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TOPICAL REVIEW

The brain–computer interface cycle

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Abstract

Brain–computer interfaces (BCIs) have attracted much attention recently, triggered by new scientific progress in understanding brain function and by impressive applications. The aim of this review is to give an overview of the various steps in the BCI cycle, i.e., the loop from the measurement of brain activity, classification of data, feedback to the subject and the effect of feedback on brain activity. In this article we will review the critical steps of the BCI cycle, the present issues and state-of-the-art results. Moreover, we will develop a vision on how recently obtained results may contribute to new insights in neurocognition and, in particular, in the neural representation of perceived stimuli, intended actions and emotions. Now is the right time to explore what can be gained by embracing real-time, online BCI and by adding it to the set of experimental tools already available to the cognitive neuroscientist. We close by pointing out some unresolved issues and present our view on how BCI could become an important new tool for probing human cognition.

1. Introduction

Continuing global research in cognitive neuroscience has led to substantial progress in understanding the brain and deciphering important aspects of the neural code. In a general sense, the neural code has not been cracked yet, but important components have been identified and can be exploited to infer the state of cognitive processes directly from measurements of brain activity. This has resulted in a wide range of applications, such as the brain–computer interface (BCI), which forges a direct online connection between brain and machine [1, 2]. In BCI technology, covert mental activity is measured and used directly to control devices such as a wheelchair or computer, or to modify one's own patterns of brain activation. Spectacular breakthroughs have been reported in the literature (e.g., [3–5]), achieving large press coverage, even though progress in exploiting the new discoveries in products and effective therapies is still slow. This makes it particularly important to maintain a critical mind set in which facts, such as advanced but not completely locked-in amyotrophic lateral sclerosis (ALS) patients learning to communicate without any overt behaviour [6], can be separated from fiction.

In order to be able to discuss different BCI approaches, we use the framework shown in figure 1, presenting the data flow through the various components of a BCI, referred to as the *BCI cycle*. The aim of this review is to give a concise overview of the components of the BCI cycle, to discuss some of the issues arising in each of the components, and to describe some of the (potential) applications of the BCI technology. For more in-depth treatment, we refer to other reviews addressing particular aspects of the BCI cycle such as signal processing [7], machine learning [8, 9] or neurofeedback [10]. Our main focus will be on non-invasive, inexpensive and portable electrophysiological BCI in humans, although we also briefly

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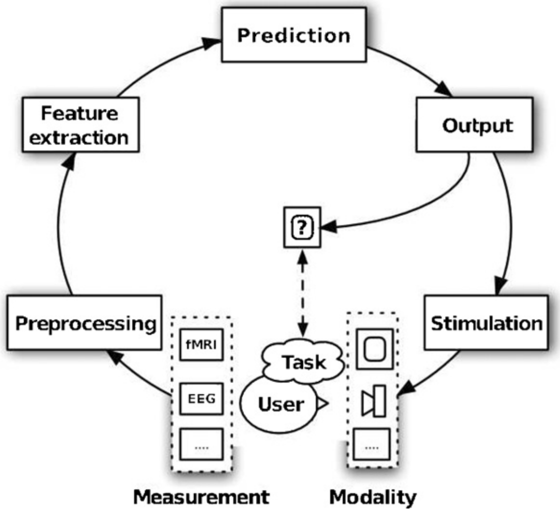

Figure 1. The BCI cycle starts with the user engaging in a cognitive task while receiving possible stimuli. Traces of brain activity are picked up by sensors. These signals are preprocessed, relevant features are extracted, and an outcome is predicted that is supposed to reflect the user's intention, either on a continuous scale or as discrete symbols. The outcome acts as an output signal for controlling an external device. The cycle is closed by the user perceiving the output, which allows a judgement about the appropriateness of the device's behaviour and an adaptation of the mental activity. The output can be presented in multiple forms and modalities, depending on the user's abilities. While iterating through the cycle, both the user and the computer may learn to adapt, thereby increasing the performance of this man–machine system.

discuss issues arising from BCIs based on invasive [11] or haemodynamic measurements [12]. We end this review with an appraisal of the future of BCI and its impact on society as a whole.

2. Tasks and stimuli

The ideal BCI task should be easy to perform with little effort to prevent fatigue, generating large brain signals to guarantee reliable and fast interpretation of the signals in a paradigm which uses patterns of brain activity that are easy to control and fast to switch, and produce output that provides user-friendly and effective feedback. Unfortunately, there is no BCI task that meets all these criteria. Often, significant mental effort is required to produce sufficiently large signals such that subjects may easily become fatigued [13]. Furthermore, even though some studies suggest that subjects can learn to perform a task without their full attention (e.g., [14]) they return to using effortful cognitive tasks on occasions when the automatic skill fails them [13].

For communication of symbols between a user and the environment, the user's intention needs to be extracted from brain signals. The first systems that were developed used voluntarily generated or modulated brain activity. A good example is the spelling device which, after extensive training, allowed paralysed subjects to control a cursor by modulating slow cortical potentials [15]. An alternative approach is neurofeedback training, where particular features from brain activity are fed back to the subjects, allowing them to control their activity (and thus the system) in a conditioning paradigm. Section 8 presents a more elaborate overview of applications for the disabled and healthy user.

Since the described paradigms need a long training period and are not successful for everyone, as discussed in [16], more recent approaches have focused on instructed cognitive tasks. These tasks range from perceptual tasks, such as selective attention, via imagery of perception or movement, to higher level mental tasks such as associating concepts, reasoning and mental arithmetic. The selective attention paradigms require attention to one of a set of stimuli that are presented simultaneously or sequentially (as in an oddball paradigm). The stimuli may be abstract, such as attending to a part of space as in [17], or 'watermarked' by some tag which is reflected in the neuronal signature. An example of such a tag in the visual domain is the detection of a symbol in a matrix of symbols with rows and columns flashing in a pseudo-random order [18]. Among imagery tasks, motor imagery is currently the most popular [13]. Other imagery tasks include visual imagery [19], mental navigation [20] and music imagery [20–23]. Higher level cognitive tasks such as word association and mental arithmetic are often used in cross-modal BCIs, where the classes to be distinguished do not all fall within the same modality [19, 24]. The paradigms that make use of a stimulus to the user are typically synchronous (or cue-based), meaning that the response is time locked to the stimulus. Asynchronous (self-paced) BCI systems, where the system also has to figure out *when* a response happens, are more natural for control but also much harder to realize.

The spectrum of cognitive BCI tasks may extend much beyond what is currently used. Internal speech would be the most direct type of communication interface and may be the modality that comes closest to detecting thoughts. One of the challenging questions is at which level of abstraction this could be detected (e.g., meaning, lexical units or speaker timbre). In recent functional magnetic resonance imaging (fMRI) classification work, there are indications that this may become possible in the future [25].

3. Measurement technology

BCI measurement technology encompasses non-invasive and invasive methods (see figure 2 for an overview). Non-invasive electroencephalography (EEG) and magnetoencephalography (MEG) reflect the average activity of dendritic currents in a large population of cells. The temporal resolution of EEG and MEG to measure changes in neuronal activity is very good but the spatial resolution to determine the precise position of active sources in the brain is poor. The poor spatial resolution, particularly for sources deeper in the brain, is due to spatial mixing of electrical activity generated by different cortical areas and passive conductance of these signals through brain tissue, bone and skin. Furthermore, these kinds of measurements are very susceptible to artefacts arising from muscle and eye movements.

Some studies have used fMRI for BCI applications (e.g., [26–28]). fMRI measures changes in blood haemoglobin concentrations associated with neural activity, based on differential magnetic properties of oxygenated and deoxygenated haemoglobin. It has a much better spatial resolution than EEG and MEG, but the temporal resolution is poor, which puts an upper bound on the bit rate for fMRI in BCI applications. Near-infrared spectroscopy (NIRS) is a non-invasive optical imaging technique based on the different resonance properties of oxygenated and deoxygenated haemoglobin in the near-infrared spectrum. It offers an inexpensive and portable alternative to fMRI, enabling investigations in freely moving subjects. The study in [29] was one of the first to demonstrate BCI control based on NIRS. However, NIRS can only be used to scan cortical tissue, whereas fMRI can be used to measure neural activity throughout the brain. Spatial resolution of NIRS is generally poor and temporal resolution is similar to that of fMRI.

A much better performance could be obtained using invasive methods (but see [30] for some concerns), which involves implantation of electrodes on or in the neocortex [11, 31, 32]. As early as 1969, the notion that electrical recordings of neurons could be applied for BCI arose from non-human primate research [33]. Invasive methods, such as the electro-corticogram (ECoG), have a superior signal-to-noise ratio and allow a much better detection of high-frequency oscillatory activity [34–37]. ECoG is often used in epileptic patients with presurgically implanted subdural electrodes to determine the precise location of the epileptic source in the brain. An alternative to ECoG is to use a single micro-electrode (ME) or a micro-electrode array (MEA), which consists of many micro-electrodes (up to several hundreds) implanted in the brain. These electrodes are capable of recording multiple forms of electrical potentials, including single or multi-neuron spiking, as well as local field potentials (LFPs), which reflect the synaptic currents and spiking activity in a local ensemble of neurons. This technique started with monkeys [5, 38], but has recently been used successfully in human subjects [39]. Although initially successful, current invasive BCI systems are far from ready for clinical application. Next to the risks of operation and problems with the sustainability of electrode contacts, it takes a dedicated team of experts and complicated hardware to keep the system working on a daily basis.

Advances in brain imaging have made BCI possible, and further developments in measurement technology can greatly enhance its potential. Issues concerning biocompatibility and tissue scarring, and making electronics fully implantable and wireless are currently at the forefront of invasive BCI research [40]. Less bulky scanners, lower noise levels, better spatial and temporal resolution and novel combinations of measurement techniques are also on the wish list of many neuroscientists.

4. Signatures

Any design of brain–computer interfaces should aim at the crucial task of extracting the characteristics of the brain signal which are uniquely caused by a mental process or state. We call such characteristics a *signature*. An example of a well-known reliable signature is the sleep spindle, which is a specific waveform that occurs when the subject is asleep. For most mental processes however, the search for robust signatures is still ongoing. The signatures that have shown to be useful for BCI can be broadly categorized into *evoked* and *induced* responses. Evoked responses are time- and phase-locked to an event. This means that averaging repeated signals will increase the signal-to-noise ratio. Induced responses are not phase locked but the power, rather than the phase, *is* time locked to the stimulus. That is, the power in specific frequency bands has to be calculated before averaging across trials [41]. The measured response is usually referred to as an event-related potential (ERP) or event-related field (ERF) [42].

Slow cortical potentials (SCPs) [43] were among the first signals to be used to drive a BCI system [15] and can be interpreted as an evoked response. They can be operant conditioned with direct positive feedback but, as previously mentioned, require extensive training periods. Furthermore, modulation of SCPs is relatively slow, which limits the bit rate (the amount of information transmitted per unit time). The evoked response that is used most often for BCI is the P300 [18, 44]. It appears as a positive deflection roughly 300 ms after stimulus presentation and is related to the amount of attention by the subject to the stimulus. The visually evoked P300 has been used repeatedly for speller applications in which a letter matrix with flashing rows and columns is presented [18]. Another family of evoked responses is the steady-state-evoked potential (SSEP) [45]. When perceiving a stimulus (visual, somatosensory, or auditory) that is modulated with a known periodic pattern, this pattern can be traced in measurements of brain activity. This watermark can be pseudo-random, periodic, or spread spectrum (e.g., [46]). The power and phase of the signal can be influenced by selective attention by the subject thus providing a suitable task for a BCI [47, 48]. Other well-known evoked responses that have been used in a BCI context are the error potential (EP) for automatic detection of misclassifications made by the system [49], and the readiness potential (RP), which has been studied to improve the reliability of BCI systems [50].

Event-related desynchronization (ERD) and synchronization (ERS) are examples of induced responses, occurring as a result of changes in the oscillatory behaviour of a group of neurons. Specific mental activity is reflected in desynchronization of on-going rhythms in certain parts of the brain, which appears as an attenuation of the power in specific frequency bands. Similarly, deactivation is reflected in a synchronization rebound [51]; an increase in power at specific frequency bands. ERD and ERS of the mu and beta rhythms have been studied extensively for motor imagery tasks [41, 51, 52], as they can be measured over areas of the sensorimotor cortex. ERD was also found during other mental tasks, such as covert attention [17], mental arithmetic [53], mental rotation [54] and language related tasks [55].

In order to apply BCI to new tasks, more knowledge is necessary on the level of neural coding. Which parts of the brain are active in various tasks? What is the functional role of rhythmic neuronal synchronization? How do different brain areas communicate? The better we understand these issues, the better we can extract relevant features and

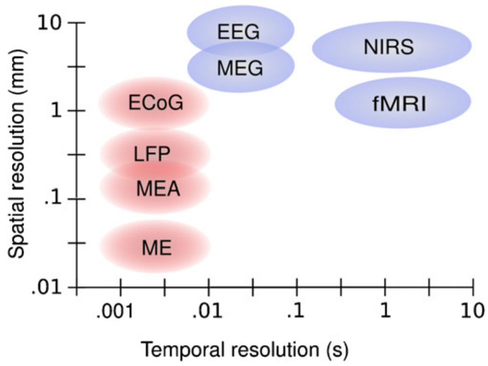

Figure 2. Schematic overview of the scale of spatial and temporal resolution of measurement methods used for BCI. Measurement methods are electroencephalography (EEG), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), electrocorticography (ECOG), local field potential (LFP) recordings, micro-electrode array (MEA) recordings and microelectrode (ME) recordings. Non-invasive methods are shown in blue and invasive methods are shown in red.

markers. Encoding also has to be understood for hierarchical combinations of representations into large units. For example, the representation of a two-finger movement in brain signals may be an additive combination of the representations of each of the movements of the individual fingers, or may give rise to nonlinear interactions and generate a new overall signature. For internal speech, the representation of a word may be different from the sum of the representations of its constituting phonemes. Breakthroughs in BCI can be expected if our understanding of the nature and hierarchy of neural representations increases.

5. Preprocessing and feature extraction

The purpose of preprocessing and feature extraction in a BCI system is to transform measured brain signals such that the signal-to-noise ratio is maximized—hence maximizing the probability of correct brain state identification. Clearly, the optimal transformations depend not only on knowledge of the signal characteristics but also on the measurement technology employed. Here, we restrict ourselves to preprocessing and feature extraction for electrophysiological signals. We refer to [56] for a discussion of signal processing in the context of fMRI-based BCIs.

The most common types of preprocessing are artefact detection, spectral filtering and spatial filtering. Artefact

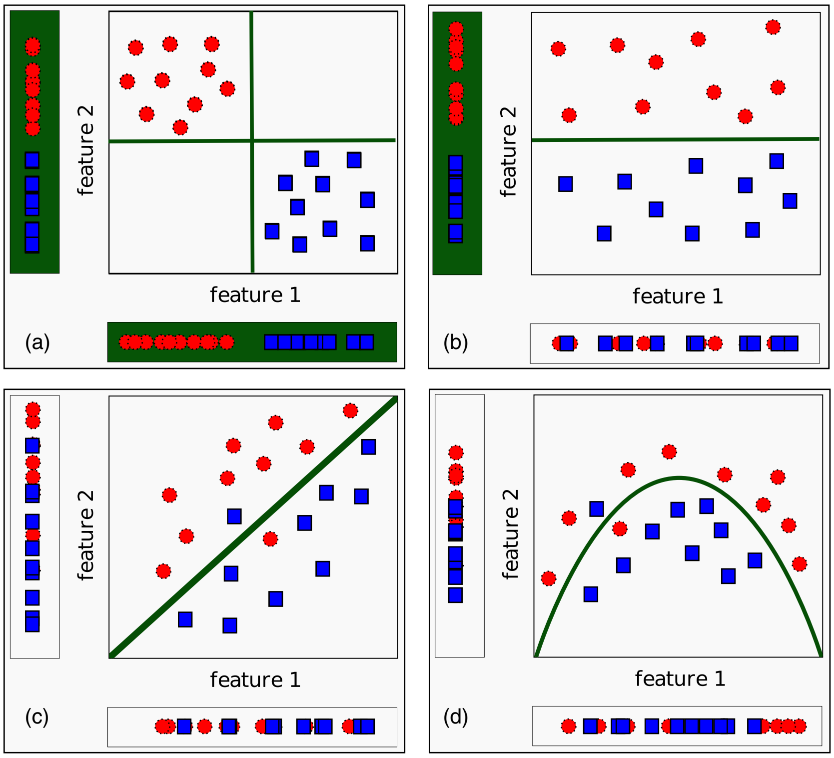

Figure 3. Interactions between features which may occur when training a classifier on data for two conditions (indicated by blue squares and red circles). Panel (a) depicts a situation where either feature 1 or 2 is sufficient to distinguish both conditions. Panel (b) demonstrates the situation where feature 1 is redundant since it does not distinguish both conditions whereas feature 2 does, as shown by the projections on individual features. Typically, we wish to eliminate as many redundant features as possible, thereby improving generalization performance and interpretability of the results. Panel (c) depicts the case where both features are necessary to disentangle the conditions. Here, a linear classifier is used to discriminate the classes (indicated by the green decision boundary which separates the classes). Contrast this with panel (d), where a nonlinear classifier is required to discriminate the classes. Trials at the wrong side of the decision boundary will be misclassified. Often, in practice, linear classifiers are sufficient for classifying neuroimaging data.

detection attempts to find confounding signals from sources outside the brain, such as eye and muscle artefacts, and then attempts to remove them from the trial data or reject the trial altogether. Spectral filtering is used to remove noise signals, such as slow drifts and line noise. Spatial filtering linearly combines signals from multiple electrodes to focus on activity at a particular location in the brain. It is used either to focus on or reject sources based upon their position. An example of spatial filtering is independent component analysis (ICA) [57], which identifies statistically independent sources of activity. Alternative spatial filtering approaches are channel re-referencing such as the common average reference or the Laplace filter [58], source imaging methods that make explicit use of a forward model (see [59]) or spatial filters that make use of class information, such as the common spatial patterns method [60] that is popular in BCI research [61, 62].

Feature extraction attempts to robustly characterise the preprocessed signals of interest, mainly by employing temporal or spectral features. Temporal features are derived directly from the signal and include the (averaged) time-course. Spectral features characterise the power of the brain signal in various frequency bands. Time-frequency representations (TFRs) combine both temporal and spectral features by describing how spectral power varies over time. There have also been attempts to use not only power but also phase information as features [63]. Other, as yet more speculative features, are measures derived from nonlinear dynamical systems theory [64, 65].

Summarizing, both preprocessing and feature extraction are important components of the BCI cycle, as they make the raw signals suitable for predicting outcomes.

6. Prediction

A critical element in any BCI is to predict the outcome intended by the subject from extracted features (e.g., band power at multiple EEG sensors). This prediction is covered by the field of machine learning. Sometimes, the output is continuous, in which case we are dealing with a regression problem (e.g., [66]), but in most designs it is discrete, in which case we are dealing with a classification problem. Many different classification algorithms have been employed in the literature [7, 9]; popular choices being linear discriminant analysis and (linear) support vector machines [67]. However, classification performance depends not only on the classifier, but also on factors such as the number of extracted features, the amount of training data available and the experimental paradigm.

Generally, neuroimaging data are characterized by many features (e.g., thousands of voxel activations or power estimates) and a small number of trials. In that case, classifiers are prone to overfit on the training data which leads to poor performance on new trials. There are various ways of tackling this problem, such as using simple linear classifiers, regularization in order to reduce the effect of outliers, and/or employing feature selection methods to reduce the number of used features [8]. Note that these methods not only improve generalization performance, but also help to interpret the parameters of the resulting classifiers (cf figure 3). An interesting related issue is how well trained classifiers generalize to new sessions or subjects [68]. This topic, known in the machine learning literature as transfer learning [69] or multi-task learning [70], receives increased attention in the BCI community [71].

Addressing the dynamic nature of the closed BCI cycle is a big challenge. The human brain is a flexible and powerful learning machine. The ability to learn the coordination of muscles for complex movements, even after a lesion [72], clearly demonstrates this power. In order for BCI systems to utilize this ability requires a continuous tracking of and adapting to the changing user state. Consequently, there is a growing interest in dynamic classifiers, such as hidden Markov models and dynamic Bayesian networks [73, 74], that allow for continuous tracking, enabling so-called asynchronous BCIs. Bayesian methods are also used as the basis for adaptive BCIs that modify their behaviour based on changes in signal characteristics; e.g., due to habituation or sensor drift [67, 75, 76].

In short, the main problem of classification is not so much the choice of a proper classification algorithm, since simple linear classifiers often perform satisfactorily, but mainly concerns optimal feature selection, the ability to perform on-line state estimation, and the capability to adapt to changes while iterating through the BCI cycle.

7. Output

The BCI output component generates information for controlling an output device, thus closing the BCI cycle by providing the user with observable feedback about the predicted intention. Output devices can be distinguished into computer applications and physical devices such as neural prosthetics or a wheelchair. Output can take a wide range of output modalities, such as text [15], auditory output [77], motor commands [67, 78], or graphical [79] and vibrotactile [80] representations of brain activity for neurofeedback. Often, signal feedback is used in combination with the actual control of an output device [81], to allow the user to adapt and learn. Output generation of discrete commands is most common [7, 82], through direct control, driven by a continuous EEG feature, is used as well (e.g., a linear combination of power in EEG frequency bands for 2D cursor control [83]).

Exciting results have been obtained with invasive recording techniques via which monkeys control robot arms [78, 84], up to the extent that they can learn to feed themselves [5]. However, as underlined in section 3 we are far away from using non-invasive BCI to control applications with similar accuracy and speed. There remains a major need to increase the dimensionality of current BCIs. It is rather ironic that we cannot control a simple machine with more than a few degrees of freedom using signals from one of the most high-dimensional systems we know.

Typically, BCI systems achieve bit rates up to 25 bits per minute [1]. The bit rate depends on the classification accuracy and speed of a BCI. It is expressed as $\mathrm{I}(C;Y)/T$, where $\mathrm{I}(C;Y)$ stands for the mutual information between the actual class C and the predicted class Y and where T represents the trial duration in minutes [67]. If not every outcome has the same utility then one should take this into account within the evaluation criterion. For instance, turning on a wheelchair while the user did not intend this should be more heavily penalized than the converse error. One evaluation criterion which takes differences in utility into account is the area under the receiver operating characteristic (ROC) curve [85]. One should always be careful when using an evaluation metric to evaluate a particular BCI application. For example, area under the ROC curve is only applicable in the case of binary classification problems whereas the bit rate can be misleading due to the exclusion of intertrial intervals or due to the fact that systematic misclassification may even increase the bit rate [44].

To the increase bit rate, knowledge from the application domain and smart user-interface design can be employed. For example, mental typing can benefit from particular layouts of target characters, probabilistic text entry techniques, or language models [86–88]. Cursor control can be reinforced using the amplitude of the extracted features and momentum of previous control commands [89]. Taking care of stimulus-response compatibility (such as mapping left–right imagined movement to left–right position of the bat in a Pong game) further facilitates ease of use. A successful example of this concept is reported in [90], where foot imagery is used for walking in virtual environments. Contextual information can also constrain the control, such as the position of a wheelchair with respect to obstacles and walls, or mouse positions relative to objects on a graphical canvas [91].

The design of guidelines for interactive systems which process ambiguous input is a well-known topic in multimodal human–computer interaction [92] and could therefore provide formalizations that may help mature the current BCI technology.

8. Applications for disabled and healthy users

EEG-based BCIs have been used for patients suffering from various degrees of paralysis. These BCIs are based on signatures such as slow cortical potentials [15], ERD/ERS [3] or the P300 evoked potential [93] to control a computer cursor for communication with the external world. Although the target users for a BCI system are mainly completely locked-in patients, relatively few systems have actually been successful for this group. One consideration is that a system, which is designed and tested for healthy subjects, does not necessarily generalize to the patient population. For example, some studies have reported that about 45% of patients suffering from ALS reveal some form of cognitive impairment [94, 95] as well as modified EEG signatures [96]. A possible reason for this cognitive impairment may be the enduring immobility, but the disease may also have effects on brain functioning that have not yet been properly clarified [97]. Next to the use of BCIs in paralysed patients, we foresee an increased use of BCI technology in monitoring or prediction of particular (pathological) functional states such as in the prediction of seizure onset in epileptics [98] or monitoring the depth of anaesthesia during surgery [99].

Quite recently, chronically implanted intra-cortical micro-electrode arrays have been used to measure multi-unit activity to restore motor function in tetraplegic subject [39]. He was able to open e-mails, to operate devices such as a television, even while conversing, to open and close a prosthetic hand and to perform rudimentary actions with a multi-jointed robotic arm. Although these results are promising, many technical problems, mainly related to electrode biocompatibility, have to be resolved before these techniques can be used on a routine basis.

Neurofeedback paradigms have been used in several clinical settings. Through operant conditioning (i.e., a reward is given when some desired activity is produced) an EEG component can be selected for training. Typically, such a component is the (ratio of) power in certain frequency bands in particular brain areas. This has resulted in several interesting clinical results showing possible beneficial effects for illnesses such as ADHD and epilepsy. Quite recently, Leins and colleagues [79] have shown that on-line feedback of slow cortical potentials and feedback of the ratio of power in theta and beta bands in ADHD children resulted in behavioural and cognitive improvements, which were stable for at least six months. This was one of the first studies with controls, which revealed significant effects of neurofeedback on cognitive performance. The use of fMRI feedback has also yielded interesting results, such as training certain brain regions to reduce chronic pain and obsessive compulsive behaviour [100].

There is a broad repertoire of potential BCI applications for the healthy user as well, ranging from the detection and amplification of particular emotional and cognitive states to new forms of human–computer interaction. Many such applications are framed in the context of BCI games. Already in 1977 visually evoked potentials were used to allow users to navigate in a maze [101]. Some BCI games are used in the development of medical applications (e.g., novel training environments in neurofeedback research) but often they are designed to illustrate BCI systems in research and entertainment. Simple and familiar video games have been placed under BCI control. For example, the Berlin brain–computer interface [86] has used motor imagery to play Pacman, Pong and Tetris. Motor imagery applications also exist for more advanced applications such as the control of a first-person shooter game [102] or for navigation in Google Earth [103]. Other games have been introduced that exploit more global brain activity. Brainball is one example, where gamers have to control a ball on a table through their state of relaxation [104], showing that such games can have a profound impact on a user's cognitive state. Several small companies currently introduce cheap and portable BCI devices on the market for non-medical use.

9. Towards the future

On the one hand, many of the aforementioned results reflect significant theoretical and practical advances. On the other hand, the low reliability, low speed and huge inter-subject variability prevent a rapid deployment of BCI techniques for clinical and consumer applications [105]. Why is it that, in all these years of development, not more progress has been achieved? We believe that in each of the steps of the BCI cycle major improvements are needed. Yet, expectations concerning BCI's potential use easily runs high, especially in the popular media. It is important, both for the research community as well as for potential users, to make a clear distinction between currently feasible and potentially possible applications in order to prevent unrealistic expectations.

Like other new and promising research areas, such as bioinformatics and nanotechnology, BCI provides cause for considering its potential philosophical, ethical and societal consequences. Research in BCI has implications for and can be influenced by discussions of general topics within neuroethics, ranging from mind-reading and privacy [106], personal identity [107], free will and mind-control [108], to human enhancement and social stratification [109]. In addition, researchers should consider several other ethical issues regarding clinical BCI applications. Specifically, acquiring informed consent from a locked-in patient should be done very carefully considering the high expectations of the patient, the difficulty in communication, and the lack of alternatives for the patient [110].

When interpreting neural activity for BCI applications it is useful to reflect what it means for a thought to drive a BCI. The described research mainly uses some specific task as a *correlate* of user intention, such as the use of imagined movement for decision making. It would be much more satisfying if the BCI employs the neural signal associated with the decision making process directly (e.g., activity in the prefrontal cortex) or if the BCI signal can be controlled using subject-specific strategies, where the user has the freedom to choose the employed brain signature [111]. In this context it is highly interesting that subjects can modulate brain areas without knowing what they really do. A good example is the study by deCharms *et al* [112] on patients with a high pain sensation. If activity in brain centres, involved in the perception of pain, was measured using fMRI and shown to the subject as the height of a fire on a monitor, subjects were able to modulate their brain activity such that the flames on the monitor became smaller. Of course, this corresponded with a reduced activity in pain-related brain centres and with a reduction of perceived pain. This illustrates that subjects somehow know what to do in order to modulate brain activity that is fed back to the subject, even when the subject is not aware of the source of that brain activity. This raises some very interesting questions about the role of introspection and modulation of brain activity in specific brain areas.

We envision that the real-time single-trial analysis, that is afforded by BCI, may also have a profound impact on the way neurophysiological data are analysed. Traditional univariate analysis of data which is averaged over multiple trials and subjects can now be augmented by sensitive multivariate methods that allow (on-line) the classification of single-trial data in single subjects [113, 114]. This not only makes it possible to quantify between- and within-subject variability but also implies that signal characteristics which previously could only be observed off-line can now be tracked in real time. This allows brain function to be probed in dynamic and natural contexts [115]. The possibility of instructing subjects to maintain a specific feature of their brain activity at a certain level, while conducting the experimental task, makes it possible to include such features as independent variable in experimental designs [116]. Conversely, stimulus presentation during an experiment can be made dependent on the presence or absence of particular brain signatures, allowing for more complex experimental designs. Finally, recent advances in single-trial analysis have led to an increased interest in brain reading, where the goal is to infer the contents of subjective perception given knowledge of the observed brain state [117–119]. This increased focus on real-time single-trial analysis should ultimately increase our understanding of human cognition.

In conclusion, we observe that much research is devoted to advance the state of the art in every step of the BCI cycle. It is our belief that this research should ultimately translate into practical applications for the healthy and disabled user as well as into novel ways of analysing neurophysiological data in cognitive neuroscience. These developments will ensure that BCI research will have a lasting impact on society even after the hype is over.

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References

[1] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain–computer interfaces for communication and control *Clin. Neurophysiol.* **113** 767–91

[2] Nijholt A, Tan D, Pfurtscheller G, Brunner C, del R Millán J, Allison B, Graimann B, Popescu F, Blankertz B and Müller K-R 2008 Brain–computer interfacing for intelligent systems *IEEE Intell. Syst.* **23** 72–9

[3] Kübler A, Nijboer F, Mellinger J, Vaughan T M, Pawelzik H, Schalk G, McFarland D J, Birbaumer N and Wolpaw J R 2005 Patients with ALS can use sensorimotor rhythms to operate a brain–computer interface *Neurology* **64** 1775–7

[4] Lebedev M A and Nicolelis M A L 2006 Brain–machine interfaces: past, present and future *Trends Neurosci.* **29** 536–46

[5] Velliste M, Perel S, Spalding M C, Whitford A S and Schwartz A B 2008 Cortical control of a prosthetic arm for self-feeding *Nature* **453** 1098–101

[6] Nijboer F, Sellers E, Mellinger J, Jordan M, Matuz T, Furdea A, Halder S, Mochty U, Krusienski D and Vaughan T 2008 A P300-based brain–computer interface for people with amyotrophic lateral sclerosis *Clin. Neurophysiol.* **119** 1909–16

[7] Bashashati A, Fatourechi M, Ward R K and Birch G E 2007 A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals *J. Neural Eng.* **4** 32–57

[8] Müller K-R, Krauledat M, Dornhege G, Curio G and Blankertz B 2004 Machine learning techniques for brain–computer interfaces *Biomed. Tech.* **49** 11–22

[9] Lotte F, Congedo M, Lécuyer A, Lamarche F and Arnaldi B 2007 A review of classification algorithms for EEG-based brain–computer interfaces *J. Neural Eng.* **4** R1–R13

[10] Abarbanel A 1995 Gates, states, rhythms, and resonances: the scientific basis of neurofeedback training *J. Neurother.* **1** 15–38

[11] Nicolelis M A L 2003 Brain–machine interfaces to restore motor function and probe neural circuits *Nat. Rev. Neurosci.* **4** 417–22

[12] DeCharms R C 2008 Applications of real-time FMRI *Nat. Rev. Neurosci.* **9** 720–9

[13] Curran E A and Stokes M J 2003 Learning to control brain activity: A review of the production and control of EEG components for driving brain–computer interface (BCI) systems *Brain Cogn.* **51** 326–36

[14] Miner L A, McFarland D J and Wolpaw J R 1998 Answering questions with an electroencephalogram-based brain–computer interface *Arch. Phys. Med. Rehabil.* **79** 1029–33

[15] Birbaumer N, Ghanayim N, Hinterberger T, Iversen I, Kotchoubey B, Kübler A, Perelmouter J, Taub E and Flor H 1999 A spelling device for the paralysed *Nature* **398** 297–8

[16] Birbaumer N 2006 Brain–computer-interface research: coming of age *Clin. Neurophysiol.* **117** 479–83

[17] van Gerven M A J and Jensen O 2009 Attention modulations of posterior alpha as a control signal for two-dimensional brain–computer interfaces *J. Neurosci. Methods* **179** 78–84

[18] 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. Neurophysiol.* **70** 510–23

[19] Keirn Z A and Aunon J I 1990 A new mode of communication between man and his surroundings *IEEE Trans. Biomed. Eng.* **37** 1209–14

[20] Cabrera A F and Dremstrup K 2008 Auditory and spatial navigation imagery in brain–computer interface using optimized wavelets *J. Neurosci. Methods* **174** 135–46

[21] Curran E, Sykacek P, Stokes M, Roberts S J, Penny W, Johnsrude I and Owen A M 2003 Cognitive tasks for driving a brain–computer interfacing system: A pilot study *IEEE Trans. Neural Syst. Rehab. Eng.* **12** 48–54

[22] De Kruif B J, Schaefer R S and Desain P 2007 Classification of imagined beats for use in a brain–computer interface *Proc. 29th Ann. Int. Conf. IEEE EMBS, Lyon, France* pp 678–81 Cite Internationale

[23] Schaefer R S, Guimaraes M Perreau, Desain P and Suppes P 2008 Detecting imagined music from EEG *Proc. Int. Conf. on Music Perception and Cognition (Sapporro, Japan)* vol 10

[24] Sepulveda F, Dyson M, Gan J Q and Tsui C S L 2007 A comparison of mental task combinations for asynchronous EEG-based BCI's *Proc. of the IEEE EMBS (Lyon, France)* pp 5055–8

[25] Formisano E, De Martino F, Bonte M and Goebel R 2008 'who' is saying 'what'? Brain-based decoding of human voice and speech *Science* **322** 970–3

[26] Weiskopf N, Scharnowski F, Veit R, Goebel R, Birbaumer N and Mathiak K 2004 Self-regulation of local brain activity using real-time functional magnetic resonance imaging (fMRI) *J. Physiol.* **98** 357–73

[27] Hinterberger T, Veit R, Wilhelm B, Weiskopf N, Vatine J-J and Birbaumer N 2005 Neuronal mechanisms underlying control of a brain–computer interface *Eur. J. Neurosci.* **21** 3169–81

[28] Caria A, Veit R, Sitaram R, Lotze M, Weiskopf N, Grodd W and Birbaumer N 2007 Regulation of anterior insular cortex activity using real-time fMRI *NeuroImage* **35** 1238–46

[29] Sitaram R, Zhang H, Guan C, Thulasidas M, Hoshi Y, Ishikawa A, Shimizu K and Birbaumer N 2007 Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain–computer interface *NeuroImage* **34** 1416–27

[30] Wolpaw J R 2007 Brain–computer interfaces as new brain output pathways *J. Physiol.* **579** 613–9

[31] Carmena J M, Lebedev M, Crist R E, O'Doherty J E, Santucci D M, Dimitrov D F, Patil P G, Henriquez C S and Nicolelis M A L 2003 Learning to control a brain–machine interface for reaching and grasping by primates *PLoS Biol.* **1** 1–16

[32] Schwartz A, Cui X, Weber D and Moran D 2006 Brain-controlled interfaces: Movement restoration with neural prosthetics *Neuron* **52** 205–20

[33] Fetz E E 1969 Operant conditioning of cortical unit activity *Science* **163** 955–8

[34] Leuthardt E C, Schalk G, Wolpaw J R, Ojemann J G and Moran D W 2004 A brain–computer interface using electrocorticographic signals in humans *J. Neural. Eng.* **1** 63–71

[35] Ramsey N F, Van den Heuvel M P, Kho K H and Leyten F S S 2006 Towards human BCI applications based on cognitive brain systems: an investigation of neural signals recorded from the dorsolateral prefrontal cortex *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 214–7

[36] Miller K J, Den Nijs M, Shenoy P, Miller J W, Rao R P N and Ojemann J G 2007 Real-time functional brain mapping using electrocorticography *NeuroImage* **37** 504–7

[37] Schalk G, Miller K J, Anderson N R, Wilson J A, Smyth M D, Ojemann J G, Moran D W, Wolpaw J R and Leuthardt E C 2008 Two-dimensional movement control using electrocorticographic signals in humans *J. Neural Eng.* **5** 75–84

[38] Musallam S, Corneil B D, Greger B, Scherberger H and Andersen R A 2004 Cognitive control signals for neural prosthetics *Science* **305** 258–62

[39] Hochberg L R, Serruya M D, Friehs G M, Mukand J A, Saleh M, Caplan A H, Branner A, Chen D, Penn R D and Donoghue J P 2006 Neuronal ensemble control of prosthetic devices by a human with tetraplegia *Nature* **442** 164–71

[40] Schwartz A B 2004 Cortical neural prostheses *Ann. Rev. Neurosci.* **27** 487–507

[41] Pfurtscheller G and Lopes da Silva F H 1999 Event-related EEG/MEG synchronization and desynchronization: basic principles *Clin. Neurophysiol.* **110** 1842–57

[42] Gazzaniga M S 2004 *The Cognitive Neurosciences III* 3rd edn (Cambridge, MA: MIT Press)

[43] Rockstroh B, Elbert T, Canavan A, Lutzenberger W and Birbaumer N *Slow Cortical Potentials and Behavior* (Baltimore, MD: Urban & Schwarzenberg)

[44] Sellers E W and Donchin E 2006 A P300-based brain–computer interface: initial tests by ALS patients *Clin. Neurophysiol.* **117** 538–48

[45] Regan D 1977 Steady-state evoked potentials *J. Opt. Soc. Am.* **11** 1475–89

[46] Desain P, Farquhar J, Blankespoor J and Gielen S 2008 Detecting spread spectrum pseudo random noise tags in EEG/MEG using a structure-based decomposition *4th Int. BCI Workshop and Training Course 2008 (Graz, Austria)*

[47] Middendorf M, McMillan G, Calhoun G and Jones K S 2000 Brain–computer interfaces based on the steady-state visual-evoked response *IEEE Trans. Neural Syst. Rehab. Eng.* **8** 211–4

[48] Allison B Z, McFarland D J, Schalk G, Zheng S D, Jackson M M and Wolpaw J R 2008 Towards an

independent brain–computer interface using steady state visual evoked potentials *Clin. Neurophysiol.* **119** 399–408
[49] Schalk G, Wolpaw J R, McFarland D J and Pfurtscheller G 2000 EEG-based communication: presence of an error potential *Clin. Neurophysiol.* **111** 2138–44
[50] Krauledat M, Dornhege G, Blankertz B, Losch F, Curio G and Müller K-R 2004 Improving speed and accuracy of brain–computer interfaces using readiness potential features *Conf. Proc. IEEE. Eng. Med. Biol. Soc.* **6** 4511–5
[51] Pfurtscheller G, Brunner C, Schlögl A and Lopes da Silva F H 2006 Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks *NeuroImage* **31** 153–9
[52] Toro C, Deuschl G, Thatcher R, Sato S, Kufta C and Hallett M 1994 Event-related desynchronization and movement-related cortical potentials on the ECoG and EEG *Electroencephalogr. Clin. Neurophysiol.* **93** 380–9
[53] Chochon F, Cohen L, van de Moortele P F and Dehaene S 1999 Differential contributions of the left and right inferior parietal lobules to number processing *J. Cogn. Neurosci.* **11** 617–30
[54] del R Millán J, Renkens F, Mouriño J and Gerstner W 2004 Noninvasive brain-actuated control of a mobile robot by human EEG *IEEE Trans. Biomed. Eng.* **51** 1026–33
[55] Petersen S E, Fox P T, Posner M I, Mintun M and Raichle M E 1988 Positron emission tomographic studies of the cortical anatomy of single-word processing *Nature* **331** 585–9
[56] Pereira F, Mitchell T M and Botvinick M 2008 Machine learning classifiers and fMRI: A tutorial overview *Neuroimage* **45** S199–209
[57] Hyvärinen A and Oja E 2000 Independent component analysis: algorithms and applications *Neural Netw.* **13** 411–30
[58] Hjorth B 1975 An on-line transformation of EEG scalp potentials into orthogonal source derivations *Electroencephalogr. Clin. Neurophysiol.* **39** 526–30
[59] Baillet S, Mosher J C and Leahy R M 2001 Electromagnetic brain mapping *IEEE Signal. Proc. Mag.* **18** 14–30
[60] Koles Z 1991 The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG *Electroencephalogr. Clin. Neurophysiol.* **79** 440–7
[61] Lemm S, Blankertz B, Curio G and Müller K-R 2005 Spatio-spectral filters for improving the classification of single trial EEG *IEEE Trans. BioMed. Eng.* **52** 1541–8
[62] Ramoser H, Müller-Gerking J and Pfurtscheller G 2000 Optimal spatial filtering of single trial EEG during imagined hand movement *IEEE Trans. Rehabil. Eng.* **8** 441–6
[63] Brunner C, Scherer R, Graimann B, Supp G and Pfurtscheller G 2006 Online control of a brain–computer interface using phase synchronization *IEEE Trans. Biomed. Eng.* **53** 2501–6
[64] Stam C J 2005 Nonlinear dynamical analysis of EEG and MEG: review of an emerging field *Clin. Neurophysiol.* **116** 2266–301
[65] Woon W L and Cichoki A 2007 Novel features for brain–computer interfaces *Comput. Intell. Neurosci.* **2007** (7 pages)
[66] McFarland D J and Wolpaw J R 2005 Sensorimotor rhythm-based brain–computer interface (BCI): feature selection by regression improves performance *IEEE Trans. Neural Syst. Rehab. Eng.* **13** 372–9
[67] Dornhege G, Millán J del R, Hinterberger T, McFarland D J and Müller K-R (ed) 2007 *Oward Brain–Computer Interfacing* 1st edn (Cambridge, MA: The MIT Press)
[68] Wong D K, Grosenick L E, Uy T, Guimaraes M P, Carvalhaes C G, Desain P and Suppes P 2008 Quantifying inter-subject agreement in brain-imaging analyses *Neuroimage* **39** 1051–63
[69] Raina R, A Y Ng and Koller D 2006 Constructing informative priors using transfer learning *Proc. 23rd Int. Conf. on Machine Learning* pp 713–20
[70] Caruana R 1993 Multitask learning: a knowledge-based source of inductive bias *Proc. 10th Int. Conf. on Machine Learning* pp 41–8
[71] van Gerven M A J, Hesse C, Jensen O and Heskes T 2009 Interpreting single trial data using groupwise regularisation *Neuroimage* **46** 665–76
[72] Moritz C T, Perlmuter S I and Fetz E E 2008 Direct control of paralysed muscles by cortical neurons *Nature* **456** 639–42
[73] Obermeier B, Guger C, Neuper C and Pfurtscheller G 2001 Hidden Markov models for online classification of single trial EEG *Patt. Recogn. Lett.* **22** 1299–309
[74] Shenoy P and Rao R P N 2005 Dynamic Bayesian networks for brain–computer interfaces *Advances in Neural Information Processing Systems* vol 17 ed L K Saul, Y Weiss and L Bottou (Cambridge, MA: MIT Press) pp 1265–72
[75] Sykacek P, Roberts S J and Stokes M 2004 Adaptive BCI based on variational Bayesian Kalman filtering: an empirical evaluation *IEEE Trans. Biomed. Eng.* **51** 719–29
[76] Vidaurre C, Schlögl A, Cabeza R, Scherer R and Pfurtscheller G 2006 A fully on-line adaptive BCI *IEEE Trans. Biomed. Eng.* **53** 1214–9
[77] Nijboer F, Furdea A, Gunst I, Mellinger J, McFarland D J, Birbaumer N and Kübler A 2007 An auditory brain–computer interface (BCI) *J. Neurosci. Methods* **167** 43–50
[78] Nicolelis M A L 2001 Actions from thoughts *Nature* **409** 403–7
[79] Leins U, Goth G, Hinterberger T, Klinger C, Rumpf N and Strehl U 2007 Neurofeedback for children with ADHD: a comparison of SCP and theta/beta protocols *Appl. Psychophysiol. Biofeedback* **32** 73–88
[80] Chatterjee A, Aggarwal V, Ramos A, Acharya S and Thakor N V 2007 A brain–computer interface with vibrotactile biofeedback for haptic information *J. Neuroeng. Rehabil.* **4** 40
[81] Birbaumer N and Cohen L G 2007 Brain–computer interfaces: communication and restoration of movement in paralysis *J. Physiol.* **579** 621–36
[82] Mason S G, Bashashati A, Fatourechi M, Navarro K F and Birch G E 2007 A comprehensive survey of brain interface technology designs *Ann. Biomed. Eng.* **35** 137–69
[83] Wolpaw J R and McFarland D J 2004 Control of a two-dimensional movement signal by a noninvasive brain–computer interface in humans *Proc. Natl. Acad. Sci. USA* **101** 17849–54
[84] Nicolelis M A L and Chapin J K 2002 Controlling robots with the mind *Sci. Am.* **287** 24–31
[85] Bamber D 1975 The area above the ordinal dominance graph and the area below the receiver operating characteristic graph *J. Math. Psychol.* **12** 387–415
[86] Krepki R, Blankertz B, Curio G and Müller K-R 2007 The Berlin brain–computer interface (BBCI)—towards a new communication channel for online control in gaming applications *Multimed. Tools. Appl.* **33** 73–90
[87] Felton E A, Lewis N L, Wills S A, Radwin R G and Williams J C 2007 Neural signal based control of the dasher writing system *3rd Int. IEEE/EMBS Conf. on Neural Engineering* pp 366–70
[88] Perelmouter J and Birbaumer N 2000 A binary spelling interface with random errors *IEEE Trans. Neural Syst. Rehabil. Eng.* **8** 227–32

[89] McFarland J and Wolpaw J 2003 EEG-based communication and control: speed-accuracy relationships *Appl. Psychophysiol. Biofeedback* **28** 217–31

[90] Leeb R, Friedman D, Mueller-Putz D, Scherer R, Slater M and Pfurtscheller G 2007 Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegic *Comput. Intell. Neurosci.* **2007** (8 pages)

[91] Vanacker G, del R Millán J, Lew E, Ferrez P W, Moles F G, Philips J, van Brussel H and Nuttin M 2007 Context-based filtering for assisted brain-actuated wheelchair driving *Comput. Intell. Neurosci.* **2007** (12 pages)

[92] Dix A, Finlay J, Abowd A and Beale R 2004 *Human-Computer Interaction* 3rd edn (Englewood Cliffs, NJ: Prentice-Hall)

[93] Piccione F, Giorgi F, Tonin P, Priftis K, Giove S, Silvoni S, Palmas G and Beverina F 2006 P300-based brain–computer interface: Reliability and performance in healthy and paralysed participants *Clin. Neurophysiol.* **117** 531–7

[94] Abe K, Fujimura K, Toyooka K, Sakoda S, Yorifuji S and Yanagihara T 1997 Cognitive function in amyotropic lateral sclerosis *J. Neurol. Sci.* **148** 95–100

[95] Rippon G A, Scarmeas N, Gordon P H, Murphy L P, Albert S M, Mitsumoto H, Marder K, Rowland L P and Stern Y 2006 An observational study of cognitive impairment in amyotrophic lateral sclerosis *Arch. Neurol.* **63** 345–52

[96] Münte T F, Troger M C, Nusser I, Wieringa B M, Johannes S, Matzke M and Dengler R 1998 Alteration of early components of the visual evoked potential in amyotrophic lateral sclerosis *J. Neurol.* **245** 206–10

[97] Kübler A and Birbaumer N 2008 Brain–computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients? *Clin. Neurophysiol.* **119** 2658–66

[98] Mormann F, Kreuz T, Rieke C, Andrzejak R G, Kraskov A, David P, Elger C E and Lehnertz K 2005 On the predictability of epileptic seizures *Clin. Neurophysiol.* **116** 569–87

[99] Rezek I, Roberts S J and Conradt R 2007 Increasing the depth of anesthesia assessment *IEEE Eng. Med. Biol. Mag.* **26** 64–73

[100] Decharms C 2008 Applications of real-time fMRI *Nat. Rev. Neurosci.* **9** 720–9

[101] Vidal J J 1977 Real-time detection of brain events in EEG *Proc. IEEE* **65** 633–41

[102] Pineda J A, Silverman D S, Vankov A and Hestenes J 2003 Learning to control brain rhythms: making a brain–computer interface possible *IEEE Trans. Neural Syst. Rehabil. Eng.* **11** 181–4

[103] Scherer R, Schlögl A, Lee F, Bischof H, Janša J and Pfurtscheller G 2007 The self-paced Graz brain–computer interface: methods and applications *Comput. Intell. Neurosci.* **2007** (9 pages)

[104] Hjelm S 2003 Research + design: the making of Brainball *Interactions* **10** 26–34

[105] Desain P, Farquhar J, Haselager P, Hesse C and Schaefer R S 2008 What BCI research needs *Proc. ACM CHI 2008 Conf. on Human Factors in Computing Systems (Venice, Italy)*

[106] Farah M J 2005 Neuroethics: the practical and the philosophical *Trends Cogn. Sci.* **9** 34–40

[107] Moreno J D 2003 Neuroethics: an agenda for neuroscience and society *Nat. Rev. Neurosci.* **4** 149–53

[108] Roskies A L 2006 Neuroscientific challenges to free will and responsibility *Trends Cogn. Sci.* **10** 419–23

[109] Caplan A and Elliott C 2004 Is it ethical to use enhancement technologies to make us better than well? *PLoS Med.* **1** 172–5

[110] Neumann N and Kübler A 2003 Training locked-in patients: a challenge for the use of brain–computer interfaces *IEEE Trans. Neural Syst. Rehabil. Eng.* **11** 169–72

[111] Schalk G, Brunner P, Gerhardt L A, Bischof H and Wolpaw J R 2008 Brain–computer interfaces (BCIs): detection instead of classification *J. Neurosci. Methods* **167** 51–62

[112] deCharms R C, Maeda F, Glover G H, Ludlow D, Pauly J M, Soneji D, Gabrieli J D E and Mackey S C 2005 Control over brain activation and pain learned by using real-time functional MRI *Proc. Natl. Acad. Sci. USA* **102** 18626–32

[113] Haynes J-D and Rees G 2006 Decoding mental states from brain activity in humans *Nat. Rev. Neurosci.* **7** 523–34

[114] Norman K A, Polyn S M, Detra G J and Haxby J V 2006 Beyond mind-reading: multi-voxel pattern analysis of fMRI data *Trends Cogn. Sci.* **10** 424–30

[115] Spiers H J and Maguire E A 2007 Decoding human brain activity during real-world experiences *Trends Cogn. Sci.* **11** 356–65

[116] Sitaram R, Caria A, Veit R, Gaber T, Rota G, Kübler A and Birbaumer N 2007 fMRI brain–computer interface: a tool for neuroscientific research and treatment *Comput. Intell. Neurosci.* **2007** (10 pages)

[117] Kay K, Naselaris T, Prenger R J and Gallant J L 2008 Identifying natural images from human brain activity *Nature* **452** 352–5

[118] Mitchell T M, Shinkareva S V, Carlson A, Chang K-M, Malave V L, Mason R A and Just M A 2008 Predicting human brain activity associated with the meanings of nouns *Science* **320** 1191–5

[119] Miyawaki Y, Uchida H, Yamashita O, Sato M, Morito Y, Tanabe H C, Sadato N and Kamitani Y 2008 Visual image reconstruction from human brain activity using a combination of multiscale local image decoders *Neuron* **60** 915–29