PADS: Enhancing Gaming Experience Using Profile-Based Adaptive Difficulty System

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Abstract

In this paper, we present a novel methodology to improve gaming experiences by automatically adjusting the game difficulty throughout the game play using a Profile-based Adaptive Difficulty System (PADS). We utilize a player's gaming experience and objective to create a player profile. Utilizing this profile and a performance-based algorithm, the PADS customizes the game's difficulty levels to accommodate each individual. Our experimental results successfully demonstrate improvements in both perceptual and actual gaming experiences. With our approach, traditional program-centered video games can be transformed to provide individualized, player-centered gaming experiences.

CR Categories: H.1.2 [Information Systems]: Models and Principles—User/Machine Systems; K.8 [Computing Milieux]: Personal Computing—Games

Keywords: gaming experience, player-centric gaming, difficulty adjustment, player profile, game difficulty

1 Objectives

The video game industry is growing at a rapid rate. A recent study by the NPD group [2009] demonstrates that North Americans spend more time playing video games than going out to the movies. As this trend continues, the gaming industry will attract more customers from diverse backgrounds and consequently presents game designers with opportunities and challenges of creating games that provide individualized gaming experiences.

Consider one facet of user experience: difficulty. Over time, video games have migrated toward providing more personalized gaming difficulty. First, games were made independent of challenge levels, leaving this parameter uncustomizable. Then, the industry introduced a few varying difficulty levels (such as easy, medium, and hard) selectable from an options menu. In recent years, games such as Max Payne [Tolentino 2008] and Left 4 Dead [2007] have dynamically altered difficulty during the game-play. Dynamic Difficulty Adjustment (DDA) gives game designers a way to modify and enhance game players' experience by adding a new layer of flexibility to the game-play.

Several studies in the area investigated the effect of altering game difficulty based on player performance [Andrade et al. 2005; Hunicke and Chapman 2004; Leigh et al. 2008]. Although player performance is indeed an indicator of difficulty, it should not be the sole factor in determining difficulty levels. Game designers should also consider what the players really want out of their gaming experiences. Some players enjoy video games when they win, while others enjoy facing challenges. To accommodate the wide spectrum of player preferences, game designers often grouped different players into types. This notion is called *player profiling* and has been well documented in the gaming research community [Bartle 1996; Weber and Shaw 2009].

In this paper, we introduce a novel Profile-based Adaptive Difficulty System (PADS) that incorporates both a player's profile and performance to adaptively adjust the game difficulty throughout the game to enhance the player's gaming experiences. Unlike other methods where algorithms alone attempt to find appropriate difficulty level while disregarding the player's background, the PADS uses player profiles (prior gaming experience and preference) as parameters to determine the most appropriate difficulty level. These parameters are utilized to set game difficulty adjustment thresholds. Once the thresholds are set, the PADS adjusts the player's difficulty settings using a performance-based algorithm. The difficulty level increases or decreases whenever the thresholds are crossed.

2 Related Work

Game profiling is one of the core components of this work. This concept, however, is not brand new. Bartle [1996] explored profiles in multi-user dungeons. He was able to define four distinct classifications of players. Each of these player profiles grouped players with distinct desires and interests in the game. We argue that this information could be used to customize a player's experience depending on which group he/she belongs to. Yee [2006] further expanded the Bartle's work into the MMORPG (Massively Multiplayer Online Real Player Game) realm. He worked on creating a framework for finding different player types, and successfully found profiles for a different game type. Weber and Shaw [2009] created a cognitive model that discovers why people play certain types of games. They found the best predictors of game types are when models incorporate player profiling in the prediction process.

Aside from game profiling, we also need to look at DDA-based approaches. Andrade *et al.* [2005] use a reinforcement learning technique to detect player skills in a fighting game. They use Q-learning algorithm to perform the actual game balancing step. Hunicke and Chapman [2004] developed a framework for DDA called Hamlet where a probabilistic method is used to determine when the player needs help. When the player is in need of help, they alter the game environment to aid the player. Leigh *et al.* [2008] explore yet another route in game balancing. Using a coevolutionary algorithm, they explore possible game strategies providing the player with one that best suits his or her game play. This prevents the game program from becoming either too dominating or too easy. Another intriguing methodology was proposed by Yun *et al.* [2009]. Instead of profiling players, they dynamically alter game difficulty based on a user's stress level using a StressCam. These stress levels implied a particular player desire. While they proposed a customizable user experience which takes player desire into consideration, they force the player to use an expensive external device that limits player

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movement. Furthermore, using such a device is not always realistic in an ordinary gaming setting.

3 Methods

The algorithm of the PADS relies on placing the current player into a predefined player profile. The game profiles are likely to change depending on which genre the game is in. In the previous work [Bartle 1996; Yee 2006], one can deduce profiles created for most game types. Without the loss of generality, the sample game genre used in this work is a third-person shooter. To achieve our categorization, we ask the player two questions: their gaming expertise (years of experience), and their goal in games (challenge, victories, or both). Then we adapt the amount of influence based on their profile at each update interval. Each of these profile characteristics would vary for every game since each game has different rules, goals, and character sets.

Once guidelines are established, we tune our difficulty settings with the player's performance data. In our sample game, the performance data includes: how many enemies the player killed, how many enemies the player has seen or come in contact with, how many health points the player has lost or gained, and the amount of time the player has died since the last update. At each update step, this data is sent to a decision-making module that controls the game's difficulty level.

We first pass the performance data into a converter that transforms the player's performance data into a point scale by using player-profile information. Points are awarded or taken away for the player's health level, enemy performance information, and enemy death total. The points are calculated using a predefined threshold system which changes depending on which player profile is invoked. The points are a decimal number between -1 and 1, with 1 being the best and -1 being the worst performance. All of the performance points are then sent to a global point calculation module. At the global point level, the performance points are added up and put into another threshold system called the difficulty decision module. If the output is greater than the positive threshold, we increase the difficulty level. If the output is less than the negative threshold, we lower the difficulty mode. If the global points are within a certain range near zero, we maintain the current difficulty mode. Before the difficulty is changed, we use the player's profile to verify whether a change should be made. In this case, we are not only considering the player's performance but also his/her desires. Figure 1 shows the schematic workflow of the introduced PADS system.

4 Experimental Design

In our study, we used an XNA sample game, Robot Game (http://creators.xna.com). It is a three-dimensional, third-person shooter game where the player controls a robot to destroy enemy robots in fighting arenas. The game runs on a Windows PC environment with a Microsoft Xbox360 controller being used as the input device. We added code to allow the Game to have three difficulty levels: easy, moderate, and difficult. In the easy level, the player's robot is stronger and faster than enemy robots. In the moderate level, the strength of the player robot and enemy robots are comparable. Finally, the difficult level makes the enemy robots stronger and faster than the player's robot, which requires additional time and effort for the player to destroy the enemies. We then implemented our PADS into the game. The PADS became active only when the automatic mode was selected. In the automatic mode, the difficulty level was dynamically switched among easy, moderate, and difficult. For verification purposes, we also added code that recorded enemy and player information (e.g., health level and number of enemies) to a file during every minute of the game-play.

A total of 57 participants volunteered for our study. Of these, 46 were male and 11 were female with ages ranging from 18 to 37 (average = 22.95, standard deviation = 3.72). Each participant sat approximately six feet from a 42 inch HDTV. Prior to the experiment, we asked each participant to fill out a questionnaire. The questionnaire asked for demographic and gamer information. The gamer information included prior gaming experience and their primary objective in playing games. As reported in the existing literature [Chen 2007], some players will become anxious if challenge exceeds their game-play abilities. Likewise, other players will lose interest if challenge levels are not sufficient. To combat this, our player profiles include player experience levels. Using the prior gaming experience, we categorized each participant as either a: beginner (BEG), intermediate (INT), advanced (ADV), or expert player (EXP). Lazzaro [2004], however, discussed a different game enjoyability criterion that includes players that seek challenges and victories regardless of their abilities. We make use of this notion in our gaming profiles as well. Their primary objective told us if they are: challenge seekers (CHA), balanced players (BAL), or victory seekers (VIC). It is noteworthy that the participants were not aware that their responses would affect gameplay for two reasons. First, this knowledge might have given the participants an indication of the automatic difficulty adjustment mode, which could have led them to change their playing style in order to change the game. This would have skewed our survey findings. Second, this knowledge could have created certain expectations about the video game for the participants. If the expectations were not met, their post-study surveys might have been affected.

After completing the pre-study survey, each participant played the game four times: one practice session and three real sessions. During the practice session, the participant learned how to play the game for approximately five minutes. Afterward, the participant played the game in easy, difficult, and automatic modes for ten minutes each. In first two sessions, the game ran in fixed easy and difficult modes. In the last session, the game ran in the automatic mode where the PADS dynamically altered game difficulty in every minute. During each session, the game was paused in each minute and an in-game survey popped up. The participants were required to select one of following selections that indicated their perception toward the difficulty and enjoyability of the game per minute:

1. (TE/E) Too easy, but I am enjoying the game
2. (TE/PD) Too easy and I am beginning to lose interest in the game unless it gets more difficult
3. (M/E) Moderate in difficulty and I am enjoying the game
4. (M/PE) Moderate in difficulty but I want the game to be easier to have more fun
5. (M/PD) Moderate in difficulty but I want the game to be more difficult to have more fun
6. (TD/E) Too difficult, but I am enjoying the game
7. (TD/PE) Too difficulty and I want to give up on the game unless it gets easier

The game resumed only when he/she responded the above in-game survey. The design of this perceptual, in-game survey was inspired by the Microsoft TRUE system [Kim et al. 2008]. Although these pop-ups could annoy some participants, it was crucial to obtain in-game data to see how the change of difficulty made by the PADS was perceived by them in each minute. The in-game survey did not influence our algorithm in any way. It was used only for post-experiment analysis. The automatic mode invokes PADS every

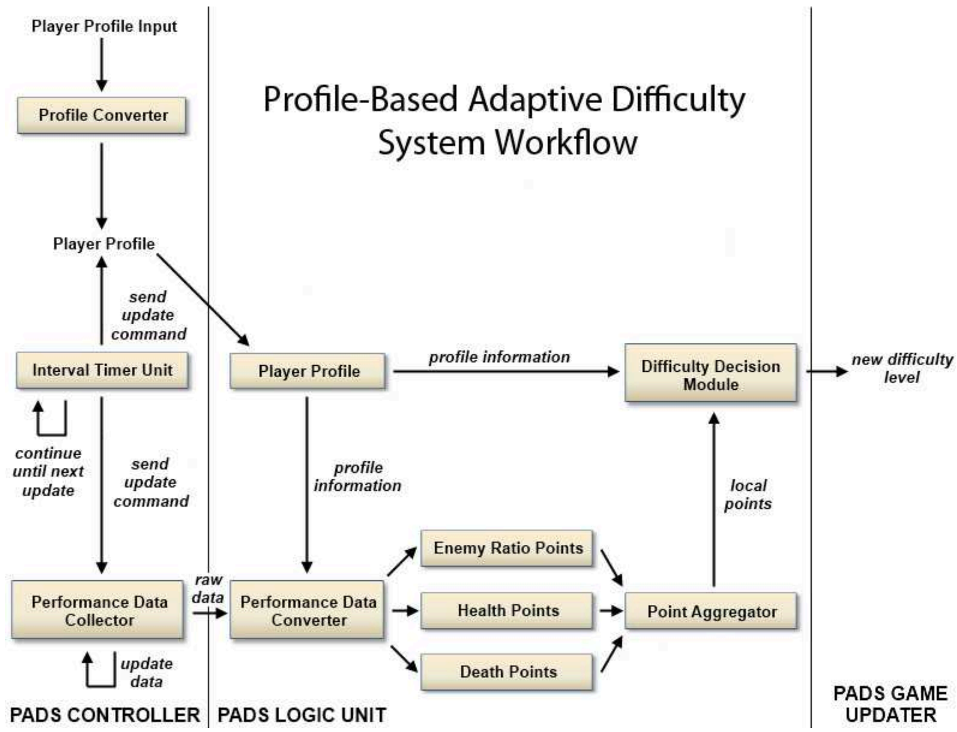

Figure 1: *The schematic workflow of the proposed PADS system.*

minute to coincide with the minute-by-minute perceptual survey timing. This requires a full 60 seconds to fix any outlier concerns with gameplay. Without the interval matching stipulation imposed for data analysis purposes, PADS could run at a much quicker interval correcting outlier problems.

Using the in-game survey, we observed whether the PADS improved the participants' gaming experiences in each minute when compared with the data from either static easy or difficult mode. Each participant played the trials in the same order (easy, difficult, then automatic mode) and not a randomized order. Initially, we considered counter-balancing (i.e. Latin Square) our experimental trials. However, we opted to not implement it for the following two reasons. First, in computer/video games, players usually start in the easy mode and gradually progress to a more difficult mode. Reversing this order would have caused some groups (e.g., groups with lower expertise and those that prefer victories over challenges) to lose interests in the game. Second, for psychological reasons, we structured our trials in such a way that would minimize frustration and interest-loss over subsequent trials to obtain more accurate results.

After each trial (except the practice session), we conducted a post-trial survey. This survey asked perceptual questions similar to the in-game survey. Even though the two surveys were quite similar, we were interested in seeing how results differ while not engaged in game-play activities.

5 Results

We observed how well our algorithm improved the participants' gaming experiences by analyzing the data. We first kept track of player profile information. We also collected minute-by-minute performance data for fine tuning the player's difficulty level. Finally, we recorded minute-by-minute, in-game survey information. Using these data sets, we compare the player's desires and the difficulty adjustment to determine whether we were successful in increasing user satisfaction. Figure 2 summarizes the in-game survey data from 12 out of 57 participants while the game ran in the automatic mode, and Figure 3 graphically illustrates the survey data of the participant #23 (P23) listed in Figure 2.

As shown in Figure 2, the first three participants (P05, P08, P55) were beginners with less than one year of gaming experience. Due to their low experience, the PADS adjusted the game difficulty to remain in either the easy or moderate difficulty throughout the game. Contrary to the actual difficulty, in approximately two-thirds of the game time, the participants perceived they were in the moderate difficulty level. This indicates they were satisfied with the gaming experience since the game is not perceived as too easy or too difficult. In addition, the data indicates that they enjoyed the game nearly all the time.

The next three participants (P32, P49, and P54) were intermediate players with one to three years of experience. Due to their relatively low gaming experience, these players were mostly restricted to easy and moderate levels. While it was not impossible for a participant to reach difficult level, he/she had to perform exceedingly well to reach it because the PADS set the difficult level threshold very high. However, the gamer preference also contributed in controlling the thresholds. P49 and P54 remained in easy and moderate levels since their desires were not on experiencing challenges extensively. On the other hand, P32 was allowed to play in difficult level since this participant was a challenge seeker. In another word, since P32 preferred to face challenges, the PADS lowered the threshold and allowed the difficult level be more readily accessible to P32 compared to P49 and P54. The PADS used the profile information to prevent (or endorse) the participants to play certain difficulty levels for a greater user experience. The participants' perceptual survey data showed the PADS successfully captured their playing desires.

The next three participants (P03, P38, and P45) were advanced players with three to five years of experience. Since they had more experience, the difficulty level was centered on the moderate level. P03 and P45 sought out challenges so the PADS made it easier for them to reach the difficult mode. As a victory seeker, P38 desired an easier game so the PADS set the difficulty level to the moderate. Their characteristics were reflected well on the survey data.

The final three participants (P06, P09, and P23) were experts with more than five years of gaming experience. Due to their expertise, the PADS placed them in mostly moderate and difficult levels. Here, we see that P06 sought for game balance so the PADS placed this participant in mostly moderate and difficult levels. P09 desired a more challenging gaming experience so the PADS allowed the participant to stay in the difficult level for the majority of game time. P23 was a victory seeker, allowing the PADS to make all levels of difficulty available to this participant.

Therefore, utilizing the performance data and player desires, our introduced PADS was preliminarily successful in customizing the gaming experience for each player type. This resulted in each participant playing in a difficulty mode appropriate for his/her gaming experience and desire.

Figure 4 compares the perceived and actual amount of time in the automatic mode. Here, our data shows that the participants played the game on average 6.14% of their 10 minute game time in the easy level, 52.81% in the moderate level, and 41.05% in the difficult level ($F_{2,112}$= 42.43, $p < .0001$). However, the in-game survey data revealed that the participants believed they played the game in average 18.44% of their game time in the easy level, 72.75% in the moderate level, and 7.54% in the difficult level ($F_{2,112}$ = 50.08, $p < .0001$). A perceived moderate level means the game was perceived to not be too difficult nor too easy. This demonstrates the PADS was successful since it understood the composition of the participants' gamer expertise and preferences to adjust the gaming difficulty accordingly.

To further validate the effectiveness of the PADS, we offer three sets of data. First, we asked the participants which game mode they preferred among the three difficulty modes. Out of 57 participants, 2 (or 3.51%) preferred easy mode, 5 (or 8.77%) preferred difficult mode, and 50 (or 87.22%) of the participants preferred automatic mode. The data signifies that the participants have an overwhelming preference toward the automatic mode. Second, in our questionnaire, we asked the 57 participants about their entertaining experience from each difficulty mode based on a 9-point Likert scale (1 being "not entertaining at all" and 9 being "extremely entertaining"). Overall, they rated the easy mode as 6.19, difficult mode as 6.32, and automatic mode as 7.14 ($F_{2,112}$ = 9.48, $p < .0001$). Therefore, our data indicates that the participants had a more entertaining experience when they played the game in the automatic mode. Finally, in the collected in-game survey data, we counted blocks of minutes each participant enjoyed the game (corresponding to the in-game survey responses 1 (TE/E), 3 (M/E), or 6 (TD/E)) out of 10 minutes of the game play in easy, difficult, and automatic modes. On average, a participant enjoyed the game 72.11% of the time (or 7 min 13 sec) in the easy mode, 71.23% (or 7 min 7 sec) in the difficult mode, and 85.61% (or 8 min 34 sec) in the automatic mode ($F_{2,112}$ = 5.38, $p < .01$). The data indicate that the participants had longer duration of enjoyable game time in the automatic mode by more than 13.38% (or 1 min and 21 sec), compared to the other static difficulty modes. These data also confirm that our previous qualitative assessment was correct and the introduced PADS captivated the interests of the majority of the participants. Furthermore, they provide concrete evidence that the automatic mode successfully improved the entertainment factor both in quality (i.e. more entertaining experience) and in quantity (i.e. longer entertaining time duration).

	Game Time (in min)									
	1	2	3	4	5	6	7	8	9	10
P05	0.800	-3.833	0.000	-0.767	0.767	0.300	1.700	1.467	1.733	-1.000
BEG	MDRT	MDRT	EASY	EASY	EASY	EASY	EASY	MDRT	MDRT	MDRT
CHA	M/PD	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E
P08	0.833	-0.504	-0.967	0.767	0.967	1.000	1.400	0.250	1.867	-0.500
BEG	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT
BAL	TD/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E
P55	0.000	-0.750	-0.350	-0.967	0.500	1.000	2.000	0.700	-2.834	0.000
BEG	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	EASY
BAL	TD/E	TD/E	TD/E	TD/E	TD/E	TD/E	TD/E	M/E	M/E	TD/E
P32	0.600	-0.517	0.233	1.117	-0.325	0.000	0.000	-2.433	0.175	-0.850
INT	MDRT	MDRT	MDRT	MDRT	DIFF	DIFF	DIFF	DIFF	MDRT	MDRT
CHA	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E
P49	-0.313	-0.313	-2.700	0.633	1.600	0.967	0.250	0.283	-1.467	-0.167
INT	MDRT	MDRT	MDRT	EASY	EASY	MDRT	MDRT	MDRT	MDRT	EASY
VIC	M/E	M/E	TE/E	TE/E	TE/E	TE/E	TE/E	TE/E	M/E	M/E
P54	0.700	0.000	0.000	-0.933	-0.053	0.733	-1.001	0.467	-0.567	-0.633
INT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	EASY	EASY	EASY
BAL	TE/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E
P03	0.987	1.347	1.347	0.000	0.167	0.913	-1.693	0.800	0.647	0.700
ADV	MDRT	MDRT	DIFF	DIFF	DIFF	DIFF	DIFF	MDRT	MDRT	MDRT
CHA	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E	M/E
P38	1.000	0.175	-0.500	0.733	0.533	0.733	1.067	-0.158	-0.500	0.208
ADV	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT	MDRT
VIC	M/PE	M/PE	TD/E	M/PE	M/PE	M/E	M/E	TD/E	TE/PD	M/E
P45	0.833	1.800	0.747	1.213	1.000	-2.833	0.700	0.300	0.633	0.700
ADV	MDRT	MDRT	DIFF	DIFF	DIFF	DIFF	MDRT	MDRT	MDRT	MDRT
CHA	M/E	TE/E	M/PE	M/E	M/E	M/E	TE/E	TE/PD	TE/PD	M/E
P06	0.525	0.750	2.000	0.000	-1.567	0.933	1.933	0.625	-1.008	1.117
EXP	MDRT	MDRT	MDRT	DIFF	DIFF	MDRT	MDRT	DIFF	DIFF	MDRT
BAL	M/E	M/E	M/E	TE/PD	TD/E	TE/PD	TE/PD	M/E	M/E	TE/E
P09	2.000	0.000	1.500	1.300	1.000	0.500	0.950	0.883	1.000	1.500
EXP	MDRT	DIFF	DIFF	DIFF	DIFF	DIFF	DIFF	DIFF	DIFF	DIFF
CHA	TE/PD	M/E	M/E	M/E	M/E	M/E	M/PE	M/E	M/E	M/E
P23	0.600	-3.833	0.350	0.331	1.250	1.200	0.000	-0.708	-1.833	1.000
EXP	MDRT	MDRT	EASY	EASY	EASY	MDRT	DIFF	DIFF	DIFF	MDRT
VIC	TE/E	TD/PE	M/E	TE/E	TE/PD	TE/E	M/PE	M/E	TE/E	M/E

Figure 2: *Summary of minute-by-minute in-game survey data collected for 12 out of 57 participants. First column indicates each participant's id, gamer expertise (BEG, INT, ADV, or EXP) and preference (CHA, BAL, or VIC). Succeeding columns contain each participant's minute-by-minute global points data, difficulty levels (EASY, MDRT for moderate, DIFF for difficult), and subjective feedbacks.*

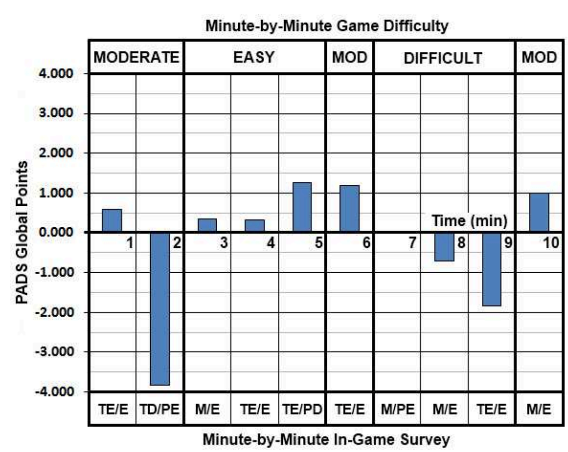

Figure 3: *The visual graph of minute-by-minute, in-game survey data of the participant #23 (P23).*

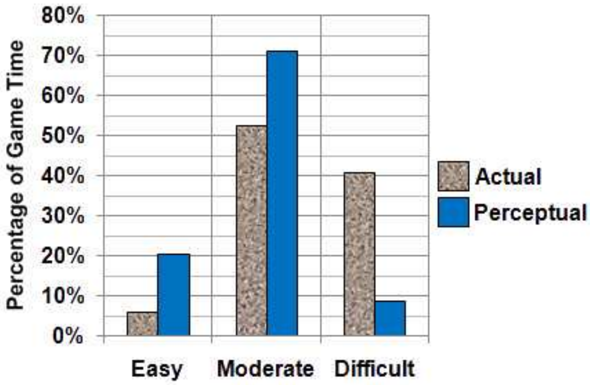

Figure 4: *Average perceived versus actual difficulty play percentages*

6 Conclusions

In our study, we utilized player profiles in a video game that implements an adaptive difficulty system (PADS) to improve player-gaming experiences. The difficulty of the game was automatically adjusted every minute depending on the performance of the player and the player's profile. The PADS uses gamer expertise and preference to determine on which difficulty level the gamer should play. We showed that our approach was able to successfully transform a traditional program-centric game to provide a unique, player-centric gaming experience. We claim that the gaming experience enhanced with the PADS is player-centric, because the game adjusts difficulty based on both player performance and player profile, which contrasts to previous approaches that attempt to blindly adjust game difficulty based solely on player performance.

However, our current work does not come without limitations. We only defined three levels of difficulty so the transition from one difficulty to the next was obvious to some players, which hindered what should have been seamless game-play. Also, the PADS was only tested on a third-person shooter game. Finally, the duration of the experimental game sessions was also too short to observe the full effect of the PADS, since playing typical video games usually lasts several hours or more.

7 Future Work

In the future, we plan to expand the studied difficulty levels from 3 to 7 or 10. There is a fine line between too large of a step between difficulty levels and too small, so we plan to work on an efficient compromise between these two concepts. We also plan to expand our algorithm to other gaming genres. It has already been shown that player profiles can be made in other game genres [Bartle 1996; Yee 2006]. Expanding our current work to other game genres will serve as a launching platform for other dynamic difficulty altering methods. Finally, we would like to extend game-play duration to see how it affects our results. A longer experiment scenario will more closely replicate real-world game play.

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