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A collaborative BCI system based on P300 signals as a new tool for life log indexing

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ABSTRACT

Analyses on single-trial ElectroEncephaloGram (EEG) have been investigated toward realizing real-time Brain-Computer Interface (BCI). In general, the information transfer rates of current BCI systems with single-trial EEG are generally lower than those with averaging EEG. In recent years, the concept of collaborative EEG analyses has been proposed with the purpose of improving the BCI performances with collaborative single-trial EEGs of individuals. In this paper, a collaborative BCI system is developed based on P300 evoked potentials. The collaborative BCI system with Global Positioning System (GPS) can be operated with three subjects by using three wearable EEG recording devices and wireless communications. As the results, the P300 waveforms could be observed and it was found that the collaborative P300 analyses could improve the BCI performances than individual P300 analyses. The result of this study is to be applied to P300-based big data mining and life log indexing, in particular, in outdoor environment.

KEYWORDS: Collaborative Brain-Computer Interface (BCI), ElectroEncephaloGram (EEG), Event-Related Potential (ERP), P300, Life Log, Indexing, Big data, Global Positioning System (GPS).

1 INTRODUCTION

In a research field of Brain-Computer Interface (BCI) [1], the improvement of signal processing method is one of the most important works as well as the improvement of the sensor preparations. In particular, the classification of brain signals based on machine learning has been investigated in detail today. In the classification studies, the classification performances on single trial brain signals are to be improved for disseminating BCI systems. If the Event-Related Potential (ERP), which is one of the ElectroEncephaloGram (EEG) and is very prosperous for BCI applications [2], can be classified with high accuracy, the dissemination of BCI systems is expected with the development of high-quality mobile EEG sensors. However, the classification performances of the single trial ERP are basically at most 80% and thus this fact limits the applications of ERP-based BCI systems. The remarkable improvements on single trial EEG classification accuracies might require more studies.

On another hand, a new and another direction of EEG analyses has been proposed today. This new method is collaborative EEG analyses [3][4][5], and the analyses are based on the improvement of signal to noise ratio by considering the average EEG or collaborative EEG activities of multiple persons. Yuan *et al.* studied this type of EEG analyses and concluded the improvement of classification accuracies was achieved based on the collaborative ERP activities [3]. Wang *et al.* also investigated the collaborative BCI system [4] and they analyzed the EEG signals of 20 subjects. In that work, the increasing number of subjects yielded improved accuracy in the EEG classifications. In recent, Bonnet *et al.* proposed two-brain operations for one gaming system [5]. In these ways, the collaborative EEG leads to improved BCI performances, and thus it becomes one of the most attractive research topics in BCI studies.

Owing to the ubiquitous environments and mobile devices such as smart phones, big data and life log [6] is one of the prosperous concepts for new applications with information communication technology. Because the big data mining and life log indexing is one of the powerful tools for marketing and discovering the important events in the social activities etc. Touyama *et al.* proposed the concept of life log indexing by using P300 signals in outdoor environment [7]. In that work, the virtual camera shooting system was developed and could be operated in online. It was reported that the P300 signals [8] could be detected with high accuracy even in ambulatory conditions in outdoor environment. This concept of the EEG-based life log indexing might be developed with the collaborative EEG recording techniques.

In this paper, a P300-based collaborative BCI system is developed and the system is operated by groups with three subjects. The system is connecting to the smart phone device and the information of the subjects' location can be recorded by GPS when the P300 signal occurrences are detected in the system. It is noticed that this type of BCI with positioning system has not been studied in detail in the previous works. This paper is organized as follows. The next section describes the collaborative BCI system we have developed. The third section explains our preliminary experiments including the subjects, apparatus and tasks we have conducted. The fourth section presents the signal processing and the classification techniques used to assess the collaborative BCI system. The last two sections are devoted to results, discussions and conclusions of this study.

2 COLLABORATIVE BCI

We developed a collaborative BCI system, which is illustrated in Figure 1. The system can record simultaneously individual EEG signals of three persons. The measured individual EEG signals are amplified in each portable EEG device (Polymate II AP216, TEAC Corp.) and recorded in each laptop computer.

This system has wireless communications with UDP protocol and the individual EEG signals are transmitted to a workstation in which the individual EEG data are merged consistently. After that, the merged EEG data were send to signal processing server and were collaborated altogether with simple averaging method. In the processing server, the P300 occurrences could be judged in real time by using the hyperplanes which was decided by the machine learning mentioned in Sec.4. The information of P300 occurrences and non-occurrences are stored in the signal processing server in

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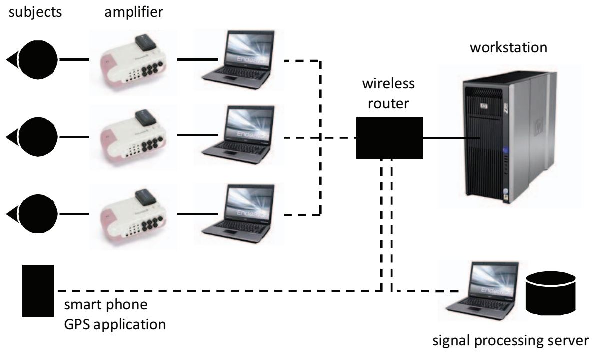

Figure 1 A collaborative BCI system.
(solid lines: wired, dashed lines: wireless)

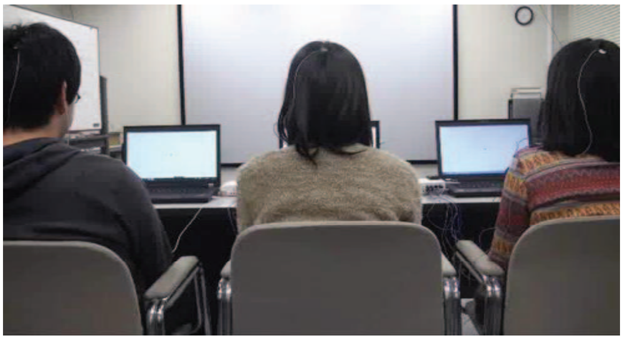

Figure 2 Three subjects during EEG measurements.

real time. At the same time, the location information (time-stamp, latitude, longitude) is also send to this processing server from a smart phone device (Xperia SO-01B docomo, Sony Mobile Communications Inc.) operated with an Android OS.

3 EXPERIMENTAL

We conducted the offline experiments to confirm the occurrences of P300 signals in our collaborative BCI system. It is noticed that the basic experimental settings in this study are very similar to those in our previous work [7]. The EEG signals were recorded by active electrodes at Cz and Pz, which were selected from the international 10/20 system. These are the locations where the P300 is expected to appear clearly. The reference electrode was placed on the left ear lobe, and the ground electrode was on the forehead. The EEG sampling frequency was set to 200 Hz. Furthermore, two pairs of electrodes were attached around the eyes. These electrodes measured the vertical and horizontal ElectroOculoGraphic (EOG) activities, and by monitoring these waveforms we could identify the user's eye blinks and movements, which would lead to the serious artefacts in EEG signals. All these electrodes were attached using an adhesive paste so that the impedances did not exceed about 10 k ohm.

In this preliminary study, EEG was recorded in sitting condition in indoor environment as shown in Figure 2. Totally, nine healthy subjects (7 males and 2 females, early and mid 20s.) participated in this experiment. Most of all subjects had already experienced the P300 measurement experiments several times in indoor or outdoor environment. Three of nine subjects consisted of one group and thus there were totally three groups (Group1, 2 and 3) in our experiments.

By applying oddball paradigm, the subjects could hear three kinds of sounds in the headphones. These sounds were generated every one second and appeared in a random order. One of the three sounds was the target sound which was presented less frequent than the other standard and deviant stimuli. For the target stimuli, a simple tone (2,000 Hz) was used. Other tones were 1,200 H and 500 Hz for standard and deviant, respectively.

The task of the subjects in this oddball paradigm was to think silently count the number of appearances of the target stimulus. As this stimulus was rare and owing to the instruction in advance, the sound appearance was expected to trigger a P300 in the individual EEG signals. On the other hand, the subjects were instructed to ignore standard and deviant stimuli. During this oddball tasks, the eye gaze was fixed to a fixation point on the LCD monitor. If the subjects wanted to do eye blinks and movements, they were instructed to do so as less as possible. One measurement session consisted of about 2 minutes. There were 5 sessions for each group.

4 ANALYSES

4.1 Preprocessing

With UDP protocol, there existed the loss of the data in wireless communications, and then the system interpolated the corresponding data in the workstation. After interpolating EEG signals of three individuals, the preprocessing is performed in the signal processing server. There were four main steps in the preprocessing, which was explained in our previous work [7].

At first, we selected a time window of 1 s starting immediately after the stimulus. This time window should contain the P300, as this P300 is supposed to appear approximately 300 ms after the stimulus. In second, EEG signals with eye blinks and movements were removed from the analysis. Muscle and eye movement artifacts are generally of much larger amplitudes than real EEG signals. In our experimental settings, the amplitude more than 100 microvolts in EOG were basically caused by eye blinks and movements. Thus the simple judgment was performed to remove the deteriorated EEG if the corresponding EOG exceeded the threshold value. At third step, the band-pass filtering was applied. This aimed at reducing the undesired slow variations of the EEG as well as high frequency noise. It is noticed that P300 is a slow wave known to be located within this range of frequencies. And finally, the signals were down-sampled. This aimed at reducing the dimensionality in order to ease the task of the subsequent classifier.

4.2 Collaborative EEG analysis

After the preprocessing above, the collaborative EEG signal was considered. The individual EEG signals of three subjects in one group are synthesized together and the collaborative EEG signals are taken into account for the following feature extraction and selection. To do so, the EEG signals after the onset of the sound stimulations are extracted and simply averaged altogether. Then, the signal to noise ratio is to be improved and therefore the classification accuracy is expected to be improved.

4.3 Feature Extraction and Selection

The collaborative EEG analysis led to a feature vector from two EEG channels of Cz and Pz. From these features, a subset of them was selected using the Principal Component Analysis (PCA) algorithm [7]. PCA was used to select the subset of features which

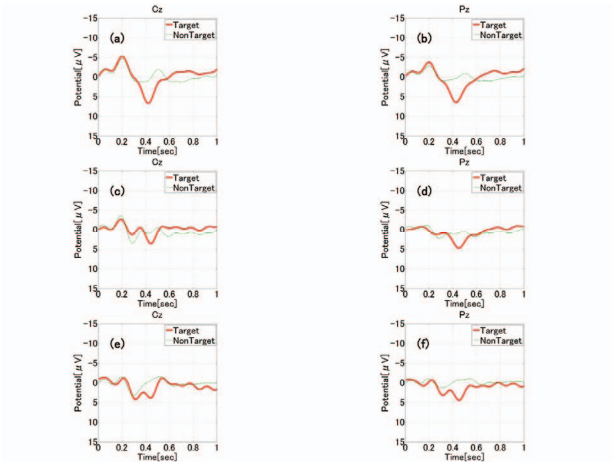

Figure 3. Collaborative EEG waveforms at Cz and Pz.
(a) and (b) : group 1, (c) and (d) : group 2, (e) and (f) : group3

maximize the classification rate by using the training data recorded in the machine learning phase. The classification rate was estimated using leave-one-out cross validation on the training set, with the classifier described in the next section. In other words, we selected the subset of features which would maximize the detection performance of the collaborative BCI system.

4.4 Classification

In order to classify the features extracted in the previous subsection, we relied on a Linear Discriminant Analysis (LDA) classifier [7]. The aim of LDA is to learn a hyperplane that can separate the data representing the two classes. This classifier is popular and efficient for real-time BCI. The training set was used to select the features and to train the LDA classifier. Then, the trained LDA was used to classify the features extracted from the new-coming testing data in online system.

5 Results

5.1 P300 signals

The observed EEG signals are shown in Figure 3. At electrode Cz and Pz, we could see clear P300 signals for each group (Group 1, 2 and 3) as expected in target condition, but no such positive increases at about 300 ms in standard condition. The amplitude of the P300 signals in target condition could be about 5 microvolts. From these results, our collaborative BCI system enabled us to detect P300 averaged in three individual subjects.

5.2 Classification performances

In order to show whether the classification between EEG signals in target and those in standard stimuli, we investigated the classification accuracy in offline. The results are summarized in Figure 4 and 5. From the confusion matrix, the F value in collaborative condition was found to be 0.730, 0.654, 0.703 for the group 1, 2, 3, respectively, and was larger than those in individual condition. It is noticed that the accuracy was derived with single-trial EEG signals and thus the classification can be achieved in real time in online experiments.

		Result				
		Target	NonTarget	Recall	Precision	F Value
Task	Target	66	24	0.733	0.532	0.617
	NonTarget	58	220	0.791	0.902	0.843
	Average			0.762	0.717	0.730

		Result				
		Target	NonTarget	Recall	Precision	F Value
Task	Target	35	20	0.636	0.393	0.486
	NonTarget	54	171	0.760	0.895	0.822
	Average			0.698	0.644	0.654

		Result				
		Target	NonTarget	Recall	Precision	F Value
Task	Target	49	21	0.700	0.510	0.590
	NonTarget	47	151	0.763	0.878	0.816
	Average			0.731	0.694	0.703

Figure 4. Accuracies of collaborative P300 detection with three subjects in offline analysis.
(from upper to lower: group 1 to 3)

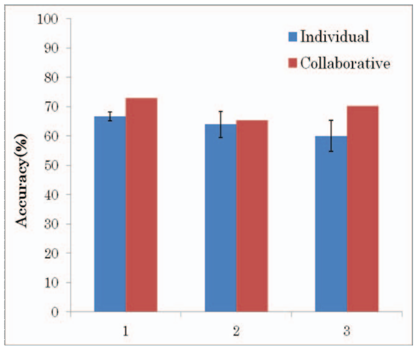

Figure 5. Accuracies of P300 detection comparing individual with collaborative condition.
(The horizontal axis denotes the group number.)

5.3 Collaborative P300 with nine subjects

Finally, we investigated the classification of P300 occurrences by using grand average EEG signals with nine subjects. In this case, the performance was expected to be improved than that in the case of three subjects.

5.4 Online experiments

In addition, we performed the online collaborative BCI experiments. In these online studies, three subjects were standing still in indoor environment and could hear only the target stimuli. The subjects paid attention to the target stimuli. One of the three subjects had a smart phone for the positioning. The P300 occurrences in target stimuli were recognized and the positioning information was recorded in the signal processing server.

6 RESULTS AND DISCUSSIONS

The operation of online system was tested in pseudo-online experiments. The accuracy in the pseudo-online experiments was derived by using the first and second half of data, which was pre-recorded in one day, as training and testing datasets, respectively. The online collaborative BCI system was successfully operated and the accuracy in the online classification was found to be 0.777. We concluded the current study revealed the feasibility to analyze collaborative P300 signals with multiple persons connecting to GPS data in real time.

In summary, the collaborative P300 detection worked well in offline and online experiments. The P300 waveforms were clearly observed in the target stimuli and the collaborative classification performances were higher than those of individual EEG analyses. Furthermore, the grand average EEG of nine subjects enhanced the performances of P300 occurrence detection. The enhanced accuracy was 0.803.

By connecting to GPS data, the collaborative BCI system can specify the location where the P300 occurrences were observed in indoor or outdoor environment. This concept of the collaborative BCI would lead to the application of life log indexing or brain big data analyses. In recent years the ambulatory BCI system was investigated [7]. And the collaborative BCI will be studied in outdoor environment with multiple subjects in ambulatory conditions.

There were a few problems in the current investigation. In our collaborative BCI system, it is expected that the CPU performances are much required in the signal processing server when processing the EEG signals of large number of users. Furthermore, the wireless communications are to be established with no data loss. When the data loss is detected, the effective interpolation or other method would be required. These are to be studied in our future works.

7 CONCLUSIONS

In this paper, a collaborative BCI system is developed based on P300 evoked potentials. The system with GPS can be operated with three subjects by using three wearable EEG recording devices and wireless communications. As the results, the P300 waveforms could be observed and it was found that the collaborative P300 analyses could improve the BCI performances than individual P300 analyses. The result of this study is to be applied to P300-based big data mining and life log indexing, in particular, in outdoor environment.

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