Decision-Making of Football Agents with Support Vector Machine

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Abstract: Robocup has attracted much attention for Artificial and Computational Intelligence researchers. Robocup involves various aspects of problems, i.e., cooperation with team mates, dynamic problems, imperfect information, uncertainties caused by noise, and so on. Therefore, it is quite difficult to design football agents. In this paper, Support Vector Machines, one of the most famous machine learning algorithms, are used to decide if the agents carry out basic skills, such as shoot and through balls, which are given in advance. That is, firstly, data, i.e., the position and directions of balls and players, is collected by playing given skills naively. Then, labels indicating the success/fault of the skills are added to the data. Secondly, SVM learns the data. Finally, the SVM decides if the skill should be carried out. Several experiments on game plays with stronger team binaries at Japan Open elucidate the effectiveness of the proposed method.

1. INTRODUCTION

Introducing new skills into football agent is a hard task. Such difficulty is composed of 1) the description of the skills, and 2) decision-making if the skills should be carried out. In this paper, support vector machines Bernhard [2002] are used to aid designer for making such skills. That is, agent designers firstly describe skills. Then, SVM learns situations where the skills should be used: Learning data is collected through games by using the designed skills with relaxed condition. Then, SVM learns player distribution which causes the skills are successful. After learning, learned SVM is used as decision-maker for the skills. That is, the skills will be activated if SVM predicts the skills will be successful.

2. ROBOCUP SOCCER SIMULATION

There are several Robocup Soccer leagues Nakashima [2006]. Simulation league is the oldest one and is one and only simulation-based league, i.e., other league uses robots. The team consists of 12 agents (11 players and coach). In robocup soccer simulator, the following commands can be used by each player.

kick: kick a ball to any directions.
dash: player runs toward the body direction.
turn: turn the body direction.
tackle: tackle to the ball

The size of the field is set to be 105m × 64m The coordination systems of the filed is depicted in Fig. 1. Own team takes the offense from the left half to the right half in this figure. The origin coordination of set to be the center of the field. 0 degree of the orientation is set to be from center to opponent goal. The orientation system is defined as counterclockwise.

3. PROPOSED METHOD

3.1 Overview

Agent 2D systems developed by Akiyama is used as a basic program of football teams in this paper Akiyama [2007]. Hence, additional mechanism proposed in this paper is developed for the agent2d. The proposed method is composed of two parts: Firstly, basic skills are designed in advance. Then, such skills are examined on games with several opponent teams. At that time, the state data and results of skills played are stored, where the state data of playing skill indicates the position and angle of players and the position of the ball and the results of skills played mean whether the skill played is of success or otherwise. Secondly, SVM learns situations which tend to become successful for playing skills. That is, the input part of

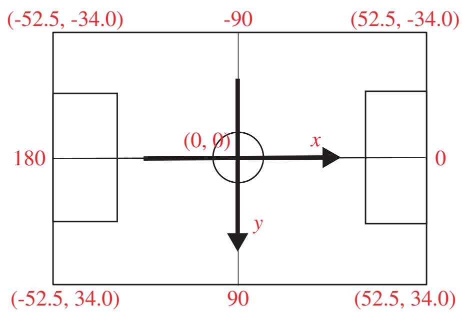

Fig. 1. The coordination systems of Robocup Soccer Simulation

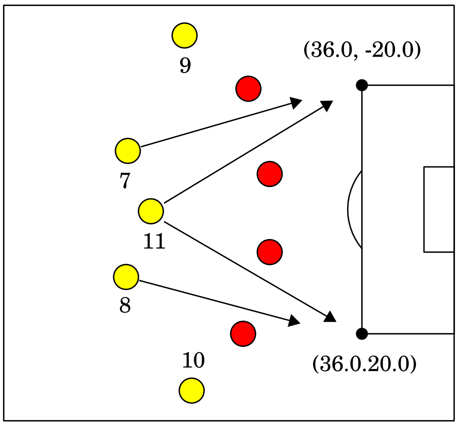

Fig. 2. A depiction of a through ball

learning data consists of the state data at playing skills mentioned above while the teacher part of learning data denotes corresponding results.

In this paper, two skills are implemented: through balls and shoots. The following two subsections explain these skills.

3.2 Through balls

Through balls are a sort of pass to back of opponents. They play crucial roles not only in robocup but also in human football games. In order to implement them easily, passer and receiver players are predefined. Two offensive midfielders and a center forward are played as passer. Two side forwards plays as receivers in this skill. For some couples of passer and receiver, SVM algorithms are associated. Hence, 4 SVM algorithms are prepared for couples of (right offensive midfielder, right side forward), (center forward, right side forward), (center forward, left side forward), and (left offensive midfielder, left side forward). These SVM algorithms separately learns with different learning data. In addition, Pass points are defined in advance: $(x, y) = (36.0, \pm 20.0)$. If y of passer is greater than 0, then the passer will kick a ball to $(36.0, 20.0)$. Otherwise, the passer will kick a ball to $(36.0, -20.0)$. The passer kick a through ball if potential receiver reaches at two meters short of the "offside line." Receivers, i.e., two side forwards, cope with either of two pass points. Receivers run to the pass point on the corresponding side if passer in the side holds a ball.

After SVM learning, the passer will kick a through ball if receivers reach at two meters short of the "offside line" and SVM predicts current input data may be able to be successful of the through ball.

3.3 Shoots

In original agent2d systems, shoot is made if it would be successful. That is, only in key situations, shoots are carried out. It is quite difficult to yield such situations so that there are few shoots by the agent2d systems. In order to improve it, decision-making for shoots is also learned by SVM. The basic skill for taking a shoot is defined as follows: Players take a shoot if a certain player is in the penalty area. The shoot point for this skill is predefined as depicted in Fig. 3: $(x, y) = (52.5, -6.5)$ if y of the position of the opponent keeper is greater than 0. Otherwise, the shoot point is defined at $(x, y) = (52.5, 6.5)$. This skill is implemented for two offensive midfielders and center forward. As in the through ball skill, Each player separately collects learning data on games and learns with SVM.

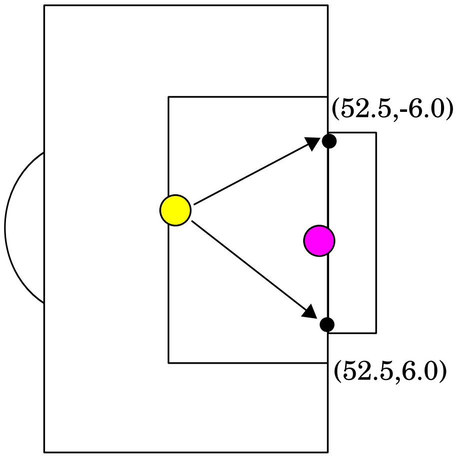

Fig. 3. Shoot points

4. EXPERIMENTS

4.1 Overview

Binary files for 5 different teams, which perform well at the Japan Open competition, are used as opponent teams. For each team, 50 games, i.e., totally 250 games, are carried out for collecting learning data. SVM learns this learning data. After learning, 25 games (5 game per a team) with SVM predictions are carried out the above manner in order to confirm the effectiveness of learning. The following subsections show the experimental results of the proposed method.

4.2 Through balls

First of all, we examined a through ball skill described in section 3.2. Two sets of input attributes are prepared as enumerated below:

(1) the position of ball (x_b, y_b), its velocity (v_x, v_y), the position of team member (x_i, y_i), whose uniform numbers are 6∼11, their body angles, the position of opponents (x_{oj}, y_{oj}), whose uniform numbers are 2∼10, and their body angles.
(2) the position of ball (x_b, y_b), its velocity (v_x, v_y), the position of passer (x_p, y_p) and receiver (x_r, y_r), their body angles, the position of 4 opponents (x_{oj}, y_{oj}) around the receiver, and their body angles.

The numbers of input attribute for the first and second sets are set to be 49 and 23.

Table 1 summarize experimental results for the different numbers of input attributes. Columns "failed," "succ.," "fieldout," and "No. pass" denote that "failed pass," "success of pass," "ball goes out of the field," and "the number of passes examined during 25 games," respectively. As we can see from this table, the SVM with 23 input attributes shows the best performance among them. the SVM with 49 input attributes seems to be conservative one since the total number of passes attempted was only 28 within 50 games.

Table 1. Experimental results for the different numbers of input attributes

	failed	succ.	fieldout	No. pass
unlearn	81.8%	9.1%	9.0%	132
learn w. 49 attr.	75.5%	13.0%	11.4%	28
learn w. 23 attr.	66.7%	20.8%	12.4%	95

4.3 Further analysis of failed situations

In this section, failed cases in the previous section are analyzed since the SVM with 23 input attributes still have higher failed rate (66.7%). The main reasons of this are 1) the affection of noise, i.e., players cannot always kick a ball precisely as in real football players, and 2). Therefore, "failed" situation is redefined, and new situation "intercepted" is added as depicted in Fig. 4:

intercepted: balls are directory passed to opponent players.

turnover: through balls are successfully kicked while no receivers can touch the balls.

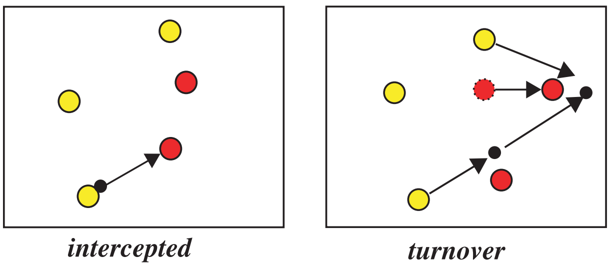

Fig. 4. Depiction of two failed situation: "intercepted"– direct pass to opponents (LEFT); "turnover" – thorough balls are caught by opponents (RIGHT).

25 games are carried out by using these new classification labels. Table 2 show the experimental results. As shown in this table, by using SVM, the ratio of direct pass to opponents, i.e., intercepted, is decreased. On the contrary, turnover is increased. This means that SVM helps passer to pass through the faced opponent players.

4.4 Experiments on Shoots

In this subsection, decision-making for kicking shoot described in section 3.3 is examined. 25 games (5 games per opponent team, 5 teams) are carried out for comparing the proposed method (SVM for through balls and for shoot) with original agent 2d systems. Tables 3 and 4 show the experimental results for the original agent 2D systems and the proposed method with shoot SVM, respectively. Numbers in the tables are denoted by sum of 5 games. These 5 opponent teams are so strong that there is no chance to goal for original agent 2D systems. On the other hand, the proposed method score several goals while it is still defeated by four opponent teams. The proposed method could defeat team E. The number of goal scored by opponent teams is decreased by using SVM for through balls and shoots.

Table 3. Experimental results by original agent 2D systems

team	A	B	C	D	E
Goals for	0	0	0	0	0
Goals against	10	9	11	11	1

Table 4. Experimental results by the proposed method

team	A	B	C	D	E
Goals for	0	1	0	1	7
Goals against	4	6	7	4	0

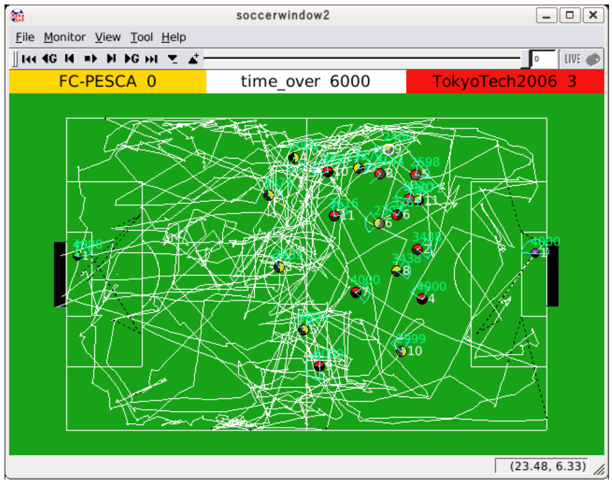

Fig. 5. Ball trajectories for original agent 2D systems

4.5 Game analysis with overhead view of fields

Tables in the previous subsections show some interesting results: The proposed method is designed for effective offense, i.e., through passes and shoots. However, the number of goals scored by the opponent teams is decreased by using the proposed method. Hence, in this subsection, in order to investigate the reason of this decrease, game analysis with team B with overhead view of the field is carried out.

Figs. 5 and 6 show the ball trajectories during a game with Team B for the original agent 2D systems, and for the proposed method, respectively. In the case of the original agent 2D systems, balls are not occasionally in the opponents half in the field. The ratio of ball possession of the team seems to be quite low. On the contrary, the proposed method can cope with balls in the opponent's half of the field. Some through balls can be observed. By these offenses, the opponent team is difficult to have balls in the own half.

Figs. 7–9 show the player distribution in which the passer, right offensive mid-fielder (uniform number: 7), kicks through balls to right forward. Fig. 7, Fig. 8, and Fig. 9 correspond to the player distribution of "Intercepted," "Success," and "Turnover," respectively. In the figures, numbers in legend mean uniform number. Based on the comparison of Fig. 7 and Fig. 8, the difference between "Intercepted" and "Success" is obviously. In the case of "Intercepted," the position of passer is closed to own half, that is, the pass length is long.

Table 2. 25 games are carried out again with new classification labels

	intercepted	successful	field-out	turnover	No. pass
unlearn	57.4%	12.2%	13.7%	16.6%	111
learn w. 23 attr.	41.5%	22.0%	9.7%	26.8%	85

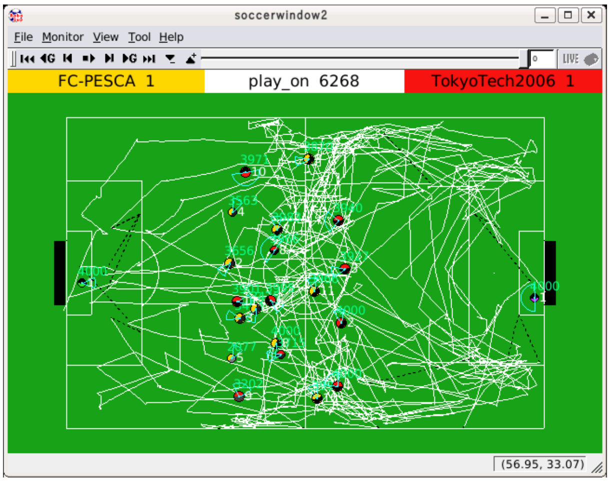

Fig. 6. Ball trajectories for the proposed method

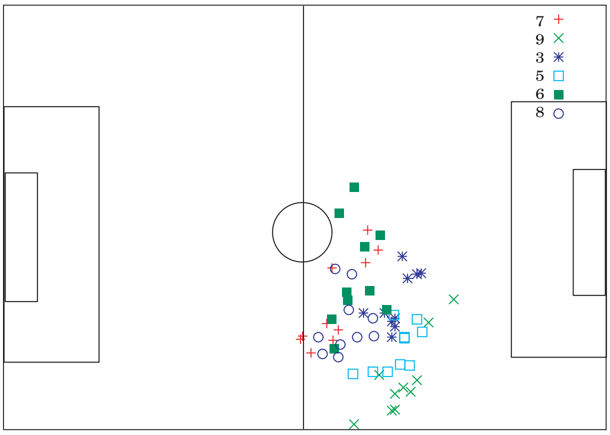

Fig. 7. players distributions in which the passer kicks through balls (intercepted)

In the case of turnover, some receivers cannot catch up with the through ball. They were still around the center line in the hand-written circle in the figure.

5. CONCLUSIONS

In this paper, decision making systems with Support Vector Machine for robocup soccer agents are proposed. Basic idea behind the proposed method is that skills are first developed by hand, game is played with the skills, where criteria for doing the skills are relaxed. SVM learns situations in which the skills is successful. Learned SVM is used for further games.

In this paper, two skills, i.e., through balls and shoots, are implemented. The effectiveness of the proposed method was confirmed on games with stronger opponent teams at Japan Open. Although our implementations in this paper is for offense, they brought in the decrease of goals scored by opponent teams. By analyzing ball trajectories

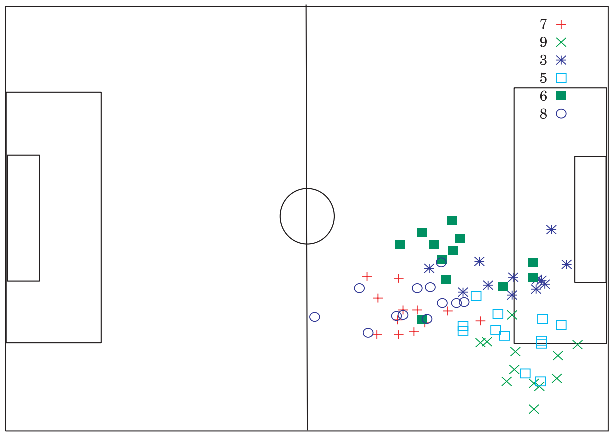

Fig. 8. players distributions in which the passer kicks through balls (success)

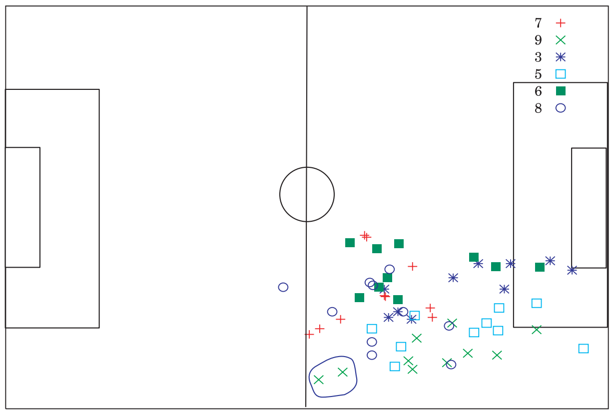

Fig. 9. players distributions in which the passer kicks through balls (turnover)

in games, the increase of ball possession by the proposed method plays crucial roles in the improvement of defense.

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