HELIOS2025: Team Description Paper

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Abstract. This paper presents an overview of the previous work and recent research efforts of Team HELIOS2025, a leading team in RoboCup competitions. This year, we focus on the trajectory prediction task using Long Short-Term Memory (LSTM) networks. The model predicts the future positions of both players and the ball based on game logs from 1,000 matches between HELIOS2022, the RoboCup 2022 champion team, and HELIOS Base, a publicly available sample team. The dataset comprises 12,197 sets of ball and player trajectories, which were divided into training and test sets. Our LSTM model accurately predicted one cycle ahead, with a mean squared error (MSE) consistently below 0.1. The trained LSTM model successfully captured the dynamics of ball and player movements, showing promising results under typical conditions. However, the accuracy of the model decreased when the ball's direction changed suddenly. In this paper, we also discuss the potential to extend the model to predict multiple cycles ahead, as well as strategies for improving its robustness to rapid changes in movement. This study contributes to the development of more accurate trajectory prediction models for simulated soccer, which have applications not only in RoboCup competitions but also in real-world human behavior analysis, such as sports tactics and autonomous systems.

1 Introduction

Team HELIOS has been participating in the RoboCup competitions since 2000, and has won seven championships [2,3,4], achieving three consecutive victories since 2022. The team has consistently ranked among the top four teams since 2005.

One of our recent research studies focuses on creating machine learning benchmark tasks using game logs generated by the simulator, particularly on trajectory prediction tasks. Trajectory prediction is expected to facilitate the development of techniques for studying real-world human behavior and to foster collaboration between simulation and reality.

2 Previous Works

We have publicly made some of our team's source code and debugging tools available to assist new teams in participating in the competitions [1]. Currently, the released source code is accessible on our project site[3]. We have also worked on the generation of datasets using simulated soccer. The development of tools for data generation is an ongoing process, and several datasets have already been published [5][4]. Additionally, we are planning and organizing a competition utilizing these datasets[5].

3 Trajectory Prediction

In real-world soccer, players implicitly or explicitly predict the movements of both the ball and opponents during games, formulating effective attacking and defensive strategies. Simulated soccer requires a similar level of predictive accuracy as real-world soccer, which leads to optimal action selection. In RoboCup 2025, the Soccer Simulation 2D League will hold a trajectory prediction challenge competition. Our team is expected to participate in the competition. Thus, preparations are being made, such as predicting the trajectories of players and teams using game logs generated by the simulator.

3.1 Trajectory Prediction using LSTM

We have explored a method that employs Long Short-Term Memory (LSTM) to predict the ball's and players' trajectories, focusing on attacking maneuvers that lead to goal-scoring opportunities.

LSTM is a type of Recurrent Neural Network (RNN) that is well-suited for processing time-series data. Time-series data analysis requires consideration of temporal dependencies; therefore, LSTMs are often used alongside linear regression models and moving average methods, as they can capture long-term dependencies. LSTM incorporates a three-gate structure (forget gate, input gate, and output gate) and context vectors, enabling selective retention of past information and preserving long-term dependencies. The trajectories of the ball and players in the 2D competition are also time-series data and can be effectively analyzed using LSTM.

The input values correspond to the ball's and players' coordinates over the previous five cycles, including the current cycle. In contrast, the output values represent the predicted coordinates of the ball and players for n cycles ahead. As shown in Figure 1, the predicted coordinates of the ball and players, obtained as output, are iteratively used to make predictions for multiple future cycles. "Init Input" represents the initial input value, and the number within each circle

[3] `https://github.com/helios-base` (Please cite [1] when using the code from this site in your publications.)
[4] `https://github.com/hidehisaakiyama/RoboCup2D-data/`
[5] `https://sites.google.com/view/stp-challenge/`

denotes the time frame. "Pred n" represents the predicted coordinates n cycles ahead.

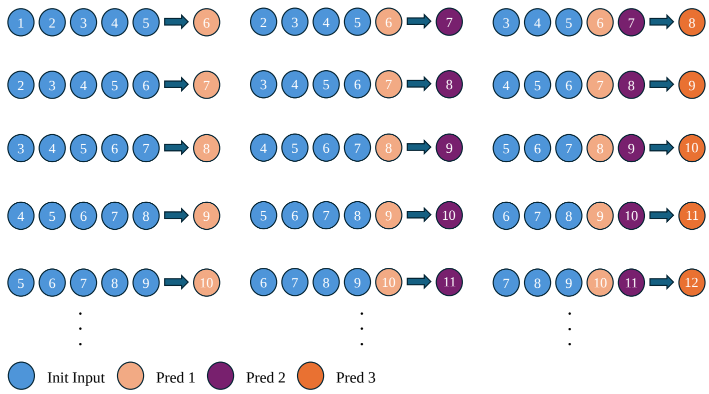

Fig. 1: Prediction model using LSTM.

3.2 Experimental Setup

LSTM Setup We implemented the LSTM model using `torch.nn.LSTM` class in PyTorch. The configuration of the employed LSTM model is summarized in Table 1. The input consists of the ball's and players' coordinates over five cycles, as described in Section 3.1. Consequently, the input dimension is 230, calculated as follows:

$$23 \text{ (ball and players)} \times 2(x \text{ and } y) \times 5 \text{ (cycles)} = 230. \quad (1)$$

Table 1: The configuration of torch.nn.LSTM.

Parameter Name	Value
input_size	230
hidden_size	256
num_layers	1
bias	True
batch_first	True
dropout	0
bidirectional	False
proj_size	0

The output is obtained through a fully connected (FC) layer, as illustrated in Figure 2. The predicted coordinates of the ball and players form a 46-dimensional output where the dimensionality is calculated as follows:

$$23 \text{ (ball and players)} \times 2(x \text{ and } y) = 46. \tag{2}$$

The batch size is set as 64, the number of epochs to 500, and the optimizer used is Adam with a learning rate of 0.001.

The model is trained using the Mean Squared Error (MSE) loss function, which measures the discrepancy between the target and the predicted coordinates of the ball and players one cycle ahead. The MSE is computed as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} |x_i - \hat{x}_i|^2 \tag{3}$$

where x_i denotes the ground-truth coordinate vector of the i-th ball or player, $\hat{x}_i$ represents the predicted coordinates, and N is the total number of predicted elements.

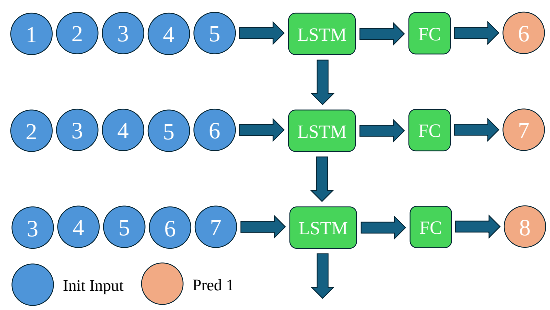

Fig. 2: Output from LSTM.

Dataset We used data from 1,000 games between HELIOS2022 and HELIOS Base. HELIOS2022 was the champion team of RoboCup 2022, while HELIOS Base is a publicly available sample team. The scoring scenes of HELIOS2022 were extracted from the game log files, resulting in a total of 12,197 sets of ball and player trajectory data. Of these, 8,537 sets (70%) were used for training, and 3,660 sets (30%) were used for testing. Each trajectory data set contains the coordinates of up to 50 balls and players leading up to a scoring event.

3.3 Results

Figure 3 illustrates the learning curve for each epoch based on the MSE metric. The MSE consistently remains below 0.1, indicating high prediction accuracy for one cycle ahead. As training progresses, the MSE for the test data converges to a value close to that of the training data.

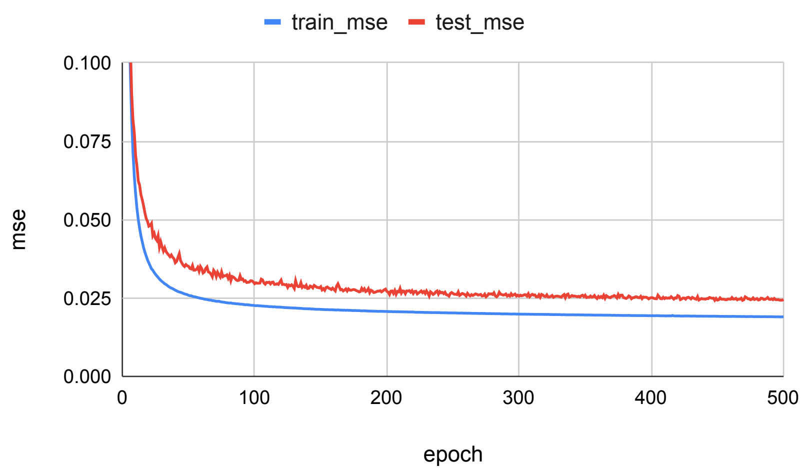

Fig. 3: MSE of the predicted and actual coordinates at each epoch. `train_mse` represents the MSE for the training data, while `test_mse` represents the MSE for the test data.

To evaluate the accuracy of trajectory predictions n cycles ahead, we conducted a new match between HELIOS2022 and HELIOS Base, from which 17 sets of trajectory data were collected. Figure 6 presents the predicted and actual ball trajectories for one of these 17 sets. The results indicate that deviations between the predicted and actual trajectories become more pronounced when the ball changes direction.

4 Conclusion

We proposed an LSTM-based trajectory prediction model for the RoboCup Soccer Simulation and evaluated its accuracy. Using data from 1,000 matches between HELIOS2022 and HELIOS Base, we trained an LSTM model to predict ball and player positions one cycle ahead. The experimental results demonstrated that the model achieves high prediction accuracy, with the mean squared error (MSE) consistently remaining below 0.1.

Further evaluation using newly collected game data revealed that the model performs well under normal movement conditions but exhibits deviations when the ball changes direction. These results highlight the model's effectiveness in trajectory prediction while also indicating potential areas for improvement, such as enhancing robustness to sudden movement changes.

In future work, we plan to extend the prediction horizon beyond one cycle and explore techniques to improve accuracy in scenarios involving rapid direction changes. Additionally, incorporating more sophisticated recurrent architectures or attention mechanisms could further enhance the model's performance.

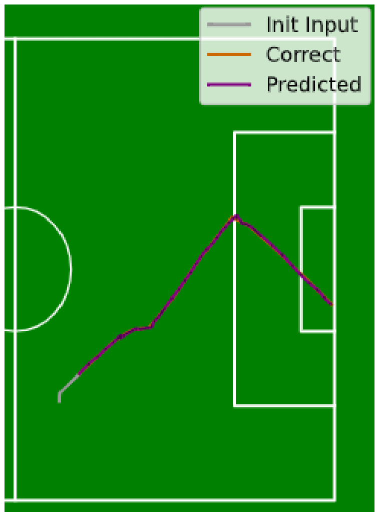

Fig. 4: Pred 1

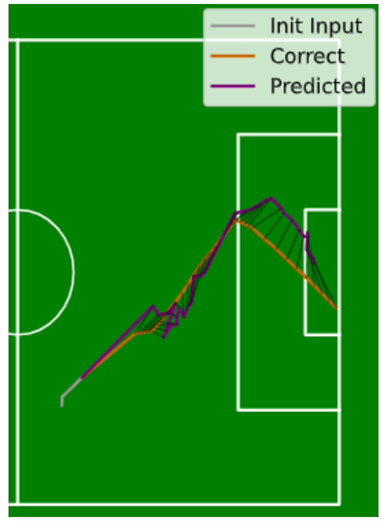

Fig. 5: Pred 10

Fig. 6: Ball trajectory prediction results for 1 cycle and 10 cycles ahead.

References

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