

THE EFFECT OF HIGH AND LOW FREQUENCIES IN C-VEP BCI

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ABSTRACT

Broadband code modulated visual evoked potential (BB-VEP, c-VEP) is the basis of one of the fastest brain-computer interface (BCI) paradigms. Unlike other systems, like those based on steady-state visual evoked potential (SSVEP, f-VEP), the stimulus specificity of c-VEP has not been thoroughly studied yet. One of the important stimulus characteristics that can influence both performance and user comfort is the frequency (the bit clock or frame rate). In this study, we evaluated the effect of stimuli presented at various frame rates (40, 60, 90 and 120 Hz) on c-VEP using LED lights. Accuracy and ITR were used to assess the performance and a questionnaire was used to evaluate the visual comfort. No significant differences in the performance of different frequencies were found, so comfort can be the main factor in the design decision. However, there is a trend for the frame rates of 40 and 90 Hz to yield a higher accuracy as compared to 60 and 120 Hz.

INTRODUCTION

One of the well-known brain computer interface (BCI) applications is a speller, in which the user can select a letter and type it on the screen. Different paradigms are used to develop such BCI spellers, in which the frequency-modulated visual evoked potential (f-VEP) and the code-modulated visual evoked potential (c-VEP) have gained increasing attention due to their high information transfer rate (ITR) [1].

In an f-VEP-based BCI, the user is presented with visual stimuli flickering at different frequencies. The attended stimulus generates steady-state visual evoked potential (SSVEP) responses over the occipital brain areas at the same (or harmonics) frequency of the stimulus [2]. A wide range of frequencies (between 4 and 90 Hz) can be used to elicit SSVEPs [2, 3]. The lower frequency range (<20 Hz) induce higher amplitude SSVEP responses compared to the higher frequency stimuli. However, the higher frequency stimuli are visually more comfortable and cause less visual fatigue [4]. Many research groups have investigated the effect of different frequencies on the SSVEPs response [5] and on the BCI performance [6]. For example, to compare the accuracies from high and low frequencies, Won and colleagues designed an experiment using 30 LED lights flickering at different frequencies. In their studies, they achieved higher classification

accuracy using high-frequency stimuli (26-34.7 Hz) compare to the low-frequency stimuli (6-14.7 Hz) [6, 7]. Unlike the f-VEP, the stimulation frequency of c-VEP has not been thoroughly studied yet.

In c-VEP, a set of pseudo-random bit-sequences (codes) is used to modulate intensity of the visual stimuli. Though many types of codes are used in BCI, the stimulation codes are often a single m-sequence with a different phases, or are constructed as a Gold code family generated with a special pair of m-sequences. They can be run at different stimulation frequencies, we will call them frame rates, even though we use LED's and no video frame is involved. In most of the c-VEP BCI studies, due to limitations in display refresh rates, 60 and 120 Hz are commonly used in the experimental setups. However, using the latest monitors with a higher refresh rate, recent studies investigated the effect of higher stimulation frequencies on c-VEP [8, 9]. In the study by Gembke and colleagues, they compared the results of high-frequency stimulation rates (120 and 200 Hz) with the traditional 60 Hz and found a lower but comparable result in terms of accuracy and ITR for 200 Hz compared to 60 and 120 Hz. Başaklar and colleagues, examined stimulus presentation rates of 60, 120, 240 Hz and revealed that 120 Hz is better than 240 Hz for higher number of classes. Nevertheless, to understand the effects of different stimulation frequencies and their boundaries on c-VEP systems more research is needed.

In this study, we used modulated Gold codes to investigate the effects of low and high stimulation frequencies (40, 60, 90 and 120 Hz) in terms of performance and visual comfort. We used LEDs instead of a monitor to be more flexible in presenting the stimulation frequencies. In addition, in order to make the BCI experiment more practical and pleasant for the participants, water-based EEG electrodes were used.

MATERIALS AND METHODS

Participants: 10 subjects (age: 31.2 ± 11.71 , average \pm standard deviation, 5 male) with normal or corrected-to-normal vision took part in the experiment. The subjects agreed voluntarily to participate in the experiment. The study was approved by and conducted in accordance with the guidelines of the Ethical Committee of the Faculty of Social Sciences at the Radboud University. Prior to the experiment, all subjects read and signed a written

informed consent.

Experimental design: The visual stimuli were presented to the subjects using eight RGB LED lights. Each LED was surrounded by a plastic cylinder to create a circular target (4 cm diameter, 1 cm inter-target distance). Then, all LEDs were covered using a light diffusion sheet to prevent uneven light distribution. Subsequently, eight small transparent sheets with a picture of an animal were placed at the center of each light as shown in Figure 1(A). The LEDs were controlled by an ARDUINO UNO micro-controller to send the eight flashing patterns of the modulated Gold codes (See further, m-Gold codes). During the experiment, subjects were sitting on a chair in front of the LED box with a distance of 35 to 50 centimeters. The exact distance was chosen by each participant for a comfortable view of the LED box. The experiment consisted of four runs, one for each frame rate stimuli (i.e., 40, 60, 90, 120 Hz). Each run consisted of 10 trials of 4.2 seconds at that specific frame rate with an inter-trial interval of one second. In each trial, one LED was cued randomly as a target. After the cue, all LEDs started flashing their own code at the specific frame rate, for 4.2 seconds. The time course of one trial is shown in Figure 1(B). The subjects were instructed to focus their attention to the cued target and gaze at its center during the stimulation. The stimulation frequencies were presented to the subjects in a random order. To prevent visual fatigue, the subjects could take a short break between each run.

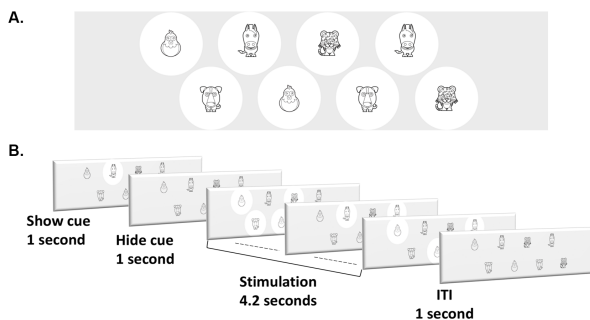


Figure 1: A. Layout design of the LED box, all are blinking at the same frame rate, but with different bit sequences; B. Time-course of one trial during the experiment. ITI: Inter trial interval.

m-Gold codes: Gold codes are a set of pseudo-random bit sequences with minimum cross-correlation and optimal auto-correlation [10]. A set of Gold codes is formed by XORing a preferred pair of m-sequences of the same length with a time-lag. Each time-lag yields a new member of a Gold code family. An m-sequence is generated by a special type of linear feedback shift register (LFSR) that has a longest non-repeating sequence for a given tap sequence. Although an m-sequences has better auto-correlation properties than a Gold code, a set of m-sequences may have large and unpredictable cross-

correlation values.

In this study, we used a set of Gold codes created with a 6-bit linear feedback shift register and feedback taps at positions 6,5,2,1 and at 6,1 (See [10, 11] for the generation process). In our study, the Gold codes were modulated with a double bit clock to force a transition in each bit. These modulated codes (m-Gold codes) retained the good correlation properties while restricting the run-length distribution, as a code can be considered as a series of short (i.e., '10' or '100') and long (i.e., '110' or '1100') on-off runs, which represent short and long flashes, respectively (See Figure 2). The family consisted of 65 codes, each with a 126 bits length. In this study, we used the first eight sequences of these m-Gold codes to send to the eight LED lights.

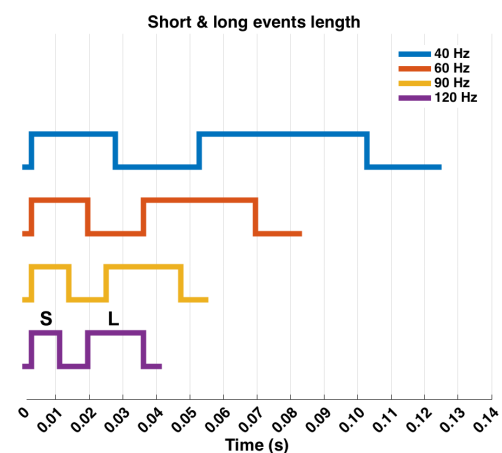


Figure 2: Pulse duration for 4 bits of the first sequence of the modulated Gold codes in different frequencies. S: short event; L: Long event.

Recording: EEG was recorded using the Twente Medical Systems International (TMSi) Porti system with 32 EEG channels and a common average reference at a sampling rate of 1000 Hz. The EEG data was collected using seven water-based electrodes located over the parietal and occipital cortex at CP5, P3, Pz, POz, Oz, P4, and CP6 according to the international system of EEG measurement [12]. The ground (GND) electrode was located over the left temporal site (T7).

Preprocessing: The raw signals were down sampled to 360 Hz. To be able to create suitable roll-on roll-off spectral sensitivity the down sampled signals were high-pass filtered at 2 Hz using a 2nd order Butterworth filter, and low-pass filtered at 50 Hz using a 4th order Chebyshev type II filter with 50 dB stop-band attenuation. The stimuli presentation and the preprocessing were implemented online using the BrainStream software [www.brainstream.nu].

Comfort scores: To assess the visual comfort at each frame rate, subjects filled out a four-level satisfaction questionnaire, (with levels: very uncomfortable = 0,

uncomfortable = 3, comfortable = 7, very comfortable = 10). Participants rated the questionnaire based on their subjective experience after each run of the experiment. Thereafter, we calculated the mean score over all subjects for each frame rate.

Analysis: In the c-VEP, template matching is applied to identify the attended target. To create a template, we used a generative model called re-convolution (see [13] for details). Re-convolution is a method that models the brain response to a sequence of events (here, m-Gold codes) as the linear summation of the responses to the individual events (i.e., short and long flashes, see Figure 2). The re-convolution method used in [13] has been implemented in two sequential steps. First, it generates transient responses by performing deconvolution and subsequently learns the spatial distribution by means of Canonical Correlation Analysis (CCA). Here, we integrated re-convolution in the CCA to simultaneously derive both temporal as well as spatial dynamics of the responses [14]. Therefore, we defined the CCA as follows:

$$W, R = \underset{W, R}{\operatorname{argmax}} \frac{W^T X \cdot M^T R}{\sqrt{W^T X X^T W \cdot R^T M M^T R}} \quad (1)$$

Where, $X \in \mathbb{R}^{k \cdot m \cdot c}$ is the concatenation of k single-trials of m samples and c channels, and $m \in \mathbb{R}^{k \cdot m \cdot c}$ is the concatenation of k structure matrices of m samples and c channels. The structure matrix, M , is a design matrix created for each event type (i.e short and a long flash), which in the first column, lists a 1 whenever the event type occurred, and zero elsewhere, and in each subsequent column the ones shifts down a row to the length of the transients (See Fig.5 in [13]). Therefore, M contains two structure matrices, $M = [M_s, M_l]$, with M_s the structure matrix listing a 1 when the short event happened, and M_l listing 1 whenever the long event happened. Thus, the CCA derives a spatial filter $W \in \mathbb{R}^{c,1}$ and a temporal filter $R \in \mathbb{R}^{l,1}$ with the responses to the short (R_s) and long (R_l) events, $R = [R_s, R_l]$. The CCA does that by optimizing the spatial and temporal filter in such a way that the correlation between spatially filtered data ($W^T X$) and the predicted responses ($R^T M$) is maximized. Thereafter, a template matching can be performed to classify a new single-trial using W and R as follows:

$$y = \underset{i}{\operatorname{argmax}} \{ \operatorname{corr}(W^T x, R^T M_i) \} \quad (2)$$

in which, M_i is the structure matrix for the i th class and $T_i = R^T M_i$ is the predicted responses for stimulus i .

Performance evaluation: To estimate the system performance, we measured the accuracy of the classifier, the corresponding information transfer rate (ITR) [15], as well as (correct) symbols per minute (SPM) [16], which includes the time needed for a backspace to correct misspelled symbols. The accuracy was measured using 10-fold cross-validation. The maximum correlation between the spatially filtered data and the generated templates was

used as an indicator of the predicted class. We measured the ITR (in bits/minute) and the SPM (in symbols/minute) calculated as follows:

$$ITR = (\log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{N - 1}) * \left(\frac{60}{T} \right) \quad (3)$$

$$SPM = (P - (1 - P)) * \frac{60}{T} \quad (4)$$

Where N is the number of classes, P is the detection accuracy of targets and T is the time needed to convey each symbol, including both trial time and inter-trial time (in seconds). The maximum ITR value during the stimulation time was determined for each subject at each bit rate, to report as ITR.

Statistics: Since accuracy rates and comfort scores were not normally distributed, a non-parametric Friedman test was performed. This test was used to compare the result of each pair of frame rate stimuli. The significant threshold was set to 0.05.

RESULTS

Comfort scores: Figure 3 shows the score provided by volunteers about the level of visual comfort regarding different frame rate stimuli. As can be seen, the higher frequencies tend to be more comfortable than the lower frequencies. None of the subjects reported "(very) uncomfortable" for the frame rate of 120 Hz and in contrary, no subjects reported "very comfortable" for the frame rate of 40 Hz. Interestingly, some subjects reported a difficulty to attend the 120 Hz stimulation because the flicker was less perceptible compared to the other frequencies.

To determine any significant differences in the comfort scores due to different frame rate stimuli, we performed non-parametric Friedman test. The results from Friedman test revealed a significant main effect of frame rate ($\chi^2(3) = 17.077$, $p = 0.001$) on comfort scores. Subsequent post-hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction, resulting in a significance level set at $p < 0.008$. Interestingly, the results showed only a statistically significant difference between the frame rates of 40 and 120 Hz ($Z = -2.762$, $p = 0.006$). No significant differences were found between other pairs of the frame rate stimuli (40 vs. 60 Hz ($Z = -1.801$, $p = 0.072$); 40 vs. 90 Hz ($Z = -2.585$, $p = 0.010$); 60 vs. 90 Hz ($Z = -1.633$, $p = 0.102$); 60 vs. 120 Hz ($Z = -2.264$, $p = 0.024$); 90 vs. 120 Hz ($Z = -1.511$, $p = 0.131$)).

Performance evaluation: In addition to classification accuracies, Figure 4 also shows the corresponding ITRs (in bits/min) and the SPM (in sym/min) for the different frame rate stimuli. In terms of accuracy, the frame rates of 40 and 90 Hz gained higher accuracy and SPM compared to the 60 and 120 Hz. Looking at the results of the ITR, the frame rate of 40 Hz leads to the highest ITR of

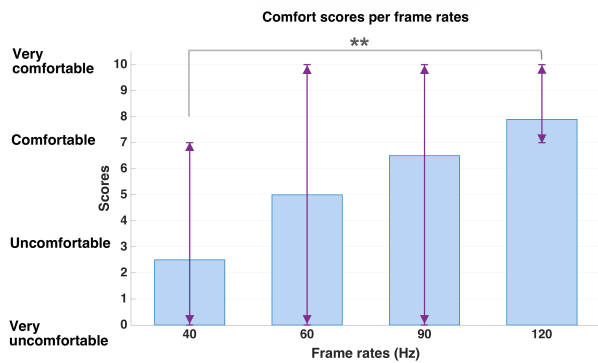


Figure 3: Scores of visual comforts provided by subjects for different frame rate stimuli. The error bars represent the maximum and minimum of the scores. ** $p < 0.01$.

53.69 ± 7.33 (mean \pm SE, in bits/min) and followed by the frame rate of 60 Hz (50.41 ± 6.75) and 90 Hz (50.03 ± 6.52). In comparison, the frame rate of 120 Hz gained the lowest ITR (37.53 ± 6.89). However, the corresponding Friedman test did not reveal a significant difference between any pair of stimulation frequencies, neither in accuracy ($\chi^2(3) = 5.76$, $p = 0.12$) nor ITR ($\chi^2(3) = 6.45$, $p = 0.09$).

To inspect the evolving classification performance over time, we calculated the accuracy for each frame rate, starting from 0.5 second with time intervals of 0.1 second. The average results are depicted in Figure 5. As can be seen in this figure, the lower frequencies (40 and 60 Hz) have a tendency for better performance for short time intervals below 2 seconds as compared to the higher frequencies (90 and 120 Hz). The performances then converge close to ceiling performance at 4 second without significant difference. The frame rate of 120 Hz has a tendency to the lowest accuracy.

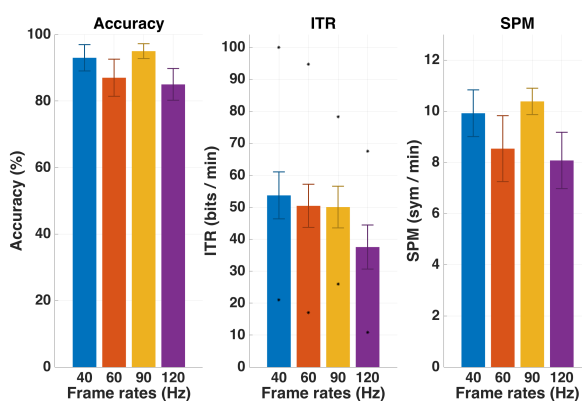


Figure 4: Average accuracy, ITR and SPM over subjects for different frame rate stimuli. The error bars indicate the standard errors. The starts show the maximum and the minimum ITR over subjects. Note: the ITR is calculated based on the maximum value during the stimulation time at each frame rate with an inter-trial interval of one second.

DISCUSSION AND CONCLUSION

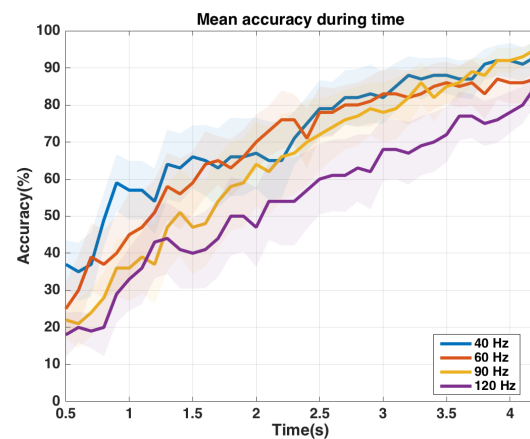


Figure 5: Average classification accuracy with respect to time for all frame rate stimuli. The shaded bars show standard errors.

In this study, we investigated the effect of high and low stimulation frequencies (40, 60, 90, 120 Hz) on c-VEP in terms of accuracy and ITR. A family of modulated Gold codes was used to control the visual stimuli on eight LED lights. The responses to these m-Gold codes were predicted by re-convolution and used as templates for a template matching classifier. To evaluate the visual comfort, a questionnaire was filled in by the subjects after each run of the experiment.

Comfort scores: The results from the questionnaire showed that most participants favor the higher stimulation frequencies especially 120 Hz while 40 Hz was irritating for most of the participants. This can be due to the fact that for high frame rates the stimuli are less perceived as flicker and this may be less tiring and more comfortable.

Performance evaluation: In terms of performance, there was a tendency for 40 and 90 Hz to yield higher accuracy compared to 60 and 120 Hz and for 90 Hz to achieve the highest accuracy and SPM. If we assume this gain will prove to be robust, 90 Hz should be considered as a good frame rate for c-VEP where traditional 60 and 120 Hz has been used. It is a happy coincidence that in Virtual Reality goggles 90 Hz is used often as frame rate. Previous studies have shown that the average accuracy from 120 Hz monitor refresh rate was slightly higher than 60 Hz [8, 9], however, our results don't substantiate that. Although the results about visual comfort showed the highest score for 120 Hz, some subjects reported a difficulty to attend the 120 Hz. This can be explained by the fact that the higher frequencies are less perceivable compared to the lower frequencies which can make it difficult for subjects to attend.

Our results showed no significant differences in the performance (accuracy and ITR) of different stimulation frequencies. This may be due to the effect of two competing mechanisms: higher frame rates yield more events per time unit thus in principle can support higher transfer rates, but the responses to fast events become smaller thus leading to a weaker discrimination. The fact that the frame rate does not affect performance much allows for

choosing 120 Hz, the most comfortable one without loss of performance. However there was a tendency for 90 Hz to be better than 120 Hz in terms of accuracy and ITR that may turn out to make up for somewhat less comfort.

ACKNOWLEDGEMENT

We would like to thank Philip van den Broek for technical assistance, Jos Wittebrood at Mindaffect company for helping in the setup, Tsvetomira Tsoneva for her help and insight and the participants for sharing their time.

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