Enhancing Human-Computer Interaction with input from active and passive Brain-Computer Interfaces

Thorsten O. Zander, Christian Kothe, Sabine Jatzev, Matti Gaertner

thorsten.zander@mms.tu-berlin.de

Department of Psychology and Ergonomics, Chair for Human-Machine Systems, Team PhyPA, Berlin Institute of Technology, Berlin, Germany

Accessing and utilizing user state for Human-Computer Interaction

Today's interaction between machines and human beings in general is related to discrete and overt events, demanding a high degree of awareness from the user. Commands are messaged by explicit manual actions, like button presses, or speech control, and information is fed back from the machine through visual, auditory and/or tactile displays. But in the last decades—especially in Human-Computer Interaction (HCI)—a strong development towards increasing diversity in information flow could be observed, approaching a complexity of interaction which can saturate the user's capabilities. User-friendly design of HCI has therefore become an important part of current research. New approaches evolved such as adaptive or interpretative HCI heading for optimal support of the user (Chen & Vertegaal, 2004; Rötting et al., 2009). With that, *context-sensitivity* is added to already existing human-machine systems. The key information for the design of such systems is knowledge about the *current* user state within the interaction.

Utilizing user state for Human-Computer Interaction

The context of interaction between humans and machines can be divided into three major parts: The state of the environment, of the technical system and of the user. A large portion of relevant information is encompassed by user state. In particular, cognitive processes like the user's internal interpretation of the situation are of high interest. This can be made clear by taking a look at another type of interaction – that between humans. One form of social interaction is explicit – by intentionally sending a message to another actor. In addition, there is an *implicit* information flow. By observing aspects of user state accompanying the explicit interaction, such as gestures, mimics, or body posture, actors gain access to information about inner states of each other. Reading intentions of others is an important ability that involves representing and embedding the mental states of others in one's own mind, as, for example, postulated by the "theory of mind" (Premack and Woodruff, 1978). Such information might also be relevant for a more intuitive HCI (Asteriadis et al., 2009; Moldt & von Scheve, 2002). Hence, integrating information on *cognitive aspects of user state* into HCI could lead to a more natural way of interaction between human and machine. We distinguish between two types of information possibly accessible from the user's cognition, given as:

Cognitive Conditions *A cognitive condition reflects an aspect of cognition which is always present, but which varies over time, influenced by internal as well as external factors.*

Cognitive Events *A cognitive event is a cognitive process bounded in time. It can be triggered in many ways, such as by interpretation or expectation connected to a perceived change in external or internal parameters.*

Examples of cognitive conditions are the level of (mental) workload or arousal. But these can also be more complex, like the perceived loss of control (Jatzev et al., 2008). In cognitive neuroscience the field of cognitive events is investigated extensively, providing a source of inspiration for implementations within HCI. First investigated examples from this area are processing of errors (Blankertz et al. 2002, Zander et al. 2008), bluffing in a game context (Reissland and Zander, 2009) or surprise (Farwell and Donchin, 1987).

If cognitive conditions and events are made accessible, the computer receives relevant and context-sensitive information about the current interaction, which is deduced from the perspective of the user. This can be seen as input from the user to the machine which is not sent intentionally – hence as *implicit* commands. This allows for a more detailed modelling of the user and also for a better adaptation of the machine to the needs and intentions of its user.

Due to the fact that implicit commands are generated automatically in the course of interaction, there is an increase of information flow, while the effort of the user is *not* increasing. Hence, the use of information on aspects of user state is a highly efficient way for enhancing HCI. But—unfortunately—especially these aspects are hard to access by a technical systems.

Accessing user state with psycho-physiological measures

User state has covert parts, which are hard to observe from the outside. Examples for these parts are physiological processes within the human body or processes of cognition. There are approaches to utilize overt measures, like the users behavior, and of extracting information correlated to aspects of user state (Becker et al., 2007). Further, physiological measures like haptic data (Park et al., 2005) or eye gaze (Asteriadis et al., 2009; Rötting et al., 2009) have already proven to provide useful information on user state.

Yet, the scope of these methods is limited, as they can only generate information which is weakly correlated the actual user state (Müller, 2009). This gives the basis to define these parts as *covert aspects of user state* (CAUS), analogously to covert attention (Posner & Cohen, 1984).

Covert Aspects of User State *A covert aspect of user state is a process occurring within the user which can only be detected with weak reliability by using overt measures.*

As the user's cognition is inherently hard to access by overt measures, a big portion of cognitive conditions and cognitive events are CAUS. Hence, we need an elaborate and continuous measure of accessing and providing those as input to HCI like proposed in the previous section.

As the electroencephalogram (EEG) gives insight into the processes of the human brain, the source of all cognition, in high temporal resolution, it is a potentially suitable measure. Combined with methods recently developed in the field of Brain-Computer Interfacing (BCI) they provide a powerful tool for enriching HCI with information on CAUS of cognitive conditions and events. In the next section, an overview of more broad definitions of the term *Brain-Computer Interfaces*, namely passive and *hybrid BCIs* will be given*,* extending them from medical applications to HCI in general.

Classical BCIs

Multiple definitions for BCIs have been stated in the past, for example as systems which "give their users communication and control channels that do not depend on the brain's normal output channels of peripheral nerves and muscles" (Wolpaw et al. 2002). These BCIs can be divided into two subtypes, which we now summarize from the perspective of HCI, to embed them in a more comprehensive framework.

Directly controlled Some BCIs allow for direct communication with a technical system, by mapping consciously controlled mental activity onto a new artificial output channel. Thereby, they can bypass the natural outputs of the brain, which is integral for their clinical applications. Examples are BCIs based on sensorimotor imagery (Blankertz et al. 2007), where the type of mental imagery is mapped to a multi-valued control signal.

Despite its power and novelty, applying this type of control to general Human-Computer Interfaces is a challenge. Specifically, present equipment makes is difficult to complement or to replace conventional means of interaction with a computer, such as manual input. A reason is that the user's resources for parallel conscious communication are limited, creating a conflict between BCI and conventional control. Second, brain activity which can be both consciously controlled and at the same time measured with present non-invasive equipment largely overlaps with the brain's primary output modality—muscular control—creating another resource conflict. This limitation may eventually vanish with further advances in detecting more subtle cognitive processes and commands. Finally, if viewed as a replacement to manual control instead of a complement, BCIs are currently slower, more prone to errors, and more difficult to use. Therefore, research is underway towards identifying largely conflict-free output modalities or *mental gestures* for BCIs, to provide users with a "third hand", and towards exploiting other key benefits of BCIs, such as their potentially very low latencies.

Indirectly controlled BCIs in the second major group rely on conscious modulation of brain activity, as it arises in response to external stimulation. In these, the modulated activity is mapped to an artificial control signal. Examples are P300 spellers (Farwell and Donching 1988): systems which detect a characteristic brain response, the P300, which is elicited whenever an on-screen letter focused by the user lights up. Thus, brain activity is indirectly controlled by shifting attention.

In this interaction technique, another resource of the user—the attention focus in visual, auditory, or tactile perception—is modulated for the purpose of communication, and therefore occupied. For this reason, this category of BCIs, as well, is not easily applied meaningfully in Human-Computer Interfaces.

Generalized notions of BCIs

A change in perspective from the user side to the application side allows for a widened definition of BCIs:

> *A BCI is a system to provide computer applications with access to real-time information about cognitive state, on the basis of measured brain activity.*

In this context, it is reasonable to not restrict the information available to BCIs to brain activity alone. Instead, context parameters may be used by BCIs to help improve the accuracy of their predictions, leading to hybrid BCIs (Wriessnegger et al. 2006). Specifically, when moving from controlled laboratory conditions to highly varying real-world situations, context parameters help factoring out variations in brain activity which would otherwise render aspects of interest insignificant. These parameters may include state of the application, such as events, state of the environment, or state of the user as acquired by other physiological measures, such as body posture, voice tone, or gaze direction.

The classical BCI occupies, in the framework of the above definition, the role of providing information which is actively messaged or modulated by the user in order to control the application. What is not covered, however, is information which is not consciously chosen by the user, spanning a large fraction of implicit user state. BCIs which sidestep voluntary control are clearly restricted, but they have several benefits which are critical for their effective use in Human-Computer Interfaces, which will be outlined in the following.

BCI Categories

We have proposed a categorization of BCIs into three types (Zander et al. 2008)..

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

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

Passive BCI *A passive BCI is a BCI which derives its outputs from arbitrary brain activity without the purpose of voluntary control, for enriching a human-computer interaction with implicit information.*

Active and reactive BCI are the two subtypes of classical BCIs introduced previously as means for direct and indirect control, respectively, and passive BCI accounts for all other BCIs. These categories form a partition of the space of BCIs, since first, conscious control does either depend on external influences, rendering it reactive, or works independently from it, making it active, and second, passive BCIs are defined as complementary, in purpose, to this conscious control. The boundaries between these categories are smooth, since neither conscious controllability nor dependence on external events are binary properties of brain activity.

Passive BCIs

Restricted forms of passive BCIs predating these notions have been proposed in the past, for example for detecting forms of mental workload (Kohlmorgen et al. 2007), deception (Fang et al. 2003), and perception of self-induced errors (Blankertz et al. 2002). They have, however, not been analyzed and evaluated online with respect to a Human-Computer Interaction, and focus on user-state detection alone. More recent examples include measuring working memory load (Grimes et al. 2008), and detecting and correcting machine-induced errors (Zander et al. 2008). The latter, detailed at the end of this chapter, is one of the first cases of using passive BCIs to enhance a Human-Computer Interaction.

Key Properties

Passive BCIs have the following three distinguishing aspects which account for their practical prospects in Human-Computer Interfaces:

Complementarity The concept of passive BCI is complementary to other means of Human-Machine Interaction, in the sense that it does not interfere with it, in contrast to most forms of active or reactive BCIs, for reasons mentioned earlier. A passive BCI can be reliant on either the presence or the absence of an ongoing conventional Human-Computer Interaction, or be invariant under it.

Composability An 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 them.

Controlled Cost Since no conscious effort is required for the use of passive BCIs (besides preparation), their operational cost is determined by the cost of their mis-predictions. Passive BCI detectors producing probabilistic estimates, together with their *a priori* probability of operating correctly, are sufficient for arbitrary cost-optimal decision making at the application level, with zero benefit in the worst case.

Perspectives on passive BCI

Passive BCIs can be viewed as a secondary communication channel in Human-Machine Systems: a Human-Machine System linked by some primary communication channel (e.g. manual input) can be complemented by an optional secondary communication channel formed by a passive BCI, influencing and enriching the ongoing primary interaction with implicit user information (Zander et al. 2008).

Passive BCIs—referred to as "BCI as a measure" by some—give rise to physiological measures with semantics related to the user's cognitive state, specifically to CAUS. In this function, the bitrate of passive BCIs is rarely a good performance metric, but rather is the cost or benefit of their application in a particular scenario.

Accessible State

A broad spectrum of cognitive state can be accessed with passive BCIs. This includes latent cognitive state such as arousal (Chanel et al. 2006), fatigue (Cajochen et al. 1996), vigilance (Schmidt et al. 2009), working memory load (Grimes et al. 2008), visual/auditory/tactile/cross-modality attention focus (Kelly et al. 2005), and possibly some emotional state, etc. on one hand, and temporary cognitive events such as surprise, perception of user/machine errors (Blankertz et al. 2002, Zander et al. 2008), or decision-making load (Heekeren et al. 2008) , etc. on the other hand. Significantly more subtle state could be accessed with better, but not easily deployable, measurement equipment (Shinkareva et al. 2008).

For EEG or Near Infrared Spectroscopy, a simple rule of thumb is: what is represented in a large and compact area of the cortex and is close to the scalp should also be detectable. Thus, brain atlases (Toga and Mazziotta 2000) give a useful overview of what could potentially be accessed by passive BCIs.

Potential Applications

Passive BCIs have various potential applications, such as for augmenting or improving existing systems, e.g. by improving safety and usability via operator monitoring. In this role, they allow to better respect the human factor in a Human-Machine System. Another application is for creating highly interactive and sensitive Human-Machine Interfaces: having information about the ongoing activity profile of the user, the system can adapt to avoid cognitive overload, and further, information about the interpretation of events by users can serve as a better basis for making decisions. As a third example, passive BCIs can help better connect multiple users by accounting for more aspects of user state, both in professional multi-operator scenarios as well as in recreation.

Refining the BCI training sequence

Applying BCI technology for healthy users poses new problems of user acceptance. The time-consuming *preparation phase* of EEG systems and the *calibration* of BCI detectors limit the scope of possible applications. But there are several ways of optimizing these procedures.

Currently, there is a development in sensor technology towards *dry electrode* systems, which should substantially reduce the preparation time (Popescu, 2007). The calibration phase can be optimized is several ways. First, in spite of the strong variability between EEG sessions, there are approaches for porting information between sessions (Krauledat, 2008). In line with this thought, there might even be the possibility of defining universal detectors applicable to users or groups of users with short or no recalibration. However, a prerequisite for that would be the existence of an aspect of cognitive state which is consistent across subjects. Nevertheless, even if these problems are solved, there still are other hurdles to take.

Shifting BCI applications into the context of general HCI leads to a more complex, and hence noisier, environment, and diversified user state induced by multiple forms of interaction. Also, applications will not only be controlled by BCI input. The user still will rely on standard methods of input, like mouse or keyboard, and other innovative input methods could be combined with BCI input into a hybrid BCI.

Another problem is defined by the increasing number of artifacts recorded in the EEG data in a more complex context. These can be divided into parts resulting from the environment and uncorrelated user state and those resulting from correlated user state, such as correlated eye blinks and other types of behavior. As the first category of artifacts always decreases the signal to noise ratio, these should be filtered out for BCI applications. In contrast, artifacts from the second category may be used as features for BCI applications. But it is unclear whether these signals are as robust as cognitive events and states, with respect to context changes.

As there is a high variability in the signals recorded between sessions or between subjects, and even within sessions (mostly due to changes in context) in EEG data, an initial calibration of methods used for detecting patterns in brain activity is a necessity. In classical BCI applications this and the user's learning of the task in the application are the only methods of learning about the state of the interacting system. This defines the first stage of *adaptation*. With that, we address the adaptation of the machine to the user as well as the adaptation of the user to the machine. But it is very likely that the user still will be learning while interaction within the application. Hence, the user state will change in time which might lead to later performance drops. Then, a readaptation of the classifier can be of use (Shenoy et al, 2006; Jatzev et al., 2008), defining the second stage of adaptation. In general, one faces the problem of two adaptive systems which may diverge in time. Both machine and user have to be trained to let their adaptations converge.

To cope with the previously defined problems arising from that shift in context, the definition of procedures defining BCI applications has to be more elaborate. Therefore, we propose the following sequence consisting of five stages, for structuring a BCI session:

User Training In this stage the user gets familiar with the task of the Machine Training stage. This task could be generating BCI detectable signals, mostly in active or reactive BCIs, or a predefined Human-Computer Interaction usually independent from BCI input, for generating passive signals.

Machine Training In a standardized paradigm the user is guided to generate prototypes of brain activity which can be used as input for the proposed BCI application. In this stage all artifacts should be controlled. The outcome of this stage is a system, usually a combination of feature extraction and classifier, able to distinguish the intended commands or to infer an aspect of cognitive state. We call this system a detector.

Confluence Stage Here, a simple BCI application is defined which can be controlled by the outcome of the previously defined detector. Depending on the performance of the detector in that initial application, parameters of the detector might be adjusted. In active BCIs also the user is able to learn how to interact with the system. Then there can be several iterations of detector adjustment and user learning.

Validation Stage This stage is the first test of the intended BCI application. Its outcome is a performance estimate of the defined detector. Depending on this, it can be decided to repeat some of the previous three stages to obtain better results.

Application Stage The defined and validated detector is applied for generating input to the technical system resulting from brain activity of the user. Methods capable of online adaptation might be used to (continuously) adjust parameters of the detector to relevant changes of user state.

Defining a Hybrid BCI: Combining eye gaze input with active Brain-Computer Interaction for touchless interaction in HCI[1]

The integration of new input modalities into HCI has been pursued by various researchers. Already in 1982 Bolt and others investigated eye movements as an alternative input modality to improve efficiency in HCI (Bolt, 1982). Moving the mouse cursor via eye movements has been shown to be intuitive and facilitate search (Engell-Nielsen et al., 2003; Nilsson et al. 2007; Jacob, 1993; Murata, 2006; Hutchinson, 1993). However, defining adequate mechanisms for the selection command or click operation remained a challenge. The prevalent solution for Gaze controlled User Interfaces are dwell times. Items are selected when they are fixated by the user for a pre-defined duration. This allows for a faster interaction than using a mouse (Sibert and Jacob, 2000), but creates the problem of finding the appropriate dwell times for complex stimuli or icons. The user cannot rest the gaze anywhere without making a selection (Jacob et al. 1993), which is stressful when complex icons must be understood, leading to the “Midas Touch” problem (Pierce et al., 2009).

A hybrid BCI solution

In this study, an active Brain-Computer Interface (BCI) is added as a second input modality, serving as an action selection device within an eye gaze controlled environment (Vilimek and Zander, 2009). A two-dimensional cursor control is realized by tracking the user’s eye gaze and a BCI-detectable mental gesture, an imagination of a two-handed movement, serves as the selection command. The integration of an active BCI application within HCI allows for direct conscious control and communication for healthy users via BCI. This way, disadvantages of the two modalities can be counterbalanced: the Eye Gaze based system compensates for the

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[1] This investigation was conducted in collaboration with Roman Villimek (Corporate Technology, Siemens AG)

BCI restriction to binary inputs, not suitable for cursor movements, while the BCI enables a natural and selection command under complete user control.

For an application, the hybrid BCI system should not be significantly slower than dwell times. But since the activation thought and BCI processing will require some time, it is assumed that it will also not be faster than dwell times. Secondly the BCI-based solution should result in lower error rates (false selections), especially in the presence of complex stimuli, since it is based on an explicit conscious action. It was investigated whether this hybrid BCI provides a successful solution to the "Midas Touch" problem, not dependent on stimulus complexity.

Experimental Task

The newly developed BCI-based target selection was compared against two dwell time solutions. Ten participants (five female, five male) took part in the study, performing a search-and-select task. Within a circular arrangement of 11 similar distractor strings, subjects had to find the string identical to the target string, which was presented in the middle of the circle (see Fig. 1). The task included two levels of difficulty: an "easy" condition presenting strings of four characters and a "difficult" one (seven characters), reaching the upper boundary of working memory capacity. This implies that the user is forced to rest gaze for encoding. Lengths of dwell times appropriate for stimulus complexity were tested in pre-experiments. This resulted in a long, well controllable dwell time of 1.300 ms and a short dwell time of 1.000 ms, not perceived as slowing down performance.

Fig. 1. Examples for easy (left) and difficult (right) search tasks.

Experimental Design

The structure of the experimental blocks was determined by the training sequence (see Section XY) required for BCI application. During the user training, participants were assisted to imagine the hand movement. The machine training followed, with approximately 15 minutes duration. After classifier training, the BCI command was practiced during the confluence stage, enabling readjustments of the threshold probability for selection. The motor imagery chosen for the BCI activation thought was: “wringing a towel with both hands into opposite directions”. During the application stage, the experimental task was performed by the participants, using the three types of activation techniques for each of two levels of task difficulty. To ensure robustness of the detector, the experimental task for the machine training was a variant of the application stage, with the difference that a box containing the word “search” was jumping randomly from string to string, covering letters behind. Participants were to follow the box until the word “select” appeared. In this case, they had to perform the imagined hand movement.

This training elicits prototypes for two mental conditions or BCI classes. One class was characterized by search (following the “search box”), the other one was characterized by the selection command (motor imagery).

BCI Control

For BCI analysis 32 EEG channels were used, with a focus on sensorimotor areas around C3 and C4. EMG on arm positions was recorded to control for movements during motor imagery. BCI feature extraction was performed according to the imagined hand movements, causing reduced amplitude of the sensorimotor rhythm (SMR), 7-13 Hz, over the respective sensorimotor brain regions (Pfurtscheller et al., 1997). For feature extraction, the Spec-CSP algorithm (Tomioka et al., 2006) was utilized, which finds optimal linear combinations of weights for each electrode and frequency by maximizing variance between classes.

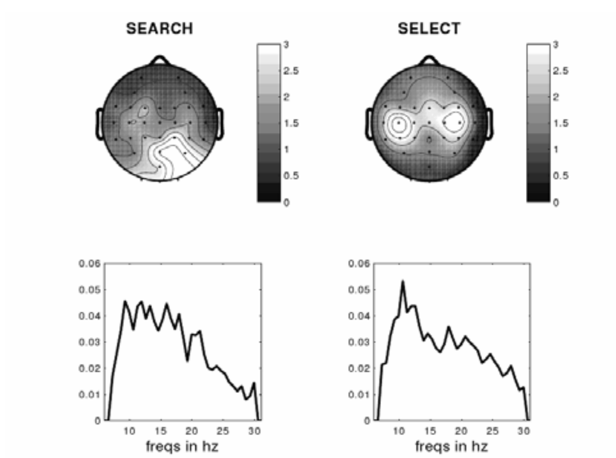

Fig. 2. Mean electrode and frequency weighting over all subjects calculated by the Spec-CSP algorithm. The units of all weights shown are arbitrary.

Results

Advantages of the hybrid BCI were investigated by measuring effectiveness, efficiency, cognitive demand (mental workload) and user acceptance. Effectiveness of task performance was measured by errors (false target selections), and accuracy of target selection, respectively. For the "easy" condition, the subject's accuracy using the BCI-based solution was slightly lower (88%) compared to the long dwell times (93%), with short dwell times resulting in the lowest accuracy (83.3%) (see Fig. 3). Remarkably, the BCI achieves the best results in accuracy for the "difficult" condition (78.7% correct), but only the difference to the short dwell time (51.1% correct) was significant. With respect to efficiency, indicated by time needed for task completion, the BCI solution was significantly the slowest activation method over both conditions (5.90 s; 8.84 s) (see Fig. 3). Overall mental workload effects, measured via NASA task Load Index, showed no differences, except for one subscale: 'amount of frustration'. Here, the BCI method was rated significantly lower ($p < 0.05$) than dwell time solutions. In addition, nine out of ten participants preferred using the combined BCI/Eye Gaze Interface. Many participants stated to use a strategy to avoid mis-selection by dwell times, moving their eyes shortly to an item and then quickly to a 'safe area'. With respect to BCI classification, the mean accuracy, obtained by cross-validation during the training phase, was 89% (standard deviation of 10.1%). Spec-CSP showed highest electrode weights over motor cortex (see Fig. 2) and highest weights for frequency range was in the alpha band, characteristic for SMR.

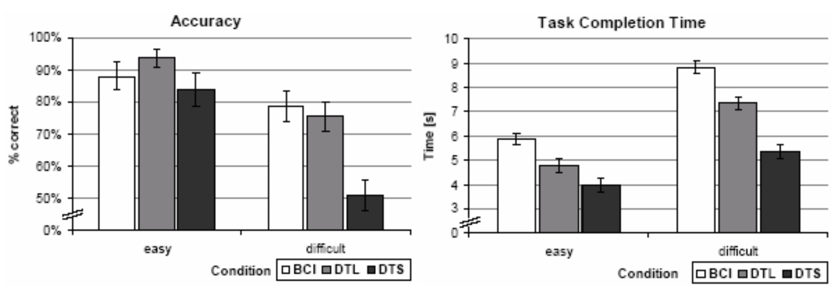

Fig. 3. Left: shown is the percentage of correct selection: Brain-Computer Interface (BCI), long dwell times (DTL) and short dwell times (DTS). Right: shown are task completion times for the respective conditions.

Discussion and Conclusion

The more accurate interaction regarding the 'difficult' stimuli, a strong user preference and low frustration ratings support the idea of applying a BCI as an additional input modality in Eye Gaze based systems. This study demonstrates that an active BCI can be successfully integrated into HCI, ensuring an accurate selection command for Gaze-controlled User Interfaces, which is, in contrast to dwell time based solutions, independent from stimulus complexity.

The Error-BCI: Automated Error Detection to enhance Human-Computer Interaction via secondary input of a passive BCI

The rapid development of automation technology has increased the precision and efficiency of HCI, but has also been shown to be a source of errors in such systems. Sometimes these systems have even been referred to as "clumsy automation" (Wiener, 1989), causing additional cognitive workload for the human instead of reducing it. The passive BCI investigated here, however, could reduce the additional cognitive workload and the error-proneness of automated systems, by supplying the machine with continuous information about related CAUS via a passive BCI and thus lead to an optimized HCI.

Here, we developed an *Error-BCI (*Zander et al., 2008*)* that enables single trial detection of brain responses to machine errors as caused by for example erroneous automation processes. These perceived errors are fed back to the system and thus enable a correction or adaptation. The direct access to the cognitive state results in a more suitable and context-sensitive adaptation compared to other automation technologies that have to rely on behavioural or other implicit data (Wiener, 1989). Since BCI error detection is based on a non-intended and automatic reaction of the brain to the environmental context, a passive BCI is defined, with no additional cognitive effort for the user. In addition, there is no conflict with the primary mode of interaction.

Experimental Design

The applicability of the Error-BCI to enhance HCI efficiency was investigated by utilizing a game as experimental task, in order to simulate a real-world like situation and to ensure proper user motivation. This game simulates the situation of faulty adaptation. The goal of the player is to rotate one of two letters letter from the set {L,R} displayed in front of a circle, until a given target position is reached.. The letter L is rotated clockwise by a left key press and the letter R counter-clockwise by a right key press (see Fig. 4). A round of the game is completed when the target position is reached. The letters are automatically changing colors in 1000 ms intervals, where color indicates the degrees of rotation upon key press. The following mapping rules hold: red indicates rotation of 90 degrees and green indicates rotation of 30 degrees upon key press. Only one press is possible per color phase, and there is an intermittent grey phase, where no rotation is possible. Players are free to choose the time point of the key press, and therefore have the chance to build up an efficient strategy, in order to achieve the goal of the task: to be as fast and accurate as possible. The game is played in two modes: in the first mode, the subject has full control over the game (Full Control Mode). During the second mode (Reduced Control Mode) false rotation angles (machine errors) appear randomly. In these, rotation angles are smaller than expected: in 30% of all key presses, red letters would rotate by 30 degrees instead of 90 degrees and the green letter would not rotate by 30 degrees, but not at all. To increase motivation, a second player competing to the first one is participating in the RLR game. Performance is measured and fed back to both players, by presenting the score after each round. A player wins a round when reaching the target earlier than his/her opponent. Hence, the artificially induced machine errors have a negative valence for the user, since they decrease the performance and also lead to frustration. Faulty trials are defined as rotating the stimulus too far (beyond the target position) or pressing the non-appropriate button (left versus right). In these cases the opponent wins the point automatically. Two different experiments were performed using the RLR game, presented next.

Offline Experiment

The first experiment took place in the EEG laboratory of the university under controlled experimental conditions, involving 14 participants (6 female, 8 male, age: 21-30 years). During the user training, participants learned the rules of the game by practicing it without an opponent. In this first session they played in the Full Control Mode. In a second session, the Reduced Control Mode was introduced, generating machine errors. During a third session, participants played against a trained opponent in the Reduced Control Mode. The experimental task of this machine training phase was identical to the user training, except for the opponent, sitting closely nearby. In one session, approximately 40 rounds were played in both modes. No online feedback by BCI was given, but EEG was recorded at 54 electrode positions according to the 10/20 system for offline analysis.

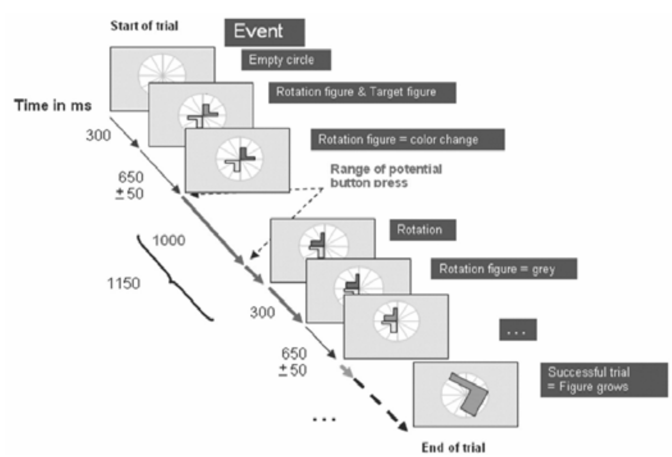

Fig. 4. Example for single trial of the RLR-Design.

The Error-BCI, used offline here, discriminates two classes of conditions: (1) erroneous rotations and (2) correct rotations. The classification scheme is aimed at detecting event related potentials (ERP), since the EEG pattern of interest is an

ERP. The grand average ERP for the Error condition is characterized by a negative wave with a peak latency of 350 ms and a positive wave 100 ms later, very similar to the feedback Error Related Negativity (f-ERN) as described by Holroyd (2004). The f-ERN occurs in response to a negative feedback referring to incorrect performance, a punishment or negative reward (Nieuwenhuis et al., 2004). The ERP related with the machine error response is also present for the respective difference wave (error minus correct) as it has been reported for the f-ERN (Holroyd, 2004). For BCI feature extraction, the data was resampled at 100 Hz, epoched from 0 – 800 ms relative to stimulus rotation and an FFT bandpass filter was applied using a frequency range of 0.1 – 15 Hz. Subsequently, a pattern matching method was utilized (Blankertz et al., 2002). Six time windows of 50 ms were used for pattern matching. A classifier was trained on these features, utilizing regularized Linear Discriminant Analysis as a learning algorithm. In this study, classification results were obtained offline by 10-fold outer and 8-fold inner nested cross validation on the data of the Reduced Control Mode with opponent.

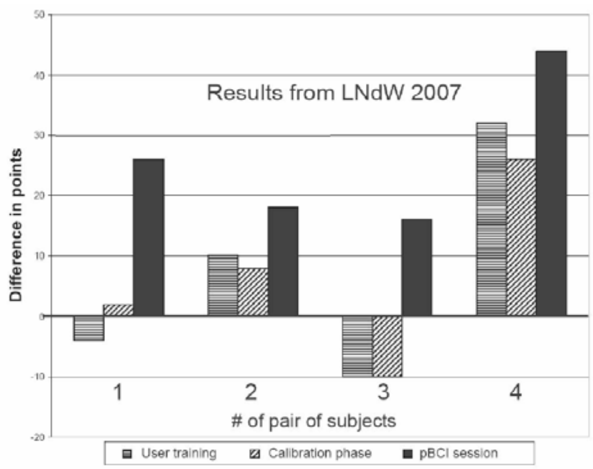

Fig. 5. Results of the LNdW 2007. The bars indicate difference in points of Player A (up if better) and Player B (down if better). Horizontally striped bars show the results from the user training (no machine errors), where the rule system is learned. Results from the machine training (machine errors included) are represented by the diagonally striped bars. In the application stage, results shown in black, BCI support was given to Player A.

The mean classification error for the automated error detection was 11.8 % with a mean standard deviation of 5.0 %. The false positive (FP) and false negative (FN) rates were moderately balanced with a mean FP rate of 9.54% and a mean FN rate of 16.42%.

Online Experiment

The second experiment was conducted at the Open House of the Berlin Institute of Technology (LNdW 2007). Four times two different players from the audience played the RLR game against each other. The setting at the LNdW served as an uncontrolled environment to test if the classifier is robust enough to work properly in such situations. Each pair played three sessions, consisting of 40 trials per class, and lasting for about 15 minutes. First, the user training included one session without error states. The machine training followed introducing machine error trials with a probability of 30%. A classifier was trained based on the sample trials of the machine training.

For BCI classification, the same pattern matching method as in the offline experiment has been utilized. Automatic error detection and adaptation via Error-BCI was applied in the last session, but only for one player. While points were equally distributed between session 1 and 2, the performance of all BCI supported players increased significantly during the third passive BCI session. This is indicated by a substantially higher score of the BCI-supported player, compared to the opponent and to his own former sessions, plotted in Fig. 5 as difference in points between players. The classifier had an accuracy of 81.2% with error ratios equally distributed over the two classes.

The studies presented in this part show that it is possible to enhance the efficiency of HCI via passive BCI, constituting an additional information channel. By providing the technical system with information about the perceived errors, the system was able to adapt the actions to the user's covert cognitive state of perceiving an error. Especially the second study shows that this significantly optimizes the Human-Machine Interaction in real-world environments.

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