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Christoph Guger · Brendan Z. Allison
Günter Edlinger *Editors*

Brain–Computer Interface Research

A State-of-the-Art Summary

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State of the Art in BCI Research: BCI Award 2011

Christoph Guger, Brendan Allison and Günter Edlinger

Introduction

Brain–Computer Interfaces (BCIs) analyze brain signals in real-time to control external devices, communicate with others, facilitate rehabilitation or restore functions (Wolpaw et al. 2002; Graimann et al. 2010; Wolpaw and Wolpaw 2012). BCIs, unlike other communication and control systems, rely on direct measures of brain activity. That is, people simply think, and a computer does the rest. In most BCIs, people must either think about performing certain movements, or pay attention to specific items on a monitor. However, many new BCI paradigms are emerging, many of which are discussed in this book.

The first BCI was described almost fifty years ago (Graimann et al. 2010). It was an invasive BCI, meaning that it relied on sensors placed under the skull via surgery. Almost ten years later, the first noninvasive BCI was published, in an article that also coined the term "brain–computer interface" (Vidal 1973). Like most BCIs today, it was based on the electroencephalogram (EEG) recorded from electrodes on the surface of the head (Allison et al. 2012). In other early work, Farwell and Donchin described a BCI that used the P300 brainwave for communication (Farwell and Donchin 1988). Up to the early 2000s, no more than 5 groups were active in brain–computer interface (BCI) research. Now, over 300 laboratories are focused on this work. This dramatic growth has been driven by many factors, including:

1. Cheaper, smaller, and faster electronics and related instrumentation;
2. Increased understanding of normal and abnormal brain function;

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3. Improved interfaces and environments;
4. Additional testing and experimentation with target users in field settings;
5. Improved methods for decoding brain signals in real time;
6. Improved sensors, such as active and dry electrodes and improved invasive electrodes.

The BCI Award

As a result, the performance and usability of BCI systems have advanced dramatically over the past several years. To highlight these trends and developments of BCI technology, g.tec began to sponsor an annual BCI Award in 2010. g.tec is a leading provider of BCI research equipment and has a strong interest in promoting excellence in BCI research (Guger et al. 2012). The prize, endowed with 3,000 USD, is an accolade to recognize outstanding and innovative research in the field of brain–computer interface research and application. The competition is open to any BCI group worldwide. There is no limitation or special consideration for the type of hardware or software used in the submission.

Each year, a renowned research laboratory is asked to assemble a jury, help judge the submitted projects and award the prize. This year, the jury was recruited by its chair, Dr. Gert Pfurtscheller of the University of Technology in Graz, Austria. The jury consisted of some of the most respected and accomplished experts in the BCI community: Theresa Vaughan, Michael Tangermann, Guan Cuntai, Robert Leeb and Jane Huggins. The jury selects and announces the winner and presents the prize.

The winner is announced at a public ceremony attached to a major conference. The 2010 BCI Award was presented at the BCI Meeting 2010 in Asilomar, California, and the 2011 BCI Award was presented at a gala dinner during the Fifth International BCI Conference in Graz, Austria (see Fig. 1). The 2012 Award was just presented at the Society for Neuroscience in New Orleans, Louisiana.

Fig. 1 The *left panel* shows the BCI Meeting 2010 in Asilomar, CA, where the 2010 BCI Award was presented. The *right panel* shows the gala dinner where the 2011 BCI Award was presented at the prestigious Hotel Gollner in Graz, Austria

The jury scored the submitted projects on the basis of the following criteria:

- does the project include a novel application of the BCI?
- is there any new methodological approach used compared to earlier projects?
- is there any new benefit for potential users of a BCI?
- is there any improvement in terms of speed of the system (e.g., bits/min)?
- is there any improvement in system accuracy?
- does the project include any results obtained from real patients or other potential users?
- is the used approach working online/in real-time?
- is there any improvement in terms of usability?
- does the project include any novel hardware or software developments?

The Ten Nominees in 2011

We received a total of 64 high quality submissions in 2011. Out of these submissions, the jury nominated the 10 nominees for the BCI Research Award in June 2011. Being nominated for the BCI Award is a major honor. Prof. Dr. Gert Pfurtscheller, Chairman of the 2011 Jury, said, "The BCI Award is outstanding because the whole world competes and only one project can win." Each nominee receives a certificate at the public ceremony, an invitation to summarize their work in a chapter in this book, and a mark of distinction on their resume or curriculum vita. Figure 2 presents two of the nominees receiving their certificates.

The authors, affiliations and project titles of the 10 nominated projects are:

Fig. 2 Both of these panels show nominees receiving the certificate for their team's project. The *left panel* shows (from *left* to *right*): Prof. Dr. Gernot Müller-Putz, organizer of the Fifth International BCI Conference; Prof. Dr. Gert Pfurtscheller, Chairman of the Jury; Lisa Friedrich, who is receiving the certificate for her nomination; Dr. Christoph Guger, CEO of g.tec, and Dr. Brendan Allison, the emcee. The same people are shown in the *right* panel, except that another nominee, Dr. Reinhold Scherer, is in the *middle*

- Tim Blakely, Kai Miller, Jeffrey Ojemann, Rajesh Rao (University of Washington, USA). Exploring the cortical dynamics of learning by leveraging BCI paradigms.
- Jonathan S. Brumberg, Philip R. Kennedy, Frank H. Guenther (Boston University, USA). An auditory output brain–computer interface for speech communication.
- Samuel Clanton, Robert Rasmussen, Zohny Zohny, Meel Velliste, S. Morgan Jeffries, Angus McMorland, Andrew Schwartz (Carnegie Mellon University, University of Pittsburgh, USA). Seven degree of freedom cortical control of a robotic arm.
- Felix Darvas (University of Washington, USA). Utilizing high gamma (HG) band power changes as control signal for non-invasive BCI.
- Elisabeth V. C. Friedrich, Reinhold Scherer, Christa Neuper (University of Graz, Austria). User-appropriate and robust control strategies to enhance brain computer interface performance and usability.
- Moritz Grosse-Wentrup, Bernhard Schölkopf (Max Planck Institute for Intelligent Systems, Germany). What are the neuro-physiological causes of performance variations in brain–computer interfacing?
- Eric C. Leuthardt, Charles Gaona, Mohit Sharma, Nicholas Szrama, Jarod Roland, Zac Freudenberg, Jamie Solis, Jonathan Breshears, Gerwin Schalk (Washington University in St. Louis, USA). Using the electrocorticographic speech network to control a brain–computer interface in humans.
- Daniele De Massari, Carolin Ruf, Adrian Furdea, Sebastian Halder, Tamara Matuz, Niels Birbaumer (University of Tübingen, IRCCS, International Max Planck Research School, Germany). Towards communication in the completely locked-in state: neuroelectric semantic conditioning BCI.
- Qibin Zhao, Akinari Onishi, Yu Zhang, Andrzej Cichocki (RIKEN, Japan). An affective BCI using multiple ERP components associated to facial emotion processing.
- Raphael Zimmermann, Laura Marchal-Crespo, Olivier Lambercy, Marie-Christine Fluet, Jean-Claude Metzger, Johannes Brand, Janis Edelmann, Kynan Eng, Robert Riener, Martin Wolf, Roger Gassert (ETH Zürich, Switzerland). What's your next move? Detecting movement intention for stroke rehabilitation.

Each of these ten projects is described in a separate chapter of this book.[1] Nominees described the projects they submitted, and provided some additional background material and new developments since their submissions. In the concluding chapter, the submissions are analyzed to show key properties and trends that help identify the dominant and emerging directions of BCI research.

[1] The 2010 nominees are summarized in **Recent Advances in Brain-Computer Interface Systems,** edited by Reza Fazel, InTech, 2011: State-of-the-Art in BCI research: BCI Award 2010.

References

B.Z. Allison, J. Faller, C. Neuper, BCIs that use steady-state visual evoked potentials or slow cortical potentials, in *Brain–Computer Interfaces*: *Principles and Practice*, ed. by J.R. Wolpaw, E.W. Wolpaw (Oxford University Press, New York, 2012), pp. 241–250

L.A. Farwell, E. Donchin, Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroenceph. Clin. Neurophysiol. **70**, 510–523 (1988)

B. Graimann, B.Z. Allison, G. Pfurtscheller, A gentle introduction to brain—computer interface (BCI) systems, in: *Brain–Computer Interfaces: Revolutionizing Human–Computer Interaction*, ed. by B. Graimann, B.Z. Allison, G. Pfurtscheller (Springer Verlag, Berlin Heidelberg, 2010), pp. 1–28

C. Guger, G. Krausz, B.Z. Allison, G. Edlinger, A comparison of dry and gel-based electrodes for P300 BCIs. Frontiers Neurosci. **6**, 60 (2012)

J.R. Wolpaw, E.W. Wolpaw, Brain–computer interfaces: something new under the sun, in *Brain–Computer Interfaces: Principles and Practice*, ed. by J.R. Wolpaw, E.W. Wolpaw (Oxford University Press, New York, 2012), pp. 3–12

J.J. Vidal, Towards direct brain–computer communication. Annu. Rev. Biophys. Bioeng. **2**, 157–180 (1973)

J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, Brain–computer interfaces for communication and control. Clin. Neurophysiol. **113**(6), 767–791 (2002)

An Auditory Output Brain–Computer Interface for Speech Communication

Jonathan S. Brumberg, Frank H. Guenther and Philip R. Kennedy

Abstract Understanding the neural mechanisms underlying speech production can aid the design and implementation of brain–computer interfaces for speech communication. Specifically, the act of speech production is unequivocally a motor behavior; speech arises from the precise activation of all of the muscles of the respiratory and vocal mechanisms. Speech also preferentially relies on auditory output to communicate information between conversation partners. However, self-perception of one's own speech is also important for maintaining error-free speech and proper production of intended utterances. This chapter discusses our efforts to use motor cortical neural output during attempted speech production for control of a communication BCI device by an individual with locked-in syndrome while taking advantage of neural circuits used for learning and maintaining speech. The end result is a BCI capable of producing instantaneously vocalized output within a framework of motor-based brain-computer interfacing that provides appropriate auditory feedback to the user.'

Introduction

One of the primary motivating factors in brain–computer interface (BCI) research is to provide alternative communication options for individuals who are otherwise unable to speak. Most often, BCIs are focused on individuals with locked-in

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syndrome (LIS) (Plum and Posner 1972), which is characterized by complete paralysis of the voluntary motor system while maintaining intact cognition, sensation and perception. One of the many reasons for this focus is that current assistive communication systems typically require some amount of movement of the limbs, face or eyes. The mere fact that many individuals with LIS cannot produce even the smallest amount of consistent motor behavior to control these systems is a testament to the severity of their paralysis. Despite such comprehensive motor and communication impairment, individuals with LIS are often fully conscious and alert, yet have limited or no means of self-expression.

A number of BCIs and other augmentative and alternative communication (AAC) systems provide computer-based message construction utilizing a typing or spelling framework. These interfaces often use visual feedback for manipulating the spelling devices, and in the case of BCIs, for eliciting neurological control signals. A common finding in patients with LIS is that visual perception is sometimes impaired, which may adversely affect subject performance when utilizing visually-based BCI devices. We address this issue through design of an intracortical auditory-output BCI for direct control of a speech synthesizer using a chronic microelectrode implant (Kennedy 1989). Part of our BCI approach benefits from prior findings for the feasibility of BCIs with dynamic auditory output (Nijboer et al. 2008). We extended the auditory output approach employing a motor-speech theoretical perspective, drawing from computational modeling of the speech motor system (Guenther 1994; Guenther et al. 2006; Hickok 2012; Houde and Nagarajan 2011), and our findings of motor-speech and phoneme relationships to neural activity in the recording site (Bartels et al. 2008; Brumberg et al. 2011), to design and implement a decoding algorithm to map extracellular neural activity into speech-based representations for immediate synthesis and audio output (Brumberg et al. 2010; Guenther et al. 2009).

Auditory Processing in Speech Production

Our speech synthesizer BCI decodes speech output using neural activity directly related to the neural representations underlying speech production. Computational modeling of the speech system in the human brain has revealed the presence of sensory feedback control mechanisms used to maintain error-free speech productions (Guenther et al. 2006; Houde and Nagarajan 2011). In particular, sensory feedback in the form of self-perception of auditory and somatosensory consequences of speech output is used to monitor errors and issue corrective feedback commands to the motor cortex. Our BCI design takes advantage of two key features: (1) auditory feedback in the form of corrective movement commands and (2) intact hearing and motor cortical activity typically observed in cases of LIS. These features are combined in our BCI to provide instantaneous auditory feedback driven through speech-motor control of the BCI. This auditory feedback is expected to engage existing neural mechanisms used to monitor and correct errors in typical speech production and send feedback commands to the motor cortex for updated control of the BCI.

Other groups have also investigated methods for directly decoding speech sounds from neural activity during speech production from a discrete classification approach using electroencephalography (DaSalla et al. 2009), electrocorticography (Blakely et al. 2008; Kellis et al. 2010; Leuthardt et al. 2011) and microelectrode recordings (Brumberg et al., 2011). These studies all illustrate that phoneme and word classification is possible using neurological activity related to speech production. The same LIS patient participated in both our microelectrode study of phoneme production and online speech synthesizer BCI control study. The results of our earlier study (Brumberg et al. 2011) confirmed the presence of sufficient information to correctly classify as many as 24 (of 38) phonemes above chance expectations (Brumberg et al. 2011). Each of these speech-decoding results could greatly impact the design of future BCIs for speech communication. In the following sections, we describe some of the advantages of using a low degree-of-freedom, continuous auditory output representation over discrete classification.

The BCI implementation (described below) employs a discrete-time, adaptive filter-based decoder which can dynamically track changes in the speech output signal in real-time. The decoding and neural control paradigms used for this BCI are analogous to those previously used for motor kinematic prediction (Hochberg et al. 2006; Wolpaw and McFarland 2004); specifically, the auditory consequences of imagined speech-motor movements used here are analogous to two-dimensional cursor movements in prior studies. Ideally, we would like to use motor kinematic parameters specifically related to the movements of the vocal tract as output features of the BCI device. Such a design is similar to predicting joint angles and kinematics for limb movement BCIs. However, there are dozens of muscles involved in speech production, and most motor-based BCIs can only accurately account for a fraction of the degrees of freedom observed in the vocal mechanism. We therefore chose a lower, two-dimensional acoustic mapping as a computational consideration for a real-time auditory output device.

The chosen auditory dimensions are directly related to the movements of the speech articulators. This dimension-reduction choice is similar to those made for decoding neurological activity related to the high degree of freedom movements of the arm and hand into two-dimensional cursor directions. Further, the auditory space, when described as a two-dimensional plane, is topographically organized with neutral vowels, like the ‘uh’ in ‘hut,’ in the center and vowels with extreme tongue movements along the inferior–superior and anterior–posterior dimensions around the perimeter (see Fig. 1 left, for an illustration of the 2D representation). In this way we can directly compare this BCI design to prior motor-based BCI utilizing 2D center-out and random-pursuit tasks.

Auditory Output BCI Design

The speech synthesis BCI consists of (1) an extracellular microelectrode (Bartels et al. 2008; Kennedy 1989) implanted in the speech motor cortex (2) a Kalman

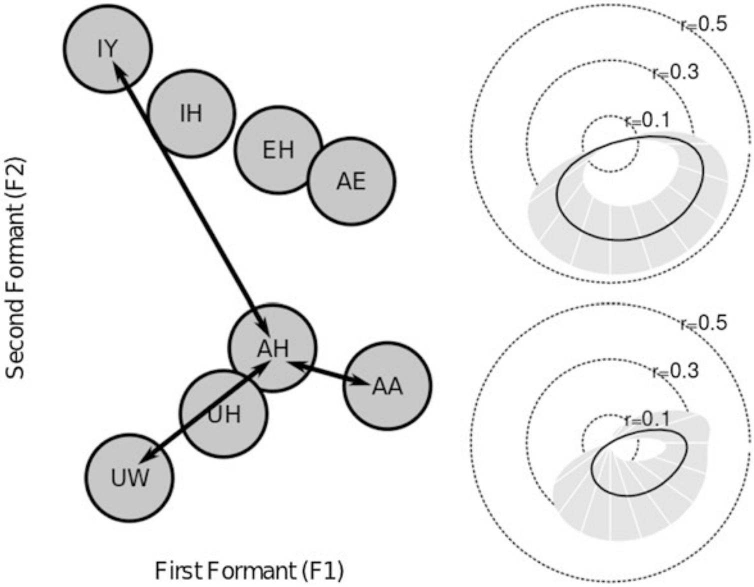

Fig. 1 *Left* 2D representation of formant frequencies. The *arrows* indicate formant trajectories used for training the neural decoder. *Right* examples of formant tuning preferences for two recorded units. The *black curve* indicates mean tuning preferences with 95 % confidence intervals in gray. The *top tuning curve* indicates a primarily 2nd formant preference while the *lower curve* indicates a mixed preference

filter decoding mechanism and (3) a formant-based speech synthesizer. The Kalman filter decoder was trained to predict speech formant frequencies (or formants) from neural firing rates. Formants are acoustic measures directly related to vocal tract motor execution used in speech production, and just the first two formants are needed to represent all the vowels in English. According to our speech-motor approach, we hypothesized that formants were represented by the firing rates of recorded neural units. This hypothesis was verified from offline analyses of the recorded signals (Guenther et al. 2009).

BCI Evaluation

To evaluate our speech synthesizer BCI, a single human subject with LIS participated in an experimental paradigm in which he listened to and repeated sequences of vowel sounds, which were decoded and fed back as instantaneously synthesized auditory signals (Brumberg et al. 2010; Guenther et al. 2009). We minimized the effect of regional dialects by using vowel formant frequencies that were obtained from vocalizations of a healthy speaker from the subject's family. The total delay from neural firing to associated sound output was 50 ms. The subject performed 25 sessions of vowel–vowel repetition trials, divided into approximately four blocks of 6–10 trials per session. At the beginning of each session, the decoder was trained using the neural activity obtained while the subject attempted to speak along with a vowel sequence stimulus consisting of repetitions of three vowels (AA [hot], IY [heed], and UW [who'd]) interleaved with a central vowel (AH [hut]). The vowel training stimuli are illustrated graphically in Fig. 1. These four vowels allowed us to sample from a wide range of vocal tract configurations and determine effective preferred formant frequencies, examples of which are shown on the right in Fig. 1.

Following training, the decoder parameters were fixed and the subject participated in a vowel-repetition BCI control paradigm. The first vowel was always AH (*hut*) and the second vowel was chosen randomly between IY (*heed*), UW (*who'd*) or AA (*hot*). By the end of each session, the participant achieved 70 % mean accuracy (with 89 % maximum accuracy on the 25th session) and significantly ($p < 0.05$, t test of zero-slope) improved his performance as a function of block number for both target hit rate and endpoint error (see Fig. 2). The average time to target was approximately 4 s.

These results represent classical measures of BCI performance. However, the true advantage of a system that can synthesize speech in real-time is the ability to create novel combinations of sounds on-the-fly. Using a two-dimensional formant representation, steady monophthong vowels can be synthesized using a single 2D position while more complex sounds can be made according to various trajectories through the formant plane. Figure 3 illustrates an example in which the 2D formant space can be used to produce the words "I" (left) and "you" (middle), and the phrase "I owe you a yo–yo." These words and phrases do not require any additions

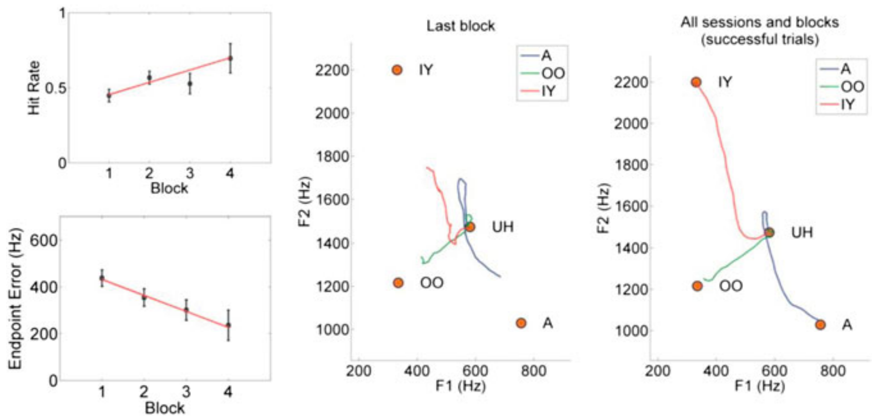

Fig. 2 Results from the speech synthesizer BCI control study. *Left* classical measures of performance, vowel target accuracy (*top*) and distance from target (*bottom*). *Middle* average formant trajectories taken for each of the three vowel–vowel sequences over all trials. *Right* average formant trajectories for each vowel–vowel sequence for successful trials only

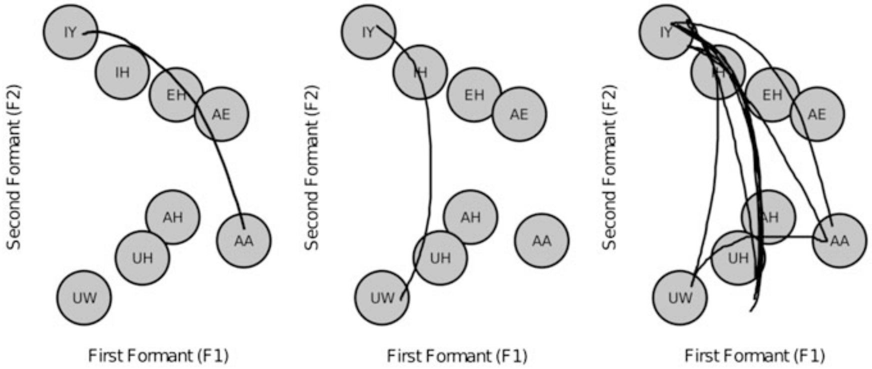

Fig. 3 An example of possible trajectories using manual 2D formant plane control. From *left* to *right*: selection of single formant pairs yields monophthong vowels; Trajectory from AA to IY yields the word "I"; Trajectory from IY to UW yields the word "you"; Complex trajectory shown yields the voiced sentence "I owe you a yo–yo"

to a decoding dictionary, as would be needed by a discrete classification BCI. Instead, the novel productions arise from new trajectories in the formant space.

Conclusion

These results are the first step toward developing a BCI for direct control over a speech synthesizer for the purpose of speech communication. Classification-based methods and our filter-based implementation for decoding speech from neurological recordings have the potential to reduce the cognitive load needed by a user to communicate using BCI devices by interfacing with intact neurological correlates of speech. Direct control of a speech synthesizer with auditory output yields further advantages by eliminating the need for a typing processes, freeing the visual system for other aspects of communication (e.g., eye contact) or for additional control in BCI operation. Future speech BCIs may utilize hybrid approaches in which discrete classification, similar to what is used for automatic speech recognition, are used in parallel to continuous decoding methods. The combination of both types of decoders has the potential to improve decoding rates while making the BCI a general communication device, capable of both speaking and transcribing intended utterances. Further, we believe that speech-sound feedback is better suited to tap into existing speech communication neural mechanisms, making it a promising and intuitive modality for supporting real-time communication.

The system as currently implemented is not capable of representing a complete speech framework, which includes both vowels and consonants. However, the results of our vowel-synthesizer BCI have led to a new line of research for development of a low-dimensional (2-3D) articulatory-phonetic synthesizer for dynamic production of vowels and consonants. In addition, we are currently conducting studies using a non-invasive EEG-based sensorimotor (SMR) rhythm BCI for control of the vowel synthesizer as an alternative to invasive implantation. Early results from the non-invasive study with a healthy pilot subject have shown promising performance levels ($\sim$71 % accuracy) within a single 2-hour recording session. We expect users of the non-invasive system to improve performance after multiple training sessions, similar to other SMR approaches.

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References

J. Bartels, D. Andreasen, P. Ehirim, H. Mao, S. Seibert, E.J. Wright, P. Kennedy, Neurotrophic electrode: method of assembly and implantation into human motor speech cortex. J. Neurosci. Methods **174**(2), 168–176 (2008)

J.S. Brumberg, A. Nieto-Castanon, P.R. Kennedy, F.H. Guenther, Brain–computer interfaces for speech communication. Speech Commun. **52**(4), 367–379 (2010)

C.S. DaSalla, H. Kambara, M. Sato, Y. Koike, Single-trial classification of vowel speech imagery using common spatial patterns. Neural Netw. **22**(9), 1334–1339 (2009)

F.H. Guenther, A neural network model of speech acquisition and motor equivalent speech production. Biol. Cybern. **72**(1), 43–53 (1994)

F.H. Guenther, S.S. Ghosh, J.A. Tourville, Neural modeling and imaging of the cortical interactions underlying syllable production. Brain Lang. **96**(3), 280–301 (2006)

F.H. Guenther, J.S. Brumberg, E.J. Wright, A. Nieto-Castanon, J.A. Tourville, M. Panko, R. Law, S.A. Siebert, J.L. Bartels, D.S. Andreasen, P. Ehirim, H. Mao, P.R. Kennedy, A wireless brain-machine interface for real-time speech synthesis. PLoS ONE **4**(12), e8218 (2009)

G. Hickok, Computational neuroanatomy of speech production. Nat. Rev. Neurosci. **13**(2), 135–145 (2012)

L.R. Hochberg, M.D. Serruya, G.M. Friehs, J.A. Mukand, M. Saleh, A.H. Caplan, A. Branner, D. Chen, R.D. Penn, J.P. Donoghue, Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature **442**(7099), 164–171 (2006)

J.F. Houde, S.S. Nagarajan, Speech production as state feedback control. Frontiers Human Neurosci. **5**, 82 (2011)

J.S. Brumberg, E.J. Wright, D.S. Andreasen, F.H. Guenther, P.R. Kennedy, Classification of intended phoneme production from chronic intracortical microelectrode recordings in speech-motor cortex. Frontiers Neurosci. **5**(65), 1–14 (2011)

S. Kellis, K. Miller, K. Thomson, R. Brown, P. House, B. Greger, Decoding spoken words using local field potentials recorded from the cortical surface. J. Neural Eng. **7**(5), 056007 (2010)

P.R. Kennedy, The cone electrode: a long-term electrode that records from neurites grown onto its recording surface. J. Neurosci. Methods **29**(3), 181–193 (1989)

E.C. Leuthardt, C. Gaona, M. Sharma, N. Szrama, J. Roland, Z. Freudenberg, J. Solis, J. Breshears, G. Schalk, Using the electrocorticographic speech network to control a brain–computer interface in humans. J. Neural Eng. **8**(3), 036004 (2011)

F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D.J. McFarland, N. Birbaumer, A. Kübler, An auditory brain-computer interface (BCI). J. Neurosci. Methods **167**(1), 43–50 (2008)

F. Plum, J.B. Posner, The diagnosis of stupor and coma. Contemp. Neurol. Series **10**, 1–286 (1972)

T. Blakely, K.J. Miller, R.P.N. Rao, M.D. Holmes, J.G. Ojemann, Localization and classification of phonemes using high spatial resolution electrocorticography (ECoG) grids, in *IEEE Engineering in Medicine and Biology Society*, vol. 2008, pp. 4964–4967, 2008

J.R. Wolpaw, D.J. McFarland, Control of a two-dimensional movement signal by a noninvasive brain–computer interface in humans. Proc. Natl. Acad. Sci. U. S. A. **101**(51), 17849 (2004)

User-Appropriate and Robust Control Strategies to Enhance Brain–Computer Interface Performance and Usability

E. V. C. Friedrich, R. Scherer and C. Neuper

Abstract This project aimed to enhance performance and usability of mental imagery-based BCIs by evaluating (1) user-appropriate and robust control strategies, (2) whether mental imagery-based BCIs are robust and stable enough for real-world applications and (3) user-comfort in able-bodied and disabled individuals. Three studies were conducted to address these issues. The results showed that alternatives to motor imagery can provide a great benefit especially to severely motor impaired users. Individually chosen control strategies from a broad range of reliable and stable mental tasks can improve BCI usability and performance substantially. Furthermore, participants could operate the BCI while simultaneously perceiving or reacting to deviant auditory stimuli and could attain stable long-time BCI control despite longer breaks without any BCI use. This project paid special attention to practical issues and helped to pave the way out of the laboratory into real-world application for mental imagery-based BCIs.

Introduction

Despite the scientific and technological progress in the field, it is still not possible to use a mental imagery-based brain-computer interface (BCI) independently and comfortably in one's everyday life (Wolpaw et al. 2002; Zickler et al. 2009). Therefore, we aimed to enhance various aspects of BCI usability. In the first study, we focused on control strategies used to encode the user's intent. Motor imagery

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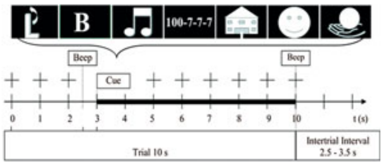
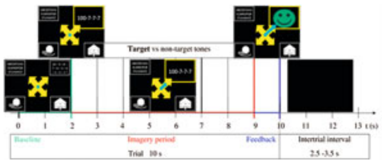
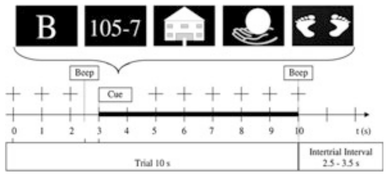
tasks are most commonly used (e.g. Kübler et al. 2005; Pfurtscheller et al. 2006; Neuper et al. 2009; McFarland et al. 2010). However, the best strategy to modulate brain activity might be to use multiple mental tasks to better account for individual-specific differences (Curran and Stokes 2003; Millán et al. 2004). Thus, our first study aimed to provide a broad range of user-appropriate mental tasks. In the future, users could choose between them based on discriminative performance and preferences. We expect that selection of appropriate strategies will allow more people to gain better BCI control and also feel more comfortable when using a BCI. In a second study, we evaluated whether control of such a mental-imagery based BCI was robust and stable enough for real-world applications. To communicate and control BCIs independently in their everyday lives, individuals will not only have to operate a BCI while other people around them are talking or watching television but also have to multi-task, e.g. to react to important stimuli while controlling a wheelchair or neuroprosthesis with the BCI. Furthermore, long-term stability of BCI control—including when the training is interrupted for months—is very important for both severely disabled and able-bodied individuals. Therefore, the most discriminative mental tasks from the first study were implemented in a 4-class feedback paradigm. Users were not only exposed to auditory distraction while controlling the BCI with mental imagery tasks but were also asked to multi-task. A follow-up session—weeks after the BCI training stopped—was used to evaluate the long-term stability of the different mental tasks. Both presented studies were conducted with able-bodied participants. However, a choice between different mental tasks for BCI control might be most valuable for individuals with neurological disorder. For example, individuals suffering from stroke that affects cortical motor areas may use a mental subtraction task rather than a motor imagery task for BCI control. Hence, two different motor imagery tasks and three non-motor tasks were evaluated with severely disabled users. Not only performance but also user-comfort is a big issue for the success of a BCI—especially for individuals with motor impairment, who would benefit from using a BCI in their everyday life. Consequently, in a third study, we not only investigated which mental tasks were suitable for motor impaired individuals, but also whether there are differences between able-bodied and motor impaired users in experienced quality of imagery, task ease and enjoyment.

To summarize, our studies aimed to enhance usability of BCIs by evaluating (1) user-appropriate control strategies, (2) whether mental imagery-based BCIs are robust and stable enough for real-world applications and (3) user-comfort of able-bodied and disabled individuals.

Methods

The methods of all three studies are summarized in Table 1. The methodological details of Study 1 are described in Friedrich et al. 2012; 2013, of Study 2 in Friedrich et al. 2011a; in press and of Study 3 in Friedrich et al. 2011b. Below we briefly review the studies.

Table 1 Summary of the three studies

	Study 1 (Friedrich et al. 2012; 2013)	Study 2 (Friedrich et al. 2011a; in press)	Study 3 (Friedrich et al. 2011b)
Participants	9 ♀ (20–32 years)	7 ♀ + 7 ♂ (20–35 years)	7 ♀ + 5 ♂ (20–57 years)
Diagnose	Able-bodied	Able-bodied	Motor disabled (stroke or spinal cord injury)
EEG	30 electrodes	29 electrodes	30 electrodes
Sessions	4 offline	2 off- + 8 online + Follow-up	2 offline
Classification	CSP and LDA	CSP and LDA	CSP and LDA
Tasks	Mental rotation Word association Auditory imagery Mental subtraction Spatial navigation Imagination of faces Motor imagery (hand)	Word association Mental subtraction Spatial navigation Motor imagery (hand)	Word association Mental subtraction Spatial navigation Motor imagery (hand) Motor imagery (feet)
Paradigm			
Results	Combination of brain-teasers (e.g. word association, mental subtraction) and dynamic imagery tasks (e.g. motor imagery) is most promising for BCI control ERD/S values of the word association, mental subtraction and spatial navigation task revealed the highest consistency over sessions	Distraction had no adverse effect on BCI performance in none of the tasks Motor imagery imposed least workload and yielded best performance Performance stayed stable long-time.	Motor impaired participants generally enjoyed performing the mental tasks less than able-bodied participants. Task evaluation and classification accuracy was especially low in the motor imagery task for the motor impaired users in contrast to the able-bodied participants

Study 1 included 9 able-bodied participants (ages 20–32, 9 female, right-handed) who participated in 4 sessions without feedback. The participants were asked to perform the mental task indicated on the screen for 7 s while staying relaxed and trying to avoid movements. The mental tasks occurred in randomized order and included: mental rotation (visualize a 3-dimensional L-shaped figure that rotates 3-dimensional space); word association (generate as many words as possible that begin with the presented letter); auditory imagery (imagine listening to a familiar tune without articulating the words but rather focusing only on the melody); mental subtraction (perform successive elementary subtractions by a presented fixed number); spatial navigation (imagine navigating through a familiar house); imagination of familiar faces (imagine the face of the best female friend) and motor imagery of the hand (imagine repetitive self-paced movements of the own hand). EEG was recorded from 30 electrodes distributed over the whole scalp.

Study 2 included 14 able-bodied participants (ages 20–35, 7 female, right-handed) who participated in 2 screenings and then 8 feedback sessions within a 5 week time period. After 10 weeks without any training, 12 of the 14 participants performed another feedback session as follow-up. The mental tasks word association, mental subtraction, spatial navigation and hand motor imagery were implemented in a real-time 4-class BCI. The participants were asked to control a bar graph by performing mental imagery for 7 s (i.e. imagery period) as indicated by the visual cue in randomized order. EEG was recorded from 29 electrode positions. In addition to the continuous online feedback in form of the bar graph, discrete feedback (reward) was provided. The discrete feedback was given at the end of a trial each time the given mental task was detected either correctly for a period >2 s or longer than any other task. In the last two sessions, tones were presented every second during the imagery period with the aim of distracting users. Five 1 kHz and one 2 kHz tones were played in each trial in pseudorandom order like in an oddball paradigm. Users were asked to either ignore all tones or to react to the 2 kHz tones with a button press.

Study 3 included 12 motor impaired participants (ages 20–57, 7 female, right-handed) who participated in 2 sessions without feedback. The participants were diagnosed with spinal cord injury or stroke. The users were asked to imagine word association, mental subtraction, spatial navigation, motor imagery of the hand and motor imagery of the feet. The experimental paradigm and the EEG recordings were identical to study 1.

In all studies, common spatial patterns (CSP) and Fisher's linear discriminant functions (LDA; with majority voting for study 2 were used for classification (Müller-Gerking et al. 1999; Ramoser et al. 2000; Duda et al. 2001; Blankertz et al. 2007). In study 3, for each task true positive detection rates (TPRs) were computed by dividing the number of correctly classified samples with the same time lag from cue onset by the number of trials.

In all studies, participants rated each of the mental tasks on a 5-point rating scale concerning the quality of imagery (1 = no image at all, you only 'know' you are thinking of the object and 5 = perfectly clear and as vivid as normal vision), the task ease (1 = very exhausting and full concentration needed and 5 = very relaxing and possible to perform despite major distractions such as activated television, visit of friends or in the traffic) and the enjoyment (1 = no fun at all and very frustrating and 5 = a lot of fun and not frustrating at all) after every session.

Results

The classification results and oscillatory EEG activity patterns (i.e. Event-Related (De)Synchronization, ERD/S) of the first study indicated that reliable and stable classification of the studied mental tasks is possible (Friedrich et al. 2012). The pair-wise discrimination of mental subtraction/motor imagery (average peak accuracies of 85 %), word association/motor imagery and mental subtraction/auditory imagery (both 83 %) resulted in the highest single-trial classification performance in single-sessions. When the classifier was applied to unseen data (off-line BCI simulation), mental rotation also showed high classification results. On an individual basis, accuracy of specific combinations of mental tasks reached > 95 % accuracy. The reliability of the underlying brain patterns as to ERD/S was determined by Cronbach's Alpha consistency coefficients (Friedrich et al. 2013). Most consistent over sessions were ERD/S values in both alpha bands, which ranged between 0.80 and 0.92 for the three most consistent tasks, which were word association, mental subtraction and spatial navigation. The classification results as well as the brain patterns indicated that a combination of 'brain-teasers'—tasks that require problem specific mental work (e.g. mental subtraction, word association)—and 'pure imagery'—tasks that include dynamic imagination (e.g. motor imagery, spatial navigation)—is most promising for BCI control.

Taking the above results into account, the mental tasks word association, mental subtraction, motor imagery and spatial navigation were implemented in a real-time feedback paradigm (study 2; Friedrich et al. 2011a; in press). Online performance was based on the percentage of correct selections (rewards; i.e. the ability of maintaining the desired activation long enough for selection). Except for one user, all users were able to control at least 3 classes and 8 participants managed to control all 4 classes simultaneously in single-sessions significantly over chance level. Motor imagery achieved highest performance. Additionally, the P300 components and reaction times upon the target stimuli in the distraction conditions indicated that motor imagery imposed the lowest workload (Friedrich et al. 2011a). However, performance neither decreased in the distraction situation, nor in the follow-up session, in any of the mental tasks (Friedrich et al. in press). In runs in which users were asked to ignore the tones, users achieved higher performance than in runs without any distraction and in runs in which they were asked to react to the target stimuli.

In study 3, the results from study 1 could be generally confirmed. However, when evaluating the TPR, the motor disabled participants achieved poor classification accuracy in the motor imagery task in contrast to able-bodied participants. Furthermore, motor impaired participants did not only enjoy the mental imagery-based BCI generally less than able-bodied participants but rated the motor imagery task as especially less enjoyable (Friedrich et al. 2011b). A correlation between the task enjoyment of motor imagery and the TPR of motor imagery was significant by trend ($\rho = 0.3$; $p < 0.1$) for a sample of 35 participants including users from all three studies. Additionally, the task ease correlated with performance.

Discussion

The aim of our studies was to enhance usability and improve BCI-control focusing especially on practical issues. Multiple mental tasks were identified that are suitable for BCI control. Individually chosen control strategies from the investigated range of mental tasks could improve performance substantially. This is very valuable for users since BCIs could be designed individually according to users' preferences and individual classification results. Additionally, all mental tasks were easily and voluntarily producible any time; thus, they also could be implemented in asynchronous systems. In an asynchronous system, the user can send messages or commands without any predefined time window or external cue needed. Furthermore, we demonstrated that operating a four class mental imagery based BCI and simultaneously perceiving or reacting to deviant auditory stimuli has no adverse effect on the BCI performance. The real-time BCI system also worked reliable in the long-term in spite of longer breaks without its use. These results are extremely encouraging for real-world application as participants succeeded in operating the 4-class BCI during auditory distraction and after months without any training. The study including motor impaired users showed that although motor imagery tasks are mostly used—and also work very well for able-bodied individuals - this might not be the best choice for motor impaired individuals. Motor disabled persons did not only perform worse in motor imagery tasks in comparison to able-bodied users but also enjoyed them less. The significant correlations over all users demonstrated that user-comfort should not be treated as minor point but that there is a relation with performance. Future studies should make more efforts to make BCIs more enjoyable and appropriate for potential users who really need them.

To conclude, the project included individuals with severe motor disabilities, some of whom were already in a locked-in state and thus would potentially benefit from BCIs. User appropriate control strategies were not only tested offline but also implemented in a real-time feedback study and evaluated under distraction and long-term use. For this, a new methodological approach was used. A 4-class BCI with different mental tasks was implemented for the first time and the method of CSP was proven to work for different mental tasks besides motor imagery for which it was normally used. We believe that the new insights of user-appropriate control strategies, robustness and stability of mental tasks and user-comfort of able-bodied and disabled individuals will significantly enhance BCI usability and performance. Our research provides great benefit to potential users and helps to pave the way out of the laboratory into real-world application for mental imagery-based BCIs.

Subsequent Work

We are developing this project further and are currently focusing on improving performance by optimizing methods and evaluating the findings in the patient population.

First, we are working on improving the 4-class real-time BCI. As all conducted studies also revealed individual differences between the users in best task combinations and task evaluation, we aim to select mental tasks individually in future. Our initial results suggest that high accuracies are possible with such a mental imagery-based 4-class BCI. Additionally, the continuous online feedback should be improved to facilitate feedback learning. Nijboer et al. (2008) suggested that motivation and mood are also important factors for feedback learning and Kleih et al. (2011) found significant correlations between motivation and task performance. Therefore, we also aim at examining changes of motivation, mood, quality of imagery, task ease and enjoyment over training sessions in future studies.

Second, a high priority for future work is to evaluate the real-time BCI with different mental tasks with severely motor impaired individuals. The differences between able-bodied and disabled participants in Friedrich et al. (2011b) suggested that results from able-bodied persons cannot be projected to disabled individuals. Besides suffering from brain injury, their impairment may be associated with other neurological or attentional deficits that make it difficult to perform certain tasks (Kübler et al. 2001). Furthermore, BCI applications should be adapted to the individuals' special needs and user-comfort should also be taken into account (Allison and Neuper 2010; Friedrich et al. 2011b).

The goal of our subsequent work is to optimize the mental imagery-based BCI in a way that performance and usability can be further improved by individual selections of user-appropriate and robust mental tasks for able-bodied as well as disabled individuals.

References

B.Z. Allison, C. Neuper, Could anyone use a BCI?, in: Applying our minds to human-computer interaction, brain-computer interfaces, human-computer interaction series, ed. by D.S. Tan, A. Nijholt, (Springer Verlag, London, 2010) pp. 35–54

B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, G. Curio, The non-invasive Berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects. NeuroImage **37**, 539–550 (2007)

E. Curran, M. Stokes, Learning to control brain activity: a review of the production and control of EEG components for driving brain-computer interface (BCI) systems. Brain Cogn. **51**, 326–336 (2003)

R.O. Duda, P.E. Hard, D.G. Stork, *Pattern classification,* 2nd ed. (John Wiley, New York, 2001)

E.V.C. Friedrich, R. Scherer, K. Sonnleitner, C. Neuper, Impact of auditory distraction on user performance in a brain-computer interface driven by different mental tasks. Clin. Neurophysiol. **122**, 2003–2009 (2011a)

E.V.C. Friedrich, R. Scherer, J. Faller, C. Neuper, Do user-related factors of motor impaired and able-bodied participants correlate with classification accuracy?, in: *Proceedings of the 5th International Brain-Computer Interface Conference 2011*, ed. by G.R. Müller-Putz, R. Scherer, M. Billinger, A. Kreilinger, V. Kaiser, C. Neuper (2011b) pp. 156–159

E.V.C. Friedrich, R. Scherer, C. Neuper, The effect of distinct mental strategies on classification performance for brain-computer interfaces. Int. J. Psychophysiol. **84**, 86–94 (2012)

E.V.C. Friedrich, R. Scherer, C. Neuper, Stability of event-related (de-) synchronization during brain-computer interface-relevant mental tasks. Clin. Neurophysiol. **124**, 61–69 (2013)

E.V.C Friedrich, R. Scherer, C. Neuper. Long-term evaluation of a 4-class imagery-based brain-computer interface. Clin. Neurophysiol. (in press)

S.C. Kleih, A. Riccio, D. Mattia, V. Kaiser, E.V.C. Friedrich, R. Scherer, G. Müller-Putz, C. Neuper, A. Kübler, Motivation influences performance in SMR-BCI, in: *Proceedings of the 5th International Brain-Computer Interface Conference* 2011, ed. by G.R. Müller-Putz, R. Scherer, M. Billinger, A. Kreilinger, V. Kaiser, C. Neuper (2011) pp. 108–111

A. Kübler, B. Kotchoubey, J. Kaiser, J.R. Wolpaw, N. Birbaumer, Brain-computer communication: Unlocking the locked in. Psychol. Bull. **127**, 358–375 (2001)

A. Kübler, F. Nijboer, J. Mellinger, T.M. Vaughan, H. Pawelzik, G. Schalk, D.J. McFarland, N. Birbaumer, J.R. Wolpaw, Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface. Neurology **64**, 1775–1777 (2005)

D.J. McFarland, W.A. Sarnacki, J.R. Wolpaw, Electroencephalographic (EEG) control of three-dimensional movement. J. Neural Eng. **7**, 1–9 (2010)

J.d.R. Millán, F. Renkens, J. Mouriño, W.Gerstner, Brain-actuated interaction. Artif. Intell. **159**, 241–259 (2004)

J. Müller-Gerking, G. Pfurtscheller, H. Flyvbjerg, Designing optimal spatial filters for single-trial EEG classification in a movement task. Clin. Neurophysiol. **110**, 787–798 (1999)

C. Neuper, R. Scherer, S. Wriessnegger, G. Pfurtscheller, Motor imagery and action observation: Modulation of sensorimotor brain rhythms during mental control of a brain-computer interface. Clin. Neurophysiol. **120**, 239–247 (2009)

F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D.J. McFarland, N. Birbaumer, A. Kübler, An auditory brain-computer interface (BCI). J. Neurosci. Methods **167**, 43–50 (2008)

G. Pfurtscheller, C. Brunner, A. Schlögl, F.H. Lopes da Silva, Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. NeuroImage **31**, 153–159 (2006)

H. Ramoser, J. Müller-Gerking, G. Pfurtscheller, Optimal spatial filtering of single trial EEG during imagined hand movement. IEEE Trans. Rehabil. Eng. **8**, 441–446 (2000)

J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, Brain-computer interfaces for communication and control. Clin. Neurophysiol. **113**, 767–791 (2002)

C. Zickler, V. Di Donna, V. Kaiser, A. Al-Khodairy, S. Kleih, A. Kübler, M. Malavasi, D. Mattia, S. Mongardi, C. Neuper, M. Rohm, R. Rupp, P. Staiger-Sälzer, E.-J. Hoogerwerf, BCI applications for people with disabilities: defining user needs and user requirements, in Assistive technology from adapted equipment to inclusive environments, AAATE 2009, ed. by P.L. Emiliani, L. Burzagli, A. Como, F. Gabbanini, A.-L. Salminen. in *Proceedings of the 10th European conference of the association for the advancement of assistive technology in Europe* (2009) pp. 185–189

What's Your Next Move? Detecting Movement Intention for Stroke Rehabilitation

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Abstract BCIs have recently been identified as a method to promote restorative neuroplastic changes in patients with severe motor impairment, such as after a stroke. In this chapter, we describe a novel therapeutic strategy for hand rehabilitation making use of this method. The approach consists of recording brain activity in cortical motor areas by means of near-infrared spectroscopy, and complementing the cortical signals with physiological data acquired simultaneously. By combining these signals, we aim at detecting the intention to move using a multi-modal classification algorithm. The classifier output then triggers assistance from a robotic device, in order to execute the movement and provide sensory stimulation at the level of the hand as response to the detected motor intention. Furthermore, the cortical data can be used to control audiovisual feedback, which provides a context and a motivating training environment. It is expected that closing the sensorimotor loop with such a brain-body-robot interface will promote neuroplasticity in sensorimotor networks and support the recovery process.

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Introduction

Patients with neurologic injuries (e.g. after a stroke) often suffer from sensorimotor impairments, hampering the control of their affected limbs (Roger et al. 2011). The hand plays a unique and important role in numerous activities of daily living, and impairments of its functionality can lead to a loss of independence and reduced interaction with the environment.

Motor rehabilitation can be defined as the process of restoring impaired sensorimotor function. While rehabilitation is traditionally supported by physiotherapy (Pollock et al. 2008), robot assisted therapy approaches were proposed recently, making alternative rehabilitation strategies possible. Often equipped with a variety of sensors to control and measure kinematics and dynamics, such rehabilitation robots allow not only for massed practice without causing excessive physical fatigue in therapists, but also for the precise and objective assessment of the patient's performance and an easy integration into a virtual reality (VR) environment (Takahashi et al. 2008; Lambercy et al. 2011).

Active participation of the patient during exercises has been identified as a key parameter in the success of rehabilitation. Active movement therapy (AMT) is an approach that encourages patients to initiate a motor task at free will. It has been shown to yield better therapeutic outcomes compared to passive movements, in which the impaired limb is moved without the patient's intention to do so (Takahashi et al. 2008; Hogan et al. 2006). However, a major limitation of AMT is that it relies on remaining motor function, thus excluding patients with severe impairments. Approximately one third of stroke survivors suffer from severe post-stroke impairment (Buch et al. 2008), which strongly limits their capacity for active participation in physical tasks. There is thus a need to rethink therapeutic approaches for this important patient population, and one promising option is to shortcut motor impairment by using cortical signals as a way to engage in therapeutic physical exercises supported by a robotic interface (Ward et al. 2007).

Tackling the Problem from the Roots: Brain–Computer Interface for Hand Rehabilitation

The direct inclusion of the source of the problem—the injured brain—into the therapy is characteristic of all forms of AMT and is key for a successful therapeutic outcome. In conventional AMT, the brain is included via remaining sensorimotor pathways. Employing a brain–computer interface (BCI), this concept is adapted to the severely impaired: the injured sensorimotor pathways can be bypassed by estimating the intention to move—the *active* command—directly from cortical measurements.

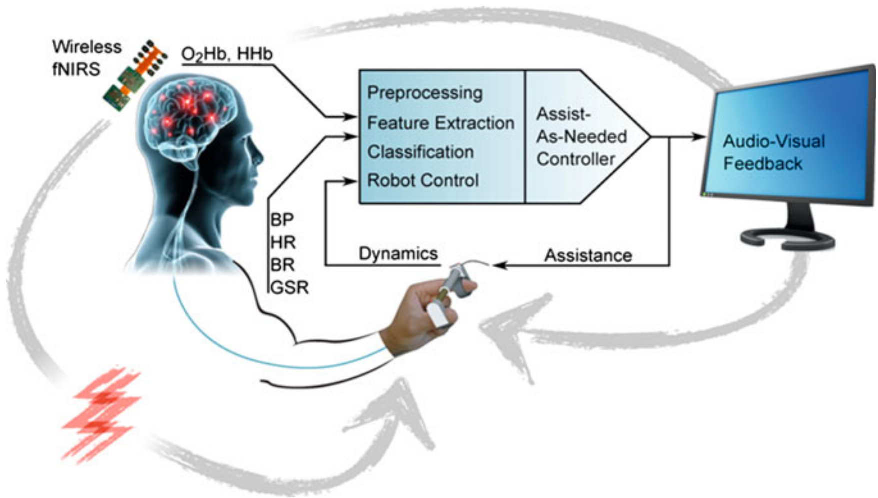

Fig. 1 Schematic representation of the projected therapy approach. Since muscle activation cannot be used to initiate a movement (indicated by the interrupted arrow), a classifier detects the intention to move based on brain activity measured with functional near-infrared spectroscopy (fNIRS) and various biosignals, i.e. blood pressure (BP), heart rate (HR), breathing rate (BR) and galvanic skin response (GSR). Assistance is then provided by a robotic device as needed. O_2Hb/HHb: oxy-/deoxyhemoglobin, respectively. Audiovisual feedback of the intended motor task is provided using a virtual reality environment

Our approach is to develop a novel interface detecting motor intention at the cortical level in order to trigger assistance to the hand through a dedicated robotic device (Fig. 1). The intention detection is furthermore supported by the simultaneous acquisition of the patient's physiological state (see section "Pilot Study"). Together with a VR environment, this BCI–robot combination induces proprioceptive, visual and auditory consequences of an intended hand movement to the brain, essentially expanding standard BCI architectures by an additional component: the body. We define this approach as brain–body–robot interface (B^2RI). Unlike the conventional non-invasive BCI architecture with a unidirectional interface between brain and computer, the proposed system also enables the reverse communication from the computer to the brain, via the assistive robot and the induced haptic sensation.

This BCI-based rehabilitation approach has the potential to provide a therapy which opens the wide horizon of AMT to the, until now left out, severely impaired. It is assumed that combining the intention to perform a motor task with its proprioceptive and audiovisual consequences helps to promote the neuroplastic effects that are the key for functional hand recovery (Cramer et al. 2011; Wang et al. 2010).

Near-Infrared Spectroscopy for Brain–Computer Interfaces

A BCI relies on signals from the brain. To use a BCI in a rehabilitation environment, the acquisition of brain signals should be safe, non-invasive and easy to use. From the different non-invasive methods to record brain activity (such as fMRI, MEG and EEG), functional near-infrared spectroscopy [fNIRS, see (Wolf et al. 2007) for an introduction] is well suited for day-to-day use, possibly even at home without supervision of a therapist. This is because it is safe, achieves a high temporal resolution while maintaining sufficient spatial resolution, offers a simple attachment of the probes to the head, is relatively robust to motion artifacts and is available at comparatively low prices. Further benefits could include miniaturization and wireless operation (Muehlemann et al. 2008).

fNIRS is a spectroscopic approach, hence making use of wavelength-dependent properties of human (brain-) tissue. Light at discrete wavelengths from the near-infrared region [approx. 650–950 nm (Wolf et al. 2007)] is guided into the head. Due to the high scattering properties of human tissue, a fraction of this light can be detected on the head's surface a few centimeters away from the source. A part of the detected light reaches the cortex, carrying information about this region. The photons are not only scattered, but also absorbed. The amount of absorbed light is wavelength-specific and depends essentially on the local concentration of the two major absorbers in human tissue, i.e. oxygenated hemoglobin (O_2Hb) and deoxygenated hemoglobin (HHb). By measuring the attenuation of the injected light of at least two discrete wavelengths, changes in O_2Hb and HHb can locally be determined. Changes in local brain activity can be inferred based on the phenomenon called neurovascular coupling (Pasley and Freeman 2008). It describes the relation between increased neuronal activity and the resulting increase in metabolic demand, which is met by a regional increase in cerebral blood flow. Essentially, this cascade leads to a locally increased concentration of O_2Hb and a reduction in the HHb concentration, which both can be quantified with fNIRS.

Since fNIRS relies on the detection of hemodynamic changes in the cortex that directly result from changes in brain activity, natural brain processes produce detectable signal patterns and no intensive user training is required to operate a fNIRS based BCI (Coyle et al. 2004; Sitaram et al. 2005).

State of the Art in fNIRS-Based BCIs

Several different tasks elicit signal patterns in the brain that can be used to control fNIRS-based BCIs. Besides simple motor tasks such as overt motor execution (e.g. finger tapping or pinching) (Ward et al. 2007; Cui et al. 2010) and the kinesthetic imagery of the execution of a motor task (motor imagery, MI) (Sitaram et al. 2007; Coyle et al. 2007; Holper and Wolf 2011), signal patterns arising from more cognitive tasks have been successfully classified. Examples for the latter include arithmetic (Naito et al. 2007; Power et al. 2010), music imagery (Naito et al. 2007; Power et al. 2010; Falk et al. 2011), preferring (Luu and Chau 2009), and emotional induction (Tai and Chau 2009).

The ideal placement of the fNIRS probes (and hence the region from where the brain signals are measured) strongly depends on the task. While motor tasks generally alter the brain activity in motor regions such as the primary motor area (M1) and the premotor cortex (PMC), the brain activity changes arising from tasks such as arithmetic or emotional induction are generally measured from frontal regions. It is worth mentioning a small but important difference between frontal measurements and recordings over motor regions. Often, the scalp over frontal brain areas is free of hair, unlike over motor regions. Since an efficient coupling between light sources or detectors and the scalp is of great importance, hair that obscures the optics can lead to poor signal quality (Coyle et al. 2007). Furthermore, the hair roots might absorb reflected light, further reducing the detected signal level.

Not only different tasks and measurement locations have been explored, but also numerous strategies in processing the data prior to the classification. In general, the fNIRS data cannot be classified directly. The selection of informative feature signals that capture the essential differences between various brain states is hence a key element in fNIRS-based BCIs, and diverse strategies have been employed. Concerning the classifiers, a multitude of approaches have been applied, e.g. support vector machines (SVM), linear discriminant analysis (LDA) and hidden Markov models (HMM). Predominantly, binary classifiers have been employed so far, which decode two classes (e.g. *left* vs. *right* motor tasks, or—as in the work described here—*motor intention* vs. *rest*).

In the following, a summary of important recent publications on fNIRS-based BCIs is given. Table 1 lists the key facts of these relevant studies in chronological order. It becomes evident that the field is rather young and still in its infancy. The studies conducted to date are essentially pilot studies, with rather small sample sizes. From the employed features and classification architectures, we conclude that neither consensus has been found on the ideal signal processing approaches, nor a standard classifier. However, HMMs seem to outperform other approaches.

To summarize, recent studies on fNIRS based BCIs have underlined the potential of fNIRS as a modality to detect cortical activity directly from motor regions with decent accuracy, while requiring minimal setup time and training. This makes fNIRS a very promising candidate for rehabilitation applications. In the next section of this chapter, we will present results of a pilot study (Zimmermann et al. 2011) towards the B^{2}RI concept introduced earlier in this chapter. The proposed setup uses fNIRS as BCI modality. Furthermore, it also investigates the feasibility of using physiological measurements to form a hybrid BCI (Falk et al. 2011; Tai and Chau 2009), as outlined below.

Table 1 Summary of the state of the art in fNIRS-based BCIs

	LOC	TASK	N	FEAT	P	CLASS	ACC [%]
Sitaram et al. (2007)	M1 (bilat.)	Left versus right MI	5	O_2Hb and HHb	20	SVM and HMM	73.1 (SVM) 89.1 (HMM)
Naito et al. (2007)	PFC	High versus low mental load[a]	40	Intensity amplitude and oscillation numbers	1	Non-linear discriminant analysis	79.6[b]
Coyle et al. (2007)	M1 (bilat.)	Left versus right MI	3	Mean change in O_2Hb from rest	2	Online comparison	80.0
Ward et al. (2007)	M1 (bilat.)	Isometric elbow pivoting versus rest	4	Mean change in O_2Hb from rest	2	Online comparison	62.4–93.0
Luu and Chau (2009)	PFC	Preference over two drinks	9	Mean intensity[c]	24	LDA	80.0
Tai and Chau (2009)	PFC	Positive versus negative valence	10	208 different candidate features,[d] selected using GA	8	LDA and SVM	75.0–96.7 (max. acc.)
Power et al. (2010)	PFC	MA versus music imagery	10	Intensity	9	HMM	77.2
Cui et al. (2010)	MC (bilat.)	Finger tapping versus rest	6	Various, CNR channel selection	48	SVM	~85[e]
Holper and Wolf (2011)	PMC, SMA	Simple versus complex MI	12	Various, selection: exhaustive search	4	LDA	81.3
Falk et al. (2011)	PFC	Music imagery versus rest	8	O_2Hb, HHb and biosignals	8	HHM (trained on rest data)	80.0 (fNIRS) 89.3 (fNIRS + biosignals)

A selection of recent studies was reviewed for the measured brain regions (LOC), the task to elicit classifiable brain patterns (TASK), the number of subjects that were reported (N), the feature signals used (FEAT), the number of light paths of the employed fNIRS system (P), the classification method (CLASS) and the achieved classification accuracy (ACC). *Bilat.* bilaterally, *PFC* prefrontal cortex, *GA* genetic algorithm, *MA* mental arithmetic, *SMA* supplementary motor area, *MC* motor cortex, *CNR* contrast-to-noise ratio

[a] High mental load: MA or fast mental singing. Low mental load: number/sheep counting, slow mental singing, landscape imaging

[b] Only subjects considered whose data showed good separability post hoc (23/40)

[c] The intensity values were corrected for influence from superficial tissue

[d] Simultaneously acquired respiration signals were removed from O_2Hb and HHb using a least mean squares adaptive filter

[e] Estimated from published bar plot

Pilot Study

In order to include the injured brain in the proposed rehabilitation process, brain activity in areas that are involved in the planning and execution of a motor task needs to be measured. A motor task was therefore chosen as stimulus and recordings using fNIRS were made from contralateral M1 and PMC.

The spatial sensitivity of fNIRS is not restricted to cortical tissue alone, but essentially includes the whole path that photons undergo between source and detector. It is thus not exclusively sensitive to hemodynamic changes in cortical tissue, but also to systemic effects such as heart beat, variations in blood pressure, and respiration. The additional measurement of these physiological signals is assumed to be beneficial for two reasons: first, it might help to clean the fNIRS data and efficiently reveal the cortical signal components, and second, knowledge about the physiological state alone can be informative to decode motor intention. Therefore, the experiment also included the simultaneous acquisition of the subject's physiological state (Fig. 1).

The goal of the study was to investigate and compare fNIRS and physiological signals of healthy subjects during rest and an overt motor task, and to identify the most informative signals. To the best of our knowledge, this combination of functional fNIRS measurements from motor areas together with a set of informative physiological parameters is novel in a BCI application with the potential to be used in stroke rehabilitation.

Methods

Seven healthy subjects (26.0 ± 2.2 years old) participated in this pilot study. The motor task consisted in isometric pinching with the right index finger and thumb. Besides rest periods in which subjects were asked not to move, they were requested to pinch a force sensor (CentoNewton, LPM-EPFL, Switzerland) such that the applied force matched a visually presented reference trajectory, which was generated from a truncated Fourier series.

fNIRS data were acquired by a commercially available tissue oximeter (Oxiplex TS, ISS Inc., USA). Contralateral M1 and ventral PMC were located using the international 10–20-system for EEG electrodes (C3 and FC5, respectively) and the probes were accordingly placed with adhesive bandages. In order to investigate the differences in the cortical response between rest and pinching phases, the fNIRS samples from rest periods in a three second window were averaged and compared to the averages in a three second window in the subsequent pinching period. The latter window was shifted to account for the latency in the hemodynamic response. The shift was individually adjusted from 6 to 8 s after onset of the pinching period.

The physiological state was monitored by measuring the electrocardiogram to obtain the heart rate (HR), the nasal respiration flow to obtain the breathing rate

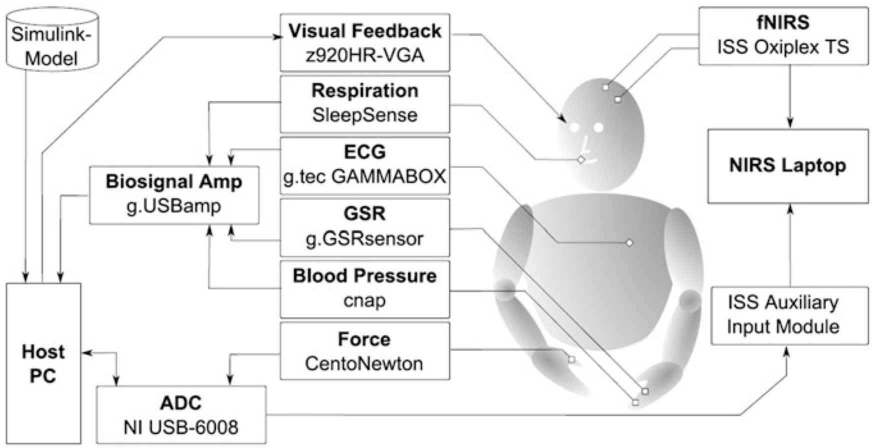

Fig. 2 Measurement setup. The biosignal amplifier was used to acquire physiological signals in real time. A Simulink® model was running on the host PC to control the protocol, measure the pinching force and provide visual feedback. fNIRS data from M1 and PMC were recorded in synchrony on a separate laptop PC. © 2011 IEEE. Reprinted, with permission, from Zimmermann et al. (2011)

(BR), the galvanic skin response (GSR) and the mean blood pressure (BP). Differences in the physiological signals between rest and pinching phases were investigated by comparing the averages in five second windows, like the analyses with fNIRS signals. The different temporal characteristic of the obtained signals was accounted for by applying different latencies between these windows (3 s for GSR and 5 s for all the other physiological signals). Figure 2 illustrates the measurement setup. Details on data acquisition and post-processing can be found in (Zimmermann et al. 2011).

Results

In M1, O_2Hb increased at the group level during pinching (mean $\pm$ SD: 0.184 ± 0.134 µM; $p = 0.011$, paired t-test), accompanied with a consistent decrease in HHb, which was weaker (0.064 ± 0.062 µM; $p = 0.033$). GSR increased significantly (0.369 ± 0.126; $p = 0.003$) as well as BP (3.327 ± 2.335 mmHg; $p = 0.018$) and BR (1.293 ± 1.076 bpm; $p = 0.033$). The individual results are displayed in Fig. 3. No consistent effect was observed for changes in HR, nor was a consistent brain activity change found in ventral PMC.

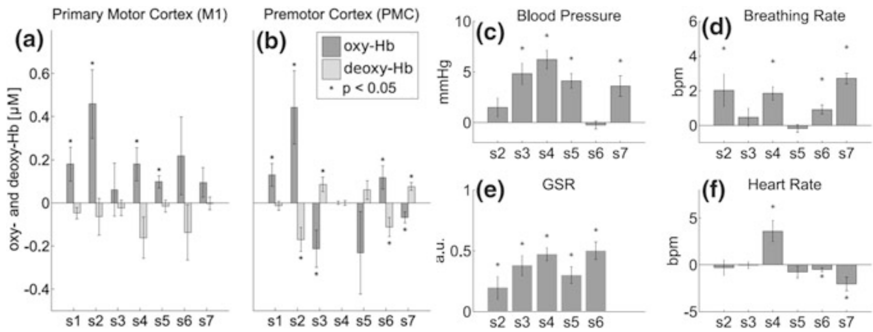

Fig. 3 Changes of hemodynamic and physiological parameters during a finger pinching task compared to rest. **a**, **b** hemodynamic response in M1 and PMC, respectively. **c**–**f** physiological parameters. Error bars indicate standard error of the mean, * indicate significance on the 5 %-level (paired t-test). © 2011 IEEE. Reprinted, with permission, from Zimmermann et al. (2011)

Discussion

The above results lead to the conclusion that the proposed system is capable of simultaneously measuring meaningful data from the motor cortices as well as from the body during a pinching task. In M1, a consistent activation pattern (increased O_2Hb, decreased HHb) was observed across participants, which is in agreement with the expected theoretical hemodynamic response. From all signals, GSR showed the clearest signal change and hence was identified as an important physiological parameter to consider in the B^2RI.

A large interindividual variability of the hemodynamic responses was found in PMC, which might be due to the somewhat approximative nature of the 10–20-system. However, a BCI is generally trained for each user individually. Thus one still could make use of subject-specific responses such as data from PMC or the HR.

Subsequent Work and Outlook

For a BCI to be employed in a rehabilitation application, robust online single-trial classification in real-time is required. In the B^2RI, the BCI output then triggers assistance from a robotic device, and audiovisual feedback is provided by means of a VR environment. In the following, these three aspects are introduced.

Towards Single-Trial Classification of fNIRS Data

As a first step towards a robust classification of fNIRS data on the single-trial level, we investigated (Zimmermann et al. 2013): (1) how the fNIRS data could be classified on a single-trial basis and (2) how the inclusion of the simultaneously recorded biosignals could affect classification performance.

Using the data from the above-mentioned pilot study, a classifier based on HMMs was designed and evaluated. HMMs are known to build an adequate framework in the classification of time series as shown in previous fNIRS studies (Sitaram et al. 2007; Power et al. 2010; Falk et al. 2011). Furthermore, they inherently provide the possibility of a multidimensional observation space, i.e. multiple simultaneously acquired measurement data.

Training samples were used to individually find the most informative feature signals from the fNIRS data, and to train two HMMs separately, one HMM for data where the subject was at rest and one with data where she/he was pinching. Two cases were investigated: first, the observations were limited to fNIRS data only, and second, the observation space was extended by the physiological signals. The classification of a single signal segment that belonged to the test data set was carried out by considering the two trained HMMs as generative models and comparing the likelihood that either model produced the observed signal. The performance was assessed by a fourfold cross-validation, and the HMM topography was adjusted post hoc for each subject separately.

This approach led to a classification accuracy of 79.4 ± 11.7 % (mean ± SD) when only fNIRS data were used, which significantly increased to 88.5 ± 7.3 % for the combination of fNIRS data and biosignals (Zimmermann et al. 2013).

The extent to which fNIRS signals contained components that were due to physiological effects and vice versa was not systematically analyzed. The employed HMM framework was in principle capable of accounting for possible correlations between signals. This gives rise to the speculation that the classifier implicitly revealed the most informative cortical signal components from fNIRS data by making use of the physiological signals. Future research should, however, focus on a more explicit formulation of this problem, possibly by making use of adaptive filtering techniques.

In this pilot study, isometric pinching was chosen to elicit changes in cortical hemodynamics and the physiological state of subjects, mainly because it restricts participants to a well-defined task. As shown in Table 1, not only motor execution, but also motor imagery yielded signal patterns that were successfully classified in BCI applications. This is appealing, as severely impaired patients that are unable to move could trigger robotic assistance through motor imagery. Further research therefore will be required to test whether motor imagery can be used as a substitute for overt movement in stroke patients.

Ultimately, however, our aim is to extend this concept by detecting movement intention, a neurological process that is more natural for BCI-naive users and may also be better accessible by patients with severe motor impairments. This issue is especially challenging in terms of data processing, as the conscious preparation of a movement happens in a relatively short time. Therefore, novel classifiers based on event-related data need to be developed.

BCI-Triggered Assistance and Haptic Feedback

In our B^2RI, the BCI is used to trigger assistance from a robotic device, in order to provide sensory stimulation at the level of the hand as response to the detected motor intention. In severely impaired patients, fingers can be moved passively by the robotic interface. If some remaining motor function is present and as the patient recovers, the robot will reduce its support (assist-as-needed). To meet these requirements, the robotic system is required to generate sufficient forces to open and close the hand of a hypertonic patient (resistance of up to 200 N) and allow for a reduction of its supporting behavior based on the patient's abilities. Integrated position and force/torque sensing allows for a constant monitoring of the patient's physical contribution to the movement and on-line adaptation of assistance.

The *ReHapticKnob* is a two degrees of freedom (DOF) robotic device previously developed to train grasping and pronation/supination (Fig. 4) (Metzger et al. 2011). The patient's fingers can be fastened to two handles, each of which is mounted on a six DOF force/torque sensor (mini40, ATI Industrial Automation, USA). This allows for the implementation of different interaction control strategies and precise assessment of hand function during grasping. As the force applied by the patient is recorded in all directions, assist-as-needed support can be adapted based on small forces even if not aligned with the grasping direction. Thanks to a

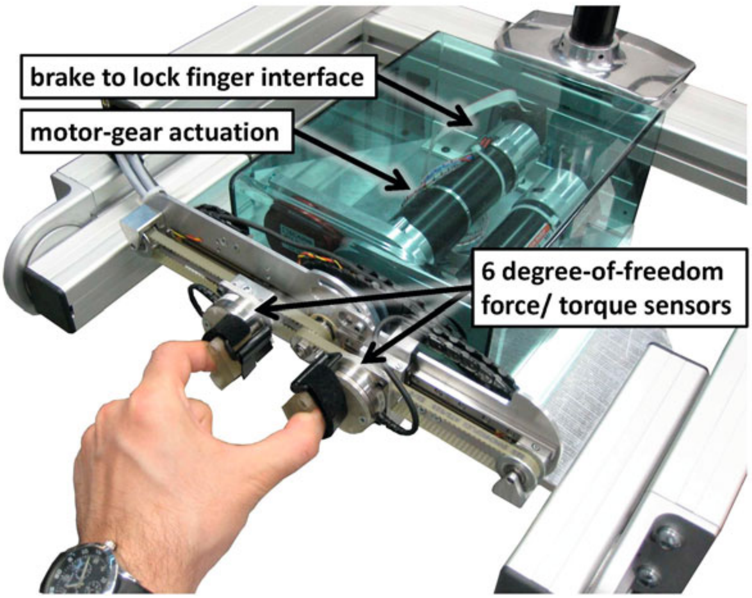

Fig. 4 *ReHapticKnob*: high-fidelity haptic interface for the rehabilitation of hand function and the precise assessment of the force vectors applied by the patient

strong motor-gear combination (Re40, 150 W and GP 42C, Maxon Motor, Switzerland) and advanced impedance control algorithms taking advantage of the force sensor data, the grasping DOF can be used to render a large dynamic range of impedances (Z-width). Therefore, the whole range from rendering *transparency* (no resistance to the patient's movement) up to complete support of hypertonic patients can be achieved with the device (Metzger et al. 2012). A brake is attached to the motor–gear combination to lock the finger supports such that isometric tasks can also be performed while monitoring the force applied by the patient. Several safety features have been implemented on the ReHapticKnob and include mechanical and software workspace limitations, emergency buttons, redundant position sensing and an isolation transformer to avoid leakage currents.

As it is possible to actively or passively train and precisely monitor grasping tasks, the ReHapticKnob ideally meets the requirements of the B^2RI application. Further, the robot is equipped with a moveable monitor that can be overlaid on the user's hand, providing the ideal support to display the visual feedback proposed in our B^2RI concept.

Virtual Reality for Context and Augmented Feedback

VR is used in the B^2RI to motivate specific training tasks and to enable augmented audio-visual feedback to the patient. It has already been shown that adequate visual feedback during rehabilitation has significant therapeutic benefits (Merians et al. 2002). Notable in particular are feedback paradigms that make use of virtual representations of limbs, since they can activate the action-observation system and thereby motor regions by visual observation only (Holper et al. 2010). However, the effect of visual feedback on the patient might change in the course of therapy or possibly even within a single training session. Detecting the effects of visual feedback in the fNIRS signals during training could hence allow for an individually optimized VR environment.

In the light of this, an experiment to study the effect of visual feedback manipulations on the fNIRS signal during simple finger movements was conducted (Fig. 5) (Brand et al. 2011). Two healthy subjects were asked to repeatedly flex/extend their right index finger. They received distorted visual feedback (3D animation of a forearm) about the amount of the extension during the movement in lieu of the observation of their actual movement, provided by a LCD-monitor/mirror system. fNIRS data were obtained from F3 according to the 10–20-system (presumably PMC).

The preliminary data showed an increase of the hemodynamic response in PMC for augmented visual feedback. It was, however, not significant and a large trial-to-trial variability, as well as possible adaptation effects, were observed. Nevertheless, our findings underline the prospects of fNIRS to be used as a tool to detect

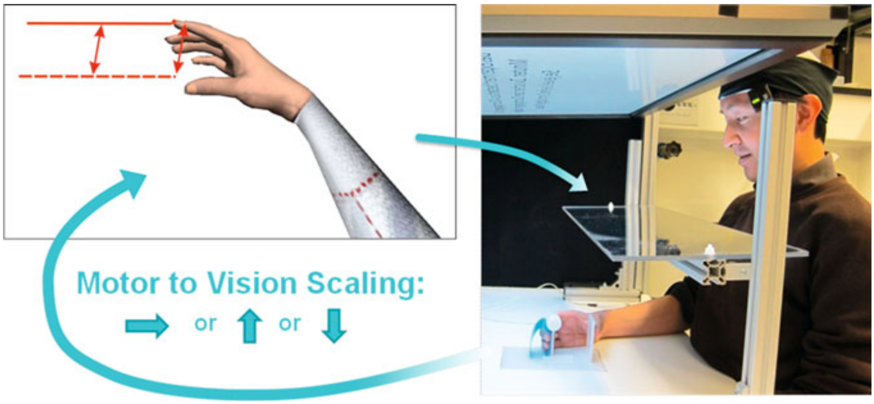

Fig. 5 Experimental setup to investigate effects of visual feedback distortions. Subjects receive distorted feedback by viewing a virtual hand, while performing simple finger movements. The virtual hand moves according to an upscaled, downscaled or veridical version of the real movement. Refer to (Brand et al. 2011) for details

changes in the response to visual feedback on a multiple trial basis. Not only could knowledge about the contribution of visual feedback to the hemodynamic signal help to optimize the VR environment, but it could possibly also help to increase the performance of our BCI for movement intention detection.

Concluding Remarks

There is a need for novel rehabilitation strategies that allow severely impaired patients to participate in active movement therapy to promote recovery of hand function. fNIRS can provide a promising tool to record from the brain for BCI applications. Physiological influences on fNIRS data may be accounted for by the simultaneous acquisition of physiological parameters. However, the decoder has to be based on online single-trial classification of potentially rather brief stimuli, while at the same time being accurate and robust. Once these challenges are met, fNIRS-based BCIs can be used to trigger assistance as well as haptic feedback from dedicated robotic devices. Together with a virtual reality environment that allows for control of the audiovisual feedback, the patient receives a multitude of sensory consequences of his/her intended movement. This coupling of motor intentions and their consequences could lead to a breakthrough in the efficacy of motor rehabilitation systems for the severely impaired.

References

V.L. Roger et al., Heart disease and stroke statistics–2011 update. Circulation **123**, e18–e209 (2011)

A. Pollock, G.D. Baer, P. Langhorne, V.M. Pomeroy, Physiotherapy treatment approaches for stroke. Stroke **39**, 519–520 (2008)

C.D. Takahashi, L. Der-Yeghiaian, L. Vu, R.R. Motiwala, S.C. Cramer, Robot-based hand motor therapy after stroke. Brain **131**, 425–437 (2008)

O. Lambercy, L. Dovat, H. Yun, S.K. Wee, C. Kuah, K. Chua, R. Gassert, T. Milner, C.L. Teo, E. Burdet, Effects of a robot-assisted training of grasp and pronation/supination in chronic stroke: a pilot study. J. NeuroEng. Rehabil **8**, 63 (2011)

N. Hogan, H.I. Krebs, B. Rohrer, J.J. Palazzolo, L. Dipietro, S.E. Fasoli, J. Stein, R. Hughes, W.R. Frontera, D. Lynch, B.T. Volpe, Motions or muscles? Some behavioral factors underlying robotic assistance of motor recovery. J. Rehabil. Res. Dev. **43**, 605–618 (2006)

E. Buch, C. Weber, L.G. Cohen, C. Braun, M.A. Dimyan, T. Ard, J. Mellinger, A. Caria, S. Soekadar, A. Fourkas, N. Birbaumer, Think to move: a neuromagnetic brain–computer interface (BCI) system for chronic stroke. Stroke **39**, 910–917 (2008)

T.E. Ward, C.J. Soraghan, F. Matthews, C. Markham, A concept for extending the applicability of constraint-induced movement therapy through motor cortex activity feedback using a neural prosthesis. Comput. Intell. Neurosci. **51363**, 1–9 (2007)

S.C. Cramer et al., Harnessing neuroplasticity for clinical applications. Brain **134**, 1591–1609 (2011)

W. Wang, J.L. Collinger, M.A. Perez, E.C. Tyler-Kabara, L.G. Cohen, N. Birbaumer, S.W. Brose, A.B. Schwartz, M.L. Boninger, D.J. Weber, Neural interface technology for rehabilitation: exploiting and promoting neuroplasticity. Phys. Med. Rehabil. Clin. N. Am. **21**, 157–178 (2010)

M. Wolf, M. Ferrari, V. Quaresima, Progress of near-infrared spectroscopy and topography for brain and muscle clinical applications. J. Biomed. Opt. **12**, 062104 (2007)

T. Muehlemann, D. Haensse, M. Wolf, Wireless miniaturized in vivo near infrared imaging. Opt. Express **16**, 10323–10330 (2008)

B.N. Pasley, R.D. Freeman, Neurovascular coupling. Scholarpedia **3**, 5340 (2008)

S. Coyle, T. Ward, C. Markham, G. McDarby, On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. Physiol. Meas. **25**, 815–822 (2004)

R. Sitaram, Y. Hoshi, C. Guan, Near infrared spectroscopy based brain–computer interface, in *Society of Photo-Optical Instrumentation Engineers* (*SPIE*) *Conference Series*, vol. 5852, pp. 434–442 (2005)

X. Cui, S. Bray, A.L. Reiss, Speeded near infrared spectroscopy (NIRS) response detection. PLoS One **5**, e15474 (2010)

R. Sitaram, H. Zhang, C. Guan, M. Thulasidis, Y. Hoshi, A. Ishikawa, K. Shimizu, N. Birbaumer, Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain–computer interface. NeuroImage **34**, 1416–1427 (2007)

S.M. Coyle, T.E. Ward, C.M. Markham, Brain–computer interface using a simplified functional near-infrared spectroscopy system. J. Neural Eng. **4**, 219–226 (2007)

L. Holper, M. Wolf, Single-trial classification of motor imagery differing in task complexity: a functional near-infrared spectroscopy study. J. NeuroEng. Rehabil. **8**, 34 (2011)

M. Naito, Y. Michioka, K. Ozawa, Y. Ito, M. Kiguchi, T. Kanazawa, A communication mean for totally locked-in als patients based on changes in cerebral blood volume measured with near-infrared light. IEICE Trans. Inf. Syst. **E90-D**, 1028–1037 (2007)

S.D. Power, T.H. Falk, T. Chau, Classification of prefrontal activity due to mental arithmetic and music imagery using hidden Markov models and frequency domain near-infrared spectroscopy. J. Neural Eng. **7**, 026002 (2010)

T. Falk, M. Guirgis, S. Power, T. Chau, Taking NIRS-BCIs outside the lab: towards achieving robustness against environment noise. IEEE Trans. Neural Syst. Rehabil. Eng. **19**, 136–146 (2011)

S. Luu, T. Chau, Decoding subjective preference from single-trial near-infrared spectroscopy signals. J. Neural Eng. **6**, 016003 (2009)

K. Tai, T. Chau, Single-trial classification of NIRS signals during emotional induction tasks: towards a corporeal machine interface. J. Neuroeng. Rehabil. **6**, 39 (2009)

R. Zimmermann, L. Marchal-Crespo, O. Lambercy, M.C. Fluet, R. Riener, M. Wolf, R. Gassert, Towards a BCI for sensorimotor training: initial results from simultaneous fNIRS and biosignal recordings, in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2011* (*EMBC 2011*), pp. 6339–6343 (2011)

R. Zimmermann, L. Marchal-Crespo, J. Edelmann, O. Lambercy, M.C. Fluet, R. Riener, M. Wolf, R. Gassert, Detection of motor execution using a hybrid fNIRS-biosignal BCI: a feasibility study. J. NeuroEng. Rehabil. **10**, 4 (2013)

J.C. Metzger, O. Lambercy, D. Chapuis, R. Gassert, Design and characterization of the ReHapticKnob, a robot for assessment and therapy of hand function, in *IEEE/RSJ International Conference on Intelligent Robots and Systems* (*IROS*), *2011*, 25–30 Sept 2011, pp. 3074–3080 (2011)

J.C. Metzger, O. Lambercy, R. Gassert, High-Fidelity rendering of virtual objects with the ReHapticKnob—Novel avenues in robot-assisted rehabilitation of hand function, in *IEEE Haptics Symposium*, 4–7 March 2012, pp. 51–56 (2012)

A.S. Merians, D. Jack, R. Boian, M. Tremaine, G.C. Burdea, S.V. Adamovich, M. Recce, H. Poizner, Virtual reality-augmented rehabilitation for patients following stroke. Phys. Ther. **82**, 898–915 (2002)

L. Holper, T. Muehlemann, F. Scholkmann, K. Eng, D. Kiper, M. Wolf, Testing the potential of a virtual reality neurorehabilitation system during performance of observation, imagery and imitation of motor actions recorded by wireless functional near-infrared spectroscopy (fNIRS). J. NeuroEng. Rehabil. **7**, 57 (2010)

J. Brand, O. Geisseler, L. Holper, M.C. Hepp-Reymond, M. Morari, D. Kiper, K. Eng, The effects of manipulation of visual feedback in virtual reality on cortical activity: a pilot study, in *2011 International Conference on Virtual Rehabilitation* (*ICVR*), 27–29 June 2011, pp. 1–2 (2011)

A Review of Performance Variations in SMR-Based Brain–Computer Interfaces (BCIs)

Moritz Grosse-Wentrup and Bernhard Schölkopf

Abstract The ability to operate a brain-computer interface (BCI) varies not only across subjects but also across time within each individual subject. In this article, we review recent progress in understanding the origins of such variations for BCIs based on the sensorimotor-rhythm (SMR). We propose a classification of studies according to four categories, and argue that an investigation of the neuro-physiological correlates of within-subject variations is likely to have a large impact on the design of future BCIs. We place a special emphasis on our own work on the neuro-physiological causes of performance variations, and argue that attentional networks in the gamma-range ($>$ 40 Hz) are likely to play a critical role in this context. We conclude the review with a discussion of outstanding problems.

A Brief History of BCI-Research

From the early days of research on brain-computer interfaces (BCIs) until about a decade ago, subjects had to undergo intensive training in order to acquire the new skill of operating a BCI (Vidal 1973; Wolpaw and McFarland 1994; Birbaumer et al. 2000; Pfurtscheller and Neuper 2001; Wolpaw et al. 2002; Wolpaw and McFarland 2004; Kübler et al. 2005). In the past ten years, machine-learning algorithms have shortened training procedures and enabled higher information transfer rates (Lal et al. 2004; Blankertz et al. 2007; Lotte et al. 2007; Grosse-Wentrup and Buss 2008; Grosse-Wentrup et al. 2009). Even though machine-learning continues to make important contributions to the field, advances have somewhat slowed down: recent studies often report only minor enhancements in classification accuracy (Zhang et al. 2011; Barachant et al. 2011; Samek et al. 2012). At the same time, variations in

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DOI: 10.1007/978-3-642-36083-1_5,

performance across subjects remain substantial. In a recent study based on a two-class sensorimotor-rhythm (SMR) BCI, 30 out of 80 healthy participants (37.5 %) did not achieve a classification accuracy of or above 70 %, which is considered as the lower limit for reliable communication (Hammer et al. 2011). While this constitutes an improvement of 11.2 % relative to a large-scale study published in 2003 (Guger et al. 2003), in which 48.7 % of subjects did not exceed 70 % accuracy, a substantial percentage of users remains incapable of communicating by means of a SMR-BCI. Unfortunately, completely locked-in patients in late stages of amyotrophic lateral sclerosis (ALS), i.e., those subjects that stand to benefit most from BCI technology, appear to belong to this group of incapable subjects (Kuebler et al. 2009). Inter-subject variations in performance have been reported to be less severe for P300-systems based on visual stimuli (Guger et al. 2009). These results, however, may have been confounded by overt visual attention (Brunner et al. 2010)—a skill not readily available to many patients in need of a BCI. Accordingly, the subsequent focus of this review is on SMR-based BCIs. Other experimental paradigms are briefly discussed in section "Discussion".

Performance Variations in BCIs

The substantial variation in performance across subjects has triggered a new research direction that aims to identify variables associated with good and poor BCI performance. This in turn may lead to enhanced training strategies and novel ways to adapt machine-learning algorithms to different types of users. Studies on BCI performance variations can be classified according to (at least) four categories:

1. **Type of explanatory variables:** Different types of variables may serve as the independent variable(s) in models used to explain variations in BCI performance. These range from psychological characteristics, such as the IQ score or level of depression, through neuroanatomic properties, e.g., as obtained by MRI scans, to neuro-physiological features such as resting-state α-power. While each type of variable may provide interesting insights, their utility may differ. For instance, neuroanatomical features that are unlikely to undergo substantial changes over a subject's lifetime may be useful for predicting whether a subject is capable of operating a BCI. They are less likely to be useful, however, for assessing learning-related changes across multiple training sessions. Accordingly, studies should not only identify the types of variables under investigation, but also discuss their potential utility in BCI research. This issue is closely related to the second category.
2. **Correlates or causes of performance variations:** Any type of variable found to correlate with BCI performance may, at least in theory, be used to predict whether a novel subject is likely to be able to operate a BCI. Only certain types

of variables, however, are amenable to procedures, subsequently termed *interventions* (Judea Pearl 2000), that transform poorly performing subjects into able BCI operators. For instance, it is conceivable that age correlates with BCI performance, with younger subjects performing better than an elderly (but otherwise matched) control group. It is difficult to conceive of an intervention, however, that alters the age of an individual subject. As such, this correlation would constitute an interesting insight, but would not give rise to novel strategies for enhancing performance in individual subjects. In contrast, a correlation between depression levels and performance could be interpreted as indicating that psychotherapy would influence a subject's ability to operate a BCI. The conceivability of such an intervention is not sufficient, however, to demonstrate its utility in BCI research. According to Reichenbach's principle, a correlation between two variables x and y can arise either because x is a cause of y, y is a cause of x, or both share a (possibly unobserved, i.e., latent) common cause h. In the present example, it is conceivable that both BCI performance and depression levels are affected by age. The ensuing spurious correlation between depression and performance could then lead to the erroneous belief that psychotherapy would influence BCI performance. In order to increase the probability that novel insights translate into actual benefits for BCI users, we consider it important to focus on variables that are likely to be actual causes, rather than mere correlates, of performance. We denote a variable as a cause of BCI performance if a) it is conceivable to construct a setup that experimentally sets the value of this variable, and b) if setting this variable to different values would result in statistically significant changes in performance. While ultimately only randomized controlled trials can establish such causal relations, the field of causal inference provides powerful tools that support the identification of causal relations from non-interventional data (cf. "Within-Subject Variations and the Role of Attentional Networks"). Future studies should clearly indicate whether they aim to identify correlates or causes of BCI-performance.

3. **Inter- or intra-subject variations:** Variations in performance may be studied on the inter- and intra-subject level. In the former case, each subject's BCI performance, in combination with one personal attribute, constitutes one observation pair. Observation pairs from multiple subjects may then be used to uncover potential correlations. This approach implicitly assumes that there exist invariant traits that determine a subject's capability to operate a BCI. In contrast, the intra-subject level focuses on changes in performance levels of individual subjects over time. In this case, multiple observations may consist of individual trials or separate recording sessions. As such, the actual time scale of such measures may vary from several seconds, as in the case of trial-to-trial variations, to multiple months, e.g., when investigating learning related differences across multiple sessions. Insights into inter- and intra-subject correlations may give rise to different strategies for enhancing BCI performance. For instance, inter-subject variations may be useful for predicting which subjects are likely to benefit from intensive training procedures. Intra-subject variations,

on the other hand, might be used to monitor non-stationarities in recorded data and adapt machine-learning procedures accordingly.

4. **Healthy subjects or patient populations:** Even though the potential benefit for patients often serves as a primary motivation for BCI research, most existing studies have been carried out with healthy subjects (Mason et al. 2007). While these studies undoubtedly provide relevant insights, their conclusions may not transfer to patient populations. Diseases such as ALS have profound and system-wide effects that may eliminate or even reverse effects found in healthy populations. Furthermore, certain interventions may be feasible for healthy subjects, but unrealistic to carry out with patients in late stages of ALS. Such issues need to be openly discussed.

In the following, we review studies published by other groups on BCI performance variations, and discuss how they relate to the four categories described above. The presentation of our own work is deferred to "Within-Subject Variations and the Role of Attentional Networks".

To date, all types of variables listed under the first category have been considered as potential correlates of BCI performance. Hammer et al. have assessed correlations between online classification accuracy in a SMR-BCI and a variety of psychological tests, including measures of visuo-motor coordination, attention span, intelligence, and verbal- as well as non-verbal learning abilities (Hammer et al. 2011). They found that visuo-motor coordination skills and the ability to concentrate on a task both exhibited significant positive correlations with classification accuracy ($\rho = +0.42$ and $\rho = +0.50$, respectively). A link between concentration and BCI performance is consistent with previous reports that motivation, which may facilitate concentration, plays an important role in BCIs (Nijboer et al. 2010). This has led to the suggestion that feedback in BCIs should be designed to minimize frustration (Barbero and Grosse-Wentrup 2010; Zander and Kothe 2011b). Contrary to the case of psychological measures, very little is known about neuroanatomic correlates of good and poor BCI performance. One notable exception is the study by Varkuti et al., which indicates that the structural integrity of the corpus callosum differs between able and non-able subjects (Varkuti et al. 2011). As white matter structures, such as the corpus callosum, are known to be affected by ALS, this may provide an explanation for the poor performance of these patients in SMR-based BCIs. More attention than to neuroanatomic features has been paid to neuro-physiological correlates of performance. Halder et al. have compared fMRI scans of well- and poorly performing BCI subjects during motor-imagery and motor-observation, and found that capable subjects exhibited larger activations in supplementary motor area (SMA) and right middle frontal gyrus (Halder et al. 2011). This is consistent with the interpretation that altered activity in SMA, as reported in ALS patients (Kew et al. 1993), may adversely influence BCI-performance. Blankertz et al. have presented empirical evidence that the resting-state amplitude of the SMR is positively correlated with subsequent classification accuracy ($\rho = +0.53$) (Blankertz et al. 2010). This result suggests that the ability to suppress the SMR by means of motor-imagery, which constitutes the basic principle of SMR-BCIs (Pfurtscheller and Neuper 2001), is related to its resting-state amplitude. Furthermore, it indicates that mental strategies that are aimed at enhancing resting-state SMR-amplitude could result in improved BCI performance. While the nature of suitable mental strategies is at present unknown, it is reasonable to assume that they may be related to psychological correlates of performance as investigated by Hammer et al. (2011).

It is interesting to note that most studies published to date, with the exception of Varkuti et al. (2011), refrain from openly discussing the distinction between correlates and causes of performance. Nevertheless, some studies propose interventions to enhance performance, indicating that a causal relation is suspected. For instance, Blankertz et al. suggest to train subjects to increase their resting-state (or pre-trial) SMR-amplitude by neurofeedback (Blankertz et al. 2010). As the SMR's amplitude is used to infer a subject's intention, it is reasonable to assume that there exists a genuine causal link between idling SMR-amplitude and BCI performance. Furthermore, a pre-training strategy could be realized for healthy subjects as well as patients in late stages of ALS. This appears more challenging for the results obtained by Hammer at al., who also suggest training strategies for enhancing the ability to focus attention and improving visuo-motor coordination (Hammer et al. 2011). While it is conceivable that a training programme in visuomotor coordination might enhance BCI performance in healthy subjects, possibly via modulation of the SMR's resting-state amplitude, it appears non-trivial to design such a programme for subjects with no (or only residual) movement capabilities. In general, studies that reproduce the results reviewed here in patient populations are urgently needed, as only the study by Nijboer et al. is not based on healthy participants (Nijboer et al. 2010).

Somewhat surprisingly, none of the studies discussed above consider intrasubject variations. In the following section, we first argue that an investigation of the causes of trial-to-trial performance variations in individual subjects is likely to have a large impact on the design of future BCI-systems, and then review our recent progress in this domain.

Within-Subject Variations and the Role of Attentional Networks

When investigating BCI performance across subjects, variables of interest are typically correlated with session-averaged classification accuracy. This implicitly assumes that a subject's skill in operating a BCI remains constant over the course of a recording session. Interestingly, this is not the case. Subjects exhibit large variations in performance over the course of individual sessions. Figure 1 displays trial-to-trial variations in performance of two subjects performing a left-/right hand motor-imagery task (adapted from Grosse-Wentrup and Schölkopf 2012). Here, each cross represents one trial, recorded over the course of one experimental session lasting for 20 min. The y-axis denotes the *certainty* of the employed machine-learning algorithm in correctly classifying a trial. As such, large positive values indicate easy to classify trials, values with small absolute values represent uncertain trials, and negative values denote incorrect decisions (more precisely, the values on the y-axis represent the distance of the trial's features from the separating hyperplane, with positive/negative values indicating that the trial's features are on the correct/incorrect side (Grosse-Wentrup and Schölkopf 2012)). While both subjects are able BCI performers, with a session-average classification accuracy of 83.3 and 95 %, respectively, there is a distinct temporal structure to each subject's performance. In the first few minutes of the recording session, subject S1 exhibits excellent performance, with no trials falling into the red region. After about 6 min, however, his performance starts to slowly decline, as seen by a downward trend of the decoding algorithm's certainty. For a few further minutes, however, his performance is sufficient to avoid incorrect classification. Only after about nine minutes into the session the first trial is incorrectly decoded. For the next 7 min a large proportion of trials are not correctly classified. Only towards the end of the session a slight positive drift in performance is noticeable. Subject S2, on the other hand, shows a different temporal structure. While he already makes only few errors in the first few minutes of the session, his performance exhibits a further constant improvement. From about 9–15 min into the session, not a single trial is misclassified. At 15 min, however, there is a sudden drop in performance, followed by a slow recovery extending all the way to the end of the session.

A subject's skill to operate a BCI may thus vary on a time-scale of a few minutes. Such changes are overlooked if only session-averaged classification accuracy is being investigated. But what are the causes of these variations? As for the case of inter-subject variations, this may be investigated on several levels. We have placed the focus of our work on the neuro-physiological level, which is based on the following considerations. Consider Fig. 2, which depicts a thought experiment on the potential effect of a neuro-physiological cause of performance variations in a SMR-BCI. Assume we perform a study in which subjects are either at rest of perform motor-imagery of the right hand, and we record the electromagnetic field of the brain over primary motor cortex (MI). Depending on whether the subject is at rest or executes motor-imagery, we observe different distributions of bandpower in the μ-range (10–14 Hz) (upper right corner). In this example, the optimal decision boundary for differentiating trials of rest- versus trials of motor-imagery is given by the green line. Note that the overlap between the distributions, shown in dark gray, specifies the minimum Bayes error. Now assume that there exists a region in the brain, e.g., the prefrontal cortex (PFC), that modulates activity in MI. Further, assume that a change in PFC's activity induces a shift of the class-conditional distributions of μ-power in MI to the right. In this case, which is depicted in the right lower corner of Fig. 2, the original optimal decision boundary (shown in red) would be sub-optimal. Instead, the new optimal decision boundary would also have to be shifted to the right. If we knew that PFC modulates MI, we could monitor its activity and adapt our decoding procedure accordingly. This could give rise to new algorithms for adaptive BCIs

(Sykacek et al. 2004; Vidaurre et al. 2006; Shenoy et al. 2006; Sugiyama et al. 2007). It is also conceivable, however, that such modulatory effects do not induce a shift in the distributions of μ-power, but rather alter their variance. This situation is depicted in Fig. 3. Here, the optimal decision boundary for different activity levels of PFC remains identical. Strong activation of PFC, however, leads to a smaller overlap between the distributions of μ-power at rest and during motor-imagery, resulting in a smaller minimum Bayes error (as indicated by the overlap of the two distributions shown in dark gray). In this thought experiment, the lower panel in Fig. 3 thus represents a state-of-mind beneficial for operating a BCI, while the situation depicted in the upper panel results in lower performance. Knowledge about such a causal relation between PFC and MI could be exploited by several strategies. First, activity in PFC could be monitored and the initiation of a new trial could be delayed until a state-of-mind is observed that is likely to result in a correct decision of the BCI. This could increase information transfer rates and reduce frustration. Second, subjects could be presented with feedback on their current state of PFC activity, thereby teaching them how to induce a state-of-mind beneficial for operating a BCI. And finally, it is conceivable that such a causal link could be utilized by stimulating PFC, e.g., by transcranical direct current stimulation (TDCS), artificially inducing a state-of-mind in which subjects are capable operators of a BCI. To summarize, understanding the neuro-physiological causes of trial-to-trial performance variations would give rise to a variety of novel strategies for enhancing BCI performance in individual subjects.

In a series of recent studies, we have identified neural processes that qualify as potential causes of sensorimotor rhythms, thereby inducing changes in subjects' performance levels. In a study published in 2010, we presented empirical evidence that the amplitude of spatially distributed oscillations in the γ-range (55–85 Hz) correlates with a subject's capability to induce a lateralization of the SMR, as measured by the trial-wise performance metric shown in Fig. 1 (Grosse-Wentrup et al. 2011). Interestingly, we found these γ-oscillations to only correlate with how

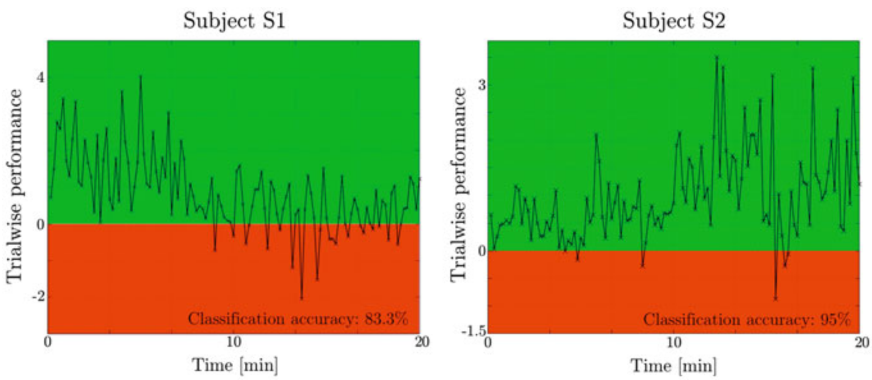

Fig. 1 Trial-to-trial variations in performance of two subjects performing a left-/right hand motor-imagery task (adapted from Grosse-Wentrup and Schölkopf (2012))

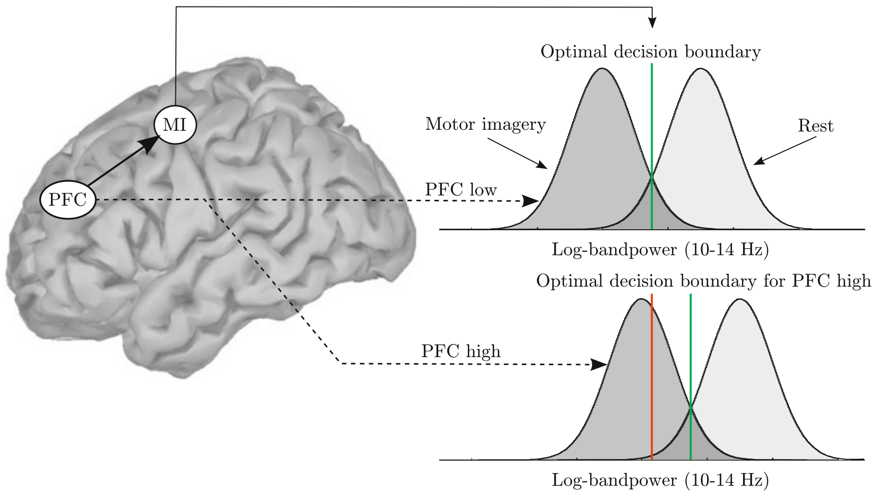

Fig. 2 Thought experiment on the potential effect of causal relations between cortical areas on BCI-performance: shift of distributions

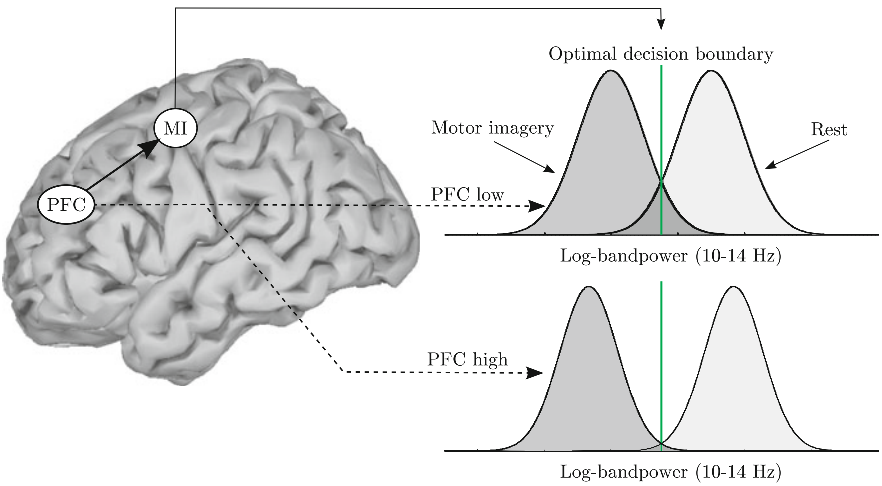

Fig. 3 Thought experiment on the potential effect of causal relations between cortical areas on BCI-performance: changes in variance of distributions

well a subject modulated the SMR. They did not provide any information on its lateralization, i.e., whether subjects performed left- or right-hand motor-imagery. We analyzed these observations in the framework of Causal Bayes Nets (Judea Pearl 2000; Spirtes et al. 2000; Ramsey et al. 2010), and argued that they provide evidence for a causal influence of the neural substrate of γ-range oscillations on the SMR. Based on this conclusion, we then hypothesized that the amplitude of γ-range oscillations would allow us to predict whether an upcoming trial is likely to be correctly decoded. We tested this hypothesis in a new group of subjects, and could present evidence that baseline γ-power (between 70–80 Hz) indeed predicts whether a subject is in a state-of-mind beneficial for operating a SMR-BCI (Grosse-Wentrup and Schölkopf 2012). To obtain a better insight into the nature of the involved processes, we carried out a source localization procedure. The obtained results indicate that BCI performance can be predicted from differences in γ-power between two fronto-parietal networks (cf. Fig. 5 in Grosse-Wentrup and Schölkopf 2012), which are believed to be involved in attentional processes (Corbetta et al. 2008). This is in agreement with the observation that γ-range oscillations best predicted very slow changes in BCI performance, i.e., on a time-scale of multiple minutes, which is the dominant frequency range of attentional- and default mode networks (Ko et al. 2011). In summary, these studies indicate that variations in activity between different attentional networks have an impact on a subject's capability to operate a SMR-BCI. The results discussed so far have been obtained with healthy subjects. Preliminary evidence indicates that similar relations may also be reproducible in subjects in late stages of ALS (Grosse-Wentrup 2011b), but further evidence is required before any general conclusions may be drawn.

The next question, then, is how these insights may be used to enhance BCI-performance in individual subjects. Following the strategies outlined above, we first tested by how much we could increase session-average classification accuracy by rejecting trials according to their predicted probability of being correctly decoded (Grosse-Wentrup and Schölkopf 2012). This analysis indicated that, on a group level, classification accuracy could be enhanced by up to 15 %. This, however, required rejecting 93.1 % of trials. In any practical situation, a sensible trade-off between the two values would have to be chosen. It is important to note, however, that in this setup the prediction of performance was based on spontaneous variations in fronto-parietal activity. As all subjects had been instructed to focus attention on the task at hand, these natural variations may have been rather small relative to the extent that can be induced by volitional shifts of attention. Accordingly, we designed an experimental setup to test whether subjects could learn how to modulate fronto-parietal γ-power and use this skill to induce a state-of-mind beneficial for operating a BCI. As our previous results indicated γ-range oscillations to be an actual cause of the SMR (Grosse-Wentrup et al. 2011), we hypothesized that modulation of fronto-parietal γ-power can be used to generate a strong idling SMR. In a pilot study, we trained three healthy subjects to modulate fronto-parietal γ-power by means of neurofeedback based on online beamforming (Grosse-Wentrup 2011a). Two of the three subjects displayed statistically significant control of γ-power after one and three training sessions, respectively. As hypothesized, volitional attenuation of fronto-parietal γ-power was accompanied by a statistically significant increase in μ-power over sensorimotor cortex. These results indicate that subjects can learn how to generate a strong SMR by regulating fronto-parietal γ-power, thereby achieving a state-of-mind known to positively correlate with BCI-performance (Blankertz et al. 2010). Before any general conclusions can be drawn, however, these results need to be reproduced in a larger population including subjects in late stages of ALS.

Discussion

In this article, we have reviewed recent progress on the correlates and causes of performance variations in SMR-based BCIs. While substantial progress has been made, this field of research is still in its infancy. In particular, a demonstration that the insights obtained to date transfer into enhanced classification accuracy in online BCIs remains outstanding. Considering the results obtained so far, it is quite likely that this will be achieved in the near future - probably by the SMR pre-training strategy proposed by Blankertz et al. (2010) as well as by teaching subjects to attenuate fronto-parietal γ-power (Grosse-Wentrup 2011a).

While such a demonstration would constitute an important advancement, many interesting problems remain. For instance, the results discussed in "Within-Subject Variations and the Role of Attentional Networks" only explain (a certain percentage of) performance variations on a time-scale of multiple minutes. From Fig. 1 it is apparent, however, that subject performance further varies on a trial-to-trial basis, i.e., on a time-scale of roughly 10 s. We are not aware of any studies investigating the neurophysiological origins of such fast variations. Also, there is at present insufficient evidence to conclude that ALS patients exhibit performance variations similar to those of healthy subjects, or that the same neural processes can be used to predict performance. Finally, it remains an open question how the neurophysiological correlates of performance, as discussed here, can be mapped back onto psychological states. For instance, mindfulness has been reported to enhance performance in SMR- as well as P300-based BCIs (Mahmoudi and Erfanian 2006; Lakey et al. 2011), and experienced meditators are more likely to be able to operate a SMR-BCI than healthy controls (Eskandari and Erfanian 2008). While it is reasonable to assume that these observations are related to the attentional networks discussed above, direct empirical evidence for such a relation is currently not available.

While we have placed the focus of this review on SMR-based BCIs, similar progress has been made in investigating the correlates of performance variations in P300-based systems. For instance, Mak et al. report that fronto-parietal θ-power (4.5–8 Hz) is negatively correlated with inter-subject variations in a visual speller system (Mak et al. 2012). As θ- and γ-power often exhibit a positive correlation (Canolty et al. 2006), the results of Mak et al. may be based on similar neural processes as those reported by us (Grosse-Wentrup and Schölkopf 2012). Further support for this hypothesis is lend by a recent study of Ahn et al., who found both θ- and γ-power to predict inter-subject performance variations in SMR-based BCIs (Ahn et al. 2012). As such, it is not unlikely that the results discussed in this review are not specific to SMR-based BCIs, but may be linked to attentional networks that are relevant for a variety of experimental paradigms.

In the end, we hope that this new research focus will provide the necessary insights to construct BCIs that can be operated not only by healthy subjects but also by completely locked-in patients, no matter whether these systems will be based on the SMR, the P300, or utilize altogether different experimental paradigms (Hill and Schölkopf 2012; Allison and Neuper 2010).

References

M. Ahn, H. Cho, S. Ahn, S. C. Jun, Performance predictor using the neuro-physiological factors of an ERD-based brain computer interface. Adv. Sci. Lett. (2012) (in press)

B.Z. Allison, C. Neuper, in *Could Anyone Use a BCI?* ed. by D. S. Tan, A. Nijholt. Brain-Computer Interfaces, Human Computer Interaction Series (Springer, London, 2010), pp. 35–54

A. Barachant, S. Bonnet, M. Congedo, C. Jutten, Multi-class brain computer interface classification by riemannian geometry. IEEE Trans. Biomed. Eng. **59**(4), 920–928 (2011)

Á. Barbero, M. Grosse-Wentrup, Biased feedback in brain-computer interfaces. J NeuroEng. Rehabil. **7**(34), 1–4 (2010)

N. Birbaumer, A. Kübler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, H. Flor, The thought translation device (TTD) for completely paralyzed patients. IEEE Trans. Rehabil. Eng. **8**(2), 190–193 (2000)

B. Blankertz, G. Dornhege, M. Krauledat, K.R. Müller, G. Curio, The non-invasive berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects. NeuroImage **27**(2), 539–550 (2007)

B. Blankertz, C. Sannelli, S. Halder, E.M. Hammer, A. Kübler, K.R. Müller, G. Curio, T. Dickhaus, Neurophysiological predictor of SMR-based BCI performance. NeuroImage **51**(4), 1303–1309 (2010)

P. Brunner, S. Joshi, S. Briskin, J.R. Wolpaw, H. Bischof, G. Schalk, Does the'P300'speller depend on eye gaze? Journal of Neural Engineering **7**, 056013 (2010)

R.T. Canolty, E. Edwards, S.S. Dalal, M. Soltani, S.S. Nagarajan, H.E. Kirsch, M.S. Berger, N.M. Barbaro, R.T. Knight, High gamma power is phase-locked to theta oscillations in human neocortex. Science **313**, 1626–1628 (2006)

M. Corbetta, G. Patel, G.L. Shulman, The reorienting system of the human brain: from environment to theory of mind. Neuron **58**(3), 306–324 (2008)

P. Eskandari, A. Erfanian, Improving the performance of brain-computer interface through meditation practicing. In 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS 2008), pages 662–665. IEEE, 2008

M. Grosse-Wentrup, Neurofeedback of fronto-parietal gamma-oscillations, in *Proceedings of the 5th International Brain-Computer Interface Conference*, Verlag der Technischen Universität Graz, pp. 172–175 (2011a).

M. Grosse-Wentrup, The neural correlates of BCI performance variations in ALS: A pilot study. Front. Comput. Neurosci. 00117 (2011b). doi://10.3389/conf.fncom.2011.53.00117.

M. Grosse-Wentrup, M. Buss, Multiclass common spatial patterns and information theoretic feature extraction. IEEE Trans. Biomed. Eng. **55**(8), 1991–2000 (2008)

M. Grosse-Wentrup, C. Liefhold, K. Gramann, M. Buss, Beamforming in non-invasive brain-computer interfaces. IEEE Trans. Biomed. Eng. **56**(4), 1209–1219 (2009)

M. Grosse-Wentrup, B. Schölkopf, J. Hill, Causal influence of gamma oscillations on the sensorimotor rhythm. NeuroImage **56**(2), 837–842 (2011)

M. Grosse-Wentrup, B. Schölkopf, High gamma-power predicts performance in sensorimotor-rhythm brain-computer interfaces. J. Neural Eng. **9**(4), 046001 (2012)

C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, G. Pfurtscheller, How many people are able to operate an EEG-based brain-computer interface (BCI)? IEEE Trans. Neural Syst. Rehabil. Eng. **11**(2), 145–147 (2003)

C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, G. Edlinger, How many people are able to control a P300-based brain-computer interface (BCI)? Neurosci. Lett. **462**(1), 94–98 (2009)

S. Halder, D. Agorastos, R. Veit, E.M. Hammer, S. Lee, B. Varkuti, M. Bogdan, W. Rosenstiel, N. Birbaumer, A. Kübler, Neural mechanisms of brain-computer interface control. NeuroImage **55**(4), 1779–1790 (2011)

E.M. Hammer, S. Halder, B. Blankertz, C. Sannelli, T. Dickhaus, S. Kleih, K.R. Müller, A. Kübler, Psychological predictors of SMR-BCI performance. Biol. Psychol. **89**(1), 80–86 (2011)

N.J. Hill, B. Schölkopf, An online brain-computer interface based on shifting attention to concurrent streams of auditory stimuli. J. Neural Eng. **9**, 026011 (2012)

J.J.M. Kew, P.N. Leigh, E.D. Playford, R.E. Passingham, L.H. Goldstein, R.S.J. Frackowiak, D.J. Brooks, Cortical function in amyotrophic lateral sclerosis. Brain **116**(3), 655–680 (1993)

A.L. Ko, F. Darvas, A. Poliakov, J. Ojemann, L.B. Sorensen, Quasi-periodic fluctuations in default mode network electrophysiology. J. Neurosci. **31**(32), 11728 (2011)

A. Kübler, F. Nijboer, J. Mellinger, T.M. Vaughan, H. Pawelzik, G. Schalk, D.J. McFarland, N. Birbaumer, J.R. Wolpaw, Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface. Neurology **64**(10), 1775–1777 (2005)

A. Kübler, A. Furdea, S. Halder, E.M. Hammer, F. Nijboer, B. Kotchoubey, A brain-computer interface controlled auditory event-related potential (P300) spelling system for locked-in patients. Ann. N. Y. Acad. Sci. **1157**(1), 90–100 (2009)

C.E. Lakey, D.R. Berry, E.W. Sellers, Manipulating attention via mindfulness induction improves P300-based brain-computer interface performance. J. Neural Eng. **8**, 025019 (2011)

T.N. Lal, M. Schroder, T. Hinterberger, J. Weston, M. Bogdan, N. Birbaumer, B. Schölkopf, Support vector channel selection in BCI. IEEE Trans. Biomed. Eng. **51**(6), 1003–1010 (2004)

F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, B. Arnaldi, A review of classification algorithms for EEG-based brain-computer interfaces. J. Neural Eng. **4**, R1 (2007)

B. Mahmoudi, A. Erfanian, Electro-encephalogram based brain-computer interface: improved performance by mental practice and concentration skills. Med. Biol. Eng. Comput. **44**(11), 959–969 (2006)

J.N. Mak, D.J. McFarland, T.M. Vaughan, L.M. McCane, P.Z. Tsui, D.J. Zeitlin, E.W. Sellers, J.R. Wolpaw, EEG correlates of P300-based brain-computer interface (BCI) performance in people with amyotrophic lateral sclerosis. J. Neural Eng. **9**, 026014 (2012)

S.G. Mason, A. Bashashati, M. Fatourechi, K.F. Navarro, G.E. Birch, A comprehensive survey of brain interface technology designs. Ann. Biomed. Eng. **35**(2), 137–169 (2007)

F. Nijboer, N. Birbaumer, A. Kübler, The influence of psychological state and motivation on brain-computer interface performance in patients with amyotrophic lateral sclerosis—a longitudinal study. Front. Neurosci. **4**, 55 (2010)

J. Pearl, *Causality: Models, Reasoning, and Inference* (Cambridge University Press, London, 2000)

G. Pfurtscheller, C. Neuper, Motor imagery and direct brain-computer communication. Proc. IEEE **89**(7), 1123–1134 (2001)

J.D. Ramsey, S.J. Hanson, C. Hanson, Y.O. Halchenko, R.A. Poldrack, C. Glymour, Six problems for causal inference from fMRI. Neuroimage **49**(2), 1545–1558 (2010)

W. Samek, C. Vidaurre, K.R. Müller, M. Kawanabe, Stationary common spatial patterns for brain-computer interfacing. J Neural Eng. **9**, 026013 (2012)

P. Shenoy, M. Krauledat, B. Blankertz, R.P.N. Rao, K.R. Müller, Towards adaptive classification for BCI. J. Neural Eng. **3**, R13 (2006)

P. Spirtes, C. Glymour, R. Scheines, *Causation, Prediction, and Search* (MIT Press, Cambridge, 2000)

M. Sugiyama, M. Krauledat, K.R. Müller, Covariate shift adaptation by importance weighted cross validation. J. Mach. Learn. Res. **8**, 985–1005 (2007)

P. Sykacek, S.J. Roberts, M. Stokes, Adaptive BCI based on variational Bayesian Kalman filtering: an empirical evaluation. IEEE Trans. Biomed. Eng. **51**(5), 719–727 (2004)

B. Varkuti, S.Halder, M. Bogdan, A. Kübler, W. Rosenstiel, R. Sitaram, N. Birbaumer. in *SMR EEG-BCI aptitude in healthy subjects varies with the integrity of corpus callosum white matter*, ed. by G.R. Müller-Putz, R. Scherer, M. Billinger, A. Kreilinger, V. Kaiser, and C. Neuper Proceedings of the 5th International BCI Conference 2011 pages 104–107

J.J. Vidal, Toward direct brain-computer communication. Ann. Rev. Biophys. Bioeng. **2**(1), 157–180 (1973)

C. Vidaurre, A. Schlogl, R. Cabeza, R. Scherer, G. Pfurtscheller, A fully on-line adaptive BCI. IEEE Trans. Biomed. Eng. **53**(6), 1214–1219 (2006)

J.R. Wolpaw, D.J. McFarland, Multichannel EEG-based brain-computer communication. Electroencephalogr. Clin. Neurophysiol. **90**(6), 444–449 (1994)

J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, Brain-computer interfaces for communication and control. Clini. Neurophysiol. **113**(6), 767–791 (2002)

J.R. Wolpaw, D.J. McFarland, Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. Proc. Nat. Acad. Sci. U.S.A. **101**(51), 17849 (2004)

T.O. Zander, C. Kothe, Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general. J. Neural Eng. **8**, 025005 (2011)

H. Zhang, Z.Y. Chin, K.K. Ang, C. Guan, C. Wang, Optimum spatio-spectral filtering network for brain-computer interface. IEEE Trans. Neural Netw. **22**(1), 52–63 (2011)

Exploring the Cortical Dynamics of Learning by Leveraging BCI Paradigms

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Abstract Brain-computer interfaces (BCIs)—systems that can record neural activity and translate them into commands for computer systems—are sufficiently advanced to allow users to volitionally guide them through simple tasks. Contemporary BCI research focuses on squeezing additional functionality out of standardized paradigms, be it achieving more bits per second, increased degrees of freedom, or increasing accuracy. While these studies have shown marginal advancements in recent years, our lack of understanding concerning the underlying neurophysiology continues to be the limiting factor in BCI development. In this chapter, we propose turning the way research is done on BCI systems on its head; instead of using our understanding of neural signals to incrementally advance the state of brain-machine interfaces, we apply a BCI system as a form of experimental control to study changes in neural activity. By using current BCI systems as a tool for neuroscientific study, we can probe the underlying neuroanatomy in novel, behaviorally controlled ways.

Significance: Recent studies have shown brain-computer interfaces (BCIs) are viable, leveraging changes in neural potentials. After the initial studies demonstrated that subjects could successfully control external devices via volitional cortical activity changes alone, further progress in BCIs have been incremental yet slow. Many studies have taken the established BCI protocol of thresholding power in a given frequency range and attempted to add additional control feature dimensions or apply novel user interfaces to marginally increase bit rate, both with limited success. Instead of attempting to incrementally improve upon these metrics, we resolved to learn more about the underlying neurophysiological changes that are occurring during learning by leveraging the learning period associated with current BCI paradigms with the hope of shedding light on novel future BCI paradigms.

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Experiment: We asked 7 subjects implanted with subdural ECoG electrodes to perform the standard 1-dimensional right justified box task, where the vertical velocity of a cursor on a screen is controlled by increasing and decreasing the power in a broadband high frequency bin (usually 80–100 Hz) around a linear threshold. Subjects were instructed to move the cursor to one of two targets occupying the top or bottom half of the right hand side of the screen. This method of BCI relies on a well-established method of control: the control feature is driven by a single electrode, providing a 1D signed, scalar output based on difference from the threshold. Control electrodes were chosen based on prior overt motor screening. Subjects performed overt or imagined movements of the hand or tongue, with all subjects gaining significant control over the cursor and performing as well or better in the final runs as the initial period.

Results: All 7 subjects were able to modulate the power in the band chosen for control. Over the course of the use of the BCI, three distinct periods of learning were observed in all subjects: identification, amplification and refinement (see Fig. 1). Identification periods—occurring at the beginning of training—showed no initial difference in mean power between active (up) versus inactive (down) targets, followed by a separation between the two about the set linear threshold, accompanied by an increase in successfully reached targets. After identification of the threshold, an amplification period that showed significantly higher cortical power for active targets was observed. These periods exhibited both an increase in the mean power for each target along with an increase in the variance of the means and a constant or increased successful target hit rate. During refinement, the subject continues to use and learn the BCI system with a decrease in the cortical variance between runs and a further improvement to accuracy. However, the continuing power increases observed during identification and amplification stages do not continue and in some cases actually decrease but remain above the

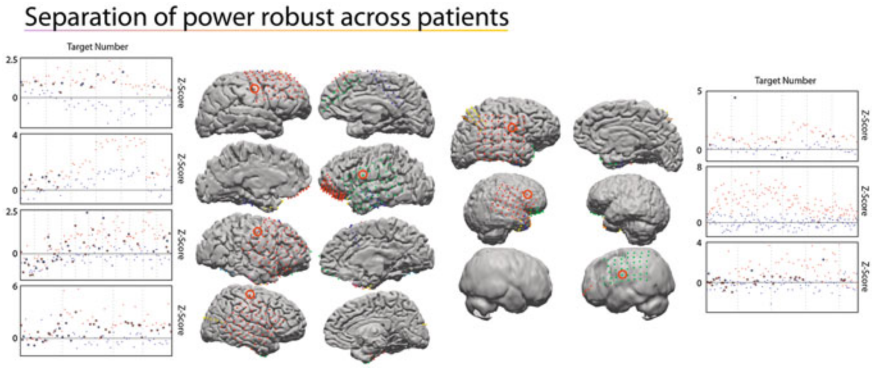

Fig. 1 Each subject's mean cortical power for active/"up" targets (*red*) versus inactive/"down" targets (*blue*). All subjects show the common pattern of identification, amplification, and refinement. Missed targets are identified by a *box*. Control electrodes for each patient are circled in *red*

threshold. This implies the subjects were producing less cortical activity while retaining the same or better accuracy, and that any increases in separability of the BCI control feature do not stem from absolute increases in power but rather from identification of the classification threshold and a refinement of cortical activity around it.

Further studies and results: Two of the patients who performed exceptionally well in the BCI task were asked to perform the 1D control task with an increased number of targets (3, 5, 6 or 7) occupying a smaller area of the screen (33, 20, 16.8 and 14.3 %, respectively), requiring finer control of the ending position of the cursor. The three periods identified during learning of the 2-target task were also present in the multi-target task, demonstrating that the subjects were able to volitionally modulate the mean cortical power into one of many bins. Initial analysis has identified areas in dorsolateral prefrontal cortex that show significantly increased cortical activity only for "middle" targets (not top-most or bottom-most) suggesting that these areas might be involved in some type of attention or gain modulation (see Fig. 2). We are currently investigating these areas of cortex and their correlations with the BCI task so that we can more clearly identify their role in BCI system use.

Discussion: Where other groups have investigated cursor trajectories, accuracy rates and/or bitrate output, instead we chose to investigate the underlying changes that occur in the neural activity between the initial trials where the subject was unfamiliar with the task and the final trials after a period of training lasting anywhere from minutes to days—analogous to how one would learn any new activity such as throwing a ball or driving a car. The advantage of using a BCI to explore the learning process is that the task itself is simple, tightly controlled, and provides a metric for the efficacy of learning in the form of target accuracy.

Our results have important implications for BCI: all three periods were observed with a relatively short amount of training on the BCI system. This implies continued training would not elicit continual increases in power up to the metabolic limit, but rather a refinement in fine-grain neural activity control.

This ongoing investigation demonstrates the importance of BCIs lies not only in the rehabilitation world, but also in providing a controlled platform for the scientific community studying the human brain to investigate naturally occurring cortical changes.

Subsequent Work

Present Utility of BCI is Limited

There is a lot of promise in the concept of a BCI. Should someone suffer some type of accident or disability that renders them with limited or insignificant interaction with the outside world, a device that would allow them to bypass their disability by

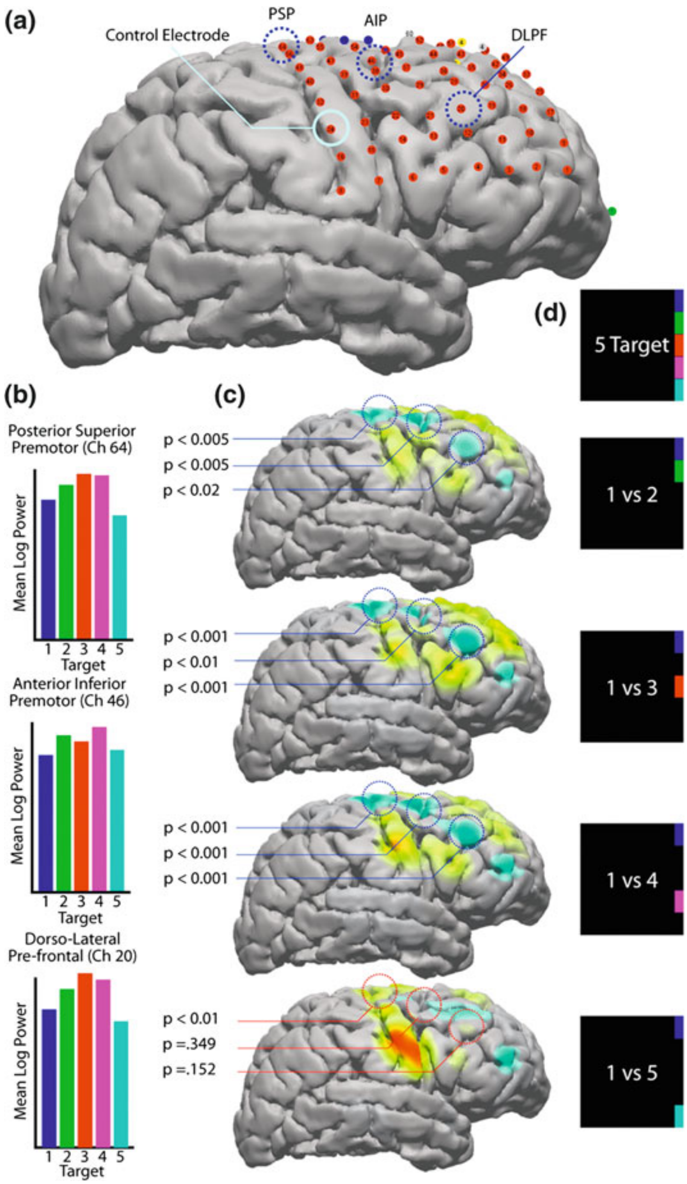

Fig. 2 **a** One subject who used a multi-target BCI. Control electrode is identified in cyan, with electrodes showing significant activity highlighted in blue. **b** Graphs of mean log power for each target (1–5 correspond to top-bottom targets). Note that posterior superior premotor (PSP) shows more activity for all targets requiring movement whereas the anterior inferior premotor (AIP) and doors-lateral pre-frontal (DLPF) electrodes show higher mean power for targets 2-4, the targets requiring finer grain control. **c** Significance of electrodes of interest when comparing the mean power between targets 1 & 2, 1 & 3, 1 & 4, 1 & 5. Blue areas indicate areas greater in the latter electrode, with yellow-red indicating higher power in the former electrode. **d** Illustration of the targets compared

directly reading desires where they are generated—at the cortex—and translating them into real-world motions would be life-changing for the affected individuals. Just about every neural engineering lab is working towards this vision and contributing a piece to the whole puzzle. Unfortunately even the most optimistic among neuroscientists must concede that a flexible, robust BCI system is still a long way off; the current understanding of the way the brain processes input and generates patterns of activity is simply not understood well enough. The most advanced BCIs to date still have severely limited degrees of freedom and can decode intentions at sub-perfect levels. Many contemporary systems can decode the intent of the user at a significance level of $P < 0.05$. However, thinking about it logically paints a somewhat bleaker picture. Take the example of applying a BCI to drive a wheelchair. This type of BCI could potentially provide a level of freedom for paralyzed individuals, something that many labs have attempted (Tanaka et al. 2005; Galán et al. 2008; Rebsamen et al. 2006). And yet, even operating at a confidence level of 95 % means that the BCI system can only correctly decode the user's intent 19 out of 20 times. Any number of frustrating and/or disastrous situations can be imagined for that 1 erroneous decoding; a missed "door open" signal; an incorrect word chosen when writing; an erroneous "stop wheelchair" decode at the top of a stairwell.

Optimizing a classifier based on the current understanding of the brain seems to provide diminishing returns, when squeezing 2 more bits/sec of information out of the brain means designing a new paradigm around the limited number of available controls. Why use a complex decoder for these simple tasks when a simpler approach may provide a better control signal? Anything from eye tracking to tongue movement can be substituted and decoded at a much higher accuracy than current BCI models. Even a control scheme based on nasal sniffing can be more accurate than the best BCIs available (Plotkin et al. 2010). Our current understanding of the brain is insufficient; we need to better understand how the brain processes and encodes goals and intents before we begin to apply BCIs in the real world. Ironically, BCIs may actually be just the tool to investigate these cortical networks and provide insight into the working of the brain.

Leveraging BCIs as a Neuroscience Tool

It is an understatement to say that the brain is complex. It is capable of processing huge amounts of data, encoding it, and executing complex coordinated motions all simultaneously. Trying to study how the brain accomplishes this can prove difficult due to the asynchronous, parallel nature of neural networks. The fields of psychology and philosophy have been struggling with these types of problems for a long time. Given a novel scenario, how does one "learn" to solve or approach a problem? How does the brain plan and encode motor movement? Is the brain capable of producing unique, volitional patterns of activity? It becomes nearly impossible to design a non-invasive experiment that can have enough scientific controls to begin to investigate these types of questions.

By their very nature, current studies that use BCIs are simple, tightly controlled experiments. Scientists are required to design paradigms in such a way as to remove confounding factors that may interfere with the operation of the BCI. The control signal that drives the BCI is likewise easily identifiable: a single control electrode, a certain ICA component, a single frequency band, etc. It is precisely these types of limitations that can show the true value of BCIs as a tool for investigating more complex questions. It has been shown with many different types of electrophysiological recordings that over a period of time, users of BCIs can get better with training (Miller et al. 2008; Blakely et al. 2009), much like someone may learn to kick a soccer ball better or learn to play a violin. While the latter examples have complex and unknown inputs and outputs during the learning process, the BCIs have very clearly established control signals, priors, and parameters (the decoding model) that can be directly correlated to a known, measureable output (the BCI output). Changes in the input control feature are inherently linked with both the output feedback the subject receives and the conscious and subconscious changes the subject makes to optimize their use of the BCI. In this way, BCIs offer a unique, compelling and controlled way of studying the process of feedback-driven learning.

Local Control Signals and Remote Area Activations

Many BCI studies concentrate on the activity and changes in the region of the brain used to control the BCI, concentrating on the link from brain activity to the output bits per second. Yet many of the modalities currently used to record electrophysiological activity have the capability of recording from many cortical sources in synchrony. In our ECoG BCI studies we ensure that while we are recording from a control electrode that drives the BCI, we are simultaneously recording activity from other remote sites that are covered by the numerous other electrodes that have been implanted. This allows us to investigate possible interactions that occur during the course of the experiment and identify changes that may occur during learning on a novel task. In this manner we are leveraging BCI to explore interactions and information flow in a tightly controlled manner in a way that is not possible to do with other less-constrained experimental settings.

Novel Questions About the Brain can be Addressed with BCIs

For example, take the simple change of varying the number of targets in the standard right-justified-box-task from two to three. This simple change does not complicate the experimental paradigm in any way, nor the control features required for control. From an engineering perspective, the change is marginal; while you may be able to get one more output state from your BCI, the user's accuracy will most likely be lower, thus limiting the return investigating from a bits-per-minute perspective. But looking at it from a neuroscience perspective, such a small change can possibly net huge insights into the way the cortex works.

The initial binary BCI asks the basic neuroscientific question "Can the brain volitionally modify the amount of noise-like activity under the control electrode around an arbitrary threshold?" By driving the cursor to the "active" target, the subject volitionally increases the cortical activity under the control electrode above an artificial threshold. Similarly, by driving the cursor to the "inactive" target, it shows that the subject has either decreased the activity or maintained a sub-threshold baseline of activity. Previous studies have demonstrated that subjects can rapidly learn to control these types of systems as quick as 20 min, sometimes even faster. This demonstrates that the ability to volitionally modulate specific areas of cortex are likely not the product of synaptogenesis and rather a selective activation of subnetworks within the brain, a unique insight into neurophysiology illuminated by using a BCI paradigm.

Increasing the number of targets in the BCI doesn't tell us much new about BCIs beyond the number of bits per second or accuracy of the system in decoding the user's intent. Yet at the same time it opens up a number of interesting—and very important—neuroscientific questions. This new third target, placed in between the "maximally active" and "minimally active" requires the user to modulate the activity generated to be on average higher than the upper limit of the "inactive" and yet below the lower limit of the "active" target. Suddenly, the concept of "a subject can volitionally activate and deactivate a specific area of cortex" becomes much more complex. How does the brain attempt to solve this middle-ground area? If the subject can hit these targets, it means that not only can they volitionally turn these cortical areas on and off, they can also control the *level* of activity under the electrode. What is the resolution of this modulation? Is there an upper limit to how fine-grained the brain can generate activity levels? Are there any known models of anatomical structures could provide this type of neuromodulation? Answering these types of questions could have a greater scientific significance than the concept of "output bits-per minute" of a BCI system.

Unique Activity in Remote Cortical Areas

Our work in ECoG represents an interesting opportunity with regards to BCI in that while our control signal originates from one frequency band from one electrode, we are simultaneously recording a large number of other electrodes over various parts of the cortex. And this is the inherent advantage of ECoG-based BCIs: its broad cortical coverage combined with high temporal resolution. We have been running multitarget BCIs on a number of subjects and post hoc analyzing the signals recorded from areas of the brain that were not directly involved in the generation of the control signal. As Fig. 2 suggests, there are remote areas that show significant changes during the BCI, yet were not involved in the actual control. These co-interested areas are prime targets for future studies and further experiments can be designed to investigate their role.

References

T. Blakely, K.J. Miller, S.P. Zanos, R.P.N. Rao, J.G. Ojemann, Robust, Long-term control of an electrocorticographic brain-computer interface with fixed parameters. Neurosurg. Focus. **27**, E13 (2009), http://www.ncbi.nlm.nih.gov/pubmed/19569888. Accessed 28 July 2011

F. Galán, M. Nuttin, E. Lew, P.W. Ferrez, G. Vanacker, J. Philips , J.D.R. Millán, A brain-actuated wheelchair: asynchronous and non-invasive Brain-computer interfaces for continuous control of robots. Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol. **119**, 2159–2169 (2008), http://www.ncbi.nlm.nih.gov/pubmed/18621580. Accessed 12 March 2012

K.J. Miller, T. Blakely, G. Schalk, M. den Nijs, R.P.N. Rao, J.G. Ojemann, Three cases of feature correlation in an electrocorticographic BCI, in *Conference Proceedings*: *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2008), pp. 5318–5321 http://www.ncbi.nlm.nih.gov/pubmed/19163918

A. Plotkin, L. Sela, A. Weissbrod, R. Kahana, L. Haviv, Y. Yeshurun, N. Soroker, N. Sobel, Sniffing enables communication and environmental control for the severely disabled, in *Proceedings of the National Academy of Sciences of the United States of America*, vol 107 (2010), pp. 14413–14418, http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2922523&tool=pmcentrez&rendertype=abstract. Accessed 27 March 2012

B. Rebsamen, E. Burdet, M. Ang, C. Laugier, A brain-controlled wheelchair based on P300 and path guidance, in *First IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, 2006 BioRob* (2006), pp. 1101–1106. http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1639239

K. Tanaka, K. Matsunaga, H.O. Wang, Electroencephalogram-based control of an electric wheelchair. IEEE Trans. Rob. **21**, 762–766 (2005)

An Affective BCI Using Multiple ERP Components Associated to Facial Emotion Processing

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Abstract P300-based brain computer interfaces (BCIs) have successfully demonstrated that attention to an oddball stimulus can enhance the P300 component of the event-related potential (ERP) phase-locked to the event. However, it was unclear whether the more sophisticated face-evoked potentials can also be modulated by related mental tasks under the oddball paradigm. This study investigated ERP responses to image stimuli of objects, neutral faces, and emotional faces when subjects perform attention, face recognition and discrimination of emotional facial expressions respectively under the oddball paradigm. The results revealed the significant difference between target and non-target ERPs for each mental task. In addition, significant differences among the three mental tasks were observed for vertex-positive potential (VPP) over the fronto-central sites, late positive potential (LPP)/P3b over the centro-parietal sites and N250 over the occipito-temporal sites. These findings indicate that a novel affective BCI paradigm can be developed based on detection of multiple ERP components reflecting human face encoding and emotion processing. The high classification performance for single-trial emotional face-related ERPs demonstrated the effectiveness of the affective BCI.

Introduction

Brain computer interfaces (BCIs) are communication systems that enable the direct communication between humans and computers through decoding of brain activity (Wolpaw et al. 2002), which can be used to assist patients who have

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disabled motor functions. The P300 speller is one of the most popular BCI paradigms first introduced by Farwell and Donchin (Farwell and Donchin 1988). The P300 ERP, elicited when users attend to an oddball stimulus, i.e., a random series of stimulus events that contains an infrequently presented target, is a positive deflection occurring at 300–500 ms post-stimulus over parietal cortex. This is usually done by performing a mental count of the number of times the target visual object is highlighted, implying the fact that neural processing of a stimulus can be modulated by attention (Treder et al. 2010). In recent years, a number of variations of the P300 speller have been explored such as an apparent motion and color onset paradigm (Martens et al. 2009; Guo et al. 2008; Jin et al. 2012), the checkerboard paradigm (Townsend et al. 2010) and the auditory oddball ERP (Furdea et al. 2009). Although the speed and accuracy of P300 BCIs have been significantly improved by various signal processing methods (Lenhardt et al. 2008; Xu et al. 2011), the single-trial classification of the P300 ERP remains a challenging problem. Recent studies showed that a larger N170 ERP is elicited in response to facial stimuli than non-face objects and scrambled faces (Sadeh et al. 2008), and face-selective N250r is elicited by immediate repetitions of faces (Schweinberger et al. 2004; Nasr and Esteky 2009; Neumann et al. 2011). Emotional face type and anxiety modulated ERP responses have also been investigated and divided into three stages around 200, 250, and 320 ms (Dennis and Chen 2007; Luo et al. 2010; Kaufmann et al. 2011). The neural processes involved in switching associations formed with angry and happy faces diverged a peak occurring at 375 ms after stimulus onset (Willis et al. 2010). The early posterior negativity (EPN) and late positive potentials (LPP) related to emotional processing can be enhanced when the subjects see a fearful face compared to a neutral face (Lee et al. 2010).

In contrast to highlighting letters in the classical P300 speller, we investigate the three oddball BCI paradigms utilizing randomly flashed images of objects, neutral faces and emotional faces (Zhao et al. 2011). The subjects were requested to perform three different mental tasks, i.e., visual attention, face recognition (identification), emotion discrimination, corresponding to three types of images. The main objectives were to find the ERP waveforms elicited by neutral faces and emotional faces stimuli and to investigate whether it is feasible to apply face-related ERPs for BCI paradigm. Furthermore, the amplitude and latency of ERPs under these three paradigms as well as classification performance were compared.

Experiment Procedure

Subjects and Data Collection

Five male subjects aged 25–31 years participated in the study. All participants were healthy, right-handed, and had normal or corrected to normal vision. We recorded the EEG from 16 electrodes (F5, Fz, F6, T7, C5, Cz, C6, T8, P7, P5, Pz, P6, P8, PO7, Oz, PO8) using an 16-channel amplifier (g.tec, Guger Technologies

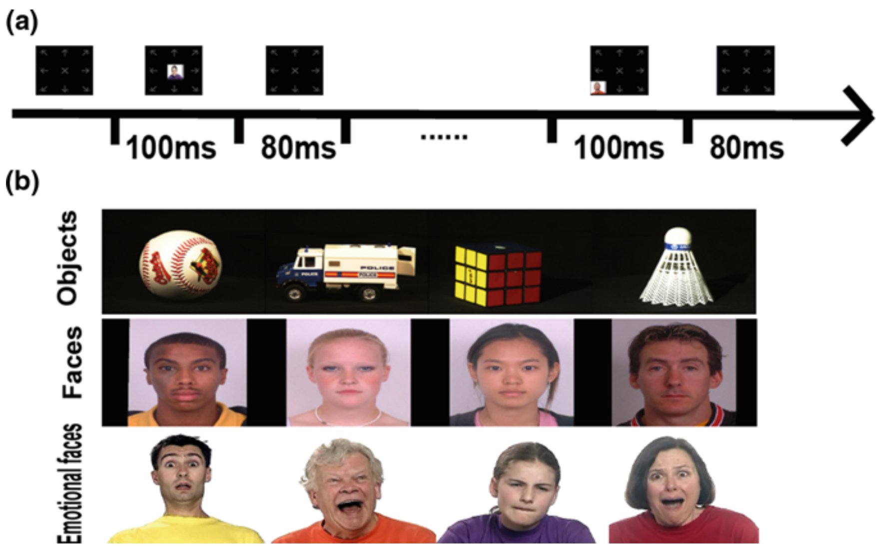

Fig. 1 **a** The procedure of BCI paradigm. The stimuli were shown for 100 ms each with an ISI of 80 ms. **b** Three groups of images were used as stimuli corresponding to three different experimental conditions

OG, Austria). The left mastoid and Fpz served as reference and ground, respectively. The EEG signals were sampled at 256 Hz and band-pass filtered to 0.1–100 Hz with a notch filter of 50 Hz.

Oddball Paradigm

Subjects were seated in a comfortable chair and the screen presented a 3×3 matrix of 9 arrows with gray color and black background, corresponding to the 9 commands for the concrete BCI application. We collected data under three experimental conditions.[1] In condition 1, the subjects were asked to focus on the target item and silently count the number of flashes. Instead of highlighting the target arrow, the images from objects group were shown randomly at each of 9 positions. In condition 2, the images from the neutral faces group were utilized for flashed targets and the subjects were asked to perform the face recognition tasks. In condition 3, the images from the emotional faces group were presented as flashed targets and the subjects were asked to perform emotion discrimination tasks whenever the desired target is intensified. The stimulus duration (SD) was

[1] The video of experimental stimuli is available at http://www.bsp.brain.riken.jp/bci/emotiaonfacefull.avi.

100 ms and the inter-stimulus interval (ISI) was 80 ms for all three conditions. The inter-trial interval (ITI) was 2 s. The procedure and the image groups are shown in Fig. 1. The subjects performed two sessions for each experimental condition. Each session consists of 5 runs and each run presented 9 different target items in succession with only 2 repetitions for each target.

Methods

Preprocessing

The EEG signals were band-pass filtered between 0.1 and 20 Hz. The one second time window of EEG after each stimulus onset was extracted as an epoch and the baseline of each EEG epoch was corrected using a 100 ms pre-stimulus interval. All epochs containing amplitudes exceeding $+/-75\mu V$ were removed as artifacts. For ERP analysis, the target epoches, when the desired image was flashing and the subject was performing the corresponding mental tasks, and the non-target epoches were averaged respectively.

Classification

The classical decoding in the visual P300 based BCI consists of feeding an epoch of EEG after each stimulus event to a classifier. The classifier is trained on target and nontarget responses from a training set and assigns a classifier output value larger than the threshold for a target response and smaller than the threshold for a nontarget response.

We organized an nth EEG epoch by a matrix $\mathbf{X}_n \in \mathbb{R}^{J \times K}$ with J channels and K time samples (e.g., 16×256). Note that the number of training samples (epochs) was typically rather small, up to a few hundred samples. In order to classify the EEG signals as target and non-target, we use the EEG epochs from 0 to 1000 ms after each stimulus, as this epoch should contain all face-related ERP components. For online classification, EEG signals were downsampled to 50 Hz in order to reduce the dimensionality of the data, which is generally used in P300-based BCI designs (Thulasidas et al. 2006). The signals from all EEG channels are concatenated into a single feature vector which is then fed into a classifier.

The support vector machine (SVM), which has been widely used for ERP classifications, was adopted in this study to perform target detection. The principle of the SVM is to seek the maximal margin between two classes, to form the hyperplane with the best generalization capabilities. In our study, we employed a linear kernel SVM, and chose the optimal parameters individually for each subject by 5-fold cross-validation.

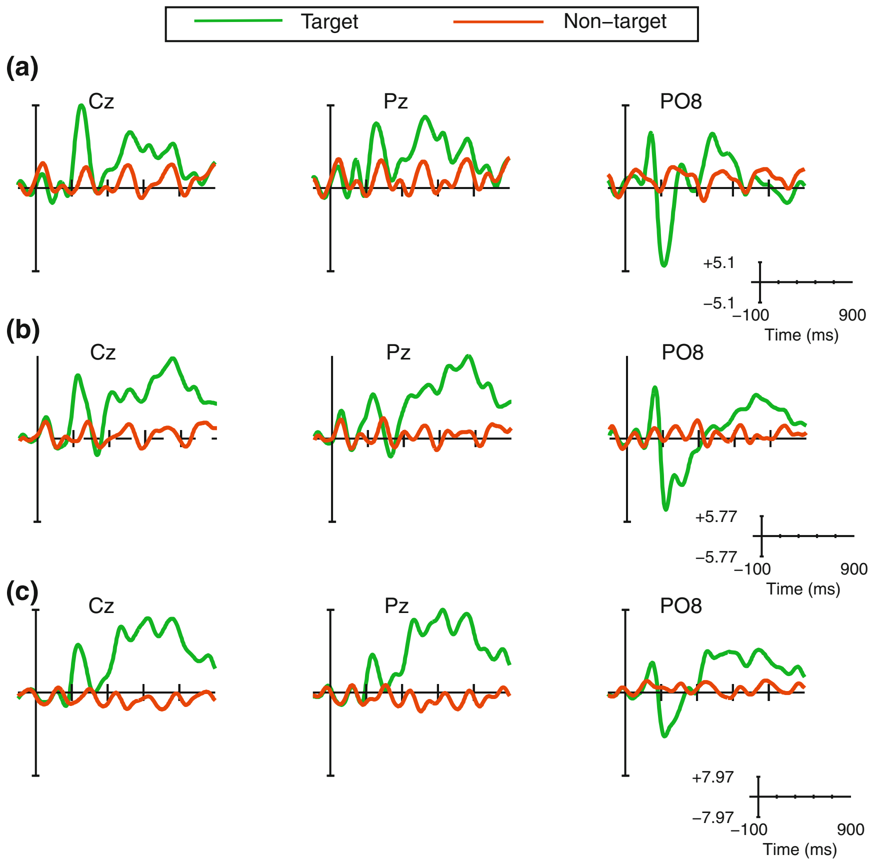

Fig. 2 Grand averaged ERPs at Cz over fronto-central region, Pz over centro-parietal region and PO8 over occipito-temporal region corresponding to target (*green*) and non-target (*red*) stimuli. ERPs using objects, neutral faces, emotional faces as stimuli are shown in panel (**a**), (**b**) and (**c**), respectively

One EEG trial consisted of nine EEG epoches corresponding to each stimulus, which generally must be repeated several times to provide a reliable output. In order to improve the performance, the classifier outputs from repeated epoches corresponding to the same stimulus were averaged. This way, the influence of signal fluctuation was decreased and the classification score was more robust. There are two strategies for averaging. One is to average all epochs for the same stimuli and classify these as a single trial, and another option is to classify each epoch individually and average over the classifier score. We took the second strategy, as preliminary results showed better performance for this method.

Results

Off-Line ERP Analysis

For each experimental condition, grand-averaged ERPs were calculated individually for target and non-target events. We focus on key components of ERPs elicited by faces such as the face-specific N170 (150–190 ms), VPP (140–200 ms), N250 (240–280 ms), P300 (250–350 ms), P3b/LPP (400–800 ms). Early components are thought to reflect basic structural encoding of faces, whereas later components may reflect categorization and attention to motivationally relevant information, including emotion, gender, or familiarity. Thus, different experimental conditions may evoke different responses.

Figure 2a shows the grand-averaged ERP waveform elicited by objects stimuli. Analyses of variance (ANOVA) on stimuli (target vs. nontarget) revealed a significant modulation of attention related ERP components including VPP at Cz electrode (F(1, 18) = 8.08, $p < 0.01$), P300 at Cz electrode (F(1, 18) = 13.41, $p < 0.002$) and LPP at Cz electrode ($F(1, 18) = 5.41$, $p < 0.032$). Although both N170 and VPP were face selective, they also showed some responses to object stimulus categories.

The ERPs elicited by neutral faces stimuli are shown in Fig. 2b. We observed the significant VPP at Cz ($F(1, 18) = 14.15$, $p < 0.02$), P300 at Cz ($F(1, 18) = 24.29$, $p < 0.0001$) and LPP at Cz ($F(1, 18) = 7.98$, $p < 0.012$), indicating the modulation of the face identification task for multiple ERP components during oddball paradigm. In response to the faces stimuli, the occipitotemporal N170 at PO8 electrode is clearly observed ($F(1, 18) = 6.37$, $p < 0.02$). N250 activities were recorded at the same electrode sites as N170 indicating that N250 is sensitive to face stimuli but not to object stimuli.

The ERPs elicited by emotional faces stimuli are shown in Fig. 2c. The late segment of the ERP is dominated by the P300 component and the following LPP component that appears over a broad latency interval, implying elevated positivity to affective face stimuli. Analysis of VPP amplitude revealed a significant effect of emotion information processing at Cz electrode ($F(1, 18) = 12.13$, $p < 0.003$) and Pz electrode (200 ms) ($F(1, 18) = 16.09$, $p < 0.0008$). The LPP were significantly larger for target stimulus compared to non-target stimulus at Cz electrode ($F(1, 18) = 27.97$, $p < 0.0004$) and Pz electrode ($F(1, 18) = 19.99$, $p < 0.0003$). Additionally, LPP at PO8 electrode was also significant ($F(1, 18) = 8.08$, $p < 0.011$).

Further analyses have been performed to explore the effects of ERPs among the three mental tasks and three stimulus categories in order to find the best paradigms for ERP-based BCI. The VPP at Pz electrode revealed a significant difference between the object (task 1) and face (task 2, 3) stimuli ($F(2, 27) = 5.9$, $p < 0.01$), but there was no significant difference between neutral faces and emotional faces.

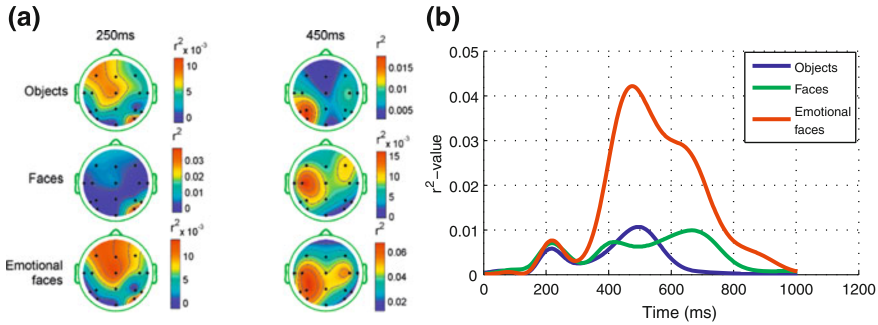

Fig. 3 Spatial and temporal distribution of discriminative information. **a** topographic map of r^2-value at 250 and 450 ms. **b** r^2-value for temporal features

The main effects of emotional faces at Pz and Cz electrodes indicated significantly larger LPP (Cz: $F(2, 27) = 3.94$, $p < 0.032$, Pz: $F(2, 27) = 3.45$, $p < 0.05$) compared to the neutral faces and objects stimuli and N250 at PO8 also revealed larger negative potentials for neutral faces and emotional faces compared to the objects stimuli ($F(2, 27) = 7.48$, $p < 0.003$).

In order to investigate the effects of multiple ERP components related to discrimination between target and non-target epochs, we applied the bi-serial correlation coefficient r^2 index to evaluate the discriminant ability of spatio-temporal ERPs. Figure 3 illustrates that the most discriminative information consisted of two parts: (1) VPP and N250 around 200 ms and (2) LPP at the time window (400–800 ms). The r^2 of LPP observed in the time window 400–800 ms were more pronounced for affective face stimuli than the other two types of stimuli, demonstrating that the main effects of emotion processing are reflected in the LPP.

Performance

To compare the performance of the three oddball paradigms, we performed a 5-fold cross-validation procedure on single trial datasets by using various epoch lengths changed between 100 and 800 ms after stimulus onset, as illustrated in Fig. 4a. It is clear that the paradigm exploiting emotional faces with emotion discrimination tasks outperform both of objects and neutral faces paradigms, especially when the epoch length is longer than 400 ms. The ROC curve, as shown in Fig. 4b, indicates that both emotional and neutral faces paradigms are superior to the objects paradigm; in particular, the emotional faces paradigm greatly improves the classification performance of the single trial EEG.

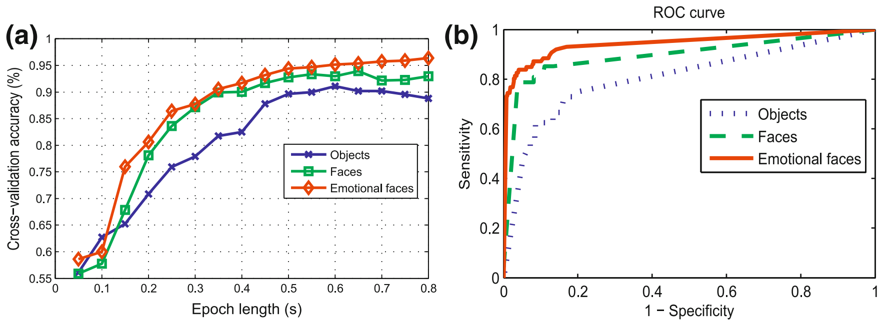

Fig. 4 **a** Cross-validation accuracy for ERPs with varying length of EEG epoches. **b** ROC curves under three different experimental conditions

Real-Time Robotic Arm Control

We developed an online affective BCI system (Onishi et al. 2011) for controlling a robot arm to deliver the food or drinks to the subject, which is potentially helpful for the locked-in patients.[2]

Subsequent Work

Face perception may rely more on configural information (i.e. prototypical spatial relationships between parts of the face) rather than other visual object perception (Moscovitch et al. 1997). The inversion of a face can disrupt the configural face information, thereby making the face processing slower and more difficult (Rossion et al. 1999; Marzi and Viggiano 2007) (see Fig. 5). The two components of N170 and VPP are believed to reflect the configural processing of the face (Eimer 2000; Itier and Taylor 2004), and their amplitudes and latencies can be modulated by the inversion of the face (Itier and Taylor 2002). The modulation results from the greater effort of face selectivity, since the increased difficulty for inverted face perception recruits additional selectivity mechanisms besides those for upright face perception. Hence, a preliminary BCI paradigm (Zhang et al. 2012) based on the inverted faces has been developed.[3] Also, the emotion information could be integrated into the face perception, thereby resulting in emotion expression processing. Then, how the loss of configural face information affects the emotion expression processing and whether the effect is helpful for improving the performance of BCI systems are interesting issues.

[2] The videos are available at http://www.bsp.brain.riken.jp/bci/.

[3] see http://www.bsp.brain.riken.jp/bci/inverted_face_paradigm.wmv.

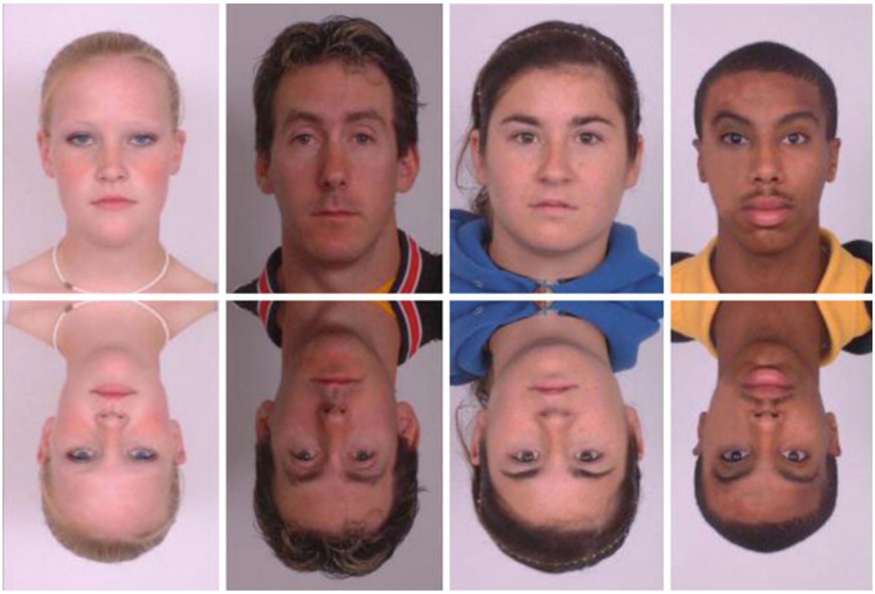

Fig. 5 Stimuli of upright faces and inverted faces used for ERP-based BCI

Although the face-sensitive potentials N170 and VPP have an evocation mechanism different from that of the motion-onset potential N200 (Guo et al. 2008), both of them are elicited by visual stimuli and have closed latencies with relatively small inter-subject variability. Hence, it is possible that the combination of face and motion perception may induce ERP components with relatively high detectability and improve target detection performance for the visual stimuli-driven BCI system. A BCI paradigm using stimuli of rotating (moving) faces has been designed.[4] Recently, a specific paradigm, named rapid serial visual presentation (RSVP), has been increasingly studied for BCI, since it requires no eye movements and provides therefore higher applicability for the patients whose oculomotor systems are impaired (Acqualagnav et al. 2010). Then, a facial image-based RSVP paradigm can be accordingly employed with our affective BCI.[5] More studies are needed for the aforementioned perspectives. Our current research explores these issues and we expect to develop an improved BCI system using the stimuli of facial images.

The EEG dynamics of emotional processing have attracted increasing interest in recent years. For instance, the potential feasibility of emotion-classification and augmented emotional communication system via a live musical performance has been demonstrated in Makeig et al. (2011). Workshops on affective brain computer interfaces were successfully held in the past two years, aiming to bring researchers

[4] see http://www.bsp.brain.riken.jp/bci/RotatingFace.wmv.

[5] see http://www.bsp.brain.riken.jp/bci/RSVP_Face.wmv.

from the communities of brain computer interfacing, affective computing, neuroergonomics, affective and cognitive neuroscience together to present state-of-the-art progress and visions on the various overlaps between those disciplines (Nijholt et al. 2011).

The social interactions between two subjects will be explored in our future research by connectivity patterns and causality networks, since it is of high importance to understand how the subnetworks in two brains interact and synchronize under the specific designed experimental protocol. In particular, the hyperscanning of multiple brains or brain to brain (B2B) interfaces may help us to extract more reliable features corresponding to the emotional state of subjects via multiview learning theory.

Conclusions

In summary, our affective BCI paradigm and platform has the following features and advantages: (1) Due to applying emotional faces and optimization of visual stimuli, the classification accuracy can be significantly improved and the number of repetition can be dramatically reduced as compared to the standard P300 using stimulus of letters or symbols; (2) Instead of the standard P300, we rather exploit emotion related multiple ERPs (VPP at Cz, LPP at Cz, N250 at PO8), which allows us to increase reliability and performance of the visual stimuli driven BCI; (3) Our BCI system is relatively easy to use and it is more reliable; (4) Since the high level cognitive functions are involved to express the subjects' voluntary intention, our BCI is promising for rehabilitation of cognitive dysfunction rather than motor dysfunction.

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References

L. Acqualagnav, M. Treder, M. Schreuder, B. Blankertz, A novel brain-computer interface based on the rapid serial visual presentation paradigm, in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE* (IEEE, 2010), pp. 2686–2689

T. Dennis, C. Chen, Emotional face processing and attention performance in three domains: neurophysiological mechanisms and moderating effects of trait anxiety. Int. J. Psychophysiol. **65**(1), 10–19 (2007)

M. Eimer, Effects of face inversion on the structural encoding and recognition of faces: evidence from event-related brain potentials. Cogn. Brain Res. **10**(1–2), 145–158 (2000)

L. Farwell, E. Donchin, Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr. Clin. Neurophysiol. **70**(6), 510–523 (1988)

A. Furdea, S. Halder, D. Krusienski, D. Bross, F. Nijboer, N. Birbaumer, A. Kübler, An auditory oddball (P300) spelling system for brain-computer interfaces. Psychophysiology **46**(3), 617–625 (2009)

F. Guo, B. Hong, X. Gao, S. Gao, A brain-computer interface using motion-onset visual evoked potential. J. Neural Eng. **5**(4), 477–485 (2008)

R. Itier, M. Taylor, Inversion and contrast polarity reversal affect both encoding and recognition processes of unfamiliar faces: a repetition study using ERPs. NeuroImage **15**(2), 353–372 (2002)

R. Itier, M. Taylor, N170 or N1? spatiotemporal differences between object and face processing using ERPs. Cereb. Cortex **14**(2), 132–142 (2004)

J. Jin, B. Allison, X. Wang, C. Neuper, A combined brain-computer interface based on P300 potentials and motion-onset visual evoked potentials. J. Neurosci. Methods **205**(2), 265–276 (2012)

T. Kaufmann, S. Schulz, C. Grünzinger, A. Kübler, Flashing characters with famous faces improves ERP-based brain-computer interface performance. J. Neural Eng. **8**(5), 056016 (2011)

K. Lee, T. Lee, S. Yoon, Y. Cho, J. Choi, H. Kim, Neural correlates of top-down processing in emotion perception: an ERP study of emotional faces in white noise versus noise-alone stimuli. Brain Res. **1337**, 56–63 (2010)

A. Lenhardt, M. Kaper, H. Ritter, An adaptive P300-based online brain-computer interface. IEEE Trans. Neural Syst. Rehabil. Eng. **16**(2), 121–130 (2008)

W. Luo, W. Feng, W. He, N. Wang, Y. Luo, Three stages of facial expression processing: ERP study with rapid serial visual presentation. NeuroImage **49**(2), 1857–1867 (2010)

S. Makeig, G. Leslie, T. Mullen, D. Sarma, N. Bigdely-Shamlo, C. Kothe, First demonstration of a musical emotion BCI, in *Affective Computing and Intelligent Interaction*, 2011, pp. 487–496

S. Martens, N. Hill, J. Farquhar, B. Schölkopf, Overlap and refractory effects in a brain-computer interface speller based on the visual P300 event-related potential. J. Neural Eng. **6**, 026003 (2009)

T. Marzi, M. Viggiano, Interplay between familiarity and orientation in face processing: an ERP study. Int. J. Psychophysiol. **65**(3), 182–192 (2007)

M. Moscovitch, G. Winocur, M. Behrmann, What is special about face recognition? nineteen experiments on a person with visual object agnosia and dyslexia but normal face recognition. J. Cogn. Neurosci. **9**(5), 555–604 (1997)

S. Nasr, H. Esteky, A study of N250 event-related brain potential during face and non-face detection tasks. J. Vis. **9**(5), 5 (2009)

M.F. Neumann, T.N. Mohamed, S.R. Schweinberger, Face and object encoding under perceptual load: ERP evidence. NeuroImage **54**(4), 3021–3027 (2011)

A. Nijholt, B. Allison, S. Dunne, D. Heylen et al., Affective brain-computer interfaces (abci 2011), in *Proceedings of the 4th International Conference on Affective Computing and Intelligent Interaction-Volume Part II* (Springer-Verlag (2011), pp. 435–435

A. Onishi, Y. Zhang, Q. Zhao, A. Cichocki, Fast and reliable P300-based BCI with facial images, in *Proceedings of the 5th International Brain-Computer Interface Conference*, 2011, pp. 192–195

B. Rossion, J. Delvenne, D. Debatisse, V. Goffaux, R. Bruyer, M. Crommelinck, J. Guérit, Spatio-temporal localization of the face inversion effect: an event-related potentials study. Biol. psychol. **50**(3), 173–189 (1999)

B. Sadeh, A. Zhdanov, I. Podlipsky, T. Hendler, G. Yovel, The validity of the face-selective ERP N170 component during simultaneous recording with functional MRI. Neuroimage **42**(2), 778–786 (2008)

S. Schweinberger, V. Huddy, A. Burton, N250r: a face-selective brain response to stimulus repetitions. NeuroReport **15**(9), 1501 (2004)

M. Thulasidas, C. Guan, J. Wu, Robust classification of EEG signal for brain-computer interface. IEEE Trans. Neural Syst. Rehabil. Eng. **14**(1), 24–29 (2006)

G. Townsend, B. LaPallo, C. Boulay, D. Krusienski, G. Frye, C. Hauser, N. Schwartz, T. Vaughan, J. Wolpaw, E. Sellers, A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns. Clin. Neurophysiol. **121**(7), 1109–1120 (2010)

M. Treder, B. Blankertz, (C) overt attention and visual speller design in an ERP-based brain-computer interface. Behav. Brain Funct. **6**(1), 28 (2010)

M. Willis, R. Palermo, D. Burke, C. Atkinson, G. McArthur, Switching associations between facial identity and emotional expression: a behavioural and ERP study. Neuroimage **50**(1), 329–339 (2010)

J. Wolpaw, N. Birbaumer, D. McFarland, G. Pfurtscheller, T. Vaughan, Brain-computer interfaces for communication and control. Clin. Neurophysiol. **113**(6), 767–791 (2002)

P. Xu, P. Yang, X. Lei, D. Yao, An enhanced probabilistic LDA for multi-class brain computer interface. PloS One **6**(1), e14634 (2011)

Y. Zhang, Q. Zhao, J. Jin, X. Wang, A. Cichocki, A novel BCI based on ERP components sensitive to configural processing of human faces. J. Neural Eng. **9**(2), 026018 (2012)

Q. Zhao, A. Onishi, Y. Zhang, J. Cao, L. Zhang, A. Cichocki, A novel oddball paradigm for affective BCIs using emotional faces as stimuli. Lecture Notes in Computer Science, vol. 7062, 2011, pp. 279–286

Seven Degree of Freedom Cortical Control of a Robotic Arm

Samuel T. Clanton, Angus JC McMorland, Zohny Zohny, S Morgan Jeffries, Robert G Rasmussen, Sharlene N Flesher and Meel Velliste

Abstract We have recently established simultaneous 7 degree-of-freedom (DoF) brain-computer interface (BCI) control of a robotic arm. Using signals recorded from single units of monkeys with implanted chronic microelectrode arrays, we can now demonstrate brain control of a prosthetic arm that exhibits the following features: (1) simultaneous 7-degree of freedom (DoF) brain control over 3-D robot hand translation, 3-D rotation, and finger aperture, (2) integrated kinematic (movement) and dynamic (force) control of a brain-controlled prosthetic robot through a novel impedance-based movement controller, (3) simplified methods for constructing cortical extraction models based only on observation of the moving robot, and (4) a generalized method for training subjects to use complex prosthetic robot devices using a novel form of operator-machine shared control.

Introduction

Since the discovery of models relating arm movement to neuronal population activity in the motor cortex (Georgopoulos et al. 1982), there have been efforts to recruit this activity to control external devices directly with the brain. Brain-computer interface (BCI) prosthetic devices have the potential to aid the over 250,000 people in the US alone who suffer from debilitating motor deficits such as spinal cord injury and ALS (Wyndaele and Wyndaele 2006). BCI systems can do

This work was completed in the laboratory of Andrew Schwartz at the University of Pittsburgh.

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this by bypassing motor lesions located outside of the CNS; cortical activity reflecting subject intent can instead be expressed directly by action in a machine.

Progressively more sophisticated BCI systems have been demonstrated over the last decade, moving from 2 and 3-dimensional control of a cursor on a computer screen (Serruya et al. 2002; Taylor et al. 2002) to indirect (Taylor et al. 2003; Carmena et al. 2003) and finally direct control of a 4 degree-of-freedom (DoF) robot arm (Velliste et al. 2008). In the 4-DoF experiment, the use of an anthropomorphic physical arm facilitated the monkey incorporating arm behaviors related to its physical structure into its control. As we progress towards the control of increasingly sophisticated prosthetic arms, the related concept of embodiment gains importance; BCI prosthetic devices that incorporate features of natural movement may be more easily mapped into familiar patterns of neural control. Natural arm movements integrate hand rotation with translation and are characterized by fluid transitions between arm and hand motions when reaching to and interacting with objects. While these types of movements are desired in prosthetic control models, no prosthetic arm will be able to directly reproduce the exact movements and dynamics of a specific subject's natural arm. Therefore, effective models for BCI control will incorporate general principles of natural movement without reliance on exact replication of subject physiology. We have recently developed a brain-computer interface robot control system that directly addresses these issues. Recording from single units in the motor cortex, we can now demonstrate brain control of a prosthetic arm that exhibits the following features:

(1) simultaneous 7 DoF brain control over robot hand translation, rotation, and finger aperture, (2) integrated kinematic (movement) and dynamic (force) BCI control of a prosthetic robot, (3) simplified methods for constructing cortical extraction models based on only observation of the moving robot, and (4) a generalized method for training subjects to use complex prosthetic robot devices using a novel form of operator-machine shared control.

7-DoF BCI Experiment

Two monkey subjects (F and G, both naive to brain control) were implanted with 96-channel chronic intracortical microelectrode arrays. Monkey F had a single array in the right hemisphere while G had three arrays, two in the left and one in the right hemisphere. Array locations for both monkeys are shown in Fig. 3. Cortical activity captured with these arrays was used to drive the movement of a 7-DoF robot arm with 4-DoF attached robot hand (Barrett WAM arm and Hand, Barrett Technologies, Cambridge, MA) that was mounted to the right of the subject (Fig. 1) in the experiment. The arrangement of the links of the prosthetic robot were anthropomorphic except at the robot wrist, which replaced the abduction/adduction joint at the hand with an additional axial rotation joint. The reachable space of the WAM endpoint was similar to that of the human arm with different joint space configurations in each endpoint pose. The brain-controlled

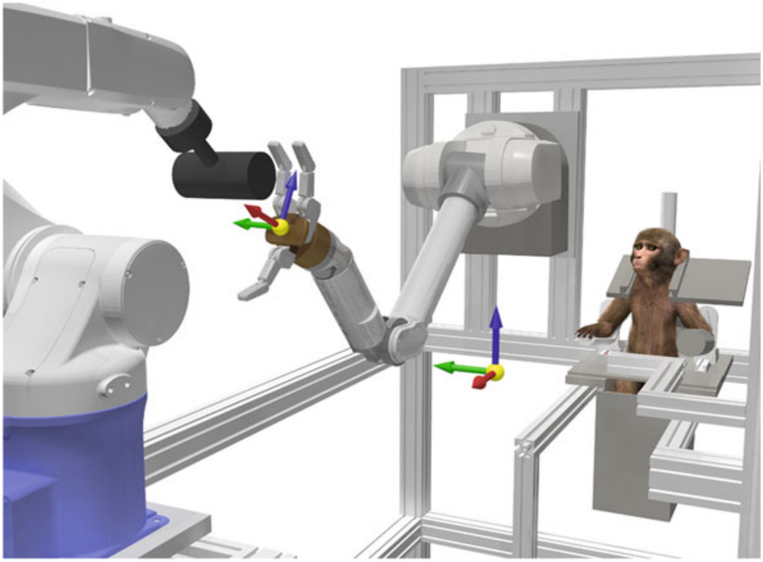

Fig. 1 The BCI control experimental setup with monkey, prosthetic, and targeting robot. Axes representing robot base and hand coordinate frames are superimposed. *Arrows* correspond to the X-Y-Z axes of the experiment

movement variables in the experiment were the Cartesian linear and rotational velocities of the whole hand, along with grasp aperture. Finger movements of the hand were not always available due to malfunction, so that many control sessions were reduced to 6-DoF execution.

Spiking activity in the brain was recorded using RZ2 (TDT Inc., Alachua, FL) signal processing systems. For monkey F, a threshold at each electrode channel was fixed at 5–7.5 times the standard deviation of measured voltage deflections and all threshold crosses were counted as a neural spike of a single cortical unit. Monkey G units were at first manually sorted from within waveforms crossing the threshold, but later automatic threshold crossing was used with a small number of additional units (10–15) manually sorted. Spike events were transformed to firing rates using inter-spike interval times in 30 ms bins. Firing rates were filtered with an exponential filter (width 15 bins, decay constant 0.95) throughout the experiment.

Cortical Decoder Calibration

During the first part of each daily control session, subjects observed the prosthetic robot as it autonomously executed oriented grasping tasks. Each movement execution was prompted by the monkey reaching out and pressing a button with its own unrestrained right hand. The presentation robot then moved the target to one

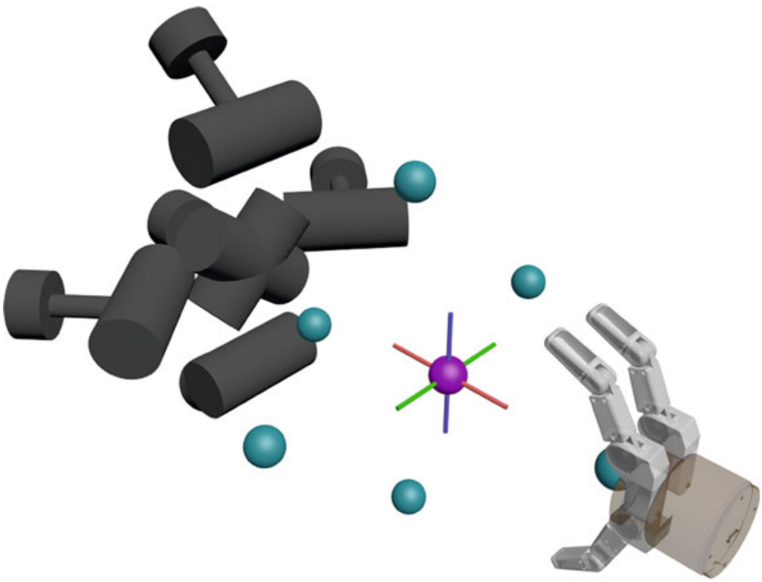

Fig. 2 Starting positions of the hand (*spheres*) and orientations of the target object. 2 axial rotation targets are superimposed in the center of the target set. The robot hand moved backwards from the sphere closest to the center of the targets before orienting

of six orientations while the prosthetic robot moved to one of six positions on the edges of the robot workspace (Fig. 2 illustrates the set of starting positions and target orientations). Next, an audible cue was emitted to begin the trial. The robot hand autonomously translated, rotated towards, then grasped the target as measured cortical spike rates and robot movement velocities were recorded in 30 ms intervals. When the robot grasped the target, a liquid reward was delivered to the monkey, the robot positions were reset, and the system waited for the next button press. Trials timed out and were failed after 12–14s if the hand had not grasped the cylinder. Trials were also aborted if the monkey stopped attending to the task or was moving in the chair.

At the end of 18–40 observation trials, a cortical decoder was calibrated to produce a model for generating movement commands from sampled spike rates. Sampled robot velocities were filtered with a 15 bin boxcar filter. Samples of firing rates and velocities in which a significant amount of movement was taking place (>0.02 m/s or rad/s total velocity) were used for calibration. 1000–3000 samples were normally used for model calibration in each session.

The calibration process first fit a preferred-direction (PD) model of the relationship between individual unit firing rates and robot movements that included the 3-D linear and rotational velocities of the hand. PD models were originally used to describe the cosine tuning properties of cortical neurons observed during hand movements (Georgopoulos et al. 1982). A separate PD model working in parallel was used to relate cortical firing rates to 1-D robotic hand aperture velocity.

Sampled linear and rotational velocities were related to firing rates by linear and rotational PD coefficients that comprised 6-D preferred directions for each unit. The grip model employed a 1-D preferred direction model. By using linear and rotational velocities as the controlled motor quantities in the arm movement equation, the 6-D PD model operates over a 6-D vector space to control both linear and rotational motion of the hand.

PD model calibration was followed by application of the minimal variance Optimal Linear Estimation (OLE) method (Salinas and Abbott 1994; Chase et al. 2009) to produce a decoding matrix that transformed spikes to movement commands for the remainder of the experimental session. OLE is similar to the well known Population Vector Algorithm (PVA) but avoids bias introduced by non-uniform distributions of preferred direction.

Linear and rotational tuning parameters (linear and rotational preferred directions) from one experimental session are shown in Figs. 4 and 5, showing the distribution of PDs for both types of movement.

BCI Operator Training

After the model calibration period of each session, the experiment entered a training phase in which the monkey learned to use the calibrated model to perform the oriented grasping task. When naive monkeys were first introduced to the task, they started by first performing 3-D linear control while the 4 remaining DoF of the oriented grasping task were controlled automatically. After proficiency was gained, the monkeys performed the 3-D rotational portion of the otherwise autonomously controlled task. Finally, the 6-DoF control task was performed

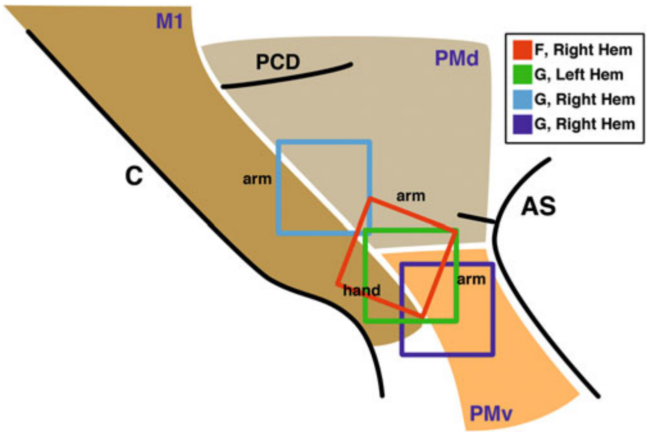

Fig. 3 Locations of cortical implants in both monkeys. Square outlines are silhouettes of Utah electrode arrays. *M1* primary motor cortex, *PM(d/v)* dorsal/ventral premotor area, *C* central sulcus, *PCD* precentral dimple, *AS* arcuate sulcus, Topography adapted from He et al. (1993)

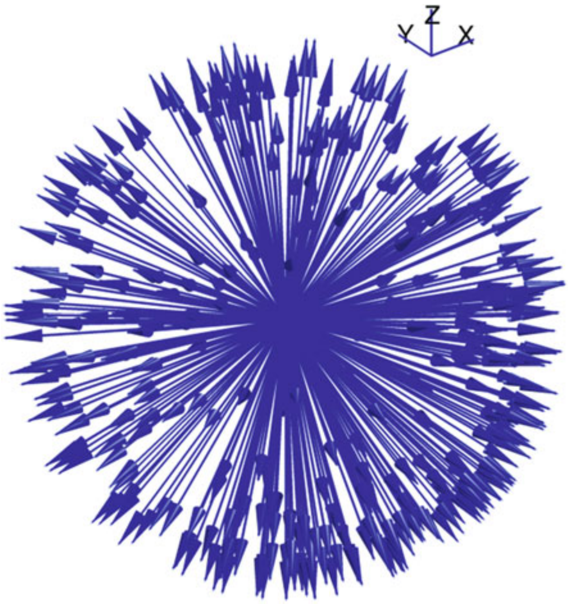

Fig. 4 Distribution of linear preferred directions of individual units from monkey G calibration based on observation data. An increase in spike rate for each cortical unit contributes to moving the overall robot command signal in the direction of its corresponding preferred direction

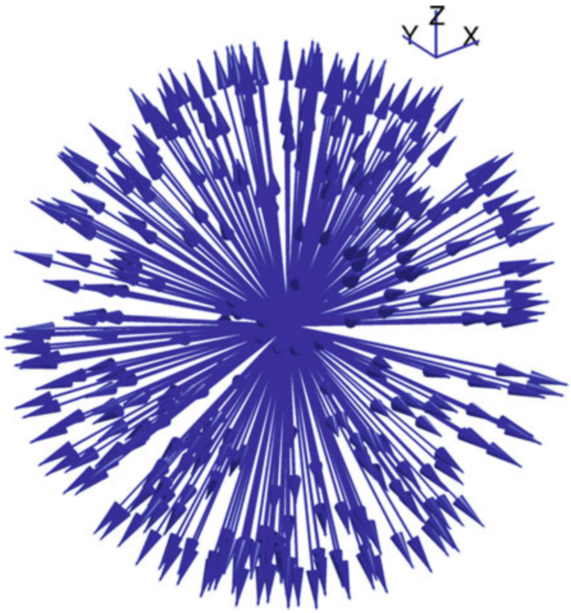

Fig. 5 Distribution of rotational preferred directions for the same units as Fig. 4. Increases in spike rate for each unit contribute a rotational velocity command with an axis in the direction of the unit's PD

under brain control (examples shown in Fig. 6). Grip control was also performed during all phases when the robot hand was available.

For each DoF under brain control, an operator-machine shared control system adaptively modified subject control commands by comparison to sets of model

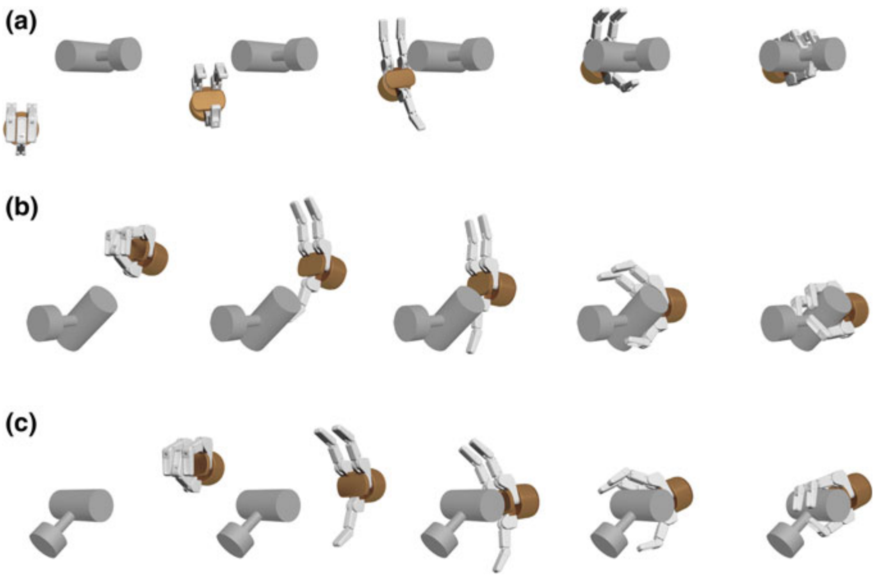

Fig. 6 Three successful 7-DoF brain control trials with movement in different linear and rotational dimensions. **a** Upward linear, left yaw motion, **b** Downward linear, right twist motion, **c** Forward linear, downward pitch motion

commands provided by an autonomous software program that modeled the motor task in real time. The autonomous controller generated multiple movement commands simultaneously that represented motion toward and approximation of the range of robot poses that would complete the grasping task. This reflected the fact that there are many ways that hands grasp objects, so that we allowed that flexibility in using the brain-controlled arm and hand.

This is an extension of a type of error limiting shared control that was used for training by Velliste et al. (2008). Using this system, robot movement was not driven directly by the autonomous controller during training, but instead provided a template for reducing noise and error in the brain-control signal. The use of multiple commands in the template pointing towards the boundaries of allowable grasps allowed flexibility in how the task was completed, while still providing overall assistance.

The autonomous controller was also aware of the solid-body characteristics of the target cylinder and hand; when the path towards task completion poses was obstructed (e.g. the hand was behind the cylinder), generated commands would point toward intermediate poses preceding those from which the task could be completed. Automatic movements and the shared control algorithm at first provided a method for the monkey to learn the task sequence by demonstration and to connect grasping task completion with reward; this set up the operant conditioning paradigm used for training the monkeys. As the monkeys began to learn the relationship between intent and movement control, the shared control system prevented cortical activity unrelated to the task and control error from taking over robot movements. As the monkeys gained control skill, the shared control algorithm acted like a set of adjustable training wheels on a bicycle. By manipulating the underlying difficulty of the task using the shared control parameters, successful completion and reward delivery were maintained at gradually increasing levels of monkey skill, supporting monkey motivation throughout large numbers of control training trials.

The shared control coefficients were raised over time in accordance with heuristics developed by the investigators as a function of performance and perceived motivation level of the monkey. By independently changing the rotational and linear shared control coefficients, control challenges in each movement type could be effected, allowing skill to be acquired at different rates for each movement component. The goal of using the shared control system was to gradually reduce its influence so that the monkey eventually fully controlled the device. Progress toward full control was represented by the maximum shared control parameter level at which task success could be maintained. Shared control provides a consistent method to constrain the complexity of the BCI system, which is a major factor for enabling training to take place when a large number of effector DoF are present.

Robot Motion Controller

PD model translational and rotational velocities were defined as the movement of the robot about a control point with a fixed relationship to the hand (Fig. 1, coordinate axis attached to robot hand). Linear velocity DoF describe movement of this point through space, while rotation of the hand around this point was the basis for the rotational DoF. During grasping of an object, the control point was located at a location near the interface of the hand and the object. When the hand was approximated to the object, we described the coordinate system as "object centered" such that linear and rotational degrees-of-freedom approached independence. Translational and rotational DoF could be manipulated independently while maintaining a relatively consistent relationship between the hand and object in the other DoF. Use of this method allowed us to avoid problems with dependency between the linear and rotational DoF during grasping which would result from alternate motion parameterizations.

Velocity commands from the shared control system drove the movement of a torque-controlled robot arm using a novel low-level motion controller that smoothly integrated the control of arm kinematics and forces/torques at the hand. This system was based on a method for Cartesian impedance control (Hogan 1985) with a superimposed kinematic control model. Robot endpoint velocity was commanded directly during unconstrained movements, but these commands also indirectly controlled interaction forces when the arm was under an external load. This control model is similar to one proposed for the interaction of force and velocity in the cortical control of natural movements (Todorov 2000). It allows an intuitive mechanism for transition between movement and force interactions, in addition to providing a controllably compliant and safe way to control the prosthetic arm in a realistic environment. While more traditional rigid robots and robot controllers would not be able to safely interact with objects, the monkey was able to use impedance control characteristics of this arm to interact with the cylinder target and other objects (including the monkey itself) even when its control skill was very low.

In addition to allowing trials to continue through frequent collisions between the robot arm and objects, controlled compliant force interactions with environmental objects augmented the realism of the overall task and enhanced the performance of control trials. For instance, both monkeys were observed to use the vertical extension of the fingers and linear translation to tilt the hand towards pitched targets. The hand often became stuck behind the target cylinder; this was allowed to happen freely. Both monkeys were observed to pull the hand backwards in cases where the robotic compliance behavior of the robot would allow it to free the hand, or around the object when it would not.

References

J.M. Carmena, M.A. Lebedev, R.E. Crist, J.E. O'Doherty, D.M. Santucci, D.F. Dimitrov, P.G. Patil, C.S. Henriquez, M.A.L. Nicolelis, Learning to control a brain-machine interface for reaching and grasping by primates. PLoS Biol. **1**(2), E42 (2003)

S.M. Chase, A.B. Schwartz, R.E. Kass, Bias, optimal linear estimation, and the differences between open-loop simulation and closed-loop performance of spiking-based brain-computer interface algorithms. Neural Netw. : Off. J. Int. Neural Netw. Soc. **22**(9), 1203–1213 (2009)

A.P. Georgopoulos, J.F. Kalaska, R. Caminiti, J.T. Massey, On the relations between the direction of two-dimensional arm movements and cell discharge in primate motor cortex. J. Neurosci. : Off. J. Soc. Neurosci. **2**(11), 1527–1537 (1982)

S.Q. He, R.P. Dum, P.L. Strick, Topographic organization of corticospinal projections from the frontal lobe: motor areas on the lateral surface of the hemisphere. J. Neurosci.: The Off. J. Soc. Neurosci. **13**(3), 952–980 (1993)

N. Hogan, Impedance control: An approach to manipulation–part II: Implementation. J. Dyn. Syst. Meas. Control **107**, 1–7 (1985)

E. Salinas, L.F. Abbott, Vector reconstruction from firing rates. J. Comput. Neurosci. **1**(1—-2), 89–107 (1994)

M.D. Serruya, N.G. Hatsopoulos, L. Liam Paninski, M.R. Fellows, J.P. Donoghue, Instant neural control of a movement signal. Nature **416**(6877), 141–142 (2002)

D.M. Taylor, S.I.H. Tillery, A.B. Schwartz, Direct cortical control of 3D neuroprosthetic devices. Science **296**(5574), 1829–1832 (2002)

D.M. Taylor, S.I.H. Tillery, A.B. Schwartz, Information conveyed through brain-control: Cursor versus robot. IEEE Trans. Neural Syst. Rehabil. Eng.: Publ. IEEE Eng. Med. Biol. Soc. **11**(2), 195–199 (2003)

E. Todorov, Direct cortical control of muscle activation in voluntary arm movements: a model. Nat. Neurosci. **3**(4), 391–398 (2000)

M. Velliste, S. Perel, M.C. Spalding, A.S. Whitford, A.B. Schwartz, Cortical control of a prosthetic arm for self-feeding. Nature **453**(7198), 1098–1101 (2008)

M. Wyndaele, J.-J. Wyndaele, Incidence, prevalence and epidemiology of spinal cord injury: What learns a worldwide literature survey? Spinal Cord : Off. J. Int. Med. Soc. Paraplegia **44**(9), 523–529 (2006)

Utilizing High Gamma (HG) Band Power Changes as a Control Signal for Non-Invasive BCI

M. Smith, K. Weaver, T. Grabowski and F. Darvas

Abstract Current electroencephalography (EEG) Brain-Computer Interface (BCI) methods typically use control signals (P300, modulated slow cortical potentials, mu or beta rhythm) that suffer from a slow time scale, low signal to noise ratio, and/or low spatial resolution. High gamma oscillations (70–150 Hz; HG) are rapidly evolving, spatially localized signals and recent studies have shown that EEG can reliably detect task-related HG power changes. In this chapter, we discuss how we capitalize on EEG resolved HG as a control signal for BCI. We use functional magnetic resonance imaging (fMRI) to impose spatial constraints in an effort to improve the signal to noise ratio across the HG band. The overall combination lends itself to a fast-responding, dynamic BCI.

Introduction/Rationale

A Brain-Computer Interface (BCI) is a system that acquires and analyzes brain signals with the goal of creating a communication channel between brain and the computer (Wolpaw et al. 2002). BCIs have great potential to facilitate the lives of paralyzed individuals with intact brain function but damaged cortico-spinal pathways. Current BCIs typically rely on comparably slow cortical rhythms such

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as mu/alpha (8–12 Hz), beta (17–25 Hz), or evoked potentials (e.g. P300) as control signals. While these systems are working, overall efficacy is limited due to the time latency it takes, which is on the order of several hundred milliseconds, for the rhythm amplitude to evolve (Wolpaw et al. 1997; Pfurtscheller 1999; Pfurtscheller and Lopes da Silva 1999a; Prückl 2012). That is, the reliable detection of a response can take seconds for BCIs based on these control signals. This makes such systems unintuitive and cumbersome to use. Ideally a smaller response lag is desired, i.e. 100 ms or less, to ensure a fluid, natural, and practical alternative to input devices that rely on motor movements, such as keyboards, mice, eye trackers, etc. This requires cortical responses that can change rapidly within the desired lag time of the system. The high gamma (HG) band has these properties; oscillations are greater than 80 Hz and detectable power shifts within this frequency band occur on very short time scales ($\sim$50 ms) (Darvas and Scherer et al. 2010). Another desirable property of the HG rhythm is that it is spatially more focal than more slowly evolving potentials and thus highly specific to a given task (Miller 2007). The HG band has been successfully used for BCI control using invasive electrocorticography (ECoG) techniques, e.g. (Leuthardt et al. 2004). It has been shown that HG activity can be detected non-invasively by electroencephalography (EEG) around primary motor cortex prior to finger movements (Darvas 2010). However, HG signals in EEG-BCIs suffer from two problems, (1) low signal-to-noise ratio (SNR) and (2) overlap with electromyogram (EMG) activity, i.e. muscle artifacts, which we propose to overcome by a combination of signal processing and cortical mapping, utilizing the subject's individual head anatomy and constraining the signal source to fMRI-guided regions of interest (Fig. 1). The objective of this project is to develop a rapid EEG-based BCI that is capable of detecting motor preparatory signals prior to self-paced finger movements, so that the decision is approximately coincident with EMG onset, i.e., real-time.

Methods

Due to the highly focal nature of the HG rhythm, single scalp electrodes, if not placed directly over the location of the source, can 'miss' power shifts in this band. However, due the large range of potential changes for point sources, the entire EEG montage can pick up these changes collectively, but with a very small signal in each electrode. By forming a suitable linear combination of electrodes, i.e. by using a linear inverse method, where scalp activity is mapped back to the cortical sources, HG changes can be recovered (Fig. 2a).

In order to extract localized HG activity with EEG during motor tasks, we use functional magnetic resonance imaging (fMRI) to determine an individual subject's motor areas (Fig. 2b). fMRI allows us to indirectly localize brain regions of interest (ROIs) that are active during specific tasks. fMRI contrast is rooted in the blood oxygenation level dependent (BOLD) signal, which is thought to be a result

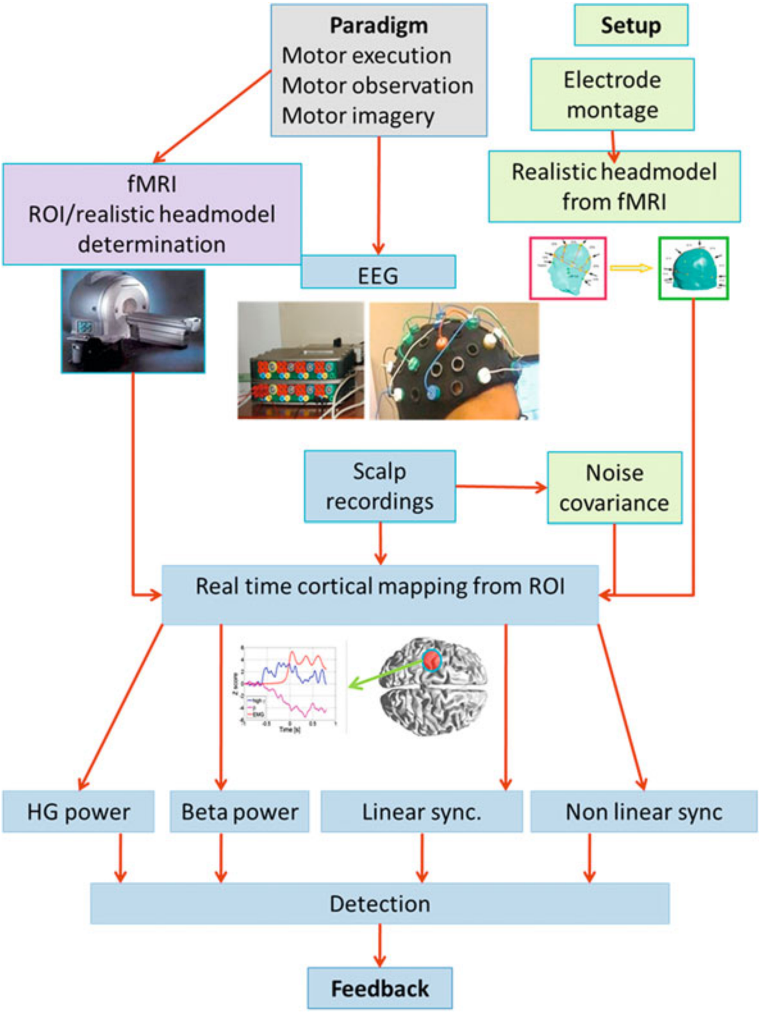

Fig. 1 General outline of the proposed BCI system

of changes in blood flow, blood volume, and oxygen consumption that accompany neural activity (Kwong 1992). For our study, subjects participated in three movement related, block-designed fMRI tasks with interspersed periods of rest accompanying each active task period: 1. *Motor imagery*, where the subject was instructed to imagine moving their fingers in a specified sequence (pinch the thumb and index finger, pinch the thumb and middle finger, and then pinch the thumb and ring finger together) without actually executing the movement. The hand that the subject was cued to image moving was presented at random. 2. *Movement observation*, where the subject was instructed to watch a random presentation of 3 s video clips showing either a person's hand performing the same finger tapping

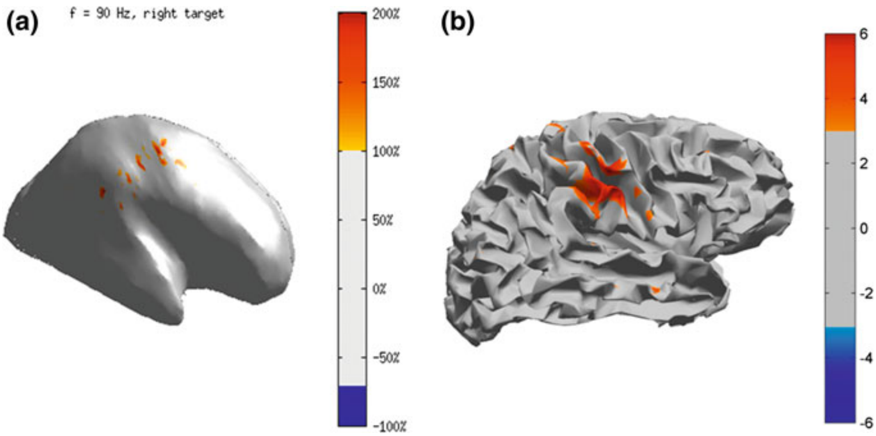

Fig. 2 Comparison of local brain activity mapped from **a**. An EEG-BCI motor imagery feedback session. Map shows 90 Hz power changes relative to rest, where the subject was using left hand imagery to hit a target on the right half of the screen. Activity has been mapped to the smoothed white matter surface. **b**. fMRI BOLD signals projected onto white matter surface obtained from left hand motor imagery sessions

sequence the subject performed in the imagery task (see Fig. 3, top row), or trees blowing in the wind (Fig. 3, bottom row) 3. *Active movement*, where the subject physically executed a self-paced finger tapping sequence (pressing a button with the index finger, middle finger, and then thumb). The motor imagery and active movement tasks were performed in an interval-based fashion, alternating between 3 s movement blocks and rest.

Scanning was conducted at 3T (Philips Achieva) using an 8-channel head-coil. Functional images for each task-based scan were collected using a gradient echo T2* weighted sequence (TE/TR = 21/2) and fMRI data processing was carried out using FEAT (FMRI Expert Analysis Tool) Version 5.98, part of FSL (FMRIB's Software Library, www.fmrib.ox.ac.uk/fsl). The preprocessing pipeline included motion correction, high-pass temporal filtering for removal of liner drift, a spatial filter of 5 mm full-width half maximum (FWHM) and a pre-whitening filter to remove signal autocorrelations throughout the time-course. BOLD

Fig. 3 Video clips presented to the subject during the movement observation fMRI task

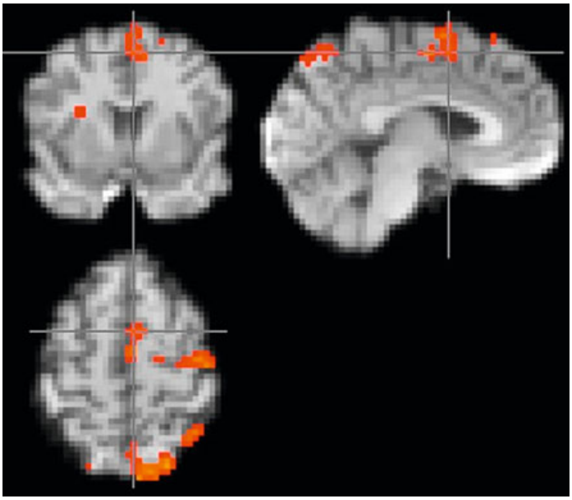

Fig. 4 Example of an fMRI map showing active brain regions in one subject during the left hand motor imagery task. Clusters were masked into ROIs (images are displayed in radiologic convention)

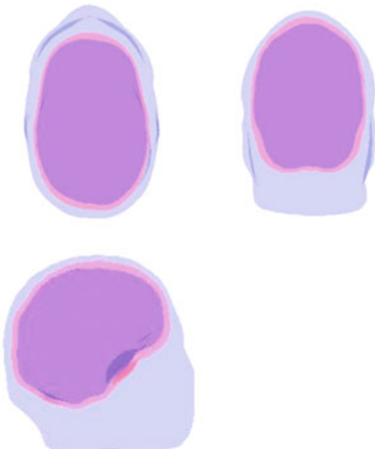

Fig. 5 An example of an individual subject's segmented head model reconstructed from MEMPRAGE and FLASH MRI scans. Segmentation shows the boundaries of the outer skull, inner skull and skin surfaces

responses were estimated on an individual subject basis by applying a box-car, general-linear model design with a standard hemodynamic response convolution. Whole-brain BOLD activity was contrasted between active and rest periods, converted into Z-scores and thresholded at $Z > 2.3$ (uncorrected). Clusters of significant active were masked into ROIs (Fig. 4). For each participant, all functional data sets were co-registered into native MPRAGE space using a rigid-body (6 degrees of freedom) registration and trilinear interpolation.

For source estimation and cortical surface reconstruction, T1-weighted high-resolution MEMPRAGE and FLASH structural images were acquired using a 3.0 T Philips Achieva scanner. A 3D structural image was created for each participant (Fig. 5) by averaging across all acquired echo times within the MEMPRAGE scan and incorporating 2 FLASH sequences (flip angle = 5 and 30 deg) using

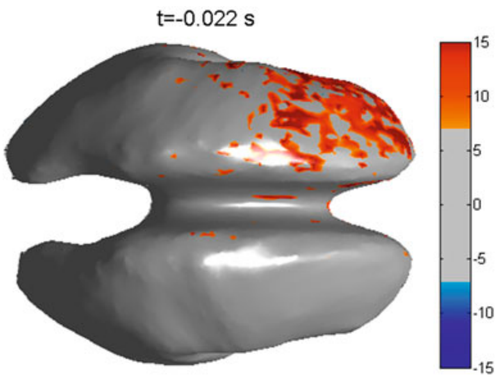

Fig. 6 Example of EMG contamination. The cortex surface has been smoothed for better visibility. Note that there is a widespread activity in the frontal cortex, probably caused by facial muscle contraction

FreeSurfer (http://surfer.nmr.mgh.harvard.edu/ Fischl (2012). "FreeSurfer." NeuroImage.) and MNE software (http://www.martinos.org/martinos/userInfo/data/sofMNE.php).

After constructing an individual's headmodel and localizing ROIs, we then use a LCMV beamformer or MNLS approach (Darvas et al. 2004) to extract source time series from specific ROIs (i.e. the motor areas) in real time using a 32 or 64 channel EEG montage. We propose to use a combination of HG, beta, and inter-hemisphere synchronization frequency changes to drive a BCI from these ROI time series. While the primary input signal will be the HG rhythms, we will use beta power changes and phase-locking in the HG and mu frequencies, which show specific changes during motor execution, to specify discrete on/off states, during which the system will respond to HG power changes.

When mapping by an inverse method, muscle artifacts lead to spatially widespread HG signal that masquerades as cortical activity (Fig. 6). We will utilize this property of EMG artifacts to block the system's response during muscle activity. In our current implementation of the HG feedback BCI, which is externally paced, we record baseline data prior to the control task and, in addition to spatial patterns, we also use excessive HG power changes relative to baseline to detect muscle artifacts.

Preliminary Results

Our preliminary HG-BCI (Fig. 7) test paradigm consists of a simple, externally paced 1D cursor control paradigm. The subject is presented with a fixation cross for 2 s, followed by a target cue, i.e. either left or right. A cursor then moves up for 10 s, during which the subject can use left or right primary motor HG power to move the cursor to the left or right half of the screen. We ran 4 healthy subjects with 20 trials per subject. Overall, subjects achieved a mean success rate of 65 % (60–70 % CFI at alpha < 0.05) on HG power changes alone. In order to test whether these non-random outcomes were achieved by genuine cortical activity or

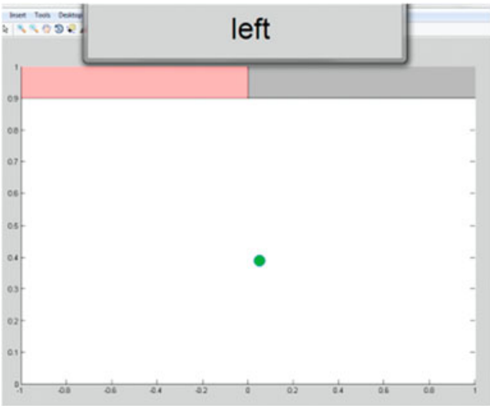

Fig. 7 BCI paradigm

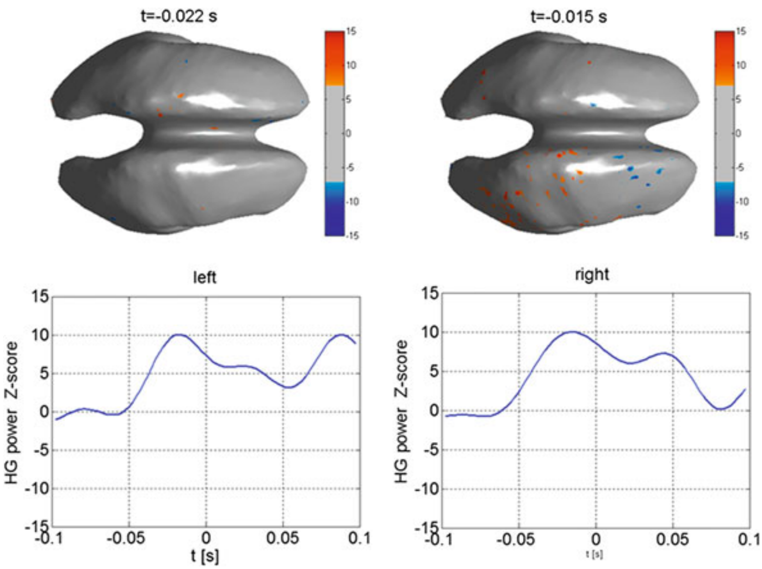

Fig. 8 Mapping of HG power during left or right cursor movements. *Top row* Snapshot of HG power 15–22 ms prior to cursor movement. *Bottom panel* time course of activity from −100 to 100 ms around cursor movement. There is a specific HG increase localized in the motor areas

involuntary muscle artifacts, we segmented each successful trial, i.e. where the correct target was hit, based on movements in the correct direction to form an average map of cortical HG changes during such movements. Results are shown in Fig. 8, revealing the lateralization of HG power with respect to the target (note that subjects were instructed to imagine left hand movement for right targets and vice versa for left targets).

Future Directions

Another goal of these experiments is to identify additional cortical areas in non-motor regions (i.e. prefrontal regions) that are activated during voluntary movement, movement observation, or motor imagery. Real time measures of synchronization/interaction between these areas can be used to enhance specificity of the premotor activity and thus facilitate real time detection.

Several additional future experiments are prompted by the observation that ECoG signals for a given function (e.g. index finger flexion) differ depending on the task's context, such as pinching the thumb and forefinger together versus making a fist. These cortical signals are also evident outside of the motor cortex. Thus, it may be possible to decode movement context using information in primary motor or secondary motor areas, such as supplementary motor area (SMA). By using these same fMRI approaches it may be possible to identify locations where a specific activity pattern can decode motor context or intention among movements such as: (1) simple, self-paced index finger flexion, (2) a pinch task involving repetitive approximation of the tips of the thumb and index finger, (3) fist-formation repeated over the interval, and (4) tactile exploration of objects. After localizing these context specific regions, we can then attempt to use them to support a BCI that will distinguish imagined from real hand movements. Incorporating signals that occur outside of the motor cortex to drive a BCI will have a significant impact on people with impaired or limited brain and motor control, as well as support a BCI with a more flexible range of output.

References

F. Darvas, D. Pantazis et al., Mapping human brain function with MEG and EEG: methods and validation. Neuroimage **23**(Suppl 1), S289–S299 (2004)

F. Darvas, R. Scherer et al., High gamma mapping using EEG. NeuroImage **49**(1), 930–938 (2010)

K. Kwong, J. Belliveau et al., Dynamic magnetic resonance imaging of human brain activity during primary sensory stimulation. Proc. Natl. Acad. Sci. **89**, 5675–5679 (1992)

E.C. Leuthardt, G. Schalk et al., A brain-computer interface using electrocorticographic signals in humans. J. Neural Eng. **1**(2), 63–71 (2004)

K.J. Miller, E.C. Leuthardt et al., Spectral changes in cortical surface potentials during motor movement. J. Neurosci. **27**(9), 2424–2432 (2007)

G. Pfurtscheller, EEG event-related desynchronization (ERD) and event-related synchronization (ERS), in *Electroencephalography: Basic Principles, Clinical Applications and Related Fields*, 4th edn, eds. by E. Niedermeyer, F. H. Lopes da Silva (Williams and Wilkins, Baltimore, 1999), pp. 958–967

G. Pfurtsheller, F.H. Lopes da Silva, Event-related EEG/MEG synchronization and desynchronization: basic principles. Clin. Neurophysiol. **110**, 1842–1857 (1999)

R. Prückl, B.Z. Allison, C. Hintermüller, B. Großwindhager, C. Kapeller, C. Guger, G. Edlinger, Poor performance in SSVEP BCIs: are worse subjects just slower? in *34th Annual International IEEE EMBS Conference of the IEEE Engineering in Medicine and Biology Society* (2012)

J.R. Wolpaw, N. Birbaumer et al., Brain-computer interfaces for communication and control. Clin Neurophys **113**, 767–791 (2002)

J.R. Wolpaw, D. Flotzinger et al., Timing of EEG-based cursor control. J. Clin. Neurophysiol. **16**, 529–538 (1997)

Towards a Speech BCI Using ECoG

Eric C. Leuthardt, John Cunningham and Dennis Barbour

Abstract Electrocorticography (ECoG) has emerged as a new signal platform for brain–computer interface (BCI) systems. Classically, the cortical physiology that has been commonly investigated and utilized for device control in humans has been brain signals from sensorimotor cortex. More recently, speech networks have emerged as a new neurophysiological substrate that could be used to both further improve on or complement existing motor-based control paradigms as well as expand BCI techniques to new clinical populations. We review the emerging literature associated with the scientific, clinical, and technical findings that provide the motivation and capability for speech-based BCIs.

Disclosures: ECL has stock ownership in the company Neurolutions.

Introduction

The use of electrocorticographic (ECoG) signals has recently gained cogent interest as a potential platform for clinical application for impaired patients. This interest is based in part on ECoG's optimal tradeoff of signal fidelity and invasiveness. Compared with scalp-recorded electroencephalographic (EEG) signals, ECoG has much larger signal magnitude, increased spatial resolution (mm vs. cm

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for EEG), and higher frequency bandwidth (0–500 vs. 0–40 Hz for EEG) (Ball et al. 2009; Freeman et al. 2003; Boulton et al. 1990; Slutzky et al. 2010). Of particular note, amplitudes in frequencies higher than 40 Hz carry information that appears to be particularly amenable to BCI operation. These signals, which are difficult to detect with EEG, are thought to be produced by smaller cortical ensembles and show stronger correlation with neuronal action potential firings than lower frequency rhythms (Ray et al. 2008; Heldman et al. 2006). Furthermore, these high-frequency changes have also been associated with numerous aspects of speech and motor function in humans (Crone et al. 2001a, b, 1998b; Leuthardt et al. 2004; Schalk et al. 2007a; Wisneski et al. 2008; Pei et al. 2010). Because ECoG electrodes do not penetrate the brain, they have been shown to have superior long-term stability in different animal models (Bullara et al. 1979; Loeb et al. 1977; Yuen et al. 1987; Margalit et al. 2003; Chao et al. 2010). In addition to its superior long-term stability, a study recently showed that the neural substrate that encodes movements is also stable over many months (Chao et al. 2010). In summary, there is substantial evidence that ECoG may have important advantages for brain-computer interface (BCI) operation.

Up to now, ECoG signals have been used to achieve rapid acquisition of control in one- and two-dimensional cursor tasks in humans using actual and imagined motor movements (Leuthardt et al. 2004; Schalk et al. 2008). It was unknown whether other neurophysiological substrates, such as the speech network, could be used to further improve on or complement existing motor-based control paradigms. Human speech has been extensively studied using different types of neuroimaging (i.e., positron emission spectroscopy (PET) or functional magnetic resonance imaging (fMRI)), neurophysiological functional mapping (i.e., magnetic resonance imaging (MEG) or ECoG), lesional models, or behavioral studies (Crone et al. 2001a; Price et al. 1996; Fiez and Petersen 1998; Towle et al. 2008; Sinai et al. 2005; Pulvermuller et al. 2006; Dronkers et al. 2004). These and other studies have shown that speech processing involves a widely distributed network of cortical areas that are located predominantly in the perisylvian regions (Specht and Reul 2003; Scott and Johnsrude 2003). In particular, these regions include Wernicke's area, which is located in the posterior–superior temporal lobe, and Broca's area, located in the posterior-inferior frontal gyrus (Fiez and Petersen 1998; Towle et al. 2008; Billingsley-Marshall et al. 2007). Other findings have suggested that left premotor cortex also plays a major role in language tasks, in particular for the planning of articulation and speech production (Duffau et al. 2003; Heim et al. 2002). Given the broadly distributed network associated with speech and the intuitive nature by which people regularly imagine speech, the separable physiology and the different cognitive tasks of using linguistic intent may provide the basis for BCI control that can be used independently or as an adjunct to motor-derived control. Some recent studies have begun to explore the value of these language networks for the purpose of neuroprosthetic applications. Early on, Wilson et al. demonstrated that auditory cortex can be used for real-time control of a cursor (Wilson et al. 2006). More recent studies have shown initial evidence that some phonemes and words are separable during actual speech with

ECoG (Blakely et al. 2008; Kellis et al. 2010; Schalk et al. 2007b), but concrete evidence that BCI control can be achieved using the speech network has only recently been demonstrated (Leuthardt et al. 2011).

In this chapter, we will examine the relevant scientific and clinical findings to support the motivation of a linguistic BCI, the methods of ECoG–BCI, the current demonstration of feasibility, and future directions for translating the current state of the art towards a clinical application.

Motivation for Speech BCI

The most human of all abilities is the capacity to verbally communicate rich and varied ideas to other members of our species. Neurological disorders that rob individuals of this capacity are consequently some of the most dehumanizing. A subset of these disorders spares the speech and language brain centers while eliminating the capacity to engage the vocal apparatus itself (Karnell et al. 1999; Roy et al. 2005; Altman et al. 2007). A diverse number of diagnoses fit into this category, ranging from locked-in stroke patients, ventilator-dependent high spinal cord injury, post-laryngectomy for head and neck cancers, and a number of voice disorders affecting motoric control within the larynx. Altogether, an estimated 7.5 million Americans have trouble using their voice (http://www.nidcd.nih.gov/health/statistics/vsl/Pages/stats.aspx).

Much as individuals with spinal cord injuries could benefit from a treatment that reliably extracts intended movements from the brain and turns them into actions (Leuthardt et al. 2006), patients with aberrant vocalization capability could also benefit from a treatment capable of turning their thought patterns into spoken or written words. A brain–computer interface (BCI) represents a combination of hardware and software that together can extract intentions from the subject's cortical physiology to enhance the user's control and communication capability (Wolpaw et al. 2000). To date, extensive BCI work has aimed to infer motor intentions using both invasive and noninvasive cortical signals (Leuthardt et al. 2004; Schalk et al. 2008; Taylor et al. 2002; Hochberg et al. 2006; Wolpaw and McFarland 2004). Work performed on a speech BCI, however, has thus far been more limited. While numerous techniques have been developed to transpose motor-derived intentions/signals onto various types of spellers, only a few studies have attempted any form of direct linguistic decoding. The earliest example is work in which a neurotrophic electrode was placed in motor cortex and used to decode various phonemes in a single locked-in subject (Kennedy and Bakay 1998). When used for real-time vowel articulation, moderate information transfer rates were achieved (0.57 and 6.97 bits/min) (Guenther et al. 2009). More recent studies using electrocorticography (ECoG) have proven promising (Kellis et al. 2010). Substantial decoding capability has been demonstrated in perisylvian cortex associated with the perception and articulation of speech (Leuthardt et al. 2011; Pei et al. 2011; Mesgarani and Chang 2012; Pasley et al. 2012). In the expression of both overt and covert speech, left posterior inferior frontal lobe (putatively Broca's region) appears to yield the substantial phonetic information (Pei et al. 2011). Phoneme-related ECoG signals were also recently shown to enable rapid and effective choice selection in four human subjects (Leuthardt et al. 2011).

Taken together, a critical need exists to devise alternate methods for patients with vocalization impairments to communicate their wishes. If motor BCIs are analogous to a computer mouse, then a linguistic BCI is analogous to a keyboard, allowing the juxtaposition of many discrete commands (keys/letters) to convey complex ideas (e.g., sentences using a particular vocabulary). Just as communicating ideas with a mouse alone would be cumbersome and inefficient, so too would using a continuous-style BCI to communicate the wishes of a patient unable to speak. Recent research is emerging that the possibility for such a communication technology is now possible.

General ECoG–BCI Methods

A BCI is a device that can decode human intent from brain activity *alone* in order to create an alternate communication channel for people. More explicitly, a BCI does not require the "brain's normal output pathways of peripheral nerves and muscles" to facilitate interaction with one's environment. (Wolpaw et al. 2000, 2002) Thus, a true BCI creates a completely new output pathway for the brain. As a new output pathway, the user must have feedback to improve the performance of how they alter their electrophysiological signals. The brain must change its signals to improve performance, but additionally the BCI may also be able to adapt to the changing milieu of the user's brain to further optimize functioning. This dual adaptation requires a certain level of training and learning curve, both for the user and the computer. The better the computer and subject are able to adapt, the shorter the training that is required for control.

There are four essential elements to the practical functioning of a brain computer interface platform.

1. Signal acquisition, the BCI system's recorded brain signal or information input.
2. Signal processing, the conversion of raw information into a useful device command.
3. Device output, the overt command or control functions that are administered by the BCI system.
4. Operating protocol, the manner in which the system is altered and turned on and off (Wolpaw et al. 2002).

All of these elements play in concert to manifest the user's intention to his or her environment.

Signal acquisition is some real-time measurement of the electrophysiological state of the brain. This measurement of brain activity is usually recorded via electrodes. In the case of ECoG, the electrodes are beneath the skull and either above or below the dura. (Leuthardt et al. 2004, 2006b; Schalk et al. 2004). Once acquired, the signals are then digitized and sent to the BCI system for further interrogation.

In the signal processing portion of BCI operation, there are two essential functions: feature extraction and signal translation. The first function extracts significant identifiable information from the gross signal, the second converts that identifiable information into device commands. The process of converting raw signal into one that is meaningful requires a complex array of analyses. These techniques can vary from assessment of frequency power spectra, event related potentials, and cross-correlation coefficients for analysis of ECoG signals (Moran and Schwartz 1999; Levine et al. 2000; Pfurtscheller et al. 2003) The impetus for these methods is to determine the relationship between an electrophysiologic event and a given cognitive or motor task. As an example, after recordings are made from an ECoG signal, the BCI system must recognize that a signal alteration has occurred in the electrical rhythm (feature extraction) and then associates that change with a specific cursor movement (translation). As mentioned above, it is important that the signal processing be able to adjust to the changing internal signal environment of the user. In regards to the actual device output, this is the overt action that the BCI accomplishes. As in the previous motor-based BCI examples, this can result in moving a cursor on a screen, controlling a robotic arm, and driving a wheelchair (Leuthardt et al. 2006a). In the case of a linguistic BCI, this would control would be manifested as the articulation of speech in the form of an auditory or visual output. This output could be the discrete conjunction of linguistic components (i.e. letters or phonemes) (Leuthardt et al. 2011) or be the continuous representation of formants (Mesgarani and Chang 2012).

An important consideration for practical application is the overall operating protocol. This refers to the manner in which the user controls *how* the system functions. The "how" includes such things as turning the system on or off, controlling what kind of feedback and how fast it is provided, how quickly the system implements commands, and switching between various device outputs. These elements are critical for BCI functioning in the real world application of these devices. In most current research protocols, these parameters are set by the investigator. In other words, the researcher turns the system on and off, adjusts the speed of interaction, or defines very limited goals and tasks. These are all things that the user will eventually need to be able to do by himself in an unstructured applied environment.

Linguistic ECoG–BCI

Study Overview

Leuthardt et al. demonstrated for the first time that ECoG signals associated with different overt and imagined phoneme articulation can enable invasively monitored human patients to control a one-dimensional computer cursor rapidly and accurately (Leuthardt et al. 2011). This study included four patients (ages 36–48) with intractable epilepsy undergoing temporary placement of a subdural electrode array for clinical monitoring to identify and resect their epileptic foci. In addition to standard clinical arrays (64 electrodes (8 × 8) spaced 10 mm apart, with a 2.3 mm diameter), Subject 2 had an experimental microarray placed consisting of 16 microwires, 75 microns in diameter, that were spaced 1 mm apart (Fig. 1). Electrocortical signals were acquired using g.tec biosignal amplifiers (Graz, Austria) with sampling rate of 1200 Hz, and bandpass filter between 0.1 and 550 Hz.

Patients underwent initial screening to identify control features for use in subsequent closed-loop control experiments. This screening procedure began with an experiment in which ECoG signals were recorded while the subject either overtly (patient 1, 2, and 3) or covertly (patient 3 and 4) expressed a series of four phonemes (‘oo’, ‘ah’, ‘eh’, and ‘ee’) or rested. Cues for the rest and phoneme tasks

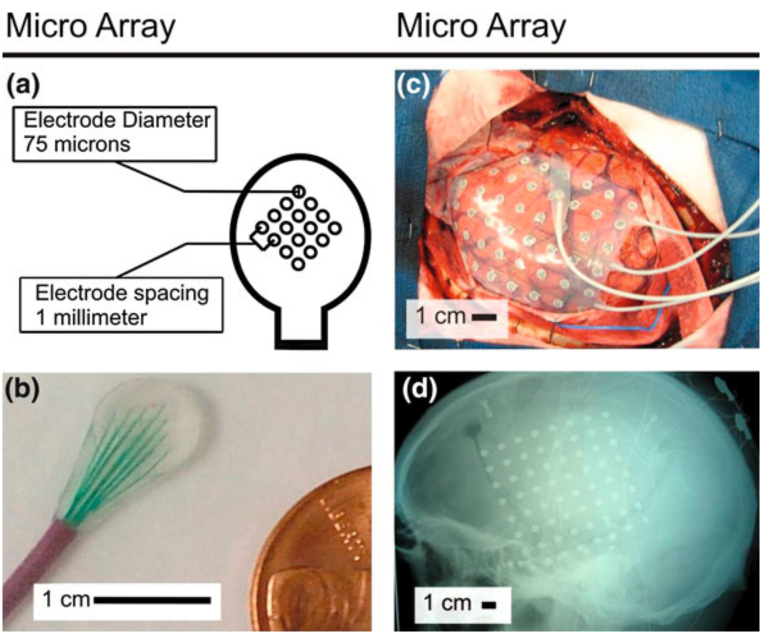

Fig. 1 Clinical and research electrode arrays. Reprinted with permission from Leuthardt et al. (2011)

were presented as words on a video screen. During intervals between cued activity, patients were instructed to remain inactive. The data was converted to the frequency domain by autoregressive spectral estimation in 2 Hz bins ranging from 0 to 550 Hz. For each electrode and frequency bin, candidate features were identified by calculating the coefficient of determination (r^2) between the "rest" spectral power levels and the activity spectral power levels for each phoneme, and also between spectral power levels for all possible phoneme combinations. Those ECoG features (particular electrodes and frequency bins) with the highest r^2 values were chosen as control features for subsequent closed-loop control experiments. Electrode selection was further constrained to anatomic areas associated with speech processing (i.e., motor cortex, Wernicke's, and Broca's area).

Using the ECoG features and their associated tasks that were derived using the screening procedure above, the patients participated in closed-loop control experiments during which the patients' objective was to perform the particular phoneme articulation task so as to move a cursor on a screen along one dimension to hit a presented targeted on either side of the screen. Two scenarios were tested, (1) phoneme versus phoneme (patients 1 & 2); and (2) phoneme versus rest (patients 3 & 4). Cursor velocity was derived from the ECoG features in real-time by the BCI2000 software package. Accuracy, calculated as number of successes divided by the total number of trials, was assessed after each block. Performance curves were assessed over the entire duration of the closed-loop experiments (multiple blocks) after training with a particular task and associated set of control features. Patients performed between 61 and 139 trials for control.

Each subject demonstrated notable widespread cortical activations associated with overt and imagined phoneme articulation. Additionally, in each subject, particular locations and ECoG frequencies separated phonemes from rest, and also phonemes from each other (Fig. 2). These locations were in Wernicke's area, Auditory Cortex, Premotor Cortex, and Sensorimotor Cortex. For each of the patients, one or more sites were used to either distinguish the phoneme articulation versus rest (subject 3 & 4), or one phoneme versus another phoneme (subject 1 & 2). Consistent with findings by Gaona et al., which demonstrated significant nonuniform behavior of gamma activity during speech tasks, we observed that a cortical activation for different phonemes could occur at different gamma frequencies, even within the same location (Gaona et al. 2011). These frequencies varied substantially and occurred as high as 550 Hz. Also of note in the patient who was screened for both real and imagined phonemes, the ECoG differences, with regards to their topographical and frequency distribution, were often distinct between real and imagined phoneme articulation. These differences are shown for Subject 3 in color-coded time–frequency plots with the correlate anatomic location (Fig. 3). Our findings demonstrate that there are widespread variations in topographic activations between different phoneme articulations that provide signals that could be used for device control. Such differences between phonemes were also present on the microscale. The time course of the subject's performance during online control is shown in Fig. 4. Final target accuracies for all patients were between 68 and 91 %. Closed-loop control experiment durations ranged from 4 to 15 min. Subject 2 had a

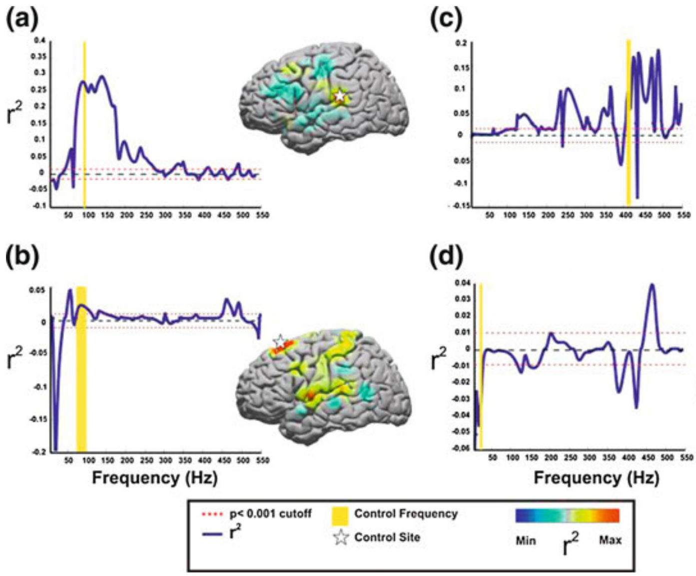

Fig. 2 The optimal comparisons of various phoneme articulations against each other or against rest are shown for each subject. In the r^2 versus frequency line plots, the *dotted red* line represents a p value cutoff of $p < 0.001$ for the r^2 values displayed. The data from these line plots are anatomically derived from the site identified by the *star*. These sites were also chosen as subsequent control features. The *yellow* bar represents the frequency that was chosen for control. The color distribution on the adjacent standardized brains represents the topographic distribution of the maxima and minima of r^2 values acquired for the conditional comparisons of the selected frequency band. **a** Patient 1: 00 vs EE **b** Patient 2: 00 vs AH **c** Patient 3: EH vs Rest **d** Patient 4: EE vs Rest. Reprinted with permission from Leuthardt et al. (2011)

microgrid that was placed over dorsal premotor cortex. Feature plot demonstrated anatomically and spectrally diverse changes that occurred at very high frequencies that enabled effective control of a cursor.

This study reports the first demonstration that ECoG signals associated with different actual and imagined phoneme articulations can be used for rapid and effective BCI control. This novel demonstration of ECoG–BCI is also the first evidence that microscale ECoG recordings can be utilized for device control in humans. It is also notable that, distinct from the motor physiology experience, cortical signals between real and imagined speech articulation are different. This is an important consideration for optimally screening signals that will be subsequently used for BCI control when the speech network is to be used. Taken together, these findings further expand the range of ECoG signals and cognitive operations that could be used for neuroprosthetic operation, demonstrate important methodological considerations for use of a speech BCI, and also demonstrate that the implanted array hardware may be quite small and minimally invasive.

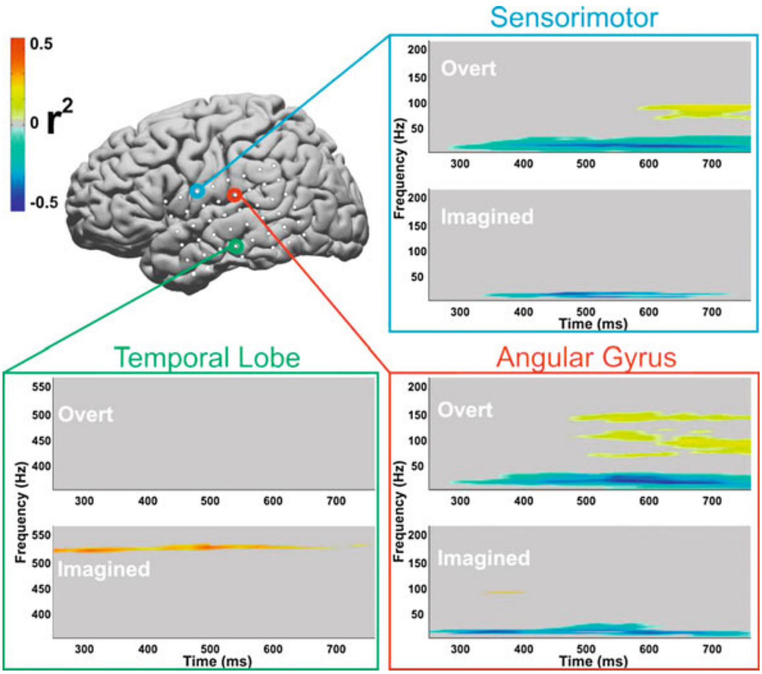

Fig. 3 Time frequency plots from three exemplar electrodes that demonstrate substantial differences in power modulation depending on whether overt or imagined speech screening was performed. Time zero indicates the time when the visual cue for a phoneme was presented. Significant power modulation was thresholded to a p value < 0.05. Only power modulations surpassing that threshold are shown. Reprinted with permission from Leuthardt et al. (2011)

Future Directions

Implant Localization

Preoperative planning takes on new importance as neuroprosthetic research translates from scientific enquiry to clinical applications. The necessary first step towards the creation of a speech-relevant neuroprosthetic is knowing where to surgically implant it. Given the variability in location of speech cortex in neurologically intact human subjects (Sanai et al. 2008; Ojemann et al. 1989), correctly identifying the anatomic location for a small cortical implant is critically important. There will need to be special considerations for expressively impaired subjects that will be distinct from current patient populations that require brain mapping. Centrally, these will be patients that have the cognitive capability to speak, but are unable to physically do so due to motor or articulatory impairment.

Currently, preoperative mapping is principally performed in patients with lesions (e.g. seizure focus or tumor) that are adjacent to eloquent cortex. Typically, these patients are intact and able to participate in a cognitive task that corresponds

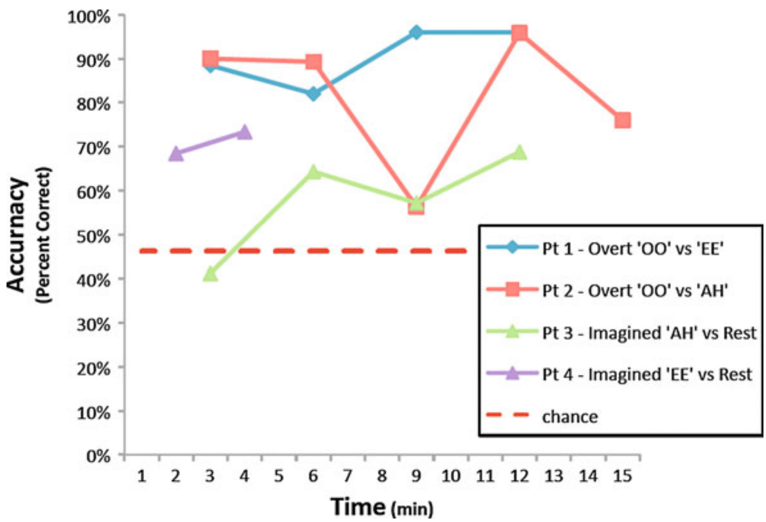

Fig. 4 Learning curves for BCI control tasks. *Dotted* line represents chance. Reprinted with permission from Leuthardt et al. (2011)

to the site of interest. The most common technique for identifying functional anatomic sites is the use of task-based functional MRI. In a typical application, the subject alternates between a passive resting state and performing a task. During these periods, the BOLD signal is measured in the MR scanner and the two images are subtracted from each other to reveal areas of the brain that were activated during the prescribed task (Bandettini et al. 1992; Kwong et al. 1992; Ogawa et al. 1992). While this task-based approach has been explored for preoperative mapping in the context of BCI applications in the past (Hermes et al. 2011a, b), this may not be an optimal approach in that there is limited validation that the patient is "imagining" the appropriate task and that this will be similar to the actual cognitive task performed when trying to use a prosthetic. Rather, a more uniform approach is needed that does not depend on the impaired patients' participation for localization, yet is still able to identify their unique functional topography.

The localization of eloquent regions with resting-state cortical physiology as measured by spontaneous BOLD fluctuations (extra-operatively) will likely overcome these participation related problems. Spontaneous BOLD fluctuations are low frequency (<0.1 Hz) oscillations in neuronal activity that are anatomically correlated within distinct functional networks (Fox and Raichle 2007). First reported by Biswal et al., there is strong coherence which is reproducibly present between the left and right somatomotor cortices (Biswal et al. 1995; Fox et al. 2006), between language areas (Cordes et al. 2000; Hampson et al. 2002), and between numerous other functional regions in the absence of task performance. Using spontaneous activity, one can generate resting-state correlation maps that are similar to the functional maps obtained from task activations (Smith et al.

2009). Additionally, it appears that these resting state networks are stable throughout transitions in sleep wake cycles and transitions in consciousness from anesthesia (Breshears et al. 2010; He et al. 2008; Vincent et al. 2007), making them potentially more useful in that not only are these networks task independent, but also independent of the level of consciousness. Thus far, the use of resting state networks for pre-surgical planning is a very recent development with limited publications (Kokkonen et al. 2009; Liu et al. 2009). Moreover, the comparisons performed thus far between resting state fMRI and brain mapping have been in regards to cortical stimulation and not the endogenous activity when the subject is performing a cognitive operation.

To date, two perisylvian regions have been shown to demonstrate significant linguistic information in the surface cortical electrophysiology. ECoG recordings from posterior superior temporal gyrus (pSTG) have been used to decode complex auditory speech perceptions (Mesgarani and Chang 2012), and posterior inferior frontal regions have been optimal in decoding overt and covert speech vowels and consonant expressions (Pei et al. 2011). Given the large degree of variability in speech localization, it will be important to identify these high information bearing regions prior to their surgical exposure when considering device implantation. Taken together, there is a strong emerging need to integrate these physiologic findings to the state invariant cortical architecture. These findings will provide the foundation for an important tool in neuroprosthetics, namely identifying optimal loci for neuroprosthetic implantation in a clinically efficient manner.

Advanced Recording and Signal Analysis Techniques

Electrocorticography was developed within neurosurgery as a tool to probe cortical physiology to better define seizure foci and map eloquent cortex (Goldring et al. 1994; Goldring and Gregorie 1984). The development of implanted electrode arrays to monitor seizure behavior in epilepsy patients revealed for the first time high-resolution brain activity in humans performing cognitive tasks (Lesser et al. 1987). Naturally, these arrays were optimized for clinical considerations to localize seizure foci. Only relatively recently was it appreciated that, though significantly weaker, high frequencies could be recorded from ECoG electrodes reliably enough to control a BCI (Crone et al. 1998b; Leuthardt et al. 2004). High-frequency potentials are known to reflect more local brain activity (Crone et al. 1998b; Manning et al. 2009; Miller et al. 2009) than the more traditional lower frequencies (Crone et al. 1998a), raising the possibility that compact ECoG arrays ("microscale arrays" or "microgrids") could record independent signals on each channel and enable multichannel BCI control on a smaller scale. This combination of a compact, nonpenetrating, multichannel BCI represents a compelling combination of characteristics for a communication prosthetic. Compact penetrating arrays have indeed been successful at extracting linguistic intent from motor cortex (Brumberg et al. 2011), and although Broca's region has been postulated to be an excellent candidate area for a linguistic BCI (Brumberg et al. 2010), this possibility has only been minimally explored (Leuthardt et al. 2011). Before an ECoG Broca's prosthetic can be exploited, several basic questions must be addressed. (1) Are linguistic ECoG signals concentrated spatially? (2) Can linguistic ECoG signals be reliably extracted with small electrode contacts? (3) What is the resolution of linguistic ECoG signals that can be independently controlled by subjects? The resolution of linguistic signals within a speech center, such as Broca's or Wernicke's, is an unsettled question. Theoretical studies of surface electrodes sampling current sources from the brain surface imply that electrodes spaced as closely as 600 microns may extract nearly independent signals (Slutzky et al. 2010). Experiments seeking to address this question in macaque monkey primary motor cortex during closed-loop control tasks yield estimates of independent signal spacings of 2–4 mm (Rouse et al. 2010; Wheeler et al. 2011; Wodlinger et al. 2011). Independent signals in human Broca's region likely lie within this range. The functional heterogeneity with this area implies that the optimal electrode array spacing for extracting the most independent channels could be variable and/or different from other brain areas (Sahin et al. 2009). Thus, regarding hardware optimization for electrode interfaces for a speech BCI, there still is a large need for empiric evaluation.

In addition to hardware optimization, there is also a need to developed advanced analytic tools that are optimized both for ECoG-based platforms and speech-related physiology. To address the first point, as ECoG–BCI platforms become more widely studied and applied for clinical translation, new techniques of signal analysis and feature extraction that are specifically tailored to ECoG will be critical. The majority of feature extraction algorithms for ECoG–BCI have borrowed heavily from techniques originally developed from electroencephalography (EEG) (Wolpaw et al. 2000; Schalk and Leuthardt 2011). Currently the most widely published paradigm has been the use of amplitude modulation of sensory motor rhythms of somatomotor cortex or motor-associated cortex site (Leuthardt et al. 2004; Wilson et al. 2006; Leuthardt et al. 2006b; Felton et al. 2007). A key distinction between EEG and ECoG, however, has been ECoG's more robust access to higher frequency gamma rhythms. Because these changes in gamma power have a more local cortical topography (Miller et al. 2007) and are more correlated with single neuron action potential firing (Manning et al. 2009), they have enabled rapid learning of simple BCI tasks (Leuthardt et al. 2004). Moreover, ongoing research has demonstrated gamma rhythms to be more spatiotemporally complex than initially inferred from the original EEG-influenced descriptions. Early reports distinguished between a lower gamma band (35–45 Hz) and a higher gamma band (80–100 Hz) in ECoG signals (Crone et al. 2001b). Gamma activity has also been posited to be the net result of asynchronous neuronal firing, which results in a more uniform broadband noise-like phenomenon that declines in amplitude as frequency rises. More recent findings provide new evidence for functionally separable frequency bands. Gaona et al. showed that, during a word repetition task, gamma sub-bands distinguished stages of the task (for a given location) and differentiated cortical locations (for a given stage of task) (Gaona et al. 2011). Additionally, these different gamma sub-bands, both on the macroscale and microscale, have been used for device control in humans (Leuthardt et al. 2011). Beyond these specific examples, numerous signal analysis techniques have been used to investigate information content in ECoG signals, across various motor, speech, perceptual, and attentional related cognitive tasks (Schalk et al. 2007a; Chao et al. 2010; Mesgarani and Chang 2012; Pei et al. 2011; Gunduz et al. 2011; Wang et al. 2011). Thus, while much foundational work has explored both the broadband and narrowband phenomenology, further algorithmic advances are required to fully utilize the complexity of these signal features for more advanced BCI operation.

Regarding the second point, advanced analytic techniques that capitalize on the unique physiology and technical aims of a speech BCI still need to be refined. Here, we draw principally from penetrating electrode BCI work, including early developments in speech categorization (Kennedy and Bakay 1998; Guenther et al. 2009; Brumberg et al. 2011) and other work in motor communication prostheses (Santhanam et al. 2006; Shenoy et al. 2006; Cunningham et al. 2008). Most BCI/BMI literature focuses on decoding moment-by-moment parameters from the recorded signal. In the context of communication such as a speech BCI, decoding the *discrete goal* of the brain activity is critical, *not* the moment-by-moment parameters. The same recognition has been made in motor prostheses: if used as a communication device (such as typing on a keyboard), the discrete choice of which key to type is the goal, not the intended path to reach to that key. This distinction has been successful in motor cortex with penetrating electrodes to accomplish a high bit-rate BCI in primates (Santhanam et al. 2006; Shenoy et al. 2006; Cunningham et al. 2008). More closely, work has been done with penetrating electrodes in speech categorization. Most notably, the recent work of Brumberg demonstrates proof of concept and a number of relevant classification algorithms (Brumberg et al. 2011). Thus, between the needed developments in ECoG signal recording and analysis, and the needed algorithmic advances for decoding, a specific need exists to develop decoding and control algorithms that are both ECoG and speech specific.

Conclusion

The ability to vocalize speech is central to a human being's ability to engage and interact in a modern society. Recent advances in brain imaging and cortical recordings from both humans and monkeys make the possibility of converting speech intentions from the human brain a plausible future consideration for patients with vocalization impairment. Creating a speech neuroprosthetic that is reliable and will convey a functional level of linguistic content will require further research in the cortical physiology underpinning human speech and the imaging methodology, hardware, and software to implement these insights into real world clinical application.

References

K.W. Altman, S.D. Schaefer, G.P. Yu, S. Hertegard, D.S. Lundy, J.H. Blumin, N.C. Maronian, Y.D. Heman-Ackah, J. Abitbol, R.R. Casiano, The voice and laryngeal dysfunction in stroke: a report from the Neurolaryngology Subcommittee of the American Academy of Otolaryngology-Head and Neck Surgery. Otolaryngol. Head Neck Surg. **136**(6), 873–881 (2007)

T. Ball, M. Kern, I. Mutschler, A. Aertsen, A. Schulze-Bonhage, Signal quality of simultaneously recorded invasive and non-invasive EEG. Neuroimage **46**(3), 708–716 (2009)

P.A. Bandettini, E.C. Wong, R.S. Hinks, R.S. Tikofsky, J.S. Hyde, Time course EPI of human brain function during task activation. Magn. Reson. Med. **25**(2), 390–397 (1992)

R.L. Billingsley-Marshall, T. Clear, W.E. Mencl, P.G. Simos, P.R. Swank, D. Men, S. Sarkari, E.M. Castillo, A.C. Papanicolaou, A comparison of functional MRI and magnetoencephalography for receptive language mapping. J. Neurosci. Methods **161**(2), 306–313 (2007)

J.R. Binder, K.A. McKiernan, M.E. Parsons, C.F. Westbury, E.T. Possing, J.N. Kaufman, L. Buchanan, Neural correlates of lexical access during visual word recognition. J. Cogn. Neurosci. **15**(3), 372–393 (2003)

F. Biswal, V. Yetkin, J. Haughton, Hyde, Functional connectivity in the motor cortex of resting human brain using echo-planar MRI. Magn. Reson. Med. **34**, 537–541 (1995)

T. Blakely, K.J. Miller, R.P.N. Rao, M.D. Holmes, J.G. Ojemann, Localization and classification of phonemes using high spatial resolution electrocorticography (ECoG) grids. Paper presented at the 30th Annual International IEEE EMBS Conference, Vancouver, British Columbia, 20–25 Aug 2008

A.A. Boulton, G.B. Baker, C.H. Vanderwolf, *Neurophysiological techniques, II: applications to neural systems* (Humana Press, Clifton, 1990)

L.A. Bullara, W.F. Agnew, T.G. Yuen, S. Jacques, R.H. Pudenz, Evaluation of electrode array material for neural prostheses. Neurosurgery **5**(6), 681–686 (1979)

J.D. Breshears, J.L. Roland, M. Sharma, C.M. Gaona, Z.V. Freudenburg, R. Tempelhoff, M.S. Avidan, E.C. Leuthardt, Stable and dynamic cortical electrophysiology of induction and emergence with propofol anesthesia. Proc. Natl. Acad. Sci. U.S.A. **107**(49), 21170–21175 (2010)

J.S. Brumberg, A. Nieto-Castanon, P.R. Kennedy, F.H. Guenther, Brain–Computer Interfaces for Speech Communication. Speech commun. **52**(4), 367–379 (2010)

J.S. Brumberg, E.J. Wright, D.S. Andreasen, F.H. Guenther, P.R. Kennedy, Classification of intended phoneme production from chronic intracortical microelectrode recordings in speech-motor cortex. Frontiers in Neuroscience **5**, 65 (2011)

Z.C. Chao, Y. Nagasaka, N. Fujii, Long-term asynchronous decoding of arm motion using electrocorticographic signals in monkeys. Front Neuroengineering **3**, 3 (2010)

V.M. Cordes, K. Haughton, G.J. Arfanakis, P.A. Wendt, C.H. Turski, M.A. Moritz, M.E. Quigley, Meyerand, Mapping functionally related regions of brain with functional connectivity MR imaging. Am. J. Neuroradiol. **21**, 1636–1644 (2000)

N.E. Crone, D.L. Miglioretti, B. Gordon, J.M. Sieracki, M.T. Wilson, S. Uematsu, R.P. Lesser, Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. I. Alpha and beta event-related desynchronization. Brain **121**(Pt 12), 2271–2299 (1998a)

N.E. Crone, D.L. Miglioretti, B. Gordon, R.P. Lesser, Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. II. Event-related synchronization in the gamma band. Brain: a journal of neurology **121**(Pt 12), 2301–2315 (1998b)

N.E. Crone, D. Boatman, B. Gordon, L. Hao, Induced electrocorticographic gamma activity during auditory perception. Brazier Award-winning article. Clin. Neurophysiol. **112**(4), 565–582 (2001a)

N.E. Crone, L. Hao, J. Hart Jr, D. Boatman, R.P. Lesser, R. Irizarry, B. Gordon, Electrocorticographic gamma activity during word production in spoken and sign language. Neurology **57**(11), 2045–2053 (2001b)

J.P. Cunningham, B.M. Yu, V. Gilja, S.I. Ryu, K.V. Shenoy, Toward optimal target placement for neural prosthetic devices. J. Neurophysiol. **100**(6), 3445–3457 (2008)

N.F. Dronkers, D.P. Wilkins, R.D. Van Valin Jr, B.B. Redfern, J.J. Jaeger, Lesion analysis of the brain areas involved in language comprehension. Cognition **92**(1–2), 145–177 (2004)

H. Duffau, L. Capelle, D. Denvil, P. Gatignol, N. Sichez, M. Lopes, J.P. Sichez, R. Van Effenterre, The role of dominant premotor cortex in language: a study using intraoperative functional mapping in awake patients. Neuroimage **20**(4), 1903–1914 (2003)

E.A. Felton, J.A. Wilson, J.C. Williams, P.C. Garell, Electrocorticographically controlled brain-computer interfaces using motor and sensory imagery in patients with temporary subdural electrode implants. Report of four cases. J. Neurosurg. **106**(3), 495–500 (2007)

J.A. Fiez, S.E. Petersen, Neuroimaging studies of word reading. Proc. Natl. Acad. Sci. U.S.A. **95**(3), 914–921 (1998)

M.D. Fox, M.E. Raichle, Spontaneous fluctuations in brain activity observed with functional magnetic resonance imaging. Nat. Rev. Neurosci. **8**(9), 700–711 (2007)

M.D. Fox, A.Z. Snyder, J.M. Zacks, M.E. Raichle, Coherent spontaneous activity accounts for trial-to-trial variability in human evoked brain responses. Nat. Neurosci. **9**(1), 23–25 (2006)

W.J. Freeman, M.D. Holmes, B.C. Burke, S. Vanhatalo, Spatial spectra of scalp EEG and EMG from awake humans. Clin. Neurophysiol. **114**(6), 1053–1068 (2003)

C.M. Gaona, M. Sharma, Z.V. Freudenburg, J.D. Breshears, D.T. Bundy, J. Roland, D.L. Barbour, G. Schalk, E.C. Leuthardt, Nonuniform High-Gamma (60–500 Hz) Power Changes Dissociate Cognitive Task and Anatomy in Human Cortex. J. Neurosci. **31**(6), 2091–2100 (2011)

S. Goldring, E.M. Gregorie, Surgical management of epilepsy using epidural recordings to localize the seizure focus. Review of 100 cases. J. Neurosurg. **60**(3), 457–466 (1984)

S. Goldring, G.W. Harding, E.M. Gregorie, Distinctive electrophysiological characteristics of functionally discrete brain areas: a tenable approach to functional localization. J. Neurosurg. **80**(4), 701–709 (1994)

F.H. Guenther, J.S. Brumberg, E.J. Wright, A. Nieto-Castanon, J.A. Tourville, M. Panko, R. Law, S.A. Siebert, J.L. Bartels, D.S. Andreasen, P. Ehirim, H. Mao, P.R. Kennedy, A wireless brain-machine interface for real-time speech synthesis. PloS One **4**(12), e8218 (2009)

A. Gunduz, P. Brunner, A. Daitch, E.C. Leuthardt, A.L. Ritaccio, B. Pesaran, G. Schalk, Decoding covert spatial attention using electrocorticographic (ECoG) signals in humans. Neuroimage **60**(4), 2285–2293 (2011)

M. Hampson, B.S. Peterson, P. Skudlarski, J.C. Gatenby, J.C. Gore, Detection of functional connectivity using temporal correlations in MR images. Hum. Brain Mapp. **15**, 247–262 (2002)

B.J. He, A.Z. Snyder, J.M. Zempel, M.D. Smyth, M.E. Raichle, Electrophysiological correlates of the brain's intrinsic large-scale functional architecture. Proc. Natl. Acad. Sci. U.S.A. **105**(41), 16039–16044 (2008)

S. Heim, B. Opitz, A.D. Friederici, Broca's area in the human brain is involved in the selection of grammatical gender for language production: evidence from event-related functional magnetic resonance imaging. Neurosci. Lett. **328**(2), 101–104 (2002)

D.A. Heldman, W. Wang, S.S. Chan, D.W. Moran, Local field potential spectral tuning in motor cortex during reaching. IEEE Trans. Neural Syst. Rehabil. Eng. **14**(2), 180–183 (2006)

D. Hermes, K.J. Miller, M.J. Vansteensel, E.J. Aarnoutse, F.S. Leijten, N.F. Ramsey, Neurophysiologic correlates of fMRI in human motor cortex. Hum. Brain Mapp. **33**, 1689–1699 (2011a)

D. Hermes, M.J. Vansteensel, A.M. Albers, M.G. Bleichner, M.R. Benedictus, C. Mendez Orellana, E.J. Aarnoutse, N.F. Ramsey, Functional MRI-based identification of brain areas involved in motor imagery for implantable brain–computer interfaces. J. Neural Eng. **8**(2), 025007 (2011b)

L.R. Hochberg, M.D. Serruya, G.M. Friehs, J.A. Mukand, M. Saleh, A.H. Caplan, A. Branner, D. Chen, R.D. Penn, J.P. Donoghue, Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature **442**(7099), 164–171 (2006)

L.H. Karnell, G.F. Funk, J.B. Tomblin, H.T. Hoffman, Quality of life measurements of speech in the head and neck cancer patient population. Head Neck **21**(3), 229–238 (1999)

S. Kellis, K. Miller, K. Thomson, R. Brown, P. House, B. Greger, Decoding spoken words using local field potentials recorded from the cortical surface. J. Neural Eng. **7**(5), 056007 (2010)

P.R. Kennedy, R.A. Bakay, Restoration of neural output from a paralyzed patient by a direct brain connection. Neuroreport **9**(8), 1707–1711 (1998)

S.M. Kokkonen, J. Nikkinen, J. Remes, J. Kantola, T. Starck, M. Haapea, J. Tuominen, O. Tervonen, V. Kiviniemi, Preoperative localization of the sensorimotor area using independent component analysis of resting-state fMRI. Magn. Reson. Imaging **27**(6), 733–740 (2009)

K.K. Kwong, J.W. Belliveau, D.A. Chesler, I.E. Goldberg, R.M. Weisskoff, B.P. Poncelet, D.N. Kennedy, B.E. Hoppel, M.S. Cohen, R. Turner et al., Dynamic magnetic resonance imaging of human brain activity during primary sensory stimulation. Proc. Natl. Acad. Sci. U.S.A. **89**(12), 5675–5679 (1992)

R.P. Lesser, H. Luders, G. Klem, D.S. Dinner, H.H. Morris, J.F. Hahn, E. Wyllie, Extraoperative cortical functional localization in patients with epilepsy. J. clin. neurophysiol.: official publication of the American Electroencephalographic Society **4**(1), 27–53 (1987)

E.C. Leuthardt, G. Schalk, J.R. Wolpaw, J.G. Ojemann, D.W. Moran, A brain–computer interface using electrocorticographic signals in humans. J. Neural Eng. **1**(2), 63–71 (2004)

E.C. Leuthardt, G. Schalk, D. Moran, J.G. Ojemann, The emerging world of motor neuroprosthetics: a neurosurgical perspective. Neurosurgery **59**(1), 1–14 (2006a), discussion 1–14

E.C. Leuthardt, K.J. Miller, G. Schalk, R.P. Rao, J.G. Ojemann, Electrocorticography-based brain computer interface—the Seattle experience. IEEE Trans. Neural Syst. Rehabil. Eng. **14**(2), 194–198 (2006b)

E.C. Leuthardt, C. Gaona, M. Sharma, N. Szrama, J. Roland, Z. Freudenberg, J. Solis, J. Breshears, G. Schalk, Using the electrocorticographic speech network to control a brain-computer interface in humans. J. Neural Eng. **8**(3), 036004 (2011)

S.P. Levine, J.E. Huggins, S.L. BeMent, R.K. Kushwaha, L.A. Schuh, M.M. Rohde, E.A. Passaro, D.A. Ross, K.V. Elisevich, B.J. Smith, A direct brain interface based on event-related potentials. IEEE Trans. Rehabil. Eng. **8**(2), 180–185 (2000)

H. Liu, R.L. Buckner, T. Talukdar, N. Tanaka, J.R. Madsen, S.M. Stufflebeam, Task-free presurgical mapping using functional magnetic resonance imaging intrinsic activity. J. Neurosurg. **111**(4), 746–754 (2009)

G.E. Loeb, A.E. Walker, S. Uematsu, B.W. Konigsmark, Histological reaction to various conductive and dielectric films chronically implanted in the subdural space. J. Biomed. Mater. Res. **11**(2), 195–210 (1977)

J.R. Manning, J. Jacobs, I. Fried, M.J. Kahana, Broadband shifts in local field potential power spectra are correlated with single-neuron spiking in humans. J. Neurosci. **29**(43), 13613–13620 (2009)

J.D. Margalit, R.E. Weiland, G.Y. Clatterbuck, M. Fujii, M. Maia, G. Tameesh, S.A. Torres, S. D'Anna, D.V. Desai, A. Piyathaisere, E. de Olivi, M.S. Juan Jr, Humayun, Visual and electrical evoked response recorded from subdural electrodes implanted above the visual cortex in normal dogs under two methods of anesthesia. J. Neurosci. Methods **123**(2), 129–137 (2003)

N. Mesgarani, E.F. Chang, Selective cortical representation of attended speaker in multi-talker speech perception. Nature **485**(7397), 233–236 (2012)

K.J. Miller, E.C. Leuthardt, G. Schalk, R.P. Rao, N.R. Anderson, D.W. Moran, J.W. Miller, J.G. Ojemann, Spectral changes in cortical surface potentials during motor movement. J. Neurosci. **27**(9), 2424–2432 (2007a)

K.J. Miller, S. Zanos, E.E. Fetz, M. den Nijs, J.G. Ojemann, Decoupling the cortical power spectrum reveals real-time representation of individual finger movements in humans. J. Neurosci. **29**(10), 3132–3137 (2009)

D.W. Moran, A.B. Schwartz, Motor cortical representation of speed and direction during reaching. J. Neurophysiol. **82**(5), 2676–2692 (1999)

S. Ogawa, D.W. Tank, R. Menon, J.M. Ellermann, S.G. Kim, H. Merkle, K. Ugurbil, Intrinsic signal changes accompanying sensory stimulation: functional brain mapping with magnetic resonance imaging. Proc. Natl. Acad. Sci. U.S.A. **89**(13), 5951–5955 (1992)

G. Ojemann, J. Ojemann, E. Lettich, M. Berger, Cortical language localization in left, dominant hemisphere. An electrical stimulation mapping investigation in 117 patients. J. Neurosurg. **71**(3), 316–326 (1989)

B.N. Pasley, S.V. David, N. Mesgarani, A. Flinker, S.A. Shamma, N.E. Crone, R.T. Knight, E.F. Chang, Reconstructing speech from human auditory cortex. PLoS Biol. **10**(1), e1001251 (2012)

X. Pei, E.C. Leuthardt, C.M. Gaona, P. Brunner, J.R. Wolpaw, G.Schalk, Spatiotemporal dynamics of electrocorticographic high gamma activity during overt and covert word repetition. Neuroimage. **54**, 2960–2972 (2010)

X. Pei, D.L. Barbour, E.C. Leuthardt, G. Schalk, Decoding vowels and consonants in spoken and imagined words using electrocorticographic signals in humans. J. Neural Eng. **8**(4), 046028 (2011)

G. Pfurtscheller, B. Graimann, J.E. Huggins, S.P. Levine, L.A. Schuh, Spatiotemporal patterns of beta desynchronization and gamma synchronization in corticographic data during self-paced movement. Clin. Neurophysiol. **114**(7), 1226–1236 (2003)

C.J. Price, R.J. Wise, E.A. Warburton, C.J. Moore, D. Howard, K. Patterson, R.S. Frackowiak, K.J. Friston, Hearing and saying. The functional neuro-anatomy of auditory word processing. Brain **119**(Pt 3), 919–931 (1996)

F. Pulvermuller, Y. Shtyrov, R.J. Ilmoniemi, W.D. Marslen-Wilson, Tracking speech comprehension in space and time. Neuroimage **31**(3), 1297–1305 (2006)

S. Ray, N.E. Crone, E. Niebur, P.J. Franaszczuk, S.S. Hsiao, Neural correlates of high-gamma oscillations (60–200 Hz) in macaque local field potentials and their potential implications in electrocorticography. J. Neurosci. **28**(45), 11526–11536 (2008)

A.G. Rouse, J.J. Williams, J.J. Wheeler, D.W. Moran, The effect of electrode distance and neural plasticity on an epidural electrocorticographic (EECoG) closed-loop brain-computer interface (BCI). Soc. Neurosci. Abs. **85**, 14 (2010)

N. Roy, R.M. Merrill, S.D. Gray, E.M. Smith, Voice disorders in the general population: prevalence, risk factors, and occupational impact. Laryngoscope **115**(11), 1988–1995 (2005)

N.T. Sahin, S. Pinker, S.S. Cash, D. Schomer, E. Halgren, Sequential processing of lexical, grammatical, and phonological information within Broca's area. Science **326**(5951), 445–449 (2009)

G. Santhanam, S.I. Ryu, B.M. Yu, A. Afshar, K.V. Shenoy, A high-performance brain–computer interface. Nature **442**(7099), 195–198 (2006)

N. Sanai, Z. Mirzadeh, M.S. Berger, Functional outcome after language mapping for glioma resection. N. Engl. J. Med. **358**(1), 18–27 (2008)

G. Schalk, E.C. Leuthardt, Brain–computer interfaces using electrocorticographic signals. IEEE Rev. Biomed. Eng. **4**, 140–154 (2011)

G. Schalk, E.C. Leuthardt, D. Moran, J. Ojemann, J.R. Wolpaw, *Two-dimensional cursor control using electrocorticographic signals in humans* (Presented at the Society for Neuroscience, San Diego, 2004)

G. Schalk, J. Kubanek, K.J. Miller, N.R. Anderson, E.C. Leuthardt, J.G. Ojemann, D. Limbrick, D. Moran, L.A. Gerhardt, J.R. Wolpaw, Decoding two-dimensional movement trajectories using electrocorticographic signals in humans. J. Neural Eng. **4**(3), 264–275 (2007a)

G. Schalk, N. Anderson, K. Wisneski, W. Kim, M.D. Smyth, J.R. Wolpaw, D.L. Barbour, E.C. Leuthardt, *Toward brain-computer interfacing using phonemes decoded from electrocorticography activity (ECoG) in humans* (Presented at the Society for Neuroscience Annual Meeting, Washington DC, 2007b)

G. Schalk, K.J. Miller, N.R. Anderson, J.A. Wilson, M.D. Smyth, J.G. Ojemann, D.W. Moran, J.R. Wolpaw, E.C. Leuthardt, Two-dimensional movement control using electrocorticographic signals in humans. J. Neural Eng. **5**(1), 75–84 (2008)

S.K. Scott, I.S. Johnsrude, The neuroanatomical and functional organization of speech perception. Trends Neurosci. **26**(2), 100–107 (2003)

K.V. Shenoy, G. Santhanam, S.I. Ryu, A. Afshar, B.M. Yu, V. Gilja, M.D. Linderman, R.S. Kalmar, J.P. Cunningham, C.T. Kemere, A.P. Batista, M.M. Churchland, T.H. Meng, Increasing the performance of cortically-controlled prostheses. Conf. Proc. IEEE Eng. Med. Biol. Soc. Suppl:6652–6656 (2006)

A. Sinai, C.W. Bowers, C.M. Crainiceanu, D. Boatman, B. Gordon, R.P. Lesser, F.A. Lenz, N.E. Crone, Electrocorticographic high gamma activity versus electrical cortical stimulation mapping of naming. Brain **128**(Pt 7), 1556–1570 (2005)

M.W. Slutzky, L.R. Jordan, T. Krieg, M. Chen, D.J. Mogul, L.E. Miller, Optimal spacing of surface electrode arrays for brain-machine interface applications. J. Neural Eng. **7**(2), 26004 (2010)

S.M. Smith, P.T. Fox, K.L. Miller, D.C. Glahn, P.M. Fox, C.E. Mackay, N. Filippini, K.E. Watkins, R. Toro, A.R. Laird, C.F. Beckmann, Correspondence of the brain's functional architecture during activation and rest. Proc. Natl. Acad. Sci. U.S.A. **106**(31), 13040–13045 (2009)

K. Specht, J. Reul, Functional segregation of the temporal lobes into highly differentiated subsystems for auditory perception: an auditory rapid event-related fMRI-task. Neuroimage **20**(4), 1944–1954 (2003)

D.M. Taylor, S.I. Tillery, A.B. Schwartz, Direct cortical control of 3D neuroprosthetic devices. Science **296**(5574), 1829–1832 (2002)

V.L. Towle, H.A. Yoon, M. Castelle, J.C. Edgar, N.M. Biassou, D.M. Frim, J.P. Spire, M.H. Kohrman, ECoG gamma activity during a language task: differentiating expressive and receptive speech areas. Brain **131**(Pt 8), 2013–2027 (2008)

J.L. Vincent, G.H. Patel, M.D. Fox, A.Z. Snyder, J.T. Baker, D.C. Van Essen, J.M. Zempel, L.H. Snyder, M. Corbetta, M.E. Raichle, Intrinsic functional architecture in the anaesthetized monkey brain. Nature **447**(7140), 83–86 (2007)

W. Wang, A.D. Degenhart, G.P. Sudre, D.A. Pomerleau, E.C. Tyler-Kabara, Decoding semantic information from human electrocorticographic (ECoG) signals. Conf. Proc. IEEE Eng. Med. Biol. Soc. **2011**, 6294–6298 (2011)

J.J. Wheeler, J.J. Williams, W. Wang, J.C. Williams, D.W. Moran, An evaluation of chronic epidural electrode arrays for long-term recording and stimulation. Soc. Neurosci. Abs. **592**, 18 (2011)

J.A. Wilson, E.A. Felton, P.C. Garell, G. Schalk, J.C. Williams, ECoG factors underlying multimodal control of a brain–computer interface. IEEE Trans. Neural Syst. Rehabil. Eng. **14**(2), 246–250 (2006)

K.J. Wisneski, N. Anderson, G. Schalk, M. Smyth, D. Moran, E.C. Leuthardt, Unique cortical physiology associated with ipsilateral hand movements and neuroprosthetic implications. Stroke **39**(12), 3351–3359 (2008)

B. Wodlinger, A.D. Degenhart, J.L. Collinger, E.C. Tyler-Kabara, W. Wang, The impact of electrode characteristics on electrocorticography (ECoG). Proceedings of Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference **2011**, 3083–3086 (2011)

J.R. Wolpaw, N. Birbaumer, W.J. Heetderks, D.J. McFarland, P.H. Peckham, G. Schalk, E. Donchin, L.A. Quatrano, C.J. Robinson, T.M. Vaughan, Brain–computer interface technology: a review of the first international meeting. IEEE Trans. Rehabil. Eng. **8**(2), 164–173 (2000)

J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, Brain-computer interfaces for communication and control. Clin. Neurophysiol. **113**(6), 767–791 (2002)

J.R. Wolpaw, D.J. McFarland, Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. Proc. Natl. Acad. Sci. U.S.A. **101**(51), 17849–17854 (2004)

T.G. Yuen, W.F. Agnew, L.A. Bullara, Tissue response to potential neuroprosthetic materials implanted subdurally. Biomaterials **8**(2), 138–141 (1987)

Towards Communication in the Completely Locked-In State: Neuroelectric Semantic Conditioning BCI

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Abstract We introduced a Pavlovian semantic conditioning paradigm to enable basic communication in completely locked-in state (CLIS). Patients in CLIS have no means of communication and they have represented the target population for brain–computer interface (BCI) research in the last 15 years. Although different paradigms have been tested as well as different physiological signals have been used, to date no documented CLIS patient was able to control a BCI over an extended time period. We designed a novel paradigm based on semantic conditioning for online classification of neuroelectric or any other physiological signals to discriminate between covert (cognitive) 'yes' and 'no' responses. The paradigm

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comprised the presentation of affirmative and negative statements used as conditioned stimuli and only affirmative statements were paired with electrical stimulation. A CLIS patient diagnosed with amyotrophic lateral sclerosis (ALS) participated in the study and underwent 37 daily sessions. The online classification accuracies of the slow cortical potentials, identified as the electroencephalographic (EEG) signature differentiating between covert 'yes' and 'no' responses, were around chance level on average, with peaks of high communication accuracy in some sessions.

Several neurological diseases such as amyotrophic lateral sclerosis (ALS), muscular dystrophy or high spinal cord injury may lead to severe or complete motor paralysis, making communication hard or even impossible. In case of ALS, the disease could progress to total paralysis and is fatal unless the patient chooses to be artificially ventilated and fed. The state of severely paralyzed patients with residual voluntary control of particular muscles (e.g. eye muscles, lips, fingers) is known as the locked-in state (LIS) (Bauer et al. 1979; Kübler and Birbaumer 2008). There are also patients who lose all motor control resulting in the completely locked-in state (CLIS) (Birbaumeret al. 2008). These patients have the greatest need for a system that restores communication and interaction with the social environment. In this framework, a Brain-Computer Interface (BCI) represents an attractive alternative as a communication aid.

In the past, numerous studies described BCIs successfully controlled by LIS patients (e.g. to select characters and thus to communicate) with different paradigms, e.g. using slow cortical potentials, sensory motor rhythm modulation or the P300 event-related potential (ERP) component (Birbaumer et al. 1999; Neuper et al. 2003; Kübler et al. 2005; Halder et al. 2010). However, in the literature there are no studies reporting a case of successful control of a BCI by patients in CLIS. In their meta-analysis of 29 patients in different stages of physical impairment and trained with BCIs, Kübler and Birbaumer (2008) showed that none of the seven CLIS patients ever achieved BCI control despite intact passive cognitive functioning assessed with a battery of cognitive event-related potential-tests (Kotchoubey et al. 2002, 2003). Moreover, all of the CLIS patients were already in CLIS at the beginning of their BCI training. At the same time, the analysis revealed that patients with some remaining muscle control learned to use the BCI (Kübler and Birbaumer 2008). More recently, Murguialday et al. (2011) monitored the transition from LIS to CLIS of an ALS patient with electrophysiological measures which led the authors to suggest the use of afferent pathways which are different from the visual system for feedback in order to achieve reliable BCI-based communication in CLIS. Indeed, most patients with extended paralysis of eye-muscles develop disorders of fixation and vision due to necrosis of the cornea (Birbaumer 2006; Murguialday et al. 2011). For this reason, the experiment introduced herein used auditory and electrical stimuli, which involved different afferent pathways.

One possible explanation for the failure of CLIS patients to achieve BCI communication can be found in learning theory. According to this, if thoughts or intentions are not reliably followed by their anticipated consequences in the outside world, they extinguish as any other behavior. In this respect, it has been hypothesized that CLIS patients present an extinction of output directed and goal oriented thoughts, which could lead to a state incompatible with operant learning (Kübler and Birbaumer 2008). Consequently a classical conditioning rather than instrumental-operant learning paradigm, requiring less attentional resources and voluntary efforts could represent a better alternative for people in CLIS. This supposition is supported by the work performed by Dworkin and colleagues during the 70s and 80s. They could not replicate the results obtained previously by Miller's group (Miller 1969) who were able to train artificially ventilated and curarized rats to control autonomic function, such as heart rate, through operant learning. Dworkin hypothesized that the failure was due to the absence of a homeostatic effect of the reward involved (Dworkin and Miller 1986). The body functions of curarized and artificially ventilated rats were kept constant, thus no change in the equilibrium of these functions occurred during the experiment and the reward did not induce any homeostatic restoration. Similarly, external medical devices keep the body functions of a CLIS patient constant, depriving any reward of its homeostasis-restoring effects.

Classical conditioning is a type of learning that was discovered by Ivan Pavlov (1960) during his studies on digestion. Commonly, during classical conditioning a neutral conditioned stimulus (CS) is repeatedly paired with a biologically relevant (e.g. aversive) unconditioned stimulus (US). Once a CS-US association has been formed the CS produces a conditioned reaction (CR) in anticipation of the US (Moore 2002). Another associative learning technique is semantic conditioning which is based on the generalization of CRs along a semantic dimension (word-to-word transfer). Specifically, semantic conditioning refers to conditioning of a reflex to a word or sentence irrespective of the particular constituent letters or sounds of the words (Razran 1961). It has been shown that CRs (e.g. saliva secretion, galvanic skin response, heart rates) to specific words or sentences can be transferred to other words or sentences with similar meaning (Razran 1939, 1949; Lacey and Smith 1954). For instance, if a subject is exposed to the pairing of the word 'stone' with an electric shock until the word alone generates a heart rate change (CR), typically this CR would be elicited also by presenting a semantically related word (e.g. 'rock' in this example). This concept is known as semantic generalization, whereas phonological generalization is based on the principle that the subject would also manifest the CR in response to a phonologically similar word (e.g. 'stain' in this example) (Motley 1974).

Within this project we propose a classical semantic conditioning design to allow basic yes/no communication. More precisely, we intend to condition cortical responses to the correctness of a statement. Previously, the study of Furdea et al. (Furdea et al. 2012) investigated the applicability of semantic classical conditioning within a BCI setting using unpleasant auditory stimuli as USs. Four different classifiers were employed to separate covert 'yes' from 'no' responses, providing classification accuracies around chance level. It was concluded that the poor discriminability between the two cortical CRs could be due to the nature of the two auditory USs used for conditioning. Consequently, in the present study, we used as US short electrical stimulation consisting of 1ms electrical pulse delivered over the left thumb whose intensity was set according to threshold tracking test performed at the beginning of each daily session. The electrical pulse was generated by a bipolar direct current stimulator (DS5, Digitimer Ltd, United Kingdom). True and false statements were presented through in-ear headphones, subject being asked to think 'yes' and 'no', according to the type of the statement. During the conditioning phase true sentences, and thus thinking 'yes' (CS+) were immediately followed by US whereas false sentences (thinking 'no' = CS−) were never paired with the US. The correctness of a statement was given by the last word and for each statement there was a proper false and true ending word: therefore, the subject could listen to both versions of a statement due to the randomized order of appearance of the statements.

As reported in the literature (Hilgard and Marquis 1940), the conditioned response does not have to be identical to the reaction elicited by the US. Therefore, to distinguish between 'yes' and 'no' thinking, the classifier was trained and tested on electroencephalogram (EEG) epochs acquired in trials when the electrical stimulation was not delivered. In other words, the model generated during the training of the classifier did not contain any information concerning the somatosensory ERP triggered by the US, since the neuronal CR was not expected to resemble it.

A CLIS patient underwent 37 daily sessions over 10 months. Each session comprises 5 blocks and there were three different types of blocks: *conditioning* block (in this phase the conditioning was established) which consisted of 25 true statements followed by stimulation (US+) and 25 false statements (US−) in a random order; *acquisition* block (in this phase the trials used to train the classifier were acquired), which consists of 15 US + , 30 US- and 15 true statements not followed by stimulation (CS+ alone) in a random order; and *feedback* block which consists of 15 US+ , 15 US−, 15 CS + alone and 15 CS-alone, during which the patient received auditory feedback based on the classified EEG. The feedback consisted of an auditory stimulus (e.g. 'You thought yes' or 'You thought no'). Each block lasted for 7–8 min with a break of 2 min between two consecutive blocks, with an inter-trial-interval of 5 s. In the first session of the first week, 4 *conditioning* and 1 *acquisition* blocks were recorded, therefore no feedback was delivered. All the other sessions comprise 5 blocks: 1 *conditioning* block, 2 *acquisition* blocks, and 2 *feedback* blocks, see Fig. 1 for an overview. The CS+ alone and CS− alone trials recorded during the *acquisition* blocks were used to train the classifier. The model obtained from the training of the classifier was used to predict the CS+ alone and CS− alone trials of the *feedback* block. In each *feedback* block 10 predictions were performed, 5 for true and 5 for false statements: each of those 10 statements was repeated three times intermingled by US+ and US− trials and the averaged cortical response was used for the prediction. The US+ and US− trials consisted of statements extracted from the general knowledge (e.g. 'Berlin is the capital of Italy/ Germany') whereas the CS+ alone and CS− alone trials contained statements based on the patient's life and experience (e.g. 'My daughter's name is Jana/Sarah'). Those personalized statements were introduced to enhance the involvement and attention

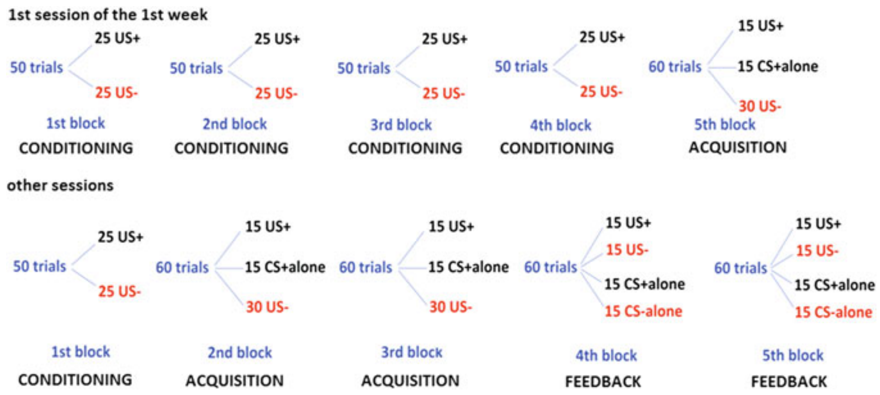

Fig. 1 Experimental paradigm. The figure presents a schematic overview of the experimental paradigm

of the patient. Additionally, it is clear in this experimental paradigm to which class, either false or true, each statement belongs, except for the statements contained in the CS+ alone and CS− alone trials of the 5th block, which were personalized statements whose answer was not known in advance (open statements). These statements were presented in order to ask real life questions. From the ninth session on, a sixth (*feedback*) block was added at the end of each session containing the semantically reversed version of the open statements presented in the fifth block (e.g. 'Last night I slept well' was changed to 'Last night I slept badly'). Therefore, it was possible to calculate the accuracy of the classifier comparing the classifier outcome for the EEG response to the two versions of each open statement presented in block 5 and 6. Additionally, from session 12 to session 19 the electrical pulse was substituted with a train of pulses (duration of 1 s, frequency of 20 Hz, width of single pulses of 200 μs) generated by a Functional Electrical Stimulation (FES) device (UNAFET 8, UNA Systems, Serbia) and paired with an auditory stimulus (75 dB) resembling that of metal scraping. The FES stimulation was delivered over the left upper arm through two patch electrodes positioned over extensor communis digitorum muscle which is responsible for the extension of the fingers. This combination of stimuli was introduced in order to involve both the auditory system and the proprioceptive afferent channels, as suggested in Murguialday et al. (2011).

During the entire experiment, the EEG was recorded from 32 surface electrodes using a standard EEG cap following the International 10–20 System. The reference lead was an electrode positioned on the tip of the nose and the ground electrode was placed on the mastoid area behind the right ear. All electrode impedances were reduced to 5 kΩ before data recording. EEG signal was sampled at 200 Hz, and band-pass filtered between 0.009 and 40 Hz. Segments with a length of 4 s relative to the end of the statement were extracted and used to compute the input features for a Linear Discriminant Classifier. The features consisted of wavelet coefficients (WC) computed using a fast (discrete) wavelet transform (FWT) focusing on the spectral components below 3.125 Hz.

The accuracy on yes/no discrimination went up to 90 %; that is, 9 out of 10 correct predictions per day. Nevertheless, the daily accuracies were not stable across sessions, which means that (including all sessions) the classifier performed around chance level. Additionally, an offline analysis was performed on the data to test a different classifier (support vector machine, SVM, with non linear kernel) and different input features. Besides WC, the SVM was also provided with signal amplitude (SA) values obtained after low-pass filtering of the data below 5 Hz, moving-average-filtering and decimation using a factor of 5. Both types of features were extracted from those EEG segments acquired during CS $\pm$ alone trials, and the classifier accuracy was computed using a 10-fold cross-validation approach. The offline classification provided performance results around chance level across all sessions, with peaks of high communication accuracy between 60 and 70 %.

In addition, the cognitive status of the patient was assessed through a battery of neurophysiological examinations based on ERP (Neumann and Kotchoubey 2004). The above mentioned paradigm was performed four times in separate days with respect to the conditioning paradigm and revealed the largely intact cognitive ERPs of the CLIS patient. Taking into account these findings, one may conclude that attention and arousal requirements for this semantic classical conditioning BCI are perhaps still too high, and patients with reduced vigilance and drowsiness during many of the training sessions fail to demonstrate stable above chance level classification. Moreover, it is possible that the proposed 'extinction of goal-directed thinking' also prevents semantic conditioning, because the 'intention' to anticipate a 'yes' or 'no' answer after the CS is attenuated or extinguished (Perky 1910).

This experiment represented the first attempt to classify EEG data in real-time recorded in a CLIS patient for communication purposes within a semantic conditioning paradigm. The patient was diagnosed with spinal and sporadic ALS four years before the initial session. She entered the CLIS one year before participating to the first measurement, and since then no communication has been possible through any means (score 0 out of 48, in the ALS Functional Rating Scale-Revised (Cedarbaum et al. 1999)).

The paradigm described here provides a slow communication speed compared to other communication aids. Nevertheless, in the clinical situation of a CLIS patient, the information transfer rate is not crucial because those patients have no means of communication, neither by BCIs nor by other assistive technologies. On the other hand, the lack of a communication channel is also of great concern for the investigators, who cannot infer the current emotional and cognitive condition of the patient. In this context, real-time decoding of macroscopic brain states becomes of the utmost importance (Blankertz et al. 2010) because future BCIs should adapt to the users, for instance changing the stimulus presentation rate or turning off the system according to the users' brain state of consciousness and awareness. Particularly for ALS, it is essential to monitor the level of attention and fatigue of the patient to avoid overloading his actual and instantaneous cognitive efficiency to avoid frustration and disappointment. In this context, anodal transcranial direct stimulation or high frequency transcranial magnetic stimulation can be used to avoid fading of vigilance, changing the brain excitation level (Cohen et al. 1998).

The ultimate goal of BCI research is to provide a non-muscular communication channel for individuals who are no longer able to communicate by any means due to severe physical impairment. According to this main aim, this study represents an innovative attempt to investigate the applicability of a semantic conditioning paradigm in a BCI setting that could enable yes/no communication for people in CLIS without the need for operant learning. Future applications of this paradigm should also look for different neuronal signatures such as travelling alpha-waves, which were shown to play a role in semantic memory representations (Fellinger et al. 2012).

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References

G. Bauer, F. Gerstenbrand, E. Rumpl, Varieties of the locked-in syndrome. J. Neurol. **212**, 77–91 (1979)

N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, H. Flor, A spelling device for the paralysed. Nature **398**, 297–298 (1999)

N. Birbaumer, A.R. Murguialday, L. Cohen, Brain-computer interface in paralysis. Curr. Opin. Neurol. **21**, 634–638 (2008)

N. Birbaumer, Brain-computer-interface research: coming of age. Clin. Neurophysiol. **117**, 479–483 (2006). http://www.ncbi.nlm.nih.gov/pubmed/16458595

B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe, C. Maeder, L. Ramsey, I. Sturm, G. Curio et al, The Berlin brain-computer interface: non-medical uses of BCI technology. Frontiers Neurosci. **4**, 198 (2010). http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3002462&tool=pmcentrez&rendertype=abstract

J.M. Cedarbaum, N. Stambler, E. Malta, C. Fuller, D. Hilt, B. Thurmond, A. Nakanishi, BDNF III A , The ALSFRS-R: a revised ALS functional rating scale that incorporates assessments of respiratory function. J. Neurol. Sci. **169**, 13–21 (1999)

L. Cohen, U. Ziemann, R. Chen, J. Classen, M. Hallet, C. Gerloff, C. Butefisch, Studies of neuroplasticity with transcranial magnetic stimulation. J. Clin. Neurophysiol: Off. Publ. Am. Electroencephalogr. Soc. **15**, 305–324 (1998). http://journals.lww.com/clinicalneurophys/Abstract/1998/07000/Studies_of_Neuroplasticity_With_Transcranial.3.aspx

B.R. Dworkin, N.E. Miller, Failure to replicate visceral learning in the acute curarized rat preparation. Behav. Neurosci. **100**, 299–314 (1986). http://www.ncbi.nlm.nih.gov/pubmed/3730136

R. Fellinger, W. Gruber, A. Zauner, R. Freunberger, W. Klimesch, Evoked traveling alpha waves predict visual-semantic categorization-speed. NeuroImage **59**, 3379–3388 (2012). http://www.ncbi.nlm.nih.gov/pubmed/22100769

A. Furdea, C.A. Ruf, S. Halder, D. De Massari, M. Bogdan, W. Rosenstiel, T. Matuz, N. Birbaumer, A new (semantic) reflexive brain-computer interface: in search for a suitable classifier. J. Neurosci. Methods **203**, 233–240 (2012)

S. Halder, M. Rea, R. Andreoni, F. Nijboer, E.M. Hammer, S.C. Kleih, N. Birbaumer, A. Kübler, An auditory oddball brain-computer interface for binary choices. Clin. Neurophysiol.: Off. J. Int. Fed. Clin. Neurophysiol. **121**, 516–523 (2010)

E.R. Hilgard, D.G. Marquis, *Conditioning and Learning*, 6th edn. (Appleton-Century, Oxford, England, 1940)

B. Kotchoubey, S. Lang, V. Bostanov, N. Birbaumer, Is there a mind? Electrophysiology of unconscious patients. News Physiol. Sci.: Int. J. Physiol. Prod. Jt. Int. Un. Physiol. Sci. Am. Physiol. Soc. **17**, 38–42 (2002)

B. Kotchoubey, S. Lang, S. Winter, N. Birbaumer, Cognitive processing in completely paralyzed patients with amyotrophic lateral sclerosis. Eur. J. Neurol.: Off J. Eur. Fed. Neurol. Soc. **10**, 551–558 (2003)

A. Kübler, N. Birbaumer, Brain-computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients? Clin. Neurophysiol.: Off. J. Int. Fed. Clin. Neurophysiol. **119**, 2658–2666 (2008)

A. Kübler, F. Nijboer, J. Mellinger, T.M. Vaughan, H. Pawelzik, G. Schalk, D.J. McFarland, N. Birbaumer, J.R. Wolpaw, Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface. Neurology **64**, 1775–1777 (2005)

J. Lacey, R. Smith, Conditioning and generalization of unconscious anxiety. Science **120**, 1045–1052 (1954)

N.E. Miller, Learning of visceral and glandular responses. Science 163, 434–445 (1969). http://www.ncbi.nlm.nih.gov/pubmed/5812527

J. Moore (ed.), A neuroscientist's guide to classical conditionin (Springer, New York, 2002). http://www.lavoisier.fr/livre/notice.asp?id=O2SWL6ASLSLOWF

M.T. Motley, Verbal conditioning-generalization in encoding: a hint at the structure of the lexicon. Commun. Monogr. **4,** 151–162 (1974). http://www.tandfonline.com/doi/abs/10.1080/03637757409375830

A.R. Murguialday, J. Hill, M. Bensch, S. Martens, S. Halder, F. Nijboer, B. Schoelkopf, N. Birbaumer, A. Gharabaghi, Transition from the locked into the completely locked-in state: a physiological analysis. Clin. Neurophysiol.: Off. J. Int. Fed. Clin. Neurophysiol. **122**, 925–933 (2011)

N. Neumann, B. Kotchoubey, Assessment of cognitive functions in severely paralysed and severely brain-damaged patients: neuropsychological and electrophysiological methods. Brain Res. Brain Res. Protoc. **14**, 25–36 (2004). http://www.ncbi.nlm.nih.gov/pubmed/15519949

C. Neuper, G. Muller, A. Kubler, N. Birbaumer, G. Pfurtscheller, Clinical application of an EEG-based brain–computer interface: a case study in a patient with severe motor impairment. Clin. Neurophysiol.: Off. J. Int. Fed. Clin. Neurophysiol. **114**, 399–409 (2003)

I. Pavlov, in *Conditioned Reflexes: an Investigation of the Physiological Activity of the Cerebral Cortex* (1927), ed. by G.V. Anrep. New York: Boyer . http://scholar.google.it/scholar?hl=it&q=Conditioned+reflexes%3A+An+investigation+of+the+physiological+activity+of+the+cerebral+cortex&btnG=&lr=#6 (1960)

C. Perky, An experimental study of imagination. Am. J. Psychol. **21**, 422–452. http://www.jstor.org/stable/10.2307/1413350 (1910)

G. Razran, A simple technique for controlling subjective attitudes in salivary conditioning of adult human subjects. Science **89**, 160–161 (1939)

G. Razran, Some psychological factors in the generalization of salivary conditioning to verbal stimuli. The Am. J. Psychol. **62**, 247–256 (1949)

G. Razran, The observable unconscious and the inferable conscious in current Soviet psychophysiology: interoceptive conditioning, semantic conditioning, and the orienting reflex. Psychol. Rev. **68**, 1–147 (1961)

Conclusion

The preceding ten chapters summarized the ten projects that were nominated in 2011. The nominees are still active in BCI research, and have already produced some exciting follow-up work. In this concluding chapter, we announce the winner of the 2011 BCI Award, present some analyses of nominees and submissions, and preview the 2012 award.

The 2011 Winner

The nominations were difficult, since many of the 64 submissions were also excellent. The jury had an even more difficult task after choosing the nominees: selecting the winner of the 2011 BCI Award. In addition to the honor of being chosen, the award of $3000, and the statue, the winner was also publicly announced at the Graz BCI conference in September 2011.

The winning team was Moritz Grosse-Wentrup and Bernhard Schölkopf from the Max Planck Institute for Intelligent Systems in Germany (Fig. 1). Their project was titled "What are the neuro-physiological causes of performance variations in brain-computer interfacing?" The project addressed a very important point: making BCI systems more robust. Their project even utilized gamma activity in the EEG spectrum.

Directions and Trends Reflected in the Awards

One of the goals of the BCI Award is to help identify major directions in BCI Research. By analyzing the different characteristics of the projects that were nominated in 2011, we can learn more about which facets were most appealing to the jury. Table 1 summarizes the BCI Award 2011 nominees. The nominees are categorized according to the control signals that were utilized and application areas.

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Fig. 1 The winner of the 2011 BCI Award, along with the jury and presenters. From *left to right*: Michael Tangermann, Gernot Müller-Putz, Gert Pfurtscheller, Theresa Vaughan, Moritz Grosse-Wentrup (*fifth from left*, *holding the Award*), Christoph Guger, Brendan Allison, Jane Huggins, Cuntai Guan, Robert Leeb

Table 1 shows that 4 projects used invasive technology (ECoG - Electrocorticogram/Spikes) and 6 projects measured non-invasively. Two nominated projects used evoked potentials and three projects motor imagery (MI) as principle. The division into application areas shows that control applications are most prominent, followed by robot control, communication and speech reconstruction and finally by stroke rehabilitation.

The BCI Award is also meant to show trends, such as themes that become more or less popular across different years. To more broadly explore the different facets of BCI research, we conducted another analysis with all 64 projects submitted to the 2011 BCI Award, and compared the results to all 57 projects submitted to the 2010 BCI Award. Table 2 summarizes the results. Among other trends, the 2011 Award drew more submissions that described real-time BCIs, and also introduced many new properties.

Interesting is that only two projects worked on off-line algorithms which was much higher in the past and this shows also that BCIs became real devices. Most of the BCIs use motor imagery, P300 principles and just a few use steady-state visual evoked potentials (SSVEP) or auditory steady-state response (ASSR). More than 70 % of the submission are using the EEG because of its simplicity and high time resolution compared to just a few fMRI, ECoG and NIRS projects. The most common applications under the 64 submissions are control, stroke/neural plasticity

Table 1 Summary of the 2011 BCI Award nominees

Title	Control Signal					Application				
	ECoG	Spikes	N200/ P300	NIRS/ physio	MI	Robot	Stroke	Control	Communication	Speech
Exploring the cortical dynamics of learning by leveraging BCI paradigms	X							X		
An auditory output brain-computer interface for speech communication		X								X
Seven degree of freedom cortical control of a robotic arm		X				X				
Utilizing high gamma (HG) band power changes as control signal for non-invasive BCI					X			X		
User-appropriate and robust control strategies to enhance brain computer interface performance and usability					X			X		
What are the neuro-physiological causes of performance variations in brain-computer interfacing?					X				X	
Using the electrocorticographic speech network to control a brain-computer interface in humans	X									X
Towards communication in the completely locked-in state: neuroelectric semantic conditioning BCI			X						X	
An affective BCI using multiple ERP components associated to facial emotion processing			X			X				
What's your next move? Detecting movement intention for stroke rehabilitation				X			X			

Table 2 Properties of all of the projects submitted to the BCI Awards in 2010 and 2011

Property	Number	2011 (%) (N=64)	2010 (%) (N=57)	Property	Number	2011 (%) (N=64)	2010 (%) (N=57)
Real-time BCI	61	95.3	65.2	Stroke/Neural plasticity	8	12.5	7.0
Off-line algorithms	2	3.1	17.5	Spelling	8	12.5	19.3
P300	16	25	29.8	Wheelchair/Robot	4	6.2	7.0
SSVEP	8	12.5	8.9	Internet/VR	2	3.1	8.8
Motor imagery	19	29.7	40.4	Control	22	34.4	17.5
ASSR	1	1.6	-	Platform/Technology	6	9.4	12.3
EEG	45	70.3	75.4	Monitoring	1	1.6	-
fMRI	2	3.1	3.5	Speech	3	4.7	-
ECoG	3	4.7	3.5	Coma	2	3.1	-
NIRS	3	4.7	1.8	Authentification	1	1.6	-
Spikes	8	12.5	-	Mechanical ventilation	1	1.6	-
Other signals	1	1.6	-	Learning	2	3.1	-
Electrodes	1	1.6	-	Sensation	1	1.6	-

and spelling. But there are also many new applications like monitoring, speech, coma, authentification, mechanical ventilation, learning and sensation that did not exist 2010.

Conclusion and Future Directions

Overall, the BCI Awards have helped to encourage excellence in BCI research, identify key directions, and promote BCI research around the world. The ten projects summarized in this book represent some of the most promising accomplishments from the top research groups. However, the 2012 BCI Award, which is underway as of this writing, has so far been even more competitive than before. We editors plan a book summarizing the nominees, their follow-up work, and further analyses of major trends.

g.tec has already committed to host the fourth annual BCI Award in 2013. Researchers are encouraged to keep abreast of relevant announcements at bci-award.com, and consider submitting their research. Given the level of competition, extra time to develop the best submission is strongly recommended. We editors would like to conclude by thanking all the groups who submitted projects to the BCI Awards over the years, and the many other innovators in BCI research.