Brain-Computer Interfaces
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tbci20

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Published online: 14 May 2014.

To cite this article: Christian Mühl, Brendan Allison, Anton Nijholt & Guillaume Chanel (2014) A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges, Brain-Computer Interfaces, 1:2, 66-84, DOI: 10.1080/2326263X.2014.912881

To link to this article: http://dx.doi.org/10.1080/2326263X.2014.912881

Brain-Computer Interfaces, 2014
Vol. 1, No. 2, 66–84, http://dx.doi.org/10.1080/2326263X.2014.912881

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A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges

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(*Received 22 December 2013; accepted 3 March 2014*)

Affective states, moods and emotions, are an integral part of human nature: they shape our thoughts, govern the behavior of the individual, and influence our interpersonal relationships. The last decades have seen a growing interest in the automatic detection of such states from voice, facial expression, and physiological signals, primarily with the goal of enhancing human-computer interaction with an affective component. With the advent of brain-computer interface research, the idea of affective brain-computer interfaces (aBCI), enabling affect detection from brain signals, arose. In this article, we set out to survey the field of neurophysiology-based affect detection. We outline possible applications of aBCI in a general taxonomy of brain-computer interface approaches and introduce the core concepts of affect and their neurophysiological fundamentals. We show that there is a growing body of literature that evidences the capabilities, but also the limitations and challenges of affect detection from neurophysiological activity.

Keywords: brain computer interfaces; affect; emotions; moods; EEG; fNIRS

1. What are affective brain-computer interfaces?

Affective phenomena, such as moods and emotions, are at the core of human nature and behavior, and are crucial in our interactions between each other and the external world. However, cognitive phenomena, like perception, memory, or decision-making, have long been viewed as the primary path to an understanding of the human mind. Consequently, affect and associated concepts have been rather neglected by psychologists, economists, and neuroscientists for a good part of the twentieth century – until they experienced a strong comeback in scientific interest at the end of the twentieth century.[1] Nowadays, the relevance of affect for cognition [2] and, vice versa, the involvement of cognitive processes in affect-generation [3] seem firmly established. In the wake of the increasing popularity of the affective sciences, the computer sciences, especially the human-computer interaction (HCI) community, discovered affect as a factor that cannot be neglected any longer. Affect-related phenomena entered the HCI domain in the form of user experience evaluations, factors for successful intelligent tutoring systems, or natural and expressive virtual agents. Researchers who were working at the intersection of computer science and the affective sciences established the field of affective computing (AC), defined as 'computing that relates to, arises from, or deliberately influences emotions'.[4] Research foci of the field are the sensing of affective states, the modeling of the processes involved in affect, the synthesis of emotional expressions and behaviors, and the interaction between human and machine according to the affective context (see [5] for a brief recent overview).

Affective brain-computer interfaces originated from the field of AC as a general research program that attempts to create devices able to detect affective states from neurophysiological signals and that are able to take this information into account to advance human-computer interaction (see Figure 1). Research in this domain is highly interdisciplinary, using theories and methods from psychology (concepts and protocols), neuroscience (brain functioning and signal processing), and computer science (machine learning and HCI) to induce, measure, and detect affective states and to apply the resulting information to improve interaction with machines. In this context, neural signals are just another signal modality that can supplement video or voice analysis: less dependent on overt behavior, less susceptible to deception, but requiring more intrusive sensors. Neurophysiological signals are also closer to the origin of affective states than physiological signals, such as heart rate, skin conductance, or muscle tension, although this advantage is mitigated by the difficulties in recording brain signals in real-world settings and interpreting them in a participant-independent manner. However, affective phenomena have turned out to be quite engaging to specialists from computer vision, natural language processing, and physiological computing. Therefore, researchers from the field of AC have embraced

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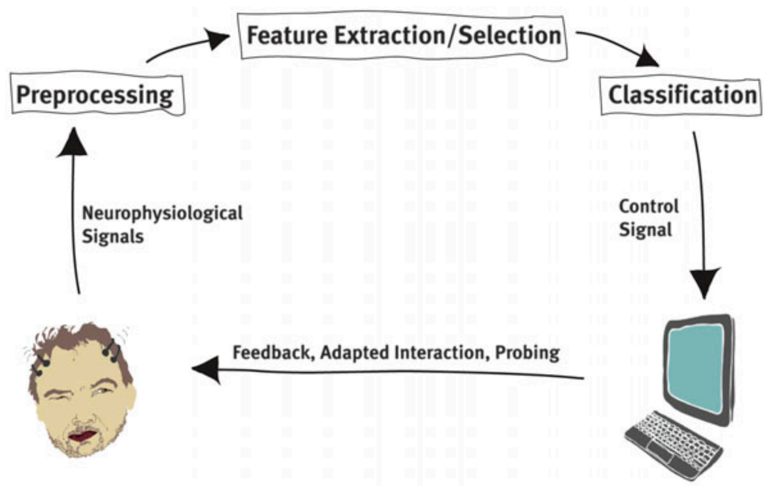

Figure 1. (Color online) The aBCI loop adapted from [6]. The parts are the same as for BCI, but instead of feedback the system can also adapt interaction with devices according to the affective user state. For example, the system recognizes that a user is frustrated by a challenging learning task and adapts the task difficulty, offers assistance, or introduces more engaging elements, thereby decreasing the user's frustration, maintaining or increasing motivation, and avoiding failure.

neurophysiological measurements as a novel modality, delivering new and complementary insights.

Affective brain-computer interfaces are, of course, also an extension of the field of brain-computer interfaces (BCI), which itself is a multidisciplinary endeavor, and which starts to unfold its full potential for HCI outside its original purposes in the medical domain. Original definitions of BCI clearly stressed the active communicative act that these systems were supposed to support, based on users', mainly patients', voluntary mental activities.[6] More recent works have included passive BCI systems for entertainment, life-style, and ergonomic applications.[7,8] aBCI, with their focus on affective aspects of HCI, can be used for active communication of emotional states and moods, and for passive sensing of affect to inform machines about the affective states of their users.

The aim of this article is to survey the work done on aBCI for the general BCI community. In the following sections, we give an overview of aBCI applications (Section 2), introduce the most important concepts of affect (Section 3), briefly discuss the neuroanatomical and neurophysiological basis of aBCI (Section 4 and 5), survey the state-of-the art of aBCI (Section 6), and outline the biggest challenges (Section 7).

2. aBCI applications in the context of general BCI paradigms

As for BCI in general,[8] approaches of neurophysiology-informed affect sensing can be categorized in terms of their dependence on user volition and stimulation. In [9] we extend the three-legged categorisation (active, reactive, and passive BCI) of [8] to a two-dimensional classification scheme explicating two axes. The first axis describes BCI systems in terms of the dependence on external stimuli. The second axis describes systems in terms of their dependence on the level of user intention required to properly interact with them. Figure 2 gives an overview of the classic BCI paradigms and potential affective BCI paradigms within this taxonomy[1].

The first axis stretches from stimulus-dependent (stimulus-evoked/exogenous) to stimulus-independent (self-induced/endogenous) input to a system via a BCI. The stimulus-dependent extreme of this scale covers all forms of BCI that require an external stimulus controlled by the system to elicit specific brain signals, such as SSVEP [10] or P300 [11]. Stimulus-independent BCIs, on the other hand, do not require such external stimuli. Examples include active BCIs based on motor imagery [12] or common mental tasks,[13] as well as passive monitoring of affective or cognitive states. Although these approaches may not require stimuli to elicit specific brain signals, they do typically rely on visual stimuli for other critical functions, such as providing feedback or an immersive virtual environment.

The second axis spans from active to passive input. Active input reflects a user's voluntary decision to send each message or command, entailing some mental effort, while passive methods do not. Methods that probe the user's affective or cognitive state, with or without the use of stimuli, may provide information about the user without any interruption or distraction. The hitherto suggested and implemented aBCI approaches can be located in several of the four quadrants (categories) spanned by the two dimensions.

The typical aBCI approach is the *stimulus-independent passive BCI*, which includes general affect sensing for

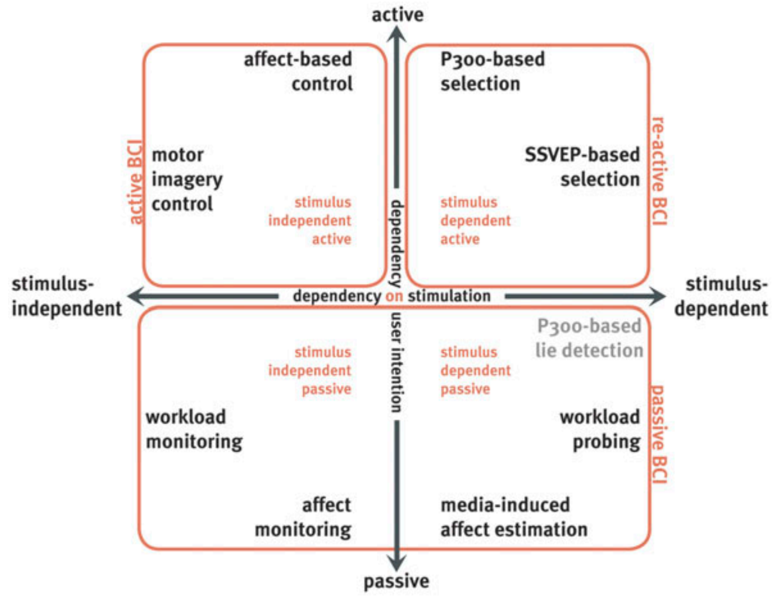

Figure 2. (Color online) A classification of BCI paradigms, spanning dependency on the user's intention to control the BCI system (passive vs. active) and stimulus dependency (stimulus-dependent vs. stimulus-independent) of the BCI systems.

applications in HCI scenarios where adapting an application according to a user's state is important. 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 found neurophysiological responses in the theta and alpha frequency bands to differentiate between episodes of frustrating and normal game play.[14] Applications could respond with helpful advice or clarifying information to allay the frustration of the user. 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.[15] Another approach is the manipulation of the game world and mechanics in response to the player's affective state, as demonstrated in 'alpha World of Warcraft',[7] 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. Rani et al.[16] showed that players' skills improve more and they have a more enjoyable experience when the level of a simulation's challenge is adapted to their affective or mental state rather than their performance.

Moving further to the right along the first axis, we find more *stimulus-dependent passive BCIs*, which come in two varieties: those using stimuli to probe the affective state and those where the stimuli themselves are the object of the affect inquiry (i.e., are tagged with their affective value for later re-use by a recommendation system). Regarding the first variety, BCI research has suggested that evoked responses can be informative about the state of the user. Allison and Polich [17] 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, the detection of error-potentials, in response to errors in human-machine interaction, to trigger system adaptation [18,19] might also be related to aBCI, as goal conduciveness is a determining factor of affective responses.[3] Finally, neurophysiology-based lie detection, assessing neurophysiological orientation responses (P300) to compromising stimuli, has been shown to be feasible in specific situations.[7,20][2] The second variety of stimulus-dependent passive BCIs includes affective tagging of media and communication of preference. Affective tagging uses affective 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 is possible to detect the user states that are associated with them. A possible application for such approaches is automatic media recommendation, which monitors the user response to media exposure and labels or tags the media with the affective state it produced. Later on, such systems could selectively offer or automatically play back media items that are 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.[21,22] Liberati et al.[23] showed that aBCI can be used for the communication of emotional responses toward a certain object. They devised an approach for the communication of agreement/disagreement for Alzheimer's patients using spared neurophysiological affective responses, in the face of fundamentally impaired cognitive responsiveness. This approach could be used to guide practitioners in their interaction with patients unable to overtly communicate their wishes.

Also *stimulus-independent* but *active BCI approaches* are 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.[24] 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 self-induce them. More recent work has shown that affective self-induction techniques, such as relaxation, are a viable control modality in gaming applications.[25,26 but see 27] However, such stimulus-independent passive approaches (see below) might 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.[28] As [29] note, 'if through practice, the player becomes proficient in controlling their natural physiological responses; the awareness of volitional control makes the game become a biofeedback game once again'.

The *stimulus-dependent (re-)active* varieties of BCI are currently not used for aBCI approaches. This category requires the volitional control of affect in response to presented stimuli and seems yet unexplored, while standard BCI paradigms that use stimulus-dependent brain activity are among the most common (P300 speller or SSVEP-based control).

In the next sections we will discuss the meaning of affect and related terms and the neuroanatomical and neurophysiological basis of affect recognition.

3. Affect and emotion models

The term 'affect' might seem best defined here by opposing it to the term 'cognition'. While affective phenomena are subjective, intuitive, or based on a certain emotional feeling, cognitive phenomena are objective, often explicable, and not necessarily associated with any emotional feeling (e.g., attention, remembering, language, problem-solving). Despite these apparent contrasts, it is becoming ever clearer that affective and cognitive processes not only interact with each other, but are tightly intertwined.[4,30,31]

The term affect is an umbrella for a number of phenomena that are encountered in daily life. According to [3], we can distinguish between several different concepts that constitute affect, most importantly emotions and moods. A precise definition of the phenomenon 'emotion' is seemingly difficult, as there are multiple aspects to emotions. From almost 100 definitions, Kleinginna & Kleinginna [32] created a working definition, covering various of these aspects of emotions: 'Emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can (a) give rise to affective experiences such as feelings of arousal, pleasure/displeasure; (b) generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labeling processes; (c) activate widespread physiological adjustments to the arousing conditions; and (d) lead to behavior that is often, but not always, expressive, goal-directed, and adaptive.' These short-lived (seconds or minutes) and intense states are contrasted by longer-lasting (hours or days), less intense moods that do not directly relate to a specific event, though they might build up from one or more events over time. There is an ongoing debate about the nature of affective responses in which three main approaches, foremost dealing with emotions but transferable to moods, can be differed: discrete, dimensional, and appraisal models.

Discrete emotion models assume that emotional responses can be described by a small number of universal, discrete emotions or 'emotion families' of related states. These families of emotions have been developed during the course of evolution and are assumed to be universal in the sense that they can be found to a certain extent in all cultures, are partially inborn, and to a degree shared with other primates. Such 'basic' emotions can be clearly differentiated from each other in terms of physiological and behavioral response patterns that were adapted in a species-dependent manner during the course of evolution. As one of the most influential proponents of discrete or basic emotions, [33] suggested happiness, anger, surprise, fear, disgust, and sadness as basic emotions. Other discrete emotion models have proposed different sets of emotions (see [33, p. 27], for a comprehensive overview). The lack of consent regarding the number and types of emotions and inconsistencies regarding their physiological patterns are the main criticisms from opponents of this model, which deem the definition of basic emotions too vague and not reflecting the complexity of emotions.

Dimensional emotion models aim at an abstraction of the discrete or basic emotion concepts by postulating several dimensions on which specific emotional feelings, 'core affect', are definable. One of the most popular dimensional models is the circumplex model of Russel [35]. It assumes that any emotional feeling can be localized on a two-dimensional plane, spanned by the axes of valence, ranging from negative to positive feelings, and arousal, ranging from calm to excited. This type of model has the advantage that it inherently takes care of the possibility that affective states are not always clearly assignable to specific basic emotions. In this model, such mixed or complex emotions could be represented by being located between two or more clearly ascribed emotions. As is true for basic emotion models, however, different theories about the precise nature and the number of the fundamental dimensions exist, some including dimensions such as dominance and unpredictability.[36] However, as for basic emotion models, dimensional models focus on the structure of emotional responses, but are rather vague in terms of underlying processes that lead from an event to a specific emotion.

Appraisal models and construction theories are functional attempts to disentangle the complexity of emotional responses in brain and body with respect to the specific contexts in which they appear. Specifically, appraisal models postulate a number of checks (appraisals) that a stimulus event undergoes, and which in consequence determine the nature of the (emotional) response that is most suited to deal with the event. For example, Scherer's *Component Process Model* [3] postulates that during an emotional episode several subsystems (associated with cognitive, motivational, neurophysiological, motor expressions, and subjective feeling components) change synchronously and in an interrelated manner in response to a stimulus event that is deemed relevant for the organism. The emotional responses are determined by complex appraisal mechanisms, including a number of sequential event checks on different analysis levels: relevance, implications for current goals, coping-potentials, and normative significance. These checks are informed by a number of cognitive and motivational mechanisms, including attention, memory, motivation, reasoning, and self-concept. It is the outcome of this evaluation process that defines ('constructs') a specific response pattern of physiological reactions, motor expression, and action preparation.[3]

Though describing the same phenomenon, the different models are of relevance for the classification of affective states from behavioral, physiological, or neurophysiological signals. They differ in their assumptions and predictions regarding their neural correlates. Furthermore, different aBCI problems might be better tackled in terms of affect categories, dimensions, or aggregation of several processes. Below, we will discuss the neuroanatomical basis of affect and neurophysiological correlates in the EEG.

4. Affect in the brain

In affective neuroscience, as in psychophysiology and psychology in general, one can differ between faculty and constructionist frameworks.[37] The *faculty approach* refers to the traditional idea that certain mental faculties – cognitive ones such as memory, attention, and decisions, or affective ones such as anger, happiness, and sadness – can be isolated from each other. These faculties can then be mapped to their specific behavioral and physiological responses, and last but not least to the activity of specific brain structures and circuits.[38] With regard to affect, and specifically for emotions, the notion of discrete emotions is closely related to the faculty approach. Each emotion can be mapped to a specific set of brain structures: fear can be related to the activation of the amygdala, disgust to that of the insula, ventral prefrontal cortex, and amygdala, sadness to that of the medial prefrontal cortex, anger to that of the orbitofrontal cortex, and happiness to the rostral anterior cingulate cortex (see [39] for a fMRI meta-study supporting the faculty view). Figure 3 gives an overview of these structures.

Constructionist approaches, on the other hand, assume the existence of more basic operations, so-called 'psychological primitives', which are domain-general in the sense that they are not exclusively associated with affective, cognitive, or perceptual faculties. These primitives are represented by the brain. The constructionist approach fits well with appraisal theories, which postulate the emergence of an emotional response from a number of (evaluation) processes that are themselves associated with (networks of) brain structures. Meta-analyses of fMRI studies of emotion have indeed shown the involvement of large brain networks related to perceptual, motor, or cognitive processes.[40,41] Barrett et al.[31] outline 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 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: medial temporal lobe (including the amygdala, insula, and striatum), orbitofrontal cortex (OFC), and ventromedial prefrontal cortex (VMPFC). The basolateral complex of the amygdala, the ventral and lateral aspects of the OFC, and the anterior insula are involved in the

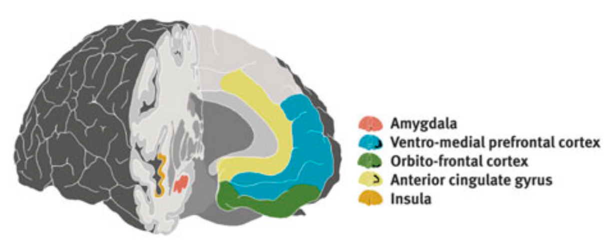

Figure 3. (Color online) Several affect-related structures of the human brain (depicted from the right side, front is to the right).

gathering and binding of information from external (via amygdala and OFC) and internal (via insula) sensory sources, creating thus a value-based representation of the event or object. The VMPFC (including the anterior cingulate cortex (ACC)) and the amygdala are involved in the modulation of parts of the value-based representation via its control over autonomous, chemical, and behavioral visceromotor responses. The VMPFC can be considered as an affective working memory, which 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, establishing 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 the perceptive, cognitive, and behavioral responses necessary to deal with the event. The 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.

While there is still much to clarify, the evolving consensus seems to hold that a simple one-to-one mapping between emotions and a specific set of brain structures is difficult to reconcile with observations of different emotions activating the same structure and one emotion activating several structures.[38] However, for the sake of aBCI, we are primarily interested in the accessibility of affect-related neural activity – which can be at least partially affirmed for fMRI. Below, we will review evidence for the accessibility of affect-related neurophysiological activity via EEG.

5. Neurophysiology of affect in the EEG

The neurophysiological measurement of affect with the EEG is complicated by the working principles and low spatial resolution of the EEG. Furthermore, since most of the core affective structures are located in the ventral part of the brain (but see [42,43]), a direct assessment of their activity by EEG, which primarily records signals from superficial neocortical regions, is difficult. Hence, we concentrate on electrophysiological signals that have been associated with affect and on their cognitive functions, but mention their neural origins if available.

Time-domain correlates

A significant body of research has focused on specific electrophysiological potentials in the time domain and explores the consequences of emotional stimulation on such event-related potentials (ERPs). ERPs are prototypical deflections of the recorded EEG trace in response to a specific stimulus event, for example a picture stimulus. Examples of ERPs responsive to affective manipulations include early and late potentials. Early potentials, for example P1 or N1, which appear about 100 ms after stimulation, indicate processes involved in the initial perception and automatic evaluation of the presented stimuli. They are affected by the emotional value of a stimulus; different ERPs are observed in response to negative and positive valence as well as low and high arousal stimuli.[44] 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 relatively heavily influenced by 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 (LPP), both appearing about 300 ms after stimulation and later. The P300 has been associated with attentional mechanisms involved in the orientation toward an especially salient stimulus, for example very rare (deviants) or expected stimuli.[45] Coherently, P300 components show a greater amplitude in response to highly salient emotional stimuli, especially aversive ones.[46] The LPP has been observed after emotionally arousing visual stimuli, [47] and was associated with a stronger perceptive evaluation of emotionally salient stimuli as evidenced by increased activity of posterior visual cortices.[48]

An alternative to ERPs for the detection of affective responses – more feasible for single trials and when stimulus/response onsets are unknown – 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 correlates of (affective) states.[49] There is a growing body of evidence that oscillatory characteristics or brain rhythms, in specific broad frequency bands, have a functional significance for the workings of the human mind. Below we will 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 rhythm* (0.5 to 4 Hz), prominent during the late stages of sleep,[50] has been associated during waking with motivational states such as hunger, sexual arousal, and drug craving.[51] In such states, they are supposed to reflect the workings of the brain reward system, whose structures (e.g., medial prefrontal cortex, ventral tegmental area, nucleus accumbens) are potential generators of delta oscillations. This, and the correlation between delta oscillations and P300 responses to salient stimuli, has led to the belief that delta oscillations play a role in the detection of emotionally salient stimuli.[51] Congruously, increases of delta band power have been reported in response to more arousing stimuli.[52–54]

The *theta rhythm* (4 to 8 Hz) has been observed during a number of cognitive processes, and its most prominent form, fronto-medial theta, is believed to originate from limbic and associated structures in the medial prefrontal cortex.[55–58] These theta oscillations subserve central executive function, integrating affective and cognitive sources of information, as necessary in working memory tasks [59,60] as well as in action monitoring.[58] Concerning affect, early reports mention an increasing 'hedonic' theta activity after interruption of pleasurable stimulation, but studies in children between 6 months and 6 years of age showed increases in theta activity upon exposure to pleasurable stimuli.[61] Recent studies on musically induced feelings of pleasure and displeasure found an increase of fronto-medial theta activity with more positive valence.[56,57] For emotionally arousing stimuli, increases in theta band power have been reported over frontal [53,62] and parietal regions.[52] Similarly, a theta increase was also reported during anxious personal object rumination compared to non-anxious object rumination.[63]

The *alpha rhythm* (8 to 13 Hz) is most prominent over parietal and occipital regions, especially when the eyes are closed, and decreases in response to visual,[64] auditory (tau-rhythm [65]) and tactile (central mu-rhythm [66]) stimulation or during mental tasks. The event-related desynchronization in the alpha band (decrease of alpha power) in response to stimulation is believed to represent increased sensory processing, and hence has been associated with an activation of task-relevant sensory cortical regions.[67] The most prominent association between affective states and neurophysiology has been reported in the form of frontal alpha asymmetries,[68] which vary as a function of valence [69] or motivational direction.[42,43] The stronger rightward-lateralization of frontal alpha power during positive or approach-related emotions compared to negative or withdrawal-related emotions is believed to originate from the stronger activation of left compared to right prefrontal structures involved in affective processes. Despite fMRI studies (e.g., [70]) 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,[71,72] music pieces,[73–75] or film excerpts.[76] The alpha rhythm has also been associated with a relaxed and wakeful state of mind.[61] Coherently, increases of alpha power are observed during states of relaxation, as indexed by physiological measures [77,78] and subjective self-report.[79,80]

The *beta rhythm* (13 to 30 Hz) over central regions has been associated with the sensory-motor system as it is weak during motor activity, motor imagination or tactile stimulation, but increases afterwards.[81] That has led to the view that the beta rhythm is a sign of an 'idling' motor cortex.[82] 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 [83]). Concerning affect, increases of beta band activity have been observed over temporal regions in response to visual and self-induced positive, compared to negative, emotions.[84,85] 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.[86] See the gamma rhythm section below for an 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,[87] which are also involved in frowning and smiling.

The *gamma rhythm* (above 30 Hz) is a potential key mechanism in the integration of information represented in different sensory and non-sensory cortical networks.[88] Accordingly, these rhythms have been observed in association with a number of cognitive processes, such as attention,[89] multi-sensory integration, [90] memory,[91] and even consciousness.[92] Concerning valence, the gamma rhythm's amplitude has been found to increase with increasingly positive valence.[85,93] For arousal, posterior increases of gamma band power have been associated with the processing of high versus low arousing visual stimuli.[62,94,95] Similarly, increases of gamma activity over somatosensory cortices have also been linked to the awareness of painful stimuli.[96,97] However, [86] found lower frontal gamma power for stimuli *with* compared to 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 identified as having a specific emotional effect, and hence without impact on subjective experience.

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 simple one-to-one mappings will be found between any oscillatory activity and a given affective or cognitive function. However, the abundance of studies showing the association of brain rhythms with affective responses suggests that aBCI can make use of time-domain, but especially frequency-domain, characteristics of EEG signals to detect affective states. Moreover, further neurophysiological indicators of affective states have been explored, such as functional connectivity between brain regions [98–100] or measures of signal complexity [101] that may help to better describe and differentiate affective states. In the next section, we will survey a number of central studies that approached affect recognition from neurophysiological signals.

6. A survey of aBCI studies

Affect brain-computer interfaces is an emerging topic, which attracts increasing interest. One of the first studies in neurophysiology-based affect detection was conducted in 2000.[102] As can be observed from Figure 4 (Q1 and Q2), the organization of the first aBCI workshop in 2009 stimulated the research in this domain and increased the number of published aBCI studies. Furthermore, BCI researchers also acknowledge the importance of affect in more traditional BCI paradigms, as demonstrated by the increase of BCI studies mentioning affect and emotions (Figure 4, Q3). The number of studies relating emotions and BCI clearly indicate the emergence of aBCI as a new research field.

The design of aBCI systems should include a model able to infer users' emotional states from their brain activity, as well as an application which adapts to users and ensures a closed-loop feedback (see Figure 1). Moreover, the creation and calibration of the model, including the feature extraction step and the classification algorithm, play an important role, as they are important for the emotion assessment accuracy and the system performance. It is thus not surprising that most aBCI studies have focused on improving these aspects by testing different feature extraction methods and classification algorithms. The aim of this section is to give an overview of these studies and of current aBCI research based on the non-exhaustive list of publications in Table 1. Each column of Table 1 represents an important property that most aBCI should include: the number of participants used to train and test classifiers, the type of method used for elicitation of emotions, the duration of trials, the assessed emotion, the signal and number of channels recorded, the signal-processing techniques employed for noise reduction, the extracted features, the classifiers used and the performance obtained. These columns will be analyzed below with respect to performance to determine the current aBCI trends and to elucidate unanswered research questions.

Number of participants

The first column of Table 1 shows the number of participants used for emotion assessment and indicates whether the affective model is participant-independent or not. Participant-independent classifiers are advantageous over participant-dependent classifiers, as the former are trained on data from several persons and hence do not need a training phase for each user. However, the design of accurate participant-independent models remains a challenging task, as described in Section 7. The main advantage of participant-dependent models is their high accuracy compared to participant-independent models. This advantage could be decisive, especially if the duration of the training phase can be shortened to a minimum. This ambivalence is demonstrated by the number of studies in each category: nine for participant-dependent systems and six for participant-independent systems. In both cases, the higher the number of participants employed in a study, the more the results can be regarded as generalizable (i.e. a similar accuracy distribution can be expected for any other participants). The number of trials per participant also impacts the performance of aBCIs, especially for participant-dependent models. Determining an acceptable number of

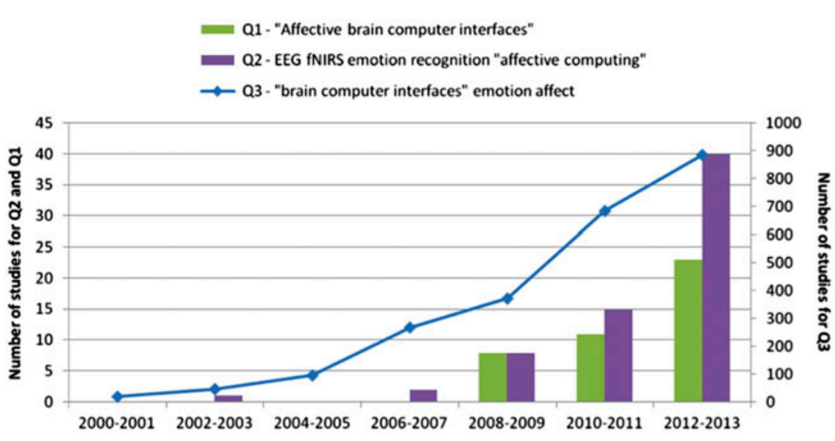

Figure 4. (Color online) Number of studies returned by several queries on google scholar (scholar.google.com as retrieved on 22 November 2013). The search was limited to the period from 2000 to 2013. The objective of query 1 (Q1) and query 2 (Q2) is to measure the evolution of 'affective brain computer interfaces' studies. Query 3 (Q3) was designed to represent the evolution of traditional BCI researchers' interest in affect.

Table 1. Characteristics of many articles relating to affective BCIs. The results column indicates the best average of the reported accuracy. Signals acronyms are: electromyography (EMG), electrocardiogram (ECG), electrodermal activity (EDA), electroencephalography (EEG), blood volume pulse (BVP). Classification acronyms are: sequential floating forward search (SFFS), linear / quadratic discriminant analysis (L/QDA), mean square error (MSE), multi-layer perceptron (MLP), discrete cosine transform (DCT), support vector machine (SVM).

Reference	Number of part.	Emotion elicitation	Time aspects	Assessed emotions	Signals/sensors	Number of channels	Noise processing	Features	Classification / Regression	Performance for brain activity only
[102]	7 User-independent	Images from IAPS Sounds from IADS	6 – 10 s	Happy, neutral, unhappy	EEG	19	Ocular artifacts removed, Muscle artifacts rejected	Spectral features Coherence measures	MLP	64%
[118]	12 User-independent	Film clips	N/A	Joy, anger, sadness, fear, relaxation	EEG, BVP, EDA	3 (forehead)	50 Hz notch filter	Statistics (mean, standard deviation, mean of the absolute value of the first derivative, etc.)	Linear SVM one vs. all	42%
[133]	4 User-dependent	Images from IAPS	6 s	2 or 3 levels of arousal	EEG, EDA, BVP, respiration, finger temperature	34 (grouped by zones)	Band-pass filter	Spectral features	Naïve Bayes	3 levels of arousal:46% 2 levels of arousal: 60%
[134]	10 User-dependent	Recall of emotional events	8 s	Calm, positive excited, negative excited	EEG, EDA, BVP, respiration, finger temperature	64	Band-pass filter	Time frequency features, Mutual information between electrodes pairs	SVM	63%
[103]	20 User-independent	Game played at different difficulty levels	5 min	Boredom, engagement, anxiety	EEG, EDA, BVP, respiration, finger temperature	19	Band-pass filter	Spectral features Ratio alpha / (beta + theta)	LDA FCBF feature selection	56%
[135]	26 User-dependent	Music	30 s	4 emotions	EEG	32	Band-pass filter, Visual inspection	Spectral features Hemispheric asymmetry	SVM	82%
[136]	24 User-dependent	Musical video clips	35 – 117 s	2 classes for each valence, arousal and dominance dimensions	EEG, facial expressions	32	Bandpass filter	Spectral features Hemispheric asymmetry	Gaussian Naïve Bayes Bayesian ridge regression	66–71% F1:65–71 MSE 0.073 – 0.1
[115]	28 User-independent	Images from IAPS	2.5 s	4 classes of the VA space (four quadrants of low / high arousal / valence)	EEG	3 (Fz, Cz, Pz)	Band-pass filter, Ocular artifacts removed	ERPs averaged from 40 trials (1 ERP / participant / emotion class) Spectral features	Classifiers are gender specific Two-stage classification: first arousal and then valence SVM	81%

[137]	11	Images from the IAPS	0.5 s	4 basic emotions	EEG, images content	12	Band-pass filter	Spectral features Beta/alpha ratio Hemispheric asymmetry	Fuzzy clustering and neuro-fuzzy inference	Only reports multi-modal results
[105]	24 User-independent	Video clips	81 s on average	3 valence classes 3 arousal classes	EEG, pupillary response and gaze distance	32	Band-pass filter, Asked not to move	Spectral features Hemispheric asymmetry	ANOVA feature selection SVM RBF	Arousal: 62% Valence: 50%
[119]	16 User-independent	Images of facial expressions	5 s	6 basic emotions	EEG	4 (Fp1, Fp2, F3, F4)	Participants were asked not to move / express emotions, Band-pass filter	Signals averaged per participants and emotions Adaptive filtering High-order crossing	SVM	85%
[124]	5 User dependent	Images from IAPS	12.5 s	positively excited, negatively excited, and calm	EEG, EDA, respiration, BVP, temperature	54	Band-pass filter	Statistics (mean, standard deviation, mean of absolute value of the first derivative, etc.) Correlation dimension	QDA	77%
[138]	18 User-dependent	Movie clips Musical video clips	51 – 128 s 35 – 117 s	2 classes for each valence, arousal and dominance dimensions	MEG, ECG, horizontal EOG, Trapezius EMG	306	Band-pass filter, Channel correction	Spectral power Compressed DCT features	Linear SVM	Arousal: 61% Valence: 57% Dominance: 59%
[122]	26 User-dependent User-independent (average over trials)	Images from IAPS	3.5 s	Postive vs. negative valence	EEG	21	Artifact rejection, Eye-movement correction	Spectral turbulence (correlation of adjacent columns of the spectrogram)	Linear SVM with features selection	User dep.: 67% Average over trials, user indep.: 82%
[108]	24	Images from IAPS Sounds from IADS	6 s	Excited, happy, neutral, sad, fearful, disgust	EEG, EDA, respiration, facial EMG (zygomaticus major and corrugator supercilii)	1 (Fpz)	Participants were asked not to blink, Band-pass filter	Spectral features Ratio beta to alpha	Feature projection using LDA KNN Rule based classifier	Only reports on multimodal results: IAPS F1: 0.76 IADS F1: 0.76
[139]	12 User-dependent	Guided imagery (recall and imagination)	On average 218 s 6 s windows were used for affect estimation	Positive vs. negative valence	EEG	250 recorded, 124 used	High-pass filter	Filter bank common spatial pattern	Logistic regression with elastic-net regularization	71%

(*Continued*)

Table 1. (*Continued*).

Reference	Number of part.	Emotion elicitation	Time aspects	Assessed emotions	Signals/sensors	Number of channels	Noise processing	Features	Classification / Regression	Performance for brain activity only
[140]	8 User-dependent	Images from IAPS Sounds from IADS	35 s windows were used for affect estimation	Neutral vs emotional	fNIRS	16	Low-pass filter	Mean of HbO2 and HbR signals	Mutual information based feature selection Radial basis function SVM	65%
[114]	10 User dependent	Music excerpts	45 s	High arousal vs. brown noise (low arousal) Positive vs. negative valence	fNIRS	18	Low-pass filter	Mean, slope, variation Laterality features	Feature selection based on Fisher criterion LDA	Arousal: 72% Valence: 72%

participants and trials remains an open problem. In [103], the authors report a similar accuracy using either 13 or 19 participants for participant-independent training. This suggests that using around 15 participants might be enough to have an aBCI that can correctly generalize. However, more studies on this issue are needed to confirm that this number is valid in other contexts.

Emotion elicitation

Designing an acquisition protocol is at the basis of any emotion assessment study. This includes the definition of an emotion elicitation strategy, the choice of a ground-truth and the determination of the stimuli duration. As can be seen from Table 1, a majority of studies employed images, most of the time from the International Affective Picture System (IAPS), to elicit emotions. The preference for IAPS stimuli is due to the availability of extensive affective rating of the images, which allow for easy a priori selection of images as well as easy construction of a ground-truth for emotion assessment. However, studies should not limit their analysis to IAPS stimuli and should employ various types of emotional stimulations to guarantee the generalization of aBCI results. Music and movie clips are the second most used stimuli, probably because of their effectiveness in eliciting powerful emotions.[104] Employing images, sounds, and videos for emotion elicitation is also motivated by affective tagging applications, which consist in automatically assigning tags to multimedia contents.[105,106] In a psychophysiological study of emotion induced by music and film stimuli, Stephens et al.[107] replicated the finding of autonomic specific basic emotions and demonstrated that the phenomenon of autonomic nervous system (ANS) specificity of emotion was not a function of the emotion induction technique. In [108], the authors showed that the emotion assessment performance obtained using visual and auditory stimuli is similar. However, one can wonder if the results obtained for multimedia affective tagging could be generalized to other situations, such as more interactive applications and everyday situations. We are aware of only two studies which used an interactive situation where the participants were playing games to induce and measure emotions.[27,103] Similarly, two studies [109,110] relied on mental imagery, which is expected to elicit emotional patterns similar to everyday interactions. In all these cases, the experiments were carried out in the lab, and there is thus a strong need to evaluate the performance of aBCI in ecological contexts.

Time aspects

The duration of the epochs used to perform emotion assessment varies from 0.5 s to 5 min. The performance obtained from the different studies does not seem to depend on the epoch's duration. This demonstrates that EEG signals can be used for both short-term emotion assessment and for emotion assessment over long periods. These temporal aspects, coupled with the fact that emotional brain activity can be recognized a few milliseconds after an emotional stimuli,[111] constitute a major advantage over other modalities such as facial videos, peripheral physiological signals, and speech, which have a worse time resolution.

Assessed emotions

Most of the studies reported in Table 1 have focused on the use of the valence-arousal space to define emotional classes of interest. This bias might be due to the extensive use of the IAPS images as emotional stimuli since they have been previously and reliably evaluated in this space.[112] Only a few studies analyzed the accuracy of emotion recognition on other dimensions such as control, dominance, novelty, or predictability.[113] Focusing on valence and arousal, Soleymani et al.[105] argue that the arousal dimension is better discriminated by brain activity than the valence dimension. When looking at the studies which analyzed both the classification of valence and arousal on two classes [105,106,110,114,115] the valence accuracy is only marginally higher than the arousal accuracy (valence mean accuracy is 65.6%, arousal mean accuracy is 68.2%), and it is difficult to conclude any potential advantage of neurophysiological signals for arousal assessment. It is unfortunately difficult to compare valence-arousal results with those obtained with basic emotions due to the difference in the number of classes employed. Nevertheless, it seems that some reported aBCIs perform quite well with some basic emotions, demonstrating that brain signals could be used to detect either basic emotion or areas of the valence-arousal space. In addition, the combination of several modalities for emotion assessment should improve the current performance of aBCI systems.

Signals / sensors

Table 1 reveals that mainly EEG signals have been used to recognize brain emotional activity. Nevertheless, recent studies employing fNIRS signals for emotion assessment managed to obtain accuracies similar to those obtained from EEG signals. Given these preliminary results, and considering the low invasiveness of the fNIRS apparatus, more fNIRS studies should be performed to validate their interest for emotion assessment, especially in applications where a high temporal resolution is not needed. Many studies have investigated the multimodal fusion of brain activity with peripheral signals, defining a new form of multimodal aBCI.[116] All of these studies have demonstrated the interest of this fusion, especially to better assess the valence dimension, which is difficult to assess using only peripheral signals. Only a few studies have examined the fusion of brain signals with modalities that are not directly related to physiological measurements. In [105] the authors have investigated the fusion of EEG signals with pupillary dilatation and gaze distance, as measured by an eyetracker. In [106], the authors have fused EEG signals with facial expressions action units. In both those studies, the fusion improved the classification accuracy significantly. These results encourage the fusion of brain signals with a wide variety of other modalities, such as speech. The fusion of EEG with fNIRS signals should also be considered as this could increase classification accuracy while maintaining a reasonable temporal resolution.

Number of channels

The use of several sensors and electrodes can be regarded as a nuisance for the user, since wearing more sensors generally means less comfort and higher system complexity. Having many sensors also increases cost and leads to the problem of high-dimensional feature spaces, in which performing classification is a challenge.[117] For these reasons, it is preferable to use relatively few electrodes for emotion assessment. Among the reported studies, a few have used only a limited number of electrodes (3 or 4) based on assumptions about brain activity localization such as the frontal lobe lateralization.[115,118,119] The results demonstrate that it is possible to reduce the number of electrodes without suffering from a drastic drop of performance. A method based on synchronization likelihood and anatomical knowledge was proposed in [120] to automatically select electrodes of interest. The main idea behind this method is to keep a single representative electrode for each brain area which is highly synchronized with its neighbors. Especially for an unobtrusive affect assessment from neurophysiology, there is a need for studies that identify the optimal number and position of electrodes.

Noise processing

Filtering out noise is important to ensure the specificity of the signals (i.e. limiting the impact of non-emotional signals) and separability (i.e. separating the different emotional signals and sources). Most of the studies listed in Table 1 only filtered the signals to remove drifts and power-line noise by using either bandpass, lowpass or notch filters. Only a few studies performed ocular artifact correction and signal rejection. However, this may be inadequate, especially in many emotional protocols in which facial expressions are likely to occur, since EEG signals can also be contaminated by facial muscle artifacts that overlap with several EEG frequency bands.[121] It is thus important that aBCI researchers consider improving their de-noising methods, since the mentioned artifacts carry relevant emotional information that can artificially improve the performance of pattern-recognition algorithms. This was exemplified by Kothe et al.[109], who showed, using dense electrode recordings, that several discriminative EEG sources were originating from muscles. Since the goal is to achieve reliable emotion recognition, those artifacts can be considered as valuable for this task. However, it remains important to distinguish the contribution of each source of information (i.e. brain signals, facial activity, and eye activity) to the overall classification accuracy.

Features

Feature extraction is an important step in emotion assessment, as features with a high discriminative power are crucial for efficient pattern recognition. The most often used features are computed from the power spectrum of the signals. Researchers either directly use the power of the EEG signals at several frequency bands (often ranging from 2 Hz to 45 Hz and above) or combine the energy of different frequency bands, as is done by computing the ratio of energies of the left and right lobes to obtain hemispheric asymmetry indexes. ERP were only moderately used for aBCI as it is necessary to average the signals over several trials of the same emotional class to obtain reliable ERP (see Section 5). Although this limits the interest of ERP for emotion assessment, good performance was obtained using this method.[115,122] Following the theory that emotions emerge as the synchronization of several subsystems,[123] indices of brain areas' synchronization should also be relevant for emotion assessment. This has been demonstrated in [110] by computing inter-electrode mutual information and in [124] by computing the correlation dimension of a set of EEG signals. Several other methods exist to compute synchronization of brain areas [125,126] and these should be tested to confirm the efficiency of this type of feature. As the brain is certainly a non-linear dynamic system,[126] it is also worth analyzing the performance of features stemming from non-linear analysis. For instance, high-order crossing features were successfully used for emotion recognition in [119].

Classification / regression

Many pattern recognition methods have been used to achieve emotion recognition from the computed features. Unfortunately, the number of such methods, the variety of the computed features, and differences in the elicitation protocols make performance comparisons highly problematic. Thus, each aBCI study should ideally report the use of several recognition methods for comparison. An alternative would be to increase the number of studies working on common standardized datasets, as mentioned in Section 7. Among the studies in Table 1, there is only one that tries to assess emotions continuously in the valence-arousal space using regression,[106] while other studies define classes as areas in this space. Furthermore, there are no studies that have performed continuous emotion recognition over time. Researchers of aBCI should thus follow these new research paths, especially considering that brain signals can have very good time resolution and are thus valuable for continuous emotion assessment.

7. Challenges on the road toward aBCI

As mentioned throughout the last sections, aBCI research is an emerging and developing field. Therefore, as for BCI in general, there are many unsolved issues and challenges, the most relevant of which we will briefly outline below.

Standards for the evaluation and comparison of aBCI approaches

As for BCI in general, and as surveyed in Section 6, aBCI systems are a combination of various possible signal preprocessing and classification algorithms within specific application (or elicitation) contexts. This makes a direct comparison of studies and the algorithms used difficult and impedes the achieving of generalizable insights. The BCI community solved this issue by the publication of several high-quality data sets and the initiation of BCI competitions (e.g., [127]). For the aBCI community, several groups published comprehensive data sets that allow for the comparison of algorithms in different affect-elicitation contexts. Table 2 lists the data sets and their respective features. Despite the lack of unlabeled test sets and an organized evaluation, these resources offer a great opportunity to evaluate and compare different aBCI approaches. They also enable people without the means for data acquisition to develop and evaluate algorithms for aBCI problems. However, those databases are limited to the analysis of emotions induced by videos / images, and are biased toward the application of affective tagging. The development of new databases is thus critical to design innovative aBCI targeting a wide range of applications. A major advance in the field would be to introduce a data-set where the emotions are elicited naturally to reach the goal of ecological emotion assessment. This could be achieved by recording participants while they are interacting with computers and coping with events. Also, data analysis competitions, similar to those in the BCI community, could draw attention to the unique challenges of aBCI data analysis and

Table 2. A list of current databases usable for aBCI studies.

Name / link	# part.	Modalities	Stimuli	Emotions
eNTERFACE	16	Facial videos, fNIRS	Images	Happiness, disgust
http://www.enterface.net/results/	5	EEG, fNIRS	IAPS	Valence and arousal
MANHOB-HCI (emotive part) http://mahnob-db.eu/hct-tagging/	27	EEG, facial videos, sounds, eye-gaze, ECG, EDA, respiration amplitude, skin temperature	Videos (film clips)	Valence, arousal, dominance and predictability
DEAP (Database for Emotion Analysis using Physiological Signals) http://www.eecs.qmul.ac.uk/mmv/datasets/deap/	32	EEG, facial videos, EMG (trapezius), EOG, BVP, skin temperature, EDA	Music video clips	Valence, arousal, dominance, familiarity, likeliness

encourage both new and established researchers to critically evaluate and disseminate their methods.

Participant-independent and stable classification

Only a few studies approached the problem of participant-independent or participant-specific but session-independent (stable over several sessions) affect classification from neurophysiological activity. However, such general classifiers are a core requirement for practical aBCI, since otherwise classifiers have to be retrained each time the system is used. As the training procedures (affect-induction protocols) are long, intrusive, and their efficacy is limited due to habituation to the stimuli, a classifier training preceding each system use seems unfeasible. The problem of participant-independent classifier calibration is a general challenge for BCI applications and several solutions have been suggested and studied. Though the use of a general model is in general likely to be accompanied by a loss of performance compared to participant-dependent models, hybrid approaches that adapt a general model to a specific user in a specific session require a smaller number of training trials. Transfer learning [128] and multi-task learning approaches [129] have recently emerged from the field of pattern recognition and aim at transferring the knowledge acquired in a classification task or domain (e.g. classification of good and bad apples) to a different one which has similar properties (e.g. classification of good and bad pears). This could be achieved in several ways for instance by estimating the covariate shift existing between a task and another from unlabeled samples. In this framework, the physiological data of each user could be considered as a different classification domain, which we have to address using knowledge of other participants' domains.

Identification and removal of artifactual activity

Affective states are seldom encountered in isolation. Rather, they occur in response to certain (potentially still ongoing) events that initiate or feature behavioral responses as well. Affective states are accompanied by specific contexts that are characterized not only by the neurophysiological correlates of the affect, but also by behavioral covariates. For aBCI, electromyographical sources might be particularly relevant behavioral covariates, since facial expressions contribute to the EEG signals recorded from the scalp.[87] If such non-neural covariates are co-occurring with the affective state, they will be learned by a classifier since they are informative regarding the affective state. Unfortunately, in a complex world, facial expressions and other behavioral covariates also vary independently of affect, and thereby make the system susceptible to deceptive facial expressions.[4] Furthermore, these activations might obscure informative neural activity. To increase the reliability of aBCI systems, a distinction between the signal sources – neurophysiological, electromyographical, or electrooculographical – is necessary. Techniques like independent component analysis (ICA) [85,130] can separate different signal sources from each other, which may help researchers identify their nature and thereby become aware of the nature of the signals contributing to classifier performance. ICA was found to be effective for identification of electrooculographical and brain sources, but less so for electromyographical sources. Consequently, a new method was proposed for EEG decontamination, based on the assumption of low autocorrelation of EMG as compared to EEG and on canonical correlation analysis.[131]

Separation of core affective and accompanying non-affective correlates of affect

Similar to behavioral dispositions, affective states might be accompanied by different perceptive or cognitive processes.[3] And similar to behavioral dispositions, such processes can be characterized by specific patterns in the neurophysiological signal, which can inform a classifier, but which can also diminish its reliability. Different from non-neural artifactual covariates, such correlates originate in the brain and are therefore more difficult to separate from core affective correlates. An example is the higher activation of sensory cortices during emotional stimulation, potentially indicating stronger processing of these salient stimuli and reflected in the alpha band over modality-specific regions.[132] As for behavioral covariates, a separation between affective and non-affective correlates of affective responses seems necessary to warrant reliable aBCIs. On the other hand, information about perceptual or cognitive correlates of affect can contribute valuable contextual information about the nature of the affective response, revealing for example its object or the modality of origin. Moreover, modern affective neuroscience [37] postulates a strong overlap between the structures involved in affective processes and those involved in cognitive processes. More specifically, they argue that no structure is solely associated with affect, and that processes involved in affect might be, at least partly, of a more general nature, in the sense that they are also observed during non-affective episodes. Accordingly, affect detection would be the detection of *patterns* of general neurophysiological activity characteristic of certain affective states in specific contexts, whose *single* components, however, are *not only* observable during affective episodes. Such complex interplay between affective and cognitive processes bears consequences for the specificity and generalization of aBCI classifiers.[132] Progress in aBCI therefore depends on the progress of the cognitive and affective neurosciences to outline the structure of affective states in the brain and to identify neurophysiological activity that is indicative of these states.

8. Conclusion

In this article, we set out to survey the field of neurophysiology-based affect detection. We hope that this overview, besides giving insight into the current state-of-the-art of the field and its intricacies, enables a better understanding of its great potential and motivates the BCI community to partake in an exciting endeavor and to invest time and effort to drive the field of aBCI forward. We still do know very little about the workings of the brain and about the realization of affective phenomena within the human body and brain. Nevertheless, we believe that, as neuroscientific and neurotechnological methods are evolving, as our knowledge of the fundamental neurophysiological principles grows and technological progress enables faster and smaller devices, the non-intrusive and continuous detection of affective states from brain activity can become reality.

Acknowledgements

The first and the last author contributed to this survey article in equal parts. We gratefully acknowledge the help of Alan Pope, Thierry Pun, and Boris Reuderink, and thank them for their valuable comments, insightful additions, and critical requests for clarifications. It should be noted that parts of Sections 2 and 5 have been revised from [9]. The research of the last author was supported by the National Center of Competence in Research (NCCR) Affective sciences financed by the Swiss National Science Foundation (n° 51NF40-104,897) and hosted by the University of Geneva.

Notes

1. The extension enables a distinction with regard to the use of exogenous stimulation by the system and user volition in a given approach. This seems relevant to cover reactive approaches that are stimulus-dependent, but do not require user volition (e.g., engagement scoring, affective media tagging, preference communication).
2. Since lie-detection is rather used for monitoring than for the adaptation of interaction, lacking thus a direct feedback element, it is rather a marginal instance of affective brain-computer interface systems.
3. Appraisal models and notions of basic or dimensional emotion models are not necessarily incompatible. They can be viewed as treating different aspects of the same object, namely affect, in more detail, specifically the mechanisms which lead to certain affective states. Consequently, appraisal theories have also incorporated the notion of valence (or positive/negative appraisal) and arousal dimensions as underlying structure to the emotional responses.[31,34]
4. BCI systems, by definition, rely at least in part on brain signals, and researchers should strive for the identification of the sources used by the affect classifier. This is especially important for the use of such systems in contexts that preclude the use of non-neural signals, as is the case in communication systems for ALS or locked-in patients.

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