ETNA: a Virtual Reality Game with Affective Dynamic Difficulty Adjustment based on Skin Conductance

BY

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THESIS

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LIST OF ABBREVIATIONS

DDA	Dynamic Difficulty Adjustment
EDA	Electrodermal Activity
ER-SCRs	Event-Related Skin Conductance Responses
EVL	Electronic Visualization Laboratory
GSR	Galvanic Skin Response
HMD	Head Mounted Display
HR	Heart Rate
NS-SCRs	Non-Specific Skin Conductance Responses
SC	Skin Conductance
SCL	Skin Conductance Level
SCRs	Skin Conductance Responses
SVM	Support Vector Machine
UIC	University of Illinois at Chicago
VR	Virtual Reality

SUMMARY

The gaming industry is growing year after year, but one of the main problems that most developers have is how to address the right difficulty of a game to satisfy all the players that have different skills and different attitudes toward the game. The most used method to achieve this goal is the performance-based dynamic difficulty adjustment (DDA), i.e. modifying the difficulty of the game according to the player's score. Often, it is not enough to rely only on the score to adjust the game's difficulty. It is important to consider the emotional state of the person because each player is different and can enjoy playing the game in different ways. This is why affective-based DDA methods should be considered to adjust the difficulty of a game. Moreover, thanks to Virtual Reality, people can do physical exercises while playing the game and motivating them by implementing the best DDA method is even more important.

In this thesis I first discuss the performance-based and affective-based methods implemented in other games and researches, and the background theory related to flow, arousal, and skin conductance. Then, a Virtual Reality game called ETNA (Entertaining Training Neuro Affective) has been developed in 3 variants, one implementing a performance-based only DDA, one implementing an affective-based DDA only, and one implementing a mixed perfo-affective DDA, with both of them active at the same time. A user study was conducted and the results showed that affective gaming can be implemented in Virtual Reality to improve the overall gaming experience. Moreover, the perfo-affective method was the one which obtained the best results.

CHAPTER 1

INTRODUCTION

The video game industry is growing year after year and is the 4th largest entertainment market in the world behind gambling, reading, and TV and exceeds movies and music in popularity. In 2016 it generated globally around US$101.1 billion and is expected to arrive to US$128.5 billion by 2020 [2][3].

In the last 10 years, some big companies like Microsoft with Kinect and Nintendo with Wii have improved the interactivity between the player and the game by including gamer movement, opening a lot of new possible uses of video games. One of the most important improvements is the possibility of doing physical activity while playing the game, that was one of the greatest weakness of traditional gaming that requires the player stay in his seat without moving for hours.

Recently the interactivity between the player and the video game has improved even more thanks to virtual reality. With virtual reality the player can fully immerse himself into the virtual world while moving also across a predefined zone. Therefore, virtual reality can be used also to make physical activity and exercises less tedious both for casual and medical uses [4].

To exploit all the strengths of virtual reality and to be really entertaining, a video game should be neither too easy nor too hard and this is not a simple problem to solve in game design.

1.1 Problem Definition

As said before, one of the most challenging problem in game design is how to address the right difficulty in the game to entertain the player and let him feel always challenged and not bored (game too easy) or frustrated (game too difficult). There are two main methods that are used for changing the level of difficulty of a video game: through *difficulty selection* and with *dynamic difficulty adjustment* (DDA).

The most commercially used solution to solve this problem is the method of *difficulty selection*: the player can choose the level of difficulty while playing the game between some predefined values (e.g. easy, medium, hard). This one is the easiest to develop because the choice relies only on the player but it is less efficient because the level of difficulty does not adapt automatically to the player's skill level or physical state.

A more efficient way to do it is with *dynamic difficulty adjustment.* This can be done mainly in two ways: performance-based and affective-based. Both of them introduce non-trivial game design issues. The performance-based method changes the game at run-time according to the player's capabilities, while the affective-based one changes it according to physiological parameters, such as skin conductance (SC), heart rate (HR), facial recognition, etc.

For the affective-based method skin conductance will be used to evaluate the arousal of the player during the game and try to adjust it to reach the optimal arousal level. This optimal level is not fixed, changes from person to person, and also from task to task.

1.2 Objective

This thesis will be focused on implementing dynamic difficulty adjustment to change at run-time the difficulty of a virtual reality (VR) game in both ways: based on the performance of the player and based on the affective state of the player. For this thesis a VR game called ETNA (Entertaining Training Neuro Affective) was created in three versions: one implementing a performance-based only DDA, one implementing an affective-based DDA only, and one implementing a mixed perfo-affective DDA, with both of them active at the same time. The affective part was done using skin conductance values collected through an external commercial device, MindLAB Set[1]. In my research, I only collected skin conductance in the affective-based DDA as it is one of the less intrusive physiological signals to measure. Its levels are related to the arousal of a person and rise with the increasing of the difficulty of given tasks [5]. Therefore, the objectives of the thesis are: a) creating an efficient affective-based DDA based on skin conductance and b) seeing which method gives the best results in a VR Game.

1.3 Thesis Overview

Chapter 2 gives to the reader general background knowledge about psychophysiology, arousal, the concept of flow, and skin conductance, and how all of them are related to each other.
In *Chapter 3* related researches is discussed in the field of dynamic difficulty adjustment, in the use of skin conductance in games, and in the rationale of using virtual reality to achieve the optimal flow.

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[1]http://www.psychotech.it/pages/en/mindlab-set.php

Chapter 4 explains in details the game developed for the thesis, called *ETNA* (*Entertaining Training Neuro Affective*), focusing on how performance-based and affective-based DDA have been implemented.

In *Chapter 5* I discuss how the user study has been conducted and the results that can be deduced from it, coupling the survey data with the in-game data.

Finally, *Chapter 6* is a summary of the work and the results gathered from the user study.

CHAPTER 2

BACKGROUND KNOWLEDGE

In this chapter I am going to talk about all the information needed to fully understand the thesis work. Starting from the psychological theories related to emotions through the application of them in the game design process to adjust game difficulty.

2.1 Psychophysiology

Psychophysiology is the branch of psychology which focuses on the biological processes that happen inside our body and how they are influenced from internal and external stimuli. Its primary aim is to explore how the mind and body interact [6]. Some of the strongest concepts related to psychophysiology are the theories of emotions.

2.1.1 Emotions

Emotions play a crucial role in our lives, we use them mainly in three areas: intrapersonal (within each of us individually), interpersonal (between individuals in a group) and social-cultural (in the maintenance of social order within a society) [7].

There are several theories of emotion classification that range from a discrete approach to a dimensional one. The most used is the circumplex model of emotion developed by James Russell [8] that classifies emotions into two components: valence and arousal (Figure 1).

Valence (horizontal axis) is related to how positive an emotion is: positive emotions have high valence, like happiness, while negative emotions have low valence, such as sadness. Arousal (ver-

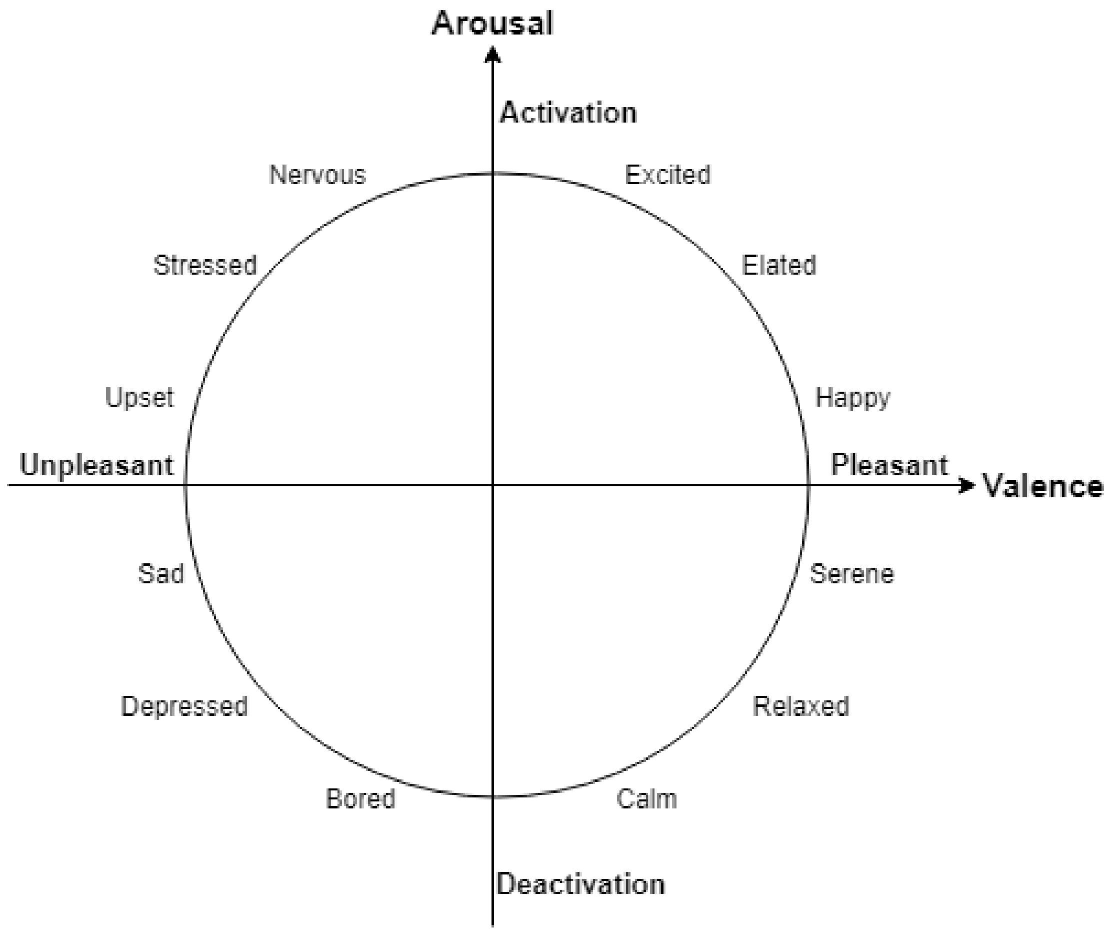


Figure 1: Circumplex model

tical axis) is related to the intensity of an emotion: low intensity corresponds to low arousal, like calmness, high intensity corresponds to high arousal, such as excitement. Different combinations of arousal and valence generate different emotions.

In the recent years a lot of research has been focused on how to recognize and evaluate changes in the emotional state through physiological changes of the human body. The changes can be external, such as facial expression, or internal, like heart rate (HR) or skin conductance (SC). These physiological manifestations of emotion are triggered by the autonomic nervous system, the component of the nervous system which governs the unconscious activities of the body [9]. So to evaluate an emotion, it is possible to measure the physiological changes in the body. Some of them give information only about the arousal of a person, like HR and SC, while some others tell only about the valence, like the facial expression. One of the most used physiological parameters concerning arousal is the electrodermal activity (EDA), in the past called also Galvainc Skin Response (GSR). More precisely, the most used and widely studied EDA property is skin conductance [10].

2.1.2 Skin Conductance

Skin conductance is a measure of how electrically conductive the skin is. It can be measured by passing a small electrical current through the skin and is directly related to the arousal of a person. It is probably the most useful indicator of arousal because people can't explicitly control their skin conductance levels and it is not affected by other body functions (like heart rate). Skin conductance is also a good indicator of cognitive activity [11] and is used also to recognize the player's emotion during interaction with video games [12].

Historically, research in the field of skin conductance began in 1849 when Dubois-Reymond in Germany noticed that human skin was electrically active. Around 30 years later, in 1878, in Switzerland, Hermann and Luchsinger found a correlation between sweat gland activity and electrical current in the skin [13].

How does skin conductance work? The skin is the principal interface between ourselves as an organism and the environment. It is extremely important for actions related to our body like regulating the immune system (protective barrier), thermo-regulation and is really important in the maintenance of the body's water balance. Temperature and water regulation are done thanks to the production of sweat that is regulated by the sweat glands. There are two types of sweat glands: the eccrine and the apocrine. The relevant one concerning skin conductance are the eccrine sweat glands. Their quantity varies across the body but the greatest number can be found on the palms, fingers, and on the sole of the feet. When those glands are triggered, they secrete moisture through skin's pores. Since the proportion of ions in the produced fluid changes, the skin conductance value changes accordingly. The most interesting fact is that even if the primary purpose of sweat emission is the regulation of body temperature, sweat is also triggered whenever we are emotionally aroused and responds more to those stimuli than to the thermal ones. That happens because sweat secretion is driven and balanced by our autonomic nervous system, specifically by the sympathetic nervous system [14].

The skin conductance signal is made up of two major components: tonic (related to the slower changes of the signal) and phasic (related to the faster changes). The most common measure of the tonic level is the skin conductance level (SCL) and it reflects changes in the arousal of subjects. The phasic refers to the skin conductance responses (SCRs) that can be event related (ER-SCRs, attributed to a specific eliciting stimuli) or non specific (NS-SCRs, that occur in the absence of an identifiable eliciting stimuli) (Figure 2) [10].

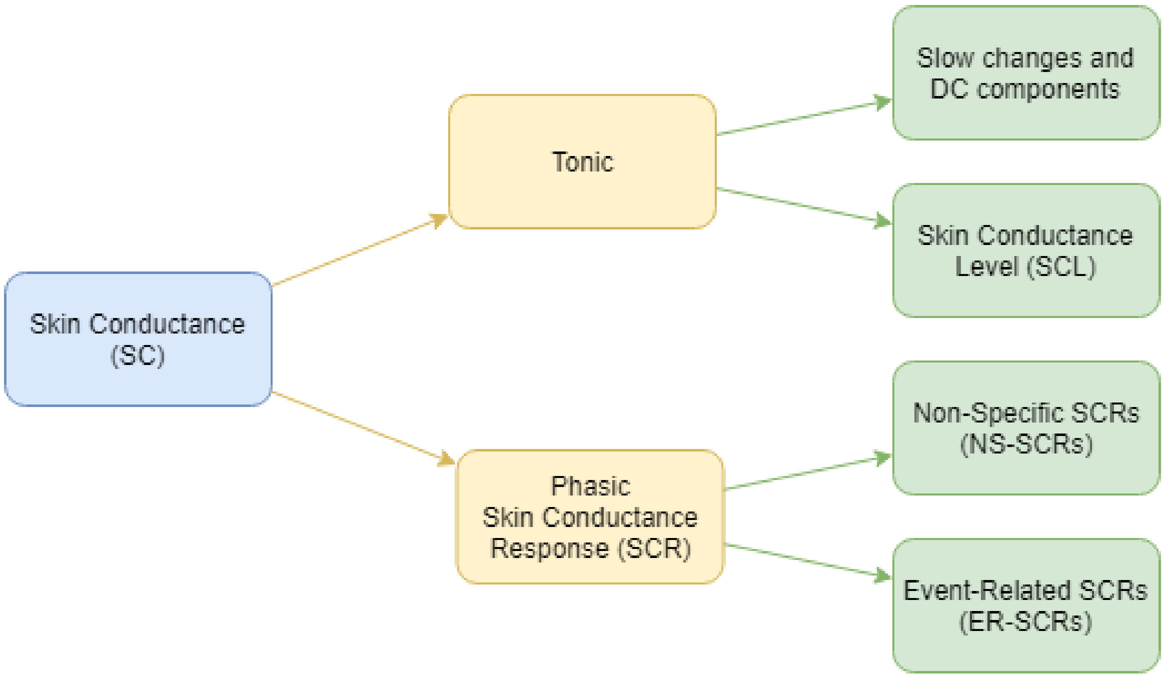


Figure 2: Skin Conductance components diagram

If the research aim is to identify responses to a particular stimuli (like an image) the component to measure is SCRs (precisely ER-SCRs). If the aim is to measure the physiological arousal over an extended period of time, the most appropriate component to measure is the SCL.

The reader can have a better comprehension of these two main components looking at Figure 3. The black curve is the SCR, with the peaks in the white rectangles (fast changes) and the blue line is the SCL (slow changes).

Researches supporting the use of skin conductance to evaluate arousal while playing video games will be discussed in section 3.2.

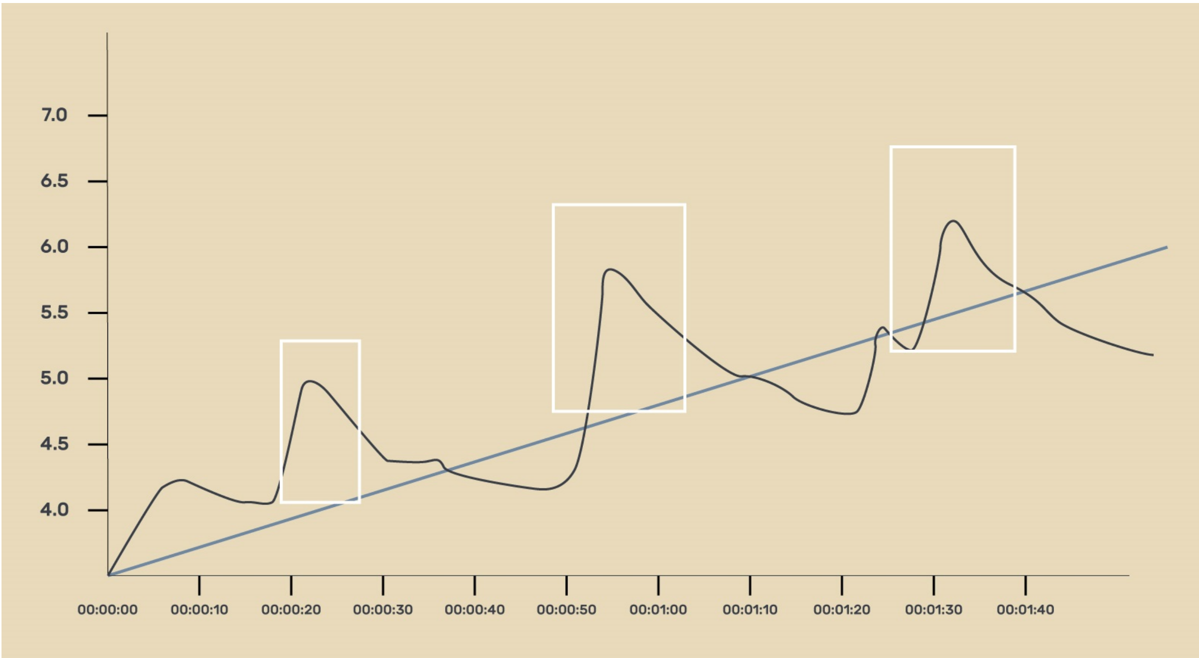


Figure 3: Skin Conductance plot example

2.2 Arousal Theory, Yerkes-Dodson Law, and Flow

The arousal theory of motivation affirms that the main reason people do any action is to keep an optimal level of physiological arousal and this optimal level differ between individuals [15]. If our arousal is too low then we are going to be motivated to engage in behaviours that will increase arousal and if our arousal is too high then we will be motivated to engage in behaviours that will help to reduce our arousal level.

We can think also about how our level of arousal is associated with our performance on different tasks and this brings us to the Yerkes-Dodson Law [16]. The idea of this law is that we have peak performance at a particular, optimal, level of arousal. Whether arousal is too low or too high both will result in impaired performance, following an inverted U-model (Figure 4).

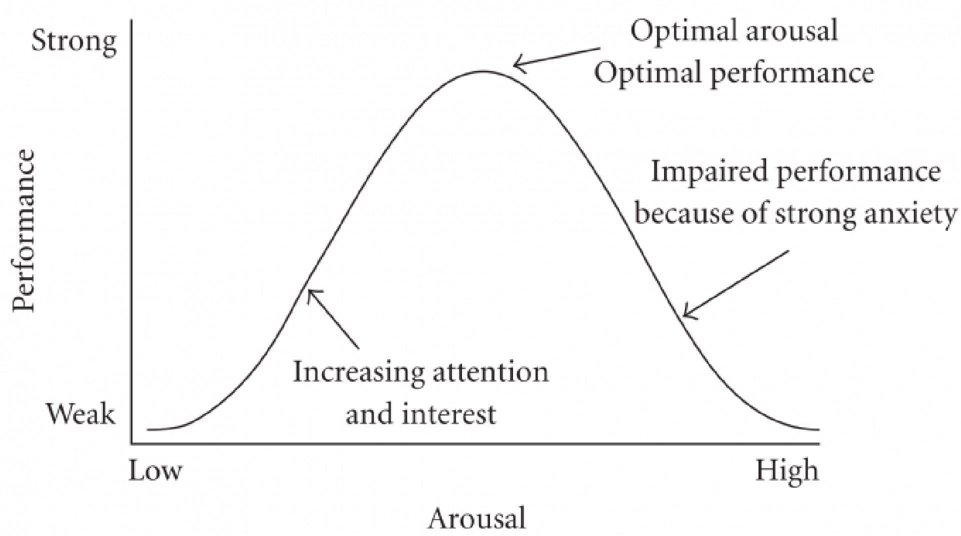


Figure 4: Yerkes-Dodson Law [1]

All of this leads to the "flow", which is the sense of full and motivated concentration in a task, with a great level of fun, satisfaction and productivity. It was coined by the Hungarian psychologist Csikszentmihalyi that identified eight main components necessary to achieve flow [17]:

- "A challenging activity requiring skill"
- "A merging of action and awareness"
- "Clear goals"
- "Direct and immediate feedback"
- "Concentration on the task at hand"
- "A sense of control"
- "A loss of self-consciousness"
- "An altered sense of time"

The concept of flow can be represented on a chart with the skill level of a person along one axis and the difficulty of a task along the other one (Figure 5). If the challenge is greater than the skills of a person, the task becomes too difficult and it causes frustration. If it is too low and does not engage the player, he loses interest and becomes bored. The optimal zone usually stays in the middle and is called "Flow Zone". The design of any interactive experience, like videogames, is centered on how to maintain people inside the "Flow Zone" while they are playing. The game must adapt its difficulty level to reflect the correct balance of challenge and ability and therefore maintain players in the "Flow Zone". But as the size of the audience

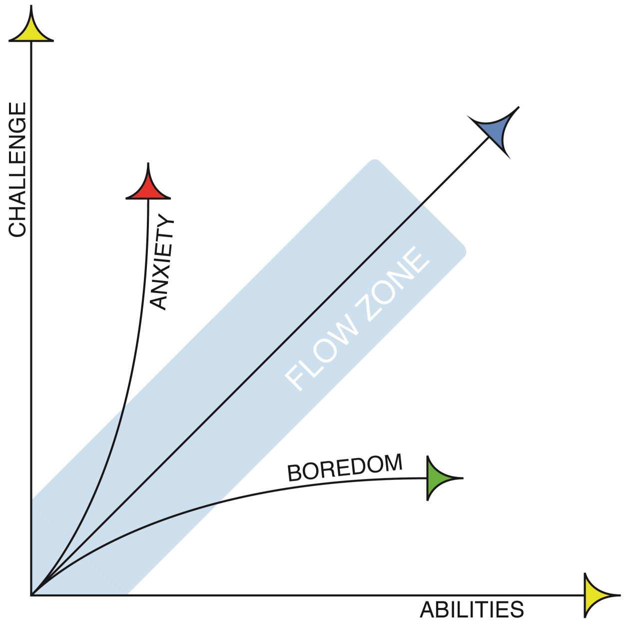


Figure 5: Flow zone factors

increases, designing such a balance becomes a more difficult task because players can have different approaches to the game (Figure 6) [17]. Hardcore players are the category of people who like to play games where the difficulty is a little bit higher than their skill level, while novices are the ones who like to be in control of the game and so they want to maintain their skill level a little bit higher than the difficulty of the game.

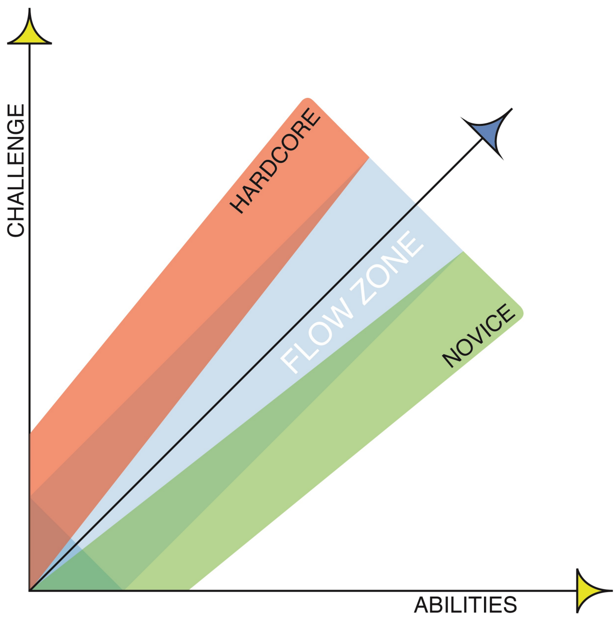


Figure 6: Different Flow Zones per player

There are two main ways to solve this problem: with active flow adjustment or passive flow adjustment. The simplest is the active flow adjustment, through which are provided different in-game choices to the players, so that the game can adapt to the single player's game style (Figure 7).

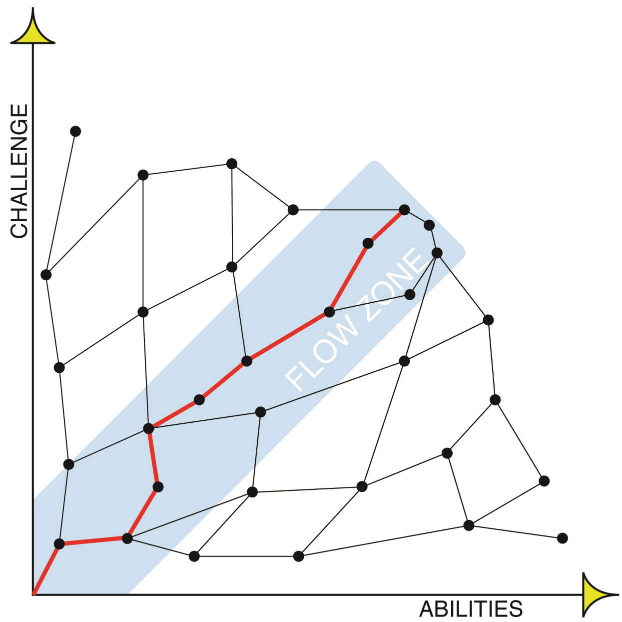


Figure 7: Players' Flow adaptation through in-game choices

In better approaches (passive flow adjustment), the game should adapt dynamically and automatically to each users' personal Flow Zone. All of this is achieved using DDA methods that generate a feedback loop between the player and the game to tailor the experience on him. Different approaches to achieve this are discussed in section 3.1.

2.3 Affective Gaming

Why we play video games? There can be many different answers to this questions: because we want to have fun, to challenge ourselves, to get excited, and so on. All of those answer have a common thread: emotions. We want to play video games (or games in general) because they can induce in us some emotions. They can sometimes be good, like excitement, and sometimes bad, like frustration because the game is too difficult. But usually games do not respond to the players' emotion, they only respond to the user input from the game controller, there is no feedback, no loop. Researchers in the affective gaming field want to fill this gap adding an emotional intelligence in the video game [18] [19]. In order to do that, first it is necessary to collect some physiological parameters of the person with some devices, then the game should be able to sense and understand the player's emotions to modify itself according to them. Concerning the first part, there are many different physiological signals that can be considered, such as skin conductance, heart rate, respiration, face recognition, blood pressure, electromyogram, pupil tracking and so on. Some approaches have also focused on studying the correlation between the difficulty of a game and the intensity with which the player presses the buttons [20]. For the second part, there are three main ways a game can be influenced by affective parameters (and so it becomes an affective game):

- *Assist me*: measuring frustration of the player and combining it with information from the game context, it is possible to understand when a player is stuck somewhere and is not enjoying the game as they should (e.g. does not know where to go or how to kill a boss). When a situation like this is recognized, the game can provide clues to the player to help them and let them enjoy the experience more.

- *Emote me*: providing a full and effective emotional experience to the players, measuring their emotional state and modifying the game content to induce again the expected emotions.
- *Challenge me*: is essentially the application of the theory of flow with affective-based DDA, the major focus of this thesis. The player's engagement in a game is measured through his arousal level and this can be used to change in a dynamic way the difficulty of the game to let the player stay inside their personal optimal flow zone. This will be discussed more deeply in section 3.1.3.

Not all the games are suited to be affective games. For example, genres like role-playing and strategy usually last for a longer time and are played slower, so it is very difficult to notice relevant changes of physiological parameters throughout the gameplay.

One of the most important features in affective games is that physiological responses from the player should not be controlled. If the player can control and consciously manipulate his physiological parameters as a means of interaction, the game becomes a biofeedback game.

An example of a biofeedback game is *Relax-To-Win* [21], a competitive racing game where two players control a dragon and their objective is to arrive first to the end of the level. SC is evaluated to see how much a player is relaxed. The more relaxed the player is, the faster his dragon moves. In this way the players use their biofeedback as an additional input to the game and have to control it in order to win the game.

However, biofeedback games are not the focus of this research.

CHAPTER 3

STATE OF THE ART

In this chapter I am first going to describe the current methods for adjusting the difficulty of games, also providing examples of commercially available games or made for research purposes that adopted those methods. Then I will talk about the research that supports my choice to use the skin conductance as a physiological parameter to evaluate during a game experience. In the last section, I will discuss similar research done in the field of virtual reality games and why it should be better than normal non-VR gaming.

3.1 Changing difficulty in games

The entertaining level of a video game is strongly based on the difficulty of it related to the skill of the player and to the attitude of the player toward the game. In order to be really entertaining, a video game should be neither too easy nor too hard for the player and this is not a simple problem to solve in game design. There are two main methods that are used for changing the level of difficulty of a video game: through *difficulty selection* and with *dynamic difficulty adjustment* (DDA).

3.1.1 Difficulty Selection

As said before, one of the most challenging problems in game design is how to address the right difficulty in the game to entertain the player and let him always feel challenged and not bored (game too easy) or frustrated (game too difficult). The player should be in his optimal flow zone, with the optimal arousal level.

The most used solution to solve this problem is the method of *difficulty selection*. The player can choose the level of difficulty while playing the game between some predefined values (e.g. easy, medium, hard). This one is the easiest to develop because the choice relies only on the player but it is not so efficient because it does not adapt automatically to the player's skill level or physical state.

An example of this approach can be found in almost all of the commercial games. In the soccer game *FIFA* you can change the difficulty of a match when it starts between 5 values and you cannot change it during the match. In the RPG *The Elder Scrolls V: Skyrim* you can change the difficulty of the game too (between 6 values), but at a certain point your skills and your character can become so strong that you will be bored even playing with the strongest difficulty (Figure 8).

In *Grand Theft Auto* or *The Sims* you can use cheat codes to ease the game and increase the fun.

A more efficient way to achieve a better balance between challenge and player's skills that leads to optimal flow is with dynamic difficulty adjustment. This can be done mainly in two ways: performance-based and affective-based. Both of them introduce non-trivial game design issues.

3.1.2 Performance-Based DDA

Performance-based DDA changes the game at run-time according to the player's capabilities. According to a study conducted by Bailey and Katchabaw [22], the most important thing to focus on when developing a performance-based DDA is to recognize what adjustments to make

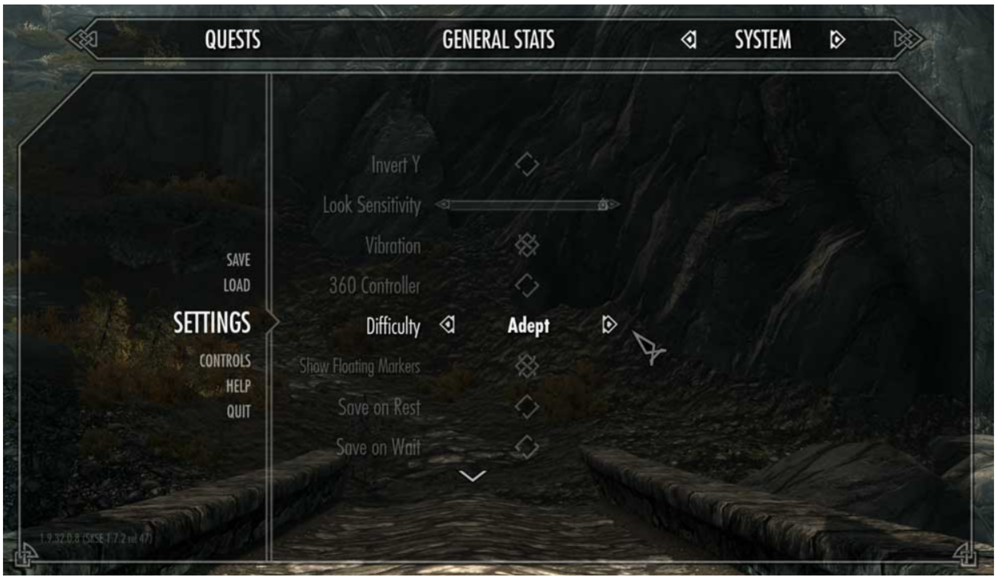


Figure 8: Skyrim's settings menu

and when and how to make them. If this is not done with the proper attention, we can negatively affect the experience, such as interrupting the immersion of the player.

To answer at the first question (*what* to adjust), four gameplay elements should be considered:

- *Player character attributes*: some player parameters such as speed, strength, jump force, health regeneration and so on, can be decreased to increase the difficulty. The opposite to make the game easier. This solution works better with non-VR games because some components like speed, jump force can't change in some VR games where the character movements are mapped onto the player ones.

- *Non-player character attributes*: all the characters controlled by the game's artificial intelligence can change their behaviour and attributes to decrease or increase the difficulty of the game. An example could be to have smarter non-player characters to increase the difficulty or less intelligent to decrease it.

- *Game world and level attributes*: the game world changes depend a lot on the type of game. For example in platform games the map can be modified to change the size of gaps, smaller to decrease difficulty and larger to increase it. Relating to level attributes we can change the spawn rate or the size of ammunition or health packs to modify the difficulty.
- *Puzzle and obstacle attributes*: while it is challenging to modify puzzles while completing them, a nice option is to adjust the difficulty of future puzzles based on how the player solves the previous puzzles of the same type.

To answer also to the second question (*when* and *how* to adjust difficulty), there are several aspects to consider. Game-related data, that depends by the type of game that we consider, like average health, hits received, percentage of enemies killed, etc. must be collected and analyzed during the gameplay. From these data the current skill level of the player should be evaluated and this should be reflected in the changes of some of the game parameters discussed before. The concept of performance DDA is not something new. It has been used since 1981 in *Astrosmash*, a modified version of *Asteroids* where the player was assisted by reducing the game's difficulty when he had few lives. Another example of performance DDA can be found in the *Mario Kart* games (or in general in racing games) with the discussed *rubber banding* AI method [23]. This feature allows computer-controlled AI to go faster and to reach the player if he is too far away in the first position, but at the same time slows down the same computer-controlled AI when the player is in the last positions. In *Mario Kart*, this is done also thanks to the many objects that can be found during the race. If the player is in the last positions he gets the best items.

An important research related to DDA has been conducted in 2005, when it was shown by Robin Hunicke, that even a simple DDA system can improve player performances in the game [24]. In the DDA system developed for his research, called *Hamlet*, if the player's probability of death were higher, more health kits were spawned to ease the game.

In 2006, Spronk used a more complex DDA technique called dynamic scripting to change non-player characters' behaviors according to the player's skills [25]. It uses an adaptive rulebase for the generation of the game AI at run-time to control enemies' behaviour. Each rule has a weight that changes according to their success rate in the game. The higher the weight, the higher the possibility that it will be selected.

The main problem of performance-based DDA is that it is usually not true that the player's score in the game reflects his emotional state. As discussed in section 2.2, players can have different approaches to the game and the optimal flow zone varies from player to player. Some enjoy having a perfect score and are frustrated even with only an error, some others are excited when they are challenged more than their possibilities even if their score is really bad. That's why, also according to Pagulayan, Keeker, Wixon, Romero and Fuller, measuring a player's affective state is a more reliable indicator of how good the game experience is [26].

3.1.3 Affective-Based DDA

Affective-based DDA uses the player's indicators of emotion, often physiological like electrocardiogram (ECG), skin conductance (SC) or electromyogram (EMG), to manipulate components related to the difficulty of a video game. There are several methods to use biofeedback for affective DDA, depending on which signals are used.

As discussed in section 2.3, there are three main heuristics for affective gaming: *assist me*, *emote me* and *challenge me* [18]. Affective-based DDA is an application of the *challenge me* heuristic. The game's difficulty is changed according to the physiological arousal level of a person, considering that low levels of arousal are related to boredom [27].

A lot of research has been conducted in the field of affective-based DDA, using different approaches and physiological signals. The most basic concept to know to create an affective-based DDA is the affective loop [28].

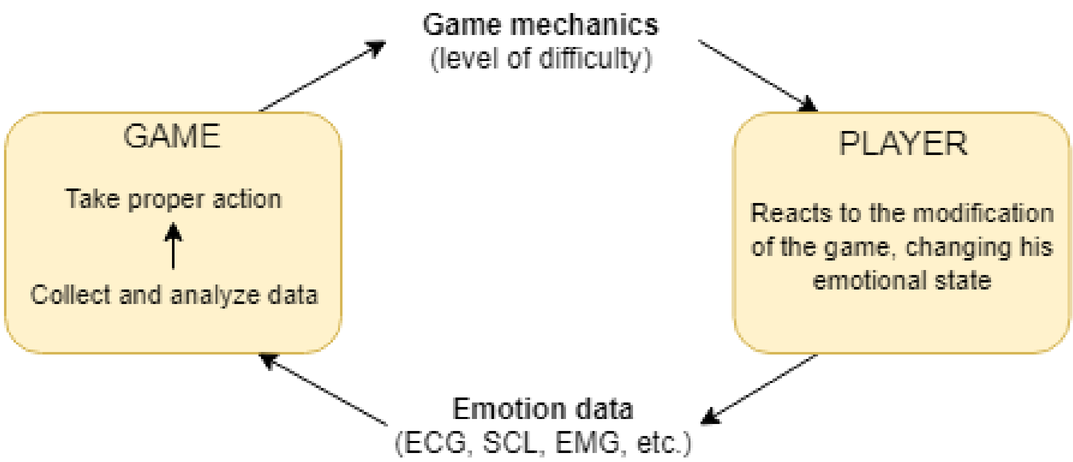


Figure 9: Affective loop

In the affective loop (Figure 9) the game collects and analyzes the player's emotional data, makes proper choices according to the values gathered and changes the difficulty level. The player reacts to those modifications and this leads to a change also in his emotional state that is collected through some sensors inside the game to restart the loop.

We can subdivide an affective-based DDA algorithm into three phases. First we should choose which physiological signals to collect and how to collect them. Then we have to evaluate the affective state from those parameters and in order to do that we can use a *model-based* approach or a *model-free* approach [29]. In *model-based* approaches the developers base their studies on famous theories of emotions, like the circumplex model shown in Figure 1, and implement some logic, for example to notify the game that the player is bored if his SCL is low. *Model-free* approaches are less rigid, but more complex. They use machine learning techniques or statistical approaches to put together different physiological signals and predict the players' affective state. At the end we have to find which parameters of the game to change according to the affective state of the player.

Imre [30] designed a game, called *Electroderma*, based on affective-DDA using skin conductance. He used the SCL to change the difficulty level of the game, choosing between low, medium and high. In order to avoid baseline problems he used an algorithm called *data subset analysis* that looks at the difference between the two most recent collected values and changes the difficulty only if it is greater than a fixed threshold. Furthermore, he coupled the measure of skin conductance with the player's in-game health, creating a sort of mix between performance and affective DDA. In this way he can deduce also the valence of emotions felt by the player (e.g.

when player health is low and SCL high, frustation is implied). More researches supporting use of SC in games are discussed in section 3.2.

In 2012 Parsons and Reinebold developed a serious adaptive virtual reality game [31]. They used HR, SC, respiration and pupillometry as physiological parameters to put into a support vector machine (SVM) to classify arousal levels and modify the difficulty of the game according to this. The game is a virtual war zone environment where the player is driving a car and has to maintain a certain distance from another vehicle in front of him. The speed of the other vehicle is modified according to the arousal level detected in order to maintain the optimal flow.

The first to do an experiment implementing an affective-based DDA and comparing it with a performance-based DDA were Liu, Agrawal, Sarkar and Chen in 2009 [32]. They used a lot of physiological signals such as cardiovascular, electrodermal, electromyographic, and body temperature to evaluate the anxiety of the player. Their work is subdivided into two phases. In *Phase I* they realized an affective model (using a regression tree) for each participant to evaluate anxiety, while in *Phase II* they did a real-time prediction performance of the affective model. They designed two computer games: *Anagram* and *Pong*. The former (used only in *Phase I*) implemented some solvable anagrams to cause low level of anxiety and some other unsolvable or difficult anagrams to cause high levels of anxiety. In the latter they changed ball speed and size and some other parameters to cause low or high levels of anxiety. Two versions of *Pong* were created: one implementing a performance-based DDA and another one implementing an affective-based DDA. The results showed that:

- Most participants have improved performance during the affective-based DDA.

- The majority of the participants perceived that the affective-based DDA version was more challenging and satisfying than the performance-based one.
- The perceived anxiety-level was reduced during the affective-based DDA session.

3.2 Skin Conductance in Games: Pro and Cons

All the games developed in the research described above collected skin conductance in order to detect the arousal level of the player. There is a large amount of research that supports the use of skin conductance in games and its importance to evaluate the affective state of the player from it.

Mandryk et Al. did several studies related to this and found a statistically significant correlation between SC and subjective evaluation of fun while playing a video game [33]. Moreover, SCL were higher when playing against a real person (a friend) instead of playing against an opponent controlled by the computer AI [34]. Another study done by Mandryk [12] found that high SCL values can be linked to different affective states, such as challenge, excitement or frustration, depending on the situation. That is a limitation of SC, because both the arousal and valence components are needed to precisely evaluate an emotion. A trivial way to solve this problem can be to couple the physiological data with the data collected from the game. A more complex way to do it is using EMG or face recognition to also evaluate the valence component.

Frijda with his studies affirms that SCL rises with the difficulty of some given tasks [5]. This statement was proved by Tijs et Al. with a modified version of *Pac-Man* [28] with different difficulty levels, noticing that SCL differed significantly between the different difficulty sessions. The most important conclusion that we can take from those studies is that SC can be used as an indicator of arousal. Low arousal values corresponds to low SCL values and high arousal values corresponds to high SCL values. In some situations SC data should be coupled with other data related to valence in order to evaluate the exact emotion. However, there are two cases in which an affective DDA can use only SC as physiological parameter:

- When the SC data is coupled with the game context (as done in *Electroderma* [30]).
- When the main objective is to maintain an optimal level of arousal and so letting the player stay in his flow zone (main focus of this thesis with *ETNA* game).

In both the situations, the biggest problem of using SC to evaluate arousal is the baseline problem. People usually have different SC baselines that depend on many factors, so it is not possible to use a prefixed baseline for everyone [10]. Moreover, a simple relaxing period before the game session is not enough because it does not guarantee emotional equilibrium [35]. A way to solve this problem can be to do an initial pre-session stimulating the player with precise stimuli that generate a controlled level of arousal. This can be done for example with some simple math calculus or with some multimedia files such as images and/or videos. In this way the optimal level of arousal relative to the player can be evaluated and used in the affective-based DDA algorithm.

3.3 Virtual Reality and Flow

As discussed before in section 2.2, flow is a state that humans aim to achieve because it is the root of much of their happiness. According to Steven Kotler [36] it has been almost impossibile to artificially stimulate flow states and the best technology that does it are video games. The limitation of video games is that they can take players into a lesser type of flow called *dopamine loop*, but cannot induce all the factors required for the flow state. That was true until some years ago, when Oculus started to develop the first modern virtual reality headset.

Virtual Reality is the medium that can help people best to achieve flow, thanks to its high immersion. With virtual reality games interactivity between the player and the game has been taken to a higher level. The player is physically at the center of the action and not external like normal pc, console or mobile games. This leads to different benefits. The most obvious is the fact that it helps people become more physically active and improve mental and physical health [37]. If we link this aspect with the fact that it is easier to achieve and maintain flow, gamers that usually do not like to move or do exercises, can use the so called *exergames* to do what they like most (play video games) and at the same time also do physical activity.

First commercial uses of virtual reality dates back to the early 1990s where people could start to experience virtual reality in arcade rooms thanks to products like *Virtuality* [38]. The main limitation of those kind of products is that people had to go to specific arcade rooms to play it, while now Oculus with the Rift brought this technology directly into the player's home.

Another good reason of using virtual reality is that it solves a problem that all the other research done in the field of affective-based DDA have: the real world distractions. When evaluating some physiological parameters while playing a normal video game, the player is not isolated from the environment and so his physiological reaction can also be a consequence of something that happened around him and not inside the game. This leads to noise in the data. With virtual reality, instead, the player is totally immersed in the virtual environment and does not have external distractions that can influence the data. Moreover, with virtual reality the player can trigger both physical and cognitive arousal, not only cognitive as in non VR video games. Virtual reality games are used a lot for rehabilitation purposes, especially for upper and lower limb, and neurorehabilitation. In this way, patients can do movement in a more enjoyable way that can also distract them and feel less pain. Furthermore, coupling a virtual reality game with a dynamic difficulty adjustment method, the game difficulty can adapt to the disabilities of the patient. In my research I will test the game on healthy people, but all the work can be also tested in the future on people that have to do rehabilitation.

CHAPTER 4

GAME DEVELOPMENT: ETNA

In this chapter I will talk about the development of the game I created for this thesis, *ETNA*.

4.1 Purpose

The name has two meanings. The first comes from the fact that the game is settled inside a volcano and so it is called Etna like the highest active volcano in Europe, located next to my home town, Catania. Then, it is also the acronym of *Entertaining Training Neuro Affective*, because the aim of this game is to create an entertaining training in virtual reality that exploits the affective-based DDA collecting physiological responses from the autonomic nervous system through skin conductance.

In this VR game all the concepts discussed in the previous chapters are applied. The objective is to take the user inside his Flow Zone and to maintain his arousal at the optimal level to maximize the performances and the enjoyment, and improve skills in a short time. In order to do that, performance-based DDA information about the player score during the game are collected and the level attributes to adjust the difficulty will be modified. For the affective-based DDA, solely the skin conductance will be used to maintain the optimal arousal level in the player. The game can also be played in a variant where both affective and performance DDA are active at the same time. The aim was to see which method will work the best. Before playing the affective-based DDA versions of the game, it should be played in three variants while collecting skin conductance in order to find the personal optimal SCL of the player. The three variants are ultra easy mode, ultra hard mode and performance-based DDA. To the best of my knowledge this is the first time a technique like this is used to find the optimal arousal level for a game with affective-based DDA.

4.2 Hardware and Software

All the hardware needed to play the game is commercially available:

- *VR head mounted display*: The game is developed for the HTC VIVE[1], a commercially available Virtual Reality Head Mounted Display (HMD) to display information to the user as well as for tracking purposes. The VR HMD is connected to a computer with a cable.
- *Audio strap*: In order to have a full audio immersion, the HTC VIVE deluxe audio strap[2] should be used and attached to the HMD.
- *VR controllers*: Similarly, the commercially available, consumer-grade HTC VIVE controllers are used.
- *Trackers*: The main reason why I chose the HTC VIVE and not the competitor's HMD is that it has some official additional trackers that can be used to better track the player

[1]https://www.vive.com/us/product/vive-virtual-reality-system/

[2]https://www.vive.com/us/vive-deluxe-audio-strap/

during the game: the HTC VIVE Tracker[1]. Two trackers are required to correctly track the feet of the player.

- *Skin Conductance device*: There are many commercially available devices to collect skin conductance, I am using MindLAB Set[2] (Figure 10). It is composed of a hardware data acquisition unit (Psychodata Acquisition Unit) and two dry, stainless steel bipolar electrodes that will be positioned onto two fingers of one hand of the player with a strap.

Figure 10: MindLAB Set

[1]https://www.vive.com/us/vive-tracker/

[2]http://www.psychotech.it/pages/en/mindlab-set.php

- *VR ready computer*: A computer with a good graphics card is needed to exploit the power of virtual reality and have a fluid experience without lag. For this thesis an Alienware Aurora with the Nvidia 1080ti was used.

The game has been developed with the Unity engine, precisely with the version 2017.3.0f3, the latest available at the time the study was performed.

4.3 Game design

ETNA is a VR room-scaled game. In this game the player has to move around a rocky platform positioned in the center of a volcano and has to hit the lava balls that will come out from 4 mini volcanoes positioned around the platform using two guns. While doing this, in order to not get penalties, the player also has to avoid the lava balls and has to pay attention to where he walks because there will be lava holes generated randomly in the platform when the game is started. In the real world the user will move around a fixed open area (max 20x20 feet) mapped into the virtual world.

The player has two guns (one per hand, mapped on the controllers) that will start with a 50% charge. Each shot costs 5% of charge and there will be some blue balls that will spawn randomly over the platform. The player can collect them by touching them with the gun in order to add the 25% of charge (Figure 11).

3D sounds are used to improve the feeling of immersion of the player. Therefore, hearing the sound of the spawn explosion, the player can feel from which direction the ball is coming. 3D audio is also used when a collectible to charge the gun spawns, so the player can know where to go instead of guessing. Furthermore, there is also a haptic feedback coupled with the sound

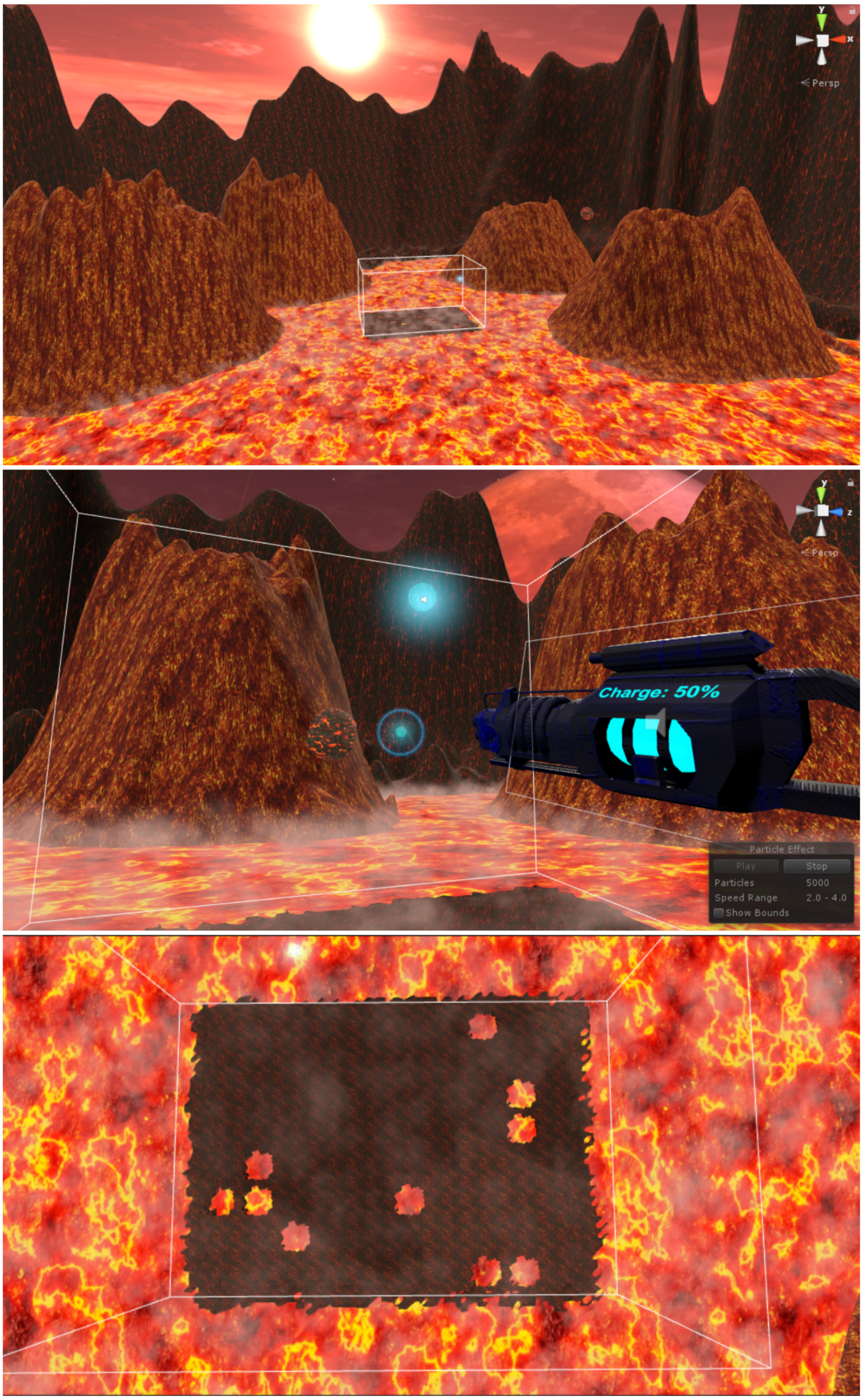


Figure 11: Screenshots from ETNA

of shooting when the gun has energy which is different than when there is no charge.

In both the dynamic difficulty adjustment methods, three level attributes will be modified: the spawn rate of the lava balls from the volcanoes, the number of volcanoes that will be active, and the speed of the lava balls.

At level 0 (the starting level for DDA methods) the speed multiplier is 1, the spawn rate is 3s and the number of volcanoes active is 2.

The code used to generate and control the scene (which includes the parameters used in ultra easy and ultra hard modes) can be found in Appendix A.

4.3.1 Performance-based DDA

In the *performance-based DDA*, the game is subdivided in sessions of 15 seconds. Each 15 seconds the number of lava balls spawned and the score of the player are counted. If the player hits a ball it counts as 1 point, if not 0 points, and for each penalty it gets -1 point. When a session ends, the ratio (in percentage) is evaluated by dividing the score with the total number of balls spawned. The difficulty level will change according to this value:

- If it is higher than 90%, the difficulty is increased by two levels
- If it is between 70% and 90%, the difficulty is increased by one level
- If it is between 50% and 70%, the difficulty does not change
- If it is between 20% and 50%, the difficulty is decreased by one level
- If it is lower than 20%, the difficulty is decreased by two levels

There is not a fixed number of levels; the game starts from level 0 and can go up with positive values and down with negative values.

The code used for the *performance based-DDA* can be found in Appendix B.

4.3.2 Affective-based DDA

Also for the *affective-based DDA* the game is subdivided in sessions of 15 seconds. During the sessions the skin conductance is collected through the MindLAB Set and is read by the pc into the game through a serial USB connection. SCL is collected every game frame and after each session the average SCL is calculated and compared to the optimal baseline SCL. The optimal baseline SCL is evaluated from the analysis of the SCL collected in the three variants ultra easy mode, ultra hard mode and performance-based DDA. The assumption that I made was that during ultra easy mode the user was bored while during ultra hard mode he/she was frustrated. I chose qualitatively an intermediate level between the two averages, adjusting it also considering the performance-based DDA SCL data. The difficulty level will change according to the result of that comparison:

- If the average SCL is higher than the optimal SCL, the difficulty is decreased by one level
- If the average SCL is lower than the optimal SCL, the difficulty is increased by one level

4.3.3 Mixed Perfo-affective DDA

The game is subdivided in sessions of 15 seconds as the other two methods. In this variant the two methods are active at the same time, so every 15 seconds are used both the score and the SCL to change the difficulty of the game. Since both the performance DDA and affective

DDA are active at the same time, the difficulty level can go up by 3 or down by 3 every 15 seconds (2 from performance DDA and 1 from affective DDA).

CHAPTER 5

EVALUATION

In this chapter I am going to talk about how the user study has been conducted and the results collected combining the surveys' data with the game data.

5.1 User Study

In the user study session the participants played the 5 variants of the game: ultra easy, ultra hard, performance DDA, affective DDA and mixed perfo-affective DDA. First, he/she played 2-3 minutes with the ultra easy mode, then other 2-3 minutes with the ultra hard mode, and at the end with the performance-based DDA version for 4-5 minutes. During those gaming sessions the skin conductance was recorded in order to find the optimal SCL to use in the two affective-based DDA. Before the performance-based DDA gaming session the participant saw a 360 degree relaxing video with relaxing audio in virtual reality with the HMD to help stabilize the arousal level. Each user study session was done individually.

5.1.1 Procedures

The total session lasted approximately 45 minutes and followed these procedures:

- **Introductory phase** (5 minutes) during which the participant was briefed on the experiment, equipped with the VR Head Mounted Display (HMD) HTC VIVE, VR Controllers, two HTC VIVE Trackers (mounted on the feet), and the skin conductance sensor was attached to two fingers of one hand. He/she was also introduced to the basic operation tasks involved.

- **Training and Baseline phase** (around 15 minutes) during which the participant played the game in three different ways:
  - Super Easy mode: 2-3 minutes of play in easy mode while collecting SC.
  - Super Hard mode: 2-3 minutes of play in hard mode while collecting SC.
  - Performance DDA: 2-3 minutes watching a relaxing video + 4-5 minutes playing the game with performance-based DDA while collecting SC.
- **First evaluation phase** (5 minutes) during which the participant put away all the equipment and filled out a short survey about his/her game experience with performance-based DDA.
- **Affective DDA phase** (around 5 minutes) 4-5 minutes playing the game with affective-based DDA while collecting SC.
- **Second evaluation phase** (5 minutes) during which the participant put away all the equipment and filled out a short survey about his/her game experience with affective-based DDA.
- **Mixed Perfo-affective DDA phase** (around 5 minutes) 4-5 minutes playing the game with both performance-based and affective-based DDA while collecting SC.

- **Third evaluation phase** (5 minutes) during which the participant put away all the equipment and filled out a short survey about his/her game experience with mixed perfo-affective DDA.

5.2 Results

27 people took part to the user study. For 3 of them the SC data was not totally reliable because of problems with the sensor, so only 24 people's data have been considered.
From the survey's data I saw that almost all the people felt really immersed in the virtual environment, like they were separated from the real-world environment, thanks to virtual reality. They also liked to move and to do physical exercise while playing the game and they where satisfied at the end of the sessions. Moreover, 2 people said that the session they liked most was the one with Performance DDA, 11 said that the one they liked most was the one with Affective DDA and the other 11 said that was the mixed Perfo-Affective DDA. I alternated one user playing with Affective DDA as the last method and one playing the mixed Perfo-Affective DDA, but I noticed that almost everyone said that the one they liked most was the last one. Therefore, from the survey's analysis I cannot assert that people on average liked the game most with a certain method.
The most interesting results come from the in-game and skin conductance data I have collected while the users were playing the game. More precisely, here it is the raw data that I have collected from each participant: variation of skin conductance (Table I, Table II), variation of the difficulty level (Table III, Table IV), variation of the score (Table V, Table VI)

TABLE I: SCL VALUES OF USERS DURING THE 3 DDA METHODS (1)

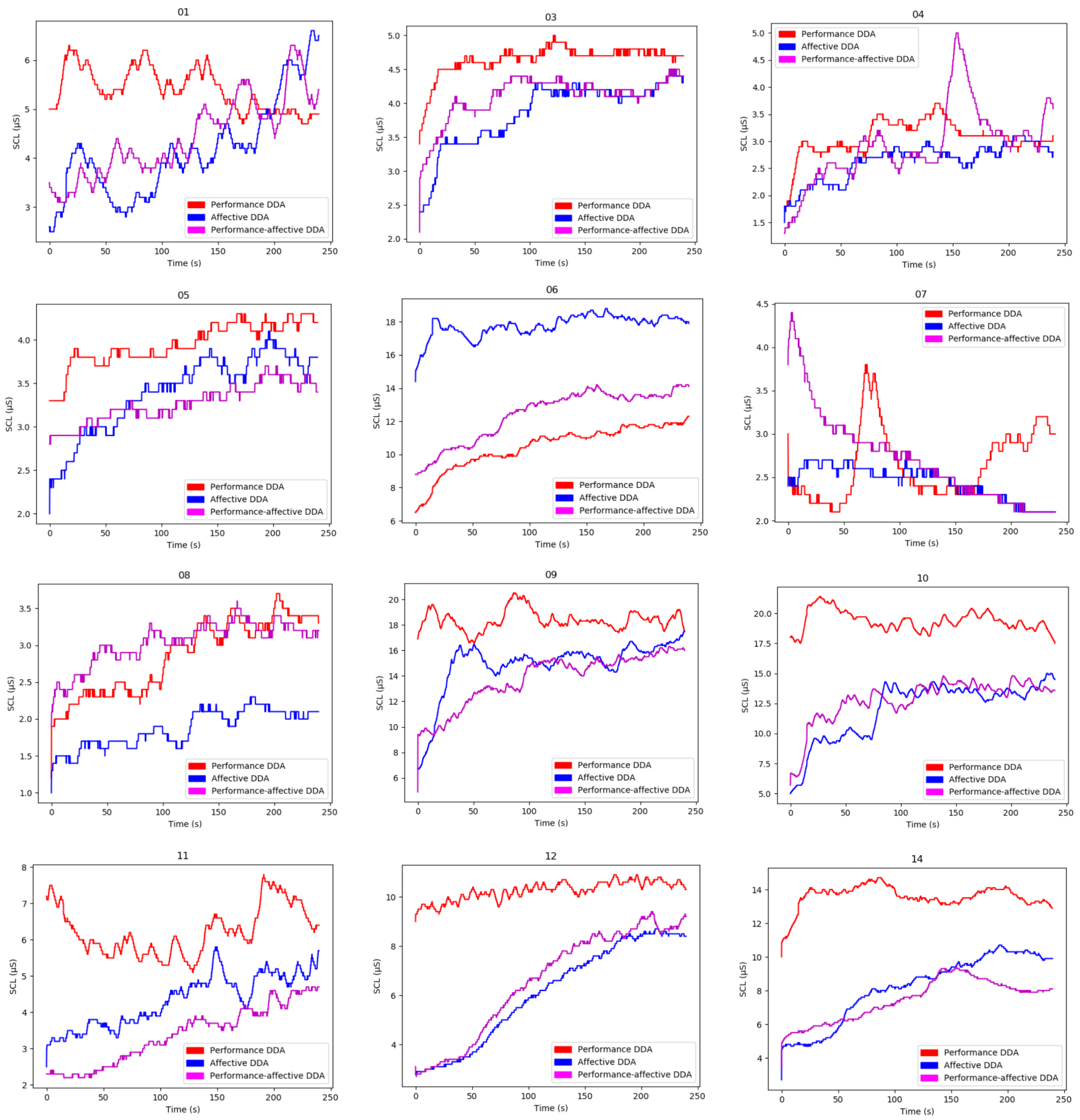


TABLE II: SCL VALUES OF USERS DURING THE 3 DDA METHODS (2)

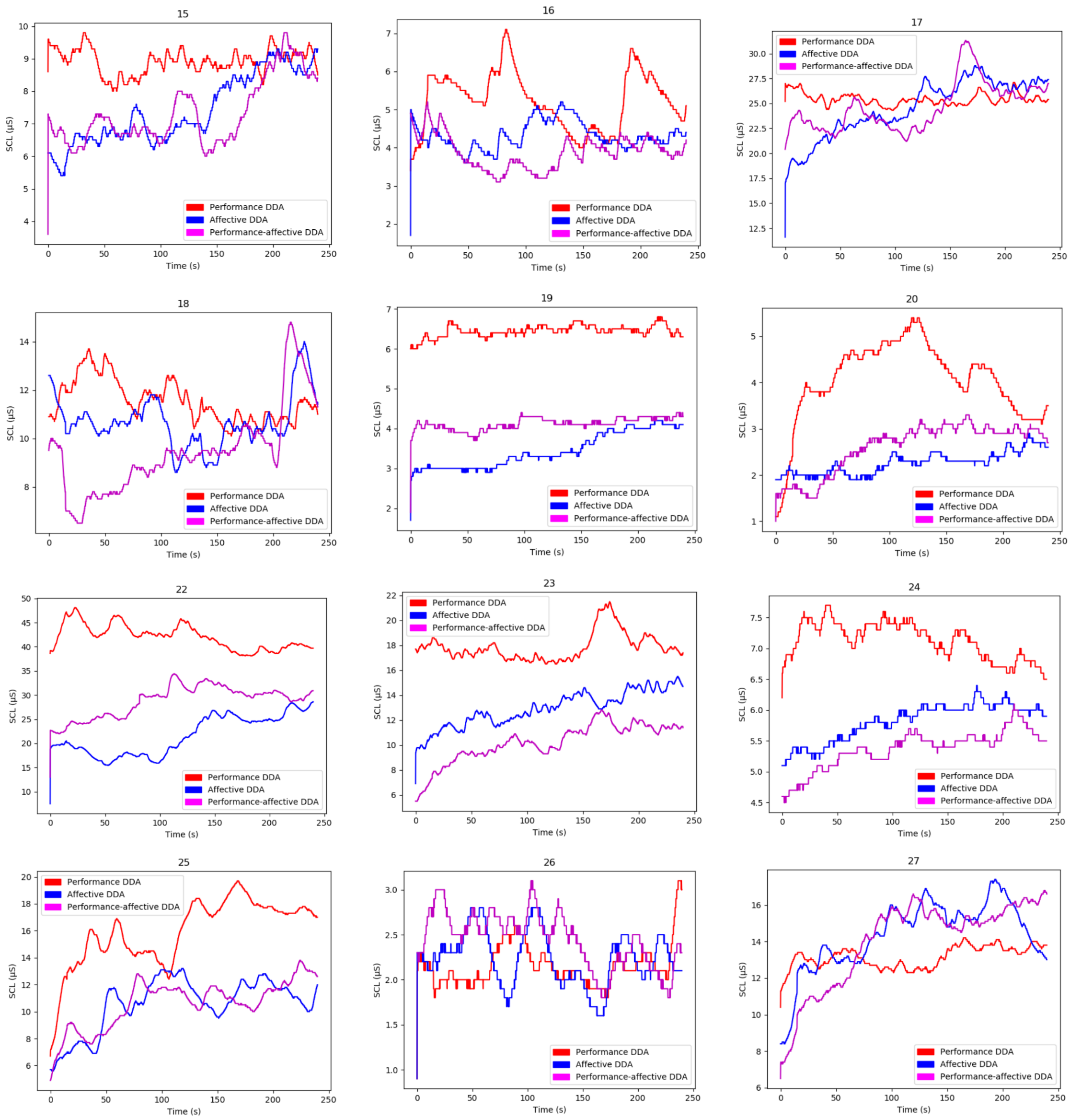


TABLE III: DIFFICULTY LEVELS DURING THE 3 DDA METHODS (1)

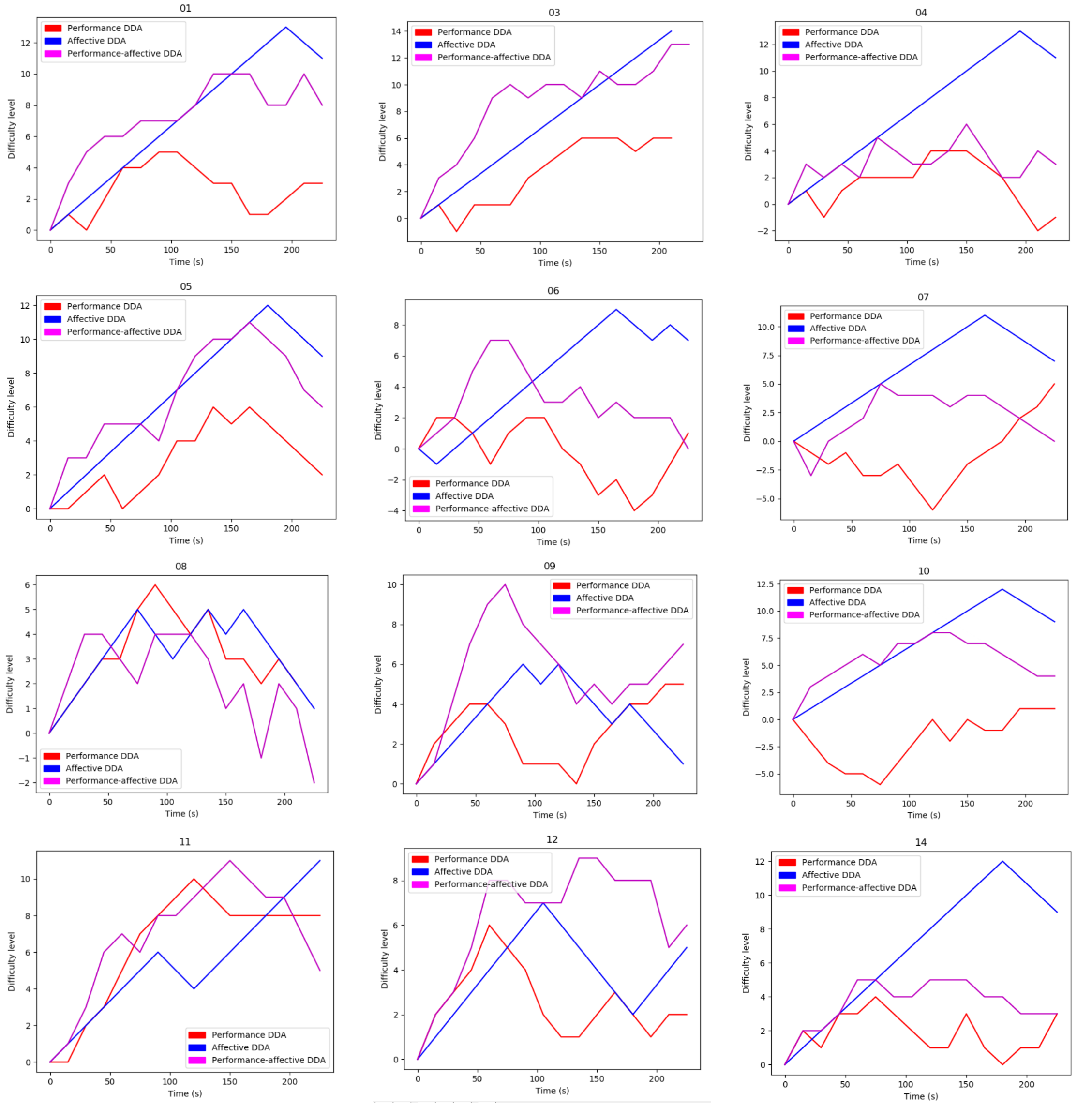


TABLE IV: DIFFICULTY LEVELS DURING THE 3 DDA METHODS (2)

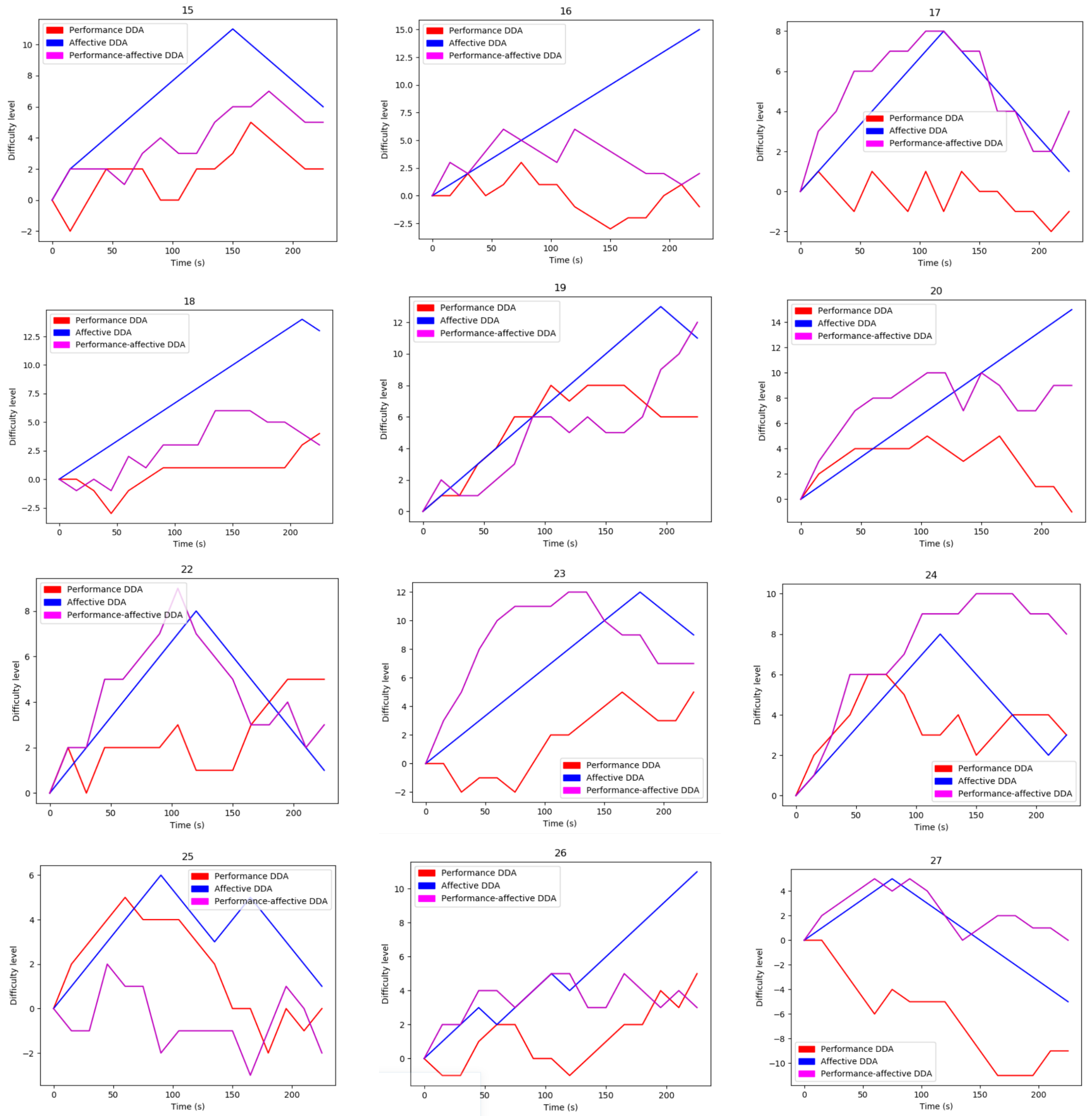


TABLE V: SCORE EVERY 15 SEC DURING THE 3 DDA METHODS (1)

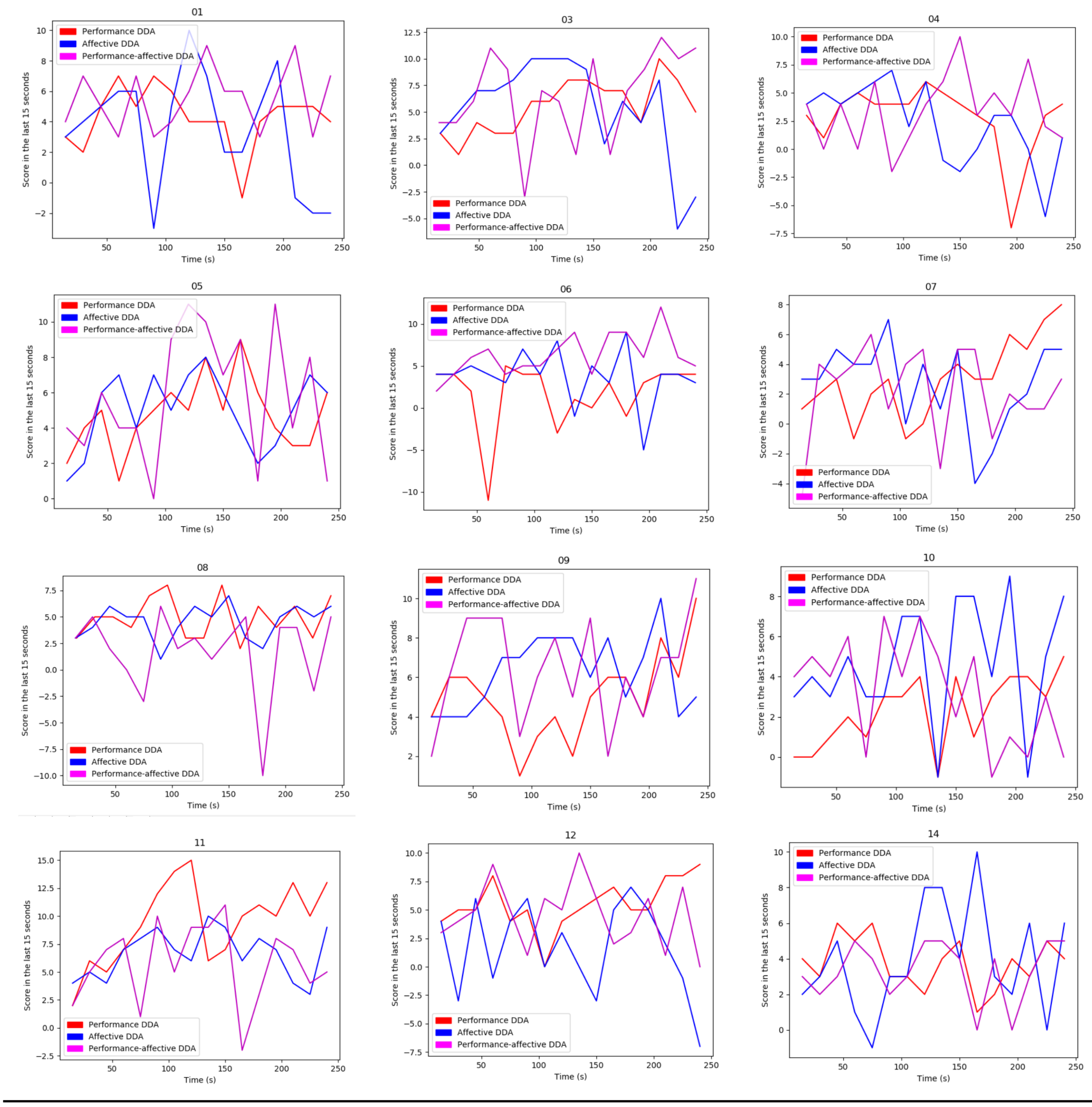
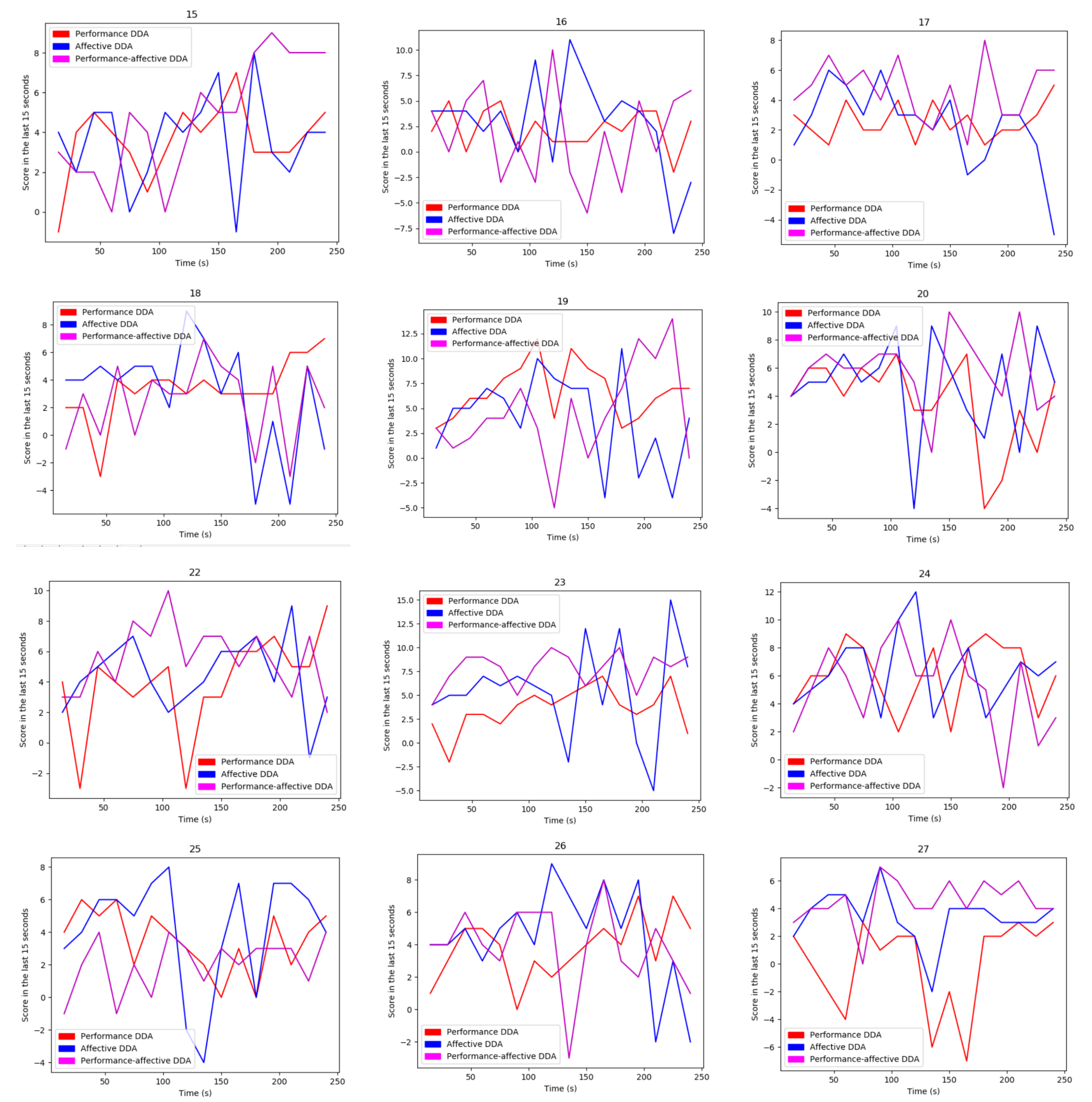


TABLE VI: SCORE EVERY 15 SEC DURING THE 3 DDA METHODS (2)



5.3 Discussion

First of all, I have plotted some graphs of the data to see if there were some correlations between them. The first thing that can be noticed, looking at the SC values collected during the Ultra Easy and Ultra Hard mode (Figure 12), is that SC is influenced by the game difficulty. In 19 sessions out of 24, the average SCL during the Ultra Easy mode was lower than the one collected during the Ultra Hard mode. The most important thing to notice is that each user has its own baseline SC level. The importance of this consideration can be demonstrated by doing an anova test on the SC data.

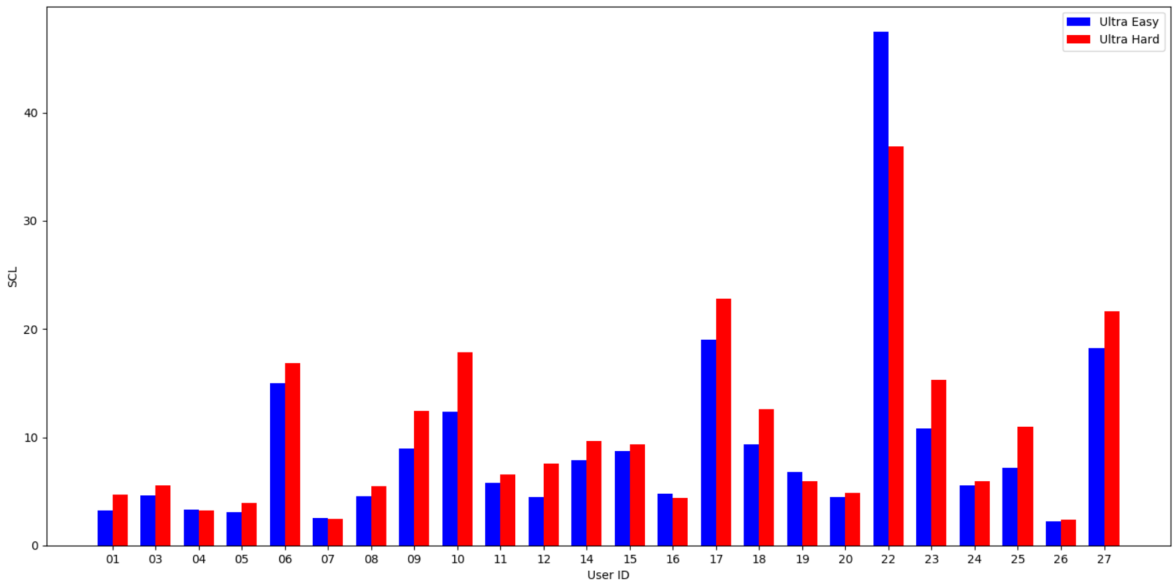


Figure 12: Comparison of Easy and Hard avg SCL across all the data

Conducting an anova test on the raw data without considering the different baselines, the p results show that the correlation is not statistically significant (Table VII).

TABLE VII: ANOVA TEST ON RAW SCL

Hard + Easy SCL	$p = 0.637$
Performance + Affective + Perfoaffective SCL	$p = 0.426$
ALL SCL	$p = 0.749$

Conducting an anova test setting the easy value to 100 and then computing the other new values to be the percentage compared to the easy value, p results show that the correlation is now statistically significant (Table VIII).

TABLE VIII: ANOVA TEST ON SCL CONSIDERING BASELINE

Hard + Easy SCL	$p < 0.001$
Performance + Affective + Perfoaffective SCL	$p = 0.011$
ALL SCL	$p = 0.001$

Comparing the SCL results evaluated from the 3 DDA methods (each value is the percentage compared to the easy value of the same person, set to 100), it can be noticed that the highest SCL was collected during the performance DDA in all but 5 cases (Figure 13). Therefore, adjusting the difficulty of the game according to the SC has helped to control and reduce the average SCL during the session.

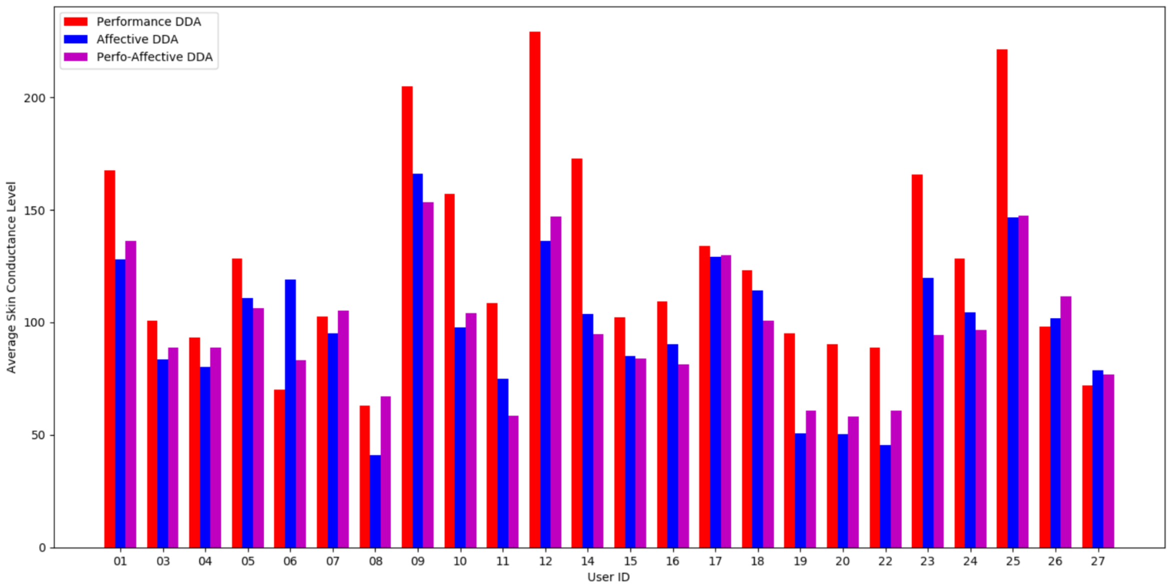


Figure 13: Comparison of avg SCL collected during the 3 DDA methods

In 14 cases the method with the highest average difficulty level was the Affective DDA, in only 1 case the highest was Performance DDA, and for the remaining 9 people the highest was the mixed Perfo-Affective DDA (Figure 14). To understand better this data, it can be coupled with the scores' results. 6 people did their best score during the Performance DDA, 6 during the Affective DDA and 12 during the Perfo-Affective DDA (Figure 15).

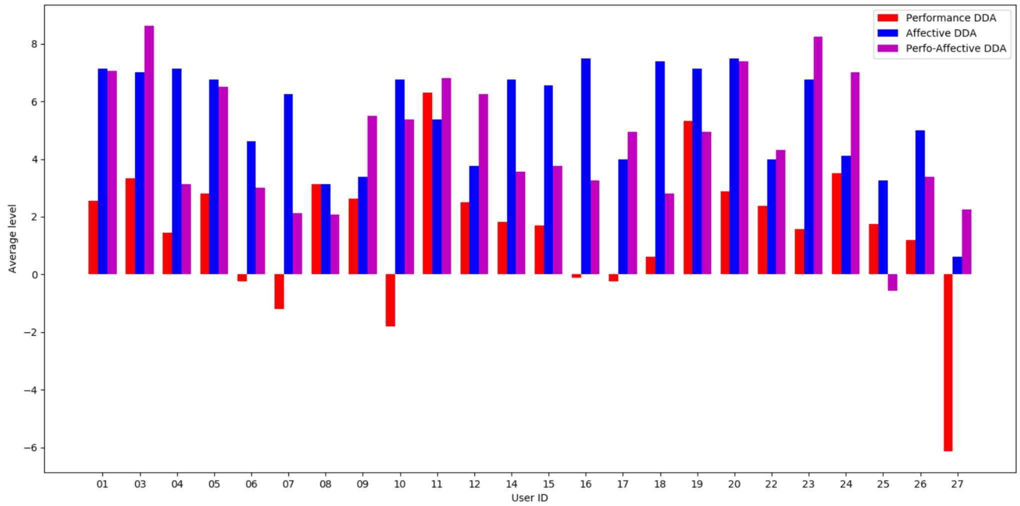


Figure 14: Comparison of avg difficulty collected during the 3 DDA methods

I have conducted some anova tests to see how significant are the results related to the scores and to the difficulty levels (Table IX).

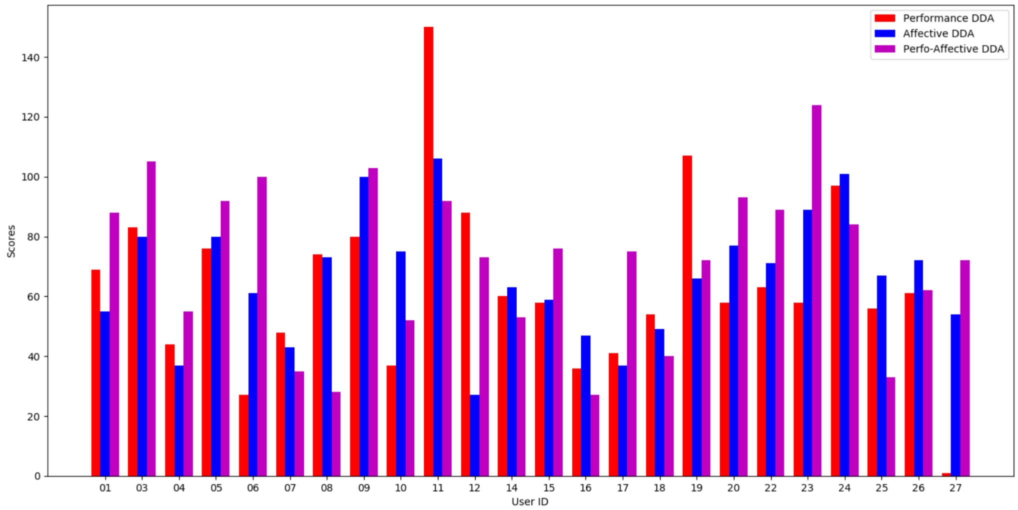


Figure 15: Comparison of people's scores collected during the 3 DDA methods

TABLE IX: ANOVA TEST ON SCORES AND DIFFICULTY LEVELS

Performance + Affective scores	$p = 0.723$
Performance + Perfoaffective scores	$p = 0.318$
Affective + Perfoaffective scores	$p = 0.424$
Performance + Affective + Perfoaffective scores	$p = 0.538$
Performance + Affective difficulty levels	$p < 0.001$
Performance + Perfoaffective difficulty levels	$p < 0.001$
Affective + Perfoaffective difficulty levels	$p = 0.169$
Performance + Affective + Perfoaffective difficulty levels	$p < 0.001$

The p results of the 4 anova tests related to scores show that the correlation is not statistically significant, while the 4 related to the difficulty levels show that the correlation is statistically significant for all except the one related to the correlation between affective and perfoaffective. Better ways to evaluate the score can be considered in future studies to see if the p results are improved. There are some nice conclusions that can be drawn out from these results: on average, Perfomance DDA was too easy, Affective DDA too difficult, but the mix of them led to the best result. This is confirmed looking at the scores, because 50% of people did their best result exactly during the mixed Perfo-Affecting DDA. Therefore, I can conclude saying that the best method was the mixed Perfo-Affective DDA.

To see if VR experience has influenced the test, I tried also to cluster the data into two main groups: people who had past experience in VR and people who did not. The p value results from the anova tests can be found in Table X.

Both these results show that the correlation is less statistically significant than the non-clustered ones. Therefore, we can conclude saying that there is no significant difference between the result collected from people who had past VR experience and people wo did not.

TABLE X: ANOVA TEST ON VR AND NOT VR EXPERIENCED PLAYERS

Legend: P = Performance A = Affective PA = Perfoaffective	Prior VR Experience	No Prior VR Experience
Hard + Easy SCL	$p = 0.004$	$p = 0.011$
P + A + PA SCL	$p = 0.132$	$p = 0.090$
ALL SCL	$p = 0.084$	$p = 0.047$
P + A scores	$p = 0.206$	$p = 0.734$
P + PA scores	$p = 0.343$	$p = 0.652$
A + PA scores	$p = 0.922$	$p = 0.238$
P + A + PA scores	$p = 0.504$	$p = 0.676$
P + A difficulty levels	$p < 0.001$	$p < 0.001$
P + PA difficulty levels	$p = 0.008$	$p = 0.002$
A + PA difficulty levels	$p = 0.394$	$p = 0.276$
P + A + PA difficulty levels	$p < 0.001$	$p < 0.001$

CHAPTER 6

CONCLUSION

The goals that this thesis sought to achieve were: a) creating an efficient affective-based DDA based on skin conductance and b) seeing which method gives the best results in a VR Game. In order to achieve these goals, a VR game called ETNA (Entertaining Training Neuro Affective) has been developed in 3 variants: performance DDA, affective DDA and perfo-affective DDA. A user study has been conducted and the results showed that the best method to adjust the difficulty of the game was the mixed perfo-affective DDA. This leads to the conclusion that coupling an affective DDA to a basic performance DDA algorithm, the game experience can be improved. Moreover, the technique of evaluating qualitatively the optimal SCL from previous sessions of the same user to create the affective DDA has worked well, even if it can be perfected to improve the affective algorithm in future works. To improve the effectiveness of the affective and perfo-affective DDA more features of skin conductance, such as SCR, should be evaluated instead that the only SCL.

This thesis has demonstrated that affective gaming can be implemented in Virtual Reality to improve the overall gaming experience and to help people making physical exercises. A game like ETNA can be also used by people who need to do rehabilitation since the game will adapt its difficulty to their disabilities and will help them to have fun while doing rehabilitation.

APPENDICES

Appendix A

ETNA MAIN CODE

```
void Start () {

        x = 360f;
        y = 3f;
        z = 500f;

        incX = 8.38f;
        incZ = 7.88f;

        sclValues = new List<float>();
        allValues = new List<string>();
        sessionValues = new List<string>();

        // 10 is the number of holes
        GeneratePlatform(10);

        tColl = -3;
        tBall = -3;
        tSession = -3;
        gamePaused = false;
        gameActive = false;
```

Appendix A (continued)

```

        if (easyMode){
            isPerformanceDDA = false;
            hardMode = false;
            normalMode = false;

            spawnRate = 5.3f;
            speedMult = 1;
            difficultyLevel = -10;
        }

        if (hardMode){
            isPerformanceDDA = false;
            easyMode = false;
            normalMode = false;

            spawnRate = 0.6f;
            speedMult = 4f;
            difficultyLevel = 10;
        }

        if (!collectAffective)
            serialController.gameObject.SetActive(false);

        gamePaused = true;
        Time.timeScale = 0;
```

Appendix A (continued)

```
        abilityLab = false;
    }


    void FixedUpdate () {
        if (Input.GetKeyDown(KeyCode.Space))
            gamePaused = !gamePaused;

        tBall += Time.deltaTime;
        tColl += Time.deltaTime;
        tSession += Time.deltaTime;

        if (tSession >= 0)
            gameActive = true;

        if (tBall>= spawnRate) {
            tBall = 0;

            int minIndex = 0;

            if (spawnRate < 2)
                minIndex = 0;

            if (spawnRate >= 2 && spawnRate < 2.8)
                minIndex = 1;
```

Appendix A (continued)

```

            if (spawnRate >= 2.8 && spawnRate < 3.8)
                minIndex = 2;

            if (spawnRate >= 3.8)
                minIndex = 3;

            int index = UnityEngine.Random.Range(minIndex, 4);
            Vector3 targetPos = platformsF[UnityEngine.Random.Range(0,
                platformsF.Count - 1)].transform.position + new Vector3(-incX
                 / 2, 0, -incZ / 2);
            volcanos[index].target.transform.position = targetPos;
            volcanos[index].SpawnBall(speedMult);
            totalBalls++;
        }

        if(tColl>= collRate && activeColl==null) {
            tColl = 0;
            Vector3 collPos;
            if (isWheelChairMode)
                collPos = new Vector3(UnityEngine.Random.Range(310,330), 25,
                     UnityEngine.Random.Range(500, 520));

            else
```

Appendix A (continued)

```
                collPos = platformsF[UnityEngine.Random.Range(0, platformsF.Count - 1)].transform.position + new Vector3(-incX / 2, 35, -incZ / 2);

            activeColl = Instantiate(collectible, collPos, Quaternion.identity);

        }

        if (collectAffective) {
            ReadSerial();
            if (scl != 0) {
                sclValues.Add(scl);
            }
        }

        if (tSession >= sessionTime) {
            tSession = 0;
            float ratio = actualScore / totalBalls * 100;
            string sessionResult= "\n" + "Session " + nSession + ":\n" +
                                  "Difficulty Level: "+ difficultyLevel + "\n"+
                                  "Total balls: "+ totalBalls + "\n" +
                                  "Spawn Rate: "+ spawnRate + "\n" +
                                  "Speed Mult:" + speedMult + "\n" +
                                  "Penalties: " + penaltyCount + "\n" +
```

Appendix A (continued)

```
                                        "Score: " + actualScore + "\n" +
                                        "Balls hitted: "+ (penaltyCount+
                                            actualScore)+ "\n" +
                                        "Ratio: "+ ratio;

            sessionValues.Add(sessionResult);
            Debug.Log(sessionResult);
            PrintOutput(sessionResult);

            if(collectAffective)
                AffectiveDDA(sclValues);

            if (isPerformanceDDA)
                PerformanceDDA(ratio);
            //IncrementalDifficulty();

            sclValues = new List<float>();
            nSession++;
            totalBalls = 0;
            actualScore = 0;
            penaltyCount = 0;
            //actualScore + penaltyCount = ballHitted
        }

    }

```

Appendix A (continued)

```
    private void GeneratePlatform(int holes){
        platformsF = new List<GameObject>();
        platformsH = new List<GameObject>();
        GameObject pF;
        GameObject pH;

        for (int i = 0; i < 10; i++) {
            for (int j = 0; j < 8; j++) {
                pF = Instantiate(platformFull, new Vector3(x, y, z), Quaternion.identity);
                platformsF.Add(pF);
                z += incZ;
            }
            z = 500f;
            x -= incX;
        }

        for (int i = 0; i< holes; i++) {
            pF = platformsF[UnityEngine.Random.Range(0, platformsF.Count-1)];
            platformsF.Remove(pF);

            pH = Instantiate(platformHole, pF.transform.position, Quaternion.identity);
            platformsH.Add(pH);
            Destroy(pF);
```

Appendix A (continued)

```
        }
    }
```

Appendix B

PERFORMANCE-BASED DDA CODE

Here is the code used to generate the performance-based DDA.

```
// ActiveVolc:  4  ,  4  ,  4  ,  4  ,  4  ,  4  ,  4  ,  3  ,  3  ,  2   , 2 ,  2  ,  2  ,  1  ,  1  ,  1  ,  1  ,  1  ,  1  ,  1  ,  1  ..
// Difficulty: +10 , +9  , +8  , +7  , +6  , +5  , +4  , +3  , +2  ,  +1  , 0 , -1  , -2  , -3  , -4  , -5  , -6  , -7  , -8  , -9  , -10 ..
// SpeedMult : 2.5 , 2.4 , 2.3 , 2.2 , 2.1 , 2.0 , 1.8 , 1.6 , 1.4 , 1.2  , 1 ,  1  ,  1  ,  1  ,  1  ,  1  ,  1  , 1   ,  1  ,  1  ,  1  ..
// SpawnRate :  1  , 1.1 , 1.2 , 1.3 , 1.4 , 1.5 , 1.8 , 2.1 , 2.4 , 2.7  , 3 , 3.3 , 3.6 , 3.9 , 4.2 , 4.5 , 4.8 , 5.1 , 5.2 , 5.3 , 5.4 ..

private void PerformanceDDA(float ratio){
    if (ratio < 20) {
        //decrease a lot difficulty
        difficultyLevel = difficultyLevel - 2;
        if (spawnRate > 1.5 && spawnRate < 5) {
            spawnRate += 0.6f;
            if (spawnRate <= 3)
                speedMult -= 0.4f;
        }

        else {
```

Appendix B (continued)

```
            spawnRate += 0.2f;
            if (spawnRate <= 3)
                speedMult -= 0.2f;
        }
    }


    if (ratio >= 20 && ratio < 50) {
        //decrease difficulty
        difficultyLevel--;
        if (spawnRate > 1.5 && spawnRate < 5) {
            spawnRate += 0.3f;
            if(spawnRate <= 3)
                speedMult -= 0.2f;
        }

        else {
            spawnRate += 0.1f;
            if(spawnRate <= 3)
                speedMult -= 0.1f;
        }
    }

    if (ratio >= 70 && ratio < 90) {
        //increase difficulty
        difficultyLevel++;
```

Appendix B (continued)

```
        if (spawnRate > 1.5 && spawnRate < 5) {
            spawnRate -= 0.3f;
            if (spawnRate <= 3)
                speedMult += 0.2f;
        }

        else {
            spawnRate -= 0.1f;
            if (spawnRate <= 3)
                speedMult += 0.1f;
        }
    }

    if (ratio >= 90) {
        //increase a lot difficulty
        difficultyLevel = difficultyLevel + 2;
        if (spawnRate > 1.5 && spawnRate < 5) {
            spawnRate -= 0.6f;
            if (spawnRate <= 3)
                speedMult += 0.4f;
        }

        else {
            spawnRate -= 0.2f;
            if (spawnRate <= 3)
                speedMult += 0.2f;
```

Appendix B (continued)

```
          }
      }
}
```

Appendix C

AFFECTIVE-BASED DDA CODE

Here is the code used to generate the affective-based DDA.

```
// ActiveVolc: 4 , 4 , 4 , 4 , 4 , 4 , 4 , 3 , 3 , 2 , 2 , 2 , 2 , 1 , 1 , 1 , 1 , 1 , 1 , 1 , 1 ..
// Difficulty: +10 , +9 , +8 , +7 , +6 , +5 , +4 , +3 , +2 , +1 , 0 , -1 , -2 , -3 , -4 , -5 , -6 , -7 , -8 , -9 , -10 ..
// SpeedMult : 2.5 , 2.4 , 2.3 , 2.2 , 2.1 , 2.0 , 1.8 , 1.6 , 1.4 , 1.2 , 1 , 1 , 1 , 1 , 1 , 1 , 1 , 1 , 1 , 1 , 1 ..
// SpawnRate : 1 , 1.1 , 1.2 , 1.3 , 1.4 , 1.5 , 1.8 , 2.1 , 2.4 , 2.7 , 3 , 3.3 , 3.6 , 3.9 , 4.2 , 4.5 , 4.8 , 5.1 , 5.2 , 5.3 , 5.4 ..

private void AffectiveDDA(List<float> currentValues){
        float avg = currentValues.Average();

        if (isAffectiveDDA){
            float diff = avg - optimalSCL;
            if (diff > 0 && diff > diffSCL){

                //decrease difficulty
                difficultyLevel--;
                if (spawnRate > 1.5 && spawnRate < 5){
                    spawnRate += 0.3f;
```

Appendix C (continued)

```
                if (spawnRate <= 3)
                    speedMult -= 0.2f;
            }

            else{
                spawnRate += 0.1f;
                if (spawnRate <= 3)
                    speedMult -= 0.1f;
            }
        }

        if (diff < 0 && -diff > diffSCL){

            //increase difficulty
            difficultyLevel++;
            if (spawnRate > 1.5 && spawnRate < 5){
                spawnRate -= 0.3f;
                if (spawnRate <= 3)
                    speedMult += 0.2f;
            }

            else{
                spawnRate -= 0.1f;
                if (spawnRate <= 3)
                    speedMult += 0.1f;
            }
```

Appendix C (continued)

```
                }
            }
    }
```

Appendix D

ALL USERS DATA

Here is all the user's data related to SCL, difficulty levels and scores collected during the work.

Each session represents an interval of 15 seconds.

```

***********************

01st

EASY:
Diff: -10.0
Score: 19.0
Ratio: 74.07407222222223
AverageSCL: 3.2446168888888893

HARD +++:
Diff: 10.0
Score: 14.0
Ratio: 6.8
AverageSCL: 4.717566100000001

```

Appendix D (continued)

```
PERFORMA:
Diff: 2.5625
Score: 69.0
Ratio: 62.44543875
AverageSCL: 5.4416848125

PERFOAFF:
Diff: 7.0625
Score: 88.0
Ratio: 50.78125
AverageSCL: 4.421326

AFFECTIV:
Diff: 7.125
Score: 55.0
Ratio: 38.44699000000001
AverageSCL: 4.158381125000001

************************

03rd

EASY:
Diff: -10.0
Score: 18.0
Ratio: 77.77777555555555
```

Appendix D (continued)

```
AverageSCL: 4.621956777777778

HARD +++:
Diff: 10.0
Score: 37.0
Ratio: 17.2
AverageSCL: 5.5453484

PERFORMA:
Diff: 3.3333333333333335
Score: 83.0
Ratio: 66.68294666666667
AverageSCL: 4.6573336

AFFECTIV:
Diff: 7.0
Score: 80.0
Ratio: 58.04916533333334
AverageSCL: 3.8708253999999997

PERFOAFF:
Diff: 8.625
Score: 105.0
Ratio: 52.913225624999995
AverageSCL: 4.107522124999999

```

Appendix D (continued)

```
**********************

04th

EASY:
Diff: -10.0
Score: -9.0
Ratio: 30.555553333333325
AverageSCL: 3.2920880833333332

HARD +++:
Diff: 10.0
Score: -146.0
Ratio: 0.0
AverageSCL: 3.2304461428571427

PERFORMA:
Diff: 1.4375
Score: 44.0
Ratio: 55.75644875
AverageSCL: 3.0741035000000005

PERFOAFF:
Diff: 3.125
Score: 55.0
Ratio: 39.672202375
```

Appendix D (continued)

```
AverageSCL: 2.9286372500000004

AFFECTIV:
Diff: 7.125
Score: 37.0
Ratio: 34.380379687499996
AverageSCL: 2.6370069375

***********************

05th

EASY:
Diff: -10.0
Score: 41.0
Ratio: 91.66666500000001
AverageSCL: 3.080245625

HARD +++:
Diff: 10.0
Score: 18.0
Ratio: 8.0
AverageSCL: 3.896804692307693

PERFORMA:
Diff: 2.8125
```

Appendix D (continued)

```
Score: 76.0
Ratio: 61.497428125000006
AverageSCL: 3.9572193749999993

AFFECTIV:
Diff: 6.75
Score: 80.0
Ratio: 42.8909493125
AverageSCL: 3.4134943125

PERFOAFF:
Diff: 6.5
Score: 92.0
Ratio: 48.77298425
AverageSCL: 3.2738053125000004

************************

06th

EASY:
Diff: -10.0
Score: 21.0
Ratio: 80.55555416666667
AverageSCL: 14.956953333333333

```

Appendix D (continued)

```
HARD +++:
Diff: 10.0
Score: -32.0
Ratio: 2.0
AverageSCL: 16.85386

PERFORMA:
Diff: -0.25
Score: 27.0
Ratio: 54.017856875
AverageSCL: 10.494023

PERFOAFF:
Diff: 3.0
Score: 100.0
Ratio: 58.2365
AverageSCL: 12.428166437500002

AFFECTIV:
Diff: 4.625
Score: 61.0
Ratio: 51.05912312499999
AverageSCL: 17.796138125

************************
```

Appendix D (continued)

```
07th

EASY:
Diff: -10.0
Score: -9.0
Ratio: 30.30302909090909
AverageSCL: 2.575149909090909

HARD +++:
Diff: 10.0
Score: -65.0
Ratio: 0.36363636363636365
AverageSCL: 2.426510636363637

PERFORMA:
Diff: -1.1875
Score: 48.0
Ratio: 62.693451875
AverageSCL: 2.6399126249999996

AFFECTIV:
Diff: 6.25
Score: 43.0
Ratio: 33.3752334375
AverageSCL: 2.4508132500000004
```

Appendix D (continued)

```
PERFOAFF:
Diff: 2.125
Score: 35.0
Ratio: 35.9185605625
AverageSCL: 2.7058194374999998

************************

08th

EASY:
Diff: -10.0
Score: 6.0
Ratio: 49.99999799999999
AverageSCL: 4.5352066

HARD +++:
Diff: 10.0
Score: -36.0
Ratio: 1.3333333333333333
AverageSCL: 5.497226666666667

PERFORMA:
Diff: 3.1333333333333333
Score: 74.0
Ratio: 59.69023666666667
```

Appendix D (continued)

```
AverageSCL: 2.857243533333333

PERFOAFF:
Diff: 2.0625
Score: 28.0
Ratio: 47.234623125000006
AverageSCL: 3.042407875

AFFECTIV:
Diff: 3.125
Score: 73.0
Ratio: 64.692460625
AverageSCL: 1.8684764999999999

************************

09th

EASY:
Diff: -10.0
Score: 12.0
Ratio: 73.80952285714285
AverageSCL: 8.984128714285715

HARD +++:
Diff: 10.0
```

Appendix D (continued)

```
Score: 10.0
Ratio: 8.444444444444445
AverageSCL: 12.454622666666666

PERFORMA:
Diff: 2.625
Score: 80.0
Ratio: 70.60267875
AverageSCL: 18.394555000000004

AFFECTIV:
Diff: 3.375
Score: 100.0
Ratio: 66.09557
AverageSCL: 14.90274525

PERFOAFF:
Diff: 5.5
Score: 103.0
Ratio: 61.51743937499999
AverageSCL: 13.791010125

************************

10th

```

Appendix D (continued)

```
EASY:
Diff: -10.0
Score: -20.0
Ratio: 18.74999875
AverageSCL: 12.343309875000001

HARD +++:
Diff: 10.0
Score: -10.0
Ratio: 0.0
AverageSCL: 17.862399999999997

PERFORMA:
Diff: -1.8125
Score: 37.0
Ratio: 57.0833325
AverageSCL: 19.388109375

PERFOAFF:
Diff: 5.375
Score: 52.0
Ratio: 36.3829393125
AverageSCL: 12.85443925

AFFECTIV:
Diff: 6.75
```

Appendix D (continued)

```
Score: 75.0
Ratio: 40.525453750000004
AverageSCL: 12.0592043125

***********************

11th

EASY:
Diff: -10.0
Score: 24.0
Ratio: 98.14814666666666
AverageSCL: 5.786382555555556

HARD +++:
Diff: 10.0
Score: 40.0
Ratio: 17.77777777777778
AverageSCL: 6.539998222222222

PERFORMA:
Diff: 6.3125
Score: 150.0
Ratio: 66.33920625
AverageSCL: 6.27787975

```

Appendix D (continued)

```
AFFECTIV:
Diff: 5.375
Score: 106.0
Ratio: 65.01755125000001
AverageSCL: 4.330754937499999

PERFOAFF:
Diff: 6.8125
Score: 92.0
Ratio: 48.133844187499996
AverageSCL: 3.3789643125000004

************************

12th

EASY:
Diff: -10.0
Score: 2.0
Ratio: 40.90909
AverageSCL: 4.480228272727272

HARD +++:
Diff: 10.0
Score: -25.0
Ratio: 1.8181818181818181
```

Appendix D (continued)

```
AverageSCL: 7.531992636363636

PERFORMA:
Diff: 2.5
Score: 88.0
Ratio: 61.114491249999986
AverageSCL: 10.261961937499999

AFFECTIV:
Diff: 3.75
Score: 27.0
Ratio: 33.189466249999995
AverageSCL: 6.102795312499999

PERFOAFF:
Diff: 6.25
Score: 73.0
Ratio: 41.651737125
AverageSCL: 6.594013375

************************

14th

EASY:
Diff: -10.0
```

Appendix D (continued)

```
Score: 23.0
Ratio: 70.83332916666667
AverageSCL: 7.865066333333334

HARD +++:
Diff: 10.0
Score: -26.0
Ratio: 0.8888888888888888
AverageSCL: 9.663176444444446

PERFORMA:
Diff: 1.8125
Score: 60.0
Ratio: 63.995535000000004
AverageSCL: 13.600907499999998

AFFECTIV:
Diff: 6.75
Score: 63.0
Ratio: 32.799725
AverageSCL: 8.158074

PERFOAFF:
Diff: 3.5625
Score: 53.0
Ratio: 36.477273749999995
```

Appendix D (continued)

```
AverageSCL: 7.4403454375

**********************

15th

EASY:
Diff: -10.0
Score: -4.0
Ratio: 21.212119090909088
AverageSCL: 8.713875272727273

HARD +++:
Diff: 10.0
Score: 3.0
Ratio: 5.5
AverageSCL: 9.319439625

PERFORMA:
Diff: 1.6875
Score: 58.0
Ratio: 60.647320625
AverageSCL: 8.921968125

AFFECTIV:
Diff: 6.5625
```

Appendix D (continued)

```
Score: 59.0
Ratio: 33.732758125000004
AverageSCL: 7.411290875000001

PERFOAFF:
Diff: 3.75
Score: 76.0
Ratio: 51.643668125
AverageSCL: 7.318957625

***********************

16th

EASY:
Diff: -10.0
Score: 11.0
Ratio: 74.99999749999999
AverageSCL: 4.792373625

HARD +++:
Diff: 10.0
Score: -22.0
Ratio: 6.0
AverageSCL: 4.428638416666666

```

Appendix D (continued)

```
PERFORMA:
Diff: -0.125
Score: 36.0
Ratio: 52.291666875000004
AverageSCL: 5.244742

PERFOAFF:
Diff: 3.25
Score: 27.0
Ratio: 33.7977124375
AverageSCL: 3.8891936874999997

AFFECTIV:
Diff: 7.5
Score: 47.0
Ratio: 34.646222312499994
AverageSCL: 4.318695249999999

************************

17th

EASY:
Diff: -10.0
Score: 30.0
Ratio: 70.83333125
```

Appendix D (continued)

```
AverageSCL: 18.997960624999997

HARD +++:
Diff: 10.0
Score: -6.0
Ratio: 10.0
AverageSCL: 22.816919000000002

PERFORMA:
Diff: -0.25
Score: 41.0
Ratio: 56.04166625
AverageSCL: 25.43121875

AFFECTIV:
Diff: 4.0
Score: 37.0
Ratio: 30.801958125
AverageSCL: 24.551558125000007

PERFOAFF:
Diff: 4.9375
Score: 75.0
Ratio: 53.5206101875
AverageSCL: 24.674443124999996

```

Appendix D (continued)

```
************************

18th

EASY:
Diff: -10.0
Score: 7.0
Ratio: 48.33332999999999
AverageSCL: 9.367521800000002

HARD +++:
Diff: 10.0
Score: -31.0
Ratio: 2.6666666666666665
AverageSCL: 12.612244444444444

PERFORMA:
Diff: 0.625
Score: 54.0
Ratio: 64.471725625
AverageSCL: 11.544668125

PERFOAFF:
Diff: 2.8125
Score: 40.0
Ratio: 39.537909375
```

Appendix D (continued)

```
AverageSCL: 9.430382624999998

AFFECTIV:
Diff: 7.375
Score: 49.0
Ratio: 38.181059375
AverageSCL: 10.678235562500001

***********************

19th

EASY:
Diff: -10.0
Score: 17.0
Ratio: 81.24999749999999
AverageSCL: 6.775216999999999

HARD +++:
Diff: 10.0
Score: -9.0
Ratio: 3.2
AverageSCL: 4.76897362

PERFORMA:
Diff: 5.3125
```

Appendix D (continued)

```
Score: 107.0
Ratio: 64.12087874999999
AverageSCL: 6.447391500000001

AFFECTIV:
Diff: 7.125
Score: 66.0
Ratio: 43.0354123125
AverageSCL: 3.4477473749999996

PERFOAFF:
Diff: 4.9375
Score: 72.0
Ratio: 47.342566874999996
AverageSCL: 4.126069125000002

***********************

20th

EASY:
Diff: -10.0
Score: 15.0
Ratio: 72.916665
AverageSCL: 4.48561425

```

Appendix D (continued)

```
HARD +++:
Diff: 10.0
Score: -73.0
Ratio: 0.0
AverageSCL: 4.898941428571428

PERFORMA:
Diff: 2.875
Score: 58.0
Ratio: 56.897321250000005
AverageSCL: 4.0554909375

PERFOAFF:
Diff: 7.375
Score: 93.0
Ratio: 52.897519375
AverageSCL: 2.6068317500000004

AFFECTIV:
Diff: 7.5
Score: 77.0
Ratio: 45.3091890625
AverageSCL: 2.2618386874999996

************************
```

Appendix D (continued)

```
22th

EASY:
Diff: -10.0
Score: 10.0
Ratio: 56.249998749999996
AverageSCL: 47.445164999999996

HARD +++:
Diff: 10.0
Score: -52.0
Ratio: 0.0
AverageSCL: 36.850591428571434

PERFORMA:
Diff: 2.375
Score: 63.0
Ratio: 64.828868125
AverageSCL: 42.130076249999995

PERFOAFF:
Diff: 4.3125
Score: 89.0
Ratio: 53.85871249999999
AverageSCL: 28.757704374999996
```

Appendix D (continued)

```
AFFECTIV:
Diff: 4.0
Score: 71.0
Ratio: 49.252465625000006
AverageSCL: 21.604125624999998

***********************

23th

EASY:
Diff: -10.0
Score: 26.0
Ratio: 81.9444425
AverageSCL: 10.801864416666668

HARD +++:
Diff: 10.0
Score: -27.0
Ratio: 13.777777777777779
AverageSCL: 15.296357777777779

PERFORMA:
Diff: 1.5625
Score: 58.0
Ratio: 61.38392875
```

Appendix D (continued)

```
AverageSCL: 17.877682500000002

AFFECTIV:
Diff: 6.75
Score: 89.0
Ratio: 53.934871875000006
AverageSCL: 12.945127499999998

PERFOAFF:
Diff: 8.25
Score: 124.0
Ratio: 63.278078125
AverageSCL: 10.214263125

***********************

24th

EASY:
Diff: -10.0
Score: 22.0
Ratio: 102.0833325
AverageSCL: 5.5621132499999995

HARD +++:
Diff: 10.0
```

Appendix D (continued)

```
Score: 1.0
Ratio: 4.0
AverageSCL: 5.958020375

PERFORMA:
Diff: 3.5
Score: 97.0
Ratio: 62.587464999999995
AverageSCL: 7.13176825

PERFOAFF:
Diff: 7.0
Score: 84.0
Ratio: 44.4020725
AverageSCL: 5.3673660625

AFFECTIV:
Diff: 4.125
Score: 101.0
Ratio: 68.596403125
AverageSCL: 5.818749125

************************

25th

```

Appendix D (continued)

```
EASY:
Diff: -10.0
Score: 11.0
Ratio: 64.58332999999999
AverageSCL: 7.217354875

HARD +++:
Diff: 10.0
Score: -20.0
Ratio: 1.3333333333333333
AverageSCL: 10.975192222222223

PERFORMA:
Diff: 1.75
Score: 56.0
Ratio: 58.048115625
AverageSCL: 15.96043375

AFFECTIV:
Diff: 3.25
Score: 67.0
Ratio: 50.69165125
AverageSCL: 10.57454675

PERFOAFF:
Diff: -0.5625
```

Appendix D (continued)

```
Score: 33.0
Ratio: 50.625
AverageSCL: 10.625759249999998

************************

26th

EASY:
Diff: -10.0
Score: 14.0
Ratio: 58.333332500000004
AverageSCL: 2.199876083333333

HARD +++:
Diff: 10.0
Score: -29.0
Ratio: 0.8888888888888888
AverageSCL: 2.3601498888888894

PERFORMA:
Diff: 1.1875
Score: 61.0
Ratio: 66.56250187500001
AverageSCL: 2.1584301249999998
```

Appendix D (continued)

```
PERFOAFF:
Diff: 3.375
Score: 62.0
Ratio: 56.753471250000004
AverageSCL: 2.4524120000000003

AFFECTIV:
Diff: 5.0
Score: 72.0
Ratio: 56.0441475
AverageSCL: 2.2378245

************************

27th

EASY:
Diff: -10.0
Score: 2.0
Ratio: 23.333330999999998
AverageSCL: 18.248347

HARD +++:
Diff: 10.0
Score: -19.0
Ratio: 3.0
```

Appendix D (continued)

```
AverageSCL: 21.645149999999997

PERFORMA:
Diff: -6.125
Score: 1.0
Ratio: 47.39583124999999
AverageSCL: 13.158278124999999

AFFECTIV:
Diff: 0.625
Score: 54.0
Ratio: 65.066961875
AverageSCL: 14.3878550625

PERFOAFF:
Diff: 2.25
Score: 72.0
Ratio: 59.19304687500001
AverageSCL: 14.043934750000002
```

[39]

CITED LITERATURE

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VITA

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EDUCATION	
	Master of Science in Computer Science University of Illinois at Chicago, May 2018, USA
	Specialization Degree in Computer Science and Engineering, Jul 2018, Polytechnic of Milan, Italy
	Bachelor's Degree in Computer Engineering, Jul 2016, Polytechnic of Turin, Italy
LANGUAGE SKILLS	
Italian	Native speaker
English	Full working proficiency
	2016 - IELTS examination (7)
	A.Y. 2017/18 One Year of study abroad in Chicago, Illinois
	A.Y. 2016/17. Lessons and exams attended exclusively in English
SCHOLARSHIPS	
Spring 2018	Research Assistantship (RA) position (20 hours/week) with full tuition waiver plus monthly stipend
TECHNICAL SKILLS	
Basic level	C++, Javascript, HTML, CSS, SQL
Advanced level	C#, Unity3D, Java, Pyhon, C
WORK EXPERIENCE AND PROJECTS	
Jan 2018 - May 2018	Research Assistant at UIC
	Creating a Virtual Reality environment with the Shirley Ryan Ability Lab to help people in the upper and lower limbs rehabilitation after stroke or other neurologic disorders
Aug 2015 - Jul 2016	Microsoft Student Partner

VITA (continued)

Organized technical events related to Azure, Office and Dreamspark in my university

Teached to more than 60 high school students with no Computer Science background knowledges how to create in a couple of hours a FlappyBird-like game with TouchDevelop

Chosen to attend to Microsoft Build 2017 conference in Seattle