HELIOS2024: Team Description Paper

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Abstract. This team description paper presents an overview of previous work and recent research topics of Team HELIOS2024. This year, we enhanced the online opponent formation identification, which our team had previously implemented. The primary contribution involves accelerating computations through the introduction of tile coding.
This paper describes one of our recent efforts, the enhancement of opponent identification.

1 Introduction

Team HELIOS has participated in the RoboCup competitions since 2000, and has won six championships [3,5,7,8]. The team has always succeeded in being among the top four teams since 2005.

One of our recent research focuses is on the adaptation of team tactics in soccer games. This involves adjusting both the team strategy and players' behaviors based on the opponent's tactics, which is a crucial task for improving the chances of winning. The contribution outlined in this paper involves the application of tile coding to enhance the opponent identification method, a technique previously implemented by our team. The primary goal of this extension is to boost computational efficiency and streamline operations with fewer computational resources.

2 Previous Works

We have made some of our team's source codes and debugging tools available to assist new teams in participating in the competitions [4]. Currently, the released source codes can be accessed on our project site[3]. We have introduced two crucial methods for building a (simulated) robotic soccer team: a formation model employing triangulation [1] and a framework for action sequence planning [2]. These

[3] `https://github.com/helios-base` (Please cite [4] when utilizing the codes from this site in your publications.)

methodologies have been integrated into the released source codes, facilitating the seamless development of a functional simulated soccer team.

We are endeavoring to implement machine-learning techniques for enhancing players' behavior and team tactics. Our recent contributions primarily concentrate on refining the value function for evaluating both state and action during the planning process [11,6]. Furthermore, we are actively engaged in modeling the tactics of the opponent teams. Our objective is to develop a methodology for discerning the characteristics of the opponent team during a game and dynamically adjusting our team's tactics accordingly. Currently, we have implemented a technique that utilizes Support Vector Machine for identifying opponent team formations, and this is being applied in practical scenarios [10].

3 Enhancement of Opponent Formation Identification

Opponent modeling stands out as an essential task in soccer [12]. Understanding the tactics employed by the opponent team is crucial for adapting the tactics of our own team. As a vital component reflecting a team's cooperative behavior, the tactical arrangement of players, specifically the team formation, is considered the foundational element characterizing a team's behavior. The classification and identification of team formations remain challenging [14]. Presently, we employ SVM for real-time identification of team formations. However, in dynamic games like soccer, where there's no room for prolonged computations, the challenge lies in minimizing the computational resource overhead.

3.1 Basic Data Extraction and Classification Model

If we directly use the coordinate values of players' positions as inputs for the learning model, considering players' uniform numbers becomes necessary, posing a challenge in maintaining the order of players during the learning process. To address this, we express the opponent formation numerically by discretizing the soccer field into a grid (Fig. 1). Each cell's value, representing player count, serves as input for the learning model. These values depict the number of opponent players in a specific cycle, and the results are integrated. The average value is then computed by dividing the accumulated integration by the observed cycles. This set of average values constitutes input data for our classification model. For example, with a 6×4 grid, the opponent formation is represented by a 24-dimensional vector.

We utilized a clustering method to analyze typical formations, employing the Gaussian Mixture Model for this purpose. Subsequently, training data were labeled based on the resulting clusters, and these labeled data were used to train the identification model. At present, our classification model of choice for practical use is a support vector machine with a linear kernel [9].

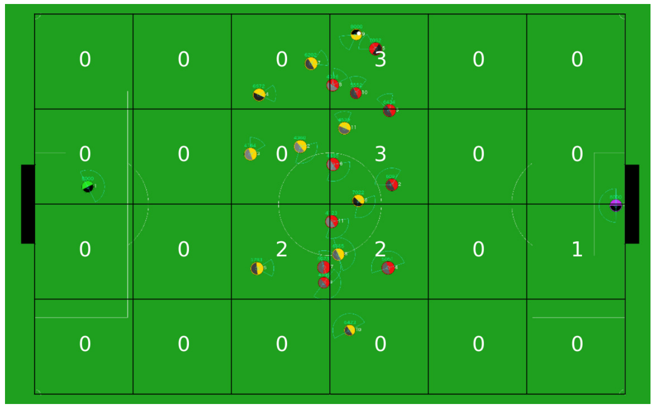

Fig. 1. Example of soccer field discretization using a grid of size 6×4.

3.2 Feature Representation using Tile Coding

The discretization of a soccer field using a grid is effective for handling a group of players without considering their uniform numbers. However, the prediction accuracy depends on the grid's resolution. While higher resolution may yield better predictions, it demands more computational resources and may cause overfitting. To address this problem, we introduce Tile Coding, a well-known state representation method in traditional Reinforcement Learning [13].

Figure 2 illustrates an example of field discretization using tile coding. Lower resolution for each tiling exponentially reduces the demand for computational resources. The linear combination of these tilings is employed as the system output, aiming to maintain prediction accuracy while reducing computational resource requirements for the entire system.

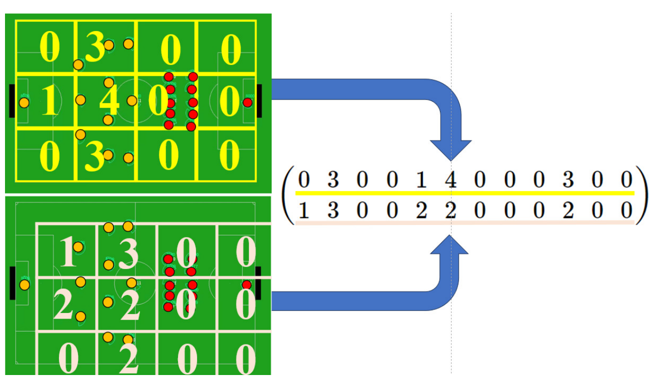

Fig. 2. Example of a soccer field discretization using tile coding. Each tiling in this example is a 4×3 grid.

3.3 Experiment

We conducted a preliminary experiment to assess the accuracy and computational time of the predictions. The primary objective of this experiment is to identify specific team formations. We prepared data for four distinct teams, labeled as A, B, C, and D, generating logs from 200 matches. We focused on cycles where the ball resided in the opponent's two-thirds of the field. As the learning model, we employed a support vector machine with a linear kernel. The feature set included tile counts 5×4 multiplied by the tiling count of 15, in addition to the ball's position represented by (x, y) coordinates, resulting in a total of 302 dimensions. To assess the effectiveness of our approach, we prepared a comparative dataset that uses coordinate values with ordered uniform numbers. Furthermore, we utilized 20% of A&D as our test data. The experimental environment was implemented using Python.

Table 1 and 2 show the computational time results for prediction based on two types of inputs. These results indicate the accuracy achieved with tile coding features is comparable to that of direct coordinate values with ordered uniform numbers, while the computational cost remains very similar.

Table 1. Result: coordinate values are used directly as input.

Training Data	Accuracy	Computational Time for Prediction(ms)
A&B	0.5914	0.2403
A&C	0.5732	0.2389
A&D	0.9846	0.2312
A&B&C&D	0.8941	0.3092

Table 2. Result: tile coding is used as input.

Training Data	Accuracy	Computational Time for Prediction(ms)
A&B	0.5914	0.2510
A&C	0.5732	0.2736
A&D	0.9652	0.3311
A&B&C&D	0.9131	0.2936

4 Conclusion

In this paper, we briefly introduced the enhancement of our opponent formation identification. We introduced tile coding to represent feature vectors, aiming to reduce the computational cost of classifying the opponent team formation. The experimental results demonstrate that our approach achieves practical performance in identifying the opponent team. Our future work is to improve the accuracy of identification while maintaining the computational cost.

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