Tell Me How You Play: Exploring Ways to Enhance the Gaming Experience in Asymmetric Multiplayer VR Games through Affective State Visualization

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Abstract

Researchers have implemented physiological sensing and feedback technologies to reveal the emotional states of the players engaged in VR games; however, these methods have not previously been used in asymmetric multiplayer VR games, in which players do not have equal roles, abilities, or objectives. In the current study, we developed an algorithm capable of inferring arousal states from EEG signals. We also developed a gaming interface that displays a quantitative indication of arousal states with the aim of reducing asymmetry between players with and without VR headsets in order to foster stronger social connections and enhance a sense of presence. Based on the proposed affective game design, we have outlined the within-subject study design to compare the effects of visualized arousal states on players with and without VR headsets. Through this study design, we aim to investigate the effects of arousal state indicators on the overall gaming experience.

CCS Concepts

• **Human-centered computing → Empirical studies in collaborative and social computing**.

Keywords

Virtual reality, asymmetry, multiplayer VR game, emotion

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1 Introduction

The continual evolution of electronic games has led to the development of multiplayer virtual gaming environments that include distinct groups of players with different abilities, preferences, and gaming interfaces. Virtual Reality (VR) gaming is well-suited to an asymmetric gaming environment in which each player is a distinct entity with its own highly personalized experience [5, 30].

Researchers have sought to enhance the gaming experience by incorporating physiological sensing and feedback technologies [13, 43]. Gilleade et al. [13] explored the physiological aspects of affective gaming and the integration of biometric feedback with traditional input methods. Walmink et al. [43] demonstrated the benefits of sharing heart rate data to increase user engagement. Houzangbe et al. [17] demonstrated that physiological feedback can elevate the immersive quality and engagement of single-player VR games. To the best of our knowledge, no prior study has explored the possibility of using sensing and feedback technologies to display the affective state of other players engaged in asymmetric multiplayer VR games.

In the current study, we developed an algorithm capable of inferring the affective state of gamers (quantified as a arousal score) based on EEG signals (alpha- and beta-band activity) [4, 34, 46, 47]. The efficacy of the algorithm in differentiating between affective states was assessed in a pilot study involving 10 participants. The pilot study laid the groundwork for subsequent work assessing the effects of emotional state indicators (i.e., visual cues) on the user experience and emotional state of players in asymmetric multiplayer VR games. Our objective was to design a gaming interface capable of visually conveying the arousal state of all players in order to alleviate the asymmetry between players utilizing VR headsets and those without, with the ultimate aim of nurturing more robust social connections and enhancing the feeling of presence.

2 Binary Affective State Inference Algorithm

In accordance with the valence-arousal emotional model [36], valence pertains to the category or quality of an emotional response, while arousal pertains to the intensity of an emotional response. It is possible to determine whether an individual has entered a flow state by measuring the valence or the degree of arousal [12]. Among these two dimensions, researchers [13, 41] have demonstrated that that arousal is related to the degree of engagement experienced by the player; i.e., the effort exerted by the player in response to the difficulty they must endure. Thus, we presented discrete indicators of emotional arousal in the form of visual feedback, and made this feedback available to other players as well.

In the current study, we focused on inducing emotional states rather than on recognizing emotional responses [11]. Our aim was to use affective feedback as "indirectly controlled signals”, which could be used to alter game world elements and/or player characteristics rather than as explicit commands with direct control over game operations or events [31, 32]. Essentially, the algorithm calculates arousal values based on EEG signals for use in characterizing the current emotional state of the individual as High arousal or Low arousal.

2.1 Calculating Arousal from Brain signals

Emotion can reliably be linked to oscillatory neural activity in the alpha band (8–12.6 Hz) and beta band (13.0–25.0 Hz) [4, 34, 46, 47]. The properties of alpha and beta waves in specific brain regions were used to infer the degree of emotional arousal associated with a given signal. The alpha waves detected in EEG signals are generated when a person is relaxed but not asleep [1, 21]. The beta waves are associated with an alert and active state of mind [21]. Previous research has revealed that the negative correlation between alpha signal strength and arousal is particularly evident in the parietal region [16, 23, 27], and that alpha waves in parieto-occipital regions can be used to predict emotional arousal [16]. The beta waves associated with intensely focused mental activity are commonly observed in the frontal cortex [21, 46]. Thus, it is reasonable to hypothesize that the ratio of average beta band power in the frontal region versus average alpha band power in the parietal region could be used to determine the degree of arousal [44].

As shown in Figure 1(b), the degree of emotional arousal was estimated by measuring beta band power in the frontal region ($\beta_{frontal}$), and alpha band power in the central parietal region ($\alpha_{parietal}$). We then used the ratio of $\beta_{frontal}$ and $\alpha_{parietal}$ to determine the degree of arousal, as follows:

$$Arousal(t) = \frac{\beta_{frontal}(t)}{\alpha_{parietal}(t)} = \frac{\beta_{F3}(t) + \beta_{F4}(t)}{\alpha_{P7}(t) + \alpha_{P8}(t)} \tag{1}$$

where $\beta_{F3}(t)$ and $\beta_{F4}(t)$ respectively refer to beta band power at electrodes F3 and F4 (middle frontal region; both brain hemispheres); $\alpha_{P7}(t)$ and $\alpha_{P8}(t)$ respectively refer to alpha band power at electrodes P7 and P8 (parietal region; both brain hemispheres); and t is the timestamp associated with this data sample.

2.2 Binary classification of Arousal

Before deriving a focus score, mean correction and standard deviation correction were used to mitigate variations in the amplitude of EEG signals associated with individual differences among subjects. This involved collecting EEG data while subjects were watching videos designed to induce either a high or low state of arousal. Z-score normalization [40] was then applied to standardize the raw arousal values. This normalization process ensured that the corrected mean value of all subsequent samples was set to 0, and the corrected standard deviation was set to 1. In practical terms, the normalized TAR values were primarily distributed within the range of -1 to 1, with a few extreme values falling outside this range.

We used a median (nonlinear) filter [37] designed specifically for impulse noise to remove noise-related spikes in the EEG signals [29]. This filter smoothed the arousal results, with each filtered output sample computed as the median value of the input normalized arousal values within a defined time window. Note that eliminating spikes from the EEG signals lowered the median values in sample data and altered the data distribution. Finally, during subsequent VR sessions, an arousal value equal to or exceeding zero indicated a state of High Arousal (HA), whereas an arousal value below zero indicated a state of Low Arousal (LA).

3 Pilot Study

3.1 Participant

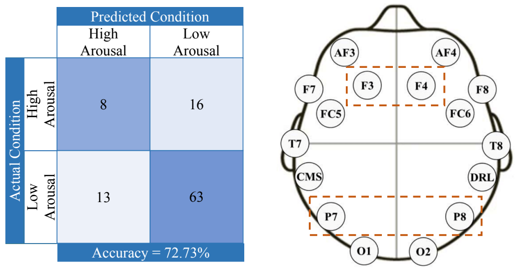
In this pilot study, we recruited 11 volunteers (E1 ∼ E11) from National Tsing Hua University via snowball sampling. This sample of undergraduate and graduate students included three males and seven females ranging in age between 20 and 27 years (mean = 22.09; SD = 2.49).

3.2 Device

EEG brain signals were collected in real-time using the Emotiv EPOC X system [10]. Measurements of spectral power in the alpha and/or beta bands were derived from EEG signals collected at electrodes F3 and F4 located in the frontal region of both brain hemispheres. Measurements of spectral power in the alpha band were derived from EEG signals collected at electrodes P7 and P8 located in the parietal region of both brain hemispheres (Fig. 1(b)). Data transmission and spectral analysis were performed using EmotivPro software [10]. A Meta Quest 3 VR headset was used to display 360-degree video clips to elicit emotional responses.

3.3 Dataset of 360-degree video clips

In this experiment, we employed 73 immersive VR clips in a public database [26], each of which had been previously assessed in terms of arousal using a self-assessment Manikins (SAM) scale [6]. Based on the arousal values collected in a previous study, we selected two reference clips two calibration videos (one inducing high arousal and the other induce low arousal) plus eleven 90-second test clips (with average arousal values equally spaced across the valence-arousal emotional space proposed by Russell) [24, 33, 36]. Previous research [38, 39] has indicated that test videos should be at least 60 s in duration to induce emotional fluctuations. In the current study, all videos were edited to the same duration of 90 s.



(a) High/Low arousal (b) Positions of used electrodes

Figure 1: (a) Confusion matrix of binary classification of arousal. (b) The positions of F3, F4, P7, and P8 electrodes

3.4 Procedure

Researchers first explained to the participants the goal of the pilot study and introduced the procedures that they were to follow. With the assistance of the researchers, the participants put on the VR headset and EEG sensing device. The configuration of the VR controller allowed users to input answers via point-and-click gestures. The researchers then explained how to operate the VR user interface to report their self-assessments of arousal based on a Self-Assessment Manikin (SAM) scale [6].

To facilitate the collection of baseline EEG signals, each subject was first shown two calibration videos (one inducing high arousal and the other induce low arousal) in random order. Ground-truth arousal values were derived for each clip based on self-reported answers obtained using the VR interface immediately after watching each video clip. The subject was then shown one clip selected at random from the eleven clips mentioned above, after which they self-reported a response indicating their degree of arousal [6]. The same procedure was repeated for the remainder of the video clips. Note that we counterbalanced the order of the eleven video clips. Note also that the induced affective states were assessed immediately after watching each video. The subjects did not remove the headset or brain sensor array until all video-watching tasks had been completed.

3.5 Results

Figure 1(a) presents a confusion matrix of arousal levels (binary classification). The ground-truth arousal values associated with each video were the self-reported scores (high/low). Using Eq. 1, we calculated arousal values based on EEG data collected during the last 20 s of the video. We then inferred the final arousal state using the methods used for the binary classification of arousal outlined in the previous section. A comparison of the two values was then used to identify the arousal associated with each video. The overall accuracy of the algorithm in predicting the state of arousal was 72.73%. Note that while the current detection algorithm's accuracy could still be enhanced, ongoing efforts are being made to improve it further. Nevertheless, the binary affective states inferred from EEG signals could be used in many applications, such as the disclosure of player emotions while engaging in games.

4 Preliminary Study Design

This section outlines current study design to investigate the impact of visualized affective states on the overall experience of asymmetric multiplayer VR games. Our objective is to obtain insights into the way that these visualizations could be used to facilitate a positive gaming experience in asymmetric multiplayer VR games.

4.1 Device

In this study, we will use the same devices employed in the pilot study, including an EEG sensor (Emotiv EPOC X sensor [10]) and VR helmet (Meta Quest 3). Predictions of arousal will be inferred using the same spectral analysis methods via EmotivPRO software [10]; however, the data will be visualized in real-time within the game interface, thereby making it perceivable to all players with or without a head-mounted display.

4.2 Affective Asymmetric Multiplayer VR Game: Affective VR Giants

Our goal is to design an emotionally engaging asymmetric multiplayer VR game with an interface that exhibits the affective states of all players. Therefore, from the Unity Asset Store, we obtained an asset template [8] inspired by the popular asymmetric VR game, "VR Giants" [19]. Players will use EMOTIV wearable EEG devices [10] for real-time collection of brain signals, which are then used to deduce the affective state (i.e., level of arousal) for presentation in real-time on their respective interfaces (see Figure 2). This information serves as a visual cue aimed at enhancing the immersive quality of the game experience as well as a cooperative dynamic between players.

4.2.1 Game design of the Affective VR Giants In multiplayer games, the personality, physiological condition, and psychological state of one's team members can affect the perceived flow [3] Researchers have established that the sharing of physiological feedback can enhance the VR gaming experience and foster positive feelings in multiplayer collaboration [9]. The spread of positive emotions throughout the team can enhance collaboration and task performance, while reducing conflict [2]. Note that this approach differs distinctly from the visualization of biometric information during gameplay in previous studies [17, 22, 43]. Thus, we sought to optimize the gaming experience for both players by depicting the emotional state of both players in real-time. The binary classification algorithm will be used to infer the HA/LA state of players from EEG signals to enable the presentation of emotional information in real-time.

Figure 2(a) presents the interface observed by the HMD player with the arousal state of the HMD player displayed in real-time in the upper-right corner. The yellow humanoid figure in the center of the screen is the avatar of the PC player with the corresponding arousal state appearing above. Figure 2(b) presents the interface observed by the PC player with the arousal state in the upper-right corner as well as a giant floating figure (comprising a head and two hands) representing the avatar of the HMD player with the arousal state displayed beside it. In accordance with the suggestion of Hirsch et al. [15], we used red heart-shaped icons to represent arousal states. Heart symbols are common social and emotional metaphors capable of eliciting positive associations [20, 25, 35]. People also associate colors with particular emotions [28, 45]. For most people, red is an indicator of heightened arousal [14]; therefore, we

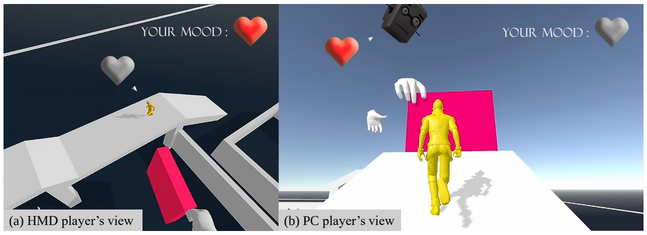


Figure 2: Screenshots captured from the perspectives of (a) HMD and (b) PC players. These scenes were created and modified based on an asset purchased from the Unity Asset Store [42] (Oculus Quest Asymmetrical VR Template [8])).

used red heart-shaped icons to represent the HA state and non-red icons to represent the LA state.

4.2.2 Playing Affective VR Giants. In our game, asymmetry is introduced through the HMD player's ability to observe the PC player from above (God's angle), while the PC player is confined to a view of the immediate surroundings from behind the avatar. This difference in viewpoint allows the HMD player to pave the way for the PC player, such as filling a gap with bricks to enable the PC player to pass. The PC player, lacking special abilities, can only run until reaching the endpoint. Under these collaborative conditions, an awareness of high arousal levels in both players could lead to emotional consensus, enhancing their sense of connection and facilitating effective communication and interactions. If the HMD player became aware that the PC player was operating under low arousal (due perhaps to boredom or uncertainty), then the HMD player could initiate speech communications to formulate a collaborative strategy. This approach ensures that emotional cues are integrated into the game dynamics, enriching the overall gaming experience.

4.3 Procedure

The final phase of this study will involve a within-subject study comparing the experiences of players using different interfaces (conventional 2D screens vs. VR) and with or without visualizing affective states. This study will be implemented in three stages: (1) Pre-study, (2) VR simulation, and (3) Post-study.

4.3.1 Pre-study Stage. The researchers will explain to the participants the objectives and methods employed in the in-lab study. They will also provide assistance in donning the VR headset and EEG brain sensing device to ensure the reliability of data collection.

4.3.2 VR simulation Stage. This stage will be implemented in three phases: (1) Familiarization, (2) Visualization, and (3) Exit.

4.3.2.1 Familiarization phase (5 minutes). This phase is meant to facilitate a smooth transition from the physical realm to the virtual. To assist participants in navigating the game world, they will be shown a brief VR tutorial demonstrating how to interact with the game using the controllers. Once they are comfortable within the VR environment, the subjects will be invited to click a button to enter the game environment via their avatar.

4.3.2.2 Visualization phase (24 minutes for each condition).

Gaming (10 minutes under each condition). At the beginning of each gaming session, the pair of participants will receive instructions regarding their roles in the ensuing game, the ultimate goal of which is to clear as many levels as possible. The same game will be played under two conditions (with or without visualizations of affective states), each of which is expected to last for 10 min. Note that the conditions under which each game is played will vary randomly.

Question-answer sequences (4 minutes). After completing an actual trial of the game, the participants will immediately engage in a question-and-answer session (Q&A session) to gather feedback pertaining to the immersive quality of the user experience.

4.3.2.3 Exit phase (one minute). This stage is the counterpart to the entry stage, aimed at ensuring a smooth return from the virtual world back to reality. Immediately before leaving the VR world, the participants will find themselves in a digital replica of the meeting room in which they started and to which they are about to return.

4.3.3 Post-study Stage. Researchers will assist participants in removing the VR headset and EEG sensing devices. In the event that a participant feels sick or uncomfortable, the researchers will help them to calm down via self-regulation exercises. Finally, each player will be asked to complete a questionnaire pertaining to their gaming experience while playing Affective VR Giants [18]. Each player will also be asked to participate in a semi-structured interview to discuss the way that the visualizations affected gameplay.

4.4 Data Analysis

Measures of immersive quality will be extracted from self-reported recollections (Q&A) obtained from participants immediately after they view each video clip. Scores reflecting the gaming experience will be obtained from the game experience questionnaire. Participant responses will be recorded during semi-structured interviews and then transcribed. The transcripts will then undergo iterative coding independently by three experienced researchers with the objective of identifying salient themes in accordance with established protocols [7] to understand how visualized arousal state would impact the HMD's or PC player's gaming experience.

5 Conclusion

We are currently refining the detection algorithm to further improve the detection accuracy and working on the development of the asymmetric multiplayer VR game. Once this has been completed, we will conduct user studies with the aim of determining the effects of affective information on the gaming experience. The results of the following study are expected to provide insight into the means by which feedback visualizations should be incorporated in the design of asymmetric multiplayer VR games.

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