Biofeedback Sensors in Electronic Games: A Practical Evaluation

Rodrigo Soares[1] * Elton Sarmanho[1] Marco Miura[2] Tiago Silva[2] Ricardo Jacobi[1]
Carla Castanho[1]

[1]Universidade de Brasília, Departamento de Ciência da Computação, Brazil
[2]Universidade de Brasília, Departamento de Design, Brazil

ABSTRACT

In the electronic games industry, many ways of testing a new game are used in order to determine some aspects of the game, such as fun, replay value and immersion. One way to evaluate these characteristics is through the use of sensors, more specifically the ones that measure player's biophysiological variables, called biofeedback sensors. The purpose of this study is to perform a practical evaluation of the use of biofeedback sensors, when employed to know the behavior of the player in different genres of games. More precisely, an experiment with three biofeedback sensors (Electrocardiography, Electrodermal Activity Sensor, and Electromyography) was conducted to verify the suitability of these sensors in identifying the player's emotions according to the genre of the game. The results showed that intense emotions, like the ones felt in horror or action games, are more detectable in general, but they are more notable when using the Electrocardiography sensor.

Keywords: Game analytics, user data telemetry, biofeedback sensors.

1 INTRODUCTION

When developing a new game, most companies rely on marketing studies and existing frameworks to define many of its financial aspects, like reception, sales and market share, for example [15]. The product value in game industry is determined by a set of key players, products and channels that converge to provide a fun experience to the consumer [5]. However, the player's evaluation is often expressed by personal and social indicators, such as involvement, positive emotions during gameplay, wish for mastering the game (replayability), and recommendation in social networks. To measure these aspects, developers and publishers often use playtesting, which consists of external audience viewing and playing the game before its release in order to check their opinions continuously as the game is developed [2].

The measurement of the impact of game content on the player's experience has been pointed out as a holdback to predict a game's achievement in market. Despite being an objective measure, ratings by the players can be misleading due to the misfit between the game's goals and the player's expectations. Using questionnaires and opinion surveys has been found unsatisfactory, so many companies are relying on biofeedback sensors to physically obtain that impact from players, including the usage of sensors within the playtest sessions [1].

While many research initiatives discuss the use of biofeedback sensors in games [16], they are often related to one sensor or one genre of game. Therefore, it is difficult to define which sensor is best suited for a specific genre or to detect specific emotions, like sadness or joy.

*email:rodrigo.teixeira0@gmail.com

This study intends to employ the usage of different sensors in players while playing different game genres. Ideally, presenting a comparison of different sensors, defining which is best in detecting specific emotions in a spectrum of game genres, in order to suggest a more suitable use of such sensors to the game industry.

To accomplish this purpose, an experiment with three sensors, Electrocardiography (ECG), Electrodermal Activity Sensor (EDA), and Electromyography (EMG) was conducted. They were selected among the sensors in the survey presented in [16] and used to obtain physiological variables from participants during several game sessions, each one from games with different genres. More precisely, the main goal of the experiment was to verify the suitability of these sensors in identifying the player's emotions according to the game genre.

This rest of this article is organized as follows. Section 2 explains the main concepts used in the execution of the experiment. Section 3 contains the research works that are related to this study. The experiment conducted with the EDA, ECG and EMG sensors is detailed in Section 4. The results of the experiment are presented in Section 5, along with their discussion. In Section 6, the general consequences of this study and the future works are discussed.

2 FUNDAMENTAL CONCEPTS

2.1 Sensor Kit

For this experiment, the biofeedback data collection equipment selected was the Bitalino Kit[1] (Figure 1). It is an open hardware solution that allows biofeedback data acquisition in a simple and easy way.

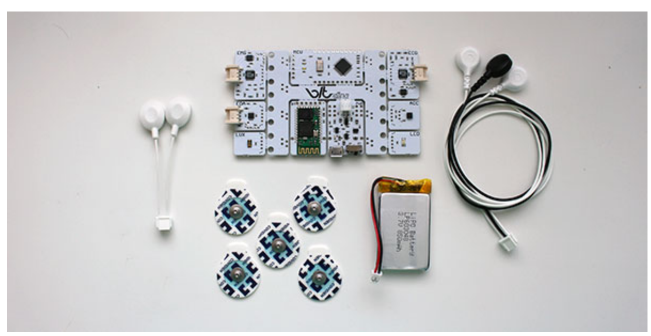


Figure 1: A Bitalino sensor kit [13].

The Bitalino kit specifications are as follows [9]:

- Sampling rate: 1, 10, 100 or 1000Hz;
- Analog ports: four 10-bit ports and two 6-bit ports;
- Digital ports: 4 input ports and 4 output ports;

[1]http://www.bitalino.com/

- Communication: Bluetooth 2.0 + EDR;
- Reach: Up to 10m (within line-of-sight);
- Sensors:
  - Electrocardiography;
  - Electromyography;
  - Electrodermal Activity;
  - Accelerometer;
  - Light Sensor;
- Actuators: LED;
- Size: 105x60x6mm.

2.1.1 ECG Sensor

The Bitalino ECG sensor is a one-channel sensor that maps electrical activity from the heart in a graph of tension by time [10]. In the Bitalino kit, it is found in two or three-electrode versions, where each version requires a different electrode positioning on the participant's body. (Figure 2). In our experiment, the three-electrode version of the sensor was used.

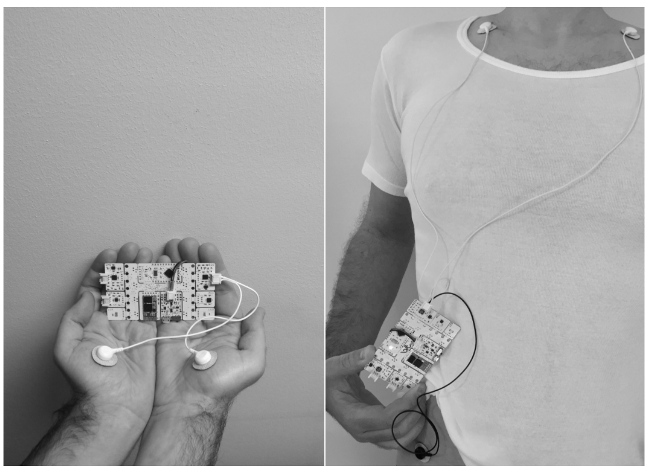


Figure 2: ECG Sensor electrode positioning [10].

The sensor obtains the voltage difference measured by two electrodes that are positioned on the participant's chest, while a third electrode is used as reference, placed on an area that has less electrical activity coming from the heart, like the belly, for example. This signal passes to the sensor, where it is mapped according to the operation voltage of the sensor and the number of bits of the analog ports of the controller. The output tension of the ECG is shown in the Equation 1 [10].

$$ECG(V) = \frac{(\frac{ADC}{2^n} - \frac{1}{2}) \times VCC}{G_{ECG}} \quad (1)$$

Where:

- $ECG(V)$ is the output voltage of the sensor;
- ADC is the analog value measured by the electrodes, mapped to equivalent values between -1,5 and 1,5 mV;
- n is the number of bits in the electrodes input channel;
- VCC is the supply voltage of the sensor;
- G_{ECG} is the sensor gain, fixed in 1000.

2.1.2 EMG Sensor

The Bitalino EMG sensor detects muscular activity using three electrodes. Similar to the ECG, two electrodes are responsible for capturing a voltage difference generated by muscles, while another is used as a reference. Figure 3 shows the electrodes placement for a correct muscular activity acquisition.

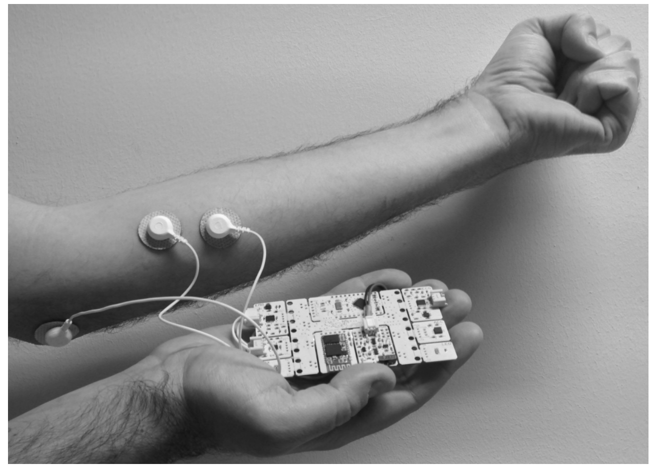


Figure 3: EMG sensor electrodes placement [12].

During muscular contraction, the electrodes capture the voltage variation generated by nerves, responsible for muscular movement. Then, this signal is transformed to the same order of magnitude of the controller, according to Equation 2.

$$EMG(V) = \frac{(\frac{ADC}{2^n} - \frac{1}{2}) \times VCC}{G_{EMG}} \quad (2)$$

Where:

- $EMG(V)$ is the output voltage of the sensor;
- ADC is the analog value measured by the electrodes, mapped to equivalent values between -1,65 and 1,65 mV;
- n is the number of bits in the electrodes input channel;
- VCC is the supply voltage of the sensor;
- G_{EMG} is the sensor gain, fixed in 1000.

2.1.3 EDA Sensor

The Bitalino kit EDA sensor obtains conductivity values from the skin through two sensors. Skin conductivity is related 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 skin, like in Figure 4.

Skin conductivity is represented in the order of μS. The values measured by the sensor are transformed in conductivity according to Equation 3 [11].

$$EDA(\mu S) = \frac{1}{1 - \frac{ADC}{2^n}} \quad (3)$$

Where:

- $EDA(\mu S)$ is the output conductivity of the sensor;
- ADC is the analog value measured by the electrodes, mapped to equivalent values between 1 and $\infty \mu S$;
- n is the number of bits in the electrodes input channel.

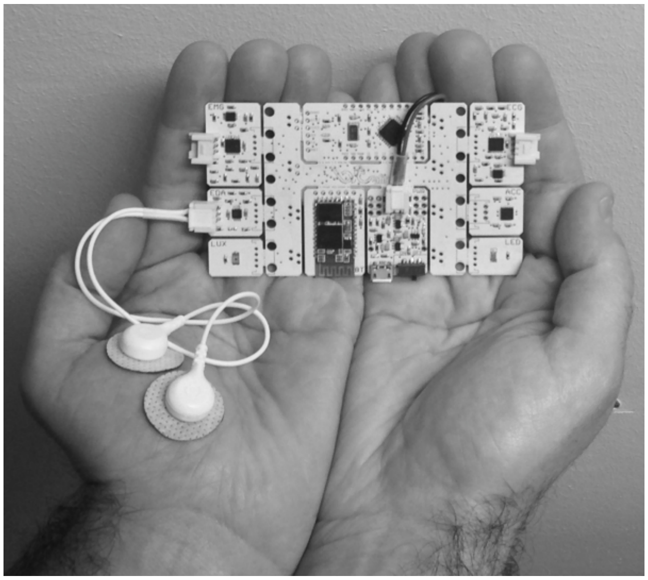


Figure 4: Posicionamento dos eletrodos do EDA sensor [11].

2.2 Emotions Classification

In this study, it was necessary to find a scientific way of sorting different types of emotions, as described by the participants. One existing method of achieving this classification is through the Circumplex Model, proposed by James A. Russel [14].

This model describes each emotion in a two-dimension chart. The x-axis represents Valence, a measurement that separates good and bad emotions, such as sadness has a negative valence, as joy has a positive valence. The y-axis represents the emotion's intensity. There are 8 emotions that are used as examples of the extreme points of valence, intensity or hybrid emotions that contain both. Figure 5 shows these emotions displaced in the chart.

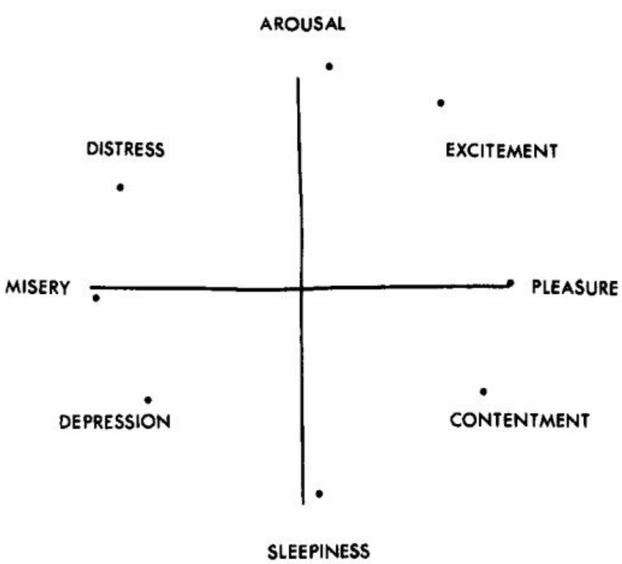


Figure 5: Example of emotions placed in the Circumplex Model chart [14].

It is possible, using some kind of criteria, to place every emotion into this chart. Russel, using his criteria described in [14], placed a substantial number of emotions (Figure 6). This was proved to be very useful in analyzing the affective description given by the participants after each game session. This analysis is shown in Subsection 4.4.3.

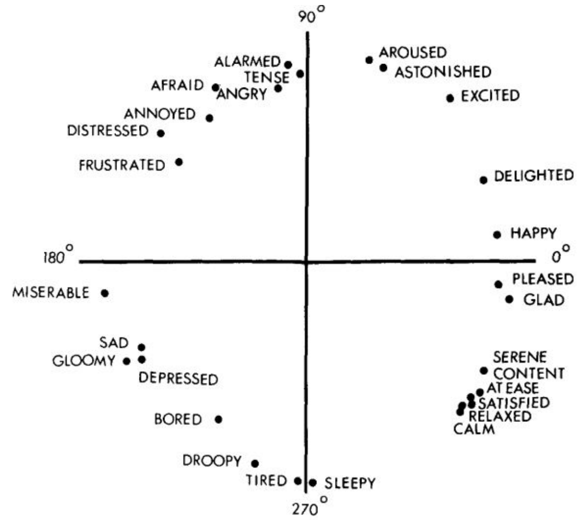


Figure 6: A number of emotions placed in the Circumplex Chart [14].

3 Related Works

Before this experiment, we have conducted a survey research in order to identify the main biofeedback sensors that are used in this field when analyzing player affect changes in video games. This survey yielded an article [16] which serves as the basis and main reference in this present work for sensor selection and research methodology choice.

The software developed in [17] is an example of tool used to facilitate the study of biofeedback sensors in playtesting. Called ”affect annotation tool”, this program recorded gameplay from the game while capturing the player's face through a camera. Both recordings were synchronized, then the participant could annotate exactly in which moments there were moments that were scary or cause strong emotions in them. A simple tool, like this, caused a big impact in the results presented. Such methodology inspired this experiment of how to make the participants mark what emotions they had during the gameplay sessions.

Moreover, in [7], the researchers used two sensors, EDA and EMG, to measure affect changes during gameplay of a first-person shooter game. They also used the game's sound effects and music as factors that could change sensor values, when compared to a session that had no sound at all. When measuring the player's emotions through the EMG sensor, each electrode was positioned on the participant's face in a different position in order to acquire positive or negative valence in their facial expressions (Figure 7). Such placement was also used in this experiment, as it was considered a satisfactory way of detecting many facial expressions changes during sensor data collection.

4 The Experiment

4.1 Overview

The objective of this experiment is, given some video game genres, determine if a specific sensor category is more adequate to identify affective changes in the players.

The general idea of the experiment consists in submitting a certain number of participants to short game sessions. Meanwhile, they are monitored through biofeedback sensors. Then, collected

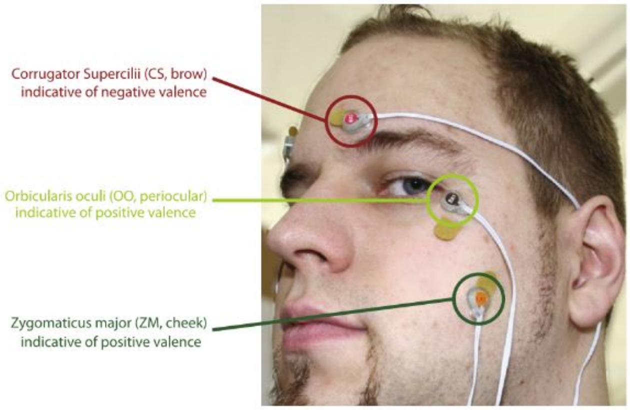


Figure 7: Electrodes placed on the participant's face [7].

data from each session are correlated with the emotional states described by the players themselves to verify if the the values given by the sensors in use are enough to determine the occurrence of any kind of emotional changes during the data collection.

For this experiment, four game genres were selected:

- Action;
- Puzzle;
- Horror;
- Racing.

The reason for this genre delimitation was to select the types of games that were more distinct in nature and, at the same time, games that caused different emotional states, given their aspects of interaction, environment and gameplay.

For this experiment, three sensors were used in the data collection: i) Electrocardiography Sensor (ECG); ii) Electromyography Sensor (EMG); iii) Electrodermal Activity Sensor (EDA). These sensors were selected due to ease of use (usability) and low noise level [16].

To validate the data collected from the sensors, a questionnaire was given for the participants to fill. They described the emotional states identified by them during the game sessions. To assist in the identification of each emotion in different moments in the game, each session was recorded. Each video contained the gameplay and the participant's face captured by a camera during the session. This way, they could determine with an acceptable level of trust every feeling present within the data acquisition. With these questionnaires completed, the sensors and emotional data were cross-checked to check if the sensors used were satisfactory for the intended purpose.

4.2 Technological Apparatus

4.2.1 Hardware

The computer used had the following specification:

- Dell XPS Computer
- Intel Core i7-4790 3.6 GHz Processor
- 16 GB RAM
- 1 TB Hard Drive
- Windows 10 Home 64 bits System

Besides the computer, a Microsoft camera was used to record the participant during the experiment.

As stated before, the Bitalino sensor kit was used as the tool to collect the participant's biofeedback data.

4.2.2 Software

Open Signals is a biofeedback data collection tool developed by Plux Wireless Biosignals[1], the same company responsible for producing the Bitalino kit. This tool is compatible with the Bitalino and it simplifies the data collection and storage process through the Bluetooth connection of the sensor. It is possible to access every channel of the kit, record them simultaneously or individually and save the collected signals in text files (.txt) or in a hierarchical data format (.h5). This last format is compatible with many data analysis tools, like *Matlab*, for example. Figure 8 shows an example of the Open Signals tool screen.

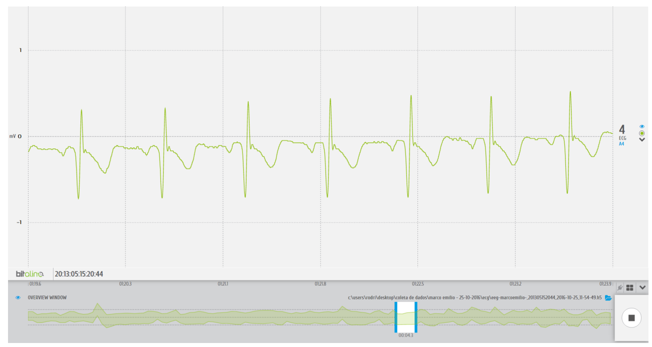


Figure 8: Example of an ECG data collection using Open Signals

Other software used in the experiment are:

- Bandicam[2] - Used to record gameplay and camera footage in a single video file.
- Google Forms[3] - Used to create the validation questionnaires that the participants filled after the experiment.
- Mathworks Matlab[4] - Used to plot the the sensor data collection graphs and to perform the statistic tests of the experiment.

4.2.3 Games

Games are an important factor in conducting the experiment, as they are the cause of the emotional changes measured by the sensors. In order to choose the games that would represent each category (racing, action, puzzle and horror), the following criteria were used:

- It must be an open-source game;
- The game code must be simple to modify;
- It should be able to run on Windows 10;
- It should allow a 10-minute full game session.

Using these conditions, the following games were selected:

[1] http://www.plux.info/index.php/en/
[2] http://www.bandicam.com/br/
[3] https://www.google.com/forms/about/
[4] https://www.mathworks.com/products/matlab.html

- **Action**: Open Source Asteroids[5] - Open-source project of an Asteroids replica, where the objective is to find a blue pill while destroying and avoiding asteroids. (Figure 9a).
- **Racing**: Super Tux Kart[6] - Racing game with famous open-source project mascots, in which the racers should use items to get advantages in the race (Figure 9b).
- **Puzzle**: Wizznic[7] - Puzzle game where the objective is to unite blocks with the same symbol (Figure 9c).
- **Horror**: pyDon't Let Animatronics Stuff You Into a Suit[8] - Open-source version of the game *Five Nights at Freddy's*, in which the goal is to survive through the night while cursed robots try to reach your room (Figure 9d).

4.3 Carrying out the Experiment

The experiment was carried out in the Integrated and Concurrent System Lab - LAICO, located in the Computing Sciences building, Darcy Ribeiro campus, University of Brasília, from October 25th to 28th, 2016.

4.3.1 Data Colletion

Six participants were invited, three of them were men, three were women, from ages between 21 and 26 years old. Before starting the game session, each one of them were introduced to every game and sensor. This way, they had an opportunity to practice with the controls and mechanics of the games. After that, the experiment followed this schedule, for each participant:

- Position the electrodes correctly and verify if the data is being collected properly;
- For 2 minutes, collect biofeedback data from the participant, while resting;
- Perform a session of each game, for no more than 10 minutes, while acquiring data through one of Bitalino sensors;
- Repeat the previous steps using a different sensor.

The experiment lasted approximately 2 hours per participant.

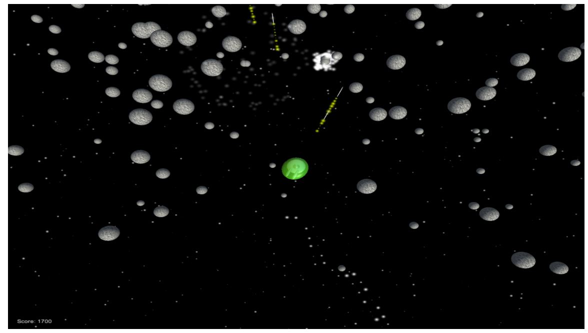
Aside from the data collection, there was also a recording of the gameplay, along with camera footage from the player. This recording was used afterwards to validate sensor data. Figure 10 shows an example of the resulting video.

Finally, as will be shown in the results tables in Section 5, the EDA sensor data collection had too few usable signals from the game sessions. This was probably caused by bad contact in the electrodes while the participant was playing the game, as they were placed in the participant's hands. Unfortunately, this compromised the further analysis on the usability of this sensor in detecting the player's emotions.

4.3.2 Data Validation

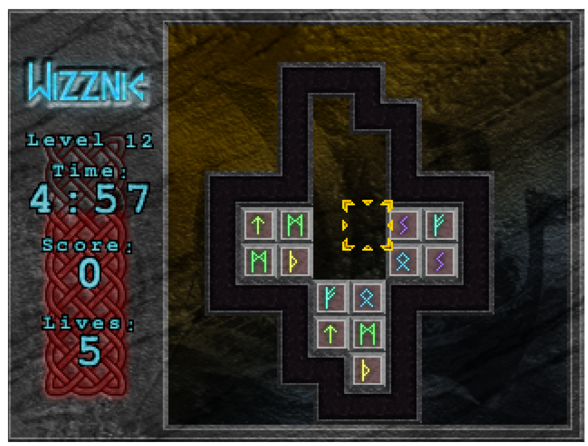
In order to reach the goal of the experiment, it was necessary to create a way to compare sensor data with actual affective information from players. To do so, after the experiment, the participants were submitted to a questionnaire. It contained a section with general questions, like name, age, gaming experience and favorite genres. After this section, there was another one where the participants were asked about their emotional state after each moment in the

[5]https://github.com/matthewrenze/asteroids
[6]https://supertuxkart.net
[7]https://github.com/DusteDdk/Wizznic
[8]https://github.com/ZDDM/pyDLASYIAS

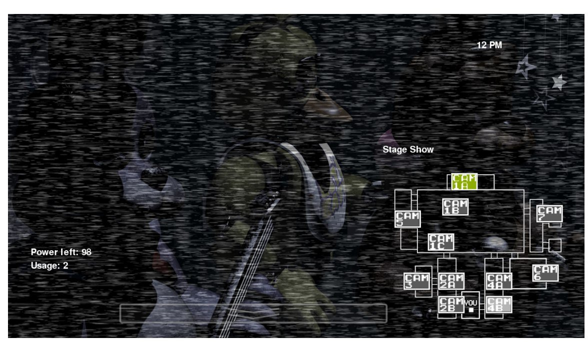


(a) Asteroids

(b) Super Tux Kart



(c) Wizznic



(d) pyDLASYIAS

Figure 9: Snapshots of the used games

Figure 10: Example of recording made during the experiment.

game. To make this possible, each question was followed by its corresponding footage.

To enable participants to fill the questionnaire remotely, it was made in the Google Forms tool, and the gameplay recordings were uploaded to YouTube. Then, for each video of a game session using one of the sensors, the participants described their own emotional states in their own words, based on their gameplay videos. This was a safer way to obtain true data from them, as they did not have to trust in their memory to remind of events of the game, for example.

Finally, to verify measured data, it was enough to cross the information given by the participants with sensor data in equivalent moments in the game, and check if there were changes in the measurements according to the emotional changes reported by the players. These results are shown in Section 5.

4.4 Sensor Data Treatment

Before crossing the information given by the sensors and the participants, it was necessary to transform both data, from sensors and questionnaires into a more adequate format to interpretation. Such transformations are discussed in this subsection.

4.4.1 Obtaining Heart Rate From ECG

Differently from the EDA and EMG sensors, where their graphs are already set for an easy interpretation, the ECG only draws a shape that represents each heart beat waveform. The highest stress indicative that can be verified through this sensor is the heart frequency. Therefore, it was necessary to transform each signal generated by this sensor into a heart rate/time graph.

With this objective in mind, from the ECG waveform peaks, found by the `findpeaks` function of Matlab[6], each heartbeat moment detected by the sensor was obtained, as shown in Figure 11.

This way, as the heart beats were detected, its was possible to find an instant heart beat rate by getting the interval between each pair of peaks. However, it can be observed in Figure 12 that these periods vary too abruptly.

In order to smooth the heart beat rate curve, it is possible to use the `smooth` Matlab function. It calculates an average of the current value with n future values. Considering that the average heartbeat rate is about 80 beats per minute[3], the smoothing was performed considering $n = 80$. The result of this operation is seen in Figure 13.

Now, it can be seen that the heart rate graph shows acceptable values in different moments in the game. These graphs were, then, used to check the excitement or boredom levels that the participant showed during the experiment.

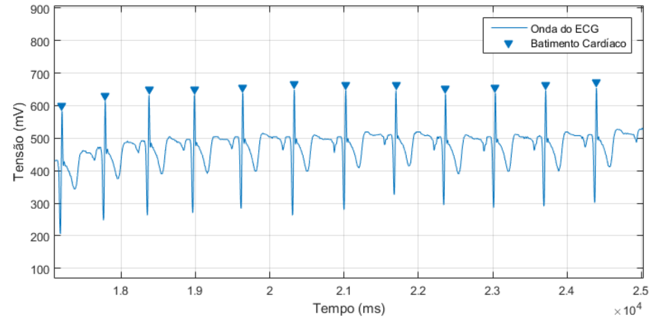


Figure 11: Example of the `findpeaks` function used in an ECG graph.

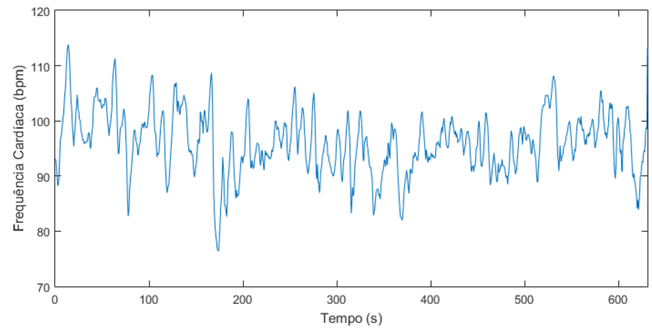


Figure 12: Example of heart beat extraction from ECG graph.

4.4.2 Reference Comparing

The first data collection of a sensor for each participant was done while they were resting. Thus, it provided a reference for a simple sensor calibration when analyzing the data. So, in each graph acquired from the gameplay session, the average value from the reference graph of that sensor was subtracted in order to highlight changes occurring in that specific biofeedback parameter.

4.4.3 Adapting the Questionnaire Answers

In the questionnaire section referring to the emotional changes of each player, the question allowed the participant to tell which feelings they could identify from gameplay footage, and in what instants they occurred. This made them able to answer all sorts of feelings. Throughout all the answers, 24 different emotions were cited. In that way, it would be rather complex to study the individ-

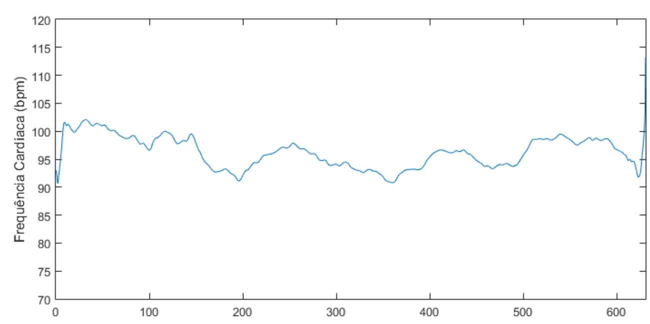


Figure 13: Heart rate curve smoothing example.

ual effects of each emotional state in relation to the signal generated by the sensors.

Therefore, in order to simplify the issue, each feeling found in the answers were divided in two categories:

- **Intense**, that cause the following effects:

  - A raise in the heart rate of the participant, detected by the ECG;

  - A raise in skin conductivity, detected by the EDA sensor;

  - A muscular reaction, detected by the EMG sensor;

- **Mild**, which do not cause the effects above.

Table 1 shows the classification of the described feelings found in the questionnaires. This sorting was based in the emotion placement in the Circumplex chart shown in Figure 6. Emotions shown in the upper section of the circle were considered as Intense, and the other ones were considered as Mild.

Mild	**Intense**
Focused	Surprised
Bored	Happy
Disappointed	Nervous
Sad	Apprehensive
Proud	Excited
Relieved	Thrilled
Unbelieving	Indignant
Confused	Afraid
Self-confident	Alarmed
Gloomy	Frustrated
Curious	Distressed
	Angry
	Annoyed

Table 1: Emotional states divided in two categories.

After that, every moment described by the participants could be classified. Then, it was possible to point out these instants in a graph, with the mild and intense emotions worth 1 or 2, respectively. Figure 14 shows an example of marked emotions in the graph.

This way, the information crossing method was well defined and, consequently, the objective of the experiment analysis was more clear. It is possible to comprehend that, according to the specification of emotion types that can be detected by the sensors, mild emotions are, at first, imperceptible using these sensors. Therefore, the study conducted was directed to the analysis of detection of intense feelings through biofeedback sensors in the games environment.

5 Results

After collecting data from sensors and questionnaires, and treating them for better interpretation, it was possible to generate a final graph for each acquisition. These graphs contain the values obtained from the sensors, subtracted from the average of the reference signal and the position in time of each emotion pointed by the participants in the questionnaires, ranked in intense or mild. Figures 15, 16 and 17 show examples of the generated graphs for each sensor.

From these graphs, it is possible to observe where the moments of intense emotions represent changes in the measured values from sensors. When this occurs, it is reasonable to say that this event was detected by the sensor. Thus, this analysis was made for each generated graph.

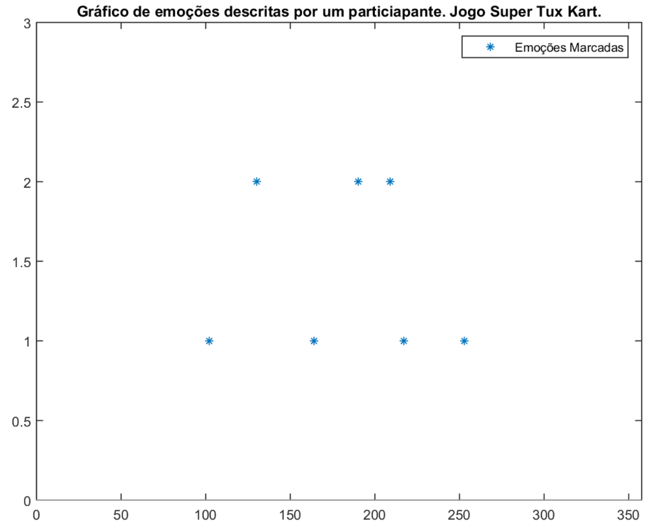


Figure 14: Example where intense and mild emotions were marked in the graph.

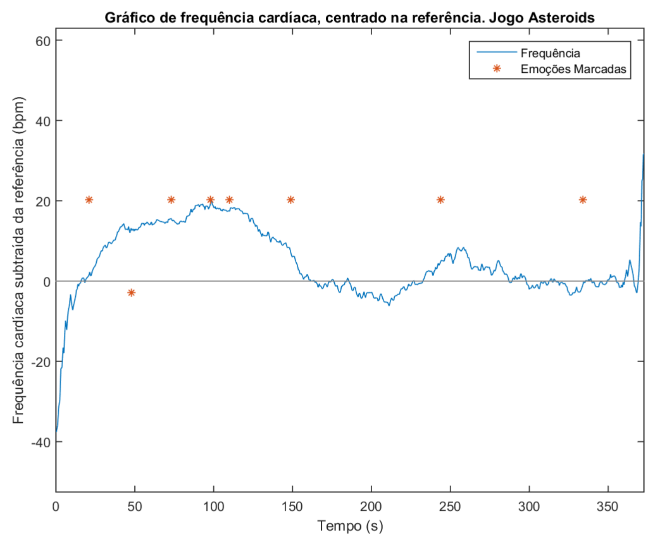


Figure 15: Example of a final graph generated for the ECG sensor.

5.1 Results by Sensor

Tables 2, 3 and 4 show, for each game genre tested, the general result for the ECG, EDA and EMG sensor, respectively.

Results ECG Sensor	Intense Events	Detected Intense Events	Detection Rate
General Result	87	49	56,32%
Asteroids (Action)	23	13	56,52%
pyDLASYIAS (Horror)	31	21	67,74%
Wizznic (Puzzle)	7	3	42,86%
Super Tux Kart (Racing)	26	12	46,15%

Table 2: Detected events caused by intense emotions, ECG sensor.

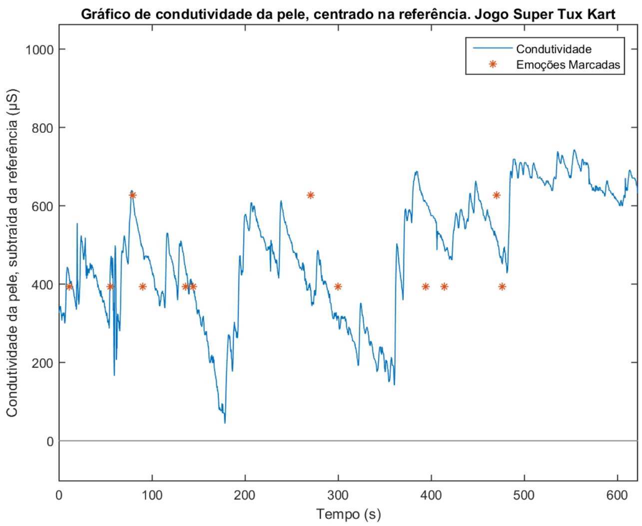


Figure 16: Example of a final graph generated for the EDA sensor.

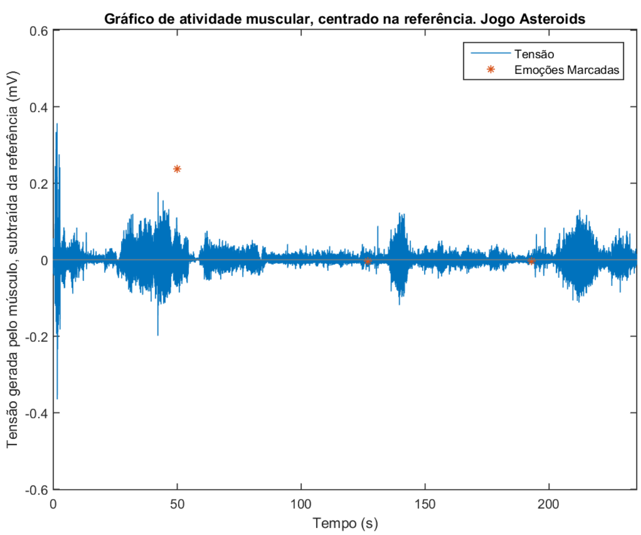


Figure 17: Example of a final graph generated for the EMG sensor.

Results **EDA Sensor**	Intense Events	Detected Intense Events	Detection Rate
General Result	20	12	60%
Asteroids (Action)	5	2	40%
pyDLASYIAS (Horror)	4	2	50%
Wizznic (Puzzle)	3	1	33,33%
Super Tux Kart (Racing)	8	7	87,5%

Table 3: Detected events caused by intense emotions, EDA sensor.

Results **EDA Sensor**	Intense Events	Detected Intense Events	Detection Rate
General Result	37	17	45,95%
Asteroids (Action)	7	5	71,42%
pyDLASYIAS (Horror)	14	8	57,14%
Wizznic (Puzzle)	5	2	40%
Super Tux Kart (Racing)	11	2	18,18%

Table 4: Detected events caused by intense emotions, EMG sensor.

5.2 Discussion

In first place, due to the problem related in Subsection 4.3.1, the EDA sensor has too little data in comparison to the other used sensors, so they will not be considered during the performance comparison. Despite this, results showed that the EDA is a promising sensor, and following previous researches [16], possesses a correlation with the user's stress levels.

5.3 General Performance Discussion

Observing the general result shown in the acquisitions, from Tables 2 and 4, it is possible to see that the ECG sensor detected the most intense emotions, 56,32% of them, against 45,95% from the EMG sensor. This is considered according to expectations, given the analysis provided by other studies [16], where heart rate is said to be one of the biggest indicatives of excitement or boredom, among the studied sensors. The inferior performance of the EMG sensor is also related to the fact that the user's facial expression changes do not happen in a deterministic way when the participant feels one of the cited emotions. Another important aspect to be noted is that the performance found in this study for these two sensors are similar of the ones found in previous studies [16], which is a sign that the methods employed in the experiment were chosen correctly.

5.4 Discussion by Game Genre

For both sensors, the genres of horror and action were the ones that had a bigger relation between related emotions and detected ones. This was expected, as they are genres that are known to have a greater stress load, compared to puzzle, which got the last position. For the racing genre it was a surprise that it got a performance worst than the expected, as its emotional load could be compared to the action and horror genres at first. In particular, in the EMG sensor analysis not even 20% of the intense emotions caused by the game could be detected by the sensor. One thing that could justify this fact is that the game could have caused a bigger immersion in the participant, which reduced the frequency that the players spoke or moved their face.

Based on the tables shown in Section 5.1, this study identified that the ECG sensor is potentially more indicated to detect intense emotions in horror games, puzzle and racing, while the EMG sensor showed bigger adequacy to obtain the same emotions in action games.

6 Conclusion

This study used mostly open-source and open-hardware tools to ensure reproducibility of the experiment by other research initiatives. Another important aspect is the fact that all games were also open-source so that their codes could be modified in future works, inserting new variables in gameplay, including biofeedback signals.

Although being inspired by other similar experiments [17][8][4], this study also contains new decisions, like categorizing emotions by intensity. The consequences were positive because it simplified the process of analyzing the collected data. However, this may have caused some kind of unexpected bias in the results that could have compromised their integrity.

The average found result was positive, and it is expected that this work contributes to enhance the comprehension of researchers in the field of Game Analytics in the usability of sensors, the importance of considering different genres of games and also which decisions to make when conducting experiments and analyzying the collected data.

To complement this study, it is suggested as a future work carrying out experiments with the Electroencephalography sensor (EEG), in order to verify its use in games that do not have a high stress load, like puzzles, for example. It is also suggested new tests with the EDA sensor, to include its results into the comparative with the other sensors analyzed here.

References

[1] M. Ambinder. Biofeedback in gameplay:how valve measures physiology to enhance gaming experience, 2011.

[2] M. S. El-Nasr, A. Drachen, and A. Canossa. *Game Analytics: Maximizing the Value of Player Data*. Springer London, 2013.

[3] Heart.org. Target heart rates, 2016. [Online; accessed 20-November-2016, Avaliable at http://www.heart.org/HEARTORG/HealthyLiving/PhysicalActivity/Target-Heart-Rates_UCM_434341_Article.jsp].

[4] K. Kuikkaniemi, T. Laitinen, M. Turpeinen, T. Saari, I. Kosunen, and N. Ravaja. The influence of implicit and explicit biofeedback in first-person shooter games. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '10, pages 859–868, New York, NY, USA, 2010. ACM.

[5] A. Marchand and T. Hennig-Thurau. Value creation in the video game industry: Industry economics, consumer benefits, and research opportunities. *Journal of Interactive Marketing*, 27(3):141–157, 2013.

[6] Mathworks. Find local maxima - matlab findpeaks, 2016. [Online; accessed 20-November-2016, Available at https://www.mathworks.com/help/signal/ref/findpeaks.html].

[7] L. E. Nacke, M. N. Grimshaw, and C. A. Lindley. More than a feeling: Measurement of sonic user experience and psychophysiology in a first-person shooter game. *Interact. Comput.*, 22(5):336–343, Sept. 2010.

[8] D. G. Park and H. C. Kim. Muscleman: Wireless input device for a fighting action game based on the emg signal and acceleration of the human forearm.

[9] Plux. Bitalino board kit datasheet, 2016. [Online; accessed 20-November-2016, Available at http://bitalino.com/datasheets/BITalino_Board_Datasheet.pdf].

[10] Plux. Bitalino ecg sensor datasheet, 2016. [Online; accessed 20-November-2016, Available at http://bitalino.com/datasheets/ECG_Sensor_Datasheet.pdf].

[11] Plux. Bitalino eda sensor datasheet, 2016. [Online; accessed 20-November-2016, Available at http://bitalino.com/datasheets/EDA_Sensor_Datasheet.pdf].

[12] Plux. Bitalino emg sensor datasheet, 2016. [Online; accessed 20-November-2016, Available at http://bitalino.com/datasheets/EMG_Sensor_Datasheet.pdf].

[13] Plux. Bitalino kit web page, 2016. [Online; accessed 20-November-2016, Available at http://www.bitalino.com/index.php/board-kit].

[14] J. Ressel. A circumplex model of affect. *J. Personality and Social Psychology*, 39:1161–78, 1980.

[15] V. Shankar and B. L. Bayus. Network effects and competition: An empirical analysis of the home video game industry. *Strategic Management Journal*, 24(4):375–384, 2003.

[16] R. Soares, E. Sarmanho, M. Miura, T. Barros, and C. Castanho. Biofeedback sensors in game telemetry research. *Simpósio Brasileiro de Jogos e Entretenimento Digital*, pages 81–89, september 2016.

[17] V. Vachiratamporn, R. Legaspi, K. Moriyama, K.-i. Fukui, and M. Numao. An analysis of player affect transitions in survival horror games. *Journal on Multimodal User Interfaces*, 9(1):43–54, 2015.