, entertainment, or to support human decision making. Hassib *et al.* (2017) used brain data from audience members to provide a real-time measure of audience engagement to the presenter. This expands on ideas from neurofeedback, enabling an individual to adapt behavior due to information from the brain signals of others. Teegi (Frey *et al.*, 2014) combines neurofeedback with a tangible interface and augmented reality to enable non-experts to explore EEG signals. Liu *et al.* (2017) explored different representations of brain data to understand how people perceive and interpret such representations and provide design considerations for interpretability, integration and privacy, which also could provide guidance for the design of neurofeedback applications.

#### 4.4 Mental State Assessment

A number of HCI papers demonstrate *mental state assessment* with brain signals. In these papers, an individual's mental or affective state is measured without leveraging the result (neither offline or online). This analysis is performed as a self-contained methodological contribution, without leveraging the result further. The goal is often to transfer the results to an interactive system at a later point. For example, Lee and Tan (2006) demonstrated task classification with EEG, and described some of the considerations for HCI researchers working with EEG data. Grimes *et al.* (2008) explored feature selection and classification of working memory load, along with other considerations that would impact HCI research, building a foundation for future work. Vi and Subramanian (2012) demonstrated that a signal called *error related negativity*, which may be triggered either when a user makes a mistake or when a system behaves in an unexpected way, could be detected in real-time using off-the-shelf commercial EEG headsets. The paper then discusses how this builds a foundation for further HCI research in areas such as gaming, object selection, navigation and teamwork. Zander and Kothe (2011) also looked at error-related responses, in the context of music, showing single trial detection of an error response, to

enable future systems that could have an auditory feedback channel. Chanel *et al.* (2009) explored aspects of emotion detection with EEG to support HCI research and Bandara *et al.* (2018) explored similar types of emotion classification using fNIRS.

## 4.5 HCI Evaluation

*Evaluation* is a special case of mental state assessment, when brain input is used as a user experience evaluation metric for interactive systems. Brain signals have the potential to measure aspects of user experience that are difficult to measure otherwise. Also, as a continuous measure, they could provide information on the changing experience of the user over time, without interrupting the task or requiring user responses. Moving toward this goal, HCI researchers are actively investigating particular aspects of user experience that can be detected with brain signals and have proposed methods for integrating these findings into HCI practice. The explorations in this direction have utilized different brain sensing technology (see Section 6 for more description of these different modalities).

### 4.5.1 HCI Evaluation with fMRI

While fMRI is expensive and has limitations on the user during scanning, it provides insight into neural activity that can inform HCI research. Sjölie *et al.* (2010) used fMRI to explore how different parameters of virtual reality applications (3D-motion and interactivity) affect brain activity, with a goal of building a foundation for future virtual reality applications of brain-computer interfaces. Anderson *et al.* (2015) demonstrated that habituation to security warnings have neural correlates that can be detected with fMRI and showed that polymorphic warnings that change their appearance lead to less habituation. Thanh Vi *et al.* (2017) identified brain areas associated with usability and perceived aesthetics by displaying static webpages and videos of interaction while study participants were in the fMRI scanner.

### 4.5.2 HCI Evaluation with fNIRS

Other work has investigated HCI evaluation methods that use functional near-infrared spectroscopy (fNIRS), (Section 6.2) which measures the hemodynamic response in the brain, similar to fMRI, but that is more practical for HCI research due to its low cost and reduced constraints on the user. Hirshfield *et al.* (2009b) showed that fNIRS could be used to differentiate workload related to different cognitive resources (spatial and verbal working memory). This can enable researchers to distinguish increased workload related to the user interface from increased workload related to the task at hand, which has implications for improving the interface design. Building on this, Hirshfield *et al.* (2011) showed that it is possible to identify additional cognitive resources (visual search, working memory, and response inhibition) that might be utilized during interaction using fNIRS and discussed how this can be used in usability testing. Peck *et al.* (2013) explored using fNIRS for evaluation of information visualization interfaces. Lukanov *et al.* (2016) demonstrated that functional near-infrared spectroscopy (fNIRS) can provide an objective measure of workload for a user study of different user interface layouts.

### 4.5.3 HCI Evaluation with EEG

There have been several studies exploring the feasibility and methods for integrating Electroencephalography (EEG) measures into usability and user experience studies. (For more detail on EEG, see Section 6.1.) Terasawa *et al.* (2017) tracked affective state during a movie through EEG. Barral *et al.* (2017) showed that humor evaluation could be done using a combination of EEG and other physiological measures. Cherng *et al.* (2016) used EEG to evaluate graphic icons based on semantic distance. Mustafa *et al.* (2012) showed that event-related potentials from EEG can reflect visual artifacts in video user perceptions of video quality.

Increasing HCI work utilizing the auditory channel in interface design have posed new challenges in evaluation and several studies have leveraged EEG signals to provide insight into such interfaces. Lee *et al.* (2014) used EEG signals of mismatch negativity to evaluate audio notifications, and Cherng *et al.* (2019) explored how changes in levels

of melody, temp and pitch of an audio notification can impact auditory perception and attention. Lee *et al.* (2019) used EEG analysis to suggest designs for repeating auditory alarms to reduce the repetition-suppression effect. Glatz *et al.* (2018) used EEG event-related potentials to investigate differences in auditory icons and verbal commands for providing auditory notifications during driving. They found that auditory icons are better for providing contextual information, and verbal commands are better for urgent requests. Bilalpur *et al.* (2018) explored EEG features related to cognitive workload during data sonification.

Several studies have looked at EEG to explore the related experiences of immersion and presence in virtual environments and games. Kober and Neuper (2012) found that auditory event-related potentials can be used to explore presence in virtual reality. Terkildsen and Makransky (2019) also explored EEG measures of presence and found that particular event related potential components (N1 and mismatch negativity) are indicative of a feeling of presence and discussed its relevance to games user research. Burns and Fairclough (2015) used auditory event-related potentials to measure immersion during a computer game. Johnson *et al.* (2015) showed differences in EEG signals during a cooperative game, depending on whether teammates were other humans or computer agents. Mustafa *et al.* (2017) evaluated virtual characters for “uncanniness” using EEG. Gehrke *et al.* (2019) showed that the early negativity component of an event-related potential was more pronounced when there was a conflict in the integration of visual and haptic feedback, which can cause loss of immersion.

Aggarwal *et al.* (2014) described a system for measuring user experience that presents user mouse movements during task performance with mental load measured by EEG represented by different colors. Frey *et al.* (2016) proposes a general framework for using EEG for evaluation of user experience, based on continuous measure of workload, attention and error recognition.



# 5

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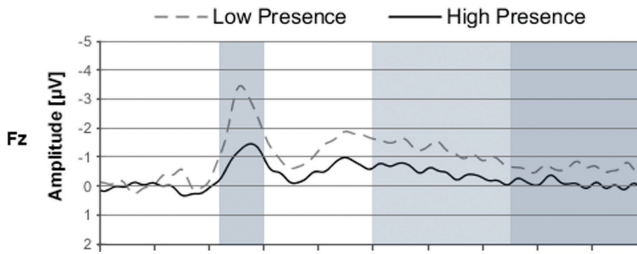
## Cognitive/Neural States and Processes

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Any brain activity measurement is done to capture certain processes or states in a person's brain. However, how the processes and states, i.e., the measured constructs that researchers try to model through the data, are conceptualized and referred to varies across different papers. This distinction is not only theoretical in nature, as the method of describing the measured construct shapes how data can be interpreted and or how classes for machine learning models can be defined.

In general, we see a spectrum of constructs used, ranging from fine-grained, low-level descriptors of individual neural responses to specific stimuli, to cognitive constructs, such as mental workload or attention, to application-related constructs, such as programming competence. To give an concrete example: A P300 is a neural response to the perception of a task-related stimulus. However, on a more abstract level, an increased P300 response can also be interpreted as a marker for attention towards the stimulus.

Interestingly, this difference in constructs is not related to differences in employed features: Both for EEG and fNIRS, there are relatively stable sets of standard features (see Section 4.1) which are used across the whole spectrum. This implies that there is not necessarily a conceptual

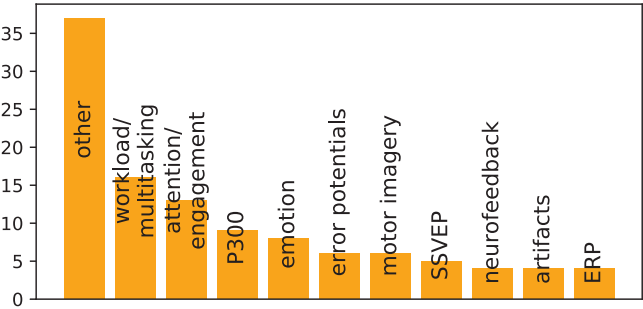


**Figure 5.1:** Analysis of averaged EEG signals at electrode location Fz to identify significant differences between “low presence” and “high presence” in certain time segments after the stimulus (a deviant sound), by Terkildsen and Makransky (2019). Regions of interest for expected EEG responses are coded with different shades of grey, time scale ranges from  $-100$  to  $900$  milliseconds ( $0$  is the time of stimulus presentation).

difference between the different constructs, but a difference in framing and interpretation.

We find a lot of work that frame the detected states from a low-level, neural perspective in the area of brain input for *evaluation*. This may be due to the fact that for evaluation, the data usually is utilized offline. Offline processing allows average-case analysis compared to single-trial analysis, increasing the signal-to-noise ratio of the averaged data and thus allowing for an analysis of finer nuances in the data. For example, Terkildsen and Makransky (2019) show that certain elements of EEG event related potentials correlate to experienced presence in a video game (Figure 5.1). As typical for this kind of analysis, the authors analyze averaged signals, comparing low- and high-presence situations. It should be noted that it is possible in principle to detect such low-level neural patterns from a single trial data (Blankertz *et al.*, 2011), although the more nuanced the effect, the more susceptible it is to be distorted by artifacts and other cognitive processes.

Another brain input paradigm that uses low-level neural features is *active control*, as such a system often directly maps specific neural responses to control commands. For example, Kosmyna *et al.* (2015b) focus on controlling brain-computer interfaces based on either SSVEP or motor imagery (see Section 4.1 for details), which are both basal neural



**Figure 5.2:** Frequency of specific neural/cognitive states or processes.

responses to elementary stimuli (in case of SSVEP) or to elementary motor behavior or the imagination thereof (in case of motor imagery).

As Figure 5.2 shows, other recurring low-level neural processes are the P300 and “error potentials”, which occur in response to the execution or observation of erroneous, unexpected behavior. In contrast to the other introduced neural processes, error potentials are also employed in real-time systems beyond active control BCIs. For example, Putze *et al.* (2017) used error potentials to detect errors of an auto-correction component during mobile text entry, with the intent of repairing them automatically. Low-level processes are clearly defined and well-known in their neural origin. However, these processes are usually not tied directly to events in the HCI application or to states that users are aware of.

At the other end of the spectrum, we have the brain input paradigms that respond to certain cognitive states, namely *implicit input*, as well as corresponding works on *mental state assessment* as a building block to such interfaces. There is a small number of recurring cognitive states which appear frequently. The most important ones are “workload” (or “cognitive load”, “mental load”) and “attention”. For example, Afergan *et al.* (2014a) used fNIRS signals to classify low and high workload conditions during the task to control a group of unmanned aerial vehicles. Workload was modulated through and the system could respond in real-time to detected high load by simplifying the task. In contrast to narrow, precisely defined effects like the P300, concepts like workload are

broader and encompass several aspects, such as multitasking (Solovey *et al.*, 2011, 2012) or task difficulty (Yuksel *et al.*, 2016). Regarding attention, we observe a similar pattern, as this concept summarizes a number of complex aspects under one umbrella term. While much work quantifies the level of attention with a scalar value or identifies attention with the related concept of general task engagement (see for example Szafrin and Mutlu, 2012), others look at more specific aspects. Thus, two papers both concerned with “attention” should not immediately be treated as measuring the same aspect. Putze *et al.* (2016b) described an EEG-based approach for the classification of internal and external attention orientation for the purpose of creating user interfaces that avoid distraction through a graphical user interface. The large number of “other” states (Figure 5.2) and processes shows how broad the scope is, covering many unique aspects, such as “humor” (Barral *et al.*, 2017) or “liking” (Terasawa *et al.*, 2017).

Once the decision for a cognitive or neural state is made, the next step in any empirical investigation is then to record data about that state in an experiment. In these experiments, the state is then manipulated to capture its different manifestations. Fairclough (2009) discusses different approaches to ensure the validity of such experiments. He lists four different approaches: Validation through exposure of media (e.g., showing pictures with validated emotional content), validation by experimental tasks (e.g., a flight simulator with different levels of difficulty), validation by subjective measurements (e.g., a questionnaire on experienced presence in a virtual environment), and validation through observable behavior (e.g., head re-orientation in response to a processed stimulus). Fairclough also points out that the relationship between measurements and target states (or between low-level neural features and high-level cognitive processes) is not necessarily a one-to-one relationship. Thus, an interpretation for HCI purposes needs to take such ambiguity into account.

# 6

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## Brain Sensing Technology

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In this section, we focus on the two most commonly used brain sensing technologies for HCI: functional near-infrared spectroscopy (fNIRS) and electroencephalography (EEG). Although functional magnetic resonance imaging (fMRI) has been used in HCI research to get a better understanding of neural processes, it is not often used as input due to its high cost and highly constrained environment. Implanted sensing approaches, such as electrocorticography (ECoG), are also not currently practical, due to the need for surgery.

To choose between fNIRS and EEG modalities for brain input acquisition, it is important to identify the criteria by which we can discriminate them, such as invasiveness, spatial resolution, temporal resolution, measured physiological parameters, resource demands, and mobility/comfort. Regarding *invasiveness*, EEG and fNIRS are comparably non-invasive. *Spatial resolution* tells us how specifically we can distinguish the area of the brain the signal is coming from. fNIRS has higher spatial resolution than EEG, which suffers from the volume conduction effect. One caveat, however, is the fact that a standard placement protocol for fNIRS is not established, which can make it difficult to achieve a replicable placement

of sensors at specific locations. *Temporal resolution* refers to how specifically we can determine the timing of neural activity. EEG has much higher temporal resolution than fNIRS, which is not only due to the much higher sampling rate of current devices, but also to the different *measured physiological parameters*. While EEG directly captures parts of the electrical cortical activity at the millisecond level, fNIRS measures brain activity indirectly through the hemodynamic response occurring over 5–10 second period. Below, we discuss these in more detail, as well as other physiological measures that have been recorded. We also discuss practical considerations for synchronization and highlight recent commercial developments of brain sensing technology.

### 6.1 Electroencephalography (EEG)

Electroencephalography (EEG) is the most commonly used method for measuring brain activity in HCI contexts (Figure 6.1). It captures cortical electrical activity measured through electrodes placed on the scalp. This gives access to a number of important cognitive processes at a very high temporal resolution (EEG is often measured with sampling rates of 500 Hz or more and captures responses to events on a millisecond

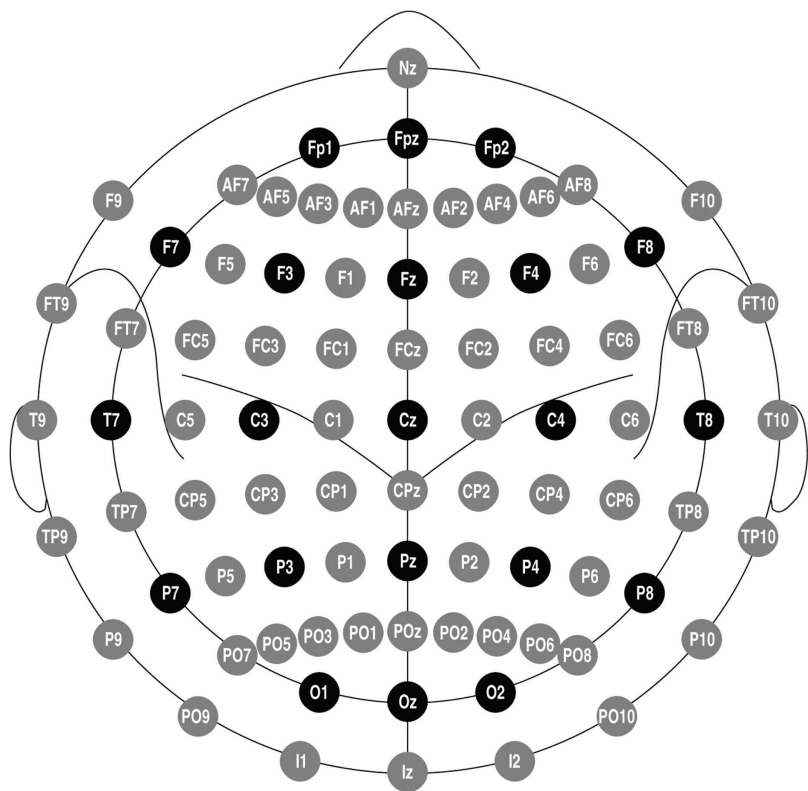


**Figure 6.1:** Electroencephalography (EEG) measures electrical activity originating in the cortex through electrodes placed on the scalp.

timescale). Section 5 gives an overview of some of the cognitive states and processes that can be discovered from EEG. It should however be kept in mind that EEG does not capture all neural processes (as it only measures cortical activity) and is limited by the low spatial resolution.

Traditionally, electrolyte gel is used to reduce impedance between electrode and signal source. In recent years, dry electrodes became more popular (Di Flumeri *et al.*, 2019); dry electrodes come with the promise to avoid the application of gel to the user's hair before using EEG sensors. In turn, dry electrodes operate with increased pressure of point-shaped electrodes on the head, which might result in reduced wearing comfort when using the device for an extended period of time and which can also impact the EEG signal quality negatively. The placement of electrodes is important as neural activity is spatially distributed across the cortex, i.e., specific neural markers are captured at specific locations. To identify recording positions reliably, the 10/20 system and its extensions (Oostenveld and Praamstra, 2001) is used to describe the positions (see Figure 6.2). However, it should be noted that due to the volume conduction effect, the spatial resolution of EEG is not very high, i.e., neighboring electrodes are strongly correlated.

There exist a number of in-depth introductory texts to the recording and analysis of neural data, usually coming from a neuroscience or cognitive science perspective. For EEG, the book by Cohen (2014) covers many fundamentals, from the recording, over pre-processing and time-frequency decomposition, to more complex topics such as connectivity analysis. Texts in cognitive science are often surprisingly close in research questions and experiment designs to typical HCI studies. In many cases, the tutorials to the established toolkits (e.g., [https://mne.tools/stable/auto\\_tutorials/index.html](https://mne.tools/stable/auto_tutorials/index.html) for the MNE library) already provide a valuable introduction to the most important concepts and come with the advantage that they are accompanied with immediately executable code which facilitates exploration and the application of the concepts to existing data.



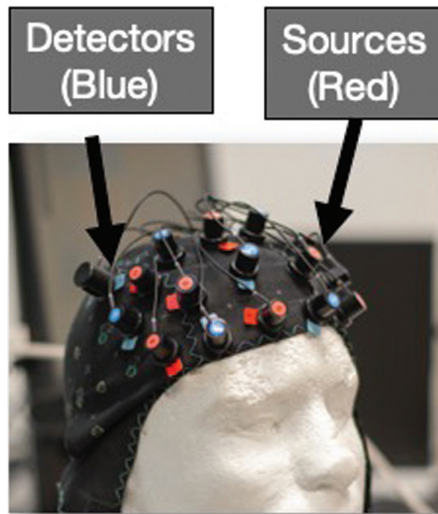
**Figure 6.2:** Electrode positions in the 10/10 extension (gray circles) of the standard 10/20 EEG positioning standard (black circles), according to Oostenveld and Praamstra (2001).

## 6.2 Functional Near-Infrared Spectroscopy (fNIRS)

Functional near-infrared spectroscopy (fNIRS) has emerged as a promising technology for real-time detection of brain signals (Figure 6.3). It is an optical measure, meaning that it uses light to probe the brain cortex.

At near-infrared wavelengths, bone and tissue are transparent to the light and the main absorber of light is the oxygen in the blood. A cap or headband secures light sources on the surface of the head that emits precisely timed and measured near-infrared light (Figure 6.4). Once the light is fully scattered in the brain, some of it reaches a sensitive light detector on the surface of the head. From the measured light that

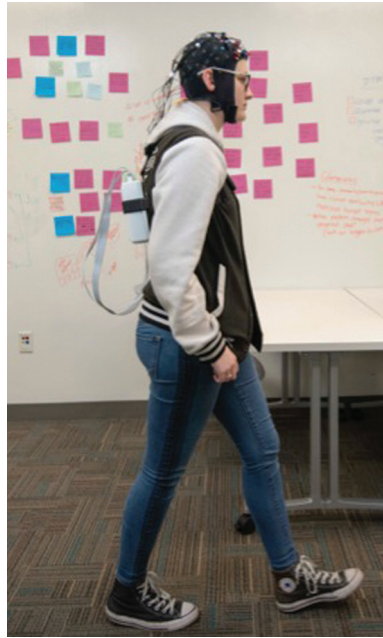




**Figure 6.3:** Functional near-infrared spectroscopy (fNIRS) caps or headbands can have different configurations. However, all will have a set of light sources (shown here in red) and light detectors (shown here in blue). For each source-detector pair, we can calculate the oxygenated and deoxygenated hemoglobin in the measured area which is an indicator of brain activity.

returns back to the surface detector, we can determine the amount of oxygenated and deoxygenated hemoglobin in a region of the brain using the modified Beer-Lambert Law. Unlike fMRI, fNIRS measurements can only robustly reflect activity approximately 3 cm into the cortex and cannot reach deeper brain structures.

Until recently, most brain signal recordings were done in highly controlled and restricted environments. However, these are not realistic for HCI research. To explore the feasibility of using fNIRS in HCI, Solovey *et al.* (2009) explored the extent to which typical HCI actions such as typing and mouse clicking could cause interference with the fNIRS signal. This work showed that mouse clicks and typing were not problematic, but that major head movements and frowning may interfere. There are numerous methods for correcting other known artifacts, such as minor head movements, heartbeat and respiration. These guidelines are detailed in Solovey *et al.* (2009). Further work confirmed the reliability



**Figure 6.4:** Functional near-infrared spectroscopy (fNIRS) measures blood oxygenation in the brain, similar to fMRI, but is more portable and less restrictive.

of fNIRS for HCI research and explored how artifacts impact verbal and spatial tasks differently (Maior *et al.*, 2015). While study participants sometimes report some discomfort after wearing sensors for prolonged period (over an hour), longer duration studies with fNIRS have been done where participants wore sensors for 3.5 hours (Boyer *et al.*, 2015).

As mentioned earlier, the temporal resolution of fNIRS is relatively low. This is due to the biological process that is being recorded. The hemodynamic response that fNIRS measures is a “slow” process, occurring over 3–8 seconds, compared to EEG, which measures brain activity in a few milliseconds. For this reason, fNIRS is suitable as a measure of the user’s changing cognitive state where latency is less of an issue. When an application requires instantaneous responses based on brain activity, fNIRS would likely not provide the sufficient signal. Much fNIRS work in HCI describes using fNIRS as an implicit, supplemental input, or as an evaluation metric.

### 6.3 Eye Tracking and Physiological Measures

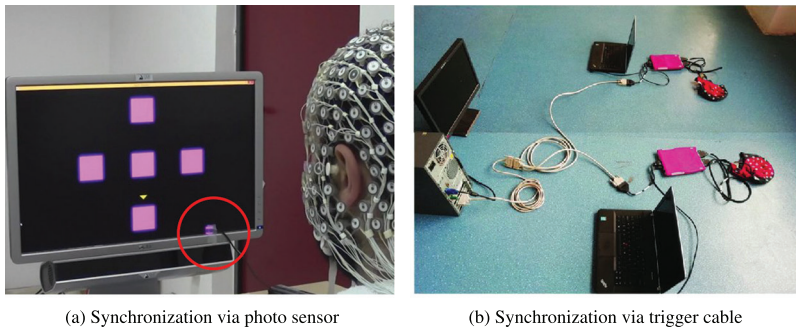
Brain data is not the only type of data that can be used to assess a person's cognitive and affective state. While brain data provides a number of unique characteristics compared to other sources, a combination can add redundancy and robustness. Cowley *et al.* (2016) gives an overview of available physiological signals and how they can contribute to HCI systems. Important types of physiological signals are: Electromyography (EMG) measures electrical muscle activity, pupilometry measures pupil size, electrocardiography (ECG), respiration, electrodermal activity (EDA), blood volume pressure (BVP) all capture aspects of the autonomous nerve system which responds to stress and emotional dynamics. For attention-related processes, eye tracking is a modality which can be combined with brain data. Eye tracking is also relevant to identify the spatial location of a stimulus that triggered a neural response (Putze *et al.*, 2016a). For fusion of modalities, the most frequent algorithmic approaches are feature-level fusion (i.e., combination of features for each modality into one large feature vector) and decision-level fusion (i.e., individual classification for each modality, followed by a voting or other integration over classifier results) (D'mello and Kory, 2015).

Physiological data is often used to determine relatively general states of a person. For example, Zhou *et al.* (2011) combines various physiological measures, namely EMG, EDA, and respiration with EEG for classification of emotions as response to affective pictures. They compare models for different cultures and genders. Jarvis *et al.* (2011) combines EDA, respiration, and BVP to measure mental workload in different multitasking situations in a driving simulator. They could show that a multimodal fusion between the employed modalities leads to an improved classification accuracy for the discrimination of a relaxed and a load state; however, for a more subtle discrimination (single tasking vs. multi tasking), EEG alone outperforms the combination with physiological signals.

## 6.4 Synchronization

It is known from meta-studies in related fields (D'mello and Kory, 2015) that multimodality is often a key mechanism to improve robustness of a classifier or to capture complementary information from different sources. When processing brain data, we can either combine multiple methods to capture neural information, or we can add different signal types. A combination of EEG and fNIRS is promising, as the two modalities capture different correlates of brain activity and have different characteristics with regards to temporal dynamics or typical artifacts (Hirshfield *et al.*, 2009a). An example of a hybrid EEG+fNIRS system is the work by Shin *et al.* (2016), which shows a significant improvement of classification accuracy for the hybrid model compared to the individual modalities for the classification of mental activities. In comparison, the work by Putze *et al.* (2014) shows the potential for complementary information for the classification of modality-specific perceptual workload: While EEG outperforms fNIRS in the detection of increased visual workload, it is the other way round for auditory workload. Interestingly, the combination of EEG and fNIRS has yet to find its way into HCI-centered research, which may be a result of the increased complexity of such recording setups.

One challenge of a multimodal system is the question of synchronization; as brain activity, especially when recorded through EEG with its high temporal resolution and sampling rate, is susceptible to temporal shifts between the brain data and recorded events during an HCI task. There are three common ways of performing synchronization between the two: First, trigger signals can be generated from the task and sent (usually via a serial interface) to the recorder (Figure 6.5(b)). This results in very accurate timing but requires both a computer with a serial port (which is becoming a rarity) and a recorder that can read the triggers. Second, a photo sensor can be used that is connected to the recorder and which captures changes in color of a prepared segment of the screen (Figure 6.5(a)). Here, no direct hardware connection between events and recording setup is necessary. Third, if the hardware solutions are not available (e.g., when using a commercial headset without the



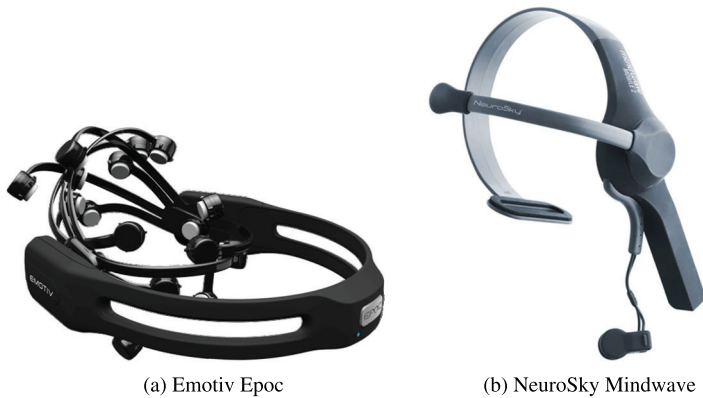
**Figure 6.5:** (a) Synchronization of two EEG headsets to a computer via serial port triggers (Barraza *et al.*, 2019). (b) Synchronization via photo sensor attached to the screen (from <http://www.mamem.eu/mamem-makes-publicly-available-a-challenging-eeeg-dataset-based-on-a-ssvep-based-experimental-protocol/>).

necessary hardware interfaces), we can rely on timestamps for synchronization. To avoid mismatch of time-stamps due to unsynchronized clocks, a protocol such as the one provided by Lab Streaming Layer (<https://github.com/sccn/labstreaminglayer>) can be used.

When very exact timing is important (e.g., especially when temporal features relative to a specific event are analyzed), it may also be necessary to take into account latency of input devices (e.g., USB buffers) or screen refresh rates.

## 6.5 Commercial Development

Given the large number of potential applications for brain input in HCI, it comes at no surprise that besides academic research, there is also a number of commercial developments. These can be mainly categorized in two different groups: On the one hand, multiple companies offer affordable, consumer-grade headsets that usually come with a number of complete applications and are targeted at curious laypersons or non-academic hackers. On the other hand, we have a line of commercially-driven research by some of the large technology companies in Silicon Valley and beyond.



**Figure 6.6:** Examples of commercial EEG headsets.

Important examples of consumer-grade EEG headsets are the NeuroSky Mindwave, the Epoc Emotiv, and the InteraXon Muse (Figure 6.6). Characteristics of consumer-grade headsets are a low cost, short setup time, no requirement for electrode gel, high comfort, but also a limited number of electrodes in a fixed montage. There has been an ongoing debate on the signal quality and susceptibility to artifacts when using consumer-grade devices, where some authors see a drastically reduced validity of these devices (Buchanan *et al.*, 2019; Ratti *et al.*, 2017), while others claim them to yield useful neural data (Rieiro *et al.*, 2019; Zerafa *et al.*, 2018), or arrive at mixed conclusions (Maskeliunas *et al.*, 2016).

Consumer-grade headsets usually come with blackbox applications which process the data and map it to certain cognitive states, such as relaxation or concentration, that can either be used in the packaged applications (usually games or other software designed for entertainment or biofeedback) or accessed from custom programs for further processing. However, raw EEG data is not always accessible. Validity of available models is not ensured, usually no clear definition or test environment exists. For example, models which capture “concentration” might actually measure muscle activity from eyebrow raises.

When trading off between usability and price on the one hand and signal quality and flexibility of recording on the other hand, a compromise

worth considering are entry-level headsets of established manufacturers (such as the g.tec Unicorn EEG headset), which are also tailored towards mobile use and thus provide light-weight devices and wireless data transmission.

Finally, there exist some well-developed open hardware platforms, such as the OpenBCI,<sup>1</sup> that are geared towards researchers open for tinkering and who can benefit from the customizability of the design (e.g., when brain activity sensors need to be integrated in a specific head gear) and the lower price entry point.

Beyond these efforts to break into the consumer market with affordable headsets with a focus on usability, there also have been recent threads of ambitious research from start-ups and established technology companies in the hope to unlock a paradigm change in the use of brain signals for commercial applications. Naturally, there is less information publicly available on the progress of the corresponding research units, but some carefully selected information is still released.

One example of such developments is the endeavour by Facebook to create a neural text-entry interface based on the processing of purely imagined speech. This work was inspired by the work of Herff *et al.* (2015), with the ambition of achieving a higher transfer rate and larger vocabulary size, while removing the need for invasive recording. The company cooperates with a number of academic institutions, who publish research on the real-time decoding of speech (Moses *et al.*, 2019), which still operates with invasive sensors.

Another example of ambitious commercial developments is Neuralink (Musk, 2019). In contrast to the Facebook initiative, Neuralink targets invasive BCI as the endpoint of their research. They describe their efforts towards a high-throughput, long-term capable cortical interface to make invasive BCI viable for the support of users with neurological disorders.

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<sup>1</sup><https://openbci.com/>.

# 7

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## Architecture and Development Tools

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The previous sections have shown how brain signals can be used in a wide variety of domains, following many different input paradigms, and by exploiting a broad spectrum of cognitive and neural processes. In this section, we will turn our attention towards the practical implementation of using brain signals in HCI research. This practical side needs to cover a large range of steps, ranging from the sensor hardware to the software for recording, processing, and classifying the signals. This section will not cover all details of all the relevant aspects; instead, we will give the reader a concise list of key points for each aspect as well as a list of references to seminal papers or books that cover that specific aspect in great detail.

An aspect of the practical implementation of each brain input paradigm is the question of how much one wants to rely on existing solutions for recurring use cases. Especially in the market of commercial devices (see Section 6.5), there are a number of closed-source solutions and tools. These devices and tools allow a quick start in using brain data. Our perspective is that a modern approach to using brain input should make use of modern tools and components that manifest a large body of knowledge and experience and contribute to a quick start;

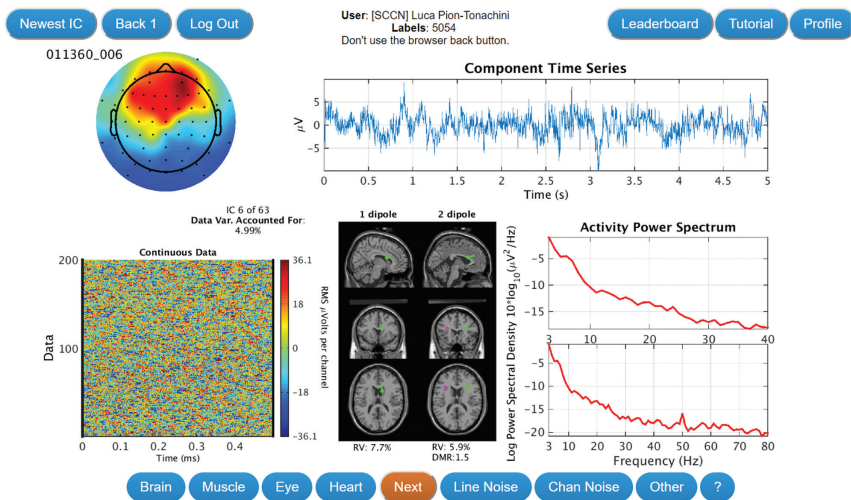


however, we suggest to concentrate on such tools which allow flexibility for custom solutions and extensions as well as for full documentation of and access to the implemented algorithms. This implies a preference for programmable, modular, open-source software and hardware with open APIs and communication protocols.

## 7.1 Signal Processing

In contrast to other signal sources (such as images), EEG and fNIRS data usually needs to be preprocessed to perform a meaningful analysis or classification. This preprocessing is done to reduce the influence of technical or biological artifacts on the target information in the signal. This is necessary as the skull, skin, and hair filter a lot of this signal and artifacts may be of larger magnitude than the neural activity itself. Artifacts can be of technical, environmental, or biological origin. Examples for technical artifacts are line noise in the EEG signal (caused by the utility frequency in the electrical power grid at [50] Hz or [60] Hz or cable movements during recording. An example for environmental artifacts is a change in lighting conditions during an fNIRS recording. Examples for biological artifacts result from eye movement, chewing or speaking, or neck movements.

There exists a large variety of methods for reducing the influence of artifacts on the signal. As typical artifacts depend on the acquisition method (e.g., EEG vs. fNIRS), the signal processing is also often specific to the modality, although a transfer of methods is sometimes possible. Standard preprocessing techniques comprise bandpass filtering and baseline normalization. Beyond that, there exists a large number of algorithms for dealing with artifacts. Minguillon *et al.* (2017) gives an overview of the most important categories, such as filtering, linear regression, blind source separation, and source decomposition. They also analyze requirements for artifact removals techniques target towards mobile, applied use and categorize existing approaches according to these criteria, such as real-time capabilities, the ability to work with a limited number of electrodes, and the necessity to evaluate the method on real life data with complex artifacts. Jiang *et al.* (2019b) gives a more technical introduction to the most important groups of algorithms.



**Figure 7.1:** Crowdsourcing process for labeling of independent components in EEG to isolate artifacts from neural data Pion-Tonachini *et al.* (2019).

Their literature analysis reveals that the most frequently employed method for EEG is the Independent Component Analysis (ICA), which is a blind source separation technique. A recent EEG-based method with leverages the potential of large available data sets, crowd sourcing, and machine learning is the ICA Labels approach (Pion-Tonachini *et al.*, 2019) (Figure 7.1). It performs an automatic classification of independent components into neural and non-neural (or mixed) sources. A drawback of ICA is that it requires a relatively large number of electrodes and is thus not applicable to single-electrode systems (although some researchers investigated to what extend a single EEG channel can be decomposed with ICA, e.g., Davies and James, 2007).

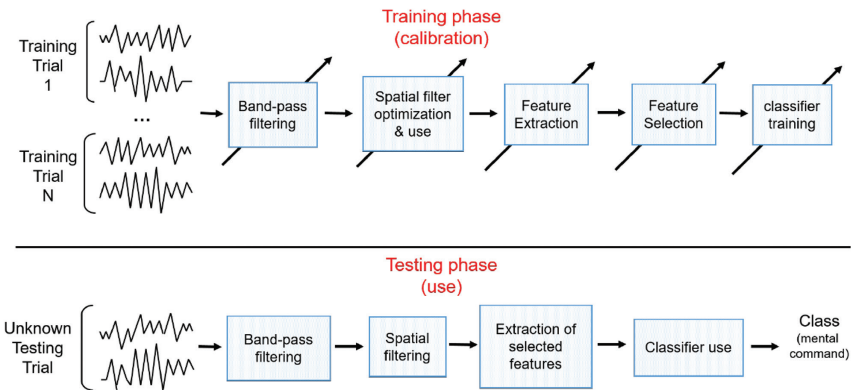
7.2 Machine Learning

Many HCI use cases of brain signals analyze the recorded data through the means of machine learning. The brain input paradigms which most often make use of such algorithms are mental state assessment, as well as open and closed loop systems. In these cases, short segments of data are either mapped to one of a small number of classes (classification) or

a real number (regression). A hybrid use case is neurofeedback, which can work both on the raw data or derived features directly, but can also derive more abstract descriptions as feedback to the user. Current machine learning algorithms are based on statistical models which learn relationships between neural features and the target variable from labeled training data. The labels according to which the data is classified are usually derived from the modeled cognitive states or processes (see Section 5).

The machine learning pipeline employed for the analysis of brain data is not fundamentally different from the standard processing steps in other domains. This implies that many standard tools for machine learning, such as Scikit-learn (Pedregosa *et al.*, 2011) or Keras (Chollet, 2015) can also be applied to the processing of brain signals. These toolkits provide well-documented implementations of many machine learning primitives and allow to set up a standard classification pipeline with few calls to high-level convenience methods. The biggest such libraries are available in the Python programming language, which has emerged as a de-facto standard in the (research-oriented) data science and machine learning community. Other options are R and MATLAB, which is still the native programming language of many neuro-specific algorithms. Figure 7.2 from Lotte *et al.* (2018) shows a flow chart of the standard pipeline for machine learning on brain data. Lotte *et al.* (2007) provide a good introduction to machine learning for BCI and an update after ten years (Lotte *et al.*, 2018) summarizes newer developments, such as the rising importance of deep learning approaches in BCI.

Besides the pre-processing (see Section 7.1), the most important part that is specific to brain data (and the concrete modality for measuring brain data) is feature extraction. For EEG, Lotte (2014) defines three general groups of information which can be encoded in the extracted features: spatial, temporal, and spectral information. Spatial information is relevant because different parts of the cortex are associated with different cognitive processes (for example, the motor cortex is associated to the planning and execution of limb movement). Temporal information represents characteristic responses to specific stimuli (for example, the P300 is an *Event Related Potential* that is triggered by the perception



**Figure 7.2:** Flowchart of a typical BCI pipeline according to Lotte *et al.* (2018).

of salient, task-relevant stimuli. Spectral information carries a lot of information about the oscillatory nature of the signal.

Characteristics which influence performance and algorithm choice for the processing of brain signals are: (1) the typically small sized datasets, with a relatively low number of available samples, (2) the low signal-to-noise ratio, and (3) the difficulty of interpreting raw brain data, which creates difficulties in interpreting results and generating labels manually.

The challenge of interpreting the learnt models is very important as it is a prerequisite to ensure validity and generalizability. This is not only an academic problem, as a failure to do so may lead to models which perform well in an offline evaluation on a given test set but actually do not capture the targeted neural activity. Instead, they react to systematic artifacts (e.g., when the stimuli in an experiment triggers eye blinks) or unrelated cognitive processes (e.g., when the model should capture mental workload, but it actually responds to the stress in the training data). Another example of such alleged relationships results from temporal relationships, for example when data is recorded block-wise (Porbadnigk *et al.*, 2009). In such cases, the model might learn temporal differences (e.g., caused by drying EEG electrode gel) instead of the actual target state. Machine learning literature knows such models as “clever Hans” results (Lapuschkin *et al.*, 2019), as they suggest intelligent

behavior which is actually only a result of a shallow interpretation of the data. For the interpretation of linear models, the weights of the model can be analyzed to understand which features are most important (Haufe *et al.*, 2014). For deep learning models, interpretation is more difficult and a topic of recent research (Schirrmester *et al.*, 2017; Sturm *et al.*, 2016).

### 7.3 Existing Software Tools

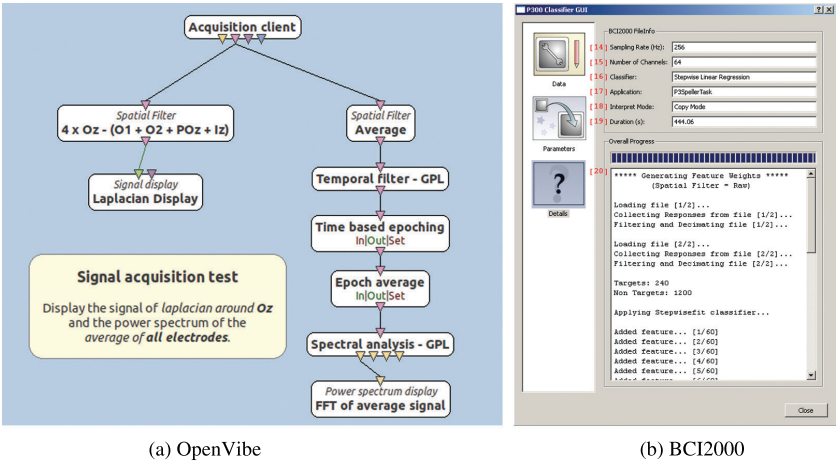
As the processing of brain signal data requires a lot of different steps during pre-processing, feature extraction, classification. Naturally, a number of frameworks have emerged which promise to provide ready-to-use implementations of the recurring building blocks. Such frameworks are especially attractive for researchers with limited experience.

While some existing tools help with brain data acquisition and signal processing, most are geared toward biomedical engineers, scientists or clinicians who mainly analyze the sensor data offline and are experts in the underlying device technology. There are few tools available that appropriately facilitate the user interface developer to conduct iterative development of the BCI application. There is a need for appropriate methods and tools to enable and support user-centered design, development and evaluation of brain input paradigms.

#### 7.3.1 EEG Tools

The two most established tools for the creation of EEG-based online BCI are “BCI 2000” (Schalk *et al.*, 2004) and “OpenVibe” (Figure 7.3) (Renard *et al.*, 2010), which both provide building blocks for many standard procedures to compose common BCI paradigms, such as a P300 speller for text entry. Both tools can be operated with limited programming effort due to the integrated graphical user interfaces. They still offer a programming interface for increased flexibility.

There are other tools which focus more on the offline processing of brain signal data, which can for example be used in HCI evaluation scenarios. Important examples of these kinds of frameworks are EEGLAB (Delorme and Makeig, 2004) (running in MATLAB) and



**Figure 7.3:** (a) Visualization of a processing pipeline for EEG data in OpenVibe. (b) Configuration options for EEG analysis in BCI2000 (from <http://openvibe.inria.fr/features/> and [https://www.bci2000.org/mediawiki/index.php/User\\_Reference:P300Classifier](https://www.bci2000.org/mediawiki/index.php/User_Reference:P300Classifier)).

MNE (Gramfort *et al.*, 2014) (running in Python). Again, both these tools offer graphical user interfaces for data loading, manipulation, and analysis, as well as a programming interface to compose individual methods in a script. This approach also allows to re-use some of the methods in a custom analysis pipeline, even if not all parts of the framework are used. That being said, using a framework can result in a lock-in to specific approach as the frameworks have proprietary data formats and pipeline constructs which make it difficult to switch between them or to integrate custom algorithms, if necessary.

### 7.3.2 fNIRS Tools

Because fNIRS is a newer tool, the supporting tools are not as well established. Most fNIRS equipment come with some capability for data acquisition, processing and analysis, but it varies from device to device (e.g., fNIRSoft by Biopac and NIRSLab by NIRx (Xu *et al.*, 2014)). Several tools have emerged that cover aspects of the fNIRS data analysis pipeline, usually implemented in MATLAB. Homer, and the later releases of Homer2 and Homer3, provide visualization, as well as several

signal processing methods and block averaging functions, along with additional fNIRS analysis methods, but is focused on offline analysis, particularly for block design studies (Huppert *et al.*, 2009). NIRS-SPM provides statistical parametric mapping for fNIRS showing activation maps of oxy-, deoxy-hemoglobin and total hemoglobin, but also is for offline analysis (Ye *et al.*, 2009). The NIRS Toolbox also provides visualization, signal processing and statistical analysis for fNIRS (Santosa *et al.*, 2018). Imperial College Near Infrared Spectroscopy Neuroimaging Analysis (ICNNA) focuses on fNIRS experiment analysis over specific images (Orihuela-Espina *et al.*, 2017). FC-NIRS provides support for doing resting state functional connectivity analysis on fNIRS data (Xu *et al.*, 2015).

Because most of these tools were not designed for HCI research, many research labs then build their own tools to facilitate work in HCI. For example, these tools are often challenging to integrate into custom applications or use with custom algorithms, have limited real-time capabilities, or require specific hardware or software. Still, if one of these tools fits the requirements of the HCI environment, they can help to quickly bootstrap a system to integrate brain data. For a more in-depth review, see Stegman *et al.* (2020), which also addresses web-based applications.

# 8

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## Evaluation Methods, Generalizability, and Reproducibility

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Evaluations have played a critical role in human–computer interaction research. When it comes to brain input paradigms, there are many different types of evaluations that might be appropriate, depending on the research goal and the stage of development. Typically, human–computer interaction evaluations focus on user performance or user experience. These are also crucial in some aspects of HCI research with brain signals, particularly when a system has been built and deployed. However, because systems using brain input are still in their relative infancy, many evaluations address system performance, speed, or model accuracy, to demonstrate the feasibility of the system, leaving user experience improvements for future work. Further, due to the reliance on models, generalizability and reproducibility is a key factor in evaluation.

### 8.1 User Focused Evaluations

Similar to any HCI work on novel input, initial studies on brain input paradigms often focus on feasibility and user performance. These studies answer questions including: Can the user perform a task with brain signals as input? How quickly and efficiently can the user perform a



task? In some work, studies go beyond feasibility and explore user experience: Does the user enjoy working with the brain input system?

Beyond these typical user evaluations, there is a need to explore additional evaluation criteria that are unique to brain signals as computer input. In particular, with implicit or passive input, it is important to consider the user's detection, perception and consideration of the adaptations that occur. For example, could we quantify the tradeoff between workload related to user perception of the brain-adaptive behavior and the potential performance improvement of the adaptive support? These could then be considered along with more traditional evaluation metrics of typical HCI systems (e.g., completion time, error rate, learnability, user experience).

## 8.2 System Focused Evaluations

Because brain input is still new, many studies focus less on user performance and experience, and more on system feasibility and performance, and especially machine learning model performance. Validation of learnt models and feature importance is necessary, especially with the existing skepticism and demand for neurological plausibility, given that brain responses are not easily interpretable. This is not a topic specific to brain input; other areas such as image classification, also have been dealing with these challenges.

When evaluating a model of brain data, a first step is the choice of evaluation metric. When applying hypothesis testing on a batch of samples *offline* (e.g., as in an evaluation approach), this comprises the standard arsenal of inferential statistics, which is discussed in great detail as a set of quantitative tools for HCI research. Usually, hypotheses concern the latency and/or amplitude of neural effects compared between different conditions (Cairns, 2019; Cohen, 2014).

Different methods of evaluation are required for *online* methods of using brain signals as computer input. When evaluating active BCI, researchers usually employ metrics that measure data transfer rates (Thompson *et al.*, 2014), taking into account the bit rate per command, error rate, and transmission rates.

For the evaluation of brain input paradigms based on classification methods (e.g., implicit input systems), you have to choose a metric to measure the performance for the evaluation. Schlögl *et al.* (2007) list and compare 19 different methods for application in BCI research. Lemm *et al.* (2011) provides an introduction to machine learning for neuroimaging and also gives practical advice on how to combine cross-validation with model and feature selection.

It should be considered that even if a classification approach is usually not tied to explicitly formulated hypotheses, inferential statistics still have a room in its analysis, as the research has to establish whether the reported classification accuracy is significantly better than random chance or a given baseline system (Billinger *et al.*, 2012; Combrisson and Jerbi, 2015).

### 8.3 Generalizability and Reproducibility

To move brain input into real-world use, the classification of user state needs improvements in accuracy and reliability, including the ability to handle classifications that may be situation and domain dependent. While several studies have applied machine learning to brain sensor datasets, it has been difficult to generalize the results, since most datasets have been small and collected in very specific contexts. Robust classification of user state remains a difficult problem, especially as we move to more realistic and noisy settings, outside of a lab.

A contributing factor is the limited datasets available, making training sets for classifiers inadequate for classification across wide groups of users. In addition, pre-processing methods are not standardized and often are not well-documented, making it hard to reproduce or build on prior findings. In addition, there are individual differences that need to be accounted for. By building large, diverse, and rich datasets containing contextual information, researchers could go further than existing work and deeply investigate and validate signal processing, noise reduction, and real-time machine learning classification techniques for brain data in the real world.

In machine learning, reproducibility is mostly concerned with reporting all relevant parameters and implementation choices of the

processing chain. When reporting machine learning research in a page-limited paper, it is often difficult to report all parameters. Therefore, it has become increasingly common to publish executable code on the basis of open toolkits and programming languages, often on version control platforms such as Github. The “Papers with Code” data base <https://paperswithcode.com/> provides a repository for publications with associated code.

Multiple processes towards this goal have been developed, such as citable open data repositories and pre-registration (such as the Open Science Framework<sup>1</sup> or Zenodo<sup>2</sup>). More and more, publication outlets and funding agencies begin to expect the publication of recorded data to ensure that other researchers can check the reported results, but also benefit from the investment of time and money.

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<sup>1</sup><https://osf.io/>.

<sup>2</sup><https://zenodo.org/>.

# 9

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## Research Directions

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The review of literature presented in this monograph documents that brain signals have become a regular addition to the toolbox of HCI research instruments, and may provide an evaluation instrument, an input modality to control an application, or a sensor for adaptive interfaces. From the work thus far, we envision future research directions expanding deeper into the domains in which brain signals have already established foundations (Section 3), as well as broadening into new domains. However, brain input is not yet where other modalities – such as speech, gesture, or eye tracking – already are, in terms of maturity and prevalence in academia and industry. We highlight directions which research in this field will take to increase its impact and prevalence in HCI. In the following, we discuss examples of these central research directions.

### 9.1 Beyond Simple Cognitive State Classifications

While we might be able to distinguish a “high workload” task from a “resting state”, or a small number of discrete states from each other, it would be more valuable if we could have a continuous measure of cognitive load, and other cognitive and affective states. In addition,

to provide value in user experience research, these states need to be distinguishable across tasks and contexts. Researchers have noted that measuring changes in workload from brain signals does not always work across all tasks (Midha *et al.*, 2020). Once we can extract several dimensions of user experience from the brain signal at a fine grain level, across many different tasks and contexts, brain signals will become tremendously valuable to HCI, both for user evaluations and real-time input to adaptive systems.

## 9.2 Advancing User Experience and User Evaluation

Brain signals hold promise for providing user experience measures that go beyond existing measures, as discussed in Section 4.5. However, converting raw brain signals into practical user experience insights is far from reality today.

There is a need to integrate this scientific knowledge into well-designed toolkits that support user studies and analysis. While research has begun to show that brain signals contain key information about the user's cognitive state, translating these findings into an easy to use measure for usability evaluations and user experience reports has not happened. With eye tracking, there was a shift from using raw data about eye position and pupil size to new representations that combine the raw eye tracking data with the task and user interface to enable clear insights about attention and workload. For example, many tools today provide heatmaps that illustrate the locations of a user's eye gaze, providing actionable information about user attention for a particular user interface design. Today, it is challenging to connect brain signals to the user evaluation tasks. Further refinement of the representations connecting brain signals to user tasks will enable adoption of brain sensing in user experience research and usability evaluations.

## 9.3 Integration with Virtual, Mixed, and Augmented Reality

As not all types of interfaces are equally well suited for the use of brain data, brain input should be applied to areas in which it can provide biggest impact. Voice-based interaction on desktop computers is and



**Figure 9.1:** Smart room control based on Augmented Reality using brain input (Putze *et al.*, 2019).

has been a niche application, but became highly impactful on devices with limited manual input capabilities, such as mobile phones or augmented reality headsets. In recent years, Augmented and Virtual Reality (AR/VR) technology has matured technically and has become widely available as a tool to create complex and immersive applications. These applications cover a wide variety of areas, for example entertainment, education, art, and therapy, among others (domains which we also find among the most frequent ones using brain input, see Section 3). AR/VR technology and BCIs can mutually benefit from each other: On the one hand, the multisensory experience or augmentation through AR/VR technology allows to create scenarios which are much more stimulating and expressive than standard desktop applications. On the other hand, BCI technology can provide additional explicit or implicit input channels to manipulate or influence the virtual scenario when standard input controllers fall short or are unavailable. Putze (2019) introduces the fundamental promises, challenges, and tools for the combination of AR/VR with the processing of brain data; it also provides a review of relevant literature in this emerging field (Figure 9.1).

#### 9.4 User Centered Design and Rapid Prototyping

There is a need to lower the entry-barriers for non-BCI researchers and non-academic developers to quickly prototype new ideas and test them

with users. Again drawing from voice-based interaction, the advent of available tool kits, web services, and data sets has stimulated many voice-based interfaces as developers no longer need the expertise and resources to build the necessary technology from scratch. User interface design patterns are only beginning to emerge for implicit brain input (Solovey *et al.*, 2015) and have not been studied thoroughly. More work on developing guidelines and best practices are necessary.

A contributing factor for the inadequate user interfaces for brain input is the fact that prototyping, developing and debugging brain-based applications is difficult and conducting user evaluations is overly burdensome. This creates a barrier preventing rapid prototyping and early feedback from users. Further, existing tools do not facilitate designers in understanding the brain signals they are recording, what they mean, and how to best use them in intelligent interactive systems. There are few tools to support their development, and none that enable user-centered design, as has been standard for graphical user interface development. Thus, much of the principles and practice from HCI has not been adopted in HCI research with brain signals.

A key component of user-centered design is getting early feedback from users, before definitive design decisions are made or implemented. However, with current tools and practices, most brain-based applications are fully developed before ever being put in front of users, resulting in poor user experience. Prototyping, developing and debugging these systems is difficult and conducting user evaluations is overly burdensome, creating a barrier preventing rapid prototyping and early feedback from users. The need for acquiring authentic, in-context brain data further slows down the innovation and development process because of the overhead, cost and time required, even for early-stage prototypes.

These issues have meant that there has been little work exploring user experience metrics that are unique to brain-based applications. Further, general interface adaptation strategies and design guidelines for the effective use of implicit brain data as input are not well defined, due to the difficulty in developing and studying alternate designs. Currently, BCI application development requires a diverse skillset, including understanding of brain function, signal acquisition methods, signal processing, and machine learning, in addition to HCI, design and

software engineering. This steep learning curve and interdependence of numerous research areas limits the pace of BCI innovation.

This means that we are currently unable to fully exploit the potential benefits of input modalities, despite the expanding research literature that shows they have promise in HCI. Thus, user-centered design of the application itself often is neglected, while developers focus on obtaining robust brain signals from emerging sensing platforms.

### 9.5 Multi-Person BCI, Computer-to-Brain and Brain-to-Brain Interaction

To date, HCI research on brain data has primarily focused on sensing brain activity from one individual and using it as input to systems. However, recent developments point toward interesting new paradigms with multiple users as well as two-way BCIs.

In particular, multi-user brain-computer interfaces are becoming an emerging research topic through *hyperscanning*, which refers to taking simultaneous measurements from two or more individuals. This could make important contributions to improving team communication and collaboration.

In addition, there are early signs of a future where the brain itself could directly receive information, bypassing typical output devices such as screens or auditory displays. Thus, brain input would be transformed to a bi-directional channel (like speech processing and speech synthesis do for the channel of voice-based communication) to remove the asymmetry of this mode of communication. Transcranial magnetic stimulation (TMS) (Barker *et al.*, 1985) and transcranial direct current stimulation (tDCS) (Nitsche and Paulus, 2000) have been explored as a non-invasive methods for stimulating the brain for neurorehabilitation as well as to augment cognitive function.

While this is still mostly used in clinical settings, we see some emerging work that brings these technologies closer to use in HCI research. McKendrick *et al.* (2015) demonstrated that a wearable fNIRS-tDCS system is feasible and has potential for investigating cognition in realistic settings, with a focus on neuroergonomics. Škola and Liarokapis (2019) showed that tDCS could be used to evoke tactile sensation in



virtual reality to enhance the perception of touch. Going beyond systems designed for individuals, Rao *et al.* (2014) demonstrated a brain-to-brain interface, in which an individual's EEG data during a motor imagery task was sent over the internet to the motor cortex of another individual, via TMS, causing a hand to move generating touchpad input. This was further expanded into a three-person system, in which SSVEP-based signals from two individuals were sent directly to the visual cortex of a third individual via TMS, creating a phosphene in a third individual, who proceeded to control a SSVEP-based BCI (Jiang *et al.*, 2019a), based on the information received. However, important ethical issues must be considered (Hildt, 2019), with regards to individual autonomy.

# 10

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## Conclusions

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In this monograph, we outlined the use of brain signals specifically in HCI contexts. The previous sections revealed a number of key strengths that using brain signals in combination with HCI methods brings to the table, which we summarize below. We then discuss limitations that have been identified, which need be considered when working with these methods. We provide our perspective on balancing the strengths and limitations to recognize the opportunities ahead for the field, and then end by summarizing the contributions of this monograph.

### 10.1 Strengths

Brain data is continuously available during an HCI session and can thus provide continuous assessment of cognitive states and processes and is not necessarily tied to the occurrence of specific events or behaviors. Section 5 showed that a large variety of such states and processes can be uncovered from brain data and Section 4 showed that a number of different paradigms can be explored for the integration of brain signals. As the modeled states and processes are often very fundamental and general, brain input can contribute to a large number of different domains.

In contrast to other sensor-based methods of measurement, brain data gives early access to effects which are otherwise unobservable; for example, while a full-blown emotional expression is clearly visible from a video recording, it is also rare and often preceded by a longer period in time in which neural correlates of emotion are already measurable but did not yet influence the person's visible (or audible) expression. Another benefit of using brain input for system adaptation or evaluation is that it does not interfere with task execution or other types of interaction; measuring brain data is purely passive and does not require the user to become active. Consequently, brain input is often a consideration in cases where hands, eyes or voice are occupied with different tasks.

## 10.2 Limitations

A foremost limitation is the requirement for additional body-worn sensors: Cameras and microphones do not need to be attached to the user at all to capture data and other sensors can be hidden, e.g., in smart watches or glasses. This is not yet the case for brain sensing, although miniaturization has come a long way in recent years and will likely continue. Still, researchers should always consider the possibility that a less cumbersome sensor (or combination of sensors) might deliver the same result for a specific application. Alternatively, they could consider applications that already involve head-mounted technology, such as virtual reality devices.

In addition, we need to consider that brain data is susceptible to artifacts. When classifying and analyzing the data, we always need to consider that detected effects result from such artifacts and not actual neural processes; i.e., validation of effects is an important part of the analysis. In complex HCI applications, especially outside the laboratory, a clear discrimination of neural activity and artifacts is often difficult. This also means that many published research results which employ brain data in uncontrolled HCI scenarios without a validation of the underlying neural signals (e.g., when using the output of commercial EEG appliance as a blackbox) need to be taken with a grain of salt. However, there is a different perspective to this argument: Friedman *et al.* (2017) in their summary of a workshop on BCI in the wild

conclude that while “From a basic research perspective it is essential to distinguish between information extracted from the brain and other types of information picked up by the brain sensors”, however “From a practical point of view, however, [they] believe there is no reason to limit ourselves to ‘pure’ brain interactions”.

Another consequence of the low signal-to-noise ratio is also the fact that most analysis is limited to a small number of classes or conditions, often only two. This can also mean that cognitive or affective states, which are actually different (such as stress and workload (Secerbegovic *et al.*, 2017)), are clustered together as the model does not provide enough classes for a more granular representation. For many HCI applications, this lack of differentiation is acceptable when taken into consideration by the system developers. Another consequence of the applied methods for capturing brain activity is that it only provides access to cortical activity. Processes that have their origin in deeper brain regions, such as the amygdala, are harder to capture. Finally, manifestations of cognitive processes are person-dependent, due to anatomical, neurological, and cognitive differences. A consequence is that especially when considering more complex constructs and/or single trial classification, calibration data has to be collected for every individual (with the chance that the classification does not work at all for a small part of the user population, a phenomenon which has been coined “BCI illiteracy” Allison and Neuper, 2010). This limits the capabilities for one-shot interfaces that are only used a single time or for very short periods of time. Even in the best circumstances, brain signal classification often peaks at the 70–80%. This means that any system or analysis which relies on the output should take the error probability into account.

In addition, most studies have explored relatively simple cognitive state classification. For example, many systems attempt to classify “high” workload and “low” workload. However, cognitive processes are more complex, overlapping and continuous. Much more work is necessary to be able to fully capture a comprehensive picture of the user state. This may involve the use of non-neural context information, as acquired from other sensors, such as cameras, microphones, accelerometers. Additionally, we may need to involve computational cognitive models or task

models as scaffolding to support any information which we can extract from brain data.

### 10.3 What to Make of This?

A large number of successful use cases show that brain activity is capable of providing a valuable and unique perspective on HCI. On the other hand, there are a number of challenges, as seen in the discussion of the different levels of modeling cognitive states and processes (from well-defined, low-level neural responses to fuzzy, high level, complex constructs) in Section 5, the discussion of “Clever Hans” effects (machine learning models learning spurious relationships between labels and features) in Section 7.2, and the discussion of limitations in terms of generalizability and accuracy in Section 10.2. How can we bring these two conflicting perspectives together and where does this leave interested HCI researchers who are curious but also intimidated? It is our strong belief that researchers in HCI should be courageous to try to leverage brain activity, but also willing to learn from good examples that demonstrate how the aforementioned challenges can be tackled. Fortunately, newcomers to the field are not on their own and can use a large number of resources available to help. Besides more and more convenient hardware (see Section 6) and powerful software toolkits (see Section 7.3), several papers address typical challenges to research with brain data which may not be obvious. For example, (Brouwer *et al.*, 2015) compiled a valuable list of six common pitfalls which can occur over the course of research, such as “Define your State of Interest and Ground Truth” or “Eliminate Confounding Factors (or at Least, do not Ignore them)”. For each item, they provide references to several positive examples of how these pitfalls can be detected, mitigated, and avoided. Another great overview on typical traps during the whole processing chain, including data collection, data processing, and experiment design is Jeunet *et al.* (2018).

## 10.4 Summary

Our analysis of the literature in the field suggests that the use of brain signals is very varied across different domains, targeted cognitive and neural states, as well as the employed input paradigms. This variety on the one hand shows the large potential of using brain signals by many different researchers. On the other hand, we also saw that there is a large variety also in the employed methods. For example, there exist no standard data processing pipelines or even common file formats for representing brain signal data in HCI. This increases the entry barrier for newcomers to the field; in this monograph, we tried to give them an introduction and a number of references for further reading as an orientation. This includes aspects of data collection and modality/sensor selection, data processing and classification, as well as aspects of system design and evaluation on different levels.

Our discussion of research directions, strengths, and limitations shows that the field is gaining traction and exciting developments are emerging and becoming possible due to new technological developments and the availability of data and sensors. That being said, a number of the promises of brain input use are more than a decade old and researchers are still making steady, but step-wise progress towards them. As researchers move further toward sharing not only the results of successful studies, but also associated code, data, paradigms, as well as tales of failed attempts and less-than-perfect studies that others can learn from and built upon, it is our belief that we can achieve many of these ambitious goals before long.

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