The Thirty-Second International Florida
Artificial Intelligence Research Society Conference (FLAIRS-32)

How do Players' Eye Movements Relate to Their Excitement in a VR Adaptive Game?

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Abstract

Interaction with games can induce emotional reactions which could have an impact on players' game experience and performance. Physiological sensors such as EEG and eye tracking represent an important mean to track these emotional reactions. In addition, virtual reality isolates the players from the external environment, strengthening the emotional measures. In this paper, we present an explorative study of the use of eye tracking for game adaptation according to the players' excitement. Results showed that there exists a relationship between the modification of the game's speed and the EEG excitement index and a correlation between eye movement and excitement as well. These results suggest that eye tracking could be a valid support or replacement of EEG data in game adaptation.

Introduction

Recent years have witnessed an increasing interest in designing adaptive and player-centric strategies within video games research studies (Frommel et al., 2018). This trend has been highlighted with the ongoing advances in Artificial Intelligence and more specifically in the field of affective computing (Brigham, 2017) One of the main challenges of these studies is to create sensing mechanisms able to infer, monitor and analyze the players' affective states, and to provide the adapted interaction in order to improve their game experience. The advent of Virtual Reality (VR), started a big shift in the current game adaptation frameworks. Despite the VR impact on the players' immersive experience, this technology significantly limits the ability to sense the players' affective states compared to traditional assessment systems as the player's face is completely hidden by the VR headset. For instance, commonly used emotion detection methods using facial expressions, traditional eye tracking devices or external judges are not compatible with VR.

In this paper we propose a novel approach in analyzing the players' states using two main sensing techniques, namely electro-encephalography (EEG) and a VR Headset with a built-in eye tracking. We will use EEG data as real-time source of players' excitement analysis as well as the main criteria of game adaptation. Eye tracking data will be, conversely, used in our offline analysis of players' excitement.

Frequently mixed up in the literature with arousal or emotional intensity, players' **excitement** represents a key factor in their overall game experience. Excitement is defined as the anticipation of a positively appraised energy-based event (Ganjoo, 2005). It is also defined as a positive emotional state that consists of a high level of pleasure and arousal (Dursun et al., 2010). Detecting and optimizing players' excitement could be highly beneficial in VR games. Therefore, the focus in this paper is to assess the efficiency using a built-in eye tracking VR headset to analyze players' excitement in an adaptive VR game environment. In particular, our hypotheses are the following; **H1**: **is there a correlation between excitement and eye tracking in video games?** And **H2**: **Is there a possibility to adapt a game using only eye tracking?**

The rest of this paper is organized as follows. In Section 2, we give an overview of the related works. In Section 3 we describe AmbuRun VR game. In Section 4, we present our adaptation approach and the physiological sensors that we use. In Section 5 we detail the experiment procedure, and finally, in Section 6 we present the obtained results.

Related Works

Game Adaptation

Game experience is considered as the most important part, in designing games. In fact, it is considered to be of key importance for creating captivating and entertaining games (Chanel et al., 2011; Frommel et al., 2018).

Research has shown that adjusting dynamically the difficulty in video games improves the game experience. However, it can be difficult to find out when adjustments and adaptation are necessary. In their study Frommel et al. (Frommel et al., 2018) proposed an approach of emotion-based dynamic difficulty adjustment that uses self-reported emotions to inform when an adaptation is necessary. In order to test their approach, they conducted a study with 66 participants so as to explore performance and effects on player experience. The results show that their approach, which consists of adapting difficulty according to emotions, provided a better player experience than other approaches which consist of adjusting dynamically the difficulty.

In the same vein, Ben Abdessalem et al. (Ben Abdessalem et al., 2018), proposed a neurofeedback approach in adapting a VR game, in order to improve the users' game experience. They intervened on the VR game, assessed the impact of the different interventions, and adapted the game using adaptation strategy according to the player's affective state. They used an adaptation strategy that focused not only on the game parameters but also the player's affective states. They evaluated this approach by conducting an experimental study involving 20 participants. The results showed that the adaptation of the game, directed by the user's emotional reactions, optimized their frustration and excitement in the game.

Moreover, Chanel et al. (Chanel et al., 2011) proposed to maintain player's engagement by adapting games difficulty according to player's emotions. They analyzed self-reports and physiological data and found that playing the Tetris game at different levels of difficulty provoked different emotional states. The results obtained from their study demonstrate the importance of adapting the game difficulty according to the emotions of the player in order to maintain his engagement.

Eye tracking and EEG

Most studies in brain assessment and emotions detection fields have used EEG signals and eye tracking to detect and assess emotions and mental states. Several researches are based on EEG signals in order to recognize the user's emotions and mental states. Horlings and his colleagues (Horlings et al., 2008) conducted a study using IAPS (International Affective Picture System) on students. They showed them different images that provoke some emotions and, in parallel, measured their mental activity with EEG. Results showed that EEG allows the recognition and classification of users' emotions.

Some other researchers used EEG data in the detection of emotions for improving learning. Chaouachi et al. (Chaouachi et al., 2015b) integrated two mental state indexes extracted from EEG which are engagement and workload in their system called Mentor. This system used different rules in order to maintain students in a positive mental state while learning (Chaouachi et al., 2015a). D'Mello et al. (D'Mello et al., 2012) used eye tracking data to detect boredom and disengagement in an intelligent tutoring system that uses a commercial eye tracker. The system reorients the attentional patterns of the students when he detects their disengagement or boredom during the activity.

Virtual Reality Games

Due to its remarkable progress in recent years, virtual reality started to be used in many fields. In fact, this technology has a lot of advantages and the major one is immersion. VR tricks the mind of the user and increases his sense of presence in the virtual environment, so that he thinks that he is really inside this environment. VR makes the user believe that he is in a real world and promotes his performance in games (Biocca, 2006). Therefore, VR is being increasingly seen as the most interesting way to present a video game to players.

In the field of serious games, (Ghali et al., 2017), designed a VR game to teach some basic physics rules. In fact, VR offered an environment in which the user can deploy intuitive reasoning and acquire knowledge faster than usual academic training. They assessed users' emotional behavior and changed assistance strategies in real-time according to player's levels of engagement and frustration in order to improve their intuitive reasoning.

Moreover, Pedraza-Hueso et al. (Pedraza-Hueso et al., 2015) introduced the development of a VR system based on a serious game in order to allow users to carry out physical and cognitive rehabilitation therapies using an interface based on Microsoft© Kinect. Their VR game consists of different types of exercises by which the user can train and rehabilitate several aspects such as cognitive capacities.

In this research, we will use VR in order to create an adaptable immersive game according to EEG and eye tracking signals.

AmbuRun VR Game

We started by creating AmbuRun VR game. This game is about an ambulance carrying a sick person. The player takes control of the ambulance and tries to arrive safely at the hospital without damage in order to save the sick person. The player should dodge the cars, buses, and tracks on the road to arrive without harm (Ben Abdessalem et al., 2018).

In this game, as shown in *Figure 1*, the user interface has three main areas, top left, top middle and top right. In the top left of the scene, the player can see the health bar of the sick person so he can monitor the person's health while driving. In the top middle of the scene, the number of attempts to arrive at the hospital. In the top right areas, the player can see the number of kilometers traveled.

As we mentioned, the player should dodge cars, buses and trucks. The difference between the cars and buses/trucks in the game play is that, if the player hits a bus or a truck (a big obstacle), the sick person will instantly die and he must try again, but if the player hits a car, the health of the sick person will just decrease and he will not die instantly but only after multiple car hits. *Figure 1* illustrates a screen capture of the game.

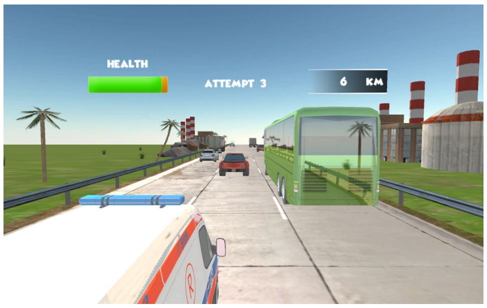

Figure 1 – Screen Capture of AmbuRun VR Game

In order to achieve our goal, AmbuRun should be adaptable and support the modification of its parameters and for that, we created this game in a way to support dynamic modification remotely from a neural agent which will be described in the next section. The possible modifications of the game are the modification of the speed and the modification of the difficulty. We change the difficulty of the game by increasing and decreasing the frequency of the obstacles. If the player encounters few cars and buses, the game will be easy, and if he cruises too many cars, the game will become hard. We change the speed of the game by increasing and decreasing the speed of the ambulance.

In the next section, we will present our game adaptation approach and the different physiological sensors we use.

Game Adaptation Approach and Physiological Measurement

In order to achieve our goals, we started by creating a game adaptation system which uses sensing technologies. We will start by presenting the sensing technologies that we will use in our approach.

Game Adaptation System

This system is composed of three main parts; the first one is the AmbuRun VR game presented in the previous section, the second one is a measuring module and the third one is the neural agent.

Measuring Module

The role of the measuring module in our system is to detect the different mental states and emotions. It receives the different signals form measuring tools (for instance EEG, Eye tracking, etc.), synchronizes, analyses them, then extracts emotions and mental states. *Figure 2* illustrates a screen capture of the measuring module; the top five gauges are: meditation, frustration, engagement, excitement and valence, the bottom five gauges are the average band power (theta, alpha, low beta, high beta, gamma) and the two middle gauges are stress and long term stress.

Figure 2 – Screen Capture of the Measuring Module

The module sends the emotions and cerebral states to the neural agent and stores these data in a local data base. In this paper we connected EEG as a measuring tool.

Neural Agent

The neural agent (Ben Abdessalem & Frasson, 2017) is an intelligent agent that was designed in order to perform two main functions: the first consists of receiving relevant information about the player's emotional state from the measuring module. The agent analyzes this information and decides of the best intervention/modification to be performed on the game in order to reach a desired emotional level. The second involves observing whether the intervention reached its expected outcomes on the player's emotional state.

Physiological Measurement

To measure the player's excitement, our approach is based on using a sensor-based technique with two physiological data channels, namely, EEG and eye tracking. These two physiological data were connected to the measuring module with two different objectives: (1) EEG data was used to feed the system with real-time information about the player's excitement for real-time game adaptation purpose; (2) Eye tracking data was recorded for offline post-experimentation processing.

EEG Measures

In this study, we used Emotiv Epoc+ EEG headset technology to track the excitement of the player. The headset contains 14 electrodes spatially organized according to International 10-20 system, moist with a saline solution. The electrodes are placed at antero-frontal (AF3, AF4, F3, F4, F7, F8), fronto-central (FC5, FC6), parietal (P7, P8), temporal (T7, T8) and occipital (O1, O2) regions with two additional reference sensors placed behind the ears. The detailed position of the measured regions is shown in Figure 3.

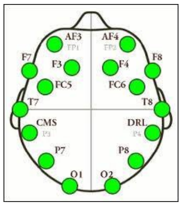

Figure 3 – Emotiv Headset Sensors Placement

Emotiv system generates raw EEG data in (µV) with 128Hz sampling rate as well as the five well-known frequency bands, namely Theta (4 to 8 Hz) Alpha (8 to 12Hz), low Beta (12 to 16 Hz), high Beta (16 to 25 Hz) and gamma (25 to 45 Hz). Furthermore, the system uses internal algorithms to measure the following mental states: mediation, frustration, engagement, excitement and valence.Even though we don't have access to the system proprietary algorithms to infer these mental states from the raw data and the frequency bands, a number of studies have established the reliability of the output (Aspinall et al. , 2015).

Eye Tracking Measurement in VR

Eye tracking data was collected using a built-in eye-tracking module inside the VR headset. The device uses a 5.7 inch display with a WQHD (2560x1440) resolution, 100 degrees as a field of view and 70 fps (frame per seconds) frame rate. The eye-tracking module is composed of 2 infrared eye tracking system (one for each eye) and has 120 fps frame rate with a tracking accuracy less than 1 degree. Fove VR headset provides software in which we can monitor the movement of eyes in real-time. *Figure 4* illustrates a screen capture of Fove software interface.

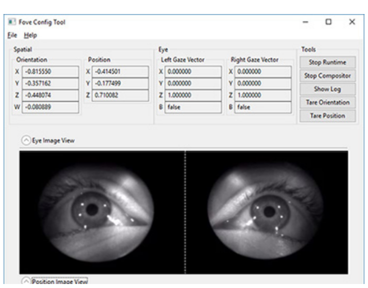

Figure 4 – Screen Capture of Fove Interface

Since Fove software output only provides eye position in the three-dimensional space, a post-processing algorithm was developed in order to compute more meaningful metrics such as the eye distance and the fixation period. We used the Equation 1 to calculate the sum of the three-dimensional Euclidean space distance between two eye tracking position over a T time period.

$$\sum_{k=2}^{T}\sqrt{(x_k-x_{k-1})^2+(y_k-y_{k-1})^2+(z_k-z_{k-1})^2}$$

Equation 1 –Sum of three-dimensional Euclidean distance for T time period

Experiment

We experimented our approach on 20 participants (10 females), with a mean age = 31.05 (SD = 4.96). Before taking part of the experiment, each player signed a consent form in which the goal of the study and the different steps of the experiment were clearly explained. Then, the player was equipped with the Emotiv Epoc+ and Fove VR headset devices described in the previous section. Once the player feels comfortable with the setup and ready to start, the measuring module, the neural agent as well as the AmbuRun VR game were simultaneously launched and the player starts interacting with the game using a wireless gamepad. Earphones connected to the device were used in order to isolate the player from the ambient environment and to intensify his level of immersion in the VR game. *Figure 5* illustrates the experimental process. Two data sources were simultaneously extracted and recorded:

- EEG data used for online game adaptation.
- Eye movement used for offline processing and analysis.

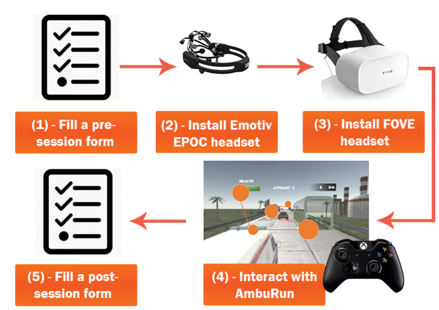

Figure 5 – Process of the Experiment

During the experiment, the measuring module continuously tracks the excitement values of the player. The neural agent computes at a periodic time interval of 20 seconds the mean level of excitement and adapts accordingly the speed of the game.

To sum up the following loop: AmbuRun → Measuring module → Excitement level → Neural agent → Game speed

→ AmbuRun was used in order to adapt the game for all the participants.

After finishing the game session, each participant was asked to fill in a post-session questionnaire in which he provided his subjective feedback about the whole experience (for instance his opinion about using VR). The goal of this questionnaire was to help us improve our future research methodology.

Results and Discussion

The first objective of this research was to discover if there is a relationship between eye movement and the adaptation performed on the game to regulate the players' excitement level. To this end, we started by analyzing the mean total distance performed by each player's eyes 20 sec before and after the game adaptation. The results showed that except for participants 1, 13 and 15, 85% of the subjects showed an **increase** in their mean eye movement distance 20 seconds after the game modification was performed. The detailed results for all the participants are shown in *Figure 6*.

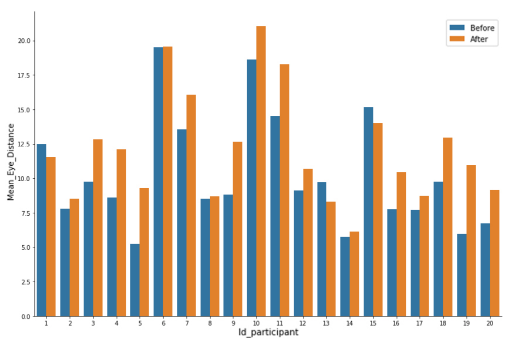

Figure 6 – Histogram of Mean Eyes Distance Before and After Adapting the Game

The averaged analysis across all the participants showed also an increase of 16 % in the eye movement distance with an average distance of 10.52 before intervention and 12.22 post intervention.

In order to confirm this interplay between the neural agent adaptive interventions in the game to regulate the players' excitement and their eye movement patterns, we also conducted a repeated measure ANOVA with the general mean eyes distance before and after the agent intervention as dependent variable. Results show that there was a significant impact of the agent intervention on the participants' eye movement ($p=0.004$ and $F=8.23732$). Table 1 details the obtained results.

Likewise, the analysis of the players' excitement level measured via EEG data showed also the same positive increase trend in the average EEG excitement data 20 seconds after the neural agent modification of the game. More precisely a repeated measure ANOVA test with players' excitement level as dependent variable revealed a significant increase of post agent intervention ($p=0.000168$ and $F=14.660$). Table 2 details the results and shows that when the agent makes the game faster, the mean excitement increase from 0.437 to 0.489 (5.2% more).

Table 1 – ANOVA Eye distance

	Eye Distance Before	Eye Distance After
Mean	10.5216	12.2227
SD	5.9772	6.4467
N	220	200
F	8.23732	
P	0.004	

Table 2 – ANOVA excitement
(More detailed study of this result could be found in XX and YY)

	Excitement Before	Excitement After
Mean	0.437	0.489
SD	0.214	0.203
N	220	200
F	14.660	
P	0.0001	

This overall trend obtained in our first analysis lead to our second research question, which is: to what extent the eye movement and the excitement level measured by the EEG data are correlated? In order to have a more fine-grained analysis at the intervention level (N=220 interventions in total across all the participants), a Pearson correlation test between the eye movement difference (before and after the intervention) and the mean excitement (before and after the agent intervention to increase the speed) was conducted. The results showed a significant fair correlation of 0.58 between these two measures ($p<0.0001$).

The detailed correlation for these two measures made for each participant confirmed also the existence of this relationship. In fact, the correlation between EEG excitement data and eye movement ranged from 0.04 (lowest correlation value for a subject) to 0.906 (highest correlation value for a subject). *Figure 7* shows a boxplot of all the correlations made for all the participants in which the median correlation is 0.6.

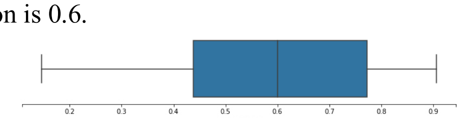

Figure 7 – Boxplot of R Score Correlation for all the Participants

The combination of our results could be summarized as follows: (1) the increase of the game's speed generates more excitement, (2) the increase of the speed of the game makes the eyes move more, and, (3) if the excitement increase, the eyes move more.

In the light of these findings, we can intuitively state that the use of eye movement as an indicator of players' excitement level could be an interesting substitute or reinforcement of EEG to **intelligently adapt the game** parameters.

We believe that eye tracking could be a very rich data source for adaptive strategies in VR games especially since they could be integrated in the VR device and they could be considerably less intrusive than EEG solutions. Nevertheless, we also believe that despite these promising results, a deeper analysis of the eye movement behavior integrating other player's eye patterns such as fixation, blink rates and saccades supported with machine learning could drastically enhance the accuracy of the excitement estimates. For example, in our study, three participants did not show an increase on their eye movement following the agent intervention. This could be attributed to several factors such as the players' characteristics or the insensitivity to the nature of the intervention itself. Therefore, Artificial Intelligence reinforcement techniques combined with other metrics could be beneficial to overcome these challenges.

Conclusion

In this paper, we presented an explorative empirical study of the use of eye tracking as indicator of players' excitement level. An experiment involving 20 participants was performed during which they interacted with an adaptive VR game designed to adapt according to their EEG excitement data. Results showed that (1) there exists a significant relationship between the modification of the game's speed parameter and the eye tracking movement; and (2) the existence of a correlation between the EEG excitement data and the players' eye movement patterns. These results established that eye tracking could be an interesting data source for VR adaptive games. In our future work we aim to build a machine learning model able to detect players' excitement and to suitably adapt the game parameters using only eye tracking data.

Acknowledgments

We acknowledge NSERC-CRD and Beam Me Up for funding this work.

References

Aspinall, P., Mavros, P., Coyne, R., & Roe, J. 2015. The urban brain: analysing outdoor physical activity with mobile EEG. British Journal of Sports Medicine, 49(4): 272–276.

Ben Abdessalem, H., Boukadida, M., & Frasson, C. 2018. Virtual Reality Game Adaptation Using Neurofeedback. In The Thirty-First International Flairs Conference.

Ben Abdessalem, H., & Frasson, C. 2017. Real-time Brain Assessment for Adaptive Virtual Reality Game: A Neurofeedback Approach. In C. Frasson & G. Kostopoulos (Eds.), Brain Function Assessment in Learning, 133–143. Cham: Springer International Publishing.

Biocca, F. 2006. The Cyborg's Dilemma: Progressive Embodiment in Virtual Environments [1]. Journal of Computer-Mediated Communication, 3(2): 0–0.

Brigham, T. J. 2017. Merging Technology and Emotions: Introduction to Affective Computing. Medical Reference Services Quarterly, 36(4): 399–407.

Chanel, G., Rebetez, C., Bétrancourt, M., & Pun, T. 2011. Emotion Assessment from Physiological Signals for Adaptation of Game Difficulty. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 41(6): 1052–1063.

Chaouachi, M., Jraidi, I., & Frasson, C. 2015a. Adapting to Learners' Mental States Using a Physiological Computing Approach. In The Twenty-Eighth International Florida Artificial Intelligence Research Society Conference.

Chaouachi, M., Jraidi, I., & Frasson, C. 2015b. MENTOR : A Physiologically Controlled Tutoring System. In F. Ricci, K. Bontcheva, O. Conlan, & S. Lawless (Eds.), User Modeling, Adaptation and Personalization, 56–67. Cham: Springer International Publishing.

D'Mello, S., Olney, A., Williams, C., & Hays, P. 2012. Gaze tutor: A gaze-reactive intelligent tutoring system. International Journal of Human-Computer Studies, 70(5): 377–398.

Dursun, P., Emül, M., & Gençöz, F. 2010. A Review of the Literature on Emotional Facial Expression and Its Nature. Vol. 48. Presented at the Yeni Symposium.

Frommel, J., Fischbach, F., Rogers, K., & Weber, M. 2018. Emotion-based Dynamic Difficulty Adjustment Using Parameterized Difficulty and Self-Reports of Emotion. In The Annual Symposium on Computer-Human Interaction in Play Extended Abstracts - CHI PLAY '18. 163–171. Melbourne, VIC, Australia: ACM Press.

Ganjoo, A. 2005. Designing emotion-capable robots, one emotion at a time. In Proceedings of the Annual Meeting of the Cognitive Science Society, Vol. 27.

Ghali, R., Ben Abdessalem, H., & Frasson, C. 2017. Improving Intuitive Reasoning Through Assistance Strategies in a Virtual Reality Game. The Thirtieth International Florida Artificial Intelligence Research Society Conference.

Horlings, R., Datcu, D., & Rothkrantz, L. J. M. 2008. Emotion recognition using brain activity (p. II.1). ACM Press.

Pedraza-Hueso, M., Martín-Calzón, S., Díaz-Pernas, F. J., & Martínez-Zarzuela, M. 2015. Rehabilitation Using Kinect-based Games and Virtual Reality. Procedia Computer Science, 75: 161–168.