OXSY 2025 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 [2], Oxsy has participated in almost every RoboCup 2D Soccer Simulation League competition [3]. 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 [5], strategy and AI-based decision-making systems, placing great emphasis on adaptability in both offensive and defensive phases. With 20 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 Adaptive Strategy with Neural Networks

Oxsy leverages adaptive strategies based on neural networks to continuously improve player decision-making and overall team performance. In this section, we explore the integration of neural networks into the team's tactical framework and how they contribute to real-time decision-making in both offensive and defensive phases.

2.1 Neural Networks for Offensive Strategy

Neural networks are used to evaluate a range of options during offensive plays, particularly in determining the best next action, whether to pass, dribble, or shoot. The neural network model processes real-time data from the match, including:

- Player positions
- Opponent movements
- Ball trajectory
- The current game phase

By analyzing these inputs, the neural network predicts the most effective action to take in any given situation. This approach ensures that the players are constantly making informed decisions, improving the likelihood of scoring.

2.2 Neural Networks for Defensive Adaptation

In defensive phases, neural networks are used to predict opponent strategies and adjust the team's defensive formation accordingly. By analyzing patterns in the opponent's movements, the network helps anticipate where the ball will go and how the opponents are likely to attack.

For instance, if an opponent consistently pushes forward through the wings, the neural network can adapt the defensive structure to apply more pressure in those areas. Additionally, the system helps identify opportunities for counter-attacks by analyzing spaces left open by the opponent's offensive plays.

2.3 Future Developments in Neural Networks for the Oxsy Team

Looking ahead, the Oxsy team plans to enhance its neural network capabilities by incorporating more sophisticated machine learning [4] techniques. This includes:

Deep Reinforcement Learning: A more advanced version of reinforcement learning that will allow the system to make even more nuanced decisions.

Meta-Learning: Allowing the network to adapt faster by learning how to learn, further reducing the time it takes to adjust to new opponents and strategies.

These developments will make the Oxsy team's strategy even more dynamic, ensuring that the team remains competitive in future RoboCup competitions.

Fig. 1. *Illustration of a neural network system analyzing player positions, ball trajectories and opponent movements to inform real-time decision-making, optimizing soccer strategies for both offensive and defensive scenarios.*

3 AI Learning Mechanisms and Neural Networks in the Oxsy Team

The Oxsy team utilizes advanced AI learning [4] mechanisms, including neural networks and reinforcement learning, to continuously improve its team's performance in RoboCup competitions. These systems allow players to learn from past matches, refine their strategies and adapt to new opponents in real time.

3.1 Reinforcement Learning for Soccer Strategies

Reinforcement learning (RL) is one of the core AI methodologies used by the Oxsy team. In RL, agents (players) learn optimal strategies by interacting with their environment and receiving feedback in the form of rewards or penalties. The goal is to maximize cumulative rewards over time.

3.2 Neural Networks for Decision-Making

Neural networks are employed to enhance the decision-making capabilities of Oxsy's players. These networks enable the players to recognize complex patterns in the game, such as predicting opponent movements or identifying the best passing options.

Input Layer: The input layer receives information from the environment, such as player positions, ball location and game phase (offense, defense, or transition).

Hidden Layers: The hidden layers process this information, allowing the neural network to learn abstract representations of the game dynamics.

Output Layer: The output layer generates a decision, such as selecting the best action (pass, shoot, or dribble) based on the current game state.

The architecture is designed to be highly flexible, allowing it to process a wide variety of game scenarios in real-time. This flexibility is crucial for adapting to the constantly changing dynamics of a soccer match.

3.3 Learning from Opponents: Adversarial Networks

Oxsy incorporates adversarial learning to improve its ability to predict and counteract opponent strategies. In this approach, two neural networks, one representing Oxsy and the other representing the opponent, have to compete against each other. This helps the system learn how to adjust its tactics dynamically based on the opponent's behavior.

Opponent Modeling: By training against an adversarial network, Oxsy can develop a more accurate model of its opponents, learning their tendencies and weaknesses.

Dynamic Adaptation: As the opponent's strategy evolves, Oxsy can adapt its own strategy in real time, ensuring that it remains competitive throughout the match.

3.4 Self-Organizing Maps for Player Positioning

To optimize player positioning on the field, Oxsy uses self-organizing maps (SOMs). SOMs allow the system to identify ideal positions based on the current game state, such as the location of the ball and the positions of both teammates and opponents.

Zone Allocation: Players are assigned to different zones on the field based on the SOM, ensuring that the team maintains optimal spacing and coverage.

Positional Awareness: SOMs help players anticipate where they should move next, improving the team's overall coordination and reducing gaps in defense.

3.5 AI Coordination: Multi-Agent Learning

Oxsy's players must not only make individual decisions but also coordinate with one another. Multi-agent learning [1] allows the system to train players to work together, improving the team's overall performance.

Shared Objectives: Each player learns to balance their own objectives (e.g., scoring goals) with the team's objectives (e.g., maintaining possession or defending).

Collaborative Strategies: Multi-agent learning enables players to develop collaborative strategies, such as executing coordinated pressing [7] or setting up complex passing sequences.

3.6 Enhancing Tactical Flexibility with Neural Networks

Oxsy's neural networks are designed to allow for greater tactical flexibility. This means that the team can shift between different strategies based on the current game situation. For example, the system can automatically adjust its formation from a defensive setup to an aggressive counter-attack [6] depending on the flow of the match.

Tactical Awareness: Neural networks analyze the state of the game in real time, allowing players to make adjustments on the fly.

Adaptive Formations: By analyzing data from past matches, Oxsy can predict when it should switch formations or make other tactical adjustments.

3.7 Future Work in AI Learning

Looking ahead, Oxsy plans to enhance its AI learning mechanisms by:

Expanding Neural Network Capabilities: Introducing deeper neural networks to handle more complex decision-making processes.

Improving Multi-Agent Coordination: Refining how players collaborate, particularly in high-pressure situations such as counter-attacks or defending set-pieces.

Incorporating New Learning Algorithms: Exploring new reinforcement learning and neural network algorithms to improve the team's adaptability and intelligence.

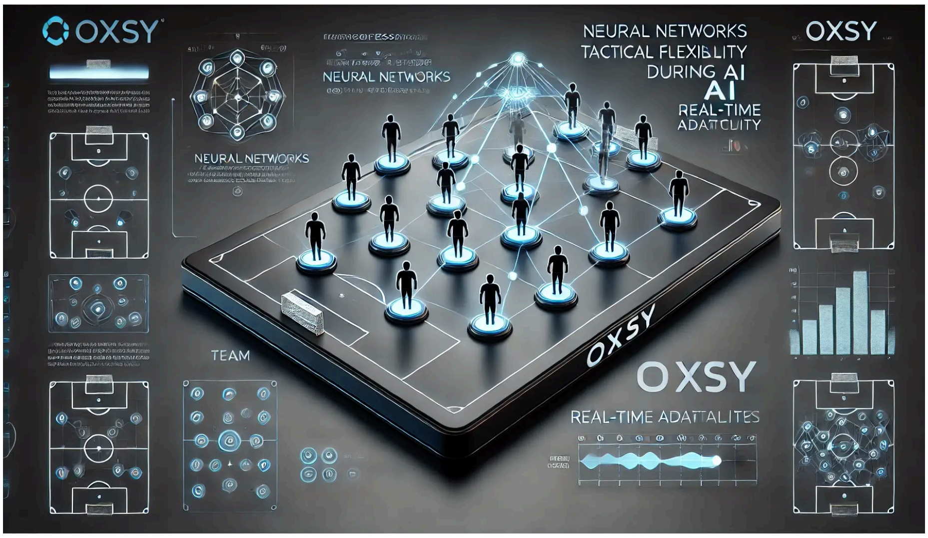

Fig. 2. *A diagram showing how neural networks enable tactical flexibility, allowing Oxsy to adapt formations and strategies during a match.*

4 Future work

For the future, we aim to continue enhancing our strategies, focusing on both offensive and defensive phases. We plan to expand the role of the coach, integrating advanced AI techniques to enable real-time decision-making and adaptations during gameplay. We will explore the integration of more advanced neural networks to enhance player adaptability. These networks will allow for real-time learning and strategy adaptation based on the evolving game situation. The future of the Oxsy team lies in the continuous development of multi-agent systems [1], allowing players to coordinate seamlessly and execute complex strategies autonomously. These systems will become increasingly dynamic, enabling each agent to adapt its role based on the game's state.

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