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Difficulty Adjustment Using Player's Performance and Electroencephalographic Data

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Abstract
For high skilled players, an easy game might become boring and for low skilled players, a difficult game might become frustrating. The purpose of this research was to create new and better ways to offer players with different skills, an appropriate experience. We focused on adapting the difficulty levels of a simple 2D platform game, designing and building levels automatically. The proposed method consists of Dynamic Difficulty Adjustment (DDA) and Rhythm-Group Theory (a procedural content generation method), combined with levels of attention obtained from Electroencephalographic (EEG) data. Experiments were designed in the way that players had to clear five different levels that were created automatically using the player's performance and EEG data obtained from a biosensor while playing. Results showed that the method successfully adapts the level difficulty according to the player's status. In addition, the designed method calculates difficulty using values computed in real time to decide the shape and structure of the levels. The method designed in this research can be implemented not only in platformers but also in other genres that involve elements of rhythm, additionally, it could be used by game developers as a tool for playtesting in order to improve the game design, receive quantitative and numerical feedback from players and create an overall better experience for their players.

1 Introduction

In the field of video games different types of players exist, some players are more skilled than others. Although the case is particular for competitive games, we can see how in games where the players' skill levels are not suitable for the difficulty of a game, for both types of players (high and low skilled players) the result might be an unsuitable experience [1].

Usually these problems exist as a consequence of an unbalanced game design and can be solved changing the game rules or difficulty to make it appropriately challenging for players [2].

Dynamic Difficulty Adjustment (DDA) is one suitable solution for this particular problem when designed well and it has proved to be successful in the past [3]. However, the experience of players can be ruined by a poor implementation when they realize that difficulty is being adjusted deliberately [4]. In order to avoid this issue, we focused on finding a complementary component that could support traditional difficulty adjustment, adding variety and better results.

The level of challenge in video games is one of the most relevant aspects that affect the player experience, however it's not the only one [5]. Immersion plays a very important role determining how the player experience is shaped in general [6] and the levels of attention of players while playing a game influence how immersion fluctuates through time [7].

The word immersion in the video games field is used in a symbolic way for explaining the experience of feeling surrounded by a different reality as if players were submerged in water, it's a way to refer to the sensation of a deep feeling, having all our senses focused on a specific reality, the virtual reality [8].

Player experience is defined as the relationship between the player and the game, the influence that causes the game on the player while playing and the reactions triggered by that interaction [9]. The proper balance between frustration, challenge, and immersion, transforms into a good player experience [10].

Prompted by the relationship between immersion and player experience, we decided to include an Electroencephalography (EEG) component to measure attention values. This adds variety to the adjustment, making it less predictable for players.

For the automatic creation of levels we used Rhythm-Group theory [11], a successful Procedural Content Generation method to construct levels with a sense of rhythm for the player.

This article constitutes the result of an extended and improved explanation of a work presented at the NICOGRAPH International 2017 conference in June 2017 [12].

2 Related Work

Dynamic Difficulty Adjustment improves the player experience in different ways [13, 14] and even in its most basic or elemental form, when done in the appropriate way, it could successfully adapt the game, making the levels of challenge more suitable for players.

This method is useful and can be implemented in games from different genres, from racing games [1], to platform games [15], from multiplayer digital games [16] to board games [17]; Dynamic Difficulty Adjustment is a method that can be adapted to each developer's or designer's necessities when using the proper approach.

For the particular case of this research, one of the most relevant studies is the work of Martin Jennings-Teats et. al [15] which propose an approach similar to ours; using DDA and Procedural Content Generation, they created a personalized and structural experience for players. Our original contribution is the inclusion of the EEG component to the previous approach.

In recent years there have been several of studies related to BCI and games, mobile games [18] showing how useful these devices could be working together with mobile devices; PC-based FPS games [19] focused on the player experience and interaction; and even for conducting research related to how players learn to play [20], etc. These devices, specifically EEG-based devices, have also proved to be useful for making adaptive games [21], which is particularly our field of study.

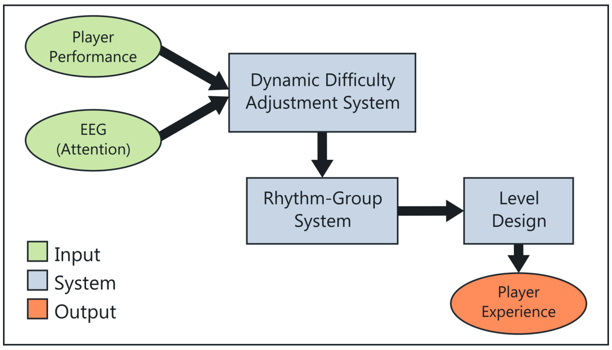

Figure 1: General design of our approach

EEG biosensors, are suitable to be used for cognitive games [22]; in multiplayer cooperative games [23], for evaluating how the cognitive activity changes while playing with teammates; also in serious games, in order to promote rehabilitation with patients that suffer from motor deficits due to a stroke, these researchers developed a new game that aims to help them with the process of rehabilitation [24].

Neurosky Mindwave Mobile device [25], which has shown positive results in reliability and commercial contexts, was used to capture the attention data from players [26]. In addition, a research particularly focused on video games has shown that the device accurately reads values of attention from players [27].

Previous researchers used a similar approach combining DDA and BCI to improve performance while doing a specific task [28]. Our research differs from theirs in different aspects: we use EEG and they use fNIRS; our field of test was games, theirs was general tasks' performance; results show that performance was improved by detecting boredom, in our case, we didn't only improve performance but also adapted the difficulty depending on the players' skills to achieve a more suitable experience.

Procedural Content Generation (PCG) methods are a good alternative to automatically modify the level design according to how players play in a game [29].

In previous research the effectiveness of PCG was demonstrated using games [30]. Georgios N. Yannakakis and Julian Togelius introduced a framework for procedural content generation applied with computational models of user experience, they created a method for developers to trigger specific experiences depending on the user decisions or status inside the game.

3 Method

Our method consists of the combination of three different elements: Dynamic Difficulty Adjustment, Rhythm-Group Theory and Brain Computer Interface. A general flow of our approach can be seen in figure 1.

3.1 Dynamic Difficulty Adjustment

Dynamic Difficulty Adjustment (DDA), is the process of changing game elements automatically in real-time, based on the player's performance, in order to adapt the game to each player and avoid frustration or boredom [31].

We calculate the difficulty using the numbers of threats present in a level, specifically the number and width of gaps, number of enemies in each platform and the type of these enemies (beatable or unbeatable).

Difficulty is adapted according to performance and attention levels calculated by the EEG device while playing.

3.2 Rhythm-Group Theory

A Rhythm-based method for 2D platform games is a type of technique for automatic level creation in which rhythm is what the player feels with his hands while playing [11]. This method is a tool for the developer to create levels with a sense of rhythm, levels that are playable and have a natural feeling for players when it comes to level shape and experience. We are using only a part of the method created by Gillian Smith et al., here we describe the parts of the method used for our research, to read the details about the original method, see [11].

3.3 Brain Computer Interface

Brain Computer Interface or BCI [32] systems are based on obtaining electroencephalogram (EEG) data, extracting relevant information to translate it into commands to be read by software or particular applications [33].

For input extraction we are using *Neurosky Mindwave Mobile*, a bioensor that digitizes brain data into concise inputs for developers to be able to interact with it in real time, using a set of predesigned algorithms API to monitor brain activity.

For this research we use the eSense value *Attention*, which is a value between 0 and 100 (being 0 the least focused and 100 the most focused) that describes the levels of attention of the user in real time.

4 Implementation

The game is a side-scrolling 2D platformer in which the player has to reach a goal placed on the right-most part of the level, very similar to *Super Mario Bros* [34]. The player is required to overcome simple challenges: gaps between platforms, beatable enemies and unbeatable enemies, both types of enemies static. In the beginning of each level players get two bars of health, once the player loses both, has start from the beginning of the level, in addition, the game time is shown on top-center of the screen.

4.1 EEG Data

According to the documentation [25], values from 80 to 100 are considered *elevated*; values from 60 to 80 are considered *slightly elevated*; values from 40 to 60 is *neutral*; values from 20 to 40 *reduced* and values from 1 to 20 *strongly lowered.*

By default, the device outputs data once a second, it means, we get as many values as the time the player plays a level. We calculate the average of all values obtained in a level, the calculation is shown in equation (1).

If a player is concentrated in a task, would perform better than if concentration levels were poor [35]. Considering this, when attention values are high, it means the player is concentrated in the game, it also means should perform better so we decided to add a higher level of challenge when the player is focused, in contrast, if the player is not focused, we reduce the level of difficulty.

$$A = \frac{1}{n}\sum_{i=0}^{n} a_i \tag{1}$$

Arithmetic Mean (A): a_i is the attention calculated by the device per second and n is the number of seconds that the player takes to finish a level. The interval time for this equation depends on how long each player takes to complete a level.

4.2 Player's Performance

To calculate the player's performance we considered two parameters: number of deaths or hits by an enemy and gameplay time (time from start to end). Low values for number of hits and play time result in a high performance, on the opposite case, high values for these parameters result in low performance.

$$P = \frac{1}{1+h+d}X_1 + \frac{g}{e}X_2 \tag{2}$$

Performance (P): d is the number of deaths; h is the number of times hit by an enemy; g is the gameplay time; e is the expected completion time and X_1, X_2 are weights that represent the influence of each term in the final calculation.

The term $\frac{1}{1+h+d}$ is calculated by cross-multiplication, the number of times hit or deaths is inversely proportional to how well players are playing, we sum 1 to avoid division by zero. The term $\frac{g}{e}$ is calculated by the same cross-multiplication principle, when players take more time to complete a level, performance decreases.

4.3 Dynamic Difficulty Adjustment

We used the attention value calculated in equation (1) and the player's performance value calculated in equation (2) and combined them in equation (3) to get a general a global value that involves both parameters. These two values can complement each other and affect the final calculation. Weight for this equation were both set to 0.5, same amount of influence for both parameters, attention and performance.

$$G = PW_1 + AW_2 \tag{3}$$

Combination of performance and attention (G): P is the performance calculated in equation (2); A is the attention average calculated in equation (1) and W_1, W_2 are weights that represent the influence of each term on the final calculation.

$$A_t = \frac{1}{n_t} \sum_{i=0}^{n_t} a_{ti} \tag{4}$$

Arithmetic Mean (A_t) for specific elements of type t: a_{ti} is the attention obtained from the device when the player interacts with elements of type t ; n_t is the number of times the player interacts with elements of type t and t = [low enemy, medium enemy, high enemy, gap]. The interval time for this equation depends on how many times the player interacts with elements of type t.

$$P_t = \frac{1}{1 + (h_t + d_t)} \tag{5}$$

Performance per type (P_t): h_t is the number of times the player has been hit by enemies of type t; d_t is the number of times a player has died due to enemies of type t; t = [low enemy, medium enemy, high enemy, gap].

The term $\frac{1}{1+(h_t+d_t)}$ is calculated by cross-multiplication, the number of times hit or deaths is inversely proportional to how well players are playing, we sum 1 to avoid division by zero.

Equation (6) shows how to calculate the global value to decide how many elements of each kind are included in the level. Equation (5) shows the performance calculation for a particular type of element and the calculation for attention values of a particular type of element is the same as equation (1) but instead of using all values, we calculated how attention values behaved when the player interacted with elements of that kind.

For example, *low jump* is one of the element types; to decide how many elements (percentage of occurrence) we assigned to *low jump* actions, when the player dies due to an element of type *low jump*, we reduce the number of *low jump* type elements in the next level, it means, we are trying to add elements that increase the player's performance. In the case of attention, if the calculated attention was registered high for *low jump* type elements, we increase the number of this type of elements to increase get better results in the next level.

There is a compensation between both values, performance and attention, that work together to calculate the final percentage of occurrence of each element, it really adds variation to the gameplay and the experience in general.

$$G_t = P_t Z_1 + A_t Z_2 \tag{6}$$

Combination of performance and attention for elements of type t (G_t): P_t is the performance calculated in equation (5); A_t is the attention average calculated in equation (4) and Z_1, Z_2 are weights that represent the influence of each term on the final calculation.

4.4 Rhythm-Group System

A set of parameters are important to take into consideration to construct a rhythm, these are: rhythm type, rhythm density, action types, number of actions. For our research we used the following values:

- Action Type: we chose the simplest ones run and jump. For the action jump, there are three different types: low, medium and high
- Rhythm Type: we are using a regular type of rhythm which means that actions are evenly distributed in the rhythm, other types of actions are random or swing.
- Rhythm Density: number of actions in a rhythm, we choose this depending on how the player results are, the better the result, the higher the density. The minimum value is 5 actions and maximum value is 50 actions.
- Rhythm Length: this is how long the gameplay time should be according to the level length (horizontally), this is decided depending on the player results, the better the results, the longer the level. The minimum value is 5 seconds, the maximum value is 30 seconds.

Figure 2 shows an example of rhythms that our system can create.

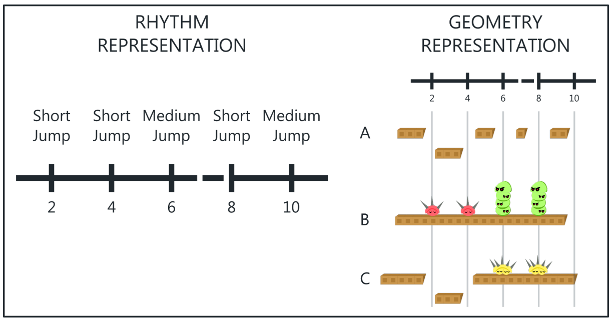

Figure 2: Rhythm Representation

To calculate the number of elements for each rhythm's value, we defined a difficulty function that is shown in equation (7).

$$D_1(p_0, p_1) = \begin{cases} D_0 + SG & \text{if } p_1 \geq p_0, \\ D_0 - SG & \text{if } p_1 < p_0 \end{cases} \tag{7}$$

Difficulty ($D_1(p_0, p_1)$): p_0 is the performance calculated in the previous level with equation (5); p_1 is the performance calculated in the current level with equation (5); D_0 is the difficulty of the previous level; S is a constant value to make the change between level and level smoother; G is calculated with equation (3).

The difficulty for the current level is calculated using the difficulty of the previous level plus a variation of the global value. This variation can take positive or negative values depending on whether we make the level more difficult or easier. The constant S represents a STEP value defined to make smooth changes of difficulty between levels so players do not feel an abrupt change.

For our implementation, the value S was set to 0.125 (calculated empirically after testing with other values). The value v is 1 if the difference between the performance for the current level and the previous level is positive and -1 if the difference is negative.

$$E_1 = E_0 + D_1 M \tag{8}$$

Rhythm density (E_1): E_0 is the rhythm density calculated in the previous level; D_1 is the difficulty calculated with equation (7); M is the maximum value for rhythm density.

$$L_1 = L_0 + D_1 N \tag{9}$$

Rhythm length (L_1): L_0 is the rhythm length calculated in the previous level; D_1 is the difficulty calculated with equation (7); N is the maximum value for rhythm length.

The rhythm density and rhythm length are calculated using equation (8) and (9) respectively. Density and Length are directly proportional to difficulty.

We simplified the elements that could be built by our system to the simplest elements in platformers, there are no special items or moving enemies, only the basic features to show the rhythm-group method working with the rest of our system.

We selected three types of challenges for each jump type, it means, we have three types for low jump, three for medium jump and three types for high jump, in total nine different elements. The first element is a gap, a separation between platforms, if the player falls through a gap, dies; the second element is a spike, the player dies when touching a spike; finally an enemy that can be beaten by the player jumping on its head. Figure 3 shows the geometry elements that the current geometry system can create.

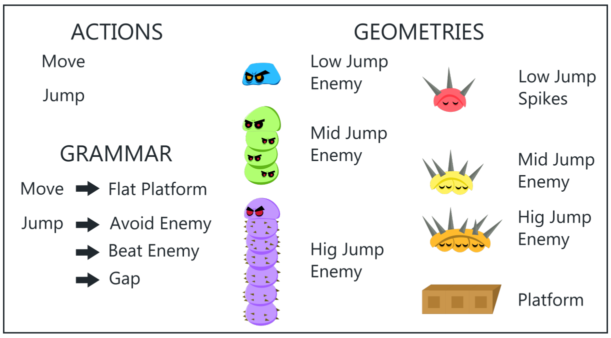

Figure 3: Rhythm System Elements

Figure 4 shows a piece of the level result for a low performance player, it's an easy level with not so many enemies or gaps; on the other hand, we can see the result for a challenging level in figure 5 which is different from the low performance result, with more enemies, gaps and challenges.

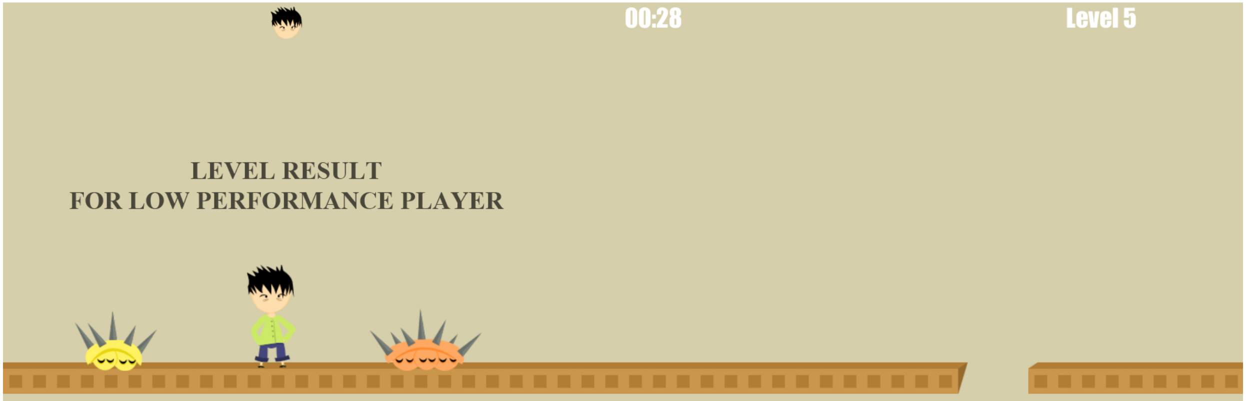

Figure 4: Low performance player: Few challenges, easier to complete.

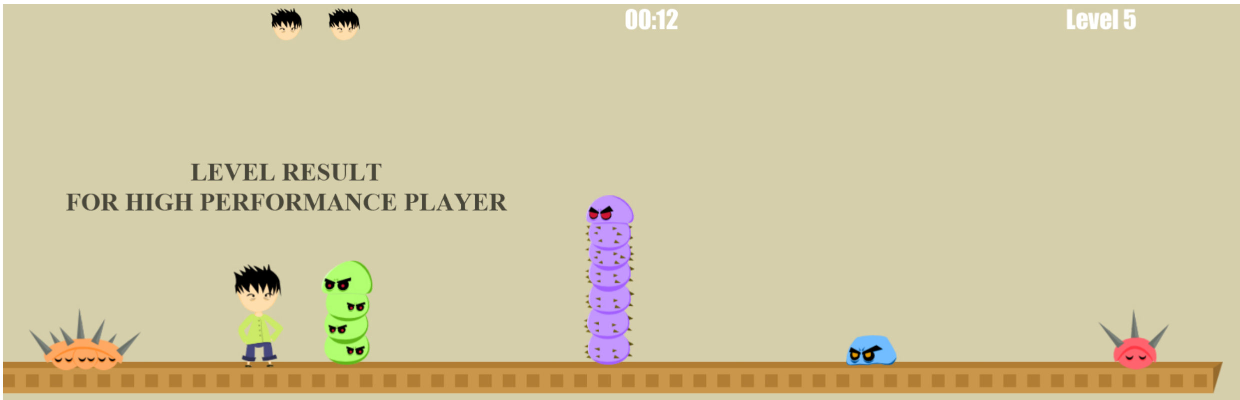

Figure 5: High performance player: More challenges, more difficult to complete.

5 Experiments & Results

Players were asked to complete five levels created automatically by our method and they wore the biosensor while playing to record their brain activity and adapt the difficulty of each level. Figure 6 shows the process.

5.1 Players and Environment

25 people between 21 and 30 years old, 7 (28%) women and 18 (72%) men completed the experiment. Before starting, players were asked: "Have you played Super Mario Bros before?" (A) and "Have you completed Super Mario Bros?" (B).

For question **A**, only 3 people (12%) answered *no*, the rest (22 people, 88%) answered *yes*; for question **B**, 9 people (36%) said *yes*, the rest (16 people, 64%) answered *no*.

The game was played on a 15inch widescreen monitor of a Dell XPS LX502 laptop, at approximately 60cm from the player, using an *Xbox360 gamepad* , with the left thumbstick to move and A button to jump. Sound was played using the laptop's speakers at a volume of 25%.

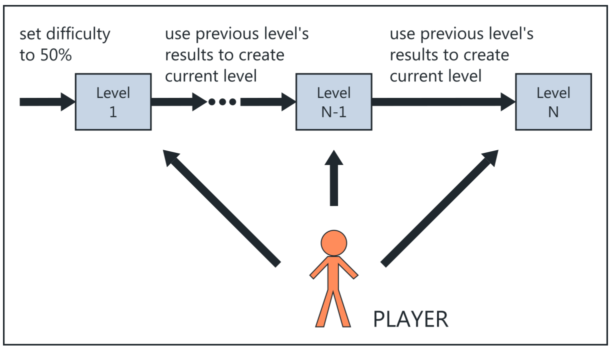

Figure 6: Experiments Process

5.2 General Features

For the first level that players played, we set the difficulty to 50%. Depending on the results of the first level the second level was created to adapt it to the player's results. Same process is repeated until players completed five levels.

5.3 Limitations

We faced some issues with the biosensor when performing the experiments. Sometimes the connection between the device and the computer (bluetooth) was not strong enough to establish a successful connection.

Besides connection issues, we found that after players wear the device for more than 10 min., they didn't feel comfortable, which lead us to decided to keep the experiments short.

For some players the device just didn't fit well, regardless its adjustable functionality, sometimes is not easy to fit comfortably in all types of players.

The result of those players that experienced problems with the connection while playing, nuisance or any kind of bad experience that could affect the results were excluded from the experiment.

In addition to Neurosky related limitations, we consider that this method would be suitable for games that involve jumping as their main mechanic and games that involve some kind of rhythm in their core mechanics. Runners, 2D or 3D, sidescroller platformers and rhythm games are among the types of games we consider this would be a good method for.

5.4 Analysis

The overall results for all players across time are shown in figure 7 (A). The graph shows the average results for all 25 players, attention, performance, global value (attention & performance) and difficulty.

5.4.1 General Results

Comparing the behavior of the global value (green curve) and the difficulty (purple curve) from level to level, we can see how in the end of the experiment both curves get close to each other, an increasing difficulty higher than the global value. This means that the method is matching the difficulty to the player's skills.

In addition there is a balance between attention (blue curve) and performance (red curve), the method combines both values and makes sure that both of them contribute with the final calculation. For example we can see the result from level 2 to level 3, performance decreases and the attention value increases, the result (green curve) is a stable value, which turns into an increase of difficulty, keeping the pace and attention for players.

Difficulty increases, comparing level 1 and level 5, showing that the level of challenge is changing, from 0.5 to 0.66, an overall increase of the difficulty until gets closer to the global value, we estimate that difficulty in upcoming levels would decrease a little and then raise along with the global value. We have to test with more levels to confirm this.

With the challenge increasing, we can also see how the global value changes, in the end of the experiment it ends up slightly higher than the beginning, meaning that players perform better with a higher difficulty.

If we performed experiments including more levels, we would expect that curves vary together, specially the global value and difficulty, the expectation is to keep increasing smoothly and both of them close to each other, demonstrating the adaptation process. We still have to make more experiments to confirm this.

5.4.2 Player Groups

In addition to the general results of our experiments, we separated and classified players' results by experience. The main reason to do this is that these players have features in common and it makes it easier and more meaningful when analyzing the results.

Figure 8 shows the results for all grouped features. We know that the number of players from graph B is low however, we can see how the behavior for both types of groups (A and B) in the end is similar, curves get closer in the end, which means that for both types of players the algorithm is adapting the difficulty.

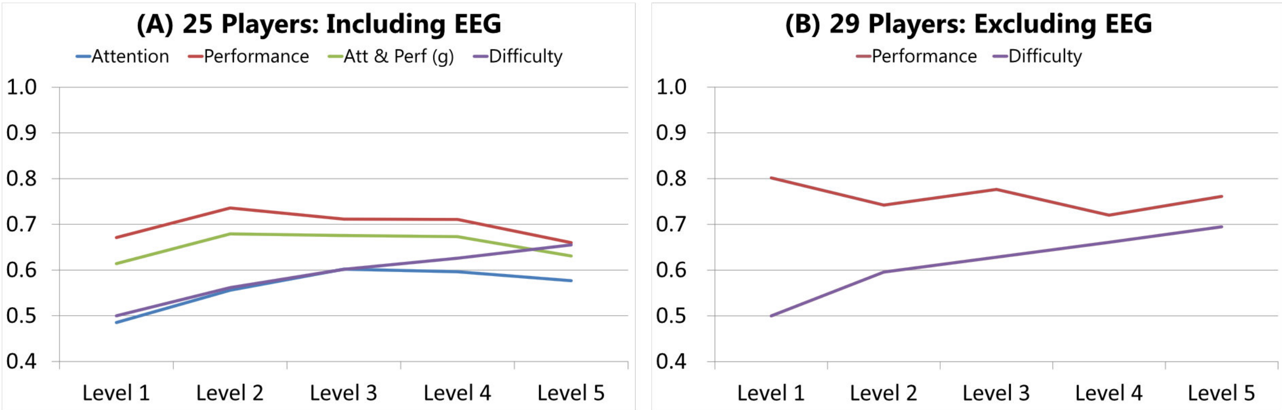

Figure 7: Experiments results: Including EEG (A), Excluding EEG (B). Each graph shows: Attention (blue line); Performance (red line); Attention and Performance (green line); Difficulty (purple line)

One of the interesting things about this particular group is we can see how the difficulty becomes lower to match players' results and in the end, curves get closer, reducing the gap while playing.

Comparing graphs C and D we can deduce that players from group C are more experienced than players from group D. In fact, by the overall performance of each group (73% for group C and 66% for group D), we can assume this. We can see that for players with different experience, the algorithm is, step by step, adapting to change and offer a suitable experience. Curves for both groups end up with a similar shape.

The difficulty for almost all groups adapts at a constant pace. Values of attention, difficulty and performance start at a particular point for each graph and in the end of the experiment they increase, it means players are getting better at the game and also challenge is increasing accordingly.

In general, for different types of players, with different characteristics and different experience we can see how the method is adapting, performance and attention are adjusting values of difficulty, the green and purple curve end close to each other.

We expect that if we perform experiments with more players and levels, the difficulty curve and globals (att. perf.) curve will keep moving at the same pace, ideally increasing with the player's abilities.

5.4.3 Players' Feedback

After playing each level of the game, we interviewed few players and collected feedback of their experience while playing. This section shows a short sample of those interviews.

All players said after that the game was fun to play however, they also mentioned that some levels (the easiest ones) are too simple and they would enjoy levels with more elements and challenges.

As a recurring comment from high skilled players, they all agree that difficult levels are more interesting than easy levels, in contrast, low skilled players felt better with easier levels but they also said that a higher level of challenge would be interesting.

When we designed experiments for this research, we implemented a game with the most basic elements from a platformer, to adjust the game and make it fit for the Rhythm-group theory parameters, in addition, graphics and in-game feedback are also very basic. Based on the feedback from players and the results of the experiment we should increase the level of challenge of the game, adding variety and improving the implementation of it.

5.4.4 EEG Influence

In order to validate the results obtained from our approach of combining player's performance and EEG to adapt the difficulty and to be able to prove the value and novelty of including this new

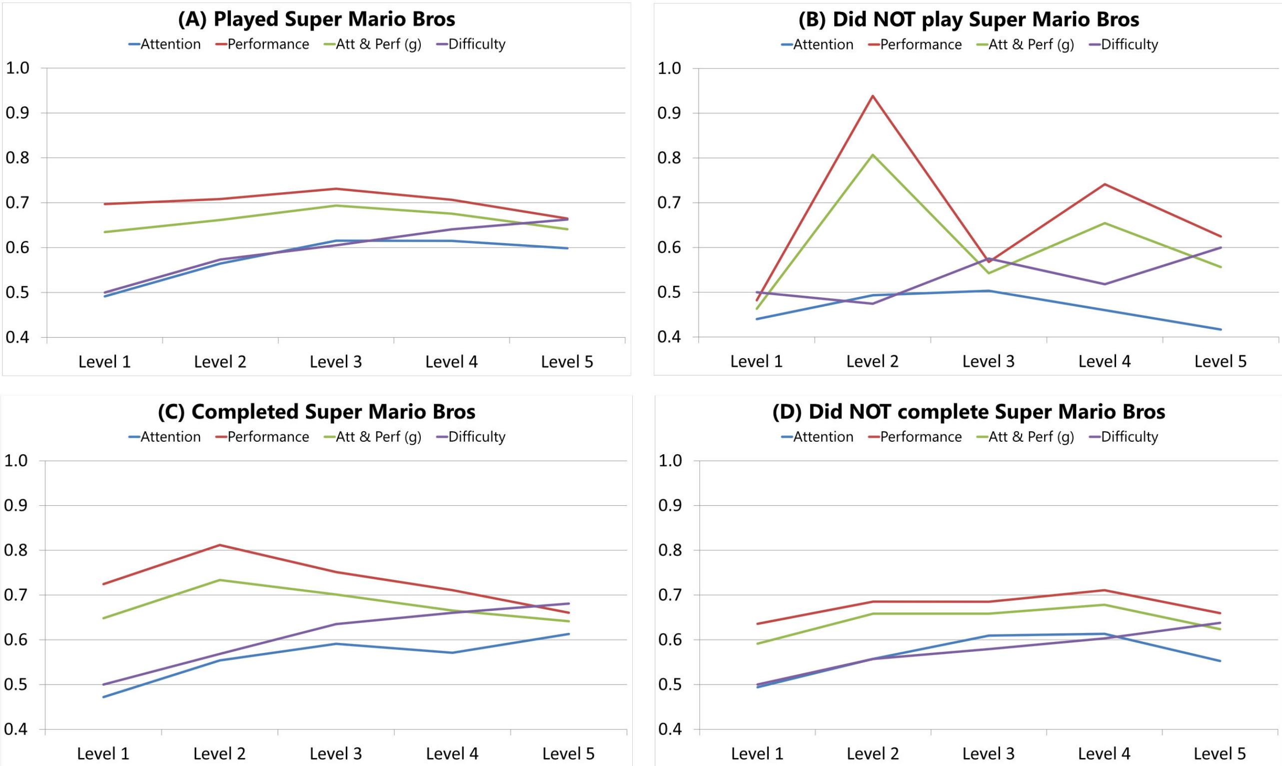

Figure 8: Results for Groups of Players. Each graph shows: Attention (blue line); Performance (red line); Attention and Performance (green line); Difficulty (purple line)

component, we conducted new experiments without the EEG data.

Using the same experiment layout shown in figure 6 and with the same approach described in figure 1, we removed the biosensor data from the calculation and gathered results from 29 players. Results from this experiment can be seen in figure 7 (B).

Comparing the results for the approach with and without the EEG component, we can observe significant differences.

As we explained before, the adaptation appears for the result with EEG at the end of the experiment, where difficulty and performance/attention values are getting close to each other, in contrast, we can see that for the experiment without EEG, these values are more separated, this demonstrates that the adaptation with EEG is better, in less time, was able to adjust the difficulty accordingly.

Results for the experiment without EEG show how the adaptation occurs abruptly, between levels we can see that changes are not smooth. One could argue that increasing or decreasing a constant in the calculation to soften these changes, the abrupt change problem would be solved, however, this could make the game less interesting by lacking variety (levels would be too similar for too long).

We can see a behavior for the experiments without EEG, show a pattern where performances decreases and increases in each level, this is due to the difficulty being too high or too low in the calculation; on the other hand we can see the results for the approach with EEG, changes occur smoothly and slower than without EEG.

6 Conclusions

We created a new method that is capable of adapting the level of challenge for players depending on their performance and degree of attention (using EEG data).

The adaptation matches different types of player's skills and status, not only experienced players but also inexperienced players, people with different characteristics. We also validated our results by comparing the results with an approach that didn't include the EEG component, demonstrating that the inclusion of brain waves related data can lead to better results.

Due to the biosensor issues and limitations, also the necessity of having the device for the process, we do not envision this method for commercial use yet, however, with a better performance and more comfortable device, this method could be implemented in other genres that involve jumping as a core mechanic or elements in which the rhythm group theory can help to add a sense of harmony to the game. Among the types of games we consider this method could be suitable for are: endless runners, 2D or 3D side-scrolling platformer or rhythm games

For game developers, this would be a good playtesting tool, this method would enable them to gather helpful information to create better levels. For instance, when designing a platformer, developers could create a base design and iterate on it dynamically using our method, evaluate and improve the design.

As future work we plan to improve the designed method, testing with different EEG biosensors, planning and performing more experiments, testing with more players and modifying the initial values to compare which values adapt the best to this approach. We also would like to include other factors on the difficulty calculation, so far we have only tested with number of elements in the level, we should also consider position and relationship between elements, which describes another level of difficulty.

In addition, we consider it would be meaningful to include new elements, other than difficulty to evaluate the player's experience. The harmony that gameplay, graphics and sounds constitute all together to shape experiences for players influence how these players perceive the game in general. As future ideas, involving graphics, sounds and new elements from gameplay would increase the value of this approach and its results.

For this research we didn't consider a specific study on psychophysical elements and their influence on the attention of players, for our next steps with this research we would like to address this area too.

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