

Personalized Dynamic Difficulty Adjustment

- Imitation Learning Meets Reinforcement Learning

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Abstract

- Balancing game difficulty in video games is a key task to create interesting gaming experiences for players.
- This study investigates a method for adjusting game difficulty balance by challenging players based on their current actions using machine learning-based agents.
- This is achieved by a combination of two agents, in which one learns to imitate the player, while the second is trained to beat the first.

Introduction

- Engaging players with an appropriate challenge is fundamental to a rewarding gaming experience.
- Dynamic Difficulty Adjustment (DDA) technique aims to maintain players in a flow state by adjusting difficulty based on their performance.
- While deep reinforcement learning (DRL) has been shown to result in human-compatible performance in a variety of gaming tasks, it is known to converge slowly, previously making it unsuitable for a real-time scenario.

Introduction

- To overcome this challenge, this study implements a two-step process and proposes a novel DDA method aimed at training personalized opponents.
 - In the first stage, have the agent imitate the player's actions.
 - In the second stage, it trains a new agent to compete against that imitation agent.
- At specific intervals, the player's current opponent is replaced with the second agent, presenting the player with a customized challenge.

Proposed Agent Model

- To realize personalized dynamic difficulty adjustment (PDDA) experiences, they propose a framework combining imitation learning and reinforcement learning agents.
- Seamless integration of PDDA machine learning-based opponent is achieved through a combination of three agents:
 - **Opponent Agent:** The agent the player is currently playing against, which is to be replaced seamlessly while playing the game.
 - **Imitation Learning Agent:** An agent that observes the player's behavior and learns to replicate its actions.
 - **Reinforcement Learning Agent:** An agent trained to win against the imitation learning agent.

Proposed Agent Model

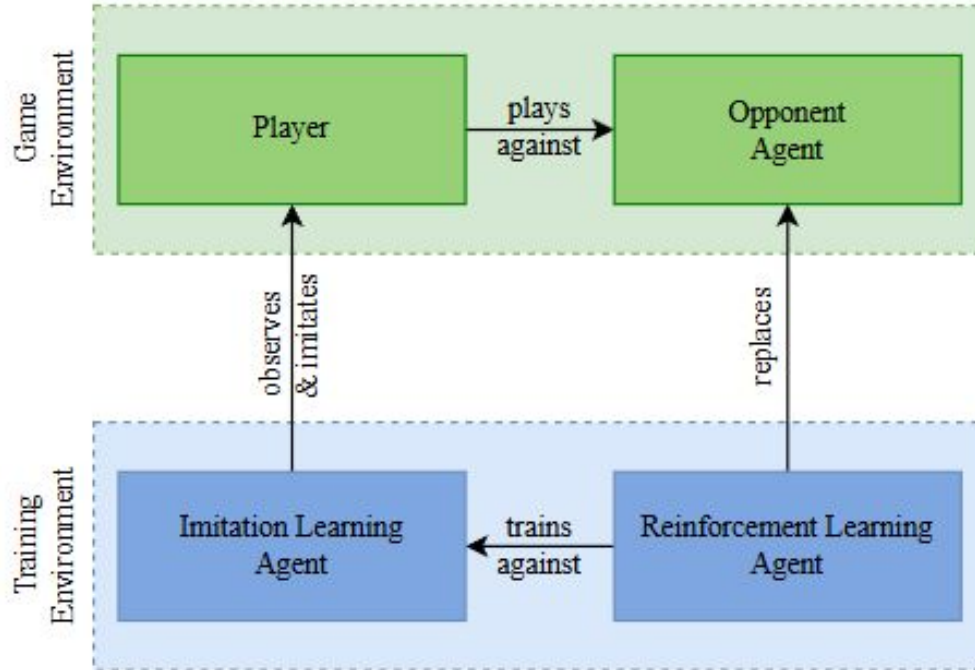
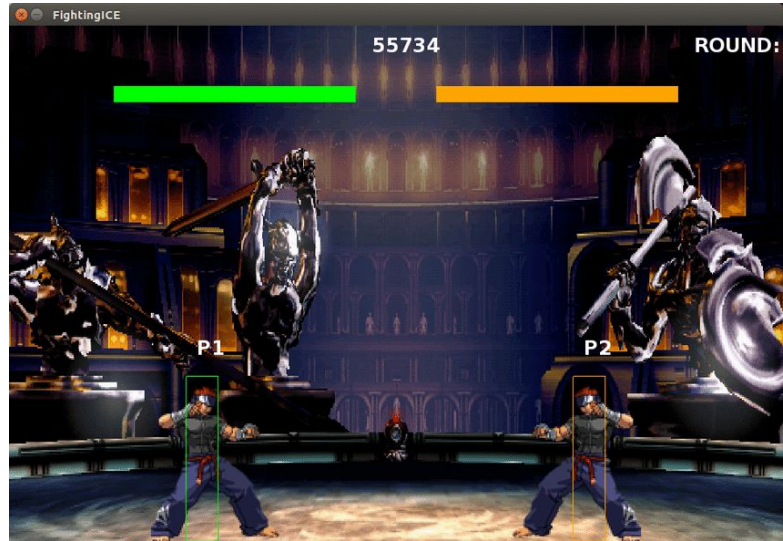


Fig. 1: Proposed agent architecture for personalized dynamic difficulty adjustment.

Experiment

- The proposed PDDA model was implemented within the context of the FightingICE framework.
- When predicting player actions, they achieved an accuracy of 82 ~ 87% using a training set with imitation learning agents.



Experiment

- The current screen was encoded as a 96×64 grayscale image as input for the reinforcement learning agent. It received a positive reward when reducing the opponent character's hit points and incurred a penalty when losing its own hit points.
- Participants in the experiment competed three times each against the agent provided by the framework(MCTS) and the agent proposed model.
- After each game, participants rated their experience on a scale of 1 ~ 10. The proposed model received higher ratings than the MCTS agent.

Agent	Average Ratings
Proposed model	7.0 ± 1.09
MCTS	6.6 ± 1.01

Conclusion and Future Work

- The framework for PDDA presented in this work provides the opportunity to challenge players according to their individual skill levels.
- PDDA system was constructed by combining imitation learning agents and reinforcement learning agents, enabling implementation with minimal configuration by designers.
- In the future, we aim to expand on the evaluation of the proposed PDDA by increasing the number of study participants and analyzing the system's impact on their perceived difficulty and player satisfaction for different opponent agents.

Thank you for your attention