Emotional brain–computer interfaces

Gary Garcia-Molina* and Tsvetomira Tsoneva

Philips Research Europe,
High Tech Campus 34,
Eindhoven, 5656AE, The Netherlands
E-mail: gary.garcia@philips.com
E-mail: tsvetomira.tsoneva@philips.com
*Corresponding author

Anton Nijholt

Universiteit Twente,
INF 2055,
Enschede, 7500 AE, The Netherlands
E-mail: A.Nijholt@ewi.utwente.nl

Abstract: Research in brain–computer interface (BCI) has significantly increased during the last few years. Additionally to their initial role as assisting devices for the physically challenged, BCIs are now proposed for a wider range of applications. As any human–machine interaction system, BCIs can benefit from adapting their operation to the emotional state of the user. BCIs already have access to the brain activity, which provides significant insight into the user's emotional state. This information can be utilised in two manners. (1) Knowledge of the influence of the emotional state on brain activity patterns can allow the BCI to adapt its recognition algorithms, so that the intention of the user is correctly interpreted in spite of signal deviations induced by the subject's emotional state. (2) The ability to recognise emotions can be used to provide the user with more natural ways of controlling the BCI through affective modulation and can potentially lead to higher communication throughput.

Keywords: BCI; brain–computer interface; electroencephalogram; emotion; valence; arousal; passive BCI; adaptive communication systems.

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Biographical notes: Gary Garcia-Molina received an MSc in Electrical Engineering from the Swiss Federal Institute of Technology Lausanne (EPFL), in 2001 and a PhD from the same institution for his work on electroencephalogram based brain–computer interfaces, in July 2004. Until May 2005, he was a Software Development Leader of the startup company EMITALL (Montreux-Switzerland). He has been with Philips Research Laboratories (Eindhoven – Netherlands) since May 2005. Currently, he leads an activity aimed at developing practical brain–computer interfaces.

Tsvetomira Tsoneva received a BSc in Computer Science (2003) from the University of Economics, Varna, Bulgaria and an MSc in Computer Science and Engineering (2007) from Eindhoven University of Technology, The Netherlands. Currently, she is a Research Scientist in the Brain, Body and Behavior group at Philips Research, The Netherlands. Her research interests include neuro-physiologic signal interpretation, affective computing and cognitive neuroscience.

Anton Nijholt received an MSc in Mathematics and Computer Science (1974) at Delft University of Technology and a PhD in Computer Science at the Vrije Universiteit Amsterdam. He has held positions at various universities in Canada, Belgium and the Netherlands. Since 1989, he has been a Full Professor of Computer Science at the University of Twente (Enschede, The Netherlands). Currently, he is the Head of the Human Media Interaction research group in the Department of Computer Science at the University of Twente. His recent interests include entertainment computing, multimodal interaction and brain–computer interfacing.

1 Introduction

The field of brain–computer interfaces (BCI) has gained enormous popularity during the last few years. BCI's multidisciplinary nature poses challenges that attract researchers from various disciplines comprising neuroscience, signal processing, machine learning and human–computer interaction.

Our goal in this paper is to present a framework to enhance BCI operation by taking advantage of the information of the user's emotional state, which can be detected from electroencephalogram (EEG) signals.

The BCI principles are first introduced in Section 2. We motivate in particular our focus on non-invasive EEG-based BCIs. In Section 3, we describe the models for emotion categorisation, the methods for emotional elicitation and the manifestations of emotions in the EEG. Our motivation for considering emotion understanding in BCIs is summarised in Section 4. Section 5 presents our approaches for BCI operation and emotion according to two scenarios:

1 accounting for the user's emotional state to adapt the algorithms that identify the user's intent in the ongoing EEG signals

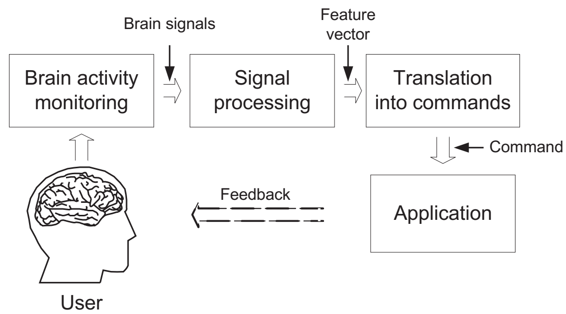
2 purposefully eliciting emotion to enhance EEG features that are relevant for BCI operation.

Section 6 proposes emotive BCI operation by allowing users to gain control of the BCI through a modulation of their emotional state. Emotive BCI operation can be more natural and easier for the user and can lead to higher communication throughput. Section 7 concludes this paper by suggesting a research agenda towards emotional BCIs.

2 BCI overview

A BCI is a communication system that allows a person to send messages to the external world by merely thinking without depending on the brain's normal output channels of nerves and muscles (Wolpaw et al., 2002).

Figure 1 Functional model of a BCI



A BCI can be functionally described as illustrated in Figure 1. Monitoring of the user's brain activity results in brain signals (e.g. electric or hemodynamic brain activity indicators), which are processed to obtain features that can be grouped into a feature vector. The vector is translated into a command to execute an action on the BCI application (e.g. a wheelchair, a cursor on a screen and a spelling device). The result of such an action can be perceived by the user, who can modulate her/his brain activity to accomplish her/his intents.

Brain activity produces various phenomena, which can be measured using appropriate sensing technology. Of particular relevance for BCIs are electrical potential and hemodynamic measurements. Electrical potential measurements include action and field potentials, which can be recorded through invasive techniques such as electrocorticography, or non-invasive techniques such as EEG and magnetoencephalogram. Hemodynamic measurements include functional magnetic resonance imaging, positron emission tomography and functional near-infrared spectroscopy. Because of its high time resolution, non-invasiveness, ease of acquisition and cost-effectiveness, the EEG is the preferred brain monitoring method in current BCIs.

To gain control of the BCI, the user executes mental activities, which produce distinctive patterns in the EEG. These are automatically recognised by the BCI and associated with actions that depend on the application. In a cursor movement application, the actions would correspond to movement directions. The type of mental activities and their corresponding EEG correlates are termed as electrophysiological sources of control (Bashashati et al., 2007). The main sources are listed below:

- *Sensorimotor activity*: mu and beta rhythms (8–12 Hz and 13–30 Hz, respectively) originate in the primary sensorimotor cortex and are more prominent when a person is not engaged in processing sensorimotor inputs or in producing motor outputs. A voluntary movement results in a power decrease in the mu and beta bands, which is termed event related desynchronisation (ERD). Desynchronisation begins in the contralateral rolandic region about two seconds prior to the onset of a movement and becomes bilateral before execution of movement. After the movement, the power in the mu and beta rhythm increase (event related synchronisation, (ERS)). Motor imagery elicits similar patterns of activity (Pfurtscheller and Neuper, 2001). The imagination of motor movements, in particular limb movements are used in several BCIs which identify the type of motor imagery (right/left hand/foot movement) using a classification algorithm that takes as features the power in the mu and beta bands at electrodes located over the primary sensorimotor cortex (i.e. electrodes C3, C4, Cz of the EEG ten-twenty international system of electrode placement (Jasper, 1958)). Hereafter, we refer to BCIs relying on motor imagery as ERD/ERS-based BCIs.

- *P300*: infrequent or particularly significant auditory, visual or somatosensory stimuli, when interspersed with frequent or routine stimuli, typically evoke in the EEG over the parietal cortex a positive peak at about 300 ms after the stimulus presentation. This peak is called as P300. P300-based BCIs operate by presenting the user with a set of choices (usually in a matrix form) and randomly highlighting all of them. A P300 appears in the user's EEG when her/his selected choice is highlighted. Detecting the choice for which a P300 was elicited allows the BCI to know the user's selection and execute the corresponding action. The P300 detection algorithm takes as features the signal samples (generally after band-pass filtering and subsampling) at parietal electrode sites (Hoffmann, 2007).
- *Steady-state visual evoked potentials*: when subjects are presented with repetitive visual stimuli at a rate >5 Hz, a continuous oscillatory response at the stimulation frequency and/or harmonics is elicited in the visual cortex. This response is called steady-state visual evoked potential (SSVEP). The SSVEP is more prominent at occipital sites. SSVEP-based BCIs operate by presenting the user with a set of repetitive visual stimuli at different frequencies, which are associated with actions. To select a desired action, the user needs to focus her/his attention on the corresponding stimulus. The SSVEP corresponding to the attended stimulus is more prominent and can be automatically detected by the BCI. Detection of SSVEPs in current BCIs relies on the application of spatial filters (across electrodes) followed by temporal filters (e.g. comb filters centred around the stimulation frequencies) and thresholding (Cheng et al., 2002; Garcia-Molina and Mihajlovic, 2010).
- *Slow cortical potentials (SCP)*: SCPs are slow non-movement potential changes voluntarily generated by the subject. They reflect changes in cortical polarisation of the EEG lasting from 300 ms up to several seconds. Operation of SCP-based BCIs is often of binary nature and relies on the subject's ability to voluntarily shift her/his SCP (Birbaumer et al., 2000).
- *Responses to mental tasks*: BCI systems based on non-movement mental tasks assume that different mental tasks (e.g. solving a multiplication problem, imagining a 3D object and mental counting) lead to distinct, task-specific distributions of EEG frequency patterns over the scalp.

Depending on their operation mode, BCIs can be categorised into *active*, *reactive* and *passive* (Zander and Jatzev, 2009). Active operation refers to the utilisation of brain activity corresponding to intended actions as electrophysiological source of control. This category comprises BCIs using sensorimotor activity, SCPs and mental tasks. Reactive operation refers to the utilisation of brain responses to exogenous stimuli as electrophysiological source of control. SSVEP and P300-based BCIs are in this category. Applications relying on the use of brain activity as an additional input, allowing the real time adaptation of the application according to the users' mental state are categorised as passive BCIs (Cutrell and Tan, 2008).

Present BCI applications have primary goal to offer means for communication and control, especially for the physically challenged. With the considerable expansion of BCI research during the last decade, BCI technology has been increasingly proposed in applications for a wider range of users. Interest in BCI technology stems from the unique advantage of having access to the user's ongoing brain activity which enables applications spanning a variety of domains such as entertainment (e.g. brain-activity-based gaming (Nijholt, 2008)), safety (e.g. detecting the level of alertness (Tzyy-Ping et al., 1997)), security (e.g. brain activity-based biometrics (Marcel and Millan, 2007)) and neuro-economics (e.g. neural correlates of consumer choices for marketing (Lee et al., 2007)).

3 Emotions

Emotions are psycho-physiological phenomena associated with a wide variety of expressed subjective feelings, observable behaviours and changes in autonomic body state. Currently, there is no universally accepted model to categorise emotions. Proponents of discrete emotion theories have suggested a number of emotions that form a core set of *basic emotions* from which all other 'secondary' emotions can be derived. Based on the universal facial expressions, Ekman (1983) identifies the basic set of *anger*, *disgust*, *fear*, *joy*, *sadness* and *surprise*, while according to Plutchik (1980) the basic emotions are innate and directly related to adaptive behaviour i.e. designed to enhance our survival and they are *acceptance*, *anger*, *anticipation*, *disgust*, *joy*, *fear*, *sadness* and *surprise*.

Other theories argue that emotions are better measured and conceptualised as differing in degree on one or another dimension, each representing a certain affective trait. An example of such a model is the *pleasure-arousal* circumplex model of affect of Russell (1980). It uses two orthogonal dimensions to model emotions. The first dimension *pleasure* (or *valence*) explains the pleasantness (hedonic value) related to a given affective state and the second dimension explains the physiological activation related to the affective state (*arousal*).

Another dimensional perspective is given by the *approach–avoidance* theory (Schneirla, 1959). Approach/avoidance motivations are characterised by tendencies to approach or avoid the stimuli. Positive valence is often related to approach motivation, whereas negative valence to avoidance. However, valence and approach–avoidance represent different aspects of emotions and emotion processing.

In line with most research we adopt the valence–arousal space in our attempt to model the effects of emotions on BCI. For ease of presentation, we refer to emotional valence (emotional arousal) simply as valence (arousal).

3.1 Emotion elicitation

Emotion elicitation techniques aim at inducing a certain affective response in one or more emotion response systems in a controlled setting via some type of stimulus. Emotion elicitation is not trivial and it raises certain practical (e.g. producing the same effect in different persons) and ethical (e.g. inducing negative emotions) issues. Picard et al. (2001) define five factors that can influence emotion elicitation results: elicitor (subject- vs. event-elicited), setting (lab setting vs. real world), focus (expression vs. feeling of the emotion), subject awareness (open- vs. hidden-recording) and purpose (emotion- vs. other-purpose). There are different strategies to elicit emotions employing a variety of modalities. For the sake of this paper drug-based emotion elicitation is excluded.

Several studies use a set of standardised emotional stimuli (e.g films, pictures, sound and odour) in order to elicit a certain emotion or emotion dimension. Rottenberg (2007) discusses the use of film clips to elicit emotions. The International Affective Picture System (IAPS) (Bradley and Lang, 2007) provides a set of normative emotional stimuli for experimental investigations of emotion and attention. Eich et al. (2007) suggest the use of music to trigger mood.

Imagination techniques use methods such as autobiographic recall and guided imagination to evoke a certain emotion. Subjects are asked to remember a particular situation from their past that elicits emotional response (Picard et al., 2001) or they are guided through a story/imagery (Lisetti and Nasoz, 2004), sometimes also including usage of audio-visual aids.

Preset social interactions use high-impact manipulations and deception to create realistic, emotion eliciting situations similar to the ones occurring in the real world. Harmon-Jones et al. (2007) give examples of social psychological methods for inducing emotions such as anger, joy, sadness, sympathy and guilt. These techniques can also include interaction with a computer to evoke emotional response.

A different way to induce emotional reaction is the directed facial action task suggested by Ekman (2007). This method does not ask participant to consciously pose a particular emotion, but to perform a combination of facial muscle movements, which form a specific facial expression. This facial expression then triggers the corresponding affective state.

3.2 Measuring emotions

Given the complexity of emotions, it is not surprising that there is no universal method to measure them. Different emotions differ in their elicitors, appraisals, physiology and behavioural responses. Selection of the measurement method depends on factors such as the targeted affective theory, the emotional aspects of interest, the context and the final goal of the evaluation. Methods trying to measure the affective state of people can be categorised into two groups: subjective and objective methods.

Subjective methods consist of questionnaires, adjective checklists and pictorial tools used as self-report instruments. Those tools assess the subjective emotional experience of a person, reported by the person himself. Examples of these methods include activation–deactivation checklist (Thayer, 1967), positive and negative affect schedule (Watson et al., 1988) and self-assessment manikin (Lang, 1985). Subjective methods can accommodate any set of emotions, including emotional blends. However, they are culturally and language biased and can only measure affective states of which the respondents are consciously aware.

Objective methods use physiological cues derived from the physiology theories of emotions, which define universal patterns of autonomic (ANS) and central nervous system (CNS) responses related to emotional experiences. Facial expression and vocal properties are among the most commonly used autonomic cues. Theories such as Ekman's (1992) and Izard's (1977) suggest a link between facial expression and affective state. Instruments use either video analysis algorithms (Cohn and Kanade, 2007) or electromyography recordings (Cacioppo et al., 1986) to recognise emotions from facial expression. According to emotion physiology literature modulations in voice are also linked to specific affective states (Johnstone and Scherer, 2001). Other modalities used for measuring emotions include heart rate, electro-dermal responses, temperature, blood pressure and respiration. CNS also plays an important role in emotion processing. Emotional responses in the CNS can be measured using EEG (Bostanov, 2003). Objective methods overcome the limitations of subjective however, different individuals can show different physiological responses to the same emotional state.

Research on automatic emotion detection has received increasing attention from the scientific community. Researchers leverage on the previously mentioned methods for emotion elicitation and measurement to devise algorithms able to identify affect. The resulting accuracy for emotion detection depends on the emotion classes under investigation, the technique used to elicit emotions and the emotion-measurement approach. For EEG-based detection of emotions, reported accuracies include 60% Chanel et al. (2006) (3 degrees of arousal) and 83% Murugappan et al. (2010) (2 degrees of valence) or 93% (2 degrees of valence) Li and Lu (2009). These early results are promising and can enable several new applications, including emotion-aware BCI systems. Section 3.3 describes the neural correlates of affect than can be used for emotional identification.

3.3 EEG correlates of emotion

In the context of this paper emotion assessment via EEG is of particular interest. This section gives an overview of the known correlates of emotion in EEG that can be related to BCI operation.

3.3.1 Spectral dynamics

Frontal activity which is characterised in terms of decreased power in the alpha band has been consistently found to be associated with emotional states (Coan and Allen, 2004). Indeed, numerous studies coincide on the fact that relatively greater trait left frontal activity is associated with trait tendencies towards a general appetitive, approach or behavioural activation motivational system, and that relatively greater trait right frontal activity is associated with trait tendencies towards a general avoidance or withdrawal system (Davidson, 1993). This phenomena is known as frontal asymmetry.

Aftanas et al. (2001) use affective pictures and ERD/ERS analysis of EEG to study cortical activations during emotion processing. In accordance with the asymmetry literature they report relatively greater right hemisphere ERS for negative and greater left hemisphere ERS for positive stimuli at anterior temporal regions. An arousal effect is also present indicating that affective pictures induce larger amount of theta ERS than neutral stimuli in the early post-stimulus period (200–500 ms). The arousal effect is further confirmed in a follow-up study (Aftanas et al., 2002), where stimuli of high and medium arousal induced larger theta synchronisation in left anterior and right posterior sites, as well as larger alpha-1 synchronisation over occipital sites compared to neutral stimuli.

Gamma activity has also been related to emotional processing, especially to negative emotions Oathes et al. (2008). Muller et al. (1999) report relatively more gamma power in the right temporal sites associated with positively valenced stimuli and relatively more gamma in the left temporal sites associated with negatively valenced stimuli.

3.3.2 Event-related potentials

Affective processing in the brain shows an effect on ERPs elicited in varied conditions. Pictures have been often used to study emotion processing. A comprehensive review of ERP studies using picture stimuli to elicit emotional processing can be found in Olofsson et al. (2008). Valence effects, although not consistently, have been reported at early latencies (100–300 ms). More consistent effects are obtained for arousal, which elicits a positive peak about 200 ms after stimulus onset that can be varying with task relevance in the P300 range. However, emotional arousal P300 effects have been obtained for passive (viewing) and active (affective categorisation) procedures as well as for the oddball and three-stimulus paradigm (Delplanque et al., 2006; Keil et al., 2002; Mini et al., 1996). The P3b component appears sensitive to both valence and arousal variations. Pleasant stimuli seems to elicit larger P3b amplitude than unpleasant and neutral stimuli when the pictures are task relevant Delplanque et al. (2006), Carretie et al. (2006).

Affective processing can be also triggered by emotionally loaded words. Kissler et al. (2006) reviews the ERP literature on visual word processing and emotions. Emotional influences are found in early and late components. A considerable number of studies show increased late positive responses for emotionally salient words (starting from 300 ms after word onset).

Emotionally loaded stimuli of other modalities also show effect on the ERP components. In a study with olfactory stimulation, a late positive component reflects the processing of odour valence (Lundstrom et al., 2006). Also, vocal emotions show an early task-specific emotion-based influence on the early stages of auditory sensory processing (Spreckelmeyer et al., 2009).

Although factors such as stimulus type, stimulus properties (colour, size, complexity, etc.), task demands (passive perception, active involvement, relevance, load, etc.) and subject specificities influence the affective modulations in ERPs, it has been shown that stimuli containing an affective component do elicit differences in the latency and the amplitude of the characteristic peaks of ERPs.

3.3.3 Steady-state visual evoked potentials

The SSVEP elicited by a repetitive visual stimulus (RVS) is modulated by the brain processes that concurrently occur. In particular, the user's emotional state influences the SSVEP amplitude and latency at different scalp locations. In Kemp et al. (2002), it is reported that presentation of emotion eliciting pictures of the IAPS overlaid with a 13 Hz RVS influence the amplitude, latency and distribution of the corresponding SSVEP. On the one hand, pleasant emotional valence is associated with a frontal amplitude increase and latency decrease bilaterally as well as an amplitude decrease and latency increase in the occipital region. On the other hand, unpleasant valence, is associated with an amplitude increase and latency reduction in the left temporo-parietal, posterior-frontal and right anterior-temporal regions.

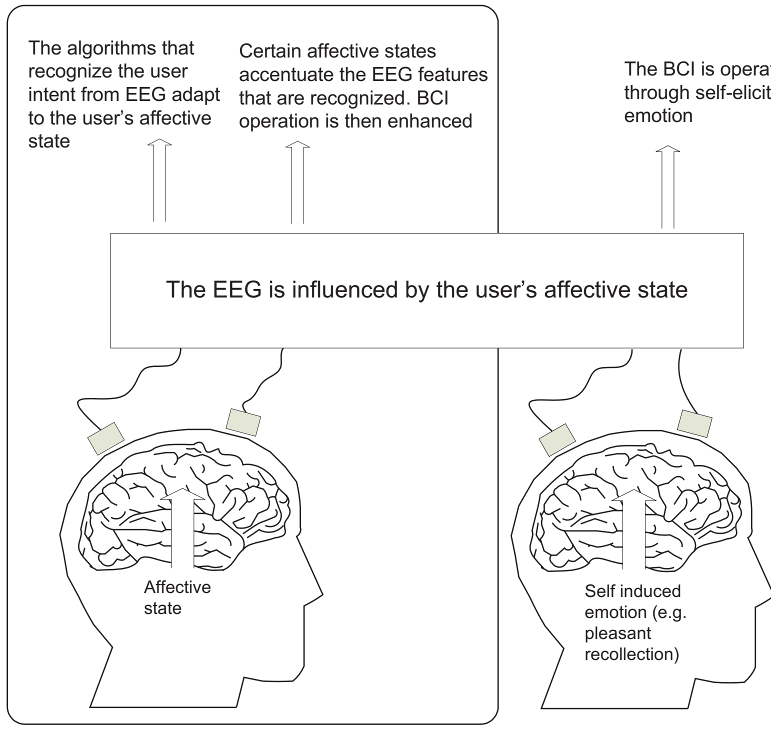
In Keil et al. (2003), presentation of IAPS pictures in a flickering mode (at 10 Hz) elicits a 10 Hz SSVEP, which has enhanced amplitude at parieto-occipital recording sites for affectively arousing (unpleasant and pleasant) pictures, as compared to neutral stimuli.

4 Why do we need to understand emotions for BCI?

Given the broad range of applications that can benefit from BCIs, it is important to ensure the usability of this technology in terms of communication throughput, accuracy and training time.

Communication throughout and accuracy influence the information transfer rate of the BCI system. The transfer rate in BCI systems ranges from 10 (SCP-based BCI) to 60 bits/min (SSVEP based BCI). The effectiveness of the BCI also depends on the ability of the user to willingly and consistently control her/his brain activity, i.e. usually ensured through training. The required training duration ranges from minutes (P300-based BCI) to weeks (SCP-based BCI). The information transfer rate and training duration are influenced by user factors such as level of concentration, motivation, fatigue and the emotional state. For robust BCI operation, we need to take into account the current state of the user and use it to enhance the interaction.

Figure 2 Why do we need to understand emotions for BCI



Adapting to the user's affective state can bring BCI technology closer to the truly personal and user friendly interaction suggested in Picard (1995). BCIs have the advantage of having access to the source of emotional processing, the brain. This knowledge can be utilised in two manners (see Figure 2):

- Understanding the influence of the affective state on brain activity would allow the BCI system to adapt its command translation algorithms:
  - to compensate for the signal deviations induced by the user emotional state, so that a user's intention is still correctly interpreted
  - to enhance the characteristic EEG features used by the BCI system in order to overcome the low signal-to-noise ratio and low spatial resolution attributes to EEG signals.
- The possibility to elicit and identify emotions can be utilised in BCIs to provide the user with more natural ways of controlling BCI systems through affective modulation (e.g. BCI control by pleasant memory recollection). This could potentially lead to higher information transfer rates and open opportunities for new applications. Also, recognising user emotional state would enable automatic adaptation of the system to users or predicting their intentions, thus, enhancing usability and minimising frustration and the amount of required interaction.

Sections 5 elaborate more about the suggested possibilities.

5 Emotions and BCI operation

5.1 Accounting for the user's emotional state

We suggest two possible strategies to account for the user's emotional state during BCI operation:

1. exhaustive training of the BCI classification algorithm under various emotional states
2. online emotional adaptation of the classification algorithm.

In the approach consisting in exhaustive training of the BCI classification algorithms, feature vectors are obtained during various emotional states, which are elicited through the techniques presented in Section 3.1. Such feature vectors are then used to train the BCI classification algorithm, which can then correctly recognise the relevant brain activity independently of the user's emotional state. In an alternative implementation, several classifiers can be constructed under different emotional states, which are again elicited through the techniques of Section 3.1. During operation, the user's emotion needs to be identified first in order to select the corresponding classifier. Identification of the user's emotional state is achieved through an additional emotion detection component, which can for instance rely on frontal asymmetry in the alpha band as explained in Section 3.3.1. In both of its implementations, this simple approach has the disadvantage of requiring long training.

In the approach consisting in the online adaptation of the classification algorithm, the information about EEG correlates of emotions is utilised to adapt the classification algorithm parameters depending on the current user's emotional state (a discrete emotion or emotional valence), which is determined through an additional emotion detection component (see Figure 3). The user's emotional state could be identified as a discrete emotion, as emotional valence (positive/negative) or motivation direction (approach/avoidance) depending on the situation at hand. The way in which the classifier is adapted takes advantage of the manner in which the emotional state influences the particular electrophysiological source of control that the BCI utilises.

- For *ERD/ERS-based BCIs*, the emotional state can change the asymmetry of the frontal alpha, which can influence the mu power associated with the sites over the primary motor cortex where imagined movements are detected. To illustrate the extent to which knowledge of the influence of emotions can be utilised, we consider a hypothetical simple classifier, which decides on the basis of a score resulting from the linear combination of the powers in the mu band of electrodes C3, Cz and C4. If a different emotional state than the one under which the classifier was trained (i.e. the linear coefficients were learned) is detected, then only the coefficients that correspond to lateral electrodes C3 and C4 have to be adjusted.
- For *P300-based BCIs* (as mentioned in Section 3.3.2), the emotional state can change the amplitude of the signal from 200 ms after stimulus presentation. Since algorithms that detect the presence of a P300 in an EEG segment following the presentation of a stimulus use features that are composed of actual signal samples, a similar strategy for the updating of the classification algorithm as in the ERD/ERS-based BCIs can be used. This means that only the coefficients that are associated with samples expected to change in function of the user's emotional state need to be updated.
- For *SSVEP-based BCIs*, the scalp distribution, as well as the amplitude and SSVEP latency, is influenced by the user's emotional state. To account for these differences, the spatial filters used in SSVEP can be changed during operation as explained in Friman et al. (2007).

Figure 3 Functional model of a BCI accounting for the user's emotional state

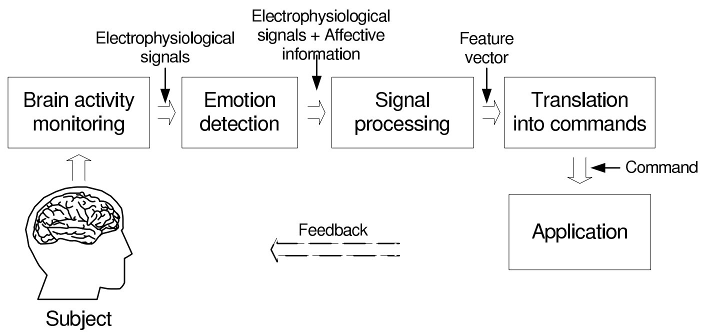
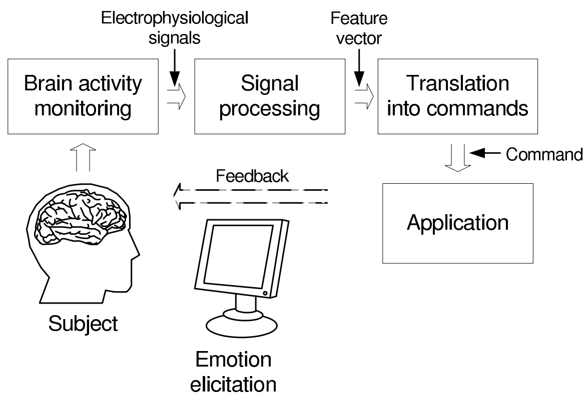


Figure 4 Functional model of a BCI operation enhanced through emotion elicitation



5.2 *Enhancing BCI operation through emotion elicitation*

We can make use of our knowledge about emotion elicitation techniques and affective processing in the brain to improve the accuracy and speed of BCIs. The proposed strategy utilises the known correlates of emotions (see Section 3.3) to enhance the electrophysiological sources of control used in BCI systems. The general approach is illustrated in Figure 4. In this solution, the user is exposed to affective stimulation i.e. supposed to enhance a specific electrophysiological source of control. The strategies specific for the different types of BCI systems are presented below:

- *P300-based BCI*: ERPs are of small amplitude compared to background EEG. Single trial ERP component recognition is challenging. Higher amplitude would facilitate component localisation. In the case of P300-based BCIs that would also lead to a better classification accuracy. Here the knowledge about the effect of emotional content on ERP responses can be applied to enforce P300-related information. According to the results presented in Section 3.3.2, the P300 component seems to be influenced by emotionally arousing images, suggesting that arousal amplifies activity in the parietal cortex. The P3b amplitude, in particular, is also influenced by both valence and arousal when the pictures are task relevant. Building on that to improve P300-based algorithms we can design an interface where P300 is evoked using emotional stimuli. In an example, implementation of such a BCI system an execution of a command would depend on an oddball paradigm where the target is an image of positive arousal.

- *SSVEP-based BCI*: SSVEP-based BCI systems can also benefit from an enhanced amplitude of brain responses. As mentioned in Section 3.3.3, emotionally arousing pictures elicit higher SSVEP amplitudes in the parietal regions compared to neutral stimuli. This convenient finding can be utilised in a BCI where flickering affectively salient pictures are used as a stimulation. Furthermore, the knowledge about the topography of emotion modulation can aid the detection of the presence of an SSVEP response in multiple electrode signals.
- *ERD/ERS-based BCI*: in accordance with the law of initial values (LIV) in psychophysiologyAndreassi (2007), a relatively high resting level of the mu rhythm will entail a more pronounced ERD. To elicit a high mu level relaxation techniques can be used. Elicitation of emotions of high arousal does not constitute a suitable choice because of the hemispheric asymmetry described in Section 3.3.1.

6 Emotive BCI operation

This section discusses the active use of emotion to control BCI operations in three scenarios. The first two scenarios entail actual user involvement and imply explicit user control, whereas the third scenario looks beyond the direct system control and suggests BCIs dynamically adapting to the user's emotional state. Possible implementations and example applications are proposed.

6.1 Active BCI operation

Current BCI algorithms are slow and require long training procedures. Their effectiveness depends on the ability of the users to voluntary and consistently control their brain activity. This can be challenging for several users. For instance, voluntary control of the SCP or limb movement imagination is not an intuitive tasks. The methods for emotion elicitation and assessment presented in Section 3 can provide novel and more natural ways for BCI control, e.g. employing the hemispheric asymmetry triggered by a recollection of a pleasant memory.

6.2 Reactive BCI operation

In the context of reactive BCIs, where an external stimulation is needed, so that the user can generate a BCI detectable brain response, we can utilise emotionally loaded stimuli. Event-related responses (e.g. ERP, ERD/ERS) to pictures, words or auditory stimuli can elicit specific responses in terms of valence and arousal that can be translated into BCI commands.

6.3 Passive BCI operation

Passive BCIs do not require active user involvement but rather rely on the interpretation of their mental state for automatic system adaptation. In the context of emotions and BCI, this signifies employing the affective state of the user to create more flexible and intelligent applications, via association of the EEG correlates of affect with timely and meaningful actions.

BCI systems aware of the affective state of the user can adjust their settings to keep the user motivated and involved. For example, an educational computer system that adjusts the difficulty of the material based on the level of interest or irritation of the user (Picard, 1995); or a computer game that adjust its objectives to balance satisfaction and challenge.

Apart from the common measures of emotions (see Section 3.2), user satisfaction or frustration can be estimated using brain responses indicating human or machine error and semantic mismatch. There are ERPs specific to erroneous responses immediately following the occurrence of an executed or observed error. Ferrez and del Millan (2008) distinguish response, feedback and interaction error-related potentials (ErrPs), which are a reaction to an error committed by the subject or by the system trying to interpret her/his intentions. These ErrPs are supposed to be generated in the anterior cingulate cortex, which is crucial for regulating emotional responses (Holroyd and Coles, 2002). Another ERP component that can be useful for improving reliability of BCIs is N400, which is a language-related ERP appearing in response to violations of semantic expectancies. Using these responses we can think of BCIs that can detect and correct their mistakes or further explain actions, confusing for the user. For example, BCI system controlling a cursor on a screen that can undo the last incorrectly inferred movement; or a spelling device that could detect words of semantic discrepancy.

In this line of thought, intelligent BCI algorithms knowing the past and current emotional state of the user could predict the user intentions and minimise the required interaction Moshkina and Moore (2001). That can happen proactively by automatic action execution or interactive via suggestions of possible following actions. In this context, emotion correlates in the brain like frontal asymmetry can be used to model the approach/avoidance response and use it to control BCIs. An example application could be a video game, where the in-game avatar is controlled based on the internal motivation of the user in a particular situation in terms of approach or avoidance; or wheel chair control BCI where the affective state of the user provide heuristics for the direction of movement.

Furthermore, detecting the degree of affect could introduce some flexibility to the BCI, allowing for more than binary outcome, i.e. instead of just left or right, the system can move a wheelchair more or less in a certain direction depending on the strength of the response.

Knowledge about the user's affective state could also enrich communication. Detecting and visualising of sincere emotions would allow physically challenged people to convey their feelings, as well as aid social interaction in virtual environments.

7 Research agenda

Emotion considerations can significantly contribute to enhance BCI operation. Clear understanding of the correlates of emotion in EEG is fundamental to the realisation of the enhancements outlined in this paper. Adapting the recognition algorithms in function of the emotional state of the user require the selection of (online) machine learning methods which allow the incorporation of application-specific knowledge. Indeed, to accommodate for the EEG changes due to emotions, not all the classifier parameters may need to be adapted.

To obtain the EEG correlates of emotion, formal emotion elicitation techniques can be used such as presentation of pictures from the IAPS or music stimulation. However, the EEG patterns relevant for BCI operation are most likely to be affected by more natural changes in emotion (e.g. user frustration and tiredness that result from erratic and/or slow BCI operation). These changes can lead to emotional states that are different from the ones elicited through formal methods. To obtain the EEG correlates of such states, long-term monitoring of various physiological signals (including EEG) can be envisioned. Alternatively, the methods mentioned in the section on passive BCI operation can serve to detect user frustration and erroneous BCI operation.

The prospect of advantageously utilising the influence of emotions in the EEG, to enhance BCI operation needs to be validated in the scenarios suggested in this paper. In the case of motor imagery-based BCIs, the suggested enhancement relies on the applicability of the LIV. While indications exist that the LIV applies to ERD/ERS phenomena, further experiments are necessary to assess the extent to which a high alpha level prior to BCI operation enhances the ERD resulting from motor imagery.

For P300-based BCIs, arousing pictures are suggested to increase the P300 amplitude to facilitate its automatic detection. This proposition requires careful analysis on the extent to which such an effect can be sustained in the long term. Similar remarks apply to the suggested enhancement for SSVEP-based BCIs.

Emotive BCI operation offers attractive benefits because it is suggested to go beyond the classical BCI operation paradigms and to allow a more intuitive control mechanism which can be truly personalised. This step, however, needs research to assess the extent to which self-induced emotion (e.g. through pleasant recollection) can be utilised in a BCI paradigm. This entails the analysis of reproducibility of the corresponding EEG patterns throughout BCI training and operation.

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