Creating a Player-Centric Dynamic Game AI

I. Problem Addressed and Importance

In video games, Game AI is primarily used to simulate human-like intelligence while keeping within the restrictions of the game environment. Game AI has a different approach over traditional AI as the computers abilities are toned down to give human players a feeling of fairness. AI opponents generally sport an increasing level of difficulty, challenging the human player.

In this project we propose the creation of an AI Game Playing agent that could play Isolation, a multiplayer puzzle game executed on a 8x8 grid. The proposed agent would be able to judge the personality type and skill level of the human playing the game and make moves to match this characterization of the player. In doing so, we aim to create a gaming system that is personalized - an important characteristic of an intelligent, interactive system.

II. Related Work

Dynamically catering the difficulty of a game to a players skill level has been the subject of several recent research initiatives. Gratch and Marsella [1] demonstrated how emotions and personalities in the AI agent could impact the reasoning process deciding which actions are taken. All this and more leads to a better game experience for the human player. Zook and Riedl [2] use tensor factorization to assess changes in a players skill level and then adjust the game difficulty accordingly in a turn-based role- playing game. They were able to explain 86% of the variance in players skill with 27 players. However, this model did not predict future player performance. Tan et. al [3] used two behaviour-based controllers, an adaptive uni- chromosome controller (AUC) and an adaptive duo- chromosome controller (ADC), on a continuous, real- time car racing simulator. The algorithms have the advantage that they can be trained online, but they only worked when there was a single player against a single AI. Our proposal is to expand these algorithms to work with multiple AIs to predict future player performance and adjust difficulty accordingly.

III. Proposed Implementation

Isolation is a three player puzzle game executed on an 8x8 grid. Players can move like the queen in chess - forward, backward, and diagonally. When a player moves, the space vacated by the player is filled and cannot be moved into. The game ends when two players can no longer move, causing the third to win.

Human players generally fall into one of five player types [4] depending on their primary focus of playing the game. The exact number and types of personalities varies depending on the type of game. For this project, we will first be implementing an AI game-playing agent that can play the game of Isolation. The basic agent will use the minmax algorithm, a tree based algorithm used to implement turn-taking games, along with alpha-beta pruning to perform adversarial search during gameplay. Next, we will collect data from humans playing Isolation against our AI agent and use this data to cluster and identify player types using either preference based clustering or action based clustering [5] with K-Means. The basic agent along with our knowledge of player types will be used to create an improved Isolation playing agent. This improved agent will monitor the player's moves and use it to predict the player's personality type and current expertise. This personality type will be taken into account during gameplay to select moves that match the player's personality. The aim of our AI agent is thus, not only to win the game, but also to make for the best game play experience by focusing on the aspect of gameplay that is important to the player and matching the expertise of the player.

IV. Evaluation

The evaluation of the two agent implementations with the alpha-beta pruning tree, k-means clustering, and personality vector will be conducted through a user experience study. Users will be asked to play a match or a series of matches against our agents. Afterwards respondents will be asked a series of questions about each of the agents. Questions would inquire about the difficulty, respondent's mood, enjoyment, etc. This subjective data will be used to evaluate our prediction that player modelling would improve the user experience by comparing how users reacted to the two agents.

Matches will generate a set of objective data for each match. Such data might include match duration, number of moves, and win/loss ratio. The k-means clustering might give additional data such as which personality type it matches. Given the subjective and objective data set comparisons between the two can be made to evaluate the results.

References

[1] J. Gratch and S. Marsella. *A Domain Independent Framework for Modeling.* Journal of Cognitive Systems Research, vol. 3, no. 4, pp. 269-306, 2004.

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[3] C. H. Tan, K. C. Tan and A. Tay, *Dynamic Game Difficulty Scaling Using Adaptive Behavior-Based AI.* IEEE Transactions on Computational Intelligence and AI in Games, vol. 3, no. 4, pp. 289-301, 2011.

[4] R. D. Laws, *Knowing Your Players.*Robin's Laws of Good Game Mastering, 1st ed. Austin, Steve Jackson Games, ch. 2, sec. 1, pp. 4, 2002.

[5] D. Ramirez-Cano, S. Colton, and R. Baumgarten.*Player classification using a meta-clustering approach.* Proceedings of the 3rd Annual International Conference Computer Games, Multimedia and Allied Technology. 2010.