Effortless Passive BCIs for Healthy Users

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Abstract. While a BCI usually aims to provide an alternative communication channel for disabled users who have difficulties to move or to speak, we focused on BCIs as a way to retrieve and use information about an individual's cognitive or affective state without requiring any effort or intention of the user to convey this information. Providing only an extra channel of information rather than a replacement of certain functions, such BCIs could be useful for healthy users as well. We describe the results of our studies on neurophysiological correlates of attention, workload and emotion, as well as our efforts to include physiological variables. We found different features in EEG to be indicative of attention and workload, while emotional state may be better measured by physiological variables like heart rate and skin conductance. Potential applications are described. We argue that major challenges lie in hardware and generalization issues.

Keywords: Passive BCI, user state monitoring, attention, workload, emotion, EEG, MEG, NIRS, physiological measures.

1 Passive BCIs for Healthy Users

We here present the results of research that was done the last couple of years by TNO Soesterberg, the Donders Institute and University of Twente in the context of Brain-Gain, a large collaborative Dutch programme on Brain-Computer Interfaces. Within our project we focused on healthy users.

C. Stephanidis and M. Antona (Eds.): UAHCI/HCII 2013, Part I, LNCS 8009, pp. 615–622, 2013.

Brain-Computer Interfaces (BCIs) are traditionally conceived as interfaces that allow paralyzed people to consciously control external devices, e.g. for communication purposes. These BCIs aim to replace conventional channels of communication and control that are not available to these users, such as speech and button presses, by intentionally produced brain signals. This idea of BCI has been called active BCI (Zander et al., 2008; Zander & Kothe 2011). Active BCI still needs to go a long way in order to be useful for healthy people since it is difficult to compete with channels of communication and interaction devices that healthy users have at their disposal in terms of ease of use and information transfer rates. In order to assist healthy people in the near term, we think that BCIs should not aim to replace input modalities like manual input and speech, but should aim to retrieve information about the user state from brain signals that is otherwise difficult or impossible to obtain (Coffey et al., 2010; Van Erp, Lotte & Tangermann, 2012). The BCI loop is closed by making use of this information online. These kinds of BCIs are also referred to as passive BCIs (Zander et al., 2008; Zander & Kothe 2011), where the term passive refers to the user: in order to use these BCIs, the user does not need to actively control the system through his or her brain signals– rather, the system uses brain signals that occur spontaneously. Examples of (prospective) passive BCIs are BCIs using error related potentials to correct the outcome of manually controlled action (Zander et al., 2008) and BCIs that monitor workload in order to switch off secondary tasks when workload gets too high (Kohlmorgen et al., 2007). Clearly, passive BCIs could be valuable for disabled users as well, possibly in combination with active BCIs.

Challenges that go with developing passive BCIs are to determine 1. which user states can be observed robustly by a BCI and 2. how information about the user state should be applied to support the user. In our studies, we focused on the first of these challenges. In examining correlates of user states, we not only included neurophysiological but also physiological measures. We indicate directions regarding the second challenge. These directions also include applications that make use of (neuro)physiological signals offline and therefore cannot be regarded as BCIs, but since they are based on the same knowledge and methods we did not want to exclude them here.

2 Robust User State Detection

2.1 Attention Detection

Several of our studies were involved with neural correlates of attention allocation. Overall, the results of our studies are consistent with the idea that alpha activity (8-12 Hz) suppresses certain brain areas and therewith enhances processing in other brain areas (Klimesch et al., 2007) rather than alpha indicating general idling of the brain (Pfurtscheller et al., 1996). Händel et al. (2011) asked their participants to covertly attend to either a left or a right random-dot kinematogram. As expected, occipital (‘visual’) alpha was higher contralateral to the unattended side than to the attended side. Furthermore, a stronger lateralization correlated to a higher chance that the direction of motion at the unattended side was not perceived correctly (i.e. was more strongly suppressed). Bahramisharif et al. (2010) showed that alpha does not only distinguish between left and right visual attention, but can be used to estimate the direction of attention relative to eye fixation with up to 51 degrees accuracy. Another study that is consistent with the Klimesch hypothesis is Brouwer et al. (2009) who found that alpha power over the occipital cortex (as well as certain eye movement parameters) indicated whether an observer attended either to visual or auditory stimuli. In this case, high occipital alpha power did not indicate that the observer was not paying attention, but that she or he was attending to auditory stimuli. A study on memorizing the order of words (Meeuwissen et al., 2011) perhaps most strongly suggested that alpha does not simply indicate general idling. Participants were presented with sequences of three words, followed by rehearsal periods. For words whose order was successfully retrieved, parieto-occipital alpha during the corresponding rehearsal periods had been higher compared to rehearsal periods following words whose order was not retrieved successfully.

Application. Brain and peripheral signals indicating the kind and amount of attention could enable a system to estimate whether a user properly processed information that was intended for him or her to be processed or remembered, e.g. in an air traffic control situation. Learning or performance could be enhanced by repeating information that is expected to be poorly processed or remembered (Jensen et al., 2011), or warnings could be issued. In addition to behavioral (eye movement) measures, (neuro) physiological signals might be useful to evaluate whether displays or advertisements draw attention as intended.

2.2 Workload Detection

Another user state that seems to be reflected well by brain signals, and which is a useful state to know about, is mental or cognitive workload. There is an abundance of studies investigating (neuro)physiological correlates of workload. While it is not clear yet which indicators are most reliable, studies that examined EEG spectral variables next to other physiological varia\bles such as different eye and heart related measures, concluded EEG to be the most sensitive or promising indicator of workload (Berka et al., 2007; Brookings et al., 1996; Taylor et al. 2010). We used the n-back task to investigate workload (or more specifically memory load which is considered to be a reasonable approximation of workload: Berka et al., 2007; Grimes et al., 2008). In the n-back task participants view successively presented letters. For each letter they have to decide whether or not it is the same as the one presented n letters before. By increasing ‘n’ memory load can be increased without affecting visual input and motor output - confounding variables that impede interpretation of results of many previous studies on correlates of workload. In one study (Brouwer et al., 2012) we found that both ERPs and power in EEG frequency bands could be used to differentiate between high and low workload for almost all participants after a short time interval. Combining both types of EEG indicators resulted in a further (albeit modest) improvement of classification performance. We are currently studying whether peripheral physiological signals can improve performance or replace brain signals. Coffey et al. (2012) used NIRS (near-infrared spectroscopy) in combination with EEG to estimate workload. While EEG measures brain activity through electrical signals emitted by the brain, NIRS measures the blood oxygenation in recorded regions of the brain, therewith providing a measure of brain activity with a very different physiological basis.

However, for combining NIRS and EEG signals we could not show significant workload classification improvement over EEG alone.

Application. Workload measures could be used online to properly dosage tasks e.g. during driving (Kohlmorgen et al., 2007) or issue warnings that help is needed. Offline, continuous measures of workload could be used to evaluate different systems (e.g. interface designs) or perhaps to evaluate an individual's mastering of a task on a deeper level than only performance measures (c.f. Koenig et al., 2011).

2.3 Emotion Detection

We identified (neuro) physiological correlates of emotion (valence and arousal) as induced by presenting blocks of emotional pictures and/or sounds. Heart rate (variability), skin conductance level and EEG turned out to be differentially sensitive to valence, arousal and the modality in which the emotion was presented (Mühl et al. 2011ab, Brouwer et al., submitted). As expected, skin conductance was higher for high arousing stimuli than for low arousing stimuli. As also found before, heart rate was higher for pleasant compared to unpleasant stimuli. The effect of arousal on heart rate in studies using perceptual emotional stimuli has been unclear; in our studies we found a decrease in heart rate (and increase in heart rate variability) with arousal. This would be consistent with increased attentional processing of arousing perceptual stimuli (Codispoti et al., 2001; Graham, 1992; Lacey & Lacey, 1970). The effects on EEG were consistent with the notion that emotion increases attentional processing of the emotional stimuli and differentiated the two modalities: posterior alpha decreased during visual stimulation and increased during auditory stimulation (especially during emotional stimuli), while it tended to be the other way around for anterior areas. Our results suggest that while brain signals are suitable to inform about user states that are related to cognitive or sensory processing, for emotion related user states peripheral signals are probably more informative. We performed two studies aimed at detecting mental stress or arousal using heart rate, skin conductance and facial temperature. One study was performed in an eye laser clinic where participants who were or were not about to undergo surgery quietly sat for two minutes while physiological measures were recorded. Individuals about to undergo surgery had a significantly higher heart rate. A classification model was correct in about 70% of the cases estimating whether a person was going to undergo eye laser surgery or not. This was mainly caused by a difference in heart rate; adding other features to the classification model did not improve results much. In the other study, we tested a new, fast and easy algorithm that turned out to effectively induce mental stress while avoiding confounding variables such as movement or speech. Participants were presented with arbitrary sentences (about vacuum cleaners), each time followed by a counter counting from 60 to 0 seconds. The final sentence assigned the task to sing a song starting at the moment that the counter reached zero. A simple sliding-window algorithm detected an increase in skin conductance after the onset of this sentence for 21 out of 25 participants. An increase in heart rate could be detected for the same number of participants. The number of participants for which the onset of the 'sing-a-song' sentence was successfully detected increased slightly to 23 when these measures were combined.

Application. Knowledge of the user's emotion could be applied online to improve different kinds of Human-Computer Interaction. Games may be adjusted to elicit the right level of valence and arousal (Gürkök et al., 2012). In exposure therapy used to treat phobias, knowledge of the patients stress or arousal level may allow the therapist to apply the right level of exposure of the fearful stimulus (Popovic et al., 2006). A sudden strong physiological-emotional response of a monitored individual may indicate that he or she is in danger. A strong physiological-emotional response to approaching security officers in a waiting cue for safety screening at the airport could be an indication of illegal intentions. Finally, measures reflecting emotions could be used (offline) to evaluate interventions taken to reduce mental stress, e.g. in a hospital's waiting room.

3 Challenges

Several challenges in different areas prevent passive BCIs from being abundantly used as yet. We discuss two major ones.

Firstly, robust, user friendly but high quality measurement equipment needs to be developed, especially to reliably and easily record EEG. Impressive progress is being made (Patel et al., 2012; Zander et al., 2011) and first user friendly EEG measurement equipment is on the market. However, it is not always clear to what extent these systems record EEG or whether they mostly capture eye and muscle movements. An interesting development in physiological measurements is measuring heart rate through analysis of images made by a conventional camera (Philips Vital Signs) which makes it possible to measure heart rate without attaching sensors. For some of the proposed applications, user friendly equipment is less of an issue, e.g. when (neuro)physiological measurements are used in an offline fashion for the purpose of system evaluation, or for patients in exposure therapy who are engaged in therapy for relatively short times.

A second major challenge is generalization. Passive BCIs (just like other BCIs) employ classifiers that need to be trained on labeled training data. Subsequently, the trained classifiers are used to classify new data. Training data should closely resemble the new data. However, it can be difficult in practice to create training sets that are similar to the data that needs to be classified, especially when one wants to have a quick and easy training phase. One of the essential differences between the training and the application phase can be in the targeted cognitive or affective state: workload as manipulated in the training phase, e.g. by using an n-back task, may (neurophysiologically) differ from workload that varies in the application phase, e.g. during air traffic control. The stimulus and task environment is likely to differ strongly as well: other, additional stimuli could be present in the application phase than in the training phase and users may be engaged in other, additional mental processes. It is difficult to simply equate the training phase to the application phase since the stimulus and task environment during the application phase is variable and unpredictable. Furthermore, it is difficult to know what the targeted mental state during application is, which is one of the reasons why tasks or stimuli are used during training that do enable labeling of data (and thus differ from those in the application phase). In-depth, theoretical knowledge of the relevant parameters and processes is indispensable to face the generalization challenge. Reuderink (2011) discusses generalization issues with respect to variability within and between users, and potential ways to make classification algorithms more robust which may help to reduce the generalization problems as described above as well.

4 Hybrid BCIs

Much of our research included other signals besides EEG which is the most commonly used input for BCI: NIRS, heart rate variables, eye movement variables, skin conductance and facial temperature were used and in some cases combined in classification models to check whether user state estimation could be improved over using a single neurophysiological measure. An improvement would be expected since different measures are differently sensitive to noise. In addition, different measures could capture different components of the same user state, both in a physiological sense (such as capturing electrical and metabolic correlates of cognitive workload) and in a psychological sense (such as capturing frustration and cognitive activity during high workload). Individuals may also differ in the extent to which certain variables reflect certain user states. Finally, more variables are simply expected to result in more robust estimates. While there were positive trends, we did not demonstrate a drastic improvement yet for the combination of NIRS and EEG to estimate workload, ERPs and EEG frequency measures to estimate workload, and peripheral physiological variables to estimate mental stress. Strong improvement is not expected when variables reflect the same processes and one of the variables is an obviously better estimator than the others.

5 Conclusions and Recommendations

Active BCIs are very important since they may dramatically improve the quality of life of a small group of individuals with severe medical conditions. Passive BCIs for healthy users hold the promise to improve the quality of life a little for a large group of people and could also be of great value to disabled users as well. Still, research in this area is relatively scarce. We would like to encourage research on passive BCIs, and we would like to stress to researchers in the field that besides brain signals other (currently still more accessible) physiological signals should not be ignored. Our (and others') research provided suggestions on user states that can be detected and first steps were taken into applying knowledge of these user states online.

Acknowledgements. Many thanks to all members of BrainGain Project 2. The authors gratefully acknowledge the support of the BrainGain Smart Mix Programme of the Netherlands Ministry of Economic Affairs and the Netherlands Ministry of Education, Culture and Science. Part of the research was done in the context of the project 'Stress from a distance', commissioned by Centrum Innovatie en Veiligheid - gemeente Utrecht.

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