Team PhyPA: Brain-Computer Interfacing for Everyday Human-Computer Interaction

Thorsten O. Zander[1*], Laurens R. Krol[1]

Abstract

Brain-computer interfaces can provide an input channel from humans to computers that depends only on brain activity, bypassing traditional means of communication and interaction. This input channel can be used to send explicit commands, but also to provide implicit input to the computer. As such, the computer can obtain information about its user that not only bypasses, but also goes beyond what can be communicated using traditional means. In this form, implicit input can potentially provide significant improvements to human-computer interaction. This paper describes a selection of work done by Team PhyPA (Physiological Parameters for Adaptation) at the Technische Universität Berlin, Germany, to use brain-computer interfacing to enrich human-computer interaction.

[1] Team PhyPA
Biological Psychology and Neuroergonomics
Technische Universität Berlin
DE-10623 Berlin, Germany
* Corresponding author, e-mail: tzander@gmail.com

1 Introduction

Personal computers and other forms of interactive technology are central to our society's productivity, livelihood, and entertainment. For many people, a large part of the day is spent operating machines in one way or another. This pervasiveness of technology has been made possible by vast improvements in, among other things, the processing power available to these machines. The machines' capabilities have increased immensely—unlike, however, our own abilities to tell these machines what to do. Although the interaction techniques have become more natural and intuitive over the years, these are, in one perspective, superficial improvements: In essence, all communication from a human to a machine still requires the human to translate their intentions into a sequence of small, discrete commands, e.g. pressing one key, opening one menu, touching one button, making one gesture… This represents a communication bottleneck [1] between the human operator (user) and the machine that is operated, as well as a source of potential error. Also in other ways can present-day human-computer interaction be said to be asymmetrical [2]: different strengths and weaknesses of humans and machines, differences in information processing capabilities, natural versus machine logic… These differences between man and machine can be complimentary if a proper division of labour and cooperation strategy can be found. At present, however, the human must ultimately abide by the machine's logic, which limits efficient cooperation.

One way to alleviate the issue of asymmetry, is to give the computer more information about its user, in order for it to be able to better interpret or even foresee the given commands, and adapt accordingly. For example, when we humans see that our colleague is currently busy, we will probably decide not to ask them for a hand with our own work. Similarly, a computer could decide not to notify us of potential updates if it could know that we are currently in thought.

The above-mentioned communication bottleneck and unnatural nature of present-day interaction techniques, however, prevents us from informing the computer of all relevant information. We must look for alternative means to provide information to our machines.

Team PhyPA, a workgroup at the Technische Universität Berlin, Germany, is working on applying brain-computer interface (BCI) methodology to human-computer interaction (HCI) in general. Using BCI, an additional communication channel can be created that can carry either explicit input (e.g. consciously communicated commands) or implicit input (e.g. information about the user state automatically inferred from ongoing brain activity).

In this paper, we briefly describe some of the projects done at Team PhyPA. We begin with a short introduction to BCI in general, and continue with examples of explicit input, where a user uses BCI to explicitly control an application (traditional, active BCI). Following that, we give examples of implicit input: how a computer can use information from the brain directly, without the user consciously communicating anything (passive BCI). We conclude with an outlook of this field.

2 Brain-Computer Interfacing

The term brain-computer interface (BCI) denotes a control system that relies solely on the brain's neuronal activity, as opposed to traditional methods that all involve the activation of peripheral nerves and/or muscles [3]. Usually, a BCI system's input is an electroencephalogram (EEG) recording of (a subset of) the brain's neuronal activity.

A typical BCI experiment begins with a calibration phase during which the specific mental or affective states are induced, in order to serve as a training set for the classifier. From this annotated data, features are extracted that represent the brain activity of interest (e.g. power in a specific frequency band, amplitude at a certain moment at a certain electrode, etc.). Supervised machine learning [4] on these sets of features is then used to calibrate a classifier, which can then detect the learned brain states in real time, from features extracted from an ongoing, un-annotated recording. In a second, online phase, this classifier is then applied: Incoming EEG data is classified in real time, and the output of the classifier is translated into control commands or other adaptations of the machine.

From the end user's perspective, keeping the above-mentioned communication bottleneck in mind, a distinction can be made based on the amount and type of conscious effort that must be made to exhibit the brain state of interest [5].

In active BCI applications, users consciously and intentionally modulate their brain activity in order to send a predetermined command. For example, they imagine moving their left hand (without actually moving it). This imagined movement is detected by the BCI as a specific pattern of activity over the motor cortex, and then translated into the movement of a prosthetic arm. (Indeed, clinical applications like these have been the main motivators of recent BCI research [6]).

Passive BCI applications, on the other hand, rely on brain activity that is not consciously modulated. Cognitive and affective states like action preparation [7] error processing [8], workload [9] etc. all produce detectable changes in brain activity, which are not voluntarily induced, but can still be used as input to a machine [10]. They happen automatically as a result of ongoing events and actions.

A third category, reactive BCI, is of little relevance to human-computer interaction and will therefore not be discussed here.

The following two sections give examples first of active BCI applications, and then of passive BCI applications, developed at Team PhyPA with the intention of providing contributions to human-computer interaction in general, outside of clinical populations.

3 Active BCI Applications

As a demonstration of the general feasibility of using BCI methodology as a control input, we first, in 2006, implemented an adaptation of the "Basket Paradigm", originally developed by the Graz BCI Lab at the Institute of Neural Engineering, Graz University of Technology, Austria [11]. This used a one-dimensional, explicit control signal to steer a cursor on the screen to the left or to the right. We later also implemented a direct analogy of this approach in a real-world human-computer interaction setting: a flight simulator. Instead of a cursor, the airplane itself was steered to the left or to the right.

A key question here is the following: Can the usually abstract, clinical BCI applications that have been developed in and for controlled environments be reliably exported or translated into real-world scenarios and applications?

3.1 Basket Paradigm
3.1.1 Motivation

The PhyPA toolbox was a BCI toolbox developed in 2006 by Christian Kothe and Thorsten Zander. It was implemented in MATLAB (The MathWorks, Inc., USA) and was intended to be easy to use even for scientists that do not have a strong background in programming, and to be at least as powerful as other BCI toolboxes that were on the market. A first example of its capabilities was the implementation and application of BCI-based direct control over the basket paradigm (described in the next section) with a naïve participant—a critical student from one of our BCI courses at the Technische Universität Berlin, who strongly doubted the feasibility of BCI control based on motor imagery.

Based on the PhyPA toolbox, Christian Kothe later developed the open source toolbox BCILAB at the Swartz Center for Computational Neuroscience, University of California, San Diego, USA [12].

3.1.2 Experimental Set-Up and Procedure

Participants were seated and looking at a display. On the screen, a round cursor (ball) appeared at the top of the screen, centred horizontally. At the bottom of the screen, two baskets were visible: one occupying the left quarter of the screen, one occupying the right quarter. One of these baskets was highlighted, indicating that the ball had to be moved into this bas-

ket. The ball moved downwards with a fixed speed. The participant's task was to steer the cursor to the left or to the right, such that it would, upon reaching the bottom of the screen, land in the indicated basket.

In order to steer the cursor, the participant performed motor imagery [13]: they imagined moving either their left hand, to steer the cursor towards the left, or their right hand, for the opposite direction. Such motor imagery produces an event-related desynchronization (ERD) that can be detected over the motor cortex contralateral to the imagined movements [14]. In brief, in the neuroelectric activity of the motor cortex, a strong oscillation can be found around 8-13 Hz (alpha band) and 14-18 Hz (central beta band) when the cortex is not actively coordinating movement. When movement is performed—or also imagined—the neuronal activity breaks away from this default synchronicity. This can be detected in the EEG. For this detection, we used common spatial patterns.

Common spatial patterns (CSP; [15]) generate a set of spatiotemporal filters for feature extraction, providing weights for each electrode representing its relevance for discriminating between the two classes of activity—in this case, imagined left and right hand movements. After filtering the signal to focus only on signals between the alpha and beta bands, CSP maximises the variance of the signal passed through the generated filters for one class while simultaneously minimising it for the other.

During the calibration phase, the participant followed instructions on the screen to repeatedly, in a given random order, imagine left and right hand movements.

The control over the basket paradigm itself was based on online application of the calibrated BCI. The real-time incoming EEG data was band-pass filtered and projected through the CSP filters generated based on the calibration data. The signal's variance then indicated whether or not a left or a right hand movement was imagined. This was then used to steer the ball into the appropriate direction.

3.1.3 Results and Conclusion

One BCI-naïve participant performed this experiment. 32 channels of EEG were recorded with a BrainAmp DC (Brain Products GmbH, Germany). Based on cross-validated estimations based on the calibration data, the classifier could, for every second of motor imagery, determine with 74% accuracy whether this was an imagined left, or right hand movement. Online, out of a 100 trials, 82% of the balls was correctly moved into the indicated basket. This performance is in line with other, partially later conducted, motor imagery experiments [13, 16, 17]. The experiment thus provided a proof of principle that naïve participants, unfamiliar with BCI technology, can use a BCI for direct control. Nevertheless, an 80% hit rate is insufficient for a direct-control input modality for HCI where near-100% accurate alternatives are available (keyboard, mouse, etc.).

After a huge initial improvement in classification accuracy through the introduction of machine learning to the field of BCI [18], later applications of more advanced machine learning and signal processing algorithms only led to marginal improvements of results. Perhaps, we believe, a ceiling has been reached and a next step is to focus on the user instead of the machine: either by improving their ability to perform the required motor imagery, or by increasing their motivation and the relevance of their performance, as discussed next.

3.2 Horizontal Control of a Flight Simulator
3.2.1 Motivation

Signal processing and machine learning techniques provide powerful tools to optimise the control signal, but the performance of a BCI system depends, ultimately, on the underlying brain activity. We hypothesise that given a more engaging environment and task, the participants will be more involved and focused, which translates into robust brain activity. This was tested by translating the above basket paradigm into a real-world, engaging environment: a certified flight simulator controlled by professional pilots [19].

3.2.2 Experimental Set-Up and Procedure

The experiments were performed in a Diamond DA42 flight training device at the Institute of Flight System Dynamics of Technische Universität München. This is a fixed-base flight simulator built with original aircraft components to achieve a highly realistic cockpit environment. Aircraft flight dynamics and systems are accurately replicated, and a 180° cylindrical screen provided a simulation of the outside world. The instruments provided to the pilot in the scope of the experiments comprised classical (backup) instruments (airspeed indicator, attitude indicator, altimeter and magnetic compass) as well as a research display.
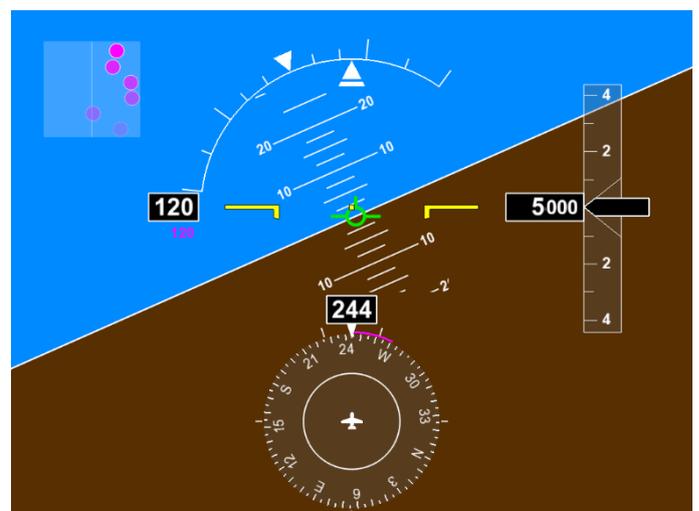
Fig. 1 Research display showing airplane indicators as well as, in the top left, a history of BCI classifier output (% left/right).

The research display was designed to be similar to that of the original display used in the aircraft, familiar to the participants. A novel addition was the output of the BCI classifier, visualised in the top left corner of the display, representing the classification results of the past 6 x 0.2 seconds. The display also contained a tracking bug, which indicated a particular heading to the participants.

Participants were given the task of steering the plane into the heading indicated by the tracking bug.. In a first phase, the tracking bug changed suddenly by large amounts and participants were given ample time to catch up. In a second phase, the tracking bug oscillated around an initial heading.

A third phase was as the second, except without world visuals displayed outside the aircraft because the aircraft was in the clouds (i.e. instrument flight rules). Upon breaking from the clouds, flying low and close to the airport where the aircraft was to be landed, participants could see that the tracking bug had in fact been providing false information, and they needed to quickly change course to prevent a crash. This latter scenario represented the strictest form of our goal, to provide an engaging, real-world scenario in which to test BCI performance.

Participants performed horizontal steering of the airplane by using motor imagery, as in the basket paradigm. Altitude and throttle were controlled automatically.

The calibration phase was as described above for the basket paradigm, except three classes of imagined movements were tested: right hand, left hand, and foot. For online operation, the two best discriminable classes were selected from these three.

3.2.3 Results and Conclusion

Seven experienced pilots took part in this experiment. The estimated classification accuracies based on calibration data was on average 94% for three participants (89, 95, and 98%, respectively), 64% for a fourth, and below 60% for the remaining three (58, 55, and 51%). Chance level for this task was at 50%. As such, we can distinguish between three pilots with good control, and three with virtually no control.

The three good-control participants, in fact, were able to perform the tasks to such a degree that their performance fell within acceptable margins required of official pilots. They could steer the plane without deviating significantly from the indicated path.

Investigating the CSP filters generated for the three good participants provided neuroscientific evidence that their control signal was based on motor imagery, as seen in Fig. 3.

In lab-based experiments of this kind we typically have an accuracy of about 82% ±11.5 with a quite homogenous distribution of accuracy across participants [20]. With an accuracy of about 94% for three participants, we can see support for our hypothesis that a highly motivated participant will be better capable of controlling a BCI. That being so, however, the three lowest-scoring participants would require an alternative explanation.
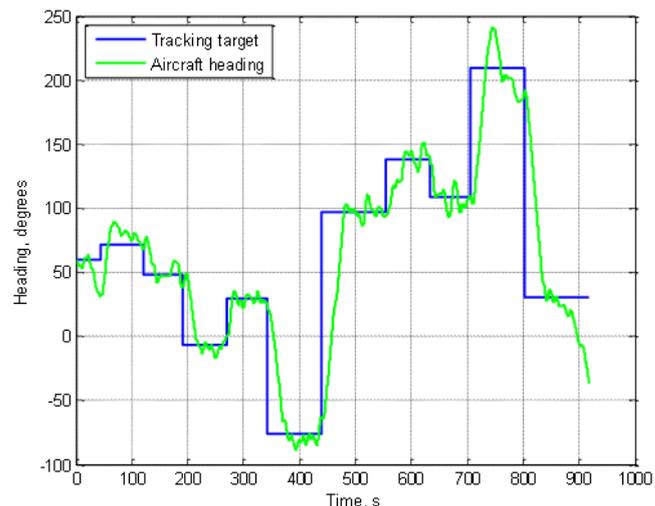
Fig. 2 Sample results from a BCI-controlled flight. Blue line indicates the heading indicated by the tracking bug. Green line indicates the plane's actual heading, controlled using the BCI.
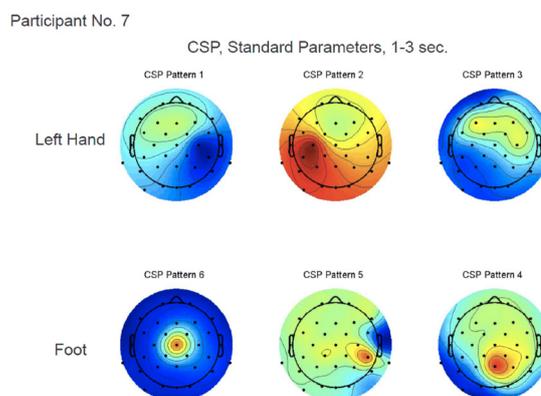
Fig. 3 Common Spatial Patterns selected for participant 7 (95% accuracy) discriminating between classes 'left hand' (upper row) and 'foot' (lower row). The patterns focus on neurophysiologically plausible areas: right motor cortex (pattern 1) and left motor cortex (2) for the imagined hand movement, and the central motor cortex (6) for the foot.

Indeed, although special care was taken to prevent this using clearly worded, personally conveyed instructions, these three participants exhibited strong overt behaviour—i.e., actual movements. One possible explanation is that these participants did not understand the concept of BCI-based direct control. A BCI is unlikely to work properly if the data it is calibrated on does not relate to the actual task. In addition, actual muscle activity strongly contaminates EEG recordings and can thus be detrimental to BCI performance.

But even if not shared by all participants, classification rates of 95% and up remain remarkable. Perhaps a ceiling has been reached with respect to algorithmic improvements, and the next step is to focus on the user: to move away from abstract tasks, and move toward engaging real-world trials.

4 Passive BCI Applications

The above two examples of active BCI indicate how BCI can offer an alternative, direct communication channel from a human user to a computer system. In these cases, communication was performed deliberately: The users voluntarily decided to imagine one or the other movement, and upon detecting the corresponding brain activity, the system responded accordingly.

This brain-based communication channel however can also be used for information that is not deliberately or voluntarily communicated. Our human brains are continuously processing our incoming perceptions and evaluating the internal and external context, without us consciously initiating or guiding this activity. The same signal processing, feature extraction, and machine learning techniques can also be applied to this "spontaneous" brain activity, allowing the system to detect cognitive and affective user states, as e.g. mentioned above.

Once such states are detected, the computer can respond accordingly: although the human user is not actively controlling the system, their cognitive or affective states do influence the system, thus serving as implicit input [21]. In this section, we give two examples from our own research.

4.1 Task-Independent Workload Classifier
4.1.1 Motivation

A much-researched cognitive state is the state of high task- or workload. Different levels of load can have a large influence on human wellbeing and performance in almost all tasks [22, 23], making it an important state to be able to detect especially in safety-critical environments, but it can also serve as a meaningful indicator in educational or leisure contexts [9].

Although we intuitively understand "workload" as a general, overarching concept, the corresponding brain activity indicating high levels of workload has been seen to depend on the exact task and context inducing the load [9]. This might reflect the fact that different parts of the brain are involved to different extents in different tasks. If "workload" would indeed only be so heterogeneously represented in the neurophysiology, then BCI-based workload detectors would need to be trained individually for all different tasks and contexts. However, a common factor in the neurophysiology of workload is the frontal-parietal theta-alpha asymmetry in EEG activity representing the interaction of the dorsolateral prefrontal cortex and the intraparietal sulcus, which are also described as anterior and posterior attentional systems in controlled attention tasks [24, 25].

We attempted to find a task-independent classifier that identifies this interaction specifically, such that this classifier could be trained once, on one task, and then be used to detect workload during a range of different tasks [26].

4.1.2 Experimental Set-Up and Procedure

Participants were seated and looking at a computer display. The experiment was designed to induce two states: one of high load, and one of low load.

The calibration phase was as follows. During high load, participants were presented with an equation of the form $a - b$, instructing them to count backwards from a in steps of b. a was any integer between 200 and 1200; b ranged from 6 to 19, excluding 10 and 15. During low load conditions, the absence of such an equation instructed participants to relax, with eyes open, calling to mind a specific, freely chosen but consistent scene from memory to focus attention inwards.

Both high and low load trials could or could not (50% chance) be accompanied by a visual distraction: 10 small 'sparkles' wandering smoothly over the screen in random walks governed by perlin noise.

High and low load trials lasted 10 seconds each and alternated. After 400 seconds, providing 200 seconds of EEG data per class, a classifier was trained using a multi-band derivative of CSP to discriminate between high versus low load.

In a second, application phase, participants were presented with three different tasks to induce high load. One task was the same distraction task. Another was a multiplication task (a number between 6 and 19, multiplied by a number between 21 and 79), and another was a word-finding task (recognising randomly scrambled 5- and 7-letter words). The low-load condition remained the same as in the calibration phase.

During this application phase, visual distraction was also present, but regulated by the classifier output: any number between 0 and 15 sparkles could be shown on the screen, depending on current levels of measured load—0 for highest load, 15 for lowest load, scaled in between.
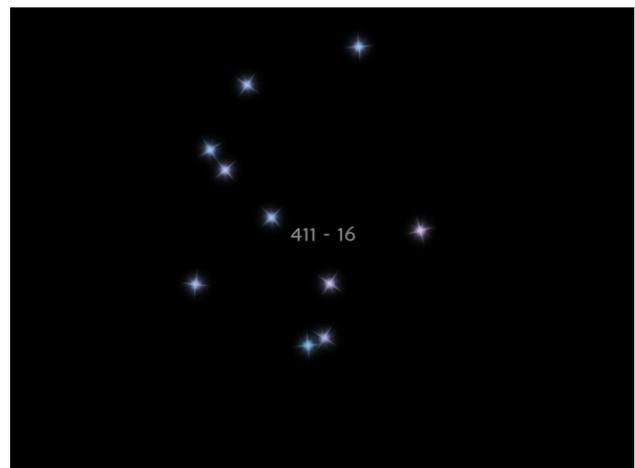
Fig. 4 A high-load trial with sparkles.

4.1.3 Results and Conclusion

The mean estimated offline classification accuracy for the subtraction task over all six participants who participated in the experiment comes to 70%±9. That is, for every second of EEG

data from the calibration phase, it could be determined with 70% accuracy whether or not load was high or low during that second. This classifier was then applied in the online phase.

During the online phase, the classifier trained on subtraction data achieved a classification accuracy of 68%±10 for new online subtraction data, 69%±13 for multiplication data, and 76%±15 for word data. These rates again describe the accuracies on all 1-second snippets of data.

We also found that during the online phase, the high-load conditions saw significantly less sparkles than the low-load conditions.

The sparkles thus provided a balancing element: when load conditions were detected to be low, additional sparkles were added to prevent boredom; when conditions were detected to be high, sparkles were removed so as not to distract from the task.

This data supports the idea of developing a task-independent workload classifier that can be quickly calibrated and applied to a number of tasks that it was not explicitly trained on. A task-independent, generalized workload classifier would continue to work reliably even when the human switches tasks, greatly enhancing its applicability in modern working environments.

4.2 Implicit Cursor Control
4.2.1 Motivation

A measure of e.g. workload can be used to support an ongoing interaction. Implicit input is used to adjust certain parameters in order to optimise the conditions for the original interaction to take place.

We have demonstrated that such implicit input can also be used to form a goal-directed interaction in itself. Here, implicit input, in this case information that was communicated without the participants even being aware of it, was used to control a computer cursor on a screen [27].

4.2.2 Experimental Set-Up and Procedure

Participants were seated and looking at a computer display. They were seeing a grid of four by four nodes, with one of the corners indicated as being the target. A cursor moved discretely over the nodes of the grid. Every three seconds, it would jump from one node to one of the (up to eight) adjacent nodes. The participant's task was to observe these movements and assess whether or not they were appropriate or not appropriate given the cursor's goal—to reach the indicated target. For each movement, its angular deviance could be calculated: the deviance (0-180º) of that movement relative to a straight line toward the target.

During the calibration phase, participants saw 600 random movements. From this data, two classes of movements were extracted: those with an angular deviance of 0º (i.e., going directly towards the target), and those with an angular deviance of 135º or more (going away from the target). These were representative of "appropriate" versus "not appropriate" movements.

A classifier was generated to discriminate between these two classes based only on the brain activity that was automatically evoked by each cursor's movement.

In an online phase, the classifier was applied to another 240 cursor movements. After each movement, the classifier determined whether or not that movement had been appropriate or not, based on the brain activity evoked by that movement. Now, instead of moving randomly, the cursor moved probabilistically with the different possible movement directions being reinforced depending on each outcome of the classifier. If a movement in a certain direction was classified as appropriate, then subsequent movements in that same direction were made more likely—or less likely if it was classified as not appropriate. As such, after a number of movements, the movements away from the target would have the lowest probability, and those taking the cursor towards the target would be the most likely. In effect, this would steer the cursor towards the target.
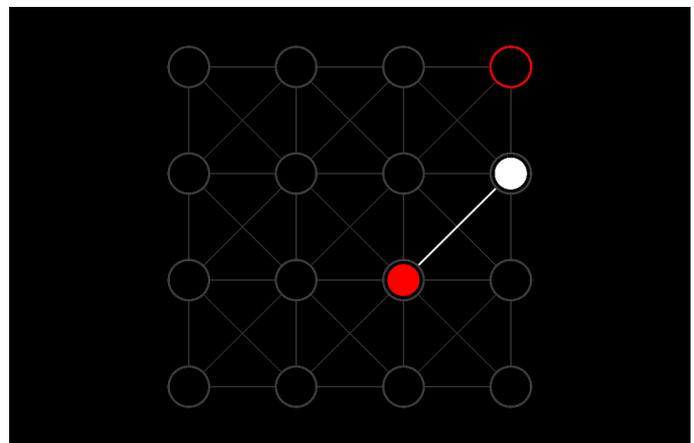
Fig. 5 A sample cursor movement. The red filled circle is the cursor in its original location; the white line indicates the direction of the shown movement. Since the target is in the top right corner, this movement has an angular deviance of 18º.

4.2.3 Results and Conclusion

Data was recorded from nineteen participants. Based on the calibration data, appropriate and not appropriate movements could be distinguished by the classifier with an accuracy of 73%±8.

Cursor performance was operationalised by the number of steps required to reach the target on one grid. In the random movement condition, the cursor requires an average of 27 movements on the four-by-four grid until the target is reached. In the online condition, this figure dropped to 13 movements per target hit.

These measures reflect a clear, goal-oriented improvement of the cursor's behaviour, i.e., effective two-dimensional cursor control, achieved through instantaneous classification of EEG data.

Neurophysiological analysis of the underlying EEG data revealed that the underlying brain activity most likely reflects human predictive coding, an automatic process of neuronal prediction of future events which is not modulated consciously.

Taken together, the results demonstrate for the first time a functional, closed interaction loop that, beyond repeated single-trial classification of specific user states, establishes an ongoing implicit dialogue between the machine and the user. This does not adhere to any classic concept of interaction: while the passive observers were unaware of even having the ability to influence the cursor, their implicit, internal responses did in fact control it.

5 Conclusion and Outlook

The studies briefly summarized here provide examples for new ways of interaction between humans and machines. They encourage us to envision new technological applications in the future.

Even though direct control is still much more reliable with standard input such as mouse, keyboard or even speech, certain use cases might benefit from active BCIs. Most prominent is the application as supportive technology for severely disabled people, where standard input is not possible. This is the core motivation for classic BCI research. However, also people without disabilities might want to use a BCI for direct control. For example, surgeons during operations who have both of their hands occupied may welcome other means to communicate with a technical device. A BCI-based, virtual "third hand" might be a solution here. A first approach, combining BCI with gaze-control indicated that this actually is feasible [28]. Another example of such an approach is the interaction with virtual objects in augmented or virtual reality applications. Here, too, a "third hand" capable of directly interacting with non-physical objects might be useful. But also passive BCI can be helpful here as envisioned in Protzak, Ihme, and Zander [29] and further investigated by Shishkin et al. [30].

In this brief overview of our work, we made a clear distinction between voluntary, direct versus passive, implicit control. In real-world applications this distinction might not always be that clear. A user who is aware of the passive BCI system might be influenced by the expectations it has of the system, and commit specific attentional resources to make sure that the "spontaneous" responses take place; or might attempt to consciously modulate this activity if results are not as expected. The other way around, an active BCI might rely on a command that is not fully voluntarily controllable by the user. This could already apply to motor imagery, which is sometimes hard to learn for specific people, resulting in longer stages of user training [31]. It becomes more salient in applications where the task is to explicitly modulate an aspect of the cognitive user state that is not usually controlled as such. This can be the case for neurofeedback applications or for games relying on BCIs. One specific example out of Team PhyPA's history is a demonstration of such an approach in a live TV show (TV Total, ProSiebenSat.1 TV Deutschland GmbH, Germany; see http://goo.gl/1ZLiCw for the video clip). Here, two players were battling over control of a quadcopter (Parrot AR.Drone 2.0, Parrot SA, France). They were standing 10 metres away from each other with the quadcopter initially placed in the middle between them. Their task was to push the drone towards the opponent such that it would land directly in front of them. To do so, both players were trying to relax as well as they could. The one who achieved the higher value of an individually calibrated measure of relaxation would move the drone towards the opponent. These measures were continuously updated for both players. This kind of control is hard to categorize as being voluntary or passive. Of course, there is some voluntary aspect to it, as both players purposefully attempt to relax. But any adverse reaction—such as the distraction induced by the quadcopter flying towards you, or excitement that you are successfully relaxing—should be seen as passive input.

In our perspective, the bigger potential clearly lies in the concept of passive BCI, as opposed to active BCI. It can be used to further narrow down the human-computer communication bottleneck by implicitly communicating information about the user to the machine, allowing it to adapt itself to the needs and aims of the user. Based on such input, neuroadaptive technology can learn more about its user over time, continuously building up and refining a user model [27]. This could ultimately lead to technology that actually understands its user, much like people understand their human communication partners in everyday communication and cooperation.

Acknowledgements

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