Decision Making by the Characteristics and the Interaction in Multi-agent Robotics Soccer

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Abstract. This paper deals with a decentralized decision-making method on multi-agent robotic system. Soccer game is adopted as an example for its dynamic characteristics. The soccer simulator has been designed and implemented which enables us to test various approaches to the multi-agent studies. The modeling of capabilities of a single robot and team strategy is explained at first. Each robotic agent has different characteristics, and the decision making by each robotic agents are done by considering its characteristics and interaction between robotic agents. Several simulation experiments with different combinations of the components and formations have been tested. The result of the simulation experiments was that similar combination of the components resulted in better performance, and the formation where robotic agents are located in the center axis between the goals showed better defense behaviors.

1 Introduction

The authors have been engaged in the research on the coordination and the cooperation of the group of autonomous robots by the decentralized approach. Although decentralized system is expected to be much more applicable in the future manufacturing system or other multi-agent system, centralized approach is still considered to be effective in current situation. One of the reasons for this is that there are little good methods for evaluating decentralized system. Another reason is that decentralized controlling system and decentralized decision-making system are often confused.

In such an decentralized robot system, robots should be autonomous enough to dynamically organize robot groups depending on the situation without any supervisor in the system. The related research are [1], [2], [3], [4], for example, where communication network is assumed and indispensable (*e.g.*, [5]).

Then the authors have concentrated in the game of soccer (association football) where each player behaves by its own decision for the victory of the team, and each player with different capabilities selects different strategy in real-time for offense and defense, depending on the situation. From this viewpoint, soccer game is an interesting example of the decentralized decision making system. For this target, our research group is constructing plural mobile robots with several sensors and wireless communication interface, and on the other hand, implementing soccer simulator on the workstation [8], [9]. Currently the implementation of this system is done apart from *RoboCup* (*e.g.*, [6]). Our research is independently done from this project, but the research domain is very similar.

In this paper, the strategy of selecting cooperative behavior in offense team and the assessment method of evaluating such behavior is described. This approach is the first step for evaluating decentralized decision-making system.

2 Modeling of the Characteristics of Robot Players

The modeling of the behavior of a single robot and that of plural robot is explained in [8]. For the ease of understanding, let us explain them here again.

2.1 Assumptions

Following assumptions have been made to implement robotics soccer on the workstation.

- The members of the teams are fixed until either team gets a goal.
- The shape of the robot is modeled by a circle with the radius 20 cm, and kinematically modeled as a differential-drive mobile robot.
- The size of the field is 12 meters by 9 meters, which is 1/10 of the maximum size of the real field, and there are invisible wall on the goal lines and touch lines, *i.e.* the ball do not go outside of the field).
- Each robot has a sensor, actuators, communication interface, and a ball handling mechanism as well as its brain.
- Robots can distinguish the ball and other robots by its own sensors. The range of the sensing area of the robot is expressed by a half-circle.
- If the ball is within a certain distance from one robot player, it is considered that the ball is owned by the robot. The ball is grabbed by opponent player if the ball is beyond that distance during dribble.
- The capabilities of robots in the same team are known to the teammates beforehand. The capabilities of robots in the opponent team are unknown.
- The position of robot itself is measured by itself by dead-reckoning, and does not consider positional errors.
- The positions of the teammates are obtained by communication interface through the data base manager. The positions of the opponents are measured by sensors.

2.2 Characteristics and the Behavior Rules of a Single Robot

Several types of characteristics are defined in this research. Although there are much more types of characteristics in real soccer, three types are assumed as shown in Table 1 in order to minimize complexity and the computing cost. This idea also accepts some multi-agent research that assumes homogeneous agents in the decentralized/distributed system. In table 1, type 1 moves faster than others and kicks strongly, but the sensing distance is shorter than others. On the other hand, type 3 moves slower and kicks less strongly, but the sensing distance is longer. Type 2 is the middle of type 1 and type 3. In this paper, type 1 is called Forward-type (F-type), type 2 is Mid-fielder-type (M-type), and type 3 is Defender-type (D-type).

Table 1. The capabilities of robots

max. value	*type 1*	*type 2*	*type 3*
velocity $[m/s]$	0.5	0.4	0.3
acceleration $[m/s^2]$	0.1	0.2	0.3
omega $[deg/s]$	80.0	90.0	100.0
sensing distance $[m]$	1.5	2.0	2.5
kick velocity $[m/s]$	5.0	4.0	3.0

Each robot player has an instinct to search the ball or opponent players until it is found within its sensing area, and also to avoid obstacles. In order to search the ball or other opponent players, the robot player wanders for a certain direction which is generated by a random number. If it finds the ball within its sensing area, it tries to dribble to the opponent goal until it can shoot. Of course, this is not always possible; in such situation, it selects to continue dribble or to pass to others by the rules defined as follows: Three behaviors, (1) dribble, (2) shoot, (3) pass, are defined in this research. Two behaviors (dribble and shoot) are considered to be the independent plays, whereas pass is considered to be the cooperative play that requires other robot players. The algorithm of pass is explained later.

3 Interaction Between Agents

3.1 Necessity of Selecting Behaviors

In multi-agent robotics, the cooperation algorithm including conflict resolution of decentralized decision-making is important. In robotics soccer, cooperative plays are, for example,

- (offense) pass to the players who is suitable for shooting,
- (offense) support motion to receive the pass,
- (defense) obstruction of shooting by positioning along the line between the opponent and defense goal,
- (defense) obstruction of passing by positioning along the line between the opponent and its teammate.

The sender of pass is always the owner of the ball, but the receiver is not fixed during the game. This relationship is dynamically configured in soccer games; although a robot who do not own the ball moves to receive the pass, that behavior could be in vain. In this sense, the cooperators do not always receive an expected result; the conflict of decisions are always resolved by the owner of the ball. In this report, pass is made only between two robots for the moment, but for the future, a kind of combination play where more than three robots are involved should be modeled.

3.2 Behavior Rules for Robot Group

Plural robots get together and organize one team of robotics soccer. The algorithm of team play is also embedded in each robot player as modeled previously. Pass is considered to be the cooperative behavior. Pass is sent based on the relative position of the robot players in the field and the capability of the robot players. The receiver of the ball is dynamically selected depending on the situation. The decision is done in the following sequences:

[offense - the robot player who owns the ball]

1. First it decides to continue dribble or to pass by comparing the capability factor of itself and the opponent who is within its sensing area.
2. If the opponent is less stronger, then continue dribble. If otherwise, it takes following procedure.
   (a) try to pass to the robot player who located nearer to the goal of the opponent
   (b) if the distances are the same, try to pass to the robot player who is better at shooting (i.e. F-type)

[offense - the robot players who do not have the ball]
It simply moves to the certain distance from the goal line of the opponent, and then tries to receive the pass.

[defense]
It simply moves to the certain distance from the goal line of its goal, and then searches the opponent players to interfere. The relationship of these behaviors are illustrated in Figure 1.

3.3 Decision Algorithm to Pass or Dribble

The algorithms of selecting the independent behaviors and cooperative behaviors as described here. These formulations are based on the evaluation which is based on the calculations of the distances to other robots in same team and the distances to the goal, and the comparison of the capabilities with other robots. There are two steps for this decision; one is for selecting dribble or pass, and the other is for selecting to which robot the ball should be passed.

The decision algorithm of selecting dribble or pass is based on the following idea. As mentioned above, if the opponent appears within the sensing area of the robot who owns the ball, the robot compares the capability of itself and that of the opponent. Since the capability of the opponent cannot be known as mentioned in the previous chapter, the average value of all types of robots are

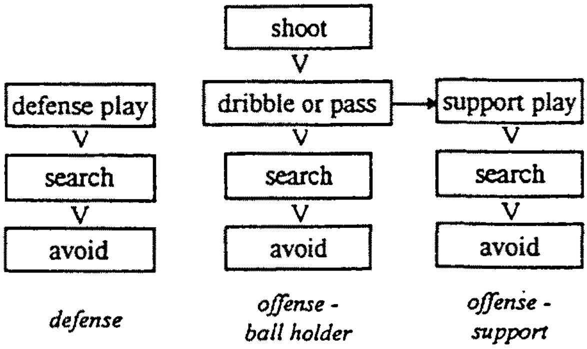

Fig. 1. The relationship of behaviors of plural robots

substituted by the capability of the opponent (This must be refined for future such that some learning algorithm should be included). If the capability of the robot who owns the ball is bigger than that of the average, it continues to dribble. It is expressed by an index *my_spec* as follows:

$$my\_spec = \alpha \frac{vel_{my\_max}}{vel_{ave}} \cdot \beta \frac{acc_{my\_max}}{acc_{ave}} \cdot \gamma \frac{\omega_{my\_max}}{\omega_{ave}} \cdot \delta \frac{kick_{my\_max}}{kick_{ave}} \tag{1}$$

where vel_{my_max} is the maximum velocity of the robot who owns the ball, vel_{ave} is the average velocity of the robots, ω_{my_max} is a maximum rotation velocity of the robot who owns the ball, ω_{ave} is the average rotation velocity of the robots, acc_{my_max} is the maximum acceleration of the robot who owns the ball, acc_{ave} is the average acceleration of the robots, $kick_{my\_max}$ is the maximum kicking capability of the robot who owns the ball, $kick_{ave}$ is the average kicking capability of the robots, α, β, γ, δ are weight coefficients (currently set to 2.0, 1.0, 1.0, 1.0, respectively, by heuristics).

Next, potential function [7] has been introduced. By using the distance r_{min} between the nearest opponent and the robot who owns the ball is calculated. The potential field U_{opp} is calculated by using the weight coefficient k_{opp} such as

$$U_{opp} = k_{opp} \frac{1}{{r_{min}}^2} \tag{2}$$

The potential field U_{opp} is compared to the threat or pressure from the opponents in the real soccer. The capability factor *my_spec* is converted to potential function form U_{self} by using weight coefficient k_{self}, such as

$$U_{self} = k_{self} \frac{my\_spec}{{r_{min}}^2} \tag{3}$$

Then the index E_{pd} for selecting pass or dribble is formulated as

$$E_{pd} = \sum U_{opp} - U_{self} \tag{4}$$

The robot continues to dribble if $E_{pd} \leq 0.0$, to pass otherwise. This means that the robot passes the ball to one of the teammate if the opponent seems to be stronger than itself.

3.4 Decision Algorithm to Whom the Pass Should Be Sent

Having decided to pass to teammate, the owner of the ball must decide to whom it should pass the ball. First, it calculates the capability index my_spec_i for every teammate i by

$$my\_spec_i = \alpha_i \frac{vel_i}{vel_{ave}} \cdot \beta_i \frac{acc_i}{acc_{ave}} \cdot \gamma_i \frac{\omega_i}{\omega_{ave}} \cdot \delta_i \frac{sensor_i}{sensor_{ave}} \cdot \epsilon_i \frac{kick_i}{kick_{ave}} \tag{5}$$

in a similar manner with the previous formulation, where my_spec_i is capability factor of the teammate i, vel_i is the maximum velocity of the teammate i, ω_i is the maximum rotation vector of the teammate i, acc_i is the maximum acceleration of the teammate i, $kick_i$ is the maximum kicking capability of the teammate i, $sensor_i$ is the maximum sensing distance of the teammate i, α_i, β_i, γ_i, δ_i, ϵ_i are weight coefficients for the teammate i (currently set to 4.0, 1.0, 1.0, 1.0, 1.0, respectively for all i, by heuristics).

Next, it calculates the distances with all teammates, and evaluates the maximum distance d_{max} of them.

$$d_{max} = \max_i(|\boldsymbol{x_i} - \boldsymbol{x}|) \tag{6}$$

Also, it calculates to the distances between all teammates and the offense goal, and evaluates the maximum distance g_{max} of them.

$$g_{max} = \max_i(|\boldsymbol{x_i} - \boldsymbol{x_g}|) \tag{7}$$

Then, the index P_i is calculated for each teammate i such as

$$P_i = (my\_spec_i)^{-1} + \zeta_i \frac{|\boldsymbol{x_i} - \boldsymbol{x}|}{d_{max}} + \eta_i \frac{|\boldsymbol{x_i} - \boldsymbol{x_g}|}{g_{max}} + \theta_i \tag{8}$$

where $\boldsymbol{x_i}$ is the position vector of the teammate i, $\boldsymbol{x}$ is the position vector of the robot who owns the ball, $\boldsymbol{x_g}$ is the position vector of the goal of the opponent, ζ_i and η_i are weight coefficients for the teammate i, θ_i is a value which represent the (equal to 1 if the opponent is on the direction to the teammate i and equal to 0 for otherwise).

Having calculated P_i for all teammates, the owner of the ball sends pass to the teammate i who has the smallest index value. The meanings of Equation (8) is as follows: the owner of the ball tries to find a teammate who is nearest to the offense goal, but if the distances are equal, it tries to send the pass to forward player who is much suitable for shooting.

The other behavior such as defense or support plays are defined similarly, and partly described in [8].

4 Simulation Experiments

4.1 Strategy Evaluation by Behavior Criteria

It is also important for the team and the manager of the team to evaluate the behaviors of all players. In other words, the team strategy must make the best use of the capabilities of all teammates. In this sense, certain assessment points are given to each behavior that represents the contribution of the player to the team. These points are defined as shown in Table 2. This method of assessment means that each player should play its assigned role in the team. The role could be assigned dynamically during the game or through some learning algorithms for future. This assessment is done in every timing of the selection of behaviors. The values of dribble in Table 2 is much smaller than others, because dribbling continues for a certain time whereas passing and shooting are done in an instant. Please note that these values are independently designed from the victory or defeat of the game.

Table 2. Assessment points for each behavior

behavior	*forward* (*points*)	*mid-fielder* (*points*)	*defender* (*points*)
dribble	3	2	1
pass	10	20	30
shoot	30	20	10

4.2 Original Soccer Simulator

Given the behavior rules for each robot and that for the team, two kinds of simulation experiments are done. The original simulator has been implemented in C language on SparcStation5, which is different from Soccer Server by Dr. Noda for *RoboCup-97* [10]. The number of robot players are limited to 5 (not 11) due to the insufficient computing power. Currently the simulator is being rewritten so as to fit Soccer Server for *RoboCup-97*.

The first experiment is to investigate the effect of the formation of robot players with the same characteristics, and the second experiment is to investigate the effect of the characteristics of the robot players. In order to fix the kick-off team, only one player in team B is initially located very near to the center circle so that the ball is found in its sensing area. An example of initial positions of robot players is shown in Figure 2. The game continues until either team gets goal, and the total assessment points are compared as well as the victory of the game. Note that the results are always the same if the same random seeds are given. In other words, the results depend on the random seeds which is used for deciding the wandering direction to search for the ball or other players.

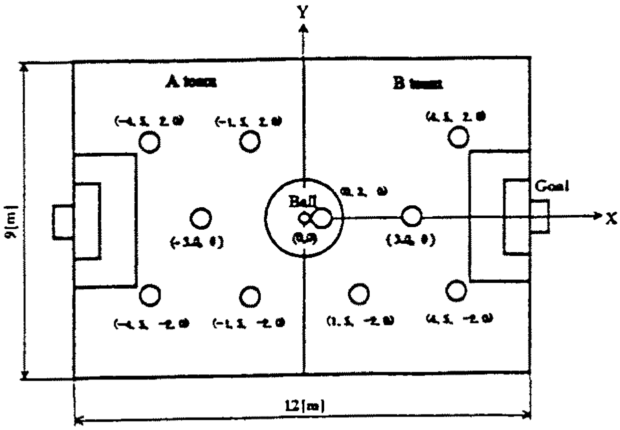

Fig. 2. An example of initial positions

4.3 Experiment 1: the effect of formation

This experiment is to investigate the effect of the formation of robot players who have the same characteristics. Provided that five robot players in one team, four kinds of formations have been used in this experiment as shown in Figure 3. The characteristics of the components in the teams are fixed into one. In order to observe the cooperative plays (passes), the robot players are set to D-type who tend to send pass rather than to dribble. The results of this experiment are shown in Table 3.

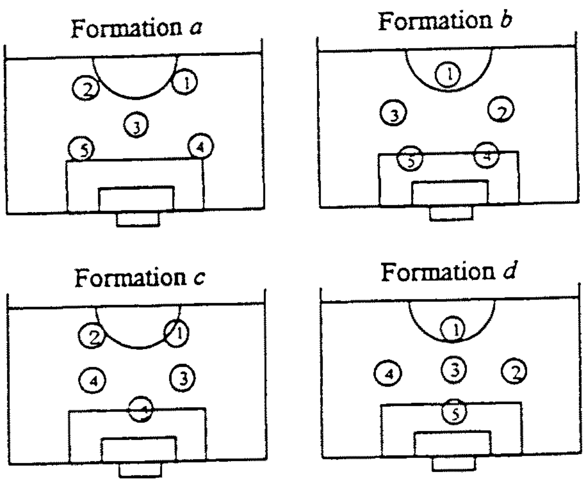

Fig. 3. The formation of robot players

Table 3. The result of experiment 1

	team A		team B (kick off)		time	winner
	Formation	total points	Formation	total points	(sec)	
(1)	b	107	a	54	703	B
(2)	c	91	a	19	504	A
(3)	d	77	a	91	358	A
(4)	a	207	b	57	1238	A
(5)	c	130	b	176	1401	A
(6)	d	69	b	16	264	A
(7)	a	128	c	52	821	A
(8)	b	151	c	20	631	A
(9)	d	85	c	36	547	A
(10)	a	334	d	316	2453	B
(11)	b	35	d	130	557	B
(12)	c	19	d	83	324	A

4.4 Experiment 2: The effect of the combination of characteristics of the robot players

Assuming one fixed formation (*formation a*, for example), several combinations of the types of characteristics are tested. The combination is shown in Figure 4. *Pattern FMD* is the reference combination which is composed of two F-types, one M-type, and two D-types. *Pattern FFF* is composed of F-types only, *pattern MMM* of M-types only, and *pattern DDD* of D-types only.

These four types of teams had some games, and the results are shown in Table 4.

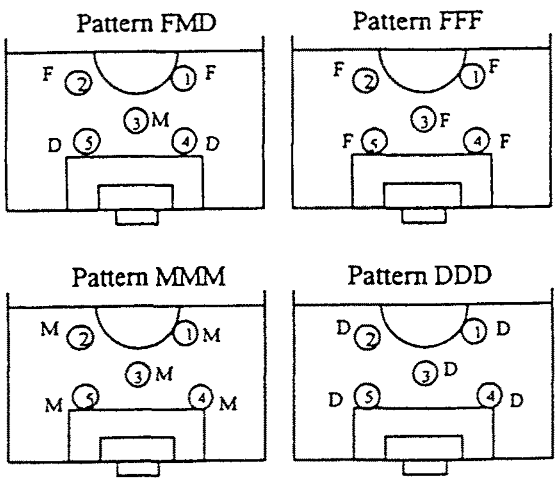

Fig. 4. The patterns of the combination of different characters

Table 4. The result of experiment 2

	team A		team B (kick off)		time	winner
	pattern	total points	pattern	total points	(sec)	
(1)	FMD	0	FMD	90	111	B
(2)	FFF	105	FMD	27	155	A
(3)	MMM	0	FMD	90	111	B
(4)	DDD	128	FMD	30	383	A
(5)	FMD	0	FFF	90	111	B
(6)	FMD	134	MMM	10	203	A
(7)	FMD	12	DDD	89	503	B

5 Discussions

5.1 Discussions on experiment 1

As expected, D-type robot players tend to send passes rather than to dribble. If all robot players were F-type, the holder of the ball would rush to the goal to the opponent and the ball would be grabbed by opponents. Generally, there is a tendency that the kick-off team loses (9 times out of 12). The reason is that the owner of the ball is the nearest to the opponent goal among the teammates so that it could not send pass and the ball was grabbed by an opponent. This is due to the combination plays; the algorithm of support plays must be refined.

In the case of (2), the team A which employs *formation c* surrounded the opponent who dribbles the ball, and grabbed the ball. On the contrary, *formation c* lost the game with kick-off (cases (7) - (9)). This means that the *formation c* is suitable for defense. *Formation d* took the best score both in kick-off side (two wins and one loss) and non-kick-off side (three wins). This is because center line is kept by three robot players in *formation d* and this is robust enough for defense. At the present condition, this formation is the best.

In cases (10) - (12), all robot players in team B obtained some assessment points. On the contrary, in cases (3) and (6), only partial robot players got points. This status comes from the relative positions of robot players, and sometimes two robot players send passes meaninglessly. On this point, the assessment point must be revised.

5.2 Discussions on experiment 2

Generally, the situation is very similar to the experiment 1. In cases (1) - (3), (5), (6), the elapsed time is very short, because the owner of the ball dribbled and shot just after the kick-off, or the opponent grabbed the ball just after the kick-off and then dribbled and shot. In the employed formation (*formation a*), there is only one robot player in the center, which is not robust enough for the defense. This means that the defensive positions (position 4 and 5) should be much closer with each other in order to cover the center with their sensing areas.

From the results in Table 4, *pattern FFF* and *pattern DDD* took the good results, while *pattern FMD* did not show any interesting features. The authors have expected that the different combination of characteristics should be stronger that others, but the results are different. Since the number of robot players are not enough, the effect if the interaction between players are small, and effect of the characteristics of each player have resulted directly. Moreover, if much more interactions (*e.g.* support plays, combination plays are defined, the result would be different.

In order to investigate the effect of the characteristics of the robot players, much more experiments should be done including other formations.

5.3 General Discussions

For the two experiments, the initial positions seem to be influential to the results. The relationships between relative positions and the sensing distance of robots is also important.

All players should keep their position considering their own sensing distance. The assessment points shown in Table 2 must be expanded to evaluate cooperative behaviors such as support plays for the passes, combination plays, etc. The success or the failure of the passes must also be introduced. As mentioned before, meaningless continuation of passes should not be evaluated.

Also, the calculations for deciding pass or dribble are too much complicated and need computing power. This part needs to be refined.

What would be the optimization function, the elapsed time, total assessment points, or the victory of the game? In many simulation experiments, the authors felt the strong correlation between total assessment points and the victory of the game. But there are exceptions in experiment 1. In order to discuss the team strategy, different formations could be taken depending on the tide of a game, for example. Or, different combinations of robot players may produce other strategy. In any case, the algorithms of the support plays and defense plays must be refined. This paper does not intentionally use any leaning methods nor game theory until now. Since some weight parameters are used in the modeling as explained in chapter 3, and since assessment points could be feedbacked to robot players, such approach can be introduces without any major changes of the system, and the authors feel that it is really necessary.

6 Conclusion

The platform of robotics soccer for multi-agent studies have been designed and implemented. Assessment points for each behavior are defined, and the total points during the game are compared. By using this simulator, several formations of the team and the several combinations of the characteristics of the robot players have been tested. Through the observation of the robotics soccer game, the simulator gave us interesting results as well as many important hints on multi-agent research. For the moment, the number of robot players are limited to five due to the lack of computing power. If enough computing power is provided, the number of the robot players in a team should be expanded to eleven.

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