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VEP-based brain-computer interfaces modulated by Golay complementary series for improving performance

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Abstract.
BACKGROUND: The goal of a brain-computer interface (BCI) is to enable communication by pure brain activity without neural and muscle control. However, the practical use of BCIs is limited by low information transfer rate. Recently, code modulation visual evoked potential (c-VEP) based BCIs have exhibited great potential in establishing high-rate communication between the brain and the external world.
OBJECTIVE: This study aims at exploring a more effective modulation code than the commonly used pseudorandom M sequence for c-VEP based BCIs (c-VEP BCIs) in order to increase the detection accuracy of stimulus targets and the resulting information transfer rate.
METHOD: Golay complementary sequence pair is used for constructing the modulation code of c-VEP BCIs due to their superior autocorrelation property. The modulation code is created by concatenating a pair of Golay complementary sequences. Sixteen target stimuli are modulated by the Golay code and its time shift versions.
RESULTS: Through offline analysis on data recorded from seven subjects and online test on five subjects, the Golay code modulated BCI yielded higher detection accuracy and information transfer rate than those achieved by M sequence.
CONCLUSION: The Golay code modulated BCI demonstrates a high performance compared with the M sequence modulated systems, and it is applicable to persons with motor disabilities.

Keywords: Brain-computer interface (BCI), visual evoked potential (VEP), code modulation, Golay complementary sequences

1. Introduction

Brain-computer interface (BCI) systems can be used to provide a direct communication channel between the human brain and the environment, and this is done by translating human intentions into control signals [1]. Thus a new communication channel is made available for people with severe motor disabilities. Recently, electroencephalogram (EEG)-based BCIs have been of interest in the field of neural engineering and rehabilitation due to their noninvasiveness [2]. While there are different kinds of BCIs, this paper focuses on a BCI system based on code modulated visual evoked potentials (c-VEPs) because so far this kind of BCI has achieved the highest information transfer rate [3].

In a c-VEP BCI, a pseudorandom binary sequence and its different circularly-shifting versions are adopted to modulate different visual stimuli. When a person fixates on one of those stimuli, a c-VEP

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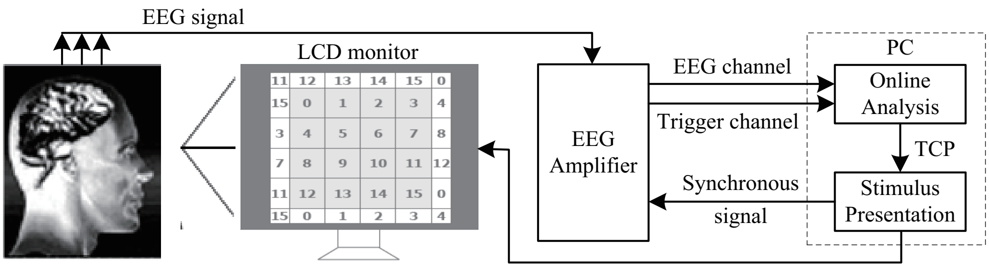

Fig. 1. The basic structure of a c-VEP based BCI.

is evoked in the occipital lobe of his brain and can be detected with the method of template matching. The idea was presented by Sutter in 1984 [4] and was tested on an amyotrophic lateral sclerosis (ALS) patient. Using intracranial electrodes for data acquisition, the subject was able to write 10 to 12 words/min [5]. Since then, the c-VEP BCI has not been paid much attention to until recently. Bin et al. revived it by building a c-VEP BCI with the highest information transfer rate among all kinds of BCIs [3]. The average information transfer rate across subjects achieved by their 32-target system was as high as 108 bits/min.

Although the c-VEP BCI yields the highest information transfer rate, the average detection accuracy is only 85% in Bin's 32-target system, which is relatively low compared with that of frequency modulated BCI systems (over 90%). Thereby, there is much room for improvement in terms of classification accuracy. To ensure high target detection speed, the modulation code could not be taken too long because the length of one stimulus period dominates the time for making a decision on the attended target. Usually, a 63-bit pseudorandom M sequence is employed in c-VEP BCI systems. For 32 stimulus targets, the difference between the two modulation sequences of two adjacent stimulus targets is only two bits. In order to obtain high target detection accuracy, it is highly required that the modulation code has excellent autocorrelation property. This motivated us to explore binary modulation codes with better autocorrelation property than pseudorandom M sequences.

This paper uses Golay complementary sequences as a new modulation code of c-VEP BCIs to improve detection accuracy. Bipolar Golay sequence pairs have attracted considerable attention for linear system identification based on a cross-correlation analysis. The system under study is often characterized by the presence of weak nonlinearities, which introduces artifacts in the linear system characteristics measured by cross correlation [6]. The proposed Golay modulation code is shown to increase the performance in offline data analysis with seven subjects and their feasibility is demonstrated in online tests with five subjects.

2. Method

2.1. System configuration

Figure 1 depicts the basic structure of a c-VEP BCI system. The system consists of an EEG amplifier and a personal computer (PC) with a cathode ray tube (CRT) or liquid crystal display (LCD) monitor. Stimulus presentation and online classification are operated in the PC. The c-VEP BCI requires a trigger signal in the EEG amplifier provided through the parallel port, which synchronizes the stimulus presentation and the EEG data. Visual stimuli are presented on the LCD monitor with a 60 Hz refresh rate. DirectX (Microsoft Inc.) is employed to ensure synchronization of the presented stimuli.

11	12	13	14	15	0
15	0	1	2	3	4
3	4	5	6	7	8
7	8	9	10	11	12
11	12	13	14	15	0
15	0	1	2	3	4

(a)

T0: 0100 0111 0100 · · · 1110 0010
T1: 0111 0100 1000 · · · 0010 0100
T2: 0100 1000 0100 · · · 0100 0111
T3: 1000 0100 0111 · · · 0111 0100
⋮
T13: 0010 1110 0010 · · · 1101 0001
T14: 1110 0010 0100 · · · 0001 0010
T15: 0010 0100 0111 · · · 0010 1110

(b)

Fig. 2. (a) Arrangement of the stimuli for the c-VEP BCI. The 16 targets distributed as 4×4 array (the gray area in the center of the screen) surrounded by 20 complementary flickers (white area); (b) The modulation sequences of 16 targets in one stimulation cycle.

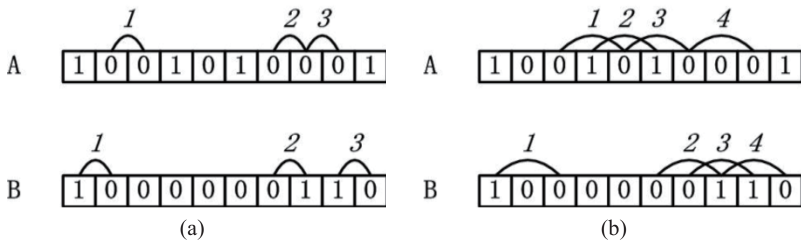

Fig. 3. Golay complementary series pairs with length 10. Like element pairs of separation one (a) and two (b).

A stimulus alternates between two states of 'light' and 'dark', which can be denoted respectively by 1 and 0 in the binary sequence. Thereby, a 20 Hz flickering can be represented by the binary sequence '100100100100· · ·' when the refresh rate of the monitor is 60 Hz.

The c-VEP BCI under study consists of 16 targets with target arrangement shown in Fig. 2(a). The 16 target stimuli are arranged as a 4 $\times$ 4 matrix in gray area and surrounded by 20 complementary non-target stimuli. The target and non-target stimuli are placed according to the principle of equivalent neighbors [5]. A 64-bit binary Golay code is used to modulate the target and non-target stimuli according to circular-shift relationship because of its good autocorrelation property. The circular-shift process is shown in Fig. 2(b), with T0 having no shift, T1 being shifted by 4 bits, T2 being shifted by 8 bits and T3 being shifted by 12 bits, etc.

2.2. Golay complementary series

A set of complementary series presented by Golay is defined as a pair of equally long, finite sequences of two kinds of elements which have the property that the number of pairs of like elements with any one given separation in one series is equal to the number of pairs of unlike elements with the same given separation in the other series [7]. As shown in Fig. 3, the Golay complementary series pair, A:1001010001 and B:1000000110, have respectively three pairs of like and three pairs of unlike adjacent elements, four pairs of like and four pairs of unlike alternate elements, and so forth for all possible separations. The basic property of Golay complementary series is its excellent autocorrelation property. Let $a(n)$ and $b(n)$ denote a pair of n-long bipolar Golay complementary series taking value of either $+1$ or -1, the

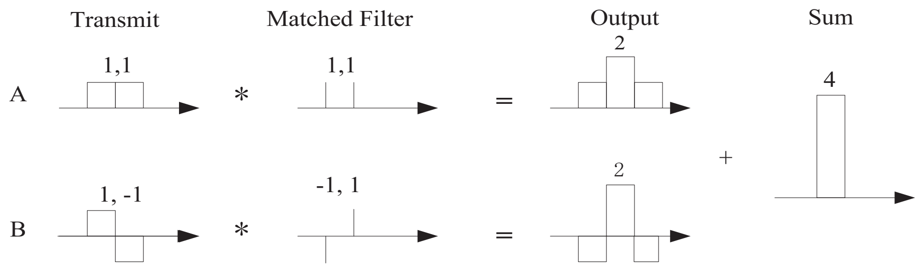

Fig. 4. Autocorrelation property of Golay complementary sequence.

sum of their respective autocorrelation series is zero elsewhere, except for the center term. This can be formulated as follows

$$a(n) * a(-n) + b(n) * b(-n) = 2N\delta(n) \tag{1}$$

which is known as the complementarity condition [7]. The autocorrelation function of unipolar Golay complementary series with elements $+1$ and 0 is not as ideal as bipolar ones, but it still has excellent autocorrelation property.

2.3. *Golay series as modulation code of c-VEP BCIs*

The ideal autocorrelation property of bipolar Golay series makes its application in several fields such as system identification, communication engineering and medical imaging [8–11]. As illustrated in Fig. 4, one way to use Golay series for ultrasound imaging is to have two transmits for each focal zone [9]. After the first firing with code A, the return echo is correlated with corresponding decode filter A; subsequently code B is fired, and the return echo is filtered with decode filter B. The two filtered waveforms are summed to complete the decoding process. The decoding result is that the main-lobe will be enhanced and meanwhile the side-lobe will be fully cancelled if there is no system noise.

For c-VEP BCI systems, only one code with different shifts is allowed to modulate all stimuli. Thus, the crucial problem for applying Golay series to a c-VEP BCI is how to adapt its two codes into one modulation code and retain complementary property. To this end, one method is to concatenate the two codes of a Golay series. For instance, a 64-bit modulation code AB is constructed by concatenating the following two codes of a 32-bit Golay series pair

$$\mathrm{A} : 01000111010010000100011110110111; \mathrm{B} : 00010010000111010001001011100010$$

The validity of the method is decided by its corresponding decoding method. The typical decoding method for detecting the attended stimulus is template matching, which is to calculate the correlation coefficient between a segment of currently recorded EEG data and all stimulus templates. Correlation coefficient is the cross correlation of two signals with zero lag and is basically the inner product of the two signals. When Golay code AB is used as modulation code, the correlation coefficient between currently recorded data and a template is equal to the sum of two inner products of the part of data and templates corresponding to code A and code B. When the lag is not zero, the side-lobe cannot be cancelled but takes small values in general. Thereby, concatenating code A and code B together as a modulation code complies approximately with the principle of Golay complementary property.

2.4. Stimulus target detection

As in Bin's system [3], template matching is used as the target detection method in our c-VEP BCI system. Thus, a template needs to be generated first for each target. The eleventh target is defined as reference target and its template is referred to as reference template. The templates for other targets can be obtained from the reference template by shifting fixed bits between two adjacent targets. In practice, any target can be selected as the reference target. To attain the reference template, the user has to attend to the reference target k times. A reference template $M_r(t)$ is obtained by averaging the EEG signals over k stimulus cycles. By using the circular-shift property of the c-VEP BCI, a template for all other targets can be generated by shifting the template $M_r(t)$ according to the following formula

$$M_x(t) = M_r(t - (\tau_x - \tau_r)), x = 1, 2, 3, \cdots 16 \tag{2}$$

where x denotes template number and τ denotes the lag. After template for each target is generated, the system can identify which target the user is attending to, by calculating the correlation coefficient ρ_k between the currently recorded EEG signal and each template as follows

$$\rho_k = \frac{\langle M_k(t), x(t)\rangle}{\sqrt{\langle M_k(t), M_k(t)\rangle\langle x(t), x(t)\rangle}} \tag{3}$$

The fixation target is decided as the one whose template achieves the largest correlation coefficient. In order to improve detection accuracy, multichannel EEG signals can be used and accordingly, the canonical correlation analysis (CCA) can be employed. The goal of CCA is to find linear transformations W_x and W_s, which maximizes the correlation between the multichannel EEG data X and the signal componentof the original EEG data [12]:

$$\underset{W_x, W_s}{Max} \frac{W_x^T X S^T W_s}{\sqrt{W_x^T X X^T W_x . W_s^T S S^T W_s}} \tag{4}$$

In practice, the optimal spatial filter W_x is employed for spatially filtering EEG data so that better target detection accuracy can be achieved.

To construct the spatial filter W_x, the user is required to fixate on the reference target, and the EEG data within k trials are collected. All trials are centered and then concatenated to a new matrix X with dimension of $n \times (k \cdot m)$. The multichannel evoked response R can be obtained by averaging all k trials, then R is replicated k times, to obtain the signal component S of the original EEG data

$$S = [RR \cdots R] \tag{5}$$

The matrices X and S can be utilized for calculating the spatial filter W_x by CCA algorithm. The two matrices need the same number of $k \cdot m$ columns but are allowed to have different number of rows. The EEG amplifier Mipower, made in Institute of Neural Engineering, Tsinghua University, is used for recording EEG data, and seven electrodes over the occipital region (O1, O2, Pz, P3, P4, T5, T6) are selected in our c-VEP BCI system.

3. Subjects and experimental tasks

Seven volunteers (four female and three male) with normal or corrected-to-normal vision participated in the experiment after receiving their informed consent. Their mean age was 23 years old with standard interval of 3 years. During the experiment, each subject was seated in a comfortable chair at 60 cm

Table 1
Offline detection accuracy (%) achieved by the M-sequence and Golay code for the seven subjects

Subject	M sequence	Golay sequence
Tong	100.00	99.69
Famo	95.94	99.38
Yrmi	88.44	94.69
Zhai	86.88	90.63
Hyin	87.50	95.00
Fong	94.06	99.69
Lhao	84.69	90.31
Mean	91.07	95.63

Table 2
The bottom width (ms) of central peak for the two modulation sequences

Subject	tong	famo	yrmi	zhai	hyin	fong	lhao
M sequence	36	36	32	38	56	46	42
Golay sequence	39	32	30	32	38	38	34

away from the stimulator in a dimly lit, quiet room. Since all subjects never had any experience of BCI experiments, each had 10 minutes to be familiar with the layout of the visual stimulator before the experiment and adapt himself/herself to the flicking stimulation.

The experiment was divided into two parts: offline and online. In either part, a 64-bit Golay code and a 63-bit M sequence were respectively used for target identification, in order to compare the modulation performance of the two codes. All the seven volunteers participated in the offline experiment, but only five of them participated in the online experiment. In the offline experiment, the sixteen targets in the stimulus matrix of Fig. 2(a) appeared sequentially. The subject attended each of sixteen targets 20 times, resulting in a total of 320 trials; in the online experiment, the sixteen targets in the stimulus matrix of Fig. 2(a) appeared randomly, but the frequency of each target appearance was equivalent. The subject attended each target five times, resulting in a total of 80 trials.

4. Results

4.1. Offline analysis

The length of templates is $T_s = 64/60s = 1.066s$, which is equal to the length of a stimulus cycle. The time lag between two consecutive targets is $\tau_s = 4/64s = 0.066s$ in our system. Table 1 reports the detection accuracy rates of the c-VEP BCI modulated by M sequence and Golay code for the seven subjects. It can be seen from the table that the accuracy rate of the Golay code is higher than that of the M sequence for all subjects except for the first subject tong. The maximal gap between the two methods is 7.50% achieved by subject hyin. On average, the detection accuracy yielded by the Golay code is 4.56% higher than that achieved by the M-sequence. This is a remarkable increase in BCI systems. A paired t-test performed at 95% confidence level reveals that the detection accuracy yielded by Golay code is significantly better than that achieved by M sequence with $p = 0.003$.

In a c-VEP BCI system, a visual evoked response with a sharp autocorrelation function is expected. To compare modulation performance of the M sequence and Golay code used in the study, the normalized autocorrelation function of the reference templates for all subjects is shown in Fig. 5. As shown in the

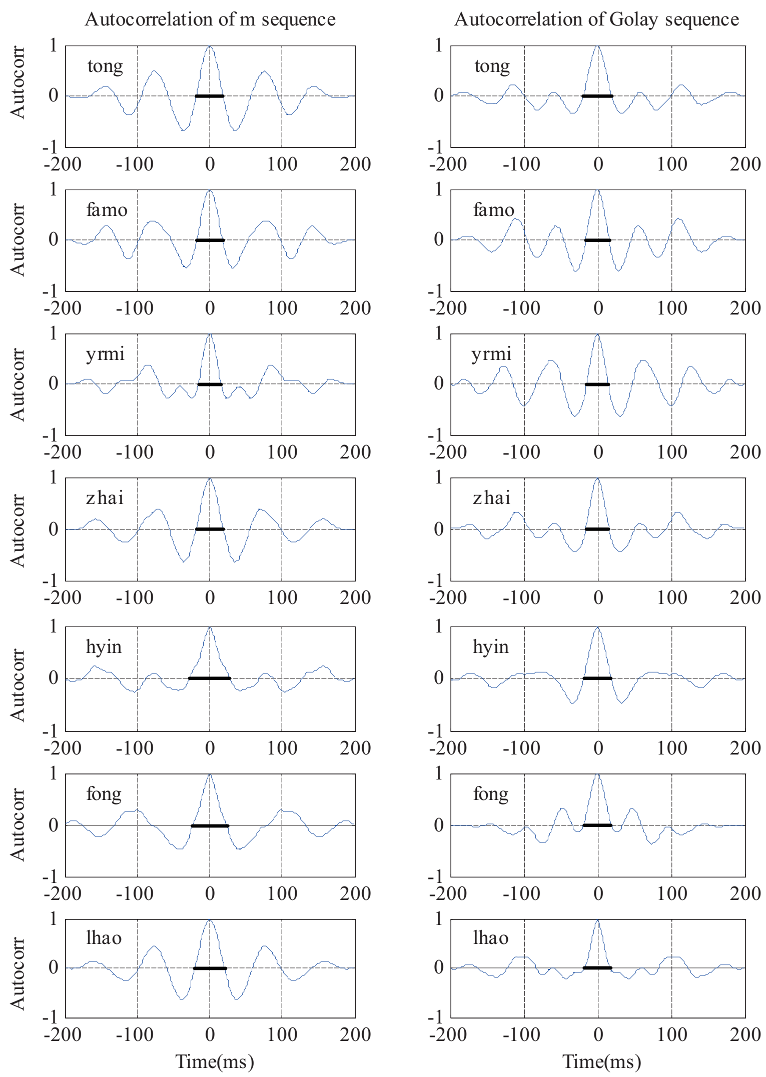

Fig. 5. Autocorrelation function of the reference template yielded by M sequence (left) and Golay code (right) for the seven subjects. The bottom width of the central peak for each of the two modulation sequences is shown in bold line.

figure, the autocorrelations of the reference templates yielded by Golay code are better than those by M sequence in terms of central peak. For all subjects except for subject Tong, the central peak of Golay code template is more acute than that yielded by M sequence template because its bottom width shown in bold line is narrower. The bottom width of central peak for each of the two modulation sequences is reported in Table 2.

Although the central peak could not decide the detection performance, it does affect the detection accuracy for the same subject. Comparing Tables 1 and 2, it is clear that the narrower the central peak, the higher the detection accuracy. Take two subjects as examples. For subject Hyin, the bottom width is 56 ms and 38 ms for the M sequence and Golay code respectively, while for subject Famo, the bottom width is 36 ms and 32 ms respectively. In Table 1, the detection accuracy rates of the M sequence are 87.50% and 95.94% for two subjects, but those of the Golay code are 95% and 99.38%, respectively.

Table 3
Online detection accuracy (DA, %) and corresponding ITR (bits/min) achieved by each of the five subjects using M sequence and Golay code modulation respectively

Subject	M sequence		Golay code	
	DA (%)	ITR (bits/min)	DA (%)	ITR (bits/min)
Fong	95.00	98.18	98.13	104.30
Tong	93.75	95.40	97.50	102.67
Famo	93.13	94.06	96.88	101.13
Yrmi	91.88	91.43	96.25	99.62
Hyin	86.88	81.68	93.75	94.00
Mean	92.13	91.95	96.50	100.21

This proves that the detection accuracy of a c-VEP based BCI is closely related to the autocorrelation property of modulation code used. Therefore, it is significant to select the optimal modulation code with best autocorrelation property.

4.2. Online evaluation

In addition to detection accuracy, information transfer rate (ITR) defined by Wolpaw [1] is used for evaluating the online performance of the proposed c-VEP BCI. The average online detection accuracy of each subject over the 80 trials and corresponding ITR yielded by both Golay code and M sequence are listed in Table 3. It can be seen from the table that the accuracy rate and ITR achieved by Golay code are higher than those achieved by M sequence for each of the five subjects. The maximal gap in detection accuracy between the two modulation methods is as high as 6.87%, which was achieved by subject hyin. On average, that is 4.37% (92.13% versus 96.5%), resulting in a gap in ITR of 8.26 bits/min (91.95 bits/min versus 100.21 bits/min). The paired t-test performed at 95% confidence level indicates that the detection accuracy and ITR achieved by Golay code are significantly better than those achieved by M sequence with $p = 0.003$ and $p = 0.002$ respectively. This proves that the proposed Golay code modulation is more effective than M sequence for c-VEP BCI systems.

5. Discussion and conclusion

In previous c-VEP BCI studies, a pseudorandom M sequence is generally used as the modulation code for its good autocorrelation property. An M sequence has an autocorrelation function which is close to a unit impulse function, and it is nearly orthogonal to its time lag sequences. In this paper, a concatenated Golay code was used as a new modulation code for target detection because it has better autocorrelation property in terms of central peak. Using CCA based template matching, the proposed Golay code modulated c-VEP BCI achieved higher detection accuracy than an M sequence modulated BCI. Experimental results verify the effectiveness of Golay code modulation.

The autocorrelation function and the detection accuracy of the M sequence and Golay code have been shown in an offline analysis with experimental data derived from seven subjects. From these results, it can be observed that the acuteness of the autocorrelation is significant for target detection in a c-VEP BCI. The autocorrelation function of Golay code is narrower and closer to a unit impulse function. As a practical evaluation of the proposed BCI, an online experiment was performed with five subjects who achieved an average ITR of 100.21 bit/min. This is a fairly high bit rate for 16 stimulus targets in a non-invasive BCI. The experimental results showed that the proposed method possesses high performance compared with the traditional M sequence modulated system and it is feasible and applicable for people with motor disabilities.

In future study, the current system will be tested online with more subjects and will be investigated if the proposed system can be enhanced by adaptive classification or the combination of several different modulation codes which could increase the number of stimulus targets. Thus, it may be possible to find an optimal sequence that would further improve the performance of the c-VEP BCI system.

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