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Position Prediction of Opponent Players by SIRMs Fuzzy Models for RoboCup Soccer 2D Simulation

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***Abstract* — In RoboCup soccer, it is important to appropriately react to the movement of the opponent players. Particularly in the situation of one-to-one defense, predicting how the opponent player moves necessary because the player facing the opponent player is the only one who handles the defense situation. In this paper, we propose a prediction technique of the position of the opponent player in the one-to-one defense situation using SIRMs fuzzy models in the RoboCup soccer simulation 2D league. By conducting a series of computational experiments, we investigate the prediction accuracy of the SIRMs fuzzy models that are trained using a training set. The training set contains the input field state vector along with its corresponding target signal. The trained SIRMs fuzzy models are used in one-to-one defense during the soccer games.**

Keywords — RoboCup soccer, SIRMs fuzzy model, machine learning, decision making

I. Introduction

RoboCup [1] is known as inter-discipline international research project that involves robotics and artificial intelligence. This research projects comprises a number of leagues where different platforms and different robot models are employed. The final goal of soccer leagues is to beat human soccer champion team by the year 2050. To this aim, the developers of participating teams have been working hard to win the competition that is held every year. In order to win the soccer game, it is important for the team to perform appropriate defense against the attack by the enemy team. Particularly, one-to-one defense is one of the frequent scenes in defending situation. The performance level of the defending action is the key to win the soccer game.

The conventional approach for developing teams is manual implementation of the behavior of the soccer players. Then the behavior is fine-tuned by iteratively modifying the parameters (or magic numbers) involved in the hand-coded programs. Therefore, it is difficult to find the optimal parameters for those behavior. In addition, the performance of one-to-one such defense depends on the opponent attacking players. In the hand-coded programming, it is necessary to prepare a set of such behavior parameters for all opponent teams. This process is time-consuming and in many cases such appropriate parameters were not found before the game. In this paper, we overcome this issue by predicting the action of the opponent attacking player so that the behavior would not be too specialized to a particular opponent team but adaptively change according to the movement of the opponent players. For example, Gabel et al. [2] proposed a method called Neuro Hassle to improve the defense action by iteratively perform the one-to-one defense and automatically adapt the parameters of the behavior.

This paper proposes a method for position prediction of opponent attacking players using Single Input Rule Modules (SIRMs) fuzzy model [3]. This prediction method is applied to one-to-one defense. Accurate position prediction of the opponent players facilitates the appropriate action decision of the defense players. The SIRMs fuzzy models are trained from a given set of training data. The training data consists of the field situation along with the actual position of the opponent player at a certain specified time. Through a series of computational experiments, the position prediction by the SIRMs fuzzy model is performed to investigate its prediction accuracy. In addition, further investigation is made to evaluate the defense performance using the predicted position by the trained SIRMs fuzzy models. The predicted position is changed in termed of the predicted time step for evaluating the defense performance. The results of the computational experiments show the effectiveness of the proposed method.

II. RoboCup

A. RoboCup Soccer

RoboCup is a research project that involves various topics such as robotics and artificial intelligence. Soccer robots,

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rescue robots, and home robots are the main subjects of the project. The aim of RoboCup soccer is to develop the autonomous robot that beats the human world champion team of soccer by the year 2050. The researchers in the project have been working hard toward this aim. There are junior leagues for upbringing next-generation robot engineers in the field of soccer, rescue, and dance. This paper focuses on the RoboCup soccer simulation leagues.

B. RoboCup Soccer Simulation 2d League

The soccer simulation is composed of two sub-leagues: 2D league and 3D league. They are different in the way the soccer agents are modeled. Figures 1 and 2 show the screenshots of the 2D league and the 3D league. We focus on the 2D league in this paper. In the 2D league, primitive actions such as kick, dash, and turn are implemented as command so that the developers do not have to build the primitive actions from scratch and are able to concentrate on high-level decision making in the development of soccer agents.

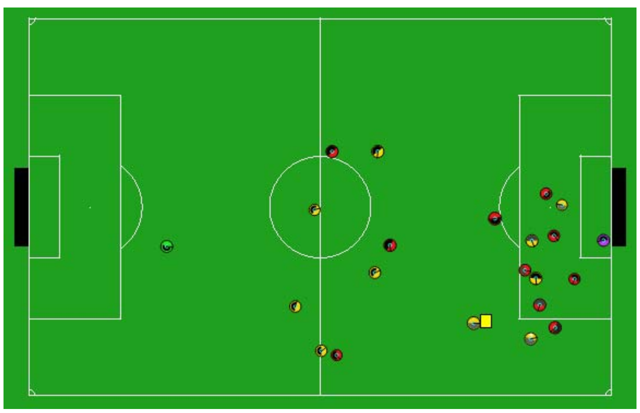

Fig. 1. Soccer 2D simulation league.

Fig. 2. Soccer 3D simulation league.

The simulation 2D league is one of the oldest leagues existing from the beginning of RoboCup project. A two-dimensional plane is prepared in a computer as the virtual soccer field where simulated soccer robots (not real robots) play a soccer game. The soccer robots are modeled as a circle with an extra circle that shows its “kickable area”. Thus, the position and the speed of the soccer robots and the ball are expressed as two-dimensional vectors. In the 2D league, the low-level actions such as kick, dash, turn are implemented within a soccer server and can be invoked by abstracted commands. The soccer game consists of two 3,000-cycle halves (6,000 cycles in total for one game). The time in the game is discretely simulated, time cycle is counted every 0.1 second. The soccer players and the coach are independent program from each other. Sensory information about the soccer field is sent to each player and the coach. The visual information is based on observable objects within the visual cone of a soccer player. Aural information is also available. Any players are allowed to send messages that are broadcast in the soccer field. The soccer players are required to determine the next action to do at the next cycle based on the visual and the aural information. However, a noise is added in the information before they are sent to the soccer players and the coaches. Furthermore, the visual information becomes vague for the players positioning at a distant. The aural information is not sent to the remote players from the one broadcasting a message. Therefore, it is not possible for the players to maintain the correct information on the field in real time.

C. Defense against Dribbles

One-to-one defense is defined as a situation where the opponent player holds the ball and the teammate player is stopping the advancement of the opponent ball. An example of the one-to-one situation is shown in Fig. 3. In Fig. 3, there is only one teammate player who takes care the opponent ball holder and the other teammate players are not participating in this action but marking opponent players for marking. The important thing for the teammate player in the one-to-one defense situation is to prevent the opponent ball holder from dribbling forward and pass through the defending teammate player. It is also important not to let the opponent player kick the ball to pass to another opponent player. Thus, the defending teammate player must get the ball from the opponent player or clear the ball. Especially, the prevention of dribble by the opponent player is the most important point in the one-to-one defense.

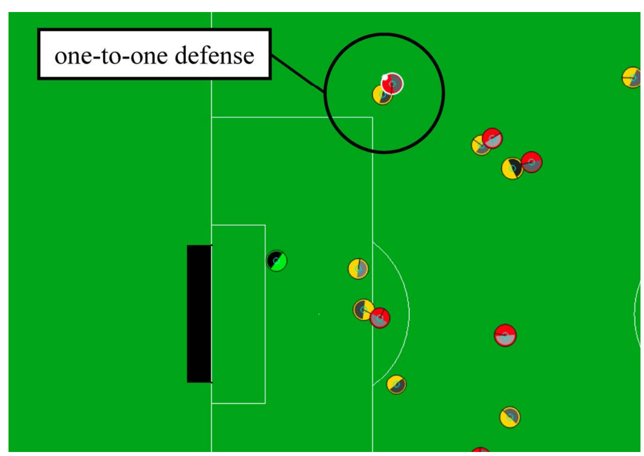

Fig. 3. One-to-one defense.

Our defense behavior has been implemented on the base of the knowledge of the programmer. The defense behavior needs to have the target point. The current target point is manually calculated. This is the main point for improving the behavior. That is, if the predicted point of the attacking opponent player is precisely calculated and set as the target point in the defense behavior, the defending performance would be better. This paper proposes to employ Single-Input Rule Modules (SIRMs) fuzzy models [3] for predicting the position of the attacking player.

III. Proposed Method

A. SIRMs Fuzzy Model

A single-input-rule modules (SIRMs) fuzzy model [3] is one variation of fuzzy systems. The overview of the SIRMs fuzzy model is shown in Fig. 4. A rule module in the SIRMs fuzzy model corresponds to an input attribute in the given set of training patterns. Thus, a fuzzy if-then rule in a rule module has only one attribute in its antecedent part. Each rule module has a weight called the degree of importance. For an input vector, each rule module produces a real-value output. The weighted sum of the output values from all the rule modules is the final output value of the fuzzy model. The SIRMs fuzzy model is advantageous when there are many input attributes in the training patterns as the computational cost for the SIRMs fuzzy model is usually lower than the other fuzzy models without any performance degradation.

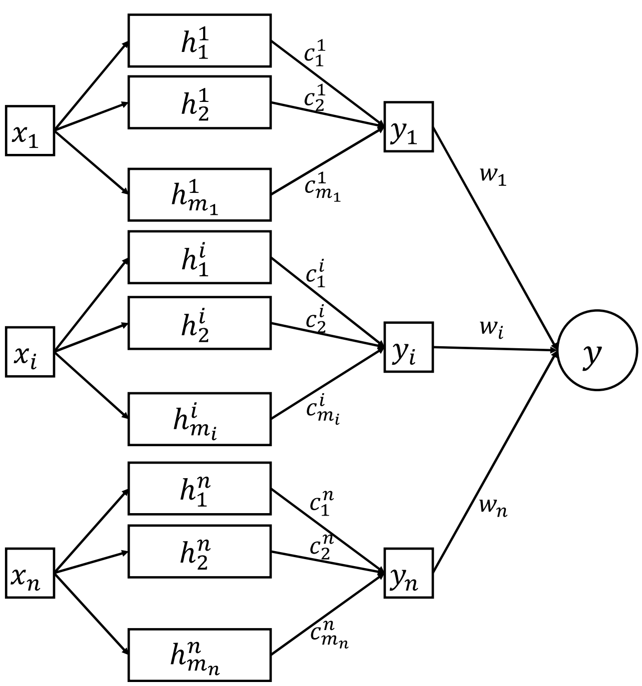

Fig. 4. Overview of an SIRMs fuzzy model

In Fig. 4, x_i ($i = 1, 2, \ldots, n$) is the i-th input attribute, y_i is the inference result from the i-th rule module, h_{ij} ($i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m_i$) is the compatibility of the antecedent part with the input vector, c_{ij} is the consequent real value of the fuzzy if-then rule, w_i is the degree of importance, and y is the final output of the SIRMs fuzzy model. Let us consider that we have an n-dimensional input real vector $\vec{x} = (x_1, x_2, \ldots, x_n)$. Then the following calculations are made for the input vector:

$$h_j^i = A_j^i(x_i), \tag{1}$$

$$y_i = \frac{\sum_{j=1}^{m_i} h_j^i \cdot c_j^i}{\sum_{j=1}^{m_i} h_j^i}, \tag{2}$$

where A_j^i ($i = 1, \ldots, n, j = 1, \ldots, m_i$) is the membership value of x_i for the j-th fuzzy if-then rule in the i-th rule module. The membership function is assumed to be a Gaussian function as follows:

$$A_j^i = \exp\left\{-\frac{(x_i - a_j^i)^2}{b_j^i}\right\}. \tag{3}$$

In the membership function in (3), a_j^i and b_j^i are the parameters of the Gaussian function. The final output y of the SIRMs fuzzy model is calculated by the weighted sum of the output from rule modules as follows:

$$y = \sum_{i=1}^{n} w_i \cdot y_i. \tag{4}$$

In this paper, the steepest descent method is used for the learning of the parameters of the SIRMs fuzzy model. The steepest descent is a technique to modify a model parameter so that the loss (i.e., the error between the true output and the model output) is minimized. The parameters to learn in an SIRMs fuzzy model are a_j^i, b_j^i, y_i, and w_i.

B. Prediction of Opponent Player Position

The position of the player is expressed in a two-dimensional real vector (i.e., x and y coordinates). Thus, two values are necessary for predicting the position of an opponent player. On the other hand, the SIRMs fuzzy model in its standard formulation has only one real output. Therefore, we prepare two SIRMs fuzzy models and learn the value of x coordinate and the y coordinate, respectively. The following 16 pieces of information are considered as the inputs for the SIRMs:

- Ball position (x_b, y_b) and velocity (v_{bx}, v_{by})
- Self-position (x_p, y_p) and velocity (v_{px}, v_{py})
- Opponent position (x_o, y_o) and velocity (v_{ox}, v_{oy})
- The nearest teammate position (x_s, y_s) and velocity (v_{sx}, v_{sy})

The above information is normalized into a unit interval [0, 1] using the minimum and the maximum limit of each variables before taken as input to the SIRMs fuzzy model.

Five Gaussian functions are initially arranged in the way any two neighbor functions intersect at the membership value of 0.5. The consequent real values of all fuzzy if-then rules are initialized to 0.0, and the initial value for w_i, $i = 1, \ldots, n$, are set to 0.25.

IV. Experiments

The SIRMs fuzzy models are trained using training data extracted from game logs. A series of computational experiments are conducted in this section to investigate the accuracy of SIRMs fuzzy models for predicting a dribbling opponent player. Then, the trained SIRMs fuzzy models are used in the defense behavior during a soccer game.

A. Evaluation of Position Prediction Accuracy

First, we investigate the prediction accuracy of a dribbling opponent player by the SIRMs fuzzy model. Training patterns for the SIRMs fuzzy model were obtained from 100 game-logs where teams HELIOS2015 and WrightEagle15 played. Both HELIOS2015 and WrightEagle15 are top teams in the recent RoboCup world tournaments. The 100 games were conducted using the binary files that were published after the 2015 competition. From the game logs, one-to-one situations are extracted to generate labeled patterns. The one-to-one situation is defined as the following:

- There is only one opponent player within a radius of five meters of the teammate player.
- The player who kicked the ball just before that is the target opponent player to be predicted.
- The ball is within a radius of less than five meters of the target opponent player.
- The teammate player who predicts the position of the target opponent player is nearest to the target opponent player.

Three versions of the target values are considered in the computational experiments of this section: the position of the target opponent player one, two or three, and five cycles later from the current time. After training the SIRMs fuzzy models, the prediction accuracy of the target opponent player is investigated using another 100 games that are different from the one for extracting training patterns. The average errors of the trained SIRMs fuzzy models are shown in Table 1.

TABLE I. AVERAGE PREDICTION ERRORS OF THE SIRMS FUZZY MODELS FOR EACH CYCLES

Prediction cycle	*1*	*2*	*3*	*5*
Average error (m)	0.6165	1.3105	2.4487	4.6011

From Table 1, it is observed that the prediction error becomes larger as the prediction cycles increases. This is because the prediction for far future states is more difficult than that for near future states.

B. Evaluation of Defense Performance

Next, the defense performance of the teammate players is investigated. The defense behavior first predicts the attacking opponent player using the trained SIRMs fuzzy models. For comparison purpose, the defense performance of the conventional players is also investigate where the position of the target opponent player is manually calculated using some developer's domain knowledge. The trained SIRMs fuzzy models are only employed by two side-back players as this position has the most number of defense chances during the games. The side-back players are shown in Fig. 5.

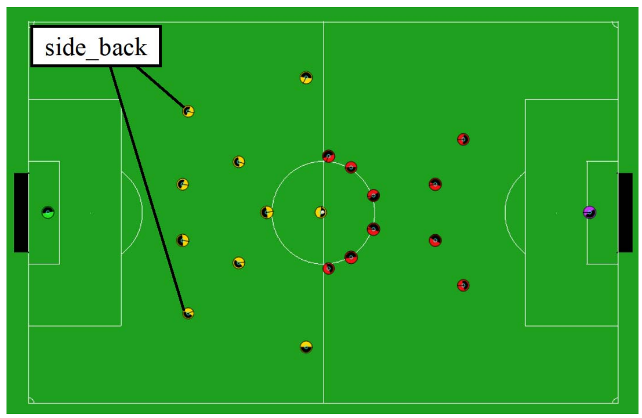

Fig. 5. Side-back players.

The defense performance is evaluated in terms of the following six criteria for the computational experiments in this subsection:

- **Pass**: The number of successful passes by the opponent players.
- **Advance with pass**: The number of times the ball was brought by more than five meters along the *x*-axis by the opponent players' passes.
- **Advance with dribble**: The number of times the ball was brought by more than 10 meters along the *x*-axis by the opponent players' dribbles.
- **Opponent setplay**: The number of opponent setplays as a result of the one-to-one defense.
- **Our setplay**: The number of self-team setplays as a result of the one-to-one defense.

- **Our kick**: The number of kicks by the defending teammate players.

Among the above criteria, advance with pass, advance with dribble, and opponent setplay are negative measure, which decreases as the performance of one-to-one defense is improved. On the other hand, the other three are positive performance measure and increasing them show the improvement of the one-to-one defense performance.

The computational experiments in this section investigate the performance of five teams: the conventional opuSCOM and opuSCOM with one-, two-, three-, and five-cycle prediction SIRMs fuzzy models. opuSCOM is the team that the authors have developed for RoboCup competitions. Each of the five opuSCOM teams played WrightEagle15 [5] a hundred times. WrightEagle15 is the champion team of the RoboCup soccer simulation 2D league in 2015. The results of the computational experiments are shown in Table 2.

TABLE II. DEFENSE PERFORMANCE OF OPUSCOM WITH/WITHOUT THE OPPONENT POSITION PREDICTION

	Predicted cycle				
	None	***1***	***2***	***3***	***5***
Pass	4899	4358	4201	4482	4252
Advance with pass	298	217	190	289	219
Advance with dribble	219	242	193	298	285
Opponent setplay	61	53	33	26	48
Our setplay	5	7	5	5	2
Our kick	24	23	32	11	25

From Table 2, we can see that the number of passes are decreased by introducing the prediction of the attacking opponent players. Especially, the number of passes is the smallest when the predicted cycle by the SIRMs fuzzy model is two. This suggests that there is an optimal cycle of prediction when it is applied to the defensive behavior. This is also the case for the other criterion except opponent setplay. The opponent setplay did not happen in the experiments and there is no significant difference for this measure comparing with the others.

One direction for improving the defense performance is to improve the accuracy of the position prediction by SIRMs fuzzy models. In order to increase the prediction accuracy, more training patterns should be generated from log data of more soccer games. This will be included in one of our future works.

V. CONCLUSIONS

In this paper, SIRMs fuzzy models are used to predict the position of the attacking opponents. The prediction performance of the trained SIRMs fuzzy models are investigated through a series of computational experiments. The trained SIRMs fuzzy models are used in the defensive behavior in one-to-one defensing situations. Another series of computational experiments were conducted to show the effectiveness of the opponent prediction. Future works include the refinement of the opponent prediction by increasing the size of training data. The proposed method should be also investigated using other opponent teams.

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