Emotional Brain-Computer Interfaces

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Abstract

Research in Brain-Computer Interface (BCI) has significantly increased during the last few years. In addition to their initial role as assisting devices for the physically challenged, BCIs are now proposed for a wider range of applications. As in any HCI application, BCIs can also benefit from adapting their operation to the emotional state of the user. BCIs have the advantage of having access to brain activity which can provide significant insight into the user's emotional state. This information can be utilized 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 still correctly interpreted in spite of signal deviations induced by the subject's emotional state. 2) The ability to recognize emotions can be used in BCIs to provide the user with more natural ways of controlling the BCI through affective modulation. Thus, controlling a BCI by recollecting a pleasant memory can be possible and can potentially lead to higher information transfer rates.

These two approaches of emotion utilization in BCI are elaborated in detail in this paper in the framework of non-invasive EEG based BCIs.

1. Introduction

The field of Brain-Computer Interfaces (BCIs) has gained enormous popularity during the last few years. BCI's multidisciplinary nature poses challenges that attract researchers from various expertise comprising brain research, signal processing, machine learning, and human-computer interaction.

Considerations on the influence of the user's affective state in BCIs are presented in [40]. where affective adaptation is suggested at two levels: 1) lower-level input signal interpretation adapted in function of the user's current state and 2) higher-level prediction of future user actions.

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

We provide first an overview of Brain-Computer Interfaces (Sec. 2). We motivate in particular our focus on noninvasive electroencephalogram (EEG) based BCIs. In Sec. 3 we describe the models for emotion categorization, the methods for emotion elicitation, and the manifestations of emotions in the EEG. Sec. 4 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, and 2) purposefully eliciting emotion to enhance EEG features that are relevant for BCI operation. Sec. 5 proposes emotive BCI operation by allowing the user to gain control of the BCI through the modulation of her/his emotional state (e.g. evoking a pleasant recollection) which can be detected from EEG signals. Emotive BCI operation can be more natural and easier for the user. In addition, it can lead to higher information throughput. Sec. 6 concludes the paper with a suggested research agenda.

2. Brain-computer interface overview

A BCI is a communication system that allows a person to convey her/his intention to the external world by merely thinking without depending on the brain's normal output channels of nerves and muscles [54].

A BCI can be functionally described as illustrated in Fig. 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 latter is translated into a command to execute an action on the BCI application (e.g. wheelchair, cursor on the screen, 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.

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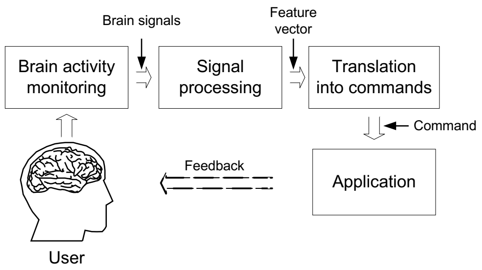

Figure 1. Functional model of a BCI.

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 (e.g. electrocorticography) and non-invasive techniques (e.g. electroencephalogram and magnetoencephalogram). Hemodynamic measurements include functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and functional near-infrared brain monitoring (fNIRS). Because of its high time resolution, noninvasiveness, ease of acquisition, and cost effectiveness, the electroencephalogram (EEG) is the preferred brain monitoring method in current BCIs.

To gain control of the BCI, the user executes mental activities which appear as distinctive patterns in the EEG. These are automatically recognized by the BCI and associated with certain actions that depend on the applications. Examples of application include: spellers, wheelchair control, and cursor movement. The type of mental activities and their corresponding EEG correlates are termed as electrophysiological sources of control [5]. The main sources are listed below:

- Sensorimotor activity. Mu and beta rhythms (8-12 Hz & 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 desynchronization in the mu and beta bands which is termed event related desynchronization (ERD), and begins in the contralateral rolandic region about 2 seconds prior to the onset of a movement and becomes bilateral before execution of movement. After the movement, the power in the brain rhythm increases (event related resynchronization, ERS). Motor imagery elicits similar patterns of activity [43]. The imagination of motor movements, in particular limb movements is 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 [28]). For convenience, we refer hereafter 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 milliseconds after the stimulus presentation. This peak is called P300. P300 based BCIs operate by presenting the user with a set of choices (usually in a matrix form) and randomly highlighting all different choices. 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 selected choice and execute the corresponding action. The P300 detection algorithm takes as features the signal samples (after band-pass filtering and subsampling) at parietal electrode sites [24].

- Steady State Visual Evoked Potentials (SSVEPs). 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 termed 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 focused 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) and temporal filters (e.g. comb filters centered around the stimulation frequencies) [22].

- Slow cortical potentials. SCPs are slow non-movement potential changes voluntarily generated by the subject. They reflect changes in cortical polarization 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 [6].

- 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.

Most of current noninvasive EEG based BCI implementations use the three first electrophysiological sources of control. Thus, in the following we focus on ERD/ERS, P300, and SSVEP based BCIs.

Present BCI applications have as primary goal to restore communication 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 [41]), safety (e.g. detecting the level of alertness [52]), security (e.g. brain activity based biometrics [38]), and neuro-economics (e.g. neural correlates of consumer choices for marketing [35]). 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 categorized as passive BCIs [13].

3. Emotions

Emotions are psycho-physiological phenomena associated with a wide variety of expressed subjective feelings, observable behaviors and changes in autonomic body state. There is presently no universally accepted model to categorize 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. Arnold [4] bases his theory on the relation to action tendencies and suggests the basic set of *anger*, *aversion*, *courage*, *dejection*, *desire*, *despair*, *fear*, *hate*, *hope*, *love*, *sadness*. According to the forms of action readiness of Frijda [21] the basic emotions are *desire*, *happiness*, *interest*, *surprise*, *wonder*, *sorrow*. James [27] states that these emotions are *fear*, *grief*, *love*, *rage* depending on the bodily involvement. Based on the universal facial expressions Ekman [17] identifies the basic set of *anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise*. According to Plutchik [46] the basic emotions are innate and directly related to adaptive behavior that is designed to enhance our survival and they are *acceptance*, *anger*, *anticipation*, *disgust*, *joy*, *fear*, *sadness*, *surprise*.

Other theories argue that emotions are better measured and conceptualized 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 by Russel [48]. 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. Another dimensional perspective is given by the *approach-avoidance* theory [49]. Approach/avoidance motivations are characterized 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. In the following, for convenience 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. For the sake of this paper drug-based emotion elicitation is excluded. 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. [45] define 5 factors that can influence emotion elicitation results: elicitor (subject-elicited vs. event-elicited), setting (lab setting vs. real world), focus (expression vs. feeling of the emotion), subject awareness (open-recording vs. hidden-recording), and purpose (emotion-purpose vs. other-purpose). There are different strategies to elicit emotions employing a variety of modalities.

Several studies use a set of standardized emotional stimuli (e.g films, pictures, sound, odor) in order to elicit a certain emotion or emotion dimension. Rottenberg [47] discusses the use of film clips to elicit emotions. The International Affective Picture System (IAPS) [8] provides a set of normative emotional stimuli for experimental investigations of emotion and attention. Eich et al. [16] suggest the use of music to trigger mood.

Imagination techniques use methods like autobiographic recall and guided imagination in order to evoke a certain emotion. Subjects are asked to remember a particular situation from their past that elicits emotional response [45] or they are guided through a story/imagery [36], 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 real world. Harmon-Jones et al. [23] give examples of social psychological methods for inducing emotions like 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 (DFA) suggested by Ekman [19]. 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 behavioral 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 categorized 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 Check List (AD-ACL) [51], Positive and Negative Affect Schedule (PANAS) [53], and Self-Assessment Manikin (SAM) [34]. 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 [18] and Izard's [26] suggest a link between facial expression and affective state. Instruments use either video analysis algorithms [12] or electromyography recordings [9] to recognize emotions from facial expression. According to emotion physiology literature modulations in voice are also linked to specific affective states [29]. Other modalities used for measuring emotions include heart rate, electro-dermal responses, temperature, blood pressure, respiration. CNS also plays an important role in emotion processing. Emotional responses in the CNS can be measured using electroencephalography [7]. Objective methods overcome the limitations of subjective however, different individuals can show different physiological responses to the same emotional state. Picard [44] argues that, actually, there is no need of universal solution to this problem if a user dependent one is possible.

In this paper emotion assessment via EEG is of particular interest. The next section gives an overview of the known correlates of emotion in EEG.

3.3. EEG correlates of emotion

3.3.1 Frontal EEG asymmetry

Frontal activity which is characterized in terms of decreased power in the alpha band has been consistently found to be associated with emotional states [11]. Indeed, numerous studies coincide on the fact that relatively greater trait left frontal activity is associated with trait tendencies toward a general appetitive, approach, or behavioral activation motivational system, and that relatively greater trait right frontal activity is associated with trait tendencies toward a general avoidance or withdrawal system [14].

3.3.2 Event related desynchronization/synchronization

Aftanas et al. [1] 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 [2], where stimuli of high and medium arousal induced larger theta synchronization in left anterior and right posterior sites, as well as larger alpha-1 synchronization over occipital sites compared to neutral stimuli.

3.3.3 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 [42]. 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 waveform from about 200 ms until 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 categorization) procedures as well as for the oddball and three-stimulus paradigm [15], [30], [39]. 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 [15], [10].

Affective processing can be also triggered by emotionally loaded words. [33] 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 odor valence [37]. Also, vocal emotions show an early task-specific emotion-based influence on the early stages of auditory sensory processing [50].

Although factors like stimulus type, stimulus properties (color, 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.

3.3.4 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 [32] 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. Unpleasant valence on the other hand, is associated with an amplitude increase and latency reduction in the left temporoparietal, posterior frontal, and right anterior temporal regions.

In [31], 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 with neutral stimuli.

4. Emotions and BCI operation

4.1. 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) On-line 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 Sec. 3.1. Such feature vectors are then used to train the BCI classification algorithm which can then correctly recognize the relevant brain activity in-

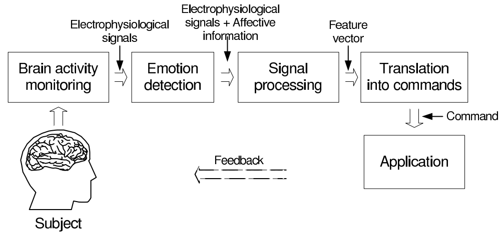

Figure 2. Functional model of a BCI accounting for the user's emotional state.

dependently 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 Sec. 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 emotion is achieved through an additional emotion detection component which can for instance rely on frontal asymmetry in the alpha band as explained in Sec. 3.3.1. In both of its implementations, this simple approach has the disadvantage of requiring long training (see Figure 2).

In the approach consisting in the online adaptation of the classification algorithm, the information about EEG correlates of emotions is utilized to adapt the classification algorithm parameters depending on the current user's emotional state which is determined through an additional emotion detection component. 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 utilizes.

- 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 utilized, 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 Sec. 3.3.3) 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.

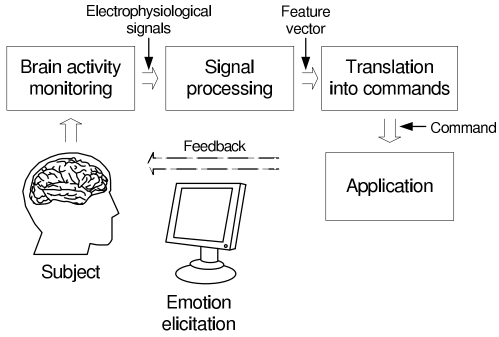

Figure 3. Functional model of a BCI operation enhanced through emotion elicitation.

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 are 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 [22].

4.2. 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 utilizes the known correlates of emotions (see Sec. 3.3) to enhance the electrophysiological sources of control used in BCI systems. The general approach is illustrated in Fig. 3. In this solution the user is exposed to affective stimulation that is 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 localization. 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 in Sec. 3.3.3, 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*. Similar to P300 based, SSVEP based BCI systems can benefit from an enhanced amplitude of brain responses. As mentioned in Sec. 3.3.4, emotionally arousing pictures elicit higher SSVEP amplitudes in the parietal regions compared to neutral stimuli. This convenient finding can be utilized 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 psychophysiology [3], 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. Emotion elicitation does not constitute a suitable choice because of the hemispheric asymmetry property of emotion elicitationSec. 3.3.1.

5. Emotive BCI operation

This section discusses the active use of emotion to control BCI operations. It presents two types of scenarios. The first scenario entails active user involvement and implies explicit user control, whereas the second type of 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.

5.1. 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 are not intuitive tasks.

The methods for emotion elicitation and assessment presented in Sec. 3 can provide novel and more natural ways for BCI control. Hemispheric asymmetry triggered by a recollection of a pleasant memory, or event related responses to emotionally loaded pictures, films and music can be utilized for this purpose.

5.2. 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 emotion 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 [44]; or a computer game that adjust its objectives to balance satisfaction and challenge.

Apart from the common measures of emotions (see Sec. 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 et al. [20] distinguish response, feedback, observation and interaction error related potentials (ErrP), which are a reaction to an error committed by the subject himself or by the system trying to interpret her/his intentions. This ErrP are supposed to be generated in the anterior cingulate cortex (ACC), which is crucial for regulating emotional responses [25]. 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 minimize the required interaction [40]. 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 video gaming 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.

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

6. Research Agenda

Emotion considerations can significantly contribute to enhance BCI operation. Clear understanding of the emotional correlates of EEG is fundamental to the realization of the enhancements outlined in this paper. Adapting the recognition algorithms in function of the emotional state of the user requires 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.

The prospect of advantageously utilizing 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 personalized. This step, however, needs research to assess the extent to which self-induced emotion (e.g. through pleasant recollection) can be utilized in a BCI paradigm. This entails the analysis of reproducibility of the corresponding EEG patterns throughout BCI training and operation.

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