Affective Brain-Computer Interfaces: Psychophysiological Markers of Emotion in Healthy Persons and in Persons with Amyotrophic Lateral Sclerosis

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Abstract

Affective Brain-Computer Interfaces (BCI) are systems that measure signals from the peripheral and central nervous system, extract features related to affective states of the user, and use these features to adapt human-computer interaction (HCI). Affective BCIs provide new perspectives on the applicability of BCIs. Affective BCIs may serve as assessment tools and adaptive systems for HCI for the general population and may prove to be especially interesting for people with severe motor impairment. In this context, affective BCIs will enable simultaneous expression of affect and content, thus providing more quality of life for the patient and the caregiver. In the present paper, we will present psychophysiological markers for affective BCIs, and discuss their usability in the day to day life of patients with amyotrophic lateral sclerosis (ALS).

1. Toward Affective Brain-Computer Interfacing

Brain-Computer Interfaces (BCI) are systems that *measure brain signals* (*e.g.* with electroencephalogram, EEG; near-infra red spectography, NIRS; electrocorticogram, ECoG), extract *certain features* from those signals and *translate* these features into *output signals*, which are fed back (this procedure is referred to as neurofeedback[1]) to the user and/or serve as commands to control computers or machines.

BCIs and neurofeedback were first developed for treatment of medical disorders. There is substantial support for the beneficial effect of neurofeedback as a therapy for neurological disorders like epilepsy [40, 83, 84] and Attention Deficit Hyperactivity Disorder (ADHD) [2, 22, 35, 49, 78]. There is some evidence that neurofeedback is beneficial for the treatment of stroke [3, 9, 69, 85]. Furthermore, it has been suggested that neurofeedback might provide therapy for migraine [41], tinnitus [10] and personality disorders [79]. However, most neurofeedback studies (but not all [2]) tested small sample sizes and lacked a control group in which participants are given sham feedback to control for placebo effects. Thus, validation studies are needed to verify these results.

BCI research also aims to compensate for loss of motor function in people with, for example, stroke, spinal cord injury, head trauma or with neurodegenerative diseases like ALS [44]. One goal is to enable brain activity to control a robotic arm, a neuroprosthesis, or with functional electrical stimulation (FES) to control a paralyzed arm. Research focuses on invasive recording with monkeys and severely paralyzed humans [26, 36, 55, 80], and on non-invasive recording with healthy persons and those with spinal cord injury [61]. In addition, severely paralyzed patients and locked-in patients can use non-invasive BCI applications for environment control [1, 37, 64, 77] or communication programs [5, 43, 56, 57, 75, 76]. Patients who are completely locked-in (lacking even the voluntary control over eye movements and of the sphincter) do not appear to be able to use a BCI [42]. Possible reasons for this go beyond the scope of this paper, but the interested reader is referred to [4, 42, 44].

Recently, a new perspective on BCI has emerged which suggests that not only voluntary self-regulated signals can be used as input but also that signals might tell us something about the state of the BCI user (*e.g.* the emotional and cognitive state) [18, 58, 59]. It is assumed

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[1]Neurofeedback means the voluntary self-regulation of signals from the central nervous system, whereas biofeedback refers to the voluntary self-regulation of signals from the peripheral nervous system (*e.g.* electromyogramm, EMG; heart rate, HR; galvanic skin response, GSR).

that relevant features from these involuntary signals (also referred to as passive signals) can be extracted and used to adapt the behavior of the HCI. Nijholt and Tan suggest that having access to the user's state is valuable to HCI and that it presents at least three distinct areas of research: 1) voluntary control over computers through brain activity, 2) evaluating interfaces and systems and 3) building adaptive user interfaces [59]. Of particular interest to HCI researchers are the user's cognitive state (*e.g.* workload of user, focus of attention) and the user's affective state (*e.g.* frustration, joy, boredom) [18]. Passive BCI could be used for healthy users and thus ease the entrance of BCIs into the market.

This notion about the passive measurement of a user's state has led to new BCI definitions [86]. First, an *active BCI* is a system that measures brain activity, extracts relevant features and translates these features into device commands or provides feedback to a user. The brain activity of the user is actively, in other words intentionally, altered. For example, the user is actively imagining opening and closing his right hand with the *intent* to alter his sensorimotor rhythm. Second, a user can be actively focusing on a certain stimulus (for example the letter "B") that he *intends* to select from a stream of stimuli (for example the whole alphabet). The desired stimulus may elicit a brain potential that can be classified by a BCI. Because the brain activity is triggered by an *exogenous* event this approach may be referred to as *reactive* BCIs. Third, a *passive BCI* (pBCI) is a system that measures ongoing, non-intentionally altered, activity from the peripheral and central nervous system, extracts relevant features and uses these features to monitor and adapt human-computer interaction. Zander and colleagues state that pBCIs are based on reactive states of the user automatically induced while interacting with a surrounding system [86].

For a schematic overview see figure 1. In this paper we aim to define affective BCI and hypothesize how to implement *affective BCIs* in healthy persons and persons with motor impairments. In our opinion, the detection of affective states begins with the discriminability of emotions, which are the smallest and most objective measurable units of affect (see section 2).

In the following paragraphs we explain the difference between emotions, feelings and moods (section 2) and introduce the field of psychophysiology in relation to emotion (section 3) and emotion theory (section 4). Furthermore, we hypothesize which psychophysiological signals might provide sensitive, reliable, and valid markers for emotion in healthy persons (section 5). Also, we explore several user scenarios in which affective BCI might be valuable for per-
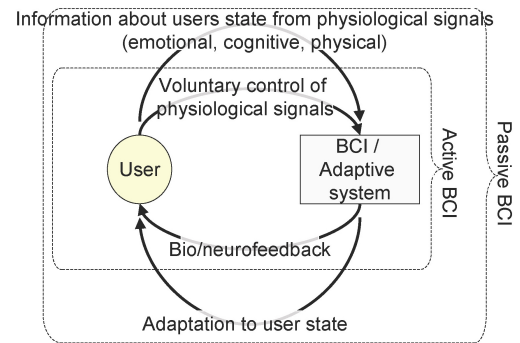

Figure 1. Schematic overview of an active and a passive BCI.

sons with motor impairment (section 6). Finally, we argue that the markers of emotion in healthy persons might be different from the markers found in persons with ALS, who are often considered as potential BCI users (section 7).

2. Emotions, Feelings and Moods

Some psychologists refer to emotion as a particular kind of subjective feeling [31], however this is a rather circular definition. In contrast, Damasio defines emotions as "*bioregulatory reactions aimed at the promotion, directly or indirectly, of the sort of physiological states that secure not just survival, but... [also] well-being*" [19]. Emotions are generally thought to be universal, short-lasting and elicited by an event, object or person. Feelings can be defined as the mental representation of the physiological changes that occur during an emotion or a mixture of emotions [19] and do not necessarily show (direct) observable peripheral reactions. In addition, a mood is a sustained tendency toward certain emotions (*e.g.* depression). From this point of view, for example, fear would be an emotion, restlessness a feeling and anxiety a mood. The whole range of emotions, feelings and moods may be called affect. Although Damasio has received some criticism [32], the neurobiological perspective of his definition seems to offer the best starting point for affective Brain-Computer Interfacing, which aims at classifying emotional states without verbally asking the subject about his or her subjective feeling.

There are two important issues that are worth highlighting in relation to the study of emotions in the context of BCI and affective computing. First, to advance the modelling of emotions by means of computing systems, researchers should not wield or attach to a particular theory or definition of emotion. The rationale for this is that the discussion on the meaning of emotions is an ongoing theoretical controversy that in 1981 had already yielded 92 different descrip-

tions of emotions [39]. Instead, technologists should work from a basis of the widespread view of emotions as a multi-element phenomenon that involves a) appraisal of events, b) psychophysiological changes, c) motor expressions, d) action tendencies, e) subjective experiences, and f) emotion regulation [27]. Affective BCI should focus on those elements of emotion that are easy to measure or to synthesize such as motor expressions, actions or physiological activation. Second, computer systems are still highly dependent on data acquired from a number of individuals who are subjected to certain type of emotional stimulation. Thus, the method to elicit emotions under controlled laboratory conditions is as important as the techniques employed to detect, classify or simulate affective states. Although not a single elicitation method can guarantee that a given targeted emotional state or class is experienced, some instruments have been shown to work well under certain circumstances(*e.g.* films, music, scripted interactions).

In this context, we argue that there are two main approaches to the study of emotions that seem to fit well with the aims of affective BCI. On the one hand Ekman's emotional classification or factorial approach represents a rather balanced way to endow subjective levels to a number of emotional states without getting into the controversy of whether there are two, twelve or more identifiable affects. Ekman's work has been traditionally associated with the use of facial expressions in emotion detection (for the corresponding facial expressions see figure 2). Ekman listed joy, sadness, fear, anger, surprise and disgust as the six basic emotions [23] (for the corresponding facial expressions see figure 2 below).

On the other hand, dimensions are very useful to quantify elements of emotions without the need to utilize pre-defined labels. The "bi-phasic model of emotion", which was proposed by Lang and colleagues, emerges from a motivational perspective that points to emotion as a behavioral tendency of a subject to approach or avoid/withdraw from a stimulus [6, 47, 72]. Emotions can be organized as pleasant/appetitive versus unpleasant/aversive and this disposition constitutes the first bipolar dimension of the model - valence. In addition, emotions can mobilize energy to different degrees, and therefore the activation or the intensity can vary. The model hereby constitutes a second bipolar dimension - arousal. An additional bipolar dimension - dominance-submissiveness - has been proposed to measure emotion [70]. However, valence and arousal level explain the greater portion of the variance in emotion [71]. For two reasons we prefer the bi-phasic model of emotion as opposed to approaches which describe four [27] or more dimensions [16]. First, Lang's two dimensions facilitate experimentation because they are applicable to a variety of affective phenomena

Figure 2. The facial expressions belonging to each basic emotion defined by Ekman [23]. From left to right; top: anger, joy, disgust; bottom: surprise, sadness, fear.

and second, they are also closely linked to a very popular elicitation method that employs a standardized set of photographs, the International Affective Picture System [46]. It is worth mentioning that the use of a factorial and/or dimensional approach to measuring emotions has also been suggested in the context of affective pervasive systems (see for example [50] and [53]).

Emotions elicited by stimuli can be rated within the valence-arousal space by using the Self Assessment Manikin (SAM) (see figure 3) [7]. SAM is a non-verbal graphical tool on which subjects have to rate on a nine-point scale how they feel. Valence is depicted as a smiling happy, figure transitioning into a frowning, unhappy figure. For arousal SAM ranges from a sleepy figure, with eyes closed, to an excited figure, with eyes open. Because SAM is a language-free, culture-free measurement it is suitable for various countries. However, before one can rate the emotion that was elicited by a stimulus, a mental reflection on this emotion is required. Thus, according to the strict definition of Damasio, one would have to say that the SAM measures feelings and not emotions. For affective BCI research however, the correlation of subjective feelings (as measured by the SAM) to psychophysiological signals (*e.g.* EEG, EMG) might result in a sensitive, reliable and valid model for affective BCI applications.

3. An Illustration from History

The search for reliable and objective indicators of emotional states stretches back as far as the period of 290 to 280 B.C. [74]. Antiochus of Apama, son of king Seleucus I, found himself hopelessly in love with his stepmother, a young woman by the name of Stratonic. Antiochus, an obedient and submissive son, fought with all his might
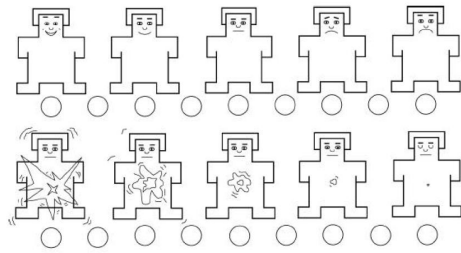
Figure 3. The self-Assessment Manikin (SAM). Top: valence; bottom: arousal

Figure 4. Eristratus classifies the cause of the illness in Antiochus. A painting by Jacques-Louis David.

against these feelings and never spoke a word with anyone about the matter. He suffered so much from his love sickness that he became seriously ill and was brought to Eristratus, a grandson of Aristotle, who was very well educated. Plutarch wrote: "*Eristratus, the 'medical man', understood without difficulty that Antiochus was in love, but as he wanted to find out who was the object of his passion - not an easy task - he installed himself in Antiochus' chamber, living therein. Whenever a goodlooking girl or a youth appeared before them, he keenly watched Antiochus' face in order to discover signs of emotions or change of expression. He also watched his body, looking out for any movements of his limbs and body or alterations of the same, which are naturally affected when the soul is under violent states. He was thus able to establish that no change was produced in Antiochus, excepting whenever Stratonic appeared, either alone or in Seleucus company. Sappho's symptoms became then all too apparent, such as a break in the voice, blushing and downcast eyes, sudden perspiration and irregularity of the pulse. He also became subject to swoons, doubts, fears, and sudden pallor. From all these manifestations Eristratus drew the conclusion that the king's son loved nobody but her, and that he was determined rather to die than to show it*" [65].

Eristratus classified emotions based on their co-occurrence with stimuli (independent variable: beautiful women; see figure 4). He operationalized emotion with the following dependent variables: voice quality, eye movements, skin responses, and blood pressure. This may have constituted the first documented psychophysiological study. It illustrates how the classification of emotion is important for understanding how emotions change our perception, guide our behavior, and shape our memory. Emotion detection and mimicry is an important requirement for maintaining successful social relations with others. However, *whether* emotions can be distinguished based on differences in the activity of the central and autonomic nervous systems is a highly debated topic in emotion theory [13, 38, 73].

4. Theories of Emotion

William James and Carl Lange simultaneously and independently hypothesized in 1890 that contrary to common belief "*the bodily changes follow directly the perception of the exciting fact, and that our feeling of the same changes as they occur is the emotion*" [38]. James states for example that we do not flee because we are afraid when we see a bear, but we are afraid because we flee from the bear. Similarly, we do not cry because we feel sad after bad news, but we feel sad because we are crying. The James-Lange hypothesis, also referred to as a a peripheral theory of emotion, implies that emotions can be differentiated by somatovisceral responses. However, bodily changes are not consistently associated with specific emotions (see section 5). The hypothesis also implies that people with quadriplegia should not show any emotional responses, which is refuted by several studies [15].

In 1928 Walter Cannon presented a critical examination of the by then popular James-Lange notion on emotion [13]. He postulated his own theory that the viscera and the innervation of the muscles were not the sources for the qualities of emotion. He held that emotions are derived from subcortical centers (*e.g.* thalamus) and that peripheral activity is not necessary for emotional experience. In other words the sight of a bear can cause fear without fleeing. Support for this theory comes from studies that show that direct brain stimulation can cause emotion experience. The Cannon's theory is sometimes referred to as a centralistic theory.

Another important emotion theory was proposed by Schachter and Singer, who suggested bodily changes qualify as emotions only when coupled with judgements that attribute these changes to emotionally relevant objects or events (this process is also referred to as appraisal) [73].

When our heart beats fast in the presence of a bear, we would attribute (appraise) that bodily change to the bear and feel afraid. In contrast, when our heart beats fast in the presence of an attractive person in the same room, we would attribute that bodily change to lust or love. Thus, Schachter and Singer state that bodily changes are essential but not sufficient.

The above mentioned theories are but few among many emotion theories. We refer the interested reader to [51, 60]. The debate in emotion theory is of high relevance to the area of affective Brain-Computer Interfacing, since this area will depend on at least some degree of distinct visceral or brain patterns underlying different emotions. On the other hand the technologies and methods developed by the BCI field might contribute to new approaches for emotion classification and might lead to a more multidisciplinary field of emotion research. In the next section we will review the evidence for the discriminability of various emotions within the EEG and some peripheral measures.

5. Psychophysiological Markers of Emotions in Healthy Persons

Emotion, defined as bioregulatory reactions [19], can be studied through psychophysiological signals from the central and the peripheral nervous system, through audio-recordings of speech signals, and through video-recordings of facial expressions. There is extensive literature about emotion assessment from audio- and video-recordings. However, these two modalities have the disadvantage that they require the active participation of the user (speak, or look into the camera) and hence cannot be measured continuously and reliably.

A literature search shows that relatively few peer-reviewed papers exist about the classification of emotions based on signals from the central nervous system. This is most probably due to the fact that it is very difficult to reliably classify emotions from non-invasively acquired brain signals such as the EEG. An exception to the scarcity of literature in this area is the line of work of Davidson et al [20] in which it is extensively argued that the prefrontal cortex plays an important role in emotional processing. In particular, hemispheric differences in alpha-power over the frontal cortex are repeatedly mentioned as indicator for emotions.
From a more practical point of view Chanel and colleagues compared three approaches to classify 3 emotions in 10 participants [14]. The classification was performed using data from 1) only EEG signals, 2) only peripheral signals or 3) a combination of both types of signals. They

report classification accuracies between 50% and 65% for classification based on either peripheral signals or EEG signals and a classification accuracy of about 70% for combining both modalities. The combination of signals from the peripheral and central nervous system thus seems promising. This is the reason why an affective BCI system should draw not only on EEG signals but also peripheral signals.

A vast amount of literature exists about the assessment of emotions based on psychophysiological measures from the peripheral nervous system. Examples of psychophysiological measures are electromyogram (EMG), skin conductivity (*e.g.* galvanic skin response; GSR), heart rate (HR), heart rate variability (HRV), blood pressure (BP), and respiration (RSP). One of the first ways to measure emotion is to instrument the muscles in the face that are responsible for facial expressions that are obvious reflections of emotions. There is a large body of research [12, 33, 82] attempting to tie specific muscle sets to types of emotions; electromyogram (EMG) of the facial muscles in specific and of others, both measuring general arousal [81] and specific indicators [48]. Another physical measurement that ties to emotional state is the heart rate, which is a good measure of arousal [12]. Skin conductivity reflects the outputs of the eccrine sweat glands, which reside on the palms of the hands and the soles of the feet and are particularly responsive to emotional activation, and only minimally responsible for thermoregulation [63, 81]. Also commonly used are blood pressure and respiration [11]. Less commonly used are such measures as pupil dilation [30], posture [21], cardiac output, diastolic blood pressure, eye blink rate, face temperature, finger temperature, heart rate variability, number of muscle tension peaks, oxygen saturation of the blood, and inspiratory time [12]. All of these can be used in combination to produce classifiers of affective states. Cacioppo and colleagues have provided an extensive meta-review of the literature in 1998 [12].

With a set of inputs (from some grouping of the psychophysiological data described above) and a list of classes (emotions) the next part of emotion recognition is the process of classification. Just like any classification problem the steps are signal acquisition, signal conditioning, feature extraction, training and finally producing a classification function. The raw data of the psychophysiological signals are typically taken as a value that is part of a waveform and then normalized and combined in various permutations and with various feature extraction functions [63]. The next step is to reduce the number of dimensions given to the classification algorithm (to reduce the possibility of overfitting the classifier to the training data) [62]. Algorithms used in classifying span from sequential floating
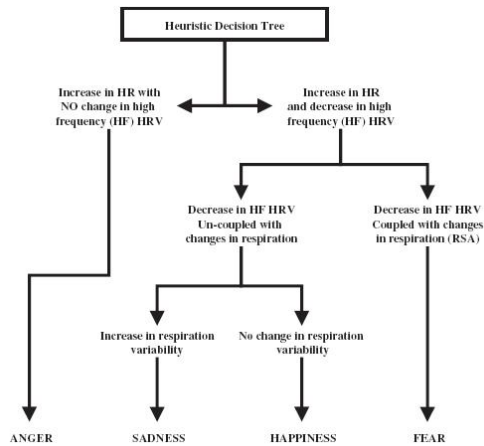
Figure 5. Heuristic Decision Tree based on heart rate and heart rate variability. Taken from [68].
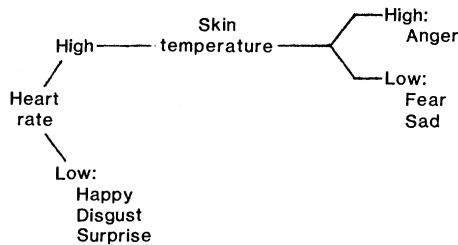

Fig. 2. Decision tree for discriminating emotions in direction facial action task.

Figure 6. Heuristic Decision Tree based on heart rate and skin temperature. Taken from [24].

forward search and Fisher projection and a permutation of both [11] to neural networks [8] and hidden markov models [7]. Several papers presented heuristic decision trees for classification, one based on heart rate and heart rate variability [68], and another on heart rate and skin temperature [24] (see figure 5 and 6 below).

How accurately a classifier can identify an emotion solely on the basis of psychophysiological data is dependent on the selected sensors, the classification process and several other parameters (which will be described below). The studies referenced in this paper obtained an accuracy range spanning 65.3 where 25 % would be chance [68] to 76.8 % [62] and 50.62 % [82] where 12.5 %would be chance, to 89.73 %, 63.76 % [33], and 63.4 % [25] where 50 % would be chance. The studies used both different lists of emotions (both in number and content) as well

as psychophysiological data so this list then is of use in confirming that emotions can be automatically recognized with some degree of confidence. Similarly, determining the optimal combination of sensors and features extracted that can best classify the presence of a given basic emotion is a goal that needs to be reached through empirical approaches in which scientists from emotion psychology, affective neuroscience, brain-computer interface and neuroinformatics should closely work together.

A review of the literature also returned several concerns that are important to keep in mind in designing BCI studies with respect to psychophysiological markers. In many cases a classifier trained on a single person will not accurately classify signals from another person, therefore every subject may need to have an individually trained classifier [63]. Secondly, it has been noted that "the features extracted from the signals are highly dependent on the day the experiment was held" [62]. Thus, it may be necessary to create a new classifier (or at least regenerate the features) for each subject and each session. Thirdly, research points out that an individual's psychophysiological response to a given emotion changes as they age [12]. Fourthly, psychophysiological markers of emotion can be easily confounded by external factors (*e.g.* day light, temperature, body position, time of day), substance intake (*e.g.* nicotine, caffeine, high caloric food) and physical activities. Technological solutions to measure these changes in the environment may include light sensors, accelerometers or a thermometer. Fifthly, multimodal classification methods need to applied to these various signals and compared. Sixthly, one will want to know whether a change in psychophysiological signals reflects an emotion (phasic change) or a steady state (tonic change). For example, a low blood pressure may indicate low emotional arousal, but it may also indicate a person is asleep. An ideal affective BCI classifier would have knowledge of time and events in the environment of the user (*e.g.* someone entered the room, there is a storm outside, time since last shower).

6. Affective BCI for Persons with Amyotrophic Lateral Sclerosis

ALS is a fatal motor neuron disease of unknown etiology and cure. ALS is a neurodegenerative disorder of large motor neurons of the cerebral cortex, brain stem, and spinal cord that results in progressive paralysis and wasting of muscles [17]. ALS has an incidence of 2/100.000 and a prevalence of 6-8/100.000 [8]. Survival is limited by respiratory insufficiency. Most patients die within 3-5 years after onset of the disease [17], unless they choose life-sustaining treatment [34].
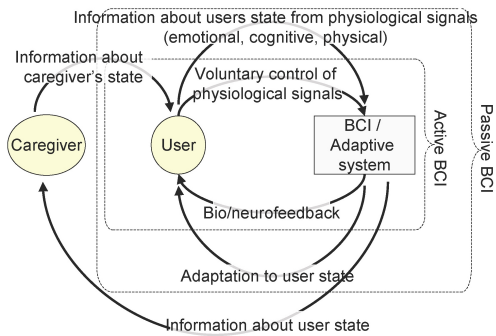
Figure 7. Schematic overview of an active and a passive BCI for people with motor impairment. Information of the user state is fed back to the caregiver with whom the user is interacting.

As the disease progresses, people become increasingly paralyzed. The first symptoms experienced by most patients include weakness in arms or legs, after which the paralysis spreads to other extremities and finally also the neck and head areas. This form of ALS is called spinal ALS. On the contrary, bulbar ALS starts with symptoms of weakness and paralysis in neck and mouth regions and then spreads to other extremities. Involuntary muscle contractions in late-stage ALS can occur during emotional experience.

An illustrative example is given from a visit from the first author (FN) to HPS, the patient who was the first to use a BCI in his daily life for communication [5]. HPS was locked-in at the time of the visit. He could raise his eye brow to say 'no' and half-close his eyes to say 'yes'. During this visit FN and HPS did not use a BCI to communicate but instead a caregiver served as an interlocutor. First, the caregiver read out loud the number of the rows in a letter matrix until HPS selected the row containing his desired letter. Then, the caregiver read out loud the letters in that row until HPS selected his desired letter. This procedure repeated itself until words and sentences were formed. HPS, being German, asked how FN, being Dutch, felt about an upcoming soccer match between the Netherlands and Germany in the following week. FN replied she was certain that the Netherlands were going to win and that "it would be a piece of cake". This remark appeared to elicit two emotions in HPS. First, he smiled involuntarily. Second, his eyes peered attentively to FN, who interpreted these expressions as an indication that HPS wanted to reply with a furious yet witty remark.

However, humor, happiness and anger, are very difficult for severely paralyzed patients to express. Even though HPS dictated his reply, he lacked the ability to modulate the tone of his voice or use his facial expression to add sarcasm.

From this example a first purpose of an affective BCI can be identified: they may offer a possibility to otherwise poker-faced patients to express their affect. Figure 7 illustrates how an affective BCI might not only adapt HCI for a patient, but also provide information about the affective state of the user to a caregiver, who is interacting with the user. From our experience we know that caregivers often leave the room while patients 'write' lengthy messages with their assistive technology, only to come back when the whole sentence is written down. Sometimes messages go unnoticed or the context of the message may be forgotten by the time the message is written. Receiving nonverbal input from a patient may provide context and constitute an important incentive to continue interacting with the patient, especially when content is conveyed slowly. Also, perception of the affective state of the user may cause mimicry of these states in the caregiver, reassuring the patient that he or she is perceived and understood. We hypothesize that affective BCI will improve the quality of life and interaction of patients and caregivers, because *affect* and *content* can be *simultaneously* expressed. An application of such an affective BCI could be a monitor attached to the patient's wheelchair displaying a face expressing the emotions detected by the algorithms.

Finally, an emotion detection system could also serve as an alarm system to cue the caregiver to check on a patient. Although medical devices surrounding the patients (*e.g.* artificial respiration) measure heart rate and blood oxygen level and give an alarm when for example blood oxygen level is too low, psychological distress does not give an alarm. Thus, a paralyzed patient is rendered powerless when a frightening event happens. An affective BCI might detect from GSR and heart rate that negative emotions with strong arousal are felt by the patient and send an alarm signal to the caregiver. However, in the next section we will discuss how emotional markers might be different in patients with ALS compared to healthy controls.

7. Emotional Processing in Patients with Amyotrophic Lateral Sclerosis

There are only few studies on affect and emotional processing in ALS. Remarkably few patients (9-11 %) develop a major depressive disorder despite the severe impact the disease has on a persons life [28, 45, 66, 67]. Lulé and colleagues investigated emotional processing in ALS [52]. Twelve ALS patients and eighteen age-matched healthy controls were (neuro)psychologically assessed. Then, they rated their emotions with the SAM after viewing negative, neutral and positive pictures from the International Affective Picture System (IAPS) [46]. In a second experiment physiological responses to the same pictures

were measured. Specifically, startle response and heart rate were measures as an index of valence and galvanic skin response as an index of arousal.

Compared to controls, patients rated positive and neutral pictures as more positive and negative pictures as less negative. Also, calm and neutral stimuli were rated as more arousing, whereas most arousing pictures (especially those with erotic content) were rated as less arousing. GSR were significantly delayed compared to controls, while the amplitude of GSR tended to be higher in ALS than in healthy controls. Both ALS patients and healthy controls showed a stronger HR deceleration after unpleasant stimuli compared to after pleasant stimuli.

The altered rating of emotional stimuli was not correlated to depression scores or frontal lobe dysfunction. Lulé and colleagues therefore suggest that emotional processing is altered due to coping mechanisms. None of the ALS participants in this study was locked-in and little is known about emotional processing in patients with late-stage ALS.

Moore and Dua provided many biofeedback training sessions to a locked-in patient with ALS. The patient was progressing to the complete locked-in state (no voluntary eye movement or sphincter control) during the experiment, which lasted over a year [54]. The patient aimed to learn to say 'yes' by raising his GSR level and to say 'no' by keeping the GSR level low. After a year the accuracy of saying 'yes' and 'no' was significantly above chance level, but probably not sufficient to reliably answer questions. GSR differs between ALS patients and healthy persons [29] and it remains questionable if self-regulation of GSR might be used for communication in ALS patients and how GSR can be used for emotion detection in ALS patients.

Furthermore, patients with motor impairment might depend on life-sustaining devices, like artificial respiration or percutaneous endoscopic gastrostomy (PEG), that may affect the peripheral and central nervous system. Also, medication, like antidepressants or diabetes medication, may cause affective states in patients to be differently classified. Finally, it must be noted that an interesting line of investigation might be to study whether facial expression that is not overtly observable might be detected by EMG measurements in severely paralyzed patients patients. Few and potentially inexpensive electrodes might classify the valence of emotions in these patients.

8. Conclusion

The concept of affective and passive BCIs has lead to a new perspective on the applicability of BCIs. Affective BCIs may now serve as assessment tools for HCI and adaptive system to improve HCI with healthy people. Affective states should be measured through a synthesis of peripheral and central measures although a solution of the optimal parameters is still not present. Also, it may be discussed whether the term *brain*-computer interface is then still appropriate or if we should find a more generic term such as body-computer interface or even human-computer interface.

Affective BCIs may improve the quality of life of persons with motor impairment and of their caregivers, by allowing the BCI user to express not only content but also affect. However, the accurate detection of affect is not a simple matter, and successful approaches with patients may differ from those used in healthy persons.

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