CHAPTER

15 Affective Brain-Computer Interfaces: Neuroscientific Approaches to Affect Detection

Christian Mühl, Dirk Heylen, *and* Anton Nijholt

Abstract

The brain is involved in the registration, evaluation, and representation of emotional events and in the subsequent planning and execution of appropriate actions. Novel interface technologies—so-called affective brain-computer interfaces (aBCI)—can use this rich neural information, occurring in response to affective stimulation, for the detection of the user's affective state. This chapter gives an overview of the promises and challenges that arise from the possibility of neurophysiology-based affect detection, with a special focus on electrophysiological signals. After outlining the potential of aBCI relative to other sensing modalities, the reader is introduced to the neurophysiological and neurotechnological background of this interface technology. Potential application scenarios are situated in a general framework of brain-computer interfaces. Finally, the main scientific and technological challenges that have yet to be solved on the way toward reliable affective brain-computer interfaces are discussed.

Key Words: brain-computer interfaces, emotion, neurophysiology, affective state

Introduction

Affect-sensitive human-computer interaction (HCI), in order to provide the choice of adequate responses to adapt the computer to the affective states of its user, requires a reliable detection of these states—that is, of the user's emotions. A number of behavioral cues, such as facial expression, posture, and voice, can be informative about these states. Other sources, less open to conscious control and therefore more reliable in situations where behavioral cues are concealed, can be assessed in the form of physiological responses to emotional events; for example, changes in heart rate and skin conductance. A special set of physiological responses comprises those originating from the most complex organ of the human body, the brain. These neurophysiological responses to emotionally significant events can, alone or in combination with other sources of affective information, be used to detect affective states continuously, clarify the context in which they occur, and help to guide affect-sensitive HCI. In this chapter, we elucidate the motivation and background of affective brain-computer interfaces (aBCIs), the devices that enable the transformation of neural activity into affect-sensitive HCI; outline their working principles and their applications in a general framework of BCI; and discuss main challenges of this novel affect-sensing technology.

The Motivation Behind Affective Brain-Computer Interfaces

The brain is an interesting organ for the detection of cues about the affective state. Numerous lesion studies, neuroimaging evidence, and theoretical arguments have strengthened the notion that the brain is not only the seat of our rational thought but also heavily involved in emotional responses that often are perceived as disruptive to our rational behavior (Damasio, 2000). Scherer's component process model (Scherer, 2005) postulates the existence of several components of affective responses that reside in the central nervous system, including processes of emotional event perception and evaluation, self-monitoring, and action planning and execution.[1]

Therefore the brain seems to possess great potential to differentiate affective states in terms of their neurophysiological characteristics, mostly of the neural responses that occur after encountering an emotionally salient stimulus event. Such emotional responses occur within tens of milliseconds; they are not under the volitional control of a person and hence are reliable in terms of their true nature. Such fast and automatic neurophysiological responses are contrasted by slower physiological responses in the range of seconds after the event and with behavioral cues that are more amenable to conscious influence.

In addition to the promises for a fast and reliable differentiation of affective states, the complexity of the brain also holds the potential to reveal *details* about an ongoing emotional response elicited by emotional stimulus events. Visual or auditory cortices reflect the modality-specific processing resources allocated to emotionally salient events (Mühl et al., 2011), allowing for conscious identification of the object that elicited the emotional response. Similarly, motor regions might reveal behavioral dispositions—that is, planned and prepared motor responses—to an emotional stimulus event.

Finally, certain patient populations that lose the ability to communicate with the outside world owing to the loss of musculature or its control; they need alternative communication channels—using the information available from unimpaired physiological and neurophysiological processes—that are able to reflect their emotions to loved ones as well as to caretakers.

However, the realization of all this potential, including the advantages of neurophysiological signals over other sources of information on affect, is dependent on the advancement of research within several disciplines: psychology, affective neuroscience, and machine learning. We begin with the introduction of relevant sensor technologies and then go on to discuss the neurophysiological basis and the technological principles and applications of aBCIs.

Sensor Modalities Assessing Neurophysiological Activity

Several sensor technologies enable the assessment of neurophysiological activity. Two types of methods can be distinguished by the way they function: one measures cortical electric or magnetic fields directly resulting from the nerve impulses of groups of pyramidal neurons while the other measures metabolic activity within cortical structures—for example, blood oxygenation resulting from the increased activity of these structures.

The first type of electrophysiological method, including sensor modalities such as electroencephalography (EEG) and magnetoencephalography (MEG), has a high temporal resolution of neural activity recordings (instantaneous signals with millisecond resolution) but lacks high spatial resolution owing to the smearing of the signals on their way through multiple layers of cerebrospinal fluid, bone, and skin. Most of the methods of the second type, including sensor modalities such as functional magnetic resonance imaging (fMRI) or positron emission tomography (PET), have a high spatial resolution (in the range of millimeters), but are slow because of their dependence on metabolic changes (resulting in a lag of several seconds) and their working principle (resulting in measurement rhythms of seconds rather than milliseconds).

Each of the neuroimaging methods mentioned above has its advantages, and their use depends on researchers' goals. Regarding affective computing scenarios, EEG seems to be the most practicable method: EEG has the advantage of being relatively unobtrusive and can be recorded using wearable devices, thus increasing the mobility and options for locations in which data are collected. Furthermore, the technology is affordable for private households and relatively easy to set up, especially the cheaper commercial versions for the general public, although these have limitations for research. Comparable wearable sensor modalities that are based on the brain metabolism, such as functional near-infrared spectroscopy (fNIRS), are currently not affordable nor do they feature a high spatial resolution.

To focus on the technologies relevant for aBCIs in the normal, healthy population, we briefly review below the affect-related neural structures of the central nervous system and then introduce the neurophysiological correlates of affect that are the basis for aBCI systems using EEG technology as their sensor modality.

Neurophysiological Measurements of Affect

The Neural Structures of Affect

The brain comprises a number of structures that have been associated with affective responses by different types of evidence. Much of the early evidence of the function of certain brain regions comes from observations of the detrimental effects of lesions in animals and humans. More recently, functional imaging approaches, such as PET and fMRI, have yielded insights into the processes occurring during affective responses in normal functioning (for reviews, see Barrett, Mesquita, Ochsner, & Gross, 2007; Lindquist, Wager, Kober, Bliss-moreau, & Barrett, 2011). Here we only briefly discuss the most prominent structures that have been identified as central during the evaluation of the emotional significance of stimulus events and the processes that lead to the emergence of the emotional experience. The interested reader can refer to Barrett et al. (2007) for a detailed description of the structures and processes involved.

The core of the system involved in the translation of external and internal events to the affective state is a set of neural structures in the ventral portion of the brain: the medial temporal lobe (including the amygdala, insula, and striatum), orbitofrontal cortex (OFC), and ventromedial prefrontal cortex (VMPFC). These structures compose two related functional circuits that represent the sensory information about the stimulus event and its somatovisceral impact as remembered or predicted from previous experience.

The first circuit—comprising the basolateral complex of the amygdala, the ventral and lateral aspects of the OFC, and the anterior insula—is involved in the gathering and binding of information from external and internal sensory sources. Both the amygdala and the OFC structures possess connections to the sensory cortices, enabling information exchange about perceived events and objects. While the amygdala is coding the original value of the stimulus, the OFC creates a flexible experience and context-dependent representation of the object's value. The insula represents interoceptive information from the inner organs and skin, playing a role in forming awareness about the state of the body. By the integration of sensory information and information about the body's state, a value-based representation of the event or object is created.

The second circuit, composed of the VMPFC (including the anterior cingulate cortex [ACC]) and the amygdala, is involved in the modulation of parts of the value-based representation via its control over autonomous, chemical, and behavioral visceromotor responses. Specifically, the VMPFC links the sensory information about the event, as integrated by the first circuit, to its visceromotor outcomes. It can be considered as an affective working memory that informs judgments and choices and is active during decisions based on intuitions and feelings.

Both circuits project directly and indirectly to the hypothalamus and brainstem, which are involved in a fast and efficient computation of object values and influence autonomous chemical and behavioral responses. The outcome of the complex interplay of ventral cortical structures, amygdala, hypothalamus, and brainstem establishes the "core affective" state that the event induced: an event-specific perturbation of the internal milieu of the body that directs the body to prepare for the responses necessary to deal with the event. These responses include the attentional orienting to the source of the stimulation, the enhancement of sensory processes, and the preparation of motor behavior. Perturbation of the visceromotor state is also the basis of the conscious experience of the pleasantness and physical and cortical arousal that accompany affective responses. However, as stated by Barrett et al. (2007), the emotional experience is unlikely to be the outcome of one of the structures involved in establishing the "core affect" but rather emerges on the system level as the result of the activity of many or all of the involved structures.[2]

Correlates of Affect in Electroencephalography

Before reviewing the electrophysiological correlates of affect, we must note that because of the working principles and the resulting limited spatial resolution of the EEG, a simple measurement of the activation of affect-related structures, as obtainable by fMRI, is not possible. Furthermore, most of the core-affective structures are located in the ventral part of the brain (but see Davidson, 1992; Harmon-Jones, 2003), making a direct assessment of their activity by EEG, focusing on signals from superficial neocortical regions, difficult. Hence we concentrate on electrophysiological signals that have been associated with affect and on their cognitive functions but also mention their neural origins if available.

TIME-DOMAIN CORRELATES

A significant body of research has focused on the time domain and explores the consequences of emotional stimulation on event-related potentials. Event-related potentials (ERPs) are prototypical deflections of the recorded EEG trace in response to a specific stimulus event—for example, a picture stimulus.

ERPs are computed by (samplewise) averaging of the traces following multiple stimulation events of the same condition, which reduces sporadic parts of the EEG trace not associated with the functional processes involved in response to the stimulus but originating from artifacts or background EEG.

Examples of ERPs responsive to affective manipulations include early and late potentials. Early potentials, for example P1 or N1, indicate processes involved in the initial perception and automatic evaluation of the presented stimuli. They are affected by the emotional value of a stimulus; differential ERPs are observed in response to negative and positive valence as well as low and high arousal stimuli (Olofsson, Nordin, Sequeira, & Polich, 2008). However, the evidence is far from parsimonious, as the variety of the findings shows.

Late event-related potentials are supposed to reflect higher-level processes, which are already more amenable to the conscious evaluation of the stimulus. The two most prominent potentials that have been found susceptible to affective manipulation are the P300 and the late positive potential (LPPs). The P300 has been associated with attentional mechanisms involved in the orientation toward an especially salient stimulus—for example, very rare (deviant) or expected stimuli (Polich, 2007). Coherently, P300 components show a greater amplitude in response to highly salient emotional stimuli, especially aversive ones (Briggs & Martin, 2009). The LPP has been observed after emotionally arousing visual stimuli (Schupp et al., 2000), and was associated with a stronger perceptive evaluation of emotionally salient stimuli as evidenced by increased activity of posterior visual cortices (Sabatinelli, Lang, Keil, & Bradley, 2006).

As in real-world applications, the averaging of several epochs of EEG traces with respect to the onset of a repeatedly presented stimulus is not feasible; the use of such time-domain analysis techniques is limited for affective BCIs. An alternative to ERPs—more feasible in a context without known stimulus onsets or repetitive stimulation—are effects on brain rhythms observed in the frequency domain.

FREQUENCY-DOMAIN CORRELATES

The frequency domain can be investigated with two simple but fundamentally different power extraction methods, yielding evoked and induced oscillatory responses to a stimulus event (Tallon-Baudry, Bertrand, Baudry, & Bertrand, 1999). Evoked frequency responses are computed by a frequency transformation applied to the averaged EEG trace, yielding a frequency-domain representation of the ERP components. Induced frequency responses, on the other hand, are computed by applying the frequency transform on the single EEG traces before then averaging the frequency responses. Induced responses therefore capture oscillatory characteristics of the EEG traces that are not phase-locked to the stimulus onset and averaged out in the evoked oscillatory response. In an everyday context, where the mental states or processes of interest are not elicited by repetitive stimulation with a known stimulus onset and short stimulus duration, the use of evoked oscillatory responses is just as limited as the use of ERPs. Therefore the induced oscillatory responses are of specific interest in attempting to detect affect based on a single and unique emotional event or period.

The analysis of oscillatory activity in the EEG has a tradition that reaches back over almost 90 years, to the twenties of the last century, when Hans Berger reported the existence of certain oscillatory characteristics in the EEG, now referred to as alpha and beta rhythms (Berger, 1929). The decades of research since then have led to the discovery of a multitude of cognitive and affective functions that influence the oscillatory activity in different frequency ranges. Below, we briefly review the frequency ranges of the conventional broad frequency bands—namely delta, theta, alpha, beta, and gamma, their cognitive functions, and their association with affect.

The *delta frequency band* comprises the frequencies between 0.5 and 4 Hz. Delta oscillations are especially prominent during the late stages of sleep (Steriade, McCormick, & Sejnowski, 1993). However, during waking they have been associated with motivational states such as hunger and drug craving (see Knyazev, 2012). In such states, they are supposed to reflect the workings of the brain reward system, some of the structures of which are believed to be generators of delta oscillations (Knyazev, 2012). Delta activity has also been identified as a correlate of the P300 potential, which is seen in response to salient stimuli. This has led to the belief that delta oscillations play a role in the detection of emotionally salient stimuli. Congruously, increases of delta band power have been reported in response to more arousing stimuli (Aftanas, Varlamov, Pavlov, Makhnev, & Reva, 2002; Balconi & Lucchiari, 2006; Klados et al., 2009).

The *theta rhythm* comprises the frequencies between 4 and 8 Hz. Theta activity has been observed in a number of cognitive processes; its most prominent form, frontomedial theta, is believed to originate from limbic and associated structures (i.e., ACCs) (Başar, Schürmann, & Sakowitz, 2001). It is a hallmark of working memory processes and has been found to increase with higher memory demands in various experimental paradigms (see Klimesch, Freunberger, Sauseng, & Gruber, 2008). Specifically, theta oscillations subserve central executive function, integrating different sources of information, as necessary in working memory tasks (Kawasaki, Kitajo, & Yamaguchi, 2010).

Concerning affect, early reports mention a "hedonic theta" that was reported to occur with the interruption of pleasurable stimulation. However, studies in children between 6 months and 6 years of age showed increases in theta activity upon exposure to pleasurable stimuli (see Niedermeyer, 2005). Recent studies on musically induced feelings of pleasure and displeasure found an increase of frontomedial theta activity with more positive valence (Lin, Duann, Chen, & Jung, 2010; Sammler, Grigutsch, Fritz, & Koelsch, 2007), which originated from ventral structures in the ACC. For emotionally arousing stimuli, increases in theta band power have been reported over frontal (Balconi & Lucchiari, 2006; Balconi & Pozzoli, 2009) and frontal and parietal regions (Aftanas et al., 2002). Congruously, a theta increase was also reported during anxious personal compared to nonanxious object rumination (Andersen, Moore, Venables, Corr, & Venebles, 2009).

The *alpha rhythm* comprises the frequencies between 8 and 13 Hz. It is most prominent over parietal and occipital regions, especially during the closing of the eyelids, and decreases in response to sensory stimulation, especially during visual stimulation but in a weaker manner also during auditory and tactile stimulation or during mental tasks. More anterior alpha rhythms have been specifically associated with sensorimotor activity (central mu-rhythm) (Pfurtscheller, Brunner, Schlögl, & Lopes da Silva, 2006) and with auditory processing (tau-rhythm) (Lehtelä, Salmelin, & Hari, 1997). The observed decrease of the alpha rhythm in response to (visual) stimulation, the event-related desynchronization in the alpha band, is believed to index the increased sensory processing and hence has been associated with an activation of task-relevant (sensory) cortical regions. The opposite phenomenon, an event-related synchronization in the alpha band, has been reported in a variety of studies on mental activities, such as working memory tasks, and is believed to support an active process of cortical inhibition of task-irrelevant regions (see Klimesch, Sauseng, & Hanslmayr, 2007).

The most prominent association between affective states and neurophysiology has been reported in the form of frontal alpha asymmetries (Coan & Allen, 2004), which vary as a function of valence (Silberman, 1986) or motivational direction (Davidson, 1992; Harmon-Jones, 2003). The stronger rightward lateralization of frontal alpha power during positive or approach-related emotions compared with negative or withdrawal-related emotions is believed to originate from the stronger activation of left as compared with right prefrontal structures involved in affective processes. Despite fMRI studies (e.g., Engels et al., 2007) suggesting that such simple models of lateralization underestimate the complexity of the human brain, evidence for alpha asymmetry has been found in response to a variety of different induction procedures using pictures (Balconi & Mazza, 2010; Huster, Stevens, Gerlach, & Rist, 2009), music pieces (Altenmüller, Schürmann, Lim, & Parlitz, 2002; Schmidt & Trainor, 2001; Tsang, Trainor, Santesso, Tasker, & Schmidt, 2006), and film excerpts (Jones & Fox, 1992).

The alpha rhythm has also been associated with a relaxed and wakeful state of mind (Niedermeyer, 2005). Coherently, increases of alpha power are observed during states of relaxation, as indexed by physiological measures (Barry, Clarke, Johnstone, & Brown, 2009; Barry, Clarke, Johnstone, Magee, & Rushby, 2007) and subjective self-report (Nowlis & Kamiya, 1970; Teplan & Krakovska, 2009).

The *beta rhythm* comprises the frequencies between 13 and 30 Hz. Central beta activity has been associated with the sensorimotor system, as it is weak during motor activity, motor imagination or tactile stimulation, but increases afterward (Neuper et al., 2006). That has led to the view that the beta rhythm is a sign of an "idling" motor cortex (Pfurtscheller et al., 1996). A recent proposal for a general theory of the function of the beta rhythm, however, suggests that beta oscillations impose the maintenance of the sensorimotor set for the upcoming time interval (or "signals the status quo") (see Engel & Fries, 2010). Concerning affect, increases of beta band activity have been observed over temporal regions in response to visual and self-induced positive as compared with negative emotions (Cole & Ray, 1985; Onton & Makeig, 2009). A general decrease of beta band power has been reported for stimuli that had an emotional impact on the subjective experience compared with those that were not experienced as emotional (Dan Glauser & Scherer, 2008) (see gamma rhythm for elaboration). A note of caution for the interpretation of high-frequency bands of beta and gamma is in order, as their power increases during the tension of (scalp) muscles (Goncharova et al., 2003), which are also involved in frowning and smiling.

The *gamma rhythm* comprises the frequencies above 30 Hz. Gamma band oscillations are supposed to be a key mechanism in the integration of information represented in different sensory and nonsensory cortical networks (Fries, 2009). Accordingly they have been observed in association with a number of cognitive processes, such as attention (Gruber, Müller, Keil, & Elbert, 1999), multisensory integration (Daniel Senkowski, Schneider, Tandler, & Engel, 2009), memory (Jensen, Kaiser, & Lachaux, 2007), and even consciousness (Ward, 2003).

Concerning valence, temporal gamma rhythms have been found to increase with increasingly positive valence (Müller, Keil, Gruber, & Elbert, 1999; Onton & Makeig, 2009). For arousal, posterior increases of gamma band power have been associated with the processing of high versus low arousing visual stimuli (Aftanas, Reva, Varlamov, Pavlov, & Makhnev, 2004; Balconi & Pozzoli, 2009; Keil et al., 2001). Similarly, increases of gamma activity over somatosensory cortices have also been linked to the awareness to painful stimuli (Gross, Schnitzler, Timmermann, & Ploner, 2007; Senkowski, Kautz, Hauck, Zimmermann, & Engel, 2011). However, Dan Glauser and Scherer (2008) found lower (frontal) gamma power for emotion for stimuli *with* versus those *without* an emotional impact on the subjective experience. They interpreted their findings as a correlate of the *ongoing* emotional processing in those trials that were not (yet) identified as having a specific emotional effect, and hence without impact on subjective experience. In general, increases in gamma power are often interpreted as synonymous with an increase of activity in the associated region.

Taken together, the different frequency bands of the EEG have been associated with changes in the affective state as well as with a multitude of cognitive functions. Consequently it is rather unlikely to find simple one-to-one mappings between any oscillatory activity and a given affective or cognitive function. In ~~Section 4~~ we elaborate on the challenge that many-to-one mappings pose for aBCI. Nevertheless, there is an abundance of studies evidencing the association of brain rhythms with affective responses. aBCIs can thus make use of the frequency domain as a source of information about their users' affective states. In the following section, we introduce the concept of aBCIs in more detail.

Affective Brain-Computer Interfaces

The term *affective brain-computer interfaces* (aBCIs) is a direct result of the nomenclature of the field that motivates their existence: *affective computing.* With different means, aBCI research and affective computing aim toward the same end: the detection of the user's emotional state for the enrichment of human-computer interaction. While affective computing tries to integrate all the disciplines involved in this endeavor, from sensing of affect to its effective integration into human-computer interaction processes, aBCI research is mainly concerned with the detection of the affective state from neurophysiological measurements. Information about the successful detection of affective states can then be used in a variety of applications, ranging from unobtrusive mental-state monitoring and the corresponding adaptation of interfaces to neurofeedback-guided relaxation.

Originally, the term *brain-computer interface* was defined as "a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles" (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). The notion of an individual (volitionally) sending commands directly from the brain to a computer, circumventing standard means of communication, is of great importance considering the original target population of patients with severe neuromuscular disorders. More recently, the human-computer interaction community has developed great interest in the application of BCI approaches for larger groups of users that are not dependent on BCIs as their sole means of communication. This development and the ensuing research projects hold great potential for the further development of devices, algorithms, and approaches for BCI, also necessary for its advancement for patient populations. Along with the development of this broad interest for BCI, parts of the BCI community slowly started to incorporate new BCI approaches, such as aBCI, into its research portfolio, thus easing the confinement of BCI to interfaces serving purely volitional means of control (Nijboer, Clausen, Allison, & Haselager, 2011).

Below, we briefly introduce the parts of the aBCI: signal acquisition, signal processing (feature extraction and translation algorithm), feedback, and protocol. Then we offer an overview of the various existing and possible approaches to aBCI based on a general taxonomy of BCI approaches.

Parts of an Affective Brain-Computer Interface

Being an instance of general BCI systems (Wolpaw et al., 2002), the aBCI is defined by a sequence of procedures that transform neurophysiological signals into control signals. In Figure 15.1, we briefly outline the successive processing steps that a signal has to undergo, starting with the acquisition of the signal from the user and finishing with the application feedback given back to the user.

SIGNAL-ACQUISITION BRAIN-COMPUTER INTERFACES

These can make use of several sensor modalities that measure brain activity. Roughly, we can differentiate between invasive and noninvasive measures. While invasive measures, implanted electrodes or electrode grids, enable a more direct recording of neurophysiological activity from the cortex and therefore have a better signal-to-noise ratio, they are currently reserved for patient populations and hence are less relevant for the current overview. Noninvasive measures, on the other hand, as recorded with EEG, fNIRS, or fMRI, are also available for the healthy population. Furthermore, some of the noninvasive signal acquisition devices, especially EEG, are already available for consumers in the form of easy-to-handle and affordable headsets.[3] The present work focuses on EEG as a neurophysiological measurement tool, for which we detail the following processing steps in the BCI pipeline. A further distinction in terms of the acquired signals can be made, differentiating between those signals that are partially dependent on the standard output pathways of the brain (e.g., moving the eyes to direct the gaze toward a specific stimulus) and those that are independent on these output pathways, merely registering user intention or state. These varieties of BCI are referred to as dependent and independent BCIs, respectively. Affective BCIs, measuring the affective state of the user, are usually a variety of the latter sort of BCIs.

SIGNAL PROCESSING—FEATURE EXTRACTION

From the signals that are captured from the scalp, several signal features can be computed. We can differentiate between features in the time and in the frequency domains. An example of features in the time domain is the amplitude of stimulus-evoked potentials occurring at well-known time points after a stimulus event is observed. One of the event-related potentials used in BCI is the P300, occurring in the interval between 300 to 500 ms after an attended stimulus event. An example for signal features in the frequency domain is the power of a certain frequency band. A well-known frequency band that is used in BCI paradigms is the alpha band, which comprises the frequencies between 8 and 13 Hz. Both the time- and frequency-domain features of the EEG have been found to respond to the manipulation of affective states and are therefore in principle interesting for the detection of affective states (see ~~Section 2~~). However, aBCI studies almost exclusively use features from the frequency domain (see Table 1.1 in Mühl, 2012). Conveniently, however, frequency-domain features, such as the power in the lower frequency bands (<13 Hz) are correlated with the amplitude of event-related potentials, especially the P300, and hence partially include information about time-domain features.

Standard BCI approaches focus on very specific features—for example, the mu rhythm over central scalp regions in the case of motor imagery paradigms (Pfurtscheller & Neuper, 2001), or the mean signal amplitude between 200 and 500 ms associated with

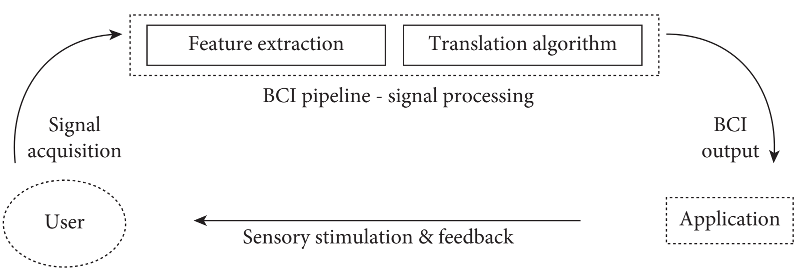

Fig. 15.1 The schematic of a general BCI system as defined by Wolpaw et al. (2002). The neurophysiological signal is recorded from the user, and the relevant features, those that are informative about user intent or state, are extracted. They are then translated into the control parameters that are used by the application to respond adequately to the user's state or intent."

each attended stimulus in P300 spellers (Farwell & Donchin, 1988). To date, however, affective BCI approaches often lack such clear-cut information on affect-related responses. Most of the current aBCI approaches make use of a wide spectrum of frequency bands, as these have been found responsive to affect manipulation (see ~~Section 2.2~~), resulting in a large number of potential features. However, large numbers of features require a large number of trials to train a classifier (the "curse of dimensionality") (Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007), which are seldom available owing to the limitations of affect induction (e.g., the habituation of the responses toward affective stimulation with time). Therefore one of the tasks on the road toward affective BCI is the evaluation and identification of reliable signal features that carry information about the affective state, especially in the complexity of real-world environments. Another important task is the development of potent affect-induction procedures—for example, using naturally affect-inducing stimuli that increase the likelihood of inducing affective responses.

SIGNAL PROCESSING—TRANSLATION ALGORITHMS

The core part of the BCI is the translation of the selected signal features into a command for the application or device, such as a cursor movement for active BCIs or the creation of an emotion label for affective BCIs. The simple one-to-one mapping between feature and command requires a feature that conveniently mirrors the state in such manner. Because such ideal features are rare in the neurophysiological signal domain, most BCI studies use machine learning approaches that are trained to find a mapping between a number of signal features and the labels for two or more classes (see Lotte et al., 2007, for an overview of BCI classifiers). These classifiers have to adapt to the signal characteristics of the particular user, adapt to changes over time and changing contexts of interaction, and deal with the changes in brain activity due to the user's efforts in learning and adapting to the system. Classifiers used for affective BCI include linear discriminant analysis (Chanel et al., 2005; Chanel, Kierkels, Soleymani, & Pun, 2009; Chanel, Rebetez, Bétrancourt, Pun, & Bétrancourt, 2011; Makeig et al., 2011; Murugappan, 2010; Winkler, Jäger, Mihajlović, & Tsoneva, 2010) and support vector machines (Frantzidis et al., 2010; Horlings, Datcu, & Rothkrantz, 2008; Koelstra et al., 2010; Li & Lu, 2009; Y. P. Lin, Wang, Wu, Jeng, & Chen, 2009; Petrantonakis & Hadjileontiadis, 2010; Soleymani, Lichtenauer, Pun, & Pantic, 2011; Takahashi, 2004).

THE OUTPUT DEVICE/FEEDBACK

Depending on the application the affective BCI is serving, the output can assume different forms. For BCI in general, the most prominent output devices are monitors and speakers, providing visual and auditory feedback about the user and BCI performance. In a few cases, robots (a wheelchair or car) have been controlled (Hongtao, Ting, & Zhenfeng, 2010; Leeb et al., 2007). An exceptional example of BCI output, however, is control of one's own hand by the BCI-informed functional electrical stimulation of a paralyzed hand (Pfurtscheller, Müller-Putz, Pfurtscheller, & Rupp, 2005). In the case of standard BCIs, the output has a major function relating to the adaptation of the user to the BCI mentioned above. As BCI control can be considered to be a skill, any learning necessitates the provision of feedback about successful and unsuccessful performance.

In the specific case of aBCI, the same is possible, but the smaller proportion of applications requiring active and volitional mental control, typical for standard BCI systems, and the dominance of passive paradigms (see ~~Section 3.2~~), make explicit performance-based feedback optional rather than mandatory. Depending on their function, aBCI systems will vary in the output device and the type of feedback employed. For example, for implicit tagging or affect monitoring (for later evaluation), the feedback is not immediate. It might take hours, days, or weeks until the information is used (e.g., during affect-tagged media replay) and then it might be in a subtle way that escapes the user's attention. Such cases, in which no clear relation between state and feedback is perceivable, make the notion of feedback in these aBCI applications almost obsolete. However, in many other aBCI applications, the feedback is still existent and relevant, since the affective data are used to produce a system response in a reasonably near future. Examples are the applications that reflect the current affective state (e.g., in a game like *Alpha World of Warcraft* (Plass-Oude Bos et al., 2010), any neurofeedback-like application (e.g., warn of unhealthy states or reward healthy states), the active self-induction of affective states (e.g., relaxation), or the adaptation of games or e-learning applications to the state of the user.

THE OPERATING PROTOCOL

The operating protocol guides the operation of the BCI system—for example, switching it on and off (how/when) if the actions are triggered by the system (synchronous) or by the user (asynchronous) and when and in which manner feedback is given to the user. Other characteristics of the interaction that are defined by the protocol are whether the information is actively produced by the user or passively read by the system and whether the information is gathered dependent of a specific stimulus event (stimulus dependent/independent). These two characteristics of BCI, voluntariness and stimulus dependency, are also the basis for the characterization of different BCI approaches in the next section.

Below, we outline the different existing applications and approaches to aBCI and try to locate aBCI within the general landscape of BCI.

The Different Approaches to Affective Brain-Computer Interfaces

There are several possible applications of neurophysiology-informed affect sensing that can be categorized in terms of their dependence on stimuli and user volition. In the following, a two-dimensional classification of some of these BCI paradigms is given. It is derived from the three-category classification for BCI approaches (active, reactive, and passive) suggested by Zander and Kothe (2011). The dimensions of this classification are defined by (1) the dependence on external stimuli and (2) the dependence on an intention to create a neural activity pattern as illustrated in Figure 15.2.

The horizontal axis stretches from exogenous (or evoked) to endogenous (or induced) input. The former covers all forms of BCI, which necessarily presuppose an external stimulus. Steady-state visually evoked potentials (Farwell & Donchin, 1988) as neural correlates of (target) stimulus frequencies, for instance, may be detected if and only if evoked by a stimulus. They are therefore a clear example of exogenous input. Endogenous input, on the other hand, does not presuppose an external stimulus but is generated by the user either volitionally, as seen in motor imagery–based BCIs (Pfurtscheller & Neuper, 2001) or involuntarily, as during the monitoring of affective or cognitive states. In the case of involuntary endogenous input—for example, during general affect monitoring—the distinction between stimulus-dependent and independent input might not always be possible, as affective responses are often induced by external stimulus events, though these might not always be obvious.

The vertical axis stretches from active to passive input. Active input presupposes an intention to

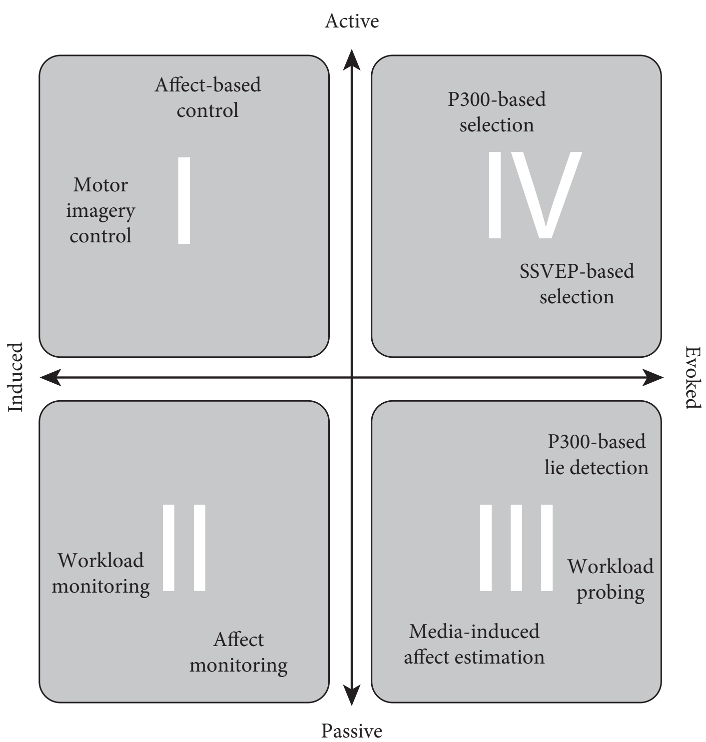

Fig. 15.2 A classification of BCI paradigms spanning voluntariness (passive versus active) and stimulus dependency (user self-induced versus stimulus-evoked).

control brain activity, while passive input does not require any effort on the part of the user. Imagined movements, for instance, can only be detected when users intend to perform these, making the paradigm a prototypical application of aBCI. All methods that probe the user's mental state, on the other hand, can also be measured when he or she does not exhibit an intention to produce it. Affective BCI approaches can be located in several of the four quadrants (categories) spanned by the two dimensions, as quite different approaches to aBCI have been suggested and implemented.

Induced-Active Brain-Computer Interfaces

This category is well known in terms of neurofeedback systems, which encourage the user to attain a certain goal state. While neurofeedback approaches do not necessarily focus on affective states, a long line of this research is concerned with the decrease of anxiety or depression by making the users more aware of their bodily and mental states (Hammond, 2005). Neurophysiological features that have been associated with a certain favorable state (e.g., relaxed wakefulness) are visualized or sonified, enabling the users of such feedback systems to learn to induce them themselves.

More recently it has been shown that affective self-induction techniques, such as relaxation, are a viable control modality in gaming applications (George, Lotte, Abad, & Lecuyer, 2011; Hjelm, 2003; but see Mühl et al., 2010). Furthermore, induced passive approaches (see below) might also turn into active approaches—for example, when players realize that their affective state has an influence on game parameters and therefore begin to self-induce states to manipulate the gaming environment according to their preferences.

Induced-Passive Brain-Computer Interfaces

This category includes the typical affect-sensing method for application in HCI scenarios where a response of an application to the user state is critical. Information that identifies the affective state of a user can be used to adapt the behavior of an application to keep the user satisfied or engaged. For example, studies have found neurophysiological responses in the theta and alpha frequency bands to differentiate between episodes of frustrating and normal game play (Reuderink, Mühl, & Poel, 2013). Applications could respond to the frustration of the user with helpful advice or clarifying information. Alternatively, parameters of computer games or e-learning applications could be adjusted to keep users engaged in the interaction—for example, by decreasing or increasing difficulty to counteract the detected episodes of frustration or boredom, respectively (Chanel et al., 2011).

Another approach is the manipulation of the game world in response to the player's affective state, as demonstrated in *Alpha World of Warcraft* (Plass-Oude Bos et al., 2010), where the avatar shifts its shape according to the degree of relaxation the user experiences. Such reactive games could strengthen the players' association with their avatars, leading to a stronger immersion and an increased sense of presence in the game world.

Evoked-Passive Brain-Computer Interfaces

BCI research suggests that evoked responses can be informative about the state of the user. Allison and Polich (2008) have used evoked responses to simple auditory stimuli to probe the workload of a user during a computer game, a measure that might reflect attentional and affective engagement. Similarly, neurophysiology-based lie detection, assessing neurophysiological orientation responses (P300) to compromising stimuli, has been shown to be feasible (Abootalebi et al. 2009). A similar approach is the detection of error potentials in response to errors in human-machine interaction. It was shown that such errors evoke specific neurophysiological responses—for example, the error-related negativity (ERN), which can be detected and used to trigger system adaptation (Buttfield, Ferrez, & Millán, 2006; Zander & Jatzev, 2009). Given that goal conduciveness is a determining factor of affective responses, such error-related potentials could be understood as being affective in nature (Scherer, 2005).

More directly related to affect, however, are those responses observed to media, such as songs, music videos, or films. Assuming the genuine affective nature of the response to experiences delivered by such stimuli, it might be possible to detect the user states associated with them. Possible uses for such approaches are media recommendation systems, which monitor the user response to media exposure and label or tag the media with the affective state it produced. Later on, such systems could selectively offer or automatically play back media items known to induce a certain affective state in the user. Research toward such neurophysiology-based implicit tagging approaches of multimedia content has suggested its feasibility (Koelstra et al., 2012;

Soleymani et al., 2011). Furthermore, assuming that general indicators of affect can be identified using music excerpts or film clips for affect-induction protocols, such multimodal and natural media seem suited to collect data for the training of aBCIs that detect affective states occurring in rather uncontrolled, real-life environments.

EVOKED-REACTIVE BRAIN-COMPUTER INTERFACES

This category seems less likely to be used for aBCI approaches, as the volitional control of affect in response to presented stimuli is as yet unexplored. However, standard BCI paradigms that use evoked brain activity to enable users to select from several choices were the first approaches to BCI and have been thoroughly explored. A prominent example is the P300 speller, which relies on the enhanced P300 potential observed in response to attended compared to unattended stimuli (Farwell & Donchin, 1988). Similarly, BCI control via steady-state evoked potentials relies on the increase of an EEG frequency response when a stimulus oscillating with the same frequency (e.g., a flicker, vibration, or sound) is attended (Vidal, 1973).

Summarizing, there are a multitude of possible applications for aBCIs that can be categorized according to the axes of induced/evoked and active/passive control. Main applications, however, are those that cover the passive control of applications. The challenges that have to be dealt with in moving beyond proof-of-concept studies and toward aBCIs working reliably in the complexity of the real world are addressed in the final section.

Controversies, Challenges, Conclusion

Although the possibility of neurophysiology-based affect detection has been suggested by theoretical and empirical works (see ~~Section 2~~ and ~~3~~), several neuroscientific and neurotechnological challenges remain on the way toward reliable aBCIs.

Neuroscientific Challenges

The primary neuroscientific challenge is the lack of reliable signal features that characterize affective states in noninvasive electrophysiological measures, such as EEG. It is often argued that EEG has neither the spatial resolution nor the necessary sensitivity to register core affective neural activity from deep subcortical structures of the limbic system. While this might *partially* be true, especially in comparison to techniques like fMRI, many studies report electrophysiological correlates of emotion manipulations in terms of amplitude changes of either potentials or oscillations (see ~~Section 2.2~~). However, it is indeed seldom assessed which parts of these responses to affective stimulation are reflected within these differentiating signal features: *core affective correlates versus cognitive coactivations of affect*. Modern emotion theories—for example, the component process model of Scherer (2005)—acknowledge the complex and interwoven nature of affective and cognitive concepts and processes that are present during emotional responses. Therefore it must be acknowledged as well that different affective states are differentiated not only by the correlates of their core affective features but also by concurrent coactivations of regions and processes that can be observed independently of affect. An example is enhanced sensory processing, which can be observed in response to emotionally arousing stimuli as well as during heightened levels of attention (see Mühl, 2012, for further elaboration).

Consequently, to avoid misclassification of cognitive state changes as affective state changes, a major challenge for aBCI is the identification of the nature of affect correlates and the development of methods that allow focus on reliable indicators of affect while still making use of the indicative power of those correlates that are not of purely affective nature. As noted earlier, richer information about the response to an affective event—for example, its origin or its behavioral consequences—is one of the major promises of aBCIs. To resolve the uncertainties pertaining to the nature of neurophysiological correlates of affect and to develop the next generation of affect-sensitive but context-aware aBCIs, the design of affect-induction approaches needs special care.[4] Beside the need to carefully balance all factors but the induced emotion to avoid confounds, affect-induction designs should vary factors that are co-occurring with affective responses and known to be reflected in brain activity. Examples are visual or auditory attention processes as elicited by the use of stimuli in the respective sensory modalities (Mühl et al., 2011).

However, this requirement for a stringently controlled affect-induction protocol conflicts with another condition for the study of reliable neurophysiological indicators: an *ecologically valid affect induction*. To ensure the generalization of the classifier from training to real-world context, the training samples must be collected in a context as similar as possible to the envisioned application scenario. Unfortunately this often means that the affect-induction approach would be of a complex nature, either using complex (e.g., multimedia) stimuli or complex interactive tasks. The many factors involved in realistic scenarios in which affect detection would be used make the limitation of changes to the factor that is to be manipulated (i.e., emotion) rather difficult, leading to the occurrence of confounding variables (e.g., stimulus features, motor responses). Furthermore, factoring out those variables that potentially reflect cognitive coactivations (see above) underlies practical limitations of experiment design (e.g., time, number of participants).

To satisfy these contradictory demands on affect-induction protocols, researchers must carefully analyze the factors implied in a given application scenario. Knowing these factors, they can devise experimental designs that manipulate the affect-relevant factors with little variation in other factors or that manipulate affective and nonaffective factors in an independent and counterbalanced manner to factor out the most prominent cognitive coactivations.

Related to the search for reliable correlates of core affect is the exploration of *novel signal features* that are informative of the affective state. As mentioned in ~~Section 2~~, the neurophysiological features that have been associated with affect manipulations are not uniquely affective in nature. These potentials and oscillations are also implied in cognitive processes. Therefore the discriminatory value of novel signal features—such as cross-regional or cross-frequency coherence (Miskovic & Schmidt, 2010), assessing the interaction between neural regions and mental processes, or the chronology of different neural processes (Grandjean & Scherer, 2008)—must be explored in the context of affect. Researchers can profit from existing neurophysiological databases (Koelstra et al., 2012; Soleymani et al., 2011) in exploring such novel features.

Neurotechnological Challenges

Neurotechnological challenges exist for software as well as for hardware components of aBCIs. Concerning *software*, the development of appropriate signal processing and classification algorithms are key issues. *Signal processing algorithms* need to become able to deconstruct the electrode signals into their components: neural activity originating from within the skull, and so-called artefacts, originating from eyes, facial musculature and other noneural sources. One can differ between informative and destructive artifacts. Muscular activity (EMG), for example, is treated as a potentially confounding influence in conventional EEG studies and hence always removed. However, in an applied context, EMG can, although it is not of neural origin, inform about the user state, especially taking into account how involved the facial musculature is during emotional episodes. On the other hand, artifacts—independent of origin—might conceal much smaller neural signals and therefore have to be removed. Nevertheless, it makes sense to also examine these artifacts for their informativeness. Techniques like independent component analysis (ICA)(Onton & Makeig, 2009) are able to deconstruct the electrophysiological signals into neural, ocular, and muscular components and might allow an independent assessment of the information of these sources.

Classification algorithms have to be able to take the complexity of the neurophysiological signals into account. Assuming a possible differentiation between core affective and associated cognitive correlates, machine learning approaches that are able to deal with these complex signals are needed. They need to be able to ignore or penalize the learning of those features that are only co-varying with affect, thus avoiding misclassifications due to the cognitive parts of the affective response (e.g., falsely recognizing increased visual attention as visually induced emotion). Alternatively, they could learn to use these coactivations to differentiate contextual details of the emotional episode, such as its origin or its intended behavioral consequence.

Another challenge for learning algorithms is the capability to learn from relatively few examples. The induction of affective states is limited by effects of habituation and the requirement of ecological validity, leading to a restricted number of samples for training and testing. A possible alternative is the development of classifiers that learn from a pool of samples of several participants, rendering their results subject-independent and thereby making subject-specific training sessions obsolete.

Concerning *hardware*, the main challenge concerns the wearability and ease of use of aBCI systems. To ensure optimal user experience, the system should have as few sensors as possible, reducing the time for setup and its intrusiveness during use. There are already several commercial devices that enable the recording of an EEG from a small number of sensors (1 to 16 compared with 32 to 256 electrodes in research devices) and that function without conductive gel. The small number of electrodes minimizes the laborious optimization of electrode contacts to improve signal quality and thereby increases usability. Furthermore, the achievable signal quality of dry or contactless electrode systems seems close to that of gel-based systems (Zander et al., 2011). However, signal processing techniques like ICA require a certain number of electrodes to deconstruct neural and nonneural signal components, posing problems for a reliable EEG/EMG differentiation. As alternatives to EEG-only aBCI systems, such systems can be combined with other affect-sensing modalities assessing physiological or behavioral cues. Such hybrid or multimodal BCI systems (Pfurtscheller et al., 2010) have the potential to assess the constellation of different aspects of an affective response—for example, preparatory homeostatic or communicative aspects—but also to enable the use of redundant information from these sources and therefore decrease the susceptibility to artifacts and increase the reliability of the prediction. For information regarding the integration of signals from body and brain, see the chapter by Kemp and colleagues in this volume.

Taken together, the main challenges for reliable aBCIs are affect-induction protocols that allow the identification and differentiation of core affective correlates and cognitive coactivations, preprocessing methods that can differentiate between neural and nonneural signal sources, and classification methods that are able to automatically acquire that information from a limited set of electrodes and samples. Should the development of smaller and cheaper sensor technology continue, wearable and easy-to-use aBCI systems could soon become an effective alternative or addition to behavior- and physiology-based affect detection.

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Notes

1. See also Kemp and colleagues' chapter in this volume, which highlights the importance of brain and body responses and their integration.
2. This constructivist position, readily compatible with functional appraisal models of emotion and with evidence collected by neuroimaging meta-analyses (Lindquist et al., 2011), is opposed by the localist position, which is defended by the proponents of basic emotion models. For a neuroimaging meta-analysis supporting the localist position, see (Vytal & Hamann, 2010). The interested reader is also referred to the chapter by Kemp and colleagues in this volume.
3. Examples of such consumer EEG devices are the emotive headset with 14 sensors (http://www.emotiv.com) and the Neurosky headset with 1 sensor (http://www.neurosky.com).
4. In this regard interested readers may wish to refer to the *Handbook of Emotion Elicitation and Its Assessment* by Coan & Allen.

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