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A Study on the Effect of Team Names on the Team Strategy

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Abstract. This paper investigates the behavioural change in team strategies according to opponent teams in RoboCup soccer simulation. The aim of this investigation is to identify the complexity of team strategies from the view point of strategy adaptation. Understanding such behavioural change will help understand the team strategies. Using the functionality of a soccer simulator, games are conducted with/without the team names. By comparing the team performance between the two cases, it is shown that some teams change their team strategies by referring the opponent team's name.

Keywords: Team strategy · RoboCup soccer · Log analysis.

1 Introduction

The general goal of multi-agent systems is to achieve a task that cannot be done by a single agent but can be only done by a group of agents. This applies to team sports like soccer, where the task is to get a score by putting the ball into the opponent's goal while preventing the opponent from getting a score. One key aspect in achieving the task is what we call a team strategy: the way players move organisationally.

Many studies have been conducted on soccer strategies to build stronger teams. In real soccer, a lot of teams change their strategy many times by analysing the opponent strategy during games. Shaw et al. present an innovative analysis technique for dynamically measuring, classifying, and studying team formations in professional soccer games [1]. On the other hand, also in the robot soccer domain, there have been many papers on strategical behaviours. For example, Kitamura et al. implements '5-lanes theory' which is used as a basic strategy in real soccer [2]. Furthermore, Reis et al. proposed an approach for coordinating a team of homogeneous agents based on a flexible common team strategy as well as on situation-based strategic positioning.[3]. On the other hand, there are authors who try to understand opponent strategy in order to overwhelm the opponent. For example, Kanai et al. investigated to extract parameters in games and decide opponent strategy by using 'K-means++'[4]. Moreover, Kuhlmann et al. developed an autonomous coach agent capable of analyzing past games of the current opponent, advising its own team how to play against this opponent, and identifying patterns or weaknesses on the part of the opponent[5]. Yasui et al. compared two situations in games and analyzed the strategies by using cluster analysis[6]. Abreu et al. analyzed parameters by using cluster analysis and made the team changed strategy according to the class [7].

A team strategy takes various elements of a field status into account such as the ball position, the ball taker, teammates' positioning, opponents' positioning, how the opponent passes the ball, and how the opponent stops our strategy. However, it is difficult to understand opponents' behaviour such as their positioning and their ball handling. The players' action is so complex that it is intractably hard to model using machine learning.

Since each team has its own team strategy, it is a good idea to use the team name as a piece of information that is taken into consideration. For example, if it is known that Team A is an offence-oriented team rather than a defence-oriented one, we can adjust our team behaviour so that our defender stays back. Then, the team-building is specialized to a particular team. It seems to be true in the case of real soccer. A professional soccer team sometimes takes a countermeasure for its next opponent team before the game.

In this paper, as the first step for understanding team strategies from their behaviour, we investigate if there are any teams that build a specialized team strategy. We use RoboCup Soccer simulation 2D for this purpose. In the computational experiments of this paper, games are conducted among those teams that participated in 2021 World RoboCup competitions. Two cases of games are considered: In the first case, games are normally held as usual. In the second case, both team names are hidden from each other. Thus, the teams do not know which team is playing against. After analyzing the game results, it is revealed that opponent team names are used to consider their team strategies.

2 RoboCup Soccer Simulation

RoboCup is an international and interdisciplinary projects. It involves research fields such as robotics, artificial intelligence, and education. RoboCup soccer is one category in RoboCup. These are further divided into several leagues according to the specification of robots such as humanoid, middle-size, small-size, standard platform, and simulation. Among these leagues, the simulation league is different from the other league in the sense that there are no physical robots but soccer robots are realized in a virtual field that is generated in a computer. The RoboCup soccer simulation is then divided into 2D league and 3D league according to the dimensionality of the soccer simulation. This paper focuses on RoboCup soccer simulation 2D league (see Fig. 1).

In the RoboCup soccer 2D simulation, various strategies are developed by various teams. It is generally accepted that there is no perfect strategy which

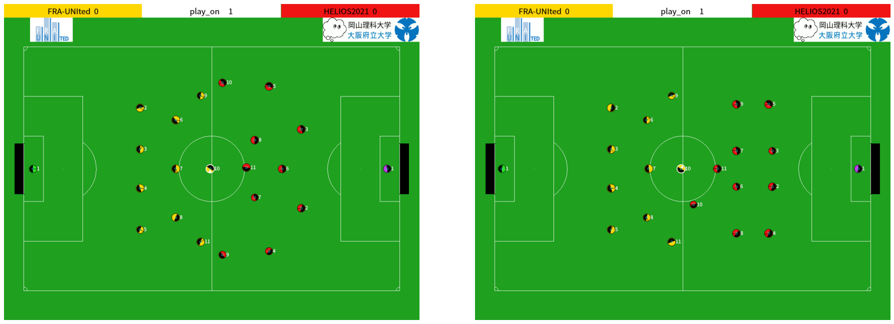
Fig. 1: RoboCup soccer simulation 2D league.

works well against any others. Thus, teams should adapt themselves by changing their strategies according to their opponent even if the adapted strategy may not work for the against teams.

2.1 behavioural change according to opponent teams

In order to score a goal in a soccer game, players in a team have to make their action in an organizational way. This is generally called a team strategy. The first step to the strategy development is to implement players' movement that is almost pre-planned before the game. The strategy that is built in this way will be rather general and not specialized to a particular team. The second step is to adapt the team strategy against its opponent's team strategy. There are mainly two ways to achieve this step. One way is to develop a highly flexible team strategy that is able to change players' movement during the game. This flexible team strategy would be the ideal one that plays well against any teams even if the opponent team is unknown. The other way is to specialize the team strategy to a particular opponent team. This specialized strategy hopefully plays well against the opponent team even if it does not perform well to the other teams. In RoboCup soccer simulation, the soccer simulator sends both team names to all the players including the coaches. This information can be used to switch team strategies to a specialized one to the opponent team.

In RoboCup soccer simulation 2D league, almost all teams have developed their own strategies while there seem to be a few teams that has specialized strategies to some particular teams. For example, Fig. 2 shows the kickoff formations in the game. In the left of this figure (Fig. 2(a)), both the right team and the left team know their opponent teams. That is, the information of the opponent's team name is known before the game starts. On the other hand, the right figure (Fig. 2(b)) shows the kickoff formation when the information on



(a) *Anonymous* setting

(b) *Non-Anonymous* setting

Fig. 2: An example team that seems to change the kickoff formation according to the opponent team name.

their opponent team (i.e., team names of each other's opponent) was not allowed to be sent to both teams. We can see that the players of the right team take different positions than when they know their opponent teams. This indicates that the right team has a specialized strategy to a particular team (in this case, this is FRA-UNIted). Because the specialized team strategies indicate that the phase of team development is shifting to the second way, investigation into this will give us some information on the progress in this league in terms of team development.

In RoboCup soccer simulation 2D league, it is possible to hide the information on the team name by changing the soccer simulator setting. We refer to this simulator setting as *Anonymous* game mode. On the other hands, when the game is held normally, the team names is not hidden (we call this server setting as *Non-Anonymous*).

2.2 *Anonymous* Challenge at RoboCup 2021

In the general regulation, both teams receive opponent team names from the soccer simulator. Thus, it is possible to adapt team strategies without knowing the opponent players' movement. Because the ideal AI soccer players are assumed to adapt their behaviour during the game even if it does not know the opponent teams beforehand, *Anonymous* challenge was held in RoboCup 2021 where all participating teams play soccer without knowing their opponent team name. Table 1 is final results in two regulation of RoboCup2021. In *Anonymous* challenge it is necessary to appropriately change team strategy against any opponent teams. This *Anonymous* challenge is realized by changing the simulators setting. While the soccer simulator in the normal settings (i.e., in *Non-Anonymous* mode) send registered team names to both teams, they are replaced with some unknown strings in the *Anonymous* mode. This paper uses this soccer simulator setting for analyzing the effect of team names on the team performance.

Table 1: Final result in RoboCup2021

team	*Non-Anonymous*	*Anonymous*
CYRUS	1	3
HELIOS2021	2	1
YuShan2021	3	4
HfutEngine2021	4	11
Alice2021	5	6
Oxsy	6	5
RoboCIn	7	8
FRA-UNIted	8	2
Jyo_sen2021	9	10
MT2021	10	7
ITAndroids	11	12
Persepolis	12	14
ARAS	13	9

3 Numerical Experiments

This section consists of two parts of numerical experiments. In the first part of the numerical experiments, we investigate the difference in team performance between *Anonymous* and *Non-Anonymous* settings of the soccer simulator. Then in the second part of the numerical experiments, the team strategies are analyzed in more details to discuss the difference in the players' behaviour between the two modes.

We have collected the binaries of the top 13 teams in RoboCup 2021. The teams played round-robin games 1000 times. In order to cancel the effect of the field side (i.e., right or left side of the field they are attacking/defending), the field sides are fixed for 500 times of the round-robin games while the field sides were changed in the other 500 times of the round-robin games. This process was applied to in both cases of *Anonymous* mode and *Non-Anonymous* mode. Because we cannot understand that which team refer to opponent team name, we compared two situations.

3.1 Difference in winning rates

In the first experiment, it is investigated if there is any difference for a team in winning rates between *Anonymous* and *Non-Anonymous* modes. In order to see whether teams change strategy according to opponent team name or not, the difference in winning rates between *Anonymous* and *Non-Anonymous* modes are calculated for each team.

The significance of the differences in the team strategies was checked by using Chi-squared test. In this paper, the test was conducted in two rounds. In the first round of the test, we used two indices that the number of winning and the others. Second, we used three indices: The number of wins, draws, and losses. If both tests proved that the difference is significant, Point 1 is given to the agent.

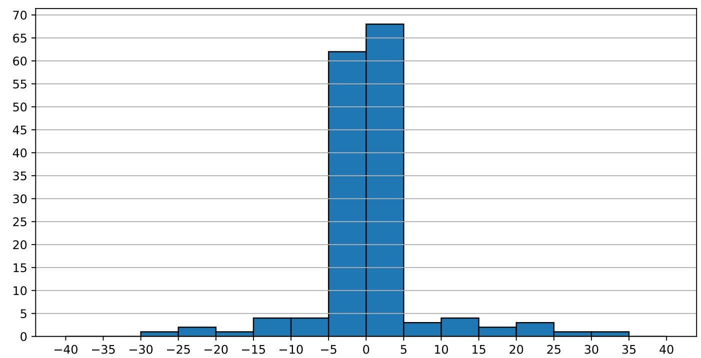
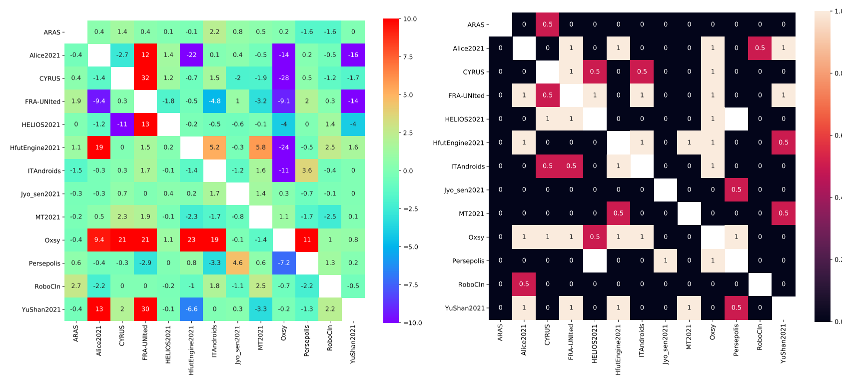


Fig. 3: Difference in winning rates.



(a) Difference of winning rate **(b)** Chi-squared test result

Fig. 4: Heat map representations.

If the significant difference is proved only from one of the two tests, the point 0.5 is given. If neither of the two tests recognize any significant difference, no point is given (i.e., the point is zero).

We show the difference in the winning rates in a histogram (Fig. 3). From Fig. 3, most of the differences in the winning rates are less than 5%. However, there are some matches where the difference was tested significant.

In order to graphically show the differences, a heat map is employed as in Fig. 4. The value represents the winning rates of the teams in a row against the teams in a column. This means that if the larger the positive value is, the stronger the corresponding team is, and if the smaller the negative value is, the weaker the corresponding team is in the *Non-Anonymous* mode. On the other hands, if the value near 0, there is not much difference between *Anonymous* and *Non-Anonymous* .

Figure 4(a) shows that Oxsy has large positive difference of winning rate. We consider that Oxsy changes advantageous strategy according to many opponent teams. On the other hands, there are many teams that decrease winning rate for Oxsy. It is ordinary that Oxsy changed strategy for these team rather than these teams change disadvantageous strategy for Oxsy. In addition, there are same teams that increase winning rate for FRA-UNIted. We consider that these teams changed strategy for FRA-UNIted.

Moreover, Fig. 4(b) shows the result using Chi-squared test. Regarding same combinations whose difference of winning rate is more several percent: We found that Chi-squared test decided that there is difference in such frequency of result.

Table 2 is total average point and rank in this experiment.

Table 2: Total average point (rank) in 1000 games

team	*Non-Anonymous*	*Anonymous*
CYRUS	26.053 (3)	26.214 (3)
HELIOS2021	32.173 (1)	32.340 (1)
YuShan2021	27.807 (2)	26.769 (2)
HfutEngine2021	16.618 (7)	16.259 (7)
Alice2021	24.398 (4)	25.499 (4)
Oxsy	21.690 (5)	18.655 (6)
RoboCIn	12.940 (9)	12.982 (9)
FRA-UNIted	17.409 (6)	19.254 (5)
Jyo_sen2021	9.097 (10)	9.041 (10)
MT2021	14.029 (8)	14.117 (8)
ITAndroids	4.833 (13)	5.210 (13)
Persepolis	7.443 (11)	7.658 (11)
ARAS	6.227 (12)	6.208 (12)

3.2 Difference in players' behaviour

In the second experiment, we look into more detail of the team behaviour and discuss the differences between *Anonymous* and *Non-Anonymous* . This is done using loganalyzer3[3] [8] that extracts detail parameters in games, e.g. pass, dribble and shoot. Here Teams Oxsy and FRA-UNIted were taken for the analysis of the second experiment. Oxsy increased the winning rate for many teams in the first experiment and FRA-UNIted significantly raised its ranking in *Anonymous* Challenge in RoboCup2021.

In this paper, we test like Fig. 5 for such parameter and use the return value. If averages of parameter in *Anonymous* game and *Non-Anonymous* game are different, return positive value. If the test judges that there is not difference of average, return -1.

As described above, we focus on such detail parameters in game. In this paper, we researched that whether there are difference of four parameters that

[3] `https://github.com/opusymcomp/loganalyzer3`

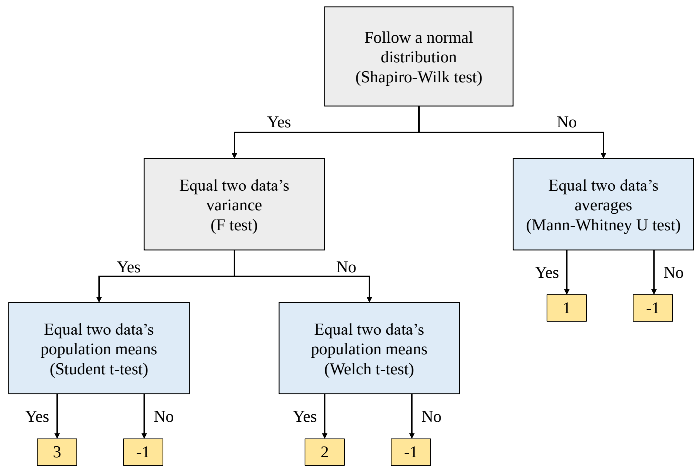
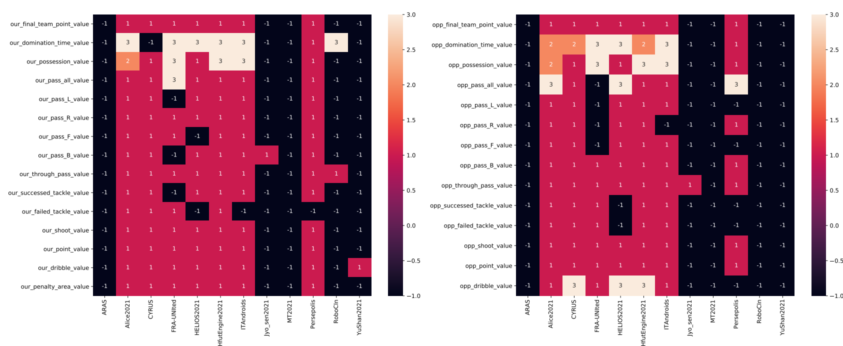


Fig. 5: Test flowchart

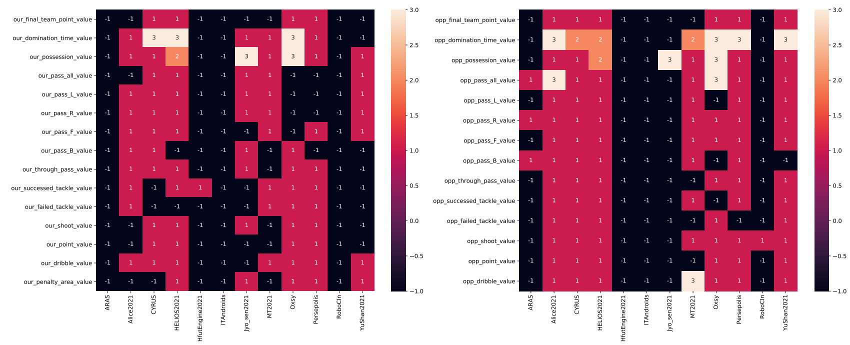


(a) Our parameter different test **(b)** Opponent parameter different test

Fig. 6: Oxsy parameter test

are our final point, domination time, the number of pass and dribble time in *Anonymous* and *Non-Anonymous* . Figures 8(a), 9(a), 10(a) and 11(a) shows the value of difference and Figs. 8(b), 9(b), 10(b) and 11(b) shows the result of tests. In this result, same teams that changed the number of winning changed the number of parameters too.

Figures 6 and 7 shows result of tests for another parameters in Oxsy and FRA-UNIted. Such parameter divide into our parameters and opponent parameters and we made figures. Oxsy that takes measure for many teams has more differences of the our parameters more than the opponent parameters. On the other hands, FRA-UNIted that was took measures by many teams has more differences the opponent parameters than the our parameters.



(a) Our parameter different test **(b)** Opponent parameter different test

Fig. 7: FRA-UNIted parameter test

4 Future work

The numerical experiments of this paper focused on the effect of team name on the team strategies. The *Anonymous* mode was employed where both teams do not know their opponent team name. In this situation, it is difficult to confirm if only one team of the game changed the team strategy or both team strategies changed. It is necessary to conduct this anonymous aspect only for one side of the team while the other side of the team knows its opponent team name.

It seems that some teams take more advantageous strategy according to their opponent teams. However, we could not find how such strategy change was realized. Thus, we hope we get more detail on those parameters that are related to the weakness of the opponent teams.

5 Conclusions

In first experiment, we examined that each team change the winning rate in *Anonymous* and *Non-Anonymous* . Furthermore, we examined the difference is significant using Chi-squared tested. The result showed that there are significant differences.

In second experiment, we focus on detail parameters. We found that when there is difference of winning rate, there are difference of parameter too. The result showed that there are significant differences.

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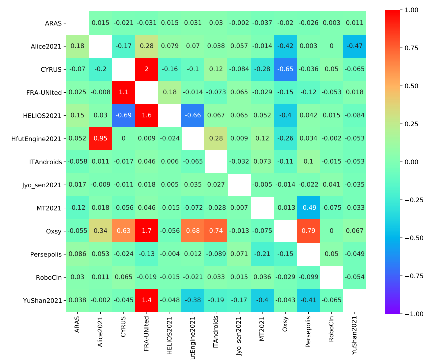
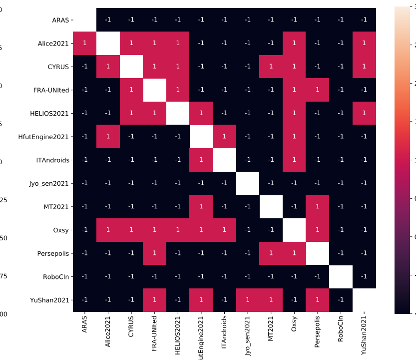
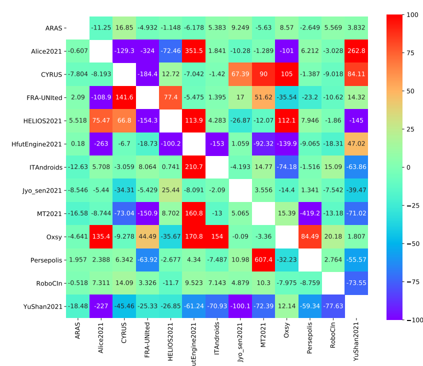


(a) Point time difference

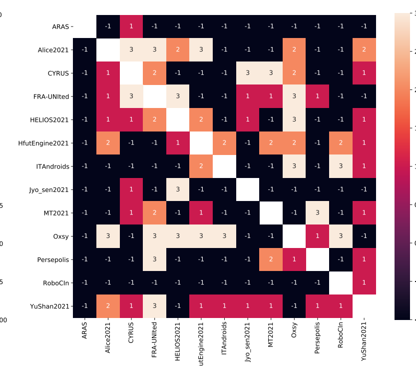


(b) Point time difference test

Fig. 8: Parameter point

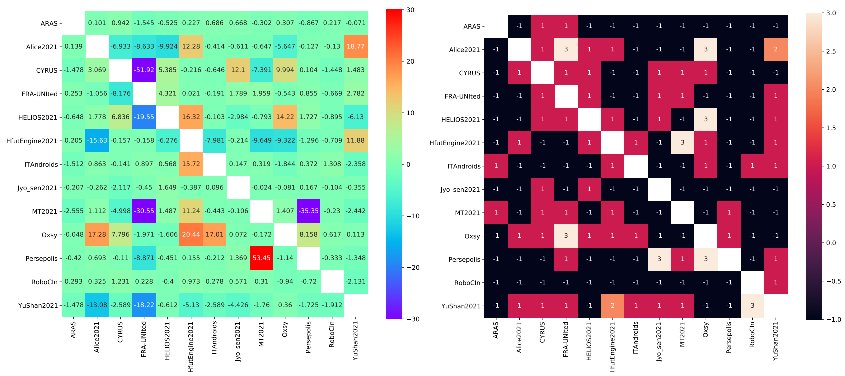


(a) Domination time difference



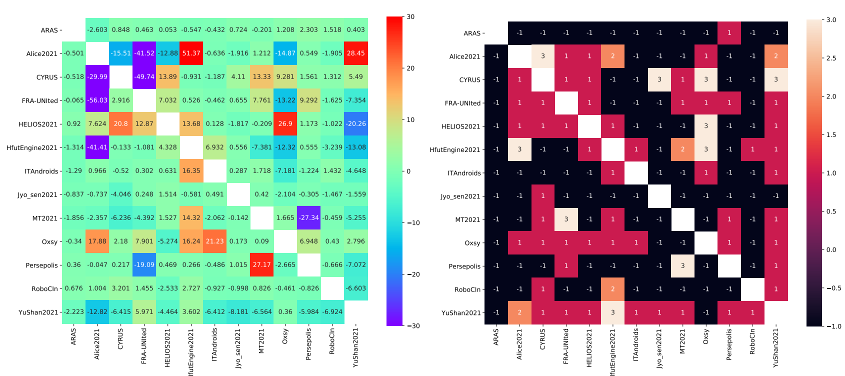
(b) Domination time difference test

Fig. 9: Parameter domination



(a) Pass time difference **(b)** Pass time difference test

Fig. 10: Parameter pass



(a) Dribble time difference **(b)** Dribble time difference test

Fig. 11: Parameter dribble