Chapter 9
Designing Future BCIs: Beyond the Bit Rate

Melissa Quek, Johannes Höhne, Roderick Murray-Smith, and Michael Tangermann

9.1 Introduction

The scope of this chapter is limited to applications where a Brain–Computer Interface (BCI) is used as an explicit interaction technique. In other words, we refer here to BCI as input which is voluntarily controlled by the user, rather than as an implicit interaction as in for mental or cognitive state monitoring. Designing applications using BCI as an explicit input technique for users with severe disability depends on understanding the control signals and how users can interact with systems using these controls. Although designing for able-bodied users has a different set of challenges, the BCI has to "add value" in both cases. Over the past 20 years of BCI research and design, the basic control functions have been realized by the collaboration of engineers, psychologists, machine learners and end users. These basic functions provide us with the freedom to design future BCI applications which are reliable in long-term use, easy to learn and set up, aesthetically pleasing, and have the potential to improve the lives of their users.

BCI can be thought of as an input technology which takes properties of other emerging input technologies to the extreme. The term "extreme" is used because the BCI interaction is much slower, noisier and more error-prone compared to other input devices, and lacks *proprioceptive feedback*. Because of these unusual characteristics, a theoretical framework which successfully analyses current BCI systems provides a springboard for developing and refining theories and practices within Human Computer Interaction (HCI). Although still important, research in

M. Quek (✉) · R. Murray-Smith
School of Computing Science, University of Glasgow, Scotland
e-mail: melissa@dcs.gla.ac.uk; rod@dcs.gla.ac.uk

J. Höhne · M. Tangermann
BBCI Lab, Berlin Institute of Technology, Germany
e-mail: j.hoehne@tu-berlin.de; michael.tangermann@tu-berlin.de

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BCI is moving beyond improving the bit rate of selection tasks to building whole systems that are enjoyable to use. This involves improving the usability and user experience of BCI applications, and requires taking into account the whole system rather than single isolated intention detection events. The following sections provide an overview of some factors we consider important for such a broader view on the design of future BCI applications.

Section 9.2 introduces the specific characteristics and problems of BCI in comparison with other HCI application fields. Section 9.3 emphasizes the focus on neuroergonomic principles in addition to usability principles especially for paradigms using Event-Related Potentials (ERP). Section 9.4 looks at how control can be shared between the user and computer. Section 9.5 looks at the structure of the application. Section 9.6 looks at how to involve end users, given the specific requirements and constraints of BCI. Section 9.7 presents analytic tools for investigating interaction designs.

9.2 Control Characteristics of BCI

In a BCI, brain signals produced by the user are directly interpreted by the computer. In contrast to most other HCI control paradigms, one major aspect of all BCI control paradigms is that there is no proprioceptive feedback. The user does not perceive the aspects of his/her brain signals which are measured by the EEG, but only perceives the feedback from the BCI. Thus, the user does not know the exact input to which the computer is responding. This uncertainty may create a series of problems in interaction design which are specific to BCIs. This is especially pronounced in the case of BCIs with low accuracy, since the user cannot know the reason for the malfunctioning interface: the input, the computer's interpretation of the input, or a combination of both.

A second difficulty associated with BCI is that the error rate is high in comparison with other input technologies. Although a typical user improves over time, a selection accuracy of 70 % has been considered acceptable for BCI use, which is rather low compared to traditional input technologies. This is not unique to BCI—other input technologies based on machine learning, for example, gestural interaction [72], also suffer from this, although there are few people who depend on such systems for interaction—they tend to be "luxury" items which allow amusing or rapid access to a small number of features, as a complement to higher throughput, more reliable input mechanisms such as keyboards. In the same way, the HCI community in these areas have typically focussed on improving the performance of these input technologies, without considering whether and how systems can be built to take into account the property of high error rate. With input technologies that have been widely studied and established (e.g. mouse, keyboard, touch input), selection error is usually very low. There is thus a huge scope for research into how users can interact with error-prone systems.

Further difficulties in BCI are associated with the amount of *measurement noise* and *uncertainty* in the system. There are several sources of uncertainty: together with the user's internal state (attention etc.), the EEG signals change over time (non-stationarity), they are furthermore prone to muscle artifacts, and the amount of class discriminative information which is extracted to drive the interface varies within and between users (see also Sect. 9.5).

9.2.1 *Issues Specific to BCI Paradigms*

Since brain signals acquired with EEG are very weak, noisy and non-stationary, there is an entire research area in signal processing [40, 41, 68, 69] and classification [2, 8, 30, 44] aiming to derive a stable control signal from the complex brain activity that enables a reliable BCI control. Various types of EEG signals and paradigms have been successfully used to drive a BCI. The two most important of them will be shortly discussed in the following, as they exhibit rather different control characteristics:

9.2.1.1 Self-Driven Paradigms

It is possible to extract signals that correlate with mental states that are voluntarily produced by the user (self-driven paradigms). The most common of these is the imagination of motor execution, where the user imagines repeated movements of a body part, for example, their hands, feet or tongue. Other mental states include imaging a cube rotating, or performing complex calculations mentally. It is then possible to train a classifier that separates the resulting EEG features. All applications based on self-driven paradigms have to deal with a very limited number of control signals: although multi-class (e.g. [48]) and multi-dimensional (e.g. [19]) paradigms have also been demonstrated, most successful paradigms are based on two mental states (i.e. imagination of left hand vs right hand). Important issues include that the paradigm is a learned skill which may take some time to acquire, that there is a delay between the imagination of movement and its detection due to the classification time window and switching between mental states, and that there must be appropriate mapping from the mental states to application controls. For example, mapping of right hand imagery to a "turn right" command is more intuitive than mapping visual rotation of a cube to the same command. Current techniques also struggle to distinguish between control states, where the user wishes to issue a command, and an idle state where the user does not wish to issue any commands. This parallels the segmentation problem in gesture recognition [60] and is currently and active area of research (e.g. [18]).

9.2.1.2 Evoked Potentials

Control signals with higher dimensionality and higher communication speed can be obtained by paradigms that present different stimuli and evaluate the corresponding neural response (Evoked Potentials, EP). Thereby, one can make use of neural correlates of attention, that are mostly found in two types of signals: steady-state evoked potentials (SSEP) and event related potentials (ERPs). When applying BCI paradigms based on ERPs or SSEPs, the user is constantly perceiving numerous stimuli which are presented either visually [17,67], via the auditory channel [33,56] or on the somatosensory pathway [11,12]. While attending to one stimulus only and ignoring all others, the target stimulus elicits an EEG response that can be separated from the EEG response of non-target stimuli.

From the user's point of view, paradigms using EPs differ strongly from those that are self-driven. Paradigms based on EPs are generally faced with the danger of overloading the senses of the user and forcing a fast sequence of stimulations and control events upon him. The constant perception of (visual, auditory, or somatosensory) stimuli may cause the user to become overwhelmed or befuddled. Using such interfaces might be uncomfortable, and the stimuli might not be aesthetically pleasing. To address the problem of unpleasant stimuli on the one hand and to increase BCI performance on the other hand, the stimulation principles should follow neuroergonomic principles (see Sect. 9.3).

9.2.2 Approaches to Overcoming the Limitations of BCI

Despite the problems of error and noise in the system, BCI applications have successfully been developed and used by able-bodied [73] and disabled [37] users. Much work has been put into developing systems for text entry input, for example, which take advantage of language models and optimal search trees. Section 9.4 and Chap. 6 of this book discuss the role of shared control in overcoming these limitations.

Users can be "deceived" into thinking that they have more control over a system than they actually do, as people are optimistic in their perception of how much control they have over a system. The phenomenon is called the *Illusion of control* [38]. This fact has been used in entertainment applications which provide some novel control but are not very accurate. The first commercially available "mind reading" devices like Mindflex by Mattel are discussed in [74]. The very successful Nintendo Wii controller often has very limited control based on accelerometer inputs, but users, especially new users, may not realise this, as the interaction makes sense within a particular game context. Often, a richer set of responses is generated by the user than is necessary for input detection, but which gives the illusion of a richer immersion in the game. For example, in the Nintendo WiiSports tennis game new players tend to interact with the system using flamboyant gestures and large swinging hand motions as they mistakenly understand the system to be requiring the same movements as in the physical sports, whereas much smaller movements can have the same effect. Such features can bring improved initial engagement and immersion in a task, which might be of benefit in training, but there is a trade-off with the effort required to use a system in the longer-term.

Recent approaches also combine BCI with other biosignals (such as EMG), aiming for a HCI with increased reliability and stability. Those approaches are called hybrid BCI [42]. Other solutions attempt to identify mental states that can be used to improve reliability of the signal or allow for error correction (e.g. error potentials [7]).

9.3 BCI: From Usability Research to Neuroergonomic Optimization

For optimizing task performance, Nielsen [45] proposed to focus on the usability components of *learnability* (how quickly novice users can learn to use a system), *efficiency* (how quickly expert users can perform tasks), *memorability* (how well users can gain control of an interface after not having used it for a period of time), *errors* and *satisfaction*. Even though Nielsen's concept has been criticised in recent years for lack of enhancing the overall user experience, these five components are widely used within the HCI design (especially in web design) community [58].

For the special case of a BCI-controlled application that is based on event related potentials (ERP), the optimization of overall task performance via the components *efficiency*, *errors* and *satisfaction* lead to a rather domain-specific target: the stimuli. During the use of an application (e.g. a text entry system) these stimuli are presented continuously and in quick succession. The stimuli are utilized to evoke brain activity that is informative with respect to the user's intention. Stimulus characteristics are thus at the core of an ERP application and their influence on the measurable (via EEG) evoked neuronal activity becomes subject of a *neuroergonomic* stimulus design approach.

The search space for neuroergonomically optimized stimuli, however, is extremely large: stimulus parameters can vary along many dimensions, with duration, intensity, stimulus timing and sequence aspects being only the most general ones. By selecting a specific stimulus modality (e.g. visual, auditory, haptic), an enormous extra amount of modality-specific parameters are to be decided upon by the designer. To add to the misery, some effects are rather subject-specific.

9.3.1 Existing Literature on Determinants for ERP

Generalized models that describe the mechanism for specific stimulus parameters in detail (or even their interplay) are not known to the authors. When it comes to the influence of cognitive and biological determinants of specific ERP components, the situation seems to be better. The neuropsychology of stimulus modality, intensity, sequence effects, etc. but also of gender, handedness, age etc. has well been studied [49, 51, 52, 54]. These results, however, were derived under well-controlled lab-conditions, used larger stimulus onset asynchrony (SOA) values and two or three stimulus classes only. Apart from a very few recent examples that will be introduced later, they report basic research from neurophysiology but do not take specific requirements of BCI into consideration. They focus, for example, on single aspects of an ERP component (e.g. the latency of P300) instead of the class discriminative information between attended and unattended stimuli (e.g via signal-to-noise ratio (SNR), area under ROC curve, classification accuracy etc). The latter is not only important for BCI, but it is even spread over a number of ERP components. Under these circumstances, it is not clear how the reported influence of the studied determinants generalizes to the rapid multi-class setups that are prevalent in BCI. The studies can, however, provide a starting point for more BCI-focussed investigations, where the goal is to obtain high class-discrimination. This goal seems to be extremely important, as it directly affects the *efficiency* of BCI control and the rate and severity of *errors*. Indirectly, it influences the level of *satisfaction*. Neuroergonomic stimulus design can attempt to improve the quality of evoked brain responses with respect to the class-discriminability or signal-to-noise ration (SNR) in a number of obvious ways: brain responses should be different for target and non-target stimuli, overall strong in order to contrast against background EEG activity, low in within-class variance etc. Less obvious aspects are of similar importance for a robust long-term efficiency: sustained brain responses are required that show minimal habituation over time and which are robust with respect to changes in the unavoidable surrounding perceptual influences. In combination, stimuli should be used that robustly result in high classification accuracy per BCI decision or (as a trade-off) in quick class decisions that use only a small number of repetitions.

So far, only a limited number of studies HAVE investigated details of stimulus design in the context of BCI, but the level of improvement that could be gained by optimized stimuli is already promising. The first attempts for stimulus optimization were described by Hill et al. [29], comparing the standard visual flash stimulus (color intensification) with a flip stimulus, where a letter was stimulated by a rotation in its background. They found that the BCI performance for the flip stimulus (virtual rotation) was higher than for the flash stimulus. It is generally possible to modify the type of stimulus individually. As already described by Allison and Pineda [1], Hill et al. [29] and others, the choice of stimulus type strongly affects the BCI performance in visual paradigms. Comparable work for auditory ERP studies were done by Schreuder et al. [55], Halder et al. [27].

To investigate the influence of stimulus characteristics, an offline study was performed with 13 able-bodied users performing a visual ERP paradigm with row-column highlighting in a grid with $6 \times 6 = 36$ entries. The highlighting effect varied in six conditions: (1) brightness enhancement, (2) scaling, (3) rotation, (4) color inversion, (5) masking with a grid, and (6) a combination of effects (1,2,3,5), see Fig. 9.1a. Conditions were presented block-randomized and with a constant stimulus onset asynchrony (SOA) of 225 ms.

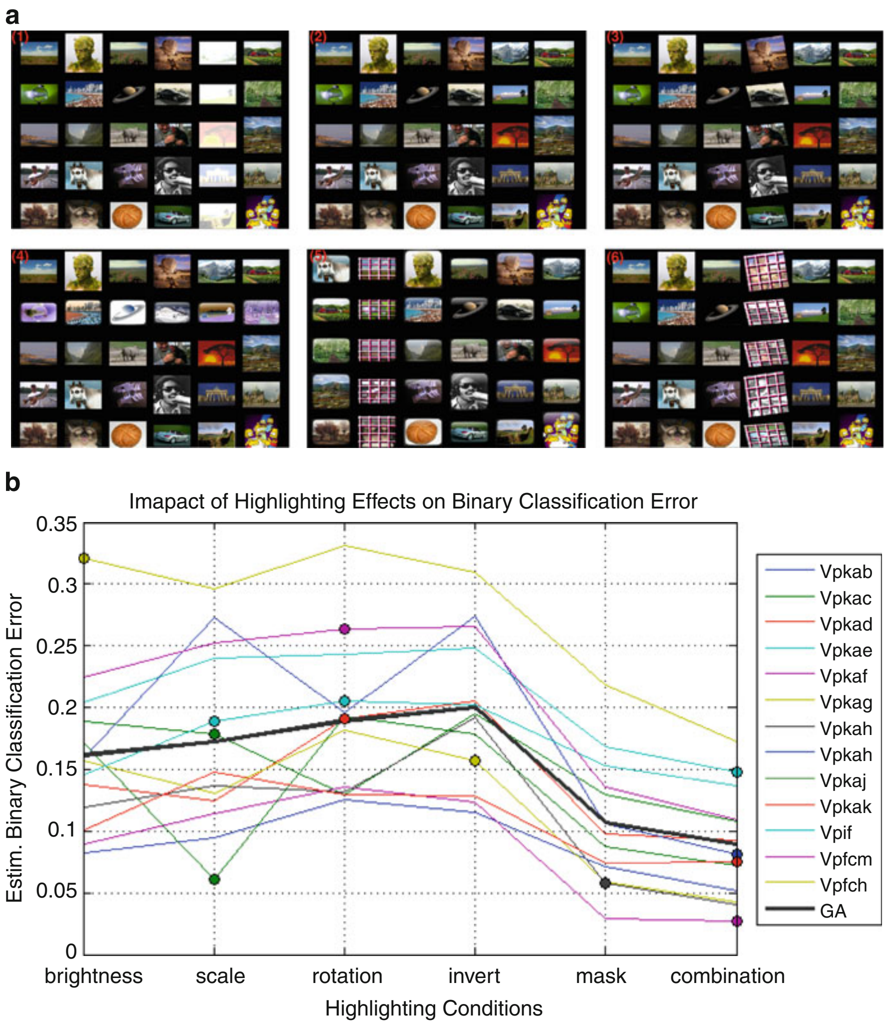

Fig. 9.1 (**a**) Visualization of the six highlighting conditions brightness, scale, rotation, invert, mask and combination (ordered from left to right). (**b**) Estimated binary classification error of 13 users performing a visual ERP paradigm in the six conditions.

Figure 9.1b visualizes the binary classification error (representing the inverse of BCI performance) of calibration data collected. The uniformity of the results is astonishing: the conditions mask and combination perform best for all but one user, indicating that those conditions should generally be used to obtain best performance. As the subjects did not get feedback about the classification error during the experiment (the analysis was done post-hoc only), it is interesting to investigate if they were aware that the different conditions had different effects on their brain response. For this reason, the users were asked which condition they considered best for long-term use (answers are marked with a circle in Fig. 9.1). It can be seen that the individually favored condition often performs poorly in terms of classification error. Thus, if users could choose the type of stimulus themselves, they would choose a highlighting effect with poor performance in ∼50 % of the cases.

9.3.1.1 Interaction of Neuroergonomic Optimization with Other Usability Goals

Obviously a faster or more reliable control interface can improve the user's level of satisfaction with an application. While the optimization of stimuli is important for increased control performance, other usability goals must not be lost out of sight. For example, the various rather indirect influences of stimulus parameters on the user's comfort level are unclear and will need evaluation. Important research questions to tackle are:

- Which stimuli lead to optimal learning curves for the discrimination and attention task?
- How can we design good stimuli to be familiar, pleasant and constant?
- Which stimuli show a low obtrusiveness level (are they recognized by a present third party? Do they disturb?)?
- How much should stimuli be allowed to interfere (perceptually and in terms of cognitive processing) with other sources of information?

9.3.1.2 Example: Comparison of User Ratings (Satisfaction)

Coming back to the study introduced in the above example, some aspects of user satisfaction were probed in addition to the analysis of pure classification performance: To collect information about how a stimulus condition was perceived subjectively, the 13 participants were asked after the EEG recording to provide ratings (among others) for how motivating, how clearly perceivable and how non-exhausting a stimulus class was, using a visual-analog-scale (VAS).

As the conditions "mask" and "combination" were found to lead to a great improvement of the binary classification error, and "combination" being the best condition on average, it is worth taking a closer look at the VAS ratings for this condition. From Fig. 9.2, it can be observed that all three VAS ratings are negatively correlated with the binary classification error. Subjects, for example, that rated the "combination" effect more motivating than other subjects are typically able to use the BCI paradigm with lower error. VAS ratings can be obtained for a new BCI user quite easily and without an EEG recording. Although based on offline data analysis only (in contrast to the more relevant online performance), such ratings may serve as powerful predictors for a subject's estimated classification error on the calibration data. Based on the error prediction, the complexity of the BCI application interface could be adapted in advance for the individual user. For poorly performing

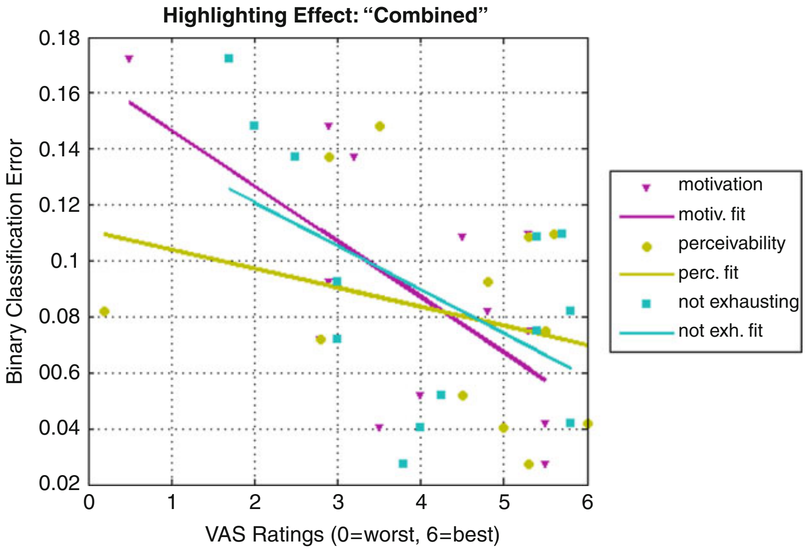

Fig. 9.2 VAS ratings vs. estimated binary classification error. For 13 subjects, the x-axis marks the subjective level of motivation, the level of perceivability of the stimuli and the rating how non-exhausting the subjects considered the "combined" highlighting effect. The y-axis marks the estimated binary classification error of single target vs. non-target EEG epochs

stimulation conditions (e.g. color inversion), however, a similar correlation between VAS and classification error could not be observed. Furthermore it is not clear, to what extent these or similar subjective ratings can be utilized to determine the best stimulation parameter from a set of alternatives for a new user.

It remains an ongoing research goal to investigate how BCIs need to be designed to co-optimize the three aspects: (1) motivation to use the applications, (2) high-level perception of the applications, and (3) neuro-ergonomics for desirable brain responses.

For long-term use, the level of cognitive workload that a user has to invest to control the BCI application should be kept low. Influencing factors might be the clarity or distinctiveness of stimuli, their intensity, whether they grab the user's attention or if they are annoying over time. Intense stimuli might be suitable to elicit strong ERP responses, but load an increased long-term burden of high workload on the user.

9.3.2 Aesthetics, Interaction Metaphors, Usability and Performance

The focus on usability in HCI came from the need to improve task performance for work-related applications. However, in recent years there has been a shift within the HCI community not just to improve usability but also the user experience [65]. This has paralleled the shift of technology usage from being used merely for work purposes to being consumer-focused. Tractinsky et al. [66] showed that a high level of perceived aesthetics of an interface is viewed as also being highly usable, regardless of the actual usability of the system. Norman [46] also proposed that products which elicit a positive emotion with regard to aesthetics are more likely to be used. Since the performance of a BCI system is often less than ideal, improving the aesthetic qualities of such a system is important in order to maximize the users' perception of and motivation to use the system.

However, aesthetics should not just be "eye candy" but should be part of creating a convincing interaction metaphor, with its rapid communication of state, indicating action affordances and helping learnability. In mainstream interfaces, aesthetic feedback is used to provide information about a system to the user. For example, a progress bar showing how much of a file is left to be downloaded can indicate that the system is still doing something. The sound of rubbish being thrown into a bin, accompanied by a "drag and drop" metaphor of a file into the waste basket provides the user with a sense of closure that the file has been deleted. Specific aspects of BCIs which can improve interaction performance (rather than just perceived usability) include presentation of stimuli which are easily interpretable and which motivate, delight and engage the user, and which are rich enough to provide feedback about the effects of the user's brain signals. They should make the system state clear to the user, and give them feedback about what they have selected or are about to select. The feedback could be across multiple channels beyond visual feedback, including audio, vibrotactile, and perhaps even smell.

Users' subjective experiences can differ from the performance of the system. For example, in investigating a single-switch scanning input system, Felzer et al. [20, 21] found that a user was faster with automatic scanning (where the scanner automatically moves on to the next selection) than self-paced scanning (where the user decides when to move on to the next selection), but made more errors. The user reported that the automatic scanning was more frustrating, and that he was surprised that he was faster with the auto scan mode as he felt more in control with self-paced scanning.

In our own experience, we find that some people prefer a paradigm like the rotate-extend (REx, a generalization of the hex-o-spell paradigm [71], Fig. 9.5), where the pace of interaction can be slower, to a discrete binary paradigm which might objectively have higher throughput. The paradigm appears to work particularly well where the 2-class classifier is biased to (tends towards) one class: the biased class is used to rotate an arrow round the centre of a circle, while the other, control, class works to extend the arrow at the correct point of time in order to select a segment. Several possible reasons for some users' preference include that the control method of switching between mental states feels easier or more natural, that there is a possibility of going round the circle again if a target is missed and hence although slower, be more accurate, and that the pace of the interaction feels more comfortable or relaxed. In the context of an application, this may allow users to feel less pressured by the system to make a quick binary decision. The example illustrates again the need for research into how enhancing other control features in addition to the performance of a BCI is important for improving the user experience, and how BCI-specific problems (e.g. the presence of a biased classifier) can be turned into features.

9.4 Shared Control

Shared control involves the co-operative control of some process between a system and a human, where autonomy is smoothly distributed between the system and the human, possibly in a time-varying manner. Shared control can be desired due to different sensing abilities in user and automated systems, speed and safety requirements, as part of a user's learning problems, or simply to reduce the effort required to control a system. In BCI, where the input channel is impoverished, the inputs of the user are too valuable to naively interpret in a mechanistic fashion. For instance, in a robot control system, a simple mapping of a brain-controlled cursor movement to robot movement is far too slow and error-prone to be practical. Similar arguments apply to text entry with a brain-controlled cursor that selects letters from a virtual keyboard. Instead, the user's actions are interpreted partly as direct control signals and partly as indications of the user's higher level intentions. The system attempts to "intelligently" infer what the user wants to do, based on knowledge about the task, and make changes to the response of the system. It uses prior information about likely or sensible behaviours (e.g., smoothness constraints, obstacle avoidance, predicted words, music file features) based on other in-built knowledge and contextual information which the system can draw upon.

The handover of autonomy between the user and the system is determined by how certain the system is about the user's intention. When the user can precisely express detailed intention, the system will follow. As communication breaks down and the system is unable to reliably and quickly infer the user's intention, the system will fall back to prior behaviours. These behaviours need not be static and can depend on knowledge of the environment, such as robot cameras to estimate likely obstacles or language models for text entry. Shared or hybrid controls can also be used to combat fatigue associated with a particular control channel or level of control, allowing the user to "dip in" to direct control as they feel appropriate during interaction [10, 63, and Chap. 6].

In Flemisch et al.'s [22] influential paper, the *H-metaphor* is introduced, which suggests the relationship between a rider and a horse as metaphor for shared control. The horse can navigate obstacles around it without rider attention; the rider can vary the level of control over the horse by tightening or loosening the reins. With tight reins, the horse obeys precisely and immediately, whereas when looser reins are used, the horse acts partially autonomously. The horse treats the tightness of the reins as an indication of the user's certainty about control actions. Although this was developed at NASA to deal with advances in cockpit automation [24], many of the core ideas can be brought over to other areas of interaction design where users can

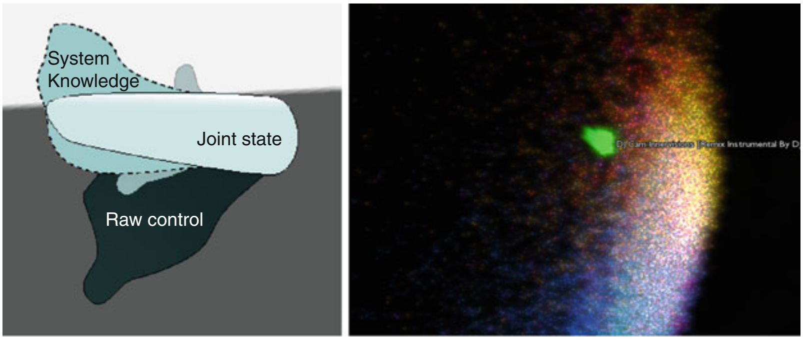

Fig. 9.3 The combination of direct user input and system knowledge into a single controllable liquid blob. The system can display the user input state and the effect of environmental constraints as shadows to a blob whose form represents the mutual control state from the fusion of user commands and prior and external knowledge (*left*). An example of this approach used in browsing a map of music files (*right*)

regulate the current level of control, via "loosening the reins." This can be seen as an example of hierarchical control where the user can change the level of control they are currently are active at. The challenge for BCI is therefore to enable the user to "take up the reins" when in good control and he feels like it; and progressively (but non-intrusively) "take over" when the person has bad control or when the person wishes to relax.

An open research question is in which ways can we enable the system to "help" the user at a level that is invisible to the user and at which the user still feels they are in control? Note the comparison to the earlier discussion of the *illusion of control*—designers need to make an ethical and practical decision about when and how transparent to be about when the user controls the system and when not. If the system does what the user wants it to do, the user has the feeling that they are in control, or they are the one controlling the system. This has an obvious impact on the learnability of BCI systems (if a user thinks they are successfully controlling it on their own, but actually all the control came from autonomous systems, they cannot improve their performance). It may also have an impact on the user experience, as during the application of BCI systems it might be that users who depend on a BCI for communication especially want the feeling of control in a system.

The liquid metaphors explored as part of the Tools for Brain-Computer Interaction (TOBI) research project show how shared control systems can be visualised http://www.tobi-project.org/, with appropriate representations of uncertainty. Figure 9.3 shows how this could work. The user's input can be visualised as a moving "blob," whose area gives an impression of the associated uncertainty. This can be combined with system knowledge about likely intended actions (e.g. obstacle avoidance), and the result displayed as another blob, which deforms and flows according to both the user input and the system's changing beliefs about intended actions. Displaying the user's raw input as a kind of "shadow blob," makes it easy to see how actions are being sensed and then re-interpreted in a shared control setting. This system is being used in a music player to combine a user input with music knowledge from the automatic systems.

9.5 Creating an Effective Application Structure: A 3-Level Task

A human being can be thought of as a control system with an unreliable input signal, often making mistakes, slips or errors in interacting with machines [15]. As such, computer interfaces should be designed such that they:

- Prevent errors whenever possible.
- Deactivate invalid commands.
- Make errors easy to detect and show users what they have done.
- Allow undoes, reverse, correct errors easily [35].

This is especially true in BCI systems where the inherent error in the input signal is higher than for other input methods. An example for such an application structure in this context can be found in the Rotate-extend (REx) control illustrated in the Hex-o-Spell text entry system [71].

So far, BCI studies have largely focussed on the selection accuracy of single events, while the dynamics of serial selection tasks or within the whole application has rarely been taken into account (text entry BCI applications that use language models are a positive exception). While it seems obvious that application learnability is of paramount importance for usability, and that the learning user has to be taken into account, BCI systems show the necessity for one further, very basic level of learning. In the following, the potential of all three levels of learnability and adaptive behaviour are visited.

9.5.1 Low Level: BCI Control Signal

Learning on the level of the BCI system is often performed by machine learning methods, that are used to establish (initially, by learning regularities from calibration data) and maintain (during the use of applications, by adaptation strategies) a robust transduction of the user's brain signals into control signals for an application. On this low-level, a BCI-system is learning about the user, and how to detect the regular patterns as well as the non-stationarities of his brain activity. Advanced BCI systems may in addition fulfill somewhat more complex, but still relatively basic tasks. They can for example be used to monitor mental background states (e.g. levels of workload or fatigue) and gain information that is not used for control but that indirectly can support the detection of control commands or take influence on e.g. the complexity of the BCI application.

Systems can also keep track of the amount of evidence accumulated over time during the use of a BCI application in order to provide different control alternatives. For example, decisions can be taken earlier by following dynamic stopping criteria (e.g. for ERP paradigms [57]), or the speed-accuracy trade-off can be utilized beneficially in special situations. This latter case immediately leads to the next level of learning and adaptation: the application.

9.5.2 Mid Level: Application

On the application level, the system should adapt to the user's behaviour rather than to his brain signal characteristics (the latter should hopefully be stabilized already by actions taken at the low level). Obvious examples of such mid-level adaptation strategies are text entry systems, that update the statistics of a supporting language model by taking previously written text into account (cp. the discussion in [33]). As the number of control signals per time is extremely limited in BCI, an efficient menu structure, the availability of shortcuts, the avoidance of errors and the simple recovery of errors is important for every kind of BCI application. Although users expect consistency and predictability in a user interface, some research shows that acceptance of adaptive systems depends on the order of presentation [59], while Gajos et al. [23] found that providing accurate hints in an adaptive toolbar was more important than predictability of the toolbar in terms of performance and perceived usability. Applied to extreme conditions like in BCI, a trade-off between consistency and efficiency might be possible and desirable for the user: future applications could learn form past user behaviour and increase efficiency by, for example bootstrapping the menu structure or introducing new shortcuts. This is important as a match between the user requirements and system functions is paramount to user satisfaction [47].

9.5.3 High Level: User

While using a BCI system, the user is learning about the application. This might affect the input characteristics. In a BCI driven by motor imagery, for example, the user continuously learns how to perform best, by e.g. optimizing the timing for motor imagery and relaxation. For paradigms driven by evoked potentials, an example would be that the user is learning about the application structure. This leads to an individually more efficient way to interact with the application. The application can be designed such that it is able to cope with these dynamics.

In general HCI frameworks, user interfaces should aim to optimize the control system (menu hierarchy) as much as possible, when the cost of input is high. Current operating systems still have some way to go in optimizing system control for assistive technologies, as there is often an implicit assumption that input mechanisms are reliable with high throughput, and there is little consideration of the perceptual difficulties of mainstream HCI technologies such as visual menu structures. The problems are exacerbated for BCI users where the cost of input is high.

9.6 Engaging End Users and the Role of Expectation

Designing interaction requires participation or evaluation by target end users since designers and developers often have different ideas and assumptions about the target group with respect to the target users' requirements and mental model about an application or interface [15]. General design guidelines and principles can help in development and design, but even in applications using typical input technologies, the requirements and experience of users are sometimes not intuitive to designers – let alone for novel input technologies such as BCI. In this section, we describe the need to choose appropriate evaluation methods for different user groups, taking into account the impact of user expectation on the methods and tools used (see Chap. 8 of this book for a more in depth discussion on the topic).

BCI user groups can be distinguished according to their physical abilities:

1. Users with no physical disability may be interested in using BCI for gaming or other conditions where physical movement is restricted. An interesting area of research here is in using cognitive workload monitoring to evaluate usability of interfaces [28]. User feedback can be collected through interviews and questionnaires during tasks or after sessions. Evaluation techniques that aim to find out about aspects of user experience are in early stages of development, see also Chaps. 11 and 13 on game evaluation.
2. Users with severe physical disabilities may wish to use BCI as a secondary input, switching from muscle to BCI input on the onset of muscle fatigue. User feedback can sometimes be collected through interviews and questionnaires depending on how easily they can communicate through other means, and it is important to condense the amount of responses required since responses will take far longer to acquire and users will tire easily.
3. Users who are locked-in (having no residual muscle control) or almost locked-in (having very limited residual muscle control), may need to use BCI as a method for communication. User feedback here is restricted to questionnaires, while access to such people is limited. Since HCI evaluation techniques typically require multiple participants, and performing a large testbed of trials is not possible, case studies have been used to elicit feedback and requirements from this group of users [36].

Motivation to use a system is dependent on expectation: able-bodied users are likely to be impatient with the inferior control properties of BCI, while for disabled users, previous experience of mainstream and assistive technologies can have a huge influence on the acceptance of new technologies. For example, someone who was highly competent with mainstream input devices and operating systems before a disability occurred might expect an assistive technology to enable him/her to attain a level of performance or autonomy similar to what they had been used to. They can often become disappointed or disillusioned when they realise that the input device will take some time to learn and be slower and more difficult to control. For BCI, this effect is augmented as the current state-of-the-art is far worse than the usual assistive technologies such as single switch devices.

Increasingly we are finding that motivation is an important factor for users learning to use a BCI paradigm [14, 39], as well as for wanting to use the system. For example, Mönßinger et al. [43] found that disabled users have a higher level of motivation than able-bodied users to use a BCI painting application. As user requirements and expectations can differ between able-bodied and disabled users [62], more work is needed to find out how user expectations can be shaped or primed to increase motivation to use BCI applications. In addition to increasing user performance and accuracy, increasing positive affect could prove to help the user overlook or better tolerate a low bitrate of communication, improving the perceived usability and overall experience of the system.

9.7 Investigating Interaction: Prototyping and Simulation

In designing applications for users, the gap between designers' *understanding* of end users and end users' *actual* requirements, abilities and perceptions means that designers need to engage with users to establish how usable or desirable their design is to actual users. A prototype is an object or system that simulates or represents some limited aspect of a future system in order to obtain feedback from the intended users. Prototypes can be used to investigate the role a system will play in users' lives, how the functionality should work, and what it should look and feel like [34]. Different tools and techniques can be used depending on the what the designer wishes to find out [61]. Although BCI is currently expensive, and time consuming to set up and use for evaluation, methods for engaging users prior to real BCI development and testing has been under utilized. These can reduce the time-costs of engaging with end users, and allow researchers and designers with limited access to BCIs and end user groups to participate. In this section, we explain the value of using prototyping and simulation to explore BCI interaction even without an EEG cap, as the known properties of control can be simulated or animated.

9.7.1 Low Fidelity Prototyping to Expose User Requirements

Low fidelity prototypes are those which look "cheap and cheerful" and whose development do not take much time. They can be used to evaluate initial designs as they have the advantage of reducing the cost of development, and have been shown to provide virtually the same feedback as usability evaluations with high fidelity prototypes [70]. A challenge for developing prototypes for BCI is that demonstrating the control characteristics are an important part of the interaction,

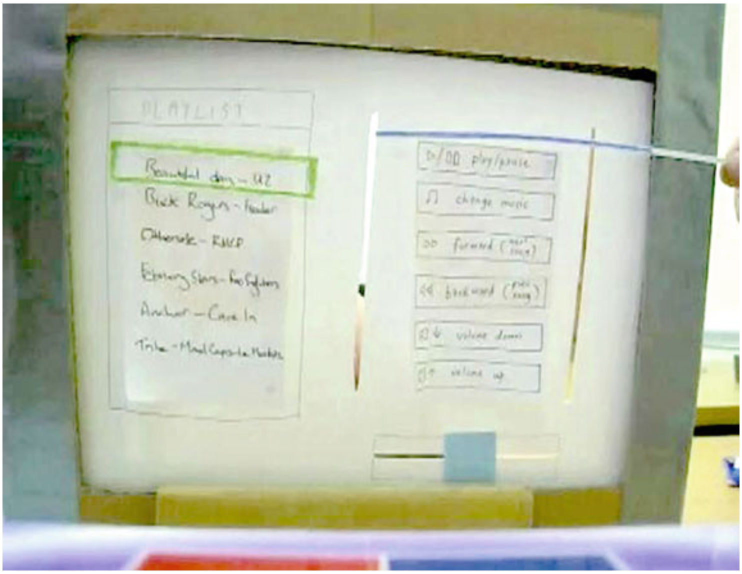

Fig. 9.4 Screen shot of video of a paper-prototype of a scanning-based BCI music player

while the usual low fidelity prototypes that involve pointing and selecting do not intuitively allow for this. Engaging end users with these prototypes has not yet received any attention in the BCI literature.

9.7.1.1 Example: Paper Prototype of a Scanning Interface

In 2010, we developed a prototype scanning interface using paper and cardboard (Fig. 9.4). The prototype was intended to gain insight into how users would want to use a BCI-controlled music player given the error properties of BCI. Participants were six users with minor—severe disabilities and one participant described as locked-in. As users were likely to be familiar with a scanning system from using other AT systems, a scanning-based system was used to demonstrate some features of the music player. The aim was to show how a motor imagery-based music player would work, and to highlight the problems with error and time taken to achieve goals that might be encountered in this system.

We created video scenarios depicting possible behaviours of the system. To address the issue of there being no true asynchronous control (i.e. a selection to the system would always be made after some period of time), users were shown a video prototype of a music player that started or stopped playing, or skipped to the next or previous track even though the listener was not trying to control anything. They were first of all asked to comment on whether they would use this music player, followed by whether they preferred one of several options, with each option having its own video simulation:

1. Do a sequence of selections to activate the player (in this example—left, right, left, left).
2. Remove some functions like back/next that would abruptly change the music being played more often.
3. Create the playlist but someone else can decide when to start and stop the music.

In general, participants thought it was ok for the music player to make mistakes where the music would start and stop randomly. Participants showed a range of tolerance to and preference for the different options, with one accepting all the solutions as better than the initial presentation of the player, even if someone else could decide when to start and stop the music—as long as he could choose when this function was enabled, while another rejected all the options. In response to (2), two of the participants suggested making these functions possible but harder to do. One participant decided that the initial option where the music started and stopped randomly was still the best, while three thought the best option was (1). A couple of participants indicated that they would be content to use BCI to create the playlist, then remove the BCI cap while listening to music. The discussions highlighted that flexibility and individual preference are major factors in developing interfaces with error-prone control; thus the ability to customize applications is paramount.

9.7.2 High Fidelity Simulations for Design and Development

One potential way of developing prototypes for BCI that represent the control characteristics is to build a simulator. Simulation in the BCI literature usually refers to running offline analysis on some raw EEG data in order to improve or explore classification techniques (e.g. [18,25,64]). Here, we refer to simulation as modelling the control of a system in order to tell us something about the interaction between the human and the machine. In this sense, simulation in HCI and BCI tends to focus either on prediction of task performance via offline analysis, or on the feel of the input via online analysis. Offline analyses of interfaces using mainstream input technologies incorporate research in cognitive psychology [15]. In AT research, some work has been carried out on estimating task performance using perceptual, cognitive and motor models of an individual [5,6]. These usually involve models of motor performance which cannot readily be applied to BCI. Bensch et al. [4] used a model to predict how many transitions it would take to select certain menu items given an error rate, but did not compare this to actual use of the system.

"Online" simulation of disability includes simulating problems that may be faced by the elderly [31, 32], simulation of deficiencies in visual perception [3], and more recently, simulation of aphasia [26]. Such simulations, if used correctly [9], can enable designers and stakeholders to understand the constraints and opportunities for development. Cincotti et al. [12, 13] used a noisy mouse input representing the noisy input of BCI to explore tactile feedback, showing that tactile feedback could compensate for visual feedback under high visual workload conditions.

Plass-Oude Bos et al. [50] asked users to imagine different mental states to control an input, showing that users preferred different mental states depending on the accuracy of detection. Other than these examples, simulation seems to be an under-used, but potentially highly valuable tool for BCI research.

Low-level simulation is not often used to make predictions about the actual performance of a user interface. One exception is the EASE tool which simulates the interaction of users with motor disabilities [16]. Using this tool, it was found that adaptive word prediction is useful only for typing speeds less than five to eight words per minute. We propose that a similar approach is useful for BCI research, where low-level simulation of the control characteristics of BCI can be used to investigate aspects of application control that have previously been discussed such as how users respond to error, delay, and the speed-accuracy trade-off. This is especially useful for investigating interaction with a wide range of individual differences in control properties. Quek et al. [53] showed that the delay and error properties could be simulated for different users using a simple model of the interaction. The next step is to model sequential interactions, perhaps where errors create more errors. Using such a tool, we hope to be able to combine the predictive capabilities of simulation with online use of the system. Our goal is to lower the pre-requisite knowledge and tools for non-BCI-specialists wanting to develop and design applications for BCIs.

Importantly, our simulator replaces real BCI input for testing BCI applications without the need to wear the cap. In our experience, problems with the application interfaces are discovered as soon as it receives real BCI input, indicating a lack of understanding of how the interaction would flow once the BCI is connected. Here we present an example which shows that knowledge gained from testing user interfaces with a simulator can inform design and be used to debug applications before testing with real BCI.

9.7.2.1 Example: Application Design and Development Using Simulators

In developing a BCI-controlled music player, we are able to employ an iterative style of development through the use of a simulator. In this case, we decided to use the rotate-extend (REx) paradigm to control the functions of a music browser (Fig. 9.5). One error was that the first segment can easily be selected unintentionally. A possible solution is to make sure that enough time is given at the start (before the feedback starts moving) for the user to prepare the correct mental state. Other solutions include making sure that the segment most likely to produce false positive errors is one of low risk (can be easily undo-able, e.g. play or pause), or ensuring that the first part of the wheel is not selectable. We were also able to experiment with ways of enabling an "intentional non-control," or idle, state. When the user selects "play," the wheel selector locks so that music can be listened to without interruption. Depending on the control properties of an individual on a given day, the parameters of the application can be tuned to make it easier or more difficult to lock and unlock the music player.

Fig. 9.5 Music player selection wheel interface based on the hex-o-spell paradigm [71]. One mental class is used to rotate the arrow in the centre of the circle, while the other class is used to extend the arrow in order to select a control segment. *Left*: while music is playing, the music player is in a locked state: the "unlock" segment must be selected in order to reactivate the player. *Right*: the selection wheel in an unlocked state where selection of any segment is possible

9.8 Conclusion

The future of BCIs is in integration. Already an interdisciplinary area, the field of BCI must be and is already starting to inform and be informed by various disciplines outside neuroscience and engineering, specifically HCI, control theory and design. BCI researchers should start to pin down the characteristics that are similar to and different from other assistive technologies, and from other emerging input technologies that deal with uncertain, noisy inputs which may provide either implicit (e.g. context awareness, bio sensing) or explicit (e.g. gesture) control. Where BCI input characteristics are similar to other more established methods, we should embrace what has been learned from these and identify areas where shared knowledge is currently lacking. Where there are differences in interaction design that are unique to direct communication with devices using brain activity, we need to further develop BCI-specific design principles and guidelines.

The extreme nature of current BCI input is well-suited to highlight the conceptual gaps in the foundations of human–computer interaction research, and will stimulate the creation of new frameworks.

Some effort is necessary to integrate what we already know about low-level brain-signal characteristics, neuroergonomics, user expectations and motivation, individual differences etc. into whole systems that are enjoyable to use. Researchers should thus focus not only on improving the communication rate of BCIs, but also on improving the user experience of systems which use BCI. This will be even more important in future applications of BCI to able-bodied users, where the user experience will need to be acceptable for users to engage with the technology at all.

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