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Abstract: This deliverable contains a contribution to the roadmap from the research perspective. The first contribution is a state of the art on BCI paradigms, BCI hardware, BCI signal processing, invasive BCIs and synergies. The second contribution is a first and preliminary report of the Researchers' Questionnaire.

Keywords: State of the Art, Questionnaire

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[1] Public
[2] Restricted to other program participants
[3] Restricted to a group specified by the consortium
[4] Confidential, only for members of the consortium

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1. Introduction

As stated in the DOW, Deliverable 2.2 is a first contribution to the roadmap from the research perspective. The current contribution to the roadmap describes the State of Art of the BCI research, the results of the first report and results derived from Questionnaire for BCI Researchers.

2. Methods

2.1 Specific State of the Art - Research

As mentioned in D2.1, three sources of information were used to generate the SoA-Research: knowledge from the Hallstatt Retreat, the Future BNCI report, and the BNCI Horizon2020 Literature database 2011-2014.

At the BNCI Horizon 2020 Retreat in Hallstatt, the first version of the roadmap structure was decided (see the matrix in D2.1) and during the Consortium Meeting in Barcelona, the structure was slightly adjusted to allow a single reading thread (see the minutes of the Consortium Meeting and the most recent version of the roadmap structure). The roadmap will contain (among others) a State of Art description from three perspectives: End-user, Research and Industry. In the current deliverable, the State of Art from a Research perspective is described.

The Research State of Art is based on the Future BNCI Roadmap, which can be considered to describe the BCI research field until the end of 2011, as well as recent literature (see BNCI Horizon2020 Literature database 2011-2014). As agreed upon for D2.1, of each year, the reviews within the top 50% of papers in the database were read by the consortium members and for each review one or more statements were entered into a dedicated online form, which included several fields, allowing categorization of each review and accompanying statements. Reading and commenting of the reviews was complete by May 14th, 2014.

During two WP2 Skype Meetings (March 12th 2014 and May 13th 2014), it was agreed that for the Research State of Art, two or three partners would work on a State of Art description of one of the five subjects of WP2:

- BCI concepts and paradigms
- BCI data processing
- BCI hardware
- Invasive BCIs
- Synergies

For each subject, a 1-page State of Art was to be composed by the sub-team. Information for the content was to be extracted from the Future BNCI roadmap, as well as recent literature, for which the review statements would function as a starting point to identify relevant subjects and articles. The Research State of the Art is given in section 3 below. Sections 1-4 are copied into the Research State of the Art section of the roadmap and an adjusted version of Section 5 has been placed in the Future Opportunities and Synergies part of the roadmap.

2.2 Researchers' Questionnaire

As mentioned in D2.1, a questionnaire was designed and the version attached to D2.1 was made available online and sent around to four members of the consortium for testing and final comments (Maria Laura Blefari, Benjamin Blankertz, Boris Reuderink and Francesca Schettini). The online version was adjusted according to their remarks and finalized. The final version is attached as Appendix A of this deliverable, and was sent around to 3291 BCI researchers by the end of May, 2014. These BCI researchers were identified after contacting several BCI research groups and societies. After sending out two reminders, the questionnaire was closed on 10 July 2014. In total, 220 responses were collected, which is 6.7 % of the BCI researchers.

In the questionnaire, people were first characterized. Second, they were asked to suggest (potential) applications, assign them to one of the six scenarios, and identify bottlenecks and future requirements for this application. Third, they were asked to think out of the box and into the far future and brainstorm about potential 'killer' applications or major research breakthroughs.

An initial analysis of the data was made using Google Analytics, resulting in a preliminary report about the questionnaire, which is given in Appendix B. A subsection of the report has been copied in the Recommendations - Research section of the roadmap document (see section 4 below).

3. Roadmap contribution- Specific State of the Art - Research

1. BCI concepts and paradigms (WUE, UT, FPING)

1.1 Control signals

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

1.2 Exogenous and endogenous EEG based BCIs

BCI paradigms can be classified into exogenous and endogenous systems, depending on whether external stimulation is required [1]. Exogenous BCIs (e.g. based on P300 or SSVEP) often use the visual modality to evoke brain responses, but auditory or somatosensory stimulation can be used as well. Endogenous BCIs do not need a stimulation device, typically offer continuous instead of discrete output (e.g use of SMR during imagined movements for cursor control [2,3]) and can be initiated at will. Finally, hybrid BCIs combine two or more CNS outputs or classifier results [4,5].

1.3 Performance

Increasing BCI performance is a field of active research. 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 [6], and optimizing the number of stimuli [7], promise to increase throughput. Performance of **SSVEP** BCIs depends on the number of discriminable frequencies, which is affected by hardware (e.g. LEDs vs. LCD screens) [1], setups [8], and coding schemes [9]. New approaches even allow continuous (e.g. smooth cursor control) instead of discrete control (e.g. choice selection) [10]. Predictors of endogenous (**SMR**-)BCI performance include psychological, neurophysiological and neuroanatomic variables. However, it still unclear whether these approaches can actually improve the BCI performance [11]. **Hybrid BCIs** rest on the idea that combining several input channels or BCIs, each optimized for a particular task, improves accuracy and reduces errors. However, not all combinations are effective, and choice of complementary signals, acquisition devices, and software algorithms must be careful [5,12]. **Intelligent control systems** reduce BCI's reliance on (potentially) noisy signals by delegating as much work as possible towards software. For example, a wheelchair user might use a BCI to select waypoints instead of controlling individual movements, and leave the implementation of the task to the system [13].

1.4 Challenges

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** [13], optimizing sensors, signal processing and classification techniques (see sections 2-4), but also to the **type of control** signal and **overall systems design**. 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, the need to permanently direct attention, and gaze control towards the stimuli, is **tiring** and the **occupation of sensory capacity** make it unavailable for other tasks. Further, the current plurality of **performance metrics** used to communicate about BCIs is critical. Although this issue is a matter of active research, generally, no single metric can capture a system's performance adequately [14]. Tests in healthy participants using typing tasks show very low bitrates (BR) for endogenous (SMR-)BCIs (BR = 0.59 [15]), but higher rates for exogenous systems (e.g. BR = 61.7 for a P300 BCI, BR = 24.5 for a SSVEP BCI [16]). However, bitrates show strong heterogeneity across implementations and settings [1], making reliable comparisons difficult. In addition, since a specific BCI may or may not use additional components within the BCI's **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**. In addition, reporting simple statistics 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** [17] metric (e.g. number of correctly spelled letters per unit of time) have emerged [14], but are not often used.

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2. BCI data processing (Berlin, EPFL)

Recorded neuroimaging data are a superposition of the signals of interest with a plethora of other signals - from the brain, from muscles, and from non-biological artifacts. Furthermore, the huge variability of brain activity between persons makes the real-time analysis of brain signals a challenge. Therefore, state-of-the-art BCI systems use adaptive signal processing and machine learning algorithms to extract specific information from brain signals. These techniques rely on a statistical analysis of calibration data to optimize classification models. Using these techniques, most BCI systems can be used without the need of lengthy training. There have been recent efforts to unify BCI data processing into unique software platforms [1] with the goal to simplify the access to novel methods and to stimulate international collaborations. Research on BCI data processing focuses on the following topics.

2.1 Increasing performance

2.1.1 Feature extraction

As stated in the state of the art on BCI approaches (section 1.1), the development of BCI classification algorithms aim 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. While the feature extraction has been optimized for each component individually, preprocessing and classification is very similar in most online BCI systems [2-6]. In order to improve performance of invasive BCIs based on multi-electrode arrays (MEAs), optimized Kalman filter approaches [7-9] have been investigated as well as alternative approaches for feature extraction [10,11].

2.1.2 Multimodal feature extraction

One way of increasing BCI performance is to fuse different streams of information in a hybrid BCI [12](see also Section 1). 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) [13-17] or to integrate the BCI into existing technology [18-21]. As multimodal feature extraction and integration is highly relevant for neuroimaging in general, numerous methods have been adopted for other domains [22,23] and some could potentially be used to improve BCI performance, as well.

2.2 Increasing applicability

The applicability of both, non-invasive and invasive BCI systems needs to be enhanced to make them ready for real world applications.

2.2.1 Addressing non-stationarity

Due to the non-stationary nature of neural data, maintaining performance over time typically requires a continuous adaptation of the BCI. Therefore, novel adaptive processing methods have recently been researched for both non-invasive and invasive settings [24-30]. Some have shown successes rate improvement up to 8 times [31] also across years [8]. For implanted multi-electrode arrays (MEAs), short-term and long-term non-stationarities may also be addressed by using more channels, or by using multi-units or LFPs [29,32,33]. There are indications that ECoG recordings are relatively stable and may require less adaptation [34,35].

2.2.2 Improving sensors

Non-invasive BCI systems need to be operated with novel sensors that are quickly applicable (e.g. dry electrodes for EEG). However, this hardware delivers highly variable signals which are commonly contaminated by numerous non-stationarities and artifacts. There is a need for novel processing tools that account for such technical artifacts.

2.2.3 Reducing calibration time

Another practical aspect is the reduction of the calibration time. This can be achieved by transferring knowledge from existing data to new users [25,36], or by using self-recalibrating classifiers [37].

2.3 Increasing interpretability

The use of powerful machine learning techniques brings about the necessity for a careful validation [38]. Moreover, purely data-driven feature extraction methods could be used to validate neurophysiological hypotheses[39] and to interpret the neuronal sources on which the BCI is relying on. Haufe and others [40] discuss that data-processing tools need to be both, highly discriminable and interpretable.

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3. BCI hardware (Graz, TUB, EPFL)

3.1 EEG

EEG is the most popular signal type for non-invasive BCIs [1]. It records electrical activity of neural assemblies on a millisecond time scale. Besides this excellent time resolution, EEG is portable and relatively inexpensive. However, the spatial resolution of EEG is rather low, and it is susceptible to many types of artifacts [2,3].

3.1.1 Current issues and limitations

Traditional EEG sensors (so-called electrodes) require gel, which is a key issue that limits a more widespread adoption of EEG. An improved approach is based on water, which does not require people to wash their hair after EEG measurement. Another emerging alternative is the use of dry electrodes [4], which ideally feature comparable signal quality, improved wearing comfort, and a drastically reduced setup time. Second, 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 are applied with active electrodes, which include small preamplifiers directly on each electrode and thus minimize artifacts induced by cable sway.

3.2 MEG

MEG measures the weak magnetic fields caused by currents within the brain [5]. Like EEG, it is a direct measurement of neural activity with high time resolution [6]. 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.

3.2.1. Current issues and limitations

A limited number of studies has demonstrated successful implementation of MEG-based BCIs [e.g. 7,8], 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 [9]. 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) [9,10].

3.3 fMRI

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 [11] by using blood-oxygen-level dependent (BOLD) contrast imaging methods. The main advantage of fMRI is its high spatial resolution.

3.3.1 Current issues and limitations

There are several approaches to improve image quality. First, signal to noise ratio increases with increasing field strength. Currently, clinical routine and research apply 1.5-3T, and 3T-7T, respectively [12]. Another way to improve image quality in defined regions is to apply multi-channel coils [13,14]. Third, new image acquisition sequences are constantly being developed, which further improve image quality [15-17]. Although physical (size, strong magnetic field), methodological (e.g. low temporal resolution, delayed haemodynamic response) and financial aspects constrain fMRI for most BCI applications [9], there is an increasing interest to use fMRI for detecting consciousness [18], neurofeedback training [19] or to prelocalize regions for subsequent electrode implantation [10,20]. 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 [9].

3.4 fNIRS

Functional near infrared spectroscopy (fNIRS) is an emerging non-invasive optical technique for the assessment of cerebral oxygenation [21,22]. Similar to fMRI, fNIRS measures hemodynamic changes in the brain, but fNIRS is less expensive and portable compared to fMRI [9]. The technique is relatively new, but BCI applications seem feasible, either as an alternative to fMRI [23] or in combination with [24,25] EEG. Due to the complementary nature of fNIRS and EEG, such a combination may be used for BCIs, if shown beneficial.

3.4.1 Current issues and limitations

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 [26]. A practical issue is the optimal fixation of the optical probes to the head, 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 [27].

3.5 Invasive methods

Multi-electrode arrays (MEAs) for BCI are arrays of tens to hundreds 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 [28] and has been used in the BrainGate(2) trials [29,30]. Electrocorticography (ECoG) measures fields generated by large groups of neurons, using cortical surface electrodes. Typical implants are grids and strips of electrodes with 1 cm interelectrode distance (approved for subdural use for 28 days), but higher resolution grids are also becoming available. ECoG-BCI control is mostly based on spectral power changes in isolated brain areas [10], but ERPs are also used [31,32]. Currently, these methods are mainly considered for severe medical applications, for which they are regarded highly promising because of the high quality signals in terms of spatial resolution and spectral width [9,10,33]. See section 4 for current issues in invasive BCIs.

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4. Current Issues of Invasive BCIs (UMCU, GTEC)

4.1 Multielectrode Arrays (MEAs)

MEA BCI research has focused on combining single unit information of many electrodes, thereby maximizing the number of degrees of freedom [1,2]. 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 [3]. 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 [2,4].

4.2 Electrocorticography

ECoG-BCI research is mainly aimed at replacing lost motor function and is mostly performed with epilepsy patients with subdural, subchronic implants [5]. 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 [6-9]. 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 [10]. One study has reported ECoG-based BCI for cursor control in a tetraplegic patient during 28 days before explantation [11]. A more long-term study using a completely implantable device [12] is currently recruiting patients.

4.3 Current issues

4.3.1 Optimizing performance

There are many efforts to optimize performance of invasive BCIs, among others by optimizing decoding algorithms, combining multiple types of signals (e.g. single unit and LFP data), studying effects of learning and plasticity on brain signals, providing additional sensory feedback besides the often used visuals (see also issue 5 below), and considering alternative brain functions and regions [9,13-15].

4.3.2 Biocompatibility and long term stability of the signals

Despite promising reports on long term, usable, recordings with MEAs [14], tissue reaction, tissue damage and the associated signal loss remain an issue of concern [6,10,14]. Approaches currently being investigated to address this issue are biocompatible coatings and optimized algorithms [14-16]. 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 [17-20].

4.3.3 Safety

Current invasive recording systems suffer from substantial infection risk due to percutaneous wires [14,16]. Several groups are working on wireless solutions for MEA [21-24] and ECoG [25,26] to solve this issue. For ECoG, epidural recordings are being investigated. In primates, stable impedance and signal to noise ratio was 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 [5,19,27].

4.3.4 Minimizing size, maximizing output

New ECoG grids, ranging from closely spaced electrodes to actual high-density micro-electrodes have been developed recently. Using these grids, more information can be extracted from a small patch of cortex, allowing more degrees of freedom [11]. 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 [5]. 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 [28,29] and spatiotemporal features for decoding and control [30-32].

4.3.5. Electrical stimulation

Recent non-human primate studies demonstrate the possibility to restore grasping with a temporarily paralyzed limb using muscle stimulation [6,16]. In addition, efforts are ongoing to induce somatosensory perception by electrical stimulation of the cortex (S1) [14,33].

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5. Synergies (UMCU, Bdigital, WUE)

BCI applied for Communication & Control aims to *replace* or *enhance* natural CNS output. **Apparel and accessories** companies are bringing out brain-controlled clothing and gadgets, such as Neurowear`s Necomimi and Shippo, which would communicate individual moods. Other industry stakeholders in the BCI sector have produced systems (Epoc, intendiX, Brainfingers, BrainGate) for brain–control of laptops and PC`s that may be beneficial for the computer industry. Potential synergies with the **Telecommunication** industry are exemplified by Neurosky`s MindWave Mobile headset. Notably, despite the claims of the company's marketing these products, for some of these systems it is not clear if control is based on neuronal (EEG) or muscle (EMG) activity.

BCI applied for Health & Neurofeedback aims to *replace, restore*, *enhance* or *improve* natural CNS output by replacing lost function, modifying brain activity, guiding neural plasticity, increasing the efficacy of rehabilitation, or improving the clinical diagnostic. Examples of potential synergies with **Health care** are brain-controlled computers, bionic legs and arms, or futuristic computerized bladders. In 2009, the FDA has approved a second clinical trial to implant BrainGate technology into severely disabled patients.

BCI applied for AT and Smart home control aims to *replace* or *supplement* natural CNS output. Synergies with **Assistive technology** are progressing rapidly as shown by the brain-controlled Darpa`s Prosthetic Arm. Projects such as MindWalker (EU funded) and Walk Again are taking steps on the long road towards mind-controlled exoskeletons for paralyzed people. Researchers at MIT are currently testing a memory prosthesis in humans. Synergies between BCI and **domotics** (automatic control for home) are emerging in EU-funded projects like BrainAble and BackHome.

BCI applied for Safety & Security aims to *enhance* or *supplement* natural CNS output. The EU-funded project 'Brainflight' showed synergy with **Aerospace** by an ambitious project investigating the feasibility of flying a brain-controlled aircraft, which would reduce the workload of pilots and increase safety. Also NASA and ESA are working on BCIs for robot and camera control as well as flight deck design. **Agriculture** and farming may see BCIs for monitoring and regulating of animal mental states, which could be integrated in farm robotics (e.g. milk robot) and improve animal welfare. Synergies between the **Automotive** industry and BCI are shown on TV (e.g. Prototype This) and comprise cars that claim to be geared, steered or provide feedback by using brain-controlled systems like BrainDriver, Google Driveless Car, or iBrain. For each of these systems, however, it remains unclear if they are based on EEG or EMG signals. The **defense** industry (e.g. Defense Advanced Research Projects Agency-DARPA) is interested in mind-control of drones, weapons, aircraft, or robotic devices, or manipulation of the brain to enhance war-fighting capabilities, maintain mental acuity and reduce the effects of traumatic brain injury.

BCI applied for Entertainment & Gaming aims to *enhance* or *supplement* natural CNS output. Synergies include educational and entertainment gaming, music, art, sports, and meditation. The industry of **Education** is one of the major targets for Open Source (Puzzlebox Orbit) or commercial (MindWave Education) brain-controlled devices. These games claim to monitor the attention levels of students performing a task. Companies in the **Entertainment and Leisure** industry are developing BCI-based games, which let you manipulate targets by concentrating on them (NeuroBoy, Mindflex and the Star Wars Force Trainer). The industry of **Music** will release a device called NEURO TURNTABLE (by Neurowear), which plays music only when the user is concentrated. The **Wellness** industry may benefit from BCI tools by devices like MUSE (Interaxon), which guides you to relax or focus before or after you perform a mentally challenging task, and which could be used for meditation. Although promising as synergies of the BCI field, many of the abovementioned applications for entertainment and gaming are based on basic scalp recording systems, the ability of which to actually record neuronal signals still has to be verified.

Synergies of **Advertising** and BCI`s are called neuro-marketing or neuro-advertising and usually aim to *enhance* natural CNS output. Neuro-marketing aims to tailor advertising to an individual, based on mood, emotional state and cognitive analysis. If successful, this could be incorporated in any device that allows for neurofeedback, including brain-controlled games and mobiles of companies such as Personal Neuro Devices, Neurosky, Nielsen, and Neurofocus.

BCI applied for R&D purposes could become a powerful *research tool*. Synergies include better real-time analysis, signal acquisition and processing, output devices, and interfaces. A new synergy with **Artificial Intelligence**, in particular with machine learning, could be an open database of BCI data sets and algorithms, which will increase competitiveness and reproducibility of results.

4. Roadmap contribution - Recommendations - Research

When asked about the bottlenecks of BCI, respondents of the 'Researchers' Questionnaire' agreed that (long-term) system durability and (long-term) system performance are still sub-optimal for both invasive and non-invasive systems. However, for invasive systems, BCI durability seems to be a more important issue (63% vs 51% agreed or strongly agreed), whereas system performance was more often selected as a bottleneck for non-invasive than for invasive systems (73% vs 53%). This could be related to insufficient evidence about (long-term) durability (invasive 53% & non-invasive 38%) and performance (invasive 63% & non-invasive 48%).

Non-invasive BCI systems are considered to be safe by a large majority (78%) of respondents, but also invasive applications are considered to be safe by 50% of the respondents (only 34% considered the risks of invasive systems as too high). To optimize invasive BCI systems, more evidence should be gathered about the risk/benefit ratio for the users (63% agreed) and the (long-term) system safety for the users (47% agreed or strongly agreed, versus 28% disagreed / strongly disagreed).

Interestingly, only a minority of researchers considers the target populations as being too small for commercialization of both BCI systems (invasive 0% & non-invasive 31%) and many respondents reported they see clear advantages of invasive (63%) and non-invasive (43%) BCI solutions compared to non-BCI solutions. In that sense, a remarkable bottleneck for both techniques is that potential users seemed to be uninformed about the existing of both invasive (72%) and non-invasive (66%) BCI applications. The price of both BCI systems was considered by many respondents as being too high (invasive 53% & non-invasive 45% agree or strongly agree) and the equipment still too complicated for home-use (invasive 56% & non-invasive 70%). Invasive and non-invasive BCI systems were considered too large (invasive 44% & non-invasive 42%), cosmetically unappealing (invasive 53% & non-invasive 51%), and to not meet the wishes and needs of the end-users (invasive 56% & non-invasive 61%).

Respondents suggested that both invasive and non-invasive BCI research should focus on the development of better hardware (invasive 84% & non-invasive 90%) and software (invasive 78% & non-invasive 83%) to improve system performance. In particular for invasive BCI, implantable multi-channel amplifiers with a long battery-life are considered essential for the future (84%).

Respondents express a wish for clinical trials that should shed light on system performance (invasive 87% & non-invasive 78%), durability (invasive 87% & non-invasive 67%). Clinical trials to establish safety seem more important for invasive (81%) than for non-invasive BCIs (46%). Clinical trials should as well show the efficacy of the devices (75%) and the risk/benefit ratio for end-users (78%) of invasive in comparison to non-invasive BCI systems. More research is needed according to respondents in order to identify the wishes and needs of end-users (87% & 60%) that use both invasive and non-invasive BCI systems.

Appendix A - Final version Researchers' Questionnaire

See WP2/Deliverables/D2.2/AppendixA_FinalQuestionnaire

Appendix B Preliminary Report on the Researcher's 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 what research activities would be needed to accomplish this?

Methods

The questionnaire consisted of three parts. In the first part, each researcher was characterized by their background, what type of BCIs they work on and what kind of tools they use for that. In the second part, they were asked 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. Then, participants were asked to rate many statements related to potential bottlenecks and future requirements for BCI, with their specific application in mind, on a five-point scale (strongly agree, agree, neutral, disagree, and strongly disagree). Third, they were asked to think above the current state of the art and into the far future and brainstorm about potential 'killer' applications or major research breakthroughs.

The questionnaire was sent around to 3291 BCI researchers by the end of May, 2014. These BCI researchers were identified after contacting several BCI research groups and societies. After sending out two reminders, the questionnaire was closed on 10 July 2014. In total, 220 responses were collected, which is 6.7 % of the BCI researchers.

Results & Discussion

General information

The majority of the respondents were engineers (36%), computer scientists (22%), and neuroscientists (18%) working mostly in Europe (56%). However, we also attracted a large number of respondents working in North America (20%) and Asia (15%). Respondents worked in universities, university medical centers or performed research in companies such as GTec or Aescusoft. The percentage of respondents working in an institute of engineering (35%), computer science (20%), and neuroscience (19%) matched strikingly well with the percentage of respondents with an engineering, computer science and neuroscience background mentioned above.

Many respondents covered more senior positions at their institutes, e.g. post-doc, dean, professor, or head of research and R&D departments. They supervised or were part of small research groups (<10 individuals; 59%). The majority of the respondents had less than 5 years of experience (59%) on their actual position and only a limited number of the respondents had more than 10 years of experience (19%), suggesting that BCI represents a young research field. Respondents (67%) spent most of their working-time (>50%) on BCI research, and focused on BCI techniques (41%) and users in- and outside hospitals (40%), whereas only a few of them focused on BCI devices and interfaces (17%).

Characterization

A large majority of the respondents (89%) predominantly used non-invasive BCI systems, almost all based on EEG (97%). For EEG recordings, wet (gel and water-based) electrodes were abundant (75%), whereas the new, dry electrodes were only used by a minority (25%) of the respondents. Respondents equally utilized active (52%) and passive (48%) electrodes, mostly in a cap (50%) or headset (28%).

The few respondents (11%) that used invasive BCI systems record signals mostly with surface electrodes (68%) placed subdurally (79%). When respondents used penetrating electrodes (32%), they used mostly microwire arrays (33%) for measuring from cortical structures (89%). For invasive BCI systems, electrocorticographic signals (ECoG; 33%) are most commonly exploited, followed by local field potentials (LFP; 23%) and single (21%) and multi-unit recordings (19%).

Respondents were mostly interested in decoding motor function (31%), attention (20%), and visual perception (18%), but also decoding language, working memory and auditory perception are a research focus.

Signals were mainly decoded from healthy subjects (61%) and patients (34%), and only a few people work with animal models (3%). The patient populations used for BCI was highly variable and included (among others) patients with stroke (19%), neuromuscular disease (16%), locked-in syndrome (16%), and spinal cord (14%) and traumatic (13%) brain injury.

Respondents used signal processing methods such as feature extraction (38%) and classification (34%) techniques. Features were extracted almost equally from the frequency (37%), time (33%) and spatial (27%) domain, whereas classification was mostly performed using linear classifiers (42%). The few respondents that used projection techniques (25%) equally preferred unsupervised (50%) and supervised (47%) methods. BCI2000 (27%) and EEGlab/BCIlab (23%) were the most often used software tools, in addition to custom made software (21%).

Respondents mainly used BCI devices to replace natural CNS output (41%), and mainly for replacing communication and control (84%). Respondents equally used replacing devices to communicate with other devices (52%) or people (48%) and mostly to replace writing and spelling (43%). These communication devices were mainly based on the ERP/P300 (29%) or SMR/motor imagery (24%) paradigm. The limited number of people working on motor substitution mainly focus on controlling robotic arms (60%), again with SMR/motor imagery (32%) and ERP/P300 (21%) as important paradigms.

A substantial number of respondents (21%) used BCI devices as a research tool, with a majority (67%) focusing on non-clinical research. BCI as a research tool is being used for a wide area of participants, with learning in the brain (30%) and functional mapping (20%) being most often mentioned. Studies are based on the SMR/Motor imagery (22%), visual attention / perception / imagination (19%), or ERP/P300 (19%) paradigms.

Only few respondents used BCI devices to supplement (10%), improve (9%), enhance (8%), restore (6%) natural CNS output or for other use (5%). These respondents use BCIs for example to supplement functioning in virtual reality environments (30%) and gaming (29%), improve motor impairments after stroke (63%), enhance attentional (25%) and emotional states (21%), and to restore grasp functions (47%). Again the most used paradigms were SMR/motor imagery, ERP/P300, visual evoked potentials (VEP) or visual attention/perception/imagination.

Now and tomorrow

In order to map the feasibility of BCI devices in the coming 5 to 10 years we asked participants to choose a BCI application from a list of scenario`s. We then asked participants to choose whether to develop the feasible application by using an invasive or non-invasive BCI system. Together this information aids to sketch the near future of BCI applications and devices.

When asked which BCI devices could be feasible within the next 5 to 10 years, most respondents (27%) chose devices that replace natural CNS output. Other respondents described BCI applications that may improve (18%), enhance (17%), supplement (13%), and restore (12%) natural CNS output or that can be used as a research tool (13%). Respondents preferred the feasible application to be developed by using a non-invasive BCI system (86%), i.e. one that would not require surgery. This large percentage aiming for a non-invasive BCI corresponded remarkably to the percentage of respondents working on non-invasive BCIs. We may infer from this correspondence that 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.

Most of the replace applications that were mentioned would be applied for communication in general and particularly for communication in locked-in patients. Other typical examples of feasible BCI applications that were suggested aimed to enhance cognitive functions, improve motor rehabilitation after stroke, supplement during gaming or home automation, restore lost movement or speech, or be used as a research tool for cognitive assessment and mapping or technique improvement purposes.

When asked about the bottlenecks of BCI, respondents agreed that (long-term) system durability and (long-term) system performance are still sub-optimal for both invasive and non-invasive systems, although for invasive systems, system durability seems to be a more important issue (63% vs 51% agreed or strongly agreed), whereas system performance was more often selected as a bottleneck for non-invasive than for invasive systems (73% vs 53%). This could be related to insufficient evidence about (long-term) durability (invasive 53% & non-invasive 38%) and performance (invasive 63% & non-invasive 48%).

Non-invasive BCI systems are considered safe by a large majority (78%) of respondents, but also invasive applications are considered safe by 50% of the respondents (34% considered the risks of invasive systems to be too high). Especially for invasive BCI systems, more evidence should be gathered about the risk/benefit ratio for the users (63%) and the (long-term) system safety for the users (47% agreed or strongly agreed, versus 28% disagreed / strongly disagreed).