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Paper:

Majority Rule Using Collaborative P300 by Auditory Stimulation

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In this study, a new method to realize majority rule is presented by using noninvasive brain activities. With the majority rule based on an electroencephalogram (EEG), a technique to determine the attention of multiple users is proposed. In general, a single-shot EEG ensures short-time response, but it is inevitably deteriorated by artifacts. To enhance the accuracy of the majority rule, the collaborative signals of P300 evoked potentials are focused. The collaborative P300 signal is prepared by averaging individual single-shot P300 signals among subjects. In experiments, the EEG signals of twelve volunteers were collected by using auditory stimuli. The subjects paid attention to target stimuli and no attention to standard stimuli. The collaborative P300 signal was used to evaluate the performance of the majority rule. The proposed algorithm enables us to estimate the degree of attention of the group. The classification is based on supervised machine learning, and the accuracy approximately 80%. The applications of this novel technique in multimedia content evaluations as well as neuromarketing and computer-supported co-operative work are discussed.

Keywords: collaborative EEG, P300, majority rule, auditory stimulus, attention, normalization, multimedia evaluation

1. Introduction

Recent developments in the brain-machine interface (BMI) [1] have been remarkable, owing to new understandings of brain functions as well as the disseminations of low-cost computers and devices. In particular, BMI systems based on event-related potentials (ERPs) [2] have been extensively studied.

P300 signals, one of the promising ERPs, are elicited when paying attention to external stimuli. The amplitude of P300 signals depends on the depends on the degree of attention or interest [3]. The P300 signals result from an endogenous potential change that occurs approximately 300 ms after the onset of the external stimulus [4, 5]. A virtual keyboard is one of the promising BMI applications [6–8]. This system is realized by detecting the P300 signals elicited when the user pays attention to the character they wish to input.

Today, ERP applications have a new direction. Usually, multimedia content evaluation has been realized with subjective indicators such as questionnaires. On the other hand, multimedia content can be objectively evaluated by biological signals of brain waves [9, 10]. J. Suzuki, H. Nittono, and T. Hori studied an ERP-based method of multimedia content evaluation [11]. Their work demonstrated the evaluation of the degree of attention to multimedia content by using the ERP induced by auditory stimuli. The ERP signals were recorded under the dual tasks. The subject paid attention to simple auditory stimuli when watching a soundless video clip. It was found that the P300 amplitudes systematically varied depending on the degree of novelty of the video content.

Previous studies were based on the averaging of the ERP signals within a subject. The within-subject averaging procedure (Averaging method) contributes to the reduction of the noise component. The signal-to-noise ratio of the ERP increases as the number of values that are averaged increases. However, in the case of the averaging within a subject, it is necessary to present the same stimulation repeatedly for numerous times. Therefore, it is not possible to evaluate a specific scene in multimedia contents. If we wish to evaluate a specific scene, single-shot analysis is inevitably required. It has been noticed that ERP signals are difficult to be classified or decoded, especially with single-shot analysis, since they are bio-signals elicited inside the human brain.

To achieve the single-shot analysis, we do not focus on the average ERP within a subject; rather, we focus on the average ERP among different subject. By applying the average among subjects, the evaluation of single-shot multimedia content is ensured. The average ERP among different subjects is called collaborative ERP, which is constructed from the single-shot ERPs of individual subjects. It has been remarked that collaborative EPR analysis leads to improved classification performances in the detection of ERP [12–15]. In these studies, the performance of ERP classification was significantly enhanced, though the simultaneous measurements of multi-user ERP were necessary. When we use the P300 signals of multiple subjects, the signals are gathered and analyzed. Then, we call the signals collaborative P300. There are two types of collaborative P300 signals. One is perfect collaborative P300 (perfect collaboration), and the other is non-perfect collaborative P300 (non-perfect collaboration). In previous research, only perfect collaborative ERP has been studied [12–15]. Y. Wang and T. Jung studied the collaborative ERP at the posterior parietal cortex (PPC) [12]. They suggested that the ERP classification performance is enhanced substantially from 66% to 80% when using collaborative ERP. Y. Wang, Y. Wang, T. Jung, X. Gao, and S. Gao studied the collaborative ERP at N2 [13]. They suggested that the ERP classification performance is enhanced substantially from 75.8% to 99.1%. P. Yung, Y. Wang, W. Wu, H. Xu, X. Gao, and S. Gao studied the visual evoked potentials (VEPs) of multiple subjects [14]. They concluded that the collaborative ERP classification performance is higher than the average individual accuracy by 11% and higher than the best individual accuracy by 6%. J. Fan and H. Touyama studied the P300 signals from multiple subjects [15]; consequently, the F-measure of P300 discrimination accuracy was improved from 63.6% to 88.6%. In these works, the ERP classification performances were improved with the collaborative EEG signals. On the other hand, the situation of perfect collaboration in which all subjects pay attention or all subjects do not pay attention is not realized in general. In other words, the P300 signals of some subjects in the group are clearly elicited, while those of other subjects are not elicited. Then, the amplitude of the collaborative P300 signals is reduced, and a new method of signals processing should be proposed to determine how many subjects elicit the P300 signals. In particular, it would be useful to realize the majority rule based on EEG signals for future application with collaborative EEG signals.

Therefore, we propose a novel method to realize majority rule based on EEG signals in the non-perfect collaborative condition. With the proposed method, we can judge whether more than half of subjects pay attention or not. The proposed method enables the applications with collaborative EEG signals to reflect the collective opinion of the subjects in the group, even when the subjects have different opinions.

The purpose of this study is to develop a method of single-shot multimedia content evaluation based on collaborative P300 signals. We focus mainly on the case of non-perfect collaboration, and the technique to achieve the majority rule is proposed in the context of multimedia content evaluation. With the proposed method, the evaluation of single-shot (short-time) content is possible with high accuracy owing to the collaborative signal analyses. To achieve this purpose, we measure the collaborative P300 signals evoked by auditory stimulation with an oddball task [16, 17].

In the next section, we explain the methodology of our experiments. In section 3, we report the signal processing methods, such as pre-processing, collaborative analysis, and classification. EEG data normalization is also explained. In section 4, the performance results of collaborative P300 waveforms and the majority rule are discussed. In section 5, the result are discussed.

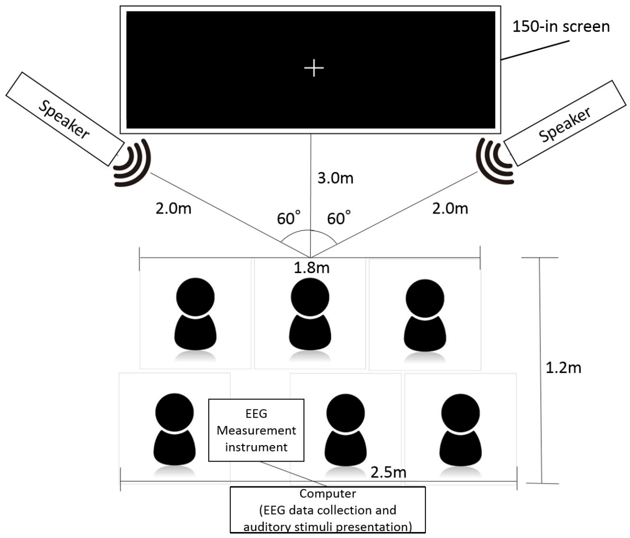

Fig. 1. Collaborative EEG measurement with six subjects. The subjects heard auditory stimuli and silently counted the number of the occurrences of target stimuli.

2. Experiment

2.1. Subject and Experimental System

In this study, twelve healthy adult subjects (males, mean age 21.41, S.D. 0.64 years) participated in the EEG experiment. Each of six subjects wore a compact EEG cap and was comfortably seated on a standard chair 3.0 m away from a 150-in screen. Two speakers were installed at left front and right front of the subjects, and auditory stimulation was presented (**Fig. 1**). In order to suppress the eye movements of the subjects, we used a white fixation cross on a black background projected on a 150-in screen by a DLP projector. During the EEG measurement, the subjects were instructed to gaze at the fixation cross.

We conducted the collaborative EEG measurements twice. First, the EEG signals of six subjects (first group) were simultaneously measured. Subsequently, the other six subjects (second group) participated in similar experiments. Therefore, in total, the EEG signals of 12 subjects could be recorded. This experiment was approved by the ethics committee of Toyama Prefectural University, and each subject gave written informed consent.

2.2. EEG and EOG Recordings

EEG and electro-oculogram (EOG) signals were recorded using two bio-signal amplifiers, which were stacked and linked. The device recorded the EEG signals with a sampling rate of 512 Hz. We applied a bandpass filter between 0.1 and 100 Hz both for EEG as well as EOG measurement. A notch filter of 60 Hz was applied to reduce the noise from environmental sources such as the power supply.

For each subject, two EEG electrodes were placed at Cz and Pz based on the extended international 10–20 system [18]. The recording reference and ground electrode were the left earlobe and AFz, respectively. For moni-

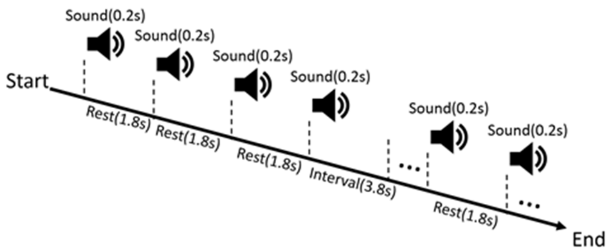

Fig. 2. Protocol of the EEG recording. Target and standard auditory stimuli were randomly presented. The sound sequence for the second group was different from that for the first group.

toring eye blinks, we recorded the vertical EOG. Then, the EOG electrodes were placed above and below the left eye. All electrodes were active sensors and attached by conductive gel; thus, we expected to obtain high-quality EEG signals.

2.3. Auditory Stimuli

In this study, we used auditory stimuli to elicit collaborative P300 signals. The stimuli were simple tones sampled at 44.1 kHz and quantized with 8 bits. Four types of auditory stimulations were created in advance. Their frequencies were 500, 1500, 2500, and 3500 Hz. The duration of al stimuli was 0.2 s. The experimental protocol of our EEG recordings is shown in **Fig. 2**. Before the measurement, we confirmed that there were no problems in the EEG measurement system and EEG signals. After the confirmation, each auditory stimulation was randomly and serially presented, which was followed by a rest time of 1.8 s. After four auditory stimuli were presented, we provided an interval of 3.8 s. During the session, each auditory stimulation was presented 10 times. There were 10 sessions of EEG recordings in total. Each session consisted of 3 min.

The auditory stimulus with a frequency of 500 Hz was the target stimulus. The other auditory stimuli were standard stimuli. According to our preliminary study, a clear P300 signal was obtained even with several standard stimuli. The subjects heard these auditory stimuli and silently counted the number of occurrences of target stimuli. Furthermore, they were instructed to ignore the stimuli with higher frequencies, which were standard stimuli. Therefore, the P300 signals were expected to appear only during target stimuli presentation, which was desired and rare.

Every time a measurement session ended, the subjects reported the number of occurrences of target stimuli. We confirmed that, in all sessions, the twelve subjects correctly reported the number of occurrences of target stimuli. In total, there were 100 target and 300 standard stimuli for each subject.

3. Analysis

3.1. Pre-Processing

To confirm the occurrence of P300 waveforms, we applied EEG signal pre-processing steps, which comprised bandpass filtering, artifacts removal, baseline procedure, and down sampling. The bandpass filter was used to extract the frequency components of P300 signals between 0.1 and 10 Hz. The filter removed lower- and higher-frequency artifacts. The P300 signals were expected to appear in that frequency band.

After the bandpass filtering, the artifacts originating from eye blinks were removed by using independent component analysis (ICA). We used the FastICA algorithm [19] to achieve artifact removal. With the FastICA algorithm, the EEG and EOG data are rotated by an unmixing matrix W to obtain the independent components. We calculated the cross correlation between each independent component and EOG. When the correlation was greater than a preset threshold (the threshold value was 0.6 in this study), the independent component was set to zero. Finally, we used the inverse matrix W^{-1} to recover the EEG data from the independent components in which the eye-blink artifacts were removed.

In the baseline processing, EEG signals for 0.25 s before the stimulus onsets were averaged, and the averaged value was subtracted from the EEG waveforms. To compress the number of feature dimensions of the EEG data, down sampling was performed to be 32 dimensions per EEG channel. Consequently, 1 s of EEG signals is expressed by 32 dimensional vectors, one dimension of which corresponds to 3.125 ms. Finally, the number of dimensions of the feature vector was 64 with two electrodes (Cz and Pz).

3.2. Normalization

In general, the P300 amplitude has individual differences. In this study, the majority decision was realized based on the P300 amplitude. If a subject elicits a mall P300 amplitude, there is a possibility that the EEG data may not be sufficiently reflected in the result of majority decision. In order to reduce such individual differences, the normalization of each subject's EEG data was required. We focused on four types of normalization methods, which were compared with each other.

A No normalization.

B Each EEG data point was normalized by the maximum value of the grand mean P300 amplitude found in the target datasets (max normalization).

C The maximum and minimum value of the EEG amplitudes were considered. The difference between the maximum and minimum value was calculated in the target condition as well as the standard condition. We calculated the average of these two differences. Each EEG data point was normalized by the averaged difference (mean normalization).

D Same as C) except for the calculation method. We calculated the geometric mean by using two differences. The normalization was performed by the geometric mean value (geometric normalization).

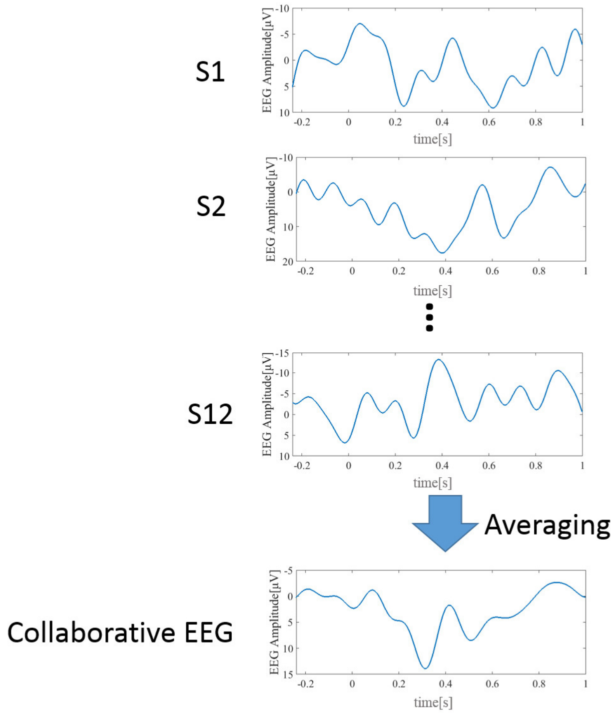

Fig. 3. Concept of the collaborative EEG analysis. Temporal-domain EEG data were averaged together. Twelve subjects contributed to the collaborative P300 signal, in which the noise components were reduced.

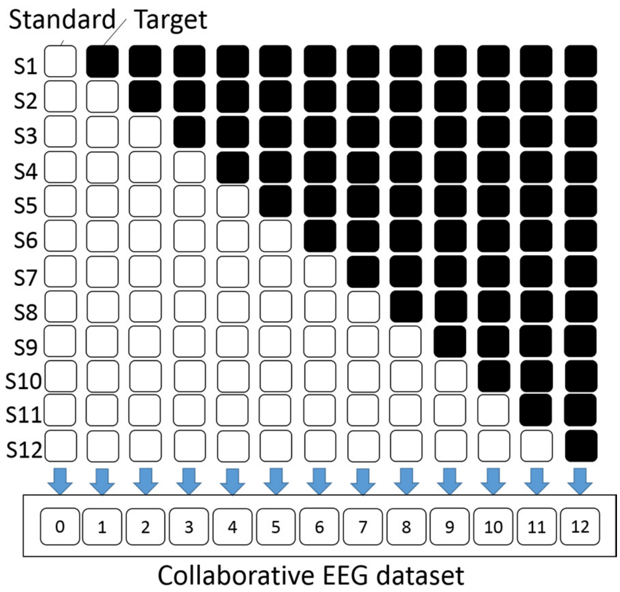

Fig. 4. An example for the preparation of the collaborative EEG datasets. A square represents one single-shot EEG signal. The ratio of the number of target/standard data varied in the collaborative analysis. The number of target data was the label in machine learning.

In these normalization methods, we considered 1.25 s of temporal EEG data.

3.3. Collaborative EEG Datasets

Majority rule is achieved by averaging single-shot EEG signals among subjects. Each single-shot EEG signal was recorded in either the target or standard condition. The 12 single-shot EEG signals were averaged together for collaborative EEG analysis (**Fig. 3**).

In the EEG datasets of the 12 subjects, the ratio of the number of target/standard data could be varied when preparing the collaborative EEG data (**Fig. 4**). For example, we prepared the datasets in which five subjects paid attention to a certain stimulus and the remaining seven subjects ignored to the same stimulus. In that case, the ratio was 5/12. If none of the subjects paid attention to the stimulus, the ratio was 0/12. In total, there were 13 patterns of the ratio (0/12, 1/12, . . . 12/12), and we labeled them as 0, 1, 2, . . . ,11, 12, respectively.

After the EEG recording experiment, we obtained 100 target and 300 standard data for each subject per channel. There were numerous combinations to select the single-shot EEG data to prepare the collaborative EEG. In this study, the target or standard data were randomly selected.

3.4. Classifications

The classification was achieved based on the supervised machine learning technique by using the prepared datasets mentioned above. We demonstrated a simple majority decision, with which the system could estimate the degree of attention of the majority (or minority).

In the supervised machine learning, the supervised data are required. In this study, the supervised data had the labels of the ratio of the target/standard data, as shown in **Fig. 4**. After setting the labels, we applied temporal principal component analysis (temporal PCA) for each EEG channel. The PCA could reduce the number of dimensions of the temporal feature vectors. The noise components were reduced as well.

The classification rate was derived by using the leave-one-out cross validation technique. We repeatedly created the collaborative EEG data and the corresponding label and performed the classification. This procedure was repeated 20 times. Finally, the average F-measure was calculated.

There could be a draw condition in which six subjects paid attention and the other six did not. In this study, we did not consider the draw condition, but we studied two cases (Case 1 and Case 2). In Case 1, the label for the dataset in which less than seven subjects paid attention were set to ‘minority’ and the residual dataset was set to ‘majority’ In Case 2, the label for the dataset in which less than six subjects paid attention were set to ‘minority’ and the residual dataset was set to ‘majority.’

3.5. Varying the Number of Subjects

In order to examine the influence of the number of subjects on the result of the majority rule performance, we varied the number of subjects. First, we selected two subjects to consider a group of two people with the ampli-

Table 1. Normalized amplitude of P300 for each subject. This amplitude of P300 is the difference between the maximum value of the target and the maximum value of the standard.

subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	mean	S.D
P300 Amplitude [μV]	0.60	0.59	0.73	0.41	0.57	0.01	0.57	0.17	0.72	0.76	0.64	0.42	0.51	0.21
P300 Latency [ms]	406	437	375	250	375	375	218	375	375	375	375	375	349	69.0

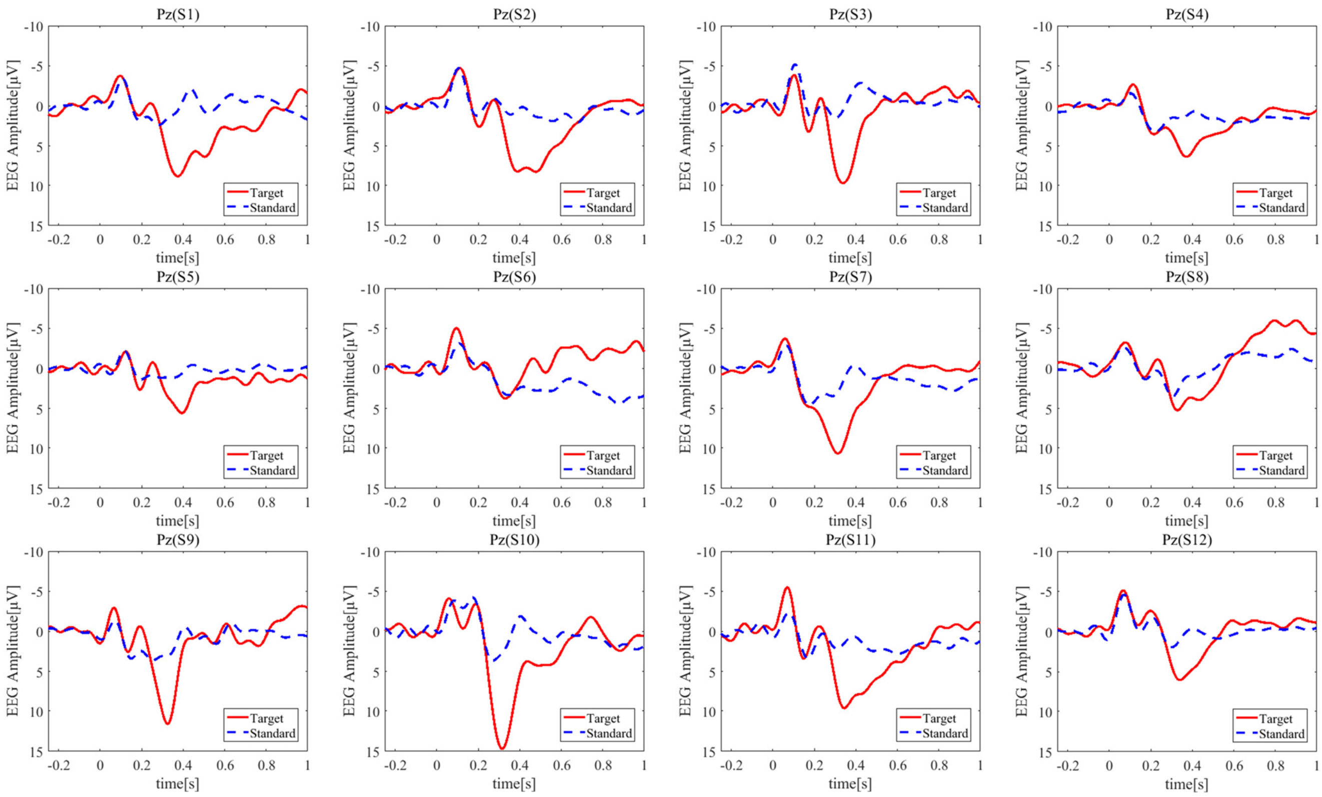

Fig. 5. Average EEG waveforms at Pz are shown in the left and right column, respectively. There were individual differences in P300 peak amplitudes and waveforms.

tude of P300 signal larger than those of the others. Furthermore, we selected the next two subjects in a similar manner. Thus, the number of subjects were varied as 2, 4, . . . , 10, 12. The performance value of majority decision is expected to increase as the number of subjects increases. Here, we considered the sort of the P300 amplitudes of 12 subjects according to normalization method D (geometric normalization). **Table 1** lists the normalized amplitude of P300 for each subject. The average EEG waveforms at Pz for each subject are shown in **Fig. 5**.

4. Result

In **Fig. 5**, it is possible to confirm a large or a clear positive peak between approximately 350 and 450 ms from the stimulation onset, except for one subject (S6). In **Fig. 6**, the average EEG waveforms were normalized by method D (geometric normalization). Here, we varied the ratio of the P300 occurrences in twelve subjects. The thirteen waveforms are shown with their label, which was the number of subjects who showed a P300 signal. For example, ‘five’ denotes a ratio of 5/12, as mentioned before. As shown in **Fig. 6**, we can confirm a tendency that the averaged P300 amplitudes increased as the number of subjects who paid attention to the stimuli increases. **Figs. 7** and **8** show the result of averaging. The EEG averaging was repeated 20 times. **Fig. 7** shows the relation between the P300 latency and the ratio of target and standard data. **Fig. 8** shows the relation between the P300 amplitude and the ratio of target and standard data. The regression line of P300 amplitude was $y = 0.046x + 0.243$.

Table 2 lists the classification results with four normalization methods. In PCA, we investigated the feature dimensions between 1 and 30. With these feature dimensions, we derived the F-measure values, and the highest-performance value was selected as the final result. As indicated in **Table 2**, the highest classification result was obtained with no normalization. Then, the accuracy of majority rule was approximately 78.0% by using auditory P300 signals with the 12 subjects. The relation between the performance of majority rule and the number of subjects is shown in **Fig. 9**. We considered the number of subjects as 2, 4, . . . , 10, 12. Here, **Table 1** was used

Table 2. Performance result of majority rule with the averaging method of four types of normalization and voting method of no normalization with 12 subjects.
Case 1. Classification between the dataset in which less than seven subject paid attention and the residual dataset.
Case 2. Classification between the dataset in which less than six subject paid attention and the residual dataset.

	Case1		Case2	
	minority	majority	minority	majority
Averaging (No normalization)	81.22± 1.02	75.98± 1.28	78.43± 0.84	78.47± 0.92
Averaging (max normalization)	78.07± 1.96	72.80± 2.65	74.51± 2.32	74.97± 2.64
Averaging (mean normalization)	80.76± 0.75	75.63± 0.99	80.77± 0.74	75.57± 1.00
Averaging (geometric normalization)	78.02± 0.86	78.15± 0.89	78.10± 0.82	78.19± 0.87
Voting (No normalization)	76.36± 0.30	43.13± 1.74	72.71± 0.78	59.53± 1.89

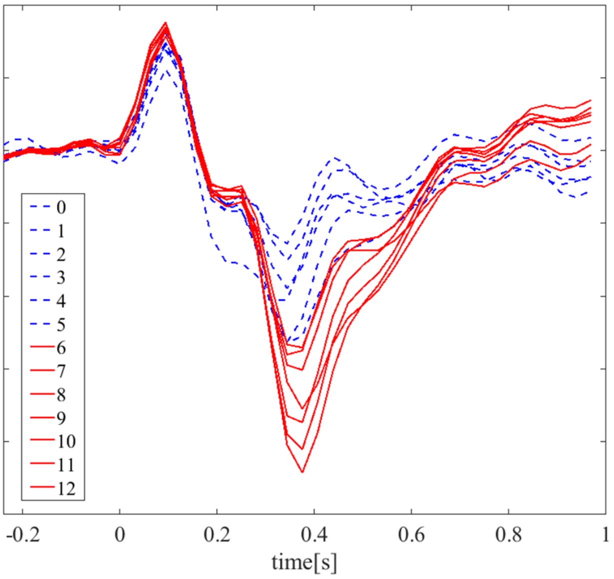

Fig. 6. Average EEG waveforms at Pz normalized with method D by varying the ratio of the P300 occurrences (target data) in twelve subjects. Graph legend: The ratio of target data.

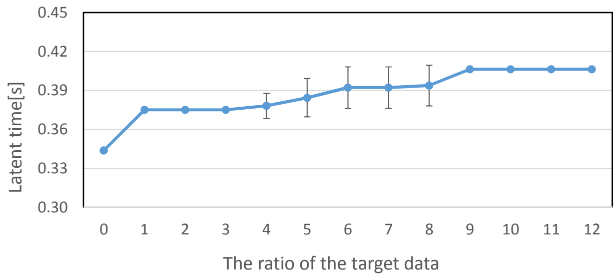

Fig. 7. Relation between the latency time and the ratio of target and standard data.

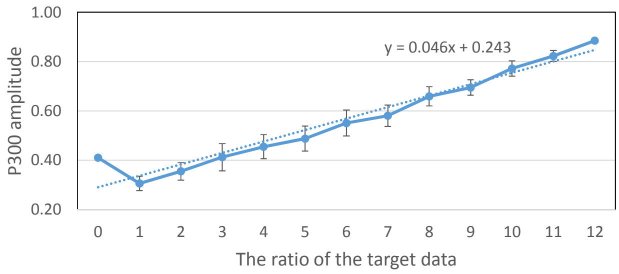

Fig. 8. Relation between the P300 amplitude and the ratio of target and standard data.

for subject sorting. The order of subjects was determined from the amplitude sorting. The performance values in majority rule were systematically varied if we varied the number of people in the group.

It has been confirmed that the latency of P300 differs depending on age and sex [20, 21]. There is a possibility that the amplitude of collaborative P300 would be decreased if the averaging process is performed when the latencies of P300 do not coincide with each other. In this study, we investigated subjects with similar ages (21.41 $\pm$ 0.64 years old). In fact, with these twelve subjects, the latency of average P300 signals was 349.0 $\pm$ 69.0 ms. Thise latency value was found to be rather small compared with the difference between the average P300 latency of younger people and that of older people [20, 21]. The latency of P300 increased with age by 1.8 ms/year. Younger people tend to have small latency compared with older people. In this study, the high performance in the majority rule could have been caused by the similar ages between of subjects.

5. Discussion

With max normalization, the classification accuracy tended to be lower than that with other methods. The other three methods had almost the same accuracies, especially with a large number of subjects. These results indicate that the methods of normalization might not be essential for high classification accuracy. However, the P300 amplitude has individual differences. With the individual differences in P300 amplitudes, a disparity in the relative value of a vote will occur in the group. Therefore, it is important to normalize EEG data. In future work, we will further investigate the normalization method by increasing the number of subjects.

In our analysis, the number of subjects was varied with the method mentioned in section 3.5. The performance of majority rule increased as the number of subjects increased. However, the accuracy was not perfect. The saturation of the accuracies in **Fig. 9** result from the method we used in the section 3.5. We increased the number of subjects by two subjects who have relatively high P300

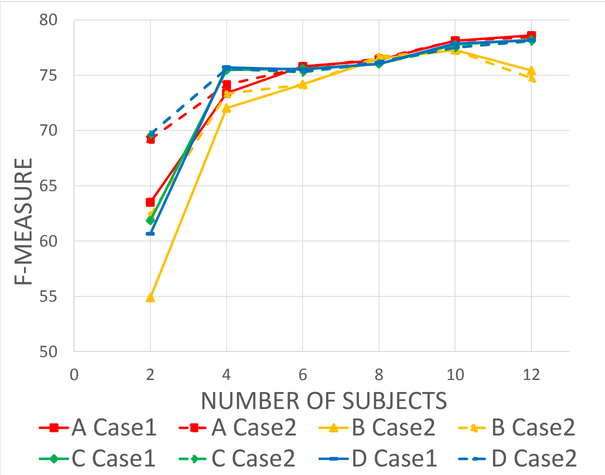

Fig. 9. Relation between the performance of majority rule and the number of subjects with four types of normalization. A. No normalization, B. Max normalization, C. Mean normalization, D. Geometric normalization

amplitudes. It is very important to consider a greater number of subjects, such as more than 100, though they might include subjects showing a relatively low P300 signal-to-noise ratio. Such analysis on P300 big data will be a subject for future works.

In this study, we focused on the method of averaging among subjects to obtain collaborate P300 signals. There is another candidate to gather collaborative P300 signals. Without averaging, the single-shot P300 signals of individual subjects were separately classified, and each classification result was aggregated. This is called the voting method. A previous study reported that, in the detection of perfectly collaborative ERP, the classification accuracy with the voting method is higher than that with the averaging method [12]. **Table 3** lists the classification results of collaborative P300 signals in the case of perfect collaboration (all members of the group have the same attentive state). This result was consistent with the reference [12]. To summarize, the voting method is better than the averaging method in the case of perfect collaboration. On the other hand, **Table 2** lists the result of majority rule (non-perfect collaboration) with 12 subjects by applying the voting method. As indicated in **Table 2**, the classification accuracy with the voting method was less than that with the method of averaging among subjects.

There might be limitations in applying collaborative P300 signals. One limitation is the ages of subjects, which has been mentioned before. Another limitation is the locations of subjects. We used a common speaker, rather than headphones, as the sound source. The locations of the subjects were distributed, which could cause a time difference in the onset of auditory stimuli. This, in turn, could lead to jitter in the P300 latencies between subjects and reduce the majority-rule performance. We briefly estimated the jitter in our experimental settings. By using the typical value of sound velocity (approximately 340 m/s), the jitter is at most approximately 5 ms, considering the locations of sitting subjects. From this estimation,

Table 3. F-measure in P300 classification by the voting and averaging method in perfect collaboration with no normalization.

	Method (No normalization)	
	Averaging	Voting
Target	77.29	78.94
Standard	92.07	93.44
Averaging	84.68	86.19

we conclude that the effect of the speaker device on the jitter in the collaborative P300 latency is not so severe. However, the effect might be significant if we consider subjects who are distributed with long distances greater than approximately 10 m. In such a case, the locations of subjects should be measured using GPS or some tracking devices. To solve the problems limiting application, it is necessary to perform the collaborative P300 averaging by aligning the latencies among subjects. The latencies of P300 can be aligned by using the adapting filter [22] proposed by Woody.

There are numerous combinations for the preparation of collaborative P300 datasets. In fact, the number of combinations was as large as 16200. In this study, we considered only 20 repetitions of random selection of the collaborative P300 datasets. The standard deviation of the majority-rule performance was found to be sufficiently small (less than 0.3%), except for the case of the max normalization method. This result might suggest that our evaluation of majority-rule performance with 20 repetitions is good.

As mentioned in the introduction, collaborative P300 signals can used in a variety of applications. One of our final goals is to realize a method of multimedia content evaluation. Attention can be one of the measures of degree of interest in the content. Y. Shigemitsu et al. suggested that the within-subject average of single-shot P300 waveforms reflected the interest in a video clip. Our study extended this concept to a multi-user situation. Furthermore, the degree of interest in a certain group (not in a single person) can be measured in terms of the degree of attention to the multimedia content.

A dual task was applied in a previous study [11]. An auditory stimulation was used as a probe to investigate the attention of the subject. However, the dual task may limit the experimental settings and future applications. Therefore, a single task should be studied extensively. This means the stimulation should be extracted from the content of the video clip itself. Furthermore, an online system can present a new strategy for evaluating a variety of content developed by enterprises for advertisement.

Marketing is another promising application of collaborative EEG signals. Based on the technique of P300 speller [4, 5], the attention of the user can be revealed from the serial visual presentation of photo images [23]. Rapid presentation was also studied in the work of cortically coupled computer vision [24]. The content of photo images might be advertisements for commercial products.

The attention to the products can be estimated from the collaborative P300 signals.

Collaborative P300 signals might be applied to the estimation of the degree of attention in educational institutions. The stimulation may be the spoken words or hand gestures of a lecturer. In this case, the audience can be large number of people, and the collaborative P300 signals may be useful to estimate the attention of the audience.

In general, P300 is detected when the subject pay attention. We consider application in remote conferencing, which a computer-supported co-operative work (CSCW). CSCW is an academic field that studies the situation in which people co-operate through computer support. It realizes co-operative work systems such as remote conference systems and remote presentation systems [25]. With remote conference systems, conference attendees can participate in a conference without gathering at one place. We can reduce travel time and cost by utilizing CSCW. However, the participants in the conference could not be able to grasp the degree of attention in the entire meeting, and thus, the remote conference's efficiency may decrease. Therefore, we can evaluate the degree of attention of participants from majority rule using collaborative P300. For a reduced degree of attention, we expect to improve the efficiency of a remote conference by presenting feedback to the conference participants. In this manner, we consider that the technology of analyzing collaborative brain signals can be applied to CSCW activities extracting the attentive states of multiple users.

In summary, when collaborative EEG signals are used, there are situations in which the thinking of all members does not agree. Therefore, if the thinking of a group does not have a consensus, we need to grasp the *averaged* thought of the group. This work contributes to realizing the majority rule with only brain-signal analyses.

6. Conclusions

In this study, a new method to realize majority rule was presented by using noninvasive brain activities. With the majority rule based on the electroencephalogram (EEG), a technique to determine the attention of multiple users was proposed. In general, the single-shot EEG ensures short-time response, but it is inevitably deteriorated by artifacts. To enhance the accuracy of the majority rule, we focused on the collaborative signals of P300 evoked potentials. The collaborative P300 signals were prepared by averaging individual single-shot P300 signals among subjects. In the experiments, the EEG signals of twelve volunteers were collected by using auditory stimuli. The subjects paid attention to the target stimuli and no attention to the standard stimuli. The collaborative P300 signals were used to evaluate the performance of majority rule. The proposed algorithm enables us to estimate the degree of attention of the group. The classification was based on supervised machine learning, and the accuracy could be approximately 80%. The applications of this novel technique in multimedia content evaluations as well as neuromarketing and CSCW were discussed. Our study suggests that decision making is possible based on majority rule by collaborative EEG. Furthermore, the proposed technique might be applicable to improve the efficiency of co-operation in CSCW by objectively measuring the state of a group.

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