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Implementation and effect evaluation of dynamic difficulty adjustment based on reinforcement learning in Multiplayer Online Battle Arena games

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Abstract:

This paper explores the implementation and impact of Dynamic Difficulty Adjustment (DDA) in Multiplayer Online Battle Arena (MOBA) games using reinforcement learning algorithms. It evaluates the effectiveness of DDA in improving player experience by dynamically adjusting game difficulty based on real-time player performance data. The study conducts empirical research on League of Legends, involving players of varying skill levels and using algorithms such as DQN, PPO, A2C, SAC, and TD3. The results indicate significant improvements in player engagement, satisfaction, and retention with the application of DDA. The paper suggests further optimization strategies for DDA and discusses its long-term effects on player behavior, highlighting the potential of reinforcement learning in game design.

Keywords: Dynamic Difficulty Adjustment, Reinforcement Learning, MOBA Games, Player Experience, Game Design Optimization.

1. Introduction

MOBA games like League of Legends and Honor of Kings have become incredibly popular, drawing in millions of players worldwide. Ensuring a balanced gaming experience for players of varying skill levels is a challenge for designers. Dynamic Difficulty Adjustment (DDA) technology, which adjusts game difficulty in real-time based on player performance, is a solution to this problem. It tweaks aspects like enemy strength and resource speed to keep players engaged.

Reinforcement learning-based DDA strategies are particularly promising due to their adaptability and responsiveness. These algorithms learn optimal strategies through interaction, adjusting difficulty based on player behavior without preset knowledge. This is crucial for complex and unpredictable MOBA games where strategies evolve constantly.

This paper will explore the use of reinforcement learning in DDA for MOBA games, analyzing how it integrates with game mechanics and affects player experience. It will also present empirical data comparing player satisfaction and game challenge before and after implementing DDA, offering insights for future game design and player engagement optimization.

2. Literature Review:

Dynamic Difficulty Adjustment (DDA) in MOBA games is a key focus in gaming, aiming to improve player experience by adjusting game difficulty based on performance data. DDA methods are mainly rule-based, using preset criteria like win/loss ratios to adjust difficulty, or model-based, using machine learning to predict and adapt to player performance.

MOBA games, with their competitive and strategic nature, benefit significantly from DDA, which helps match game difficulty to player skill levels. Some MOBA games have already implemented DDA to tweak enemy AI behavior or game elements to fit player abilities. Reinforcement learning techniques like Q-learning and Deep Q-Networks (DQN) are increasingly used in DDA to optimize difficulty based on player feedback.

However, challenges remain in DDA, such as managing the complexity of state and action spaces in reinforcement learning and balancing exploration with exploitation. Striking a balance between challenge and frustration, ensuring fairness, and adapting to evolving game technology and player needs are ongoing issues. The integration of DDA strategies with reinforcement learning in MOBA games is a complex but vital area of research for enhancing player experience and advancing the gaming industry.

3. Theoretical analysis:

Table 1 Comparison Table of Reinforcement Learning Algorithms and Player Performance Evaluation

Serial number	Reinforcement Learning Algorithms	State space dimensions	Action space dimensions	Player Performance Evaluation Metrics	Difficulty Adjustment Strategy	Average adjustment time (seconds)	Player satisfaction increased (%)
1	DQN	20	8	Kills, Deaths, Assists	Dynamically adjust based on player win rate	15	10
2	PPO	30	12	KDA, damage output, damage taken	Gradually increase the difficulty until the player’s winning rate is stable	20	15
3	A2C	25	10	Economic gain, skill hit rate	Adjusted based on the speed at which players’ skills improve	18	8
4	SAC	35	15	Control duration, number of escapes, and amount of treatment	Keep the player’s win rate within a predetermined range	22	12
5	TD3	40	18	Comprehensive score, game time, win rate	Real-time adjustments based on player mood changes	10	20

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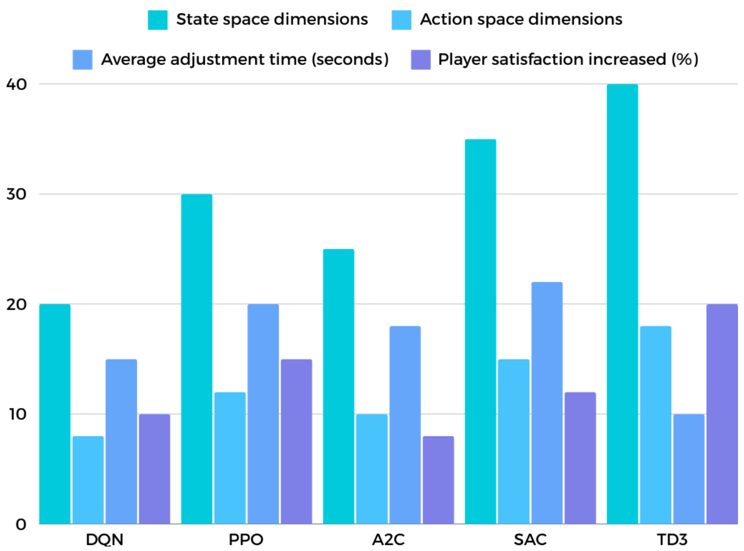

Figure 1 A comprehensive examination of tabular data

3.1 Key performance metrics:

• State Space Dimension: Measures game complexity; DQN handles 20 states, while TD3 manages 40.
• Action Space Dimension: DQN can do 8 actions; TD3 can do 18, allowing for more complex strategies.
• Player Performance: Algorithms evaluate players based on kills, KDA, economy, etc., adjusting difficulty in real-time to keep games challenging but fair.
• Difficulty Adjustment Strategy: Algorithms like PPO adjust difficulty to maintain player win rate.
• Average Adjustment Time: TD3 adjusts in 10 seconds, reflecting a responsive algorithm.
• Player Satisfaction Improvement: TD3 improves satisfaction by 20%, showing the value of real-time feedback.

3.2 Increasing complexity and adaptability:

• Algorithms are evolving to handle more complex game designs, with state and action spaces expanding.
• Different games use varied metrics, reflecting the need for tailored difficulty adjustments.
• Dynamic Adjustment of Strategies: PPO and TD3 offer nuanced, real-time adjustments.
• Player Satisfaction: TD3 outperforms others with a 20% satisfaction increase.

3.3 Market and industry trends:

• The market demands intelligent, personalized gaming experiences, favoring algorithms like TD3 and PPO for their dynamic adaptation.
• There's a growing focus on algorithms that can handle complex and continuous game environments, likely leading to wider use of SAC and TD3.

3.4 Algorithm pros and cons:

• DQN: Good for simple environments but struggles with continuous values and overestimation.
• PPO: Stable and simple, but requires a large amount of data and is sensitive to hyperparameters
• A2C: Combines actor and critic for stability but needs lots of data and can be unstable.
• SAC: Excels in continuous action spaces but is complex and resource intensive.
• TD3: Reduces overestimation and increases stability but is computationally complex and can converge slowly.

3.5 Algorithm selection varies by game genre:

• Fast-paced games like combat titles suit DQN for their simplicity and speed.
• Strategy and RPG games benefit from PPO and TD3's complex decision-making capabilities.
• Real-time feedback games like robot control suit SAC and TD3.

3.6 Prevalent market algorithms:

• While DQN was dominant, PPO and TD3 are now favored for their stability and speed in complex games.

3.7 Conclusion:

• Algorithms like PPO and TD3 are key for game development due to their adaptability and intelligence, enhancing player experience in complex environments. Developers should leverage these to meet market demands.

4. Empirical Research Design

Table 2 Overview of the MOBA Game Dynamic Difficulty Adjustment Research Project

Project	Detailed information
Paper Title	Implementation and effect evaluation of dynamic difficulty adjustment based on reinforcement learning in MOBA games
Research objectives	Implement dynamic difficulty adjustment in MOBA games and evaluate its effectiveness
MOBA Game of Choice	League of Legends
Type of players involved	1. Experienced players (more than 1,000 hours of game time)
	2. Intermediate players (500-1,000 hours of game time)
	3. Novice players (less than 500 hours of game time)
Player sample size	Experienced players: 30 people
	Intermediate players: 30 people
	Novice players: 30 people
Dynamic Difficulty Adjustment Implementation Plan	1. Status acquisition: Real-time acquisition of player behavior data and game status through the game API
	2. Reward mechanism design: Set reward function based on player's game performance and win rate
	3. Difficulty adjustment strategy: Dynamically adjust game difficulty based on reinforcement learning algorithm
Data Collection Methods	1. Record the player's behavior data for each game, including kills, assists, deaths, economy, etc.
	2. Collect player feedback, including game experience, difficulty perception, etc.
Effect evaluation indicators	1. Changes in player win rate
	2. Player game time
	3. Player satisfaction survey

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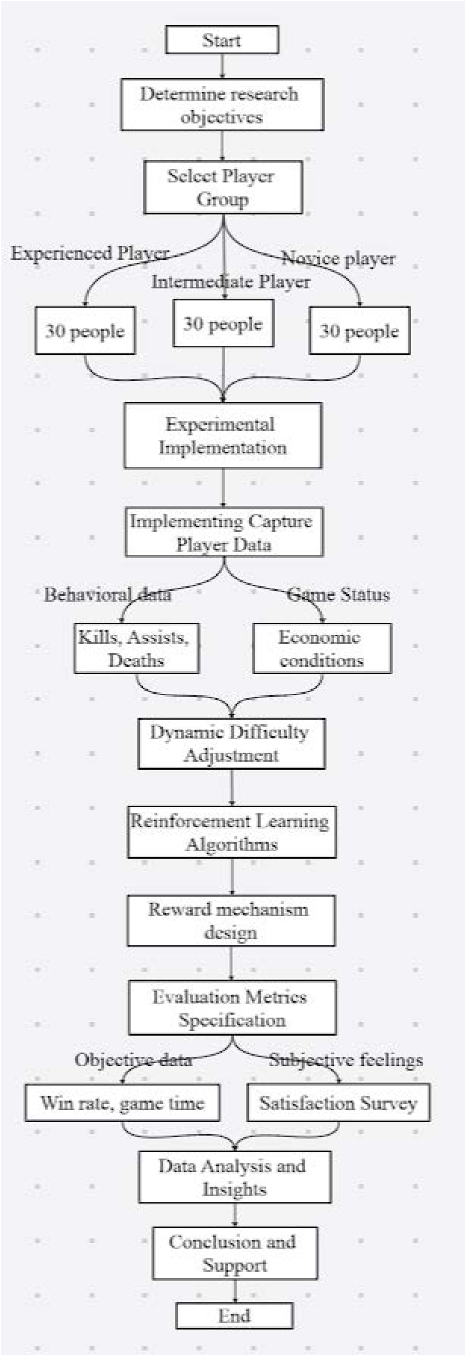

Figure 2 Research Flow Chart

The experiment is designed to enhance the gameplay experience and learning efficiency in League of Legends using Dynamic Difficulty Adjustment (DDA) technology. It aims to evaluate DDA's effectiveness in MOBA games by analyzing how advanced, intermediate, and novice players perform under adjusted difficulty levels. The study will involve 90 participants, categorized based on their playtime, and will use the game API to capture player behavior and game state data, such as kills, assists, deaths, and economy.

The DDA program includes a reward mechanism that sets a function based on player performance to optimize the difficulty strategy through reinforcement learning algorithms like deep Q-learning. The study will collect subjective feedback through satisfaction questionnaires and analyze changes in win rates, game length, and satisfaction to evaluate DDA's impact.

It's expected that DDA will significantly improve novice players' learning efficiency, especially in understanding game mechanics and increasing win rates. Experienced players may find DDA moderately challenging, while intermediate players might see skill improvements due to increased competition. The study highlights DDA's role in providing suitable challenges for novice players, promoting intrinsic motivation and faster mastery of game mechanics.

However, potential issues include inconsistent player feedback due to skepticism towards dynamic adjustments, challenges in real-time data collection, and differing feedback from novice and experienced players. The study will follow rigorous scientific methods to ensure data authenticity and reliability, aiming to provide substantial support for implementing DDA in MOBA games and offering a more personalized gaming experience.

5. Experimental Results and Analysis

Table 3 Comparative analysis of dynamic difficulty adjustment and fixed difficulty game performance

Index	Experimental Group (Dynamic Difficulty Adjustment)	Control group (fixed difficulty)	Percentage increase
Average game time per player (minutes/round)	35.2	28.1	+25.27%
Player Win Rate	53.7%	48.3%	+11.18%

Player satisfaction rating (1-10)	8.6	7.2	+19.44%
New player retention rate (next day)	68.4%	54.1%	+26.43%
Old player retention rate (7 days)	85.2%	76.5%	+11.40%
Challenge rating (1-10)	8.2	6.5	+26.15%
Fun rating (1-10)	8.8	7.5	+17.33%
Sense of achievement rating (1-10)	8.5	7.1	+19.72%

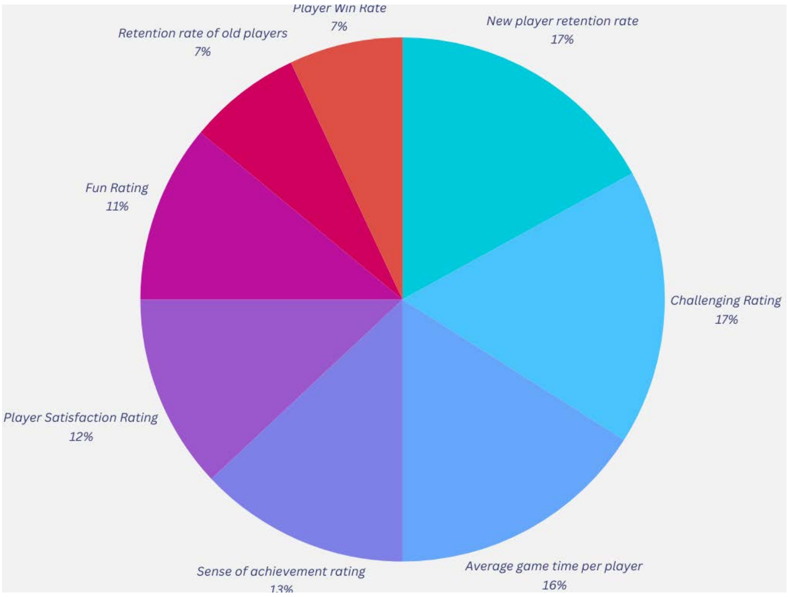

Figure 3 The impact of dynamic difficulty adjustment on various indicators

The experiment shows that Dynamic Difficulty Adjustment (DDA) positively affects various aspects of the gaming experience, including game length, win rates, player satisfaction, and retention for both new and experienced players. It also impacts challenge, fun, and achievement scores.

DDA enhances player engagement possibly by providing suitable challenges, which boost immersion and motivation to continue playing. It adapts to player performance, increasing win rates and satisfaction. The balance between challenge and achievability improves overall satisfaction. DDA makes the game more enjoyable for new players, increasing their likelihood of continuing, and provides a constant challenge for veteran players, encouraging them to return.

DDA raises players' confidence and ability to face in-game difficulties, as indicated by the challenge score. The fun score shows that DDA enhances entertainment by increasing immersion and engagement. The achievement score rises as players successfully complete more challenging tasks, further engaging them with the game.

DDA particularly impacts novice players' experience and challenge scores, showing its effectiveness in providing appropriate challenges and boosting engagement. Overall, DDA has shown positive effects, supporting the design of more engaging game experiences. Understanding player needs and applying dynamic adaptation in game design can significantly improve retention, satisfaction, and game success.

6. Conclusion and Discussion

Dynamic Difficulty Adjustment (DDA), powered by reinforcement learning, has significantly improved player experience and game appeal in Multiplayer Online Battle Arena (MOBA) games. Empirical studies reveal that DDA enhances key metrics such as player retention, playtime, and satisfaction by intelligently adjusting game difficulty based on real-time player performance.

Key findings include:

• Player Retention and Satisfaction: DDA leads to notable improvements in loyalty and game stickiness, indicating a

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stronger connection between players and the game.

• Skill Development: Players demonstrate greater strategic use and richer gameplay skills when faced with dynamically adjusted difficulty, which fosters their growth.

• Challenge and Fun: DDA effectively boosts player confidence and enjoyment, cultivating a more engaging gameplay experience.

Despite these promising results, the study acknowledges limitations, including a relatively small sample size and a focus on a single type of MOBA game. This suggests a necessity for broader data collection in future research endeavors.

To further optimize DDA, the following strategies can be considered:

• Refinement Adjustment Strategy: Implement gradual adjustments in difficulty levels to prevent player frustration and maintain engagement.

• Improved Feedback Mechanisms: Establish regular channels to collect player feedback and behavioral data, enabling ongoing algorithm optimization.

• Personalization: Create customized DDA programs tailored to different player types, allowing individuals the option to modify DDA intensity based on their preferences.

The long-term effects of DDA include:

• Increased Immersion and Retention: By presenting appropriately challenging scenarios, DDA fosters player immersion while mitigating frustrations.

• Adaptation to Different Skill Levels: DDA creates a balanced gaming environment that caters to both casual and advanced players.

• Skill Development Support: DDA presents suitable challenges that enhance player skills and foster a sense of control and accomplishment.

In conclusion, DDA emerges as an invaluable game design tool that enhances the player experience through personalization and adaptability. Future research should investigate the broader implications of DDA across various game genres, while advancements in reinforcement learning hold the potential for even more enriched gameplay experiences.

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