SRBIAU2D Soccer Simulation 2D Team Description Paper IranOpen 2024

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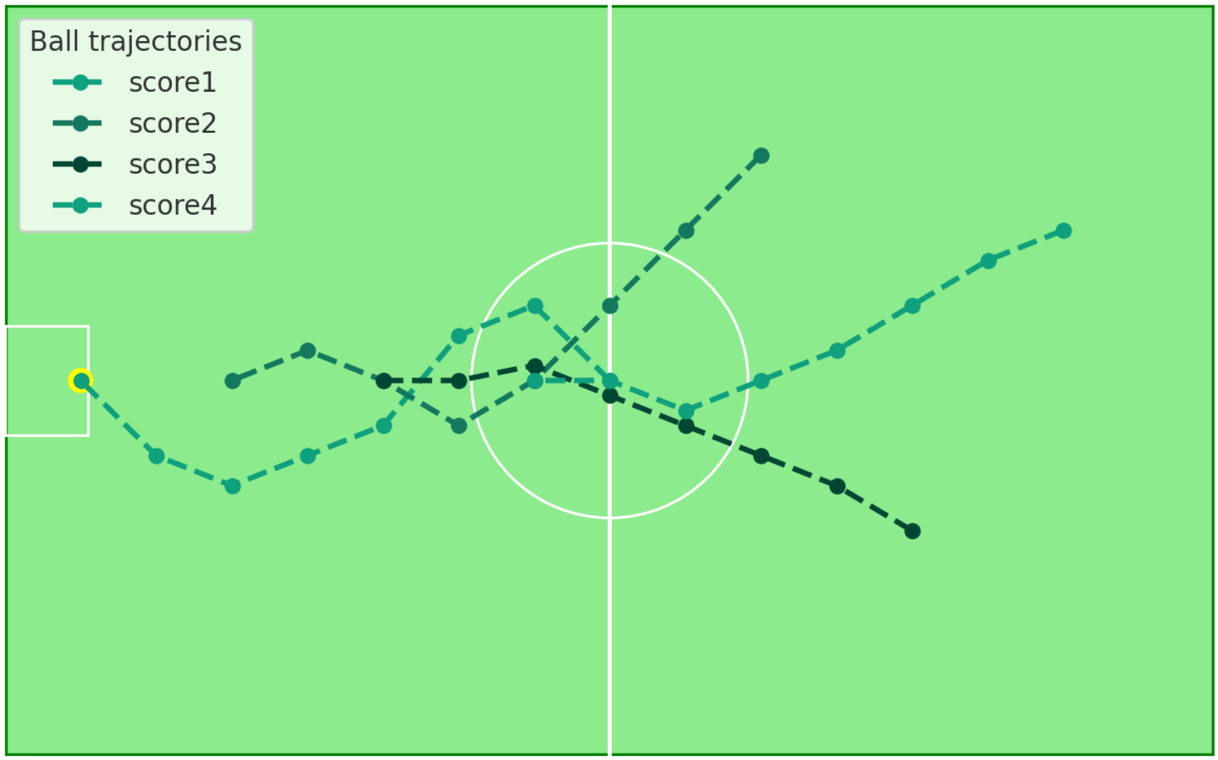
Abstract. The SRBIAU2D team proudly presents its innovative contributions to the RoboCup Soccer Simulation 2D League, leveraging the Helios base code as a foundation. Our research has led to the development of groundbreaking artificial intelligence (AI) strategies, focusing on goalkeeper optimization through deep reinforcement learning, enhanced pass decision-making via a machine learning-augmented multi-criteria framework, and sophisticated defensive tactics, including dynamic marking and coordinated blocking. A standout feature of our approach is introducing a "Super Defense" mode, activated during critical game phases, to ensure a robust defence that secures leads. By integrating cutting-edge AI and machine learning techniques, we aim to significantly elevate team performance. We demonstrate our dedication to innovation within the RoboCup community and the broader field of AI research in sports simulations.

Keywords: RoboCup, Multi-Agents Systems, Soccer Simulation 2D, Chain Actions

1. Introduction

The RoboCup Soccer Simulation 2D League presents an exciting and challenging arena for applying and developing artificial intelligence and robotic technologies. Building on the legacy of the Helios[1] base code, our team has embarked on a journey to push the boundaries of what's possible in this simulated environment. By integrating advanced AI techniques and machine learning algorithms, we have developed strategies to enhance team performance across various aspects of the game, including goalkeeper optimization, decision-making in passing, and defensive operations. Our efforts have focused on creating a system that excels in individual skills and exhibits a high degree of team coordination and strategic adaptability. This paper outlines the innovations and improvements we have introduced, demonstrating our team's commitment to advancing the field of AI through the RoboCup initiative. Our work reflects a deep understanding of the complex dynamics of soccer simulation and a forward-looking approach to solving the challenges inherent in the sport, with the ultimate goal of contributing valuable insights and methodologies to the RoboCup community and beyond.



2. Goalkeeper Strategy Optimization

Our team implemented to introduce an advanced goalkeeper AI module based on R3CESBU's [2] emphasis on goalkeeper positioning and decision-making. This module will use deep reinforcement learning to enhance the goalkeeper's ability to predict and react to shots, crosses, and through balls. By simulating thousands of game scenarios, the goalkeeper AI will learn optimal positioning, when to stay on the line versus when to come out for the ball, and how to best distribute the ball to start counter-attacks. This approach aims to significantly reduce goals conceded and improve our team's ability to maintain possession and transition from defence to attack more effectively. Leveraging the capabilities of the log analyzer tool [4], we significantly enhanced the Namira team's strategic framework. Our methodology involved an extensive pattern analysis to identify common scenarios leading to conceded goals across multiple games. Unlike previous approaches focused on single-game logs, we refined our analyzer tool to process multiple log files concurrently. This advancement allowed for the rapid, graphical representation of game statistics across numerous matches, offering a more comprehensive insight into our team's performance dynamics.

One particularly impactful aspect of our analysis was the visualization of the ball's trajectory during the final sequences, which led to the goals being scored against us. By setting 'N,' a configurable parameter, to 200 cycles, we could trace the ball's movement on the soccer pitch in the crucial moments before conceding goals. This visualization facilitated a deeper understanding of defensive vulnerabilities and enabled us to optimize the goalkeeper's positioning against various team strategies. Our goalkeeper showed improved shot-blocking capabilities through this refined defensive stance and was better equipped to interrupt opponent passes, thereby reducing goal concessions.

Figure 1: The trajectories of the ball for four scoring instances against our team

The image above in Fig.1 visually encapsulates the ball's trajectory in the critical moments before a goal is scored against our team, as observed in the soccer 2D simulation. By analyzing this path, along with the positioning of our goalkeeper and other players, we've optimized defensive strategies to better block shots and disrupt opponent plays, enhancing our overall team performance.

3. Pass Decision-Making Enhancement

Building on the pioneering fuzzy logic approach for pass decision-making showcased by The8 team [2], we have ventured to develop a nuanced, multi-criteria decision-making framework. This framework utilizes a bespoke machine learning model that harmoniously blends supervised and reinforcement learning to forecast opponent movements and calculate real-time pass success probabilities.

3.1. Supervised Learning Implementation

The supervised learning segment of our model is adept at identifying intricate patterns in opponent behavior. Trained on a rich dataset chronicling a wide array of match situations, player positioning, ball movement, and various game outcomes, it can predict with a certain likelihood where opponents may position themselves next. This predictive power is critical in determining viable passing options in a fluid match setting.

The environment's state space encapsulates all dynamic aspects of the match, ranging from player positions and ball location to player stamina and game conditions, such as noise, offside lines, and the number of teammates and opponents around the kickable player. The agent's action space is equally comprehensive, allowing for various soccer-specific strategic moves.

The culmination of these elements results in a system that dynamically tailors passing strategies, learning and adapting to both the macro and micro aspects of the game's progress. Our implementation seeks to imbue virtual players with a decision-making process that mirrors the fluidity and adaptiveness of human play.

Despite the sophistication of our model and its initial promise in simulations, its real-world efficacy has fallen short of our expectations despite some good accuracy in the test dataset. The transition from theory to practice has unveiled the need for continued experimentation and adjustments. Our team remains dedicated to refining the framework to ensure its successful application in live match scenarios.

4. Marking

The process of marking in our team consists of two main phases. Generating the mark table is done by one player in the field, and executing the mark is done by any individual defender. [5] Our marking strategy involves generating a marking table and executing physical marking. The marking table, determined by the player with the best field view, guides defenders in their positioning and actions to counter opponents' threats optimally. This approach includes aggressive marking in high-risk situations and more observational marking under normal conditions, ensuring a flexible and effective defensive posture.

4.1. Mark table generating

The marking table is created by the player with the best view. Usually, our Center_back has the best view among the other players. At the beginning of the game, this player observes the opponent's behaviors to determine which creates the most danger in the goal.

Based on this information, another player prepares for the next phase (attempt to win possession, tackle, and move to their pre-determined formation).[5][6]

4.2. Physical marking:

Physical marking includes the agent's behaviors and actions to find the best position for future cycles based on the opponent's current place.

There are two types of physical marking:

4.2.1. Physical marking during dangerous situations

In dangerous situations such as the penalty area, defenders stick to the opponent and move a short distance between the ball and the marked player to intercept the opponent's passes.

4.2.2. Physical Marking In Normal Conditions

In this case, the defender stays at a distance, not too close behind the opponent. This is done to observe the opponent so that he can immediately react to his every move. The purpose of this action is to prevent breaking our defence line.

5. Block

Agents in this system work together to stop opponents from creating goal chances. They first decide if blocking is necessary and choose the best blocker(s) using a distributed voting process. Each agent suggests two candidates, each receiving the highest score based on his probability of risk creation among other players**.** And a central authority combines these votes to pick the winner(s). This ensures coordinated defence, as everyone knows who to block. Once chosen, the blocker then executes the physical blocking action. The physical blocking process is divided into two main parts: finding the best way to approach the opponent and obtaining the ball possession or kicking it away.[6] [7] Our blocking strategy leverages a distributed voting process to identify the best candidates for blocking opponent plays. This coordinated approach ensures a unified defensive effort, with blockers executing precise physical actions to regain possession or neutralize threats. Our methodology balances aggressive and safe blocking techniques to adapt to the game's flow and opponent strategies.

5.1. Approach

The blocker guesses the opponent's dribble path based on their position, direction, speed, and previous moves. They then calculate the best interception point.

5.2. Ball Possession

a. Safe Block: The blocker uses sideways movement to cut off the opponent's dribble path precisely, preventing them from easily passing.

b. Direct Block: In low-risk situations, the blocker directly approaches the opponent to force them away from the ball (potentially with physical contact).

6. Tackle

Tackling strategies are tailored to consider previous cautions, the current game stage, and the score. This adaptive approach enables players to balance aggression and caution, prioritizing ball recovery and minimizing risks, especially during critical game moments.[8]

7. Super Defense

this mode, activated during the final minutes with a one-goal lead, our team prioritizes a highly defensive approach to safeguard our advantage. This involves assertive tackling techniques to regain possession and hinder opponents' scoring attempts. While acknowledging the potential for increased fouls or injuries, we emphasize safe and strategic tackling to maximize ball recovery and minimize risks.[9][10][11]

The SRBIAU2D team's contributions to the RoboCup Soccer Simulation 2D League underscore our commitment to advancing AI and robotics within competitive sports simulations. Our innovative strategies and techniques are designed to enhance team performance and adaptability, reflecting a deep understanding of the game's dynamics and a forward-thinking approach to overcoming its challenges. Through our work, we aim to contribute valuable insights and methodologies to the RoboCup community and the broader field of AI research.

8. Future Work

Building upon the successful implementation of advanced AI strategies in our SRBIAU2D team, we envision several avenues for future research and development to further elevate our team's performance in the RoboCup Soccer Simulation 2D League:

- **Predictive Analytics for Opponent Strategy Modeling:** We plan to develop a comprehensive predictive analytics system capable of real-time modeling and predicting opponent strategies. By leveraging machine learning algorithms to analyze historical performance data, this system will enable our team to proactively adjust our gameplay, ensuring a competitive edge against various opponents.
- **Dynamic Formation Adjustments:** Our next research phase will focus on implementing dynamic formation adjustments that respond in real time to the evolving state of the game. This innovative approach will utilize AI to assess the effectiveness of various formations against ongoing match dynamics, allowing for strategic shifts that can exploit opponent vulnerabilities or fortify our defensive stance.
- **Automated Player Role Adaptation**: Recognizing the importance of optimal role allocation, we aim to introduce an AI-driven module for automated player role adaptation. This system will analyze the game context and player conditions (e.g., stamina, position) to dynamically assign roles, maximizing individual player contributions and overall team synergy.

9. References

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