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ORIGINAL ARTICLE

Optimized stimulus presentation patterns for an event-related potential EEG-based brain–computer interface

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Abstract P300 brain–computer interface (BCI) systems typically use a row/column (RC) approach. This article presents a P300 BCI based on a 12 × 7 matrix and new paradigmatic approaches to flashing characters designed to decrease the number of flashes needed to identify a target character. Using an RC presentation, a 12 × 7 matrix requires 19 flashes to present all items twice (12 columns and seven rows) per trial. A 12 × 7 matrix contains 84 elements (characters). To identify a target character in 12 × 7 matrix using the RC pattern, 19 flashes (sub-trials) are necessary. In each flash, the selected characters (one column or one row in the RC pattern) are flashing. We present four new paradigms and compare the performance to the RC paradigm. These paradigms present quasi-random groups of characters using 9, 12, 14 and 16 flashes per trial to identify a target character. The 12-, 14- and 16-flash patterns were optimized so that the same character never flashed twice in succession. We assessed the practical bit rate and classification accuracy of the 9-, 12-, 14-, 16- and RC (19-flash) pattern conditions in an online experiment and with offline simulations. The results indicate that 16-flash pattern is better than other patterns and performance of an online P300 BCI can be significantly improved by selecting the best presentation paradigm for each subject.

Keywords Brain–computer interface · P300 event-related potential · Flash pattern · EEG

1 Introduction

Brain–computer interface (BCI) systems provide a new way to connect people with the external world. Given that BCIs do not require muscle movement, they may be appealing to users with limited neuromuscular control and perhaps to healthy users when other means of communication are not practical. Birbaumer et al. published the first BCI validated with severely disabled users, a spelling system using slow cortical potentials (SCPs) [8]. However, SCP BCIs have several disadvantages: due to their limited speed they cannot provide a high bit rate, users must be trained for weeks or months to learn to effectively control SCP, and some users can never attain effective control. Moreover, performance is reduced during positive cortical potentials [9]. BCIs based on event-related (de)synchronization (ERD/ERS) have also been widely used and validated with both able-bodied and disabled subjects, who usually attain satisfactory results even without training [10, 28, 37, 39, 40, 41, 47]. However, about 20% of people cannot use ERD BCIs, since some subjects are unable to modulate sensorimotor rhythms for effective control [18, 30, 38]. Untrained subjects have also used BCIs based on steady-state visual evoked potentials (SSVEPs) [14, 29, 34, 44, 46, 48]. Unfortunately, SSVEP BCIs do not work for some subjects [4, 29, 35, 36] and other users find the

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flickering lights annoying [5]. Importantly, P300-based BCIs also work without training, and may work in subjects who are not successful with other approaches [7]. P300 BCIs have been validated with disabled users, with visual, auditory, and tactile stimuli, and have been used for tasks including spelling, image selection, and controlling a cursor or robotic device [6, 11, 13, 15, 21, 40, 42]. Compared to other non-invasive BCIs, P300 BCIs can attain very high bit rate (also called information transfer rate or ITR), as they are able to attain high accuracy while providing more selections per minute than most other BCIs. To date, most work aimed at improving the bit rate of P300 BCIs has focused on signal processing [24, 50], classification algorithms [20, 27] and output optimization [19, 32].

However, new "flash patterns" could also improve the bit rate in P300 BCIs. Flash patterns refer to the number and distribution of possible selections that are illuminated with each flash. A new flash pattern approach that can identify a target with fewer flashes might improve the bit rate, since more characters could be chosen per minute. P300 BCIs typically use a row/column (RC) flash pattern, in which an entire row or column is illuminated with each flash. More recent work implemented a single character (SC) flash pattern, in which each flash illuminates only one character [17]. Other previous work has used random patterns [1] and quasi-random patterns [45]. Some work explored P300 BCI flash patterns [2, 3, 43] and found that reducing flashes per trial could improve bit rate [2, 43].

In this article, we simulated a keyboard with a 12×7 matrix (Fig. 1). We introduced new flash-pattern paradigms that required fewer flashes to identify the target than the conventional RC or SC approaches. We explored four flash-patterns based on our new method (called the 9-, 12-, 14-, and 16-flash patterns), and we compared these to a conventional RC approach using 19 flashes as a control condition. While the new flash pattern approaches might reduce selection time, they could also yield less discriminable ERP patterns, which would impair classification accuracy and hence bit rate [3]. Hence, the main goal of this article was to compare the bit rate resulting from these four flash-patterns to the standard RC paradigm.

Practical bit rate was used to estimate the experiential speed of the system in this article, and compared to other measures of bit rate. How much time a system takes to finish a task is important for the users. Classification accuracy and bit rate alone are not sufficient to evaluate the effectiveness of an ERP speller [15, 45]. Furdea et al. used written symbol rate to evaluate the speed of an auditory P300 BCI system [15]. This method excludes backspaces because they do not contribute to the final conveyed message. Townsend et al. presented a new method to evaluate the actual speed of a BCI system (i.e., practical bit rate) [45]. This method takes into account that for every error made, a penalty of two additional selections will incur, high bit rates can not be achieved if performance accuracy is low when practical bit rate is used to estimate the online speed of the system when it is being used to accurately convey a message. This analysis will be discussed in more detail in Sect. 2.7.

2 Methods

2.1 The flash pattern design

The flash pattern approach is based on binomial coefficients. The set of k combinations of a set n is denoted by $C(n, k) = n!/((k!(n-k)!)),\quad 0 \le k \le n$. The number of flashes per trial is n, and k is the number of flashes per trial for each character. We used the set of k combinations ($k = \{2, 3\}$) from set n ($n = \{9, 12, 14, 16\}$). $C(9, 3)$, $C(12, 3)$, $C(14, 3)$ and $C(16, 2)$ denote the 9-, 12-, 14-, and 16-flash patterns, respectively. A 12×7 matrix has 84 elements. $C(9, 3)$ contains 84 elements and is adequate to identify any element in a 12×7 matrix. $C(12, 3)$, $C(14, 3)$, and $C(16, 2)$ contain more elements than $C(9, 3)$. This approach is similar to locating a point in coordinate space. A k of 2 or 3 denotes 2- or 3-dimensional coordinate space. In this article, the coordinate corresponds to the combination and the corresponding position of a character in the stimulus matrix corresponds to a point in coordinate space. Figure 2 shows the configuration of the different flash pattern combinations. Using this method, RC flashes do not necessarily occur. The flashes are named "$flash_1, flash_2, \ldots, flash_n$." For the 9-flash pattern, n is 9; for the 12-flash pattern, n is 12, and so on. Flash_1 (1) designates the characters in Fig. 1 that flash during flash_1, flash_2 (2) designates the characters in Fig. 1 that flash during flash_2, and flash_n designates the characters in Fig. 1 that flashed during "n". The positions of the flash sequence data in Fig. 2 correspond to the cell positions in Fig. 1. If flash_1, flash_2, and flash_3 evoked a P300 in the 9-flash pattern, the character "F1" would be selected (see Figs. 1, 2a). If flash_1, flash_3, and flash_5 evoked the P300 in the 12-flash pattern, the character "F1" would be selected (see Figs. 1, 2b). If flash_1, flash_4, and flash_7 evoked the P300 in the 14-flash pattern, the character "F1" would be selected (see Figs. 1, 2c). If flash_1 and flash_{13} evoked the P300 in the 16-flash pattern, the character "F1" would be selected (see Figs. 1, 2d). In this project values of $K = \{2, 3\}$ were used. $K = 2$ is analogous to the RC pattern used when two target sub-trials are presented in each trial. $K = 3$ is selected to decrease the number of sub-trials in each trial. However, K cannot be very high because the number of characters that flash at the same time is dependent upon K;

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
ESC	! / 1	@ / 2	# / 3	$ / 4	% / 5	^ / 6	& / 7	* / 8	(/ 9	) / 0	BkSe
Tab	_ / -	+ / =	~ / `	|	: / ;	? / /	“ / ‘		{ / [	} /]	Enter
Shift	A	B	C	D	E	F	G	H	< / ,	> / .	NL/SL
Ctrl	I	J	K	L	M	N	O	P	Q	R	Is / PS
CsLk	S	T	U	V	W	X	Y	Z	Up	Keep	Dl / Sq
Off	On		WM	Space	QF	Alt	Fn	Left	Down	Right	P B

Fig. 1 Laptop keyboard. The stimulus matrix for an online system. In an online system, the characters that the subject types are presented in the *box* at the *top*

A

1,2,3	2,3,4	3,4,5	4,5,6	5,6,7	6,7,8	7,8,9	3,5,8	3,5,9	1,3,4	2,6,7	3,7,8
1,2,4	2,3,5	3,4,6	4,5,7	5,6,8	6,7,9	2,4,7	2,4,8	1,8,9	1,4,9	2,6,8	3,7,9
1,2,5	2,3,6	3,4,7	4,5,8	5,6,9	6,8,9	4,7,8	4,8,9	1,7,9	1,5,6	2,6,9	3,8,9
1,2,6	2,3,7	3,4,8	4,5,9	5,7,8	1,3,6	4,7,9	1,4,8	1,6,9	1,6,7	2,7,8	2,5,9
1,2,7	2,3,8	3,4,9	4,6,7	5,7,9	2,4,6	1,4,7	1,5,8	1,5,9	2,5,6	2,7,9	1,3,8
1,2,8	2,3,9	3,5,6	4,6,8	5,8,9	3,6,7	1,3,7	1,6,8	2,8,9	2,5,7	3,6,8	1,3,9
1,2,9	2,4,5	3,5,7	4,6,9	1,3,5	1,4,6	1,5,7	1,7,8	2,4,9	2,5,8	3,6,9	1,4,5

B

1,3,5	2,4,6	3,5,7	4,6,8	5,7,9	6,8,10	7,9,11	8,10,12	1,4,9	1,4,10	1,4,11	2,5,12
1,3,6	2,4,7	3,5,8	4,6,9	5,7,10	6,8,11	7,9,12	1,4,8	1,5,9	1,5,10	1,5,11	2,6,12
1,3,7	2,4,8	3,5,9	4,6,10	5,7,12	6,8,12	7,10,12	1,5,8	1,6,9	1,6,10	1,6,11	2,7,12
1,3,8	2,4,9	3,5,10	4,6,11	5,8,10	6,9,11	1,4,7	1,6,8	1,7,9	1,7,10	1,7,11	2,8,12
1,3,9	2,4,10	3,5,11	4,6,12	5,8,11	6,9,12	1,5,7	1,8,10	1,9,11	2,8,10	2,5,11	2,9,12
1,3,10	2,4,11	3,5,12	4,7,9	5,8,12	6,10,12	2,7,9	1,8,11	2,5,9	2,7,10	2,6,11	3,6,12
1,3,11	2,4,12	3,6,8	4,7,10	5,9,11	1,4,6	3,7,9	2,5,8	2,6,9	2,6,10	2,7,11	3,7,12

C

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

D

1,13	2,13	3,13	4,13	5,13	6,13	7,13	8,13	9,13	10,13	2,11	3,12
1,14	2,14	3,14	4,14	5,14	6,14	7,14	8,14	9,14	10,14	11,14	4,12
1,4	2,15	3,15	4,15	5,15	6,15	7,15	8,15	9,15	10,15	11,15	12,15
1,5	2,5	3,9	4,16	5,16	6,16	7,16	8,16	9,16	10,16	11,16	12,16
1,6	2,6	3,6	4,9	5,9	6,9	7,12	1,8	1,9	2,10	1,11	5,12
1,7	2,7	3,7	4,7	5,11	6,10	7,10	8,12	2,9	3,10	3,11	1,12
1,10	2,8	3,8	4,8	5,8	6,11	7,11	8,11	9,12	4,10	4,11	6,12

Fig. 2 These four panels depict the configuration of different flash patterns: 9-flash pattern (**a**), 12-flash pattern (**b**), 14-flash pattern, (**c**) and 16-flash pattern (**d**). The *numbers* indicate which of the *n* flashes would illuminate the target character. For example, the *top right* element of (**a**) would be illuminated during the third, seventh, and eighth of the nine flashes. In each panel, flash_1 (that is, the first flash of the sequence) is illuminated

increasing K will increase interference from characters neighboring the target when the flashing target is not flashing. For the 9-flash pattern, if double flashes were not avoided, higher K values would increase the probability of a double flash, which will attenuate the P300 ERP [2, 17, 43]. Thus, K was set to a value of 3 in this study and tested.

The 12-, 14-, and 16-flash patterns were optimized to eliminate successive flashes of the same character. We did this to eliminate the various errors that can be introduced by two consecutive flashes, such as reductions in P300 amplitude, variances in latency, or simply failing to see the stimulus [45]. For the 12-flash pattern, when flash_k occurred, the paradigmatic surrounds of flash_k would be flash_{k-1} or flash_{k+1}, which did not contain the characters occurring in flash_k. For example, in Figs. 1 and 2b, the first character "F1" flashed during flashes 1, 3, and 5. When flash_3 occurred this element flashed while flash_2 and flash_4 would not include the element. Figure 3 shows how the different flashes, "$flash_1, flash_2, \ldots, flash_n$" were arranged cyclically, such that flash_1 is next to flash_n ($n = 12$). For example, if k was n (12), flash_{k+1} would be flash_1, and if k was 1, flash_{k-1} would be flash_{12}. Hence, for the 12-flash pattern, the sequence of the remaining flashes was determined as soon as the first and second flashes were determined (Fig. 3a). The 14- and 16-flash patterns were similar to the 12-flash pattern. When flash_k flashed, the next flash would be flash_{k-1}, $\text{flash}_{\text{k}-2}$, flash_{k+1}, or flash_{k+2}, since flash_{k-1}, flash_{k-2}, flash_{k+1}, and flash_{k+2} did not contain the characters of flash_k. The different flashes in the 14- 16-, and 19- flash pattern conditions flash randomly. The items in the matrix are arranged to be similar with the RC pattern.

2.2 Laptop keyboard design

Figure 1 shows the display used in this study. We simulated a keyboard using a 12 × 7 matrix. English letters were adjacent and alphabetical, and numbers were arranged similarly. Function keys were arranged on the four sides of the matrix, which is similar to some laptop keyboards. To decrease interference from adjacent characters, the names of the function keys were abbreviated to leave a large distance between two adjacent characters. "BkSe" is "Backspace," "NL/SL" is "Number Lock/Scroll Lock," "Is/Ps" is "Insert/Print Screen," "Dl/Sq" is Delete/System Request, "P B" is "Pause Break," "Lt" is left, "Dn" is down, "Rt" is right, "CsLk" is "Caps Lock," "WM" is a shortcut key for start menu, and "QF" is the quick function (same as the right mouse button). "On" and "off" keys are used to open and close files, and "keep" is used to keep the state of other keys for shortcut functions. The objective of this design is to make it easy for users to find target characters and control the laptop. These items in the keyboard can allow for full keyboard emulation in future studies; however, in this study we focused on typing alphanumeric items.

2.3 The flash probabilities

The probability that any flash illuminates the target character is calculated by dividing the number of character flashes per trial by the number of total flashes per trial. Each trial contains all flashes once ($flash_1, flash_2, \ldots, flash_n$) (see Fig. 4). In other words, it is k/n. Therefore, the

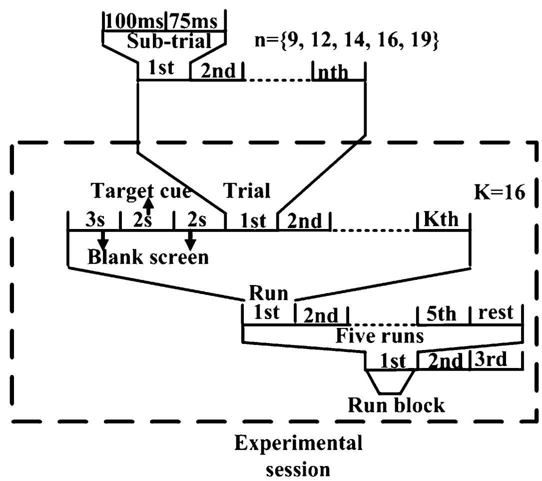
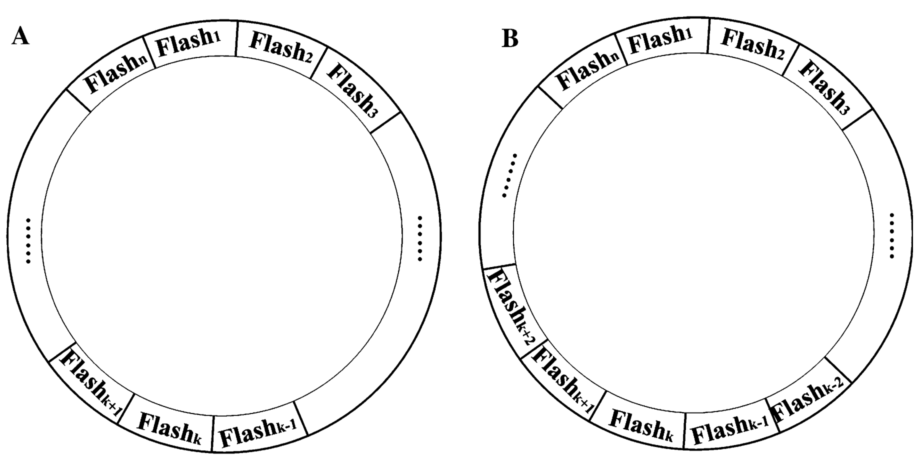


Fig. 4 The timing of each session. There were three run blocks for each experimental session and there were five runs for each run block (both online and offline). Each run contained 16 trials, and each trial contained n sub-trials based on flash patterns. Each sub-trial contained one flash, followed by a brief delay

Fig. 3 **a** The method to determine the flash sequence for 12-flash pattern, in which $n = 12$. **b** The method to determine the flash sequence for the 14- and 16-flash pattern conditions, in which $n = 14$ or 16



probability of a target flash is 3/9 = 33.3% in 9-flash pattern, 3/12 = 25% in 12-flash pattern, 3/14 = 21.4% in 14-flash pattern, and 2/16 = 12.5% in 16-flash pattern. These probabilities are roughly comparable to conventional P300 BCIs.

This is important issue because increasing the probability of a target flash decreases P300 amplitude [12, 43]. Since the inter-stimulus interval did not change in this study, changing the probability has a proportionate effect on the target-to-target interval or TTI [16]. Therefore, we sought to avoid a high target probability (or short TTI) because this could reduce P300 amplitude and thus impair classification accuracy [2, 3, 43].

2.4 Experiment setup and stimulation parameters

Ten healthy subjects (seven males and three females) participated in this study. Participants 1–3, 5–8, and 10 were between 23–28 years old. Participant 4 was 35 years old, and subject 9 was 45 years old. Participants 1 and 2 had used a P300 BCI prior to the study, and the other eight subjects were naïve to BCI use. During data acquisition, subjects were asked to relax while remaining attentive and avoid unnecessary movement.

Figure 4 shows the timing of the experimental sessions. Each subject participated in two experimental sessions on different days to reduce fatigue. Sessions were divided into three run blocks. Each run block contain five runs, and each run reflected an effort to spell one character. The first session contained three flash patterns, and the second session contained two flash patterns. The flash pattern used in each run block was chosen randomly. Data were acquired in both sessions with and without feedback to the participant. The initial data acquired without feedback were used to train a Bayesian linear discriminant analysis (BLDA) and obtain a classifier model. This model was then used online with feedback provided to the participant.

During each run block (consisting of five runs), subjects spelled five characters (i.e., one character per each run). Between each run subjects were given a 3-min rest. This process was repeated three times in each session, thus providing 15 characters per session. Participants had an additional 2-min rest after each run block. In each session, the online experiment started about 20 min after the subject completed all the calibration runs. Subjects were allowed to rest during this 20-min break, while the experimenter calculated the classifier used for the online feedback portion of the session.

In the experimental paradigm, the subjects were required to focus their attention on one of the characters and silently count each time the target character flashed. The subject focused on one of the characters from a predefined character sequence for 16 trials (i.e., one run) and then changed to another cued character. This experimental method is typically referred to as "copy spelling." At the beginning of each run, a cue was presented for 2 s to inform the subject of the character he or she was to focus on. Each flash lasted for 100 ms and then there was a 75-ms delay with a gray character matrix before the next flash began (see Fig. 4). In the second part of each flash pattern test, after classifiers were calculated, the characters identified as the targets would be shown on the top of the screen (see Fig. 1).

EEG signals were recorded using a g.tec biosignal amplifier and 32-electrode cap (arranged according to the expanded 10–20 standard system). Amplification sensitivity was 100 μV and band pass filter between 0.1 and 30 Hz. Signals were sampled at 200 Hz. The electrodes (Fz, Cz, Pz, Oz, P3, P4, P7, and P8) were selected based on the eight electrodes configuration in [21]. Jin et al. reported that detectable features of P300 could be obtained from O1 and O2 [23], and Kaper et al. selected the central electrodes C3 and C4 to extract the P300 features [25]; therefore, O1, O2, C3, and C4 were selected. Thus, the following 12 electrodes were used for signal detection: Fz, C3, C4, Cz, Pz, O1, O2, Oz, P3, P4, P7, and P8. The left mastoid electrode was used as the reference, and the right mastoid electrode was used as ground.

2.5 Feature extraction procedure

A third-order Butterworth band pass filter was used to filter the EEG between 0.1 and 12 Hz. Although P300 occurs primarily between 0.1 and 4 Hz [22], they can also be found in higher bands [26]. The data were downsampled from 200 to 40 Hz by selecting every fifth sample from the filtered EEG. Single sub-trials lasting 500 ms were extracted from the data. The size of the feature vector was $N_c \times N_t$, with N_c denoting the number of electrodes and N_t denoting the number of sample points in one channel, which was 20 points. In this article, the size of the feature vector was 240.

2.6 Classification scheme

The BLDA is an extension of Fisher's linear discriminant analysis (FLDA). The details of the algorithm can be found in [27]. Lei et al. reported that BLDA yielded higher accuracy than LDA and SVM from offline analysis [31], when they were applied to recognize motor imagery.

In this study, BLDA was selected as classifier, because it performs well and avoids overfitting [21]. BLDA was used for binary classification of targets and non-targets. Here, each trial yields 9, 12, 14, 16, or 19 classifier outputs, one output for one flash ($flash_1$, $flash_2$,…, $flash_n$). The first and second (19- and 16-flash pattern) or first to third (9-, 12-, and 14-flash pattern) maximum classifier outputs are selected to identify the target character.

2.7 Practical bit rate

Practical bit rate can estimate the actual experiment speed of the system, because it takes into account that every error results in a penalty of two additional selections. The practical bit rate is calculated by (BR * (1 − 2 * *P*)). BR is the raw bit rate and *P* is the online (with classifier) error rate of the system [45]. If $P \geq 50\%$, the classification accuracy is too low to correct the mistakes and the practical bit rate is zero. In this way, a high practical bit rate with very low classification accuracy is impossible; however, even 100% accuracy would not necessarily achieve high practical bit rates if selection time is too slow. For example, assume that the classification accuracy of system A is less than 100%. If system A could correct errors quickly and take less time to finish the task than system B (whose classification accuracy is 100%), system A would have a higher practical bit rate than system B.

3 Results

3.1 Online results

As noted, the classification model was trained offline with data acquired from offline experiment without feedback, and then the system was operated with online feedback to test the classification model. Online data were not recorded successfully from the last character communicated by subject 3 in the 14-flash pattern condition, or by subjects 2 and 5 in the 16-flash pattern condition. In these conditions for these subjects, only 14 characters were analyzed. All other subjects selected 15 characters in the online session. Table 1 shows the classification accuracy and practical bit rate (bits/min) of the online system for each condition with 16 trials per average. (In this article, one trial includes *n* flashes. Trials per average are the number of trials used for each average.) All subjects attained very high accuracies in each condition. However, because 16 trials per average were used, the practical bit rate is limited to a maximum of 15.1 (9-P), 11.4 (12-P), 9.7 (14-P), and 7.2 (16-P) bits/min. The practical bit rate does not include the delay between flashes and the rest time (see Fig. 4). Since the 9-flash pattern condition requires fewer events to identify the target, it produced a higher bit rate than the other flash pattern conditions (except S1, S6, and S8).

This study used averages of 16 trials, since this is an initial effort and we wanted to insure enough data for effective analysis. However, Table 2 showed that subjects could have communicated effectively with fewer trials per average. Hence, we explored the practical bit rates that would have resulted from fewer trials per average.

3.2 Offline analysis

Additional offline analyse were performed using the data collected while online feedback was provided. Again, practical bit rate estimates the potential online performance of the system. Table 2 lists the highest practical bit rates

Table 1 Online classification accuracy (with classifier) and practical bit rate of each subject for each pattern with 16 trials average

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Average
9-P											
Acc (%)	86.7	100	100	100	100	80.0	100	66.7	100	100	93.3 ± 11.7
BR	8.7	15.1	15.1	15.1	15.1	6.3	15.1	2.8	15.1	15.1	12.4 ± 4.6
12-P											
Acc (%)	93.3	100	80.0	100	100	86.7	100	100	80.0	100	94.0 ± 8.6
BR	8.7	11.4	4.7	11.4	11.4	6.5	11.4	11.4	4.7	11.4	9.3 ± 2.9
14-P											
Acc (%)	100	100	100	100	93.3	100	100	100	100	100	99.3 ± 2.1
BR	9.7	9.7	9.7	9.7	7.4	9.7	9.7	9.7	9.7	9.7	9.5 ± 0.7
16-P											
Acc (%)	100	100	100	100	100	100	100	100	100	100	100 ± 0
BR	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5 ± 0
19-P											
Acc (%)	100	100	100	100	100	100	100	100	100	100	100 ± 0
BR	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2 ± 0

BR practical bit rate, measured in bits/min; *Acc* accuracy; *n-P* *n*-pattern $n = \{9, 12, 14, 16, 19\}$

Table 2 The highest practical bit rate of each subject for each pattern with the corresponding accuracy

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Average
9-P											
Acc (%)	93.3	80.0	100	93.3	93.3	66.7	100	66.7	93.3	86.7	87.3 ± 12.3
BR	13.2	50.2	18.6	46.3	30.9	10.6	48.4	2.8	37.1	34.8	29.3 ± 17.0
12-P											
Acc (%)	86.7	93.3	80.0	100	93.3	86.7	80.0	93.3	80.0	86.7	88.0 ± 6.9
BR	9.4	69.5	10.8	15.1	27.8	10.4	37.7	34.7	10.8	52.1	27.8 ± 20.7
14-P											
Acc (%)	100	93.3	92.8	93.3	86.7	93.3	93.3	93.3	93.3	93.3	99.3 ± 3.1
BR	11.1	29.8	23.4	19.9	22.3	13.2	23.8	17.0	17.0	29.8	20.7 ± 6.3
16-P											
Acc (%)	93.3	85.7	93.3	100	86.7	100	100	93.3	86.7	93.3	92.2 ± 5.6
BR	20.9	37.4	26.1	45.4	39.1	27.2	27.2	34.7	26.1	19.3	30.3 ± 8.4
19-P											
Acc (%)	93.3	100	93.3	100	93.3	86.7	93.3	93.3	100	86.7	94.0 ± 4.9
BR	29.3	19.1	43.9	28.7	29.3	21.9	29.3	17.6	22.9	32.9	27.5 ± 7.7

BR practical bit rate, measured in bits/min; *Acc* accuracy; *n-P n*-pattern $n = \{9, 12, 14, 16, 19\}$

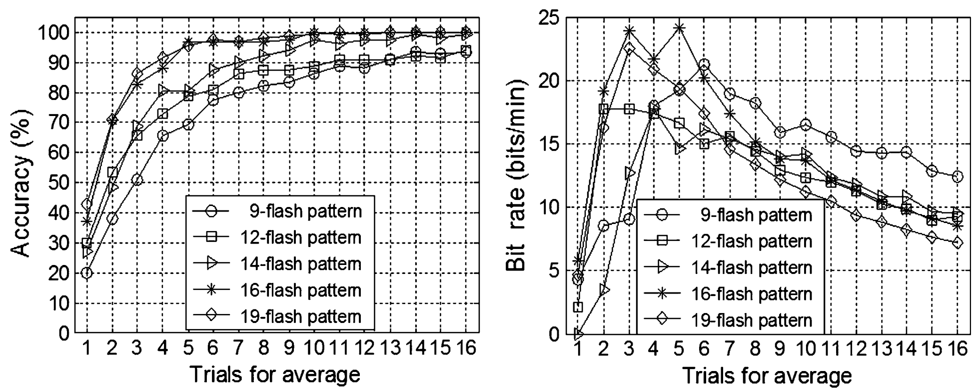


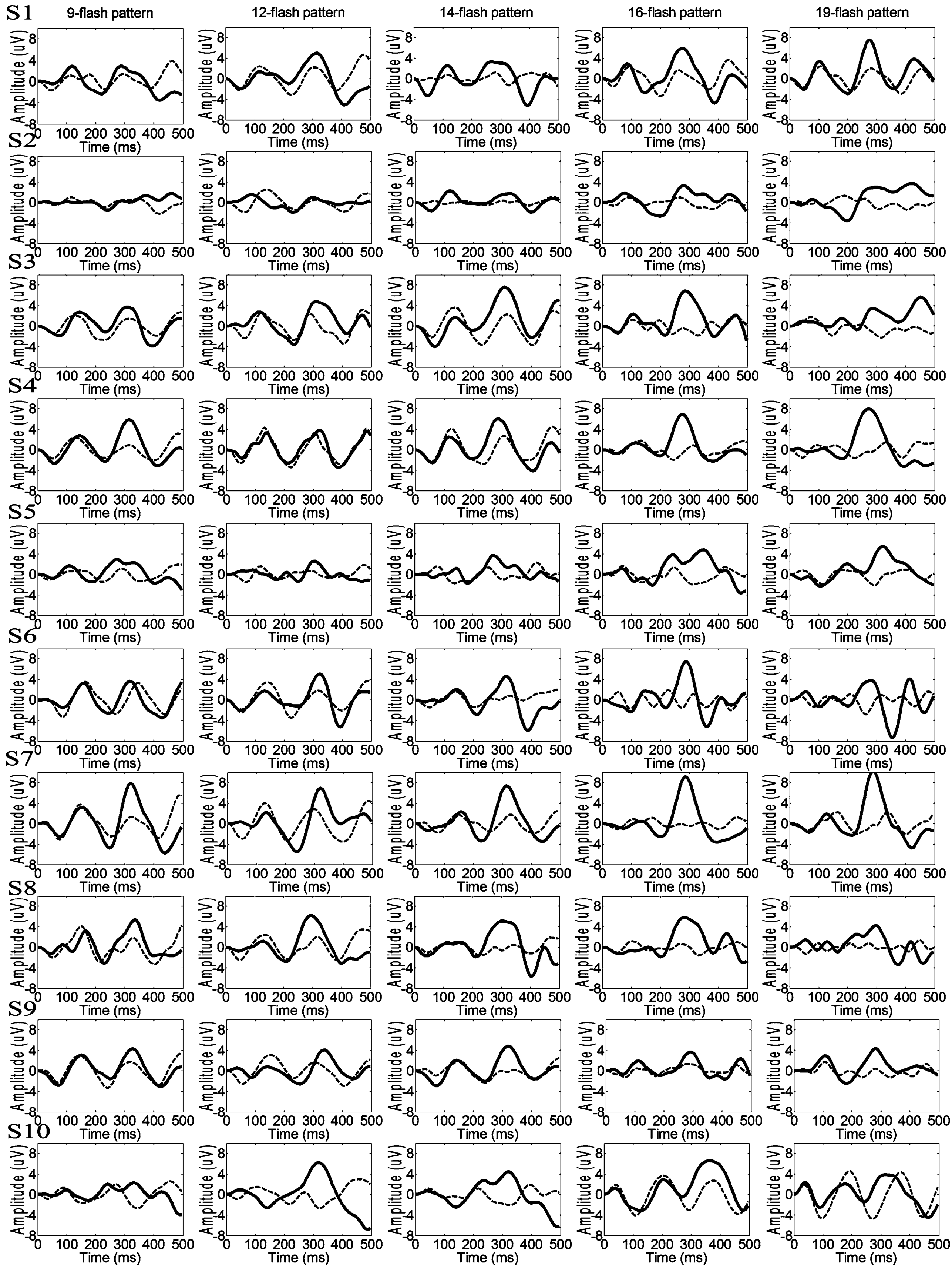
Fig. 5 The mean classification accuracy and practical bit rate of subjects 1–10 across 1–16 trials per average

for each subject and each flash pattern with the corresponding classification accuracy. The average practical bit rate of the 16-flash pattern is highest among all patterns.

Figure 5 shows the mean practical bit rate and accuracy for subjects 1–10 across 1–16 trials. The highest mean practical bit rate for subjects 1–10 was obtained from the 16-flash pattern based on averages of five trials. We compared the mean practical bit rates of the 19-flash pattern versus the 16-flash pattern for subjects 1–10, across averages of 1–16 trials, and found that these bit rates are all higher in the 16-flash pattern. A one-way ANOVA was used to examine differences in mean classification accuracy among 9-, 12-, 14-, 16- and 19-flash pattern ($P < 0.05$, $F = 2.58$). The difference in mean classification accuracy between 16- and 19-flash pattern, for subjects 1–10 across 1–16 trials, is not significant ($P = 0.39$). Figure 5 shows that the mean classification accuracies for other patterns are lower than the mean accuracies for 19-flash pattern ($P < 0.01$). Bonferroni corrected paired *t*-tests were used to test simple effects between conditions.

Figure 6 shows the P300 amplitudes of 9-, 12-, 14-, 16-, and 19-flash patterns. Large P300 amplitude was always obtained from 14-, 16-, and 19-flash patterns. As can be seen in Table 2 and Fig. 6, high practical bit rate and larger P300 amplitude could also be obtained from the 9-flash pattern or other high probability patterns for some subjects. For example, S4 and S7 obtained highest practical bit rates from the 9-flash pattern, and their P300 amplitudes during the 9-flash pattern were large. Table 2 and Fig. 6 clearly indicate that no single pattern is best for all subjects. Table 3 shows which of the five patterns provided the best practical bit rate for each subject.

Figure 7 shows the box plot of the highest practical bit rate of 9-, 12-, 14-, 16-, 19- and the individually selected-pattern and the corresponding classification accuracy. It shows that the individually selected-pattern is the best. A


S1
9-flash pattern
12-flash pattern
14-flash pattern
16-flash pattern
19-flash pattern
S2
S3
S4
S5
S6
S7
S8
S9
S10
Amplitude (uV)
Time (ms)

◀ **Fig. 6** P300 amplitude of 9-, 12-, 14-, 16-, and 19-flash patterns (it was obtained from 160 target sub-trials and non-target sub-trials)

one-way ANOVA was used to determine whether differences were present in practical bit rate among 9-, 12-, 14-, 16-, 19- and selected-pattern ($P < 0.05$, $F = 3.0$). The practical bit rate of the selected pattern is significantly better than the other patterns (9-flash pattern, $P < 0.05$; 12-flash pattern, $P < 0.05$; 14-flash pattern, $P < 0.05$; and 19-flash pattern, $P < 0.05$) with the exception of the 16-flash pattern ($P = 0.072$). From Tables 2 and 3, although the selected-pattern is not significantly better than 16-flash pattern, the practical bit rate for seven of the ten subjects for selected pattern is better than that of the 16-flash pattern and the average practical bit rate for the selected-pattern is 16.3% higher than that of 16-flash pattern. Figure 7 also clearly shows that the practical bit rate of the individually selected-pattern is better than that of 16-flash pattern.

4 Discussion

This article explored new flash patterns for P300 BCIs. The 9-, 12-, 14-, and 16-flash pattern conditions were based on binomial coefficient. The 12-, 14-, and 16-flash pattern conditions were optimized so the same item did not flash twice in succession. We also assessed a 19-flash pattern condition based on the conventional RC approach.

The 16-flash pattern condition entailed a shorter TTI than the 19-flash pattern condition, but yielded better results. Three factors may explain this result. First, the interference from adjacent flashes does not vary much between the 16- and 19-flash pattern conditions. Second, the 16-flash pattern condition has fewer flashes per trial. Third, the 16-flash pattern was optimized so that the same item did not flash twice in succession. This makes it easier for subjects to detect each target flash, which could improve the classification accuracy and reduce fatigue [3]. The results also suggested that the design in this article is better than RC pattern if fewer sub-trials per trial are used. Other tested flash patterns did not perform better than 16-flash pattern. Three factors may explain this result. First, the interference from adjacent flashes when the target was not flashing could evoke incorrect P300 responses or make the subjective flashing probability higher than the actual flash probability of the target for the participants. A high subjective flashing probability would lead to a reduction in P300 amplitude. Second, for 9-,12-, and 14-flash pattern, the higher target stimulus probability lead to a reduction in P300 amplitude (see Fig. 6). Third, for 9-flash pattern, high stimulus probability leads to higher probability of double flashes, which reduces P300 amplitude. The second of two consecutive flashes may be harder to detect because of the attentional blink and it can distort the waveform [33, 49].

Overall these data show that the highest practical bit rate does not necessarily correspond with the highest classification accuracy. This suggests that a subject could finish a task faster by using a lower accuracy system. On other hand, accuracy that is too low cannot provide high practical bit rates.

Table 3 The pattern that produced the highest practical bit rate for subjects 1–10

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Average
S-P											
Acc (%)	93.3	93.3	93.3	93.3	86.7	100	100	93.3	93.3	86.7	93.3 ± 4.4
BR	29.3	69.5	43.9	46.3	39.1	27.2	48.4	34.8	37.1	52.1	35.2 ± 12.5
Pattern	19-P	12-P	19-P	9-P	16-P	16-P	9-P	16-P	9-P	12-P	

BR practical bit rate, measured in bits/min; *Acc* classification accuracy; *n-P n*-flash pattern condition; *S-P* selected-pattern

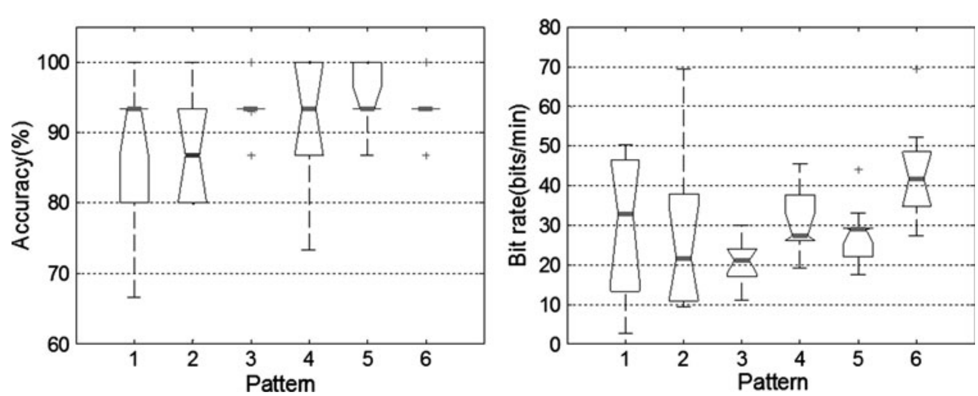


Fig. 7 The box plot of highest practical bit rate of 9-, 12-, 14-, 16-, 19- and selected-pattern and the corresponding classification accuracy. Pattern 1 is 9-flash pattern, Pattern 2 is 12-flash pattern, Pattern 3 is 14-flash pattern, Pattern 4 is 16-flash pattern, Pattern 5 is 19-flash pattern, and Pattern 6 is selected-flash pattern

In the experiment, the subject did "copy spelling task." The present data also show that testing several patterns for a given subject can indentify an optimal presentation pattern for each subject. For example, after the experiment, subjects 2, 3, 4, 7, and 10 accurately spelled their names, all of whom used fewer than eight trials per average using their optimal flash pattern. The remaining subjects did not participate in the name spelling task.

This article introduced new flash pattern approaches that can yield good performance in terms of practical bit rate. These improvements could increase usability while reducing fatigue and frustration.

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