

REVIEW

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REVIEW

Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general

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Abstract

Cognitive monitoring is an approach utilizing realtime brain signal decoding (RBSD) for gaining information on the ongoing cognitive user state. In recent decades this approach has brought valuable insight into the cognition of an interacting human. Automated RBSD can be used to set up a brain–computer interface (BCI) providing a novel input modality for technical systems solely based on brain activity. In BCIs the user usually sends voluntary and directed commands to control the connected computer system or to communicate through it. In this paper we propose an extension of this approach by fusing BCI technology with cognitive monitoring, providing valuable information about the users' intentions, situational interpretations and emotional states to the technical system. We call this approach *passive* BCI. In the following we give an overview of studies which utilize passive BCI, as well as other novel types of applications resulting from BCI technology. We especially focus on applications for healthy users, and the specific requirements and demands of this user group. Since the presented approach of combining cognitive monitoring with BCI technology is very similar to the concept of BCIs itself we propose a unifying categorization of BCI-based applications, including the novel approach of passive BCI.

1. Introduction

For decades, it has been of high interest to infer information regarding ongoing brain activity and its actual meaning. Apart from behavioral measures, like eye tracking, researchers used physical parameters that relate directly to physiological processes within the brain to accomplish this task. A large partition of neuroscientific research is based on the electroencephalogram (EEG). The reason why so many researchers choose EEG is because of its high temporal resolution, ease of use and the comparably low cost. Apart from these basic characteristics, the main advantage of EEG is

that it has been thoroughly researched, since its first application by Berger in 1929 [1]. In the last century numerous studies were conducted that were based on analyses of EEG features corresponding to cognitive processes. The drawbacks of EEG—its limited spatial resolution and vulnerability to artifact sources—are factors that potentially limit current research. However, these may be resolved in the near future using powerful methods derived from engineering and mathematics, like independent component analysis (ICA) [2], beamforming [3] or novel sensor designs [4].

Other measures too can be utilized for assessing brain activity. These can be categorized as invasive versus

non-invasive technologies. Relevant non-invasive measures are functional magnetic resonance imaging (fMRI) [5–7], magnetoencephalography (MEG) [8, 9] and functional near-infrared spectroscopy (fNIRS) [10]. fMRI and MEG share the major drawbacks of being complex in application and unsuitable for long-term use. These technologies are also comparatively expensive. fNIRS and fMRI share the drawback of having a low temporal resolution, since both rely on the blood-oxygen-level-dependent (BOLD) component. The spatial resolution of fNIRS is also low; its greatest potential therefore lies in being a secondary measure used in conjunction with EEG to provide additional information on brain activity through the BOLD component. Potential invasive techniques are represented by the use of electrocorticogram (ECoG) [11, 12] and microelectrode arrays [13], allowing for a very good signal-to-noise ratio. Apart from being invasive, microelectrode arrays share one major drawback: once placed they can only be switched to other spatial areas with great difficulty and it is not possible to cover the whole cortex with sensors. They can therefore only be used for certain applications. In the following of this paper, we will focus on EEG-based research. It is our method of choice for gaining information on the ongoing state of the human brain as it occurs and identifying the underlying processes, which we will call realtime brain signal decoding (RBSD)³ in the following. From this perspective RBSD has been applied in several research endeavors within the last 20 years. One application for RBSD is gaining information about the ongoing user state, including intentions, situational interpretations and emotions. As this is encoded in human cognition, this approach is called *cognitive monitoring* [14–18]. Cognitive monitoring focuses on *post hoc* analyses of events and conditions related to human cognition [19]. The outcome of this type of analysis can be used to give a situational evaluation of a human interaction, which can be utilized for neuroergonomics, usability tests or a user state detection related to experimental conditions [18]. Besides cognitive monitoring and user state detection, RBSD can be utilized in another valuable field of application—in brain–computer interfaces (BCIs). Here, the user voluntarily generates specific patterns of brain activity which can be detected by an automated RBSD, so that the resulting information can be used as a realtime input modality for controlling a technical device by thought. Very different approaches have been developed in the last two decades, for example see [20–24], defining new communication channels for severely disabled persons, which can be used reliably and independent of any activity outside the central nervous system [25]. A BCI defines a new input modality for human–machine interaction which could substitute or add up to [26] other input modalities like manual input. But from the perspective of human–machine system research, a given system could also benefit from information on the actual user state [27], which would define an implicit input modality, carrying information about the user state not sent intentionally by the user. This would provide a valuable portion of information about the ongoing context of a given human–machine system [28].

³ Thanks to Jeremy Hill, MPI for Biological Cybernetics, Tuebingen, Germany for a hint on this terminology.

We propose to also use RBSD for an automated inference of this information; hence, for combining the approach of cognitive monitoring for accessing the actual cognitive user state with that of BCI for detecting it automatically and feeding the resulting information back to the technical system. It can be seen as modifying the general approach of BCI and substituting the usually voluntary and directed command with passively conveyed implicit information. Hence, we propose to connect it to the definition of BCI and to embed it into a broader framework of definitions. The resulting approach of *passive* BCI opens up the field of applications based on BCI technology to a broader context, especially for using it also for healthy users. In the following we give an overview of the current status of applications based on BCI technology, briefly describe one successful approach of broadening the initial definition of BCI and finally we propose a categorization of BCI-based research that also includes passive BCI.

2. Towards passive BCI

2.1. BCI technology and its possible applications

Technologies developed in the last 20 years of BCI research have become more and more interesting for a broader community of researchers. From its relatively broad definition in the early 1970s [29], recent decades have seen BCI applications focus strongly on providing new channels of communication and control for severely disabled persons [25]. Due to the considerable improvements in the reliability and usability of EEG-based BCI systems, applications of BCI technology for healthy users have become highly interesting for devising new types of applications [19, 30–33] since the beginning of this millennium. This change of focus of part of the field from disabled to healthy users led to a concurrent shift in demands and defines new requirements for resulting applications based on BCI technology. Additionally, it should be taken into consideration that BCI for healthy users aims at partially different applications than BCIs for disabled users. In particular, direct input primarily for communication and control seems not to be the most promising BCI-related application for healthy users, due to the still low reliability and bandwidth of current BCI systems compared to standard communication channels, such as speech. Similarly, the high effort usually required by a user for communication via a BCI is a drawback, if the same information could be provided through more common communication channels. Direct and primary input solely based on BCI can be expected to be outperformed by far using conventional input methods, with the exception of gaming and special working environments. In the case of gaming, the acquisition of a new skill and the interaction with a somehow unreliable system could indeed be the core purpose and challenge of the application. At present, gaming applications still mostly have the character of neurofeedback training, ranging from controlling the level of relaxation [34] to training the level of concentration ability [35], as well as to training reaction time [36] and timing of motor imagery [37], to name just a few examples. Also, several

companies explore the field of EEG-based gaming⁴. With respect to special environments where the use of BCIs might be advantageous, hazardous environments come to mind, that limit the users' interaction capabilities and lead to temporary situational disability (e.g., an astronaut in a spacesuit [38, 39]), as well as the interaction with virtual objects [40, 41], lacking common unobtrusive and intuitive interaction channels.

2.2. Novel BCI-based applications, benefits for healthy and disabled users

Several approaches have been proposed for employing the wide range of possibilities offered by BCI-based technology for a broad community of healthy users. It is important to note that just as these new approaches benefit from decades of substantial research on BCIs for disabled users, these novel efforts targeted at healthy users can be expected to in turn contribute to and enrich efforts focusing on disabled users. Additionally, expanding the scope of BCIs to include healthy users might be helpful for patients with aggravating conditions, such as locked-in patients. Also, gaming applications can be an excellent motivation for patients to train the use of a BCI using neurofeedback, for instance with respect to speed and timing.

2.3. Extending BCIs to new definitions

Recently, one extension to the BCI definition—hybrid BCI systems—was introduced to and accepted by the majority of BCI researchers [26], lifting the restriction that BCI systems would have to rely exclusively on a single input from the brain. This novel approach seems highly promising for a variety of applications, especially for healthy users [42]. Additionally, passive input based on brain signals seems to be a valuable approach for enhancing human–machine interfaces. Cutrell and Tan [43] suppose a BCI-like systematic approach for this new form of input. Zander *et al* [19, 30] proposed the definition of passive BCI systems as a framework for this kind of input. In these studies BCI technology is used for detecting the state of the user in a given human–machine system and for augmenting the information space available to the system with context information about the user. With this the space of possible applications based on BCI technology is extended widely. It not only enables the user to send voluntary and directed commands for communication and control, but adds an additional information channel conveying highly relevant information about the user implicitly. These additions could improve the actual state-of-the-art human–machine interaction by enabling the technical system to adapt to the user without any additional effort taken by the human [19, 27]. Based on earlier work on error-related potentials in the context of BCIs [44, 45], the study presented in [30] provided evidence that this concept is indeed capable of enhancing the interaction between human beings and technical systems with regard to efficiency, effectiveness and usability. Other studies showed that the performance of a given BCI system could be enhanced by implementing additional passive

input [45]. Covert aspects of user state, which can hardly be measured using behavioral data, were investigated in studies on the perceived loss of controllability [46], interpretation of other humans' movements [47], or bluffing in a game context [47]. BCI technology can also reveal valuable information about the user state in safety-critical applications, such as driving [48], industrial environments or security surveillance. With respect to driving assistance applications, recent studies have explored the use of BCI systems in a driving simulation for assessing driving performance and inattentiveness [49], as well as for robustly detecting emergency brakes before braking onset [48]. Also, BCI systems can potentially be used for cognitive monitoring in real time the mental workload of a driver and employing this information to switch off secondary tasks when the current level of workload reaches a critical level [50]. In a different context, initial steps have been taken towards assistive technologies that use the current mental state of a user for avoiding accidents in industrial environments [51]. Similarly, a pilot study showed the potential of BCI systems to recognize and predict mental states of a user correlated with concentration [51], using the example of a simulated security surveillance system [31].

2.4. Introducing passive BCI

Based on these insights, a new categorization of BCI systems was proposed [19, 30], dividing applications based on BCI technology into active, reactive and passive BCI systems.

Active BCI. An active BCI is one that derives its outputs from brain activity which is directly and consciously controlled by the user, independent of external events, for controlling an application.

Reactive BCI. A reactive BCI is one that derives its outputs from brain activity arising in reaction to external stimulation, which is indirectly modulated by the user for controlling an application.

Passive BCI. A passive BCI is one that derives its outputs from arbitrary brain activity arising without the purpose of voluntary control, for enriching a human–machine interaction with implicit information on the actual user state.

Well-known examples of active BCI systems are the basket paradigm [52, 53], the Hex-O-Spell [54], or a hybrid BCI combining eye tracking and BCI [26, 55]. The most prominent example of a system based on a reactive BCI is the P300 speller [56], and also systems based on steady state visual/somatosensory potentials [35, 57, 58]. Novel systems based on passive BCIs can detect error potentials or the perceived loss of control over a system [19, 30, 59].

Based on the above suggested definitions, a new form of interaction is defined by passive input [43]. This is an inherently different approach than cognitive user state monitoring [16], as the use of information provided by passive BCI is interpreted automatically and is strictly restricted to improving the current interaction in a defined human–machine system. This excludes ethically disputed approaches, such as lie detection, which also come under cognitive state monitoring [60].

⁴ NeuroSky, Inc., San Jose, CA, USA / Emotiv, Inc., San Francisco, USA / Mindball, Sweden.

Passive BCIs provide one way of dealing with the challenges resulting from shifting focus from disabled to healthy users [27], as they offer the key properties of complementarity, composability and controlled costs, which are not necessarily shared by active or reactive BCI systems, as defined in the following (for details, see [19]).

Complementarity. The concept of passive BCI is complementary to other means of human–machine interaction, in the sense that it does not interfere with it, in contrast to most forms of active or reactive BCIs. A passive BCI can be reliant on either the presence or the absence of an ongoing conventional human–computer interaction, or be independent of it.

Composability. A passive BCI application can make use of arbitrarily many passive BCI detectors in parallel with no conflicts, which is more difficult for active and reactive BCIs due to the user's limited ability of consciously interacting with multiple components simultaneously.

Controlled cost. Since no conscious effort from the user is needed for the use of passive BCIs (besides preparation), their operational cost is determined by the cost of their false alarms. Passive BCIs producing probabilistic estimates, together with the *a priori* probability of predicting correctly, could potentially be designed allowing for arbitrary levels of cost-optimal decision making at the application level. In that way, theoretically, systems could be designed which would only gain in efficiency by utilizing a passive BCI and could have zero benefit in the worst case.

3. Conclusion

The fusion of cognitive monitoring and BCI technology proposed here has already found realization in many experiments and some applications. From the perspective of human–machine system research it is clear that the information provided by passive BCI systems gives valuable insights in the actual user state, and hence into the ongoing context of the system. The benefits not only resulting from the principles of passive BCIs, but also from the approach of hybrid BCI system, are found in human–machine systems in general, which include healthy users as well as disabled users. As mentioned before, it can be expected that research on active, reactive and passive BCIs are of mutual benefit to one another, enriching the methodology as well as providing new neuroscientific insights. Given the expansion of scope of BCI systems, it should be reasonable to incorporate the distinctions between these BCI systems, including passive input, into the definition of BCI systems for the sake of clarity.

References

- [1] Berger H 1929 Ueber das Elektrenkephalogramm des Menschen (About the electroencephalogram of the human) *Eur. Arch. Psychiatry Clin. Neurosci.* **87** 527–70
- [2] Makeig S, Bell A J, Jung T P and Sejnowski T J 1996 Independent component analysis of electroencephalographic data *Adv. Neural Inf. Process. Syst.* **8** 145–51
- [3] Van Veen B D and Buckley K M 1988 Beamforming: a versatile approach to spatial filtering *IEEE ASSP Mag.* **5** 4–24
- [4] Zander T O *et al* A dry EEG-system for scientific research and brain–computer interfaces *Front. Neurosci.* submitted
- [5] Weiskopf N *et al* 2004 Principles of a brain–computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI) *Biomed. Eng. IEEE Trans.* **51** 966–70
- [6] Sitaram R *et al* 2006 Functional magnetic resonance imaging based BCI for neurorehabilitation *Proc. 3rd Int. Brain–Computer Interface Workshop and Training Course* p 104–106
- [7] Nair D G, Purcott K L, Fuchs A, Steinberg F and Kelso J 2003 Cortical and cerebellar activity of the human brain during imagined and executed unimanual and bimanual action sequences: a functional MRI study *Cogn. Brain Res.* **15** 250–60
- [8] Bensch M, Rosenstiel W and Bogdan M 2006 Phase synchronisation in meg for brain–computer interfaces *Proc. 3rd Int. Brain–Computer Interface Workshop and Training Course* p 18–19
- [9] Mellinger J *et al* 2007 An MEG-based brain–computer interface (BCI) *Neuroimage* **36** 581–93
- [10] Sitaram R *et al* 2007 Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain–computer interface *Neuroimage* **34** 1416–27
- [11] Leuthardt E C, Miller K J, Schalk G, Rao R P N and Ojemann J G 2006 Electrooculography-based brain–computer interface—the Seattle experience *Neural Syst. Rehabil. Eng. IEEE Trans.* **14** 194–8
- [12] Lal T N *et al* 2005 Methods towards invasive human brain–computer interfaces *Adv. Neural Inf. Process. Syst.* **17** 737–44
- [13] Hochberg L R *et al* 2006 Neuronal ensemble control of prosthetic devices by a human with tetraplegia *Nature* **442** 164–71
- [14] Donchin E 1979 Event-related brain potentials: a tool in the study of human information processing *Evoked Brain Potentials and Behaviour* ed H Begleiter (NY: Plenum) 13–75
- [15] Isreal J B, Wickens C D, Chesney G L and Donchin E 1980 The event-related brain potential as an index of display-monitoring workload *Human Factors J. Hum. Factors Ergon. Soc.* **22** 211–24
- [16] Makeig S, Jung T P and Sejnowski T J 1996 Using feedforward neural networks to monitor alertness from changes in EEG correlation and coherence (*Neural Information Processing Systems*) vol 8 ed D S Touretzky, M C Mozer and M E Hasselmo (Cambridge, MA: MIT Press)
- [17] Gevins A *et al* 1998 Monitoring working memory load during computer-based tasks with EEG pattern recognition methods *Hum. Factors* **40** 1
- [18] Parasuraman R and Wilson G F 2008 Putting the brain to work: neuroergonomics past, present, and future *Hum. factors* **50** 468
- [19] Zander T O, Kothe C, Jatzev S and Gaertner M 2010 Enhancing human–computer interaction with input from active and passive brain–computer interfaces *Brain–Computer Interfaces—Applying our Minds to Human–Computer Interaction* ed D Tan and A Nijholt (London: Springer) pp 181–199
- [20] Farwell L A and Donchin E 1988 Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials *Electroencephalogr. Clin. Neurophys.* **70** 510–23
- [21] Pfurtscheller G, Kalcher J, Neuper C, Flotzinger D and Pergenzer M 1996 On-line EEG classification during externally-paced hand movements using a neural

- network-based classifier *Electroencephalogr. Clin. Neurophys.* **99** 416–25
- [22] Birbaumer N *et al* 1999 A spelling device for the paralysed *Nature* **398** 297–8
- [23] Blankertz B, Dornhege G, Krauledat M, Mueller K R and Curio G 2007 The non-invasive Berlin brain–computer interface: fast acquisition of effective performance in untrained subjects *Neuroimage* **37** 539–50
- [24] Li K, Sankar R, Arbel Y and Donchin E 2009 P300 based single trial independent component analysis on EEG signal *Foundations of Augmented Cognition Neuroergonomics and Operational Neuroscience (Lecture Notes in Computer Science vol 5638/2009)* (Berlin: Springer) pp 404–10
- [25] Wolpaw J R, Birbaumer N, McFarland D L, Pfurtscheller G and Vaughan T M 2002 Brain–computer interfaces for communication and control *Clin. Neurophys.: Off. J. Int. Fed. Clin. Neurophys.* **113** 767–791
- [26] Pfurtscheller G *et al* 2010 The hybrid BCI. *Front. Neuroprosth.* **4** 42
- [27] Roetting M, Zander T O, Trösterer S and Dzaack J 2009 Implicit interaction in multimodal human–machine systems *Industrial Engineering and Ergonomics Visions, Concepts, Methods and Tools* ed C Schlick (Berlin: Springer)
- [28] Zander T O and Jatzev S Context aware BCIs: exploring the information space of user, technicals system and environment *J. Neural Eng.* submitted
- [29] Vidal J J 1973 Toward direct brain–computer communication *Annu. Rev. Biophys. Bioeng.* **2** 157–80
- [30] Zander T O, Kothe C, Welke S and Roetting M 2008 Enhancing human–machine systems with secondary input from passive brain–computer interfaces *Proc. 4th Int. BCI Workshop and Training Course* (Graz: Graz University of Technology Publishing House) pp 144–9
- [31] Mueller K R, Tangermann M, Dornhege G, Krauledat M, Curio G and Blankertz B 2008 Machine learning for real-time single-trial EEG analysis: from brain–computer interfacing to mental state monitoring *J. Neurosci. Methods* **167** 82–90
- [32] Nijholt A and Tan D 2010 Brain–computer interfaces and human–computer interaction (*Brain–Computer Interfaces—Applying our Minds to Human–Computer Interaction*) ed D Tan and A Nijholt (London: Springer)
- [33] Gerson A D, Parra L C and Sajda P 2006 Cortically coupled computer vision for rapid image search *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 174–9
- [34] Hjelm S and Browall C 2000 Brainball—using brain activity for cool competition *Proc. NordiCHI* pp 177–88
- [35] Lalor E *et al* 2005 Steady-state VEP-based brain–computer interface control in an immersive 3D gaming environment *EURASIP J. Appl. Signal Process.* **19** 3156
- [36] Ramsey L, Tangermann M, Haufe S and Blankertz B 2009 Practicing fast-decision BCI using a goalkeeper paradigm *BMC Neurosci.* **2009** 69
- [37] Tangermann M *et al* 2009 *Playing Pinball with Non-invasive BCI* (Cambridge, MA: MIT Press) p 16411648
- [38] Menon C *et al* 2009 Prospects of brain–machine interfaces for space system control *Acta Astronaut.* **64** 448–56
- [39] Coffey E B J, Brouwer A M, Wilschut E S and van Erp J B F 2010 Brain–machine interfaces in space: using spontaneous rather than intentionally generated brain signals *Acta Astronaut.*
- [40] Bayliss J D and Ballard D H 2000 A virtual reality testbed for brain–computer interface research *IEEE Trans. Rehabil. Eng.* **8** 188–90
- [41] Pfurtscheller G *et al* 2006 Walking from thought *Brain Res.* **3** 145–52
- [42] Vilimek R and Zander T O 2009 BC(eye): combining eye-gaze input with brain–computer interaction 5615: *Proc. 5th Int. Conf. on Universal Access in Human–Computer Interaction. Part II: Intelligent and Ubiquitous Interaction Environments (HCI International San Diego) (Lecture Notes in Computer Science vol)* ed A Hoffmann (Berlin: Springer)
- [43] Cutrell E and Tan D 2008 BCI for Passive Input in HCI: *Proc. ACM CHI* (New York: ACM Press)
- [44] Parra L, Spence C, Gerson A and Sajda P 2003 Response error correction—a demonstration of improved human–machine performance using real-time EEG monitoring *IEEE Trans. Neural Syst. Rehabil. Eng.* **11** 173–7
- [45] Ferrez P and del R Millan J 2008 Error-related EEG potentials generated during simulated brain–computer interaction *IEEE Trans. Biomed. Eng.* **55** 923–9
- [46] Jatzev S, Zander T O, DeFilippis M, Kothe C, Welke S and Roetting M 2008 Examining causes for non-stationarities: the loss of controllability is a factor which induces non-stationarities: *Proc. 4th Int. BCI Workshop and Training Course* (Graz University of Technology Publishing House)
- [47] Gaertner M, Klister T and Zander T O 2008 Classifying the observation of feasible and unfeasible human motion: *Proc. 4th Int. BCI Workshop and Training Course* (Graz University of Technology Publishing House)
- [48] Welke S, Juergensohn T and Roetting M 2009 Single-trial detection of cognitive processes for increasing traffic safety *21st Int. Technical Conf. on the Enhanced Safety of Vehicles*
- [49] Schubert R *et al* 2008 Parieto-occipital alpha power indexes distraction during simulated car driving *Int. J. Psychophysiol.* **69** 214
- [50] Kohlmorgen J *et al* 2007 Improving human performance in a real operating environment through real-time mental workload detection *Toward Brain–Computer Interfacing* ed G Dornhege, J D R Millan, D Mc Farland and K R Mueller (Cambridge, MA: MIT press) pp 409–22
- [51] Venhur B, Blankertz B, Gugler M and Curio G 2010 Novel applications of BCI technology: psychophysiological optimization of working conditions in industry *Proc. the Int. Conf. on Systems, Man, and Cybernetics (Istanbul, October 2010)* pp 417–21
- [52] Krausz G, Scherer R, Korisek G and Pfurtscheller G 2003 Critical decision-speed and information transfer in the Graz brain–computer interface *Appl. Psychophysiol. Biofeedback* **28** 233–40
- [53] Dornhege G 2006 *Increasing information transfer rates for brain–computer interfacing PhD Thesis University of Potsdam*
- [54] Blankertz B *et al* 2006 The Berlin brain–computer interface presents the novel mental typewriter Hex-O-Spell *Proc. 3rd Int. Brain–Computer Interface Workshop and Training Course, Citeseer* pp 108–109
- [55] Zander T O, Gaertner M, Kothe C and Vilimek R 2010 Combining eye gaze input with a brain–computer interface for touchless human–computer interaction *Intl J. Hum.-Comput. Interact.* **27** 38–51
- [56] Donchin E, Spencer K and Wijesinghe R 2000 The mental prosthesis: assessing the speed of a P300-based brain–computer interface *Rehabil. Eng. IEEE Trans.* **8** 174–9
- [57] Mueller-Putz G, Scherer R, Neuper C and Pfurtscheller G 2006 Steady-state somatosensory evoked potentials: suitable brain signals for brain–computer interfaces? *Neural Syst. Rehabil. Eng. IEEE Trans.* **14** 30–7
- [58] Mueller-Putz G R, Scherer R, Brauneis C and Pfurtscheller G 2005 Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components *J. Neural Eng.* **2** 123
- [59] Zander T O and Jatzev S 2009 Detecting affective covert user states with passive brain–computer interfaces *Proc. ACII 2009* (Los Alamitos, CA: ICS Press)
- [60] Nunez J M, Casey B, Egner T, Hare T and Hirsch J 2005 Intentional false responding shares neural substrates with response conflict and cognitive control *Neuroimage* **25** 267–77