# Classification Accuracy Improvement of Chromatic and High–Frequency Code–Modulated Visual Evoked Potential–Based BCI

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**Abstract.** We present results of a classification improvement approach for a code–modulated visual evoked potential (cVEP) based brain–computer interface (BCI) paradigm using four high–frequency flashing stimuli. Previously published research reports presented successful BCI applications of canonical correlation analysis (CCA) to steady–state visual evoked potential (SSVEP) BCIs. Our team already previously proposed the combined CCA and cVEP techniques' BCI paradigm. The currently reported study presents the further enhanced results using a support vector machine (SVM) method in application to the cVEP–based BCI.

**Keywords:** Brain–computer interfaces · ERP · cVEP · EEG classification

## 1 Introduction

A brain computer interface (BCI) is a technology that employs human neurophysiological signals for a direct brainwave–based communication of a brain with an external environment, and without dependence on any muscle or peripheral nervous system actions [9]. Particularly, in the case of patients suffering from locked–in–syndrome (LIS) [6], BCI could help them to communicate or complete various daily tasks (type letters or control their environments using Internet of Things technologies, etc). The BCI shall create a feasible option for amyotrophic lateral sclerosis (ALS) or coma patients to communicate with their families, friends or caretakers by using their trained, and properly classified, brainwaves only [9].

We propose to utilize and classify EEG brainwaves in response to a code–modulated visual evoked potential (cVEP). The cVEP is a natural response to the visual stimulus with specific code–modulated sequences [3,4]. It is generated by the brain when the user gazes at a light source which flashes with a specifically designed code–modulated sequence. The cVEP–based BCI belongs


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to the stimulus–driven BCIs, which do not require a longer training comparing to the imagery–driven paradigms [9]. In this paper, we report EEG classification improvement results using a support vector machine (SVM) classification technique instead of the previously implemented by our team canonical correlation analysis (CCA) [1]. The CCA technique has been successfully used for classification of steady state visual evoked potentials (SSVEP) and it has resulted with good outcomes [5]. Next, a cVEP–based BCI has been also successfully implemented using the CCA [4]. We also successfully reproduced and further extended the above results based on a combination of cVEP stimuli and CCA–based classification [1]. A problem that raised in our previous research was related to a biased classification accuracy caused by the CCA towards some of the BCI commands. The training dataset for a classifier was created from cVEP responses when user gazed at the first flashing LED pattern (the top location in Figure 1). The remaining training patterns were created by applying circular shifts of the first LED cVEP's response. This method was responsible for the possible accuracy drop due to a limited number of training examples. We propose in this paper to use the linear SVM–based classifier to improve the cVEP BCI accuracy and to minimize any biases related to potential overfitting problems. In the presented project we also propose to use the RGB light–emitting diodes (LEDs) in order to evoke four types of cVEPs. We also utilize the higher flashing pattern carrier frequency of 40 Hz and compare our results with the classical setting of 30 Hz, of which refreshing rates has been chosen previously due to a limited computer display refresh rate of 60 Hz [2,3]. Moreover, we propose to use the chromatic green–blue stimulus [8] as a further extension in our project and we compare results with the classical monochromatic (white–black) set up.

From now on the paper is organized as follows. In the following section we describe materials and methods used in this study. Next, results and discussion are presented. Conclusions together with future research directions summarize the paper.

## 2 Materials and Methods

The experiments reported in this paper were performed in the Life Science Center of TARA, University of Tsukuba, Japan. All the details of the experimental procedures and the research targets of the cVEP–based BCI paradigm were explained in detail to the eight users, who agreed voluntarily to participate in the study. The electroencephalogram (EEG) cVEP–based BCI experiments were conducted in accordance with *The World Medical Association Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects.* The experimental procedures were approved and designed in agreement with the ethical committee guidelines of the Faculty of Engineering, Information and Systems at University of Tsukuba, Tsukuba, Japan (experimental permission no. 2013$R$7). The average age of the users was of 26.9 years old (standard deviation of 7.3 years old; seven males and one female).

### 2.1 Experimental Settings

The visual stimuli were presented to the subjects as flashing light sources delivered via the RGB LEDs. The LEDs were driven by square waves generated from *ARDUINO UNO* micro–controller board. The generator program was written by our team using *C*–language.

In this study we used $m-sequence$ encoded flashing patterns [4] to create four commands of the cVEP–based BCI paradigm. The $m-sequence$ is a binary pseudorandom string, which could be generated using the following equation,

$$x(n) = x(n-p) \oplus x(n-q), \quad (p > q), \tag{1}$$

where $x(n)$ is the $n^{th}$ element of the $m-sequence$ obtained by the exclusive–or (XOR) operation, denoted by $\oplus$ in the equation (1), using the two preceding elements indicated by their positions $(n-p)$ and $(n-q)$ in the string. In this project $p = 5$ and $q = 2$ were chosen. An initial binary sequence was decided, to create the final $m-sequence$, used in the equation (1), as follows,

$$\mathbf{x}_{initial} = [0, 1, 0, 0, 1]. \tag{2}$$

Finally, the 31 bits long sequence was generated based on the above initial sequence as in equation (2). The interesting $m-sequence$ feature, which is very useful for the cVEP–based BCI paradigm design, is an unique autocorrelation function. The autocorrelation function has only a single peak at the period sample value. If the $m-sequence$ period is $N$, the autocorrelation function will result with values equal to 1 at $0, N, 2N, \ldots$ and $1/N$ otherwise. It is also possible to introduce a circular shift of the $m-sequence$ denoted by $\tau$, to create a set of $m-sequences$ with shifted autocorrelation functions, respectively. In this study, the shifted time length has been defined as $\tau = 7$ bits. Three additional sequences have been generated using shifting by $\tau$, $2\cdot\tau$ and $3\cdot\tau$, respectively. During the online cVEP–based BCI experiments the four LEDs continued to flash simultaneously using the time–shifted $m-sequences$ as explained above. Two $m-sequence$ period lengths have been tested to investigate whether they would affect the cVEP responses. The conventional full $m-sequence$ period of $T = 516.7$ ms (based on the conventional computer screen refresh rate of 60 Hz and referred as "a low flashing frequency") and the proposed $T = 387.5$ ms (referred as "a high flashing frequency") have been tested. The experimental setting with four LEDs arranged on a square frame in front of a user is depicted in Figure 1.

### 2.2 EEG Signal Acquisition and Processing

During the cVEP–based BCI EEG experiments the users were seated on a comfortable chair in front of the LEDs (see Figure 1). The distance between user's eyes and LEDs was about $30 \sim 50$ cm (chosen by the users for a comfortable view of the all LEDs). An ambient light was moderate as in a typical office. The EEG signals were captured with a portable EEG amplifier system g.USBamp from g.tec Medical Engineering, Austria. Eight active wet (gel–based) g.LADYbird

EEG electrodes were connected to the head locations of O1, O2, PO3, PO4, P1, P2, Oz, and POz as in an extended 10/10 international system [9]. These positions were decided due to the visual cortex responses targeting experiment [9]. The ground electrode was attached to head location FPz and the reference to a left earlobe, respectively. Details of the EEG experimental set up are summarized in Table 1. An EEG sampling frequency was set to 512 Hz and a notch $4^{th}$–order Butterworth IIR filter at rejection band of $48 \sim 52$ Hz was applied to remove power line interference of 50 Hz. Moreover, the $8^{th}$–order Butterworth IIR band–pass filter at a pass band of $5 \sim 100$ Hz was applied to remove eye blinks and a high frequency noise.

The OpenViBE [7] bio–signal data acquisition and processing environment, together with in–house programmed in Python extensions, were applied to realize the online cVEP–based BCI paradigm. To avoid user's eye blinks, each trial to gaze at a single LED was separated with pauses during the experimental sessions (see details in Table 1).

In the data acquisition phase, first the users gazed at top flashing LED in order to collect classifier training dataset, as instructed verbally by the experimenter conducting the study. Twenty $m - sequence$ cycles were repeated in a single EEG capturing session. In short, sixty cVEPs to $m - sequence$ based flashing were collected for each direction in a single experimental trial. The triggers indicating the onsets of the $m - sequences$ were sent to g.USBamp directly from the *ARDUINO UNO* micro–controller to mark the beginning of each cVEP response. Finally, four experiment types were conducted for each user:

- the conventional low frequency;
- the proposed high frequency;
- and for the each above setting two color modes using white–black and green–blue flashing LEDs were applied.

**Table 1.** EEG experiment condition details

| | |
|---|---|
| Number of users | 8 |
| Single session length | 8 and 11 seconds |
| $m - sequence$ lengths $T$ | 516.7 and 387.5 ms |
| Shifts $\tau$ | 116.7 and 87.5 ms |
| EEG recording system | g.USBamp by g.tec with active wet (gel–based) g.LADYbird electrodes |
| Number of EEG channels | 8 |
| Electrode locations | O1, O2, Po3, Po4, P1, P2, Oz and Poz |
| Reference electrode | Left earlobe |
| Ground electrode | FPz |
| Notch filter | Butterworth $4^{th}$ order with a rejection band of $48 \sim 52$ Hz |
| Band–pass filter | Butterworth $8^{th}$ order with a passband of $5 \sim 100$ Hz |

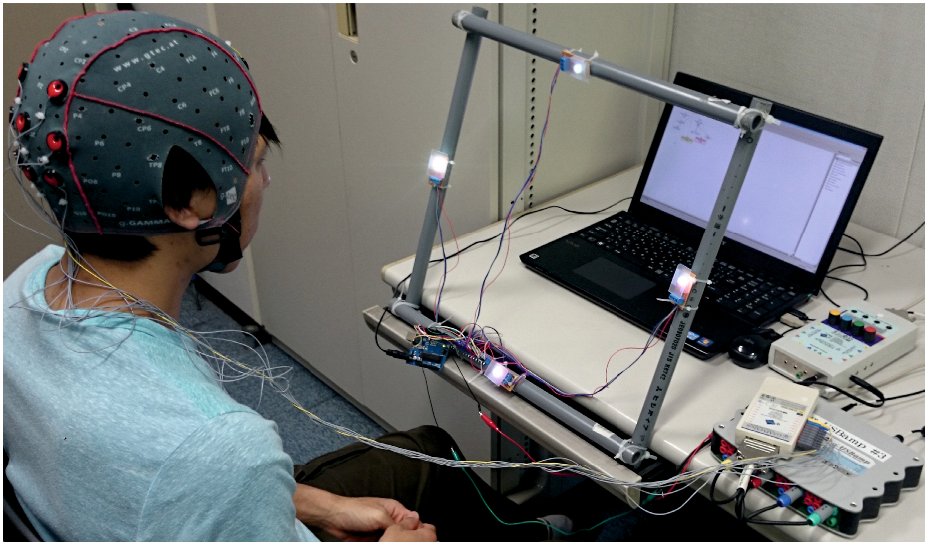

**Fig. 1.** The user is seating in front of a frame with four visual stimulation RGB LEDs used in this study. The top, bottom, right and left LEDs' flickering patterns correspond to the four different $m-sequences$, respectively. On the right side of the photograph there is the g.USBamp together with g.TRIGbox from g.tec Medical Engineering, Austria, used in the study. A laptop computer runs OpenViBE EEG data acquisition and processing environment.

### 2.3 The cVEP Responses Classification

A linear SVM classifier was used in this study to compare accuracies with a previously successfully implemented CCA method [1]. In the training session a single dataset containing the cVEP responses to top flashing LED was used. The remaining three cVEP responses were constructed by shifting the top LED response by $\tau$, $2 \cdot \tau$ and $3 \cdot \tau$, where $\tau \in \{87.5 \text{ ms}, 116.7 \text{ ms}\}$. We used the linear SVM classifier to identify the intended by the user flickering patterns. The cVEP response processing and classification steps were as follows:

1. For the classifier training purposes, capturing the EEG cVEP $\mathbf{y}_1$ obtained in response to the first $m-sequence$. A procedure to construct the remaining training patterns $\mathbf{y}_i$, $(i = 2, 3, 4)$, based on the original recorded $\mathbf{y}_1$ sequence was as follows:
$$y_i(t) = y_1(t - (i-1)\tau), \tag{3}$$
where $\tau$ was the circular shift and $t$ indicated a position in the sequence.
2. Averaging the captured $j$ cVEPs as $y_{i,j}(t)$ for each target $i$ separately. The averaged responses $\bar{\mathbf{y}}_i$ were used for the linear SVM classifier training. In this study, there were $N = 60$ training datasets and the number of averaged

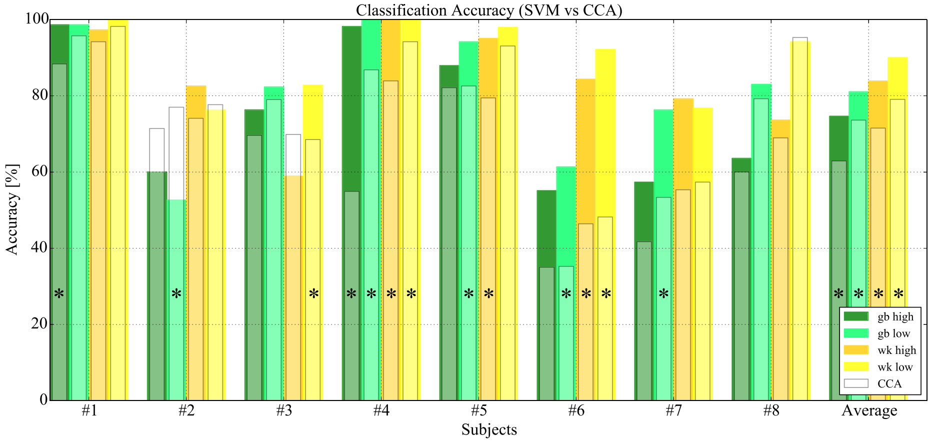


**Fig. 2.** The results of CCA and linear SVM–based classification from the eight users participating in the study presented in form of bar plots. There are four results depicted for each user, namely from the green–blue high frequency (green); green–blue conventional low frequency (light green); white–black higher frequency (orange); white–black lower frequency cases (yellow) bar color, respectively. The solid–colored bars resulted from the linear SVM application. On the other hand, the transparent bars, which overlap the solid counterparts, resulted from the CCA–based classification. The pairwise Wilcoxon–test was applied for each classification pair and the significant differences ($p < 0.05$) have been denoted with "$*$." The theoretical chance level of the experiments was of 25%.

responses was $M = 5$. The averaging procedure was as follows,

$$\bar{\mathbf{y}}_{i,l} = \frac{1}{M} \sum_{j=l}^{l+M-1} \mathbf{y}_{i,j}, \tag{4}$$

where $l = 1, 2, \ldots, N - M + 1$ was the dataset number.

3. For the test classification purposes, cVEPs from remaining BCI sessions, not used for the classifier training, to four target $m - sequences$ were applied.

The results of the above procedure applied to data recorded in the cVEP–based BCI experiments with eight users are discussed in the following section.

## 3 Results

Results of the conducted cVEP–based BCI paradigm experiments are summarized in form of accuracies as bar plots in Figure 2 and confusion matrices in Figures 3 and 4, respectively. The accuracies were calculated in experiments using the proposed green–blue high frequency, the green–blue conventional low frequency, the white–black high frequency, and the low frequency white–black

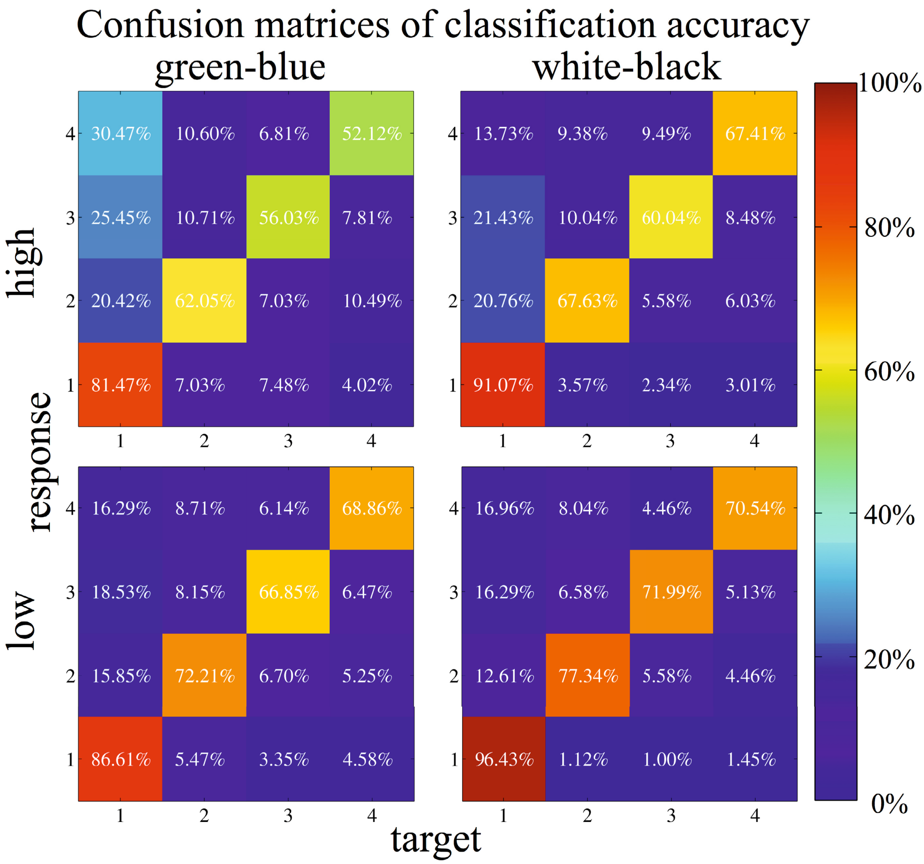


**Fig. 3.** The results of the linear CCA–based classification from the eight users depicted as confusion matrices from all the settings tested within the project.

flashing settings, respectively. The theoretical chance level of all experiments was of 25%.

To investigate command accuracy effects of cVEPs (discriminability) of CCA versus the proposed linear SVM, we applied pairwise Wilcoxon–test for a statistical analysis of median difference significances, because all the accuracy results were not normally distributed. The results of the classifiers' comparisons are presented in Table 2.

Next, a test was applied for a pairwise comparison of CCA versus linear SVM classification BCI accuracies for each frequency and color setting separately. The results presented in Figure 2 show individual bar plots, of which several have resulted with statistically significant differences (denoted with "∗"). Moreover, the averaged accuracies of all subjects resulted all with statistically significant

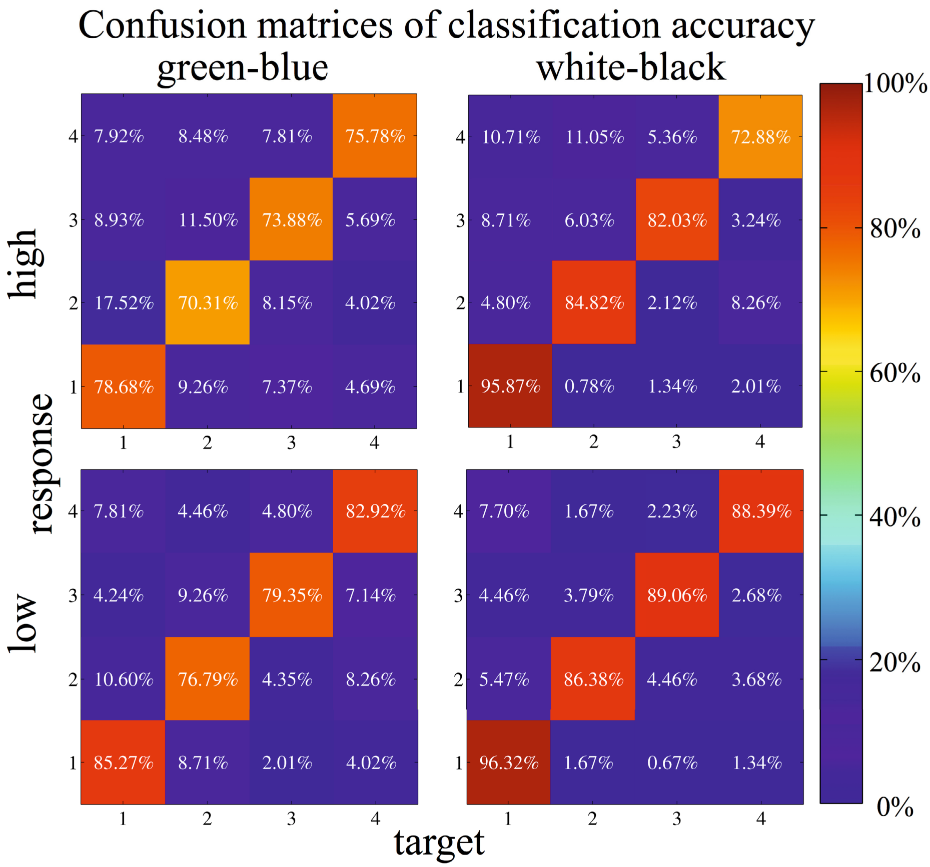


**Fig. 4.** The results of the linear SVM–based classification accuracy from the eight BCI experiments depicted as confusion matrices from all the settings tested within the project.

differences and the proposed linear SVM–based classification scored higher comparing to the CCA.

The accuracies for each command separately have been calculated and depicted in form of confusion matrices visualized in Figures 3 and 4, for CCA and linear SVM classifiers respectively. The results presented in the above mentioned figures have shown, that the biased classification result problem previously observed in the CCA case (command *one* scored relatively higher in the previous study) [1] was solved by the linear SVM application. Additionally, pairwise Wilcoxon–tests have been conducted for all users separately to evaluate differences of CCA versus linear SVM classifier accuracies in the four experimental settings. The resulting $p-$values are arranged in Table 3. There were significant

**Table 2.** The cVEP classification accuracy comparison of CCA versus linear SVM with pairwise Wilcoxon–test. The results of the BCI accuracy comparison with "$*$" symbols denote statistically significant median differences at a level of $p < 0.05$

| Command number | green–blue high | white–black high | green–blue low | white–black low |
|---|---|---|---|---|
| #1 | 0.664 | 0.122 | 0.940 | 0.870 |
| #2 | 0.327 | $0.005^*$ | 0.326 | 0.115 |
| #3 | 0.067 | $0.009^*$ | 0.242 | $0.032^*$ |
| #4 | $0.015^*$ | 0.385 | $0.036^*$ | $0.040^*$ |

**Table 3.** The cVEP classification pairwise Wilcoxon–test's $p$–value results of the BCI accuracy comparisons between linear SVM and CCA classifiers with "$*$" symbols denoting medians' difference statistical significances at the level of $p < 0.05$

| User number | green–blue high | white–black high | green–blue low | white–black low |
|---|---|---|---|---|
| #1 | $0.028^*$ | 0.730 | 0.093 | 0.200 |
| #2 | 0.122 | 0.167 | $0.001^*$ | 0.983 |
| #3 | 0.245 | 0.194 | 0.522 | $0.034^*$ |
| #4 | $0.000^*$ | $0.001^*$ | $0.001^*$ | $0.026^*$ |
| #5 | 0.154 | $0.019^*$ | $0.014^*$ | 0.066 |
| #6 | 0.105 | $0.006^*$ | $0.037^*$ | $0.006^*$ |
| #7 | 0.082 | 0.060 | $0.036^*$ | 0.169 |
| #8 | 0.743 | 0.702 | 0.374 | 0.853 |

pairwise differences observed in which the proposed linear SVM–based cVEP BCI classification accuracies scored also higher comparing to the CCA.

## 4 Conclusions

The proposed LED flashing and cVEP response–based BCI paradigm with the chromatic green–blue stimuli has been discussed in this paper. We tested linear SVM classification–based method in comparison to the classical already CCA case. The majority of the obtained linear SVM accuracy results scored higher comparing to CCA outcomes. We also resolved biased accuracies problem observed previously by our group in case of the CCA. The linear SVM classification cVEP BCI accuracies scored very good for all commands comparing to the CCA. The conducted experiments to verify the feasibility of the proposed method confirmed successfully our research hypothesis based on the results obtained from the eight healthy users. All of the cVEP–based BCI accuracies resulted well above the theoretical chance levels and there were also 100% outcomes observed.

For the future research, we plan to investigate upper limits of the stimulus frequency and an optimization of the $m - sequences$ in order to create the even better code–modulated visual BCI.

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