Dynamic Difficulty with Personality Influences

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Abstract: In this paper, we present a novel methodology to improve video game experiences by automatically adjusting video game difficulty based on both performance and personality traits. The Dynamic Difficulty with Personality Influences (DDPI) system generates a player's personality profile based on nine strategic questions. Using that profile and in-game performance data, DDPI customizes the game's difficulty level to create a player-centric gaming environment. Our experimental results successfully demonstrate improvements in both perceptual and actual gaming experiences. With our approach, traditional video games can be modified to provide personalized, player-centered gaming experiences.

Objectives

In 2010, seventy-two percent of American households played video games (Entertainment Software Organization, 2011). According to the Entertainment Software Organization (2011), 82% of game players are 18 years of age or older, 29% of game players are over the age of 50 and 42% of all game players are women. With these changes to the gaming audience, game stories and genres have changed, but difficulty levels have remained generic.

Some studies have explored dynamic difficulty adjustment (DDA) using player performance data. Using key game characteristics, such as points or health, DDA algorithms make a decision to either maintain or change the video game's difficulty level. Unfortunately, these algorithms ignore the player's desired difficulty experience.

Other studies have explored profile-based systems using player personality attributes to create distinct, but similar, game environments. Typically, these systems restrict players to one static profile limiting the diversity of accommodated players and ignoring the player's skill level. Since skill levels increase over time, this system would have to re-classify players to continue increasing player experiences.

Profile-Based Adaptive Difficulty (PADS) is an algorithm that successfully combines profile-based and performance-based methodologies creating a player-centric system. Yun, et al. (2010) uses a player's experience level and difficulty preference to create a player into a single, pre-defined player profile. Based on Yee's (2006) work, an individual player should be able to subscribe to many profiles for the optimal player personality representation. Unlike static profiles, PADS uses performance data to customize the player's difficulty level. PADS measures a player's experience by the number of years they have played video games. Years of experience, however, are not a true indicator of a player's skill level.

We offer a different approach to profile-based and performance-based dynamic difficulty. Dynamic Difficulty with Personality Influences (DDPI) extends the core methodology of PADS. Instead of creating pre-defined player profiles, we define how particular personality characteristics influence video game difficulty. Using a player's personality characteristics, we generate a profile for each player to serve as a template for the player's difficulty levels. As the game progresses, we allow the player's skill level to further personalize the difficulty level. This methodology gives us a highly personalized approach while keeping the algorithm abstract enough to be applicable to several video game genres.

Related Work

DDPI makes use of both player profiling and performance-based dynamic difficulty adjustment methodologies. Individually, both concepts are not new to the research community.

Player Profiling

Bartle (1996) was the pioneer of player profiles studying the players of multi-user dungeons (MUD). He was able to divide the player population of this game genre into four distinct categories: Achievers, Explorers, Socialisers, and Killers. These profiles were dependent on what each player hoped to gain from playing the MUD. Upon further exploration of these profiles, Bartle (1996) discusses examples of how players of each particular class behave, talk, and react similarly.

Yee (2006) surveyed players from MMORPGs. Unlike Bartle (1996), Yee (2006) believed an individual player can be partially committed to multiple profiles and therefore subscribe to different characteristics from each profile. He surveyed 3,000 players and discovered an overlap in profile characteristics.

In 2004, Lucas and Sherry (2004) studied motivating factors for video game players. Using focus groups, they have targeted six important characteristics that apply to most gaming genres: competition, challenge, social interaction, diversion, fantasy, and arousal. These player descriptions serve as the core of several post-2004 experiments, including ours.

Jansz and Tanis (2006) created a gaming focusing on eight key points: competition, challenge, social interaction, interest, entertainment, fantasy, pass-time (previously referred to as diversion), and arousal. They extended Lucas and Sherry’s (2004) previous key points by adding interest and entertainment characteristics.

Schuurman, et al. (2008) had 2,895 players complete a five point Likert scale questionnaire over eleven subjects. Each question identified the degree in which that particular factor influenced the player’s decision to play the video game. Following the self-subscription survey, they were able to use the post-analysis process to divide the players into four groups: overall convinced gamers, convinced competitive gamers, escapist gamers, pass-time gamers (Schuurman, De Moor, De Marez, & Van Looy, 2008).

Dynamic Difficulty Adjustment

Dynamic Difficulty Adjustment (or DDA) was first introduced into the gaming literature in 2003 (Demasi & de O. Cruz, 2003). DDA tackles the issue of customizing video difficulty using a performance-based approach. There are several mathematical approaches to perform these tasks.

Andrade, et al. (2005) used a reinforcement learning technique (Q-learning) to detect player skills in a fighting game. Since reinforcement learning techniques require several iterations to learn enough to challenge a player, they use off-line bootstrapping to provide a starting point of difficulty. Then online learning is invoked to dynamically alter difficulty as the player progresses throughout the game.

Hunicke and Chapman (2004) developed a framework for DDA called Hamlet where a probabilistic method is used to determine when the player needs help. They suggest altering the game environment since the player is less likely to notice the change when compared to altering the player’s character or the enemies.

Methodology

Dynamic Difficulty with Personality Influences (DDPI) contains three major components: performance characteristics, player profile and performance-based dynamic difficulty.

Performance Characteristics

Each game genre has defining characteristics that game developers can use to determine the player's skill level, such as health points or overall score. DDPI uses these pre-defined characteristics as determining factors to adjust the game's difficulty. Each characteristic is paired with a threshold level, which is used to determine if a player has achieved good, normal, or poor performance in a single category.

There are two types of performance characteristics defined in DDPI: Negative and Positive. A negative performance characteristic expects the overall value to decrease over time. Figure 1 shows how DDPI uses a negative performance characteristic. Here we have three brackets or sections: positive, neutral, and negative. These brackets are represented as equal portions in Figure 1 but their size can be altered by the developer. If the change in value from the previous update interval falls in the Positive Local Points range, then this performance characteristic produces a value between 0 and 1. A positive value means this performance characteristic wants to increase the overall difficulty with a certain degree of confidence. If the change in value from the previous update interval falls in the

Neutral Local Points (or Local Points = 0) section, then this performance characteristic returns 0 signifying no difficulty change suggested. Finally, if the change in value from the previous update interval falls in the Negative local points range, this performance characteristic will return a value between 0 and -1 requesting for the overall difficulty to decrease with a particular degree of confidence.

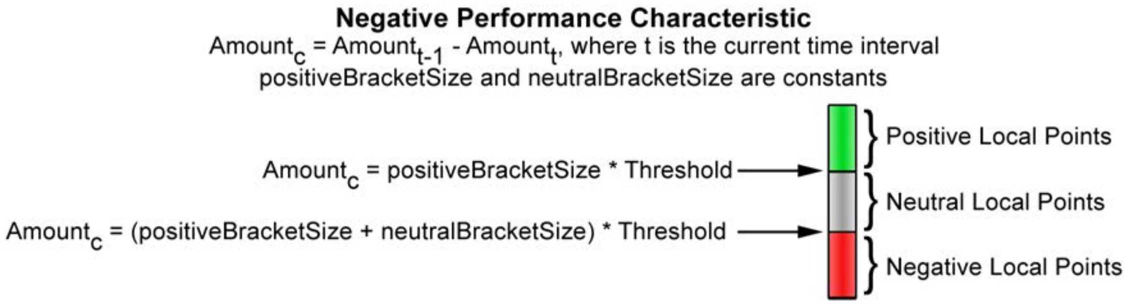

***Figure 1*: Performance Characteristic Graphic Representation**

Conversely, Positive characteristics are expected to grow over time, such as a game score. This type of performance characteristic behaves like the inverse of the Negative performance characteristic.

In a real game scenario, DDPI requires several performance characteristics allowing one characteristic to be balanced or negated by other characteristics. This provides DDPI with a holistic view of the player's performance providing more accurate adjustments.

Player Profiles

DDPI's player profiles are not pre-defined. Instead, we generate a new profile for each player based on a pre-defined set of personality traits. Each personality trait allows DDPI to alter the threshold levels and bracket sizes for specific performance characteristics. DDPI also uses personality traits to create a minimum, maximum, and starting difficulty level. This range of difficulty serves as a check system to limit the in-game DDA difficulty levels.

In-Game Dynamic Difficulty Adjustment

Once player profiles create base guidelines for the player, the game can be further personalized based on the player's performance. DDPI's dynamic difficulty adjustment (DDA) system relies on the developer's performance characteristics to make decisions about difficulty. Since these characteristics are defined by the developers for a particular game, DDPI is applicable to several game genres. By adding all of the performance characteristics together, it becomes possible to calculate a final global score. If the global score is greater than or equal to 1, DDPI increases difficulty. Conversely, if the global score is less than or equal to -1, DDPI decreases difficulty. Otherwise, the difficulty level remains the same.

Overall DDPI System

Both the profile-based and performance-based components are interdependent to create a holistic approach to dynamic difficulty. Figure 2 depicts the overall system:

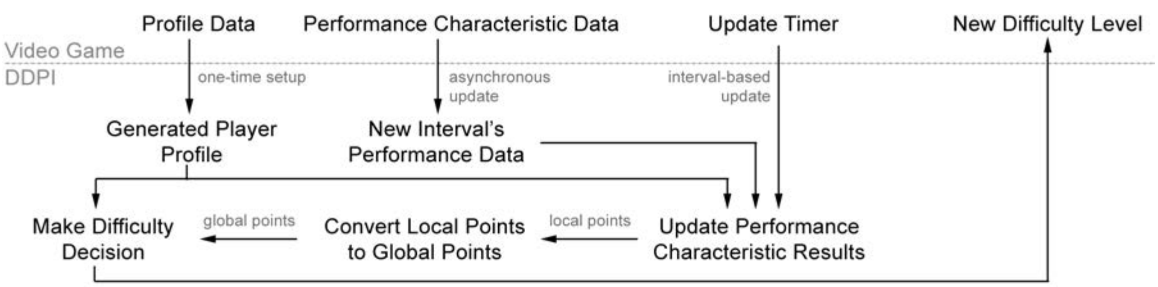

***Figure 2:* DDPI's Overall Workflow**

First, DDPI generates a player profile based on the data acquired by the video game. This data includes performance characteristics (thresholds and bracket sizes), starting difficulty, minimum difficulty, and maximum difficulty. Since this data varies for every game, DDPI requires game developers to choose accurate parameters. After setup, the player starts to interact directly with the game. When events relating to the performance characteristics update in the video game, DDPI should be notified of changes. As time progresses, the game's update timer will indicate that DDPI needs to update the difficulty level. This update interval can be fine-tuned to any value. Using the player's profile and performance data, DDPI creates local points (bound between -1 and +1) from the positive and negative performance characteristic algorithm. The local points are then aggregated to create a single global point value. Using the player profile, DDPI then selects one of three choices: raise, lower, or maintain the current difficulty level. Finally, DDPI returns the selection to the game modifying the player-centric gaming environment.

Experimental Design

Our experiment is based on a generic platformer genre video game. The participant controls an adventure seeker exploring a fictional civilization's ruins. The game's goal is to reach the end of each level without losing all of the player's health points.

Our implementation of the game features nine levels of difficulty (1 being the easiest, 9 being the hardest). While several game parameters can be modified to control the game's difficulty, not all are good candidates for variability. Hunicke (2004) states that successful DDA systems must maintain a game's internal balance and feedback mechanisms so drastic change between difficulty levels would be distracting to a player. Bailey & Katchabaw (2005) wrote about adjusting non-player character attributes to increase or decrease the difficulty of video games. We chose to alter items out of the player's control so difficulty changes are not as easily noticeable. Our platformer game has four different types of enemies featuring their own pre-set attack points, health points, and movement speeds. By changing the game's difficulty level, the enemies either increase or decrease their attack points, health points and movement velocity based on pre-determined values.

Our study consisted of 31 participants. We had 25 males and 9 females between the ages 12 and 31 (Average = 23.10, S.D = 3.67). Each participant sat in a chair in front of a Windows-based laptop with a 15 inch screen and was provided with an Xbox 360 controller to interact with the game.

Before the trials started, we explained how to play the game to each participant using screenshots and answering any questions they might have. They then were required to fill out a brief demographic survey and personality questionnaire. The questionnaire asked nine questions:

1. Do you want to play video games to be the best player in the game?
2. Do you play video games to challenge yourself?
3. Do you play video games to share an experience with others?
4. Do you play video games since they let you compete against others?
5. Do you play video games when you are bored?
6. Do you play video games to do things in games that are too challenging or impossible in real life?
7. Do you play video games because games offer exciting challenges?
8. Do you play video games because you enjoy difficult games?
9. How often do you play video games?

The first eight questions targeted particular personality traits, respectively:

1. Competition Enjoyment
2. Challenge Enjoyment
3. Social Interaction
4. Social Interaction
5. Diversion
6. Fantasy Interests
7. Arousal/Excitement
8. Entertainment

Each of the questions had the following choices: Strongly Agree, Agree, Disagree, Strongly Disagree. Using this information, we dynamically created a player profile for the participant. The final question was added after a preliminary focus group study. We found that the amount of exposure or experience with video games had an effect on the participant's skill levels and must be considered when creating a minimum and maximum difficulty level setting. The answer choices for this question were: "I rarely play games", "I don't play games often, but I have played on occasion for years", "I play games at least once a month", "I play games at least once a week."

After completing the survey, we allowed the participants to play a practice trial. The trial was set to the Easy difficult level (Difficulty Level 3). Since we were interested in how the participants felt during game play, we displayed a two question survey questionnaire every minute. The questions were loosely inspired by the Microsoft TRUE design (Kim, et al., 2008):

1. Are you currently enjoying the game?
    a. Yes
    b. No
2. Would you like the game to:
    a. Be More Difficult
    b. Maintain the Current Difficulty
    c. Be Less Difficult

The first question asked about the participant's perceived enjoyment factor. The second question asked about the participant's perceived difficulty desires.

After the practice trial, each participant played four additional trials. Each trial featured a different difficulty mode: Static Easy (Difficulty Level 2), Static Moderate (Difficulty Level 5), Static Hard (Difficulty Level 8), and DDPI. We counter-balanced the trial order so not all participants had the same exact trial order. Each trial was ten minutes long allowing ten in-game perception surveys to be displayed. After the tenth survey, the game would exit allowing the participant to relax until the next trial. After the final trial, we asked participants to complete a post-game survey. They ranked the trials from their favorite to least favorite. We also asked them to rank the overall difficulty of the DDPI trial (without the participant being aware of DDPI) on a scale between 1 and 4 where 1 was enjoyable and 4 was not enjoyable.

Results and Discussion

We observed how well DDPI improved the participants' gaming experiences by analyzing the in-game and post-game survey data. First, we collected the participants' survey information. We analyzed how DDPI categorized each participant based on this survey information. Next, we analyzed the in-game perception survey responses for all four trials. For each minute, we also recorded how DDPI adjusted difficulty during the DDPI trial. Finally, we recorded the post-game survey results.

Of the 31 participants, 25 were male and 6 were female ranging from 12 to 31 years of age (Average: 23.10, S.D: 3.67). Table 1 shows how the participants responded to our pre-game personality trait questionnaire.

Question characteristic	Strongly agree	Agree	Disagree	Strongly disagree	Overall agree	Overall disagree
1. Competition Enjoyment	3	16	10	2	19	12
2. Challenge Enjoyment	4	23	3	1	27	4
3. Social Interaction	10	14	6	1	24	7
4. Social Interaction	5	17	7	2	22	9
5. Diversion	16	9	5	1	25	6
6. Fantasy Interests	8	13	7	3	21	10
7. Arousal/Excitement	8	21	2	0	29	2
8. Entertainment	7	20	2	2	27	4

Table 1: **Personality Characteristics as defined by our participant set**

The majority of our participants categorized themselves as they (1) enjoyed challenges, (2) played games to alleviate boredom, (3) were entertained with games, and (4) were excited overall by playing games. Very few of our participants disagree that video games entertained or excited them.

In order to determine if DDPI improved the participant's gaming experience, we asked each participant to
rank their most enjoyable (favorite) trials at the end of the final trial. DDPI was ranked most favorable 10
times, second favorable 9 times, third favorable 6 times, and least favorable 6 times.

Using the participant's post-experiment perception of the trials does not give us a full picture of the whether DDPI improved player experiences. Every minute we asked the participant if they were enjoying the video game. By using this in-game survey, we found that DDPI was either the most enjoyable or tied for the most enjoyable experience for 16 participants who did not pick DDPI's trial as first. Based on in-game survey data, combined with post-game preferences, we conclude that 26 out of 31 participants favored the DDPI-based trial.

In addition to improving the player's entertainment factor, DDPI's goal is to correctly adjust difficulty for the player so the video game is not too difficult or too easy at any given time. In the in-game, minute-by-minute survey, we asked the participants if they would like the difficulty to be easier, harder, or unchanged. Based on our survey, the optimal difficulty level is when the participant replies "maintain difficulty." This implies the game is not too hard or easy for the participant at that particular point in time. Table 4 showcases the minute-by-minute results for each trial:

Trial	More difficult	Less difficult	Maintain difficulty
Easy	92	34	185
Moderate	68	53	189
Difficult	61	61	188
DDPI	61	35	214

Table 2: **In-game responses for difficulty adjustment by Trial**

DDPI optimally adjusted the difficulty for 69.03% of time played while the moderate, difficult, and easy modes optimally adjusted difficulty levels for 60.97%, 60.64%, and 59.69% of the time played, respectively. Therefore, DDPI had the highest percentage of desired difficulty for the participants.

In addition, we observed the relationship between the participant's gaming experience level and DDPI's difficulty adjustment. In our pre-game survey, we asked participants to classify how often they played video games. For participants who rarely play video games, DDPI mode was accurate for 77.50% of the time. For those who occasionally play video games, DDPI mode was accurate 85.00% of the time. For those who play games at least once a month, DDPI mode was accurate 85.00% of the time. Finally, for those who play games at least once a week, DDPI mode was accurate 51.54% of the time. It is important to note that 22.74% of all participant surveys asked for the game to be more difficult and only 14.76% of the in-game surveys asked for the difficulty to be decreased. However, for participants who play video games at least once a week requested the video game difficulty to increase 37.88% of the time. This indicates that our sample game did not have a high enough difficulty level to challenge the most skilled participants.

Conclusions and Future Work

Overall, our algorithm successfully increased the participant's gaming experience. Based on post-game surveys alone, DDPI was ranked as the most enjoyable trial 32.26% of the time making it the most favorite trial among all participants. Considering in-game enjoyment data from those who did not select DDPI as their favorite trial increases the enjoyment factor to 83.87%.

In addition to improving the player's entertainment factor, DDPI selected difficulty levels that were ideal for the participant 69.03% of the time. The closest performing static trial created an ideal difficulty environment 60.97% of the time. DDPI offers an 8.06% increase in optimal difficulty levels. Increasing the overall difficulty and optimizing the thresholds of our testing video game would further increase this spread.

Since each individual game requires the setting of performance characteristics and starting thresholds, we could improve our results by having a larger testing focus group before the experiment. Using this information, we will be able to make adjustments to increase the effectiveness of DDPI.

In the future, we will expand the experiment by conducting an additional survey after each trial. The post-game survey will ask the participants how they perceived the trial's difficulty. Using this information, we will have a better understanding of how the participants really perceived difficulty after each trial instead of waiting until all trials were completed.

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