STIMULI WITH OPPONENT COLORS AND HIGHER BIT RATE ENABLE HIGHER ACCURACY FOR C-VEP BCI

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***Abstract*—Steady state visual evoked potentials are widely exploited in EEG-based BCI systems. Frequency and code based flickering stimuli are the two major methods used to induce SSVEP responses. Considering the tiring effect of flashing icons in the long run, the less noticeable the flashes become, the more tolerable they will be. Based on the user ratings, who experienced both, code and frequency based stimulation, the code based method is less tiring. Hence, we used our SSVEP based BCI system in the code-based mode for this study. Among several aspects of stimuli affecting the system performance and user experience, for this study, we considered color, bit presentation rate and the control bit sequence length as three significant factors.**

Our main goal is to achieve more pleasant stimuli, while maintaining a high performance. Although, these factors seldom coincide, but, our findings showed that it is possible to find an almost optimum point of operation. In this study, a battery of calibration sessions with three different opponent color pairs of black and white, red and green and blue and yellow, three bit presentation rates of 30, 60 and 110 bps and three control bit sequence lengths of 31, 63 and 127 bits were performed. Our findings are suggestive of a performance increase using opponent colorful pairs as opposed to black and white, with the red-green color pair exceeding the performance of others. Consistently, among all the individuals participating in the study, one second of EEG evidence seems to be adequate to maximize the classification accuracy. This translates to {60 bps , 63 bits} and {110 bps , 127 bits} pairs of bit presentation rate and m-sequence length being the best performers. With a slight decrease in classification performance, half a second of EEG data could be considered when speed is of concern.

I. INTRODUCTION

Brain Computer Interface (BCI) systems form a new non-muscular communication channel between the brain and its surrounding environment. One of the main purposes of such systems is to help individuals who suffer from neuromuscular disabilities, e.g. complete locked-in syndrome (cLIS), live a more normal life. BCI systems have been used for a variety of applications such as typing, wheelchair control, and rehabilitation. Out of the common approaches in BCI systems, Electroencephalography (EEG) has in recent decades proven more popular due to its noninvasive nature.

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Three major brain activities are mainly used to build EEG based BCI systems: Event Related Potentials (ERPs), Event Related Desynchronization/Synchronization (ERDS) and Steady State Visually Evoked Potentials (SSVEPs). An example of an ERP based system utilizing the P300 component is the P300-based speller system [1] and its different variations [2]. ERDS responses are mainly generated in result of a motor imagery task. These responses while slow, have their alternative use in post-stroke rehabilitation. With online measurement of these signals, for instance, one can provide a feedback measure to help patients focus better on rehabilitation tasks [3].

SSVEP is the response of the visual cortex to flickering visual stimuli. Current VEP-based studies concentrate on two major approaches: Frequency-based VEP (f-VEP) and code-modulated based VEP (c-VEP). In an f-VEP scheme, each stimulus flickers with its own specific frequency. In a c-VEP scheme, each stimulus flickers according to a binary code, which creates a corresponding visual response. M-sequences, a special category of pseudorandom binary sequences, are an excellent example of such codes [4], [5]. Since the shifted versions of a given m-sequence are approximately orthogonal, different shifts of a single m-sequence allow the BCI system to produce several commands. The length of an m-sequence is always an odd number, $2^n - 1$ where n is the number of binary bits used to generate the m-sequence. The number of zeros and ones in every m-sequence is different only by one which leads to a balanced stimulus. Bin et al. compared f-VEP and c-VEP approaches and showed while f-VEP based systems have the advantage of a simple configuration without the need for training sessions, the c-VEP systems provide better accuracies and higher communication rates [6].

The amplitude of SSVEP differs between individuals and between stimulation frequencies. Herrmann et al. showed that, on average, the highest SSVEP amplitude occurs at 15Hz [7]. Hence, most studies use low frequency flicker in the range of 5-30 Hz to induce visual evoked responses. However, using low band frequencies has two major drawbacks. Firstly, stimulation in this range of frequency is irritating for subjects, because lower frequencies can be seen and picked out. The frequent changes between two different states of stimuli agitates the user and can render the SSVEP-based BCI system not so useful in the long term. Secondly, the risk of inducing photoepileptic seizure increases for frequencies between 15 and 25 Hz, compared to higher stimulation frequencies [8].

Properties of the stimuli may directly affect the performance of the BCI system. In SSVEP-based BCI studies, two kinds of stimuli have been used: complex and simple. In simple stimuli, a blinking LED or a flickering icon on an LCD screen can be used. In complex stimuli, checkerboard patterns are used instead [9]. Lalor et al. indicated using checkerboards has a clear advantage over simple stimuli. In order to elicit an SSVEP signal at a specific frequency, simple stimulus needs to be modulated with the same frequency while complex stimulus can be displayed at half of the target frequency [10], [11].

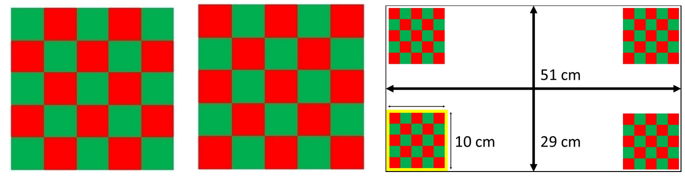
Moreover, the color of stimuli may affect the performance of the BCI system. A few studies exist on the effect of simple stimuli's color on the performance of a frequency based SSVEP BCI system [12]. However, to the best of our knowledge, no systematic study of the effect of color on complex stimuli for a BCI system exists. In the human eye, retina, i.e. the light-sensitive layer, is responsible for light perception. It contains two different types of photoreceptors: rods and cones. Rods are more in number than cones, have poor acuity and are color blind. They are suitable for human perception in low luminance conditions. In contrast, cones are color sensitive and are responsible for vision in daylight. According to the *opponent-process theory of color vision* [13], cones feed three neural channels for color processing. Each channel is composed of opponent color pairs: yellow/blue, red/green and black/white. Responses to one color of an opponent channel are antagonistic to those of the other color. In other words, opponent colors are never perceived together. Black-white visual stimulation, mostly stimulates rods. In this study, we want to examine the hypothesis that using opponent colorful pairs, cones and rods are both stimulated, more information is transferred to the visual cortex, leading to a higher classification performance.

Although, many studies have been done on SSVEP-based BCI, but, there has been no systematic study on the effect of the stimulus properties. In this paper, the effect of increasing bit presentation rate up to 110 bps, increasing the m-sequence length to 127 bits, and using opponent color pairs as stimuli will be studied. Using the user feedback on c-VEP stimulation being less tiring as opposed to f-VEP based stimulation, in this study, we will use the performance of our c-VEP based system as the performance measure. The goal is to find a set of stimuli parameters which can increase or maintain a high performance while being less tiring for the user.

II. METHOD

A. Experiment Design

Two reversed pattern 5×5 checkerboards have been used as the visual stimulus. Each checkerboard pattern consists of 25 units of opponent colors covering a $10cm \times 10cm$ area. Four of these visual stimuli are placed at the four corners of a 51×29 cm monitor. Figure 1 shows two reveres pattern checkerboards and a sample stimuli screen. Participants were seated with their head fixed, such that the distance from their eye to the stimulation screen was 80 cm. Each checkerboard pattern is arbitrarily assigned to Bit "0" or Bit "1" of an m-sequence. A different m-sequence was assigned to each stimulus, as the control bit sequence, to control the presentation order of the reverse pattern checkerboards. To ensure that visual stimulus



(a) (b) (c)

Fig. 1: (a) The checkerboard pattern corresponding to Bit "0", (b) The checkerboard pattern corresponding to Bit "1", and (c) The target arrangement of the stimuli.

m-sequence length (bit)	Bit presentation rate (b/s)		
	30	60	110
31	B/W	B/W	B/W
63		B/W, R/G, B/Y	B/W, R/G, B/Y
127			B/W, R/G, B/Y

TABLE I: Color pair, bit presentation rate and m-sequence length triplets studied. B/W represents black and white, R/G represents red and green and B/Y represents blue and yellow color pairs.

transitions occur precisely at the intended times, the monitor refresh rate is set to 60 Hz for the 30 bps and 60 bps bit presentation rates, and to 110 Hz for the 110 bps bit presentation rate. Four stimuli were presented simultaneously by placing the corresponding checkerboard patters at the four corners of the screen. Stimuli were presented using the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007). A complete presentation of the checkerboard patterns according to their control bit sequence is considered a trial. The onset of each trial is marked using a hardware trigger signal sampled simultaneously with EEG signals. Nonstop presentation of 12 trials is considered an epoch during the *Calibration* session. Each *Calibration* session consists of 20 epochs, where each stimulus is randomly selected as the target of the epoch 5 times. By eliminating the first and last trial of every epoch, every *Calibration* session results in 50 trials per stimulus. The number of trials per stimulus was determined based on the results of a previous study [14], [15] and proven to be adequate. The study consists of 12 different *Calibration* sessions.

Table I shows different color pair, bit presentation rate and control bit sequence length triplets used. Sessions with a 31 bit length control bit sequence were only collected for the black and white color pair to limit the duration of the data collection session. Table II shows the single stimulation trail duration under different settings. The *Calibration* sessions corresponding to the black and white color pair were collected first, followed by the *Calibration* sessions for the red and green color pair, and ending with the sessions for the blue

m-sequence length (bit)	Bit rate (b/s)		
	30	60	110
31	1.3 s	0.51 s	0.28 s
63		1.05 s	0.57 s
127			1.15 s

TABLE II: Stimulation trial duration.

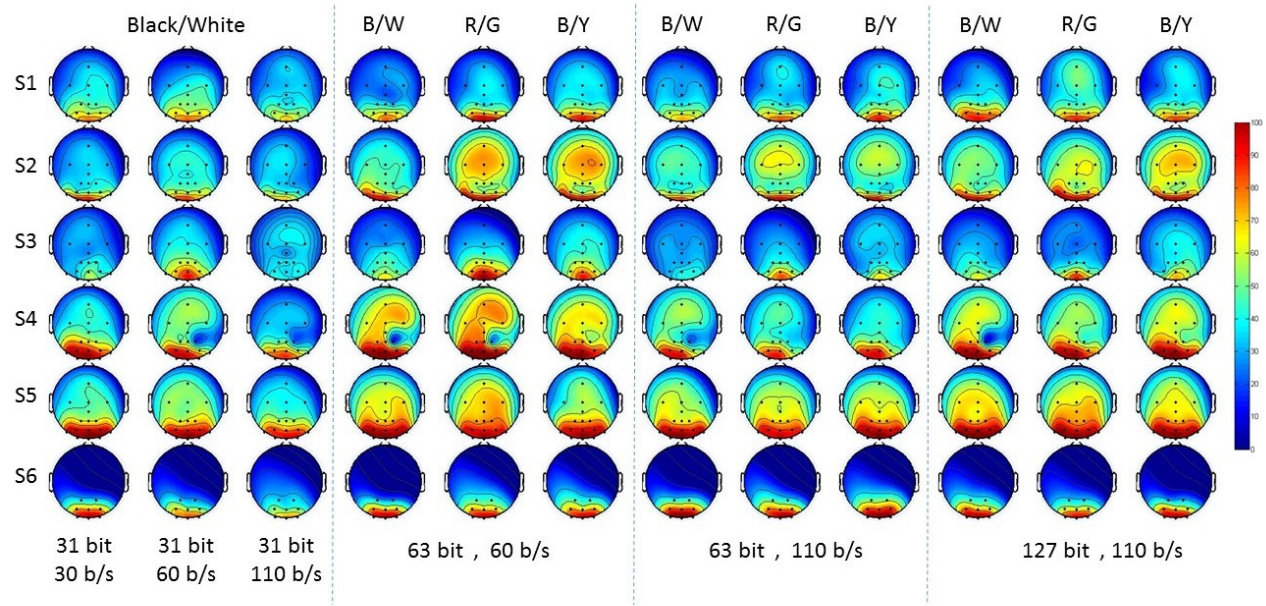


Fig. 2: Single channel classification accuracy of choosing among 4 simultaneously presented stimuli under different stimuli settings presented as a spacial scalp distribution. Every row corresponds to one participant. B/W, R/G and B/Y represent black and white, read and green and blue and yellow opponent color pairs.

Bit rate (b/s)	Fundamental frequencies (Hz)
30	15, 10, 7.5, 6, 5, 4.3, <u>3.75</u>
60	30, 20, 15, 12, 10, 8.6, <u>7.5</u>
110	55, 36.6, 27.5, 22, 18.3, 15.7, <u>13.75</u>

TABLE III: Fundamental frequency components generated by each m-sequence under different bit presentation rates. The frequency sets are identical for all the m-sequences used no matter the length, except the underlined values which are only available for the m-sequences of length 127 bits.

and yellow color pair. For every color pair, the *calibration* sessions were started with the shorter bit sequence length and slower bit presentation rate and proceed by increasing the bit presentation rate. For every m-sequence length, 4 different m-sequences were chosen such that their cross correlation is minimized. To further minimize the cross-correlation between the chosen m-sequences of each length, the pairwise Hamming distance between all the pairs and lags of the 4 different m-sequences were studied and the appropriate lags were applied. Table III illustrates the fundamental frequencies induces by each m-sequence under different bit presentation rates.

B. Data Acquisition

EEG signals along with the trigger signal indicating the onset of the events were collected using active g.Butterfly electrodes, a g.Gammabox, and a g.USBamp by G.tec. A notch filter at 60 Hz was used to eliminate the effect of AC power line noise and a bandpass filter from 0.1 to 100 Hz was applied to eliminate DC drifts in the signals. A sampling rate of 256 Hz has been used. With the focus of the study on the responses to the visual stimuli, EEG sites were selected with higher density around the visual cortex at Oz, O1, O2, Po3, Poz, Po4, P1, P2, Cpz, Po7, C4, C3, Fz, Cz, Po8, and Pz based on the 10-20 standard.

Six healthy subjects, 3 male and 3 female, with normal or corrected normal vision ranging in age from 23 to 27 participated in this study after having passed the Ishihara color blindness test [16]. Each individual consented, and participated in a two hour data collection session where the data was collected following an approved IRB by Northeastern University IRB office.

C. Offline Analysis

1) EEG Feature Extraction: A template matching method is employed to extract the EEG features for every trial. A template is an estimated EEG response to a specific stimulus being the target. To estimate the templates, the data collected during the *calibration* session is used. Trials are separated according to the target stimulus during their presentation time. Using all the trials with the same target stimulus, a template response is estimated. Sample mean has been successfully used to build these templates. [14], [17], [18] However, we can make the templates more robust to outliers by using the sample median instead. Defining the *Breakdown Point (BP)*, as the highest fraction of outliers that the estimator can handle without breaking down, [19] we compare the sensitivity of the estimation methods to outliers. Considering N_t as the number of trials per stimulus, the finite sample *BP* for the sample mean is $\frac{1}{N_t}$ resulting an asymptotic breakdown point of zero. However, for the sample median, the finite sample *BP* is $\frac{N_t-1}{2N_t}$ resulting in an asymptotic breakdown point of 0.5. In other words, even where up to half of the data points are outliers, the sample median will stay close to the actual templates.

2) Classification: Defining N_s as the total number of stimuli and N_c as the total number of EEG channels, using a leave one out method, correlation scores are calculated for each trial in the *calibration* session data.

$$r_i^c = \mathbf{s}^{cT}\mathbf{t}_i^c \tag{1}$$

where $\mathbf{s}$ is the windowed EEG signal in response to a trial, $\mathbf{t}_i^c$ is the template corresponding to the i^{th} stimulus and channel c and ^{T} represents the transpose operation. $\mathbf{r}^c$ is a vector of N_s values representing the correlation scores between the windowed EEG and all the templates for channel c. Next, using N_s dimensional correlation scores from the trials with the same target stimulus a multivariate Gaussian distribution is estimated.

$$p(\mathbf{r}) = \frac{1}{(2\pi)^{d/2}|\mathbf{\Sigma}|^{1/2}} exp\left[-\frac{1}{2}(\mathbf{r}-\boldsymbol{\mu})^T\mathbf{\Sigma}^{-1}(\mathbf{r}-\boldsymbol{\mu})\right] \tag{2}$$

where $\mathbf{r} = [\mathbf{r}_1, ..., \mathbf{r}_{N_c}]$, $\boldsymbol{\mu} = [\mu_1, ..., \mu_{N_c}]$ *mean vector* and $\mathbf{\Sigma}$ is the $N_sN_c \times N_sN_c$ *covariance matrix* with $|\mathbf{\Sigma}|$ and $\mathbf{\Sigma}^{-1}$ being its determinant and inverse [20]. It can be easily shown that sample mean and sample covariance are the maximum likelihood estimates. Although, the covariance estimate is biased, it is still close enough when the number of samples is not too small. However, by increasing the number of channels, the number of parameters to estimate will increase, which in turn requires more training samples. To decrease the number of samples needed to estimate the covariance matrices, sparse covariance estimation methods such as Graphical lasso [21] can be used. The final step of the classification is a maximum aposteriori (MAP) estimation.

$$D = \underset{i}{argmax} P(\mathbf{r}|i) \tag{3}$$

where i is the stimulus (m-sequence) index and D is the final decision. Notice the densities consider the correlation score with the target template and the cross-correlation scores with the non-target templates. This approach, models the variation of the correlation scores for the target and non-target stimuli simultaneously, leading to more robust estimates. The performance is estimated using a leave one out on the calibration set.

III. RESULTS

To separate the effects of the parameters under study, EEG channels were processed individually. In addition, multi-channel classifications with a structured and regularized covariance matrix [21] were performed and did not show any performance increase as opposed to the single channel accuracy of the channel Oz. This can be due to information content of the poor performing channels being very low. Figure 2 presents the single channel classification accuracy for all the participants and conditions.

The closer the EEG sites are to the visual cortex the higher their classification accuracy will be. However, the drop in performance is slower for sites on the center. Table IV shows the classification accuracy of the channel Oz for all the participants under different conditions. Located on the center of the visual cortex, channel Oz was previously reported as the best performing channel for black and white color pair [14], our results confirm that for all the participants and under all the conditions, Oz is the best performing channel.

Based on the results presented in table IV, red and green color pair, 60 bps bit presentation rate and 63 bit long m-sequences result in the highest performance on average. This setting, has the smallest standard deviation among all the other settings, showing the best consistency overall. A few paired t-

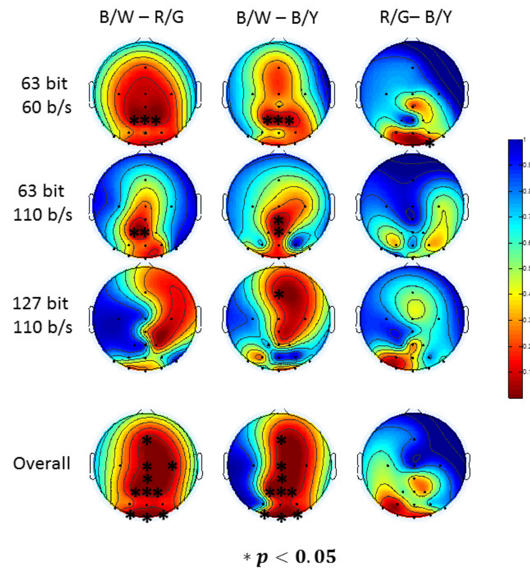


Fig. 3: Paired t-tests among different opponent color pairs under different bit presentation rates and different m-sequence lengths. Electrode locations marked with * showed significance with $p < 0.05$.

tests were performed to find out the significance of the different opponent color pairs among the same channel pairs for all the participants. Figure 3 summarizes the results of these paired t-tests. Channels P1, Pz, and P2 for 60 bps bit presentation rate for both B/W-R/G and B/W-B/Y were significantly different while they did not show a significant difference for R/G-B/Y.

For the higher bit presentation rate of 110 bps, channels P1 and Pz for B/W-R/G were significantly different and channels Pz and Fpz were significantly different for B/W-B/Y. For the bit sequences of length 127 bits and bit presentation rate of 110 bps, only one channel, Fz, was significantly different between B/W-B/Y. The last row of figure 3, shows paired t-test among all the participants and all the sessions with different color pairs.

The overall results show a significant difference in using opponent colorful pairs as opposed to black and white at channels O1, O2, Oz, P1, P2, Pz, FPz, Cz and Fz. No significantly different channel was found between the opponent colorful pairs. Based on the paired t-test results, 60 bps bit presentation rate and 63 bit m-sequence length has the most significant difference between the opponent colorful pairs and the black and white color pair.

The significant difference in using opponent colorful pairs, can come from the fact that they stimulate more photo-receptors (both Rods and Cones) resulting in a stronger SSVEP response. Figure 4 shows the template response of channel Oz for the stimulus 1 for participants with best and worst classification performance (participant S02 and S03 respectively). Template responses to the colorful opponent pairs had

Participant ID	B/W			B/W	R/G	B/Y	B/W	R/G	B/Y	B/W	R/G	B/Y
	31 bit			63 bit			63 bit			127 bit		
	30 b/s	60 b/s	110 b/s	60 b/s			110 b/s			110 b/s		
S01	80	82	71	79	**97.5**	91	89.5	85	89.5	87	89.5	87
S02	94.5	89	72	97.5	**100**	97.5	88	97.5	97.5	99.5	**100**	**100**
S03	54	85	40.5	65	**97.5**	86.5	40.5	79	65	61.5	88.5	71
S04	96	91.5	82	98.5	**99.5**	98	90	85.5	89	97	95.5	99
S05	**100**	98	89.5	99	96.5	97	98.5	92.5	98.5	**100**	99.5	99
S06	94	83	75	96	**100**	97	94	97.5	91.5	94.5	98.5	96.5
AVG	86.41	88.08	71.66	89.16	**98.5**	94.5	83.41	89.5	88.5	89.91	95.25	93.07
STD	17.26	6.05	16.77	14.05	**1.51**	4.69	21.36	7.52	12.19	14.7	5.09	10.71

TABLE IV: Performance of channel Oz based on the calibration data under different colors, bit presentation rates and control bit sequence lengths. Best performance for each individual is marked in bold. The last two rows are column wise average and standard deviation respectively.

a stronger response. While the slight decrease using 110 bps bit presentation rate might be coming from the fact that cones are less responsive to high frequency changes. Surveys collected from the participants after the experiment, were in agreement that the red and green and the 110 bps bit presentation rate were the most comfortable. This choice of color is in line with the previously reported findings [22]. Blue and yellow was the runner up and the black and white was the last. Red and green being equiluminant is one of the main factors making them more comfortable, especially against the black and white pair which makes flickers more visible.

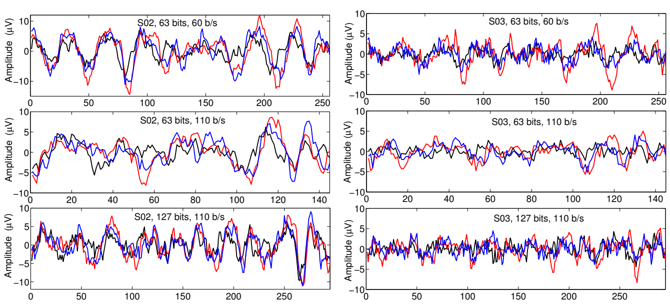


Fig. 4: Templates response of channel Oz for the stimulus 1 under different opponent color pairs for participant S02 on the left and S03 on the right. The black, red and blue lines are representing the black-white, red-green and blue-yellow opponent color pairs respectively.

IV. DISCUSSION

In summary, one second of EEG evidence and red and green opponent color pair results in the highest accuracy. Red and green opponent color pair also shows the least standard deviation for the average accuracies comparing with the other color pairs under the same presentation parameters. When the decision rate is the most important factor, with a small decrease in performance, 110 bps bit presentation rate with the 63 bit long m-sequences can be used to make decisions in almost half a second. On the other hand, to increase the comfort of the users, 110 bps bit presentation rate and 127 bit long m-sequences would be the best choice. Finally, a good compromise comes from using 63 bit long m-sequences, 60 bps bit presentation rate, and using the red and green opponent color pair. This setting, achieves the highest performance, while having the second best choice of the bit presentation rate from the comfort point of view.

Future work will be including other variables such as the effects of the pairwise distance of the stimuli, the size and the texture of the stimuli. Optimally, these results would help with the design of fast, comfortable and strong stimuli for SSVEP based BCI systems.

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