Estimating Player Experience from Arousal and Valence using Psychophysiological Signals

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***Abstract*—This work proposes a process for an assessment of Player Experience. In a simple way, the emotions are extracted according to arousal and valence values using a bi-dimensional model of affective states. The proposed process obtains affective states from two psychophysiological signals (Facial Expressions and Electrodermal Activity). Standard methods and Principal Component Analysis were used to extract a set of features from the collected signals. In this paper we propose to model a fuzzy system to assess Player Experience.**

***Keywords*-Player Experience, GUR, Emotion, Physiological Measures**

I. Introduction

The main goal of most digital games is to provide players appropriate and positive experiences that are linked to fun [1], [2]. A game designer also often crafts different game scenes to generate experiences like fear, anger and surprise, among others. For this reason, it is essential that developer teams manage to measure whether these experiences are actually reached. A great interest has been seen in emotional and affective aspects of user experience (UX), mainly in digital games. The UX in the games industry context is known as **Player Experience** (PX), which focuses on the quality of users interaction with the game, by taking users' emotions and attitudes into account [3]. In the last years, Game User Research (GUR) was often done unconventionally within game industry, e.g. the process of selection of game testers had no specific criterion. Nowadays, GUR is a strict process with its own set of methodologies, and always finding new ways to improve the player experience [4], [1]. Even with an increasing number of techniques, researchers and game developers have difficulties to make effective evaluation of the player experience [1].

The current approaches for evaluating player experience are widely based on procedures that have been adapted from other fields, repurposed in the domain of GUR [5]. It has been adopted by the game industry, as it can generate meaningful user insights, which could generate a competitive advantage for game companies [6]. However, the success of conducting GUR is largely dependent on the appropriate application of methods which are traditionally reserved for productivity analysis on software, which are not specific to games. Approaches for evaluating player experience are grounded in a variety of fields and research protocols. The evaluation process varies among game developers; also, elements like target audience, platform and genre can affect the methods for evaluating games [5].

Conventional evaluation methods have been adopted with some success for evaluating player experience, and include both subjective and objective techniques. The most usual procedure is through subjective self-reports , including questionnaires, interviews, and by means of objective reports from observational video analysis. However, these approaches solely rely on player's subjective responses, and hardly capture real experiences in while players feel them on the spot [7], [1].

In this study, we explore an approach of using physiological signals and facial expressions to evaluate player experience. This approach has some potential advantages: first, it enables in-situ assessment of player experience during the game play without breaking the player's immersion; secondly, once applied successfully, it could allow a more objective measurement of the experiences during a game session. The psychophysiological signals (such as electrodermal activity and facial expressions) are involuntary, consequently, those captured data are useful to detect the real experience of the player.

The purpose of this paper is to presented new way to evaluate the player experience by using: i) the concepts of emotion; ii) Thayer's AV-Space; iii) psychophysiological signals; and iv) fuzzy logic. These different subjects are combined in a process to more accurately estimate the actual user experience during a game session.

The remaining of this paper is organized as follows. The second section presents fundamental concepts we deal with in this work. In Section 3 we describe some related works. The details about the experiment in this study are given in Section 4. In section 5 we show the details about the fuzzy model created. The results we obtained are shown in Section 6. At last, the Sections 7 and 8 we give some final considerations.

II. Fundamental Concepts

A. Game User Research Measures

When developers and researchers carry out game user research, selecting the correct evaluation procedure depends on several factors, like: i) What kind of players? ii) What is the genre of the game? iii) Which indicators are relevant for the analysis?. Questionnaires and interviews are often used in context of the game industry, and can be used before, during, or after a play test. These procedures focus on gathering data about player behavior regarding elements contributing to a understanding about player experience [8], [1]. However, the use of self-reporting measures for data collection shows some challenges such as the difficulty in reporting the player's behavior in game situations, or the inhibition of true play experiences (that is, the players might not be totally comfortable when someone is watching or questioning them) [9]. Some authors reduced some detected problems by using video recordings of the player's gameplay session to obtain an improvement on visual memory, also known as stimulated recall. Another technique called experience graphs is used to support player's memory, where developers ask them to draw a curve showing their experience with game [10].

Psychophysiology is the another research field of game user research, which consists of procedures to infer psychological states from physiological measurements, which commonly includes electrodermal activity (EDA), electromyography (EMG), electrocardiogram (ECG) and electroencephalography (EEG) [11], [12]. The employment of physiological measures to recognize and understand physiological reactions is common in a several of science researches [12], [13], [1]. The Figure 2 shows one of the most widely used sensors in GUR literature, EDA, which is one of the direct physiological measures and a low cost sensor.

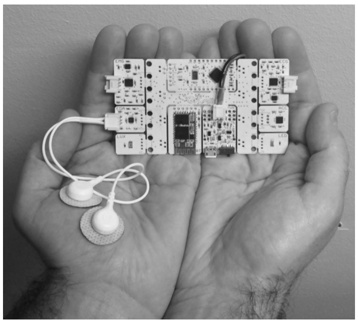

Figure 1. EDA Bitalino sensor [14].

The EDA sensor obtains conductivity values of skin, known in the literature as Galvanic Skin Response (GSR).[1] (GSR)[12]. There are specific sweat glands (eccrine glands) that change skin conductivity and result in the GSR (or GSR Intensity). Skin conductivity is associated to sweat production, which in turn can be activated by stressful or nervous events. To measure it, the electrodes are placed in the participant's hand (as shown in Figure 1). It is viewed as a good measure of arousal if used correctly [15]. Some authors have shown that GSR is directly correlated with arousal, reflecting emotional responses and cognitive activity [15], [12], [16].

The facial expressions analysis can be viewed as a psychophysiological measure [17]. It is the use of automatically recognized facial expressions to infer affective states [18]. Figure 2 shows an example of facial expression analysis. This approach is non-obtrusive compared to some other physiological approaches. It provides more authentic play experiences and allows data collection in non-laboratory settings as well [17], [2], [18].

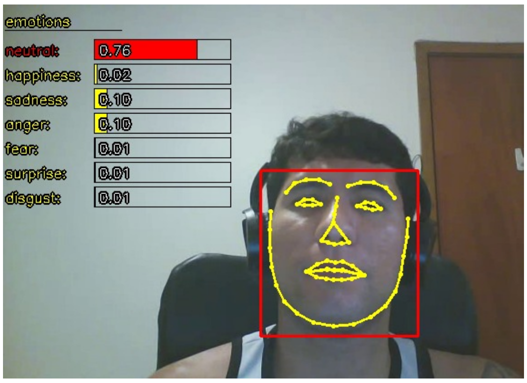

Figure 2. Facial Expression Analysis System.

B. Emotion Models

Some studies indicate that emotions appear to be an answer to an internal or external stimuli, consequently, it becomes complex to classify them accurately [1], [19], [2]. One of the main challenges in structuring or classifying emotions is language, because there are some emotions that have different meanings in different countries. Some authors have assumed that physiological response patterns could be used to identify emotions [16], and yet this view is very superficial, since the evidence suggests that not all physiological data sources can differentiate emotions [20]. In the literature, several approaches for modeling emotions have been proposed [21], [22]: i) **discrete emotion model**: this model defines a set of core emotions that are biologically determined by emotional responses whose expression and recognition are fundamentally the same for all individuals regardless of ethnic or cultural differences [21]; ii) **dimensional emotion model**: considers a continuous multidimensional space where each dimension stands for a fundamental property common to all emotions. Two of the most accepted dimensions were described by Russel [23] and Thayer [24]: **Valence** per definition is the

[1] In older terminology as "skin conductance response".

evaluation of the emotions (positive-negative or pleasure-displeasure), and **Arousal** while the definition is the degree of emotion (arousal-sleepiness or tension-relaxation) [22], [19]. The authors used the dimensions to create their models: i) Russell's Circumplex Model of Affect (or Russell's AV-Space); ii) Thayer's emotion model [24], as shown in Figure 3.

In this work, we use the Thayer's two-dimensional emotion model (in terms of valence and arousal) with some modifications to categorize emotions. This model interprets emotional mechanisms as a continuous sequence of affections. They are presented on a system of axes, where each point represents a emotion. Valence represents how much an emotion is felt by people as positive or negative (e.g., someone feeling happy has evaluated surrounding events as very positive). Arousal indicates how relevant the surrounding events are and therefore how intense the emotion is. For example, someone feeling excited will have a high arousal. Therefore, in model of affect, arousal and valence can be adequate parameters to recognize specific emotions. This simple model is used in several scientific studies about emotions, providing a reliable way for comparing results [22], [18], [19], [25].

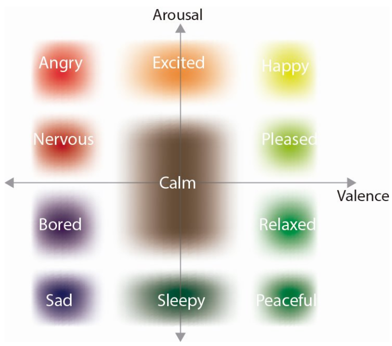

Figure 3. Thayer's two-dimensional emotion space model [26].

C. Fuzzy Logic

Fuzzy logic simulates human thinking as it uses an imprecise language to solve real problems. [27]. This system explores the imprecision of the input and output variables by determine them within fuzzy domain that are expressed in linguistic terms (e.g., low, medium, high). The IF/THEN rules (known as **rule-based fuzzy systems**, see Equation 1) are used to describe the desired system response in terms of the linguistic variables [25].

$$IF < Antecedent > THEN < Consequent > \quad (1)$$

Fuzzy logic is main characterized by imprecision and simplicity. It uses linguistic expressions that are more related with continuous data. It has been used in several research fields, such as: machine learning, prediction of time series, data mining, among others [27], [19].

The fuzzy logic system consists of inputs, outputs, membership functions, and rules (see Figure 4). The inputs are transformed to fuzzy values in the **fuzzifier**, to be processed in the **inference engine**. The membership functions are defined by the expert using knowledge and rule base, and they are elements that transform the inputs and the outputs.

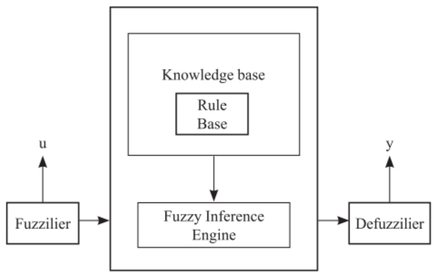

Figure 4. Generic fuzzy system with fuzzification and defuzzification units (adapted from [28]).

Membership functions can take a number of shapes. According to the studies [27], [1], [25], triangular and trapezoidal membership functions are the most usual (an example of these functions can be seen in Figure 5). The rules use the input values as weighting factors to determine their influence on the fuzzy solution sets. Once the functions are processed, they are **defuzzified** into a solution variable (outputs).

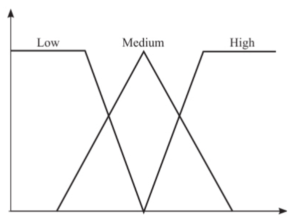

Figure 5. Example of a membership function.

III. Related Work

Psychophysiology signals such as skin conductance, cardiovascular activity, facial expressions have been studied as potential metrics to games user research domain. A systematic review of the current state of physiological game research, their advantages and limitations has been provided by Nacke [9] and Soares [12].

Mandryk et al. [25] provides a procedure for quantifying emotional states during the game session, using an approach based on fuzzy logic that classifies ECG, EMG and GSR measurements in terms of both Arousal and Valence. The work in [29] describes the use of facial Electromyography as a measure to obtain emotional valence during game session. Other papers in the area, such as in [30] which statistically correlated physiological data and subjective data of emotional components of the player experience, and [31] which has used physiological data to recognize user enjoyment in a car racing game, and [32] which presented a research on Galvanic Skin Response and Heart Rate correlations with the player experience in a First-Person Shooter game.

The studies in [33], [34], [35] investigated the correlation between physiological changes and a same game under different settings, and presented some interesting findings using Galvanic Skin Response, electroencephalogram and electromyography, confirming that players feel differently while playing a same game with different settings.

The research in [19] approaches the study of the player behavior by applying concepts from dynamics systems to infer player emotions. The authors used Russell's affect Grid (which maps emotions to cells on a grid) to collect data from participants. They were asked to mark an 'X' wherever they consider that their emotions are better represented in grid. This approach is a quick way of assessing affect along with the dimensions of the AV-Space. Lastly, to validate data they compared the real values to the outcomes of the fuzzy models.

Regarding the facial expressions, the authors [36], [37] proposed two different procedures of emotion detection using Fuzzy logic and Neural Networks, respectively. The third contribution investigates the feasibility of assessing fun only from the computational analysis of facial images captured with a low cost device (web cam). This study was based on a set of videos recorded from the faces of participants while they played three different games. The method of emotion detection is based on existing implementations of the Viola-Jones algorithm for face detection and a variation of the Active Appearance Model algorithm for tracking the facial landmarks [18].

IV. The Experimental Setup

To evaluate our model we designed an experimental setup based on a racing game. The game selected was OpenNFS1 [2] (Figure 6). Two psychophysiological measures were used in the experiment: facial expressions and Galvanic Skin Response. They were both chosen based on academic literature describing them as precise and simple measures with a low level of intrusiveness that can be collected and analyzed without wide specialized knowledge on psychophysiological measures.

The experimental setup was based on two game components, **drifting** (settings: Enable or Disable) [3] and **gearbox**

Figure 6. Screenshot of OpenNFS1 [38].

(settings: Manual or Automatic), as they would possibly affect the experience of gamers. In order to investigate how game settings can influence player's experience, we conducted a within-subject study in which participants played the OpenNFS1 under various conditions of setting in a random way. All game sessions were held in the same location, on weekdays between 9:00 and 17:00, with each test lasting approximately 20 minutes. After a short introduction including information about the play test, the participant was asked to sign a consent form informing them about the purpose of the experiment, their rights, and how the collected data would be handled and stored. The following subsections describe our experiment in details.

A. Participants

The participants include 4 females and 16 males. The age of the participants ranged from 18-32 years (mean = 23.25; SD = 3.36) and the characteristics ranged from college students to game developer. Participants were recruited voluntarily through social networks. During the pre-session interview, the participants were asked if they had prior experience with racing games. All participants played racing games (at least once in their lives) and the majority (4 females and 10 males) considered themselves casual players. Before beginning the experiment, the participants filled out a simple questionnaire, used to collect information on their experience with racing games, thus we can distinguish the participants in two groups (casual and non-causal) and to check if there is any difference in behavior between them.

B. Procedure

Participants sat in a convenient chair while electrodes were applied. They were asked to rest four minutes while a baseline for physiological measures was recorded. After the rest period, the participants were instructed about the racing game. They played each game session for approximately four minutes. To reduce the potential of carryover effects affecting the data collection, we asked the participants to perform hand hygiene and avoid getting out of the chair. Soon after, they were asked to play four game sessions with the following settings: i) **Session 1**: enabled drift and automatic gearbox; ii) **Session 2**: disabled drift and automatic gearbox; iii) **Session 3**: enabled drift and manual

[2]OpenNFS1 is an open-source rewrite of the original Need for Speed 1 game by Pioneer Studios and EA [38]

[3]Drifting implies traveling through tight corners in over steering, the rear wheels without traction, and the front wheels pointing in the opposite direction to the turn [1]

gearbox; vi) **Session 4**: disabled drift and manual gearbox. We randomized the order of the settings for each participant, in order to reduce the learning effects of the game.

The data synchronization was an important factor to the process of data analysis. We develop an Android application (Figure 7) to make data synchronization of three data sources (EDA sensor, video recording and in-game data). When sensor status was "connected" (Figure 7 (B)) and Camera was on, then we could start the game session (pressing the "start" button), and the process of data acquisition was initiated (Figure 7 (A)). The data for each game session were exported into a CSV file.

Figure 7. Android Application for the process of data synchronization.

Psychophysical data (GSR and facial expressions) were recorded during the play sessions (for all participants). Galvanic Skin Responses were measured using the Bitalino EDA sensor (Figure 1) which was attached in the palm of the hand. In addition to the physiological measurements, the face of the participants were video-recorded for later analysis of facial expressions (see Figure 8). The first experiments had some logistic problems: incorrect use of the sensor (the electrodes were in wrong place) and some participants stopped the experiment. In this cases, we excluded the participants with noisy data from data analysis.

Figure 8. A participant taking part of the game session.

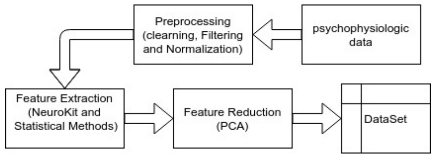

Figure 9. Block diagram representing the acquisition and processing chain.

C. Preprocessing and Feature Extraction

A block diagram of the data treatment process is shown in Figure 9. All signals were preprocessed, i.e., normalized and filtered. Afterward, the most significant features were extracted and then reduced using the Principal Component Analysis (PCA) method. The following features were identified:

- **Galvanic Skin Response**: The GSR values, GSR amplitudes, and GSR peaks/onsets were extracted from the EDA (collected at 100 Hz) as relevant features. Detected GSR with an amplitude smaller than 10% of the maximum GSR amplitude were excluded. We used a Biosignals Processing Tool in Python to facilitate the data processing [39]. In addition, GSR value has high individual variability, making a direct comparison across the subjects impossible. Thus, we used the most common procedure to normalize the GSR value (Equation 2 [1]):

$$GSR_{normalized} = \frac{GSR_t - GSR_{min}}{GSR_{max} - GSR_{min}} \tag{2}$$

- **Facial Expressions**: The fundamental step in facial expressions analysis is to recognize facial expressions. Thus, in this study, we explored a quantitative approach for the acquisition of metrics for describing facial expressions of the player. We briefly describe the acquisition process of the prototypical emotions[4]: i) The facial expression analyzer uses OpenCV to read the player's facial video, and process the Gabor filters; ii) It detect prototypical emotions using SVM (support vector machines) that is trained from two image database. Thus, we have a feature vector that contains 68 responses for each facial landmark; iii) the analyzer returns a response that contains the probabilities of each prototypical emotion (see Figure 2), such as: **Neutral**, **Sadness**, **Fear**, **Surprise**, **Anger**, **Happiness**, and **Disgust**.
  According to the data distribution (Figure 10), we checked that some emotions have same behavior between sessions. We applied ANOVA (Analysis of Variance) in each emotion, to determine whether there are any statistically significant differences among the averages of the sessions. As result, "Fear" ($F_{statistic} = 0.06$,

[4]Viera [18] provides a detailed description of the facial expression analyzer

$p_{value} = 0.98 > 0.05$), as well as "Surprise" ($F_{statistic} = 0.015$, $p_{value} = 0.99 > 0.05$) has same average in all sessions. Both have a small data density (Figure 10 shows the data distribution of the prototypical emotions through the violin plot[5]), thus we removed "Fear" and "Surprise" from this research. In addition, we used PCA to reduce the number of dimensions (or features) in this dataset without losing much information (for details on PCA, see [40]). Based in data distribution, we combined "Anger", "Disgust","Sadness" as **Negative Emotions** (this component with **Average Cumulative Variance** explains nearly 84% of the variability in the original three variables). Lastly, the prototypic emotion "Happiness" is called **Positive Emotion** and "Neutral" is like **Neutral Emotion**.

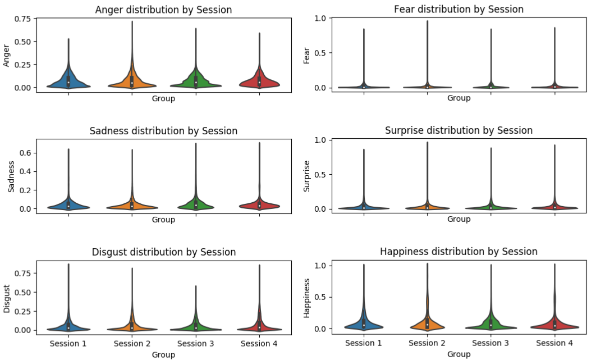

Figure 10. Prototypic Emotion Distribution by Session using Violin Plot.

Figure 11 presents the parameters monitored along a game session. Since the signals are displayed in continuous time, we may observe all the evolution of the player experience during the game session.

V. Proposed Model Overview

The strength of this research was fuzzy logic, it supply the degree of membership to the system features, such as Valence and Arousal. Using the fuzzy logic we can obtain a value from a expert-defined interval representing how much is it feature, with respect to the inputs. In this section, we describe the overall architecture of the fuzzy model and some details on the fuzzy rules and operations.

A. Building the fuzzy model

We used the GSR (normalized signal and amplitude) and facial expressions (Neutral, Positive and Negative) as inputs to a fuzzy logic model that estimated player's arousal e valence. To generate this model, we analyzed the participants' data distribution based on GSR and Facial Expressions. This work presents a high-level description of the model, providing subsidies for the construction of the proposed model.

[5]The Violin plot performs a similar function as histograms and box plots. It presents a distribution of quantitative data on several levels of one or more variables such that those distributions can be compared.

B. Modeling AV space

Considering the continuous nature of psychophysical data, we collected the complete input signals for the entire game session. Thus, we were able to generate a continuous time response in the AV space, which provides a detailed description of the game session, instead of using a single indicator, e.g., the average value of the signal.

The model of psychophysiological used to create AV space had five inputs (GSR value, GSR amplitude, Neutral Emotion, Positive Emotion, and Negative Emotion) and two outputs (arousal and valence) (see Figure 12). Inputs were normalized signals $[0.0, 1.0]$, while outputs were in a range $[-6, 6]$ for arousal and valence. For each input signal, the membership functions were created using the specific signal features for each participant. We have 24 rules, they were generated relating the psychophysiology signals to the concepts of arousal and valence. GSR correlates with arousal, and increased GSR value is directly related to increasing arousal. The extreme high and low levels of GSR were modulated by GSR amplitude. For example, if amplitude is short and GSR is high then arousal is altered, else arousal is maintained. Valence is increased with increasing levels of Positive Emotion, decreased with increasing levels of Negative Emotion, and neutralized with increasing levels of Neutral Emotion. Our membership functions for the outputs and the rules (For more details about fuzzy rules, see Appendix A) were generated by dividing valence and arousal into five class: "low", "mid low", "medium", "mid strong", and "strong".

VI. Results

We use arousal and valence average values obtained from Thayer's model, in order to map the emotions that were predominant in game session. In addition, we use scatter plot to learn about data distribution and the relationship between valence and arousal (the plots can be seen in Figures 13-16).

For our study, we mapped the dense region of the chart according to the emotional experience shown in Figure 3. Then, we infer the following information based on the results of proposed model:

- Session 1: as can be seen in Figure 13, the valence and arousal values are concentrated in the first (region means fun or pleased) and fourth quadrant (region means relaxed or peaceful), because the race was relatively easy and performance indicators (such as "Lap Time", "Lap Elapsed" and "off-road rate") of players were very good, then the most players feel happy with the Session 1.
- Session 2: in Figure 14, the valence and arousal values are concentrated in the first (region means fun or pleased) and fourth quadrant (region means relaxed or

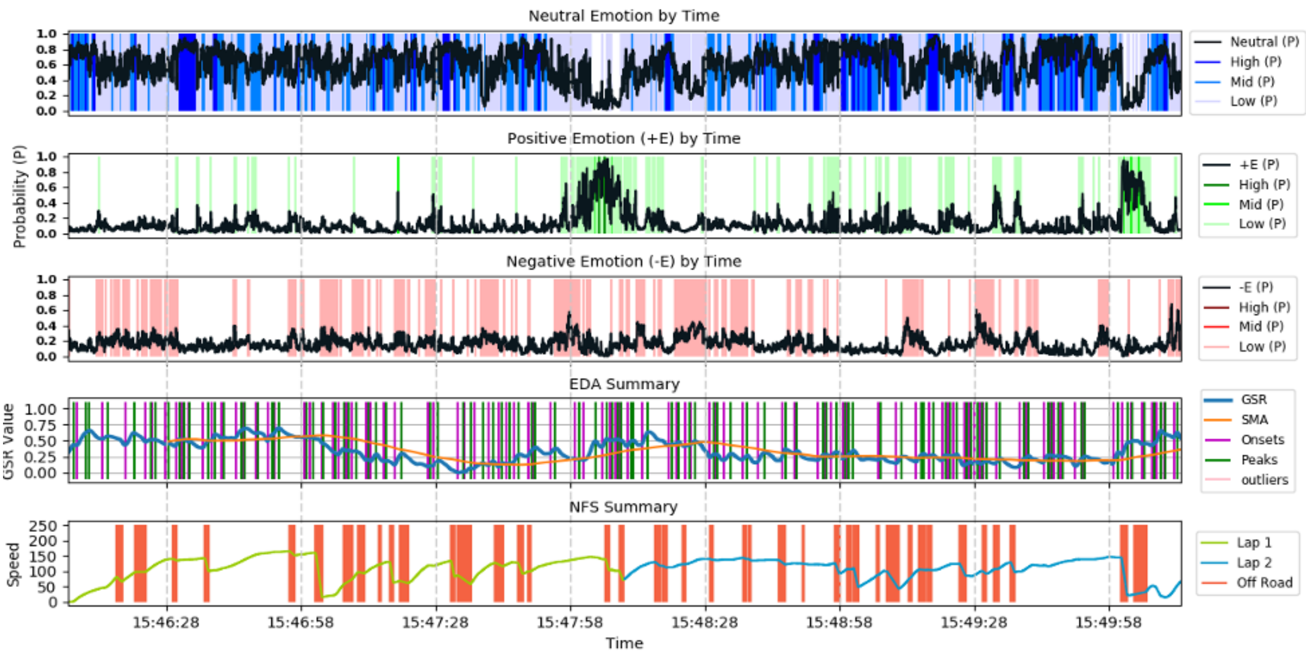

Figure 11. The 2D visualization of extracted features over game session time for a player.

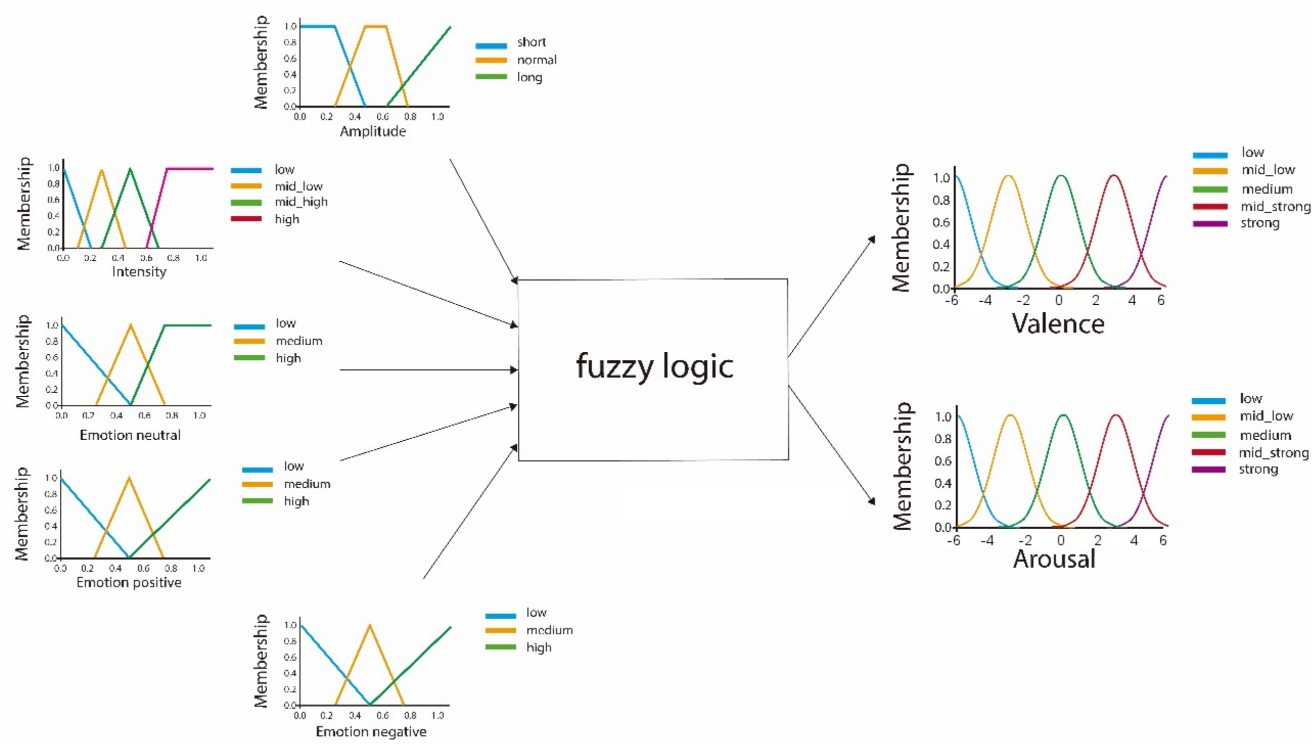

Figure 12. Modeling arousal and valence from psychophysical data.

peaceful). This behavior of the valence and arousal data is due to the following situation: Most players played the Session 2 without difficulty, the use of the commands and the race (few curves) were relatively easy.

- Session 3: in Figure 15, the valence and arousal values

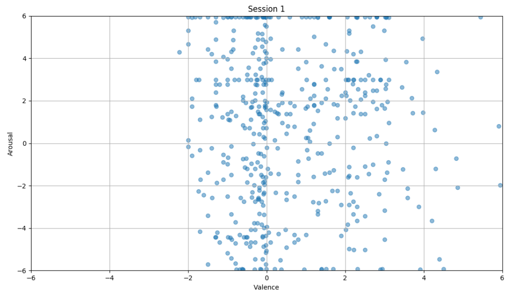

Figure 13. Scatter Plot of Session 1.

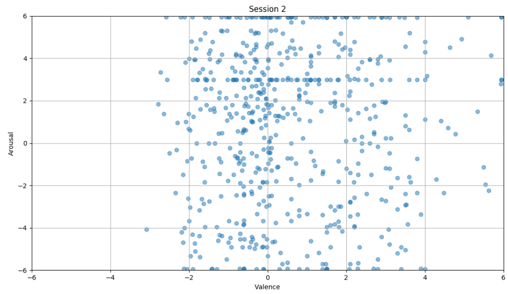

Figure 14. Scatter Plot of Session 2.

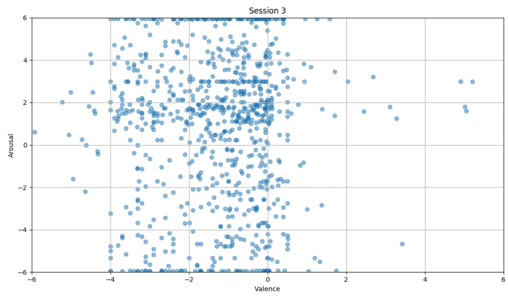

Figure 15. Scatter Plot of Session 3.

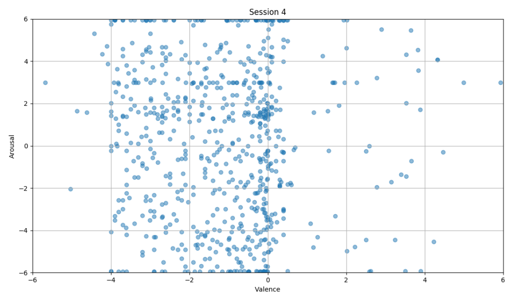

Figure 16. Scatter Plot of Session 4.

are concentrated in second quadrant (region means angry or nervous) and third quadrant (region means bored or sad). This behavior of the valence and arousal data is due to the following situation: Some players played the game the wrong way, they probably had difficulty in the settings of Session 3, where gearbox is manual.

- Session 4: in Figure 16, the valence and arousal values are concentrated in second quadrant (region means angry or nervous) and third quadrant (region means bored or sad). This behavior of the valence and arousal data is due to the following situation: In this experiment, most players have very little knowledge about the gamepad (or joystick), and they did not use it in the correct way. These players mistook the commands such as “Drift” and “Manual Gearbox” many times, consequently, their “off-road rate” and “Lap Time” were high. Therefore, a large sample of players was unsatisfied with this session.

According to the characteristics of this racing game, where it requires a lot of concentration, some players have kept focus on the screen, and they showed few physiological and facial reactions, consequently, arousal and valence values were close to the origin (region means calm) of the coordinate system more times during game session.

VII. Discussion

The model proposed shows the arousal and valence values inferred from psychophysiological data. This paper was an introduction to show the relation between fuzzy model and psychophysiological data. The model proposed is robust, nevertheless, there are many possibilities for improving its capability: i) To perform a deep analysis about different Emotion Models; ii) The use of the most promising models of biosensors: such as the smart watch or wristband (e.g. Empatica [41]) as an alternative.

In the future work, we can test other game genres to analyses and see whether we can use psychophysiological data to obtain more accuracy and recognize a more diverse set of emotional experiences. In addition, we can expand the proposed model, including other artificial intelligence techniques such as neural networks or clustering algorithms, in order to classify player experience using valence and arousal.

We plan to develop a dashboard which can provide game designers rich informations to optimize the evaluation of Player Experience based on statistical analysis of psychophysiological data collected from many players playing games with various settings.

We notice some limitations of using psychophysiological data in our study. First, collecting physiological signals requires player’s hand connected with the sensor. Although the sensor used in this research is commodity wearables, the EDA sensor is very sensitive to hand movement during game sessions, consequently, the abrupt movements may resulting in high levels of noise. In addition, the brightness of the place can adversely affects the facial recognition process, then we always did the experiments in room with ambient light.

VIII. Conclusion

This paper has investigated the use of psychophysiological data to evaluate player experience using arousal and valence values under different racing game conditions. The results show that players are most satisfied if the games settings match their capability of racing game. We have demonstrated the potential of using psychophysiological data to obtain arousal and valence under different game settings. The result of this work illustrates the possibility to evaluate player experience without the use of questionnaires and interviews. However, the traditional approach together with mixed-methods (using sensors, computational vision and among others) may make the evaluation process more robust and accurate.

Appendix A. Rules for transforming psychophysiological variables into arousal-valence space

The proposed model is composed of 24 rules that were determined by the author based on knowledge and a strong investigation in literature, and they are describe below:

- If *GSR_value* is high and *GSR_amplitude* is long Then *arousal* is strong
- If *GSR_value* is high and *GSR_amplitude* is normal Then *arousal* is mid_strong
- If *GSR_value* is high and *GSR_amplitude* is short Then *arousal* is mid_strong
- If *GSR_value* is mid_high and *GSR_amplitude* is long Then *arousal* is strong
- If *GSR_value* is mid_high and *GSR_amplitude* is normal Then *arousal* is mid_strong
- If *GSR_value* is mid_high and *GSR_amplitude* is short Then *arousal* is medium
- If *GSR_value* is mid and *GSR_amplitude* is long Then *arousal* is mid_strong
- If *GSR_value* is mid and *GSR_amplitude* is normal Then *arousal* is medium
- If *GSR_value* is mid and *GSR_amplitude* is short Then *arousal* is mid_low
- If *GSR_value* is mid_low and *GSR_amplitude* is long Then *arousal* is medium
- If *GSR_value* is mid_low and *GSR_amplitude* is normal Then *arousal* is mid_low
- If *GSR_value* is mid_low and *GSR_amplitude* is short Then *arousal* is low
- If *GSR_value* is low and *GSR_amplitude* is long Then *arousal* is mid_low
- If *GSR_value* is low and *GSR_amplitude* is normal Then *arousal* is low
- If *GSR_value* is low and *GSR_amplitude* is short Then *arousal* is low
- If *neutral* is high and *positive* is low and *negative* is low Then *valence* is medium
- If *neutral* is medium and *positive* is low and *negative* is low Then *valence* is medium
- If *neutral* is low and *positive* is low and *negative* is low Then *valence* is medium
- If *neutral* is low and *positive* is high and *negative* is low Then *valence* is high
- If *neutral* is low and *positive* is medium and *negative* is low Then *valence* is mid_high
- If *neutral* is medium and *positive* is medium and *negative* is low Then *valence* is mid_high
- If *neutral* is low and *positive* is low and *negative* is high Then *valence* is low
- If *neutral* is low and *positive* is low and *negative* is medium Then *valence* is mid_low
- If *neutral* is medium and *positive* is low and *negative* is medium Then *valence* is mid_low

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