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ABSTRACT
BCIs are presumably supposed to require the full attention of their users and to lose accuracy if they pay attention to another task. This assertion has been verified with several BCI paradigms (e.g. P300). But the cognitive demand of the promising SSVEP paradigm had never been specifically assessed yet. We measured the accuracy of an SSVEP-based BCI used by 26 participants in various conditions of mental workload. Our analysis revealed that surprisingly, for this type of BCI, little attention is actually needed from participants to reach optimal accuracy: participants were able to successfully perform a complex secondary task (N-back) without degrading the BCI accuracy. The same observation was made whether visual or auditive attention was solicited. These results indicate that SSVEP is a low-demanding paradigm in terms of cognitive resources, and are encouraging for its use in complex interaction settings.

ACM Classification Keywords
H.5.2 User Interfaces: Input devices and strategies

Author Keywords
BCI; SSVEP; cognitive load; N-back task.

INTRODUCTION
BCIs are presented as a promising mean of interaction that enable interacting with computers based on the user cerebral activity. Yet producing and maintaining the suitable mental state often requires "*intense focus of concentration*" from the user [16] whose attention can be quickly diverted by unrelated visual or auditory stimuli, for example. Studies of motor imagery [16, 29] and P300-based [27, 6, 21] BCIs have shown that attention divergence can have a strong impact on their efficiency, discouraging their use in dual-task situations.

Steady-State Visually Evoked Potentials (SSVEP) is another cerebral pattern commonly used for BCIs [32]. As for the P300, SSVEP-based BCIs are "reactive BCIs", meaning that an external stimulation is required in order to trigger the cerebral pattern. When the eye is stimulated at a fixed frequency between 4 and 60 Hz, the same frequency can be observed in the activity of the visual cortex. SSVEP-based BCIs mostly use visual targets (e.g. GUI elements) flickering at different frequencies. When the user focuses on one flickering target, the corresponding frequency is detected in EEG signals, and the corresponding command can be triggered. This method was proved very effective, and currently holds the record of the higher information transfer rate for EEG-based BCIs [32, 24]. SSVEP-based BCIs are rather robust to external noise such as EEG artifacts due to muscle activity or electronic devices. They require limited training and they have relatively stable performance across users, although the flickering stimulation can be tiring and uncomfortable [22]. Moreover, they enable in theory to select a target using visual attention when looking at a different location (e.g. center of screen), which is not possible to achieve with a gaze tracking system. But while SSVEP is one of the fastest and more reliable BCI paradigms [31], the cognitive demand it induces and its attentional requirements remain to be explored.

This note reports on a study of a dual-task situation. Participants were asked to select one of three targets using an SSVEP-based BCI (primary task) while performing an N-back memory task involving visual or auditory stimuli (secondary task). The load factor of the N-back task was controlled in order to alter its working memory demand. Our results indicate that SSVEP-based BCIs can be used while performing a complex additional mental task. The potential interferences between various types of cognitive resources (working memory, visual attention, auditory attention) do not appear to deteriorate SSVEP detection.

The remainder of this note is organized as follows. We present an overview of the related work on BCIs and mental demand. We then describe the experimental apparatus, methods and results. We conclude with a general discussion.

RELATED WORK
Most BCIs still suffer from severe shortcomings that hinder their use for explicit, active interaction. One of these obstacles is the need for users to focus their attention on the BCI. As a consequence, BCIs have so far been mostly confined to implicit, passive human-computer interaction. For example, functional Near-InfraRed Spectroscopy (fNIRS) has been used to provide insight into a user's cognitive state during interaction for evaluation or real-time adaptation purposes [26, 30]. Electroencephalography (EEG) has also been used with a similar approach [18, 19, 8].

So far, studies on active BCIs indicated that they require the full user attention. Performance of BCIs based on the commonly-used P300 cerebral pattern has been shown to decrease when the user has to focus on another concurrent task. For example, Watter et al. studied an N-back task coupled with P300 use [33]. They observed that the peak amplitude of P300 signal decreased with increasing memory load, reflecting the reallocation of attention and processing capacity. Hence, performing the memory task negatively affects the P300-based BCI accuracy. Several other studies have since observed similar results with P300, e.g. [21, 27, 6, 12, 11, 13, 15, 9], and similar observations have also been made with motor imagery [29, 16, 10]. To this day, however, we are not aware of work specifically targeting the estimation of the cognitive demand of SSVEP-based BCIs.

The Multiple Resources Theory is an approach to describe the extent to which dual-task performance will lead to decreases in time-sharing ability [34]. This model considers four dimensions of resources. It classifies the cognitive resources by stages of processing (perception, cognition, and responding), by codes of proceeding (spatial and verbal), and by modality (auditory and visual). The model is generally refined with a fourth dimension, differentiating between focal and peripheral attention. The general idea between these distinctions is that if two tasks use different levels along each of the four dimensions, time-sharing will be better [34]. Dual tasks should get higher performance if they require resources from different axes. The notion of mental workload can be derived from this model as the demand put on the cognitive resources in general. In particular, the case where the demand is less than the capacity of resources available can be distinguished from the one in which the demand exceeds the capacity, in which case performances are expected to break down.

Within the 4-D model of Multiple Resources, reactive BCIs hold a particular place. They are used as means of action, and should thus put demand on the responding resources. However, they are actually activated by visual attention. In the case of P300, for example, it has been observed that the working memory required by a secondary task competes for attention with visual perception [2]. By contrast, BCIs based on motor imagery follow the traditional perception-cognition-response order of processing stages. Motor imagery should have a high demand in cognition and responding cognitive resources, explaining the need for the user's undivided attention [16].

SSVEP is greatly influenced by the gaze focus point, but it has been shown that visual attention alone modulates the evoked signal [4]. However, it is yet unknown how much visual attention is required to operate an SSVEP-based BCI, and how difficult it is to maintain this attention while performing other demanding tasks, visual or not.

In this note, we study how SSVEP accuracy evolves, as a function of the verbal working memory required for a secondary task, with either a visual or an auditory input.

USER STUDY

In order to measure the cognitive demand of a task, the classical approach is to use a dual-task paradigm [5, 7, 17, 25]. Participants are instructed to perform a primary task (for which the mental demand is unknown) and a secondary concurrent one of which the cognitive cost can be controlled. We followed this standard procedure in this study. Participants were asked to select one target among three using an SSVEP-based BCI while performing an N-back memory task on letters.

For the N-back memory task, letters were presented in sequence. At each step, participants have to indicate whether the current letter was the same as N steps before [25]. In order to observe the effects of different types and levels of attention, the difficulty of the memory task (load factor) changed across the experiment, as well as the instruction modality (visual or auditory).

Twenty-six participants were enrolled in this study: 21 men and 5 women, aged between 19 and 41 (mean 26.3, SD 5.8), 20 right handed and 6 left handed. Half of the participants performed the memory task with visual stimuli, while the others performed it with auditory ones.

Brain-Computer Interface

EEG data were recorded using 6 passive electrodes out of a non-invasive 16-channel system (g.USBAmp, g.tec company, Austria), with a sampling rate of 512 Hz, combined with the OpenViBE software [20].

Electrodes were positioned according to the extended 10-20 system on `CPz`, `POz`, `Oz`, `Iz`, `O1` and `O2`. The reference electrode was located on the right hear, and a ground electrode on `AFz`. Signal quality was ensured using an impedance checking of each electrode.

Stimuli were disks flickering between black and white at 10, 12, and 15 Hz, with an opacity of 67% determined through informal tests (Fig. 2). These made it possible to read the visual stimuli of the N-back task (letters) without difficulty, while still providing good luminosity contrast for the flickering to be perceived. Stimuli were displayed on a DELL™Ultrasharp™2007FP 51 cm screen (20.1 inches), with a resolution of 1280×1024 pixels, and a refresh rate of 60 Hz.

Experimental design

Participants were sitting in front of a computer screen, wearing the EEG headset. Prior to the experiment, participants were asked to fill a written consent form, and a questionnaire collecting statistics about gender, dominant hand, age, and sight. The BCI was then calibrated. During the calibration phase, three targets were displayed, flickering between black and white. The size and the position of targets were the same as in the experiment. For each calibration trial, participants were asked to focus on a given target, indicated by an arrow, while their EEG activity was recorded. For each trial, flickering lasted 7 seconds. Breaks of 5 seconds separated each trial. The arrow indicated the next goal target was displayed during the break, 2 seconds before the flickering starts. No feedback was available during this calibration. The calibration phase contained 18 trials (6 trials for each frequency), for a total duration of 3 minutes and 36 seconds.

The primary and secondary tasks were then explained to participants. They were asked to fill a form in order to make

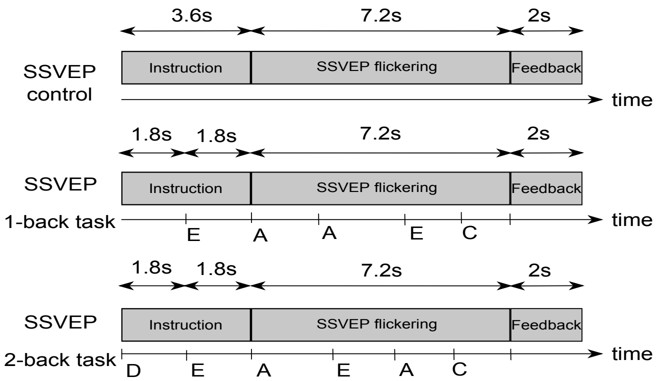

Figure 1. Synchronization of SSVEP and N-back memory tasks.

sure the instructions were correctly understood. Additionally, post-experiment questionnaires were used to assess fatigue and perceived difficulty of both tasks.

Primary task

The three flickering circular targets were displayed on screen as shown on Figure 2. For each trial, participants had to select the designated target (indicated with an arrow) by focusing their visual attention on it without looking away for 7.2s (this duration was chosen for synchronization constraint with the secondary task, as described later on). At the end of the trial, a visual feedback indicated if the selection was successful: if the target was successfully selected, it turned green, otherwise, the wrongly selected target turned red. In order to maintain the motivation of participants, we used a positively biased feedback [3], which has proven to keep up the motivation of participants with low accuracy rates. Feedback was positively biased by 25%[1].

Secondary task

The secondary task was an N-back letter task. Participants had to memorize sequences of letters presented to them and push a key when (and only when) the current letter was the same as the N-th previous one, before the next letter apparition[2]. The value of N determined the number of letters that participants had to remember, which directly determined the difficulty of the task. We used two values for N: 1 and 2, on top of a control condition, in which no letter was presented. These are the most common difficulty levels in experiments relying on the N-back working memory paradigm [25].

Each sequence of letters was 4+N letters long. Each letter has a 50% probability of being the same as the N-th previous one. At the end of each sequence, feedback was provided as a score to indicate the number of correct answers over the last 4 letters (the first N being irrelevant, as there is no N-th previous one to compare to). Consecutive letters were spaced in time with a randomized interval between 1.6 and 2.0s (as in [28] and [7]), with constraints ensuring that (1) the total duration of the first N letters was $N*1.8s$; and (2) the total duration of the last 4 letters was 7.2s (see Figure 1). These constraints ensured the synchronization with the constant pace of the primary task.

[1] When the target was correctly selected, the feedback was positive. If not, there was still a 25% probability for the feedback to be positive.
[2] In the following example, marked letters are those which should be recognized as repetitions for N=2: L H C **H** S C Q **C** **Q** L C K L H

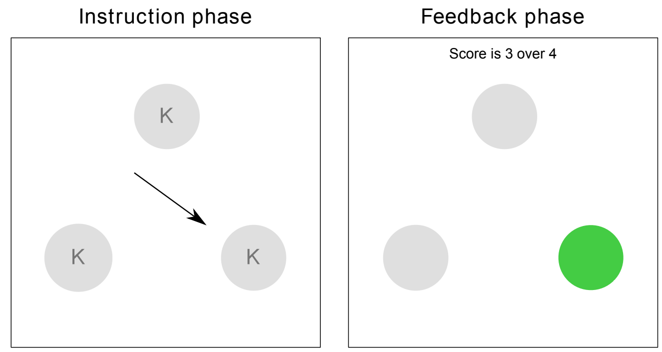

Figure 2. Visual display during the instruction (left) and feedback (right) phase. For the auditory conditions, letters are not displayed. The flickering frequencies of the three disks were the same in both conditions (10, 12 and 15 Hz). An arrow indicated the target to select. For both conditions, after each trial, the score of the N-back task is displayed on top of the screen, and the target actually selected with the BCI changed color to indicate selection error (red) or success (green).

As previously said, we used two presentation modalities for the letters: visual and auditory. For the visual condition, letters were displayed for 500ms at the SSVEP target positions, with the stimuli flickering on top of them. The same letter was displayed for every target, so that it could be read wherever the participant looked (see Figure 2). For the auditory condition, letters were spoken by a male synthetic voice [1].

Dual-task

Both tasks were performed simultaneously (see Figure 1). For each trial, the first N letters (that never require an answer) were presented before the start of the SSVEP stimulation (instruction phase). During the 7.2s of the SSVEP stimulation (SSVEP flickering), 4 letters of the N-back task sequence were presented. At the end of the trial (feedback phase), the feedback for each task was displayed for 2 seconds. In total each trial lasted 12.8s and between each trial one second of break was added.

The study has two main factors, the *difficulty* of the N-back task (within-subjects factor with two levels $N = \{1,2\}$ and a control level) and the *presentation* of the letters (between-subjects factor with two levels: visual and audio). For each level of difficulty participants performed 44 repetitions, grouped in two bocks. In total, participants did 6 blocks (2 for each level of difficulty). The presentation of the blocks was randomized to avoid ordering effects. A break was given between each block. Participants were given full control over the duration of the break. The full duration of the experiment was about one hour, including installation time and briefing.

The dependent variables were the amount of correct answers for (SSVEP-based) target selection and the N-back task. For the N-back task, the score for each trial ranged from 0 to 4, one point for each good response.

Results

Figure 3 presents the summary of the results. As the target selection accuracy and the N-back task accuracy did not followed a normal distribution (Anderson-Darling normality test, both $p < 0.01$), we performed an aligned rank transform in order to enable a full factorial ANOVA. Bonferroni post-hoc tests ($\alpha = 95\%$) were used when necessary.

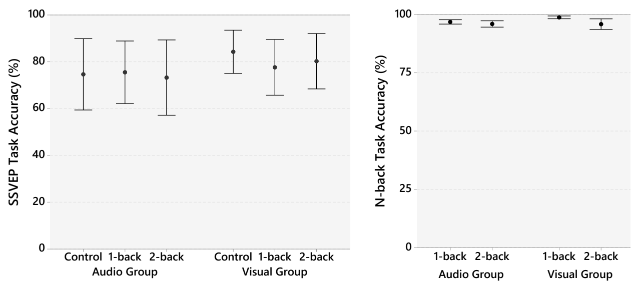

Figure 3. Confidence intervals (95%) for the mean accuracy for the SSVEP selection task (Left) and for the N-back task accuracy (Right).

SSVEP Target Selection Accuracy

The ANOVA difficulty and presentation vs. accuracy did not show any significant effect in difficulty ($F_{2,48} = 0.67$, $p = 0.516$), in presentation ($F_{1,24} = 0.075$, $p = 0.785$) nor in their interaction ($F_{2,48} = 1.65$, $p = 0.203$). The standard deviation for both the auditory ($M = 0.74$; $SD = 0.24$) and the visual $M = 0.81$; $SD = 0.18$) groups were high, especially for the auditory group (24%). Eighteen participants had scores higher than 80% (two participants had a perfect score) and six participants had scores lower than 60%. However, additional analysis taking into account this grouping did not show additional significant differences[3].

N-back Task Accuracy

The ANOVA difficulty and presentation vs. accuracy showed a main effect on difficulty ($F_{1,24} = 13.74$, $p > 0.01$) and in presentation ($F_{1,24} = 5.68$, $p > 0.05$). No two-way interaction effects were found ($F_{1,24} = 2.42$, $p = 0.133$). Post-hoc tests showed the accuracy for the 2-back tasks ($CI = [3.79, 3.89]$) was significantly lower than for the 1-back tasks ($CI = [3.89, 3.93]$) and that accuracy was significantly higher for the visual presentation ($CI = [3.84, 3.94]$) than for the audio presentation ($CI = [3.82, 3.88]$).

Questionnaires

At the end of the experiment, on a 7-point Likert scale, fatigue median rating by participants was 5, i.e. a *marked fatigue*. For N-back task perceived difficulty, the median rating was 1 in the control condition, 2 in the 1-back condition, and 3.5 in the 2-back condition (1 being *not difficult at all*, and 7 being *extremely difficult*).

DISCUSSION

We observed that performing a demanding memory task with visual or auditory stimuli did not significantly affect the level of accuracy of an SSVEP-based target selection task. This observation indicates that the visual attention required by SSVEP does not clearly impair the working memory, contrary to what was observed with P300-based BCIs [27, 6, 21].

In the N-back task with auditory stimuli, the participant's attention had to be divided between auditory attention (to hear the pronounced letters), and visual attention (to acquire a particular flickering target). Although an influence of the level of presentation was observed, it seems that participants managed to reach a satisfying level of visual attention, auditory attention and working memory at the same time. Participants were proficient on performing the task no matter the difficulty or the presentation, with accuracy above 95% for all conditions.

The visual N-back task is not only demanding in terms of working memory, but also in visual attention. One would expect this demand to interfere with SSVEP, which is known to be sensitive to visual attention [14, 4]. However, according to [23], SSVEP is modulated by the localization of visual attention, but not by its object. Our experiment tends to validate this hypothesis. When participants focused on the target position in order to read the letters of the N-back task, the amplitude of the SSVEP response in the EEG signal was still high, as it does not matter if attention is focused on the flickering or on the letter, as soon as these two stimulations are co-localized.

As predicted by the 4-D Multiple Resources model, multitasking is possible with low cost in performance when the demand lays on different cognitive resources. Our study suggests that the overlap between auditive and visual attention does not prevent participant from succeeding in the dual-task.

It can be noted that while P300-based BCIs are also influenced by attention, their compatibility with a secondary task differ. The typical approach to maintain the user's visual attention on the P300 stimulation is to give them a secondary task to perform on this stimulation. The secondary task used for P300 should help maintain visual attention but have a low cognitive cost, so that it does not impair the P300 response. Our results show that by contrast, for SSVEP, their processing cost (for N=1 or 2) does not significantly impair the BCI accuracy.

The dual-task performance observed in this study is encouraging for the use of SSVEP in Human-Computer Interaction, as this technique is compatible with various other tasks, demanding different cognitive resources. It particularly encourages the development of hybrid approaches, mixing SSVEP-based BCIs with other interaction devices. The good accuracy obtained in the auditory condition also indicates that the user of an SSVEP-based BCI could listen to music or to someone talking to him/her, while still using the BCI efficiently.

CONCLUSION

We performed an experiment on the mental resources required to operate an SSVEP-based BCI. In this experiment, SSVEP-based target selection accuracy was measured while participants had to perform a secondary task at the same time. The secondary task was an N-back memory task with visual or auditory input. Our results indicate that the difficulty of the secondary task did not significantly impact the primary SSVEP-based task. This observation was confirmed with both visual and auditory input for the N-back task.

The high dual-task performance indicates that using an SSVEP-based BCI does not strongly reduce the amount of mental resources available, as it does not significantly impact auditive attention nor working memory. These results are encouraging for HCI, indicating that the user of an SSVEP-based BCI could still think about something else when using the interface. For example, an SSVEP-based BCI user could possibly follow a conversation while using the BCI.

[3] Details available at http://ns.inria.fr/mjolnir/ssvepCog

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