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EEG-triggered dynamic difficulty adjustment for multiplayer games

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ABSTRACT

In online games, gamers may become frustrated when playing against stronger players or get bored when playing against weaker players, thus losing interest in the game. Dynamic Difficulty Adjustment (DDA) has been suggested as an intelligent handicapping mechanism, by reducing the difficulty for the weaker player, or increasing the difficulty for the stronger player. A key question when using DDA, is when to activate the difficulty adjustment.

In this paper we suggest using the Emotiv EPOC EEG headset to monitor the personal excitement level of a player and use this information to trigger DDA when the player's excitement decreases in order to ensure that the player is engaged and enjoying the game. We experiment with an open-source third-person shooter game, in a multiplayer adversarial setting. We conduct experiments, showing that the detected excitement patterns correlate to game events. Experiments designed to evaluate the DDA triggering mechanism confirm that DDA triggered based on EEG increases the players excitement and improves the gaming experience compared to the heuristic triggered DDA and the experience of playing a game without DDA.

1. Introduction

Video games are a popular activity for children and adolescents in the western world today, with almost 97% of the younger US population playing video games for at least one hour per day [20].

While the goal of a gamer in a video game may be to kill enemies, or collect prizes, game creators typically aim to keep players entertained and engaged over a long period of time [42]. It was often observed that playing against the game artificial intelligence (AI) is not as challenging as playing against other players [28,43]. When playing against other humans, however, it is important to play against players of similar levels of expertise, because when a weaker player plays against a much stronger one, often both players feel dissatisfied — the stronger player is bored, while the weaker player is frustrated. When a gamer wishes to play against one of their friends, matching suitable opponents may become even harder.

Dynamic difficulty adjustment (DDA), in which the players' abilities to influence the environment are dynamically modified throughout the game, provides a possible solution to this problem [46,47,55,32,39]. When a weaker player faces a stronger one, the level of difficulty for the weaker player can be reduced, as well as the level of difficulty for the stronger player can be increased. For example, in a first-person shooter game, where the goal of a player is to kill the avatar of his/her opponent, the bullet damage of the weaker player can be increased, and the bullet damage of the stronger player can be decreased. In addition, it may be possible to identify and implement a variety of game-specific adjustments in many games, with the aim of improving the user experience by ensuring that the games difficulty level is optimal for the players. However, one of the most challenging issues associated with DDA is knowing when to trigger such game modes.

Presumably, game modifications should be triggered only when needed, in order to avoid erratic game behavior. In the past, researchers have mainly suggested heuristics based on the game state [3,27,53]. For example, in a game that keeps an ongoing score, a decision can be made to apply DDA when the difference in the players' scores exceeds a certain predefined threshold. This heuristic addresses the situation when one player becomes too strong compared to the other player, based on the assumption that in this situation the stronger player may feel bored, while the weaker player may feel frustrated. The scoring mechanism hence contains clues to the players' state of mind.

In this paper we suggest a different approach — measuring the players excitement and activating the game modes when the excitement level drops below a predefined threshold. This approach attempts to directly address the core problem of degraded game experience, rather than relying on a scoring mechanism or similar heuristics to determine when the players are no longer excited by the game. We implement a passive feedback/affective state regulation method by using the Emotiv EPOC headset to read electroencephalography (EEG) signals and the

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Emotiv Affective Suite[1] to translate the signal into an affective state.[2] Then, based on the affective state, the game mechanism triggers DDA.

We conduct two user studies. The first user study assesses the correlation of the EEG signals to game events, and the results of this study show a good correlation between the Emotiv value for "short term excitement" (STE) and game events. Although, both positive and negative emotions can be utilized to improve gameplay [5], in this paper we attempt to improve the players' experience by maximizing STE. The second study compares our EEG-triggered DDA to a standard heuristic approach based on elapsed time and game status, as well as to a control game in which DDA is not implemented. The primary hypothesis tested here is that EEG-triggered DDA increases the players' excitement and improves the gaming experience compared to the heuristic triggered DDA and the experience of playing a game without DDA.

The contributions of the paper are twofold. First, we present a case study for the design of EEG-triggered DDA technique in a modified version of the open-source third-person shooter game, "Boot Camp".[3] Second, we study the user experience, comparing EEG-triggered DDA to standard heuristics triggering, as well as a game without DDA. Our study confirms that gamers enjoyed the EEG-triggered DDA better than the other two options and that this technique significantly increases the player's level of excitement. Our study further shows that the choice of the triggering strategy is important and significantly impacts the way players experience the game.

The rest of the paper is structured as follows: We begin by providing some background on brain-computer interfaces, EEG, and DDA in Section 2. We review the Boot Camp game that we use in our experiments and discuss additional related work. Then in Section 3 we discuss our EEG-triggered DDA triggering technique, and the modifications that we added to Boot Camp in order to allow DDA. We also explain the heuristic method of triggering DDA which is also evaluated in our experiments. In Section 4 we move to the user study that we conducted, first showing that EEG measurements in this setting correlate well with game events, and then comparing EEG to heuristic triggering of DDA. We discuss the main results of this study in Section 5 and conclude in Section 6 with a summary of this research and an indication of future research directions.

2. Background

In this section we briefly review the rapidly growing field of brain-computer interfaces and assessment of the affective state. We discuss BCI application to games, dynamic difficulty adjustment (DDA) in games, and the "Boot Camp" third-person shooter game.

2.1. Brain-computer interface

A brain-computer interface (BCI), also known as a mind-machine interface (MMI) or a brain-machine interface (BMI), is a direct communication pathway between the brain and a computer. In a BCI, signals from the brain are analyzed to determine the user's state of mind or intentions. By detecting features of the brain activity and creating a feedback loop, users can communicate to a computer without other types of input devices [36].

The applications of BCI are heterogeneous. Initially, BCI research was mainly aimed at medical applications [37], such as helping disabled people to recover a means of interaction with their environment and surroundings [33]. Recently there has been increased interest in the study and development of BCI for multimedia applications such as video games [7,17]. BCI can also provide subjective, time-aligned information such as the user's affective state [26], allowing for game adaptations that enhance the gaming experience [38]. In this paper we focus on the latter type of application of BCI.

Brain signals can be acquired using various non-invasive measurement methods such as electroencephalography (EEG), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), or functional magnetic resonance imaging (fMRI) [9]. In the area of healthy user BCI research, EEG has become an especially popular method, due to its relatively low cost and its high temporal resolution [52,54].

A variety of inexpensive devices have recently become available to the gaming market, mainly aimed at collecting peripheral input for analyzing a person state of mind, including the Emotiv EPOC headset which has 14 sensors. The Emotiv headset was shown to provide readings less accurate than a medical EEG system [48] but adequate accuracy for gaming applications [2,14]. The Emotiv Affective suite has been used in a number of research applications [26]. For example, in intelligent tutoring systems where the excitement and frustration recorded from the headset has been shown to reflect users' explicit feedback [29]. The Emotiv Affective suite was also used to identify users' affective states (e.g., excitement or meditation) and facial expressions, and to control an avatar in the well-known online game, World of Warcraft (WoW) [45]. Harris et al. [23] presented a tool to detect frustration during gameplay, that was also utilized in several additional studies [18,4,19]. Nacke [34] introduced physiological measures and techniques for game evaluation in the context of games user research (GUR). GUR comprises a collection of methods that allow game designers to bring their creations closer to the initial vision of the player experience.

2.2. Computing affective state from brain waves

Affective state is often discussed in the literature with respect to two main dimensions: the unpleasant-pleasant (also called *valence*) and activation-deactivation (also called *arousal*) [44]. A variety of intermediate affective states can be located along these two dimensions as presented in Fig. 1. When investigating highly emotional content, one may take into consideration both arousal and valence [30].

2.3. Dynamic difficulty adjustment

It is widely agreed that games should strive to keep players on the golden path between boredom, where the game is too easy, and anxiety, where the game is too difficult (Fig. 2). This is often called the Csikszentmihalyi flow [10]. Achieving the optimal flow can be done by adjusting the difficulty level of the game.

Many games offer various difficulty levels. For example, a player can choose a stronger or a weaker artificial intelligence (AI) algorithm for the non-player opponents. Choosing the optimal difficulty level, however, might not be trivial, requiring multiple trial and error games. Furthermore, as the player learns to play the game and becomes more experienced, he/she will likely need to increase the difficulty level constantly so as to continue to be challenged by the game. On the other hand, when the game presents novel challenges to the player, some players may want to lower the difficulty level [46,47,28].

The difficulty level can be modified in various ways. When playing against AI, the difficulty level can be increased by using more sophisticated AI algorithms that make better choices. This is a popular approach in board games such as chess or backgammon. An easier method commonly used by game developers is to modify the player attributes. For example, in real time strategy (RTS) games the resources required for constructing buildings or training soldiers can be reduced, thus reducing the difficulty level. In first- or third-person combat games the amount of damage players affect upon each other can be modified.

In contrast to static difficulty adjustment set by the player, DDA allows the game mechanism to automatically modify the difficulty level

[1] https://www.emotiv.com/.

[2] In this paper we use the term "affective state" rather loosely to refer to the output of the Emotiv EPOC headset.

[3] Boot Camp is a Unity open source demo. The game is an example of a 3rd person shooter set in a modern day scenario. http://u3d.as/content/unity-technologies/BootCamp/28W.

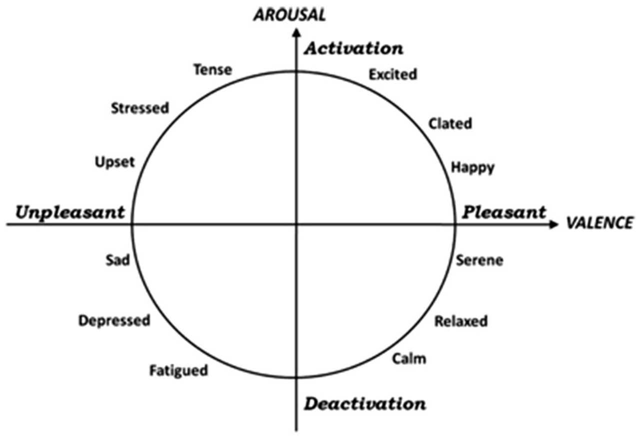

Fig. 1. A schematic map of the emotional plain [51].

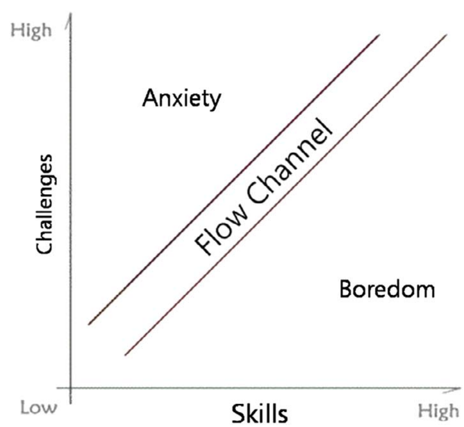

Fig. 2. Csikszentmihalyi flow [10].

given the current player state [39,1]. DDA aims at providing an ever challenging, yet possible, environment for the player, as he/she moves from novice to expert. DDA can also be used to reduce boredom and frustration [55].

Efficient DDA requires defining the game modes which affect the difficulty level and determining when each of these modes should be triggered. For example, DDA triggers can be based on the players' personal score which is constantly maintained in many games. The score increases as the player achieves more goals, acquires new skills, or collects more resources. Comparing the scores of the players can provide an estimation of the current relative progress of the players throughout the game. For example, in an RTS game the score may depend on the number of units and structures that the player has obtained. In shooter games the score may depend on the current health of the player or the set of weapons he/she has collected.

When the score difference becomes substantial, it often indicates that one player has gained an advantage over other players. A player with a significant score advantage may have obtained sufficient power to win the game easily and may become bored. The score difference can hence serve as a proxy to the player's gaming experience. As such, the score difference is often used as a heuristic to trigger dynamic game modifications (i.e. DDA) that are designed to reduce the gap between the players and prevent player boredom or frustration.

2.4. BCI game design principles

We now illustrate a few design principles motivated by BCI research that inspired us when suggesting a set of modifications for the Boot Camp game that we experiment with.

Gürkök et al. [22] identify three major aspects of BCI games that the game creator should improve in order to make the game more satisfying for players:

- **Sociality** — Digital gaming provides many opportunities for social interactions [11]. Some people enjoy playing computer games with other people, and play, not necessarily for the challenge, but merely for the social interaction [22], while others prefer playing alone or in a pseudo-social fashion [13].
- **Challenge** — A challenge is a task with a relative level of difficulty that exceeds some individual player threshold. Sweetser and Wyeth [49] suggest that a game should offer challenges matching the players' skills. Gürkök et al. [22] claims that people strive to accomplish tasks for their challenge, with little concern regarding the reward they may obtain by meeting the challenge, even when the challenge is difficult.
- **Fantasy** — Games allow actions within the game environment that cannot be performed in the real world. This may allow players to detach themselves from their everyday life and become immersed in the game experience. BCI allows further unrealistic conditions where the thoughts and feelings of the player directly modify the game environment.

A similar classification of BCI game principles was used in the GameFlow framework, in which several such aspects (heuristics) were suggested [35]. Challenges like fantasy and social aspects are also important concepts in the design of affective learning games [12].

2.5. The game environment – Boot Camp

For this study we chose a shooting game called **Boot Camp**. Boot Camp is a multiplayer, open-source, third-person shooter game that takes place in a modern day setting (see Fig. 3). In our experiments we focus on the duel mode of the game, where two opponents attempt to find the other player's avatar and kill it within a given time period.

This gaming environment has several attractive features for the purpose of our study:

- High quality visualization and graphics, making the game more enjoyable for the players [16].
- Open-source development, allowing us to modify the code to implement game modifications.
- A multiplayer option, allowing us to test DDA in a human vs. human setting [15].

In our game settings, each player begins at a different part of the game map. The game can be roughly divided into two phases. In the first phase, the players must search the map to find their opponent, and in the second phase (after identifying the enemy) the player must try to eliminate the other player. After one of the opponents is killed, the

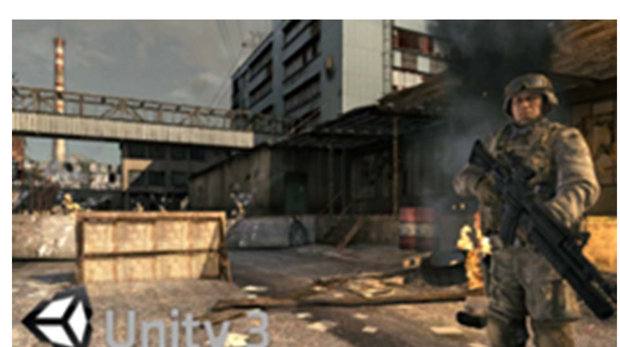

Fig. 3. A screenshot from Boot Camp.

game restarts.

2.6. Related work

Many studies use EEG-based BCI in a video game for a single player [8], multiplayer, multimodal and multiparadigm [52,7] games. Research in this area is used for developing user interfaces, evaluating the usability of the system, and measuring user experience and the social interaction of gamers [21].

Most prior BCI video game research has focused on allowing players to directly control the game behavior through the EEG interface. For example, players can imagine movements in order to navigate [31] or make selections [50]), or to change the game avatar, such as its facial expression, given the players current emotions [8]. In the context of multiplayer games, Obbink et al. [40] study the influence of using a BCI control on social interaction in a two-player game.

There have been attempts to reduce negative feelings during game play using DDA [55] and capture user emotions in games, for example, by detecting facial expressions [6].

Perhaps the work most similar to ours own, was presented by Park et al. [41] suggesting DDA powered by the Emotiv EPOC headset. Park et al. experimented with a single player game, Guitar Hero, modifying the difficulty level based on the player's state of mind. They show that the Emotiv headset captures patterns consistent with the current game state, and that the accuracy of the player improves using DDA. They do not report whether players preferred the game when using DDA and did not experiment in an adversarial multiplayer context as we do.

In adversarial multiplayer context it is possible to it is possible to avoid imbalanced matches, by forcing players to play against players of similar skills [25]. Matching players may work well in massive multiplayer online games but is not applicable to cases where a player wants to play against their real life friends. In this paper we attempt to level the playing field when two players with arbitrary skill levels are matched against one another.

3. Designing DDA triggering strategies

In this paper we design and evaluate EEG-triggered DDA for increasing the players' excitement. In this section we discuss the DDA features added to Boot Camp and the motivation for each type of game adjustment. We also describe two DDA triggering methods: EEG-triggered and heuristic.

3.1. Game modifications

We implemented four game modifications (modes), designed to either reduce the difficulty for the weaker player or increase the challenge for the stronger player:

- Berserk mode: In this mode the avatar gets super power, boosting its running speed. As previously mentioned, the game begins with the two players that are located in different parts of the environment, and the first task of each player is to find their opponent. After a while, the search phase of the game may become tedious to the players. This modification is designed to reduce the required amount of time for locating the other player and starting the battle. It also increases the social aspect of the game, reducing the amount of time that each player plays on its own without seeing the other player. However, premature activation of this game modification may reduce the thrill of searching for the opponent.
- Turret mode: In order to increase the difficulty for the stronger player, we confront this player with an automated AI turret. The turret cannot move but shoots at the avatar until it is destroyed. Thus, the stronger player will reach the battle phase after being weakened by the turret. This modification is designed to increase the challenge in the game when the human opponent may not be sufficiently challenging.
- Hulk mode: When one player is significantly weaker than his/her opponent, we reduce the damage inflicted by the bullets that hit the avatar of the weaker player. In addition, to increase the fantasy quality of the game, the avatar grows larger and gets a more threatening appearance when this mode is activated.
- Invisible mode: This modification is also applicable for weaker players. The avatar becomes invisible, that is, it disappears from the view of the opponent for a limited time. The invisible avatar can still be hit, but it is of course more challenging for the opponent to estimate the position of the invisible avatar based on, e.g., the direction the gunshots are coming from.

An avatar that enters any of these modes also issues a sound indicating the mode change. To increase the fantasy quality of the game, the sound symbolizes the change, for example, when entering the Hulk mode, a frightening growl is heard, and when entering the Berserk mode, a lightning sound is issued. Each modification, except for the Turret, is active for a short time period only, and a timer is presented to the player, showing how long the mode will be in effect.

The Berserk and Turret modes are designed for the opponent search phase of the game where the distance between the avatars is relatively large and hence are activated only when the player's avatar is far from his/her opponent's. The Hulk and Invisible modes are appropriate only in close range and are applicable when the distance between the avatars drops below some threshold (50 m in our experiments).

Note that all of the modifications mentioned above are visually noticeable to the players, i.e., players clearly observe that the game situation changes. This is not always the case with DDA. For example, one could make the opponent immune to hits, without providing any visible notification to the player. In fact, game developers may attempt to hide such adjustments so a player doesn't feel as if he/she is being cheated [27]. We speculate, however, that visually observable adjustments increase the fantasy quality of the game, the challenge that players experience, and the social interaction.

3.2. Heuristic triggering of DDA

In order to properly activate DDA we need to choose the most appropriate modification and the time of its activation. In this section we formulate a set of heuristic rules for both choosing the modification and triggering it. The rules are based on a set of game state statistics collected during the course of the game.

First, we estimate the relative experience level of each player based on their kill ratio. We count the number of opponent kill events, and the player with the higher kill ratio is considered the stronger player. Of course, in the first few games this measurement may be noisy, but after sufficient game time has passed (the first 10 min of game play in our experiments), we are generally able to identify the stronger player. When the players are almost equal, the difference in kill ratio may be minor and helping the weaker player even a little may be unfair to the slightly stronger player. Therefore, one could introduce a threshold, such that only if the difference in the players kill ratio passes this threshold, would the player with a higher kill ratio be treated as stronger. Also, in the case of repeated games this may not prove to be too unfair, because the player that received favorable adjustments may win, tipping the kill ratio in their favor. In the subsequent game this player will be considered the better player, and will not get additional alleviations.

In addition to the difference in experience levels, the distance

Table 1
List of abbreviations.

Abbreviation	Meaning
AI	Artificial intelligence
DDA	Dynamic difficulty adjustment
BCI	Brain-computer interface
EEG	Electroencephalography
STE	Short term excitement
LTE	Long term excitement
RTS	Real time strategy

Table 2
Modification applied in different distance-strength contexts.

	Short distance	Long distance
Stronger player	Hulk mode	Turret mode
Weaker player	Invisible mode	Berserk mode

After determining the modification which should be triggered, we use heuristic rules to determine the time of triggering the chosen modification. In a third-person shooter game, it is reasonable to assume that after a certain amount of time during which neither player has killed their opponent, the players may get bored. Hence, while the avatars are distant from each other, we measure the time elapsed since the players have engaged in battle. Similarly, we measure the time that the avatars are in the same area, yet no player is able to kill the other. We use these two timers to trigger the long distance and short distance modifications, respectively. For example, if the avatars are far apart for too long and are unable to find each other, we randomly activate the Turret for the strong player or the Berserk mode for the weak player. Thus, we increase the challenge for the stronger player or provide some advantage for the weaker one allowing him/her to quickly find the opponent's avatar. When the modification mode terminates we reset the timers. The heuristic triggering approach is summarized as *Heuristic DDA* in Algorithm 1.

Algorithm 1. DDA procedures

```
Learning session:
    Participants (P1, P2) play without modifications
    Strong, Weak ← estimate players' strength based on kill ratio
    LTE1, LTE2 ← mean LTE of P1 and P2
No DDA:
    Participants play as usual without modifications.
Heuristic DDA:
    Input: T: threshold delay between modification activations
    if time since last kill or modification > T then
        if avatars are in the same area then
            Activate randomly Turret for Strong or Berserk for Weak
        else
            Activate randomly Hulk for Strong or Invisible for Weak
EEG-triggered DDA:
    if LTE(P1) < LTE1 then
        if P1 = Strong then
            Activate Turret if far from P2
            Activate Hulk if near P2
        if P1 = Weak then
            Activate Berserk if far from P2
            Activate Invisibility if near P2
    Symmetrically for LTE(P2) < LTE1
```

between opponents also plays a significant role in choosing which modification to trigger as described in Section 3.1. When the avatars are far from each other, the game rapidly becomes less interesting. To prevent this, we would like to shorten the time a player needs to search for the other player's avatar. (see Table 1).

Table 2 contains the modification applicability rules.

Using the modifications too often may reduce their effect on the game and the players. Thus, we define a timeout after triggering a modification during which no modifications can be triggered. It is important to properly tune the timeouts for triggering the modifications. If the timeouts are too high, the players may get bored and frustrated before we have a chance to influence their gaming experience. In

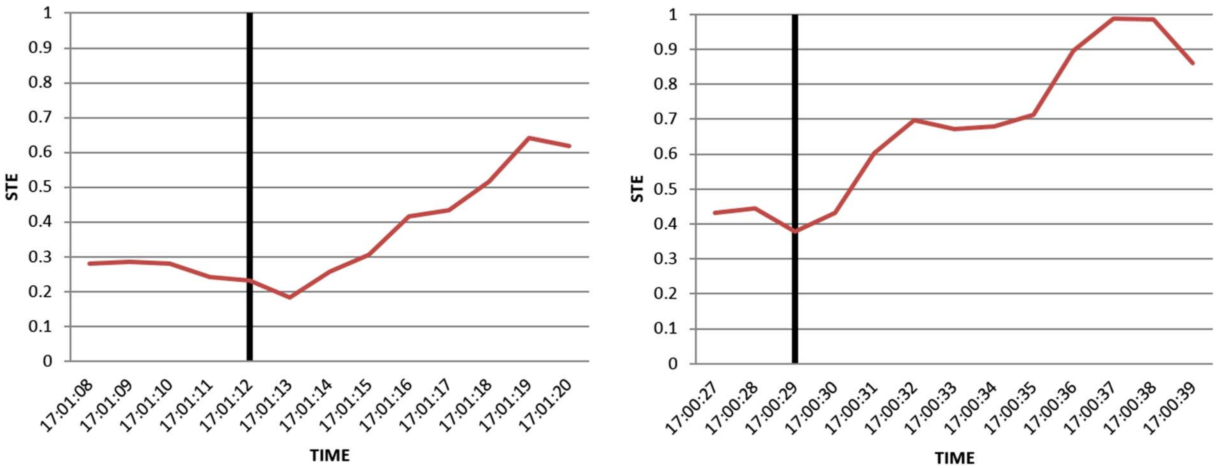

Fig. 4. Two examples of the increase in STE after an opponent's avatar is killed. The black vertical line marks the opponent's avatar's death time.

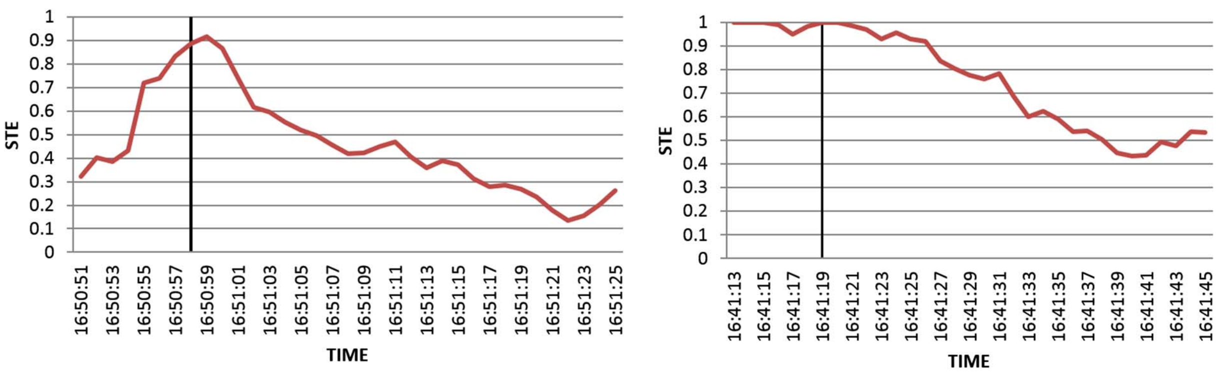

Fig. 5. Two examples of the decrease in STE after a player's avatar is killed. The black vertical line marks the avatars death time.

general, properly tuning the elapsed time is difficult, and requires either extensive experiments or a domain expert. Nevertheless, such heuristic approaches are perhaps the easiest to implement when sophisticated sensors measuring the player's state of mind are not available.

In this study we compare the games with DDA events triggered based on the EEG readings and the heuristic method described above. To avoid differences between the methods due to the elapsed time between modifications, we use the mean timeout between EEG activations of DDA described below as the timeout for heuristic-based DDA activations in our experiments, which are described in Section 4.

3.3. EEG-triggered DDA

Affective computing makes it possible to improve the players' experience in BCI games. As an alternative to the heuristic DDA triggering described in Section 3.2, we suggest triggering the modifications when the excitement level of a player drops below some personal threshold. We analyze the EEG measurements taken by the Emotiv EPOC headset using the Emotiv Affective suite to identify the excitement level of the player.

Each player has a different scale of excitement EEG measurements, and therefore, a different threshold. Thus, we need to calibrate the system for each player. In our experiments, the personal excitement threshold of each player is tuned during an introductory learning session in which players play without the use of DDA. The threshold is set at the mean excitement level experienced by the player during this phase (see *Learning session* in Algorithm 1).

As with the heuristic triggering, we identify the stronger and weaker players and use the distance between the avatars to choose the appropriate modification. The personal excitement threshold replaces the threshold set on the time elapsed between DDA activations. Other parameters, such as the distance threshold, remain intact. While the triggering of the Hulk and Turret modes depends on the excitement level of the stronger opponent, the Invisible and Berserk modes are triggered by the affective state of the weaker one (see *EEG-triggered DDA* in Algorithm 1). For example, when the weaker player's avatar is far from the stronger player's avatar, and his excitement level drops, we apply the Berserk mode. When the avatars are in close proximity, and the excitement of the strong player drops, probably because the weak player is too weak, we apply the Hulk mode to the weak player, making the task more challenging for the stronger player.

Table 3
T-Test — Player's mean frustration before and after the death of their avatar ($p < 0.001^*$).

	Before death N = 8	After death N = 8	T(7)
Mean	0.621	0.8276	-4.773^*
STD	0.038	0.0405	

Table 4
T-Test — Mean frustration of a player after killing their opponent's avatar ($p < 0.001^*$).

	Before death N = 8	After death N = 8	T(7)
Mean	0.664	0.7147	-2.47^*
STD	0.0212	0.0226	

4. Empirical evaluation

In this section we describe the set of experiments we conducted to compare heuristic-triggered DDA, and EEG-triggered DDA, in third-

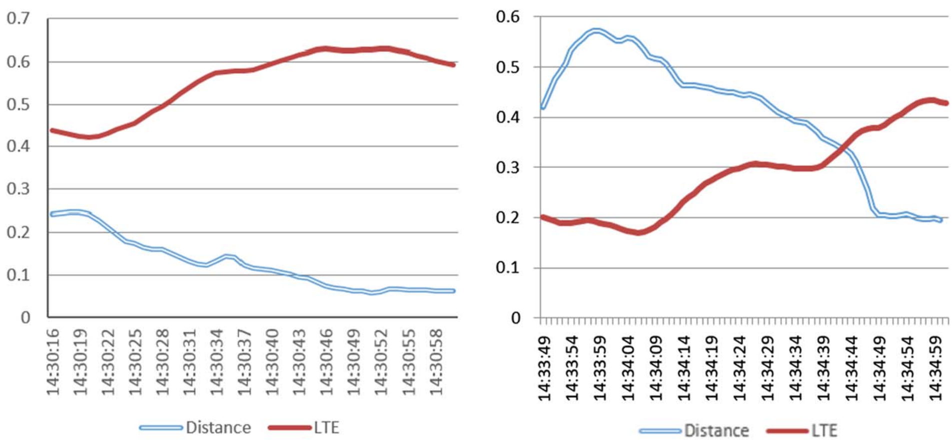

Fig. 6. Two examples of the negative correlation between the distance between avatars (solid line) and LTE (dotted line). The X-axis shows the wall clock time, while the Y-axis shows the normalized measurements (LTE and distance).

person shooter games such as Boot Camp. We begin with a preparatory experiment without DDA, designed to establish a correlation between the game events and the affective states of the players. Then we move on to a second experiment, evaluating the applicability and benefits of the EEG-triggered DDA.

4.1. EEG measurements and game events

The first experiment, designed to establish the correlation between the players' affective state and the game events, was run on the original Boot Camp game with no modifications.

4.1.1. Participants

We recruited eight subjects to participate in this experiment, one female and seven male students, in the 22–28 age range (mean ± SD of 25.09 ± 1.97 years). None of the eight participants had any previous experience with BCI in general, and Emotiv EPOC headset in particular. All participants had played computer games in the past. Currently the participants spend 7–35 weekly hours playing computer games (mean ± SD of 10 ± 2.93 h).

4.1.2. Procedure

The participants were divided into pairs, and each pair was invited to our lab at a different time. The experiment took place in an empty meeting room with two laptops. Upon their arrival, the participants were requested to complete a general questionnaire containing a self-evaluation of their gaming experience (see the Appendix for details).

Then, the participants watched a short tutorial video for the Boot Camp game[4] and played a two minute long introductory game to get familiar with the game's GUI. Next, the participants were connected to the EEG sensors and started a 15 min gaming session. The number of minigames completed during the 15 min period varied according to the players' ability to kill their opponents quickly. During the course of the experiments one of the researchers was always present and monitored the participants.

During the games we logged the distance between the avatars, the number of bullets fired, the current weapon (grenade/gun), weapon reload events, weapon change events, the events of successfully aiming at the opponent, the death of one of the avatars, and the damage inflicted to each of the avatars. The Emotiv EPOC headset and the Emotiv Affective suite were used to capture the players' frustration as well as STE and LTE. All measurements were recorded throughout the game.

4.1.3. Results

The goal of this experiment is not to validate the Emotiv EPOC headset emotion detection but rather to identify a correlation between

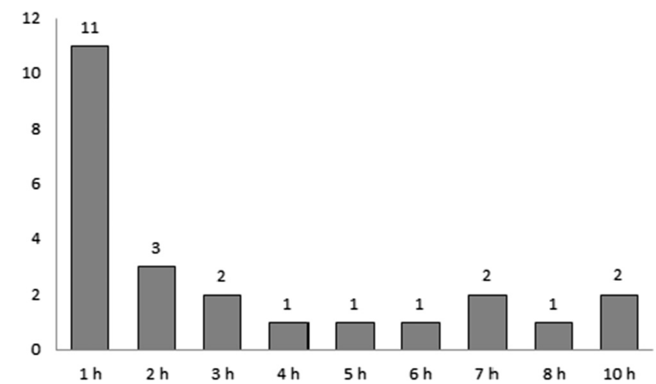

Fig. 7. Number of hours spent weekly playing video games for participants in the main experiment.

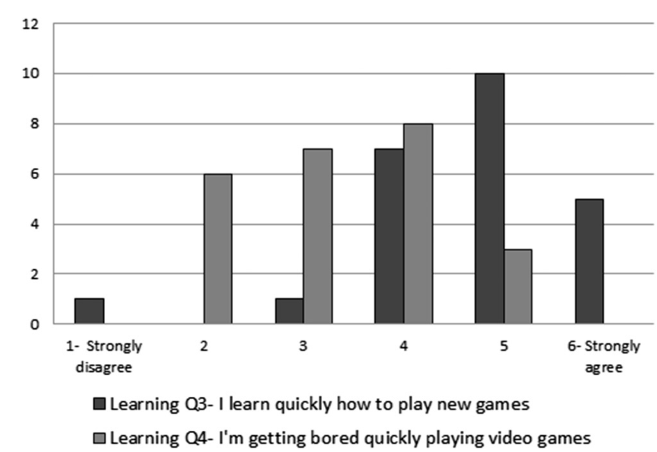

Fig. 8. Responses to questions about the life cycle of playing a game — learning to play a new game and getting tired of a familiar game.

game events and the sensor readings and determine whether the sensor readings represent true emotions or not.

Figs. 4 and 5 provide examples of the STE for a player after their avatar has died and after killing an opponent. As can be seen, STE peaks after a player kills the opponent's avatar and is at its low point after the player's avatar dies. This is an intuitive result — players are most excited when winning and least exited when they lose. Table 3 shows the mean frustration levels before and after the death of the players avatar. As we can see, the frustration is higher after the death.

Somewhat surprisingly, we also found that the frustration of the players increased after killing their opponent's avatar (Table 4). Previous studies [24] have also identified the inconsistency of the

[4] https://www.youtube.com/watch?v=oeOPRPBrfiE.

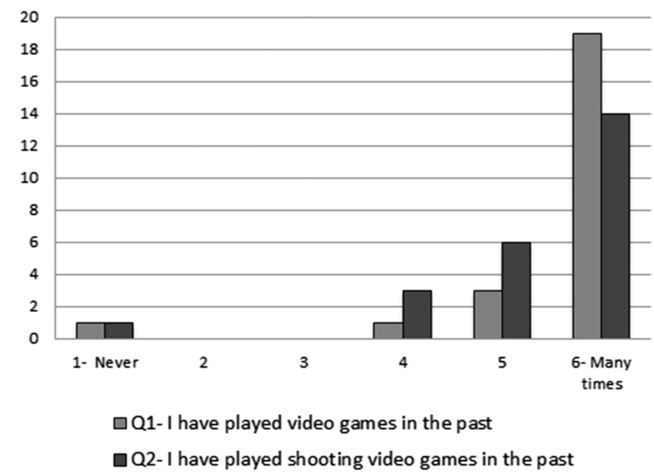

Fig. 9. Experience with shooter games vs. other types of video games.

frustration values reported by the Emotiv Affective suite. Thus, we do not use this measurement in the next experiment.

Finally, we found that the distance between the avatars is negatively correlated ($r = -0.634$, $p < 0.001$) to the players' LTE. The game displays a minimap showing the locations of both players, which allows a player to approach its opponent directly or via a detour for a surprise attack. It is expected that the game will be more exciting as the avatars get closer and engage in battle. Fig. 6 provides two examples of the (negative) correlation between distance and LTE.

To summarize the results of the first experiment, we find the strongest correlation between the Emotiv EPOC headset STE readings and game events, such as killing an opponent, and game metrics, such as the distance between avatars. However, we conjecture that triggering decisions should not be based on immediate responses to momentary events, such as an alarming sound, or a single observed movement. Instead, triggering decisions should be based on a longer time frame, capturing whether the player is excited as the game progresses, not just during the latest event.

Thus, we chose to use the LTE level for triggering DDA, which is, as stated in the Emotiv EPOC manual, more accurate than STE when measuring changes in excitement over longer time periods.

4.2. Evaluating EEG triggering of DDA

Above, we described the initial experiment, designed to establish the validity of the Emotiv EPOC sensor for capturing user experience during a first person shooter. In this section we describe the main experiment, a within subjects user study designed to compare the EEG triggering of modifications to heuristic triggering of modifications. This experiment uses a game with no modifications (no DDA) as a baseline. During the games we used the four modifications defined in Section 3.1: Hulk, Turret, Invisibility, and Berserk modes. The modifications were divided into short distance modifications, applicable when the distance between the avatars drops below 50 meters, and long distance modifications, applicable when the distance between the avatars grows beyond 50 meters.

Our primary hypothesis tested in this experiment is that modifications triggered based on the players' current affective state will enhance their excitement and improve the gaming experience compared to the heuristic triggering of DDA and the game without the use of DDA.

4.2.1. Participants

In this experiment there were 24 participants (22 male and two female), with ages ranging from 20 to 29 (mean = 25.59), all of them student volunteers. The three participants with the highest kill ratio received a cash award as an incentive to play the game well. None of the participants had previous experience with BCI, but all of them had some experience with computer games.

Similar to the preparatory experiment, we asked the participants to evaluate their own gaming experience by completing a questionnaire. The number of hours spent on computer games varied from only one hour a week (about half of the participants) to 12 h or more per week (Fig. 7). Most participants felt that they learn how to play new video games quite quickly and that they do not, on average, get bored very fast when they play games (Fig. 8). We also asked the participants about their expertise in video games and shooter games (Fig. 9). Most participants reported some experience in shooter games, although not as much as other types of video games.

4.2.2. Procedure

We randomly divided the participants into pairs by us. Each pair was invited to our lab at a different time. The participants were seated at a table across from one another in the lab, and the game was played on two laptops, with each player using a mouse and a keyboard.

The participants were first requested to answer a questionnaire in which they provided demographic information and reported their previous experience with video games (we used the Google Forms platform). After answering the questionnaire, the participants started playing the game.

During the experiments each pair of participants played four gaming sessions:

1. *L* – A learning session (10 min) designed to allow the participants to gain basic game expertise. There were no modifications during this session. During the learning session we recorded the participants' excitement level baselines in order to calibrate the EEG-triggered DDA.
2. *H* – A session with heuristic triggered modifications (15 min). As explained in Section 3.2, we set the timeout for DDA triggering based on the mean time for EEG-triggered DDA. The modifications were triggered after 10 s when in short range and after 17 s when the distance between the players was above 50 m. These thresholds were chosen after conducting the preliminary experiments.
3. *E* – A session with EEG triggered modifications (15 min). The modifications were triggered when the player's LTE dropped below their personal mean LTE, as calculated during the learning session (*L*), for the specific range (short/long).
4. *N* – A session with no modifications (15 min).

The players played the learning session; they then played the three other sessions. We tested all six possible orderings of the three (non-learning) sessions: L[HEN], L[HNE], L[ENH], L[EHN], L[NEH], L[NHE]. The session ordering was counterbalanced across participants such that each ordering of games was played by four participants (two pairs). The players were not told that there were three types of games or which type of game they were playing.

During all the four game sessions both players wore an Emotiv EPOC headset. Each pair spent 55 min playing and about 30–45 min on miscellaneous tasks and questionnaires.

Every session contained multiple minigames (as many as the time allowed) with a new minigame starting each time one of the avatars was killed. In the beginning of a minigame the avatars were randomly placed on the map, sometimes in distant corners and sometimes near each other. Each pair of participants played 13–53 mini-games.

During each session we recorded the LTE and STE levels of both participants, as well as the distance between the avatars and various game events (shooting, killing, DDA activations, and so forth). Fig. 10 provides an example of the STE increase following the activation of a DDA mode (Invisibility in this case).

After each game the players completed another questionnaire to assess their subjective user experience regarding the game they had just played. After the last game, the players also filled a questionnaire about

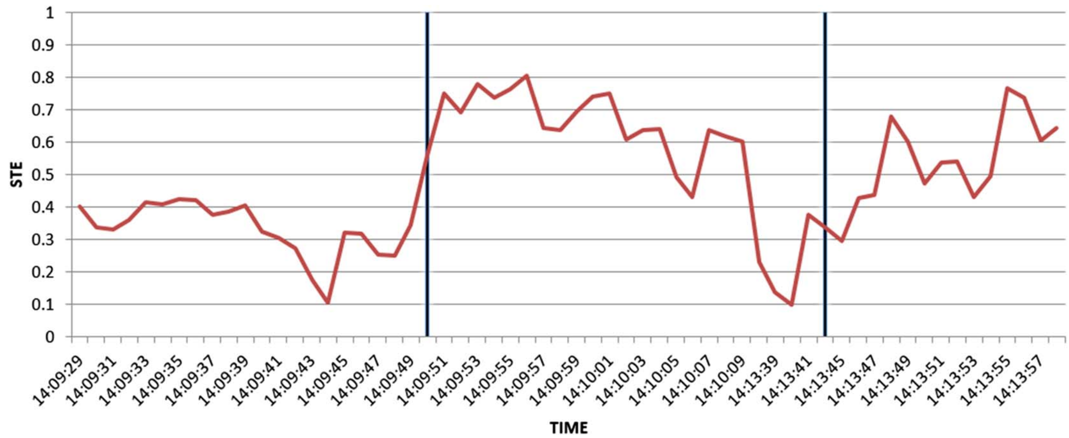

Fig. 10. STE increase following two DDA activations of the Invisible mode. The black vertical lines indicate the activation times.

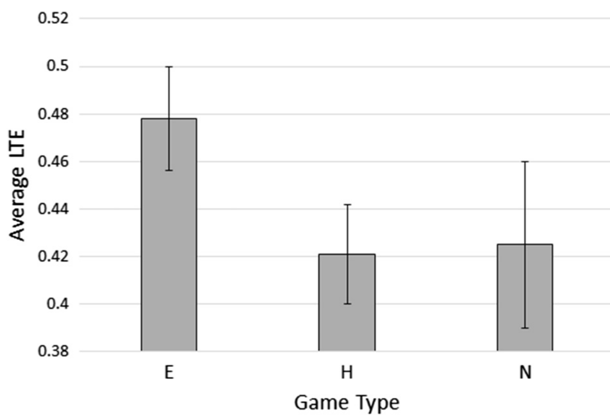

Fig. 11. Mean LTE for each game type.

Table 5
P-values in the post hoc Duncan (and L.S.D) test indicate that the mean LTE for the *E* game type is significantly higher than for the *H* and *N* game types.

Game type	*E*	*H*	*N*
E, $\mu = 0.47552$		0.007703	0.009966
H, $\mu = 0.42294$	0.007703		0.833097
N, $\mu = 0.42678$	0.009966	0.833097	

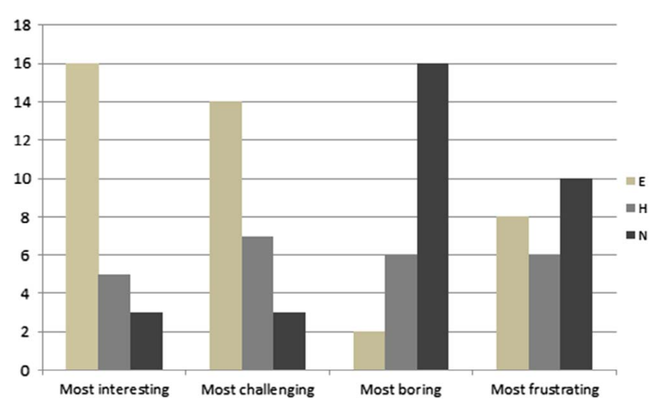

Fig. 12. Participants' answers to comparative questions over the different game types.

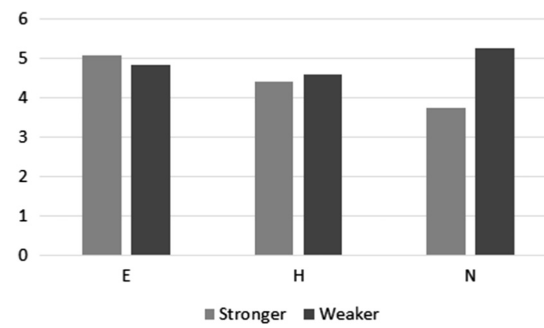

Fig. 13. Comparing the reported enjoyment of the weaker and stronger participants after each game type.

their experience during the experiment (interest, challenge, boredom, frustration).

4.2.3. Results

As can be seen in Fig. 11, the mean LTE during the *E* game was higher than during the other types of games. That is, players experienced higher levels of excitement (LTE) during the game employing EEG triggered modes. To determine the statistical significance of the differences, we conduct a one-way ANOVA test with repeated measures, where the mean LTE level was the dependent variable. The analysis shows that the effect of the game type on the LTE was significant ($F(2,46) = 5.25$, $p < 0.01$).

We also used a post hoc Duncan test (Table 5) that showed that the mean LTE was significantly higher while playing the *E* game (0.48) than during the *H* game (0.424) or the *N* game (0.426). The differences between the *N* and *H* games were not found to be significantly different.

After each game the players were asked to evaluate the game they just played, and at the end of the study the participants were asked comparative questions regarding the three games. Participants were asked about four categories — interest, challenge, frustration, and boredom. The participants were asked to name the outstanding game in each category. Results are shown in Fig. 12.

16 of the 24 participants found the *E* game to be the most interesting of the three games. Furthermore, 14 participants also found the *E* game to be the most challenging. Most players (16/24) found the *N* game (the game with no modifications) the most boring. This supports the findings by other researchers that DDA in general can improve the game experience [47,55].

Although the LTE readings were not significantly higher for heuristic triggering compared to a game without DDA, the players' subjective opinion was that the *N* game was significantly more boring than the *H* game ($Z = 4.2, p < 0.0001$), i.e., players preferred the heuristic triggering to no DDA.

It is interesting to observe the differences between the way that the stronger players experienced the various game types compared to the way the weaker players experienced the games. Fig. 13 shows the participants' responses to the statement, "I enjoyed the game" which was asked after each game session. As can be seen, the weaker players preferred games with DDA over the game with no adjustments (*N*). In contrast, the stronger players preferred the game without the use of DDA. While this may be because the modes that we used may have seemed unfair to the stronger players, only a single player commented that he felt that the modes were "unfair". An alternative explanation is that the modes for the stronger players were less exciting. In fact, looking at the LTE of the stronger players, we find a drop after the Turret mode was triggered. It seems that the players did not enjoy fighting against the Turret, causing a reduction in their enjoyment of all the DDA games. That being said, both the weaker and the stronger players preferred the *E* game over the *H* game.

5. Discussion

Our experiments demonstrate that using EEG to decide when to trigger game changes to improve the player's experience can be useful. Most players reported that they preferred the game where EEG-triggered DDA was used (the *E* game) to the alternatives.

To support our claim as to the benefit of EEG-triggered DDA in improving players experience, we analyzed a few possible alternative explanations for the preference of the *E* game over the other two options. First, it might be that the Emotiv EPOC headset triggering in the *E* game generates more mode modifications than in the heuristic triggering game, and the improved opinion of the players is due to the increased number of modifications. Although the average number of modifications in an *E* game is 13.71 (mean±SD of 13.71 ± 5.8 events), while the average number of modifications in the heuristic triggering games is 9.73 (mean±SD of 9.73 ± 8.6 events), the variances are very high, and we did not find a statistically significant difference using a two-tailed *t*-test.

A second explanation is that games with more minigames, i.e., more killings of one player by the other, are more exciting. However, there is almost no difference between the average number of minigames among the three game types, with all means close to 10 minigames. Both a *t*-test and an ANOVA analysis revealed no statistically significant difference between the means.

Finally, we checked whether there is a correlation between the number of DDA events and a higher LTE. The Pearson correlation between the mean LTE and the number of DDA events over both game types is only 0.08. Separating the game types results in a correlation of 0.43 for the *H* games, while for the *E* games we computed a correlation of −0.39 — a negative correlation between the number of events and the LTE values. Although there is a somewhat stronger correlation between LTE and DDA events when separating according to game type, the absolute value of the correlation is still lower than 0.5, which does not indicate a strong correlation, making it difficult to draw conclusions.

Overall, it seems that the various possible alternative explanations for the observed LTE values mentioned above are not supported by the data, and the correlation between game type and higher LTE still seems like the most plausible explanation.

We did not find any correlations between the information supplied by the participants concerning their expertise in games and the way they experienced the different types of games, except for one case. There was a strong correlation (0.647) between the number of weekly hours a participant plays video games, and the kill ratio of the player. The only two participants to report the largest weekly gaming time also had the highest kill ratio. Of the 11 participants to report one weekly hour at most, eight had the lowest kill ratio.

6. Conclusion

In this paper, we explored dynamic difficulty adjustments triggered using players' EEG readings in a multiplayer adversarial environment. We evaluated our suggestions by conducting a user study using the Boot Camp third-person shooter game. We suggested a set of modes appropriate for this game, in various scenarios, based on whether the players are close or far from each other, and on the identity of the better player.

The preparatory experiment showed that the EEG readings from the Emotiv EPOC headset correlate well with game events in a game without DDA. We then experimented with DDA, comparing EEG triggering to a more traditional heuristic triggering. Our results show that the EEG triggering resulted in higher excitement levels throughout the game. Participants also reported the EEG-triggered DDA games to be more interesting. The results also show that players preferred, in general, the game with the DDA rather than the game without DDA. This is also interesting because our modes were intentionally observable, yet players did not feel cheated when the opponent received some advantage.

Our findings allow us to conclude that EEG can be used to measure the player's game experience during the playtime, and to make decisions concerning the game's response to the player's experience. Thus, modern games can use such techniques in order to create more challenging and enjoyable games. Given that the gaming industry is highly competitive, it might well be that games that use EEG can have an advantage over other games, similar to the advantage of Microsoft Kinect over the Nintendo Wii sensors. It should be noted that the Emotiv EPOC headset needs improvement if it is to be used in the gaming industry. In our experiments we experienced many cases of malfunction mainly due to changes in the positioning of the headset on the participant's head.

In the future we plan to extend our results to other types of games. For example, it would be interesting to see if similar results can be obtained in turn-based strategy games, cooperative games, and so forth. It would also be interesting to see whether the Emotiv EPOC headset outputs correlate to other game events and whether different DDA modes, such as reducing an automated computer player capabilities, can also influence the Emotiv headset readings. Such studies will help to establish the generalization power of our approach.

Appendix A. Questionnaires

We now present the questionnaires that were used in the user studies that we conducted, translated into English.

A.1. Pilot experiment questionnaire

Before starting the experiment, we would like to collect some demographic information about you. This information will be used for research purposes only and will not be shared with third parties. Your anonymity will be maintained if this study is published. Please answer the questions below to the best of your ability.

A.2. Section 1- Demographic information (pre-game questions)

- First and last name:
- Age:
- Gender: (Male,Female)

For the questions below, participants had to choose an answer on a 5 point scale — Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. In addition, there was a space for comments after each question.

- I am active and slept well during the night.
- I did not smoke or consumed alcohol during 1 week before the experiment.

- I have played video games before.
- I have played shooting games before.
- I usually play online games.
- I tend to lose interest in most games quickly.
- I am a quick video game learner.

Additional questions:

- Time spent playing video games each week:
  1. Less than 1 h
  2. 1–2 h
  3. 2–4 h
  4. 4–6 h
  5. 6–10 h
  6. Over 10
  7. Other (please specify)
- BCI experience: Never, Once, More than once
- EEG experience: Never, Once, More than once

A.3. Section 2- (Post-game questions)

Again, for these questions, users had to choose an answer on the 5 point scale — Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. In addition, there was a space for comments after each question.

- I enjoyed the game.
- The game was challenging.
- I recovered quickly from attacks.
- I was better than my opponent.
- I played against a low-level opponent.
- I was on the defensive most of the game.
- It took me a long time to understand how to play.
- There were some game actions that I did not know how to perform.

- How would you describe the length of the game? Possible answers: Very Short, Short, Short to Medium, Medium to Long, Long

A.4. Main experiment questionnaire

A.4.1. Section 1- Demographic information (pre-game questions)

- First and last name:
- Age:
- Gender: (Male,Female)

For the questions below, users had to choose an answer on a 5 point scale — Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. In addition, there was a space for comments after each question.

- I am active and slept well during the night.
- I did not smoke or consumed alcohol during 1 week before the experiment.
- I have played video games before.
- I have played shooting games before.
- I usually play online games.
- I tend to lose interest in most games quickly.
- I am a quick video game learner.

Time spent in playing video games each week in hours: answers range from 1 to 10.

A.4.2. Section 2- (answered after every game type)

Please answer the following questions by selecting the relevant answer (possible answers were on the 5 point scale):

- I enjoyed the game.
- The game was challenging.
- I recovered rapidly from attacks.
- I was better than my opponent.
- I played against a low-level opponent.
- I was being defensive most of the game.
- It took me a long time to understand how to play.
- There were some game actions that I did not know how to perform.

A.4.3. Section 3 — (post-game questions)

The possible answers for the questions below were: game 1, game 2, game 3.

- Which game was the most challenging?
- Which game was the most interesting?
- Which game was the most boring?
- Which game was the most frustrating?

At the end, there was a space for general comments.

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