3D Flickers for Visually Evoked Potentials-based Brain Computer Interface Paradigm in Virtual Reality

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***Abstract*—One of the most commonly used non-invasive Brain-Computer Interface (BCI) paradigms for virtual reality control relies on particular brain signals: Visually Evoked Potentials (VEP). However, the optimization of virtual 3D targets is required in order to conciliate satisfying VEP induction - leading to high classification accuracy - and visual discomfort minimization. This constitutes a real challenge that could unlock new possibilities for rehabilitation, gaming or other applications. In the current experiment, we designed 30 original 3D-stimuli by combining particular visual patterns with various 8Hz-movements. The objectives were (1) to test new associations of stimuli for better BCI-VR(Brain Computer Interface- Virtual Reality) ergonomics and (2) to test a new paradigm of VEP-based BCI that discriminates stimuli according to their visual features (e.g., motion type) without exploiting any variation in flickers' frequency (constant frequency = 8Hz). Offline classification abilities were assessed using an EEGNet deep learning model. The results suggested the possible role of the stimulation patterns on the visual fatigue induced. The EEGNet model successfully classified all the 30 stimuli with a high level of accuracy (97.58%). This development broadens VEP-BCI stimulation possibilities and could allow overcoming the problem of epileptogenic frequencies by exploiting visual properties of targets instead of frequency variations to discriminate VEP-BCI stimuli.**

***Index Terms*—VEP, SSVEP, BCI, VR, EEGNet, Deep Learning.**

I. INTRODUCTION

There is great potential in combining Virtual Reality (VR) with non-invasive Brain-Computer Interface (BCI) within gaming and clinical fields. Visual Evoked Potential based BCI (VEP-based BCI) constitutes one of the most efficient BCI paradigms for this kind of interaction. VEPs correspond to brain activations in visual areas, which are often induced by flickering stimuli / beating effect, and which can be measured via electroencephalography (EEG). In VEP-based BCIs, subjects must shift their gaze and attention to flickering stimuli. A strong correlation between the flicker frequency and the electroencephalogram pattern can then be observed [2]. Two main types of stimuli are usually used to elicit VEP: frequency modulated VEP (f-VEP) and pseudorandom code modulated VEP (c-VEP). In the f-VEP-based BCI paradigm, stimuli flash at different frequencies and elicit periodic sequences - Steady-State Visual Evoked Potential (SSVEP) - of evoked responses with the same spectral characteristics (fundamentals and harmonics) as those of the stimulus [3]. The main advantages of this method are the stable characteristics of the signal, the high information level and accuracy [2], [26], and a good user experience (control and intuitive) [19], [24].

In the c-VEP-based-BCI, a pseudorandom sequence is repeated periodically, modulating the stimulus appearance and eliciting specific patterns in the electroencephalogram. This method requires a higher information rate and enables high-speed BCI [3]. Although VEP-based BCI can be very efficient, the flickering aspect might cause visual fatigue, and the VEP features depend on stimulus characteristics, which are limited by the refreshing rate of the system [2]. Thus, stimuli choice represents a major limitation of VR-BCI. Visual fatigue here refers to the state of reduced alertness and the feeling of tiredness which both impair the willingness and ability to perform a task [4], [8], resulting from visual stimulations.

In f-VEP-based BCI, different paradigms have been proposed to minimize performance decrease due to repeated visual stimulation. Those paradigms regard both the stimulation graphics (visual aspect such as shape, color, pattern) and the periodic motion (frequency, waveform, motion evoked potentials) [6], [7], [10], [12], [23]. For example, steady-state motion VEP paradigm has been proposed as an alternative to that of SSVEP to reduce visual fatigue while ensuring a comparable level of accuracy [5], [12], [14]. However, very few studies have compared stimulation modalities and paradigms in a VR environment yet [7]. Moreover, most did not take advantage of VR characteristics by displaying 2D targets on plain walls for instance.

Given the lack of literature on the combination of VR and BCI, and especially on using 3D objects to elicit visually evoked potentials, the combinations of VEP stimulation paradigms were investigated (with both c-VEP stimuli and f-VEP ones – SSVEP and Steady-State Motion Visual Evoked Potential (SSMVEP)). These new paradigms might overcome

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the visual fatigue induced by the beating effect of standard flickering stimuli while offering high classification performance. Thus, first, new 3D ergonomic flickers were proposed. Then, the 3D flickers were evaluated within a VR environment through ergonomics ratings and EEG signal quality. Finally, the last objective was to discriminate flickers based on their specific visual features and not their frequency, which remains constant (8Hz).

The rest of the paper is structured as follows. In Section II, we detail the experiment design and the methods. In the section III, we present our results. Finally, we conclude the work in Section IV.

II. Materials and Methods

A. Participants

Twenty-four participants consented to take part in the study. They had normal or corrected vision and were either naïve or had already experienced standard VEP stimulations (flickering objects) or VR. Data from twelve participants could not be included in the study due to technical problems or interruption of the experiment.

B. Equipment, Software and EEG Pre-processing

Participants were equipped with a Pico Neo 2 Eye, a Head-Mounted Display (HMD) with 3840x2160 pixels per eye at 75 Hz refresh rate. It has a Field of View (FOV) of 101° (diagonal) (see Figure 1). The EEG signal was recorded using an OpenBCI® EEG Electrode Cap kit (21 electrodes). The EEG data were collected at 250 Hz sampling frequency. Once acquired, EEG data were low-pass filtered at 40 Hz, high-pass filtered at 5 Hz and a 50 Hz Notch filter was also applied. Since the stimuli had to elicit VEP, electrodes located in the occipital and parietal regions [9], [14], [15] were chosen. Electrodes 'Ground', ' O1', 'O2', 'P3', 'P4', 'CPz', 'Cz', 'F3' and 'F4' whose locations correspond to the international 10-20 system (Fig. 1) were selected. EEG data were epoched into 3s windows according to the triggers of the onset of visual stimuli during the experimental task.

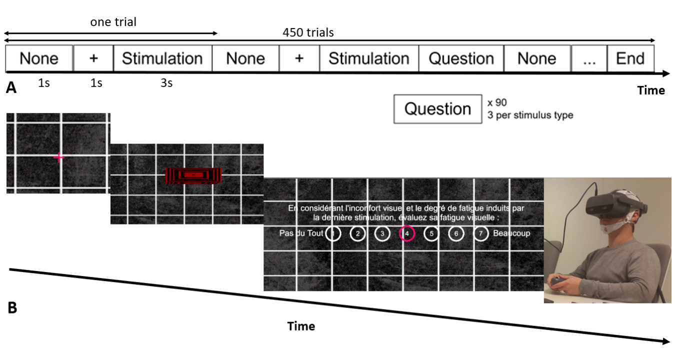

Fig. 1. **A**. Time sequence of the experiment/ **B**. Time sequence of a trial with the virtual environment (left to right) and the subject wearing the EEG cap, the HMD and carrying the controller while executing the task (right).

C. 3D Stimuli Inducing VEP

The visual 3D stimuli were generated using Unity's built-in Shader Graph tool [1]. The design of efficient VEP stimuli was inspired from the existing literature, and features to decrease visual fatigue were considered.

The targets consisted of a cuboid that behaved differently according to the stimulus types. The targets' positions were randomly changed so the participants would not lose motivation. For the duration of the task, targets were equiprobably located: up-right, bottom-right, bottom-left, and up-left on the scene. The frequency that modulated the stimuli aspect was set to 8 Hz to avoid epileptogenic frequencies – which is one major limitation of VEP-based BCI and limits visual comfort [6], [10], [15]. The color of the cuboid was set to red as this color was shown to be less uncomfortable for VEP stimuli in the low-frequency range [10]. The color amplitude was reduced to 60% as studies showed that lower contrasts or stimulation amplitude depth improved flickers ergonomics by reducing visual fatigue [16]. The virtual environment consisted of a dark cubic room with a grey grid pattern. The questions displayed on the wall in front of the participant and the targets (the cuboids with modulated behavior) appeared in the in-between space. Before each stimulation, a red cross cued the localization of the upcoming target (see Figure 1).

The 30 types of stimulations were split into two pattern categories: full (the whole cuboid was visible – i.e., the entire cuboid flickered) or fragmented (only 30 circular areas per face of the cuboid were visible – i.e., only parts of the cuboid flickered). The standard efficient VEP stimuli types and the c-VEP stimuli considered were the following: standard flash flicker (luminance variation of the object from black to full luminosity according to a sinusoidal modulation) [3], Newton's ring inspired flicker (concentric square ring with expanding movement) [25], grow-shrink stimulus [7] (an object whose size periodically changes from 60% up to 120% of its original size according to a sinusoidal function), a spinning motion around the vertical axis (according to a sine function) [12], [21] and a c-VEP flash flicker whose variation was controlled by a pseudo-random sequence square signal (further referred to as m-sequence) [3], [11], [20]. Combinations of these five basic stimuli defined the other stimulation types: all possible combinations of two sinusoidal variation-based stimulation types and the combination of the c-VEP flash with one sinusoidal-f-VEP stimulus. A video showing all the stimuli is presented here [22].

D. Experimental Design

Participants were instructed to stare at a target stimulus for 3 s per trial, with an inter-trial interval of 1s. Before each trial, a cross cue appeared at the location of the next target to indicate to the participant where to direct their gaze (see Figure 1 B). Once ready, they had to press the trigger of the right controller for 1 s. Each stimulus type randomly appeared 15 times; to assess the usability of each stimulation paradigm, participants had to answer a question at the end of the stimulation for 20% of the trials for each stimulus – three assessments per

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type in total randomly distributed across the experiment (see Figure 1 A). The order of question occurrence was balanced according to the Latin square so that with 30 participants, we could reduce the order-effect when rating the fatigue level of one stimulation. Participants rated the visual fatigue level of each stimulus using the right controller: the joystick to select the score and then the trigger for 2 s to confirm their choice. Participants were instructed not to move or blink during the visual stimulation. The task had a minimum duration of 38 minutes – with no imposed breaks, and participants could control the resting time between each trial (trials started only if the trigger was pressed for 1 s).

E. EEG Data Analysis

Canonical Correlation Analysis (CCA) is often used when studying VEP-based BCI [18] to perform the automatic classification of VEP. However, this method is quite sensitive to inter-subject variability and the quality of the EEG recordings. Thus, EEGnet proposed by Lawhern et al. [17] to classify EEG signals has been adapted to classify VEP. Thirty classes corresponding to the thirty stimulation types were considered. Data were epoched and augmented so that 438 temporal windows could be given to each class. The EEGNet was trained for each subject (within-subject). Participants were asked to rate the fatigue level of each stimulation type three times during the task to evaluate flickers' ergonomics. The questionnaire was inspired by the visual analog scale [13], which is often used in clinical research to evaluate pain intensity; it is also used to rate the discomfort or fatigue of tasks. The question was written in French and could be translated as: "considering the visual discomfort and amount of tiredness induced by the last stimulation, rate its visual fatigue level." Participants could rate the stimulation from 1 to 7 (1: not tiring at all, 7: highest fatigue level) [5], [7].

III. Results

A. Offline Classification

The average offline recognition accuracy of the 30 classes corresponding to the different stimulation types was close to ceiling (M=97.58%, SD=.0.0066) across subjects, indicating that the EEGNet classifier was very effective at classifying stimuli of the same frequency that only difered via their visual characteristics (see Figure 2). Hence, the sole modification of the visual transformation of one target might be sufficient to modulate the induced EEG response and enable proper identification of the stimulation type. In addition, the accuracy results showed a weak inter-subject variability.

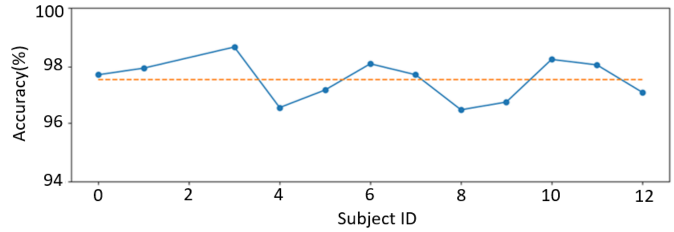

Fig. 2. Classification accuracies of EEGNet model over 30 classes corresponding to the 30 stimulation types for 11 participants. Accuracies ranged above 97%. Dotted orange line indicates the mean accuracy (M=97.58%, SD=.0.0066).

B. Stimuli Ergonomics

The analysis is conducted using Python. Since the data were not normally distributed using the Shapiro-Wilk test, a two-way repeated-measures Friedman ANOVA was performed to investigate the stimulation type's main effect on fatigue level score. The significant level was set to 0.05. A significant difference in the main effect was observed ($F = 95.31, DL = 10, p < 0.0001$). Thus, the type of stimulation could affect the scoring of its fatigue level, that is, its ergonomics. Wilcoxon signed-rank test was applied for each pair of the conditions to investigate the interaction effects of ergonomics and stimulation type. The False Discovery Rate (FDR) was corrected for the within-group comparison using the Benjamini-Hochberg procedure. The difference in the ergonomics rating for different stimuli could not be highlighted, so we could not conclude about the influence of the type of stimulation on the fatigue score. However, most of the participants rated the fatigue level of the different stimulus types in the range of 2.5 – 5 (See Figure 3 A). The combination of the c-VEP flash with a sine-modulated spinning motion in a fragmented pattern (highlighted in red in Figure 3A) was the only stimulation to have a mean fatigue level higher than 5. 12 stimuli had a mean average fatigue level per participant less than 4, i.e., were rated in the comfortable / no particular fatigue induced range (highlighted in green in Figure 3A). The sinusoidal modulation combining Newton's square range type and grow-shrink motion (28 on Figure 3A) had the lowest standard deviation, suggesting a good overall appreciation from participants. Interestingly, the hybrid c-VEP and f-VEP flash with both full and fragmented patterns were part of stimuli with an acceptable fatigue level. These results are consistent with the pattern's effect when considering the standard deviation values.

Wilcoxon signed-rank test was used to explore the possible role of the completeness effect (full vs. fragmented pattern). The average answers per subject for all stimulation types of patterns 'full' to those of pattern 'fragmented' were significantly different ($Z = 1777, p < 0.0001$). Thus, the type of completeness could affect the scoring of the fatigue level of the stimulation, with full pattern stimuli possibly being less disturbing or less uncomfortable than fragmented stimulations (see Figure 3). Indeed, the average fatigue score in the fragmented condition was higher than that in the full condition (M=4.58, SD=1.39 vs.M= 3.65, SD=0.98).

IV. Conclusion and Future Work

In order to find ergonomic visual stimulations to be implemented in a future VEP-based BCI-VR, efficient 2D VEP stimuli were converted into 3D VEP stimuli within a virtual environment. The EEGNet model managed to classify the different stimuli with a high level of accuracy based on their

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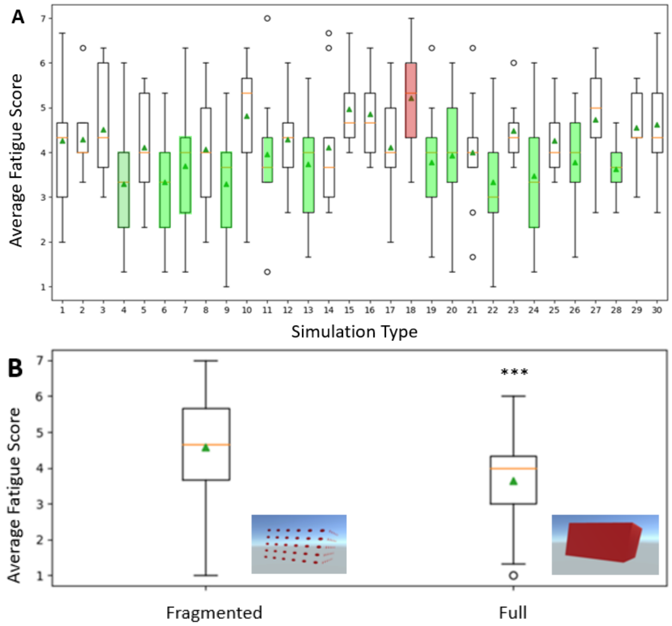

Fig. 3. **A**. Average fatigue score per simulation type, n=11 participants, (flicker inducing most fatigue highlighted in red and flickers inducing the least fatigue highlighted in green in A Figure 3) **B**. Average fatigue score depending on the pattern, n=11 participants

visual differences, which suggested that the different types of stimulation did induce VEP with their very own specific EEG signatures. This pilot study paves the way for immersive BCI-VR research and applications using 3D targets.

However due to the small number of participants, the EEG-net classification and ergonomic analyses should be nuanced but they give a good idea of the trends. More participants should be included in the study to improve the statistical power. Moreover, the EEG recording system consisted of a consumer kit with a sampling frequency of only 250hz. This could be a limitation for the accuracy of the EEG signals but as the study was intended to be applied directly to an industrial project, using the OpenBCI EEG cap kit for such a study was part of the contributions – as for the VR headset used.

In order to lighten the experimental task, we used a subjective method for assessing visual fatigue, based on a simple question [5], [7]. However, more comprehensive questionnaires could improve the accuracy of the ergonomics score in future works and the analysis of brain rythms could provide an objective evaluation method of induced fatigue (depending on the stimuli presentation and their occurence in the task) while taking advantage of the EEG recording [4].

Finally, the next step will be integrating these ergonomics flickers into a VR-based BCI application to help future patients' rehabilitation. As for existing studies in the literature, eye movements were not monitored. Using a VR headset allowing eye tracking could control this parameter and avoid artifacts in the EEG signal.

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