Adaptive Virtual Environments using Machine Learning and Artificial Intelligence

Timothy MCMAHAN\textsuperscript{a,1} and Thomas D. PARSONS\textsuperscript{a,b}

\textsuperscript{a}College of Information, University of North Texas, Denton Texas, USA
\textsuperscript{b}Computational Neuropsychology and Simulation (CNS) Laboratory

Abstract. Advances in off-the-shelf sensor technology have aided the collection of psychophysiological data in real-time. Utilizing these low-cost sensors, researchers can monitor a person’s cognitive, behavioral, and affective states (in real-time) as they interact within virtual environments. Moreover, this psychophysiological data can be used to develop adaptive virtual environments. In this paper, we explore electroencephalography-based algorithms to optimize flow models. These algorithms use various combinations of brain wave channels to develop indices of task engagement ($\beta / (\alpha + \theta)$), arousal ($\beta F3 + \beta F4 / (\alpha F3 + \alpha F4)$), and valence ($\alpha F4 / \beta F4$ - $(\alpha F3 / \beta F3$). Results support accurate determination of when a person has left a state of flow. Moreover, the reported results can be further modeled using machine learning (e.g., Support Vector Machine, Naïve Bayes, and K-Nearest Neighbor) to develop training classifiers used in our adaptive virtual environments. We purpose a set of rules for the development of an adaptive virtual environment that can adjust environmental stimuli to keep the user in a state of flow.

Keywords. Adaptive, Virtual Environments, EEG, Simulations, Gaming, Learning, Training, Diagnose, Machine Learning, Artificial Intelligence, Real-Time Feedback

1. Introduction

Advances in affective computing technologies have made it possible for researchers to investigate and manipulate neurocognitive and affective states of users as they interact in virtual environments.\cite{1,2} This allows virtual environments move from predetermined presentations of environmental stimuli to more adaptive virtual environments.\cite{3} This is important for areas using virtual environments for psychological assessment, cognitive training, education, and rehabilitation. Each user progresses through a given virtual environment at different rates and with varying neurocognitive and affective responses. Ideally, the virtual environment should adapt to the user’s ongoing neurocognitive and affective states in real time. This would allow the user to remain in a state of flow by keeping them adequately engaged.\cite{4,5}

Advances in virtual environments and psychophysiological models allow cyberpsychologists to develop adaptive virtual environments in which behavioral, biological, and/or psychophysiological information about can be processed in real time to draw reliable inferences about user’s current condition for dynamic alterations to the virtual environment. One particular area that has shown a great deal of advancement is the use of off-the-shelf electroencephalographic (EEG) systems. In addition to offering researchers an inexpensive alternative to laboratory-based systems, these wireless EEG systems offer user metrics for the determination of task engagement and arousal. Progress in sensors and algorithms for off-the-shelf EEG systems has made it possible
for researchers to perform real-time estimation of human cognitive and affective states using EEG. Various EEG processing algorithms have been applied for classification of emotions (positive and negative) stimulated by pictures [6, 7] and assessment of neurocognitive workload [8]. Using neurogaming-based EEG headsets (e.g. Emotiv), researchers have found significant differences in Gamma and Beta bands relative to a range of stimulus modalities.[9, 10] Moreover, using neurogaming-based EEG headsets, researchers have found increased power estimates when the avatars of users die.[9] These findings suggest that neurogaming-based EEG headsets (e.g. Emotiv) can detect frequency bands variances relative to stimulus modalities. Increased Beta rhythm has been found with attentional processing during video game play [11]. Changes in brain EEG wave bands have been detected as different events occurred during game play of Super Monkey Ball 2.[11]

For adaptive virtual environments, it is important to consider flow and immersion when attempting balance levels engagement and arousal.[4, 5] Too much engagement and/or arousal can frustrate the user. Too little engagement and/or arousal can cause the user to become bored and disengage. A user’s EEG data can be used to determine the user’s experience throughout entire level designs.[12] A user’s EEG data (and other physiological signals) has been used for assessing the user’s states by using game levels designed to induce boredom, flow, or anxiety.[5] While much of the research has focused on EEG data across entire levels of play, our flow model combines “Task Engagement” and “Arousal-Valence” data from a pre-established model of upper and lower thresholds indicating when the player has left a state of flow.[9, 10]

2. Method/Tools

The Emotive EEG neurogaming headset was used to collect data from 30 healthy college age participants as they played Super Meat Boy [13]. During gameplay, participants controlled a small, dark red, cube-shaped character named Meat Boy to make it jump around the level and avoid saw blades. The end goal of each level is to rescue bandage girl (see Figure 1).

![Figure 1. Screen shot of the platform puzzle game Super Meat Boy.](image)

General game play (GGP) was differentiated from specific game events (SGE) in that GGP was sampled during periods that the participant had not experienced any death events (SGEs) for one minute pre- or post-GGP sampling.
The neurogaming EEG setup (i.e., Emotiv EPOC) used 14 electrodes (saline sensors) locating at AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2 and two additional sensors that serve as CMS/DRL reference channels (one for the left and the other for the right hemisphere of the head). These 14 data channels are spatially organized using the International 10–20 system (see Figure 2). The sampling rate was 128Hz. The bandwidth was 0.2–45Hz. The digital notch filters were at 50Hz and 60Hz. OpenViBE and Emotiv TestBench were used to log raw EEG output, which was postprocessed and segmented into epochs (100 ms before stimulus onset, and 750 ms after). Epochs were calculated for GGP and SGE.

![Figure 2. Emotiv Epoc sensor locations relative to the human brain.](image)

Our EEG flow model was based upon the coordination of “Task Engagement” data with “Arousal-Valence” data. We recorded EEG data at a sampling rate of 128 Hz with 14 electrodes using Emotiv EPOC. We compared three indices of engagement found in the literature: 1) Beta/(Alpha + Theta)[14, 15] 2) Frontal Theta/Parietal Alpha,[16] and 3) Frontal Theta.[17] Given that higher levels of engagement during SGEs may reflect increase in autonomic response, we also measured arousal by using (BetaF3 + BetaF4) / (AlphaF3 + AlphaF4) and valence using (AlphaF4 / BetaF4) - (AlphaF3 / BetaF3). Given our desire to establish “Task Engagement” data with “Arousal-Valence” coordinates for a flow model, we divided the data into quartiles. This allowed us to establish upper and lower thresholds of task engagement and arousal for indices of flow. The resulting coordinate was designed for application to expressive transformations to environmental stimuli in real time by tuning different performance parameters in an Engagement-Arousal rule system.

3. Results

A repeated-measures analysis of variance assessment across the indices of engagement, arousal index, and the valence index was used to assess for differences between GGP and SGEs. Using the indices as the within subject factor for GGP and SGEs results revealed a significant main effect (F(2,28) = 183.22, p < 0.001, partial eta 2 = 0.68). Additional repeated within-subject contrasts revealed difference between GGP and SGEs within each index. Engagement level during SGEs was significantly greater than GGP (t(1,29) = 2.720, p = 0.011). Arousal was also significantly increased during SGEs in comparison to GGP (t(1,29) = 3.959, p < 0.001). While no significant differences were found between GGP and SGEs for the valence index, an interesting
trend was noted in that valence typically decreased more during SGEs that during GGP. Results revealed that Beta / (Alpha + Theta) was the preferred index for differentiating high intensity game events (participant’s character dies) from general game play ($t(1,29) = 2.720, p = 0.011$).

4. Discussion

Adaptive virtual environments require detection of changes in the user to properly decide when a change has occurred and how (as well as when) to adapt the virtual environment. Using flow thresholds based on Task Engagement and Arousal-Valence a set of rules were developed to indicate when the participant was in a state of flow: 1) If engagement levels fell below the lower threshold, then the virtual environment needed to become more complex; 2) If engagement level surpassed the upper threshold, then the virtual environment needed to become simpler; 3) If arousal levels fell below the lower threshold, then the virtual environment needed to enhance stimulation; and 4) If arousal levels rose above the upper threshold, then the virtual environment needed to become less arousing. The flow models output along with current engagement, arousal, and valence measurements can be used as input to machine learning algorithms. Upon successful training of the machine learning algorithms in the adaptive environment we can identify what changes has occurred in the user and determine the possible changes to the environment to improve their experience.

5. Conclusion

In summary, we were able to compare various EEG-based exposure indices for interpreting task engagement. These indices can be used to build classification systems for detecting changes in the user’s cognitive and affective states. Future work will utilize trained machine learning algorithms for continued development of adaptive virtual environments. These adaptive virtual environments moderate changes in environmental stimuli based on the participant’s cognitive and affective states. The adaptive algorithms can make appropriate decisions related to how to best adapt the environment. As an example, if the machine learning algorithm detects that the participant has become bored then the adaptive algorithms can select the appropriate methods to increase the difficulty of the task. Likewise, when the machine learning algorithm detects that the participant has become frustrated, the adaptive algorithms can select the appropriate method to decrease the difficulty of the task.

References


