# On the Effect of Size and Contrast of the SSVEP Visual Stimuations on Classification Accuracy and User-Friendliness in Virtual Reality

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***Abstract*—SSVEP-based BCIs are amongst the most promising BCIs in terms of speed and accuracy. However, despite significant effort from the community in order to make them more practical and user friendly, they remain particularly annoying to use. In this paper, we investigate the effect of the size and contrast of the SSVEP visual stimulations on both of the classification accuracy and the annoyance of the interface, with the global aim to find a trade-off between performance and user-friendliness. We conducted a user study on twelve (12) participants in order to evaluate the joint effect of different stimulation sizes and contrasts on the SSVEP classification accuracy in a Virtual Reality context. The results of this experiment suggest that the size of the stimulation has a significant impact on both of the classification accuracy, below a certain threshold, and on the perceived annoyance. No effect of the contrast was however found neither on the classification accuracy nor on the perceived annoyance, suggesting that it is still possible to accurately operate SSVEP-based BCIs using lower contrast stimulation.**

***Index Terms*—component, formatting, style, styling, insert**

## I. Introduction

Brain-Computer Interfaces (BCIs) are systems that exploit brain activity to enable users to interact with computer systems. As they do not rely, and often do not require, any muscle activity [1] they are a very promising set of interfaces for people with muscular disabilities [2] who are still able to modulate their brain activity.

Depending on the type of mental state that they monitor, and depending on how these mental states are elicited, BCIs are classified into two main categories [3]: Active BCIs and Passive BCIs. In passive BCIs, the brain activity of the users is passively monitored in order to infer their general mental state, while in active paradigms, users voluntarily modulate their brain activity in order to send a command to a computer system. In active BCIs, users either spontaneously modulate their brain activity to send a command (e.g. Motor Imagery based BCIs [4]), or focus their attention on sensory stimulations provided by the interface in order to send the desired command (i.e. evoked potentials [5]). The nature of the stimulation (single stimulus, periodic stimuli, or random stimuli) as well as the modality of the stimulation (visual, auditory, or somatosensory) determines the neurophysiological property that the BCI exploits for the interaction. In this paper, we focus on active BCIs based on visual stimulations, namely the Steady State Visual Evoked Potentials (SSVEP), with the aim to design a BCI for interaction in Virtual Reality (VR) devices.

When subjects focus their attention on a periodic visual stimulation such as a light flickering at a given frequency $f$ greater than 6 Hz [6], their brain responds with an increase of the signal power at the same frequency of stimulation $f$, around the occipital area. Thanks to this property, known as the Steady-State Visually Evoked Potentials, it is possible to display multiple visual stimuli flickering at different frequencies, and determine the one on which users focus their attention by identifying the dominant frequency in the EEG signal recorded by the occipital electrodes.

SSVEPs present a number of advantages that have made them very popular for achieving Brain-Computer Interaction. Given the very specific reaction of the brain as a response to a flickering visual stimulus, SSVEPs are rather easy to detect. Their location is essentially in the occipital area and their spectral components are known *a priori* from the frequencies used as stimulations. They are also relatively robust to muscle artifacts which can be generated from ocular activity, and they typically require less or even no calibration [7] data to be detected in the EEG signals. Additionally, given the large number visual stimulations that can be displayed to the users at once, and the relatively fast detection rate of the SSVEPs from EEG signals, SSVEP enables to achieve high information transfer rates (ITR) [8].

However, despite these advantages, the major drawback of the SSVEP paradigm is the important eye-strain and visual fatigue it provokes on its users. The prolonged focus on blinking objects tends to rapidly induce symptoms of visual fatigue, rendering the practical and frequent use of SSVEP rather difficult. Thus, an important line of research consists in investigating the possibility to increase the SSVEP user friendliness while maintaining satisfactory detection accuracy.

In this paper, we investigate the joint effect of size and contrast of the visual stimulations on both of the user-friendliness and the classification accuracy of SSVEP responses. We hypothesize that while reducing the contrast of the stimulation reduces the visual fatigue of the users over time and also reduces the intensity of the response, it would still be possible to compensate this decrease of intensity by simultaneously increasing the size of the visual stimulations.

The remainder of this paper is organized as follows: Section II presents previous research on the effect of several properties of the visual stimulations on the SSVEP responses. Then, Section III describes the user study which we conducted on the joint effect of size and contrast, presenting the detailed experimental protocol as well as the apparatus. Section IV presents the results of the user study, both in terms of classification accuracy of the SSVEP responses and the subjective user preference. Finally, Section V discusses the results with respect to the initial hypotheses and Section VI concludes the paper.

## II. Related work

SSVEPs have been widely exploited to design BCI-based systems. The applications of these systems ranges from the control of prosthetic arms [9] and the steering of electrical wheelchairs [10], [11] to SSVEP spellers [8] and interactive Virtual/Augmented Reality environments [12]. In addition to these applications, the contributions in the field of SSVEPs have been mainly focusing on improving the accuracy and ITR of SSVEP by designing new signal processing and classification methods [7], [13], [14]. Only few efforts have been put on reducing the discomfort and the eye strain from the use of SSVEPs, which is a major drawback and a limitation to enable a larger public to use SSVEPs.

Zhu et al. [15] proposed a survey of the different stimulation methods that have been used to elicit SSVEP responses, displaying the diversity of the configurations used to elicit SSVEPs. The nature of the stimulation was found to play an important role on the classification accuracy of SSVEP responses, but a few studies reported the effect of the stimulation type on the user friendliness.

For example, increasing the frequency range of the stimulations (above 30Hz) has been found to significantly reduce the eye strain, as the flickering itself becomes transparent to the user, but at the expense of a significant drop in the classification accuracy [15].

More recently, Ladouce et al. [16] investigated the effect of reducing the contrast (the maximum depth amplitude) of the SSVEP stimulation on both the classification accuracy and the user experience. Their results confirm that increasing the frequency range of the stimulations significantly reduces the eye strain and improves the overall user experience, but at the expense of significantly reducing the classification accuracy, rendering the design of practical SSVEP interfaces using high frequencies still difficult. On the other hand, their results were encouraging concerning the effect of reducing the contrast of the SSVEP stimulations on the user experience and the classification accuracy. The reported classification accuracy on stimulations with a depth of 40% of the maximum amplitude did not significantly differ from the classification accuracy of the maximum depth amplitude stimulations.

Despite these promising results, a trade-off has yet to be found between performance (in terms of elicited SSVEPs and their intensity) and usability (in terms of user-friendliness) as most of the times, manipulating the visual stimulation properties to increase the intensity of the SSVEP response comes at the expense of severely impairing the user-friendliness of the SSVEP interfaces.

In this paper we investigate the joint effect of size and contrast on the user-friendliness and the classification, instead of investigating each dimension separately. We hypothesize that even if significantly reducing the contrast of the stimulations reduces the classification accuracy, the increase of size can compensate while keeping satisfactory user-friendliness.

## III. Materials and methods

### A. Experimental protocol

In order to evaluate the joint effect of size and contrast on classification accuracy and user friendliness, We conducted a user experiment where participants were asked to perform a series of SSVEP selections by focusing their attention on one of the three (3) targets displayed in a VR headset (Fig. 1) and flickering at 10 Hz, 12 Hz and 15 Hz.

Twelve participants (mean age: 39 years, std: 14 years) took part in the experiment. All were right handed and all had normal or corrected to normal visual acuity. Eight participants were BCI naive, and three did not have any previous experience with VR.

The SSVEP targets consisted in white circles, with different level of brightness and size (depending on the experimental condition) displayed on a black background. In this user study, three modalities of SSVEP targets size: Small, Medium and Large, corresponding to 2°, 6°and 10° of visual angle respectively, and four levels of contrast: 25%, 50%, 75% and 100% of the maximum brightness. These modalities result in a total of twelve experimental conditions labelled X25, X50, X75 and X100, where 'X' represents the targets size (S for small,

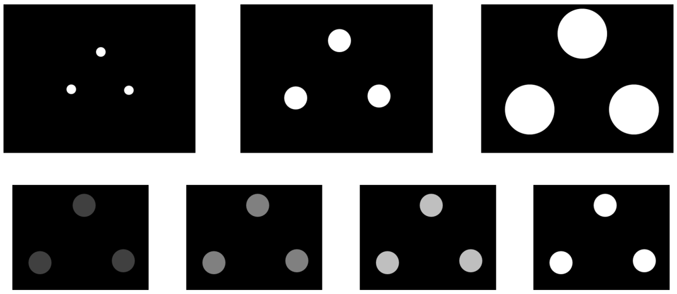


Fig. 1: Illustration of the different configurations of the stimulations. (Top) The three sizes: 2°, 6° and 10° of visual angle. (Bottom) The four level of contrasts: 25%, 50%, 75% and 100%.

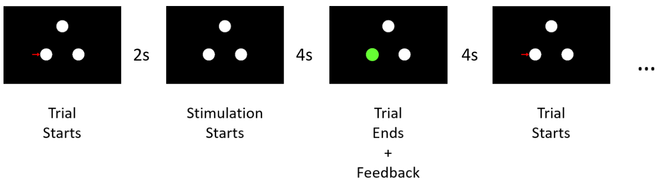



Fig. 2: Time structure of a trial. The target to focus on is designated with a red arrow before the flickering starts, and the trial ends with a coloured feedback.

M for Medium and L for Large) and the associated number represents the level of brightness. The distance between the targets in all conditions were fixed a 10° of visual angle.

All participants underwent the twelve experimental conditions in a random order, so that to minimize any learning or visual fatigue effect. Each experimental condition consisted of twenty-four trials (SSVEP selections), each target being selected eight times. Each trial began with a red arrow (displayed for 2 sec) pointing and designating the target on which subjects had to focus their attention. Following that, all the targets began flickering for 4 sec, after what a feedback was provided for 2 sec. The feedback consisted in turning the supposedly detected target into green. However, as no online analysis of the EEG signal was performed, we used a Sham feedback, consisting in turning green the correct target (which was designed in the beginning of the trial) with an 80% chance, and turning a either of the remaining wrong targets green with 20% chance. This method enabled to keep the subjects engaged in the experiment. After the feedback and a 2 sec break, the next trial started. The overall trial structure is presented in Fig. 2.

Each experimental condition lasted 4 minutes, resulting in forty-eight minutes of EEG recording. After each experimental condition, participants were asked to rate on a Likert scale the level of annoyance generated by the condition, following what, they were allowed to have as much break as they needed in order to rest their eyes. The overall duration of the experiment was around 90 minutes including breaks and equipment time.


(a)

(b)

Fig. 3: Illustration of the experiment apparatus. (a) The HTC Vive VR headset, with a refresh rate of 90 Hz. (b) The Smarting mBrainTrain EEG headset with a sampling rate of 500 Hz.


Fig. 4: True brightness level generated by the VR headset with respect to the level of alpha parameter.

### *B. Apparatus and settings*

All the visual stimulations in this user study was displayed on a HTC Vive Pro VR display (Fig. 3a) providing a refresh rate of 90 Hz, and were implemented on the Unity game engine.

In order to display different levels of contrast on the targets, we displayed different levels of alpha transparency in the RGBA color representation. However, prior to the experiment, we compared the level of brightness obtained with the alpha parameter, with the true level of brightness generated by the display, as measured with photo-diodes. Interestingly, we observed that the evolution of the true brightness level from 0% (transparent) to 100% (fully white) was not linear, and that an alpha level of 50%, did not correspond to half of the maximum brightness of the headset (Fig. 4). Given this observation, we decided to correct the levels of contrast to match the true levels of brightness generated by the display. As such, the 25%, 50%, 75% and 100% contrast levels corresponded to alpha values of 65%, 72%, 87% and 100% respectively.

The flickering frequencies were generated by adapting the sinusoidal stimulation method presented in [17] using the following equation :

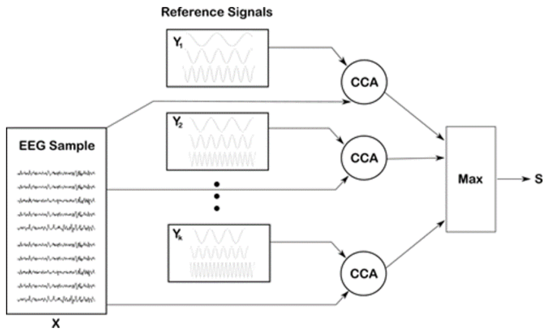



Fig. 5: Illustration of the processing pipeline of the Canonical Correlation Analysis method. $X$ represents the EEG sample, $Y_k$ represents the template signal (Fourier series) and $s$ represents the recognized class through maximization of the canonical correlation.

$$f(i) = (B * cos(2\pi fi/R) + B)/2 \quad (1)$$

where $B$ represents the maximum level of brightness for the condition, $i$ represents the frame number, $f$ represents the flickering frequency and $R$ represents the frame rate of the display.

EEG signals were acquired using an mBrainTrain Smarting wet electrodes system (Fig. 3b) with a sampling rate of 500 Hz. Five (5) occipital channels were recorded during the experiment (O1, O2, POz, Pz and CPz) which were grounded at AFz and referenced at Cz. The signals were acquired and labelled using the Openvibe software [18]. Overall, the participants wore both of the EEG and the VR headsets at the same time during each block. They could remove the VR headsets during the breaks in between the blocks, in order to reduce the long term fatigue effect.

### C. Signal processing

In order to estimate the effect of the size and contrast of the SSVEP targets on the SSVEP response, we chose to evaluate the classification accuracy EEG trials. Before classification, the EEG signals were band-pass filtered using a $4^{th}$ order *Butterworth* filter, with cutoff frequencies of 5 Hz and 40 Hz. Each trial (4 sec of SSVEP stimulation) was classified using the Canonical Correlation Analysis (CCA) method (Fig. 5) to determine on which target the user was focused on. For each stimulation frequency, the template signal for the CCA corresponded to the Fourier series at the given frequency with two harmonics.

A trial was deemed as correctly classified if the recognized detected stimulation frequency using CCA, was the frequency on which the user was asked to focus for this trial. Three classes corresponding to the three frequencies of stimulation.

## IV. Results

### A. Classification accuracy

Among all the subjects, three (S1, S6 and S12) did not perform significantly better than chance level [19] (95% confidence chance level set at 45%), which is coherent with the literature regarding BCI illiteracy [20], [21]. The data from these subjects were not included in the analyses. The mean classification accuracy across all conditions and all the remaining subjects was 63.66%. Three subjects even had classification accuracy above 70% across all conditions. The detailed results are presented in Table I.

TABLE I: Average classification accuracies per subject across all conditions. 95% confidence chance level was set to 45%.

| Subject | Avg. Accuracy |
|---|---|
| 1* | 37% |
| 2 | 55% |
| 3 | 59% |
| 4 | 89% |
| 5 | 56% |
| 6* | 34% |
| 7 | 74% |
| 8 | 56% |
| 9 | 55% |
| 10 | 51% |
| 11 | 78% |
| 12* | 43% |

TABLE II: Recognition Accuracies per class after synchronous CCA analysis.

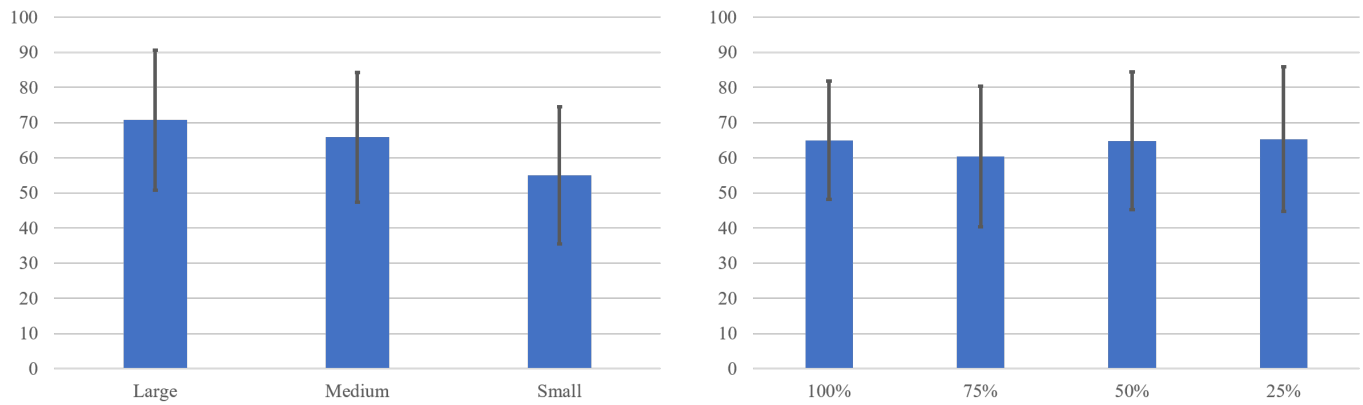
| Condition | Avg. Accuracy | Avg. Annoyance |
|---|---|---|
| L100 | 77% | 4.89 |
| L75 | 66% | 5.11 |
| L50 | 75% | 4.89 |
| L25 | 64% | 4.55 |
| M100 | 60% | 4.33 |
| M75 | 66% | 4.33 |
| M50 | 66% | 4 |
| M25 | 71% | 4.22 |
| S100 | 58% | 3.66 |
| S75 | 49% | 3.44 |
| S50 | 53% | 3.55 |
| S25 | 60% | 3.66 |

Regarding the inter-condition results, The mean classification accuracy for the *Large*, *Medium* and *Small* conditions across all brightness conditions were 70.5%, 65.75% and 55% respectively. Whilst the mean classification accuracy for brightness conditions of 100%, 75%, 50% and 25% across all size conditions were 65%, 60.33%, 64.66% and 65% (Fig. 6). The detailed results per condition are presented in Table II.

### B. Questionnaire results

In order to evaluate the effect of size and contrast on the subjective preference of the users, all the participants were asked to rate the level of *annoyance* elicited by each experimental condition, on a Likert scale for 1 to 7 (1 being not annoying at all and 7 being extremely annoying). As expected from the literature, the Large condition was deemed as the most annoying with an average rating of 4.86/7, followed by the Medium and Small conditions with averages of 4.22/7 and 3.58/2 respectively.

In terms of contrast, the perceived annoyance did not differ much between the different levels, with the average annoyance




(a) Average classification accuracy per size across all participants and contrasts.

(b) Average classification accuracy per contrast level across all participants and sizes.

Fig. 6: Average classification accuracy for each modality.

evaluated at 4.29/7, 4.29/7, 4.14 and 4.14 for 100%, 75%, 50% and 25% respectively.

### C. Statistical analyses

We performed a 2-way ANOVA on repeated measures to evaluate the effect of both size and brightness on the classification accuracy ($Accuracy \approx Size * Brightness$). Inline with our hypothesis and the literature, the results of this user study suggests a significant impact of the stimuations' size of the classification accuracy ($p = 0.002 < 0.005$). However, no significant effect of the contrast ($p - val = 0.75$) nor any interaction effect was found ($p - val = 0.49$), which suggests that it is still possible to employ low contrast stimulations to interact using the SSVEP paradigm.

We also performed a 2-way ANOVA on repeated measures to evaluate the effect of size and brightness on the subjective perception of annoyance from the visual stimulations. The results showed a significant effect of size on the perceived annoyance ($p = 0.00009$) which was expected from the literature. However, no significant effect of brightness ($p = 0.93$) nor any interaction effect of size and brightness ($p = 0.97$) were found on the perceived annoyance. Suggesting that reducing the contrast was not sufficient to increase the user friendliness of the SSVEP interface.

## V. Discussion

The first result from our user study was the confirmation of the strong effect of the stimulations' size on both of the classification accuracy ($p - value = xxx$) and the annoyance ($p - value = xxx$). Small targets elicited significantly weaker SSVEP responses and were deemed as less annoying. Medium and Large targets did not significantly differ in terms of accuracy or annoyance, which suggest that a size threshold above which the SSVEP responses are easily detected.

Secondly, contrarily to what was expected, the contrast did not seem to have a significant impact on the classification accuracy nor on the level of annoyance. In Ladouce et al. [16], the depth amplitude, which we refer to as contrast, was found to significantly lower the classification accuracy and the annoyance, below 40% of the maximum amplitude. This difference in result could be explained by the fact that the level of contrast was not corrected to the true level of generated brightness, by the difference in the background color or the difference in the hardware. Nonetheless, it remains interesting to highlight that SSVEP interfaces can still be accurate enough to be operated through reduced contrast settings. It also suggests that SSVEP interfaces require more in-depth changes and adaptation in order to truly increase their user friendliness than working on the contrast.

Finally, although the study was performed on a small number of participants which prevents us from establishing clear-cut certainties, we believe that these results can help pave the way to future studies, as the question of the user friendliness of SSVEP interfaces remains crucial. For example, future work may investigate the possibility to replace the nature of the flickering targets by moving shapes (Steady-State Motion Evoked Potentials (SSMVEP) [22]), or even design bio-inspired stimulation which could be better integrated in a more global interaction scheme.

## VI. Conclusion

In this paper, we have investigated the joint effect of Size and Contrast of the SSVEP stimulations, on the classification accuracy and the perceived annoyance. Although no interaction effect was found between the two modalities, the size of the targets was found to significantly impact the classification accuracy and the annoyance, but only below a certain threshold (6° of visual angle in our study). The contrast on the other hand, did not seem to significantly impact the accuracy nor the level of annoyance, suggesting that more in-depth adaptation of the stimulation properties may be necessary to increase the user-friendliness on the SSVEP interfaces.

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