Levity: A Virtual Reality System that Responds to Cognitive Load

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Abstract
This paper presents the ongoing development of a proof-of-concept, adaptive system that uses a neurocognitive signal to facilitate efficient performance in a Virtual Reality visual search task. The *Levity* system measures and interactively adjusts the display of a visual array during a visual search task based on the user's level of cognitive load, measured with a 16-channel EEG device. Future developments will validate the system and evaluate its ability to improve search efficiency by detecting and adapting to a user's cognitive demands.

Author Keywords
Brain-Computer Interface; Cognitive Load; Visual Search Task; Virtual Reality

ACM Classification Keywords
H.5.m. Information interfaces and presentation.

Introduction & Motivation
Brain-computer interfaces (BCIs) use brain activity as input to control the operations of external devices [18]. BCIs create direct communication between mind and machine through encephalography (EEG). However, only a handful of studies have used BCI to control virtual reality (VR) interfaces (See Lécuyer et al. [9] for a review). The *Levity* system analyzes a user's

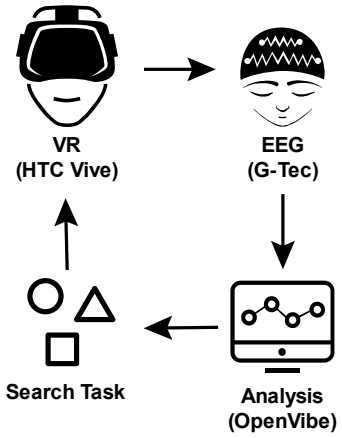


Figure 1: Overview of the Levity System. The person using VR creates EEG signals that are fed into OpenVibe for analysis, and the alpha band detected creates feedback to the user by adapting the VR Shape Search Task. All of this occurs in real time.

cognitive load, identified with a specific neural marker, and adjusts environmental features to de-clutter a visual search.

The novelty of our research is that, to the best of the authors' knowledge, at the time of publication this is the first VR system that is responsive to a user's cognitive load as measured by use of EEG. The main scientific contribution is to facilitate neurocognitive research on detecting a reliable marker for cognitive load. Direct measurement of cognitive load is difficult and often relies on indirect self-report measures of mental effort [15]. We are developing a direct neural measure of cognitive load, which we can test through performance enhancement when BCI adapts to this neural marker. The goal is to have the VR system respond directly to cognitive load and to create a training environment that has the right amount of challenge for the user.

Background and Related Work

In humans, coherent, synchronous prefrontal to parietal brain oscillatory activity, particularly in slower frequency bands (~5-10 Hz), are observed when a high level of top-down activity is necessary in different visual tasks [12]. This frequency band best corresponds to the alpha frequency on EEG (~7.5-12 Hz), and alpha activity has been shown to be affected by changes in task difficulty [6]. Thus, we use changes in alpha activity to change the virtual environment.

Previously, higher task demands have been shown to desynchronize alpha band rhythms and alpha power decrease in EEG [7] Alpha band desynchronization is often followed by an increase in theta [8]. Thus, this alpha-theta transition is related to perceived task difficulty. With EEG, power is a measure of the number of neurons that discharge synchronously. Thus, lower alpha power indicates fewer neuronal firings in this frequency range, and is an indicator of cognitive load based on attentional and executive cognitive resources at higher frequency bands.

Cognitive load is a term used to describe how hard the brain is working during a task [14]. Cognitive load theory (CLT) suggests that performance degrades at excessively high and low load [15]. Cognitive load can be influenced by perceptual load and working memory demands. We focused on perceptual load, and how a more cluttered visual environment increased alpha desynchronizations. The human perceptual system can only pay attention to a small amount of the information present in a visual scene, and thus complex visual scenes increase mental effort in search tasks [5]. Previous work has blurred out background noise in a visual scene to help guide visual attention and reduce mental effort [16].

Research on cognitive load indicates that virtual environments involving complex user interactions can lead the user to feel mentally overloaded [2]. By contrast, if an application is too automated and simple, then users will not be engaged and may feel drowsy or bored. Thus, a system to measure and track on-line cognitive engagement and load is extremely useful for VR interface and application design.

Neurogaming involves using BCIs with 3D worlds and immersive virtual environments (IVEs) [17]. Most neurogaming systems have used motor imagery (MI) to control virtual objects. For example, mentally imaging foot movements creates a MI signal on EEG that has been used to drive a virtual car and move a virtual wheelchair [10, 19].



Figure 2: In this image, a user wears the gTec EEG headcap with 16 electrodes measuring alpha band frequency power and desynchronizations during the VR Shape Search (seen on the screen on the right).

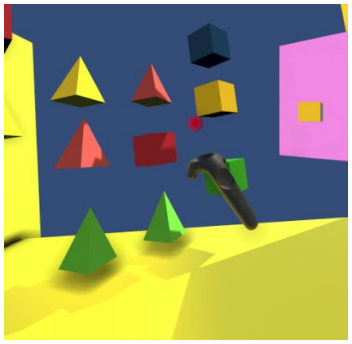


Figure 3: Screenshot of the VR Shape Search task.

The VR and BCI system that is most similar to ours involves attentional feedback training for Attention Deficit Hyperactivity Disorder, where EEG is used to remove distractions and add cues to increase user's attention and to facilitate their concentration in VR [4]. However, our system detects cognitive load as a function of increasing task demands rather than just training concentration.

The *Levity* System

The *Levity* system has users wearing an EEG cap and HTC Vive VR head mounted display while engaged in a VR visual search task. The EEG is used to detect the user's cognitive load, and the BCI is used to modify the complexity of the task. Users are given feedback about their cognitive load when alpha desynchronizations and band power decreases are detected in the user's brain. Ultimately, this is a move towards a complete adaptive system that then de-clutters the environment or triggers a facilitating cue. Figure 1 provides an overview of the Levity's adaptive cycle and Figure 2 shows user interacting with the system.

Virtual Reality Visual Search Task Design.
The visual search task design is based around classic tasks that involve searching for a target within a visual array that includes several distractors [5]. Task efficiency and performance is measured as the time it takes for participants to detect a target as a function of the number of distractors. We created a VR Shape Search in Unity with different colored 3-D shapes spawning randomly in various locations throughout a 180° virtual space (Figure 3). The user is shown a target shape and color, and must find this shape as quickly as possible. Over time, the number of distractor objects increases, making the task more difficult. Users align a gaze cursor to select the target.

Neurofeedback Display Design.
For testing purposes, we display real-time neurofeedback to the user while engaged in the task. The mean alpha power level of all EEG nodes is shown back to the user, with a higher number indicating greater alpha desynchronization.

Brain-Computer Interface Design.
The interactive BCI design uses the detection of alpha power decrease and event-related desynchronization to decrease the amount of visual distractors in the scene. Moreover, such neural markers can trigger facilitating cues to help guide the user. Previous research indicates that adding a facilitating cue, such as a pop-out visual effect or an auditory tone, improves search efficiency[3].

Experimental Design & Implementation

This research is being conducted in two phases. The first phase is aimed at validating the system components, and in the second phase we will conduct more extensive testing and an evaluation of the system's ability to reduce cognitive load.

Phase 1: Test and Validate Cognitive Load
The first phase of testing involved measuring neural activity in the VR Shape Search to validate that the task increased cognitive load.

In a pilot test, data was collected from two participants fitted with the gTec EEG headcap and electrodes. An impedance check confirmed that electrodes were receiving good conductance with minimal noise. Once electrodes were placed, an experimenter helped subjects place and adjust the HTC Vive VR headset over the EEG cap.



Figure 4: EEG placement on g.Tec headcap. Careful fitting of the HTC Vive head-mounted display prevented unnecessary pressure on electrodes.

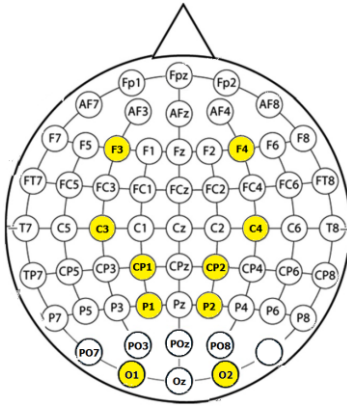


Figure 5: Map of EEG electrode locations.

First, baseline alpha was measured using the Klimesch Technique [13]. This involves measuring alpha during 2 minutes of eyes open and one minute of eyes closed. This provides a measure of individual alpha frequency (IAF). We took the maximum value from this band to determine individual peak alpha.

Electrodes were placed using the International Electrode (10-20) placement system at C3, C4, F3, F4, P1, P2, CP1, CP2, O1, and O2 (Figure 4 and Figure 5). Placement was based on potential hemisphere differences pertaining to the task, visual areas (O1 & O2), frontal regions for top-down attentional task regulation (F3, F4), and fronto-parietal areas (P1, P2, and CP1 and CP2). Reference electrode was placed on the ear with a clip, and ground electrode was placed on the forehead. The sampling rate of the EEG frequency was 256 Hz.

EEG data was collected and recorded with OpenViBE software**,** an open-source platform for BCI. Key press by the experimenter created event markers between each trial, and trial complexity increased every ten trials. EEG data was recorded for 10 minutes while playing the game.

ANALYSIS

For validation, EEG data were pre-processed using Notch filtering and LowPass Filtering and then analyzed offline in MatLab using the EEGLab toolkit.

We measured center of gravity frequency on the shape of the alpha peak based on the central tendency of alpha power within a selected frequency window, thus allowing us to identify lower (f1) and higher (f2) alpha during the task. Data from frequency window f1-f2 of alpha was compared to resting period alpha (eyes closed). Event-related desynchronization (ERD) was measured as the percentage of alpha band power decrease in a test interval. Test intervals were demarcated by increased distractors, and thus ERD was measured during these test intervals.

RESULTS

The initial analysis indicates clear alpha activity during the task (Figure 6), specifically alpha power decrease with increased task complexity. However, due to small sample size, these results need to be further validated and confirmed.

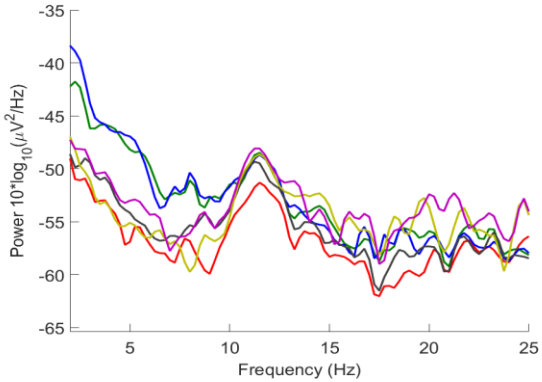


Figure 6: This spectrogram shows frequency activity amplified across 6 channels, showing clear activity in the alpha frequency during the VR Shape Search.

Further research is needed to validate event-related alpha changes in response to cognitive load in our task. As next steps, we plan to measure ERD of alpha and adjust our task to be more aligned with working memory and dual-task paradigms.

Phase 2: Test and Validate BCI Training Impact
Phase 2 has not been completed, but will involve a between-subjects experiment measuring EEG activity in the VR Shape Search with and without BCI. This will allow us to establish between-group differences in task performance, as well as level of cognitive load throughout the game.

BCI training is expected to impact change in alpha. Thus, in the no-BCI group, we expect alpha ERD and band power decrease. In the BCI group, we expect early alpha ERD and power decreases but later more stable alpha activity as a function of integrated training.

Applications

Personalized Educational Technology
A VR system that can measure a user's cognitive load and engagement can adapt instruction accordingly. For instance, a system that measures neural activity can help decipher whether a student got a question incorrect because he or she was not paying attention or because the question is too complex. Hence, the environment can either have a reminder to keep focused when it detects low attention, or it can cater the environment to present the information in a more stepwise manner.

Military Training
A variant of our system could be used to improve military training. VR simulations are already being used to train personnel. Adding EEG and BCI support would allow the training system to dynamically adapt to cognitive load to help the trainee more effectively compete the training program.

Conclusion and Future Work

In conclusion, pilot results indicate a clear cognitive load increase using EEG. Further testing will establish our neural marker as a proper index of cognitive load and explore BCI training effects. This controlled proof-of-concept study is an initial step for design and empirical considerations for Brain-VR Interfaces.

To study working memory demands on alpha, we will increase working memory demands between consistent and varied mapping conditions, following memory search paradigms [13]**.** This means that distractors will spawn in the same locations in consistent mapping conditions and in different locations in varied mapping conditions, thus creating the same memory set across a set of trials with a precise shift.

Another way to measure cognitive load relates to dual-task paradigms, which involve dividing one's attention and distributing cognitive resources between two tasks simultaneously [2]. Specifically, we will use an oddball paradigm requiring subjects to count the occurrence of a sound during the visual search task and measure EEG activity in response to the sound. Oddball paradigms result in an increase in the P300 band, an established measure, and thus decreases in P300 in response to the auditory oddball would be an indicator of cognitive load. Reduced P300 activations to the sound would be expected as task difficulty increases.

Future research will involve studying cognitive load in BCI adaptive virtual environments using different psychological measures of cognitive load. We will also involve eye tracking analysis to measure task navigation behavior [11]. In addition to EEG, we plan to integrate other physiological measures such as heart rate [18] and pupil dilation [1] to measure stress and emotional response to learning materials.

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