A Framework of Dynamic Difficulty Adjustment in Competitive Multiplayer Video Games

Alexander Baldwin, Daniel Johnson, Peta Wyeth, Penny Sweetser
Science and Engineering Faculty
Queensland University of Technology
Brisbane, Australia
alexander.baldwin@qut.edu.au

***Abstract*—The balance between player competence and the challenge presented by a task has been acknowledged as a major factor in providing optimal experience in video games. While Dynamic Difficulty Adjustment (DDA) presents methods for adjusting difficulty in real-time during singleplayer games, little research has explored its application in competitive multiplayer games where challenge is dictated by the competence of human opponents. By conducting a formal review of 180 existing competitive multiplayer games, it was found that a large number of modern games are utilizing DDA techniques to balance challenge between human opponents. From this data, we propose a preliminary framework for classifying Multiplayer Dynamic Difficulty Adjustment (mDDA) instances.**

Keywords—multiplayer; dynamic difficulty adjustment; challenge; player experience; competence; video games

I. Introduction

In the study of optimal player experience in video games, the balance between challenge and player skill level has been acknowledged as a major variable affecting enjoyment. This balance is key tenet of the theory of Flow [1] and is included in Flow's application to video games in GameFlow [2]. Additionally, subjective player experience measures including the Game Experience Questionnaire [3] and Player Experience of Needs Satisfaction [4] use a 'competence' component to investigate the degree to which a player feels challenged, yet able to succeed at the task, further indicating the importance of this component of the play experience.

While many games allow the player to select a level of difficulty they believe to match their competence, research into Dynamic Difficulty Adjustment (DDA) has investigated ways in which an automated system within a game may react to player performance in real-time. The aim is to provide a better match between the challenges provided and the player's abilities [5].

Some methods used in prior DDA research have investigated the manipulation of the behaviour of opposing artificial-intelligence (AI) agents by varying the chance of successfully executing attacks against the player [6]. Through increasing or decreasing the possibility of 'mistakes' by the AI, the properties of the enemy such as health or weapons can stay constant while still modifying the challenge presented to the player. Another method of DDA involves the adjustment of level design and resources, such as changing the number of enemies that appear in a certain location or providing a nearby health pack for the player to pick up [7]. However, research in this domain has primarily focused on singleplayer gameplay. As a result, most techniques investigated in previous DDA research are inappropriate for multiplayer gameplay. Singleplayer games provide challenge through designer-controlled AI agents or environmental obstacles. In contrast, in multiplayer games, the challenge is provided by other human players.

Consideration of dynamic difficulty in multiplayer games requires a different approach to that used in singleplayer games. While methods such as reducing an opposing AI agent's effectiveness in a singleplayer game might result in an appropriate challenge level for a low-performing player, a similar method in multiplayer gameplay of reducing a high-performing player's effectiveness could be perceived as 'punishment' of the high-performing player. This adjustment could negatively affect the high-performing player's feeling of autonomy and competence as the game forcefully attempts to reduce player performance. Alternatively, improving the performance of less competent players may be a more effective and potentially less problematic technique for balancing relative player performance in multiplayer games. To identify and categorize existing methods for balancing player competence in multiplayer games we propose the Multiplayer Dynamic Difficulty Adjustment (mDDA) framework. This framework allows the classification of existing mDDA instances and provides a tool for further research of the effects of mDDA components on the player experience.

For the purpose of identifying and examining mDDA, we define an instance of mDDA as a gameplay feature in competitive multiplayer video games designed to reduce the difference in challenge experienced by all players through adjusting the potential performance of certain players. An example of this is present in the racing game Mario Kart 7 [8] in which the chance of receiving a more effective weapon is increased for players ranked lower in the race at the time of picking up a weapon box, allowing lower-performing players an increased chance of improving their ranking.

II. Formal Review Method

A. Game Selection Method

The game review aggregator 'Metacritic' was used due to its common usage within related studies as an objective indication of game quality [10]. In order to investigate instances of mDDA already in use with current games, a total of 180 games were selected using Metacritic [9]. Normalized game quality scores are assigned by Metacritic from approved game review publications and web sites. Based on Metacritic score, games of differing quality were selected for the formal review.

Initially, a review of game genres was undertaken through Metacritic and the three genres with the highest proportion of competitive multiplayer gameplay modes were identified as First-Person Shooters (FPS), Racing and Fighting. Sixty games with competitive multiplayer gameplay modes were then selected from each of these three genres. To provide a broad range of games, we selected 30 games with a Metacritic rating of greater than 75, and 30 games with a Metacritic rating between 50 and 74 within each genre. Games with a lower rating than 50 were found to be difficult to investigate due to a lack of information provided about the games through other sources, and were therefore not included.

In order to prevent out-dated or duplicate data, the following criteria were used for game selection:

- Games had to be available for PC or home console.
- Games had to have an initial release date between 2003 (the year in which the first unified multiplayer online game services of Xbox Live, Steam and PlayStation Network were released) and 2011.
- Only the most recent version of a game with multiple iterations or re-releases was selected.

A formal review process was used to identify the presence and nature of mDDA instances within each game. The process involved the analysis of professional written reviews, previews, news and developer interviews; gameplay videos; and observations of the authors from personal experience while playing the games. Additionally, searches were undertaken of online forums related to each game and questions were also posed to experienced players of each game via the forums. If an mDDA instance was identified by players, this was then investigated gameplay by the authors to confirm its legitimacy.

B. *Analysis*

For each mDDA instance found within the formal review, three key elements were recorded: the trigger for activation, the game rules affected and the scope of the effects. The trigger for activation refers to the manner in which the performance assistance provided by the instance is initiated; either automatically by the system or at the discretion of the player. The game rules affected or manipulated by the mDDA instance informs the manner in which the instance attempts to reduce the difference in challenge experienced by players; either by assisting a low-performing player or hindering a high-performing player. Finally, the scope of the effects includes the player(s) affected by the instance as well as the limitations and extent of the assistance provided.

Once the data for all identified mDDA instances was collated, any game or genre-specific mechanics were abstracted to provide a genre-independent analysis of the way in which they affect the player. In this manner, mDDA instances were generalized beyond the game or genre from which they were identified. For example, steering assistance in a racing game may be abstracted to 'control accuracy assistance'. Through the generalization of game-specific features, we were able to use qualitative data linking [11] to sort mDDA instances from different games and genres.

The initial three elements describing an mDDA instance (trigger, rules affected, scope) were broken into more specific components. For example, within the 'scope' of the instance two different groupings were identified: the 'recipient' of the instance's capability adjustment and the 'duration' of the instance in either time or number of uses. All mDDA instances collated were then classified by the manner in which that component applies to them. For example, the 'recipient' component was found to apply to an mDDA instance as either affecting an individual player or a team. By identifying the components common to all mDDA instances, as well as the possible 'attributes' of each component, a framework for classifying and identifying the instances was formed.

III. Multiplayer Dynamic Difficulty Adjustment Framework

The mDDA framework provides a design-oriented set of components that are common to all investigated mDDA instances, irrespective of game genre or mechanics.

Each component has two or more possible 'attributes', with each mDDA instance using only one attribute per component. The mDDA framework consists of seven components and associated attributes (see Table I).

A. *Framework Summary*

TABLE I. SUMMARY OF FRAMEWORK

Component	Attributes
1) Determination	• Pre-gameplay • Gameplay
2) Automation	• Applied by system (automated) • Applied by player(s) (manual)
3) Recipient	• Individual • Team
4) Skill Dependency	• Skill dependent • Skill independent
5) User Action	• Action required • Action not required
6) Duration	• Single-use • Multi-use • Time-based
7) Visibility	• Visible to beneficiary only • Visible to non-beneficiaries only • Visible to all players • Not visible

B. Framework Definitions

1) Determination

The Determination component refers to the game state or time in which the decision to use the mDDA instance is made. The attributes of this component are:

- *Pre-gameplay*: the decision to use the instance is made before the multiplayer game match commences. In this scenario, the need to adjust the performance of certain players would be determined by their past performance in the game relative to the players they now face.
- *Gameplay*: the decision to use the instance is made in real-time during the multiplayer match. This would be appropriate if a player is currently performing significantly higher or lower than his/her opponents during play, irrespective of performance in past matches.

2) Automation

This component indicates whether the decision to use the mDDA instance is automated by the game system or chosen by the player(s) themselves. The attributes of this component are:

- *Applied by system (automated)*: the game system automatically determines the need for an mDDA instance and applies it. This relies on the game possessing a means of determining relative player performance, either simply through the difference in player score or a more complex method such as TrueSkill's player rankings [12].
- *Applied by player(s) (manual)*: players choose to use an mDDA instance based on their own judgment. This is currently widely applied in the fighting game genre, with players able to choose to distribute health handicaps before a match begins by providing increased player health for low-performing players.

3) Recipient

The recipient of an mDDA instance refers to the player(s) intended to be affected by the instance. The attributes of this component are:

- *Individual*: the instance is intended to affect a single player. This may be used both in individual and team-based gameplay modes in which the performance of an individual player is notably dissimilar to opposing players.
- *Team*: the instance is intended to affect a group of players. This would only be possible in team-based gameplay modes.

4) Skill Dependency

This component indicates whether the low-performing players are required to act with some degree of skill in order to improve performance. The attributes of this component are:

- *Skill dependent*: the low-performing player(s) must make use of the effects of the mDDA instance with a degree of skill in order for it to impact their performance. This refers to the instance effects having no direct impact on player performance, but instead providing the opportunity for an improvement in performance should the player make use of it. For example, providing increased movement speed in a first-person shooter game does not guarantee a higher number of player 'kills' but may allow the player a better chance to do so if they act with skill.
- *Skill independent*: the low-performing player(s) do not need to act with any degree of skill in order for their performance to be enhanced by the effects of the mDDA instance. In this case the assistance applied directly maps to the objective and winning conditions of the game by improving the player's performance irrespective of their behaviour. For example, increasing a player's health in a shooter game in which score is a function of number of kills scored against player deaths ensures the player will survive more damage without the player needing to act in a skillful manner for the benefit to occur.

5) User Action

This component dictates whether the intended recipient of the mDDA instance is required to interact with the interface in order to initiate the instance's effects. The attributes of this component are:

- *Action required*: the recipient must interact with the interface in order for the effects of the instance to begin. For example, pressing a certain button to activate a speed boost item provided to the recipient in a racing game.
- *Action not required*: the effects of the instance will commence without player interaction with the interface. For example, the game automatically activating a speed boost in a racing game without user input.

6) Duration

This component indicates the time-based property of the mDDA instance. The attributes of this component are:

- *Single-use*: the effects of the instance occur at a single moment before the technique has concluded. For example, a single boost to the player's health.
- *Multi-use*: the effects of the instance may occur multiple times before the technique has concluded. For example, the player is given three health boosts he/she may activate over the course of the game.
- *Time-based*: the effects of the instance occur continuously over a certain timeframe before the technique has concluded. For example, the player's health will recharge gradually over 30 seconds of play before the instance ends.

7) Visibility

This refers to whether players of the game are provided with feedback regarding the presence of the mDDA instance. The attributes of this component are:

- *Visible to recipient only*: feedback is provided to the recipient of the instance, with the intention to inform him/her of the potential performance adjustments enacted by the instanced. This may occur via visual, audio, or tactile means within the game such as a text notification in the game's Heads-Up Display (HUD) informing the player of the presence of the mDDA instance.

- *Visible to non-recipients only*: feedback is provided to the non-recipients that the target player or team is being affected by the instance. This can occur through the same methods listed above, but can additionally include the identity of the recipient. However, the recipient is not provided feedback.
- *Visible to all players*: feedback is provided to all players in the match (whether the beneficiary or not) that a certain player or team is the recipient of the instance.
- *Not visible*: no feedback is provided to any players in the match that the instance is in effect. While experienced players may be able to deduce the presence of an mDDA instance through observed variations to the game rules, no intentional feedback is provided to the recipient or non-recipients as to the instance's presence or effects.

IV. Conclusions

All mDDA instances analyzed in the formal review were identified as directly affecting the player avatar's properties such as abilities, navigation and resources rather than affecting the game environment external to the player or opposing players. This is in contrast to the DDA methods utilized in studies involving singleplayer games that affected the opposing agents [13] and level design [14] rather than the player avatar.

The mDDA instances investigated in the formal review were found to be assisting low-performing players through enhancing their capabilities, rather than hindering the capabilities of high-performing players. This included some cases that may be interpreted in either way, such as the chance of receiving weapons of varying effectiveness in Mario Kart [8]. This may be interpreted as decreasing the chance of receiving a stronger weapon for high-performing players or as an increased chance for low-performing players. However, no instances involved only decreasing the potential performance of high-performing players.

The formal review and analysis of mDDA instances in competitive multiplayer video games was successful in providing seven components and their associated attributes to create a framework. The creation of a framework of mDDA instances provides a consistent, cross-genre method for investigating the use of DDA techniques in competitive multiplayer games, irrespective of genre and mechanics. The ability to identify the component attributes of mDDA instances allows the examination of the effects of different attributes on the player experience. Additionally, further studies investigating player preferences for each component attribute between both low and high-performing players can provide insight into the most effective combinations of attributes. This allows the framework to also be beneficial in the design of future mDDA instances through a better understanding of the different ways a player's performance may be adjusted through the manipulation of individual component attributes.

The preliminary mDDA framework is expected to be refined through additional studies both planned and in progress. The goals of these studies include confirming the positive effect of mDDA on the player experience, exploring which component attributes are subjectively preferred by low and high-performing players, investigating other game genres as well as identifying any components and attributes missing from the framework. Both qualitative surveys and biometric measures are intended for use in determining the effect on the player experience.

References

[1] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience*, vol. 54, no. 3. Harper & Row, 1990, p. 303.

[2] P. Sweetser and P. Wyeth, "GameFlow: a model for evaluating player enjoyment in games," *Computers in Entertainment*, vol. 3, no. 3, p. 3, 2005.

[3] W. IJsselsteijn, Y. de Kort, K. Poels, A. Jurgelionis, and F. Bellotti, "Characterising and measuring user experiences in digital games," in *International Conference on Advances in Computer Entertainment Technology*, 2007.

[4] R. Ryan, C. Rigby, and A. Przybylski, "The Motivational Pull of Video Games: A Self-Determination Theory Approach," *Motivation and Emotion*, vol. 30, no. 4, pp. 344–360, 2006.

[5] R. Hunicke, "The case for dynamic difficulty adjustment in games," in *Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology*, 2005, pp. 429–433.

[6] G. Andrade, H. Santana, and B. P. Jussieu, "Challenge-Sensitive Action Selection : an Application to Game Balancing Vincent Corruble," in *Proceedings of the 2005 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT'05)*, 2005.

[7] R. Hunicke, "AI for dynamic difficulty adjustment in games," *Challenges in Game Artificial Intelligence AAAI*, 2004.

[8] Nintendo, "Mario Kart 7." Nintendo, 2011.

[9] "Metacritic," *CBS Interactive Inc.*, 2013. .

[10] C. Koeffel, W. Hochleitner, J. Leitner, M. Haller, A. Geven, and M. Tscheligi, "Using Heuristics to Evaluate the Overall User Experience of Video Games and Advanced Interaction Games," in *Evaluating User Experience in Games*, R. Bernhaupt, Ed. Springer, 2010, pp. 233–256.

[11] M. B. Miles and A. M. Huberman, *Qualitative Data Analysis: An Expanded Sourcebook*, vol. 2nd, no. 1. Sage Publications, 1994, p. 338.

[12] R. Herbrich and T. Graepel, "TrueSkillTM: A bayesian skill rating system," *Microsoft Research*. Microsoft Research, Redmond, 2006.

[13] R. Hunicke and V. Chapman, "AI for dynamic difficulty adjustment in games," in *Challenges in Game Artificial Intelligence AAAI Workshop*, 2004, pp. 91–96.

[14] C. Pedersen, J. Togelius, and G. N. Yannakakis, "Modeling player experience in Super Mario Bros," in *IEEE Symposium on Computational Intelligence and Games*, 2009, pp. 132–139.