Editorial

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Abstract: The research in brain–computer interfaces (BCI) has shown that brain activity can be used as an active/voluntary or passive/involuntary control modality in man–machine interaction. Until recently, BCI research aimed almost solely at improving the life of disabled persons in need of communication and physical interaction with their environment. Impressive results have been obtained where disabled persons have learned how to control an artificial limb or a wheelchair using their thoughts. Nowadays, however, we also see research aimed at using BCI for the general population. This is an interesting development. Why would a non-disabled user want to use BCI? Or, how could a computer use BCI in order to better support its user? In this Special Issue, our emphasis is on brain–computer interfacing that aims at detecting and using the mental or affective state of the user in order to adapt the interface to the user.

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Dirk Heylen received an MSc in Germanic Philology (1985 and post-graduate degrees in Computer Science and Computational Linguistics (both in 1987) at the University of Antwerpen. In 1999, he received a PhD at the University of Utrecht. In the same year, he started to work in the Human Media Interaction Group of the University of Twente. Currently, he is an Associate Professor on multimodal interaction including the study of input signals from gestures through facial expressions to physiology and BCI.

1   Introduction

Research in brain–computer interfaces (BCI) has shown that brain activity can be used as an active/voluntary, or passive/involuntary control modality in man–machine interaction. Until recently, BCI research aimed almost solely at improving the life of amyotrophic lateral sclerosis (ALS) patients, Parkinson patients or other kinds of patients in need of communication and physical interaction with their environment. Besides these applications, investigation has been done on how BCI research results can play a role in finding tools for the treatment of children with attention deficit hyperactivity disorder. Impressive results have been obtained where disabled persons have learned how to control an artificial limb or a wheelchair using their thoughts.

Nowadays, however, we also see research aimed at using BCI for healthy users. This is an interesting development. Why would a healthy user want to use BCI? Or, why would a computer want to use BCI in order to better support its user? In this Special Issue, the emphasis is on brain–computer interfacing that aims at detecting and using the mental or affective state of the user in order to adapt the interface to the user.

2   Active and passive brain–computer interfacing

Any interface to an application can profit from knowing and learning as much as possible of the persons that are using it. Knowing about brain activity in particular regions of the human brain provides information that cannot be obtained from other sensors and that can complement that information. The information can be used to inform the interface about the mental and affective state of the user and that knowledge can be used to provide more adequate feedback and also to adapt the interface and the application to a particular user. In recent years, this type of BCI has been called passive BCI. It is the system that decides how to use the information. There is no attempt by the user to control the system by consciously 'playing' with this brain activity.

The second reason that BCI is interesting for a healthy user is similar to the reason that BCI has been exploited for disabled persons: a user can use his/her brain activity as an input modality, maybe in combination with other modalities, to directly control an interface and its application. By performing certain mental tasks the associated brain activity in various regions of the brain can be distinguished and mapped onto commands that control the application. Applications include, among other things, navigating in a virtual world, controlling a robot or cursor and menu control. Clearly, it is preferable that this mapping is 'natural' or 'intuitive'. Hence the mental task that has to be performed should be related to the task that has to be performed in the real world or in the graphical user interface. This type of BCI has been called as active BCI. A nice example is imagined movement. Brain activity related to imagining a movement (whether it is the tongue, a finger or a limb) can be distinguished from other activity and can be used to steer a robot around, to control a menu and a cursor, or to have an avatar perform a movement in a virtual world.

Other types of BCI have been introduced or have been included in the definitions of active and passive BCI. For example, there are visual, auditory or tactile evoked potentials. That is, events can be designed in an application to evoke distinguishable brain activity. This allows the user to make clear to the system in which of the available alternatives he/she is interested just by paying attention to it. A possible name for this

type of BCI is reactive BCI. Of course, evoked potentials can also happen and be measured when a user is in a situation where he/she has to perform a routine task where once in a while an interesting event happens and this is noticed by the BCI because of a change in brain activity in a particular brain region. Again, an implicit command from the user to the application can be issued if this particular brain activity is detected and the application is ready to accept this command.

There are no clear-cut distinctions between the different types of BCI we have mentioned. For example, we can measure an affective state or rather changes in an affective state in order to adapt the interface to these changes. But it is also possible to design applications where the user is expected to change his or her affective state in order to issue a command. For example, in a game situation we can have a natural change, caused by events happening in the game world, from a user being relaxed to a user being stressed or the other way around. But issuing commands in such a situation by affective state changes that are consciously aimed at by a gamer can work as well. In the latter situation a gamer has, e.g. to decide to become aggressive or to become relaxed knowing what the effect will be in the game world.

We mentioned several ways in which measured brain activity can be used to issue commands or to make changes to the interface, the interaction or the particular task a user is expected to perform. A final observation that can be made is that there can be designed or naturally occurring stimuli (physical, visual, auditory, tactile and olfactory) that help the user to perform a particular mental task or to make a transition from one affective state to another.

3   Measuring brain activity

The use of physiological sensors in order to obtain physiological information and interpret this in terms of possible cognitive states of a user has been a part of human–computer interaction for quite some time now. Typically, these sensors measure changes in heart rate, blood pressure, breathing and skin conductivity. Non-invasive measuring of brain activity is mostly done with electroencephalography (EEG). Up to 256 electrodes integrated in a cap can be placed directly on the scalp (Figure 1). Their positions on the scalp make it possible to be informed about the electrical activity and, importantly, the function of this activity. This EEG technology has good temporal resolution, but spatial resolution is poor. Moreover, although we are only interested in the affective or mental state of the user, or want to know about some voluntary mental activity, we are also confronted with noise in the signals i.e. caused by muscle activity and associated brain activity: e.g. eye blinks, facial expression movements or head movements. More neuro-scientific knowledge about this 'noise' and possible ways of measuring this 'noise', e.g. with EMG (electromyography) techniques, make it nevertheless possible to detect changes in mental and affective states and to map them onto explicit user control commands or on signals to the interface and the application which are meant to adapt them to the user.

Not all applications need an EEG cap with lots of electrodes to work. Apart from being expensive, a cap with many electrodes has the disadvantage that users have to be physically connected to the computer, and a lot of time is needed to position the electrodes, to apply conductive gel and to clean up afterwards. Hence in recent years research groups and companies have developed EEG devices that use so-called dry-cap

technology and where there is a wireless connection between device and computer, so that the user can move more freely. And, depending on the application, rather than 256 electrodes it may be sufficient to have a device with 2, 8 or 16 electrodes, allowing companies to develop fancy and portable headsets that can be used for game or domestic applications and in which other sensors, such as accelerators to measure head movements, can be integrated (Figure 2).

There are of course other ways to measure brain activity than EEG, which include fMRI or invasive techniques. However, for human–computer interface research one is mainly interested in having (close to) real-time control and adaptation of the interface and in maintaining as much as possible natural interaction for natural situations. Therefore, despite its disadvantages, EEG with its high temporal resolution has become the predominant technology in BCI and HCI research and applications. More accurate signals can be obtained using invasive techniques, but although some military use can be foreseen, we do not expect to see non-medical applications for this technology in the near future. More promising is the functional near-infrared spectroscopy (fNIRS) technique to measure brain activity in a not too obtrusive way (Figure 3). This technique measures changes in blood flow that are accompanied by brain activity. Infrared light is projected into the brain from the surface of the scalp. The reflected light gives information about (changes in) oxygen concentrations and therefore of brain activity in various regions of the brain. There is high spatial resolution, similar to fMRI, but low temporal resolution (2–5 sec).

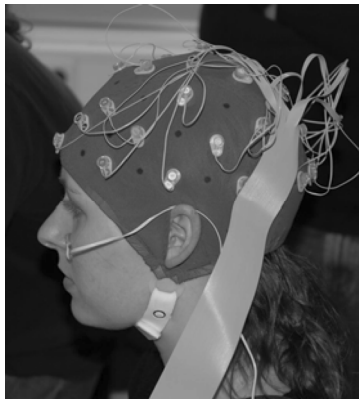**Figure 1**   EEG cap for measuring brain activity

Figure 2   Commercially available game cap (Emotiv) (see online version for colours)

Figure 3   fNIRS set for measuring brain activity

4   Background of this Special Issue

While active BCI paradigms have received a lot of attention in recent years, research on passive approaches to BCI still desperately needs concerted activity. To achieve robust passive BCIs, efforts from applied and basic sciences have to be combined. On the one hand, applied fields such as affective computing aim at the development of applications that adapt to changes in the user states and thereby enrich the interaction, leading to a more natural and effective usability. On the other hand, basic research in neuroscience advances our understanding of the neural processes associated with emotions. Furthermore, similar advancements are being made for more cognitive mental states, e.g. attention, fatigue and workload, which strongly interact with affective states. The main topics that need to be explored are:

- emotion elicitation and data collection for affective BCI

- detection of affect and mental state via BCI and other modalities

- adaptive interfaces and affective BCI.

This Special Issue of the *Int. J. Autonomous and Adaptive Communications Systems* (*IJAACS*) is devoted to research on affective BCI, in particular the topics mentioned above. The papers included in this Special Issue have been chosen from presentations given at a workshop that was organised in conjunction with *ACII 2009, the International Conference on Affective Computation and Intelligent Interaction*, held in Amsterdam in the Netherlands in September 2009. The workshop explored the advantages and limitations of using neurophysiological signals as a modality for the automatic recognition of affective and cognitive states, and the possibilities of using this information about the user state in innovative and adaptive applications. Researchers from the communities of brain–computer interfacing, affective computing, neuro-ergonomics, affective and cognitive neuroscience were asked to present state-of-the-art progress and visions on the various overlaps between those disciplines. In addition to these peer reviewed workshop papers and presentations an open Call for Papers was

issued for this Special Issue. Updated versions of the workshop papers and newly received papers from the Call for Papers were reviewed by key researchers in the field of (affective) brain–computer interfacing. To have a Special Issue of just five papers we had to decide to non-accept more than 70% of the papers that were made available for this special issue.

5   Content of this Special Issue

In this issue five papers on affective BCI are presented. The first paper looks at the role of affect in both active and passive BCI. In this paper, 'Emotional brain–computer interfaces', Gary Garcia Molina and his co-authors provide an original framework that allows the identification of the various roles emotions that can play in BCI. Firstly, knowledge about emotional processing in the brain makes it possible to elicit and identify emotions that can be utilised in BCI. For example, a BCI could be controlled through affective modulation, be it voluntarily or evoked. Hence affective states are translated into commands to the system. In addition, recognising a user's affective state enables automatic adaptation of the system to the user. Adaptation can aim at reducing the cognitive load of the user, reducing his or her frustration, adjusting to the interest of the user, trying to keep a gamer in the flow (balancing skills and challenges), etc. Secondly, knowledge about emotional processing in the brain helps us to understand the influence emotions have on brain activity in general, and therefore also on brain activity that can be measured using EEG. That is, this knowledge can be used to optimise training or to have online emotional adaptation of classification algorithms. Understanding the influence emotions have on brain activity also allows the enhancement of the BCI operation, whether it is about event-related potentials or visual or auditory evoked potentials, through the elicitation of emotions.

In 'Designing a passive brain–computer interface using real time classification of functional near-infrared spectroscopy', Audrey Girouard and her co-authors investigate the adaptation of interfaces to the 'workload state' of their users. Rather than using EEG to measure brain activity they consider the possibilities of fNIRS technology. Hence near-infrared light from light sources placed on the scalp is used to measure hemodynamic changes related to brain activity. fNIRS signals are less affected by non-mental activities than EEG signals and thus, the application of this technique is less susceptible to artefacts from eye, facial and head movements. EEG measures direct neuronal activity and therefore it is very fast and faster than the indirect measuring, looking at changes in blood oxygen concentration, i.e. done with fNIRS technology. fNIRS has been used to measure motor imagery, emotions and workload levels. In the paper, the emphasis is on measuring workload levels and real-time adaptation of the interface to the user's workload level. In the paper, the online features of their system (record, process, classify cognitive state signals and real-time adaptation) are demonstrated by comparisons with previous off-line experiments and real-time experiments (playing Tetris and watching video) that concentrated on classification accuracy and user satisfaction. Their results allow the authors to claim that they have created the first working real-time passive BCI with fNIRS technology.

While the previously mentioned paper successfully concentrated on measuring a workload mental state, in "Valence, arousal and dominance in the EEG during game play' by Boris Reuderink et al. the emphasis is on affect recognition using EEG. Clearly,

knowing about the user's affective state, whether it is frustration, anger, disappointment or boredom, allows more adequate feedback and adaptation of interface and application to the user. Robust recognition of a user's affective state has been the topic of many studies, looking at

1   responses in various frequency bands

2   various ways to elicit emotions

3   various models of affect.

In the paper, the authors report about an integrated approach to affect recognition in which these issues are investigated. The affect model is the usual two-dimensional plane obtained from a valence and an arousal axis. However, the authors add a dominance axis, i.e. the feeling of being in control, motivated by the approach/withdrawal theory of emotions and neurophysiological findings. Emotion induction is done using a variant of the Pacman game where frustration is evoked by periodically ignoring keyboard input. This allows the authors to claim that their emotion induction is ecologically valid. In the experiments they compared their measurements with ratings obtained from the users' self-assessments on the dimensions valence, arousal and dominance. The research results reported in the paper refine and add to existing results that correlate oscillations in different frequency bands with valence, arousal, domination and frustration.

In 'Capturing user engagement via psychophysiology: measures and mechanisms for biocybernetic adaptation', by Stephen H. Fairclough et al. the authors introduce the term physiological computing to refer to a class of adaptive software systems that capture psychophysiological changes in the user's state in real time. One of the core concepts for the development of such adaptive systems is claimed to be task engagement – an effortful striving on the part of the user to reach a desired level of performance. In a series of experiments, described in the paper, the authors look for physiological measures of task engagement. The experiments manipulate engagement by performance feedback, task difficulty and the presence or absence of financial rewards to disentangle the complex relations between task engagement on the one hand and mental effort, motivational orientation and affective changes on the other hand. Cardiovascular variables were found to respond to the motivational dimensions of the user state -– increased goal aspiration in response to positive feedback raised systolic blood pressure, which is an indicator of sympathetic activation. EEG measures could be linked to mental workload and other cognitive sources of engagement. Augmented frontal theta was involved, for instance, in the cognitive dimension of engagement. Besides describing and discussing the results of the experiments, the paper also looks at the implications for these and other findings in the context of the physiological computing paradigm: how can these measures be used in adaptive, implicit and intuitive interfaces. An important point to consider is the logic of adaptation. If disengagement arises from boredom, other adaptive actions are required from the system than in the cases where it arises due to excessive difficulty. This requires a differentiation between distinct categories of user disengagement and thus appropriate measures that can point to the various components involved in task engagement.

In 'Using minimal number of electrodes for emotion detection using brain signals produced from a new elicitation technique' by Mina Mikhail et al., the authors describe their work on the detection of emotions using EEG. In their approach they try to bypass several constraints that are normally found with such approaches. One of these is that in most studies that attempt to detect emotion using EEG, the participants are asked to

minimise any motion and facial muscle movements as these will contaminate the EEG data. As the authors point out, this restriction makes it hard to apply the recognition within real tasks and constrains the recognition to laboratory tasks. Therefore, in contrast to other experiments, the participants are instructed to make facial muscle movements during the experiment. In this case, this is part of the emotion elicitation procedure. Building on the facial feedback paradigm that claims that facial expressions can be strong elicitors (and not just expressers) of emotion, the participants were instructed to display emotional facial expressions. Instead of rejecting all the data that contained artefacts (which would be most of the data collected), a band-pass finite impulse response filter was used to remove the frequencies below 3 Hz and above 30 Hz, where most of the artefacts would reside.

A second problem for the real-life application of EEG measures for emotion detection, besides the movement artefacts, resides in the impracticalities of applying a large number of electrodes. Therefore, the authors experimented with a reduced number of electrodes. As the number of channels decreases, the recognition drops. However, a reasonable accuracy can still be reached using only four or six channels, which is a promising result for future real-world applications of the technology.

Acknowledgements