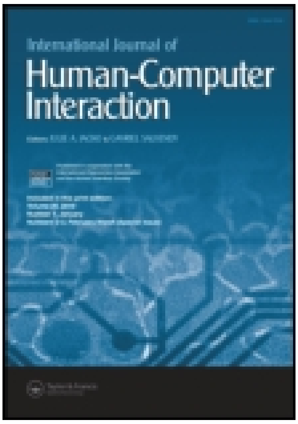

International Journal of Human-Computer Interaction
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/hihc20

Current Trends in Brain-Computer Interface (BCI) Research and Development

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Version of record first published: 28 Dec 2010.

To cite this article: Chang S. Nam, Gerwin Schalk & Melody M. Jackson (2010): Current Trends in Brain-Computer Interface (BCI) Research and Development, International Journal of Human-Computer Interaction, 27:1, 1-4

To link to this article: http://dx.doi.org/10.1080/10447318.2011.535748

INTL. JOURNAL OF HUMAN–COMPUTER INTERACTION, *27*(1), 1–4, 2011

ISSN: 1044-7318 print / 1532-7590 online
DOI: 10.1080/10447318.2011.535748

Editorial: Current Trends in Brain–Computer Interface (BCI) Research and Development

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1. INTRODUCTION TO BRAIN–COMPUTER INTERFACING

A brain–computer interface (BCI), sometimes called a direct neural interface or a brain–machine interface, detects and interprets brain signals and uses the results to communicate a user's intent (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). Because these systems directly translate brain activity into action, without depending on peripheral nerves and muscles, a major goal of BCI research has been to establish BCI technology as an assistive device to be used by people with severe motor disabilities. BCIs have shown encouraging possibilities in providing people, including those who cannot use their muscles but are cognitively intact, with alternative methods for interacting with the outside world (Nam, Lee, & Johnson, 2010; Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004).

Despite long interest in the possibility to control devices directly using brain signals (e.g., Fetz & Finocchio, 1971; Vidal, 1973, 1977), it has only been in the past 20 years that sustained research has begun, and only in the past 10 years that a recognizable field of BCI research, populated by a rapidly growing number of research groups with increasing number of publications, has developed. Early BCI efforts have been developed from the field of clinical neurophysiology in humans (using mostly scalp-recorded electroencephalography [EEG]) and basic neuroscience investigations in animals (using mostly single-neuron recordings). Thus, initial efforts began with expertise in neuroscience, neurophysiology, and psychology. In parallel with the establishment of dedicated BCI research groups throughout the 1990s, these groups began to also seek specialists in signal processing, machine learning, and software engineering. This relatively narrow focus on the technical aspects of BCI research and development served the field well in its initial stages of method development.

As the field has begun to mature, its scope has expanded to focus on application of BCI technology to the needs of people with disabilities—recent efforts are now

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beginning to establish the clinical value and practicality of BCI systems (Hochberg et al., 2006; Kubler et al., 2005; Nijboer et al., 2008; Sambasivan & Jackson, 2007). These and related efforts showed that further improvements to BCI technology are necessary to ensure that they can meet the needs of specific groups of users. In particular, the specific and varying needs of individuals implies an increased need for experts in human factors and human–computer interaction (HCI) and their contributions.

2. SPECIAL ISSUE CONTRIBUTIONS

The increased demand in contributions from the HCI community prompted the guest editors to compile this special issue, which intends to present a snapshot of current work in BCI research by including contributions from researchers from different disciplines, with a particular focus on work in HCI. Our call for papers resulted in a total of 18 submissions from groups around the world, out of which only six papers were included in this special issue after a rigorous three-stage peer review process. These articles are summarized briefly next.

The first article by Omar and colleagues ("A Feedback Information-Theoretic Approach to the Design of Brain–Computer Interfaces") focuses on a feedback information-theoretic approach to BCI design. This article employs information theory to formulate the BCI problem as a problem of communication over a noisy channel with feedback. This approach enables the design of reliable communication protocols using tools from feedback information theory. The authors validate this approach experimentally using two different EEG-based BCI approaches. In summary, the methods demonstrated in this article have the potential to improve many common designs that do not directly take feedback into account.

In the second article, Randolph and her colleagues ("Individual Characteristics and Their Effect on Predicting Mu Rhythm Modulation") propose a formal process for determining a user's ability to use a BCI system based on sensorimotor rhythms. Traditionally, users must be screened by time-consuming and tedious testing sessions to discover whether they can control a particular BCI. Particularly for people with severe disabilities, this can be a tiring and frustrating process. Randolph et al. studied 55 BCI users; collecting data on a number of characteristics such as age, lifestyle, health habits, activity level and interests; and statistically correlated these characteristics with their ability to control a mu-based BCI. The results demonstrate some clear connections between user characteristics and the ability of the users to modulate their mu rhythm. This provides a method to accurately predict which users will be able to control a mu-based BCI, saving time and effort. The significance of this work is that it can be expanded beyond mu-based systems to help users choose which brain-based assistive technologies would be the most likely to be effective for them.

The third article, by Zander and colleagues ("Combining Eye Gaze Input With a Brain–Computer Interface for Touchless Human-Computer Interaction"), describes one of the first efforts to integrate input from BCI systems with input from other devices. Specifically, this study implements and experimentally validates the integration of an eye tracker and a BCI system. In this paradigm, the subjects determined a desired choice using eye movements and then selected that choice either by staying at that choice with their eyes for a particular time (i.e., dwell time) or by using the BCI (i.e., using an "activation thought"). The results show that the BCI-based selection improved selection accuracy compared to that for dwell time-based selection and improved user acceptance. Thus, the approach presented in this article may improve communication and control options for people with remaining control over eye movements.

The fourth and the fifth articles present an empirical evaluation of a P300-based BCI, popularly known as *P300 Speller*. Li and his colleagues ("A P300-Based Brain–Computer Interface: Effects of Interface Type and Screen Size") report an empirical study that investigated the effects of interface type, screen size, and motor disability on task performance and usage preference within the context of P300 Speller. The results showed that interface type and screen size have significant effects on user performance and usage preference with varying degree of impact to participants with and without motor disabilities. The results of this study should give some insights into the future research of the P300-based BCI systems, especially the user interface design, as well as the real-world applicability of the P300-based BCI applications for people with motor disabilities. The fifth article by Ryan et al. ("Predictive Spelling With a P300-Based Brain-Computer Interface: Increasing the Rate of Communication") evaluates the impact on performance of predictive spelling with P300 Speller. The results show that predictive spelling produces significantly more characters per minute than does the nonpredictive speller, and thus demonstrate the potential efficacy of predictive spelling in the context of P300-based matrix speller.

The last article, by Mehta and colleagues ("Optimal Control Strategies for an SSVEP-Based Brain–Computer Interface"), discusses performance evaluation of a SSVEP-based BCI under variation of two BCI control parameters. SSVEP has been shown to be one of the most successful control strategies in discrete selection applications, such as spelling or choosing environmental control options (Bin, Gao, Yan, Hong, & Gao, 2009). However, there has been little work showing the utility of SSVEP for continuous control, for applications such as driving a wheelchair. This study explores methods for employing SSVEP control of navigation in a virtual environment in the form of a simple game. The results show that SSVEP can be an effective continuous-control method, which is promising for real-time control of wheelchairs, vehicles, drawing, and other continuous tasks.

3. CONCLUSIONS AND ACKNOWLEDGMENT

The topics of the selected six articles are early evidence that the HCI community can make important contributions to the field of BCI research, and thus encourage further joint work of HCI and BCI researchers. In the end, development and application of BCI systems to address the needs of different types of users strongly depends on understanding the capacities and needs of those users. Consequently, contributions by the HCI community appear to be critical to the success of a primary goal of BCI research. The guest editors wish to thank all the authors of this special issue for contributing their high-quality papers. We also thank the reviewers who have participated in the review process to critically evaluate the papers within the short stipulated time. Finally, we hope the reader will enjoy this special issue and find it useful for their own work.

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