OXSY 2026 Team Description

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Abstract. The Oxsy team was founded in July 2002 as a graduation project by Sebastian Marian in the field of Multi-Agent Systems at Lucian Blaga University (Sibiu, Romania). Over the past two decades, the team has evolved from a modest academic initiative into a competitive force within the RoboCup Soccer Simulation League and has made significant contributions to AI, robotics and multi-agent systems, continuing to evolve with each iteration of the RoboCup competitions. The team's ongoing mission is to push the boundaries of AI and robotics, leveraging new techniques and technologies to stay at the forefront of soccer simulation.

Keywords: RoboCup, 2D Soccer Simulation, AI, Multi-agent Systems, Neural Network.

1 Introduction

Since our first appearance in 2003 at the RoboCup competition in Padua, Italy, where we won the first round [1], Oxsy has participated in almost every RoboCup 2D Soccer Simulation League competition [2]. Our team steadily improved its performance, reaching milestones such as 3rd place finishes in Graz (2009), Singapore (2010), João Pessoa (2014), Nagoya (2017) and most recently, 1st place in the cooperative challenge of the 2023 RoboCup competition, held in Bordeaux, France.

In recent years, we have focused on refining our tactics [3], strategy and AI-based decision-making systems, placing great emphasis on adaptability in both offensive and defensive phases. With 21 participations in RoboCup, Oxsy has grown into a key player in the global AI and robotics landscape, striving to push the boundaries of autonomous soccer agents.

2 Increase Ball Possession through Accurate Kick Ball Decision

Having a comprehensive world model of the opponent player’s position is critical when controlling the ball. In soccer, teams with better ball possession generally have more scoring opportunities. In this section, we present our improvements in decision-making related to ball possession.

2.1 Creating a Player Map's Positions

To predict opponent player movements, we designed a positional map that simulates potential locations based on previous known data from visual ("see") and auditory ("hear") messages. The map updates after every cycle, creating a broader range of possible locations when information about the opponent is unavailable. Our system limits map complexity by setting maximum cycles (10) and constraining movement directions to 45-degree increments. This allows us to generate real-time responses while efficiently calculating probable opponent positions.

2.2 Adjusting the Player Map's Positions

Adjusting the positional map is vital to producing a reasonable estimate of opponent locations. If visual information shows that an opponent cannot be in certain areas, our system will eliminate those options from the map. This reduces uncertainty and improves the accuracy of future decisions. Players then have a clearer sense of where opponents may be located, even if some data is incomplete.

2.3 Reshaping the Player Map's Positions

Based on real-world patterns of player movement, we introduced reshaping factors, such as reaction time and ball speed. Dividing the map into four quadrants, we prioritize movement based on ball position and speed, thereby reducing the number of possibilities and focusing on more probable movements. Our analysis shows that this reshaping process significantly improves the accuracy of predicting player locations in critical game situations.

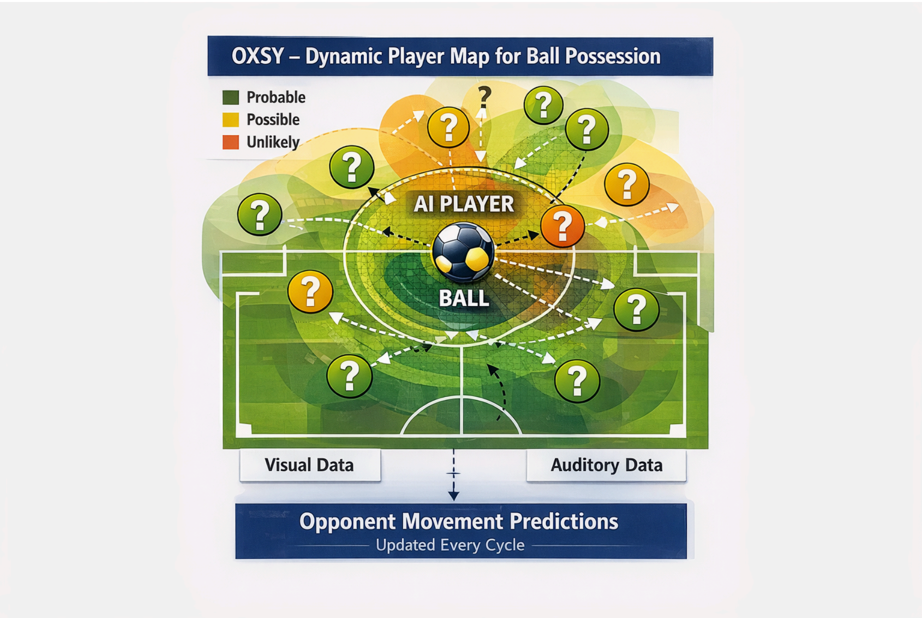

Fig. 1. *A visual representation of strategic positioning and ball control, emphasizing the creation of dynamic player maps to predict opponent movements and improve possession efficiency.*

3 Adaptive Route for Achieving the Goal

Our next innovation involves using adaptive strategies for offense, where the coach dynamically adjusts player actions [4] based on the evolving game environment. This section describes how our system clusters the pitch and selects the best possible route for scoring a goal.

3.1 Clustering the Pitch

We divided the soccer pitch into 24 clusters (6x4 grid) to analyze player routes and their effectiveness across multiple games. Each cluster stores route data, which is generated when our players pass the ball through a given area. These routes are scored based on their effectiveness in helping players advance toward the goal.

3.2 Selecting the Best Route

Once the pitch is divided into clusters, the player in possession of the ball must select the best route based on available routes within the cluster. The coach helps determine this decision by offering a ranking of possible routes, factoring in the position of teammates and opponents.

3.3 Scoring and Re-scoring the Route Achievements

Each route is scored based on how well it moves the ball closer to the opponent's goal. The coach continually observes and updates the route scores, making adjustments based on in-game changes. For instance, if the opposing team alters its strategy, routes that previously had high scores may need to be downgraded, while new routes are identified and upgraded.

Fig. 2. *Illustration of adaptive strategies for achieving soccer goals, displaying a segmented soccer field with clustered sections representing possible routes to the goal. Each route showcases strategic paths that players can select based on effectiveness and scoring potential, emphasizing dynamic adjustments to optimize scoring.*

4 RSA Accumulator for Tactical Adaptability

In this section, we explore the use of RSA accumulators [5] to handle dynamic tactical shifts during gameplay. The RSA accumulator is a cryptographic method that allows us to "remember" successful strategies in specific game scenarios and adapt team formation based on accumulated patterns.

4.1 Implementing the RSA Accumulator

The RSA accumulator [6] enables us to store a “memory” of successfully handled situations, allowing the coach to adjust the team's strategy dynamically. For example, when a specific offensive or defensive move is successfully executed, the coach creates a map with the key being the opponent’s action pattern and the value being the optimal formation to counter it.

4.2 Adapting Team Shape in Real-Time

Changing the team’s shape during a game can be crucial for handling specific situations, such as facing an opponent with a strong offensive or defensive setup. With the help of the RSA accumulator [7], our coach can recall previously successful formations in similar scenarios and apply them instantly.

4.3 Example: Dynamic Formation Change Using RSA Accumulator

Let's consider an in-game example where our team is facing an aggressive offensive play. The RSA accumulator [8] detects that the opponent is using a familiar pattern that has been successfully countered before. Based on the stored key-value pairs in the accumulator, the coach orders a formation change to counter the attack.

As the formation shifts in real-time, the team is better prepared to handle the offensive push, leading to a more effective defense and possible turnover. This quick adaptation makes a crucial difference in high-stakes moments.

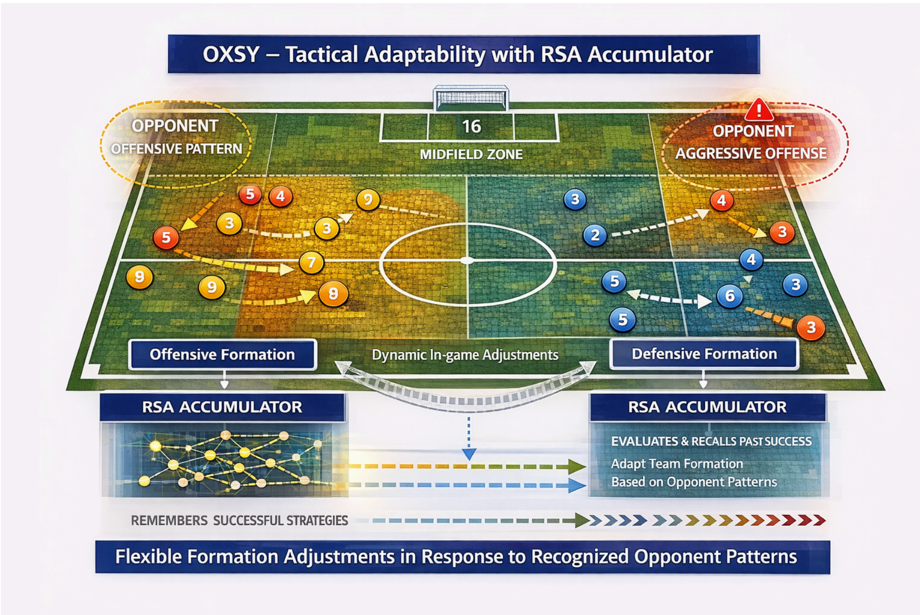

Fig. 3. *The image illustrates a strategic soccer AI decision-making system, highlighting tactical adaptability through an RSA accumulator framework. Formations and player positions shift dynamically within zones, with arrows indicating real-time adjustments and decision-making points as the game progresses.*

5 Future work

For the future, we aim to further strengthen our strategic framework by advancing both defensive and offensive capabilities. On the defensive side, we will refine offside traps, improve coverage mechanisms and enhance marking strategies through more accurate AI-based opponent behavior prediction. Offensively, we will develop more complex passing combinations and structured attacking patterns, while extending the decision-making autonomy of individual players to enable more sophisticated choices when in possession of the ball. We will also expand the integration of advanced neural networks to increase player adaptability, supporting real-time learning and dynamic tactical adjustments as the game evolves. The long-term direction of the Oxsy team centers on the continuous development of multi-agent systems [9], enabling seamless coordination, autonomous execution of complex strategies and dynamic role adaptation based on the current state of play.

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