PERIODICITY DETECTION FOR BCI BASED ON PERIODIC CODE MODULATION VISUAL EVOKED POTENTIALS

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ABSTRACT

In this paper, we studied the brain computer interface (BCI) based on periodic code modulation visual evoked potential (VEP). The code modulation VEP (c-VEP) is one of electroencephalogram (EEG)-based BCI methods, and can acheive high speed communication. In this method, by identifying a pseudorandom binary code (PRBC) that modulates visual stimulus from measured EEG, we can transfer the command related with the PRBC into external devices. However, the communication speed becomes slow inversely with increased number of commands. In order to solve this problem, we proposed extended c-VEP method using periodic pseudorandom binary codes. In this method, we identify the periodicity from the EEG by using autocorrelation, and the command related with periodicity of the EEG is transferred. As a result of computer simulation, we were able to detect the periodicity of the EEG. Therefore, we verified the feasibility of the periodic pseudorandom binary codes for VEP-based BCI.

Index Terms— Electroencephalography, Brain-computer interfaces, Visual evoked potentials, Autocorrelation

1. INTRODUCTION

Brain-computer interface (BCI) realizes a direct communication between the human brain and the external environment by translating human intentions into control signals [1]. A BCI allows an individual with severe motor disabilities or aphasia to have effective control over devices such as computers, wheelchairs and music instruments. A BCI system detects the presence of specific patterns in a brain activity and translates these patterns into meaningful control commands. Recently, electroencephalogram (EEG)-based BCI is attracting much attention due to their noninvasiveness and high communication speed. The information transfer rate (ITR) is commonly used to evaluate the communication speed of a BCI. Current EEG-based BCIs fall into four main categories such as sensorimotor activities, P300, visual evoked potentials (VEP), and common spatial pattern (CSP) [1]. In particular, a VEP-based BCI has received increasing attention due to their advantages of little user training, ease of use, and a high ITR [1–3].

VEPs are generated in response to visual stimuli such as flashing lights and these potentials are prominent in the occipital area. Two kinds of stimulus modulation method are generally used in VEP-based BCI. The method that a visual stimulus is presented repetitively at a rate of 5-6 Hz or greater is termed steady-state visual evoked potentials (SSVEP). In this method, a continuous oscillatory electrical response is elicited in the visual pathways. Current SSVEP-based BCIs have ITRs of 7-90 bits/min. On the other hands, G. Bin *et al* proposed a new prototype system based on code modulation VEPs (c-VEP) [7, 8]. Pseudorandom binary codes (PRBC) are used to modulate visual stimuli. The c-VEP BCI achieved ITR of 108 ± 12.0 bits/min and increased number of targets (32 targets). However, the c-VEP has the trade-off between communication speed and the number of targets. Therefore, the communication speed becomes slow inversely with the number of targets.

In our study, we propose the periodic code modulation VEP. In this method, periodic pseudorandom binary codes are used to modulate targets. These targets generate a periodic sequence of VEP with the same periodicity as that of the modulated targets. We can identify a target which a user is fixated by using periodicity detection method. Furthermore, we can increase the number of targets without delaying the communication speed by combining the periodicity detection method and c-VEP. In this paper, we provide a detailed description of how to build the BCI based on periodic code modulation VEP and the computer simulation that verifies the feasibility of proposed method.

2. CONVENTIONAL VEP-BASED BCI

The c-VEP proposed by G. Bin *et al.* achieved high ITR [8]. In a c-VEP BCI, pseudorandom binary codes are used. The m-sequence is the most widely used to generate pseudorandom sequences. Visual stimuli are presented on a CRT monitor. A stimulus alternated between two states: 'light' and 'dark', so a pseudorandom binary code can be used as a modulation sequence. 'Light' and 'dark' are represented as '1' and '0' in the binary codes respectively. For instance, when the refresh rate of the monitor is 60 Hz, the stimulus modulated by a binary sequence '100100100...' represents a 20Hz flickering. Each target is modulated by a binary code that has two-frame time lag between consecutive targets. Each binary code is mutually in the circular-shift relation, and nearly orthogonal to other binary codes.

In order to identify the target, the EEG templates for targets termed 'T0','T1',...,'TN' are preliminary prepared. The template for T0 can be obtained by averaging the EEG data from multiple stimulus cycles. Once the template for T0 was obtained, templates for other targets can be easily obtained by shifting the template for T0 circularly. After obtaining templates for all targets, a template matching method is used for target identification.

In this method, there is the trade-off between communication speed and number of targets. The length of psudorandom binary codes becomes long according to the number of targets. Therefore, the communication speed becomes slow.

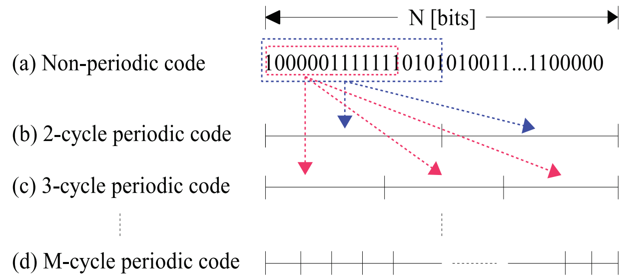


Fig. 1. An illustration of modulation codes for the proposed method. Each modulation codes are generaged from non-periodic modulation code.(a)Non-periodic modulation code. (b) Two-cycle periodic modulation code. (c) Three-cycle periodic modulation code. (d) M-cycle periodic modulation code.

3. PERIODIC CODE MODULATION VEP

In this study, we propose the VEP-based BCI using the periodic pseudorandom binary codes. A periodicity in the EEG is caused by using the targets modulated by periodic codes in addition to the non-periodic codes used in the c-VEP BCI. Therefore, target identification is realized by detecting the periodicity in the EEG. In addition, we can identify a lot of target by using circular-shifted periodic codes. We employ the autocorrelation to detect the periodicity in the EEG. In this section, the generating periodic codes process and the target identification method are described.

3.1. Periodic pseudorandom binary code

The steps of generating the periodic pseudorandom binary codes process are as follows:

1. A N bits non-periodic pseudorandom binary code are generated by using m-sequence.
2. The m-cycle periodic code is generated from a non-periodic code by the following steps.
   (a) The first N/m bits are detected from a non-periodic code.
   (b) The detected N/m bits code is aligned repeatedly until a periodic code becomes the N bits.
3. The two-bits circular-shifted codes are obtained from A non-periodic code and m-cycle periodic codes. The number of circular-shifted code that has m-cycle might be $N/2m$.

In Fig. 1, the periodic code are illustrated.

3.2. Target identification

We show the flow of the target identification. A VEP template for a target modulated by a non-periodic code can be obtained by averaging the EEG data from multiple stimulus cycle. The length of the template equals the length of a stimulus cycle of non-periodic code. The templates for other targets can be obtained by shifting along with c-VEP. The steps of preparing the templates are shown in the following four steps.

1. In the training stage, the user is required to fixate on the reference target modulated by non-periodic code. EEG data within K stimulus cycles are collected as $s_k(t), k = 1, 2, ..., K$.
2. A reference template $M_R(t)$ is obtained by averaging over K stimulus cycle.

$$M_R(t) = \frac{1}{K}\sum_{k-1}^{K} s_k(t) \tag{1}$$

3. The templates of all targets modulated by non-periodic code are obtained by shifting the reference template.

$$M_l(t) = M_R(t - (\tau_l - \tau_R)) \tag{2}$$

   where $\tau_l - \tau_R$ indicates the time lag between target l and reference target.
4. The templates of other targets modulated by periodic codes $M_l^{(m)}$ are obtained by extracting the length of a stimulus cycle of each periodic code m.

By using these steps, we can obtain all templates from only one reference template.

The target identification is composed of two steps such as periodicity detection and template matching.

1. Periodicity detection
   (a) The EEG data are collected into a buffer as $x(t)$ that length equals a stimulus cycle of non-periodic code.
   (b) The EEG data in a buffer are divided into $m, m = 2, 3, ..., M$ section. Each section is numbered as $1, 2, ...h, ...m$.
   (c) The autocorrelation coefficient r_m is calculated as the following equation.

$$r_m = \frac{1}{m}\sum_{h=1}^{m-1} \frac{(x_h(t), x_{h+1}(t))}{\sqrt{(x_h(t), x_h(t))(x_{h+1}(t), x_{h+1}(t))}}. \tag{3}$$

   (d) The periodicity p is detected by selecting the cycle m that maximizes the autocorrelation coefficient.
2. Template matching
   (a) The EEG data in a buffer are divided into p section.
   (b) The correlation coefficient ρ_l between $x(t)$ and the template $M_l^{(p)}$ is calculated as the following equation.

$$\rho_l = \frac{(M_l^{(p)}(t), x(t))}{\sqrt{(M_l^{(p)}(t), M_l^{(p)}(t))(x(t), x(t))}}. \tag{4}$$

   (c) The target is identified by selecting the target that maximizes the correlation coefficient.

After the target identfication, the meaningful command related with the identified target is entered into a external environment.

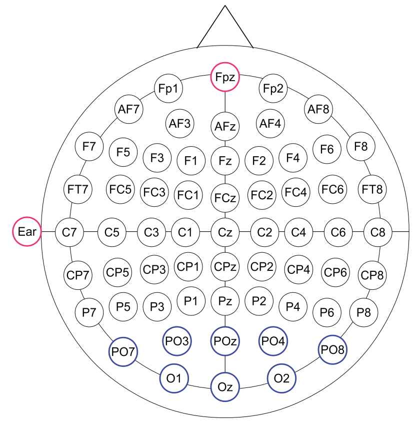
4. COMPUTER SIMULATIONS

In order to show the feasibility of the proposed method, we demonstrated the computer simulation. In this simulation, we used four targets that modulated by non-periodic code and periodic codes, and tried to detect the periodicity from the EEG.

4.1. Experimental environment

As shown in Fig.2 (a), four targets were arranged 2 $\times$ 2 matrix. Each target was termed 'T0,T1,T2,T3', and modulated by a non-periodic code, 2-cycle code, 3-cycle code, and 5-cycle code. Fig.2 (b) presents the modulation codes of all targets. The length of each code was 60 bits. Visual stimuli were presented on a LCD monitor with a 60 Hz refresh rate and 1024 $\times$ 1280 resolution. Each target size was set as 300 $\times$ 300 squares.

Three healthy adult with normal or corrected-to normal vision participated in the experiment. The subject were required to fixate on each target for about 50 stimulus periods. As shown in Fig.3, eight electrodes placed mostly over visual cortex on positions POz, PO3, PO4, PO7, PO8, O1, O2 and Oz in the international 10-20 system is adopted. The reference electrode was applied at the left earlobe and the ground electrode was applied at Fpz position. The electrodes were connected to the g.USBamp (g.tec medical engineering GmbH, Austria) as the EEG amplifier. EEG data was recorded with a sampling rate of 256 Hz.



No.	Position
1	PO7
2	PO3
3	POz
4	PO4
5	PO8
6	O1
7	Oz
8	O2

Fig. 3. The electrode position (PO7,PO3,POz,PO4,PO8,O1,Oz,O2)

4.2. EEG analysis method

In order to detect the periodicity in the EEG, the EEG data were used for offline analysis to calculate the autocorrelation coefficient. At the beginning of offline analysis, we employ the source derivation (SD) method as the preprocessing. The SD method can be applied to enhance the signal by subtracting the signals of four nearest neighbour electrodes from the signal of one center electrode multiplied by four. The SD method is composed of one center signal X_c and side signals $X_i, (i = 1, 2, 3, 4)$ which arranged symmetrically around the center signal. These signals are combined to obtain a new signal as the following function.

$$Y(t) = 4X_c(t) - \{X_1(t) + X_2(t) + X_3(t) + X_4(t)\} \quad (5)$$

In this study, Oz was chosen as the center signal X_c, and O1, O2, PO3, PO4 were chosen as the side signals X_i.

After the preprocessing, we calculated the autocorrelation coefficient of the enhanced signal $Y(t)$ in fixating each target to detect 2-cycle, 3-cycle and 5-cycle periodicity. In this paper, we analyzed the EEG to detect periodicity from 2-cycle to 5-cycle.

4.3. Simulation results

Table 1 shows the averaged autocorrelation coefficient of the EEG in fixating each target. In fixating the T0 target, the autocorrelation coefficient of each cycle calculated by using the proposed method without SD method were less than 0.09 (There was no significant difference in the T0, $\rho < 0.01$). In fixating the T1-T3 target, the autocorrelation coefficients of were less than 0.20 (There were significant differences in T1, T2 and T2, $\rho < 0.01$). However, in fixating the T1 target, the autocorrelation coefficient of 5-cycle was the highest value in the all coefficients. Therefore, there is a high possibility that the EEG in fixating T1 target can be identified as T3 target wrongly. On the other hand, in the case of proposed method with SD method, autocorrelation coefficient in fixating target modulated by periodic codes became high collectly.

Talbe 2 shows the periodicity detection accuracy. In the case of the proposed method without SD method, the accuracy was very low. The true identification ratio and the flase identification ratio were about the same vaule. On the other hand, in the case of the proposed method with SD method, the average true identification

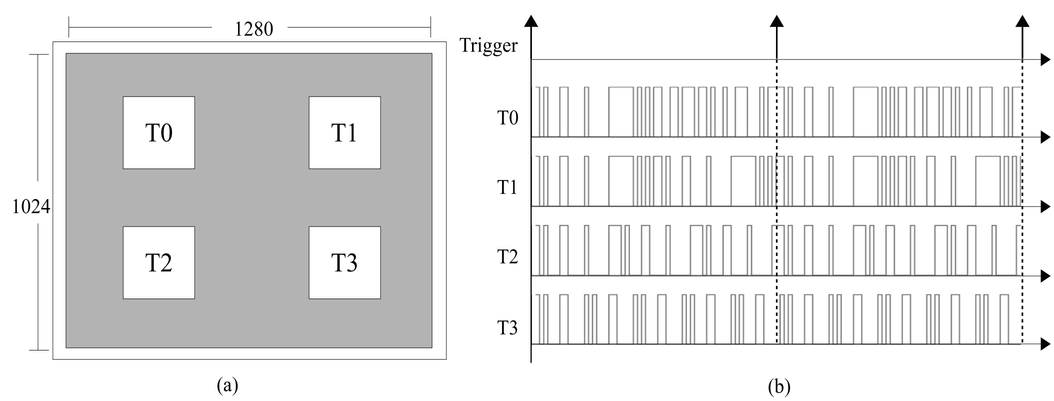


Fig. 2. (a)The target arrangement of this simulation. The four targets distributed as a 2 $\times$ 2 matrix on the LCD monitor with a 60 Hz reflesh rate and 1024 $\times$ 1280 resolution. (b)The modulation codes of four targets. The trigger became positive at the interval of a stimulus cycle. The modulation code of T0 was non-periodic code, and the modulation codes of T1, T2, T2 were 2-cycle, 3-cycle and 5-cycle periodic codes.

Table 1. Average autocorrelation coefficient (standard deviation)

Target	Proposed method without SD				Proposed method with SD			
	2-cycle	3-cycle	5-cycle	$\rho < 0.01$	2-cycle	3-cycle	5-cycle	$\rho < 0.01$
T0	-0.01 (0.26)	0.03 (0.20)	0.09 (0.19)	no	-0.06 (0.27)	-0.00 (0.18)	0.06 (0.17)	no
T1	0.12 (0.29)	-0.01 (0.21)	**0.14 (0.24)**	yes	**0.31 (0.28)**	-0.09 (0.19)	-0.19 (0.23)	yes
T2	-0.01 (0.25)	**0.10 (0.24)**	0.01 (0.17)	yes	-0.27 (0.29)	**0.36 (0.32)**	0.13 (0.16)	yes
T3	0.13 (0.26)	-0.04 (0.20)	**0.19 (0.22)**	yes	0.27 (0.34)	-0.14 (0.21)	**0.35 (0.31)**	yes

The numbers in bold represents that autocorrelation coefficients were large value. The significant difference was tested by analysis of variance ($p < 0.01$)

Table 2. Periodicity detection accuracy [%]

Target	Proposed method without SD			Proposed method with SD		
	2-cycle	3-cycle	5-cycle	2-cycle	3-cycle	5-cycle
T1	34.8	25.2	**35.6**	**64.4**	7.4	26.6
T2	25.9	**48.9**	15.6	10.4	**68.1**	11.9
T3	39.3	25.9	**48.9**	25.2	24.4	**61.5**

The numbers in bold represents that accuracy were large value.

ratio was 64.7 %, and the false identification ratio was less than or equal to 26.6 %.

4.4. Discussions

This simulation showed the feasibility of the periodic binary codes to identify the target. The periodicity can be detected from the EEG in fixating targets modulated by periodic binary codes by calculating autocorrelation coefficient. Autocorrelation coefficient and periodicity detection accuracy were increased by using source derivation method as the preprocessing. Therefore, we confirmed that the enhanced EEG signals have periodicity caused by the targets modulated by periodic binary codes. However, it is requeired to improve the periodicity detection accuracy in order to realize the periodic code modulation method that is combined periodicity detection and template matching. In future simulations, it is important to evaluate different parameter configurations (source derivations, electrode position, periodic code length, periodicity, target size, target position in LCD monitor) to optimize the proposed method.

5. CONCLUSIONS

In this paper, we showed periodic code modulation method. The novelties of our researches are (1) the detailed description of the BCI based on periodic code modulation, and (2) the feasibility of the proposed periodicity detection method. In the computer simulations, we used four targets modulated by periodic codes and non-periodic code, and tried to detect periodicity from the EEG. As a result, we were able to detect the periodicity with 64.7% accuracy from the EEG in fixating the target modulated by periodic binary codes. Therefore, we confirmed the possibility to realize the proposed multi-command BCI method. The multi-command and online BCI based on periodic code modulation VEP is the main concern as the future work.

6. REFERENCES

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