BNCI Horizon 2020

The Future of Brain/Neural Computer Interaction: Horizon 2020

Appendix A Research

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This appendix and the corresponding main document can be downloaded from
http://bnci-horizon-2020.eu/

A Research

A.1 Sources

A.1.1 Knowledge from Hallstatt Retreat

During the retreat in Hallstatt, it was decided that the final roadmap will consist of a general part (executive summary) that covers all work packages and scenarios. This part will be followed by use cases with illustrations. Use cases are potential BCI applications. Each use case will be approached from the end user (WP4), research (WP2) and industry (WP3) point of view. These three different perspectives will allow us to analyze the feasibility, bottlenecks, requirements, and commercialization aspects of each use case.

A.1.2 Future BNCI Consortium report

BNCI Horizon 2020 aims to build upon and continue the efforts initiated by the Future BNCI project, which started in January 2010 and ended in December 2011. The final report[1] (published in early 2012) provides the state-of-the-art in BCI research until the end of 2011. The chapters related to the state-of-the-art within BNCI Horizon 2020 were built upon it and extented to additionally include the period from the end of 2011 until the present (end of 2014).

A.1.3 Literature database

The BNCI Horizon 2020 roadmap was not meant to include an extensive and complete review of BCI literature. Instead, the project aims to (1) identify the most important bottlenecks in the development and commercialization of BCIs, and (2) describe the most promising research

[1] http://bnci-horizon-2020.eu/images/bncih2020/FBNCI_Roadmap.pdf

directions to reach specific goals. For this purpose, a literature database of recent and influential literature was set up, which, together with the Future BNCI Consortium Report, forms the basis for a condensed summary of the state-of-the-art in BCI research.

Only highly cited papers were eligible for inclusion in this literature database. Papers that included the term “brain-computer interface” and that were published during 2011, 2012, or 2013 were retrieved from the Web of Science database[2]. Specifically, for each year, each paper was ranked by its number of citations, and for each year only the top 50% articles were retained. The purpose of this procedure was to compensate for the fact that more recently published papers have had less chance of being cited in comparison to papers published longer ago. As of December 12th, 2013, 1001 papers were identified according to this procedure (minimum number of citations: 5, maximum number of citations: 94). For each year (2011, 2012, 2013), the top 50 percent of citations were retrieved. Cutoff values were > 1 for 2011, > 4 for 2012, > 1 for 2013.

Based on the abstracts, all papers were classified into different categories and placed into a Zotero[3] database. All review articles were subsequently read in detail. Of each review, one or more important statements or conclusions were extracted and ordered according to categories such as paradigm, end user type or recording technique. The categorized method facilitated the identification of the most relevant review articles to include in the summarized state-of-the-art sections (see A.2 below).

A.1.4 Researchers’ questionnaire

The roadmap includes researchers’ opinions and visions about the future of BCIs. Whereas the literature review is relevant for describing the current state-of-the-art, it does not suffice to obtain a vision of future developments. To this end, a questionnaire for BCI researchers was designed, in which BCI researchers were asked about their ideas on the future of the BCI field. After characterizing participants by their location, background, and expertise, researchers were invited to suggest a promising application, assign it to one of the scenarios, and identify possible bottlenecks and required research to realize this application. Furthermore, they were prompted to project themselves ahead in time and explain potential killer applications and major research breakthroughs.

The questionnaire was initially designed by the University Medical Center Utrecht (The Netherlands) and shared with four partners of the consortium for editing. After completion, a link to an online version of the questionnaire was sent around to four other members of the consortium for testing and final comments. The final version was distributed to 3291 BCI researchers by the end of May 2014. These BCI researchers were identified through direct contact with BCI research groups and societies. After sending out two reminders, the questionnaire was temporarily closed on 10 July 2014. BCI researchers that did not respond in the first round of the questionnaire received a second invitation in December 2014. This second round was closed at the end of January 2015. A complete report on the Researchers’ Questionnaire can be found in section A.3.1.

[2] http://apps.webofknowledge.com/

[3] https://www.zotero.org/

A.2 Summary of state-of-the-art

A.2.1 BCI concepts and paradigms

Possible control signals for BCIs derive from event-related potentials (ERPs) obtained during oddball paradigms (e.g. P300), modulation of spectral power (e.g. sensorimotor rhythms, SMR), brain signals obtained from the visual cortex (VEP, often steady-state visual evoked potentials, SSVEP), or from single or multiunit recordings.

The P300 ERP is a positive deflection in the scalp EEG or intracranial ECoG signal with a peak amplitude approximately 300 ms after onset of a relevant unexpected auditory, visual or somatosensory stimulus. The visual P300 speller, a typical ERP-based application, comprises a matrix of possible targets, the rows and columns of which flash randomly. If the user focuses attention on a given target, e.g. by counting how often the row/column containing the target is flashed, the P300 event-related potential over parieto-central brain areas is elicited after the target stimulus flashed. From the pattern of the flashed target and whether a P300 was elicited, the BCI system can then infer the intended target letter (Nicolas-Alonso and Gomez-Gil, 2012).

SMR refers to brain activity in the mu (7-13 Hz) and beta band (13-30 Hz) of the EEG or ECoG signal. During actual movements (e.g. briskly lifting a finger), a spatially localized pattern of event-related desynchronisation (ERD) and synchronisation (ERS) can be recorded from electrodes placed over the sensorimotor cortex. Importantly, similar patterns are produced when the movement is only imagined rather than executed, which makes it possible to use SMRs as an input signal for a BCI (Nicolas-Alonso and Gomez-Gil, 2012), for example in severely injured people who cannot move. Besides motor-related changes in mu and beta rhythms, other tasks, such as working memory, have been shown to induce changes in high frequency ECoG power that can be exploited for BCI purposes (Vansteensel et al., 2010).

SSVEPs are responses to visual stimulation. If possible targets are flashed at sufficiently high (> 6 Hz) but different frequencies, sinusoidal steady-state VEPs are elicited whose fundamental frequencies correspond to the frequencies of the focused target (Nicolas-Alonso and Gomez-Gil, 2012).

Single unit and multiunit recordings refer to the use of action potentials of individual or small groups of neurons using penetrating high impedance multi electrode arrays (Lu et al., 2012). Landmark studies in this area have extracted certain movement parameters (e.g. intended arm movement direction) from the spiking pattern of a small area in the sensorimotor cortex, and used this information for multidimensional control of a computer cursor or robotic arm (Hochberg et al., 2006; Velliste et al., 2008; Hochberg et al., 2012).

BCI paradigms can be classified into exogenous and endogenous systems, depending on whether or not external stimulation is required (Nicolas-Alonso and Gomez-Gil, 2012). Exogenous BCIs (e.g. based on P300 or SSVEP) rely on brain responses evoked by external stimuli (e.g. visual, auditory or somatosensory). Endogenous BCIs depend on brain activity that users change voluntarily, unaided by any external stimuli. Typically, they offer continuous output (such as the use of SMR during imagined movements for cursor control, e.g. McFarland et al., 2010; Allison et al., 2012a) and can be initiated at will. Finally, hybrid BCIs combine two or more central nervous system (CNS) outputs or classifier results (Pfurtscheller et al., 2010; Müller-Putz et al., 2011; Wolpaw and Wolpaw, 2012). Generally, exogenous BCIs can be used by a higher number of users, require less training, fewer sensors, and show a higher information throughput than endogenous systems. However, users need to permanently direct their attention and gaze towards the stimuli, which might be tiring in the long run. More importantly, employing a sensory channel for BCI makes this channel unavailable for other tasks.

Despite strong efforts, current BCIs still face several challenges that limit their usefulness for most medical and societal applications. These challenges are related to increasing bit rates (Allison et al., 2012b), optimizing sensors, signal processing and classification techniques, but also to the type of control signal and overall systems design. Many of these issues directly affect BCI performance, which is a field of active research and which is addressed at multiple levels of the BCI loop. At the paradigm level, with exogenous P300 BCIs, the time required to integrate over several stimuli to reach a decision limits its effective throughput. However, increasing the signal-to-noise ratio (Kaufmann et al., 2011) and optimizing the number of stimuli (Schreuder et al., 2013) have great potential for increasing throughput. Performance of SSVEP BCIs, on the other hand, depends on the number of discriminable frequencies, which is affected by hardware (e.g. LEDs vs. LCD screens) (Nicolas-Alonso and Gomez-Gil, 2012), setups (Lim et al., 2013), and coding schemes (Zhang et al., 2012). New approaches even allow continuous (e.g. smooth cursor control) instead of discrete control (e.g. choice selection) (Wilson and Palaniappan, 2011). Predictors of endogenous BCI performance include psychological, neurophysiological, and neuroanatomical variables. However, it is still unclear whether these insights can actually improve performance (Grosse-Wentrup and Schölkopf, 2013). Hybrid BCIs rest on the idea that a combination of several input channels or BCIs, each optimized for a particular task, improves accuracy and reduces errors (Pfurtscheller et al., 2010). Several technical approaches have been proposed with the objective to either fuse multiple neuronal sources (e.g., EEG and NIRS, ERP and SSVEP or ERP and spectral power features) (Allison et al., 2010; Allison et al., 2012a; Kaufmann et al., 2014; Leeb et al., 2010; Fazli et al., 2012; Speier et al., 2013; Zhang et al., 2013) or to integrate the BCI into existing technology. BCI was proposed as additional input channel for navigation control as well as gaming applications (Kim et al., 2014; Marshall et al., 2013; Leeb et al., 2013; Carlson et al., 2013). Not all combinations, however, are equally effective (Müller-Putz et al 2011; Amiri et al., 2013). Intelligent control systems can further increase the performance of a BCI system. The general idea is to reduce the dependence on (potentially) noisy signals by delegating as much work as possible away from the user towards the BCI system. For example, a wheelchair user might use a BCI to select waypoints, which would be inputs to a hierarchical control strategy (Allison et al., 2012a), namely shared control (Leeb and Millán, 2012; Carlson and Millán, 2013).

In order to objectify BCI performance and improvements therein, quantitative measures are necessary. The current plurality of performance metrics used to evaluate BCIs is critical. Although this issue is a matter of active research, generally, no single metric can capture a system's performance adequately (Thompson et al., 2013). Tests in healthy participants using typing tasks show very low bitrates (BR) for endogenous (SMR) BCIs (BR = 0.59 (Millán and Mouriño, 2003)), but higher rates for exogenous systems (e.g. BR = 61.7 for a P300 BCI, BR = 24.5 for a SSVEP BCI (Yuan et al., 2013)). However, bitrates show strong heterogeneity across implementations and settings (Nicolas-Alonso and Gomez-Gil, 2012), making reliable comparisons difficult. In addition, since a specific BCI may or may not use additional components within the BCI software ecosystem (e.g. automatic error correction, or predictive text entry), these simple measures may not accurately reflect the user's perception of the system's overall performance. Furthermore, reporting simple parameters such as accuracy ignore the need of many potential application areas to balance the tradeoff between accuracy and speed. In an attempt to address this problem, more global measures, such as the utility metric (Dal Seno et al., 2010), describing the number of correctly spelled letters per unit of time have emerged (Thompson et al., 2013).

A.2.2 BCI data processing

Real-time analysis of brain signals is challenging for two main reasons. First, recorded neuroimaging data are a superposition of the brain signals of interest with a plethora of other signals - from other brain regions, from muscles, and from non-biological artifacts. Second, brain activity exhibits a huge variability across people. State-of-the-art BCI systems use adaptive signal processing and machine learning algorithms to extract meaningful information from brain signals. These techniques rely on a statistical analyses of calibration data to optimize classification models and reduce the need for lengthy training. There have been recent efforts to unify BCI data processing into unique software platforms (see Brunner et al., 2013 for a review) with the goal to simplify the access to existing and novel analysis methods and to stimulate international collaborations.

The development of BCI processing and classification algorithms aims at providing the best performance (accuracy, speed, throughput etc.). There are three kinds of components (i.e. spectral power changes, ERP, SSVEP) that can be exploited by BCI systems based on EEG, MEG, and ECoG signals. Feature extraction, the process to extract a meaningful content from the human brain to be interpreted by a computer, has been optimized for each component individually. For example, when extracting spectral power changes or SSVEPs, linear filters are applied to increase the signal-to-noise ratio of the neuronal source of interest. Such filters can be trained in a supervised (e.g. CSP) or unsupervised (e.g. ICA) manner for each subject individually. ERP features are commonly extracted by averaging the channelwise EEG amplitudes in time intervals that are specified relative to the stimulus. Such intervals can either be predetermined or chosen individually through a heuristic or manual selection. Conversely to feature extraction, preprocessing and classification are very similar in most online BCI systems, with most paradigms being driven by a binary classifier (Blankertz et al., 2008; Krusienski et al., 2008; Blankertz et al., 2011; Wang et al., 2008; Liang and Bougrain, 2012). In order to improve performance of invasive BCIs based on multielectrode arrays (MEAs), optimized Kalman filter approaches (Malik et al., 2011; Gilja et al., 2012; Dangi et al., 2013) have been investigated as well as alternative approaches for feature extraction, such as decoding based on threshold-crossing events, instead of using isolated action potentials (Chestek et al., 2011; Homer et al., 2013).

The ease of use of both non-invasive and invasive BCI systems needs to be enhanced to make them applicable for real world applications. Due to the non-stationary nature of neural data, maintaining performance over time requires continuous adaptation of the BCI system. To this end, novel adaptive processing methods have recently been explored for both non-invasive and invasive settings (Vidaurre et al., 2011; Kindermans et al., 2014; Sanchez et al., 2014; McFarland et al., 2011; Samek et al., 2012; Lu et al., 2012; Moran, 2010). Some approaches have shown performance improvements of up to eight times (Orsborn et al., 2012) also across years (Gilja et al., 2012). For implanted multielectrode arrays (MEAs), short-term and long-term non-stationarities may also be addressed by using more channels, or by using multi-units or LFPs (Lu et al., 2012; Bansal et al., 2012; Gilja et al., 2011). There are indications that ECoG recordings are relatively stable and may require less adaptation (Blakely et al., 2009; Chao et al., 2010).

Besides the above mentioned issues, there are other challenges related to data processing for BCIs that are currently investigated in various ways. Non-invasive BCI systems need to be operated with novel sensors that are quickly applicable (e.g. dry electrodes for EEG, see below). However, this hardware delivers highly variable signals that are commonly contaminated by numerous nonstationarities and artifacts. There is a need for novel processing tools that account for such technical artifacts. Another practical aspect is the reduction of the calibration time. This can be achieved by transferring knowledge from existing data to new users (Kindermans et al., 2014; Lotte et al., 2009), or by using self-calibrating classifiers (Bishop et al., 2014). Last, the use of powerful machine learning techniques brings about the necessity for a careful validation (Lemm et al., 2011). Moreover, there are novel approaches to use purely data-driven feature extraction methods in order to validate neurophysiological hypotheses (Orsborn and Carmena, 2013) and to interpret the neuronal sources on which the BCI is relying.

A.2.3 BCI hardware and recording techniques

A.2.3.1 Non-invasive techniques

Electroencephalography

Electroencephalography (EEG) is the most popular signal type for non-invasive BCIs (Hwang et al., 2013). It records electrical activity of neural assemblies on a millisecond time scale using sensors placed on the scalp. Besides this excellent time resolution, EEG is portable and relatively inexpensive. However, the spatial resolution of EEG is rather low, and the signal is susceptible to many types of artifacts (Fatourechi et al., 2007; Sabarigiri and Suganyadevi, 2014).

At the hardware level, there are currently three types of approaches that may improve EEG-based BCI performance and usability. First, traditional EEG sensors (so-called electrodes) require gel, which is a major concern that limits a more widespread adoption of EEG due to limited usability. An alternative approach is based on water (Volosyak et al., 2010), which does not require people to wash their hair after EEG measurement, but water-based sensors only work as long as they are wet (i.e. several hours). Another emerging alternative is the use of dry electrodes (Fonseca et al., 2007), which ideally feature comparable signal quality, improved wearing comfort, and a drastically reduced setup time. A second issue is wearability. Most EEG systems use leads to connect the electrodes to the amplifier, which places restrictions on the mobility of EEG recordings. Wireless systems establish a wireless connection between the amplifier and a computer, but their power consumption and physical size must be minimized. Last, many current EEG systems ship with active electrodes, which include small preamplifiers directly on each electrode and thus minimize artifacts induced by cable sway. Alternatively, shielded cables are also used in some systems.

Magnetoencephalography

Magnetoencephalography (MEG) measures the weak magnetic fields caused by currents within the brain (Hansen et al., 2010). Like EEG, it is a direct measurement of neural activity with high time resolution (Baillet, 2011). MEG is only sensitive to tangential sources on the cortical surface. The magnetic fields are less influenced by volume conduction, and therefore MEG has a slightly better spatial resolution than EEG. A limited number of studies has demonstrated successful implementation of MEG-based BCIs (Mellinger et al., 2007; Buch et al., 2008), but this field is still in a very early stage and the relative advantages and disadvantages compared to other signal acquisition techniques are currently unclear (Nicolas-Alonso and Gomez-Gil, 2012). However, it is unlikely that these BCIs will see adoption outside the research field due to the high cost and physical constraints of the measurement device (i.e. size, requirement for magnetic shielding) (Nicolas-Alonso and Gomez-Gil, 2012; Shih et al., 2012).

Functional magnetic resonance imaging

Functional magnetic resonance imaging (fMRI) measures the hemodynamic response to neural activation in the brain. It reveals locations with changes in oxygenated and deoxygenated blood flow and volume (Hillman, 2014) by using blood-oxygen-level dependent (BOLD) contrast imaging methods. The main advantage of fMRI is its high spatial resolution.

There are several approaches to improve image quality. First, the signal-to-noise ratio increases with increasing field strength. Currently, clinical routine and research scanners work with 1.5-3T, and 3T-7T, respectively (Van der Zwaag et al., 2009). Another way to improve image quality in defined regions is to apply multi-channel coils (Parikh et al., 2011; Salomon et al., 2014). Third, new image acquisition sequences are constantly being developed, which further improve image quality (Budde et al., 2014; Mugler, 2014; Wang et al., 2014).

Although physical (size, strong magnetic field), methodological (e.g. low temporal resolution, delayed haemodynamic response), and financial aspects constrain fMRI for most BCI applications (Nicolas-Alonso and Gomez-Gil, 2012), there is an increasing interest to use fMRI for detecting consciousness (Owen, 2013), neurofeedback training (Weiskopf, 2012) or to prelocalize regions for subsequent electrode implantation (Vansteensel et al., 2010; Shih et al., 2012). In this respect, the exact relationship between the BOLD response and electrical neuronal activity is currently unclear and requires investigation. Besides these applications, this technique will remain an excellent scientific tool to complement BCI research (Nicolas-Alonso and Gomez-Gil, 2012).

Functional near infrared spectroscopy

Functional near infrared spectroscopy (fNIRS) is an emerging non-invasive optical technique for the assessment of cerebral oxygenation (Ferrari and Quaresima, 2012; Boas et al., 2014). Similar to fMRI, fNIRS measures hemodynamic changes in the brain, but fNIRS is less expensive and more portable than fMRI (Nicolas-Alonso and Gomez-Gil, 2012). The technique is relatively new, but BCI applications seem feasible, either as an alternative to (Sitaram et al., 2007) or in combination with (Pfurtscheller et al., 2010; Fazli et al., 2011) EEG. Due to the complementary nature of fNIRS and EEG, such a combination may be used for BCIs if shown beneficial. Similar to fMRI, fNIRS measures BOLD responses, which are typically slow and have a strong delay relative to the underlying neuronal events. Compared to fMRI, fNIRS has a worse spatial resolution and a lower signal to noise ratio (Cui et al., 2011). A practical issue is the optimal fixation of the optical probes to the head and finding a balance between patient comfort and stability of the recordings. Another important aspect is the large number of models that describe changes in oxygenation. For clinical application of fNIRS, analysis should be standardized (Obrig and Steinbrink, 2011).

A.2.3.2 Invasive techniques

Multi-electrode arrays

Multi-electrode arrays (MEAs) for BCIs are arrays of tens to hundreds of needles of 1-10 mm, introduced into the cortical surface. MEAs allow recording of local field potentials (LFPs), multi- and single-unit activity. The Blackrock (Utah) array is approved for long term human use (Lu et al., 2012) and has been used in the BrainGate(2) trials (Hochberg et al., 2006; Hochberg et al., 2012).

MEA BCI research has focused on combining single unit information of many electrodes, thereby maximizing the number of degrees of freedom (Georgopoulos et al., 1982; Hochberg et al., 2006). Research is mainly performed with non-human primates, and has demonstrated the use of MEA signals to control a prosthetic arm in several directions for self-feeding (Velliste et al., 2007). The BrainGate(2) trials have so far enrolled 11 tetraplegic patients, and have demonstrated multidimensional control over computer cursors and artificial limbs using imagined movement, months to years after implantation (Hochberg et al., 2006; Hochberg et al., 2012). Despite these promising reports on long-term recordings with MEAs (Lee et al., 2013), tissue reaction, tissue damage and the associated signal loss remain an issue of concern (Shih et al., 2012; Nicolas-Alonso and Gomez-Gil, 2012; Lee et al., 2013). Approaches currently being investigated to address this issue are biocompatible coatings, optimized algorithms or using LFPs or multiunit recordings (Gilja et al., 2011; Lu et al., 2012; Lee et al., 2013). Attempts to further improve and extend the usability of MEA BCI systems are the development of wireless solutions (Chestek et al., 2009; Sharma et al., 2012; Schwarz et al., 2013; Yin et al., 2013) and recent non-human primate studies that demonstrate the possibility to restore grasping with a temporarily paralyzed limb using muscle stimulation (Shih et al., 2012; Lu et al., 2012). In addition, efforts are ongoing to induce somatosensory perception by electrical stimulation of the cortex (Schultz and Kuiken, 2011; Lee et al., 2013).

Electrocorticography

Electrocorticography (ECoG) measures fields generated by large groups of neurons, using cortical surface electrodes. ECoG-based BCI control is mostly based on spectral power changes in isolated brain areas (Shih et al., 2012), but ERPs are also used (Brunner et al., 2011; Song et al., 2012). Currently, these methods are mainly considered for medical applications, for which they are regarded highly promising because of the high quality signals in terms of spatial resolution and spectral width (Nicolas-Alonso and Gomez-Gil, 2012; Shih et al., 2012; Lee et al., 2013).

ECoG BCI research is mainly aimed at replacing lost motor function and is mostly performed with epilepsy patients with subdural, subchronic implants (Ritaccio et al., 2011). Quick and accurate control over a cursor (1-3 dimensions), prosthetic hand and speller have been demonstrated using e.g. motor execution, motor or sensory imagery, working memory, visual attention and overt or imagined articulation (Vansteensel et al., 2010; Andersson et al., 2011; Shih et al., 2012; Zhang et al., 2013). Time resolution is at least comparable to that of EEG-based systems and signal quality in terms of spatial resolution and spectral width is better (Nicolas-Alonso and Gomez-Gil, 2012).

Long term stability of human ECoG recordings is not yet assessed, but recordings over multiple days in humans and multiple months in animal studies are promising (Blakeley et al., 2009; Chao et al., 2010; Moran, 2010; Henle et al., 2011). One study has reported on an ECoG-based BCI for cursor control in a tetraplegic patient during 28 days before explantation (Wang et al., 2013). A more long term study using a completely implantable device (Rouse et al., 2011) is currently recruiting patients. Long term usability of ECoG-based BCIs in a home environment will depend on completely implantable or wireless solutions (Charvet et al., 2013; Matsushita et al., 2013), since this strongly reduces infection risk and thereby increases safety. Other attempts to increase safety are epidural recordings. In primates, stable impedance and signal-to-noise ratio were obtained for 15 months without any visually detectable effects on the dura mater or the underlying brain. Signals from 3 mm apart could be modulated independently. Signal loss compared to subdural recordings is substantial, but does not hamper classification (Moran, 2010; Torres Valderrama et al., 2010; Ritaccio et al., 2011).

Typical ECoG implants are grids and strips of electrodes with 1 cm interelectrode distance (approved for subdural use for 28 days), but new ECoG grids, ranging from closely spaced electrodes to actual high-density micro-electrodes are also becoming available. Using these grids, more information can be extracted from a small patch of cortex, allowing more degrees of freedom (Wang et al., 2013). To make optimal use of the detailed organization of the cortex, even denser grids are necessary. These could be based on new, flexible materials with unique properties, allowing a wide range of electrode configurations (Ritaccio et al., 2011). It will take considerable financial and time investments to obtain regulatory approval for long term implantation of these grids in humans. Other attempts to maximize the number of degrees of freedom extracted from ECoG recordings are based on optimizing decoding algorithms (Liang and Bougrain, 2012; Do et al., 2013) and spatiotemporal features for decoding and control (Kubanek et al., 2009; Onaran et al., 2011; Mugler et al., 2014).

A.3 Future outlook

A.3.1 Report on Researchers' Questionnaire

Introduction

This questionnaire was designed to obtain the opinion of BCI researchers about their field: what BCI applications do researchers consider feasible, what hurdles still need to be taken before these applications become actual products and which research activities would be needed to accomplish this?

Methods

General

The questionnaire consisted of three parts. In part A (respondents), a list of multiple choice questions was used to characterize each researcher by a large range of criteria, such as their background and what type of BCIs they work on. In order to map the feasibility of BCI devices in the coming 5 to 10 years, we asked participants in part B (near future) to suggest a potential BCI application, assign this application to one of the six scenarios (replace, restore, enhance, improve, supplement, and research tool), and indicate if they would want to develop this application using an invasive or a non-invasive approach. Together, this information aids to sketch the near future of BCI applications and devices. Then, participants were asked to rate several statements about potential bottlenecks and future research, each with their specific application in mind, on a five-point scale (strongly agree, agree, neutral, disagree, strongly disagree). The sixth possible answer was "not applicable". In part C (far future), participants were asked to "think out of the box", step into the far future and brainstorm about potential killer applications or major research breakthroughs.

Data acquisition

The questionnaire was sent around to 3291 BCI researchers by the end of May 2014. Each researcher received an email describing the purpose of the questionnaire and an invitation to fill it out. In the email, a link to the questionnaire (Google Forms) was provided. The BCI researchers were identified after contacting several BCI research groups and societies. Two reminders were sent until the questionnaire was temporarily closed on July 10th, 2014. In early December 2014, researchers who did not respond in the first round received a second invitation to fill out the questionnaire. This second round was closed in the beginning of January 2015.

Data analysis

A. Respondents

The answers respondents gave in part A were analyzed using Google Statistics to characterize their background, expertise, and working area. Notably, for many questions, multiple answers were allowed. The total number of selections for a certain multiple choice question may exceed the total number of respondents. To ensure to represent this case in the results, percentages given in the Results section were computed relative to the total number of respondents and the total per question may therefore exceed 100%, unless stated otherwise. For readability purposes, many issues of this part of the questionnaire are not described here.

B. Near future

For part B, our aim was to identify specific bottlenecks and research directions for each of the six scenarios. As a first step of this analysis, two members of the consortium double checked the clarity of the descriptions of the BCI applications described by the respondents in part B, as well as the assignments of each of the suggested BCI applications to the scenarios, and re-assigned if necessary. Unclear descriptions were excluded from analysis. If the two raters disagreed in the first round, they discussed the application until they reached consensus.
We only included combinations of scenarios/approaches (invasive/non-invasive) with at least 10 respondents. Per scenario/approach combination, the responses were analyzed as a group. We first labeled the possible choices: ‘Not Applicable’ with 0, ‘Totally Disagree’ with 1, ‘Disagree’ with 2, ‘Neutral’ with 3, ‘Agree’ with 4, and ‘Totally Agree’ with 5. Subsequently, the center of mass was calculated by summing the product of the number of subjects in each choice and the label given to that choice. This sum was divided by the total number of respondents within that scenario/approach combination. By rounding the final outcome to the nearest integer, we could define for each specific issue the overall level of agreement with a certain statement. A score of 4 or 5 meant that most respondents agreed or strongly agreed with the statement, whereas a score of 1 or 2 was related to an overall disagreement or strong disagreement with the statement. Neutral statements (i.e. score of 3) are not reported here.

C. Far Future

Respondents’ ideas about the far future, for example killer applications or major research breakthroughs, inspired the initial list of Use Cases of the roadmap (see Appendix D of the roadmap for a selection). Besides that, some representative examples were identified and described in the Results section.

Results

A. Respondents

Two rounds of the questionnaire resulted in 298 (9.1%) responses. Most respondents worked in Europe, but we also received a substantial number of responses from people working in North

America and Asia (Figure 1). The majority of BCI researchers had some form of background or training in the field of Engineering (>60%). Computer Science and Neuroscience came second and third respectively. Notably, many respondents reported two training backgrounds. Respondents covered a wide range of positions in their institute, such as post-doc, dean, PhD student or head of research and R&D departments, and more than 70% entered the field less than 10 years ago.

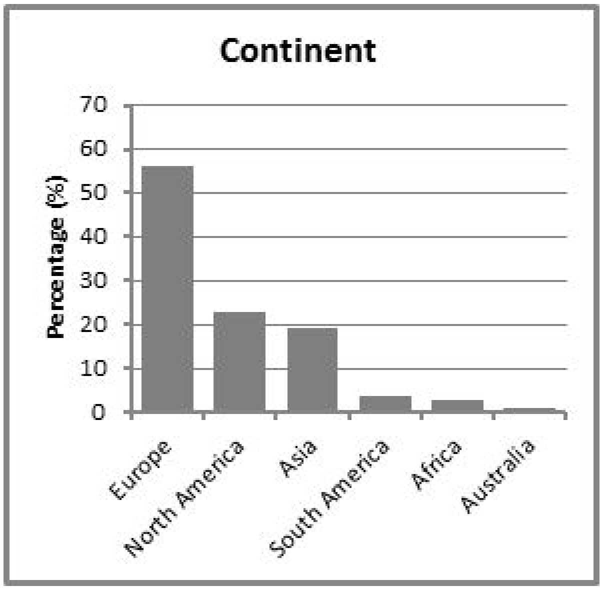

Figure 1. Continent where respondents perform BCI research.

A large majority of the respondents (n=264, 89%) predominantly used non-invasive BCI systems, almost all based on EEG (>90% of researchers working on non-invasive BCIs). The respondents that used invasive BCI systems (n=34, 11%) recorded signals mostly with surface electrodes (>60% of researchers working on invasive BCIs).

There was an interesting distribution over continents of respondents working on invasive and non-invasive BCIs: Only 8% (13/167) of respondents from Europe and 4% (2/57) of respondents from Asia worked on invasive BCIs, whereas this percentage was 26% (18/68) for respondents of North America and 18% (2/11) for South America (Figure 2).

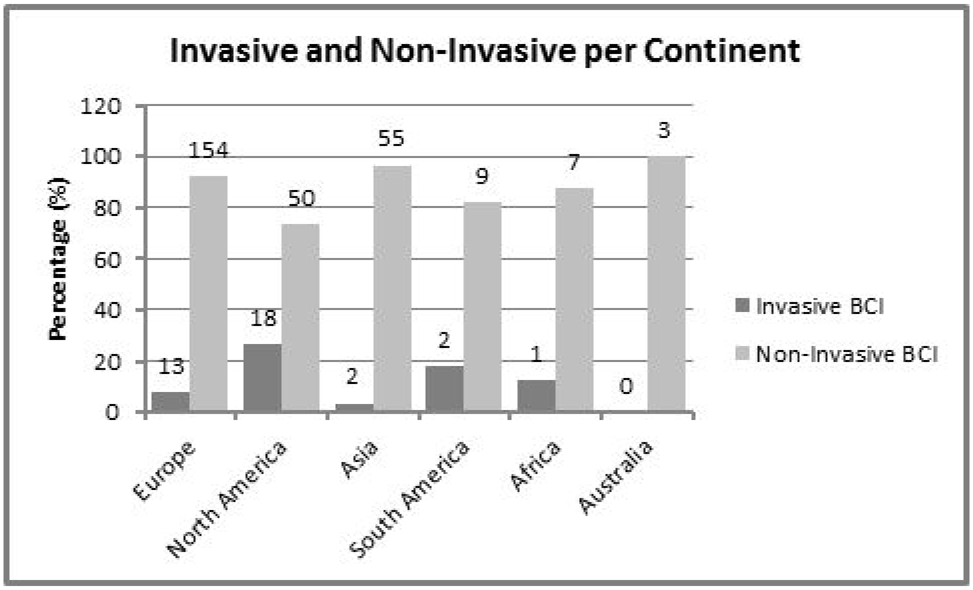

Figure 2. Percentage of respondents in invasive and non-invasive BCI research, per continent. Absolute numbers are indicated above each column.

Brain functions used for decoding were mainly motor function (>70%), but also other functions, such as attention and visual perception are addressed by many respondents (>40% each). Signals were mainly decoded from healthy subjects (>80%) and patients (>40%), and only a few people worked with animal models (<10%, Figure 3).

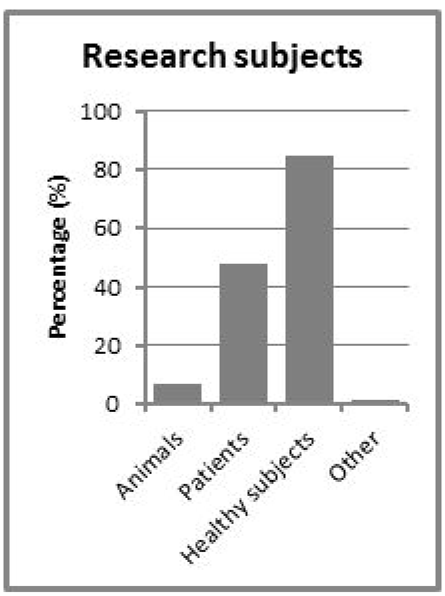

Figure 3. Research subjects of respondents.

B. Near future

The 298 respondents of the questionnaire together submitted 364 BCI applications: 232 people submitted one application, and 66 submitted two applications. The descriptions were unclear in 46 cases and these responses were excluded from analysis, leaving 318 usable descriptions of BCI applications. In some of the 318 cases, the description was clear, but the consortium members reviewing the descriptions did not agree with the scenario it was assigned to. In 69 cases, we reassigned the BCI application to another scenario than it was originally assigned to by the respondent.

When asked which BCI devices could be feasible within the next 5 to 10 years, most respondents (34%) chose devices that replace natural CNS output. Other respondents described BCI applications that may improve (26%), enhance (16%), supplement (12%), and restore (5%) natural CNS output or that can be used as a research tool (7%). Respondents preferred the feasible application to be developed by using a non-invasive BCI system (86%), i.e. one that would not require surgery (see Table 1). This large percentage aiming for a non-invasive BCI corresponded remarkably to the percentage of respondents working on non-invasive BCIs.

	Replace	Restore	Improve	Enhance	Research	Supplement	**Total**
Invasive	22	6	9	3	4	1	**45 (14%)**
Non-invasive	83	11	75	47	19	38	**273 (86%)**
Total	**105 (34%)**	**17 (5%)**	**84 (26%)**	**50 (16%)**	**23 (7%)**	**39 (12%)**	**318**

Table 1. Number of respondents describing an invasive and a non-invasive solution for an application within one of the 6 scenarios.

Most of the replace solutions described would be applied for communication, specifically for communication in locked-in patients. Other representative examples of feasible BCI applications aimed to *(i)* enhance cognitive functions, *(ii)* improve motor rehabilitation after stroke, *(iii)* supplement during gaming or home automation, *(iv)* restore lost movement or speech, and *(v)* be used as a research tool for cognitive assessment and mapping or technique improvement purposes.

In the subsequent analysis, only groups of 10 or more scenario/approach combinations were included. Whereas all non-invasive scenarios could be analyzed, only the Replace scenario was included for the invasive approach, since only for this scenario, a sufficient number of respondents (i.e. 83) described an invasive approach (Table 1).

Potential Bottleneck	Replace	Restore	Improve	Enhance	Research Tool	Supple-ment
(Longterm) system durability is not yet good enough						
(Longterm) system performance is not yet good enough						
(Longterm) risks to the user are too high						
There is currently insufficient evidence about (longterm) system durability						
There is currently insufficient evidence about (longterm) system performance						
There is currently insufficient evidence about (longterm) safety of the user						
Potential users do not know about this BCI tool						
The size of the target population is too small for commercialization						
The advantages over existing non-BCI solutions are too small						
It is unclear what the advantages of the BCI system are, compared to existing non-BCI solutions						
The price is too high						
The currently available equipment is too complicated for home-use						
The currently available hardware is cosmetically unappealing						
The currently available systems do not meet the needs and wishes of the user appropriately						
The currently available systems are too large						
The end-user image is stigmatized by wearing a BCI system						

Table 2. Bottlenecks considered relevant (green, score 4 or 5) or irrelevant (grey, score 1 or 2) for non-invasive applications within each of the six scenarios. White means a (rounded) score of 3.

General issues for non-invasive scenarios

Analysis of the responses given in part B revealed that several issues applied to all or almost all of the six non-invasive scenarios (Table 2). When asked to rate potential bottlenecks, participants did not agree with the statements that the long term risks are too high (6/6 scenarios) and that there is insufficient evidence for user safety (6/6), indicating that the long term risks of non-invasive applications are considered acceptable and there is sufficient evidence for this conclusion. Most people agree or strongly agree, however, that (long term) system performance of BCI tools is not yet good enough (6/6), that potential users do not know about the BCI tools (5/6), and that current systems are too complicated for home use (5/6). When asked about the focus of BCI research in the coming 5-10 years (see Table 3), participants agreed on the need for the development and testing of new sensors (6/6) and new signal processing techniques for improving system performance (6/6). Participants also indicated that there is a need for clinical trials to demonstrate system performance (5/6) and for identifying the wishes and needs of the end users (6/6).

Possible Research Direction	Replace	Restore	Improve	Enhance	Research Tool	Supple-ment
Developing and testing new sensors						
Developing and testing advanced signal processing techniques for improved system performance						
Clinical trials to demonstrate system durability						
Clinical trials to demonstrate system performance						
Clinical trials to demonstrate system safety						
Identifying the wishes and needs of the end-users						
Clinical trials to demonstrate risk-benefit ratio for end-users						

Table 3. Research directions considered relevant (green, score 4 or 5) or irrelevant (grey, score 1 or 2) for non-invasive applications within each of the six scenarios.

Invasive replace scenario

For the invasive replace scenario, participants believe that this approach has clear advantages over other non-BCI tools and that there is sufficient evidence for this (Table 4). They also agree that current system durability and performance are insufficient and that there is insufficient evidence for system performance and the risk/benefit ratio for end users. The lack of awareness about BCIs, which was mentioned as a bottleneck for all non-invasive solutions, was also reported by participants addressing invasive replace solutions. Much research is still needed for this type of applications (Table 5). All statements provided in the list of required BCI research received a rating of 4. This means that new sensor and amplifier techniques are needed, as well as signal processing techniques that improve system performance. Also, the BCI community needs to investigate the wishes and requirements of the end users, and perform clinical trials on system durability, performance, safety, efficacy (compared to non-invasive), and risk-benefit ratio for end users.

C. Far Future

About 60% of respondents described what they considered a major breakthrough in invasive or non-invasive BCIs, such as a killer application or major research advancement. For both types of BCI applications, many of the responses could be roughly divided into the following categories: (1) issues related to signal acquisition and decoding, (2) applications for patients, and (3) applications for healthy users.

Concerning non-invasive signal acquisition and decoding, respondents for example described 'a BCI system [...] small in size, accurate, easy to operate and install, portable, efficient and non-expensive', 'wireless, thin sensors that can be placed on the head without preparation time', or 'dry electrodes that actually work well'. Typical phrases for invasive acquisition and decoding issues were 'very simple, an electrode technology that works long term', 'safe, long term implants for signal acquisition', or 'wireless invasive BCIs that could stay inside the user's brain (for lifetime), without other people recognizing the device (no cables hanging out, etc.)'.

Potential Bottleneck	Replace - Invasive
(Longterm) system durability is not yet good enough	
(Longterm) system performance is not yet good enough	
(Longterm) risks to the user are too high	
There is currently insufficient evidence about (longterm) system durability	
There is currently insufficient evidence about (longterm) system performance	
There is currently insufficient evidence about (longterm) safety of the user	
There is currently insufficient evidence about the (longterm) risk/benefit ratio for the user	
Potential users do not know about this BCI tool	
The size of the target population is too small for commercialization	
The advantages over existing non-BCI solutions are too small	
It is unclear what the advantages of the BCI system are, compared to existing non-BCI solutions	
The price is too high	
The currently available equipment is too complicated for home-use	
The currently available hardware is cosmetically unappealing	
The currently available systems do not meet the needs and wishes of the user appropriately	
The currently available systems are too large	

Table 4. Bottlenecks considered relevant (green, score 4 or 5) or irrelevant (grey, score 1 or 2) for invasive Replace applications.

Possible Research Direction	Replace - Invasive
Developing and testing sensors for bio-compatible, longterm invasive measurement	
Developing and testing advanced signal processing techniques for improved system performance	
Developing and testing fully implantable, multi-channel amplifiers with long battery-life	
Clinical trials to demonstrate system durability	
Clinical trials to demonstrate system performance	
Clinical trials to demonstrate system safety	
Clinical trials t o demonstrate system efficacy in comparison to related non-invasive solutions	
Clinical trials t o demonstrate risk/benefit ratio for end-users in comparison to related non-invasive solutions	
Identifying the wishes and needs of the end-users	

Table 5. Research directions considered relevant (green, score 4 or 5) or irrelevant (grey, score 1 or 2) for invasive Replace applications.

Non-invasive solutions described for patients seem to focus largely on the 'improve' scenario: 'A non-invasive killer application would be the use of BCIs for in-home treatment of stroke with dry electrodes in a headset. It would be something that could be rented, sent home with a patient, and monitored remotely. It would result in restored physical function' or 'rehabilitation and neurofeedback of individuals with brain injuries in particular stroke'. Invasive killer applications for patients were often related to prosthesis control: 'Natural control of artificial limbs (replace) or reactivation of lost functionality (restore), including sensory input to the brain' or 'control of an artificial limb outside a laboratory setting'.

Both invasive and non-invasive BCI applications were described for healthy end users. Respondents foresee non-invasive gaming applications (e.g. 'A BCI that provides a gamer with a real, practical advantage in a popular online game. This means: someone using a BCI (probably with conventional interfaces) has an advantage over someone who uses no BCI'), but also 'personal brain health care system' and 'operators mental states recognition in working places'. Invasive applications for this group of people were for example 'tweeting messages directly between brains', 'self-training games on phones that work using single electrodes' or 'BCI should give all possible information about our body and we are supposed to be able to detect our diseases and problems within the body for informing the doctors'.

Discussion

As far as the authors are aware, this Researchers' Questionnaire is the first in which BCI researchers are asked about their view on the future of the field, to describe the most promising applications, and to identify the most important hurdles in getting these products available for end users. With two rounds of the questionnaire, we obtained 298 responses, which is 9.1% of the 3291 BCI researchers we identified through various channels. Notably, this percentage may be an underestimation, since it is unknown how many of the contacts are still active in BCI research. Nevertheless, the relatively limited response rate is an obvious limitation of the current study. Another limitation is that we potentially have a bias towards European respondents: more than 50% of the responses came from people working in Europe. Considering the rationale of the questionnaire, being part of the BNCI Horizon 2020 roadmapping activities, this large percentage of European respondents may not be surprising: they may have more incentive to give their opinion about where the BCI field should head in the future. Despite these constraints, the questionnaire identified a number of interesting issues that are worth mentioning.

A. Respondents and current state of BCI research

Respondents

The background and training of the respondents of our questionnaire was quite variable, with a strong representation of technical disciplines and neurosciences. This corresponds with a previous survey among BCI researchers about ethical issues (Nijboer et al., 2013) and with the multidisciplinary character of the BCI research and development process, in which in-depth knowledge about brain functions needs to be combined with advanced mathematical and engineering solutions in order to develop products that can be used in the daily life of patients or healthy subjects. Almost 10% of BCI researchers had a medical training, which may be indicative for a considerable interest from the treatment and rehabilitation professions.

Current state of BCI research

Although there are a number of attempts to use metabolic signals for BCI purposes (e.g. fNIRS, fMRI), the field remains dominated by electrical signals: more than 95% of respondents indicate that they use EEG, MEG, or invasive electrodes as their main signal acquisition technique. This outcome corresponds to a recent survey among BCI game developers, researchers, and users, which indicates that EEG is by far the most often used non-invasive acquisition technique (Ahn et al., 2014). The poor time resolution of metabolic signals is the main reason that fNIRS and fMRI are not often used for real time applications (Sitaram et al. 2012). However, in earlier stages of BCI development fMRI has a significant value, such as in the search for usable brain functions, regions and paradigms. In this respect, it is interesting to note that (imagined, attempted or executed) movement remains the brain function most often used in BCI studies, although more cognitive functions increasingly gain attention. Almost half of our respondents indicate they investigate attention or visual perception for decoding.

BCI research seems to be dominated by non-invasive approaches. This may not be surprising considering the practical difficulties of invasive BCI research, the most important one of which is the limited number of available (human) subjects. In this respect, the large difference between continents in the ratio of invasive/non-invasive researchers is striking. Whereas the percentage of respondents working on invasive BCIs is 8% (13/167) within Europe, this number is three times as high among our North American respondents (26%, 18/68). This discrepancy is well-known in the BCI field (Berger et al., 2007), and may be attributed to a different perception of e.g. the risk of implants, or to different regulations for invasive human and animal studies. Interestingly, the percentage of 'invasive BCI researchers' (11%) within the current sample corresponded largely with the percentage of invasive BCI applications that were suggested in part B (14%). We may infer from this correspondence that many respondents who work with invasive or non-invasive BCI systems described an application within this same niche, and therefore the opinion of respondents about the bottlenecks and requirements for future research for this application is likely to be based on actual expertise and thorough knowledge about these issues. Indeed, more than 90% of the applications described in part B used the same approach (invasive/non-invasive) as the researcher used for his/her research.

B. Near future

When asked to describe a BCI application that may be feasible within the next 5-10 years, many (one in three) researchers described a 'replace' application, such as '*BCI for communication with locked-in patients*'. Also, 'improve' applications (for instance '*BCI for rehabilitation after stroke*') were described often. Together, the replace and improve scenario applications covered 60% of all descriptions submitted. One may conclude that BCI researchers view these kind of applications as the most promising within the near future. It cannot be excluded, however, that the majority of the researchers are most familiar with applications that are currently eligible for funding, and that the other four scenarios, which represent relatively new BCI directions, may be less well-known among BCI researchers, and may therefore have generated less descriptions.

There was a remarkable consistency in the reported least and most important bottlenecks identified for the non-invasive applications. Across all six scenarios, respondents indicated that safety issues are not a bottleneck, indicating that the risks of non-invasive BCI systems are considered negligible and there is sufficient evidence for this. Notably, this result corresponds with the conclusions on the safety of non-invasive BCIs in the Asilomar researchers' survey on ethical issues (Nijboer et al., 2013). A significant hurdle for non-invasive BCI tools, however, is the (long term) system performance, which is considered insufficient for most applications described. In fact, overall, for 209 of the 273 submitted non-invasive applications, the respondent agreed or strongly agreed with the statement '(long term) system performance is not yet good enough', whereas only 25 disagreed or strongly disagreed. Not surprisingly, respondents identified a clear need for improved sensors and signal processing techniques to improve system performance. Interestingly, this finding confirms the results from a recent survey among BCI game researchers (Ahn et al., 2014), and extends it to other non-invasive BCI applications. Other generally applicable issues that need to be overcome are the complexity of the systems, which currently renders them not usable in the home environment of end users. Importantly, the limited knowledge of end users about BCI applications, together with the insufficient incorporation of their needs and wishes in the developed systems.

The scenario that received the largest (absolute) number of descriptions for invasive applications was 'replace'. Over 20% of the described BCI tools within this scenario were based on implants, suggesting that a significant number of scientists consider invasive solutions for replacement of lost brain function as feasible within the coming 5-10 years. Moreover, the invasive approach is clearly marked as relevant for 'replace' applications, in that respondents see clear advantages over non-BCI solutions. Long-term performance and durability were identified as important technical bottlenecks. Here, much research is still needed (all possible research directions are considered relevant) to overcome the current hurdles and bring invasive replace solutions to the market. This is a logical consequence of the early stage in which this type of research is.

C. Far future

Considering the descriptive nature of part C (far future), it is not possible to draw quantifiable conclusions from this section. However, several clear and dominant issues, relevant for both invasive and non-invasive systems, surfaced from the provided descriptions: (1) issues related to signal acquisition and decoding, (2) applications for patients, and (3) applications for healthy users. For non-invasive BCIs, the issues related to signal acquisition and decoding were largely dominated by the wish for easy-to-use EEG systems that are applicable in any environment. Also, for invasive BCIs, there is a strong need for improved acquisition methods, such as wireless systems and improved long-term stability. Systems have to become easy-to-use, wearable, durable, and it should be possible to use them in any environment.

It was interesting to note that people foresee a role for invasive and non-invasive systems for both patients and healthy end users, indicating that invasive BCI applications may, in the long run, have a niche outside the patient-oriented 'replace' scenario. Future non-invasive applications described for patients were for example rehabilitation after stroke or BCI for communication and environmental control. Many invasive BCI applications that were described for patients were related to the control of artificial hands, arms or complete exoskeletons. Also speech prostheses were mentioned several times.

For healthy users, respondents foresee gaming applications, as well as mental state monitoring in personal and professional life. Invasive applications for healthy end users were related to, for example, brain-to-brain communication or to other futuristic enhance and supplement scenarios. Notably, for both approaches, a number of respondents indicate the importance of systems that can be used anywhere, at home and in the community.

Conclusions and recommendations

From the current study, we conclude that BCI researchers are quite optimistic about the feasibility of BCI applications for both patients and healthy end users. They described many types of applications that would be viable in the near and far future. Especially applications for patients, to replace or improve lost brain functions, are considered promising by many BCI researchers. However, before these products may appear on the market, a number of issues have to be addressed. Improving system performance is crucial for non-invasive directions together with an increased awareness among end users, and an increased incorporation of their wishes and needs. For invasive BCI applications, steps have to be taken to develop completely implantable systems with adequate performance and durability. Also, the field has to start with clinical trials to demonstrate in larger numbers of people that invasive BCIs are safe and durable, have good performance and to identify the added value compared to non-invasive solutions.

We identify the following crucial topics for the near future:

- Long-term system performance
- User friendly systems
- Increased interaction between BCI research field and end users
- Completely implantable systems

For the far future, the following topics are crucial:

- Wearable systems that are easy to use
- Improved durability
- Implants for non-medical applications

A.3.2 Conclusions

Taken together, from the research perspective, there are a number of key issues that need to be addressed before BCI applications can be considered usable solutions for the daily life of patients and healthy end users:

- Improving the stability of scalp sensors. Technological development is needed so that stable, lab quality recordings can be obtained in the daily life of people, at home or outside.
- Development of (affordable) implantable systems. Focus should be to maximize safety, performance and long term stability.

- Incorporation of the wishes and needs of healthy and patient end users during the research and development process. To increase awareness, improve acceptance and assure the use of BCI tools by end users, the field needs to fully exploit the concept of User Centered Design.
- Simplification of systems. Data acquisition and user interfaces should become user friendly and wearable.

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