A Collaborative Brain-Computer Interface

Yijun Wang, Yu-Te Wang, Tzyy-Ping Jung*
Swartz Center for Computational Neuroscience
University of California San Diego
San Diego, USA

Xiaorong Gao, Shangkai Gao
Dept. Biomedical Engineering, School of Medicine
Tsinghua University
Beijing, China

***Abstract*—Electroencephalogram (EEG) based brain-computer interfaces (BCI) have been studied for several decades since the 1970s. Current BCI research mainly aims to provide a new communication channel to patients with motor disabilities to improve their quality of life. The BCI technology can also benefit normal healthy users; however, little progress has been made in real-world practices due to low BCI performance caused by technical limits of EEG. To overcome this bottleneck, this study uses a collaborative BCI to improve overall performance through integrating information from multiple users. A dataset involving 15 subjects participating in a Go/NoGo decision-making experiment was used to evaluate the collaborative method. Using collaborative computing techniques, the classification accuracy for predicting a Go/NoGo decision was enhanced substantially from 75.8% to 91.4%, 97.6%, and 99.1% as the number of subjects increased from 1 to 5, 10, and 15, respectively. These results suggest that a collaborative BCI can effectively fuse brain activities of a group of people to improve human behavior.**

Keywords-Brain-computer interface (BCI); collaborative computing; Electroencephalogram (EEG); human performance; Go/NoGo decision making

I. INTRODUCTION

The human brain is the most complex system in the world. The functional brain imaging technologies such as functional magnetic resonance imaging (fMRI) and Electroencephalogram (EEG) give us an opportunity to observe brain activities related to thoughts, emotions, and behavior, and therefore, help us understand the relationship between the brain and behavior. Recently, a new technology known as brain-computer interface (BCI) or brain-machine interface (BMI) has made a significant progress in brain science [1]. The BCI study covers the three aspects in exploring the human brain: understanding the brain, protecting the brain, and creating the brain. During the past two decades, the BCI technology has become a hot research topic in the areas of neuroscience, neural engineering, medicine, and rehabilitation [2][3].

In essence, a BCI is a communication channel that bypasses the traditional pathway of peripheral nerves and muscles, and creates a direct link between the human brain and an output device [1]. Currently, the main focus of BCI research lies in the clinical use which aims to provide a new communication channel to patients with motor disabilities to improve their quality of life. In current BCI systems, commonly used neural recording technologies include EEG, Magnetoencephalogram (MEG), Electrocorticogram (ECoG), fMRI, near infrared spectroscopy (NIRS), and neuronal recording. Among these methods, EEG is the most widely used modality in current BCI studies due to its advantages such as simple and inexpensive equipment, flexibility and mobility, and short time constants. In present-day BCIs, the following EEG signals have been paid much attention: visual evoked potential (VEP), sensorimotor mu/beta rhythms, P300 evoked potential, slow cortical potential (SCP), and movement-related cortical potential (MRCP) [1].

Although the EEG-based BCI technology has achieved great successes, moving a BCI system from a laboratory demonstration to a real-life application still poses severe challenges to the BCI community. Applications of the BCI technology are very limited due to bottleneck problems including high system cost, low communication speed, low recognition accuracy, and easy user fatigue [4]. To overcome these problems, a practical solution is to develop a multi-user collaborative BCI system, which can utilize collective intelligence from a group of users. Recently, we first proposed the framework for a collaborative BCI system and further investigated the feasibility and practicality of the system [5]. The development of group-synchronized neural recording systems and group collaborative cognitive computing methods will open a totally new direction for BCI research.

In this study, we propose to study the feasibility of using a collaborative BCI system to improve human decision making in a Go/NoGo decision-making task. In the Go/NoGo task, the N2 event-related potential (ERP) component, which reflects the processing of motor inhibition, will be used as a feature for identifying the NoGo condition. To evaluate the performance of the collaborative BCI, EEG-based prediction of a Go/NoGo decision will be executed using a single-trial classification paradigm and a collaborative classification paradigm respectively.

II. METHODS

A. System diagram

Figure 1 shows the system diagram of a collaborative BCI. Similar to a single-user BCI, a collaborative BCI consists of three major parts: a data acquisition module, a signal processing module, and a command translation module. Consequently, there are three major procedures in system operations:

1) Brain signals from a group of users are acquired by multiple EEG recording devices, and then are synchronized with common environmental events.

2) Integrated EEG and event data are processed for extracting features for decoding users' intentions.

3) Extracted features from a group of users are directly translated to operation commands, which can also be used to give sensory feedback to the users.

Compared to a single-user BCI, the complexity of system input from multiple users will lead to technical challenges in both data recording and signal-processing procedures. For example, new algorithms for implementing collaborative computing have to be developed to perform the procedure of collaborative EEG analysis, which plays the most important role in the data processing module.

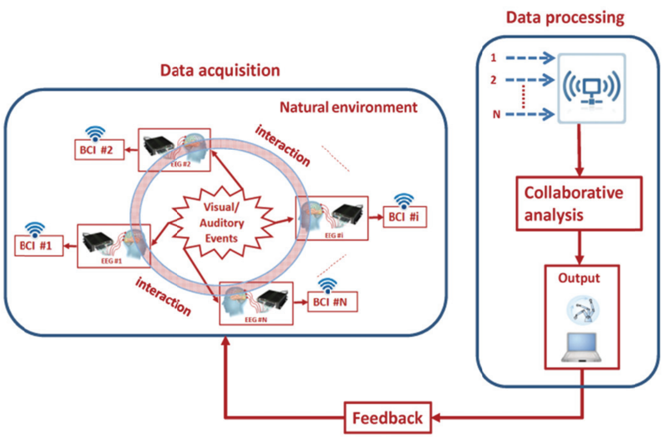

Figure 1. System diagram of a collaborative BCI.

B. System implementation

The implementation of a collaborative BCI has posed several specific requirements for hardware and software designs:

1) Multiple EEG recording systems need to work independently and simultaneously.

2) Multiple-subject data need to be received and synchronized with respect to the common environmental events.

3) Multiple-subject data recording and data processing procedures have to be performed in real time.

Ideally, the system can be implemented using a centralized paradigm similar to a conventional BCI (Figure 2(a)). In this paradigm, EEG data from multiple subjects are received and recorded, then thrown into a conventional BCI module for signal processing and command translation using a data server. A centralized paradigm is optimal for designing a collaborative BCI system; however, practicality of system implementation may be limited for the following reasons:

1) *Data transmission:* When wired EEG systems are used, all systems need to be connected to the data server for data sending/receiving in real time. Therefore, the data sever requires high capacities of data communication, memory, and storage. Because users' natural behaviors such as standing and walking are always limited when using wired EEG systems, portable and mobile EEG recording devices are more preferable in natural environments. Then, a data server requires a low-latency, high bandwidth, and reliable wireless infrastructure, which might be very costly.

2) *Computational cost:* Advanced signal processing and machine learning techniques have been widely used in current BCI studies [6] [7]. These approaches always require large amount of computational resources. In a collaborative BCI where a large amount of subjects are involved, the computational cost will significantly increase. Because real-time data processing in a collaborative BCI will lead to a large amount of computation, the data server has to be equipped with high-performance CPUs and large amounts of memory.

3) *System robustness:* A collaborative BCI system inevitably consists of multiple EEG recording and processing devices. To assure the stability of the system, the software should have the ability to keep the whole system working even when subsets of the whole system fail (e.g., data connection loss). In other words, the overall system performance should not be seriously affected by the failure of a subsystem or subsystems.

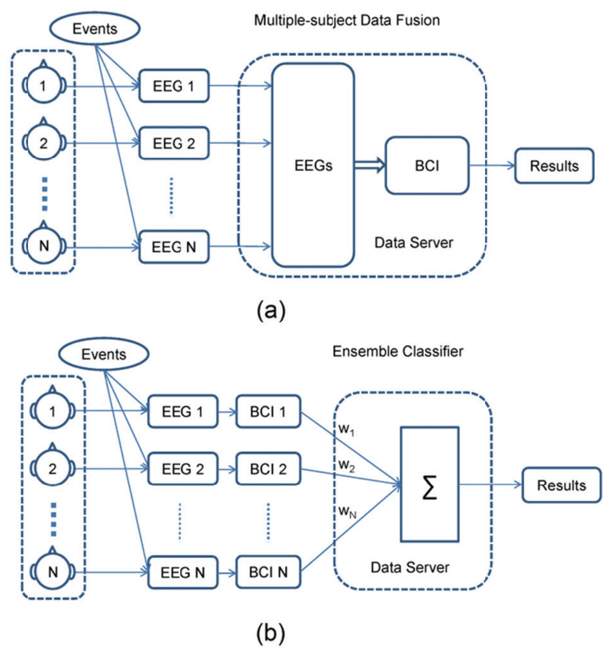

Figure 2. (a) A centralized paradigm and (b) a distributed paradigm for a collaborative BCI.

To solve the problems existing in the centralized paradigm, this study proposes a distributed paradigm to facilitate the implementation of a collaborative BCI. As shown in Figure 2(b), the whole system consists of multiple distributed BCI subsystems and a simplified data server. For each subject, a BCI subsystem works independently, each subsystem has its capability in EEG data acquisition and processing. In this paradigm, the amount of data transmitted between subsystems and the data server, as well as the computational cost for data processing, are significantly reduced. The single-user BCI has been well studied in previous studies. Therefore this distributed paradigm is a more practical solution for implementing a collaborative BCI. The only disadvantage of the distributed paradigm is that the overall costs of the system hardware might increase due to the employment of a data-processing platform for each user. In practice, portable data-processing platforms can be integrated into the EEG recording device to reduce the system cost, and improve system practicality as well [8].

C. Go/NoGo decision-making experiment

Following a Go/NoGo paradigm, 15 human subjects performed in alternation an "animal" categorization task and a single-photograph recognition task. Details of the experimental setup and the images used in the experiment can be found in [9]. During the experiment, target (Go) photographs were randomly mixed with non-target (NoGo) images and flashed for 20 ms on a computer screen. For each target, subjects had to lift their finger from the button as quickly and accurately as possible. When non-target images appeared, subjects had to withhold their button press. For each subject, 32-channel EEG data of 10 blocks (100 trials each), were recorded together with stimulus/response related event codes at a 1000 Hz sampling rate and downsampled to 200 Hz for offline analysis, totally resulting in 500 trials per condition.

D. Single-trial EEG classification

This study performed a single-trial EEG classification on each subject using a standard machine-learning paradigm. First, independent component analysis (ICA) was employed to remove eye-movement and muscle artifacts [10]. Second, ERP segments in a predefined time window were extracted after removing the ERP baseline calculated within [-100 ms - 0 ms]. Third, the intercepted ERPs from all 32 electrodes were concatenated, and then inputted to a support vector machine (SVM)-based classifier to predict the Go/NoGo decision. For each subject, a 10x10-fold cross validation was used to estimate the classification performance.

E. Collaborative classification

Using the distributed system paradigm (Figure 2(b)), the collaborative data analysis was performed with an ensemble classifier [11], which consists of multiple sub-classifiers and a voting system. In the case of a binary classification where two classes are labeled as +1 and -1 respectively, the procedure for a weighted voting can be described as follows:

$$\mu = \operatorname{sign}\left(\sum_{i=1}^{m} w(i)y(i)\right) \tag{1}$$

where m is the number of subjects, $w(\mathrm{i})$ is the subject specific weight and $y(\mathrm{i})$ is the output of a sub-classifier. An SVM classifier was trained as a sub-classifier for each subject, and the training accuracy was used as the voting weight.

III. RESULTS

A. Event-related potentials

As shown in Figure 3, during 180 ms - 250 ms after an image onset, the N2 ERP component, which located over the medial frontal cortex (MFC), showed a significant difference between the Go and NoGo conditions (paired t-test, $p<10^{-5}$, at the Fz electrode). Compared to the Go trials, the NoGo trials showed a larger N2 component (-9.8 uV vs. -4.5 uV), which might reflect the motor inhibition process. A subsequent P3 component also largely differed under two conditions over the medial frontal and parietal areas. The distinct spatio-temporal patterns of N2 and P3 components under the Go and NoGo conditions provide the basis for predicting a Go/NoGo decision using EEG [12].

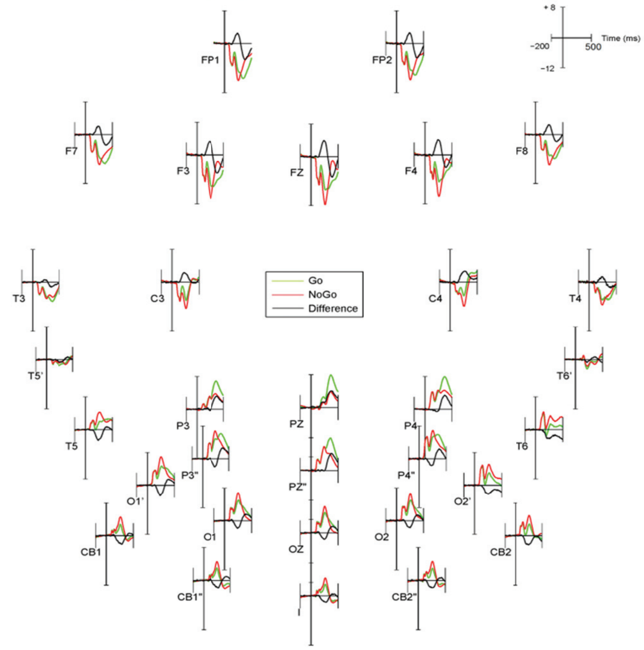

Figure 3. Scalp ERP wave forms and difference waves under Go and NoGo conditions at all electrode positions.

B. Single-trial classification

The single-trial EEG classification achieved accuracy significantly higher than the chance level (50%) using data prior to mean response time (RT) of the Go trials across all subjects (377±48 ms). Figure 4 shows the accuracy for all subjects when using the time window of [0 RT] (mean±std: 75.8±6.7%, range: 64.4% - 85.2%). Consistent with the time courses of the N2 and P3 components, the prediction accuracy was enhanced from 61.2±4.1% to 68.1±4.3%, 70.9±4.5%, and 74.4±6.3% as the length of time window increased from 200 ms to 250 ms, 300 ms, and 350 ms, respectively. These results suggested that a Go/NoGo decision can be reliably predicted by single-trial EEG classification.

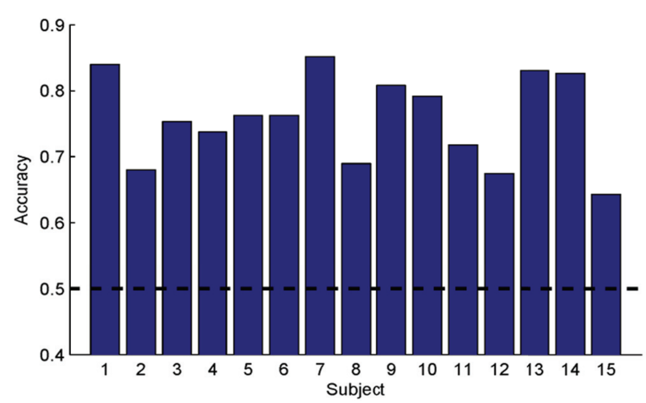

Figure 4. Accuracy of single-trial EEG classification for all subjects. The dash line indicates the chance level (50%).

C. Collaborative classification

Figure 5 shows the classification accuracy as a function of the length of time windows used for data analysis. Results for 1, 5, 10, and 15 subjects were put together to show the interaction between the number of subjects and the prediction time. Using the time window of [0 RT], the classification accuracy for predicting a Go/NoGo decision was enhanced substantially from 75.8% to 91.4%, 97.6%, and 99.1% as the number of subjects increased from 1 to 5, 10, and 15, respectively. The results also clearly showed that the acceleration of decision-making depended on both the desired accuracy and the number of subjects involved in the collaborative system. As shown in Figure 5, when all 15 subjects were included, the Go/NoGo decision could be made around 200 ms after the stimulus onset, which was more than 150 ms earlier than the subject's actual motor response, by decoding the group ERP activities arising mainly from the medial frontal cortex, which are related to the processing of motor inhibition.

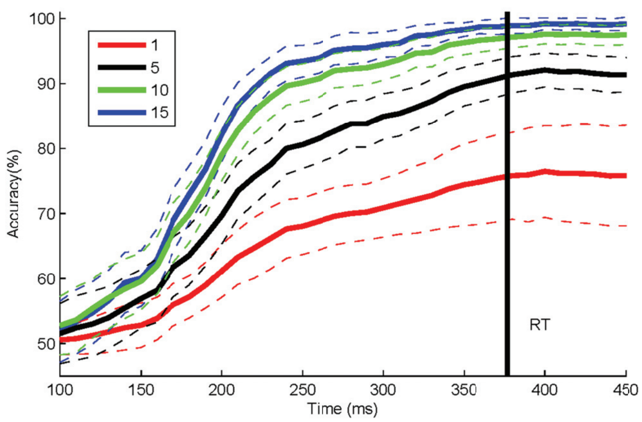

Figure 5. Classification accuracy of different numbers of subjects as a function of the window length. The vertical line indicates the mean response time (RT) across all subjects (377 ms). The dash lines indicate mean accuracy ± standard deviation.

IV. Conclusion and Discussions

This study demonstrated an application of the collaborative BCI to accelerate decision-making in a Go/NoGo task. The classification accuracy of the system showed a significant improvement over that of the single-user BCI. Furthermore, the collaborative BCI allowed the subject's decision to be made much earlier than his/her actual motor response. In summary, this study designed and demonstrated the use of the collaborative BCI technology to improve human performance.

The prototype system demonstrated in the current study can be directly transferred to an online system if the hardware and software requirements can be met. Currently, there are several challenges that have to be resolved before an online collaborative BCI system can become a reality. First, a collaborative BCI needs multiple BCI platforms, which consist of an EEG recording system and a real-time signal-processing platform. Because commercial EEG products used for EEG research are still expensive, the total cost for building a collaborative BCI will be high. Second, a collaborative system requires specific software development, which allows seamless communication between EEG systems and signal-processing platforms, and between the BCI subsystems and the data server. Furthermore, data processing in BCI subsystems and the data server has to be implemented in (near) real time. With advances in biomedical electronics and telecommunication technology, it will soon be possible to implement an online collaborative BCI system.

Acknowledgment

This work is supported by a gift fund from Abraxis Bioscience Inc. Research was also sponsored in part by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-10-2-0022. The views and the conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S Government. The U.S Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

The authors would like to thank A. Delorme for providing the EEG data.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, T. M. Vaughan, "Brain-computer interfaces for communication and control," Clin. Neurophysiol., vol. 113, pp. 767-791, 2002.

[2] M. A. Lebedev, M. A. L. Nicolelis, "Brain-machine interfaces: past, present and future," Trends Neurosci., vol. 29, pp. 536-546, 2006.

[3] N. Birbaumer, "Brain-computer-interface research: Coming of age," Clin. Neurophysiol., vol. 117, pp. 479-483, 2006.

[4] Y. Wang, X. Gao, B. Hong, C. Jia, S. Gao, "Brain-computer interfaces based on visual evoked potentials: feasibility of practical system designs," IEEE EMB. Mag., vol. 27, pp. 64-71, 2008.

[5] Y. Wang, T. P. Jung, "A collaborative brain-computer interface for improving human performance," PLoS ONE, vol. 6, no. 5, e20422, doi:10.1371/journal.pone.0020422, 2011.

[6] D. J. McFarland, C. W. Anderson, K. R. Muller, A. Schlogl, D. J. Krusienski, "BCI Meeting 2005 - Workshop on BCI signal processing: Feature extraction and translation," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 14, pp. 135-138, 2005.

[7] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche, B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," J. Neural Eng., vol. 4, pp. R1-R13, 2007.

[8] Y. T. Wang, Y. Wang, T. P. Jung, "A cell-phone based brain-computer interface for communication in daily life," J. Neural Eng., vol. 8, 025018, 2011.

[9] A. Delorme, G. Rousselet, M. Mace, M. Fabre-Thorpe, "Interaction of Bottom-up and Top-down processing in the fast visual analysis of natural scenes," Cog. Brain Res., vol. 19, no. 2, pp. 103-113, 2004.

[10] A. Delorme, S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," J. Neurosci. Meth., vol. 134, pp. 9-21, 2004.

[11] Duda RO, Hart PE, Stork DG, Pattern Classification (2nd Edition). New York: Wiley Interscience Press, 2000.

[12] K. Yamanaka, Y. Yamamoto, "Single-trial EEG Power and Phase Dynamics Associated with Voluntary Response Inhibition," J. Cog. Neurosci. vol. 22, no. 4, pp. 714-727, 2010.