12

Brain–Computer Interfaces for Human–Computer Interaction

Research on BCIs has so far usually focused on processing and classifying brain signals with the objective of improving the speed and precision of the interface. Progress in these areas has allowed us to diversify the applications of BCIs. It is now time to work on improving the interactions that occur through these interfaces.

We will study in this chapter the relationship between BCIs and Human–Computer Interaction (HCI), and we will see how our knowledge in HCI can be applied to BCIs. We will first begin with a general overview of the principal concepts of HCI. We will then study the most important properties of BCIs in terms of these concepts. This chapter will also discuss the problem of choosing the right cerebral pattern for a given interaction and usage context. Finally, we will present the most promising recent paradigms of BCI interaction.

12.1. A brief introduction to human–computer interaction

Human-computer interaction (HCI) is a discipline concerned with the design, evaluation and implementation of interactive computing systems for human use [HEW 92]. In this section, we will simply define a few important

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concepts from this vast field of research. Interested readers can refer to [JAC 12] for a much more complete introduction to the subject.

12.1.1. *Interactive systems, interface and interaction*

An *interactive system* is a system whose operations depend on an unpredictable input from an external environment that it does not control [GOL 06]. The *interface* is the set of hardware and software mechanisms that allow a person to operate, control and supervise an interactive computer system. *Interaction* occurs between the user and the system. This is the object of study in HCI, which aims to understand it (i.e. observe it, describe it, explain it) and improve it.

12.1.2. *Elementary tasks and interaction techniques*

The operation and control of an interactive computer system are founded on a set of *elementary tasks* that the user can achieve. Each task can be performed by means of a set of various *interaction techniques*. The elementary tasks are the smallest units of operation possible in a given context. An interaction technique is a certain combination of hardware and software mechanisms that accomplishes a given task. The task represents part of the objective, whereas the technique represents part of the means by which that objective is achieved.

Elementary interaction tasks vary in nature according to the domain of application. For example, Foley *et al.* list six elementary tasks for graphical interactions: selecting, positioning, orienting, tracing, quantifying, and text input [FOL 84]. Touching an object on a touch screen or indirectly specifying it by clicking on it with a mouse are two examples of interaction techniques for selecting that object. Operating a physical potentiometer, a virtual potentiometer with the mouse or entering text are three possible techniques for specifying a numerical value. Voice recognition or keyboard input are two possible techniques for entering text.

12.1.3. *Theory of action feedback*

The *theory of action* outlined by Norman deconstructs the act of performing a task into seven stages: establishing the goal, forming the intention, specifying the action sequence, executing the action, perceiving the system state, interpreting the state, and evaluating the system state with respect to the goals and intentions [NOR 86] (see Figure 12.1). These seven stages are not all necessarily present, and can occur in a different order, but this decomposition is nonetheless useful for analyzing and designing interactive systems.

The user's mental picture of certain concepts might be very different from the way that these concepts are implemented by the system. For Norman, there are two gulfs separating the user's conceptions from the system's conceptions: the gulf of execution and the gulf of evaluation. The terms *distance of execution* and *distance of evaluation* describe the effort that the user or the system designer must invest in order to cross these gulfs. The adjectives *semantic* and *articulatory* are used to distinguish efforts related to the meaning of user-system exchanges from efforts related to the form that these exchanges take.

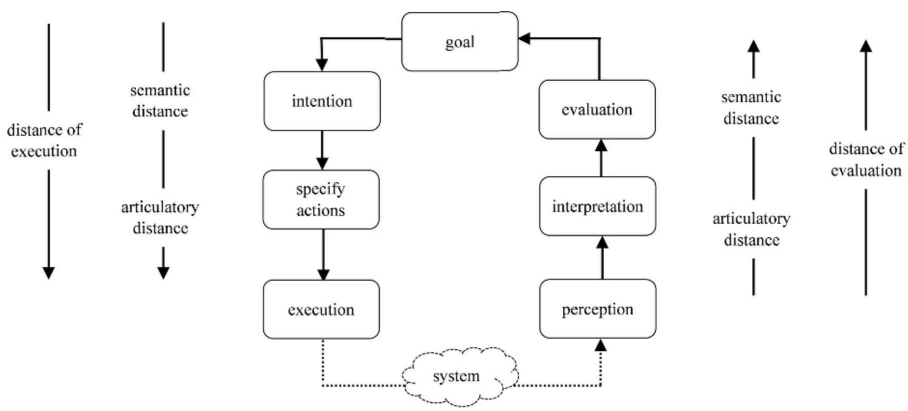

Figure 12.1. *The seven stages of user activity when performing a task and the corresponding distances [NOR 86]*

The speed and the form of the *feedback* produced by the system largely determine the capacity of users to perceive, interpret and evaluate their state changes, and thus affect the evaluation distance. For instance, prompt feedback builds a continuous representation of the state of the system, and the effect of actions as they are performed. Prompt feedback also contributes to the sensation that the user is acting directly upon the objects of interest, allowing the user to feel engaged in the task.

Interaction techniques are usually designed around the requirements of the tasks, leveraging as fully as possible the users' cognitive, motor and perceptual skills to reduce the execution and evaluation distances. But no matter how carefully the technique is designed, an interaction technique that is perfectly adapted for one task in a certain context may prove unsuitable in others. Text input by voice recognition is undoubtedly preferable to using a keyboard while driving, for example. The question of whether a certain interaction technique is suitable for a certain task in a certain context is the question of *usability*.

12.1.4. *Usability*

Usability is defined by the ISO 9241 standard as *the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use* [ISO 98]. Effectiveness refers to the capacity of attaining specified goals, efficiency describes the resources spent in order to achieve these goals and satisfaction describes how the user perceives the process.

Usability may be evaluated using a variety of different criteria. One might wish that inexperienced users find a system easy to use. Relevant indicators in this case might, for example, include the percentage of tasks successfully performed on the first attempt, the amount of time required to do so and the proportion of deliberately performed actions. Alternatively, one might wish a system that is robust to user mistakes. In this case, the percentage of errors corrected by the system, the time taken to do so and the user's appraisal of the corrections made are of interest. Another possible choice is a system that is easy to learn. We would then look at the number of functions acquired, the time taken to do so and the user's appraisal of the training process. The choice of usability criteria naturally depends on the domain of application.

12.2. Properties of BCIs from the perspective of HCI

BCIs measure cerebral activity signals, filter these signals, extract features from them and then classify the vector of features thus obtained. The class that is determined at the end of this chain of processes is then used to activate or configure an interaction technique. The characteristics of the interaction controlled by BCI vary greatly depending on the chosen cerebral pattern. Certain interfaces use potentials triggered by external stimuli, such as P300 or SSVEP. These interfaces often achieve relatively high information transfer rates, but a long exposure to the flickering can be tiring. Conversely, cerebral patterns such as SCP or sensorimotor rhythms can be controlled by experienced users without external stimulation. For a more complete review of the most commonly used cerebral patterns with BCIs, interested readers can refer to Chapter 4.

Despite differences in their individual characteristics, there is a set of common properties shared by all BCIs in general, which may be compared with those of more standard interfaces. For example, the information transfer rate of a BCI is always significantly lower than the expected transfer rate achievable with a keyboard or a mouse. We will now present the most important of these aspects, common to all BCIs.

Latency is one of the more obvious properties of BCIs. The latency of most current interfaces is of the order of a few seconds. Indeed, the features of the signals must be measured over a minimum period that is sufficiently large that the cerebral patterns can be classified with reasonable levels of accuracy. For example, at a measured neuronal activation frequency of $5\,\mathrm{Hz}$ (i.e. the period of the signal is $200\,\mathrm{ms}$), we cannot reasonably expect to obtain acceptable levels of precision in less than a second. The acceptability of latency in an interactive system depends on the sensory perception threshold of the user. A latency period of one second very distinctly exceeds the thresholds of auditory and visual perception. Fortunately, in the case of BCIs, the effective threshold is somewhat higher, as our perception of the point in time at which a specific mental state was produced is less precise than our perception of the point in time at which a button was pressed, for example. For comparison, interactive graphical systems controlled via mouse and keyboard typically have latencies of less than 100 ms between the physical action performed by the user and the display of updated information on the screen. The *precision* of a BCI when identifying a command is equally relatively low. Errors can arise from the user, who may not be able to adequately produce the required mental state, or, as is more commonly assumed, from the signal processing and classification steps. Most BCI research until now has focused on improving this precision, and significant progress has been made. Despite this progress, the precision still remains strongly user dependent, and for certain kinds of cerebral pattern the classification rate is still fairly low. For a BCI, a classification rate of 90% is considered to be good, whereas in normal conditions virtually every action performed with a mouse or keyboard is accurately registered by the peripheral.

The *number of commands* that may be accessed via a BCI is limited. Even for experienced users, the current levels of classifier precision do not generally allow for large numbers of classes without a drop in the detection rate. However, for some applications, having only three or four available commands does not necessarily represent a limitation. Note also that the P300 method makes it possible to choose from a large number of commands by successively selecting subsets without requiring the user to explicitly alter their mental state for each command.

The *information transfer rate* between the user and the computer through the BCI, largely limited by the properties of BCIs listed above, only exceeds 100 bpm in very rare cases [DON 00, WAN 08]. For comparison, the information transfer rate that an experienced user can achieve with a keyboard is of the order of 900 bpm (assuming a typing speed of 300 characters per minute and a Shannon entropy of the order of 3 bits/character). With a mouse, the information transfer rate is of the order of a few hundred bits per minute [MAC 92].

There is significant *variability in the performance* between different BCI users. Some users manage to operate BCIs much more effectively than the average, whereas others, sometimes called “BCI-illiterate”, are completely incapable of using them. Even between users that can use BCIs effectively, large degrees of variability are observed from session to session.

BCIs do not require any *motor activity* from the user, as they take input directly from brain activity. They may therefore generally be used by individuals with motor handicaps. Furthermore, other channels of interaction, such as the hands, remain available for controlling other devices (hybrid approach). It can, however, be difficult to divide attention between multiple different tasks, even if adapted methods of feedback (e.g. tactile) can help [LEE 13a]. Muscle activity also represents a source of noise in the signal with potentially very high amplitude, which can make it more difficult to interpret. Blinking and jaw contractions are particularly problematic. These artifacts can be corrected using an EOG based method for "cleaning" the signal [SCH 07b]. The compatibility of BCIs with other interfaces such as a keyboard or mouse is currently a subject of research [MER 13, LEE 13b]. The *distance of execution* (see section 12.1.3) of BCIs is high, as the mental state associated with the desired task must be produced by the user. With practice, the association between accomplishing a goal and producing an intermediate mental task becomes more intuitive. The distance of execution may be reduced by choosing mental tasks that are similar to the physical tasks, e.g. imagining a movement of the left hand to move a cursor to the left.

The *hardware and software* used by BCIs is relatively complex to install and operate. This complexity may slow the propagation of BCIs in domestic environments (e.g. for video games), and is also the subject of research [DUV 12, FRE 14].

12.3. Which pattern for which task?

We saw in section 12.1.2 that any interactive task may be decomposed into elementary tasks. Depending on the nature of the elementary task, certain cerebral patterns are more suitable than others; choosing appropriately allows the distance of execution to be further reduced.

Text entry involves entering sequences of characters into the system. It is typically achieved with a keyboard. This task was one of the first tasks to be realized using BCIs, usually with the P300 [LOT 08], motor imagery [BLA 06] or SSVEP [WAN 08]. The performance achieved is in the region of seven characters per minute [DON 00], compared to 20–40 using a keyboard for a non-expert user.

Quantification involves specifying a numerical value between some maximal and minimal thresholds. BCIs have not often been used for this task, but producing motor imagery patterns with specific or high amplitude levels has been used as a challenge in video games [LÉC 13, HJE 03].

Selection involves choosing one or multiple elements from a set of fixed size (e.g. menus, radio buttons, checkboxes) or of variable size (e.g. 2D or 3D targeting, dropdown boxes, selectboxes). P300 allows users to select one element from a few dozen, striking a good compromise between speed and precision, e.g. one element from 36 in 7.7 s, with an 80% success rate [DON 00]. SSVEP also allows users to perform selection tasks. For example, one target can be selected out of six in 1 second, with a precision of 86.7% [WAN 08]. For selection by targeting, it is possible to control two combinations of brain rhythms in the sensorimotor regions to control a cursor and select or reject a target highlighted using a third combination [VAU 06]. This technique however requires a large degree of concentration from the user, and a significant amount of practice, e.g. 5–15 h divided into sessions of 24 min over several weeks [MCF 08].

Manipulation and transformation involve modifying the position, orientation, size or shape of an object. In the case where the set of possible manipulations and transformations is small and discrete, these tasks may be performed with a selection task that chooses the desired modification, and so BCIs can be used (see previous section) [LEG 13].

Navigation involves changing the viewpoint in a virtual setting, for example by repositioning the camera in a 3D environment, or scrolling through the content of a document. An indirect form of navigation with a BCI can be achieved by specifying high-level commands. For example, the destination can be selected using a P300, then transmitted to an automatic navigation system [REB 07]. Motor imagery can provide more direct and refined navigation with low distances of execution. For example, the user can imagine moving the left or right hand to turn in that direction [LEE 07].

In addition to the classical tasks listed above, BCIs can also be used to evaluate the user's mental workload and detect certain emotional states such as wakefulness, pleasure, drowsiness, prevalence or frustration [HER 07, GEO 12]. Few other systems offer this range of possibilities. Motion tracking and physiological sensors that, for example, measure the galvanic skin response or cardiac rhythm are the main alternatives.

12.4. Paradigms of interaction for BCIs

12.4.1. *BCI interaction loop*

To integrate BCIs into applications, the exchange of information between each component of the interaction must be clearly defined. The simplest way to consider the role of the BCI within the structure of a wider interaction is to see it as an external component, as presented in [HIN 13]. The signal processing chain is the centerpiece of the BCI. The acquisition system registers a signal derived from brain activity. This signal is then filtered and transmitted to the feature extraction block. The extraction block calculates the values of the desired features. The resulting features vector must then be classified. This function is performed by the classification block, which then sends the results to the application. The application is responsible for associating the detected cerebral patterns with the command to be performed. We will now extend this conceptual model of a BCI to account for feedback, and to make a distinction between the measured brain activity and conscious thought (see Figure 12.2).

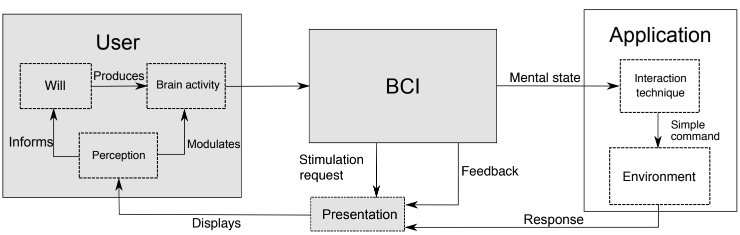

Figure 12.2. *Classical BCI interaction loop: Components of the BCI interaction loop: The user attempts to produce an intermediate mental state to interact with the machine through the BCI. Given the right stimulation, this mental state will produce a recognizable cerebral pattern for the BCI*

External *stimulation* (generally visual) is necessary for some cerebral patterns. The features that must be extracted to detect the cerebral pattern depend on the timing of this stimulation. Thus, the stimulation block must provide synchronization information to the feature extraction block. This block must also control the visual (or auditory, or tactile) display to the user. Finally, depending on the technique of interaction, it can be useful to adapt the stimulation as a function of the most recently detected cerebral patterns. Hence, the classification block also sends occasional output to the stimulation block.

The *presentaion* block is charged with gathering data and sending it to the user. This information includes neuronal stimulation, feedback and application-dependent data.

The user's *brain activity* is distinct from his or her will. Using a BCI requires the user to produce an intermediate mental state that must be controlled, much like how classical interfaces require an intermediate motor task. Ideally, any stimulation produced by the BCI should only influence the brain signal (measured by EEG), without affecting any conscious state, so that the stimulus is not irritating. In practice, if the amplitude of a certain instance of the brain activity is large enough to be picked up by EEG, it also draws the user's attention. Conversely, the application's response must access the user's conscious state, without overly interfering with the EEG signal. To be effective with BCIs, cerebral pattern must be insensitive to this type of noise.

12.4.2. *Main paradigms of interaction for BCIs*

For purposes of readability, the interaction paradigms outlined in this section are considered at a higher level of abstraction. They are not mutually exclusive and may be combined with each other:

– *Direct commands* consists in associating each recognized mental state with an explicit command (see Figure 12.2). The role of the BCI is to recognize the mental state from a finite set of classes of mental states (typically two or three classes) and to relay this information to the application. The application systematically relates each possible class to a command that will be executed when the mental state is detected.

Direct commands are probably the most widely used interaction paradigm for BCIs. Applications allow handicapped persons to operate computers or wheelchairs with direct commands [REB 07, VAU 06]. More recently, certain video games used the recognized mental state as the main input [LAL 05, NIJ 09]. Direct command BCIs are useful in situations where standard interactive devices are ineffective, e.g. because users require the use of their hands for some other task.

– The *hybrid approach* involves using the BCI as a complementary input device in combination with other devices (see Figure 12.3). Two or more interactive devices may be used simultaneously, each sending the information gathered to the application. The BCI is introduced at the same level as the other devices, and provides an additional information channel between the user and the machine. The other devices might, for example, be a keyboard, a mouse, a joystick [PFU 10] or another BCI [VAU 06]. Hybrid BCIs must be particularly insensitive to noise, because using other devices can generate additional artifacts due to eye movements and muscle contractions. The user must produce a cerebral pattern to control the BCI while simultaneously controlling the other devices as usual.

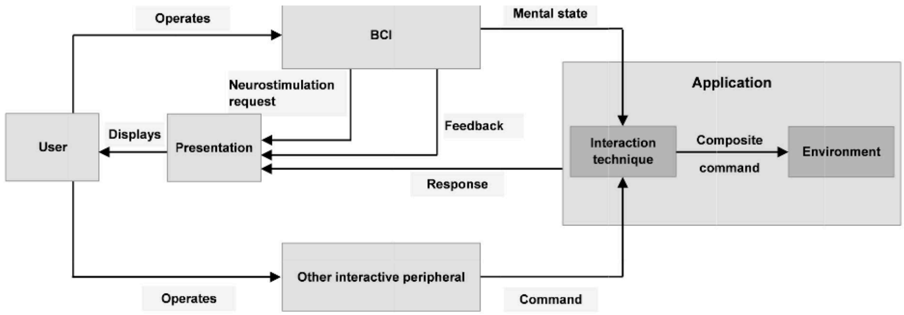

Figure 12.3. *Hybrid interaction with a BCI: one or more other complementary interaction devices are used simultaneously to accomplish a more complex interactive task*

Applications with hybrid BCIs use multiple inputs to improve the precision of the interface as a whole, or to specify different parameters of the same command [FRU 11, LI 10]. More recently, Zander *et al.* suggest using a gaze-tracking device in combination with a BCI to create a system capable of hands-free targeting and selecting that produces less false positives than traditional gaze-tracking systems, which are based on the eyes' fixation duration [ZAN 10]. As BCIs are used for increasingly complex tasks, the ability to use multiple inputs more independently could potentially become crucial. For example, in [LEE 13b], players can make their character run with a joystick and jump with a BCI.

– The *brain switch* involves using a BCI to activate or deactivate another interactive device. BCIs with a single command are sometimes also referred to as *brain switch* BCIs. From the perspective of the interaction, this is a special case of a direct command.

Two mental states are recognized by the brain switch: a "resting" state and an "action" state. Each time that the "action" state is detected, the other device is toggled. Thus, the brain switch may also be viewed as a special case of hybrid interaction. Indeed, the command to activate or deactivate the device can be transmitted to the application, which controls the device.

From the user's perspective, it is not necessary to concentrate on the BCI, except when using the specific activation command. When the user does this, he or she performs an intermediate mental task to produce the brain activity associated with the "action" command.

The need for a way of activating and deactivating BCIs has been raised by Scherer *et al.* [SCH 07a]. They suggested using the heartbeat to do this and showed that with an appropriate amount of training this input can be used as a switch. However, cardiac rhythms can be strongly affected by other phenomena. A controllable cerebral pattern might theoretically prove more reliable for this type of command [GEO 12].

The question of which patterns are best adapted to brain switch applications remains open. The "action" mental state must be detectable with a good level of precision and a low false positive rate (false positives lead to unwanted activations). On the other hand, since this command is only rarely used (typically once at the beginning of a session to activate the interface, and once at the end to deactivate it), it is acceptable for the activation period to be relatively high, with a large delay (approximately 30 s). Conservative approaches with classical cerebral patterns (SSVEP, P300) are good candidates for this interaction paradigm.

– The *passive BCI* approach involves detecting a mental state for purposes other than direct control (see Figure 12.4). The recognized cerebral patterns are sent to the application, which can use the user's mental state as an information parameter for adapting the main interaction technique [GEO 12]. From the user's perspective, there is no need to consciously control the cerebral patterns produced. Users can concentrate on their primary task rather than focusing attention on the BCI.

The "passive" approach has been used with other physiological markers such as the galvanic skin response [ALL 04] or gaze-tracking [HYR 06]. Cutrell and Tan suggested using BCIs for implicit interactions [CUT 08]. Since then, BCIs have been used to detect the level of engagement in a task, the user's mood, certain emotions, error recognition, and relaxation and mental workload [ZAN 11, GEO 12]. Detecting these kinds of mental state can be useful for adaptive automated processes (for example dynamic allocation of a task between the user and the machine), implicit markup of multimedia content, video games and error correction (see Chapter 5).

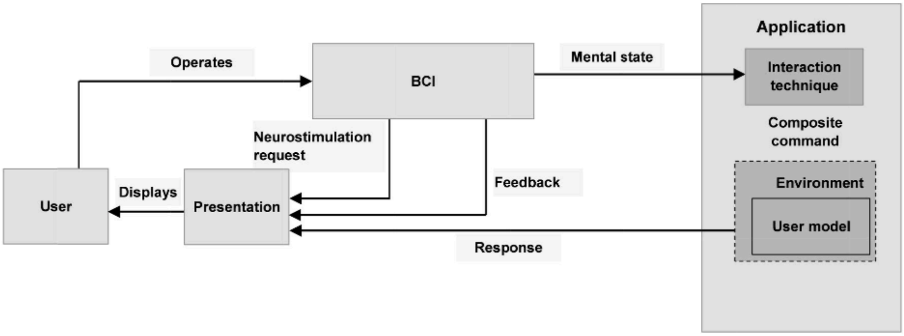

Figure 12.4. *Passive BCI: the user does not send an explicit command, but the application can construct a model of the user based on his or her mental state*

Passive BCIs can be useful in any kind of application in which the mental and emotional state of the user is relevant. From the machine's perspective, passive BCIs make it possible to dynamically adapt models of the user state.

– *Shared control* involves transforming the classes recognized by the BCI into high-level commands that are sent to the application (see Figure 12.5). Shared control is a paradigm of delegation. The machine is responsible for a certain fraction of the system's intelligence, in which high-level concepts and complementary information can be used to determine how a single brain command must be transformed into a more complex, high-level command or equivalently into several low-level commands.

From the user's perspective, the number of commands to be sent is low, even for accomplishing complex tasks. The quantity of information transmitted though the BCI is significantly reduced compared to direct command approaches. The user is therefore able to rest, while the high-level command is being executed [LOT 10].

It has been shown that shared control can be useful for operating wheelchairs [PHI 07]. For example, users can select a destination with a BCI based on the P300 paradigm, and a decision-making program equipped with a localization algorithm and object avoidance sensors decides the elementary actions that the wheelchair must perform as a result [REB 07].

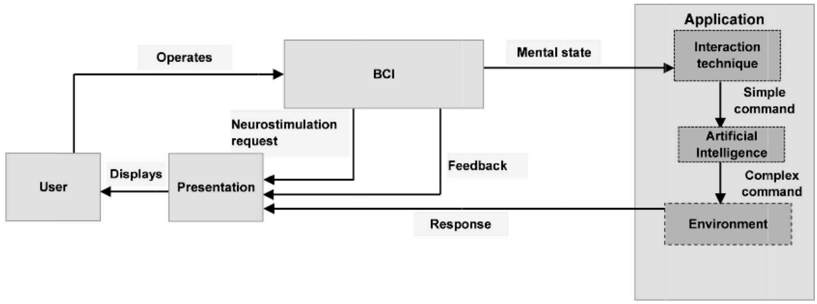

Figure 12.5. *Shared control: a unique command is analyzed and transformed into a high-level command that may be automatically deconstructed into a series of low-level commands*

Shared control can significantly speed up the interaction when the machine is capable of anticipating the user's decisions. As artificial intelligence and decision-making algorithms improve, shared control might find new fields of application.

– The *multi-user* approach involves using multiple BCI inputs to control a single application. Several mental activities may be combined at different stages of the interaction. The mental state of each user is recognized independently and sent to the application, which combines the recognized mental states in order to produce a command. The purpose of this combination might be to improve the global performance, or to increase the number of available commands. Mental activities can also be combined at the signal processing level, allowing the classifier itself to determine the multiuser command [BON 13]. Finally, multiuser approaches can be used to search for brain markers (*hyperscanning*) by observing the similarities between the brain activities of two users in similar situations [BAB 14].

An intermediate mental task must be performed by each user to create the correct mental state, and thus transmit the desired command, either in collaboration or in competition with the other user.

Recently, it was suggested that multiuser BCIs could be developed for applications in video games [NIJ 13]. Two players could attempt to synchronize their cerebral signals directly, or as a means of achieving higher level objectives. Competitive *gameplay* could also be introduced [BON 13].

Using the cerebral activity of multiple users could potentially improve the precision of BCIs, as the noise in each individual signal becomes less significant given the information from the other users. Concretely, the classifier could use features extracted from all users in a single classification step. The social presence of another user also appears to stimulate the learning process [RIC 03].

Future BCIs might belong to one of three possible usage categories. First, BCIs might be used as an alternative to the keyboard or the mouse. It is however not entirely clear that BCIs will be able to match the performance of these more classical tools. The nervous signal that directs muscular activity comes directly from the brain, whereas non-invasive technologies only have access to noisy signals. BCIs are disadvantaged at the outset by the clarity of the signal compared to traditional devices. However, direct and hybrid approaches might prove useful in assisting the interactions of handicapped individuals. For applications intended for wider audiences, BCIs might be used as complementary input devices that allow the usual channels of interaction to be kept free for other interfaces. Finally, even if other tools of interaction are more effective at accomplishing a given task, performing the task with a BCI might provide other advantages.

12.5. Conclusions

In this chapter, we saw that the cerebral patterns recognized by various different BCIs strongly affect the properties of the BCIs in terms of HCI. Nonetheless, there are many similarities (latency, precision) between BCIs and a wider set of interfaces. These similarities can limit the usefulness of BCIs for certain tasks, but are not necessarily relevant for others.

The right choice of usability criterion can vary wildly depending on the application, and the choice of a suitable cerebral pattern for controlling the BCI must be adapted to the final usage context. The classical BCI context, consisting of laboratory conditions with a single subject without distractions or any other tools, although not entirely obsolete, is too restrictive to properly describe future applications.

Until now, most research has focused on improving the precision and speed of BCIs, but in order to extend their range of applications, it is crucial that we also consider other usability criteria.

The unique qualities of BCIs make them useful for assisting handicapped individuals in situations where other interactive devices are ineffective. More recently, other fields of application have begun to emerge. In particular, BCIs might play an important role in future video games.

In order to meet the requirements of these new domains, the subject's ability to produce suitable cerebral patterns must be explored, as well as learning techniques for acquiring these kinds of skills. In parallel, the need for new cerebral patterns that can be exploited by BCIs will likely intensify. In all likelihood, we have only discovered a fraction of the possibilities. Advancements in neuroscience research might reveal new prospects.

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