Introduction

- FPS games are hard for AI: partial observability and sparse rewards
- Agents cannot see behind walls, reward only on winning
- 'Arena Breakout' used with only visual input

Training Interactive Agent in Large FPS GameMap with Rule-enhanced ReinforcementLearning

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What is Arena Breakout?

- Mobile FPS game developed by Tencent
- Large maps, realistic gunplay, extraction-style missions
- Players collect items and escape alive
- Strategic depth ideal for AI agent training

Fig. 1. The interface of Arena Breakout

Problem & Motivation

- Previous methods use internal game data
- Realistic agents must act from images only
- This paper builds a vision-only training pipeline

Method - Overview

- Uses Actor-Critic reinforcement learning
- Learns policy and value function
- Includes curriculum learning and rule-based corrections

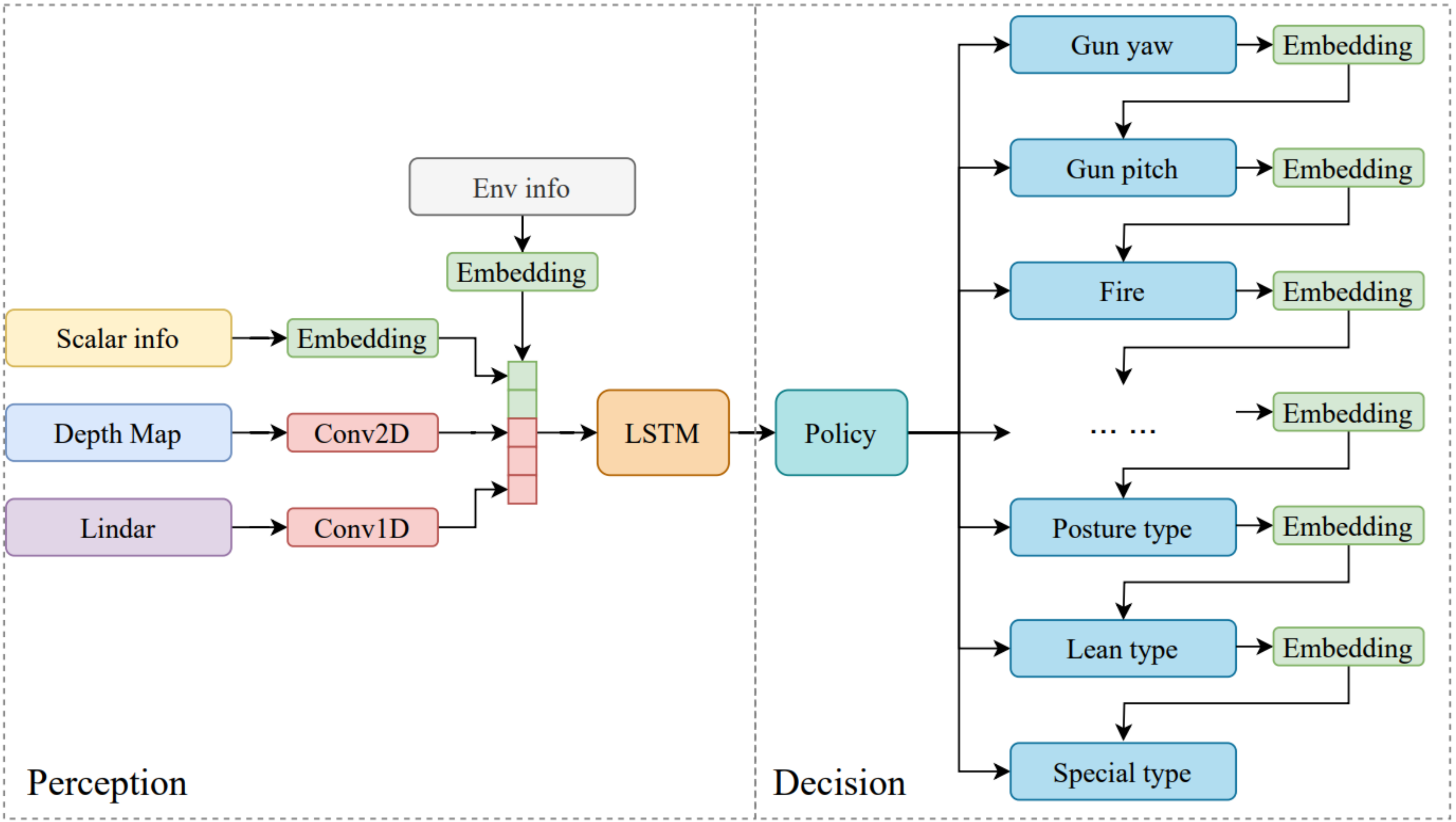


Fig. 2. Framework of PMCA.

Navmesh–enhanced Global Navigation

- Standard RL struggles with global path planning.
- Navmesh (Navigation Mesh) provides spatial graph data.
- Agent uses Navmesh to select sub-goals for long-rangetravel.
- Improved exploration and efficiency across the map.

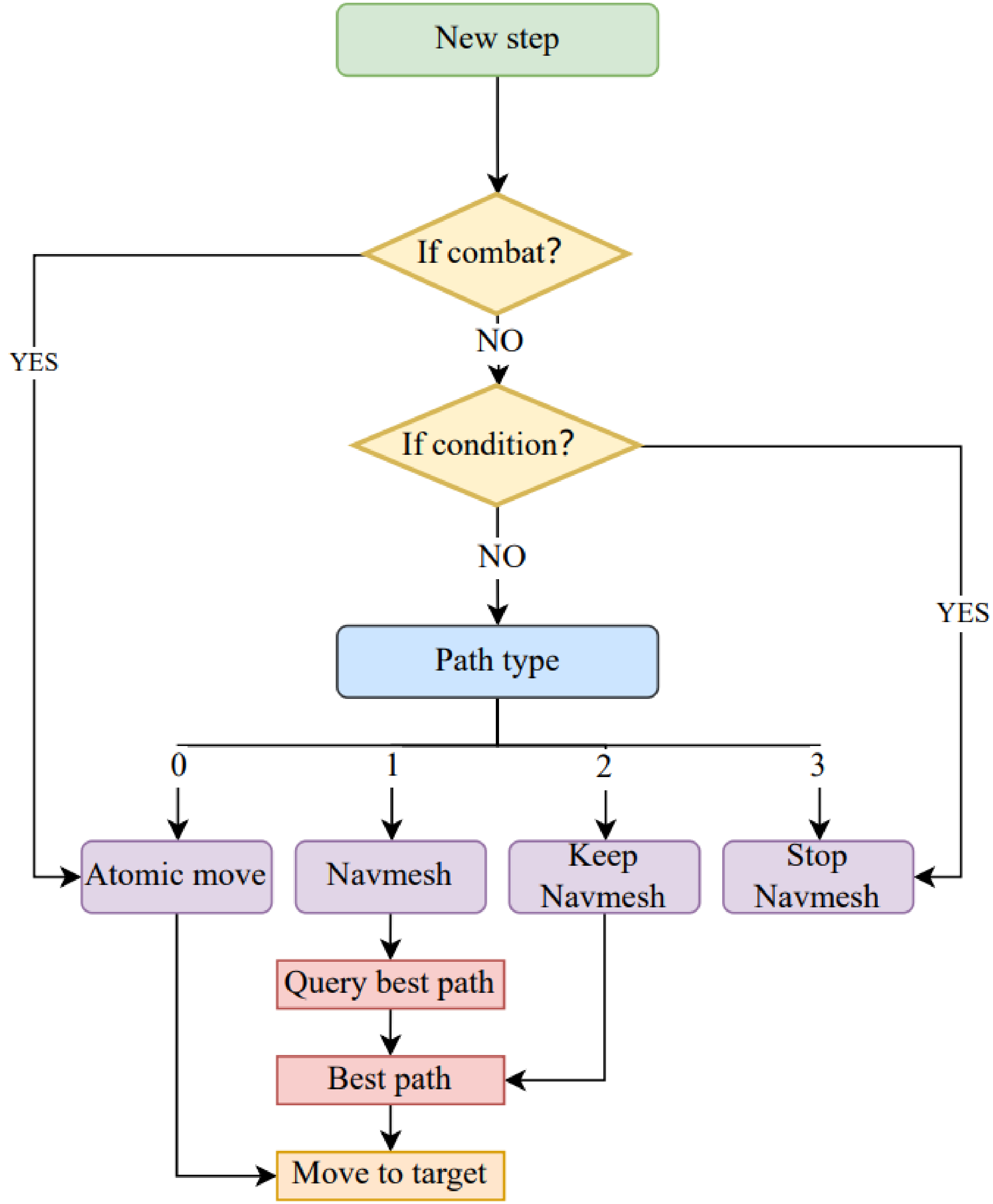


Fig. 3. The illustration of Navmesh enhanced global navigation.

Curriculum Learning

- Starts with simple maps and tasks
- Gradually increases difficulty
- Improves learning stability and performance

Rule-enhanced Design

- Rules adjust behavior like avoiding spinning or being stuck
- Improves robustness and prevents failure

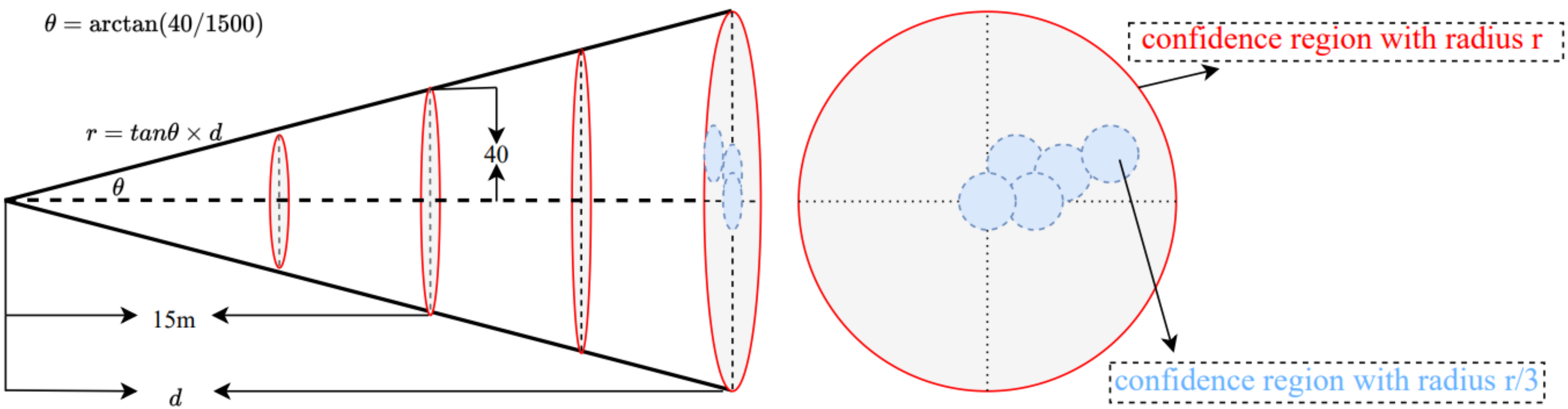


Fig. 4. The illustration of shoot rules.

Experiment Details

- The experiments were conducted in a realistic game map called "Farmland" in Arena Breakout.
- The evaluation compares three agents:
  - A baseline RL agent
  - A rule-enhanced NSRL agent
  - Human player
- Metrics included:
  - Win rate
  - Navigation coverage
  - Bullet distribution
- The NSRL agent showed:
  - Significantly better map traversal
  - More tactical behavior

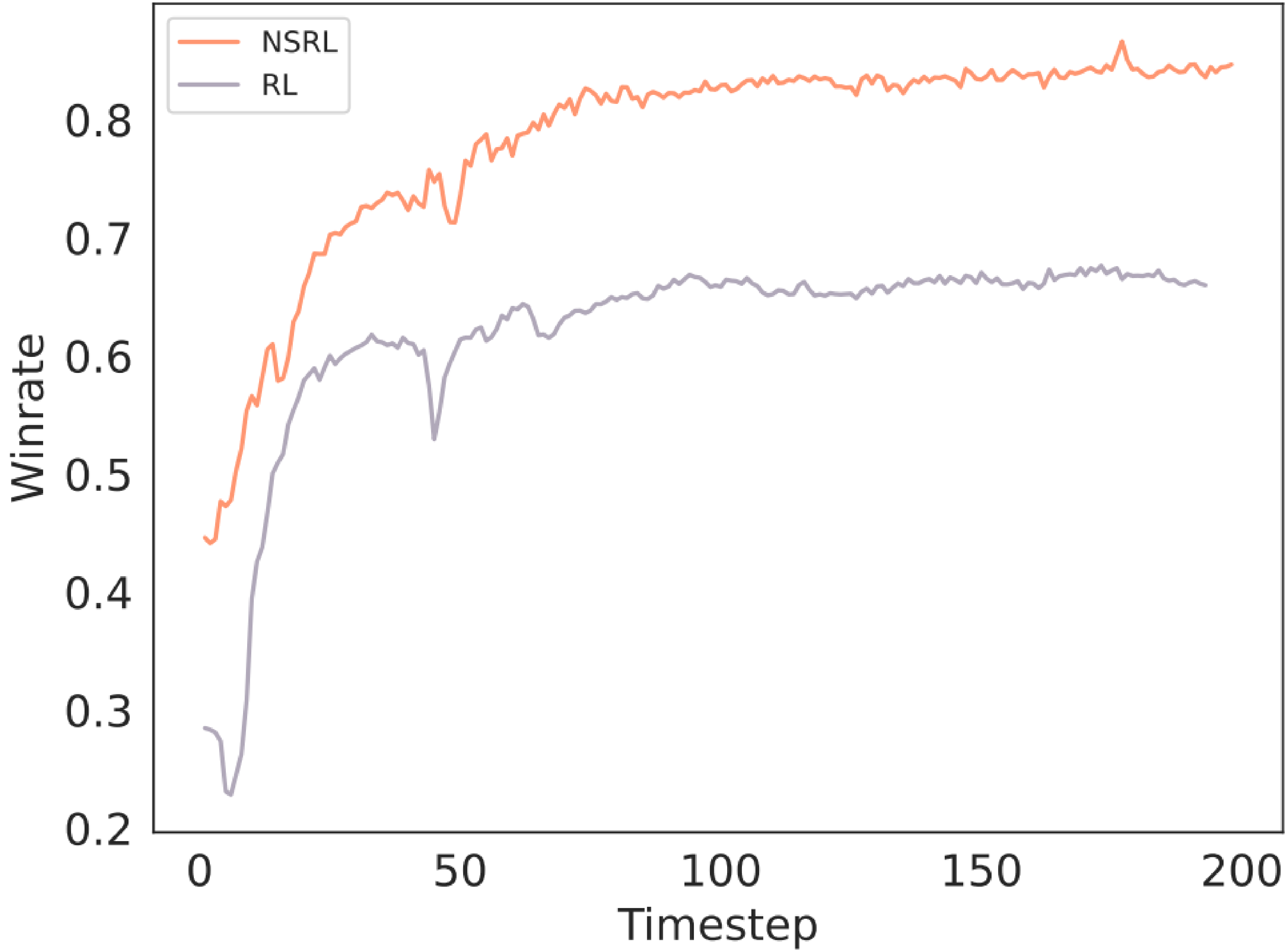
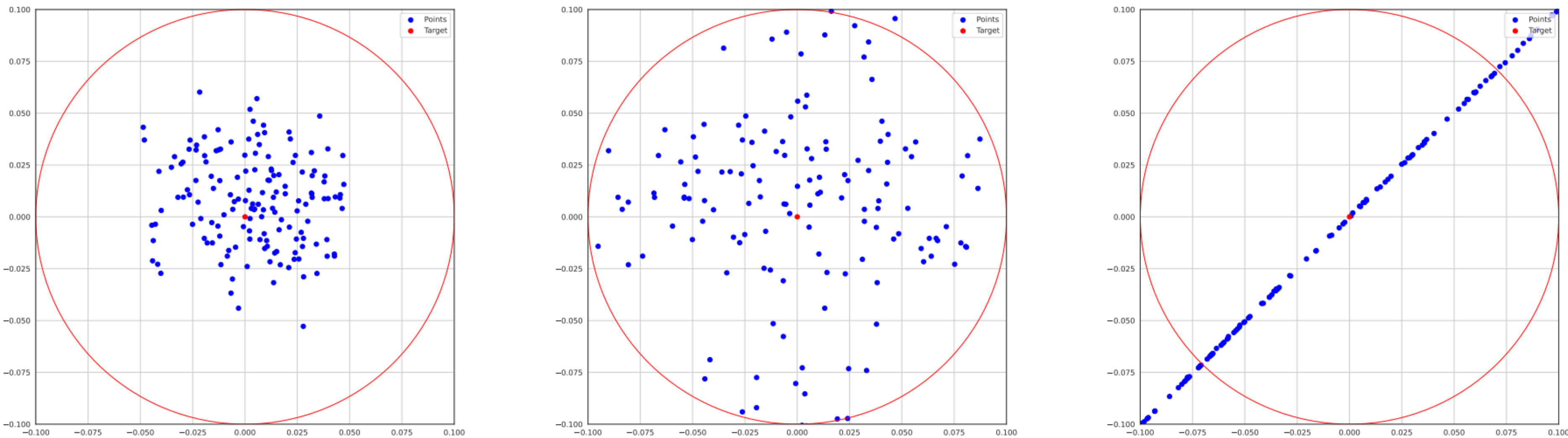


Fig. 7. The trend of win rates verses BT changes during the training process for the RL agent and NSRL agent.



(a) Bullet Distribution of Human Players

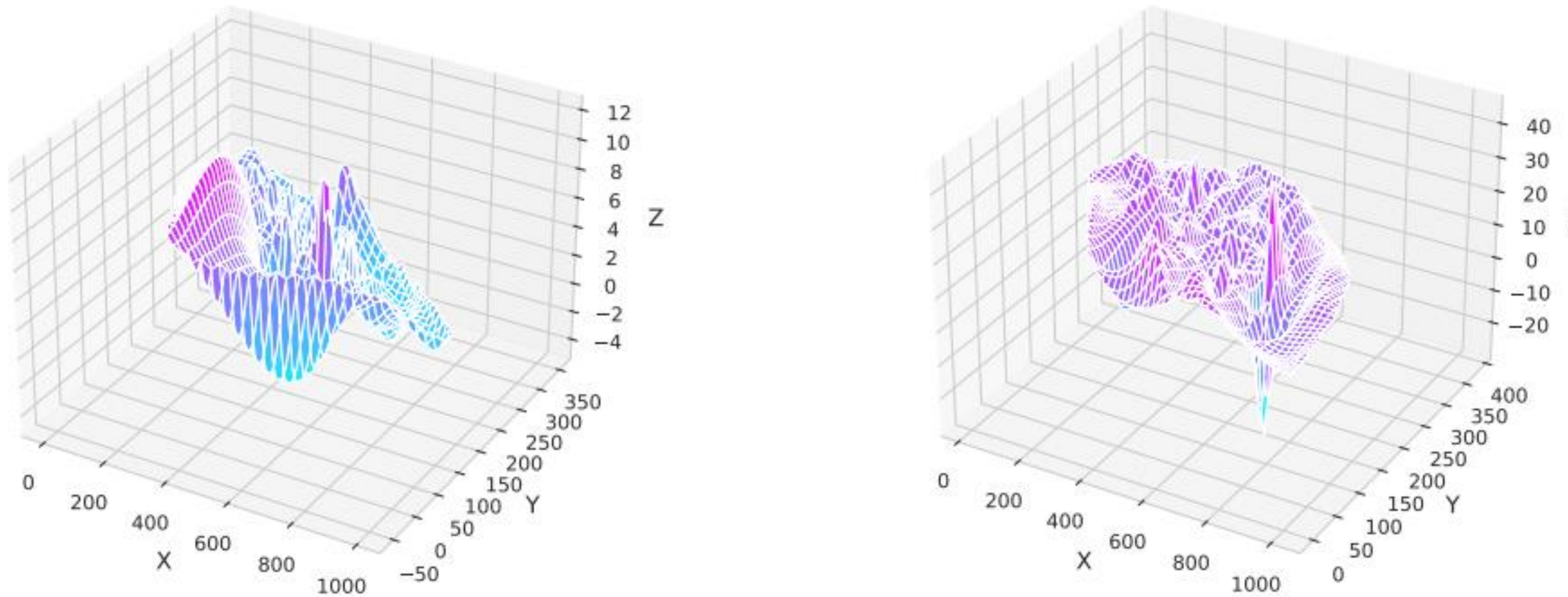
(b) Bullet Distribution of NSRL agent

(c) Bullet Distribution of RL agent

Fig. 8. Bullet Distribution of Human Players, NSRL agent, and RL agent.

Results

- Agent outperforms all baselines
- Won 10 of 11 matches, 35% higher than 2nd-best AI
- Showed smart tactics: dodging, navigation, splash damage



(a) Visualization of RL Global Navigation

(b) Visualization of NSRL Global Navigation

Fig. 6. Visualization of RL and NSRL Global Navigation. The closer the color is to purple, the higher the number of traversals, while the closer it is to blue, the fewer the number of traversals. The NSRL visualization shows that most areas are closer to purple, indicating a higher number of traversals, while there are fewer areas close to blue. On the other hand, the RL visualization reveals that only a small portion is close to purple, suggesting limitations in RL's global navigation capabilities.

Conclusion

- Combines RL, curriculum learning, and rule logic
- Achieves realistic, human-like FPS agents
- No privileged info needed, works on complex maps

Thank You

- Thank you for listening