# EEG Filtering Optimization for Code–modulated Chromatic Visual Evoked Potential–based Brain–computer Interface


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**Abstract.** We present visual BCI classification accuracy improved results after application of high– and low–pass filters to an electroencephalogram (EEG) containing code–modulated visual evoked potentials (cVEPs). The cVEP responses are applied for the brain–computer interface (BCI) in four commands paradigm mode. The purpose of this project is to enhance BCI accuracy using only the single trial cVEP response. We also aim at identification of the most discriminable EEG bands suitable for the broadband visual stimuli. We report results from a pilot study optimizing the EEG filtering using infinite impulse response filters in application to feature extraction for a linear support vector machine (SVM) classification method. The goal of the presented study is to develop a faster and more reliable BCI to further enhance the symbiotic relationships between humans and computers.



**Keywords:** Brain–computer interface; ERP; EEG classification; cVEP.


## 1 Introduction

A brain computer interface (BCI) is a symbiotic device which facilitates human–machine interaction without dependence on any muscle or peripheral nervous system actions [7]. BCI employs human neurophysiological signals for a straight brainwave–based communication of a human with an external environment. Particularly, in the case of patients suffering from locked–in–syndrome (LIS) [4], amyotrophic lateral sclerosis (ALS) or coma, 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 such patients to communicate with their families, friends or caretakers by using their trained and properly classified brainwaves only [7].

A code modulated visual evoked potential (cVEP) is proposed in this paper as a brain–computer interface (BCI) paradigm. The cVEP is a natural response to a visual stimulus generated with specific code–modulated, and also enhanced


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with color modulation, sequences [2, 3] while the user gases at the light source. The cVEP–based BCI is a stimulus–driven paradigm which does not require a long training, as compared to the imagery–driven paradigm [7].

Usually, cVEP's advantage is in its faster classification time comparing to other types of visual–BCIs using steady state visual evoked potentials (SSVEPs) or P300 responses. Theoretically a single classification interval could take less than 387.5 ms in our experiments, but actually the cVEPs have to be averaged to remove EEG noise, which multiplies the above mentioned minimum period. Usually the averaging procedure can take longer time, for example 1.9375 seconds as in our previous study based on five cVEPs' averaging [1], which limits this paradigm's advantage. In this paper, we present results of classification improvement after application of high– and low—pass filtering of EEG to create the faster cVEP–based BCI. A linear support vector machine (SVM) classifier is applied in the presented cVEP–based BCI research project.

The cVEPs used in this project are induced by four RGB light–emitting diodes (LEDs). We also utilize the higher flashing carrier frequency of 40 Hz (which is amplitude modulated with the proposed $m-sequences$) comparing to the classical setting of 30 Hz (limited to compare results with classical computer displays usually with 60 Hz refreshing rate) [2]. There are maximum of five consecutive positive pulses (continues light) and minimum of one positive/negative pulse of the LEDs in this experiment settings. If cVEP's frequency features would be evoked similarly as in a case of SSVEP, the steady–state response suppose shall appear in EEG frequency bandwidths of $6 \sim 30$ Hz or $8 \sim 40$ Hz according to our hypothesis. In other words, low–pass filtering with a cutoff frequency of 30 Hz or 40 Hz shall do the best job to remove unnecessary higher frequencies from EEG. Moreover, we propose to use chromatic green–blue stimuli [6] as a further extension in our project. We also compare our 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, and they were approved by the ethical committee of the Graduate School of Systems and Information Engineering at University of Tsukuba, Tsukuba, Japan (experimental permission no. $2013R7$). The subjects agreed voluntarily to participate in the study. The visual stimulus generating LEDs were driven by square waves delivered from *ARDUINO UNO* micro–controller board. We used $m-sequence$ encoded flashing patterns [3] to create four commands of the cVEP–based BCI. The binary pseudorandom string $m-sequence$ with a length of 31 bits was used as follows [0100100001010111011000111110011]. The special feature of the $m-sequence$,

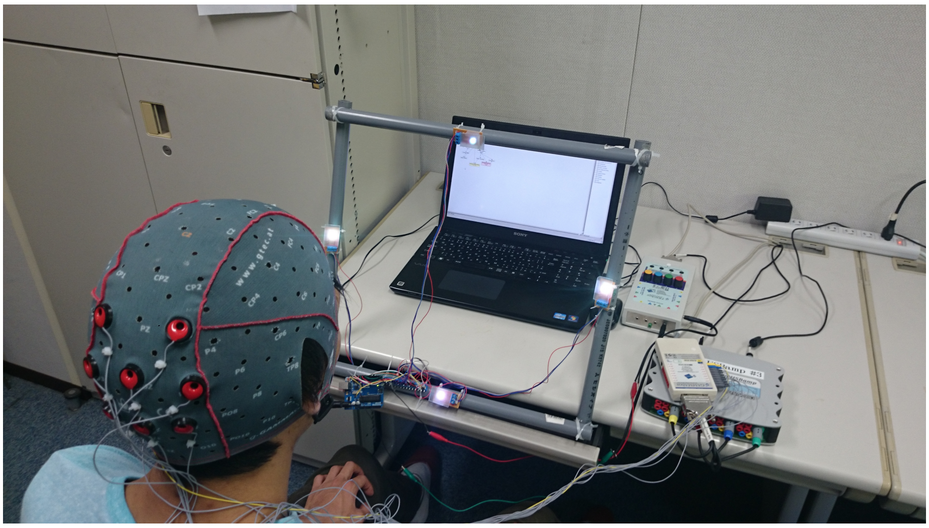

**Fig. 1.** The user seating in front of a frame with four visual stimulation chromatic LEDs used in this study. The picture was included with a permission of the photographed user.

which has been useful for the cVEP–based BCI paradigm design, was an unique autocorrelation function. The autocorrelation function had only a single peak at the $m-sequence's$ period. It was thus possible to introduce a circular shift of the $m-sequence$ denoted by $\tau$, to create a set of another 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 shifts of $\tau$, $2 \cdot \tau$ and $3 \cdot \tau$, respectively. During the online cVEP–based BCI

**Table 1.** EEG signals recording conditions

| | |
|---|---|
| Number of users | 9 (8 males and 1 female) |
| Average age of users | 26.4 years old (standard deviation of 7.0 years) |
| Single session length | 8 and 11 s |
| $m-sequence$ length $T$ | 516.7 and 387.5 ms |
| $m-sequence$ shifts $\tau$ | 116.7 and 87.5 ms |
| EEG amplifier | g.USBamp by g.tec with wet active g.LADYbird electrodes |
| Electrode locations | $O1, O2, Po3, Po4, P1, P2, Oz$ and $Poz$ |
| Reference and ground | Left earlobe and $FPz$ |
| Sampling frequency | 512 Hz |
| Notch filter | Butterworth $4^{th}$ order stopping $48 \sim 52$ Hz |
| Band–pass filter | Butterworth $8^{th}$ order with a passband of $5 \sim 100$ Hz |

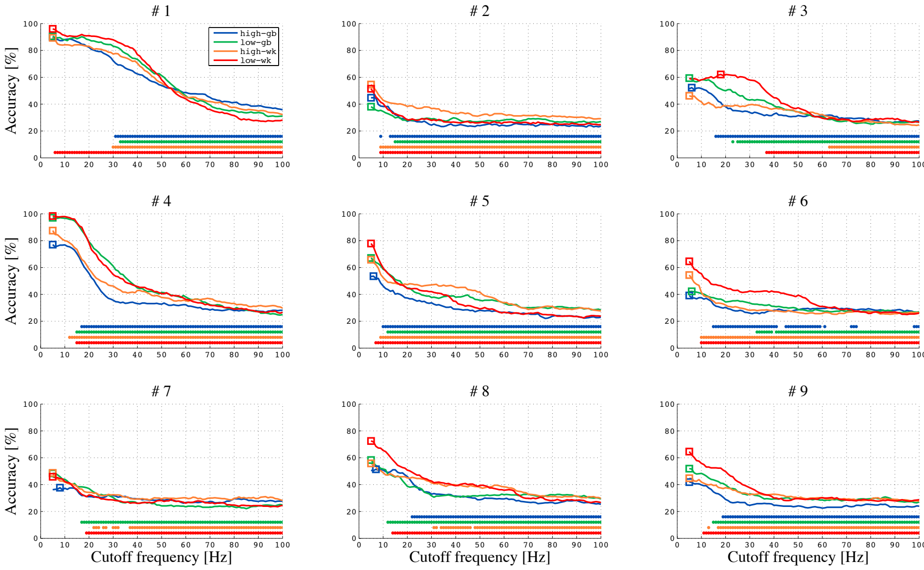


**Fig. 2.** The mean accuracy results of SVM–based classification after high–pass filtering. There are four results depicted for each user, namely from green–blue high carrier frequency (blue lines); low carrier frequency (green lines); white–black high carrier frequency (orange lines); low carrier frequency (red lines), respectively. Square markers show the maximum accuracies. Four horizontal lines, or dots, at the bottom of each panel depict the significant differences of classification accuracies between the non–filtered (raw EEG signals, of which accuracies are not shown here) and the filtered cVEPs ($p < 0.05$ of Wilcoxon–test). The theoretical chance level of the experiments was of 25%.

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 response discriminability. The conventional full $m-sequence$ period of $T = 516.7$ ms, as in case of a conventional computer display with a refresh rate of 60 Hz (referred here as “a low flashing frequency”) and the proposed $T = 387.5$ ms (referred as “a high flashing frequency”) have been tested. The LED–based visual stimulus generator is presented in Figure 1. 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). A notch filter was applied to remove power line interference of 50 Hz from EEG together with a band–pass filter to remove eye blinks and muscle–originating noise. Details of the EEG experimental set up are summarized in Table 1. To avoid user’s eye blinks, each trial to gaze at a single LED was separated with pauses. The 60 cVEPs were collected for each of four LED flashing targets. An OpenViBE [5]

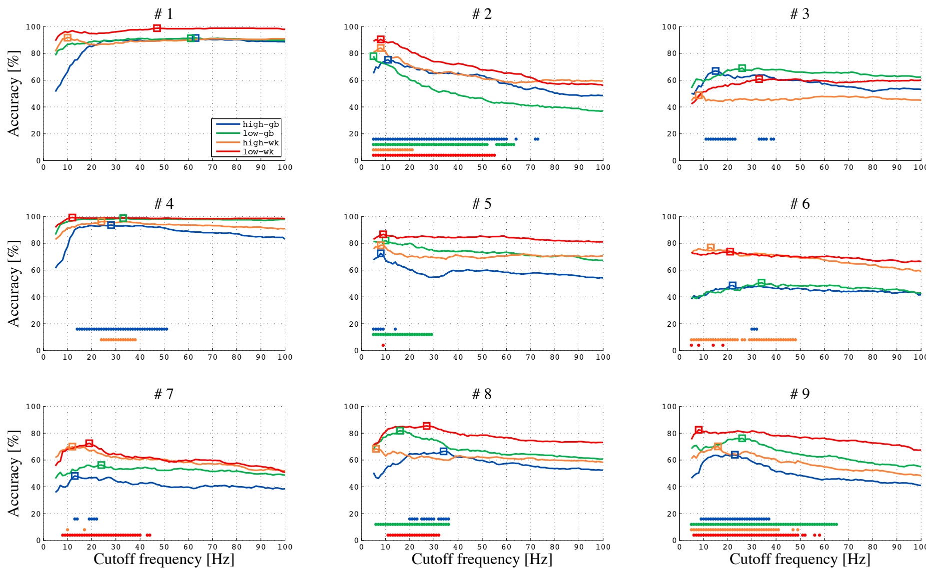


**Fig. 3.** The mean accuracy results of SVM–based classification after low–pass filtering. There are four results depicted for each user, namely from green–blue high carrier frequency (blue lines); low carrier frequency (green lines); white–black high carrier frequency (orange lines); low carrier frequency (red lines), respectively. Square markers show the maximum accuracies. Four horizontal lines, or dots, at the bottom of each panel depict the significant differences of classification accuracies between the non–filtered (raw EEG signals, of which accuracies are not shown here) and the filtered cVEPs ($p < 0.05$ of Wilcoxon–test). The theoretical chance level of the experiments was of 25%.

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. In the data acquisition phase, user gazed at four LEDs as instructed. The cVEPs to top LED were firstly collected for the classifier training and other were used for testing. The triggers indicating the onsets of the $m-sequences$ were sent to the amplifier directly from the *ARDUINO UNO* micro–controller to mark the beginning of each cVEP response.

A linear SVM classifier was used in this study to identify which of the flickering patterns the user was gazing at. The cVEP response processing and classification steps were as follows: (i) for training purpose, the EEG cVEP responses to the top flashing LED (m–sequence with $\tau = 0$) were defined as $Y(t)$ and another three cVEPs (responses to bottom, right and left LEDs as shown in Figure 1) were created by circular shifting of the original $Y(t)$ by $\tau$, $2 \cdot \tau$ and $3 \cdot \tau$ respectively; (ii) high–pass Butterworth IIR filters were applied to EEG with cutoff frequencies of $a$ and $b$ Hz, where $a \in \{6, 7, \ldots, 100\}$ Hz; (iii) four–class linear SVM classifier was trained using 60 filtered cVEPs for each flashing target, respectively; (iv) high–pass filters were applied similarly as in (ii) to EEG for testing dataset with 60 filtered cVEPs to four target $m - sequences$ linear SVM evaluations; (v) the above steps (ii)–(iv) were applied for the frequencies $a = 5, 6, \ldots, 100$ Hz. The above procedure steps (i)–(v) were also repeated by switching testing and training cVEPs to the top LED. Finally, four experiment types were conducted for each user by employing: the conventional low frequency; the proposed high frequency; and in each of the above setting in the two color modes with white–black and green–blue flashing LEDs.

## 3 Results

Results of the conducted cVEP–based BCI paradigm experiments are summarized in Figures 2 and 3. The accuracies were calculated for cVEPs induced by four types of stimulations as mentioned in previous section. The theoretical chance level of all experiments was of 25%. In the case of Figure 2, the mean high–pass filter cutoff frequency of four maximum classification accuracies for each user was of 5.58 Hz (standard deviation of 2.22 Hz). The significant differences of the above accuracies, as tested with pairwise Wilcoxon–test, between non–filtered and filtered cVEPs ($p < 0.05$) were observed as shown in form of horizontal lines in at the bottom of each panel in Figure 2.

We next applied low–pass filtering to EEG for identifying the higher frequency features, which resulted with BCI classification accuracies as shown in Figure 3. Except for subject #1, the results have shown that low–pass cut–off frequencies within a range of $10 \sim 30$ Hz scored the best for all the stimulation types. The mean cutoff frequency of four maximum classification accuracies for each user was of 20.58 Hz (standard deviation of 14.32 Hz). There were significant differences among non–filtered and filtered result ($p < 0.05$), as evaluated with Wilcoxon–test, yet the frequencies values we user–dependent as shown in Figure 3.

## 4 Conclusions

The proposed LED flashing and cVEP response–based BCI paradigm with the chromatic (green–blue) stimulus has been discussed in this paper. We tested and optimized high– and low–pass filters for cVEP–based BCI accuracy improvement using linear SVM classifier. The conducted experiments verified the optimal filter bandwidth for the proposed cVEP feature extraction within the mean range of $5.58 \sim 20.58$ Hz (which shall round up to $6 \sim 21$ Hz taking into account the exact frequency steps used in the study). We originally hypothesized that the low–pass filleting at 30 or 40 Hz cutoff frequencies shall do the good job for cVEP unrelated noise removal, but the results of the presented experiments have shown that much lower cutoff frequencies of about 21 Hz are also feasible.

For the future research, we plan to investigate further details of frequency features of cVEP, which is a broadband signal due to it's square wave pseudo–random components.

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