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Emotion-Controlled Dynamic Content Adjustment to Induce Flow

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Declaration of Authorship

This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by Ahsan Rejwan Zaman and Syed Abrar Rahman under the supervision of Mr. Hasan Mahmud, Assistant Lecturer, Department of Computer Science and Engineering (CSE), Islamic University of Technology (IUT), Dhaka, Bangladesh. It is also declared that neither this thesis nor any part of it has been submitted anywhere else for any degree or diploma. Information derived from published and unpublished work of others has been acknowledged in the text and a list of references is given.

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Abstract

A challenging research issue which has gained far-fetched traction in regards to the game development industry is the incorporation of emotions into gaming systems. In this regard, we propose an **E**motion **C**ontrolled **D**ynamic **C**ontent **A**djustment methodology. With this aim we attempt to find a comparison of a player's emotional state, the emotions induced by the game he is playing and the amount of engagement he is experiencing with the game. While many games use Dynamic Difficulty Adjustment techniques to incorporate emotion into the game, this approach has certain limitations and barriers which obstructs players from being completely engaged with the game. We propose ECDCA to overcome those limitations.

This thesis categorizes videos and games based on the emotions elicited by them. Then we attempt to take the engagement readings of players in different combinations of videos followed by games with different emotional responses. Thus, we hope to prove that emotionally different contents can affect current emotional state. We also attempt to provide a mapping table of which emotional content achieves maximum engagement response at the given emotional state of a player.

Keywords: Affective gaming, Emotion Controlled Dynamic Difficulty adjustment (ECDCA), Flow, Engagement, Emotion Elicitation.

Contents

1 Introduction

1.1 Overview

Video games as software are an important component of human computer interaction. Video games are ubiquitous in the modern world as a form of content consumption. The interaction of players with the game is essential to the gaming experience. Gaming is also transforming pop culture and redefining the ways that young people consume entertainment. Games can engage players in a virtual world that can bring with it various emotions. it begs the question to arise whether these reactions can be used by developers to find new forms of interaction. The gaming industry inspires innovation by constantly pushing the boundaries of what's possible, driving companies like Google and Microsoft to create new technology to serve the billions of players around the world.

The incorporation of emotion recognition technology in game applications, in order to improve the quality of interaction and enhance the gaming experience has gained much importance in terms of research in recent times. Including users' emotion into the game introduces a subconscious aspect of human computer interaction which is more impacting for the user experience since it is not voluntary and thus has a degree of spontaneity. Unobtrusive monitoring of user's affective state is important in order to retain his/her engagement level and not interrupting the flow during the game.[1]

Affective gaming is a trending research topic in the context of modern gaming industry. Players' emotions, their study and processes to include them into the game mechanics and feedback loop are highly relevant research topics in the status quo. In order to capture the emotions of a player, various modalities have been explored such as peripheral physiological signals (ECG, EMG, EDA) [2], facial expressions [3], combination of facial expressions and body gestures[4] and even questionnaires[5].

Interactive "choose your adventure" games aim to give more control to players over the story to fine tune the experience according to players' preferences. Players are given choices according to which the game selects a specific branch of story among the ones that stem from the given choice. Introducing an aspect of spontaneity removes the players' willful decision making which enables him to immerse into the game detaching themselves from reality resulting in complete immersion[1].

An approach to incorporate the detected emotions is to introduce the change of game content (i.e. environment, characters, task etc) which provides a more meaningful feedback to the users' emotions. This appears more natural and integrated into the gaming experience for the player, resulting in achieving the subconscious engagement with the game that is pursued in [1].

1.2 Motivations

Affective gaming has more potential to enhance complex, multilayered games with various types of gameplay and/or storylines [2]. In such games the player may be required to complete different types of tasks and experiences different storylines based on how they respond while playing the game. This paper tries to explore the extent to which player affect can be used to determine which of these aspects of story and gameplay the player will likely find stimulating.

Current research in dynamic adjustment of game experience has been widely explored in the context of difficulty. Here the difficulty of the game is tailored to how well the player performs and their emotions for e.g. degree of anxiety [3][6]. An instantaneous non-intrusive method for emotion detection is required to prevent the loss of players' immersion [1]. The method used in this paper is emotion detection through players' facial expressions while playing. However [2]. suggests that after some time experiencing the EC-DDA mechanism players catch on to how their expressions determine difficulty and start exhibiting exaggerated expressions to make the game easier or harder. This means that the player in conscious in making this choice and is therefore not disengaged from reality, which is a crucial element in achieving flow according to [1].

To maintain this sense of distorted reality, we try to introduce dynamic content adjustment (EC-DCA) where players have no incentive to abuse the emotion controlled mechanism to make changes that give them instant gratification for e.g. making the game easier, as the effect of their actions is not easily apparent.

1.3 Problem Statement

The gaming industry has been concerned with the physical aspect of input since its beginning. This obviously important in determining how the player makes conscious decisions about what to do in the game. The subconscious changes in the player's physiology and emotional or cognitive state of the player has been left unexplored. Affective gaming is concerned with these non-physical forms of input from the player.

We aim towards a system that can ultimately take subconscious input from the player and use it to tailor the game's content. The context for what this content entails is the sort of emotional reaction that this part of the game tries to elicit from the player. In doing this, the player should be guided naturally into aspects of game-play and story-line that are determined by examining the players' previous emotional response to those types of experiences. Our research will aim to show that dynamically adjusting the game in this manner is an effective way to establish better engagement from the player. In this regard our goal is to answer two specific research questions:

"Can engagement be influenced with dynamic content adjustment?"

We aim to make a player at a certain emotional state play games that have different emotional content. We will then measure their level of engagement from playing each game with respect to what emotional state the player was previously in. We will check for differences between these measurements for different emotional state transitions.

"How can emotions triggered by games influence the player's level of engagement differently?"

We hope to find correlations and patterns between emotional state and emotional content of the game from the measurements obtained. As a result we hope to find a mapping of what emotionally triggering content can engage the player more based on the emotional state of the player.

1.4 Research Challenges

For the purpose of our experiment we had to find a method to determine the emotional state of a test subject. From [3] we found Affectiva [15] to be an unobtrusive easily accessible tool to use for measuring facial expressions and emotions. Affectiva offers a SDK for unity that can be implemented to identify facial expressions and emotional state in real time from the video feed from a connected camera. This means that no specialised hardware is required as most webcams can be used for this purpose.

In order to analyse the emotional states in our work we needed a way to induce emotional states in individuals and found that emotion elicitation techniques may use clips from publicly available films[17].

A key component in our study is how we measure an individual's level of engagement after playing a game. We found a standardised Game Engagement Questionnaire(GEQ) that when used with the Rasch Model is able to produce scores for level of engagement[16][21].

1.5 Thesis Outline

This thesis is categorically divide into 7 sections. In Section.1 we introduce the basis of our work and what it entails. Section.2 describes the terms and topics relevant to our study. Section.3 contains an overview of the previous work that has been done and how it relates to what we try to achieve. The basis of our experiment and the components it requires are explained in Section.4. In Section 5 we provide a detailed description of our experimental approach. The results and findings from our experiment are discussed in Section.6. Finally in Section.7 we discuss the implications of what we have found and how it leads to possible future works.

2 Literature Review

To understand the methodologies and contributions of our research some prior study relating to various fields of psychology and gaming had to be studied.

2.1 Flow Theory

The concept of 'flow', is not new. Mihaly Csikszentmihalyi first coined and used this word to in the mid-1970s describe the feeling of complete and energized focus for a given activity with a high level of enjoyment and fulfilment.[1] Csikszentmihalyi theorized that several different elements were required to successfully achieve a state of flow, although not all elements are required at once, and the elements can appear in various combinations. The elements are:

1. Clear goals.
2. Direct and immediate feedback.
3. A balance between challenge and ability (the activity is knowingly achievable).
4. A sense of personal control over the situation or activity.
5. A high degree of focus on a limited field of attention.
6. Distorted sense of time.
7. The merging of action and awareness.
8. A loss of self-consciousness.

   Csikszentmihalyi characterized Flow as an affective state of high arousal and high concentration. He describes it as "a state in which people are so involved in an activity that nothing else seems to matter; the experience is so enjoyable that people will continue to do it even at great cost, for the sheer sake of doing it."[1].

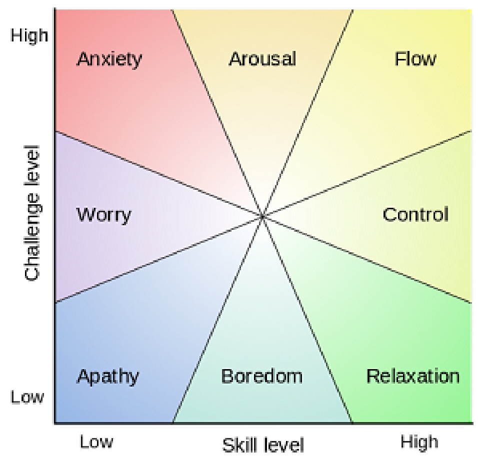

Figure 1: Representation of flow

The state of flow is encountered when a person is on the 'edge of control' and experiencing success while applying all their skills and knowledge to a task. "Flow is a constant balancing act between anxiety, where the difficulty is too high for the person's skill, and boredom, where the difficulty is too low." [1]. This is illustrated in 2.1. More recently, flow has been recognized as a learning related or epistemic emotion, along with frustration, boredom, confusion, anxiety, curiosity, and delight. In this context, the state of flow is conceived as an emergent state that results from small scale cycles of modest challenge and timely achievement. These cycles result in transitions between mild cognitive disequilibrium where a learner experiences confusion or even frustration, and cognitive equilibrium where the confusion is resolved. As in other contexts, the learning-related flow state is associated with deep engagement.

In terms of context, flow can be perceived on various grounds. Mihaly originally coined his term flow in [1] but this was more generalized to any task in general including educational and sports activities. More specific researches were done by many researchers based on only flow in games.

Jones [20] specified flow for using in game research. Here he identified elements of flow in terms of tasks and their difficulties, control over the game mechanics, immediate feedback etc. Cowley et al. [18] provided a mapping of flow elements to game elements. He emphasized on the on cognitive elements being crucial to describing flow inducing games.[7] He conceptualized the sense of identity while playing as an important element of flow. Sweetser and Wyeth [19] also provided a mapping of flow elements. They introduced the social context into consideration for elements of flow. They acknowledged that social interaction is a metric for game enjoyment but not as important as an element of flow. Lennart [7] performed a comparative and analytical study of the different mappings of flow elements to provide a synthesized flow model encompassing all elements with the following generalized features:

1. **Effectance** is the feeling of empowerment in player's when they can witness the result of their actions.
2. (Identification refers to the changed perception of identity.
3. **Transportation** describes the feeling of immersion in games analogous to being transported to the game world.
4. **Mental Workload** is a combination of all elements that affect the mental workload and cognition of the player.

2.2 Affective Gaming

According to [3], a detailed study of affective gaming is available from studying many of their reference papers. Affective computing is a term used to describe AI computing technology that can detect, simulate, or affect a human user's emotional state . Entertainment oriented games may be considered an almost pure expression of an affective computing application, since they exist for no purpose other than to affect players' emotions. However, there has been little application of the emotional detection aspect of affective computing in games to date. Basic affective states are fear, joy, excitement, disgust, or anger.[18] Affective states have also been described using a 'circumplex model' where affective states are categorized using hedonic valence and physiological arousal. [22]

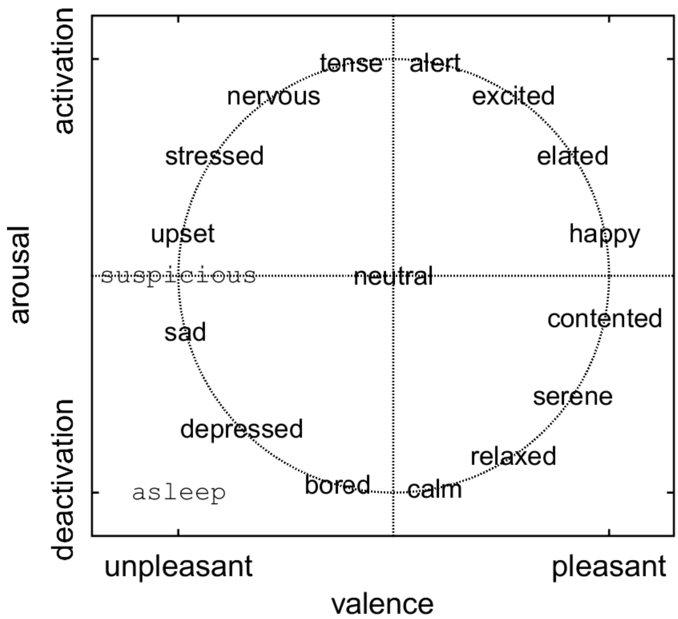

Figure 2: Representation of flow

Valence represents the pleasantness or unpleasantness of a mood and arousal is the strength of that mood. Affective states corresponding to varying valence and arousal are shown in 2.2. 2.2 shows that boredom is characterized by moderately low valence and low arousal, while frustration is characterized by low valence but moderately high arousal. Flow is not recognized as a basic affective state. Csikzentmihalyi's suggested it to be associated with high valence and high arousal [1]. However, Graesser and D'Mello suggested that it may be a more dynamic state that emerges from transitions between other more basic affective states.[3] Player valence and arousal can be measured at runtime and mapped to affective state . This affect information can be used directly to modify the game difficulty, to implement an Emotion Controlled Dynamic Difficulty Adjustment system (EC-DDA), EC-DDA would allow a game to be tailored automatically to suit all player types. and applied affective computing to modify game difficulty.Researches used ECG signals to modify difficulty in both a puzzle game and a game of Pong. Others used EEG signals to modify difficulty levels in a Tetris like game. Some describes using skin conductance, heart rate, and two types of facial electromyography measurements as input to a system that generated events intended to keep player interest and arousal high. A common feature of all these approaches is the rather intrusive sensor setup (the 'borg' approach). Another approach to detecting affective state is through the analysis of facial expressions. One non-game study demonstrated that this approach could produce better results than generated using an EEG sensor. Xiang used this approach to control the difficulty of a Tetris game, and reported that it improved the player experience. Facial expression recognition software has improved greatly in recent years. High performance facial recognition toolkits are now available as CoTS software components.

2.3 Emotion Detection in games

Emotion of a player can be detected through many ways. [2] used physiological responses of players to detect and recognize emotion through (i) peripheral physiological signals: ECG, EDA, EMG, respiration and body movement with a 3-axis accelerometer, (ii) facial recording, (iii) game screen recording, (iv) meta-information such as player skill level, game difficulty level, and game resulting score. [2] recognizes emotion detection and recognition as separate tasks. They state: (i) emotion detection aims to distinguish the segments with psychophysiological response from those without psychophysiological response. The effects of segmentation lengths and relevant signals are discussed in it. (ii) emotion recognition aims to distinguish the different emotional states related to the emotional segments. The effects of segmentation lengths and relevant features, as well as three normalization methods (standard normalization, neutral baseline referencing normalization, precedent moment referencing normalization) aiming at reducing individual variabilities are discussed in it. [4] attempts to combine facial expression analysis along with body movement analysis to detect flow in serious game applications. These were recorded using high end webcams and Kinect sensors and the analysis of two were combined using pre-trained NN models. [6] used EEG headsets in their experiment combining haptic-enabled 3- dimensional physically-based virtual environment and real-time emotion monitoring based on the users EEG. They used such recognition for rehabilitation of post-stroke patients to determine the level of stress in the exercises for physiotherapy. [3] used the emotion detection technology offered by Unity Engine used to create games. It utilized Unity's Affectiva SDK and Affdex libraries to identify emotions from facial features available in the live webcam feed while playing. [5] and [8] used explicit feedback from players like questionnaires and player performance reports

Our research aims to keep the emotion detection module subliminal in order to remove awareness of the player while playing. EEG headsets used [6] or physiological peripherals used in [2] alerts the user of his emotions being used continually while video feed used in [3] and [4] marginalizes this effect. Thus Affectiva and Affdex used in [3] seemed the most efficient approach for us.

2.4 Emotion Controlled Dynamic Difficulty Adjustment

The most basic approach to maintaining a player in the flow zone is a static progression of difficulty [3]. Progression of difficulty recognizes that a player increases their skills through practice and that challenge must then rise to maintain player engagement in the game [10]. The concept was developed to provide a better gameplay experience avoiding both frustration (too hard) or boredom (too easy) [9, 12]. Each game genre has its own way of adjusting difficulty. A puzzle games may drop a hint or reduce/increase game difficulty based on how long a player takes to resolve a puzzle. A first person shooter may analyse a player's shooting accuracy versus death ratio to evaluate player performance. For a generic game a global difficulty scale could be modified for each success and failure event in the game, increasing difficulty on success and lowering it on failure [11]. A good dynamic difficulty adjustment system should be transparent and non-intrusive to avoid detection from the player. The game risks losing immersion, or even offending the player if the player notices the game's difficulty level changing dramatically over a short period [14].

Difficulty adjustment has its applications in games for entertainment as well as serious gaming. [8] uses players experience in gaming to determine difficulty with respect to their skills and recorded flow through posing questions. The entire experiment was performed online. [6] adjusts the difficulty of a serious haptic-based game for post-stroke patients. The stress level of the patients are detected continuously using EEG headset, and the weight of the haptic device to be lifted as an exercise is adjusted according to their stress levels in combination of their performance.

2.5 Problems of EC-DDA

A. Burns and J.Tulip [3] identified a problem of EC-DDA in their experimentation. The users gradually became conscious about their emotions being used as a parameter to adjust difficulty. The users then started to mimic emotions to lower difficulty so they can progress through levels easier. According to the elements of flow proposed as 'losing track of place and time' [1] and 'losing self identity and transportation into game world' [7], the user retains reality and cannot properly attain flow. Thus, it opens the scope of research on an alternative to inducing flow in affective gaming other than EC-DDA. We attempt to propose such an alternative in this thesis.

Emotion recognition and detection in game context is an up and coming research topic for present times. Various Researchers have aimed to detect emotions through various modalities while playing games and studying their implications. EEG, ECG, EDA etc are used to obtain peripheral physiological signals for emotion analysis [2] [4]. [4] uses actors to identify multi modal affective states from raw features regarding emotions. Some researchers use facial emotion recognition techniques to identify player's emotional states [3]. The implementations of these emotion detection techniques are games that utilize these emotional values and input them as parameters into the game. This gave rise to EC-DDA (Emotion Controlled - Dynamic Difficulty Adjustment) for various applications. Player's emotions such as stress, anger and frustration are used to identify if the difficulty is too high for them and thus adjusts it dynamically. These have applications in serious games like haptic rehabilitation, physiotherapy etc. [6] [13]. They also have applications in ensuring proper game engagement of players to maximize enjoyment and utility [9] [11] [12]. The metric of player engagement is set by the flow theory [1]. Flow is generically discussed as the measure of skill level compared to the difficulty of challenge such that the players can enjoy maximum fulfillment [1] [10]. Researchers then used these concepts to be applied into game contexts to find elements of flow that should be present in games to induce maximum engagement among players as to taking them to a 'flow state' [7] [18] [19] [20].

3 Proposed Methodology

We have already established in 2.5 that immersion will break if emotions can change difficulty. This leads us to our proposed approach of using emotions to dynamically determine the type of content the game offers. This will not directly alter the difficulty of the game so the player is not rewarded in any meaningful way from exaggerating their expressions. We aim towards a system where emotion input will be used to alter the next part of the game and the player will not be aware of how this is being done. From the 7 emotions that Affectiva can identify as we will discuss in 3.1, we have selected 3 emotions based on accuracy, contrast and feasibility. The emotions we have selected are Joy, Disgust and Sadness. These are the three emotional states we will be working with in our approach.

Our proposed methodology can be broken down into the following stages:

1. Categorising videos and video games according to the type of emotional response they trigger.

2. Using the categorised videos to trigger specific emotional states in individuals.

3. At each emotional state we have the individual play a categorised game that triggers each relevant emotion. This transition of emotional states is needed to obtain a mapping of each emotional state to every other emotion.

4. Have the individual answer a GEQ and obtain scores for level of engagement after each test.

5. Analyse these scores and determine a correlation between the state transitions and engagement scores.

3.1 Emotion detection using Affectiva

Details of Affectiva have been collected from their website[15]. Affectiva can provide output in the form of 7 emotion metrics and 20 facial expression metrics.Furthermore, the SDK allows for measuring valence and engagement. Affectiva uses the area under a Receiver Operating Characteristic (ROC) curve to report detector accuracy. The ROC score values range between 0 and 1 and the closer the value to 1 the more accurate the classifier is. The classifiers for emotions have ROC scores greater than or equal to 0.8. It has a higher accuracy for joy, disgust, contempt and surprise. Anger, sadness and fear are harder to detect and have lower accuracy. Affectiva uses deep learning to solve problems for tasks that they address which include face detection and tracking and emotion classification. The deep learning architecture they use include CNN, RNN, LSTM and CNN + RNN nets.

3.2 Emotion Elicitation

We used excerpts from publicised films to elicit emotional states in individuals. This approach has been used in [17]. The clips collected are all 3-5 minutes in length and collected from YouTube.

3.3 Game Engagement Questionnaire(GEQ)

The questionnaire contains 19 questions. The Rasch model is implemented for these questions. The questions have weights according to their assigned difficulty. The responses to each question are Yes, Maybe and No. For our purpose we have assigned No to Yes as 1 to 5, with 3 being Maybe and 2 and 4 being the values in between.

In 3.3 we can see how weights are assigned to the question responses according to the difficulty of the question. On the x-axis we have the score for each response. From top to bottom the difficulty of the questions decreases and the response weights gradually shift to the left. We can see the question with highest difficulty "I feel scared" has a minimum score of 0.83 for No and a maximum of 4.17 for Yes. In contrast the easiest question, "i really get into the game", has a minimum score of for -3.5 No and a maximum score of -0.17 for Yes. The maximum score obtainable from this questionnaire is 31.5, and the minimum score is -31.5. From this result we applied min-max normalisation to get an engagement score in the range 0 to 1.

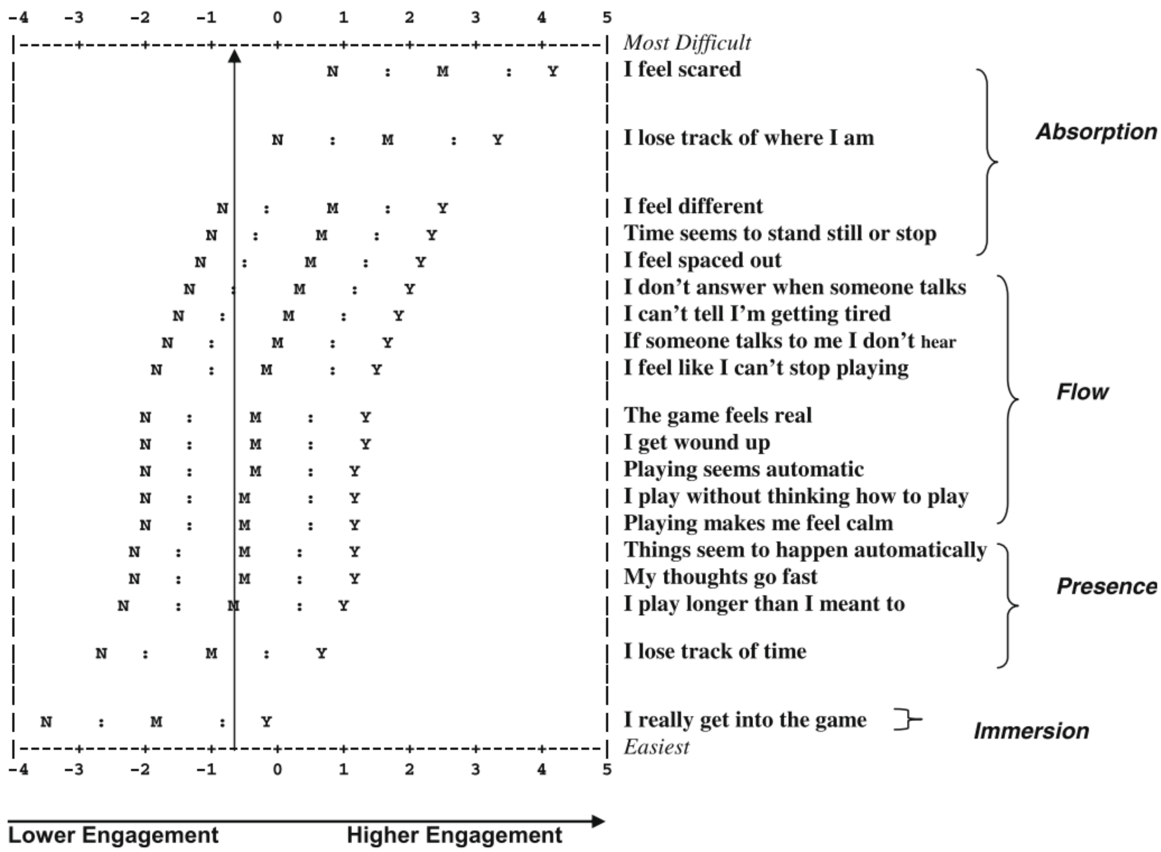

Figure 3: GEQ using Rasch model to assign weights to questions[16].

3.4 Storage and analysis of results

We stored all results in CSV files. For the first phase of our experiment to categorize videos and games, we stored individual values for each emotion with each row representing a frame and columns representing the three emotions we worked with. In the second phase of our experiment we stored the individual responses to the 19 GEQ questions along with the flow score and min-max normalized scores for every participant.

We used Matlab to generate analysis and graphs from these CSV files to study our result.

4 Experimental Design

4.1 Overview

The experimentation was divided into two phases. (i) The first phase dealt with obtaining videos to elicit emotions[17] among the players and the emotionally differentiated games to be played by the users. In this stage we made participants watch videos and play games that were attached with Unity Affectiva that recorded their emotional responses. Affectiva provides each emotion score from 0 to 100 based on the intensity of the emotion felt. The average response from all our participants gave us the validation of our videos and games eliciting different emotional responses from our participants. (ii) The second phase involved players watching a video from our above categorized videos of every specific emotion followed by playing a game of every emotional content. We measured their flow to identify the correlation between emotional state of players and game content towards achieving flow.

We used a standard gaming pc with the following configurations: Processor: AMD Rizen 51600 Ram: 16 GB GPU: NVIDIA GTX 1050ti

The games were played using controllers.

- The videos of the three emotions are described as follows.

    1. The videos for were from the movie 'Home Alone' and two clips from episodes of 'Mr. Bean'.
    2. The videos disgust were clips taken from different sequels of SAW, with gore-filled instances.
    3. The videos for sadness were taken from an ad of metlife insurance, a clip from the movie Hachiko and a video containing police brutality.

- The games for the three emotions were:

    1. 'Trover Saves the Universe' for Joy made by the creators of 'Rick and Morty'

2. 'Mortal Kombat XL'was used for disgust since it contained many scenes with gore fighting.
3. 'Limbo' was used for sadness as it was a game with a gloom environment as well as a sad storyline.

4.2 Categorizing Videos and Games according to the emotions they induce

We designed a tool in Unity to detect and record emotional responses to the three emotions (Joy, Disgust, Sadness) we selected in section 3. We selected 3 videos and 1 game for each emotion.

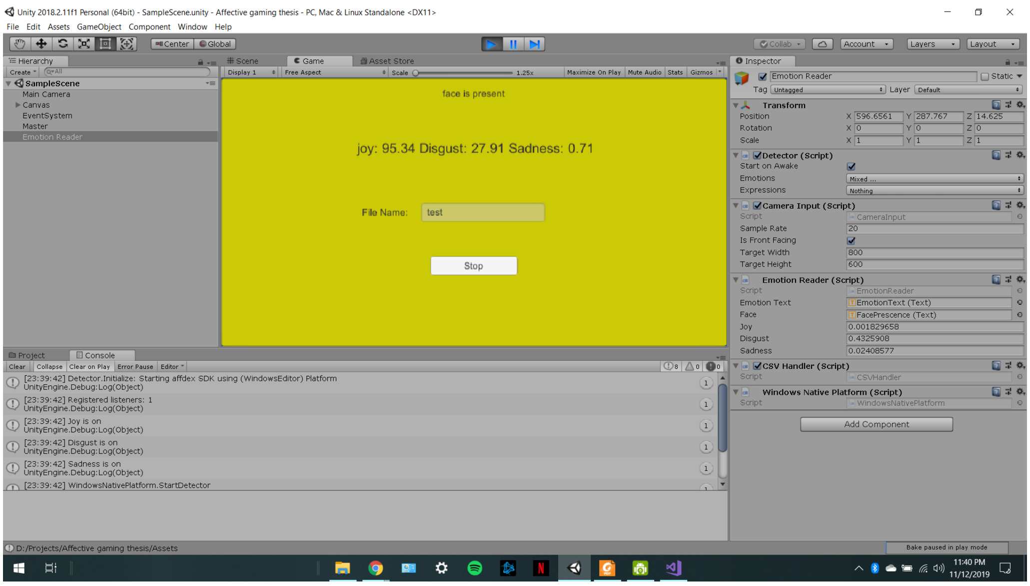

Figure 4: Emotion Reader Made in Unity

- The videos were of movie clips taken from YouTube.

1. **Videos for Joy:** "Home Alone (1990) - Thirsty for More? Scene (4/5) — Movieclips", "Fast Food — Funny Clip — Classic Mr. Bean", and "Fast Food — Funny Clip — Classic Mr. Bean" (0:00 - 3:02).
2. **Videos for Disgust:** "Saw VI (1/9) Movie CLIP - A Pound of Flesh (2009) HD", "Saw: The Final Chapter (6/9) Movie CLIP - Speak No Evil (2010) HD" and "Saw (1-7) Deaths in Correct Order" (1:05 - 4:14).

3. **Videos for Sadness:** "My dad's story - Dream for My Child — MetLife", "HACHIKO- Try not to cry" and "Disturbing video shows unarmed man begging before fatal police shooting"

- The games for corresponding emotions were downloaded from publicly available platforms.

  1. **Game for Joy:** "Trover Saves the universe"
  2. **Game for Disgust:** "Mortal Kombat XL"
  3. **Game for Sadness:** "Limbo"

The videos were watched full-length or for the time specified. The games were played on a desktop computer using controller for 5 mins. approximately. The emotional responses for every frame were recorded in respective CSV files. The maximum value among the average values of the responses was used to categorize the video to be eliciting that specific emotion i.e, the video having maximum average response for joy was categorized as a joy inducing video. Likewise, we stratified the games according to emotion.

4.3 Measuring flow for different mappings of Videos to games

We made 18 participants take part in this experiment. Each participant had to watch a video from a certain class and then play a game from one of the classes. This concluded one iteration. So players had to go through nine iterations of the experiment, e.g - 'Joy video, Joy game', 'Joy video, Disgust game', 'Joy video, Sadness game' and so on.

After each iteration, the participants had to answer the GEQ(Game Engagement Questionnaire) explained in 3 which generated a score of flow for each emotion. This way we obtained a mapping for how players engaged with different games provided a particular emotional state.

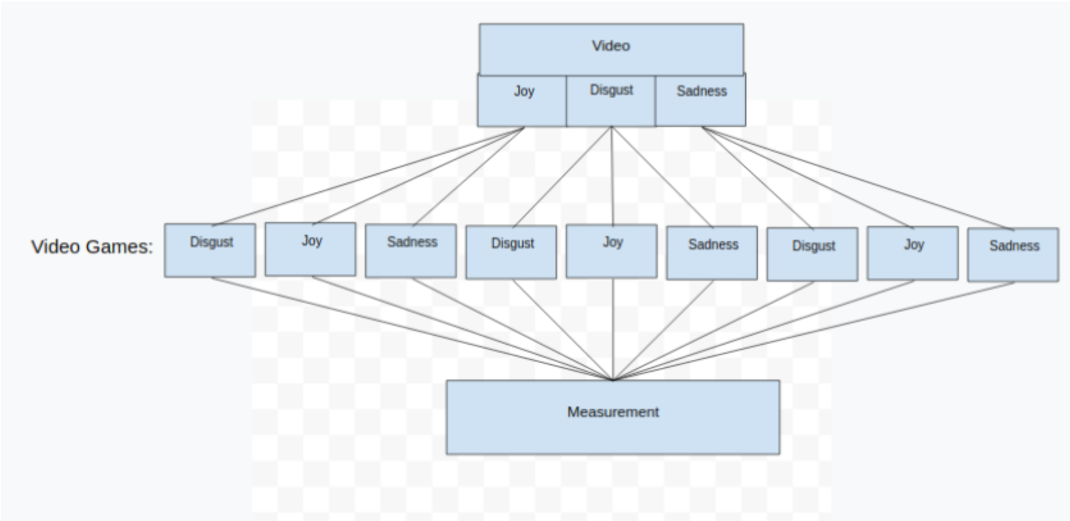

Figure 5: Experimental Architecture for Phase -2

5 Results & Discussion

5.1 Phase - 1

We obtained the average response for each emotion in every video. The emotion with highest average response for a specific video was identified as the emotional state reached after watching the specific video.

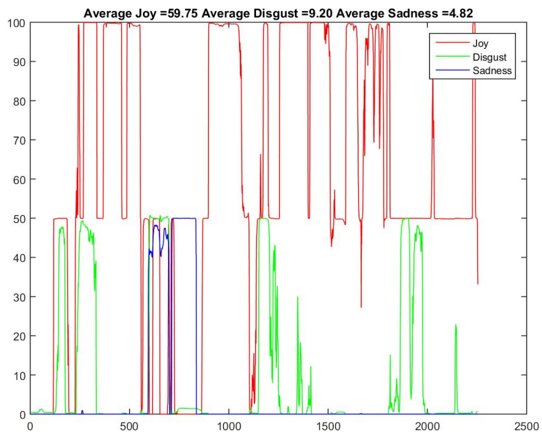

Figure 6: Average reading for each emotion for a joy inducing video

Videos mentioned in 3 having similar responses as 5.1 were categorized as joy inducing videos. The videos had average values of joy as 59.75, 59.82 and 53..95 respectively.

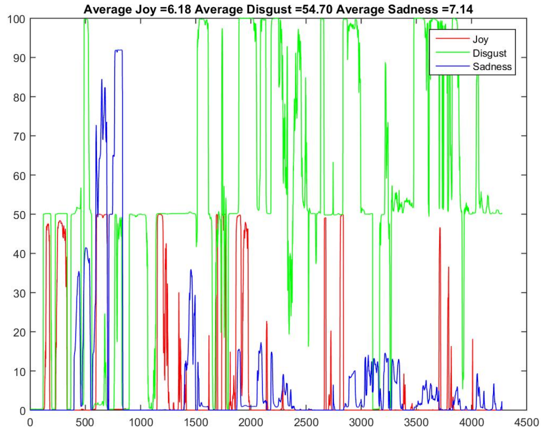

Figure 7: Average reading for each emotion for a disgust inducing video

Videos mentioned in 3 having similar responses as 5.1 were categorized as disgust inducing videos. The videos had average values of joy as 54.70, 33.70 and 36.92 respectively.

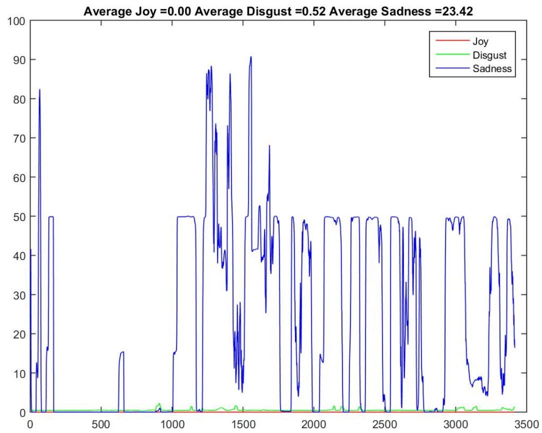

Figure 8: Average reading for each emotion for a sadness inducing video

Videos mentioned in 3 having similar responses as 5.1 were categorized as sadness inducing videos. The videos had average values of joy as 23.42, 9.29 and 18.92 respectively.

Similarly we took average responses for games and selected 3 games which induce joy, disgust and sadness respectively.

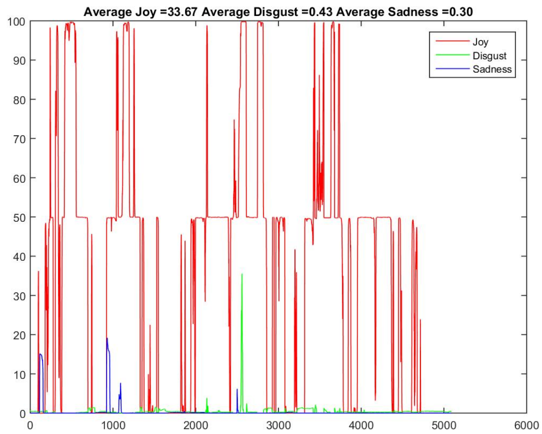

Figure 9: Average reading for each emotion for 'Trover Saves the Universe' game

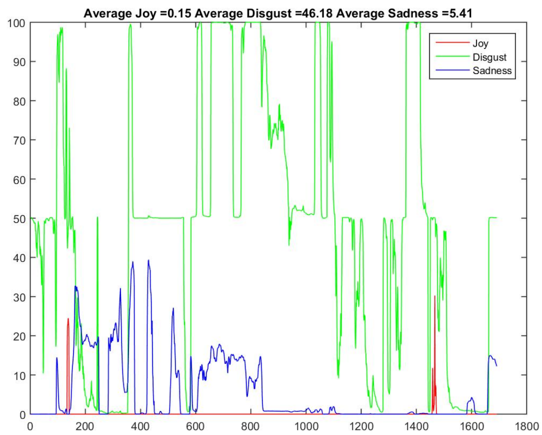

Figure 10: Average reading for each emotion for 'Mortal Kombat XL' game

The average readings for each game are given in the above figures. The games were selected to induce the mentioned emotions among the players.

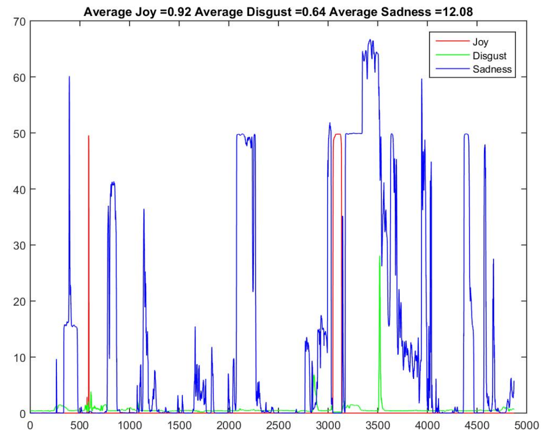

Figure 11: Average reading for each emotion for 'Limbo' game

5.2 Phase - 2

The Phase - 2 experimentation gave us flow readings of 18 participants each watching videos of one emotion followed by playing games that induce every emotion. The results are analyzed below.

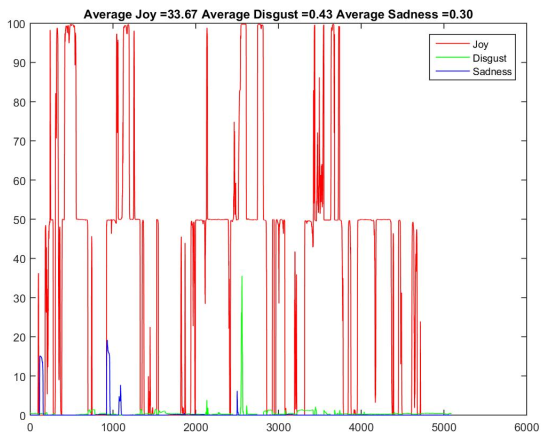

Figure 12: Average Flow Readings for Different Games at Joy state

5.2 depicts the average flow readings for every participant watching a joy video to induce emotional state and then playing games of every emotion. The analysis shows that joy game has higher values for flow. But sadness also has close value which means some amount of flow is also induced by sad game content at joy state.

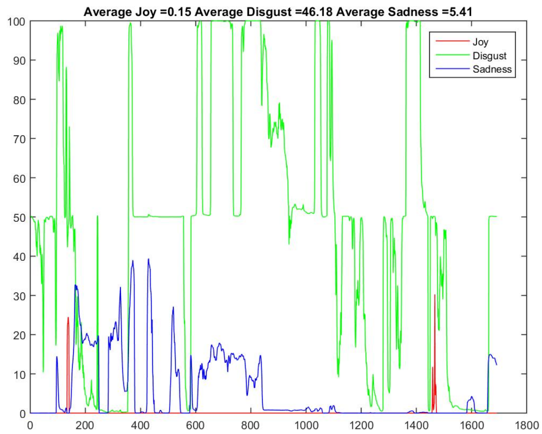

Figure 13: Average Flow Readings for Different Games at Disgust state

5.2 depicts the average flow readings for every participant watching a disgust video to induce emotional state and then playing games of every emotion. The analysis shows that joy game has higher values for flow.

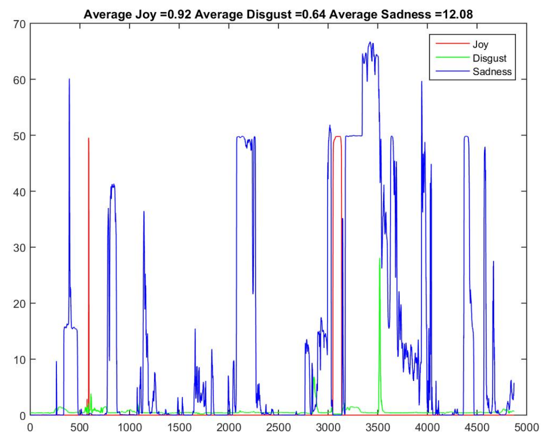

Figure 14: Average Flow Readings for Different Games at Sadness state

5.2 depicts the average flow readings for every participant watching a sadness video to induce emotional state and then playing games of every emotion. The analysis shows that sadness game has higher values for flow.

Players' Emotional State	Emotion induced by game		
	Joy	Disgust	Sadness
Joy	13.43518519	-8.518518333	8.018518519
Disgust	16.61111296	-3.962962778	-11.53703519
Sadness	-2.851851852	-17.74074259	20.86111111

Table 1: Average Values of Flow for each iteration of experimentation

5.3 Analysis

We collect all the flow readings and form the following mapping table where each cell(i,j) represents the flow score for playing a j-inducing affective game while at i emotional state.

From the table and graphical representation of results we see that people at **joy** state enjoy playing games that induce more joy in them. They also like games with sadness influenced since its flow score is closer to that of joy. Players at **disgust** state also have higher flow score for playing joy inducing games. Players who are at a **sad** state have higher flow scores for games that induce further sadness.

6 Conclusion and future works

We had some limitations in our research which can be improved to establish the legitimacy of our idea.

- In terms of emotion recognition techniques we chose to rely on affectiva SDK, so the limitations of affectiva became our limitations. It can detect 7 limited emotions of which only 4 are detected effectively.
- We managed to use 3 emotions in our experimental framework. Incorporation of more emtotions can give a more reliable and accurate mapping.
- We used three different games for testing users' flow reading. But flow depends on the game design, playing mechanics etc. as well. So some amount of bias due to the variety of games is observed. This can be overcome by designing emotional modules of the same game where the design and mechanics factors along with storyline will be consistent.

We hope to extend on our research in the future by performing it in ideal situations with a more efficient emotion detection method and keeping the game contents consistent by designing all the modules by ourselves. In the extension, we can be able to incorporate a wider range of emotions to encompass a more detailed mapping table.

With these research we claim to answer our two research questions.

- Games with different emotional contents asymmetrically affected the flow of a player in same emotional state. Thus, we prove that Emotion Controlled Dynamic Content Adjustment (EC-DCA) can be used to induce flow.
- We provide a mapping table which shows what game content induces most flow among players who are at a given emotional state. e.g - when players are at a state of joy, the most engaged by games that trigger further joy (flow average: 13.35)

The implications of this thesis can be used by game developers to design affective games where players emotions are recorded and they progress through levels that elicit the emotion that are most likely to induce higher flow.

Emotion Controlled Dynamic Content Adjustment can be an interesting scope for research both in fields of serious games and games intended for entertainment purposes. The induction of flow from EC-DCA increase player engagement which ultimately enhances players utility from the game, be it rehabilitation in serious contexts or purely entertainment.

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