International Journal of Control and Automation
Vol.7, No.3 (2014), pp.267-272
http://dx.doi.org/10.14257/ijca.2014.7.3.26

Dynamic Game Difficulty Control by Using EEG-based Emotion Recognition

Sangyong Park[1], Hanmoi Sim[2] and Wonhyung Lee[1*]
[1.2.1*] *Chung-Ang University, Republic of Korea*
{Psypher9, kmusic13}@gmail.com, whlee@cau.ac.kr

Abstract

Computer games are steadily one of major way to enjoy leisure time. Main goal of game entertainment is to keep the player's immersion. Thus, balance design taking game difficulty into account has an important role in game design. In recent years, a number of studies tried to adaptive difficulty by using various algorithms which detect player dependent difficulty. Most of these algorithms need customizing itself for each game. Measuring features which determine game difficulty is the major problem of these ways of game balancing. But, it can be easy by using the player's immersion during playing games. And, player's immersion is detected by analyzing electroencephalogram (EEG) signals. In this paper, we propose a dynamic game difficulty control system, by using this emotion recognition technique with PAD model by using players' EEG signals during playing a rhythm game which has three different difficulty levels.

Keywords: *Electroencephalogram, Emotion Recognition, Dynamic Game Difficulty Control*

1. Introduction

In recent years, computer games become one of most popular form of human-computer interaction systems [1]. After inventing computer game, it is one of most major tool for entertainment. Although gaming technology has advanced, there has been dissatisfaction if players with the current computer games because of their inadequacy of providing optimal challenge levels to accommodate individual player's characteristics such as skills, capacities to learn and adapt, and emotional traits [2]. General games provide static difficulty levels, such as, easy, medium, and hard. But most of players don't know that their own skills are good or not. And they have no information about the each difficulty levels. Therefore, they can't select the adaptive difficulty levels. Also, game designers have similar problem.

Game could derive emotion of game players. According to flow theories [3], strong involvement in a task occurs when the skills of an individual meet the challenge of a task as shown on Figure 1 [4]. Too much challenge would induce anxiety. Also, not enough challenge would induce boredom.

When a player plays a game, an emotional state changes to another consistently. It is occurred by two reasons. First, the increasing speed of the difficulty is faster than the increasing speed of competence of the player. Second, the increasing speed of competence of the player is faster than the increasing speed of the difficulty. In first case, emotion state would be moved to anxiety, and in second case, emotion states would be moved to boredom. Based on this theory, we propose a dynamic game difficulty control system, by using emotion recognition technique.

ISSN: 2005-4297 IJCA

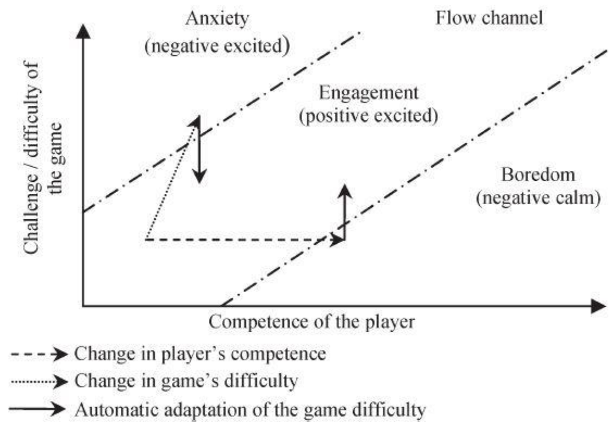

Figure 1. Flow chart and the automatic adaptation to emotional reactions [4]

2. Backgrounds

Human interacting with computer is a part of recent life. Emotion recognition techniques provide a possibility in enhancing the interacting with computer. As the technology of emotion recognition are advancing, there are growing opportunities for computer games.

There is a number of research on emotion recognition using text, speech, facial expressions [5]. But, emotion recognition technique based on physiological signals is more passive and less intrusive for the human. There are several ways of recognition human emotion, for example Galvanic Skin Response (GSR), Electromyography (EMG), Electrocardiogram (ECG), and Electroencephalography (EEG).

In this paper, we used emotion recognition technique by analyzing Electroencephalography (EEG) signals. The asymmetry among left and right brain hemispheres are the major areas where the emotion signals can be captured [6, 7]. A classification about a emotion state as positive or negative lies under valence whereas the level of excitation lies under arousal [8]. And, linear classifiers [9, 10, 11] are considered to be the most appropriate classification technology due to their simplicity, speed and interpretability.

3. System Design

Rhythm games are suitable for this system because of the following three reasons: First, it is simple to control the difficulty of game by regulating the frequency of notes and changing the speed of notes. Second, it is also easy to measure difficulty. Finally, it is a widely spread and well-known genre.

A rhythm game with three different difficulty sets of notes was designed and a song named “come to me” was chosen which has 1 minute 20 seconds play time with 125 bit per minutes. These three difficulty sets of notes have respectively 74, 159, 280 notes, and the speeds of each sets are same. This game logged all results of player with every note during experiments. Because of this character of our game, it is easy to compare between emotion states and player’s log.

Difficulty of this game is switched by player’s emotion which is extracted by analyzing EEG signals. When player is in boredom state, game difficulty is switched to higher difficulty, and when player is in anxiety state, game difficulty is switched to lower difficulty. When player is in engagement state, game difficulty is not changed. Figure 2 shows the finite state machine with three states to switch difficulties. When player starts playing, the initial difficulty is medium. And game difficulty is switched by the player's emotion states such as boredom, engagement, and anxiety.

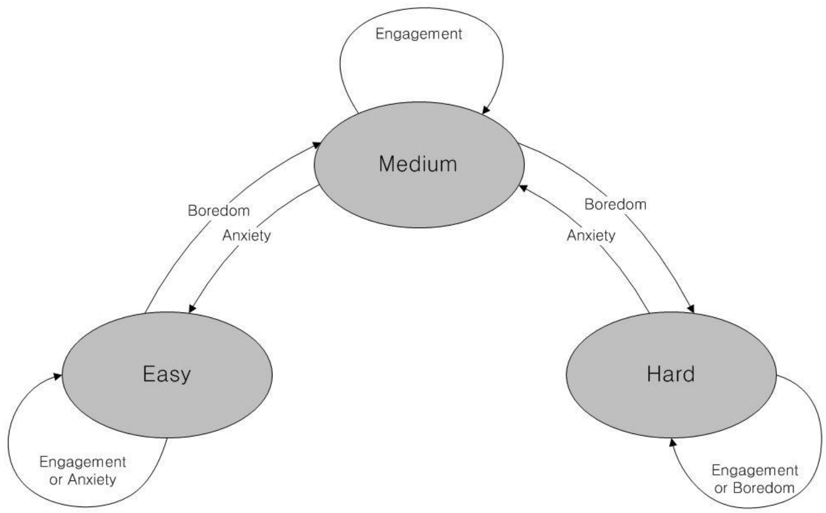

Figure 2. State diagram

Figure 3 shows the interface of our system. The left side of system interface shows the results of analyzing player's EEG signals and the right side show the current game playing by player.

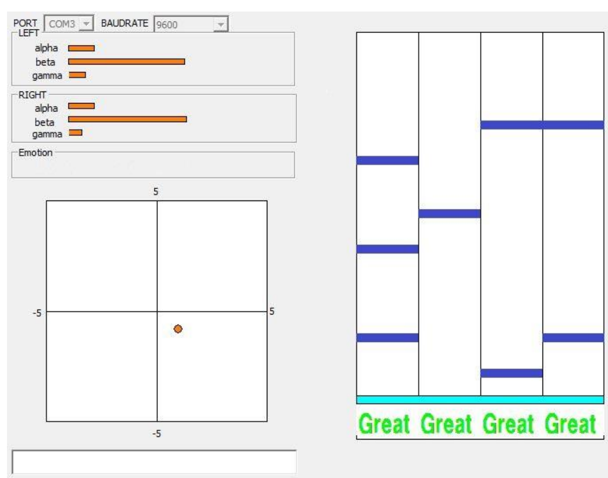

Figure 3. System interface

4. Experiment

This experiment was needed two phases. Phase 1 is for normalizing the emotion states of each participant. EEG patterns of each participant are different, thus it is needed to establish the criteria. Phase 2 is for verifying our dynamic game difficulty control system with the criteria which was established in phase 1.

During the first phase, participant started from a low level and finished up high level and had 1 minutes 30 seconds rest period between each session. During the second phase, participant started from a medium level and the difficulty was switched by emotion states of that participant.

The experiment implemented with eight participant (mean age is 30.4, all right handed). The experimental setup to measure the EEG signal, participants were equipped with several sensors where Fp1, Fp2, Ground, Reference.

5. Results and Discussion

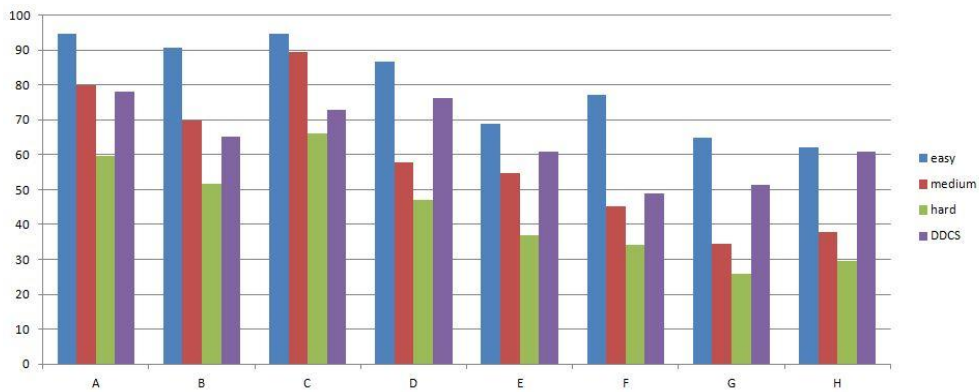

Figure 4. Percentage of participant's accuracy

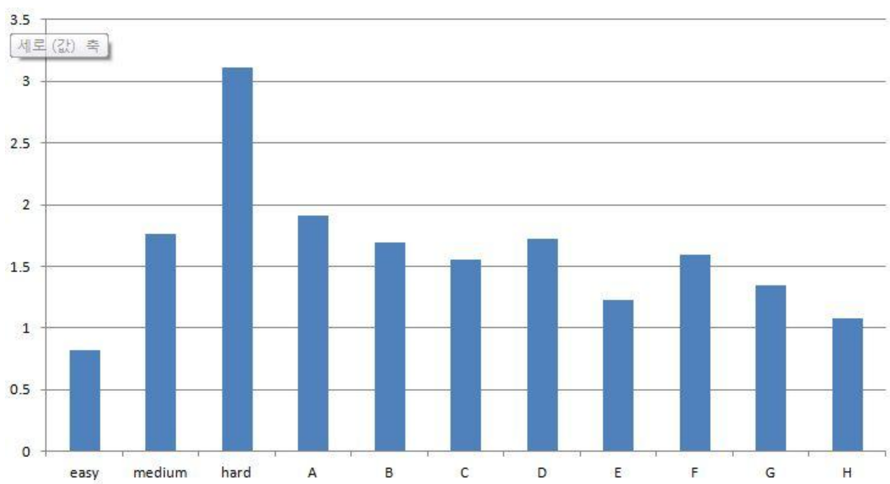

Figure 5. Frequencies of notes

Figure 4 shows the result of eight players A~H. Easy, medium, and hard are the ratio of correct hit with each difficulty sets of notes during phase 1. DDCS is the ratio of correct hits during phase 2. The averages of Player A~H during phase 1 are 78%, 70.7%, 83.3%, 63.8%, 53.5%, 52.2%, 41.7%, and 43.2%. The averages of Player A~H during phase 2 are 77.9%, 65.1%, 72.9%, 76.1%, 60.9%, 48.9%, 51.2%, and 60.8%. The standard deviations of phase 1 and phase 2 are 15.64 and 10.88.

Figure 5 shows the frequencies of notes of easy, medium, and hard. A~H are the frequencies of notes of each players during phase 2. It shows the frequencies of notes are relevant to each player's skills.

The above experimental results demonstrate two points. First, EEG signals can be a indicator of dynamic game difficulty control system. Second, player dependent dynamic game difficulty control system by analyzing EEG signals has a possibility to be a useful tool for game design.

6. Conclusion

In this paper, we propose the dynamic game difficulty control system by using player's emotion. The performance of this system is not competent. We used valence-arousal model, and analyzed EEG signals induced by difficulty of a game for game difficulty control. The experimentation has been designed to gather participants' EEG signals from dynamic game difficulty levels. The results shows that dynamic game difficulty control system by using EEG signals provide the adaptive difficulty levels to participant.

The used method for determining player's emotion is well-known and simple to apply. Thus, it is needed to compare among various methods.

Future work will improve the accuracy of distinguishing emotion of player and modify the game for compare with dynamic game difficulty control system by using player's behavior.

Acknowledgements

This Work was supported by the Brain Korea 21 PLUS Project in 2014.

References

[1] P. Zaphiris, "HCI issues in computer games", Interacting with Computers, vol. 19, no. 2, pp. 135-139.
[2] K. Gilleade, A. Dix and J. Allanson, "Affective Videogames And Modes of Affective Gaming: Assist Me", Challenge Me, Emote Me", Proceeding of DIGRA, Vancouver, **(2005),** pp. 16-20.
[3] M. Csikszentmihalyi, "Flow: The psychology of optimal experience", Harper Colins, New York, **(1991)**.
[4] G. Chenel, C. Revetes, M. Betrancourt and T. Pun, "Emotion Assessment from Physiological Signals for Adaptation of Game Difficulty", IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans, vol. 41, no. 6, **(2011)**.
[5] Y. Liu, O. Sourina and M. K. Nguyen, "Real-Time EEG-Based Human Emotion", Proceeding of the 2010 International Conference on Recognition and Visualization, **(2010)**.
[6] E. Harmon-Jones, "Clarifying the Emotive Functions of Asymmetrical Frontal Cortical Activity", Psychophysiology, vol. 40, no. 6, **(2003)**, pp. 838-848.
[7] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis", IEEE Transactions on Affective Computing, vol. 1, **(2010)**, pp. 81-97.
[8] R. J. Davidson, P. Ekman, C. D. Saron, J. A. Senulis and W. V. Friesen, "Withdrawal and cerebral asymmetry: Emotion expression and brain physiology", Journal of Personality and Social Psychology, vol. 58, **(1990)**, pp. 30-341.
[9] R. Fisher, "The use of multiple measurements in taxonomic problems", Annal of Human Genetics, vol. 7, **(2008)**, pp. 179-188.
[10] B. Efron, "Least angle regression", Ann. Statist, vol. 32, **(1997)**, pp. 407-499.
[11] T. Jaakkola and M. Jordan, "A variational approach to Bayesian logistic regression models and their Extensions", Proceedings of the 6th International Workshop on Artificial Intelligence and statistics, **(2008)**.

Authors

Sangyong Park

Sangyong Park received M.S. degree from the Dept. electronics and electronical engineering in Chung-Ang University, Korea, in 2004. Currently, He is a Ph.D candidate in Graduate School of Advanced Imaging Science, Multimedia, and Film, Chung-Ang University, Seoul Korea. His research interest include computer game technology, human-computer interaction and game AI.

Hanmoi Sim

Hanmoi Sim received M.S. degree from the Chung-Ang University in 2012. Currently, He is a Ph.D candidate in Graduate School of Advanced Imaging Science, Multimedia, and Film, Chung-Ang University, Seoul Korea. His research interest include computer game technology, human-computer interaction and game AI.

Wonhyung Lee

Wonhyung Lee received M.S. degree from the Kookmin University in 1988.and Ph.D. degree at University of N.S.W. in 1998. From 2002, he is a president of Korean Society for Computer Game and he is currently a professor with the Graduate School of Advanced Imaging Science, Multimedia, and Film, Chung-Ang University, Seoul, Korea where he leads the Culture technology/Game Lab. His research in terest include computer game technology, information protection and game AI, game rendering.