



2009 Special Issue

Recent advances in brain–machine interfaces

1. Introduction

The recent development of interfaces that enable direct communication between the brain and machines is having a significant impact on systems neuroscience and will enable many innovative advances in neuroprosthetics. Brain–machine interfaces (BMIs) and brain–computer interfaces (BCIs) will allow humans to operate computers, robotic arms, wheelchairs, prosthetic devices and other instruments by using only the signals generated by their brain. This new neuro-technology may help severely disabled but cognitively intact patients to better communicate and interact with the outside world. Because regeneration and transplantation of nerve tissue remains problematic, the medical care of patients disabled by neurological deficits such as strokes and physical damage of the nervous systems has been considered to be very limited. For patients with impaired limb functions, possible treatments were limited mainly to enhancing the remaining ability of the brain with rehabilitation and/or assisting limb functions with prostheses. For more severely disabled patients, such as those with a locked-in syndrome, the development of effective ways to read their mind and enable their communication with the outside world has been sought. Under such circumstances, BMIs and BCIs have promised to enhance the quality of life of the patients. At the same time, this technology can lead to innovative modalities of interaction for the healthy. BMIs/BCIs are now becoming a new tool of communication and they are expected to be used in various social sectors such as operation of robots and vehicles, mass communication, telecommunication and even entertainment and games. Developing new algorithms to decode cognitive information from individual brain signals and learning how the brain adapts to novel environments when interacting directly with computers will also lead to better understanding of the brain. Thus, BMI/BCI research is generating major advances in brain science and information technology.

Historically, the term BCI has been used to designate noninvasive recording methods whereby subjects learn to control their brain activity for manipulation of cursor on a computer display. This required subject training through biofeedback and involved a relatively low bandwidth for effective communication. In contrast, the term BMI was introduced during the last decade to designate new methods for recording and analyzing large-scale brain activity, microchip design, decoding algorithms and robotics. It utilizes the neurally coded intention of movements from premotor and motor cortices to control robotic devices. But nowadays, BMI and BCI research involves largely common issues and the fields are becoming borderless.

Clearly, BMI/BCI research is multidisciplinary in nature, combining basic and computational neurosciences with signal processing, machine learning, robotics, rehabilitation engineering, MEMS and electronic devices. In addition, ethics play an important role in the advancement of this young field. The interest in this field of research has grown tremendously during the last decade. Thus, publishing this special issue to integrate multidisciplinary studies on BMIs is very timely for catalyzing further development in this active field.

The goal of this special issue was to incorporate papers from a broad range of disciplines: invasive and noninvasive BMIs/BCIs, techniques for decoding brain-derived signals, neuroethics and applications of neuro-technology. This seemingly wide thematic spread reflects both the growing field but also a simultaneous specialization and convergence of topics and technical directions.

2. Papers in this special issue

This special issue received 28 submission, among which the guest editors selected 17 articles that cover various aspects of BMI/BCI research, ranging from animal experiments employing multi-channel recordings of neuronal activities to decode the signal for execution of movements and decision, through both invasive and non-invasive recording of brain signals, to ethical issues.

Chase et al. compare algorithms for decoding movement direction from neural population spike activity and demonstrate that the differences in the optimal decoding capabilities obtained with off-line “open-loop” neural decoders are greater than the differences seen when operating in real-time closed-loop mode. The ability to adapt performance under closed-loop conditions is an important factor that must be taken into account.

Most of the previous studies to reconstruct limb movement from the neuronal activities in the premotor and motor cortex of non-human primates aimed at decoding dynamic movement parameters, so controlling posture had been considered difficult. *Choi et al.* divided an artificial neural network into two networks: one for movement control and the other for postural control. Furthermore, they trained a gating network to switch between the two neural networks and tested the accuracy of the estimated joint angles, which resulted in better fitting than that obtained with only one artificial network. *Suminski et al.* show that motor cortex cells have responses to visual and proprioceptive input from passive movement that resemble their activity during active movement, and suggest how these signals may be used to improve BMI performance.

A number of methods have been developed for estimating neural firing rates. *Cunningham et al.* compare the advantages and

drawbacks of these estimators by applying the standard prosthetic decoding algorithms and, interestingly, found minimal differences. Not only the motor BMI, but BMI devices utilizing signals encoding the decision processes have been sought. Hasegawa et al. analyze the neural activity of the superior colliculus, a key node for the control of saccadic eye movements for decoding the binary decision signal therein.

Several theoretical articles concern the handling of brain activities of human subjects.

Gunduz et al. describe methods for decoding hand trajectories from broadband ECoG recordings, and demonstrate the advantages of certain non-linear algorithms.

van Gerven et al. show that covert attention to spatial locations in the visual field can be decoded efficiently with a sparse logistic regression approach with low subject training. Farquhar shows that by first mapping the data to a feature space constructed from frequency-specific detector covariance tensors, a simple linear classifier can directly learn optimal spatial and frequency filters. If the loss function of the classifier is convex, the whole process is a convex minimization problem. This view allows a joint understanding of spatial and temporal filters and classification under one framework. Adaptive classification and handling of missing or erroneous labeling is a key issue in BCI decoding. Yoon et al. propose new algorithms, which might be useful not only for BCIs but also in other application domains to impute sequential missing labels. Sannelli et al. propose a new algorithm based on novel machine learning methods, to remove noise derived from the subjects' failure to produce the required mental state, which is rather common, particularly for naïve subjects. Fazli et al. introduce ensembles of classifiers derived from a large database of subject-specific training data acquired during many calibration sessions. Then they generalize it reliably to the data of subjects not included in the ensemble, which will enable naïve users to start real-time BCI without any prior calibration. Vidaurre et al. introduce a new feature called Time Domain Parameters for the EEG-based BCI, which is defined by the generalization of the so-called Hjorth parameters. They report a comparison of their new features with the most commonly used logarithmic band-power estimates and suggest their advantages.

Besides the EEG- or MEG-based BCIs, noninvasive methods such as functional near-infrared spectroscopy (NIRS) and functional magnetic resonance imaging (fMRI) can acquire hemodynamic signals from the brain. Sitaram et al. review the principles, recent developments, application and future directions of NIRS- and fMRI-based BCIs.

Based on the decoding algorithms including relative conventional ones such as support vector machines, some actual examples of BCI instruments are also introduced.

Finke et al. present a BCI game, based on the P300 event-related potential. In their MindGame interface, P300 events are translated into movements of a character on a three-dimensional game board.

DaSalla et al. propose their newly developed speech prosthesis by which they read out on a single-trial basis the imagined speech of English vowels with EEG.

Song et al. describe a non-linear dynamic model for neural processing in hippocampus. It converts the population spiking activity at the inputs to multiple output stimulation patterns and has promise for application to neural prostheses.

In addition to the above scientific papers we have included an article on ethical issues of BMIs/BCIs. Haselager et al. discuss the difficulties involved in acquiring informed consent from locked-in patients and related issues such as communication with media.

In summary, the papers in the present special issue contribute to a range of significant advances in the fields of BCIs and BMIs.

Tadashi Isa, Professor*

Department of Developmental Physiology, National Institute for Physiological Sciences, Myodaiji, Okazaki 444-8585, Japan
E-mail address: tisa@nips.ac.jp.

Eberhard E. Fetz, Professor

Department of Physiology & Biophysics, University of Washington, Seattle, WA 98195-7290, USA
E-mail address: fetz@u.washington.edu.

Klaus-Robert Müller, Professor

Berlin Institute of Technology, Faculty IV – Institute for Software Engineering, and Theoretical Computer Science, Franklinstreet 28/29, 10587 Berlin, Germany
E-mail address: klaus-robot.mueller@tu-berlin.de.

* Corresponding editor. Tel.: +81 564 55 7761; fax: +81 564 55 7766.

Papers in this issue

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

Choi, K., Hirose, H., Sakurai, Y., Iijima, T., & Koike, Y. (2009) Prediction of arm trajectory from the neural activities of the primary motor cortex with modular connectionist architecture. *Neural Networks*, 22(9), 1214–1223.

Suminski, A. J., Tkach, D. C., & Hatsopoulos, N. G. (2009) Exploiting multiple sensory modalities in brain-machine interfaces. *Neural Networks*, 22(9), 1224–1234.

Cunningham, J. P., Gilja, V., Ryu, S. I., & Shenoy, K. V. (2009) Methods for Estimating Neural Firing Rates, and Their Application to Brain-Machine Interfaces. *Neural Networks*, 22(9), 1235–1246.

Hasegawa, R. P., Hasegawa, Y. T., & Segraves, M. A. (2009) Neural Mind Reading of Multi-dimensional Decisions by Monkey Mid-Brain Activity. *Neural Networks*, 22(9), 1247–1256.

Gunduz, A., Sanchez, J. C., Carney, P. R., & Principe, J. C. (2009) Mapping broadband electrocorticographic recordings to two-dimensional hand trajectories in humans. *Neural Networks*, 22(9), 1257–1270.

van Gerven, M., Bahramisharif, A., Heskes, T., & Jensen, O. (2009) Selecting Features for BCI Control based on a Covert Spatial Attention Paradigm. *Neural Networks*, 22(9), 1271–1277.

Farquhar, J. (2009) A linear feature space for simultaneous learning of spatio-spectral filters in BCI. *Neural Networks*, 22(9), 1278–1285.

Yoon, J. W., Roberts, S. J., Dyson, M., & Gan, J. Q. (2009) Adaptive classification for Brain Computer Interface systems using Sequential Monte Carlo sampling. *Neural Networks*, 22(9), 1286–1294.

Sannelli, C., Braun, M., & Müller, K.-R. (2009) Improving BCI Performance by Task-Related Trial Pruning. *Neural Networks*, 22(9), 1295–1304.

Fazli, S., Popescu, F., Danózy, M., Blankertz, B., Müller, K.-R., & Grozea, C. (2009) Subject independent mental state classification in single trials. *Neural Networks*, 22(9), 1305–1312.

Vidaurre, C., Krämer, N., Blankertz, B., & Schlögl, A. (2009) Time Domain Parameters as a feature for EEG-Based Brain Computer Interfaces. *Neural Networks*, 22(9), 1313–1319.

Sitaram, R., Caria, A., & Birbaumer, N. (2009) Hemodynamic Brain-Computer Interfaces for Communication and Rehabilitation. *Neural Networks*, 22(9), 1320–1328.

Finke, A., Lenhardt, A., & Ritter, H. (2009) The MindGame: A P300-Based Brain-Computer Interface Game. *Neural Networks*, 22(9), 1329–1333.

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

Song, D., Chan, R. H. M., Marmarelis, V. Z., Hampson, R. E., Deadwyler, S. A., & Berger, T. W. (2009) Nonlinear Modeling of Neural Population Dynamics for Hippocampal Prostheses. *Neural Networks*, 22(9), 1340–1351.

Haselager, P., Vlek, R., Hill, J., & Nijboer, F. (2009) A note on ethical aspects of BCI. *Neural Networks*, 22(9), 1352–1357.