From Local Behaviors to Global Performance in a Multi-Agent System

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Abstract

In this paper, we show our current work on the relationships between local behaviors of agents and global performance of multi-agent systems. We conduct our experiments on RoboNBA[1], which is a multi-agent system testbed. We introduce local behaviors and global performance in RoboNBA. We address the problem of how to quantitatively measure global performance in RoboNBA. Through experiments and discussions, we try to examine how agents' local behaviors can lead to interesting global performance of a match (e.g., optimized match results) in three problems: (1) cooperation between agents; (2) rational decision making; (3) coordination among agents.

1. Introduction

The study on the relationships between local behaviors and global performance is an interesting topic in MAS research. Usually there is a common task to be handled by agents. Beckers [3] studied how the size of a group of robots affected the efficiency of collective task performance, where the robots used stigmergy as the coordination method. Jone [11] showed that a relatively simple set of local transition rules can generate very complex global patterns. Mataric studied [13] collective intelligence emerged from simple local interactions. Ekenberg [7] analyzed how a set of local strategies based on credibility affected the global rationality for handling imprecise information. In [16] [17], Sen and Saha discussed the global performance of selfish agents, reciprocative agents and other types of agents. Lesser et al. did some similar work [2] [18] [21] [22] .

However, the above work had some limitations. Ekenberg [7] only provided some statistical analysis. He did not define what was a task. In [3] [13], no cooperation was needed except for avoiding robot collisions. The task was simple object gathering, which could be done by a single agent. In [11], the goal was confined to form structures or patterns. In Sen and Lesser's work [2] [18], the tasks were clearly defined, which could have *arrival time, length, deadline* and other properties, such as *reward*. These tasks had static time constraints, and they needed a predefined fixed time for an agent to finish. The agent actions are to select a task, execute it and decide to cooperate with others or not. These definitions are incorrect in some situations, e.g., the services time are dynamically defined at run time. And the number of agent actions was too limited.

1.1. Problem Statement

In this paper, we aim to study the local behaviors and global performance in a more complex environment, which requires cooperation as well as competition. Each agent has allies as well as opponents. The goal of an agent is to finish and to assist allies to finish as many tasks as possible, while on the other hand an agent has to prevent opponents from finishing tasks. The characteristics of a task are more dynamic. There is no predefined service time for a task. The service time depends on the temporal and spatial characteristics of the environment. In the above scenario, we will study three problems:

1. Cooperation between agents. Cooperation [5] occurs in two conditions: (1) agents have a common goal and their actions tend to achieve the goal;(2) the agents perform actions that will not only achieve their goals, but also the goals of other agents.
2. Rational decision making. It refers to when a agent has a number of choices, the agent will evaluate each choice and choose the best one, based on its current situation.
3. Coordination among agents. Coordination means that agents act in a way such that their community acts in a coherent manner. Coherence means that the agents'

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1 A demonstration of this system will be available to be shown at the conference.

actions get well, and that they do not conflict with one another [15].

1.2. Organization

The rest of the paper is organized as follows. Section 2 gives an overview of the RoboNBA testbed. Section 3 formulates the agent local behaviors and provides several measurements for the global performance of an MAS. Section 4 presents our experimental results and discusses the problems studied. Section 5 concludes the paper and proposes our future work.

2. An Overview of the RoboNBA Testbed

RoboNBA is a testbed for us to study the relationships between agent local behaviors and global performance of MASs.

2.1. Motivation of Using RoboNBA as a Testbed

RoboNBA is a game platform where two teams of autonomous robots (agents) can play basketball with each other. Players, which are considered essentially autonomous agents, have to use certain strategies so that their team as a whole can have good performance.

As we know, RoboCup [2] has served as a good MAS testbed. Why do we need to implement RoboNBA? The reasons are as follows:

1. Many parameters in RoboCup are fixed so as to maintain a fair comparison between different strategies. However, it is not convenient to study the local behaviors and global performance of RoboCup;
2. RoboCup clients of good performance are very hard to implement. In RoboNBA, players have simpler actions and accurate perceptions. So it is easier to implement RoboNBA clients.

2.2. The RoboNBA Components

1. **The Server Environment**

   The RoboNBA environment consists of n players that move on a $xmax \times ymax$ grid (representing the basketball field), trying to shoot the ball to gain scores. The set of players is denoted as $P = \{ p_j \}$. The position of p_j is denoted as (x_j, y_j). The positions of players are subject to the constraint: $(x_i \neq x_j) \vee (y_i \neq y_j)$ for $i \neq j$.

2 In this paper, we refer to RoboCup simulation leagues only.

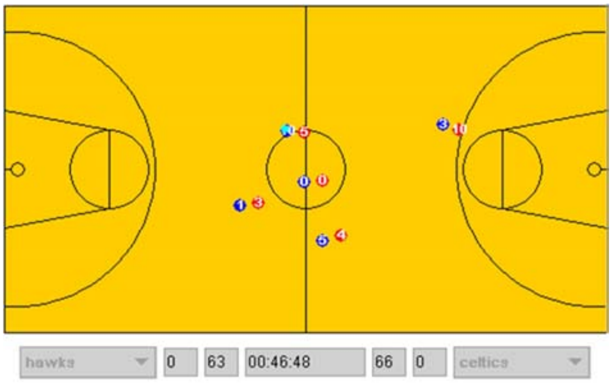

Figure 1. The demo of a basketball match.

2. **Player Actions**

   A player has a limited number of actions to execute. What's more, a player can only execute a single action in a cycle. The basic actions players can perform are as follows:

   (a) shoot(power Pow, direction Dir).
   The player shoots with the power Pow and direction Dir. If the shoot is successful, the team has gained scores. Otherwise, the ball goes to the position calculated by Pow and Dir. When a player executes a shoot, there is a probability that the ball is blocked by an opponent, if the player is within the block range of an opponent.

   (b) pass(power Pow, direction Dir).
   The player passes with the power Pow and direction Dir. The ball goes to a specified position and switches to the free state. When a player executes a pass, there is a probability that the ball is intercepted by an opponent,, if the player is within the intercept range of an opponent.

   (c) run(power Pow).
   The player runs with the power Pow in the current body direction. When a player executes a run, there is a probability that the ball is stolen by an opponent, if the player is within the steal range of an opponent.

   (d) turnDirection(Direction Dir).
   The player changes its body direction by Dir.

   (e) catch().
   If $Distance((P_i.x(t), P_i.y(t)), (ball.x, ball.y)) \leq catchableDistance$, the ball belongs to the player P_i executing the catch() command. The ball switches to the busy state. Otherwise nothing is done. If more than one players are within $catchabledistance$ to the ball, the ball will go to the nearest player. Note catch() is executed only when the ball is free.

3. **The Sensor Model**

The server will send the information of P_j to P_i only when Distance(($P_i.x$, $P_i.y$),($P_j.x$,$P_j.y$)) $\leq R$, where R is the visible distance of P_i. Similarly, the server will send the ball's information to player P_i only if Distance(($P_i.x, P_i.y$),($Ball.x$,$Ball.y$)) $\leq R$. The information is defined in the following manners:

- The player information includes its position, teamID, playerID, stamina and so on.
- The ball information includes its position, the state (free or busy), and the information of the player who controls the ball, if the ball is not free.

3. Formulations

In order to understand the relationships between agent local behaviors and global performance of MASs, we formulate the agent local behaviors and provide several measurements for the global performance in RoboNBA in this section.

3.1. Local Behaviors in RoboNBA

We examine how the changes in agent local behaviors affect the global performance of a RoboNBA game. Agent local behaviors mean those behaviors which have only local influences. The local behaviors we study in this paper are:

- Strategies to pass the ball. Obviously these strategies are local because a player cannot pass the ball to a teammate if the distance between the two players is bigger than the ball holder's assistance distance. And a player uses its local information to determine which teammate to pass the ball. Only accumulation of passes has impact on the global performance of a game. We study the effectiveness of two different pass strategies.

  When a player needs to pass the ball, it selects a teammate with the highest evaluation. The evaluation is defined as:

  $TMEval = \langle t_1^0, t_1^1, \cdots, t_1^n \rangle$ indicates the evaluation for each visible teammate. $t_1^n \in R$. The greater t_1^n is, the safer the nth teammate is.

  There are two evaluation functions we study here:

  1. Version 1 is defined as:
  $$t_1^n = f(d_1^n), \tag{1}$$
  2. Version 2 is defined as:
  $$t_1^n = f(d_1^n) + \sum_{\forall m, d_{2m}^n < \epsilon} g(d_{2m}^n) \tag{2}$$

  where

  - d_1^n is the distance between nth teammate and the hoop.
  - d_{2m}^n is the distance between nth teammate and the mth visible opponent.
  - $f(x)$ is a function that evaluates the goodness to shoot for the teammate.
  - $g(x)$ is a function that evaluates the threat from the opponents.

- Strategies to determine to attack or to defend when the ball is free. It is intuitive that when an opponent controls the ball, a player needs to defend. If a teammate controls the ball, a player needs to attack. But when the ball is free, what strategies should the player deploy?

  When a player sees a ball free, it has three options: (1) go to catch the ball; (2) go to the attack half; (3) go back to the defense half. Naturally it is interesting to study different strategies on how to choose these options. One strategy uses no ball state prediction at all. A player always goes to to catch the ball, if it sees a ball free. The other strategy uses ball state prediction. The mechanism is defined as the followings:

  $BallEstimate \in \{0, 1, 2\}$ indicates the estimate who will control the ball in a few cycles' time. It is denoted as E_1. E_1 = 0 means the player will control the ball. E_1 = 1 means one teammate will catch the ball. E_1 = 2 refers to the belief that an opponent will get the ball first.

  - IF($t_0 \leq t_1$)$\wedge$ ($t_0 \leq t_2$) THEN E_1 = 0;
  - ELSE IF($t_1 \leq t_2$) THEN E_1 = 1;
  - ELSE E_1 =2,

  where

  - t_0 is an integer and refers to the cycle the player is estimated to catch the ball.
  - t_1 is an integer and refers to the shortest cycle a teammate needs to catch the ball.
  - t_2 is an integer and refers to the shortest cycle an opponent needs to catch the ball.

  After having defined the value of E_1, we can define the actions for a player when it sees a ball free.

  - IF(E_1 = 1) THEN Go to the attack half;
  - ELSE IF(E_1 = 0) THEN Go to get the ball;
  - ELSE IF(E_1 = 2)) THEN Go back to the defense half.

- Strategies to defend. Basketball defense can be mainly divided in two categories: zone defense [3] and man to

3 In zone defense, players are assigned to positions in a particular formation, such as a 2:1:2 zone. They are responsible for an area (zone) of the court in which their position is located.

man defense [4][1]. We focus on the man to man defense in this paper. How to select an opponent is an difficult problem [14].

When the ball is controlled by an opponent, a team needs to defend. For each player in RoboNBA, defense means two things: (1) select an opponent; (2) try to be as near to the opponent as possible. We study the impacts of two different methods to select an opponent in this paper. One method uses adaptive mark defense. The other method uses fixed mark defense.

The adaptive mark defense works as follows:

– IF (There is opponent in the visible area) THEN select the opponent with the highest opponent evaluation and defend it.

– ELSE Go back to my defense area.

The $OppoEva = \langle o_1, o_2, \cdots, o_5 \rangle$. The evaluation function is defined as:

$$o_n = f(d_1^n) + h(d_2^n) + l(d_3^n) - k(d_{41}^n, \cdots, d_{44}^n) + q(d_5^n) \tag{3}$$

where

– d_1^n is the distance between the nth opponent and the hoop.

– d_2^n indicates if the nth opponent controls the ball or not.

– d_3^n indicates if the nth opponent is my mark opponent or not

– d_{4m}^n, is the distance between the nth opponent and the mth teammate.

– d_5^n is the distance between the nth opponent and the player.

– $f(x)$ is a function that evaluates the distance from the opponent to the hoop.

– $h(x)$ is a function that evaluates if the opponent holds the ball or not.

– $l(x)$ is a function that evaluates if the opponent is the player's predefined target or not.

– $k(x1, \cdots, x4)$ is a function that evaluates the defense for the opponent from other teammates.

– $q(x)$ is a function that evaluate the distance from the player to the opponent.

The fixed mark defense works like the followings:

– IF (My mark opponent in the visible area) THEN try to defend my mark opponent

– ELSE IF (There is opponent in the visible area) THEN select the opponent with the highest opponent evaluation.

– ELSE Go back to my defense area.

4 In the man-to-man set, players are responsible primarily for guarding a particular opponent.

3.2. Global Performance in RoboNBA

The global performance of a match can be measured by the average ball control time of a team, the average team scores and so on. In this paper, we do not propose an integrated measurement of a match. Rather, we study the relationships between agent's local behaviors and a certain measurement of global performance of a RoboNBA match. The measurements adopted in this paper are:

- Ball Control Time. The ball has two states. One is the free state and the other is the busy state. When the ball is busy, it is controlled by a player. A team controls a ball whenever one of its players controls the ball. If a interval of time the ball is free, this interval belongs to the team, whose player is able to control the ball first immediately after the interval.
- Pass Accuracy. A Pass Success means when a player passes a ball, one of its teammates first catches the ball within an interval, N cycles. P_s denotes the number of Pass Success of a team in a match. A Pass Fail refers to when a player passes a ball, one of its opponents first catches the ball within an interval, N cycles. P_f denotes the number of Pass Fail of a team in a match.

$$PassAccuracy = \frac{P_s}{P_f + P_s} \tag{4}$$

- Stamina Remained. At the beginning of a match, each player has a fixed stamina (We used 3000 for all experiments in the paper). Each time a player executes an action, some amount of stamina is deducted from the player. Stamina Remained is the averaged stamina for a team of players at the end of a match.
- Ball Lost Time. Count for the number of times when a ball is stolen, intercepted and blocked for all players in a team.
- Score. The score of a team is just the summation of all scores gained by its players.

4. Experimental Results and Discussions

In this section, we report the preliminary results obtained from our experiments. In all experiments, abilities of players, such as block abilities, intercept abilities, etc. are set to the same to ensure fair competition between strategies. In the following experiments, strategies for team A and team B are the same unless mentioned.

Experiment 1 *When a player needs to pass the ball to a teammate, it has to choose a teammate first. We study the mechanism to select a teammate for passing in this experiment.*

Team A uses Version 2 pass while team B uses Version 1 pass. Table 1 is 10 times averaged results:

	Team A	Team B
Ball Control Time	144.2	137.2
Pass Accuracy	**0.9359**	**0.8631**
Stamina Remained	300.8	322.6
Ball Lost Time	6.2	5.4
Score	22	16

Table 1. Version 2 Pass V.S. Version 1 Pass

Observation 1 *We has the followings observations on Experiment 1:*

1. *The Pass Accuracy of team A is significant higher than that of team B. It is because Version 2 pass considers the threat from the opponents. Higher evaluation value in Version 2 pass means fewer opponents nearby, given the same distance to the hoop.*
2. *Team A has a little bit more Ball Control Time than team B.*
3. *The Stamina Remained of team A is more or less the same with that of team team B. The strategies on pass do not have much influence on the stamina remained.*
4. *Team A has a little bit higher Ball Lost Time.*
5. *Team A has significant higher Score than team B. Even though team A has a higher Ball Lost Time, it has significant higher score. We can conclude the effectiveness of version 2 pass is much higher than that of version 1 pass.*

Remark 1 *In Experiment 1, we studied how pass strategies affect the global performance of a RoboNBA match. Obviously passing the ball to an teammate is an cooperation action. And we did not use communication for pass. For introduction to cooperation in MASs, readers are referred to [5]. Ito proposed an algorithm for cooperative actions for MAS [9]. It was cooperation with communication [5]. Lesser and Sen's works [17] [18] deal with negotiation between agents. Negotiations are a type of cooperation [5]. We studied the impact of non-communicative cooperation in a more complicated environment. From Table 1, we can see Team A has higher Pass Accuracy and significant higher Score. From these results, we can conclude better cooperation mechanism in MAS leads to better global performance of an MAS.*

Experiment 2 *Team A uses no ball state prediction at all. A player always goes to to catch the ball, if it sees a ball free. It can be considered as a greedy algorithm, because a player assumes that it can get the ball first at all situations. Team B uses ball state prediction. Table 2 is 10 times averaged results:*

	Team A	Team B
Ball Control Time	144.4	137.3
Pass Accuracy	0.8833	0.9023
Stamina Remained	**68.34**	**210.82**
Ball Lost Time	7.1	6
Score	17	19

Table 2. No Ball State Prediction V.S. Ball State Prediction

Observation 2 *On Experiment 2 we observe the followings:*

1. *The Stamina of team B is significant higher than that of team A. Ball state prediction helps players to do the correct thing in advance. Obviously it saves stamina.*
2. *Team A has minor more Ball Control Time than team B.*
3. *The Pass Accuracy of team B is more or less the same with that of team A. It is reasonable because the two teams use the same pass strategy (Version 2 Pass).*
4. *Team A has a little bit higher Ball Lost Time. Often many players in team A try to get the ball at the same time. In this way, many player scatter in a small region. Naturally it is easier for the opponent team to defend. Thus it results in higher Ball Lost Time for team A.*
5. *Team B has higher Score than team A, but not very significant. It is because team B has fewer Ball Lost.*

Remark 2 *In Experiment 2, we compared the performance of agents without ball state prediction and agents with ball state prediction. Agents without ball state prediction can be viewed as irrational agents since it does not analyze which choice is better. On the other hand, agents with ball state prediction can be viewed as rational agents. Although we do prove it here, we argue the strategy adopted by team A will maximize its expected utility. From Table 2, we can see Team B has higher Pass Accuracy and higher Score. From these results, we can conclude the rational agents is better than irrational agents in MAS. [6] [19] are good literature in rational decision making.*

Experiment 3 *We study the strategies to defend in this experiments. Team A uses adaptive mark defense. Team B uses fixed mark defense.*

Table 3 is 10 times averaged results:

Observation 3 *The followings are our observations on Experiment 3:*

1. *The Pass Accuracy of team A is significant higher than that of team B. So we can conclude the adaptive mark*

	Team A	Team B
Ball Control Time	145.2	136.7
Pass Accuracy	**0.9495**	**0.8987**
Stamina Remained	146.2	181.7
Ball Lost Time	6	6.9
Score	20.8	15.2

Table 3. Adaptive Defense V.S. Fixed Defense

defense is more efficient than fixed mark defense in RoboNBA.

2. *Team A has a little bit more Ball Control Time than team B.*

3. *The Stamina of team B is a little bit higher than that of team A. The adaptive defensive requires the player to defend different opponents at different situations. Consequently, team A consumes more stamina.*

4. *Team B has a little bit higher Ball Lost Time. It also demonstrates the adaptive mark defense is superior to the fixed mark defense.*

5. *Team A has significant higher Score than team B. Better defense, higher score.*

Remark 3 *In Experiment 3, we studied the mechanism to select an opponent in order to defend. We consider it a distributed coordination problem in MAS, because each agent has to make a decision for itself based on its local information, such that the team as a whole has an effective defense. For more information in coordination in MASs, readers are referred to [4] [10] . The coordination techniques used in both two teams can be considered as short-term coordination [10]. Every few cycles, an agents use a specified mechanism to select an opponent and defend it. From Table 3, we can see Team A has higher Pass Accuracy, lesser Ball Lost Time and significant higher Score. Based on the result, we can conclude the coordination techniques has significant impact on the global performance of an MAS.*

5. Conclusions and Future Work

In this paper, we summarized previous work on local behaviors of agents and global performance of MASs and highlighted our contribution. Because of the limitations in previous work, we studied the relationships in a more complex environment, RoboNBA. Then we formulated the local behaviors and provided the measurements for the global performance in RoboNBA. After that, through experiments and discussions, we discovered local behaviors of agents had great influence on the global performance of MASs. From the experiment results, we can see cooperation mechanism to select an teammate to pass can significant affect the Pass Accuracy for a team. And using rational decision making, players do the correct thing in advance and thus they can save stamina. At last better coordination technique among agents has a more effective and coherent defense against the opponents.

In the future, we will try to refine our model of RoboNBA, e.g., add a turn neck function. And we will refine the pass, ball state prediction and defense strategies in the above experiments. In addition, we will study non-linear aggregation phenomena in MASs, e.g., phase transitions. For concrete definitions and examples, please refer to [8] [12] [20]. We can use assistance distance as the independent variable and the global performance of a team as the order parameter.

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