Improvement of SSVEP Detection Accuracy via Additive Averaging of Binaural Peripheral Electrodes

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***Abstract*—Recently, Brain–Computer Interfaces for healthy subjects have attracted considerable attention. Steady–State Visual Evoked Potential (SSVEP) has garnered particular attention because it can be used by anyone without training. However, SSVEP is mainly used for head measurements and is unsuitable for daily measurements. We attempted to measure SSVEP via the application of electrodes around the ears. The highest average macro F–value was 45.33±16.84 %, and the highest average Information Transfer Rate (ITR) was 13.86±13.21 bits/min with the L2+R2 method. A comparison between electrodes 1–3 and the head showed no significant difference, except in the occipital area, and the combination of right and left electrodes around the ear produced the same accuracy as that of the head.**

***Keywords*—Steady–State Visual Evoked Potential (SSVEP); Canonical Correlation Analysis (CCA); ear EEG.**

I. INTRODUCTION

Recently, several efforts have been made to apply brain information to engineering. One example of such an application is the Brain–Computer Interface (BCI), which is being actively pursued, particularly in the medical and welfare fields. This is because BCI can operate machines using only brain information without the use of limbs and can be used to replace some body functions. However, because devices for measuring brain information are now commercially available at a relatively low cost, research on BCI using healthy subjects has also attracted attention. Many studies using brain information from healthy subjects have reported using ElectroEncephaloGraphy (EEG), among other methods to collect brain information.

Steady–State Visual Evoked Potential (SSVEP) is a type of EEG that has attracted considerable attention for its applications. The frequency range of the SSVEP is wide, ranging from 1 to 100 Hz [1]. In 2006, a previous study [2] using Canonical Correlation Analysis (CCA) to discriminate SSVEP detected a higher discrimination accuracy than that obtained using the conventional Fourier transform. This indicates that the analysis of SSVEP is more accurate than the conventional Fourier transform and that CCA is a useful method for analyzing SSVEP.

One factor that has drawn attention in CCA is that it does not require prior preparation, in contrast to analysis methods using machine learning and other methods. In 2015, Nakanishi et al. [3] reported the results of a comparison of various analysis methods based on CCA. In 2021, Li et al. [4] reported in a review article that there is a wide range of analysis methods based on CCA and that CCA is superior as a discrimination method for BCI using SSVEP.

Other EEGs used for BCI, such as the P300, generally require prior training on the task and data collection for machine learning. However, SSVEP does not require subject training because it is an exogenous visual–evoked potential. Therefore, SSVEP can exploit the previously mentioned benefits of requiring no prior preparation. In addition, compared to other EEG methods, SSVEP is easy to detect even when the measurement time is short, and has a high Signal–to–Noise ratio (S/N), rendering stable measurements relatively easy. In 2009, Parini et al. [5] reported that the Information Transfer Rate (ITR), a BCI evaluation index, is excellent. Furthermore, in 2017, Botani et al. [6] proposed an algorithm for a menu selection interface with SSVEP using six different visual stimuli, with an average correct response rate of 83.3 % and an average ITR of 30.5 bits/min. In 2018, a robot control method based on SSVEP, which can operate in virtual reality space, was proposed by Stawicki et al. [7], with an average correct response rate of 98.91 % and an average ITR of 32.00 bits/min.

As described above, BCIs using SSVEP have been actively studied in various settings. However, most current reports are based on head measurements using the international 10–20 method. Thus, electrodes must be applied to the scalp to measure SSVEP when using these systems. In 2017, Wang et al. [8] attempted to measure SSVEP in hairless areas such as the neck and behind the ears, and recently, ear EEG, wherein electrodes are applied around the ears, has been gaining popularity as a method for measuring SSVEP outside the head.

In 2011, Looney et al. [9] proposed a method to measure EEG signals from inside the ear, and in 2013, Kidmose et al. [10] developed an earpiece–type EEG measurement device. The signal measured inside the ear is also being investigated to determine whether it is similar to an EEG signal. In 2016, Zibrandsen et al. [11] used in–ear and on–head EEG to classify sleep stages and reported 90.9 % accuracy in discriminating between awake and REM sleep states.

However, the amplitude values of measurements inside and around the ears are lower than those of head measurements, and it is difficult to significantly improve the accuracy [12]. Here, we attempted to create a new signal by applying electrodes to both ears and performing additive averaging of EEG between the two ears. We expected the accuracy to improve as a results of using this new additive averaging method. In addition, we investigated the optimal location for detecting SSVEP from electrodes affixed around the ears when visual flashing stimuli are provided. The performance of the BCI was examined by comparing the monopolar induction electroencephalograms applied around the ears and the electroencephalograms based on the additive averaging of the electrodes around both ears.

The remainder of this paper is organized as follows. Section 2 describes the methods including experimental design and EEG data recording. Section 3 describes the EEG data analysis and evaluation methods. Section 4 presents the analytical results obtained in this study. Based on the results, a discussion of the binaural additive electrode method is presented in Section 5. Finally, the conclusions are presented in Section 6 .

II. METHODS

A. Experimental Design

The subjects remained in a resting, sitting position. A display (27 in.) was placed 50 cm ahead of the subject for stimulus presentation. Stimuli were presented within 19.3° of the visual field.

For the SSVEP elicitation task, a black–and–white square (17 cm) was presented as a visual flashing stimulus on a display in front of the subject (Figure 1). Four types of flashing stimuli were selected in the low-frequency band [13] at 5, 7, 9, and 11 Hz, where high–amplitude values were easily recorded in the SSVEP. The stimuli were presented in the order described for 12 s with a 60 s rest between each stimulus (Figure 2). The subjects were instructed not to blink except for a minimum amount of blinking during the blinking stimuli, and to rest their eyes sufficiently during the rest period. This task was performed in one session, followed by two sessions of SSVEP–evoked tasks.

Figure 1. Image stimulation in SSVEP-induced experiment.

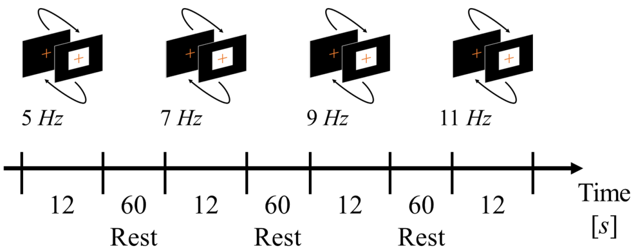

Figure 2. Experimental protocol.

B. Data recording

BIO–NVX 52 (East Medic, Japan) was used to record the biometric data with a temporal resolution of 2000 Hz. A bandpass filter (0.50–70 Hz) was applied to eliminate noise. The electrode positions were Oz, O1, and O2 based on the extended 10–20 method [14]. The ground electrode was AFz and the reference electrode was the average value of both earlobes (A1 and A2). For the measurement around both ears, electrodes were affixed at eight locations around each ear, with the reference electrode for the electrode around the right ear being the right earlobe (A2) and that for the electrode around the left ear being the left earlobe (A1) (Figure 3(c, d)).

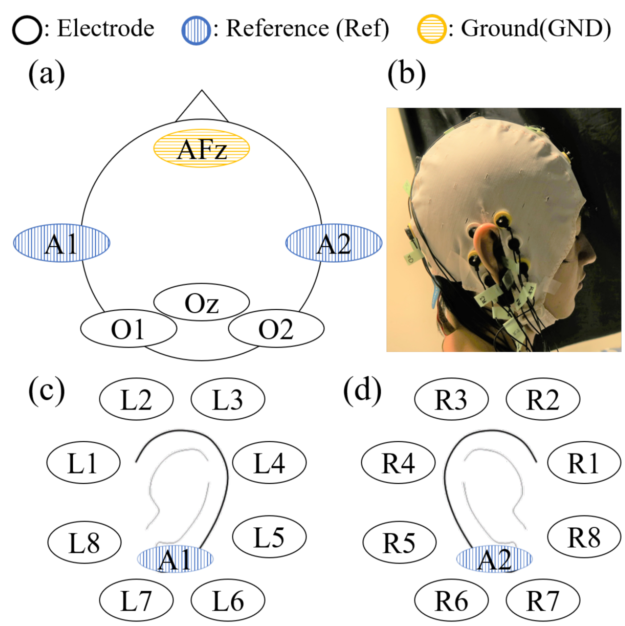

Figure 3. Electrode position.

The subjects were 14 healthy males and females (10 males, 4 females, Mean±SD: 21.93±0.83 years) enrolled in universities and graduate schools. Subjects with visual acuity problems were corrected to achieve normal vision. The subjects were given a thorough explanation of the experiment and their consent to participate was obtained. The experiment was conducted after obtaining approval (H31-9) from the Ethics Committee of Toyama Prefectural University.

III. DATA ANALYSIS

A. Pre–processing

In this experiment, each stimulus was measured for 12 s. Time–series data for 10 s were obtained by excluding data immediately after starting the stimulus presentation and data for 1.0 s before ending the stimulus presentation. The 10 s data were divided into ten segments with a time window of 1.0 s to avoid overlap of the data used. A bandpass filter of 4–35 Hz was applied. When performing additive averaging between left and right electrodes, the difference in amplitude between the electrodes may significantly affect the discrimination accuracy of one of the two electrodes. Therefore, we employed a robust z-score after applying the bandpass filter. The position of the electrodes to be averaged was between the electrodes with the same number of binaural peripheral electrodes, as shown in Figure 3.

B. Analysis, discrimination method, and performance evaluation

The waveforms used in CCA were sine and cosine waves of the same length as the time window length, which were used for comparison. The sine and cosine waves started at 5, 7, 9, and 11 Hz, similar to visual stimuli. Those with frequencies that were two or three times higher than the harmonics were also used for discrimination. According to Bedard et al. [15], EEG also elicits harmonics that are multiples of the frequency of the visual–evoked stimulus. Therefore, using CCA without considering harmonics in the SSVEP analysis may result in them being classified as other frequencies [2]. Therefore, we classified the doubled and tripled frequencies as the same frequency as those provided as visual stimuli.

The Canonical Correlation Coefficient (CCC) calculated by CCA was used to discriminate the EEG signals by creating a 4×4– dimensional mixing matrix at 5, 7, 9, and 11 Hz. For discrimination, CCC was calculated from the frequencies of the four stimuli per data–set, and the highest CCC was predicted as the given stimulus. The discrimination index using this mixed matrix was evaluated by calculating the macro F–value, which is the average of the F–values of each of the four stimuli.

ITR was proposed by Wolpaw et al. [16], where N is the number of discriminations, P is the percentage of correct responses, and t is the time required per trial (min).

$$\mathrm{ITR} = \frac{\log_2 N + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N-1}\right)}{t} \ldots (1)$$

The calculated CCCs, macro F-value, and ITR were compared between the left and right additive electrodes and the left and right unipolar electrodes by performing a Friedman test using the Bonferroni method in the EZR software [17]. The significance level for this study was set at $p = 0.05$.

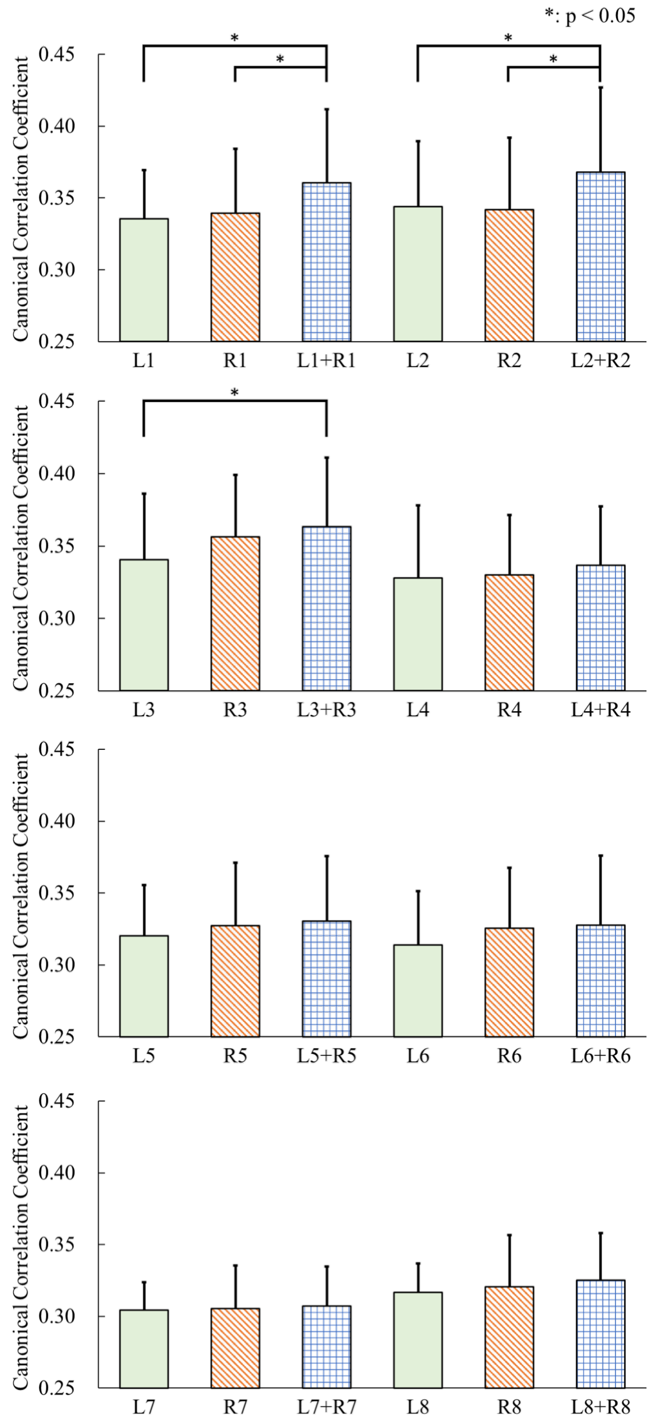

Figure 4. Canonical Correlation Coefficient of each position (Mean±SD).

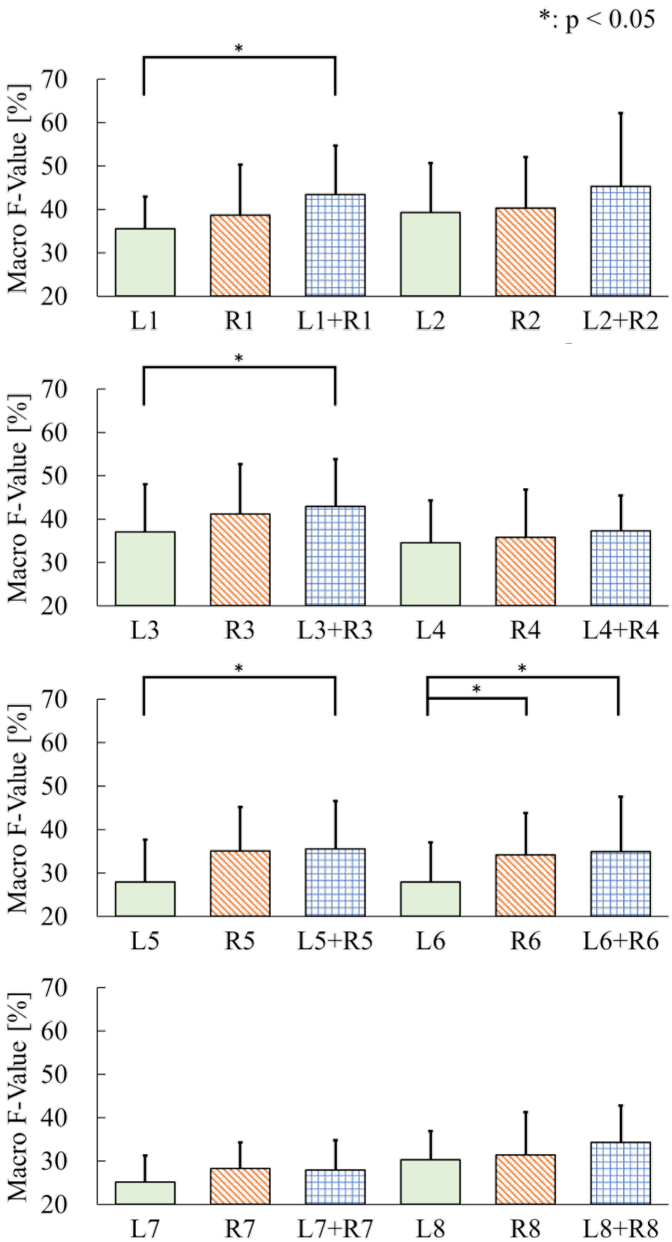

Figure 5. Macro F–value of each position (Mean±SD).

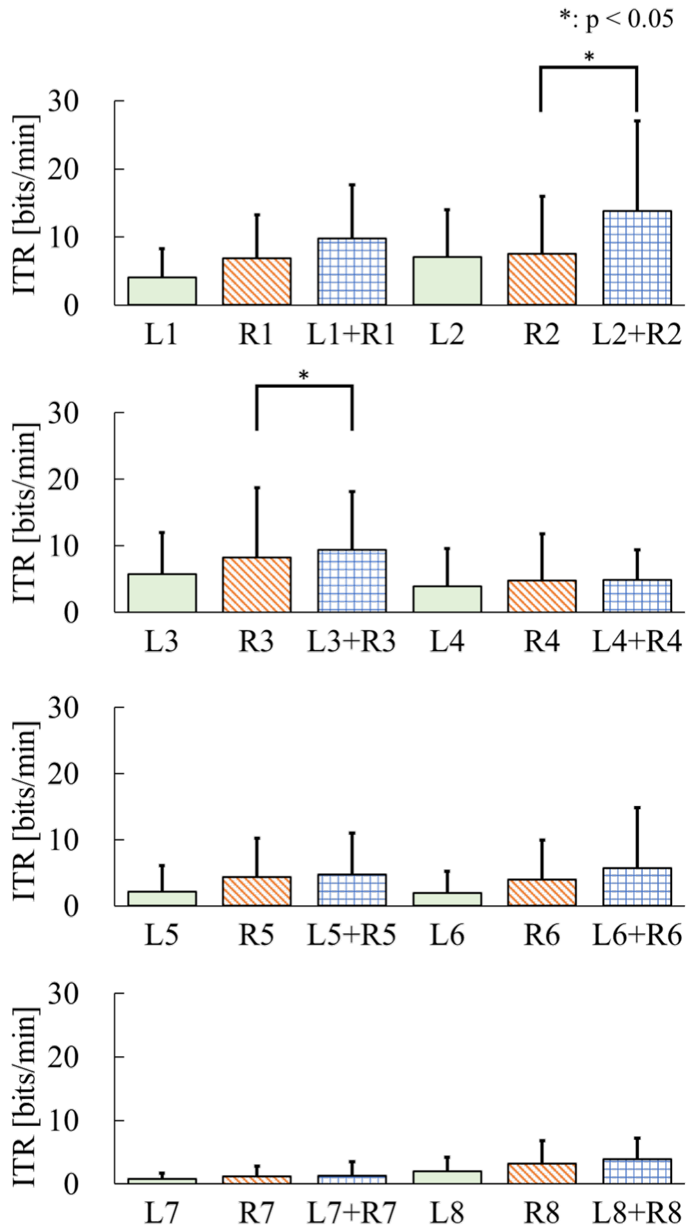

Figure 6. ITR of each position (Mean±SD).

IV. RESULTS

A. Canonical correlation coefficient

The mean value of CCC was the highest at L2+R2, 0.37±0.06 (Mean±SD). Comparisons were made between the left, right, and added electrodes. Significant differences were found for electrodes 1, 2, and 3 as well as between the electrodes (Figure 4).

B. Macro F–value and ITR

Figure 5 shows the macro F–value results. The highest mean value was obtained for the L2+R2 electrodes (45.33±16.84 %). Comparisons were made between the left, right, and added electrodes. Significant differences were found between electrodes 3, 5, 6, and 8 as well as between electrodes.

The highest mean ITR value was observed for L2+R2, at 13.86±13.21 bits/min. Comparisons were made using electrodes of the same number on the left, right, right, and left sides. The results showed a significant difference between the two electrodes at the 2– and 3–number electrodes (Figure 6).

V. DISCUSSION

In a previous study, Sun et al. [18] attached electrodes to the mirror legs of glasses and acquired data from the upper part of each ear. Data from the left and right ears were treated as separate signals with unipolar induction and were classified

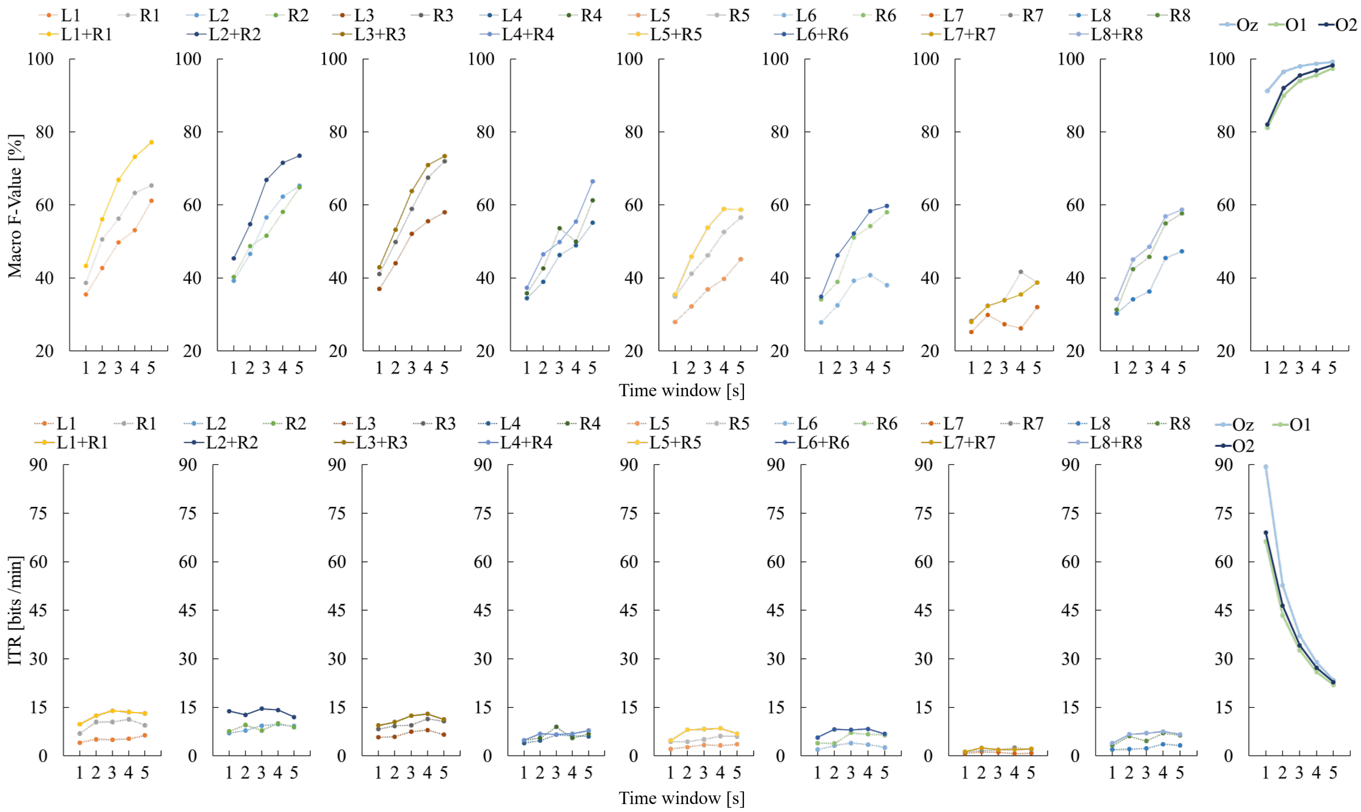

Figure 7. Macro F–value and ITR of change time window. (Mean).

using CCA. Thus, one stimulus of four different frequencies was presented on the screen, which was similar to the present study in terms of the presentation of visual stimuli. The results of the experiment by Sun et al. [18] showed that the estimated correct response rate for the gazing stimulus was 32.75 % when a simple CCA without prior learning was applied using a window length of 1.0 s. However, the estimated correct response rate increased to 43.75 % when the method was pre–trained with the participants' data. The estimated correct response rate based on binaural additive averaging in this study was 45.33 %, which is equivalent to that of the pretraining method proposed by Sun et al. [18]

Conventional CCA does not require prior learning, which is an advantage; however, Time–'Weighting Canonical Correlation Analysis (TWCCA) with prior learning reported by Sun et al. [18] boasts an accuracy equivalent to that of the present study, although it is a monopole induction. Therefore, further improvements in the accuracy of binaural additive averaging data can be a chieved by employing methods such as TWCCA and msetCCA [21], which perform prior learning.

We performed binaural additive averaging using only electrodes attached to the corresponding positions on the left and right sides of each ear. However, it has been reported that the accuracy of stimulus estimation also improves when multiple electrodes are used for binaural additive averaging using only electrodes in one ear [22]. From the above, we believe that by selecting areas with high CCCs and exhaustively applying various additive averaging methods in both ears, rather than between the corresponding positions on the left and right, electrode combinations that still improve the accuracy can be determined. In this study, the highest CCC was R3 for the right periapical electrode only, whereas L2+R2 was the highest when additive averaging was applied to both periapical electrodes. In ITR, R3 was the highest at 8.25±10.45 bits/min for the right periapical electrode alone, and L2+R2 was the highest at 13.86±13.22 bits/min when the bilateral periapical electrodes were added and averaged.

The results of the analysis with different time–window lengths showed that the F–value increased with the window length (Figure 7). In the occipital lobe area (Oz, O1, O2), a prominent peak was observed at a window length of 1 s in ITR. However, in the case of binaural additive averaging, ITR was not larger at a window length of 1 s.

In this experiment, only one type of flashing stimulus was presented, and there was a discrepancy with the actual use of the BCI. Therefore, in the future, we would like to measure and analyze SSVEP when two or more different flashing stimuli are simultaneously presented. In particular, the SSVEP component can change depending on the visual attention. By including the covert SSVEP [23], which does not involve eye movement, we can expect to detect visual attention in the ear's vicinity of the ear, which is impossible with eye–tracking devices. In such research, it is also imprtant to attach the electrodes easily. In the future, we will develop an earpiece–type sensor device to measure the electroencephalograms around the ear.

In this study, we included subjects who were younger in age. Previous studies have reported [24] an increase or decrease in accuracy with age, and the age range considered in this study was the one reported to exhibit high accuracy. In the future, it will be necessary to investigate whether the same level of accuracy can be achieved in older subjects by using periapical electrodes.

In addition, as mentioned above, when the number of subjects is increased, the accuracy converges in case the subjects are of the same age; therefore, the electrode addition method and the position of the attachment may be briefly discussed. However, the accuracy of SSVEP has been observed to change with age. Moreover, the change in accuracy when subjects are randomly selected is uncertain. Therefore, dividing the subjects into groups based on factors that affect accuracy, such as age, may aid in improving the accuracy of SSVEP around the ear.

VI. Conclusion

Although BCIs have been extensively studied in healthy subjects, it is difficult to apply electrodes to the head of a single person. In this study, eight electrodes were applied around each ear and the potential activity induced by SSVEP was discriminated using CCA. To improve the accuracy, new waveforms were derived by adding and averaging the time–series data between the electrodes attached to the target sites in both ears and were compared with the single electrode results for the periapical electrodes.

The L2+R2 electrode exhibited the highest mean CCC of 0.37±0.06, with Macro F–value of 45.33±16.84 % and ITR of 13.86±13.21 bits/min. The CCC at L2+R2 was significantly higher than that at L2 and R2 monopoles. The CCC at other sites was also significantly higher for the additive electrodes than for the monopoles. In addition, when comparing the head and additive electrodes around the ears, there was no significant difference in the macro F–value for electrodes 1–3, and no significant difference in the ITR was observed only for Oz and L4+R4. In the future, we will examine the detailed electrode placement, time window length, and algorithms to improve the accuracy of measurements around the ear.

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