# Towards BCI-based Implicit Control in Human-Computer Interaction

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**Abstract**

In this chapter a specific aspect of Physiological Computing is defined and discussed: implicit Human-Computer Interaction. Implicit Interaction aims at controlling a computer system by behavioural or psychophysiological aspects of user state, independently of any intentionally communicated command. This introduces a new type of Human-Computer Interaction, which in contrast to most forms of interaction implemented nowadays, does not require the user to explicitely communicate with the machine. Instead, users can focus on understanding the current state of the system and developing higher-level strategies for optimally reaching the goal of the given interaction. For example, the system can assess the user state by means of passive Brain-Computer Interfaces, which the user need not even be aware of. Based on this information, combined with information about the given context, the system can adapt automatically to the current strategies of the user. In a first study, a proof of principle is given by implementing Implicit Interaction to guide simple cursor movements in a 2D grid to a target. The results of this study clearly indicate the high potential of Implicit Interaction and introduce a new bandwidth of appications for passive Brain-Computer Interfaces.

# 1 Introduction

Technology affects almost every aspect of our lives—our jobs, transportation, entertainment, communication and social integration. As advances in technology serve as a catalyst for the steady progress of our society, industrial, scientific and governmental efforts focus on stimulating the development of new hard- and software which become more powerful day by day. As a result, information can be processed, analyzed and distributed by technical systems at a speed, in an amount and with an accuracy which far exceed the capabilities of human beings. Nevertheless, a human user is needed to control most technical systems because computers still lack the capabilities of intelligent thinking. However, a Human-Machine System (HMS) would work most efficiently if more parts of the human information processing system could be delegated to a machine. Ideally, the user would just be observing and interpreting the current state of the system and deciding on high-level strategies to reach the goal of the HMS based on information smartly distilled by the machine. Low-level control tasks executing those strategies are best left to the machine.

An everyday example for this line of reasoning would be an adaptive, open-ended electronic book. While reading the story, the reader evaluates the current events as either 'good' or 'bad'. If the book could assess these evaluations, it could 'steer' the story accordingly, by re-writing the storyline to better suit the reader's apparent preferences. Regardless of the reader's evaluations being conscious or not—they may simply be automatic, affective reactions to reading a story—the reader is not actively composing a story, nor explicitly instructing the system how it should continue: The focus is on reading and interpreting the story as it unfolds, while the actual changes to the book happen automatically, potentially even unbeknown to the reader. In a highly automated way, the computer would 'understand' the concepts developed by the user. Humans would give guidance to machines to efficiently solve a task.

Currently, Human-Computer Interaction (HCI) is far from such an ideal system. Firstly, users have to request information manually and, secondly, they need to give very detailed commands, usually in a cumbersome way. The first problem results from the fact that computers can store and process large amounts of information, and do that very differently from humans. Think about a logfile storing network activity over one day. Such information can be processed in a short amount of time by a computer, but is hardly accessible by users. The user must thus explicitly instruct the computer to parse it for them. The second problem is twofold. Firstly, humans usually think in larger concepts, while a computer is controlled by triggering small actions leading to the realization of such concepts. If you want to change the colour of a two dimensional figure of a cube, you easily could advise a human painter to do this by a simple sentence ("Please, paint the cube blue."), but when communicating this concept to a computer, you have to go step by step (defining areas, selecting specific shades of blue etc.). Secondly, input mechanisms like mouse and keyboard are cumbersome and often unnatural means for communicating intentions and instructions. In the above example, the step "defining areas" will likely consist of a large number of mouse movements and button presses. The user has to spend effort on translating intentions into commands, such that they can be processed by the machine. All of these problems lead to a high user workload resulting from tasks in infrastructural areas.

A lot of effort has gone into increasing the usability of technical systems by resolving one aspect of this problem. Current systems smartly aggregate and present available information such that it is easily accessible for the user when needed and can be perceived quickly and effortlessly. However, the other direction in human-computer interaction, that of sending information from the user to the machine, is also highly relevant. Communicating to the computer is still complicated and demanding. It mainly works based on explicitly sending detailed and small-stepped commands formulated by the user, as described in the examples above. Each communication in this direction increases the effort by the user to keep the interaction running. Hence, an increase in the overall efficiency of a given HCI could be achieved by dissolving most of the direct and explicit communication, which is unwieldy due to form, style and complexity from a human perspective. Once this is achieved, the user can focus on the task of guiding the interaction to its goal.
In such a scenario, the machine would still need to have information about the user's concepts, in order to process and provide appropriate information and prepare specific tasks in

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the interaction. This must thus, still, be communicated to the system somehow. But with *Implicit Interaction*, the machine is expected to infer this information automatically. This can only be achieved by extending the user model used by the machine—which is currently restricted to directly formulated commands—by information about the user's emotions, intentions and situational interpretations. Passive Brain-Computer Interfaces can be a tool for this as they provide information about even covert aspects of the (cognitive, affective) user state in real time. They can be used for implementing a secondary, implicit interaction loop which supports users in their main interaction, leading to an automated adaptation of the system.

The following parts of this chapter focus on the capabilities of passive Brain-Computer Interfaces for establishing implicit Human-Computer Interaction. An example shows that this could lead to a completely new type of interaction which reaches its goals even without the need for any command that is consciously generated. The user only needs to focus on understanding the current state of the interaction and the machine learns to reach the goal by investigating the user's cognition and interpretation automatically.

# 2 Brain-Computer Interfaces

## 2.1 The roots and history of BCI

The idea of "reading thoughts" with the electroencephalogram (EEG) was first mentioned by Berger in 1929 (as cited in Birbaumer 2006). He speculated on the possibility of processing human EEG waveforms using sophisticated mathematical analyses. The development of the first EEG-based "Brain-Computer Interface" (BCI) was pioneered in the early 1970s by Vidal (1973, 1977), who also coined the term BCI. Since then BCI has evolved "into one of the fastest-growing areas of scientific research" (Mak and Wolpaw 2009).

A BCI was originally defined as a new, non-muscular communication and control channel for sending messages and commands in real-time to the external world (Wolpaw et al 2002). By measuring brain activity associated with the user's intent and translating it into control signals for communication systems or external devices, a BCI bypasses the brain's normal output channels of peripheral nerves and muscles. Brain activity can be recorded from electrodes in the skull (invasive BCIs) or outside (non-invasive BCIs). Invasive BCI involves brain signals such as action potentials from nerve cells or nerve fibers, synaptic and extracellular field potentials and electrocorticography (ECoG) (for a review see Birbaumer 2006). A variety of methods may serve as non-invasive BCI. Besides EEG, these methods include magnetoencephalography (MEG, e.g. Lal et al 2005; Mellinger et al 2007), functional magnetic resonance imaging (fMRI, e.g. Lee et al 2009; Weiskopf et al 2003), and near-infrared spectroscopy (NIRS, e.g. Coyle et al 2004). Due to its relatively simple and inexpensive equipment and high temporal resolution, BCI research mainly focused on EEG as preferred recording method in recent decades.

From the early beginning in the 1970s, EEG-based BCIs have given rise to the hope of restoring independence to people suffering from diseases that disrupt the neural pathways through which the brain communicates with and controls its external environment. Among these are neurodegenerative and genetic neuromuscular diseases such as amyotrophic lateral sclerosis (ALS), Friedreich's ataxia or muscular dystrophies, multifactorial and polygenic disorders like multiple sclerosis, cerebral palsy or the Guillain-Barré syndrome, as well as severe neuromuscular impairments due to brainstem stroke or brain and spinal cord injuries. For severely paralyzed patients for whom the remaining control (e.g. eye movement) is weak, easily fatigued, or unreliable (Wolpaw et al 2002) BCI serves as the only remaining channel for communicating with the outside world. The resulting condition is called locked-in state (LIS) if the basic control of at least one muscle is present (Birbaumer 2006). However, for most cases an easier and more efficient communication can be established by exploiting any remaining muscle rather than employing a BCI (e.g. communication via eye blinks or cheek muscles). As neuronal degeneration progresses the patients become completely paralyzed (e.g. late-stage ALS). They lose control over all voluntary muscles including eye movement and respiration and are "locked in to their bodies, unable to communicate in any way" (Wolpaw et al 2002). For completely locked-in state (CLIS) patients, research has shown that basic communication cannot be restored with BCI (Birbaumer 2006; Kübler

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and Birbaumer 2008). Whether CLIS constitutes a unique BCI-resistant condition or if individuals are able to retain the capacity for BCI use if they begin employing it before becoming completely locked-in, remains an open empirical question (Kübler and Birbaumer 2008). Beyond this initial motivation for BCI research to enable communication, other BCI applications can be used to transmit brain signals to muscles or to external orthotic devices in order to restore movements in paralyzed limbs. Such so-called neuroprostheses generally use functional electrical stimulation (FES) to "elicit action potentials of the efferent nerves, which provoke contractions of the innervated but paralyzed muscles" (Müller-Putz et al 2006b). Based on this principle, neuroprostheses artificially compensate for the loss of voluntary muscle control. These originally intended BCI applications have in common that they usually require voluntary and directed commands by the user to enable spelling or the control of an external device.

## 2.2 Categorization of BCIs

Alongside these accomplishments, a recent direction within the research field of BCI attempts to broaden the general BCI approach by substituting the user's command with passively conveyed implicit information. Based on this thought, a new categorization of BCI systems was proposed by Zander and colleagues (Zander et al 2010b), dividing BCI-driven applications into active, reactive and passive BCI systems.

**Active BCI**. An active BCI derives its outputs from brain activity which is directly and consciously controlled by the user, independent of external events, for controlling an application.

**Reactive BCI**. A reactive BCI derives its outputs from brain activity arising in reaction to external stimulation which is indirectly modulated by the user to control an application.

**Passive BCI**. A passive BCI derives its outputs from arbitrary brain activity arising without the purpose of voluntary control, for enriching a human-machine interaction with implicit information on the user state.

## 2.3 Important Applications of BCIs

### 2.3.1 Active BCI

Early examples of active BCI systems are based on slow cortical potentials (SCP). SCPs are slow voltage changes generated in the cortex that can last from less than half a second up to several seconds (Birbaumer et al 1990). With frequencies down to 1 Hz they are among the lowest frequency features of the EEG. It could be shown that both healthy users and paralyzed patients can be trained to self-regulate these positive and negative voltage shifts in order to control external devices by means of a BCI (Birbaumer and Cohen 2007). Most commonly SCP-based BCIs are used for cursor control and target selection, such as spelling (Birbaumer et al 1999, 2003; Hinterberger et al 2004). Despite acceptable accuracy rates, a SCP-based BCI needs long training time, sometimes up to several months, and provides only slow communication with usually around one letter per minute (Birbaumer 2006).

More popular active BCI systems utilize the sensorimotor rhythm (SMR). SMR comprise "mu and beta rhythms, which are oscillations in the brain activity localized in the mu band (7-13 Hz) [...] and beta band (13-30 Hz)" (Nicolas-Alonso and Gomez-Gil 2012). SMR-based BCIs operate on the principle of movement-related frequency changes in the ongoing EEG activity over sensorimotor areas. Due to decreased synchrony of the underlying neuronal populations during the performance of such movements, the power in the mu-rhythm decreases (Pfurtscheller and Lopes da Silva 1999). This phenomenon is called event-related desynchronization (ERD, Pfurtscheller 1977) and is measured to effect control in SMR-based BCIs. Besides ERD, post-movement beta rebound (event-related synchronization (ERS), Pfurtscheller 1992) can also be employed for classification (Bai et al 2008). For BCI, the significance of SMR definitely lies in the fact that it is not only attenuated by actual movements, but also by intended (Kübler et al 2005) or imagined ones (Wolpaw et al 2000) in paralyzed patients and healthy subjects respectively. For the latter, the term motor imagery (MI)-based BCI has been established in the field of research. SMR-based BCIs have been extensively investigated since the mid-1980s (Wolpaw et al 2002). Similar

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to SCP-based BCIs they are most commonly used for cursor control in order to select letters or icons on a screen (Daly and Wolpaw 2008). Besides one-dimensional control, both two-dimensional (Blankertz et al 2007; Wolpaw 2004) and three-dimensional control (McFarland et al 2010) can be achieved by employing MI of several limbs, such as right hand, left hand and foot. Furthermore, the multidimensional control of neuroprostheses (Müller-Putz et al 2005; Tavella et al 2010) and orthotic devices such as robotic arms (McFarland and Wolpaw 2008; Pfurtscheller et al 2000) has been accomplished with the support of MI-based BCIs. However, due to its relatively low bit rates and only moderate accuracy rates compared to for example reactive BCIs (Guger et al 2003, 2009), the real-world application of MI-based systems is extremely limited. Beyond that, a non-negligible portion of users (15-30%)—so-called BCI illiterates—fail to gain any MI-based BCI control (Blankertz et al 2010).

### 2.3.2 Reactive BCI

The vast majority of systems based on reactive BCI employ event-related potentials (ERP). An ERP is the brain response to an external or internal event such as a visual, auditory or tactile stimulus. The most prominent and best-studied ERP is the P3 (also P300) component, a large positivity that is elicited in the central-parietal region of the brain 300-500 ms post-stimulus upon rare events. For BCI purposes an oddball paradigm is usually applied. A rare target event (e.g. the target letter) is presented among frequently appearing nontarget events (e.g. remaining letters of the alphabet). The user's focused attention on the presented target leads to a noticeable increase of the P3 amplitude that can be extracted from the EEG. Based on this principle, the target letter will be selected. The first P3-based speller, the so-called matrix speller, was introduced by Farwell and Donchin (1988). Since then, similar P3 spellers have been extensively investigated and developed (Nijboer et al 2008; Sellers and Donchin 2006). Another constituent of the ERP, the N2 (also N200), a parieto-occipital negativity typically evoked 180-320 ms following the stimulus presentation, appears also to be closely associated with cognitive processes of perception and selective attention (Patel and Azzam 2005). For this reason Treder and Blankertz (2010) advocate the use of the term ERP-based BCI in order to emphasize the fact that "there is a multitude of ERP components that is affected by attention and can be exploited by classifiers". Most recently, advances have been made towards gaze-independent spellers (Acqualagna and Blankertz 2011; Treder et al 2011) or spellers adapted to non-visual modalities by using auditory (Furdea et al 2009; Schreuder et al 2011) and tactile stimulation (Brouwer and van Erp 2010) (for a review also see Riccio et al 2012).

Other reactive BCIs are frequency-based by exploiting steady-state evoked potentials (SSEP) that occur in response to a visual, auditory or tactile stimulus that is presented at a steady rate. For instance in a steady-state visually evoked potential (SSVEP)-based BCI several stimuli, each flickering at different frequencies (typically in the range of 3.5-75 Hz, Beverina et al 2003), are presented to the user (Bin et al 2009; Gao et al 2003). By the user's focused attention on one of the steadily flashing stimuli, the brain produces detectable oscillations of the same frequency in the visual cortex. Further examples for BCIs utilizing steady-state somatosensory evoked potentials (SSSEP, Müller-Putz et al 2006a) or steady-state auditory evoked potentials (SSAEP, Hill and Schölkopf 2012) have been proposed.

### 2.3.3 Passive BCI

Systems based on passive BCI can provide information about Covert Aspects of the User State (CAUS), i.e. task-induced states which can only be detected with weak reliability using conventional methods such as behavioural measures (Zander et al 2010b). Restricted forms of passive BCIs have in the past proven to be valuable tools for detecting mental workload (Kohlmorgen et al 2007), working memory load (Grimes et al 2008), fatigue (Papadelis et al 2007), self-induced errors (Blankertz et al 2002a), deception (Fang et al 2003), or anticipation (Gangadhar et al 2009). However, those systems only focused on user-state detection alone and the information gained about CAUS has not been fed back into the system to enrich the human-machine interaction. More recent examples pursuing this notion include detecting and correction of self-induced (Schmidt et al 2012) or machine-induced errors (Zander et al 2010b).

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## 2.4 Extending the definition of BCI for applications including users without disabilities

In contrast to active or reactive systems, a passive BCI does not interfere with other means of the human-machine interaction. It can be "reliant on either the presence or the absence of an ongoing conventional human-computer interaction, or be independent of it" (**complementarity**, Zander and Kothe 2011, p. 4). Furthermore, "a passive BCI application can make use of arbitrarily many passive BCI detectors in parallel with no conflicts, which is more difficult for active and reactive BCIs due to the user's limited ability of consciously interacting with multiple components simultaneously" (**composability**, Zander and Kothe 2011, p. 4). "Since no conscious effort from the user is needed for the use of passive BCIs (besides preparation), their operational cost is determined by the cost of their false alarms. Passive BCIs producing probabilistic estimates, together with the a priori probability of predicting correctly, could potentially be designed allowing for arbitrary levels of cost-optimal decision making at the application level. In that way, theoretically, systems could be designed which would only gain in efficiency by utilizing a passive BCI and could have zero benefit in the worst case" (**controlled costs**, Zander and Kothe 2011, p. 4).

As the concept of passive BCI offers the key properties of complementarity, composability and controlled cost, its application spectrum is not limited to users with disabilities. Moreover, it adds an additional information channel conveying highly relevant information about the user. Besides information about the user state, data of the environment and the technical system could augment the available information space and thereby add *context awareness* to the system (Zander and Jatzev 2012). These additions can be used to "improve the actual state-of-the-art human-machine interaction by enabling the technical system to adapt to the user without any additional effort taken by the user" (Zander and Kothe (2011), p. 3).

# 3 Brain-Computer Interfaces and Physiological Computing

Physiological Computing (PC) aims at integrating real-time physiological measures into an HMS, such that the technical system gains insight into the cognitive and emotional state of the user, allowing it adapt itself accordingly.

## 3.1 Passive Brain-Computer Interfaces for Implicit Human-Computer Interaction

### 3.1.1 Explicit and Implicit Interaction

In a given HMS, the user and the technical system communicate with each other to reach a certain goal, as described in Rötting et al (2009). In the more specific context of HCI, this is usually done through an interaction cycle where user and computer exchange information in an *explicit* way: Changes in the state of the machine are explicitly communicated to the user so that this information can feed the next cycle. Similarly, all communication from the user to the machine is based on specific commands which are explicitly formulated and directed by the user. Hence, we define explicit control as the intentional directing of commands at the interface of a computer system, which then follows the instructions.

We define overt and covert commands as being dependent on, respectively, overt and covert aspects of the user state (cf. overt and covert attention). Explicit commands are usually overt, but they do not have to be, as in the case of an active BCI (see section 2.3.1). Other examples of explicit control are the use of a computer through peripheral controls such as mouse or keyboard, or more recently also speech and gesture recognition.

*Implicit Control* on the other hand, we define as an automatic state change of a technical system based at least in part on an evaluation of the user's current state, without any actual commands to that effect being intentionally communicated to the system by the user (see also Fairclough 2009). Although the user may be aware of neither the communication nor

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the system's state changes, these state changes are ultimately based on the user's state. Just like explicit commands, implicitly sent commands can be covert or overt.

In interpersonal interaction the verbal context of speech is an example of explicit interaction, as described in Schmidt (2000); Rötting et al (2009). But often implicit information has to be taken into account so that the intent of the message can be understood more easily, as sometimes the speaker's intention can hardly be inferred from the words alone. Intonation, volume, gestures or facial expressions are examples of *implicit* information which can change the meaning of a message entirely. A sarcastic statement is a good example for a message that can change its meaning depending on implicit information. It can be taken as proof for the importance of the affective context of communication that *Emoticons* (Rivera et al 1996) have become an important part of text-based interaction.

In the following we refer to a given HCI based on implicit commands as *Implicit Interaction*.

### 3.1.2 Forms of Implicit Interaction

Implicit Interaction is not only relevant for interpersonal interaction. As described in Schmidt (2000), information about the context of a given system and the user's behavioural actions can be used for implicit interaction. In addition, forms of HCI can potentially be improved if the technical system is able to detect cognitive processes such as attention, engagement or workload. Such information could be used to enable a system to adapt to the users state and thereby make HCI more usable, comfortable, intuitive and entertaining (Rötting et al 2009). Also the affective state of the user such as frustration, confusion, disliking or interest (Picard 1999) carries useful information.

An attempt at a Human-Computer Interface that adapted to behavioural measures of the user, which can be seen as an early realization of the ideas stated in (Schmidt 2000), was *Clippy*, the automated assisstance in Microsoft Office '97 (Microsoft Corp., Redmond, USA.). Most users found Clippy to be highly intrusive, as it was inaccurate in estimating the users intentions, which introduced switching costs (Squire and Parasuraman 2010) and led to frustration (Whitworth 2005). The reason for the low accuracy of this automated adaptation is that it is based solely on short-termed information about the user's behaviour, which can be an unreliable source of information (Müller et al 2008). Incorporating implicit information about the user state, i.e. information about the situational interpretation, could potentially have improved this system, without increasing the users workload, and may hence have led to a better user acceptance.

### 3.1.3 Assessment of Implicit Information

Even though we can assert that adding implicit information about the cognitive or affective state is important, it is unclear how this can be achieved in an efficient way. One promising approach is using psychophysiological measures, as these are suited to convey information about changes in the user state. Galvanic skin response, which measures change in conductance of the skin, is sensitive to changes in cognitive constructs such as workload (Shi et al 2007) or stress (Lazarus et al 1963) but also relative to specific events such as errors committed by the subject (Hajcak et al 2003). Similarly, cardiac measures such as heart rate or electrocardiogram (ECG) are responsive to cognitive, physical and environmental influences (Hankins and Wilson 1998; LeBlanc et al 1976). Yet these methods have clear downsides. The relation of such signals to the user's cognitive state is inherently indirect. Physical effects such as these are usually the result of cognitive or affective changes, and thus carry only indirect information about these. As bodily processes are also modulated by other factors, they can indeed be sensitive but are usually not very specific to any one aspect of cognition or affect.

For certain aspects of cognitive and affective state the EEG appears to be a more direct and hence better measure. Often changes in cognitive and affective state are initiated in the human brain. As EEG reflects changes in cortical activity, it is capable of providing direct information about the source of certain state changes. As CAUS (see section 2.3.3) are only hardly reflected in bodily processes, measuring cortical activity might be the only way to access information about these specific changes in cognitive and affective state. An example for this can be found in Zander et al (2011), where a passive BCI is used to

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detect the (covert) intention of moving an index finger, before the onset of muscular activity.

As the the autonomic nervous system (ANS) and the human brain are inherently interconnected, changes in cognition also might be triggered by the ANS, and hence, the EEG is not necessarily the most direct link to cognition. Nevertheless, EEG is a multi-channel biosignal, that can measure direct, physical manifestations of cognition. In addition, even though the EEG has clear limitations in spatial resolution, it allows for simultaneous assessment of different aspects of human cognition (see composability, section 2.4), as we can identify multiple cortical sources contributing to it. EEG provides a comparably fast temporal resolution, modulations in the ECG for example may be as fast as 2-3 seconds, while EEG signals usually respond within hundreds of milliseconds. The evaluation of EEG data in real time for Implicit Interaction is one main application for passive BCI and directly follows its definition (see section 2.2). Hence, it is a direct and worthwhile means for assessing information about the user state.

## 3.2 Possibilities for Beneficial Multidisciplinarity of BCI- and PC-Research

The combination of PC- and BCI-based research can provide mutual benefits. The methodology of BCI research can prove valuable to PC, in particular single-trial classification of physiological measures, and PC can open a new variety of applications for BCI technology.

### 3.2.1 Passive BCI Methodology for Physiological Computing

Over the past four decades of BCI research, machine learning has become a fundamental part of the field. Initially BCIs consisted of predefined classifiers which the users had to adapt to, as described in 2.3.1. Machine learning made it possible to shift this training effort from the user to the machine (Müller et al 2004).

To allow the technical system to learn the characteristics of a certain signal, exemplary data is collected in a calibration phase. Multiple trials for each experimental condition are recorded. Features are extracted from these data sets, for example, certain temporal, spectral or spatial aspects or distributions. Machine learning then derives a model that emphasizes features that provide maximal discriminability between the conditions. This model is used in the BCI to evaluate new data sets and assign them to one of the cognitive states that are of interest. This still relatively time-consuming calibration has to be undertaken individually for each subject and usually for each session. In future BCIs this problem might be solved through subject-independent classifiers, also called universal classifiers (Reuderink et al 2011; Zander 2011; Wolpaw et al 2002). Such classifiers are predefined (for example through training on a group of subjects) and are capable of accurate single-trial classification of an aspect of the users state independent of the subject. Individual training of the subjects can then be omitted. The BCI community has developed and advanced many different approaches to feature extraction and machine learning, and adopted approaches and techniques from other fields of neurophysiological analysis. For the definition of predictive models many different approaches from machine learning have been used: from support vector machines (SVM) to linear or quadratic discriminant analysis (LDA and QDA) (Duda et al 2001) to non-linear kernel SVM (Schöllkopf and Smola 2002) and up to advanced methods building on artificial neural networks (Balderas et al 2011). Because features usually are gaussian and due to the low complexity (low Vapnik-Chervonenkis dimension) of LDA, LDA is less prone to overfitting (Vapnik and Chervonenkis 1971). Another major advantage of LDA over SVM is that it is robust against imbalanced trial numbers between classes, as it is based mainly on an estimation of covariance matrices (Duda et al 1973).

Implementations of these approaches have been made public through toolboxes and platforms such as BCILAB (Kothe and Makeig 2013), BCI2000 (Schalk et al 2004) or OpenVIBE (Renard et al 2010) that allow for easy access to BCI tools and methods.

### 3.2.2 New Applications of BCI technology in Physiological Computing

For a long time, the main purpose for BCI research was to provide people with severe physical impairments with a form of communication. This was usually achieved through active or reactive BCIs (see section 2.1, 2.3.1 and 2.3.2). With the introduction of passive

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BCI applications it was shown that new possibilities arise if the initial methodology is extended (Zander et al 2010a,b) (see also 2.4).

Since then, the main application of passive BCI technology is automated adaptation of a technical system in an HMS. This can be achieved through the interpretation of the user state (Zander and Kothe 2011), containing interpretations of situational events like errors committed (Blankertz et al 2002b) or perceived (Ferrez and Millán 2008) or user intentions, like intending to interact with the system (Protzak et al 2013). Passive BCI technology can also be used to monitor the user state or to give neurofeedback.

Since its initial definition, BCI research mainly focused on one input modality reflecting brain activity. Recently, it opened up for multi-modal approaches, as described in Pfurtscheller et al (2010). This development allows for an interconnection between the field of PC and BCI, such that the bandwidth of applications for BCI technology is extended significantly. PC already found application in different types of HCI, which can now easily be combined with (passive) BCI technology. One main aim of PC is to extend the range of possible applications and promote the development of hybrid systems, and hence, its methodology allows for combining different sources of information such as galvanic skin response, cardiac measures or even behavioural measures into combined feature spaces. Such measures make it possible to assess the user's emotions quite accurately, which has proven to be difficult through BCI only. Under the term affective computing (AC) emotions such as anger, happiness, sadness and surprise were classified successfully through a combination of psychophysiological measures (Canento et al 2011).

Another benefit of combining BCI with physiological input was shown through the combination of eye tracking with a passive BCI. This provides an elegant approach to overcome a common problem in gaze-based interaction. Usually the affirmative action is executed through dwell times, blink patterns or active BCI (Vilimek and Zander 2009) which are not always easy to control and also are not comfortable to use. This is called the *Midas Touch problem* (Jacob et al 1993). It was shown that one efficient solution is to assess the user's intent to interact with an icon through a passive BCI (Protzak et al 2013) and to combine it with a dwell time selection. In this study Protzak et al. showed that in a dwell-time based interaction the intention to interact can be detected by a passive BCI. Activity in parietal cortex showed a significant difference during trials where subjects interacted with the system compared to trials where they just looked at items on the screen. A pseudo-online evaluation revealed that it is possible to correctly predict the users intend to interact in single trial with an average accuracy of 81%. A system that uses eye tracking and a passive BCI combined is an excellent example for a HMS using PC to establish intuitive HCI.

### 3.2.3 Influences on the EEG-Signal: Artifacts or Features

In PC, eye movements or muscular activity are considered to be input modalities used for HCI. Contrarily, in BCI research signals generated from such activity are considered artifacts. Strictly speaking, a BCI should process input solely from electrical activity within the central nervous system (CNS, Wolpaw et al 2002). Factually this requirement can hardly be met. Even under laboratory conditions, first degree artifacts, such as eye or neck muscle movements, and second degree artifacts, such as changes in the electromagnetic field, will always be part of the recorded EEG signal (Zander 2011). The amplitude of these signals exceeds that of any cortical signal by an order of magnitude. Where the artifacts are independent of the context investigated in the experiment they are uncritical but merely lead to a lower signal to noise ratio. If artifacts are dependent of conditions investigated, they will contribute strongly to the predictive model of the BCI. In that case, the resulting BCI model may be more dependent on artifacts than on cortical activity. Whether artifacts can be used as a reliable control signal that can be included in passive BCI is strongly dependent on the type of interaction investigated. In systems where such artifacts are significantly related to the aspects of user state under investigation, they can be useful additions to or even replacements of cortical signals.

Hence, the question whether artifacts should be used for HCI (as proposed in section 3.2.2) based on passive BCI is hard to answer. Our behaviour and our physiology are sensitive to changes in environmental context. Think about changes in your mimicry during social interaction compared to it in privacy. Such changes also affect artifacts produced by such behaviour. Therefore, an interaction including artifacts will also be dependent on the context of the interaction. We assume that basal brain activity representing cognitive or

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affective processes of interest are more robust to contextual modulation. Nevertheless, this still needs to be proven.

### 3.3 Passive BCI for Implicit Interaction Beyond Secondary Input

The differentiation between explicit and implicit interaction is important for HCI because both forms contain information that is needed for comprehensive interaction. In most applications of passive BCIs, it is intended for secondary input supporting the primary interaction (Schmidt et al 2012; Zander et al 2010b; Blankertz et al 2002a). However, passive BCI technology could ultimately be used as the only input. In such a scenario the user acts as a critic of an external autonomous system and in doing so, effectively controls it. This would be a completely new type of HCI that renders any explicit input from the user unnecessary since the perception and interpretation of the environment would serve as input.

This form of interaction would be highly intuitive to use since it does not need any instructions (Fairclough 2008). The HCI converges to the goal of the HMS by tracking the process of the user learning about and understanding the current system state. The user does not need to intend to interact with the system, and does not need to translate any mental abstract concepts to small-stepped command sequences, which reduces the workload to a minimum. This also satisfies the demand made in the introduction, for an HMS that runs autonomically and only shifts effort to the user that needs intelligent thinking.

In the following section an example is given of a system which only is guided only by Implicit Interaction based on passive BCI.

## 4 Passive BCI for Implicit Interaction: An Example Study

The following study by two of the authors may serve to illustrate the concept of implicit interaction.

Krol, Gramann and Zander (in press) investigated the use of a passive BCI to control the movement of a cursor in two dimensions. The cursor was not controlled directly, but moved autonomously: Implicit interaction with the cursor was realised by adapting its directional movement biases, based on the presence or absence of error negativities evoked by the cursor's movements. An error negativity is a "negative deflection in the ongoing EEG seen when human participants commit errors" (Holroyd and Coles 2002), and can also be seen after the passive observation of errors being committed (Van Schie et al 2004).

When, for example, an upwards movement of the cursor was followed by an error negativity, as detected by the passive BCI, the probability of repeating that movement was reduced. In short, rather than actively controlling the direction in which the cursor should go, the subjects were passively observing and interpreting the cursor's initially random movements, and the cursor responded to those interpretations by making its movement increasingly less random.

### 4.1 Experimental Design

The cursor as used in the study was a red circle, that could move from one node to any of the adjacent nodes in grids of varying size. These grids consisted of grey open circles, slightly larger than the cursor, connected by grey lines, on a black background. Depending on the cursor's position in the grid, then, there were up to eight possible movements.

An animation allowed the subjects to be able to anticipate the moment of each movement. As illustrated in figure 1 (top), over the course of one second, a white 'ghost cursor' would grow inside the actual cursor. As soon as this ghost reached the same size as the actual cursor, it would instantaneously jump to the next node, also highlighting the grid line connecting the two nodes in white. The movement remained visible for one second, with the red original cursor still on the initial node, the white ghost cursor on the new node, and a white line connecting them. Following that, the white elements disappeared and the (red) cursor would instantaneously move to and remain at its new position, on the new node, for another second, before the animation would start over for the next movement.

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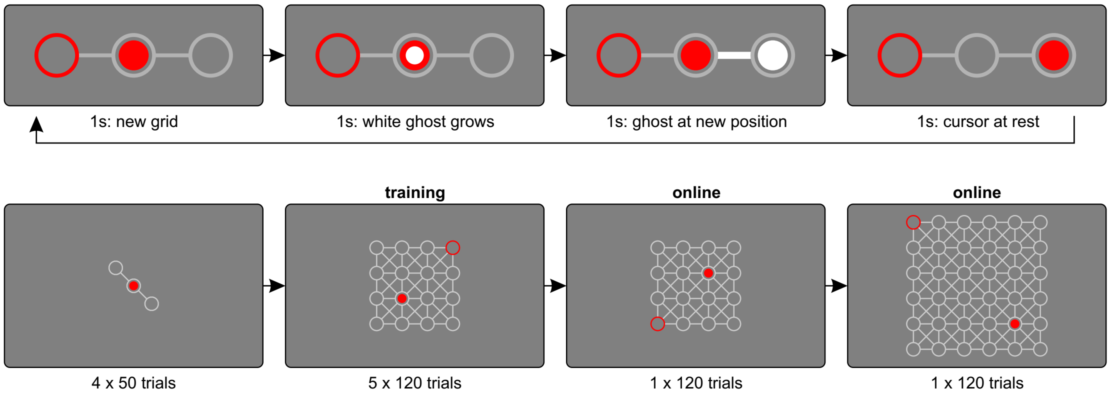


Figure 1: *Above*: Stimuli over the course of one ('incorrect') trial in the example study, on a one by three grid. *Below*: Illustration of the study's blocks and grids. The number of blocks and trials for each grid is indicated. Data from the blocks labelled 'training' were used to train the classifier. The last two blocks, labelled 'online', were BCI-supported.

Three different grids were used in the study: One by three nodes, four by four, and six by six. In each grid, a single red node in one of the corners indicated the target. Whenever the cursor reached this target, a new grid was started of the same size. For the one by three grids, each new grid was rotated a random integer multiple of 45 degrees as compared to the previous grid. The four by four and six by six grids did not rotate, but a new target was selected for each new grid, such that no two subsequent grids had a target in the same corner. In all of these grids, the cursor's starting position was one node away from the opposite corner, in a straight line to the target. Each newly started grid was displayed for one second before the first movement was initiated.

Additionally, a new grid was started when a certain number of movements had been made without reaching the target. For the one by three grids, the maximum number of moves was one; for the four by four grids, the maximum was 55, which is one and a half times the mean number of random movements required to reach the target. No maximum other than the block's length (120) was set for the six by six grid.

With the one additional second added for the subjects to orient themselves after a new grid was started, a trial in the one by three grids took four seconds. In the other two grid sizes, a trial took three seconds.

## 4.2 Subjects, Setup, and Procedure

A total of sixteen subjects participated in this study, with an average age of 25.9 years $\pm$ 3.4. All had normal or corrected to normal vision.

After preparation and setting up the EEG cap, which took up to one hour, subjects were seated comfortably in a padded chair in a dimly lit room. In writing, they were instructed to judge every individual movement of the cursor as either 'acceptable' or 'not acceptable',with respect to reaching the goal, and to indicate their verdict by pressing either 'v' or 'b', respectively, on a standard German layout computer keyboard using the same finger of one hand. This task was intended to keep the subjects focused on the cursor's movements. The subjects performed this task during all blocks.

EEG was recorded continuously using 64 Ag/AgCl electrodes mounted according to the extended 10-20 system on an elastic cap (Easy Cap, Falk Minow Services). The signal was sampled at 500 Hz and amplified using a 250 Hz high cutoff filter via BrainAmps (BrainProducts, Munich). All electrodes were referenced to FCz.

The experiment itself took about one hour. As illustrated in figure 1 (bottom), subjects were first shown four blocks of 50 trials on a one by three grid, and following that, five blocks of 120 trials on a four by four grid. These latter five blocks were used to train the passive BCI classifier. This classifier was then used in two online blocks: One block of 120 trials on a four by four grid, and one block of 120 trials on a six by six grid.

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## 4.3 Feature Extraction and Classification

Two groups of cursor movements were built to train the classifier. One group consisted of those movements that went directly towards the target ('correct' movements), and the other of those whose direction deviated 135 degrees or more from a straight line to the target ('incorrect' movements). Of all 600 trials in the four by four grids, this selection left between 162 and 217 (mean: 185.3) trials per subject for the classifier to be trained on.

Note that the subjects' judgements, indicated using button-presses, were ignored: Only a movement's angle with respect to the target determined its group.

The open-source toolbox BCILAB (Delorme et al 2010) was used to define and implement the BCI. Features were extracted by the Windowed Means approach (Blankertz et al 2011), which calculated the average amplitudes of eight sequential time windows of 50 ms each, starting at 300 ms after cursor movement. For this feature extraction, the data was first resampled at 100 Hz, and bandpass filtered from 0.1 to 15 Hz. Classification of these features was done through Linear Discriminant Analysis (Duda et al 2001), regularised by Shrinkage (Blankertz et al 2011).

A [5,5]-times nested cross-validation (Duda et al 2001) with margins of 5 was used to select the Shrinkage regularisation parameter, and to generate estimates of the model's online reliability, as reported below. A model was trained before the first online block, for each subject individually.

## 4.4 Implicit Control

In the two online blocks, the trained classifier was applied to all cursor movements without any knowledge of the angular difference to the target. Each new grid started with all directions having equal probabilities. If a movement was classified as 'correct', the probability of that movement's direction was increased, as well as, to a lesser extent, the probabilities of its two neighbouring directions. When a movement was classified as 'incorrect', these probabilities were reduced. The cursor did not undo incorrect movements or directly repeat correct movements, but merely altered the relevant probabilities for subsequent trials. Over time, then, this system was hypothesised to gradually "steer" the cursor more and more into the target's direction. This steering would be done on the basis of event-related potentials evoked by the subjects' judgement of the cursor's own, autonomous movements—*not* by any actual *intent* to steer the cursor.

## 4.5 Results

The average classification rate over all sixteen subjects, as estimated using the method described above, was 71%, with a standard deviation of 7.6 percentage points. This indicates a substantial improvement over chance level, which is 50% for a binary classifier as used here.

It is important to note that classifiers trained on cursor movements and cursor movements alone, outperformed classifiers that somehow took button presses into account. For example, a classifier trained to distinguish between trials where the subject pressed one or the other button, respectively, had a lower accuracy than a classifier trained to distinguish only between different cursor movements (e.g. deviating $< 45°$ versus $\geq 45°$ from a straight line to the target). This suggests that classification was, at least in part, performed on passive, implicit signals that differed from the subjects' conscious acts.

The performance of the cursor was operationalised as the average number of movements required to reach one target. For the BCI-supported performance, averages were calculated per subject over all 120 online trials of the respective grid size. Trials at the end of a block that did not contribute to reaching a target or hitting the maximum number of trials for that attempt, were discarded. The BCI-supported data was compared to an equal sample size of non-supported (random) performance measures over the same number of trials. A Wilcoxon rank-sum test revealed significant differences between non-supported performance (median = 27.6) and BCI-supported performance (median = 19.9) on both the four by four grid, $W = 171.5$, $z = 3.5$, $p < 0.001$, $r = 0.61$, and on the six by six grid (median = 76, unsupported, versus 22.6, supported), $W = 123$, $z = 2.7$, $p < 0.01$, $r = 0.53$.

In summary, these results indicate that the classifier was reliably capable of differentiating between movements going towards, and away from the target, without itself knowing where the target was. When this information was used to adapt the cursor's behaviour, a

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marked improvement was seen in terms of cursor performance. This enabled the subjects to effectively guide the cursor towards the target, even though they were attending to a fundamentally different task.

# 5 Discussion and Conclusion

The main result of the theory and the experiment presented in this chapter is that implicit human-computer interaction, incorporating information about the user state, is indeed a realistic concept. The development of and experience with passive BCI provides tools which perfectly fit in this concept. Implicit control theoretically allows for a highly efficient way of interacting with technical systems, as it aims at distributing tasks between the machine and the user along their specific capabilities. In the best case, this distribution is optimal and both machine and human learn from one another during the interaction—their strategies converge efficiently.

The implicit approach might not always be the most effective way to solve a task. In the study presented here it is clear that a user focusing fully on the task and having standard explicit control would reach the target much faster. This is mostly a result of the fact that the scenario is very simple, the optimal strategy to reach the goal is obvious and an intuitive explicit control is easy to establish with eight direction keys. However, a more elaborate passive BCI approach could be applied in scenarios closer to real-world applications. One could envision an example, where a technical system is distributing tasks between a team of experts, e.g. air traffic controlers in a tower, along their current level of workload or stress. In that scenario mistakes resulting from over- or underloading team members could be reduced. The interpretation of the passive BCI output would then be more complex but it should still be feasible for a computer system. Hence, implicit control might not be the most suitable way of interacting in every given HMS, but it could be for some and it defines a new and more intuitive interaction. This becomes particularly clear when we take into account that most of the systems we currently have available are designed for explicit control. Over several steps such systems could be enhanced by adding implicit control, for example for automated error correction during automated adaptation as described in Zander (2011). Future systems, directly designed for implicit control, might then reveal the full potential of this new type of HCI.

From the perspective of BCI research, the main advantage of passive BCI comes into play: Its independence of bitrate (Zander 2011). As most BCI approaches, active and reactive, aim at realizing an interface for direct communication and control, but provide only a very limited reliability, they often do not succeed reaching their goal. Additionally, users have to spend a significant amount of effort to keep control and often perceive this as being frustrating (Lorenz et al 2013). With the statistical approach of implicit control based on passive BCI presented here, it is shown that even with a low accuracy of 70% the system reaches its goal efficiently, and with no additional effort taken by the attentive user.

Nevertheless, from a usability perspective, there are still significant hurdles to be taken. Most realizations of BCIs based on Machine Learning, like the one presented here, need a time-consuming calibration phase. A significant number of prototypes of the features, in current BCI systems typically at least 40 to 80 per class, have to be generated to calibrate the BCI model. In currently available BCI frameworks, this has to be repeated before each session, which is time consuming and might be annoying for the user, both depending on the complexity of generating the investigated user state. In addition, the setup of an EEG system is cumbersome and time consuming, as usually several dozens of electrodes need to be gelled on the user's head. Several solutions to these problems have been proposed and are currently being investigated. Universal classifiers (Zander 2011) or reduced-training BCIs (Krauledat et al 2008) could reduce the calibration time to an acceptable level. The time needed for setting up an EEG system can be reduced by using dry electrodes [96] and by reducing the number of electrodes by identifying which are the most relevant through applying methods from computational neuroscience. Nevertheless, due to the complex structure of the brain and to volume conduction, a significant number of electrodes will always be needed for a reliable BCI system.

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Also, the application of BCIs outside the lab is still mostly uninvestigated. In standard experiments most environmental factors are strictly controlled. As this hardly is possible for real-world environments, different approaches have to be investigated. One solution is to model the given HMS completely by incorporating contextual information about user, environment and the technical part. In this approach context information would counterbalance the lack of control and support the information gained about of the user state (see Zander and Jatzev 2012).

As it is likely that there will be significant advances in solving the above-mentioned problems in the near future, BCIs will become more practical and more useable. The theory presented here and the first proof of concept of implicit HCI can be seen as a starting point for a new type of research. It opens up a large variety of applications that need to be investigated in upcoming research endeavors. With passive BCIs a new horizon for HCI is defined, carrying the potential to significantly increase the intuitivity and efficiency of future computer systems.

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