



DIRECT NEURAL INTERFACE IN GAMING

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ABSTRACT

The Direct Neural interface (DNI) technology reliably produce changes of individuals electroencephalographic (EEG) activity, while users experience evaluation in games refers to assess the players experience (like fun, boring, engaged, etc.) in playing games. Thus the DNI technology could be used as an effective alternative means of measuring the users emotions or User Experience in playing games, which in turn will help practitioners to evaluate as well as to re-design the computer or mobile games. Therefore, the objective of this research is to propose a system based on direct neural interface (brain-computer interface technology) for evaluating the user experience in playing computer games. To attain this objective, in this paper, firstly with the help of a headset that reads electroencephalogram (EEG) signals, raw data of individual's brain were extracted while the individual was playing a computer game. After that, the brain signal curves were generated from the extracted raw data. Next, the brain signals were analyzed to detect the individual's mood or emotion, which in turn provide the player's (user) experience while playing games. The system was also demonstrated with a single player while playing the 'DX-Ball' game to assess the system's performance in evaluating the User experience of 'DX-Ball' game.

Keywords—Direct-neural interface, human-computer interaction, emotion detection, user experience, UX evaluation, EEG, Computer Games.

I. INTRODUCTION

At present we are living in a world which is totally dependent on technology. A significant portion of this is computer based. As a result, in this era of Information Technology, Human-Computer Interaction (HCI) has become a popular field of interest. People interact with computers everyday through different kinds of peripheral devices. However, nowa- days interaction can be very much appreciable which does not require any physical movement. Thus Direct neural interface (DNI) has become a field which is capable of adding new dimensions in the field of HCI. DNI is defined as a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, [informs], or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment, more simply, it can be interpreted as a system which translates brain signals into new kinds of outputs.

DNI is a field with vast amount of development opportunities. Although the practice of using DNI among general mass is still infrequent, research and studies centering on DNI are taking place to an increasing level. Although it is largely being used for medical and health purposes, there is a lot of other areas where it's benefits can be discovered and thus utilized. One of those area is gaming.

Computer games are an easily accessible form of entertainment which is very important for a sound mind and body. Playing computer games can help increase problem solving skills and keeping the mind active. Gamers are often better at visual tasks and have a higher ability of multitasking. Studies show that games can also improve our memory. Video games have become a

prominent field of entertainment over the past few years. With the advancement of technology, it is being entangled in almost every stratum of our life.

As a result the developing technology is being utilized in gaming as much as possible to make it more interesting to the players. Usage of augmented reality, virtual reality, gesture recognition, wearable gaming devices etc. are the examples of technology involvement in gaming. In recent years, lots of development work is going on to use brain-waves to control games. Even new games have emerged that use brain-wave headsets to play and control the objects in the game.

Most games have a purpose, some are only to entertain, some are educational, some are thought provoking etc. Considering the importance of Games, it become crucial for practitioners to know whether there game is actually serving its purpose and how the focused users are experiencing the game. Thus game development and evaluation has recently become an emerging topic for conducting research. A number of studies have been carried out on game evaluation concepts, algorithms and its importance.

However, to evaluate a game, the most important aspect is the user and their experience, mood or emotion in playing games, i.e., the user experience that can be defined as a person's emotions and attitudes towards a particular product, service or system that they have used.

The effectiveness of any game depends highly on its interactivity and the user experience. Many studies have been performed over the past few years to relate video games with player's emotions. These studies primarily focuses on how the emotional state of a player during a game defines how interesting or enjoyable that game is. Thus it is apparent that the of a game will determine its playability and popularity among gamers. Many existing way of evaluating are by facial expression, heuristic evaluation, brain signal analysis and so on. The more recent way of evaluating is DNI. Since DNI has the capability of portraying a persons brain conditions or in simpler words his moods, it has the potential to be used in games to measure it's effectiveness . Therefore, the objective of this research is to propose a system for analyzing a person's mood while playing a particular game with the help of DNI which can contribute to show the user experience to that game.

II. RELATED STUDY

First of all, there have been many studies conducted on detecting emotions through EEG signal. Murugappan conducted a research on identify different emotions through studying EEG(electroencephalogram) using discrete wavelet transform. In their study, an audio-visual system was developed to induce 5 discrete emotions which were happy, disgust, surprise, fear and neutral. Three types of frequency band were extracted - alpha, beta, and gamma. The maximum subsets of emotions classification rate were 91.67% for disgust, 81.67% for happy and surprise, 81.25% for fear and 93.75% for neutral.

Liu et al. chose 3D virtual environment as experimental domain and studied real-time applications of emotion recognition algorithms. They selected a two dimensional model to describe emotions after designing and performing emotion induction experiments. It was able to detect six emotions but the study did not apply this detection in any particular field.

In studies of evaluation and design of games, Nacke wanted to evaluate and measure GX (Gameplay Experience) to determine a good gameplay experience and through this presented an approach by which they can formalize and apply the mechanisms in the context of serious games. They found out that the user experience was especially important in assessing a serious game. This was primarily done to evaluate a game during it's design process to improve the user experience and contextual/personal value to know what a game can provide for it's players. But the study was done for serious games only.

Chanel in 2008, proposed a system where they defined how the difficulty of a game can affect the players experience. The proposed approach was based on emotion to keep players engaged in the game by modulating the difficulty of the game. The results were shown that playing at different difficulty levels had increased the level of engagement and playing at the same difficulty level had induced boredom. They found out that medium level of difficulty was the best level.

Afterwards, a model called GameFlow was invented by Penelope and Peta in 2005. The main objective of the model was to evaluate a players level of enjoyment while playing a game. GameFlow consisted of 8 elements which were concentration, challenge, skills, control, clear goals, feedback, immersion, and social interaction. All of the elements were linked to enjoyment in a game. The study was done using two strategy based games, one of high rating and one that had a low rating. After the study was conducted, it was showed that the GameFlow model can identify the strengths and weaknesses of a game and can be used as an evaluation tool for strategy based games. They concluded that GameFlow model can be used to review games.

In sum, the previous work has been focused on either emotions or gamification. To the best of our knowledge, no study has been conducted yet to evaluate user experience of games basing on real time data using the DNI technology. Thus this work is aimed to propose a solution that can help game developers to design and evaluate the UX of their game more effectively and efficiently.

III. PROPOSED SYSTEM

The basic motive of this research is to find out the emotions of a player while playing video games and thus measure the user experience. To do this, an EEG headset will be used to capture the raw brain wave of a player (user), while playing the game. The raw brain waves captured by the headset will be processed by a mobile application in order to extract the alpha and beta values of brain wave. These parameters will play a vital role in determining users emotional state. In order to have a more understandable representation, values of these parameter can be plotted in a graph. Using this graphical representation, emotions of the user can be identified comparing it with some ideal (referenced) values.

The emotional states of the player will provide an overall UX state of a particular game for a particular user. The UX reported generated through this system can be used by the practitioners (evaluators and developers) to analysis the UX state based on multiple game theories in order to come to an approximate verdict on the game effectiveness and user experience. A conceptual diagram to depict the whole process is showed in Figure 1.

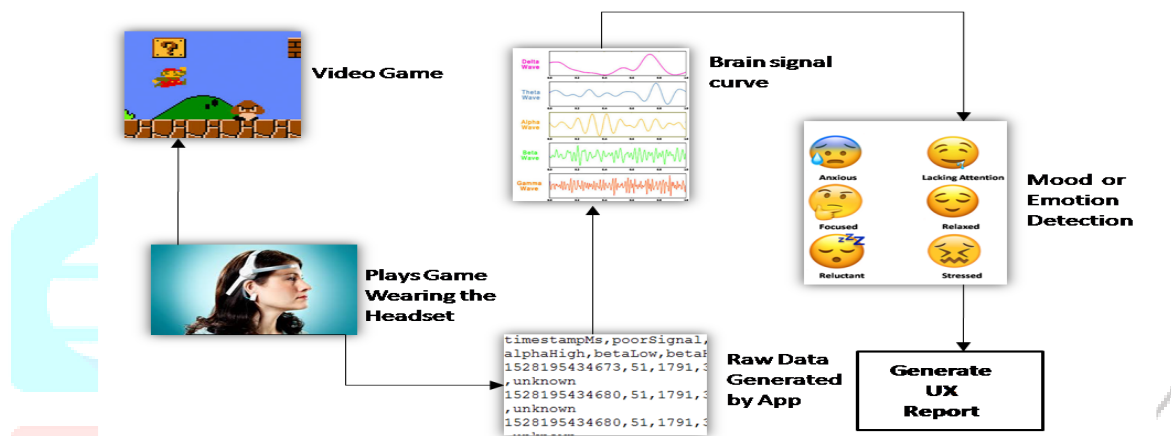


Figure 1: Proposed Architecture

IV. DEVELOPING THE SYSTEM

The system was developed in three steps : Brain signal acquisition, waveform generation and user mood/emotion detection. The steps are briefly discussed in the following subsections :

A. Brain Signal Acquisition

For the development of the proposed system, we have used Neurosky Mindwave Mobile 2 Headset and eegID application to extract EEG signals . The eegID application reads the EEG signal values and writes it in a text file as showed in Figure 2. The eegID application reads the values maintaining a specific time interval, i.e., one second (as set by us). This text file then works as the input file for our system.

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  alphaHigh,betaLow,betaHigh,gammaLow,gammaMid,tagEvent,location
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Figure 2: Brain Signals

B. Waveform Generation

In order to represent the raw data graphically, we transformed it into waveform using Python 3.4 programming language. At first, we read each line from the text file containing brain data. Each line contains all the brainwave signal values for a specific time period. All the values are comma separated, so we splitted the lines by comma and accessed individual signal value. As it is a text file, the extracted information are of string type. In order to plot the values, we converted the string type to integer type and inserted them in different arrays depending on which brainwave we were reading. We also maintained another array in which we have inserted all the time intervals.

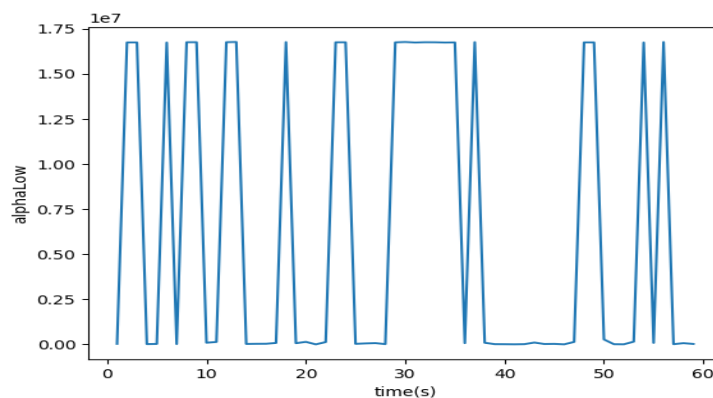


Figure 3: Waveform extracted from brain

After reading the entire text file and inserting all the brainwave values in their respective arrays, we have plotted it against the time interval and generated the waveform. The output waveform is showed in Figure 3. To plot the value we have used Matplotlib library.

C. User Mood/Emotion Detection

User mood was detected from the generated waveform, which was created from the raw brain data. According to, low, high and optimum values of alpha and beta wave indicate different types of moods as showed in Table I. We asked 20 participants to play various video games wearing the headset. We took their data with their full consent and explained them that the purpose of this data is to detect their emotional state. We used these 20 different text files containing the raw data of 20 different people playing various video games to determine reference values of low, high and optimum alpha and beta. For alpha, highest among all the data were 16776374, lowest was 774 and average was 2541388.326 and for beta, highest was 16776121, lowest was 626 and average value among all data were 1988141.054. To determine the minimum, maximum and average values of alpha and beta from these raw data files, we followed the following process as well as showed in the Figure 4.

- 1) To determine lowest alpha value, we have taken the minimum alpha-low value from the text files.
- 2) For highest alpha value we have taken highest alpha high value.
- 3) To determine the average alpha value which was our reference optimum value, at first we have calculated the mean of alpha-high and alpha-low for each raw data file and then we have summed all of them and divided it by twenty to determine the overall average.

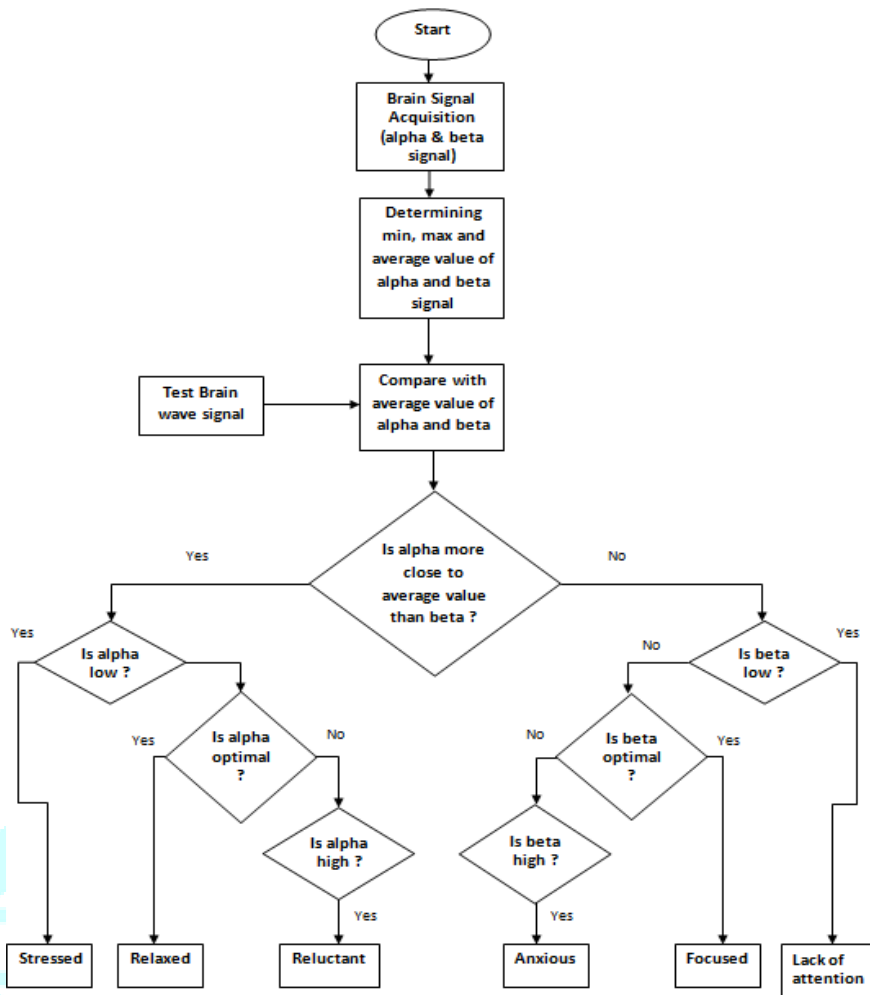


Figure 4: Flow diagram to develop the proposed system

Similarly we have determined lowest, highest and optimum beta value. By doing this we received the reference values. To detect the emotion of a user, we extracted his/her raw data file and analyzed the values with respect to our reference values. If the difference between alpha average and test alpha value is less than or equal to the difference between beta average and test alpha value is less than or equal to the difference between beta average and test beta value, then we have assessed the emotion basing on alpha value and vice verse. If we were assessing the test data basing on alpha value, then we have determined its and test beta value, then we have assessed the emotion basing on alpha value and vice verse. If we were assessing the test data basing on alpha value, then we have determined its difference with lowest alpha, highest alpha and average alpha respectively. We have considered the test alpha value as low, if its difference with lowest alpha was the minimum. Similarly test alpha was considered high if its difference with highest alpha was minimum and optimum if difference with average alpha is minimum.

TABLE I
DIFFERENT TYPES OF MOOD BASED ON ALPHA & BETA WAVES

Brainwave	State	Emotion
Alpha	Low	Stressed
	High	Reluctant
	Optimum	Relaxed
Beta	Low	Lack of Attention
	High	Anxious
	Optimum	Focused

In the same manner, we have labeled test beta as high, low or optimum comparing it with highest, lowest and average beta value respectively. As human emotion does not change that frequently we have considered any emotion will last for at least five seconds. So for every five second interval we have taken all the test values and determined their average. Then we have compared it with all the reference values and gave our verdict on users emotion as showed in Figure 5.

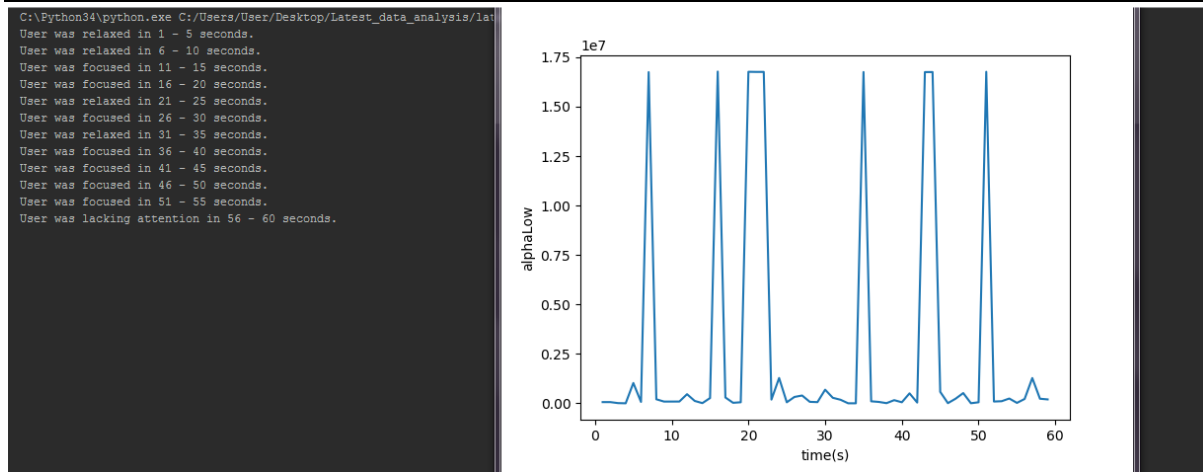


Figure 5: System output- Emotional state with respect to time and the curve of

V. EVALUATING THE SYSTEM

A light weighted experiment was conducted to evaluate the system. The 'DX-Ball' computer game was selected to evaluate its UX. For this, we invited one participant having age 22 and who has experience of playing computer and mobile games. The player (participant) was not familiar with (had never played) the selected game. At the beginning, we briefed him about the purpose of our experiment and confirmed him that we are not testing him, rather we are intended to test the developed system for understanding the UX of the studied game. A few pictures of data collection are showed in figure 6.

TABLE II
USERS EMOTION FOR 1 MIN WHILE PLAYING DX-BALL : LEVEL-1

Time Interval(In seconds)	User's Emotion
1-5	Relaxed
6-10	Focused
11-15	Lacking Attention
16-20	Relaxed
21-25	Focused
26-30	Lacking Attention
31-35	Lacking Attention
36-40	Relaxed
41-45	Stressed
46-50	Focused
51-55	Lacking Attention
56-60	Relaxed

TABLE III
USERS EMOTION FOR 1 MIN WHILE PLAYING DX-BALL : LEVEL-2

Time Interval(In seconds)	User's Emotion
1-5	Relaxed
6-10	Relaxed
11-15	Focused
16-20	Focused
21-25	Relaxed
26-30	Focused
31-35	Relaxed
36-40	Focused
41-45	Focused
46-50	Focused
51-55	Focused
56-60	Lacking Attention

During the test session, the participant (player) was asked to play the game wearing the EEG headset. The player's brain data while playing the game was extracted and later on analyzed through the proposed system to detect his emotional states or user experience. The outcome of his emotional states are presented in a tabular format in Table II and Table III. The tables represent the emotional state of the player in the first minute when he was playing level 1 and level 2 of the game. The results showed that in level 2 the player was more focused than level 1. As the difficulty of the game increases, the user needs to focus more to survive in the game.

VI. DISCUSSION AND CONCLUSION

In this paper, we have proposed a DNI technology-based system to evaluate UX of players while playing games. The outcome of the system is a verdict on how the user is feeling. To the best of our knowledge, there is no other existing system that gives verdict on users emotion with respect to the alpha and beta values of brain waves. The proposed system is simple yet efficient to detect users emotion, which in turn provides the user experience to assess the suitability and acceptability of a computer game towards end-user(players).The proposed system can detect the users emotion for a specified interval of time, it can be used to test the user experience of gamers playing a game. The feeling of excitement or joy or attentiveness during a game would proof that game to be effective and on the contrary, the feeling of boredom or distraction can tell that the game might not be very compelling to the players. Hence it can be effectively used in terms of design and development of games. The developer of a game can evaluate the emotional responses of users while they are playing the game to understand whether their game design is effective or not. They can also understand which aspects the game is lacking and can improve the game. Thus the proposed system will help practitioners to improve usability and user experience of games.

To maintain simplicity of the system, we have considered that a person's emotion will remain constant for at least five seconds. However exception of this consideration can happen. In those cases the system will not be able to pin point emotional changes. Another limitation is that since we have used a commercial device and a freeware application to extract the data, the values of the brainwaves may not be accurate. Moreover, the system was demonstrated with only one player while playing a single game.

Our future work will focus to implement an automatic tool for the evaluation of UX for system designers and developers so that it can be practically used in terms of measuring UX in order to design and develop effective computer or mobile games. Moreover, other kind of brain wave (e.g., Gamma wave) will bring in consideration to detect more emotional states to make the system more effective. An extensive evaluation study will also be conducted involving multiple players for multiple games to assess how the UX changed from one level to another for a particular game as well as how the overall UX differ while a particular user (player) playing different games.

VII. REFERENCES

- [1] J. Wolpaw, E. W. Wolpaw, "Brain-computer interfaces: something new under the sun,". In *Brain-Computer Interfaces: Principles and Practice*, Oxford University Press, Incorporated; 2012. pp. 3-12.
- [2] "The Future of Direct-neural interface technology," in *in-Training*, Feb. 08, 2018. [Online]. Available: <http://in-training.org/future-braincomputer-interface-technology-15655>.
- [3] "7 Reasons to Play Computer Games," in *Psychology Today*. [Online]. Available: <https://www.psychologytoday.com/us/blog/the-matinggame/201603/7-reasons-play-computer-games>.
- [4] L. Ingham, "Brain-Computer Interfaces: The video game controllers of the future," in *Factor*. [Online]. Available: <http://factor-tech.com/feature/brain-computer-interfaces-the-video-game-controllers-of-the-future/>.
- [5] K. Emmerich and M. Bockholt, "Serious games evaluation: processes, models, and concepts," in *Entertainment Computing and Serious Games Lecture Notes in Computer Science*, pp. 265-283, 2016.
- [6] "User experience," in *Wikipedia*, Aug. 24, 2018. [Online]. Available: https://en.wikipedia.org/wiki/User_experience.
- [7] M. Murugappan, N. Ramachandran, and Y. Sazali, "Classification of human emotion from EEG using discrete wavelet transform," in *Journal of Biomedical Science and Engineering*, vol. 03, no. 04, pp. 390-396, 2010.
- [8] D. O. Bos, "EEG-based emotion recognition." in *The Influence of Visual and Auditory Stimuli*, 56(3), pp.1-17, 2006.
- [9] D. Cernea, C. Weber, A. Ebert, and A. Kerren, "Emotion-prints: interaction-driven emotion visualization on multi-touch interfaces," *Visualization and Data Analysis*, Aug. 2015.
- [10] Y. P. Lin, C. H. Wang, T. L. Wu, S. K. Jeng, and J. H. Chen, "Support vector machine for EEG signal classification during listening to emotional music," in *IEEE 10th Workshop on Multimedia Signal Processing*, 2008.
- [11] S. Koelstra, C. Muhl, M. Soleymani, J. S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "DEAP: A Database for Emotion Analysis Using Physiological Signals," in *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18-31, 2012.
- [12] Y. Liu, O. Sourina, and M. K. Nguyen, "Real-time EEG-based human emotion recognition and visualization," in *International Conference on Cyberworlds*, 2010.
- [13] J. Atkinson, D. Campos. "Improving DNI -based emotion recognition by combining EEG feature selection and kernel classifiers," in *Expert Systems with Applications*, 47, pp.35-41, 2016.
- [14] H. Feng, H. Golshan, and M. Mahoor, "A wavelet-based approach to emotion classification using EDA signals," in *Expert Systems with Applications*, 112, pp.77-86, 2018.
- [15] L. E. Nacke, A. Drachen, and S. Gbel. "Methods for evaluating gameplay experience in a serious gaming context." in *International Journal of Computer Science in Sport*, vol. 9, no. 2, pp. 1-12, 2010.
- [16] G. Chanel, C. Rebetez, M. Btrancourt, and T. Pun, "Boredom, engagement and anxiety as indicators for adaptation to difficulty in games," in *Proceedings of 12th international conference on Entertainment and media in the ubiquitous era - MindTrek 08*, 2008.
- [17] C. G. Majoor, "Exploring the Effects of Game Mechanics in Changing User Behavior", *A Literature Study supervised by Anton Eliens*, MSc. Computer Science, Multimedia Vrije Universiteit Amsterdam.
- [18] P. Sweetser and P. Wyeth, "GameFlow," *Computers in Entertainment*, vol. 3, no. 3, pp. 3, Jan. 2005.
- [19] "eegID," in *Google Play*. [Online]. Available: <https://play.google.com/store/apps/details?id=com.isomerprogramming.application.eegIDhl=en>.
- [20] "MindWave," [Online]. Available: <https://store.neurosky.com/pages/mindwave>.
- [21] "Your 5 Brainwaves: Delta, Theta, Alpha, Beta and Gamma," in *Smart Pill Resources by Lucid*, Sep. 09, 2018. [Online]. Available: <https://lucid.me/blog/5-brainwaves-delta-theta-alpha-beta-gamma/>.