Volume : 4 | Issue : 12 | December 2015 • ISSN No 2277 - 8179

Research Paper

Engineering

KEYWORDS : BCI,MULTIPLE USER BCI,COLLABORATIVE BCI, NEURAL BRIDGE,NEURAL LOAD IN COLLABORATIVE BCI.

Multiple Connection Neural Bridge in a Brain-Computer/Machine Interface

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ABSTRACT

Electroencephalogram (EEG) based brain-computer interfaces (BCI) have been studied since the 1970s. Currently, the main focus of BCI research lies on the clinical use, which aims to provide a new communication channel to patients with motor disabilities to improve their quality of life. However, the BCI technology can also be used to improve human performance for normal healthy users. Although this application has been proposed for a long time, little progress has been made in real-world practices due to technical limits of EEG. To overcome the bottleneck of low single-user BCI performance, this study proposes a collaborative paradigm to improve overall BCI performance by integrating information from multiple users. To test the feasibility of a collaborative BCI, this study quantitatively compares the classification accuracies of collaborative and single-user BCI applied to the EEG data collected from 20 subjects in a movement-planning experiment. This study also explores three different methods for fusing and analyzing EEG data from multiple subjects: (1) Event-related potentials (ERP) averaging, (2) Feature concatenating, and (3) Voting. In a demonstration system using the Voting method, the classification accuracy of predicting movement directions (reaching left vs. reaching right) was enhanced substantially from 66% to 80%, 88%, 93%, and 95% as the numbers of subjects increased from 1 to 5, 10, 15, and 20, respectively. Furthermore, the decision of reaching direction could be made around 100–250 ms earlier than the subject's actual motor response by decoding the ERP activities arising mainly from the posterior parietal cortex (PPC), which are related to the processing of visuomotor transmission. Taken together, these results suggest that a collaborative BCI can effectively fuse brain activities of a group of people to improve the overall performance of natural human behavior.

INTRODUCTION:

Brain–computer interfaces (BCI) are systems that mediate signaling between the brain and various technological devices. The first demonstrations of BCI in humans and animals took place in the 1960s. IT was demonstrated in 1964 that use of non-invasively recorded encephalogram (EEG) signals from a human subject could control a slide projector [Graimann , 2010]. Shortly thereafter it was shown that, by providing food reward to awake, non-human primates along with auditory or visual feedback on the firing rates of neurons in the motor cortex, these neurons could be errantly conditioned to increase their firing rates by 50–500% [Fetz, 1969]. Following the initial demonstrations, the field of BCI has expanded significantly, encompassing both invasive and non-invasive neural recordings in humans and animals, spanning a range of sensorimotor and cognitive functions, and incorporating novel feedback mechanisms in closed-loop systems.

The primary application of BCI is to provide a mechanism for movement or communication by patients who are unable to move or communicate through normal methods. Such methods have included the translation of recorded neural signals associated with sensory mechanisms into navigation or selection commands, enabling the patient to move through a virtual or real environment[Thurlings , 2010]. Other approaches have included decoding of neural signals directly associated with the intention to move [Collinger ,2003]. In addition to these approaches, BCI has been utilized to provide neural-feedback to users, enabling them to regulate neural and behavioral functions normally not under volitional control. Such functions include attention, pain, emotion, and memory [Birbaumer, 2009].

MATERIALS AND METHODS

A collaborative BCI and a conventional BCI differ in many aspects. A conventional BCI mainly aims to help the individual with motor disability to communicate with the environment, whereas a collaborative BCI is specifically designed for improving human interaction and performance of a healthy user. The rudimentary design and operation of a collaborative BCI is shown in the figure below. Similar to a conventional BCI , a collaborative BCI consists of three major parts:

1) A data-recording module
2) A signal processing module
3) A command translation module.

Following this there are three main procedures in the system:

1) Brain signals from a group of individuals are recorded by more than one(multiple)EEGs and then are synchronized with common environmental events.
2) Integrated EEG and event data are then processed for decoding the features for user's intentions.
3) Extracted signals are directly translated to operating commands, which then can also be used to trigger sensory feedbacks to the users. Compared to a single-subject BCI, the complexity of system input from multiple users might lead to technical challenges in both data recording and signal processing parts

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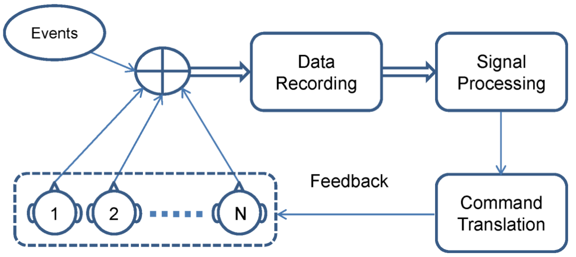


For proper functioning of a collaborative BCI, there are certain specific requirements for hardware and softwares that should be employed for multiple users.

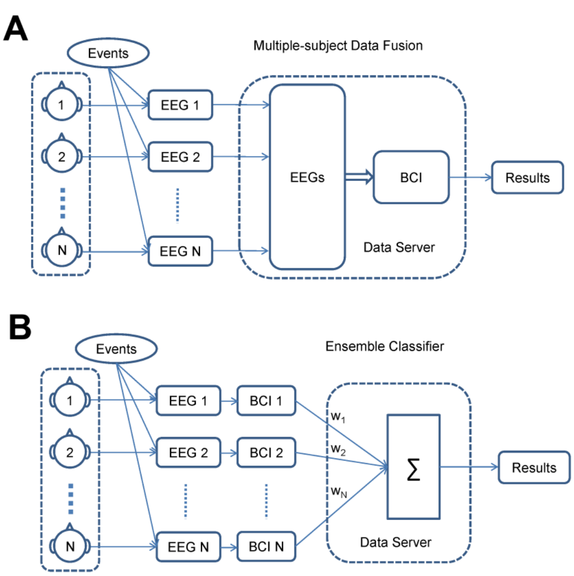
A) Multiple EEG recording systems have to work completely independent of each other and be simultaneous.
B) Multiple user data has to be received and synchronized with respect to the common environmental events.
C) Multiple subject data recording and data processing methods have to be performed in the vicinity of real time. Ideally speaking the system can be implemented using a centralized paradigm similar to a conventional BCI . In the so called paradigm, EEG data from multiple subjects are received and recorded, then thrown into a conventional BCI block 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 by heavy loads of data transmission and high computational costs caused by advanced signal processing and machine learning techniques as well as low hardware/software robustness due to the involvement of multiple BCI subsystems.

Volume : 4 | Issue : 12 | December 2015 • ISSN No 2277 - 8179

REMEDY

To find a solution to these problems associated with the centralized paradigm it is proposed that a distributed paradigm might help us facilitate the implementation of a collaborative BCI. Shown in second is the entire system consisting of multiple distributed BCI subsystems and a simplified data server. For each subject, a BCI subsystem works completely in an independent fashion and each subsystem has its own capability in EEG data acquisition and processing. In this paradigm, the volume of data transmitted between subsystems and the data server, as well as the computational cost for data processing, are significantly reduced. Because the data server only functions as an ensemble classifier for integrating all the classification results sent by the subsystems, the system robustness can also be improved. Therefore this distributed paradigm is a more practical solution for implementing a collaborative BCI.

The ONLY disadvantage of the distributed paradigm system is that costs of subsystem hardware might increase due to the employment of a data processing platform for each subject. In practical use, portable data processing platforms such as a digital signal processor (DSP) platform can be integrated into the EEG recording device to reduce the overall system cost, and improve system practicality. A collaborative BCI using the distributed regime can be considered a distributed computing system, in which each BCI subsystem solves the classification task independently in order to achieve a common goal.



BCI EXPERIMENT

This BCI study adopted a motor action paradigm. In the experiment, a visually guided reaching or gazing was employed as a motor response task. For the purpose of improving human performance, brain activities in the PPC, which occurred before actual motor response, were extracted for predicting the directions of upcoming movements. As shown in figure, the response time (RT) of a cue-guided reaching movement consists of five stages:

A) Target identification
B) Visual-motor transmission
C) Motor planning
D) Motor execution
E) Motor control.

These processes occur sequentially in the visual cortex, the PPC, the premotor cortex, the primary motor cortex, and the nerve-muscle pathways. Through directly extracting embedded information from the PPC and bypassing the motor related procedures, this BCI system could accelerate a motor response by using an artificial limb.

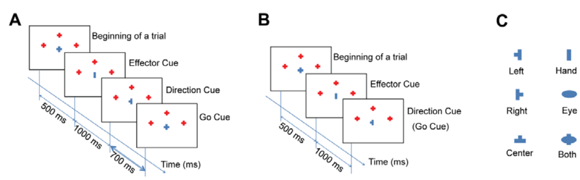
Subjects:

An EEG and a behavior experiments were run separately on two groups of subjects. Twenty right-handed participants (12 males and 8 females, mean age 25 years) with normal or corrected-to-normal vision participated in the EEG experiment. Another group of 18 subjects participated in the behavior experiment (12 males and 6 females, mean age 23 years).

Stimuli and procedure:

A delayed saccade-or-reach task was used in the EEG study, allowing us to look for direction information in the EEG during the phase of movement planning. The experiment was comprised of nine conditions differing by movement types (saccade to target, reach without eye movement, or visually guided reach) and movement directions (left, center, or right). Each task was indicated to the subject by, first, giving an effector cue telling the type of action to be performed, followed by a direction cue and, finally, by an imperative action cue. Subjects were seated comfortably in an armchair at a distance of 40 cm from a 19-inch touch screen. A chin rest was used to help them maintain head position.

Subjects used their right hands to perform the reaching tasks. At the beginning of each trial, the subject's forearm rested on the table with an index finger holding down a key on a keypad placed 30 cm in front of screen center. The sequence of visual cues in each trial is shown . At the beginning of a trial, a fixation cross (0.65°×0.65°) was displayed at the center of the screen plus three red crosses (0.65°×0.65°) indicating potential target positions. The left and right targets had a vertical distance of 6° and a horizontal distance of 15° from the central fixation cross; the central target was 12° upwards. After 500 ms, an effector cue (0.5°×0.5°, rectangle, ellipse indicating hand and eye movements respectively appeared at the screen center for 1000 ms. Next, a central direction cue (0.65°×0.65°, , , for left, center, and right respectively) was presented for 700 ms. Subjects were asked to maintain fixation on the central cue until they started their responses, to perform the indicated response as quickly as possible following the disappearance of the direction cue (and reappearance of the fixation cross), and finally to return to their initial (key-down) position. There was a 400–600 ms interval for rest before the next trial started. Total trial duration amounted to 3500–4000 ms.



Data Recording:

In the EEG experiments, EEG data were recorded using Ag/AgCl electrodes from 128 scalp positions distributed over the entire scalp using a BioSemi ActiveTwo EEG system [Biosemi, Inc.]referenced to the CMS-DRL ground. Eye movements were monitored by additional bipolar horizontal and vertical EOG electrodes. All signals were amplified and digitized at a sample rate of 256 Hz. Three cue presentation events and two manual response events ("button release" and "screen touch") were recorded on an event channel synchronized to the EEG data by DataRiver software [A. Vankov]. EEG and behavioral data were recorded from 20 subjects on different days using the exactly same target presentation sequences. Some practice blocks were run before starting the EEG recording. For each subject, the experiment consisted of four blocks (with breaks in between) each including five runs of 45 trials. Within each block, there was a 20-second rest between runs. A total of 900 trials were equally distributed between the nine tasks, which were presented to the subject in a pseudorandom sequence.

In the behavior experiment, only the events were recorded for obtaining the actual RT for a reaching response. For each subject, the experiment consisted of three blocks with a total of 675 trials equally distributed among the nine tasks.

Data pre-processing.

This study focused on the estimations of planned direction of movement. For simplicity, we only used "left" and "right" conditions for "hand" tasks for further analysis. The same analysis could be applied to data under "eye" and "both" conditions. Epochs from the response delay period, 0 to 700 ms following the onsets of direction cues, were extracted from the continuous data, and labeled by movement directions. The period [−100 ms 0 ms] was used as the baseline for each trial. Electrodes with poor skin contact were identified by their abnormal activity patterns and then removed from the data.

We used independent component analysis (ICA) as an unsupervised spatial filtering technique to remove artifacts arising from eye and muscle movements. For each subject, all trials were band-pass filtered (1–30 Hz), concatenated, and then decomposed using the EEGLAB toolbox[30]. To retain the low-frequency EEG activities, ICA weights of the decomposition were applied to original unfiltered data before artifact removal. To extract the direction-specific activity of the ERPs, we compared the spatiotemporal patterns of EEG corresponding to different movement directions. As shown in figure, we found a hemispheric asymmetry over the parietal cortex during the delay period (0–700 ms) in which motor planning can be presumed to have continued until the cued movement onset (appeared after 700 ms). Two lateral electrodes representing PPC activities showed a significant contralateral negativity and ipsilateral positivity with respect to the intended movement direction . Across all subjects, difference waves between reaching left and reaching right conditions showed two peaks located at 210 ms and 320 ms after the direction cue. ERP scalp maps of two conditions and their difference at these two selected frames were illustrated

Collaborative BCI data analysis:

For each subject, classification of "left" versus "right" trials was performed using a standard machine-learning paradigm. For a collaborative classification based on data from multiple subjects, we propose three approaches to fuse the informationfrom multiple subjects:

(1) ERP averaging across subjects
(2) feature combination (e.g., concatenating features from multiple subjects)
(3) voting using an ensemble classifier. All these approaches can be implemented in the centralized paradigm, but for the distributed paradigm, only the voting approach is practical because data from each subject are processed separately in each of the BCI subsystems.

ERP AVERAGING

A widely used method for analyzing ERP has been to average EEG measurements over an ensemble of trials within a subject or across subjects . Ensemble averaging can enhance the SNR of ERP given a linear mixing model:

$$EEG(t) = ERP(t) + Noise(t)$$

where *ERP*(*t*) is a constant signal (i.e., the evoked brain response) and *Noise*(*t*) is a random signal with zero mean (i.e., the background EEG activity) in different trials. In a collaborative BCI system, multiple trials can be obtained through collecting single-trial data from multiple subjects.

Therefore, the ensemble averaging method can be implemented across subjects

$$\overline{EEG}(t) = \frac{1}{m}\sum_{i=1}^{m}\left(ERP(t,i) + Noise(t,i)\right)$$

where *i* is subject index and *m* is the total number of subjects.

FEATURE COMBINATION

According to ERP studies, the model in equation (2) is not true when considering a more complicated ERP model, which involves multiple components :

$$EEG(t,i) = \sum_{k=1}^{n} A(k,i) \times ERP(t-\tau(k,i),k) + Noise(t,i)$$

where ERP is assumed to consist of n components, with independent amplitude modulation indicated by $A(k,i)$ and latency jitter indicated by $\tau(k,i)$. Under this circumstance, ensemble averaging might lose information due to individual differences among subjects. For example, latency jitter might cancel out ERP signals when two adjacent components have different polarities. Therefore, to maintain intact information from all the subjects, the feature combination method might be more suitable for a collaborative system.

In the machine learning theory, feature combination can improve overall classification accuracy due to independence between features. Recently, following the wide employment of machine learning techniques in BCI studies, feature combination methods have been introduced in EEG classification [5], [27]. For simplicity, we use a feature concatenating method, which is easy to implement

$$EEG_s(t) = \left[\, EEG(t,1) \quad EEG(t,2) \quad \cdots \quad EEG(t,m) \,\right]$$

where the combined feature vector is a concatenation of feature vectors from *m* subjects.

Theoretically, feature combination is optimal for a collaborative BCI. However, considering the fact of a BCI system that training data is always limited and feature combination will significantly increase the dimensionality of feature space, the feature combination method might encounter an overfitting problem. For example, the dimension of features from a single subject is 50 in equation (1) when using the time window of [0 ms 500 ms], which will be increased to 1000 for 20 subjects. However, the number of the training samples remains the same as in the single subject condition (100 trials per condition). Therefore, the performance gain of feature combination will be weakened due to a small training-set size.

VOTING

Ensemble classifiers have been widely used in the area of machine learning . An ensemble classifier consists of multiple subclassifiers 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:

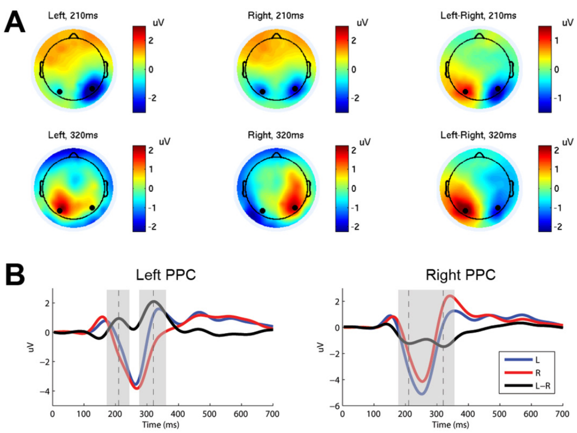
$$\mu = \text{sign}\left(\sum_{i=1}^{m} w(i)y(i)\right)$$

where *w, i.* is the subject specific weight and *y, i.* is the output of a sub-classifier. In our study, an SVM classifier was trained as a sub-classifier for each subject, and the training accuracy was used as the voting weight.

As mentioned before, the voting method is the only solution for a collaborative BCI using the distributed paradigm. Ideally, if there is no interaction between subjects, the voting method is supposed not to lose useful information for classification.

RESULTS

It is shown in the fugure the accuracy of single-trial classification for all 20 subjects using a single-subject classification paradigm. The classification accuracy increased in accordance to the increase of the time window length used for feature extraction. With window length shorter than 150 ms, the average accuracy was around the chance level (mean±standard deviation: 51.1±5.9%). After 150 ms, the accuracy increased gradually and reached 67.0±7.5% at 500 ms. The tendency of performance improvement is consistent with the differences in time courses of ERP waves between left and right conditions, which reflect temporal dynamics of the PPC activities during directional movement planning. There was a large individual variability in single-trial classification accuracy: <60% in four subjects, 60–70% in 10 subjects, and >70% in six subjects. These results indicate that EEG activities near the PPC can provide useful information for predicting the intended movement direction. Although single-trial classification performance for single subject is low, it provides a substantial basis for building a collaborative BCI.



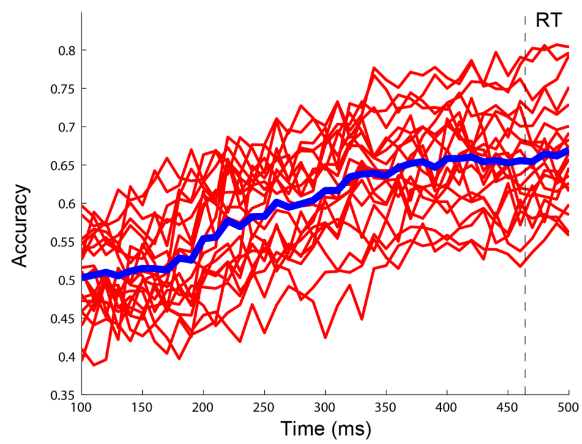
Theoretically, the collaborative classification is expected to achieve a significant gain in the overall system performance. Three major findings are summarized as follows:

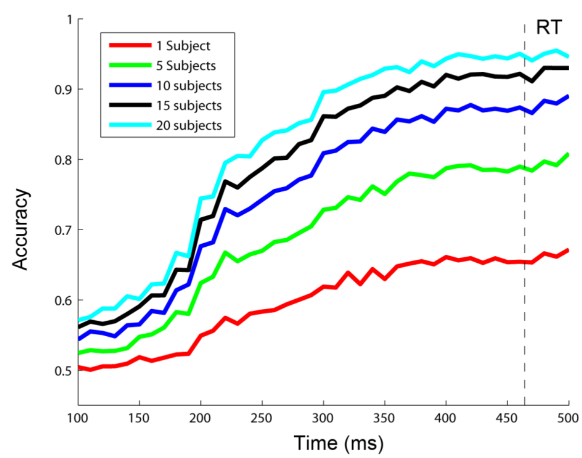
Classification performance for all three collaborative methods had been significantly improved when data from multiple subjects were combined and integrated. The ANOVA showed a highly significant effect of 'number of subjects' on classification performance (Voting: F(19, 9980)=3061.83, p=0.00; ERP averaging: F(19, 9980)=1634.06, p=0.00; Feature concatenating: F(19, 9980)=809.35, p=0.00). When data of two subjects were combined, the T-test showed a significant difference between the individual performance and the collaborative performance when using the Voting method (p<0.01) and the Feature concatenating method (p<0.001) respectively. For the ERP averaging method, at least three subjects were required to reach a significant level (two subjects: p>0.05, three subjects: p<0.0001). A more prominent significance was obtained when the number of subjects increased. Although classification accuracy for single subject was low (mean across subjects: 66%), the collaborative method could still reach a high classification performance. For example, when using all 20 subjects, all three methods showed significantly improved accuracy (95% for the Voting method, 92% for the Averaging method, and 84% for the Feature Concatenating method).

The classification accuracy was enhanced substantially as well as the standard deviation decreased when the number of subjects increased. For example, using the Voting approach, the accuracy increased from 66% to 80%, 88%, 93%, and 95% as the number of subjects increased from 1 to 5, 10, 15, and 20, respectively, meanwhile, the standard deviation reduced from 7.0% to 1.0% when the number of subjects increased from 1 to 20. These results proved the existence of independence between subjects, which made all subjects contribute to the improvement of system performance and robustness.

The Voting method is optimal for collaborative EEG classification. The Voting method always outperformed the ERP averaging method when multiple subjects were involved. Accuracy of the Feature concatenating method was obviously affected by the overfitting problem. As shown in figure attached, when the number of subjects was small (<4), the Feature concatenating method and the Voting method showed similar results, both outperformed the ERP averaging method. When the number of subject increased above 4, the Voting method outperformed the Feature concatenating method. Further, when the number of subjects was above 6, the Feature concatenating method was even worse than the ERP averaging method. When using all 20 subjects, the ERP averaging method had accuracy much higher than the Feature concatenating method (92% vs. 84%).

As mentioned before in the method section, time required to make a prediction is a very important parameter to evaluate the performance of a BCI system in a motor action paradigm. Figure below shows the classification accuracy as a function of the length of time windows used for data analysis. Results for 1, 5, 10, 15, and 20 subjects were put together to show the interaction between the number of subjects and the prediction time. The results clearly showed that the acceleration of decision-making depended on both the desired accuracy and the number of subjects involved in the collaborative system. For example, when an accuracy of 70% was required, decisions could be made at 200 ms by 20 subjects, which was around 250 ms ahead of subjects' actual responses. If 95% was required, the prediction time had to be extended to 400 ms. Concerning the number of subjects, the decision could be made faster with more subjects when the same classification accuracy was required. For example, toward an accuracy of 70%, 280 ms and 200 ms were required for 5 and 20 subjects, respectively.





CONCLUSION

This study proposed a collaborative BCI paradigm, which fused single-trial EEGs from multiple subjects to improve the overall BCI system performance. By comparing system designs and data analysis methods, this study showed that a distributed paradigm combined with a Voting classifier is a practical solution for implementing a collaborative BCI system. The feasibility and efficacy of the proposed BCI system was demonstrated through a collaborative BCI that could accelerate motor decision-making of a cue-guided reaching movement. The classification accuracy of the system showed a significant improvement over that of the single-subject BCI. Furthermore, the collaborative BCI allowed the subject's reaching direction to be estimated 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 in natural environments.

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