Improving engagement assessment in gameplay testing sessions using IoT sensors

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***Abstract*—Video game industry is a multimillionaire market which makes solo indie developers millionaire in one day. However, success in the game industry it is not a coincidence. Video game development is an unusual kind of software that mix multidisciplinary teams, as software engineers, designer and artists. Further, for a video game be well received, it must be fun and polished, so exhaustively well tested.**

Testing in video game development ranges from different types, in different parts of the process. For example, measuring the engagement of players in a test session can drive the development drastically. The designers/developers analyze actions taken by players and how they behave facing each decision in the game. Based on that, they decide if that feature/level requires rework or cut it. It is very common to throw out many hours of man/work in a feature just because it is not fun.

As the designers (usually) assess the gameplay session by hand, how can they be sure that specific feature is (or is not) good enough? If we could provide more meaningful data for the designers to review we can have a better assessment of what is happening in the gameplay, what could be wrong and if there is a real need to remove or rework.

In this paper, we propose an IoT environment platform to assess the player's engagement in gameplay session by adding IoT sensors together with game devices which will produce a rich output for the designers.

***Index Terms*—iot, sensors, game development, testing, game design**

I. Introduction

For decades, playing video games had been a joyful hobby for many people around the world [1]. It is not surprising this industry is multibillionaire surpassing the cinema and music combined [2]. However, the fantastic graphics and smooth gameplay hide constant and non-ending problems regarding the game development [3]. Most of which are related to bad practices and management, leaving a trail of burnout developers after long period of crunchs[1] [4, 5, 6, 7, 8, 9].

For a game to be well received by players, it must be a well-polished product. One key aspect of this process is testing. Testing a game implies not only searching for bugs but also finding the fun aspects. The aspects are how engaged a player (tester) is in the game regarding a specific feature or build. This task is the gameplay testing[2]. Gameplay testing means endless iterations by development teams in the last mile of the production. These iterations sometimes involve months of crunches by the team [10].

Gameplay testing sessions are crucial to delivering the fun (successful) game. In this sessions, testers play a specific build of the game, most of the time not knowing the game, on which, at the same time, the game designer assess the level of the game or a feature recently implemented. In the end, what the developers want to see is if the game is fun and if the players were engaged while playing.

Consequently, gameplay testing is hard. Video games are complex systems that include a large number of actions to be tracked [11]. As stated by Pascarella et al. [12], automate tests in the context of video game development is hard given its differences from traditional software. However, we claim the information gathered through a game session is not enough to explain the behaviour of the player/tester. In the majority of cases, the developers have only the actions performed by testers and their vocal or corporal expressions. It can lead to wrong interpretations which can cause delays in the development and, in the worst case, the commercial failure of the product.

Another issue is that game designers rely only upon their expertise and senses to asses the gameplay session. There is no metrics nor data to compare or be based. The lack of metrics happens because engagement and fun are abstract attributes and there is not (yet) a straightforward way to measure it.

To address all these concerns, we claim that a more rich set of data regarding the gameplay session can improve the game designer's judgment about the feature being tested. Which can contribute to the development process pace by (1) avoiding discarding an implemented feature; if the implemented feature was good enough, consequently increasing the reliance in the game success and improve the team performance; (2) raise the awareness of the path the game design is going to if the game/feature is not fun.

In this paper, we propose an IoT environment platform to assess the player's engagement in gameplay session by adding

[1]In video game development, crunch time is the period where developers work extra hours to complete the tasks and deliver the game in time.

[2]Gameplay testing could be playing a prototype, a slice of the final product or all the game.

IoT sensors together with game devices which will produce a rich output for the designers.

Several approaches are trying to measure the fun and engagement in video games (see section II) by creating a set of metrics, postmortems forms or biometric measures of the body. However, our solution aims to extend and improve those approaches by (1) using low-cost sensors allowing indie developers to afford and customize the solution; (2) aiming to specific requirements, that is, serve as a tool for video game designers; and (3) adding more sensors/information that are relevant to assess the gameplay testing session.

The proposal is to use biometric data, together with a screen recorder and joystick input tracker to enhance what the game designers can see about the behaviour of the testers. It can show spikes in the data related to a specific moment in the game.

The Figure 1 shows the workflow of the process we propose. The yellow blocks represent the game development team; the red block is regarding the test team, which may or may not be part of the main team; and finally, the blue blocks depict where our approach lies. As the development is iterative, we can consider the beginning when the development team produce a new build of the game (sometimes referred to as vertical slice). The tester then plays the game while the sensors capture the data, synchronize the information and compile a video with all the information. Lastly, the game developers analyze the video with the information and make his/her judgment. The process is then restarted as soon as the team decides to produce a new build or check a new feature.

The remainder of the paper is organized as follows. In the Section II we present the related works and how our proposal differ from it. In the Section III we describe how is the IoT architecture and how we are going to implement it. In Section IV we discuss the benefits of our approach and some threats. Finally, the summary of the paper in the Section V.

II. Related Work

Some authors already tried to use biometrics feedback to assess the gameplay session. Clerico et al. [13] proposed a "predictive model" that show the fun experience of players based on the physiological responses by using biometric indicators as ECG, EMG, EDA and respiratory activity. To do so, they used a set of variables for each metric in a Support Vector Machine (SVM) to classify the fun. They validated it with a postmortem review of the gameplay made by the player after the session.

Martey et al. [14] attempted to measure the engagement of players using self-report, content analyses of videos, electrodedermal activity, mouse movements, and click logs. They concluded that engagement is complex to be measure by a single attributes and should be measure by a set of metrics, that is, "engagement is a multi-dimensional construct".

Johnson et al. [15] tested how diversity in games affect players. They used psychophysiological measure like electrodermal activity (EDA) and heart-beat rate (ECG) as well as post-experimental forms in video game sessions. They found that more diversity in the game results in better enjoyment by the players.

Moura et al. [11] propose a method to better analyze players' behaviour in a specific set of games, in this case, RPGs or Action/Adventure where navigation, collection and talking with NPCs are important for the game. The tool proposed helps to visualize the players': time spent in each area, interaction with characters, if maps were activated, items collected, and characters' path. Their contributions allow the designers to: see the temporal progression of the player; compare the behaviors of different players to check the play styles. They do not explain how the tool was done, but we can infer that they collect data from the game directly.

Roose [16] proposed a method to evaluate the skill of players by using interviews (Cognitive Task Analysis) and eye tracking. Fowler et al. [17] used a tool called SMI RED500 to track the eye blinks of each participant with the goal to measure the learning curve in games. Saas et al. [18] explored the players' pattern by analyzing the meta-data from the games.

Some authors used non-biometric approaches to assess the gameplay. Fowler [19] proposed a method to qualify and quantify the learning aspect during video game sessions in children from 3 to 5 years old. They do not use bio-metric measures, where the assessment consisted only in normal observation. Ravaja et al. [20] investigated the emotional response patterns with 37 players by playing different games in random order. They assessed by using post-experiment forms. Desurvire et al. [21] tested the method of assessment of non-game usability professionals in a game context. To do so, they used forms after the game session. Tyack et al. [22] investigate what brings engagement to players using survey and interviews.

Some works tried to analyze the players behavior to improve the gameplay on-the-fly. Ang [23] investigated the impact of dynamic difficulty in games by using interviews to gather the feedback from the players. Some authors used AI in dialogs [24], wireless signals [25], and facial electromyography (EMG) [26], to improve the gameplay experience by detecting the players' emotions and changing the game accordingly.

There are some attempts to use IoT sensors to monitor ECG for the health care domain. Lacirignola and Pasero [27] created an ad-hoc solution for ECG monitoring with low energy consumption and less noise in the data. The authors made use of a self made board to this purpose.

Walke and Deshpande [28] proposed, although not validated, a architecture that makes use of cloud computing to gather, in real time, the data from ECG sensors.

Gia et al. [29] presented a low cost and energy efficiency wearable device to monitor the ECG, respiration rate, humidity, body and room temperature. Also, they presented a Fog node to display the data in graphical form. Their focus is on remote health monitoring. In this case, again, they used an ad-hoc approach, building the architecture from scratch.

An interesting proposal is from Aleman-Soler et al. [30] which used *Arduino* and *Libelium* for build a low cost solution

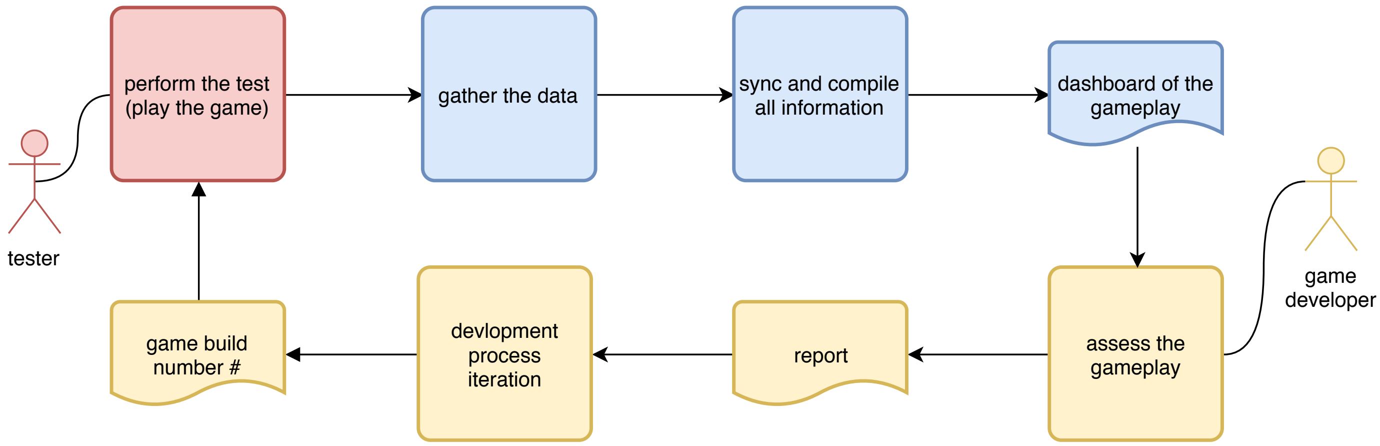

Figure 1: Workflow of the framework.

to monitor biomedical signals as Electromyogram (EMG), Electrocardiogram (ECG) and the Galvanic Skin Response (GSR). The goal of their approach is gather different biomedical signal to improve health problems detection.

Our approach borrow some of these ideas and brings it to the light of IoT and Software Engineering. We are trying to extend the analysis of gameplay sessions by combining more sensors. Also, we do not rely on players feedback using forms or interviews. Many, if not all approaches cited, use a off-the-shelf solution (black box), which is expensive and not extensive/customized solution. Our focus is on low cost sensors and programmable devices where the development team can modify by their needs. Finally, we are focusing in a tool to aid developers, more specifically, game designers. Aside form the work from Moura et al. [11], other authors had other objectives in theirs papers.

III. Implementing the architecture

The Figure 2 shows the proposed architecture in UML2 component diagram. The whole system is based on low cost sensors and *Arduino*[3]. The basic setup for a game session is the **screen**, **game system** (console, computer, etc.) plus the game (version of the build to be tested) and a input device, **joystick** in this case.

The **screen recorder** here is described as a software, but there are some specific devices for this purpose, however, as we are focusing in low cost sensors, we decided to use a simple screen recorder software. The same for the **input tracker** in the joystick. We use a software to map the commands. The data from both are put together by the main server and then stored.

As for the **camera**, there is no caveats. It is a camera focusing on the tester, all the time. The data is then sent directly to the main server as it does not need treatment.

[3]https://www.arduino.cc/

The **force sensitive resistor** is attached to the joystick to capture the pressure force made by the tester. It them send this data to the **edge node** to be normalized and then stored in the main server.

Finally, the bio-metrics are taken by a set of sensors, **ECG**, **EMG**, **EDA**, and **GSR**. These sensors are connected with an *Arduino* board which is responsible for gather this data and send them to the **edge node** for pre-processing. After that, the edge send it to the main server to be stored.

We will briefly describe each sensor, however, their functionalities as well how to measure their output are not in the scope of the article.

A. Electrocardiography (ECG)

Electrocardiography (ECG or EKG) is the process of recording the electrical activity of the heart over a period of time using electrodes placed over the skin [31]. The electrocardiogram (ECG) is the graphical representation of the electrical activity of the heart, as the Figure 3 shows.

In this regard, we can add electrodes on the skin of the tester to monitor the changes provoked by the hear beat. As the output is line with a pattern, we can check the variance and spikes and, therefore, correlate with the level/area in the game. More research must be done to list what each pattern in the line means. As an example, the AD8232 sensor for *Arduino* is a low cost alternative.

B. Electrodermal Activity (EDA)

The principle of Electrodermal Activity (EDA) is that skin resistance varies with the state of sweat glands in the skin, which sweating is controlled by the sympathetic nervous system. In this way, skin conductance can be a measure of emotional and sympathetic responses [32].

EDA is associated with emotion and cognitive processing, moreover, some emotional responses, like threat, anticipation, salience, and novelty, may occur unconsciously [33]. Additionally, EDA peak (height and rate) (see Figure 4) describe the stress level of a person [34].

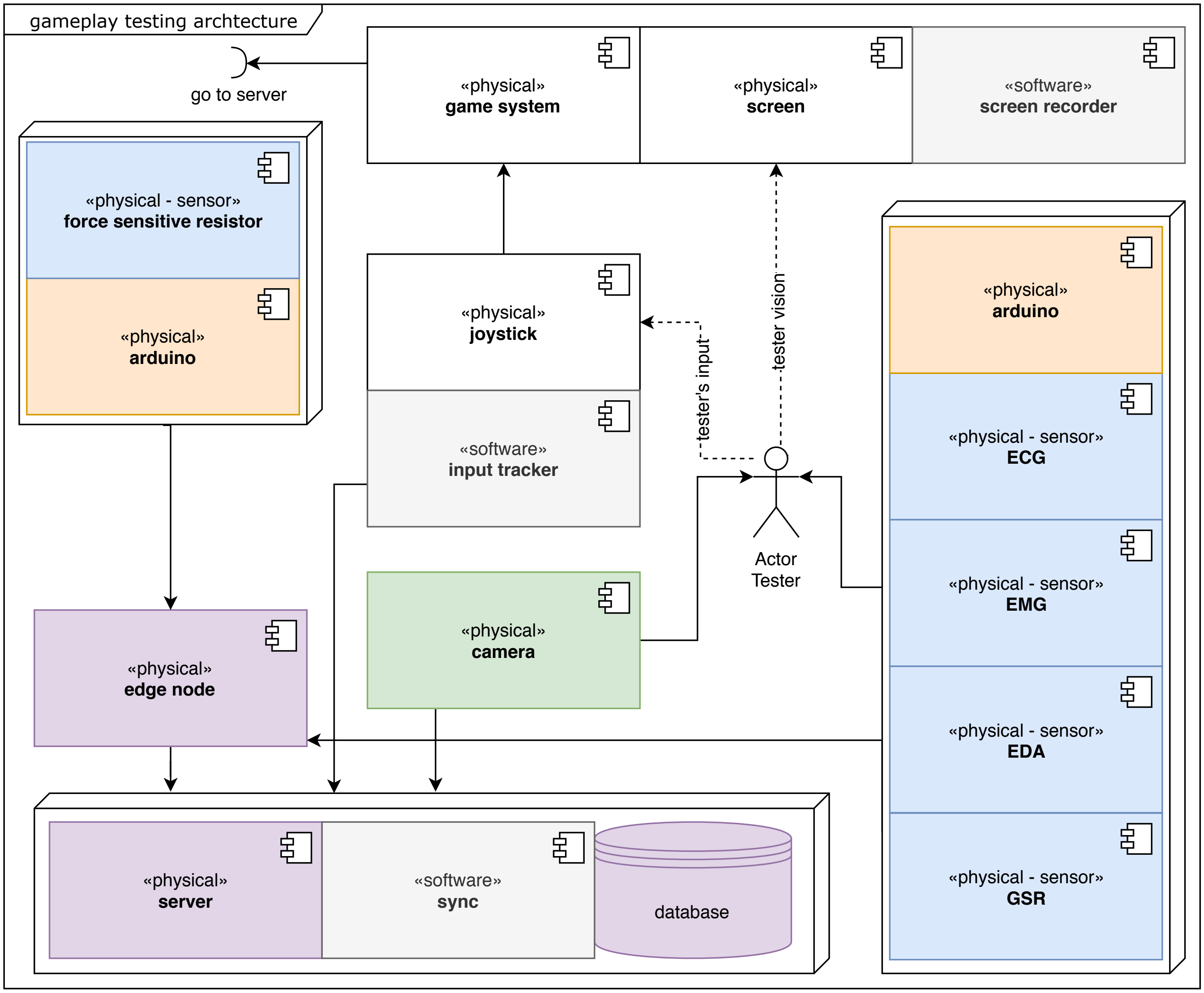

Figure 2: Proposed architecture in UML2 component diagram.

With this method we can measure the excitement and arousal of the tester during the session. A lower cost option is using two electrodes in a *Arduino*, inducing voltages through one electrode and measuring using a second one.

C. Electromyography (EMG)

Electromyography (EMG) is a technique that record electrical activity produced by skeletal muscles [36]. The output of this measure is the electromyogram (see Figure 5). It detects potential difference that actives the muscle cells, which can be used to detect abnormalities in the movement. The less invasive method to measure EMG is using electrodes to control the overall activation of the muscle [30]. A lower cost sensor for *Arduino* is the MyoWare Muscle Sensor.

D. Galvanic Skin Response (GSR)

Galvanic Skin Response (GSR) is the property of the human body that causes continuous variation in the electrical characteristics of the skin. GSR measure the electrical condictance of the skin, which varies according to sweat glands, which in turn is controled by the sympathetic nervous system, finally indicating psychological or physiological arousal [30]

The measurement is made putting sensors in two fingers. The more the subject sweat level increases, the bigger is the conductivity, as, for example, in the graph output in Figure 6.

E. Force Sensitive Resistor (FSR)

Force Sensitive Resistor (FSR) is a sensor that allow to detect physical pressure, squeezing and weight. We can attach this sensor on the joystick and measure with which intensity the tester are holding it. It can show how he behave facing certain scenarios of the game. With a proper baseline, we can even infer the player boredom and excitement.

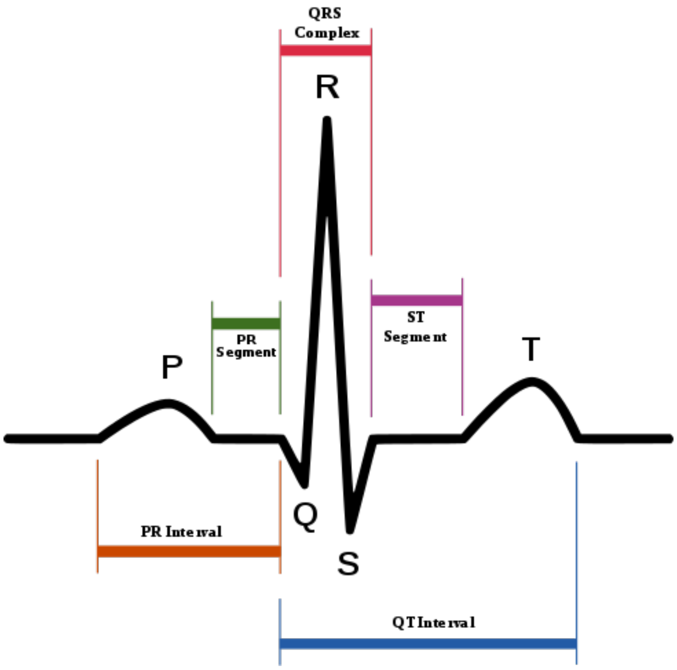

Figure 3: Schematic diagram of normal sinus rhythm for a human heart as seen on ECG [31].

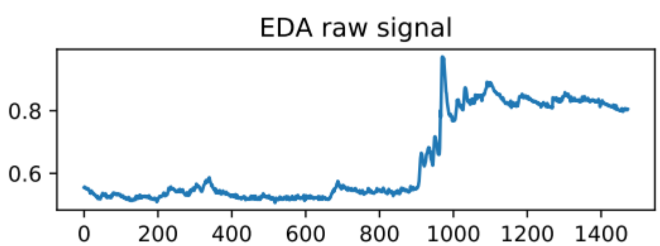

Figure 4: The decomposition of an EDA signal [35].

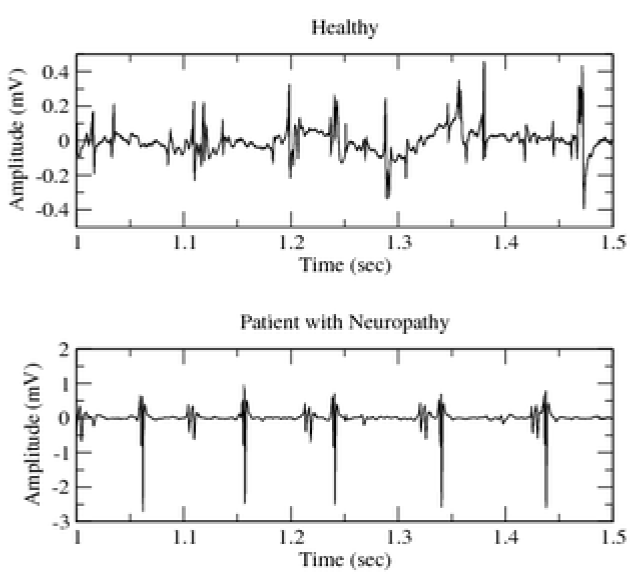

Figure 5: Electromyogram output example [37].

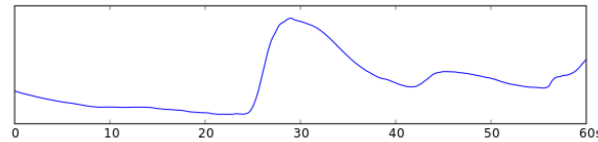

Figure 6: A sample GSR signal of 60 seconds duration [38].

F. Joystick Input Tracker, Camera and Screen Recorder

The idea of the **Joystick Input Tracker** is to get all the commands (input) performed by the tester and map it to a virtual representation of the same and display it on the screen. It can help keep track of some detected bug of failure captured during the gameplay session and reproduce it during the development.

The purpose of the **camera** is simple: record the tester and to observe his reactions. The body expressions might reveal interesting things about the tester emotions. Moreover, we can apply some image pattern recognition.

Finally, the **screen recorder**, which is the main link between all the sensors and data. Without the gameplay video the game designers cannot correlate the gathered information and the part of the game.

G. Dashboard

The Figure 7 show the dashboard comprising the output of the sensors after synchronizing with the gameplay video. Aside of the gameplay scene, it shows the graph, in real-time, of the data from all the sensors (ECG, EMG, EDA, GSR, and FSR) in the upper left corner. The footage of the tester is on the lower left corner with the virtual joystick inputs. We are adding the FPS (frames per second) and APM (actions per minute) to enhance the information set.

IV. Discussion and Threats

Our approach aims to use the concepts of finding fun and engagement by making use of biometrics to aid game designers to assess their game features, on the development phase, during the gameplay sessions. It focuses on low-cost sensors and an extensible platform.

The idea also can be applied for the validation of a concept, during the pre-production, where the developers test new ideas with prototypes. In this case, a more robust measurement can prevent many months of rework or even years of development.

Although the related problem is to help video game designers in their task, the underlying issues on how to build and synchronize the IoT architecture is real. The related works that used biometrics to asses the gameplay focused on black-box solutions, which prevent any change or adding new sensors that the developers might want to use.

With the amount of information gathered from the sensors, we can apply machine learning to cluster some of the attributes (pattern recognition) and transform them into metrics. For example, a determined type of spikes in the ECG graph can imply a specific emotion or difficulty in the game. A bug, for instance, can induce a typical reaction of the tester, and

Figure 7: Dashboard of the prototype. The image is from the game Darkest Dungeon.

with this, we can generate a report with all possible bugs to investigate.

Aside from testing new features, this kind of enhanced feedback can bring new light to the game design. By observing the tester reaction and data, we can make correlations with parts of the gameplay that it enjoyed more. With that, developers can extract the core mechanic and apply to other games. It can become a library of core mechanics, rated by "fun level", that can be useful in new projects.

The output of this project can be interesting for researches in the design field as well. There are many attempts to measure the engagement in video games, and a platform that is customizable should help them to propose and test new hypotheses.

As threats, we need to mention that maybe it will not be possible to use only one *Arduino* to manage all sensors at once. Moreover, the setup of the board with the sensor may disturb the tester during the session. Finally, the synchronization of all the sensors data is very sensible, the delay of seconds can lead to a wrong interpretation of the results.

V. Preliminary Conclusions

In this paper, we present an IoT architecture to assess video game testing. It is composed of a set of sensors and applications forming a low-cost framework which can be afforded by independent studios and developers. The goal of this approach is to provide a contextual output of the gameplay session, that is, besides the gameplay video, information regarding the biometrics of the tester or user as well as technical details of the game. With such solution, game developers (especially game designers) can use and customize their game projects, by gathering a more rich set of data from the gameplay test sessions, and, therefore, improve the quality of their games.

Although our approach project is large, it can be made in modules, so one sensor/module by the time. For example, the first step can be the set up the screen recorder, the edge node and server. Then adding the input tracker for the joystick and so on.

Although the contribution of this approach aims to solve a problem in video game development, the solution comes from IoT area. The challenge of creating and implementing this architecture and synchronize all the data is, in our words, relevant to the IoT community.

Last but not least, the outcome this tool can provide is broad regarding what can be done with the gathered data. By reasoning on the extracted information, we can create a model to evaluate, with a set of metrics, the gameplay session attributes, like engagement and fun. Then, our approach can improve the time to assess the gameplay session and its efficiency.

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