Designing a Physiological Loop for the Adaptation of Virtual Human Characters in a Social VR Scenario

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Abstract

Social virtual reality is getting mainstream not only for entertainment purposes but also for productivity and education. This makes the design of social VR scenarios functional to support the operator's performance. We present a physiologically-adaptive system that optimizes for visual complexity in a dual-task scenario based on electrodermal activity. Specifically, we propose a system that adapts the amount of non-player characters while jointly performing an N-Back task (primary) and visual detection task (secondary). Our preliminary results show that when optimizing the complexity of the secondary task, users report an improved user experience.

Index Terms: Human-centered computing—Collaborative and social computing Human-centered computing—Virtual reality

1 Introduction

Given the growing interest in the design of Social VR scenarios [16], it is still unclear how social crowdedness (i.e., namely, the number of characters allowed to inhabit per unit of virtual space) impacts the user experience (UX), how such characters should be displayed [7] while still respecting peripersonal space [15]. From the UX perspective, the number of virtual characters can impact the sense of presence and the performance on fluidity, synchrony, and annoyment [7]. The increased complexity of the visual scene due to the heightened amount of virtual characters seems to impact the user's physiological not only on the VR experience but also on cognitive workload, and likewise, physiological arousal [10]. As task demands are correlated with physiological arousal [6], a challenging task might be reflected in increased physiological arousal. Workload-induced arousal can be detected by various physiological signals such as electrodermal activity (EDA), electrocardiography (ECG), and electroencephalography (EEG). In this work, we focus on EDA as a noninvasive and easy-to-implement method to measure physiological arousal [13].

Mehler et al. [12] showed how EDA correlated with changes in cognitive workload at different points in a demand curve reflecting the spare cognitive capacity of participants. Fairclough and Venables [4] reported increased sympathetic activation with lower task engagement and higher stress in high-demand, multi-component tasks. In the context of cognitive workload detection, an increasing VR complexity can induce cognitive overload that manifests as high physiological arousal [11]. Conversely, long-term use of a VR system and boredom can generate low arousal levels. Implicit user-state monitoring and adaptation can bolster more immersive VR experiences and improve the well-being of users [2]. We argue that monitoring the user's physiological state and cognitive workload when engaged in a social VR scenario allows dynamic adjustment, thus supporting the user's comfort. Therefore, this work aims to enable the system to detect the user's state, adapt to it, and thus, support specific needs of the users tailored to their psychophysiological state [3]. Here, we propose a novel physiologically-adaptive social VR system that aims to increase user satisfaction by optimizing the secondary task's complexity to maintain stable physiological arousal using EDA. In detail, we built a VR scene in which our novel physiologically-adaptive system changes the number of social avatars (presented by non-player characters – NPCs) is dynamically adjusted depending on the load of the VR user.

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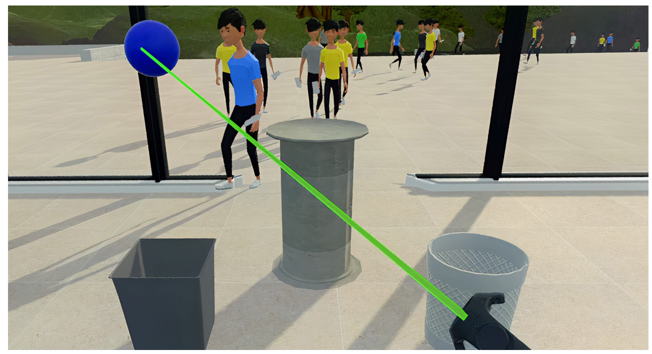

Figure 1: A single trial of the VR n-back ($n = 1$) and the visual detection tasks. Participants were required to place a sphere into the corresponding bucket. If the sphere matched the color of the previous sphere 1 step before, participants placed it into the right bucket. If not, the sphere had to be placed on the left bucket. The visual detection task required participants to monitor if visitors of a museum either possessed a ticket to enter the building or not. Detection was performed by selecting the NPC without a ticket.

2 User Study

We designed a VR scenario to evaluate if our physiologically-adaptive VR system, based on EDA, supports users' comfort and usability as compared to not adaptive ones. We conducted a within-subjects study for the factor of Adaptability (with adaptive system vs no adaptive system). We followed the guidelines reported in [1] for the EDA recording. The experimental design conceives an initial three-minutes baseline recording of EDA, followed by five non-adaptive blocks of six minutes duration and one adaptive test block of the same duration. We randomized the order of the conditions. As a primary task, we chose the N-back task adapted from [14], in an immersive VR environment, see Fig. 1. At the same time, participants were asked to perform a secondary visual detection task. The "adaptive" condition involved the manipulation of the

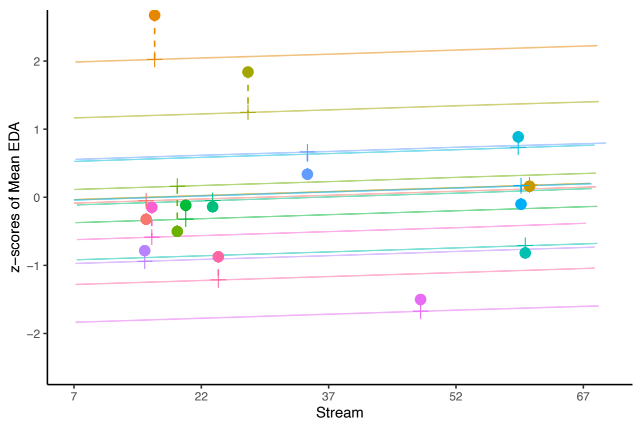

Figure 2: The predicted standardized Mean EDA at optimal STREAM for the non-adaptive condition (crosses) with regression lines and the actual Mean EDA (points) at local maxima of adaptation.

visual complexity (i.e. a stream of non-player characters, NPCs) in the visual detection task through changes in the participant's arousal level as measured by EDA. Our novel physiologically-adaptive system processes the signal online To adapt to the stream of NPCs. In detail, the pipeline derives a mean EDA value by a 5s moving average window replacing each data point by the average of its 20 neighboring data points. To allow for user-dependent adaptation, the adaptive algorithm is initialized with a 3-minutes baseline recording to compute a baseline slope, i.e., the slope between the average of the initial and final 20 seconds of the baseline period. Therefore, when the EDA slope computed in the 20-seconds window was greater than the baseline slope added to the threshold slope, 2 NPCs were removed from the scene. On the contrary, 4 NPCs were additionally spawned. In the remaining five non-adaptive conditions, we fixed the stream of human characters at 7, 22, 37, 52, or 67 characters per minute. We evaluated two aspects of the system: EDA and subjective experience (desire to use). We recruited eighteen participants ($M_{range} = 23-31$; $M_{age} = 27.9$, $SD_{age} = 2.9$; $male = 9$, $female = 9$) to take part in our study; however, we had to exclude 3 participants due to lost contact of the EDA electrodes.

3 Preliminary Results

We fit a linear mixed model via a restricted maximum likelihood approach to predict physiological arousal, performance, and subjective report in adaptive and non-adaptive conditions as a function of STREAM, cf. Fig. 2. We found that the actual EDA was 0.040 (SD=1.074) and the predicted EDA -0.023 (SD=0.9570), see Fig. 2. While the date is normally distributed ($W = 0.976$ $p > 0.937$), a Welsh-corrected t-test did not show a significant reduction in EDA, $t(17) = 0.515$. With regards to the *Desire to Use*, giving the data was not normally distributed, a Wilcoxon-rank test showed that the actual *Desire* ($M = 3.533$, $SD = 0.640$) significantly differed ($Z = 120$, $p = 0.08$) from the predicted *Desire* ($M = 1.728$, $SD = 0.591$).

4 Discussion and Conclusion

We presented an novel online adaptive social VR system that adjusts for the social crowdedness of virtual characters based on physiological arousal as measured by EDA. Our results show that a higher STREAM of virtual characters affects EDA and desire to use the system. In the first place, even though an EDA increase might seem counterintuitive, our system never aimed to decrease the level of physiological arousal. Given the -2/+4 adaptation function, we urged the users to deal with more NPCs while gradually removing NPCs, allowing them to avoid overload. Together with this, the adaptation function is functional in that it aims to keep NPCs in the scene to maintain a sense of social presence. With regards to the practical implications of this work, skin-interfaced wearable systems are no longer far from implementation in virtual scenarios, i.e., smartwatches or controllers [9] open up many fields of application for personalized assessment and physiological adaptation dynamics. This opportunity is consistent with the recent interest in entertainment computing, where the user's emotional state and its physiological correlates have been used to predict actions in a game [8] or dynamically adapt the narrative inducing changes in arousal by providing emotional cues [5]. Furthermore, given the social VR nature of the presented system, arousal in these scenarios may be influenced by violations of personal space and thus adapt proxemic interaction in VR [10]. Our findings also impact collaborative environments; virtual characters can jointly perform tasks within a collaborative VR environment in future VR applications. Such systems could implement online physiological adaption to adapt VR visual complexity. This enables performing concurrent tasks without prioritizing performance over usability or cognitive overload.

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