Waveform-Coded Steady-State Visual Evoked Potentials for Brain-Computer Interfaces

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ABSTRACT This study presents a novel waveform-coding method for multi-target steady-state visual evoked potential (SSVEP)-based brain–computer interfaces (BCIs). Three periodic waveforms including square, sawtooth, and sinusoidal waves at various frequencies and initial phases were employed to elicit discriminable SSVEPs. A virtual keyboard was first designed using 36 visual stimuli modulated by the combinations of different frequencies, phases, and waveforms. With the virtual keyboard, 13 healthy participants performed offline and online BCI experiments with a cue-guided spelling task. The task-related component analysis (TRCA)-based algorithm was used to identify a target visual stimulus. The offline results showed that the visual stimuli tagged with different properties could accurately be identified by analyzing the elicited SSVEPs. Moreover, the online spelling task achieved promising performance with an averaged information transfer rate (ITR) of 62.6 ± 32.5 bits/min. This study validated the feasibility of implementing a multi-command SSVEP-based BCI using the hybrid waveform-, frequency- and phase-coding method. The proposed waveform-coding method provides a completely new channel for multi-target stimulus coding, expanding the research fields of an SSVEP-based BCI.

INDEX TERMS Brain–computer interfaces (BCI), electroencephalography (EEG), multiple stimulus coding, steady-state visual evoked potentials (SSVEP), task-related component analysis (TRCA), waveform coding.

I. INTRODUCTION

STEADY-STATE visual evoked potentials (SSVEPs) are the electroencephalographic (EEG) responses to flickering visual stimulation. In the human visual cortex, the activation of neurons synchronizes to the flickering of the visual stimuli, resulting in an SSVEP characterized by a sinusoidal-like waveform at the stimulus frequency and its harmonics [1], [2]. The frequency components in SSVEPs are nearly stationary, and therefore the stimulus frequency can be reliably recognized by analyzing SSVEPs in the frequency domain [3]. Due to the robust frequency characteristics of SSVEPs, the frequency tagging technique, which encodes multiple visual stimuli with different flickering frequencies, has been widely used in implementing multi-command brain–computer interfaces (BCIs) [4]. In an SSVEP-based BCI, an user gazes at one of multiple visual stimuli tagged with different flickering frequencies, and the target stimulus, which the user is gazing at, can be identified through analyzing the recorded SSVEPs [5]. In this way, the system can indirectly translate users’ intentions into commands tagged with the target stimulus for controlling external devices. With its advantages of little user training, ease-of-use, and high information transfer rate (ITR), the SSVEP-based BCI has received increasing attention.

It has been a main challenge in a practical SSVEP-based BCI to increase the number of visual stimuli without compromising the discriminability (i.e., classification accuracy) of the SSVEPs elicited by different stimuli [6]. In the past decade, many researchers have attempted to solve this problem by designing advanced visual stimulation. The multi-step approaches, which require multiple selections to input a final command, have succeeded in implementing more possible...
commands than the number of visual stimuli (i.e., available frequencies) [7]–[9]. For example, Ceocotti demonstrated a 27-command SSVEP speller using 3 visual stimuli with 3-layer selections (i.e., $3^2 = 27$) [7]. Another approaches such as the multiple frequencies sequential coding (MFSC) [10] and the frequency shift keying (FSK) [11] made it possible to render a large number of visual stimuli tagged with code words consisting of the sequences of distinct frequencies. In addition to the traditional frequency-coding method, a phase-coding method has also been popularly used to modulate visual stimuli in an SSVEP-based BCI [5], [12]. In particular, the effectiveness of hybrid frequency and phase coding methods in improving the discriminability of SSVEPs has been demonstrated in several studies [6], [13], [14]. Indeed, the SSVEP-based BCI that marks the highest ITR of 325 bits/min to date employed the joint frequency-phase modulation (JFPM) approach to enhance target identification accuracy [15].

In target identification, harmonic components can be considered as important features to characterize SSVEPs as well as its fundamental frequency and phase properties. In fact, it has been well demonstrated that the use of harmonics as features in classification significantly enhances its accuracy [16]–[18]. However, sparse studies have explored the importance of incorporating harmonic components into visual stimulation. In an SSVEP-based BCI, visual stimuli are generally modulated by square or sinusoidal waves, which would produce different linear combinations of fundamental and harmonic frequency components. The latest comparison study revealed that employing square waves could lead to a better performance than sinusoidal waves due to their distinct harmonic responses [19]. Our preliminary study indicated that visual stimuli modulated by different waveforms indeed elicited SSVEPs with unique frequency responses which were discriminable from each other [20]. However, the effectiveness of waveform-coding method has yet to be validated in an online BCI experiment. Furthermore, it still remains unknown whether the waveform-coding method can be combined with hybrid frequency- and phase-coding methods.

This study aimed at validating the applicability of the waveform-coding method integrated with a hybrid frequency- and phase-coding method to an online BCI system. We designed a virtual keyboard with 36 visual stimuli, which were modulated by the combinations of different frequencies, phases and waveforms. Three periodic functions including sinusoidal, square, and sawtooth waves were employed in this study. Target identification is done by a state-of-the-art method based on task-related component analysis (TRCA) [15] in this study. With the visual stimuli, an offline experiment was first conducted to collect SSVEP data for estimating the classification accuracy. A cue-guided online BCI experiment was then conducted to validate the feasibility of an online SSVEP-based BCI using the waveform-coding method.

II. METHOD

A. PARTICIPANTS

Nine males and four females (mean age: 21.9 ± 1.2 years) with normal or corrected-to-normal vision took part in our experiment. This study was approved by the research ethics committee of Tokyo University of Agriculture and Technology. All the participants were given an informed consent before participating in the experiment.

B. WAVEFORM-BASED STIMULUS CODING

This study employs different periodic waveforms including square, sinusoidal, and sawtooth waves to modulate multiple visual stimuli. The luminance changes of the stimuli can be modulated by stimulus sequences whose dynamic range is $[0, 1]$, where 0 and 1 represent black and white, respectively. The stimulus sequences based on square $s_{\text{square}}(f, i, \phi)$, sinusoidal $s_{\text{sin}}(f, i, \phi)$ and sawtooth $s_{\text{saw}}(f, i, \phi)$ waves at a stimulus frequency $f$ and an initial phase $\phi$ can be generated by the following equations:

\[ s_{\text{square}}(f, i, \phi) = \frac{1}{2} \left( 1 + \text{square} \left( 2\pi f \left( \frac{i}{f_r} \right) + \phi \right) \right) \]  
(1)

\[ s_{\text{sin}}(f, i, \phi) = \frac{1}{2} \left( 1 + \sin \left( 2\pi f \left( \frac{i}{f_r} \right) + \phi \right) \right) \]  
(2)

\[ s_{\text{saw}}(f, i, \phi) = \frac{1}{2} \left( 1 - \text{sawtooth} \left( 2\pi f \left( \frac{i}{f_r} \right) - \phi \right) \right) \]  
(3)
where $i$ indicates the frame index and $f_r$ indicates the refresh rate of a monitor. In addition, the square[-], sin[-], and sawtooth[-] are the functions that generate square, sinusoidal and sawtooth waves ranging from -1 to 1, respectively. Fig. 1 illustrates the concept of waveform-coding method using the waveforms described in (1), (2), and (3).

### C. Stimulus Design

Thirty-six target visual stimuli were presented on a ViewPtxx 3D 23-inch liquid crystal display (LCD) screen (VPtxx Technologies, Inc.) with a resolution of $1,920 \times 1,080$ pixels and a refresh rate of 120 Hz. As shown in Fig. 2(a), the visual stimuli were arranged in a $4 \times 9$ matrix as a virtual keyboard with 26 English alphabet letters and 10 other symbols. Each stimulus was rendered within a $4.8- \times 4.8$-cm square with an interval between two neighboring stimuli of 1.15 cm. Each stimulus was modulated by a combination of different frequencies (7.5, 10.0, and 12.0 Hz), initial phases (0, 0.5 $\pi$, 1.0 $\pi$, and 1.5 $\pi$ rad), and three waveforms (square, sinusoidal, and sawtooth waves) as shown in Fig. 2(b). The stimulus program was developed under MATLAB (MathWorks, Inc.) using the Psychphysics Toolbox Version 3 [21].

### D. Data Acquisition

EEG data were acquired using g.SCRABEO Ag/AgCL active electrodes (g.tec medical engineering GmbH) placed over parietal and occipital areas with reference to an earlobe and ground at AFz. The EEG signals were amplified by MEG-6116 (Nihon Kohden, Corp.) and digitized by an AIO-163202F-PE A/D converter (Contec, Co.) at a sampling rate of 1,200 Hz. The amplified signals were band-pass filtered between 0.5–300 Hz before the digitization. Eighteen electrodes were located at Pz, P1, P2, P3, P4, P5, P6, P7, P8, POz, PO3, PO4, PO7, PO8, Oz, O1, O2, and Iz in accordance with the international 10–10 system [22].

### E. Experimental Task

The experiment in this study consisted of an offline and an online stages. All the participants completed the two stages on the same day. The offline experiment was first conducted to collect individual training data used to optimize subject-specific parameters and to calibrate target identification method in the following online stage. The online experiment was then conducted to evaluate the performance of the proposed BCI system. Through the experimental procedure, the participants seated in a comfortable chair in front of the LCD screen.

1) Offline Stage

The offline stage consisted of 15 blocks. In each block, participants were asked to gaze at one of the visual stimuli for 3 s, and completed 36 trials corresponding to all 36 stimuli. Each trial started with a visual cue indicating a target stimulus, which a participant was supposed to gaze at. Participants could start stimulation by pressing a “space” key on a keyboard whenever they were ready after shifting their gaze to the target stimulus. To avoid ocular artifacts, participants were asked to avoid eye movements and blinks during the stimulation period. There was a short break for several minutes between two consecutive blocks to avoid visual fatigue.

2) Online Stage

In the online stage, participants completed a cue-guided spelling task. The online stage consisted of nine blocks, in which participants were instructed to gaze at one of the visual stimuli indicated by the stimulus program. The stimulus program randomly chose one of the following three sentences: 1) “THE QUICK BROWN FOX”, 2) “JUMPS OVER” and 3) “THE LAZY DOG” at each block, and each participant completed three blocks for each sentence. In the cue-guided task, the stimulus duration was fixed to $d$ s, which was optimized for each participant in the offline stage, with 1-s gaze shifting time. After target selection, visual feedbacks were provided to the participants in real time. The TRCA-based method described below was used to identify target stimuli. The data recorded in the offline stage were used as training data to calibrate the target identification algorithm for each participant.

### F. Target Identification

1) Spatial Filtering

This study used the ensemble TRCA-based spatial filtering to remove background noises and/or artifacts [15]. TRCA is the method that extracts task-related components efficiently by maximizing the correlation among EEG signals during task periods [23]. Here, two source signals are assumed: task-related signal $s(t) \in \mathbb{R}$ and task-unrelated signal $n(t) \in \mathbb{R}$. A linear generative model of observed multichannel EEG signal $x(t) = (x(t)) \in \mathbb{R}^{N_c}$ is assumed as:

$$x_j(t) = a_{1,j}s(t) + a_{2,j}n(t), j = 1, 2, \ldots, N_c \quad (4)$$

where $j$ is the index of channels, $N_c$ is a number of channels, and $a_{1,j}$ and $a_{2,j}$ are mixing coefficients that project the source signals to the EEG signal. The problem is to recover the task-related component $s(t)$ from a weighed sum of observed EEG signal $x(t)$ described as:

$$y(t) = \sum_{j=1}^{N_c} w_j x_j(t)$$

$$= \sum_{j=1}^{N_c} (w_j a_{1,j}s(t) + w_j a_{2,j}n(t)) \quad (5)$$

Ideally, TRCA finds a solution of $\sum_{j=1}^{N_c} w_j a_{1,j} = 1$ and $\sum_{j=2}^{N_c} w_j a_{2,j} = 0$, leading to final solution $y(t) = s(t)$. This problem can be solved by the inter-trial covariance maximization. Let $x^{(h)}(t)$ and $y^{(h)}(t)$ be the $h$-th trial of EEG signal and the estimated task-related component, re-
This constrained optimization problem can be solved as:

\[ \hat{w} = \arg \max_w w^T S w \]  

The optimal weight vector is obtained as the eigenvector of the matrix \( Q^{-1} S \) corresponding to the largest eigenvalue. In an SSVEP-based BCI, TRCA can be used to obtain spatial filters for removing noises and spontaneous EEG activities.

2) Classification

This study employed a template-matching-based classification method, which uses correlation coefficients between individual templates and ongoing EEG signals as features [6, 14, 15, 24]. The filter-bank analysis was also integrated to decompose SSVEPs into sub-band components so that independent information embedded in the harmonic components can be extracted efficiently [18]. Let \( \chi^{(m)} \in \mathbb{R}^{N_s \times N_s \times N_t} \) be a individual calibration data and single-trial test data \( X^{(m)} \in \mathbb{R}^{N_s \times N_t} \) of \( m \)-th sub-band, where \( N_n \) is the number of stimuli, and \( N_t \) is the number of trials. The first step to classify SSVEPs is to obtain spatial filters for the \( n \)-th stimulus and \( m \)-th sub-band \( w_n^{(m)} \) through applying the aforementioned TRCA for the individual calibration data of \( n \)-th stimulus \( \chi^{(m)} \). The next step is to obtain an ensemble spatial filter \( W^{(m)} \in \mathbb{R}^{N_s \times N_f} \) by concatenating the spatial filters obtained from all the stimuli \( w_n^{(m)} \) for each sub-band as follows:

\[ W^{(m)} = [w_1^{(m)}, w_2^{(m)}, \ldots, w_{N_f}^{(m)}] . \]  

Then, the correlation coefficients between single-trial test data \( X^{(m)} \) and templates (i.e., averaged calibration data across trials) for the \( n \)-th stimulus \( \chi^{(m)} \) is calculated by the following equation:

\[ \rho_n^{(m)} = \rho \left( \left( X^{(m)} \right)^T W^{(m)} , \left( \chi^{(m)} \right)^T W^{(m)} \right), \]

where \( \rho(a,b) \) indicates the Pearsonâ€™s correlation analysis between two signals \( a \) and \( b \). Then, a weighted sum of squares of the combined correlation coefficients corresponding to all harmonic components was calculated by the following equation:

\[ \rho_n = \sum_{m=1}^{N_h} a(m) \cdot (\rho_n^{(m)})^2 , \]

where \( N_m \) is the total number of harmonics and \( a(m) \) is defined as \( a(m) = m^{-1.25} + 0.25 \) according to [18]. Finally, target class \( k \) is identified by the following equation:

\[ k = n \rho_n, n = 1, 2, \ldots, N_f. \]
G. PERFORMANCE EVALUATION

The performance of the proposed waveform-coding method was first evaluated by classification accuracies using the offline dataset. Data epochs comprising 18-channel SSVEPs were extracted according to event triggers generated by the stimulus program. Considering a latency delay in the visual offline dataset. Data epochs comprising 18-channel SSVEPs was first evaluated by classification accuracies using the... performance than its chance-level accuracy regardless of the classification: 33.33%, respectively. Fig. 3(b) shows that all the participants toward his/her comfort.

On the other hand, the gaze shifting duration was fixed to 1 s for all the participants. The averaged ITR across participants was 62.7 ± 32.5 bits/min. Across individuals, the minimum and maximum ITRs were 10.4 bits/min (s12) and 121.6 bits/min (s4), respectively.

IV. DISCUSSIONS

Multiple stimulus coding plays an important role in designing an SSVEP-based BCI for various applications. In the present study, the waveform-coding method was proposed as an alternative channel to elicit discriminable SSVEPs. The results showed that the three different waveforms were able to be identified accurately by analyzing the elicited SSVEPs. The waveform-coding was also successfully integrated with the mixed frequency and phase coding method [6], [13], leading to significantly increased number of visual stimuli. Although the feasibility of the waveform coding has been proven (Fig.3), it was also revealed that there was a large individual difference in the classification accuracy. It should be noted that the individual difference was seen not only in the waveform-only classification but also in the frequency-only and the phase-only classifications. Fig. 4 depicts the relationships among the classification accuracy corresponding to the three coding properties with 0.2-s data epochs. In the figure, each dot indicates the classification accuracy for an individual participant. The accuracy of waveform-only classification was significantly associated with the ones of frequency-only classification \( (R^2 = .910, p < .001) \) and of phase-only classification \( (R^2 = .860, p < .001) \). Table 2 lists the \( R^2 \) for all the combinations between the coding properties at different data lengths from 0.2 to 2.0 s with an interval of 0.2 s, and showed there were significant associations for all the combinations at any data length. This results suggest that it is possible to estimate the accuracy of classifying single or mixed coding properties for new users, if they have experiences of using an existing BCI based on one of the other properties. For instance, users, who have achieved an accuracy of 95% in a frequency-coded SSVEP-based BCI, would most likely achieve that of approximately 80% (95% prediction interval: 69.1–90.6%) in the waveform-

### Table 1. Result of the online cue-guided BCI experiment.

| Participant | Trial length, \( T \) [s] | No. of trials (Correct/Incorrect) | ITR [bits/min] |
|-------------|-----------------|-------------------------------|----------------|
| s1          | 2.0 (1.0 + 1.0) | 33/79                         | 33.8           |
| s2          | 1.8 (0.8 + 1.0) | 47/85                         | 30.9           |
| s3          | 2.0 (1.0 + 1.0) | 61/71                         | 42.5           |
| s4          | 1.3 (0.3 + 1.0) | 90/42                         | 121.6          |
| s5          | 1.7 (0.7 + 1.0) | 73/59                         | 66.5           |
| s6          | 1.8 (0.8 + 1.0) | 87/45                         | 83.2           |
| s7          | 1.5 (0.5 + 1.0) | 64/68                         | 61.1           |
| s8          | 2.5 (1.5 + 1.0) | 62/70                         | 34.9           |
| s9          | 2.5 (1.5 + 1.0) | 83/49                         | 55.5           |
| s10         | 2.0 (1.0 + 1.0) | 87/45                         | 74.9           |
| s11         | 1.5 (0.5 + 1.0) | 85/47                         | 96.2           |
| s12         | 1.8 (0.8 + 1.0) | 25/107                        | 10.4           |
| s13         | 1.5 (0.5 + 1.0) | 89/43                         | 103.5          |

Mean ± STD - - 62.7 ± 32.5

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FIGURE 3. (a) Averaged target identification accuracy across participants, and (b) target identification accuracy for each participant as a function of data length (d). In each panel, the accuracy of frequency-only, phase-only, waveform-only, and mixed frequency-phase-waveform classifications were shown separately. The error bars in (a) indicate standard errors.

TABLE 2. The relationship, $R^2$, among the coding properties

| Data length [s] | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 | 1.2 | 1.4 | 1.6 | 1.8 | 2.0 |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Mixed vs. frequency | .887 | .907 | .954 | .972 | .964 | .956 | .921 | .936 | .956 | .941 |
| Mixed vs. phase | .855 | .900 | .946 | .960 | .916 | .930 | .897 | .891 | .911 | .914 |
| Mixed vs. waveform | .955 | .935 | .945 | .943 | .936 | .954 | .918 | .933 | .917 | .922 |
| Frequency vs. phase | .973 | .987 | .961 | .982 | .935 | .952 | .945 | .938 | .954 | .989 |
| Frequency vs. waveform | .910 | .830 | .854 | .882 | .866 | .914 | .841 | .834 | .814 | .802 |
| Phase vs. waveform | .860 | .840 | .897 | .905 | .856 | .915 | .786 | .780 | .788 | .762 |

The asterisks indicate statistical significance ($p < .001$)

coded SSVEP classification.

This study also validate the effectiveness of the proposed waveform-coding method via the online BCI experiment. The averaged ITR obtained in this study was 62.7 bits/min, which was not as high as the ones reported in the previous studies of high-speed BCIs (e.g., 267 bits/min and 325 bits/min reported in [14] and [15], respectively). This might be because the waveform-coding requires relatively longer data length to achieve the equivalent level of accuracy to the frequency- and phase-coding methods as shown in Fig.3. Another explanation is that the present study used 1-s gaze shifting time, which is longer than the previous studies (i.e., 0.5 s) [14], [15]. Depending on the gaze shifting time, a drastically different online ITR would be obtained. For example, if the gaze shifting time could be shorten to 0.5 s, s4 would achieve an ITR of 197.7 bits/min, which is significant improvement from the present one of 121.6 bits/min. In that sense, it is of importance to conduct sufficient training sessions, in which users could get familiar with the user-interface of the system, toward maximizing the online BCI performance. Importantly, the experiment confirmed the feasibility of implementing an online BCI system with the proposed waveform-coding method.

The proposed waveform-coding method could be generalized by employing flexible combinations of fundamental and harmonic frequency components in stimulus sequences. The periodic functions used in this study (i.e., sinusoidal, square, and sawtooth waves) are the specific examples of them. By optimizing the mixing coefficients of fundamental and harmonic components, the BCI performance could further be enhanced compared with using the periodic functions. To this end, a novel and systematic method for the parameter search needs to be proposed. In addition, there might still be a room for improvement in target identification algorithms.
This study employed the ensemble TRCA-based method to analyze the waveform-coded SSVEPs since it has shown the greatest performance in the previous literature of an SSVEP-based BCI [15], [24], [27]. To precisely capture fine-tuned fundamental and harmonic components in SSVEPs, more suitable algorithms than the TRCA-based methods, which might be model-based ones, need to be developed.

V. CONCLUSION

The waveform-coding method was introduced as a novel approach for designing a multi-command SSVEP-based BCI in this paper. The offline and online BCI experiments were conducted using the visual stimuli modulated by the mixed frequency-, phase-, and waveform-coding method. The classification accuracy obtained from the offline data revealed that the three coding properties including the waveform could be reliable detected by using the TRCA-based target identification algorithm. The feasibility of implementing online applications using the proposed stimulus-coding method was also validated in the online experiment with the cue-guided spelling task. Since the proposed waveform-coding method is completely a new way to elicit SSVEPs, this study will expand the research field of an SSVEP-based BCI, encouraging more BCI applications requiring a large number of commands.

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