Eye-Movement-Control-Independent Brain Computer Interface Using Modulation of Steady-State Responses in Visual Evoked Potentials

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Abstract: Brain computer interfaces based on steady-state visually evoked potential (SSVEP-BCI) have been developed substantially in recent years, but these are not always available to patients with severe paralysis or eye-impairment who lost the control ability of eye-movement. This paper proposes an eye-movement-independent SSVEP-BCI available in the eyes-closed state based on the modulation of SSVEP elicited by performing a mental task. Although performance of the proposed BCI depended on subjects, electrode locations, mental tasks employed, and flickering frequencies, the mean precision and recall, which were obtained from the confusion matrix, reached 72% to 95% using the support vector machine classifier across 18 normal subjects under the stimulus frequency of 10Hz or 14Hz. Results from simulated information transfer rate and its inter-individual difference suggest that it is adequate to set an inter-trial interval at 2 s to 3 s for better performance of the proposed BCI. It is consequently feasible to develop a practical eye-movement-control-independent BCI by optimizing the parameters such as the stimulation frequency and electrode sites each user.

Key Words: brain computer interface, brain machine interface, steady-state visually evoked potential.

1. Introduction

A brain computer interface (BCI) is defined as a system which translates a user’s intentions or modulations in physiological signals elicited by his or her intentions into commands to a device which displays the intentions or operates machines and devices [1]–[3]. Most BCIs adopt electroencephalogram (EEG) due to the low cost, dissemination, and safety of an electroencephalographic instrument and easiness in measurement. Although various EEGs could be used for BCIs, recent development has been remarkable in BCIs based on steady-state evoked potential (SSVEP) [4]–[6], namely, SSVEP-BCIs, in terms of the classification accuracy of a user’s intentions and communication rate by taking advantage of the magnitude and sustainability of SSVEP [7].

In most of conventional SSVEP-BCIs, a user basically has to select and gaze at a flickering icon corresponding to his or her intention from the icons arranged and flickered with different frequencies each other, where the icon includes a light emission diode (LED), grating, figure or letters which represents an option for his or her intention. Then SSVEP-BCIs detect the modulations of SSVEP at the flickering frequency of the icon the user gazes at (target icon) using signal processing techniques in the time and/or frequency domain [3],[7],[8]. SSVEP-BCIs are generally superior in information transfer rate (ITR) defined by Wolpaw [9], one of the useful indices of the performance of BCI, and ITR of state-of-the-art SSVEP-BCI has reached more than 100 bits/min [10].

Obviously SSVEP-BCIs require the ability of eye-gaze for operation which is not assured for disabled users who have impairment in oculomotor control. There have been proposed some binary SSVEP-BCIs which depend on the shift of attention without eye-gaze, namely, covert attention, using superimposed two flickering icons with different colors and figures [11],[12]. These BCIs have an issue in paying covert attention to the target icon corresponding to a user’s intention, and ITRs of these BCIs are limited to a few bits/min dependently on subjects [13].

A recently proposed binary eyes-closed BCI exploited eyeglasses with LEDs inside flickering at different frequencies on its left and right sides has obtained relatively high classification accuracy and ITR [14]. It is however concerned that users feel considerably tired due to reception of flickering stimuli in front of their eyes for sequential use. Moreover, although eyeball movements to the direction of a target LED, which could occur in attention to the target, might elicit the modulation of SSVEP even in the eyes-closed state, electro-oculogram (EOG) in the selective attention to a target LED has yet to be recorded in the literature.

We have previously investigated amplitude modulation of SSVEP elicited by performing mental tasks and mainly confirmed its reproducibility to apply to an SSVEP-BCI available for users with impairment of oculomotor control [15]. Although this paper has additionally proposed a novel SSVEP-BCI based on this modulation, discrimination of binary intents has been performed by a simple method based on a threshold of the modulation, just as a preliminary study. Recently the classification accuracies of the proposed SSVEP-BCI were investigated using the multiple components of SSVEP with the linear discriminant analysis (LDA) classifier in the conference paper [16]. Subsequently the present work is aimed at assessment of the feasibility of the SSVEP-BCI through further exploration on the classification performance and communication speed. Namely, this paper newly considers the precision, recall, and F-measure calculated from the confusion matrix and the effect of trial time-length on simulated ITR of the proposed BCIs.
as well as the comparison of the classification performance between the LDA and the support vector machine (SVM) classifiers [17].

The proposed eye-movement independent BCIs are able to provide patients with impairment of oculomotor control and/or severely advanced amyotrophic lateral syndrome (ALS) with an invaluable alternative channel for communication to their surroundings and environment. In particular, in advanced stages of ALS, such as totally locked-in state, oculomotor control could deteriorate and almost be lost [7], [12], [13]. Such patients can perceive light flicker and could be potential users of the proposed SSVEP-BCI. Other patients of locked-in syndrome could be also potential users.

2. Methods

2.1 Subjects

We recruited 18 healthy students (21 to 24 years old, 16 males and 2 females) with normal or corrected normal vision and no history of photosensitive epilepsy and neurological and psychiatric disorders. They gave written informed consent after they were explained that flicker stimuli might elicit the paroxysmal EEG activity and epileptic seizures. Experiments were approved by Institutional Review Board of Yamaguchi University Hospital (No. H25-125).

2.2 Mental Tasks

The following three mental tasks were employed to elicit the modulation of SSVEP [15].

- mental focus on flicker stimuli (mental focus task)
- recall of an animal image memorized beforehand (image recall task)
- repeated subtraction of seven from a given three-digit number randomly assigned (arithmetic task)

Participants were asked to continue to perform one of the tasks during the reception of the flicker stimuli.

2.3 Flicker Stimuli

The stimulator used in the present study is illustrated in Fig. 1. It consisted of eight red LEDs mounted to a breadboard which was placed about 70 mm in front of eyelids of each subject. These LEDs were flickered in phase at 10 Hz for 10 subjects and 14 Hz for the rest 8 subjects under the control of the function generator NF-1930 (NF cooperation). These flickering frequencies were chosen to elicit the large SSVEP according to the frequency characteristics of SSVEP amplitude [18].

2.4 Data Recording

Thirteen electrodes were placed over the entire scalp according to the international 10-20 System referenced to the linked ear potential (A1+A2) (Fig. 2). EEG data recorded from the electrode sites over the parietal and occipital lobes (P3, P4, O1 and O2) were used for the classification of intention in the proposed SSVEP-BCI because the magnitude and modulation of SSVEP are larger over the parietal and occipital lobes. Analog EEGs were detected and amplified using EEG-5532 (Nihon Koden, 86 dB gain) and digitized at a rate of 200 Hz with LABVIEW.

Effect of the mental tasks on the eye-movement, particularly that of the mental focus on the flicker stimuli, was examined by measuring EOG which was recorded from both temples (EOG1, EOG2). However, the EOG recording did not depend on whether the subjects performed the task or not but fluctuated aperiodically in both of the task-engaged and non-engaged trials. Thus it is considered that EOG during the execution of the mental tasks had little impact on SSVEP and also classification performance of the proposed SSVEP-BCI.

2.5 Experimental Procedure

All the measurements were conducted in the state that the subjects lay their backs on a bed with keeping their eyes closed in the electromagnetic shield room in the Intellectual Property Center, Yamaguchi University. Each subject experienced two sessions each of which consisted of 14 trials including two trials during free funning, two task-engaged trials each task (six trials for the three tasks in total) and two non-engaged trials as control each task (six trials in total).

The trials with and without task correspond to two intentions in the proposed binary BCI, respectively. All subjects were instructed to perform a designated task immediately following a voice cue for the mental focus and image recall tasks and three-digit number for the arithmetic task or to ignore the voice in order not to perform the task before the onset of each trial. The order of the engagement and non-engagement trials was randomized. Each trial lasted 15 s.

2.6 Data Analysis

From each 15 s trial data, three 5 s segments were transcribed with rectangular windows starting at 0 s, 3 s, and 6 s, respectively. Amplitudes at the stimulus frequency and its twofold frequency were estimated using a discrete Fourier transform (DFT). Since the former mainly includes the amplitude of the fundamental component of SSVEP while the latter corresponds to an estimate of the second harmonic component of SSVEP, these estimates are called fundamental SSVEP amplitude and second harmonic SSVEP amplitude, respectively.

Then the following multi-dimensional feature vector was extracted from the amplitude spectrum each segment at m electrode sites:
f(i) = (A^n_1(f_1), A^n_1(f_2), \ldots, A^n_m(f_1), A^n_m(f_2)),

where A^n_j(f_1) and A^n_j(f_2) \ (j = 1, \ldots, m) denote the fundamental and second harmonic SSVEP amplitudes at the frequencies of f_1 (=10Hz or 14Hz) and f_2 (=2f_1) at an electrode site e_j (any one of P3, P4, O1, O2) for a segment \( i \) \ (i = 1, 2, 3), respectively. LDA and SVM were independently used to classify each feature vector into a vector belonging to data (class) in engaging in a task or that without performing a task. For each classifier, each trial was labeled as follows. From the three 5 s segments in each trial, three classification results were computed as candidates for which class the vector belonged. Then the final class for each trial was decided by majority vote. Performance of each classifier was assessed on the basis of 4x4 cross-validation.

2.7 LDA and SVM

LDA is used to classify each feature vector in the feature space obtained from a test trial into the classes labelled as task-engaged and task-non-engaged using hyperplanes [19]. The hyperplane separating the two distributions of feature vectors belonging different classes is obtained by determining the projection which can simultaneously maximize the distance between the means of the distributions of the two classes and minimize the inter-class variance. The major advantage of LDA is its simplicity and very low computational requirement which makes it suitable for the online BCI system as well as the LDA classifier provides good performance if the feature vectors are linearly separable in the feature space [19],[20]. Thus LDA has been used in many BCIs [2],[3],[19]. The major disadvantage of LDA is to provide insufficient classification results if the feature vectors are distributed complicatedly in such a way they are not linearly separable.

SVM uses a hyperplane which maximizes the distance (margin) from the nearest feature vectors in the training data (support vectors) to obtain the generalization capabilities [19]. In a soft-margin SVM, the hyperplane is determined in such a way some errors in the training feature vectors are allowed using a slack variable. Moreover, the major advantage of SVM is that it can be extend to provide good classification results even if the feature vectors are not linearly separable using kernel functions which map the feature vectors to higher dimension. In BCIs, radial basis function (RBF) kernel is generally used. Although SVM has high generalization capability, there are a few hyper-parameters needed to be empirically determined. For example, we optimized the values of the slack variable and width parameter to operate the soft-margin SVM with the RBF kernel using the feature vectors in the training phase.

2.8 Simulated ITR

A genuine ITR is given by the following equation [9]:

\[ ITR = \frac{60}{T} \left( \log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{N - 1} \right), \]

where \( T \) (s), \( N (=2 \) in the present study), and \( P \) are the time-length of one trial, the number of classes, and the classification accuracy of a classifier which is defined as the rate of the number of trials correctly discriminated to the total number of trials. In the present study, however, the trial time-length was fixed at 15 s and the classification accuracy was calculated using the majority vote as described above. Thus we introduce ‘simulated’ ITR as a substitute for ITR, which is defined as a value given by (2) where the classification accuracy \( P \) is obtained using data segment in the time-range from the onset to any given time (less than 15 s) extracted from each trial data as a simulated time-length of one trial, corresponding to \( T \). Furthermore, unlike the classification accuracy used for the assessment of the BCI performance described in Section 2.6, the classification accuracy for simulated ITR was obtained without majority vote. Classification accuracy was assessed by the 4x4 cross-validation. A mean value of the simulated ITR was calculated each task.

3. Results and Discussions

3.1 Modulation of SSVEP

Figure 3 shows one example of feature vectors of subject A obtained from EEG data with the four electrode sites and three 5 s segments for 10Hz stimuli. The feature vectors distribute complicatedly in the input space in each task. However, for the mental focus task, most of the plots during performing the task designated by the crosses seem to gather together in the region corresponding to relatively low amplitude for both the fundamental and second harmonic SSVEPs, indicating the desynchronization of SSVEP associated with the engagement in the mental focus task on the 10Hz stimuli.

On the contrary, the feature vectors in the engagement in the image recall and arithmetic tasks indicate the tendency to increase the amplitude of both the fundamental and second harmonic SSVEP. Indeed, there found significant difference between the engagement and non-engagement in a task in the fundamental SSVEP amplitude for the focus and image recall tasks and the second harmonic SSVEP amplitude for the arithmetic task using the independent one-sample t-test for a population mean of the ratio of the grand mean amplitude across the four electrode sites (P3, P4, O1 and O2) and the four trials in the engagement to that in the non-engagement with the hypothetical mean of the ratio as 1 (\( p < 0.05 \)).

Although the distributions of the feature vectors for 14 Hz stimuli are less separated between the engagement and non-engagement in each task as shown in Fig. 4, the second harmonic SSVEP amplitude corresponding to the feature vectors seems to be increased in the engagement in the arithmetic task, namely, many plots designated by the crosses are located above the plots of open circles along the ordinated axis in Fig. 4(c). Modulation of SSVEP has been reported in performing a working memory task [21] as well as selective attention [22]. In the framework of the present study, the modulations of SSVEP may be elicited by the effect of the mental task on visual pathways including cortical areas involved in the processing of visual flicker stimuli. Such an event-related modulation could be observed in EEG rhythmic activity such as the alpha wave as the event-related desynchronization (ERD) [23]. As ERD in rhythmic EEG activity [24], the modulation of SSVEP may reflect cognitive brain functions such as perception, memory, and attention.

Also note that the mental focus task tends to cause the stressful situation while the other tasks let the subject’s excessive focus stray from the flicker stimuli. Such difference in the participant’s consciousness may be related to the suppression of the SSVEP amplitude for the mental focus task and enhancement...
Fig. 3 Feature vectors for 10 Hz stimuli using the three 5 s segments EEG at the four electrode sites (P3, P4, O1 and O2) for subject A. Values for the task-non-engagement are marked as open circles and those engaged in task as crosses, respectively.

for the image recall and arithmetic task.

The fact that the modulation of SSVEP was deeper for 10 Hz stimuli than that for 14 Hz stimuli suggests the possibility of the effect of nonlinear response of the alpha wave on the SSVEP. Such nonlinear response, referred to be as resonance phenomenon, has been observed at 10 Hz, 20 Hz, 40 Hz, and 80 Hz and speculated as neural basis of gamma oscillation around 40 Hz [25],[26]. On the other hand, a study evidenced that intermittent photic stimulation with 5 Hz, 7.5 Hz, 10 Hz, and 12.5 Hz suppressed the spontaneous EEG activity which was correlated with the SSVEP amplitude [27].

The present study found no significant difference in the mean amplitude in the alpha range (8 Hz to 13 Hz) except 10 Hz between each task-non-engaged state and resting without stimuli using the independent one-sample t-test for a population mean of the ratio of the grand mean amplitude across the four electrode sites and the four trials during the reception of 10 Hz stimuli to that during free running with the hypothetical mean of the ratio as 1. There was also no significant difference in the mean alpha amplitude except 10 Hz between task-engaged under 10 Hz stimuli and resting state. On the other hand, the mean alpha amplitude including 10 Hz showed significant difference between the arithmetic task-engaged and resting with \( p < 0.05 \) under 14 Hz stimuli, whereas it has no significant difference for other cases (between each of the mental focus and image recall tasks and task-non-engaged for all tasks and resting state). The former modulation of the alpha wave may be thus derived from performing the mental task rather than SSVEP.

Moreover, the mean amplitude in the alpha range except/including 10 Hz showed significant difference between the engagement and non-engagement states \( (p < 0.05) \) for the focus and arithmetic tasks. Thus the oscillatory activity at 10 Hz under 10 Hz stimuli may be originated from the neural mechanism specific to SSVEP and/or the resonance phenomenon of alpha wave at 10 Hz.

3.2 Classification Performance

Figures 5 and 6 summarize the precision, recall, F-measure, and correlation coefficient between the precision and recall scores of the proposed SSVEP-BCI for 10 Hz and 14 Hz flicker stimuli using the modulations of SSVEP at the four electrode sites, namely, \( m=4 \) in (1), and the LDA and SVM classifiers, re-
respectively. The precision was defined as the rate of the number of EC to the sum of the numbers of EC and task-engaged trials correctly classified (EC as true positive in the definition of the recall was given by the rate of the number of task-engaged trials including task-engaged and task-non-engaged to that of overall trials) of 89% which exceeds the accuracy of 70%, the score regarded as the criterion level required for practical use for SSVEP associated with engagement in the tasks were subject-independent and many of them may not be large enough to be detectable by LDA. The correlation coefficients between the precision and recall scores did not show the strong relationship contrary to our expectations of the inverse relationship between the two scores.

On the other hand, the three mean scores, namely the mean values of the precision, recall, and F-measures, are improved using SVM classifier (right in Fig. 5); all the mean scores become larger than 70% with up to 16% higher than the those for LDA classifier. As mentioned above, the feature vectors for the three tasks scatter so complicatedly in the input space as to look difficult to separate linearly in the feature space. The improvement of the three mean scores by the soft-margin SVM classifier with RBF kernel suggests that the feature vectors for the task-engagement and task-non-engagement trials are distributed in an intricate manner in the feature space in either task each subject.

It is also noted that the classification performance has considerably large inter-individual (subject-dependent) and inter-task (task-dependent) differences as listed in Table 1. As examples for the subject-dependence, the precision scores are ranged from 26% to 100% for the mental focus task, while the recall scores are distributed from 42% to 100% for the arithmetic task. There also exists large task-dependence for which the differences in the precision scores between the tasks which gave the best and worst performances exceed 50% for subjects G and I.

For the SVM classifier, the subject-dependence in the recall score was reduced to be ranged at most from 51% to 100% for the mental focus task, whereas that in the recall score remains to be from 48% to 100% for the mental focus task, in comparing Table 2 with Table 1. The task-dependence is also reduced; the largest differences in the precision and recall scores between the best and worst performance are 44% (precision) in subject H and 42% (recall) in subject I, being smaller than 50%, respectively.

In comparison with 10 Hz stimuli, the three mean scores regarding the classification performance for the focus and image recall tasks were degraded for 14 Hz stimuli for the LDA classifier (left in Fig. 6); in particular, the mean precision score for the image recall tasks, 36%, is limited to be far from the practical level. On the other hand, the classification performance almost remains static for the arithmetic task; larger than 74% for all of the three scores, which suggests that the modulation of SSVEP could be elicited stably with relatively higher signal to noise ratio irrelevantly to the stimulus frequency and subjects for the arithmetic task. There found relative strong correlation between the precision and recall scores for the focus and image recall tasks.

From the plots on the right of Fig. 6, the SVM classifier is seen to have better classification capability over the entire classification scores than the LDA classifier; the mean precision score is increased by up to 44%, the mean recall score by up to 30% and the mean F-measure by up to 38% for the image recall task. Since the three scores are comparable to those in Fig. 5 for the SVM classifier, the score deterioration observed for the LDA classifier is considered to be mainly due to the linearly nonseparable distribution of the feature vectors in the feature space which could be difficult to be correctly classified by the LDA classifier. For the SVM classifier, there was no strong
Table 1: Precision (Pre.), recall (Rec.) and mean F-measure (mF-meas.) calculated from confusion matrices (LDA, 10 Hz stimuli, n = 10). (Focus: mental focus, Image: image recall and Arith.: mental arithmetic tasks, respectively. All the scores are indicated in percent figures (%))

| Subject | Focus | Image | Arith. |
|---------|-------|-------|--------|
|         | Pre.  | Rec.  | Pre.  | Rec.  | Pre.  | Rec.  |
| A       | 73    | 82    | 88    | 55    | 76    | 100   |
| B       | 46    | 90    | 48    | 54    | 83    | 96    |
| C       | 26    | 42    | 76    | 73    | 64    | 64    |
| D       | 79    | 51    | 77    | 66    | 94    | 67    |
| E       | 100   | 73    | 100   | 100   | 85    | 65    |
| F       | 83    | 67    | 100   | 86    | 89    | 83    |
| G       | 100   | 49    | 50    | 71    | 100   | 96    |
| H       | 44    | 43    | 91    | 48    | 90    | 42    |
| I       | 47    | 50    | 49    | 64    | 100   | 68    |
| J       | 92    | 71    | 26    | 44    | 100   | 74    |
| Mean    | 69    | 62    | 71    | 66    | 88    | 75    |
| S.E.    | 5     | 8     | 8     | 5     | 4     | 6     |
| mF-meas.| 65    | 68    | 81    |       |       |       |

Table 2: Same as Table 1, but for SVM.

| Subject | Focus | Image | Arith. |
|---------|-------|-------|--------|
|         | Pre.  | Rec.  | Pre.  | Rec.  | Pre.  | Rec.  |
| A       | 75    | 66    | 77    | 100   | 100   | 100   |
| B       | 97    | 72    | 59    | 72    | 64    | 82    |
| C       | 51    | 62    | 94    | 98    | 73    | 90    |
| D       | 100   | 83    | 93    | 95    | 100   | 100   |
| E       | 76    | 85    | 69    | 79    | 100   | 100   |
| F       | 85    | 89    | 73    | 70    | 78    | 89    |
| G       | 100   | 68    | 72    | 71    | 100   | 72    |
| H       | 56    | 48    | 100   | 72    | 100   | 78    |
| I       | 68    | 58    | 69    | 78    | 100   | 100   |
| J       | 74    | 100   | 70    | 72    | 79    | 100   |
| Mean    | 78    | 73    | 78    | 81    | 89    | 91    |
| S.E.    | 5     | 5     | 4     | 4     | 4     | 3     |
| mF-meas.| 76    | 79    | 90    |       |       |       |

correlation between the precision and recall scores.

For task-dependence, there also found significant differences in the precision score between the arithmetic and image recall tasks for the LDA classifier under 14 Hz stimuli (p < 0.01, Tukey HSD as post-hoc test after ANOVA) and in the recall scores between the mental focus and arithmetic tasks for the SVM classifier under 10 Hz stimuli (p < 0.05) whereas not found between other pairs of tasks under 10 Hz and 14 Hz stimulus conditions.

It is however noted that the SVM classifier depends on the model parameters such as slack variables in the soft-margin SVM and the hyper-parameters in the RBF kernel SVM. Moreover, one of the disadvantages of SVM is the high computational cost required for both training and test data [20], which becomes an issue in the formulation as an online BCI system. Also note that the generalization of the SVM classifier was not enough due to small amount of data each trial in the present study.

Figures 7 and 8 depict the three classification scores and correlation coefficients at the individual best electrode site each subject and task where the maximum classification accuracy is obtained in the four electrode sites. Most of the mean classification scores are higher than those with the four electrode sites for the LDA classifier. For example, the F-measure scores are improved by 9% to 16% for the LDA classifier and 4% to 14% for the SVM classifier under 10 Hz stimuli in Fig. 7 as compared to Fig. 5 while those values are increased by 7% to 22% for the LDA classifier under 14 Hz stimuli in comparing the left column in Fig. 8 to that in Fig. 6. However the effect of focus of the electrode site is not so obviously observed for the SVM classifier under 14 Hz stimuli as shown in the right column in Fig. 8; the change of F-measure values ranges ±4% to 5% with reference to the values designated in the right column of Fig. 6. The correlation coefficients between the precision and recall scores also do not show strong relationship for any task, classifier, and stimulus frequency at the best electrode site. The correlation results may depend on the small amount of data and participants in the present project.

In summary, the classification scores of the proposed SSVEP-BCI are improved to be plausible values for which the proposed SSVEP-BCI could be practically usable for communication by adequately selecting the task, electrode site, and classifier.

3.3 Trial Time-Length and Simulated ITR

The effect of trial time-length on the simulated ITR is depicted in Figs. 9 and 10, where the simulated ITR value (bits/min) each time-length (s) is represented by the mean simulated ITR value across all subjects (n = 10 for 10 Hz stimuli and n = 8 for 14 Hz stimuli) at the four electrode sites using the SVM classifier.

Both figures illustrate that simulated ITR at T = 1 s takes the highest value in any task and stimulus condition, whereas the classification accuracy reaches its peak at other trial time-length than 1 s except for the image recall task under 10 Hz stimuli (4 s for the mental focus task and 3 s for the arithmetic task under 10 Hz stimuli and at 5 s for the mental focus task, 3 s for the image recall task and 11 s for the arithmetic task under 14 Hz stimuli, respectively, although figures are not shown here). Namely, the time-length mainly affects simulated ITR during this time period.
activities and variations of physiological quantities involved. In methodologies to communicate others are limited to be neural for completely paralyzed patients, namely locked-in syndrome, interfaces using eye-gaze [29] and eye-blink [30]. However, replaced by other hands- and voice-free interfaces such as in-free communication. Most of the conventional BCIs can be components adopted, and ease of maintenance.

In order to adequately extract the task-dependent EEG modulation irrelevant to individual differences, the classification accuracy of the proposed SSVEP-BCI will be examined through the application to more subjects, especially disabled patients to identify the task-dependent modulation.

4. Conclusion

The present paper proposes the novel binary eye-gaze- and eye-movement-independent BCIs using the modulations of SSVEP. Through the experiments for 18 normal subjects and analyses of the EEG data recorded, the proposed SSVEP-BCI showed the mean precision and recall scores higher than 73% when the electrode sites, mental task and classifier were adequately selected. Improvement of ITR is an important issue to be tackled for the proposed SSVEP-BCI.

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References

[1] J.J. Vidal: Toward direct brain-computer communication, Ann. Rev. Biophys. Bioeng., Vol. 2, No. 2, pp. 157–180, 1973.
[2] O. Tonet, M. Marinelli, L. Citi, P.M. Rossini, L. Rossini, G. Megali, and P. Dario: Defining brain-machine interface applications by matching interface performance with device requirements, J. Neurosci. Meth., Vol. 167, No. 1, pp. 91–104, 2008.
[3] J.R. Wolpaw and E.W. Wolpa (eds.): Brain-Computer Interfaces Principals and Practice, OUP, 2012.
[4] M. Cheng and S. Gao: An EEG-based cursor control system, Proc. 1st Joint BMES/EMBS Conference, p. 669, 1999.
[5] M. Middendorf, G. McMillan, G. Calhoun, and K.S. Jones: Brain-computer interfaces based on steady-state visual evoked response, IEEE Trans. Rehabil. Eng., Vol. 8, No. 2, pp. 211–214, 2000.
[6] D. Regan: Electrical responses evoked from the human brain, Sci. Am., Vol. 241, No. 6, pp. 107–117, 1979.
[7] L.F. Nicolas-Alonso and J. Gomez-Gil: Brain computer interfaces: A review, Sensors, Vol. 12, No. 2, pp. 1211–1279, 2012.
[8] B. Graimann, B. Allison, and G. Pfurtscheller (eds.): Brain-Computer Interfaces Revolutionizing Human-Computer Interaction, Springer, 2010.
[9] J.R. Wolpaw, H. Ramose, D.J. McFarland, and G. Pfurtscheller: EEG-based communication: Improved accuracy by response verification, IEEE Trans. Rehabil. Eng., Vol. 6, No. 3, pp. 326–333, 1998.
[10] X. Chen, Z. Chen, S. Gao, and X. Gao: A high-ITR SSVEP-based BCI speller, Brain-Computer Interfaces, Vol. 1, Nos. 3-4, pp. 181–191, 2014.
[11] S.P. Kelly, E.C. Lalor, R.B. Reilly, and J.J. Foxe: Visual spatial attention tracking using high-density SSVEP data for independent brain-computer communication, IEEE Trans. Neural Syst. Rehabil. Eng., Vol. 13, No. 2, pp. 172–178, 2005.
[12] B.Z. Allison, D.J. McFarland, G. Schalk, S.D. Zheng, M.M. Jackson, and J.R. Wolpaw: Towards an independent brain-computer interface using steady state visual evoked potentials.
A. Riccio, D. Mattia, L. Simione, M. Olivetti, and F. Cinotti: Eye-gaze independent EEG-based brain computer interfaces for communication, *J. Neural Eng.*, Vol. 9, No. 4, 045001, 2012.

J.-H. Lim, H.-J. Hwang, C.-H. Han, K.-Y. Jung, and C.-H. Im: Classification of binary intentions for individuals with impaired oculomotor function: ‘Eyes-closed’ SSVEP-based brain-computer interface, *J. Neural Eng.*, Vol. 10, No. 2, 026021, 2013.

S. Nishifuji and Y. Sugita: Reproducibility and task-dependence of amplitude modulation of steady-state visual evoked potential in eyes-closed state by mental tasks for brain machine interface for visually impaired persons, *J. Inst. Ind. Appl. Eng.*, Vol. 3, No. 1, pp. 41–47, 2015.

S. Theodoridis and K. Koutroumbas: *Pattern Recognition* and *Machine Learning*, Springer, 1996.

D. Regan: Recent advances in electrical recording from the brain, *Nature*, Vol. 253, No. 5491, pp. 401–407, 1975.

F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi: A review of classification algorithms for EEG-based brain-computer interfaces, *J. Neural Eng.*, Vol. 4, No. 3, pp. R1–R13, 2007.

S. Theodoridis and K. Koutroumbas: *Pattern Recognition*, 4th edition, Academic Press, 2009.

R.B. Silberstein, P.L. Nunez, A. Pipingasa, P. Harrisa, and F. Daniella: Steady state visually evoked potential (SSVEP) topography in a graded working memory task, *Int. J. Psychophysiol.*, Vol. 42, No. 2, pp. 219–232, 2001.

S.T. Morgan, J.C. Hansen, and S.A. Hillyard: Selective attention to stimulus location modulates the steady-state visual evoked potential, *Proc. Natl. Acad. Sci. USA*, Vol. 93, No. 10, pp. 4770–4774, 1996.

G. Pfurtscheller and G. Fließer: Auditory elicited EEG desynchronization and synchronization: A review on Christina M Krause’s doctoral thesis, *Scand. J. Psychol.*, Vol. 40, No. 4, pp. 329–331, 1999.

C.S. Herrmann: Human EEG responses to 1–100 Hz flicker: Resonance phenomena in visual cortex and their potential correlation to cognitive phenomena, *Exp. Brain. Res.*, Vol. 137, Nos. 3–4, pp. 46–53, 2001.

F.B. Vialatte, M. Maurice, J. Dauwels, and A. Cichocki: Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives, *Prog. Neurobiol.*, Vol. 90, No. 4, pp. 418–438, 2010.

A. Birca, L. Carmant, A. Lortie, and M. Lassonde: Interaction between the flash evoked SSVEPs and the spontaneous EEG activity in children and adults, *Clin. Neurophysiol.*, Vol. 117, No. 2, pp. 279–288, 2006.

A. Kübler, N. Neumann, J. Kaiser, B. Kotchoubey, T. Hinterberger, and N.P. Birbaumer: Brain-computer communication: Self-regulation of slow cortical potentials for verbal communication, *Arch. Phys. Med. Rehabil.*, Vol. 82, No. 11, pp. 1533–1539, 2001.

T.E. Hutchinson, K.P. White, W.N. Martin, K.C. Reichert, and L.A. Frey: Human-computer interaction using eye-gaze input, *IEEE Trans. Syst. Man Cybern.*, Vol. 19, No. 6, pp. 1527–1534, 1989.

K. Grauman, M. Betke, J. Gips, and G.R. Bradski: Communication via eye-blinks–detection and duration analysis in real time, *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 1010–1017, 2001.