SRBIAU2D Soccer Simulation 2D Team Description Paper 2025

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Abstract. The SRBIAU2D team presents its latest improvements in the RoboCup Soccer Simulation 2D League, based on the Helios framework. Our work focuses on smarter shooting, flexible defense, and better player positioning. The Dynamic Shooting System predicts and selects the best shot, while the Adaptive Hybrid Marking System adjusts between zone, man-to-man, and group marking depending on the game. An Unmarking Strategy helps players reposition effectively. We have also improved the R3-Autotest framework, making testing 30% faster and more efficient. A Hybrid Static-Dynamic Evaluation Mechanism enhances decision-making, and Super Offense Mode increases attacking pressure in crucial moments. By improving both attack and defense, we aim to boost team performance and advance soccer simulation strategies.

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

1 Introduction

The SRBIAU2D team, built upon the Helios[1] base code, continues to improve AI-powered soccer simulation by developing smarter strategies for both attack and defense. Our latest work focuses on making shots more accurate, improving defensive flexibility, and helping players work better together through smart positioning. By using prediction models, quick decision-making, and automated testing, we fine-tune our game strategy to perform better in competitions. These improvements, along with real-time evaluation, help our team quickly adapt to changing match situations. Through ongoing research and development, we aim to advance AI-driven tactics in the RoboCup Soccer Simulation 2D League.

2 Dynamic Shooting Based on Pyrus2D Idea

This dynamic shooting system is inspired by the Pyrus2D[14] concept and aims to determine the optimal path for shooting toward the goal. In this method, all possible paths from the ball current position to the opponent's goal are generated and evaluated. The evaluation process considers factors such as ball speed, distance to the target, the goalkeeper's ability to respond to the shot, and the likelihood of the path being intercepted by opposing players. A key feature of this system is its ability to predict the movements of both the goalkeeper and opponents using data such as speed, direction, and acceleration. This predictive capability ensures that selected paths are beyond the goalkeeper's reach and have the least chance of being intercepted by defenders.

To assess potential threats from opposing players, a combined metric is used, which takes into account their distance from the ball's trajectory, their ability to reach the ball, and their position relative to the ball and the goal. Additionally, the system analyzes the goalkeeper’s technical and tactical attributes, such as body orientation, reaction time, and movement range, to identify paths that are harder for the goalkeeper to defend. Smart scoring of trajectories also enables the system to balance risk and safety favoring riskier paths in critical moments of the game and safer paths when maintaining possession is crucial.

This dynamic shooting system, by simulating the ball’s motion and factoring in its speed decay along the path, delivers reliable and adaptive performance. It analyzes real-time game conditions effectively, ensuring precise and efficient shot selection for diverse scenarios.

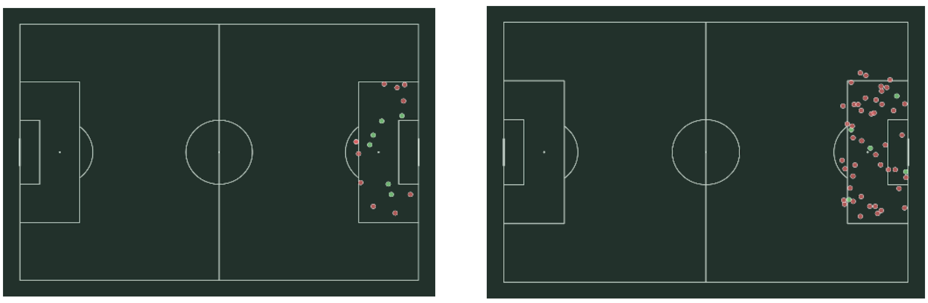


Fig. 1. This is our comparison of the shot positions before and after the match against Thunderleague. We took fewer shots but scored more goals. While the changes aren't huge, it shows an improvement in shot quality and accuracy.

3 Adaptive Hybrid Marking System

Our previous marking approach relied heavily on predefined roles and a single decision-maker for marking table generation. This static decision-making process had several limitations, such as Slower adaptability, wrong marking decisions due to limited vision, and Limited prediction capabilities.

To address these issues, we developed a new Hybrid Marking Strategy, which dynamically assigns marking responsibilities using real-time Marking Priority Score calculations. Our marking strategy dynamically adapts between zone marking, man-to-man marking, and swarm marking based on the game situation. The process consists of key phases: calculating a dynamic threshold, executing different marking strategies, and performing threat analysis to ensure optimal defensive positioning.[2][6][7][8]

3.1 Threat Metrics

These metrics assess the danger posed by opponents based on their position, speed, and proximity to key areas (goal, ball, etc.).

- **Goal Threat:** goalThreat = max(0, 80.0 − 1.2 × distanceToGoal) The closer an opponent is to the goal, the higher their goal threat.
- **Ball Threat:** ballThreat = max(0, 60.0 − 1.5 × distanceToBall) The closer an opponent is to the ball, the higher their ball threat.
- **Speed & Goal Angle Threat:** This factor combines the opponent's speed with their direction relative to the goal, indicating how dangerous their movement is.
- **Possession Threat:** A fixed value of 50 is added when an opponent is very close to the ball.

These metrics combine into an overall threat score that measures the risk an opponent poses.

3.2 Assignment and Prediction

- **Hungarian Algorithm:** Used to optimally assign defenders to opponents or passing lanes. The algorithm considers:
  - Distance (×1.2): How far the opponent is from the defender.
  - Threat Score (×1.8): The opponent’s overall threat based on their proximity and actions.
  - Opponent Speed (×1.0): The speed of the opponent relative to the defender.
- **Predictive Modeling (Kalman Filter):** Kalman Filter method for forecasting the future positions of the ball and opponents over a short period (~0.3 seconds), guiding defensive actions and anticipating the opponent's next move

3.3 Hybrid Marking Strategy

The hybrid marking strategy integrates zone, man-to-man, and swarm marking approaches based on the game context

- **Zone Marking** focuses on guarding specific areas rather than individual opponents. It is particularly applied when the ball is near the defensive zone to maintain structural integrity. Players are assigned to cover specific zones based on a calculated target position, ensuring optimal defensive coverage

- **Man-to-Man Marking** is used when a specific opponent poses a significant threat. In this approach, defenders are assigned to shadow and block the most dangerous opponent. The system dynamically selects the target based on threat level calculations, including proximity to the ball and goal, velocity, and pass threat probability. This ensures effective marking while allowing smooth positional transitions.
- **Swarm Marking** involves deploying multiple players to converge around the ball in high-pressure situations. This strategy prevents excessive clustering by enforcing a minimum distance threshold between defenders. Additionally, it prioritizes counterattack positioning when applicable, enhancing both defensive and offensive transitions.

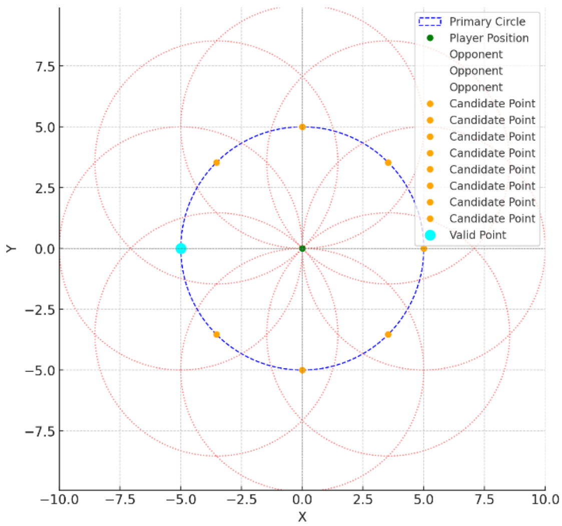
The improvement of our Hybrid Marking Strategy impacted on our defensive resilience, resulting in a 16% decrease in goals conceded compared to our previous marking system.

4 Unmarking Strategy with Candidate Point Scoring

Unmarking is essential for transitioning from defense to attack, ensuring that players maintain optimal positioning without unnecessary defensive constraints. Our Hybrid Unmarking Strategy allows players to release from marking dynamically when it benefits the overall team strategy.

In this strategy, the player generates candidate points around a circular area centered on their position. These points are rated based on various parameters to determine the best position for movement. The scoring parameters include distance from opponents, distance from the ball, angle of view toward teammates, safety of the movement path, and relative position toward the opponent's goal. The point with the highest score is selected as the target, and the player moves to that position.

This approach reduces opponent pressure, creates space for effective playmaking, and improves team coordination. Over and above that, it offers the potential for development using machine learning and advanced optimization techniques to further enhance performance.[3][4][5]



$$SCORE(P) = W_1 \cdot \Delta G + W_2 \cdot \Delta T + W_3 \cdot \Delta B + W_4 \cdot \Delta O + W_5 \cdot \Delta P$$

- W_1, W_2, W_3, W_4, W_5 are the weights assigned to each parameter.
- ΔG : Distance from the point to the opponent's goal.
- ΔT : Distance from the point to the nearest teammate.
- ΔB : Distance from the point to the ball.
- ΔO : Distance from the point to the nearest opponent.
- ΔP : Distance from the point to the teammate who has the ball.

5 Automate testing

To streamline development and testing, we have enhanced the R3-Autotest[1] framework with an automated script. This addition allows team members to evaluate their individual implementations against a specified opponent, providing key performance metrics like win rate, goals scored, and goals conceded. While R3-Autotest already runs team-based simulations and offers statistical insights, it lacks a direct method to assess individual contributions across different Git branches.
To address this limitation, a new script has been developed to work alongside R3-Autotest, offering branch-specific testing functionality. The key features of this script are:

5.1 Branch Selection Interface

The Branch Selection enhances the efficiency of the process for identifying and working with different branches in the main Git repository. Rather than manually searching through various branches, the script automatically lists all available ones, allowing developers to quickly choose the branch corresponding to their current development work.

5.2 Latest Commit Testing

Once a branch is selected, the script retrieves its latest commit and provides it to the R3-Autotest framework for execution. This automation removes the need for manual setup and greatly simplifies testing, as developers no longer have to identify and copy specific commit hashes themselves.

5.3 Automated Performance Evaluation

After testing the selected commit, the script records key metrics like win rate, goals scored, and goals conceded and compares them to previous results. This streamlined evaluation quickly highlights improvements or regressions, ensuring each branch's contributions are effectively assessed.[1]

By implementing this automated script, our testing process is now significantly faster and more simplified. Removing manual setups and automating performance evaluations not only reduces testing time but also enhances result accuracy. As a result, our development speed has improved by 30%, enabling smoother reviews and more effective refinements.

6 Evaluation Mechanism

6.1 Previous Version: Static Evaluation

In the previous version of our system, the evaluation mechanism relied only on a static scoring model. Each position on the playing field was mapped with a predefined score, and players selected the highest available score to determine their target position. The ball then directed toward that point through a series of generated actions. This approach provided a simpler decision-making process but lacked adaptability to dynamic in-game scenarios.[2]

6.2 New Version: Hybrid Static-Dynamic Evaluation

To enhance decision-making flexibility, we have transitioned to a hybrid evaluation model that combines both static and dynamic scoring. In this updated approach:

- Players generate multiple possible actions, each associated with a ball target position.
- The system dynamically evaluates each action based on real-time conditions, considering various factors beyond the predefined static scores.
- Static scores still affect the dynamic evaluation, providing a weighted effect on action selection.
- The action with the highest overall score computed from both static and dynamic evaluation will be chosen by the player.

In Special Cases, the static score does not significantly impact the dynamic evaluation, allowing for more adaptive decision-making. Additionally, we have introduced a special case where players can take control of the ball while rotating to reposition themselves strategically. This enables them to create better opportunities for gameplay, improving tactical flexibility and offensive efficiency.[4][5][11]

Table 2. This table shows the team's performance results before and after implementing the changes. The data provided is based on 100 matches.

Team Name	Previous Version(WinRate)	New Version(WinRate)	Previous Version(Goal)	New Version(Goal)
Thunderleague	32%	44%	99	132

[1] https://github.com/cserobotic/R3-autotest

Yushan 2020	52%	71%	190	247
Robo2D 2023	42%	76%	151	235

7 Dynamic Formation

Building on the Gravity Strategy, 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.[12]

$$Z_{\text{move}} = \min\big((\alpha_1 \Delta E)(\alpha_2 \Delta B)\big) - \frac{\Delta P}{\alpha_3 \Delta B} - \frac{\Delta G}{\alpha_4 \Delta B} + (\alpha_5 \Delta O) + (\alpha_6 \Delta T) - (\alpha_7 \Delta TG)$$

$$f(\quad) = -\frac{\Delta T}{\alpha_8} - \frac{Py}{\alpha_9} - (\alpha_{10} \Delta G) + (\alpha_{11} \Delta E) + (\alpha_{12} \Delta O) + (\alpha_{13} \Delta TG)$$

By integrating dynamic formation adjustments with the Gravity Strategy, we aim to create a more adaptive and intelligent team behavior, enhancing both offensive and defensive capabilities. This approach allows for real-time strategic shifts based on AI analysis of match dynamics, ensuring optimal player positioning and tactical execution.

- Z_{move} is the calculated weight for movement.
- ΔE is the distance to the nearest edge of the field.
- ΔB is the distance to the ball.
- ΔP is the distance to the player.
- ΔG is the distance to the opponent’s goal.
- ΔO is the distance to the closest opponent.
- ΔT is the distance to the closest teammate.
- ΔTG is the distance to the goal

8 Super Offense

This mode, activated during critical moments when we need to score or equalize, our team adopts an aggressive offensive strategy aimed at breaking the oppo-nent's defense. This strategy includes fast, dynamic attacking plays, with players focusing on high-pressure tactics to increase scoring chances. Quick ball move-ment, well-timed runs, accurate passes, and through balls are key to breaking through the opponent's defensive lines. By using through passes, we create gaps in the defense, allowing us to set up direct goal-scoring chances and create more offensive options. Although this approach increases the risk of counter-attacks, we prioritize maintaining possession in advanced positions, creating weaknesses in the opponent's defense, and applying high pressure. Through calculated risks and fast transitions, we aim to shift the high ground in our favor and secure the potential goal.[2][9][10]

conclusion

This paper presents a set of algorithmic enhancements and system-level integrations applied to the RoboCup Soccer Simulation 2D League. The approach featured a predictive dynamic shooting module, a hybrid marking mechanism combining zone, man-to-man, and swarm strategies, and an unmarking strategy based on candidate point utility scoring. These components operate within a hybrid static-dynamic evaluation framework, which integrates both fixed and adaptable evaluation criteria to enable context-sensitive decision-making by dynamically adjusting strategies based on the current game state.
Empirical evaluations across multiple simulated match scenarios demonstrated quantifiable improvements in performance, including increased win rates and a 16% reduction in goals conceded. The automated extension of the R3-Autotest infrastructure further accelerated development workflows by approximately 30%.
The techniques form a modular, adaptable, and reproducible control framework for multi-agent coordination in adversarial environments, aligning with the research objectives of the RoboCup community.

Future Work

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

- **Dynamic Pass Optimization** : In the future, expanding the variety of passes, improving alignment with team strategies, and implementing intelligent feedback could significantly enhance the performance of the passing system. Adding passes like "diagonal passes" to break defensive lines or "long defensive clearances" in high-pressure situations would improve the system's adaptability to various game scenarios. Additionally, integrating the passing system with overall team strategies would enable seamless transitions between offensive and defensive approaches. Designing a system to provide feedback after each pass, such as analyzing success or failure, could also optimize the system's decision-making through continuous learning.[5]
- **Optimized Kicker Decision-Making** : Our team is planning to enhance our offensive strategy by employing an imitation learning approach focused on refining

our kicker decision-making. We intend to compile a comprehensive dataset capturing the movements of elite kickers and use it to train a deep neural network that will determine the optimal shot parameters, namely trajectory, timing, and power. By incorporating real-time factors such as the goalkeeper's positioning, defensive coverage, and the ball's dynamic movement. Our model aims to identify the most effective shot even under high-pressure situations. We expect that this data-driven strategy to reduce the amount of wasted shot opportunities and substantially boost our goal-scoring potential, setting the stage for a more adaptive and efficient offensive play in our RoboCup 2D Simulation League efforts.[13]

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