Multiagent RoboNBA Simulation: From Local Behaviors to Global Characteristics

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In this article, the authors show their current work on the relationship between local behaviors of agents and global characteristics in a multiagent NBA simulation, which is called RoboNBA. Two sources of different local behaviors are introduced: decision-making mechanisms and agent strategies. The global characteristics consist of global performance and global patterns. The authors address the problem of how to quantitatively measure the global performance and global patterns in RoboNBA. For global patterns, they focus on the diversity of attack patterns of a team. Through experiments and analysis, they try to examine how agent local behaviors can lead to different global performance and interesting global patterns in RoboNBA.

Keywords: RoboCup, RoboNBA, multiagent systems, global patterns, entropy

1. Introduction

In multiagent systems (MAS), there are usually several system-level goals that agents need to achieve. In most cases, we can only directly control and engineer single agents rather than an MAS. For example, in RoboCup [1], two teams of players play a soccer game with each other. We need to design and implement intelligent players that understand how to organize effective attack and defense maneuvers together with its teammates, so that a team can win a match by scoring higher. Therefore, to achieve the system-level goals, understanding the relationship between local behaviors of agents and global characteristics of MAS is crucial.

1.1 Related Work

The relationship between local behaviors of agents and global characteristics of MAS has been extensively studied by researchers in the following five domains: cellular automata (CA), ecology, multiagent negotiation, collective robotics, and RoboCup.

In CA, each cell can be viewed as a single agent, and all the cells as a whole can be treated as an MAS. The problem of how the local transition rules of cells affect the evolution of CA is an interesting topic. Langton [2] illustrated that the evolution of CA dynamics (considered as team behaviors) can be classified into order, chaotic, and complex by a parameter λ, which is calculated based on the state selection probabilities of a cell. Wuensche [3] defined an input entropy to characterize the complexity of one-dimensional CA. Jones and Mataric [4] showed that a relatively simple set of local transition rules can generate complex global patterns. In the above studies, the dynamics of cells in CA are the same under all conditions. We understand that CA is very powerful and useful for theoretical computation, but its homogeneities both at the agent level and the system level are not correct in many scenarios. What is more, these agents have hardly any intelligence. For the second domain, ecology, Jánosi and Scheuring [5] showed that the spatial evolutionary process of two competing species is determined by an exponent β defined in the growth rules of the two species. Medvinsky et al. [6] showed that the development spatial distribution of the substrate concentration is closely related to a weight parameter A in the concentration updating function of a square. For ecology, research is often conducted based on CA and hence suffers from similar problems [5, 6]. Therefore, in this article, we study the aforementioned relationship in an environment where agents should be heterogeneous in different scenarios and need to be intelligent enough to find out their best actions under different circumstances.

Multiagent negotiation concerns how single agents can negotiate with each other such that the entire MAS can perform better. Ekenberg, Danielson, and Boman [7] analyzed how a set of local strategies based on credibility affects the global rationality for handling imprecise

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information. Saha, Sen, and Dutta [8] and Sen, Biswas, and Debnath [9] discussed the global performance of selfish agents, reciprocative agents, and other augmented agents of the two types, such as individual lying selfish agents. Abdallah and Lesser [10] and Shen, Zhang, and Lesser [11] did some similar work and provided a more concrete definition of tasks. Ekenberg, Danielson, and Boman [7] provided only some statistical analysis but did not define a task at all, whereas in Abdallah and Lesser [10] and Shen, Zhang, and Lesser [11], tasks are clearly defined, which have *arrival time*, *length*, *deadline*, and other properties, such as *reward*. These tasks have static time constraints (e.g., they require a predefined and fixed time to be finished). Essentially, they are more or less transactions. What is more, the agent actions are to select a task, execute it, and decide whether to cooperate with other agents. These definitions are incorrect in some situations (e.g., the service times are dynamically defined at runtime). We will study the relationship mentioned before in a more competitive environment where agents have allies as well as opponents. The goal of an agent is to finish and to assist its allies to efficiently handle their tasks and try to finish as many tasks as possible. On the other hand, an agent should prevent its opponents from finishing their tasks. Furthermore, the properties of a task are more dynamic (e.g., there are no predefined service times for tasks). They depend on the temporal and spatial characteristics of the environment.

There is also some interesting work on collective robotics, which focuses on the performance and behaviors of robot teams induced from different individual behaviors of robots as well as the interaction among them. Beckers, Holland, and Deneubourg [12] studied how the size of a group of robots affects the performance efficiency of collective tasks, where the robots use stigmergy as their coordination method. Mataric [13] demonstrated that collective intelligence emerges from simple local interactions. In Beckers, Holland, and Deneubourg [12] and Mataric [13], no cooperation is needed except for avoiding robot collisions. The task is simple object gathering, which can be done by a single robot. In addition, the environment and the task are not complex enough from the agent's point of view. We will study the aforementioned relationship in an environment where agents need to cooperate with each other so as to solve complex tasks. Besides, Balch [14] illustrated that the correlations between diversity and performance are different in two distinct applications: robot foraging and RoboCup. We consider that this investigation can be done in a more thorough fashion.

In RoboCup, two teams of players play soccer with each other. Each player behaves in intelligent ways so that a team can perform better by scoring higher. Prokopenko and Wang [15, 16] evaluated the team performance from the individual agent level to the multiagent coordination level. They studied only the diversities of individual agents but not those of teams. They demonstrated that multiagent coordination is related to team performance. However, how the agents can take advantage of coordination in their team is not clear. Raines, Tambe, and Marsella [17] analyzed team behaviors leading to successes in RoboCup matches. They aimed to provide a tool for humans to understand why a team can win a match using rule inductions. However, they did not study how the local behaviors of agents can lead to the specified team behaviors, which is the concentration of our research work.

1.2 Problem Statement

As mentioned previously, in this article, we investigate the relationship between local behaviors of agents and global characteristics of MAS in an environment with the properties discussed before. Obviously, the problem is nontrivial. Before further descriptions, we need to clarify what we refer to as local behaviors and global characteristics in this study. Two sources of local behaviors are studied, including decision-making mechanisms as well as basic strategies of individual agents. Global characteristics include global performance and global patterns of MAS. Global patterns refer to the fashion in which a team organizes its defense and attack. More specifically, in this article, we focus on the diversity of attack patterns. In more detail, we study the following problems:

1. How do decision-making mechanisms influence global performance?
2. What is the relationship between different measurements of global performance? How are they correlated in different situations?
3. Under what conditions will diversity emerge? How do we design a more diverse agent team?
4. What is the relationship between diversity and performance? Under what conditions will diversity improve performance?
5. How does the diversity of a single team evolve when competing with opponents of different defense strategies?

1.3 Organization

The rest of this article is organized as follows. Section 2 gives an overview of the RoboNBA simulation platform. Section 3 formulates two sources of different local behaviors of agents, including decision-making mechanisms and agent strategies. Section 4 provides some measurements for global performance and global patterns of RoboNBA. Section 5 presents our simulation results and discusses the problems studied. Section 6 concludes the article.

2. An Overview of the RoboNBA Simulation Platform

RoboNBA is a multiagent simulation platform on which a variety of research can be conducted, such as minority game and robotic algorithms. We use RoboNBA to study the relationship between agent local behaviors and global characteristics of MAS.

2.1 Motivation of Using RoboNBA as a Simulation Platform

RoboNBA [18] is a simulation platform where two teams of autonomous agents (players) can play basketball with each other. Players have to act in intelligent ways so that their team as a whole can have good performance. As we know, the RoboCup Simulation League [1] has served as a good MAS testbed. Why do we implement RoboNBA? The reasons are as follows:

1. Many parameters in RoboCup are fixed so as to maintain a fair comparison between different teams. 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 relatively simpler actions and accurate perceptions. Therefore, it is easier to implement RoboNBA clients.

Although simpler than RoboCup, it is still nontrivial to implement competitive RoboNBA clients. For example, it is very difficult to accurately predict teammates' and opponents' next positions, which are required when organizing defense or attack.

2.2 The RoboNBA Components

1. **The Server Environment**

   The RoboNBA simulation environment consists of n players that move on an $xmax \times ymax$ 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 $(P_j.x, P_j.y)$. The positions of players are subject to the following constraint: $(P_i.x \neq P_j.x) \vee (P_i.y \neq P_j.y)$, if $i \neq j$.

2. **Player Actions**

   A player has five basic actions to execute. It can only execute a single action each time. The actions that a player can perform are defined as follows:

   (a) shoot(power *Pow*, direction *Dir*)

   A player shoots with power *Pow* in direction *Dir*. If the shot is successful, the team gains scores. Otherwise, the ball goes to the position calculated with *Pow* and *Dir*. When a player executes a shot, there is a probability that the ball is blocked by an opponent, if the player is within the *block range* of the opponent. There is a maximum range within which a player can shoot.

   (b) pass(power *Pow*, direction *Dir*)

   A player passes with power *Pow* in 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 position to which a player wishes to pass the ball is within the *intercept range* of the opponent. There is a maximum range within which a player can pass the ball.

   (c) run(power *Pow*)

   A player runs with power *Pow* in the current body direction. When a player executes a run, there is a probability that the ball is intercepted by an opponent, if the player position after running is within the *steal range* of the opponent. If the ball is not intercepted, the ball's position is changed to the player's new position. There is a maximum range within which a player can run. If more than one player wants to go to the same position, their destinations will be slightly adjusted to ensure that only one player is in a particular position.

   (d) turnDirection(Direction *Dir*)

   A player changes its body direction by *Dir*. A total of eight directions are available for players.

   (e) catch()

   If the distance between the player and the ball is smaller than the *catchable distance* of the player, the ball belongs to the player executing the catch() command. The ball switches to the nonfree state. Otherwise nothing is done. If more than one player is within *catchable distance* of the ball, the ball will be caught by the nearest player. Note that catch() is executed only when the ball is free.

   Each executed action costs a player some stamina. However, to obtain consistent results for all initial stamina values, a player is allowed to execute actions even when its stamina is negative in the current version of RoboNBA. Nonetheless, we can compare the effectiveness of decision-making mechanisms and strategies through stamina remaining values.

3. **The Sensor Model**

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

   - The information of a player includes its position, teamID, playerID, stamina, and so on.

- The information of the ball includes its position and the state (free or nonfree), as well as the information of the player who is controlling the ball, if the ball is nonfree.

The design of RoboNBA is motivated by that of RoboCup [1]. In addition, we use probabilistic models to simplify the action process so that we can focus on player strategies and decision-making mechanisms. All actions provided in RoboCup are present in RoboNBA, except the say and the turn-neck actions. At this stage, we do not provide explicit communication through sockets; therefore, the say action is not included. In addition, we use a circle to represent the visible area of a player, and thus the turn-neck action is not required. In conclusion, the five actions are enough for the current version of RoboNBA.

Besides, in RoboNBA, we assume all players have the same abilities, which is in agreement with RoboCup. Preserving the same abilities for all players is essential to compare the effectiveness and efficiency of decision-making mechanisms and agent strategies, although they are different in real basketball matches.

Table 1 specifies parameters used in RoboNBA matches.

3. Local Behaviors in RoboNBA

Agent local behaviors refer to those behaviors that have only local influence on the global performance of an MAS. What causes agents to behave differently from each other? These causes can be divided into two categories: agent decision-making mechanisms and agent strategies.

3.1 Decision-Making Mechanisms

Simple Reactive Agents. This type of agent can only do some simple reasoning and respond to its environment reactively. There are two procedures for two distinct scenarios: a player controlling the ball and a player not controlling the ball. Figure 1 describes the behaviors of a player P_i controlling the ball. The U_{P_j} used in Figure 1 is defined in equation (15). Figure 2 describes the behaviors of a player P_j not controlling the ball. The move(area) procedure used in Figure 2 works as follows: if the current direction of a player is correct for the area, then the player will run in the current direction. Otherwise, the player will change to the correct direction. E_1 is defined in the Section 3.2.

Pseudocode for the player P_i controlling the ball

If P_i.isShootable()==true
  Calculate power p and direction d for shoot;
  P_i.shoot(p,d);
Else
  If $\exists\, P_j$, P_i.isVisible(P_j) $\wedge$ ($U_{P_j} > U_{P_i}$)
    P_i.passBall(P_j);
  Else
    P_i.move(P_i.attackArea).

Figure 1. The behaviors of a player controlling the ball

Pseudocode for players P_j not controlling the ball

If isTeamControlBall() == 1 //attack
  If P_j.isRegion(P_j.defenseArea) ==false
    P_j.move(P_i.attackArea);
  Else
    randomMove();
Else If isTeamControlBall() == -1 //defend
  IF P_j.isRegion(P_j.defenseArea) ==false
    P_j.move(P_i.defenseArea);
  Else
    Select P_j.Opponent;
    P_j.defend(P_j.Opponent);
Else If isTeamControlBall() == 0 $\wedge$ E_1 == 0
  If P_j.isVisible(Ball)
    P_j.move(Ball.posistion);
  Else IF P_j.isVisible(Ball) $\wedge$ E_1 == 1
    P_j.move(Ball.attackArea);
Else IF P_j.isVisible(Ball) $\wedge$ E_1 == 2
    P_j.move(Ball.defendArea).

Figure 2. The behaviors of a player not controlling the ball

Rational Agents. Rational agents are characterized by their selection of possible actions with the highest evaluation. The evaluation function includes two terms: the success possibility and the action reward. The success possibility attempts to evaluate the possibility that an action can be executed successfully. On the other hand, the action reward refers to the contribution that an agent can bring to its team after successfully executing the action. The contribution has a variety of meanings, such as shooting a ball, securing better attack positions, and acquiring better defense positions. The design of rational agents is motivated by Obst [19]. Similar to the case of simple reactive agents, there are two decision-making mechanisms for players controlling the ball and not controlling it.

Table 1. Parameters used in RoboNBA matches

	Value	Remark
visible distance	50	Visible distance of players
cathable distance	3	Catchable distance of players
steal range	10	Steal range of players
block range	10	Block range of players
intercept range	10	Intercept range of players
xmax	167	Length of the RoboNBA court
ymax	99	Width of the RoboNBA court

Rationality for the Ball Holder. Controlling the ball, player P_j can do the following: (1) pass the ball to a teammate, (2) shoot the ball, or (3) move to a new position. We define an integrated evaluation function for all three types of actions. Player P_j will choose an action k, such that

$$k = arg \max_i \ E_{ij}, \tag{1}$$

$$E_{ij} = \alpha_{ij} R_{ij}, \tag{2}$$

where

- E_{ij} is the evaluation for the ith action of player P_j.
- α_{ij} evaluates the possibility that the ith action will succeed. It is defined as

$$\alpha_{ij} = \begin{cases} 1 & N = 0 \\ \frac{1}{2N} & N > 0 \end{cases} \tag{3}$$

$$N = \begin{cases} |\{ l \mid Dist(P_o^l, P_j) \le P_o^l.stealRange\}| \\ \qquad move \\ |\{ l \mid Dist(P_o^l, P_k) \le P_o^l.interceptRange\}| \\ \qquad pass \\ |\{ l \mid Dist(P_o^l, P_j) \le P_o^l.blockRange\}| \\ \qquad shoot \end{cases} \tag{4}$$

  where

  - $Dist(A, B)$ calculates the distance between A and B.
  - P_o^l refers to the lth opponent of P_j.
  - P_k refers to the teammate of P_j, to whom P_j wants to pass the ball.

- R_{ij} evaluates the reward for the ith action. It is defined as

$$R_{ij} = \begin{cases} \frac{((U_{P_j})' - U_{P_j})}{U_{max}} & run \\ \frac{\sigma((U_{P_j}^k)'' - U_{P_j})}{U_{max}} & change\ to\ the\ kth\ direction \\ \frac{(U_{P_m} - U_{P_j})}{U_{max}} & pass \\ C & shoot \end{cases} \tag{5}$$

  where

  - U_{P_j} denotes the current position evaluation for P_j. It is defined in equation (15).
  - U_{max} is the maximum value of U_{P_j} for all P_j.
  - $(U_{P_j})'$ denotes the expected highest position evaluation for P_j a cycle later if it runs in the same direction.

$$(U_{P_j})' = \max_n U_{P_j}^n, \tag{6}$$

    where

  - $U_{P_j}^n$ denotes the position evaluation of P_j after it runs with a speed of $\frac{n}{N_v}$*MaxVelocity* in the same direction. N_v is the number of different velocities.
  - $(U_{P_j}^k)''$ denotes the expected highest position evaluation for player P_j two cycles later if it changes to the kth direction.

$$(U_{P_j}^k)'' = \max_n U_{P_j}^{nk}, \tag{7}$$

    where

  - $U_{P_j}^{nk}$ denotes the position evaluation of P_j after it changes to the kth direction and runs with a speed of $\frac{n}{N_v}$*MaxVelocity*. N_v is the number of different velocities.
  - U_{P_m} denotes the current position evaluation for the teammate P_m.
  - C is a constant.

$$C = \begin{cases} \kappa & Dist(Hoop, P_j) \le \\ & Shootable\ Distance \\ \lambda & Dist(Hoop, P_j) > \\ & Shootable\ Distance \end{cases} \tag{8}$$

    where

  - κ is a positive constant and λ is a negative constant.
  - σ is a discount factor. $0 < \sigma < 1$.

Rationality for a Player without the Ball. Because the actions of players without the ball are essentially to move, action differences lie on directions and velocities. These actions are deemed to be successful since the players are not controlling the ball. Therefore, we do not need to calculate the success possibilities for actions and focus on the rewards. Player P_j will choose an action k, such that

$$k = arg \max_i \ E_{ij}, \tag{9}$$

where $E_{ij} = R_{ij}$. The calculation of R_{ij} depends on whether P_j will attack, defend, or catch the ball. How to determine to attack, defend, or catch the ball depends on the defense strategy in Section 3.2.

Attack.

$$R_{ij} = \begin{cases} \frac{((U_{P_j})' - U_{P_j})}{U_{max}} & run \\ \frac{\sigma((U_{P_j}^k)'' - U_{P_j})}{U_{max}} & change\ to\ the\ kth\ direction \end{cases} \tag{10}$$

where $(U_{P_j})'$, $(U_{P_j}^k)''$, and U_{P_j} are defined as those used for the player with the ball.

Defend.

$$R_{ij} = \begin{cases} \frac{((Q_{P_j})' - Q_{P_j})}{Q_{max}} & run \\ \frac{\sigma((Q_{P_j}^k)'' - Q_{P_j})}{Q_{max}} & change\ to\ the\ kth\ direction \end{cases} \tag{11}$$

$$Q_{P_j} = k_1(d_2^j) + k_2(d_m^j), \tag{12}$$

where

- Q_{max} is the maximum of Q_{P_j} for all P_j.
- d_2^j is the distance between P_j and the hoop in the defense half of the court.
- d_m^j is the distance between P_j and its current mark opponent.
- $k_1(x)$ evaluates the goodness to defend according to the hoop in the defense half of the court.
- $k_2(x)$ evaluates the defense effect that P_j imposes on the mark opponent.
- $(Q_{P_j})'$ and $(Q_{P_j}^k)''$ are similar to $(U_{P_j})'$ and $(U_{P_j}^k)''$, as defined in equations (6) and (7), respectively.

Catch Ball.

$$R_{ij} = \begin{cases} \frac{((B_{P_j})' - B_{P_j})}{B_{max}} & \textit{run} \\ \frac{\sigma((B_{P_j}^k)'' - B_{P_j})}{B_{max}} & \textit{change to the kth direction} \end{cases} \tag{13}$$

$$B_{P_j} = b(d_3^j), \tag{14}$$

where

- B_{max} is the maximum of B_{P_j} for all P_j.
- d_3^j is the distance between P_j and the ball.
- $b(x)$ evaluates the goodness to catch the ball.
- $(B_{P_j})'$ and $(B_{P_j}^k)''$ are also similar to $(U_{P_j})'$ and $(U_{P_j}^k)''$, respectively.

3.2 Agent Strategies

Agent strategies refer to the manners in which agents handle their tasks. The specific strategies we study in this article are as follows:

- *Strategy to pass the ball.* Obviously, this strategy is local because a player cannot pass the ball to a teammate far beyond its assistance distance. In addition, a player uses its local information to make a decision on how to pass the ball. Generally speaking, only the accumulation of a series of passes has an impact on the global performance of a match. When a player needs to pass the ball, it selects a teammate with the highest position evaluation as defined by the following:

$$U_{P_j} = f(d_1^j) + \sum_{\forall n, d_n^j < \epsilon} g(d_n^j), \tag{15}$$

where

- d_1^j is the distance between P_j and the hoop in the attack half of the court.
- d_n^j is the distance between P_j and the nth visible opponent.
- $f(x)$ is a function that evaluates the goodness to shoot for P_j.
- $g(x)$ is a function that evaluates the threat from opponents.
- ϵ is a constant indicating a safe distance for defense.

- *Strategy to determine to attack or 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 strategy should a player deploy? When a player sees the ball free, it has three options: (1) catch the ball, (2) go to the attack half of the court, or (3) go back to the defense half of the court. The strategy makes use of ball state prediction, which is defined as follows: *Ball Estimate* (E_1) $\in \{0, 1, 2\}$ indicates who will control the ball in a few cycles' time. $E_1 = 0$ means that the player will control the ball. $E_1 = 1$ means that one teammate will catch the ball. $E_1 = 2$ means that an opponent will get the ball first.

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

  where

  - t_0, an integer, denotes the time the player is estimated to catch the ball.
  - t_1, an integer, denotes the shortest time a teammate needs to catch the ball.
  - t_2, an integer, denotes the shortest time 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 of the court;
  - ELSE IF($E_1 = 0$) THEN Go to catch the ball;
  - ELSE IF($E_1 = 2$) THEN Go back to the defense half of the court.

- *Strategies to defend.* Basketball defense can be mainly divided in two categories: zone defense and man-to-man defense [20]. We focus on the man-to-man defense in this article. How to select an opponent is a difficult problem [21].

  When the ball is controlled by an opponent, a team needs to defend. For each player in RoboNBA, defense means two things: (1) to select a mark opponent and (2) to be as close to the selected mark opponent as possible. We study the

1. 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.

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

impacts of three defense strategies in this article: adaptive mark defense, fixed mark defense, and greedy defense.

Adaptive mark defense works as follows:

- IF (There are opponents in the visible area) THEN Select the opponent with the highest opponent evaluation to be "my mark opponent" and defend it.
- ELSE Go back to my defense area.

$OppoEva = \langle o_1, o_2, \cdots, o_m \rangle$ indicates the evaluation for each visible opponent. The larger the o_n ($n \in \{0, \cdots, m\}$), the more relevant the player needs to defend the nth opponent. The evaluation function is defined as

$$o_n = f(d_1^n) + h(c^n) + u(m^n) + q(d_2^n), \tag{16}$$

where

- d_1^n is the distance between the nth teammate and the hoop in the defense half of the court.
- c^n indicates whether or not the nth opponent controls the ball.
- m^n indicates whether or not the nth opponent is my mark opponent.
- t_m^n is the distance between the nth opponent and the mth teammate.
- d_2^n is the distance between the nth opponent and the player.
- $h(x)$ is a function that returns a positive value if x is true and zero if not.
- $u(x)$ is a function that returns a positive value if x is true and zero if not.
- $q(x)$ is a function that evaluates the relevance of the player to defend an opponent according to the distance.

Fixed mark defense works like the following:

- IF (My mark opponent is in the visible area) THEN Try to defend my mark opponent;
- ELSE Go back to my defense area.

Greedy defense works as follows:

- IF (The ball holder is in the visible area) THEN Try to defend the ball holder;
- ELSE Go back to my defense area.

Table 2 specifies parameters used in RoboNBA players.

4. Global Characteristics in RoboNBA

Global characteristics include global performance and global patterns. Global performance means the overall performance of a team against an opponent team. Global patterns refer to the fashions in which a team organizes its defense as well as attack.

Table 2. Parameters used in RoboNBA players

	Value	Remark
κ	1	Reward for being able to shoot the ball
λ	–1	Reward for being unable to shoot the ball
σ	0.8	Discount factor
ϵ	20	Safe distance for defense

4.1 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 article, we do not aim at proposing an integrated measurement for a match. Rather, we study the relationships between agents' local behaviors and certain measurements of global performance in RoboNBA matches. The measurements adopted are as follows:

1. *Ball control time.* The ball has two states. One is the free state and the other is the nonfree state. When the ball is nonfree, it is controlled by a player. A team controls a ball whenever one of its players controls the ball. If, for an interval of time, the ball is free, this interval belongs to the team whose player controls the ball first immediately after the interval. The maximum ball control time in RoboNBA is 300 cycles. Intuitively, more ball control time means better performance. But it is not necessarily true.

2. *Pass accuracy.* A *pass success* means an instance when a player passes the ball and one of its teammates first catches the ball within an interval of N_p cycles. N_{ps} denotes the number of pass success of a team in a match. A *pass fail* refers to an instance when a player passes a ball and one of its opponents first catches the ball within an interval of N_p cycles. N_{pf} denotes the number of pass fail of a team in a match. The pass accuracy ranges in [0, 1].

$$\mathit{Pass\ Accuracy} = \frac{N_{ps}}{N_{ps} + N_{pf}}. \tag{17}$$

3. *Pass total.* The summation of pass success by all players in a team. It indicates the cooperation level of a team. The higher the pass total, the more cooperation a team exhibits.

4. *Stamina remaining.* At the beginning of a match, each player has a fixed initial stamina (we use 3000 for all experiments in this article). Each time a player executes an action, some stamina is deducted from the player. The stamina remaining is the averaged stamina for a team of players at the end of a match.

5. *Ball lost time.* This counts the number of instances when a ball is stolen, intercepted, and blocked for all players in a team. The less the ball lost time, the more effectively a team attacks. In most cases, the ball lost time falls into the range of [0, 10].

6. *Score.* The score of a team is just the summation of all scores gained by its players. It is the most important measurement in RoboNBA. In most cases, the score falls into the range of [4, 20].

4.2 Global Patterns in RoboNBA

For global patterns, we focus on the diversity of attack patterns of a team. Diversity is defined by Balch [14], based on Shannon and Weaver's entropy [22] in equation (18).

$$E = -\sum_{i=1}^{m} p_i \times \log p_i, \tag{18}$$

where p_i is a probability of the of ith instance. We apply the diversity to RoboNBA and accordingly design the following measurements:

1. *Ball entropy.* We calculate the probabilities of the ball control time shared by each of the five players in a team and the ball entropy based on these probabilities. The higher the ball entropy, the more even the distribution of ball control time among players in a team. It is in the range of [0, 2.3219].

2. *Score area entropy.* We divide the attack half of the court into six areas. Then we calculate the probability of the score gained in each of the six areas and the score area entropy based on these probabilities. The higher the score area entropy, the more diversely a team attacks. We think this measurement characterizes the essence of the diversity of attack, although it only calculates the diversity of the shooting areas. Generally speaking, diverse shooting areas imply diverse attack routes and cooperation patterns involved. It is in the range of [0, 2.5850].

3. *Score entropy.* We calculate the probability of the score gained by each of the five players in a team and the score entropy based on these probabilities. The higher the score entropy, the more diversely players are involved in scoring. In RoboNBA, it would be better that more players take the responsibility to gain scores. It is in the range of [0, 2.3219].

4. *Cooperative motivation.* This is the average number of players involved in the attacks in a match. It is not related to diversity, but it is still a good measurement for attack patterns. It indicates how willing and capable players cooperate with their teammates.

5. Experiments and Discussions

5.1 Experiments

In this section, we report the simulation results obtained from our experiments. In all experiments, abilities of players, such as block abilities, intercept abilities, and so on, are equal to ensure fair competition between teams. In the following experiments, agent decision-making mechanisms and agent strategies for teams A and B are the same unless mentioned. Note that in our following figures, the number above each data point represents how many data we have for that point in the experiments. If only one datum is available for a point on the tails, it is combined with the neighboring point.

EXPERIMENT 1. In this experiment, we study how decision-making mechanisms affect global performance and global patterns in RoboNBA. Team A is a simple reactive agent team. Team B is a team of rationale agents with greedy defense. Table 3 shows 60 times averaged results for global performance, and Table 4 presents the corresponding results for global patterns.

OBSERVATION 1. We have the following observations on Table 3:

1. The score of team B is significantly higher than that of team A.

2. Team A has much more ball lost time than team B.

Table 3. Global performance: Simple reactive agent versus rationale agent with the greedy defense

	Team A		Team B	
	Mean	Standard Deviation	Mean	Standard Deviation
Ball control time	99.13	13.47	161.68	9.82
Pass accuracy	0.96	0.05	0.98	0.02
Pass total	14.3	3.81	23.93	4.45
Stamina remaining	306.52	75.15	176.38	59.61
Ball lost time	4.75	1.79	2.70	1.66
Score	10.67	3.03	14.57	2.50

Table 4. Global patterns: Simple reactive agent versus rationale agent with the greedy defense

	Team A		Team B	
	Mean	Standard Deviation	Mean	Standard Deviation
Ball entropy	1.88	0.23	2.11	0.13
Score area entropy	1.13	0.59	1.66	0.34
Score entropy	1.07	0.53	1.76	0.31
Cooperative motivation	2.10	0.49	3.07	0.39

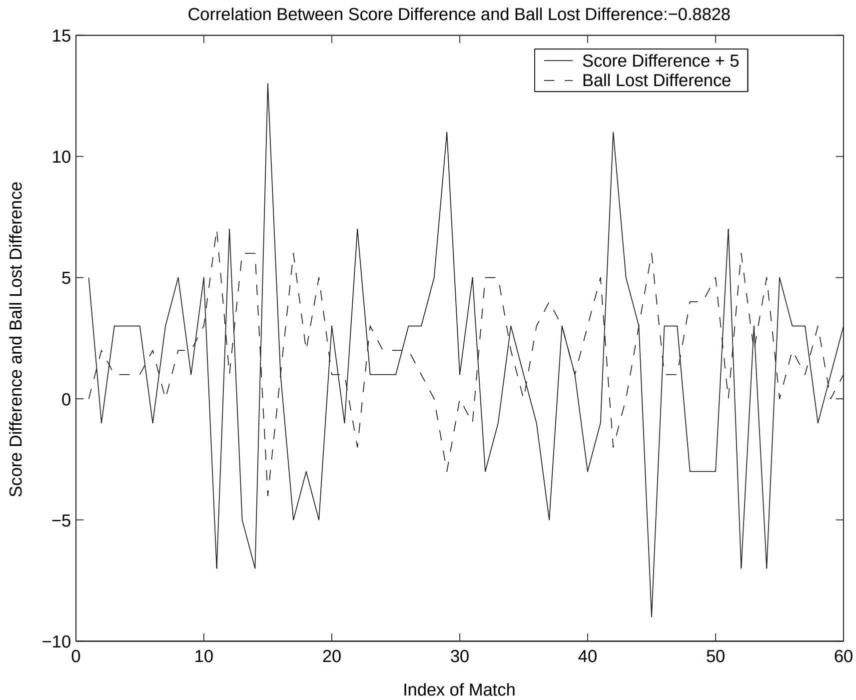

Figure 3. The correlation between the score difference and the ball lost difference for two teams in experiment 1 is –0.8828

Figure 3 shows the relationship between the ball lost time difference and the score difference. The corresponding correlation value is –0.8828.

3. The stamina remaining of team A is relatively higher than that of team B. The movement paths of simple reactive agents are not very diverse compared to those of rationale agents because simple reactive agents do not often change their directions. On the contrary, rationale agents change directions as long as they consider that it will maximize their expected utilities. It is reasonable to assume that rationale agents consume more stamina.

4. Team A has a slightly lower pass accuracy than team B. Agents from the two teams use the same evaluation function as defined in equation (15). In addition to position evaluation, rationale agents evaluate the success possibility for an action.

5. Team B has significantly more ball control time than team A.

6. Team B has a significantly higher pass total than team A. It can be inferred that rationale agents are more willing to cooperate and also more capable of doing that. Rationale agents often change directions to take a better route and thus have two benefits: (1) agents can reduce the probability of the ball being stolen, intercepted, or blocked because it is more difficult for opponents to predict their next positions, and (2) taking a more diverse route, agents can wait until their teammates enter an "unguarded" region and then pass the ball to them.

OBSERVATION 2. We have the following observations on Table 4:

1. Team B has a much higher score area entropy than team A. From Figures 4 and 5, we can observe that both score area entropies increase as score increases, although both of them decrease after the highest scores (we are not clear about this decrease at present).

2. We plot the relationship between the score area entropy difference and the score difference in Figure 6. We can observe that the score area entropy difference increases as the score difference increases within a range of $[-10, 0]$. However, this trend breaks down when the score difference exceeds zero. The corresponding correlation value is 0.4812. We can conclude that the score area entropy difference is a good indicator of the performance difference of the two teams in this experiment.

3. Team B has a much higher score entropy than team A.

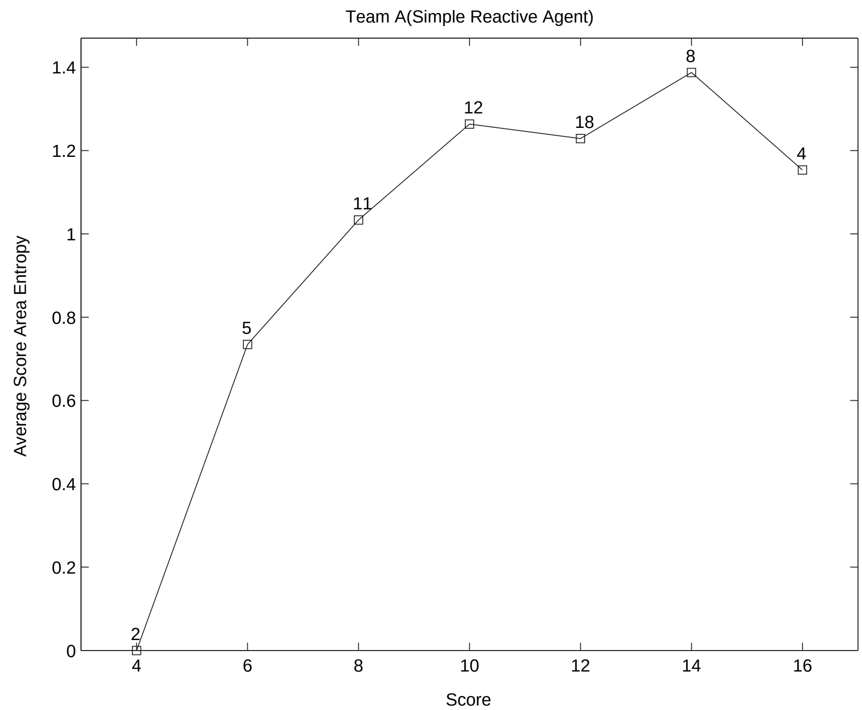

Figure 4. The relationship between score area entropy and score for a simple reactive agent team in experiment 1

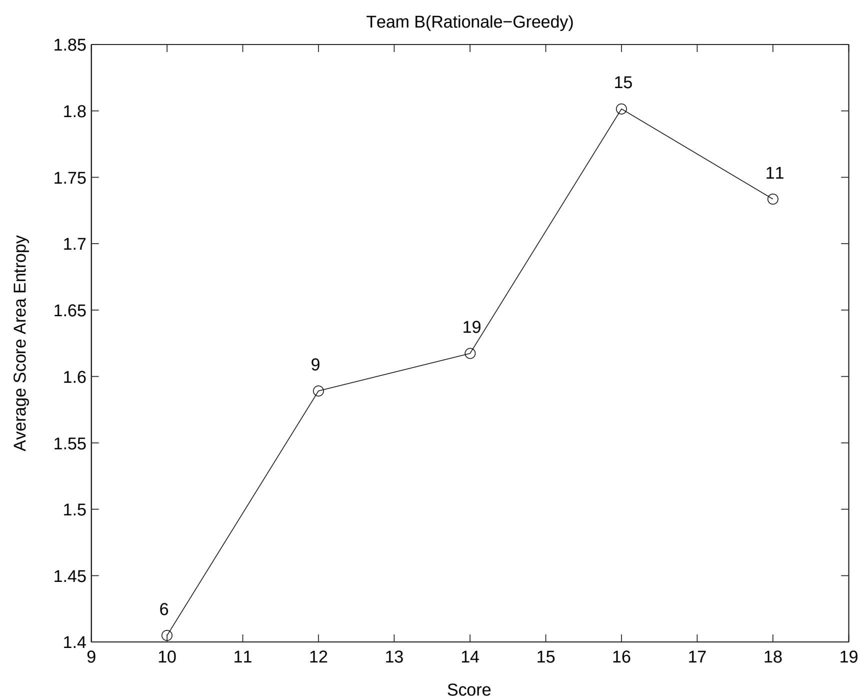

Figure 5. The relationship between score area entropy and score for the rationale agent team with greedy defense in experiment 1

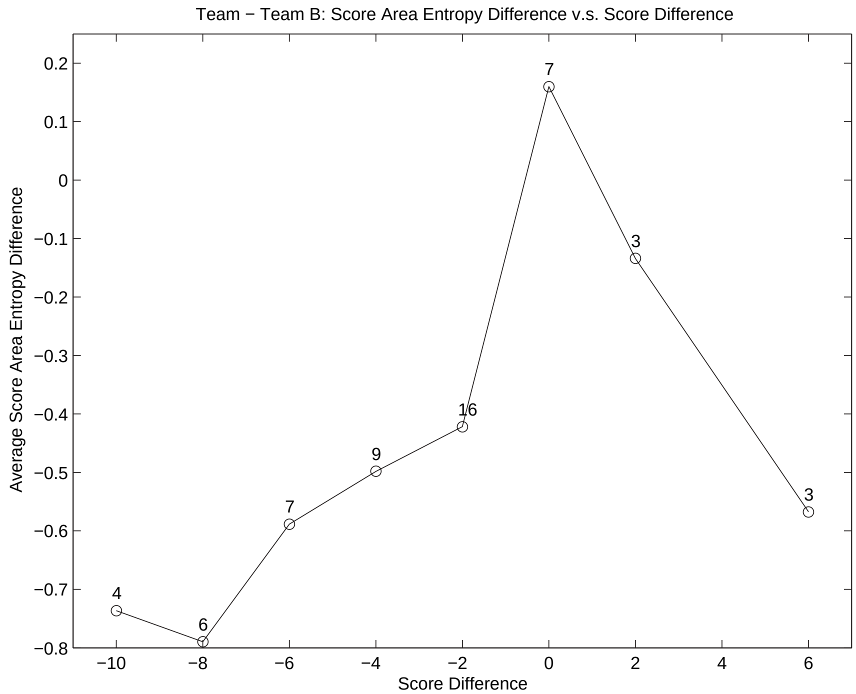

Figure 6. The correlation between the score difference and the score area entropy difference for two teams in experiment 1 is 0.4812

It means that more players in team B have chances to gain scores.

4. Team B has a significantly higher cooperative motivation than team A. From the data, we can see that, on average, one more player in team B is involved in attacks than in team A. This also demonstrates that rationale agents are more willing to cooperate and also more capable of doing that. We can infer that it is much more difficult for team A to defend effectively. In addition, we investigate the relationship between the cooperative motivation difference and the score difference and plot it in Figure 7. The correlation value between the two is 0.4205. We can conclude that cooperative motivation is a good indicator of the performance difference of the two teams in this experiment.

REMARK 1. In experiment 1, we compared a team of simple reactive agents (team A) and another team of rationale agents (team B) with the greedy defense. From Table 3, we can observe that team B has significantly more ball control time, a slightly higher pass accuracy, a higher pass total, less stamina remaining, significantly less ball lost time, and a higher score. From Table 4, we can discover that both the score area entropy and the score entropy of team B are significantly higher than those of team A. In addition, cooperative motivation of team B is significantly higher than that of team A. In summary, team B is much more competitive in terms of performance as well as more diverse in attack patterns than team A. What is more, we believe that the higher diverse attack patterns are emergent properties of rationale agents because we cannot know that the diversity of rational agents is much higher than that of simple reactive agents directly from their formulations. For more information related to emergent properties, readers are referred to Darley [23] and Mitchell and Newman [24].

EXPERIMENT 2. In this experiment, we compare two defense strategies: the greedy defense and the fixed mark defense. Team A is a team of rationale agents with the greedy defense. Team B is a team of rationale agents with the fixed mark defense. Table 5 presents 60 times averaged results for global performance, and Table 6 shows the corresponding results for global patterns.

OBSERVATION 3. We have the following observations on Table 5:

1. The stamina remaining of team B is significantly higher than that of team A. Agents in team A need to change their mark opponents frequently since they use the greedy defense. On the other hand, agents in team B always defend their predefined mark opponents. It is reasonable that agents in team A consume more stamina.

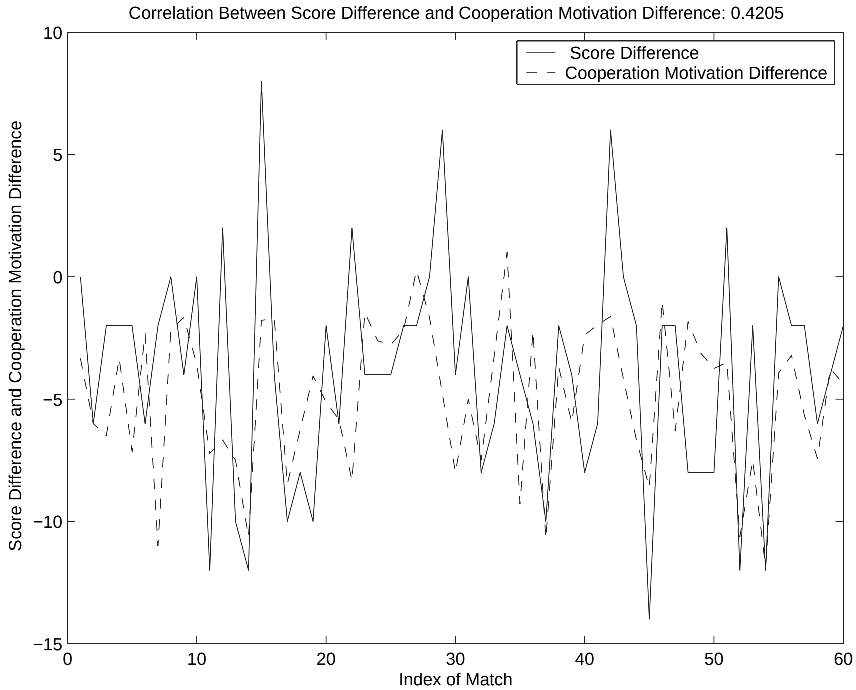

Figure 7. The correlation between the score difference and the cooperative motivation difference for two teams in experiment 1 is 0.4205

Table 5. Global performance: Rationale agents with the greedy defense versus rationale agents with the fixed mark defense

	Team A		Team B	
	Mean	Standard Deviation	Mean	Standard Deviation
Ball control time	157.77	11.48	124.97	11.53
Pass accuracy	0.98	0.02	0.99	0.02
Pass total	23.83	3.79	21.47	3.07
Stamina remaining	186.30	128.72	543.85	82.02
Ball lost time	2.67	1.62	2.37	1.51
Score	11.90	2.98	12.4	2.60

Table 6. Global patterns: Rationale agents with the greedy defense versus rationale agents with the fixed mark defense

	Team A		Team B	
	Mean	Standard Deviation	Mean	Standard Deviation
Ball entropy	2.04	0.15	2.06	0.13
Score area entropy	1.63	0.44	1.71	0.44
Score entropy	1.62	0.41	1.66	0.34
Cooperative motivation	3.06	0.33	3.20	0.30

2. Team A has a slightly more ball control time than team B.

3. Both the pass accuracy and the pass total of team B are more or less the same as those of team A.

4. Team A has slightly more ball lost time than team B. We can infer that fixed mark defense is a little bit more effective than greedy defense. Figure 8 shows the relationship between the ball lost time difference and the score difference. The correlation value between them is –0.8999.

5. Team B has a higher score than team A, but it is not very significant. It is mainly because team B has less ball lost time.

OBSERVATION 4. We have the following observations on Table 6:

1. Team B has a slightly higher score area entropy than team A. The reason might be that the defense of team A is slightly weaker and thus the attack diversity of team B is slightly higher.

2. From Figure 9, we can observe that the score area entropy increases as score increases for team B. But for the score range of [10, 16], the score area entropy

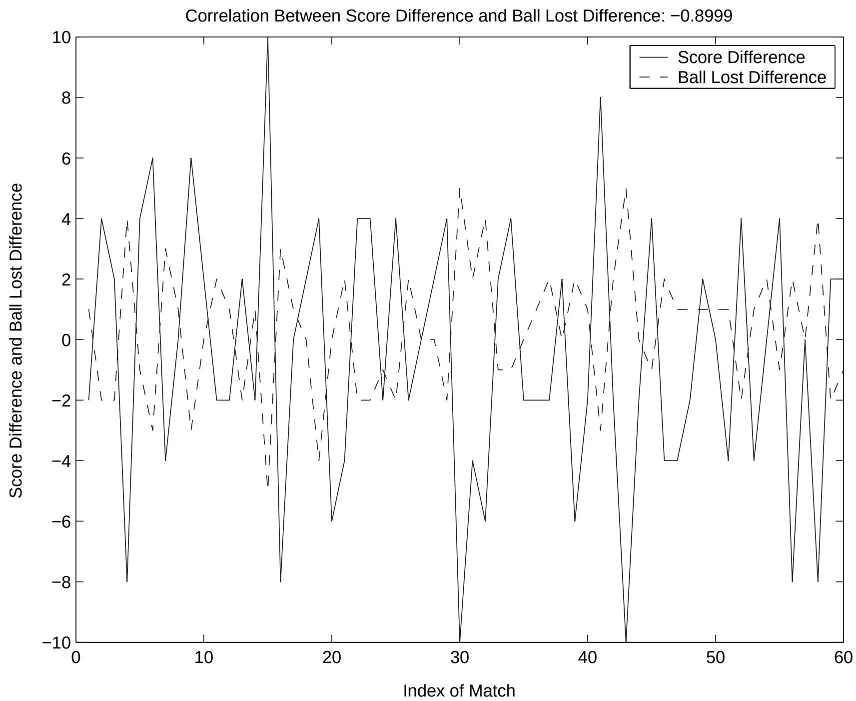

Figure 8. The correlation between the score difference and the ball lost difference for two teams in experiment 2 is –0.8999

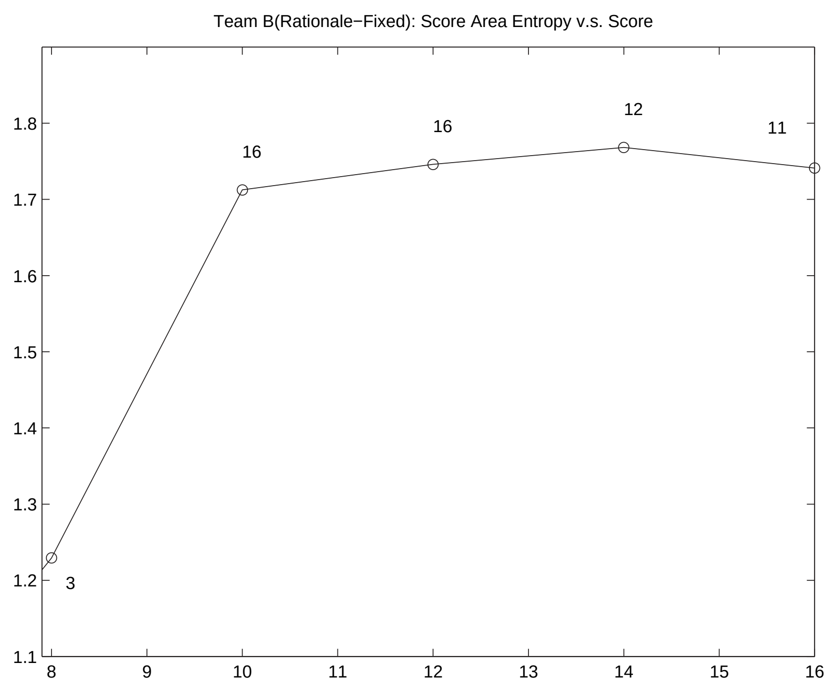

Figure 9. The relationship between score area entropy and score for team B in experiment 2

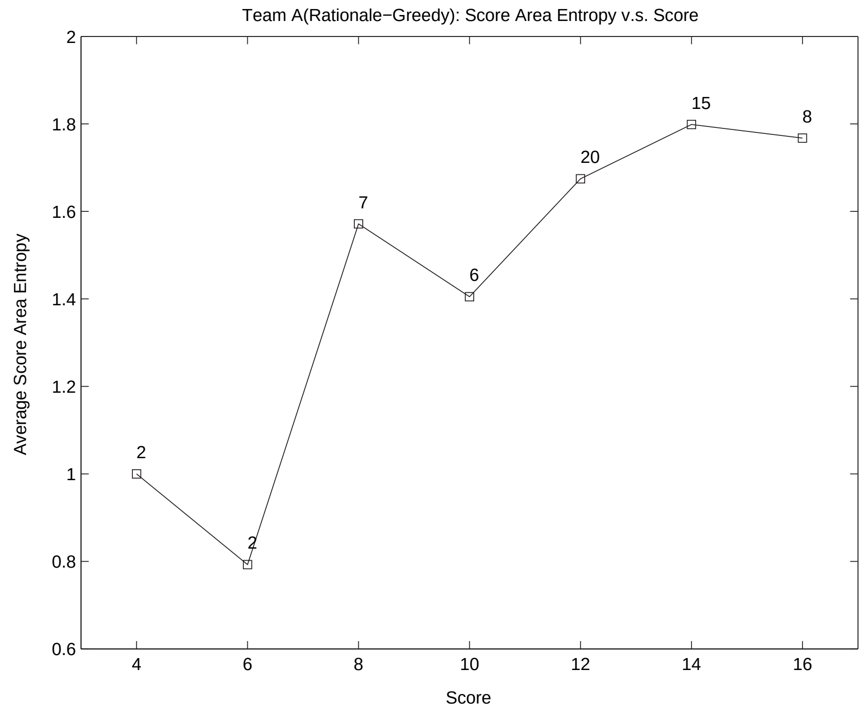

Figure 10. The relationship between score area entropy and score for team A in experiment 2

does not increase significantly. Agents in team A use the greedy defense, and they tend to cluster into a small region. Consequently, these agents are not capable of adapting to the increasing diversity of attack areas of team B.

3. From Figure 10, we can observe that the score area entropy increases as the score increases for team A, although irregular fluctuations occur when the score equals 6 and 10. Agents in team B use the fixed mark defense, and they are very diverse in geographical positions while defending. They can adapt to the increasing diversity of attack patterns of team A, and so a higher score area entropy does not necessarily guarantee a higher score for team A.

4. Figure 11 shows the relationship between the score area entropy difference and the score difference. We can observe that the score area entropy difference is greater than zero when the score difference is greater than zero, while the score area entropy difference is smaller than zero when the score difference is smaller than zero. In addition, the score area entropy difference increases when the score difference increases. The correlation between them is 0.4350. We can conclude that the score area entropy difference is a good indicator of the performance difference of the two teams in this experiment.

5. Team B has a slightly higher score entropy than team A. The reason is similar to that of score area entropy.

6. The cooperative motivation of team B is slightly higher than that of team A. The reason is similar to that of the score area entropy. In addition, we investigate the relationship between the cooperative motivation difference and the score difference. The corresponding correlation is –0.1094. We consider that this result is not convincing because both of the two values are close to zero and thus are sensitive to random noises.

REMARK 2. In experiment 2, we compared a team of rationale agents with the greedy defense (team A) and a team of rationale agents with the fixed mark defense (team B). From Table 5, we can observe that team B has slightly less ball control time, a slightly higher pass accuracy, slightly less ball lost time, significantly higher stamina remaining, and a slightly higher score. From Table 6, we can discover that both the score area entropy and the score entropy of team B are slightly higher than those of team A. In addition, the cooperative motivation of team B is slightly higher than that of team A. In summary, rationale agents with the fixed mark defense are a little bit more effective at defense than rationale agents with the greedy defense. Also, the

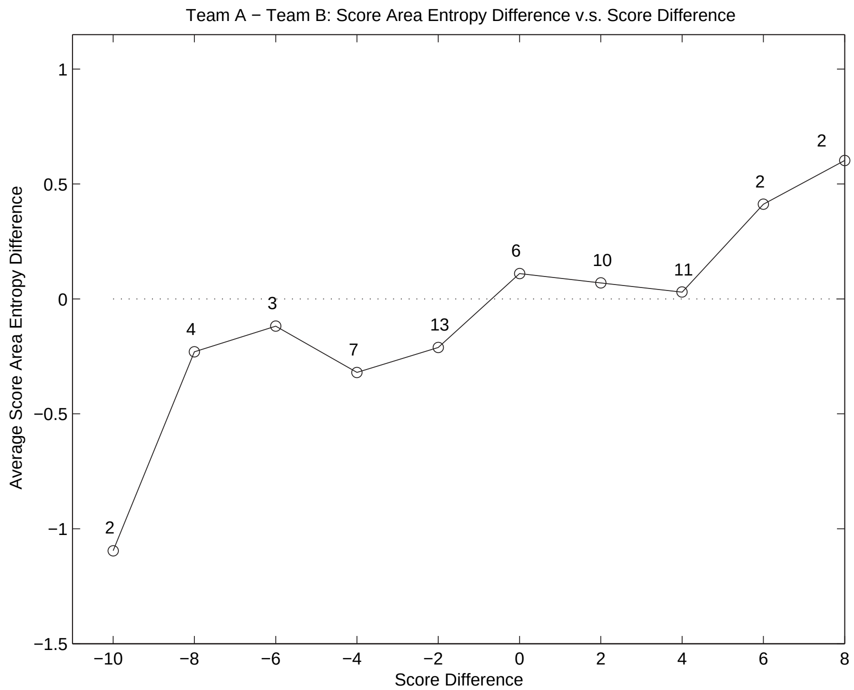

Figure 11. The correlation between the score difference and the score area entropy difference for two teams in experiment 2 is 0.4350

Table 7. Global performance: Rationale agent with the greedy defense versus rationale agent with the adaptive mark defense

	Team A		Team B	
	Mean	Standard Deviation	Mean	Standard Deviation
Ball control time	153.15	12.65	127.52	11.16
Pass accuracy	0.96	0.04	0.99	0.02
Pass total	22.82	4.64	22.30	3.11
Stamina remaining	111.68	64.48	307.13	126.37
Ball lost time	3.10	1.70	2.38	1.43
Score	11.47	2.99	14.07	2.24

Table 8. Global patterns: Rationale agents with the greedy defense versus rationale agents with the adaptive mark defense

	Team A		Team B	
	Mean	Standard Deviation	Mean	Standard Deviation
Ball entropy	2.02	0.18	2.1526	0.11
Score area entropy	1.47	0.38	1.60	0.46
Score entropy	1.60	0.36	1.80	0.34
Cooperative motivation	2.60	0.63	3.12	0.37

diversity of attack patterns of rationale agents with the fixed mark defense is slightly higher than that of rationale agents with the greedy defense due to a slightly superior defense.

EXPERIMENT 3. We study the defense strategies in this experiment. Team A consists of rationale agents with the greedy defense. Team B consists of rationale agents with the adaptive mark defense. Table 7 shows 60 times averaged results for global performance, and Table 8 presents the corresponding results for global patterns.

OBSERVATION 5. The following are our observations on Table 7:

1. Team B has a significantly higher score. It demonstrates that the adaptive mark defense is superior to the greedy defense.
2. Team A has slightly more ball control time than team B.
3. The stamina remaining of team B is higher than that of team A. Greedy defense strategy requires agents to change their mark opponents very frequently. The adaptive mark defense strategy also requires agents to change their mark opponents from time to time but not as frequently as the greedy defense strategy does. So team B consumes less stamina.

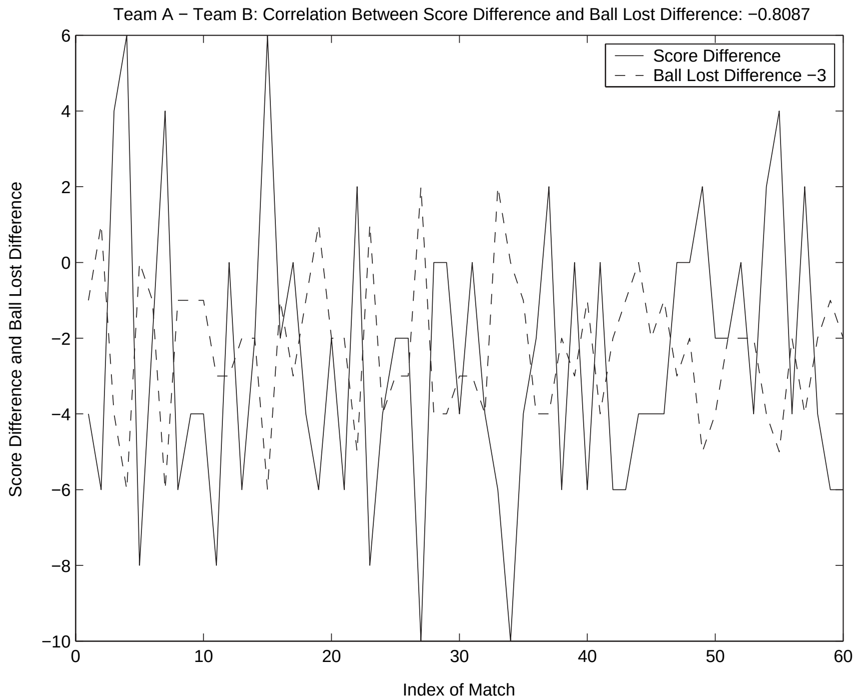

Figure 12. The correlation between the score difference and the ball lost difference for two teams in experiment 3 is –0.8087

4. Team B has slightly lower ball lost time. Figure 12 shows the relationship between the ball lost time difference and the score difference. The correlation value between them is –0.8087.

5. Team B has a significantly higher pass accuracy than team A.

Observation 6. The following are our observations on Table 8:

1. The score area entropy of team B is higher than that of team A.

2. From Figure 13, we can observe that score area entropy increases as the score increases for team B for the whole range of the score. Agents in team A use the greedy defense strategy and thus tend to cluster into a small region. We can infer that the higher diversity of geographical attack regions (score area entropy) can improve the efficacy of attack (score).

3. From Figure 14, we cannot observe any obvious relationship between the score area entropy and the score for team A since the curve fluctuates greatly. This irregularity is even greater than that observed in Figure 10. Agents in team B adopt the adaptive defense strategy and thus are capable of adapting to the increasing diversity of attack regions. Its adaptability to the diversity of attack regions is even stronger than that of the fixed mark defense strategy in experiment 2. Consequently, higher diversity of attack regions may not necessarily improve the efficacy of attack.

4. Figure 15 shows the relationship between the score area entropy difference and the score difference. The overall trend is that the score area entropy difference increases as the score difference increases. However, there are some fluctuations in several points. The corresponding correlation is 0.2648. We may conclude that the score area entropy difference is not a good indicator of the performance difference of the two teams because the strong irregularity occurs as team B uses the adaptive defense strategy described above.

5. The score entropy of team B is higher than that of team A.

6. The cooperative motivation of team B is higher than that of team A. It also demonstrates that the adaptive mark defense strategy is superior to the greedy defense strategy.

Remark 3. In experiment 3, we compared a team of rationale agents with the greedy defense (team A) and a team of rationale agents with the fixed mark defense (team B). From Table 7, we can observe that team B has less ball control time, a higher pass accuracy, higher stamina remaining,

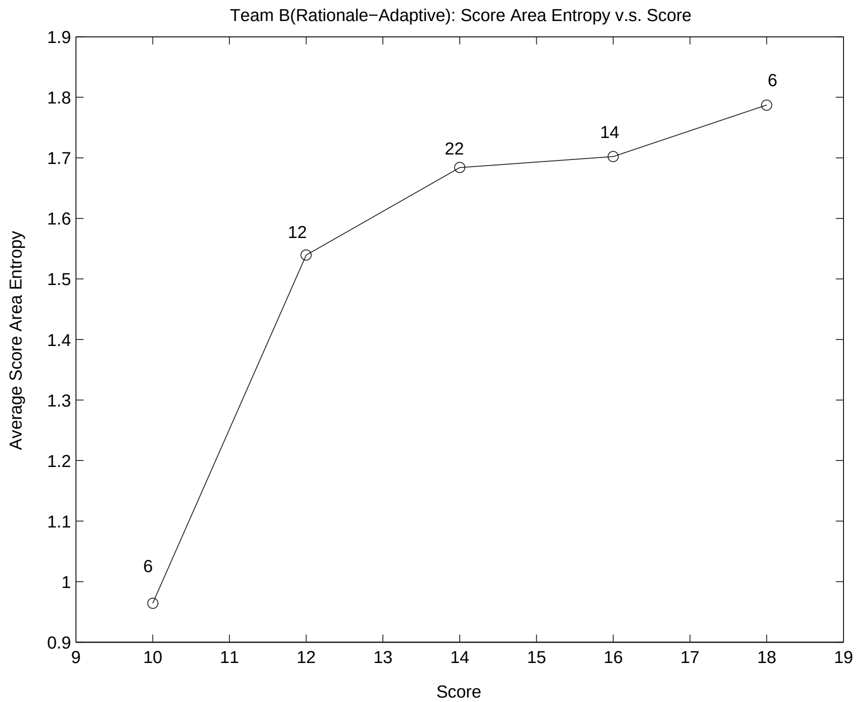

Figure 13. The relationship between score area entropy and score for team B in experiment 3

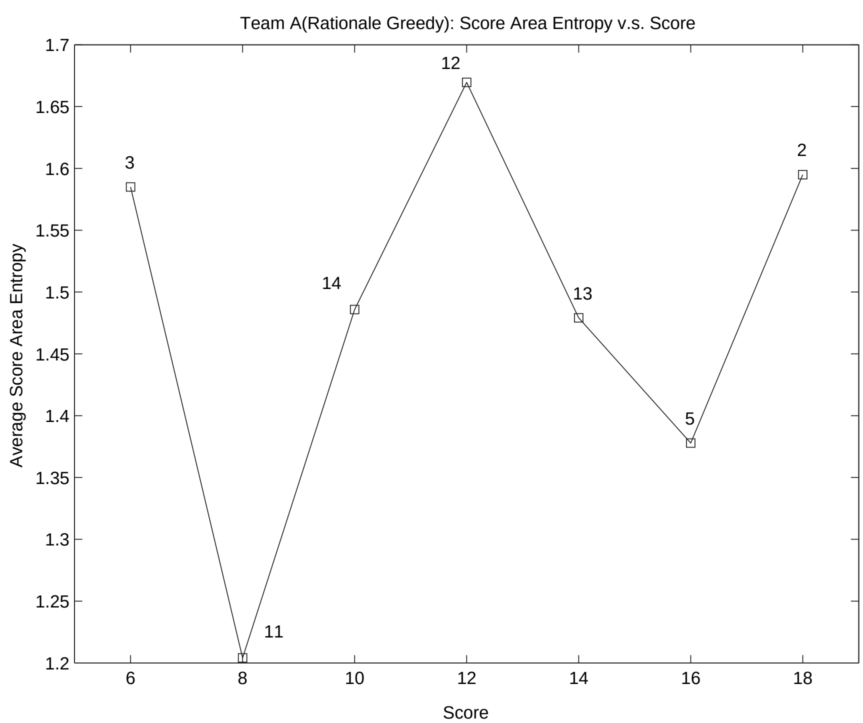

Figure 14. The relationship between score area entropy and score for team A in experiment 3

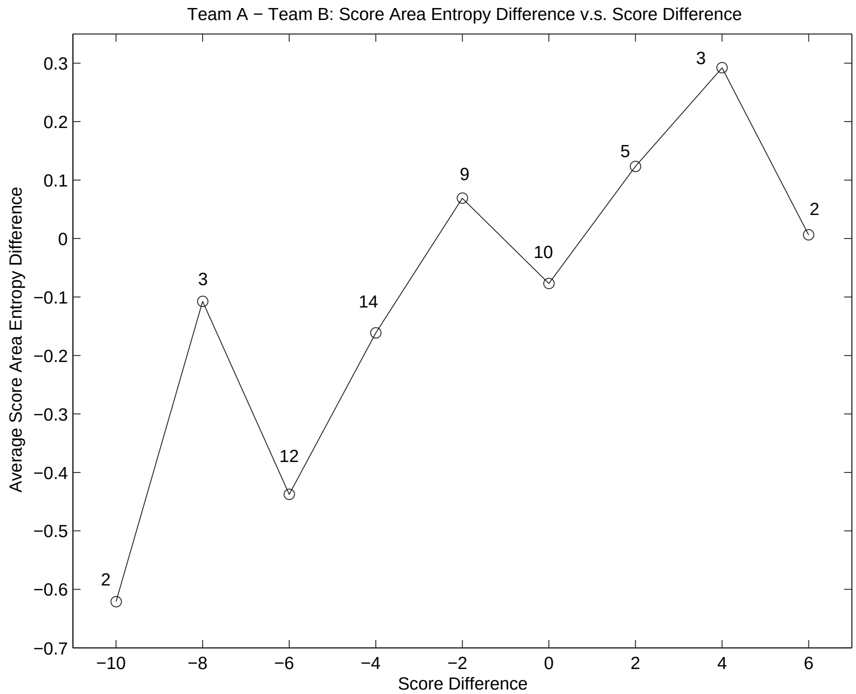

Figure 15. The correlation between the score difference and the score area entropy difference for two teams in experiment 3 is 0.2648

less ball lost time, and a significantly higher score. From Table 8, we can discover that team B has both a higher score area entropy and score entropy. In addition, team B has a higher cooperative motivation. We also find out that the relationship between the score area entropy and the score of a team depends on the defense strategy of the opposing team. In summary, rationale agents with the adaptive mark defense strategy have a significantly higher efficacy of defense as well as a superior performance than rationale agents with the greedy mark defense. What is more, rationale agents with the adaptive mark defense strategy have a higher diversity of attack patterns in terms of score area entropy, score entropy, and cooperative motivation.

5.2 Discussions

Critical Observations. In the following, we highlight some common findings throughout these experiments as well as those results that vary according to different situations:

1. The relationship between the ball lost time difference and the score difference is consistent throughout all experiments. The correlation between the two is always below –0.8, which infers that the most important factor to win a match is to minimize the ball lost time. In addition to the ball lost time, pass fail is also a source of losing control of the ball. But the differences of pass accuracy are extremely small in these experiments. Therefore, ball lost is a dominant source of losing control of the ball.

2. The relationship between the ball control time and the score varies according to different situations. We present the results in Table 9. We can see that only for team A (simple reactive agents) in experiment 1, the correlation value is significantly large. For other teams (rationale agents with different defense strategies), the correlation values are very small. Interestingly, the correlation values in experiment 3 are even negative. The reason why the relationship between the ball control time and the score is different for simple reactive agents and rationale agents can be explained in this way: attack patterns of simple reactive agents are of lower diversity and thus more predictable (e.g., they choose similar routes to attack). Consequently, simple reactive agents require a more predictable interval for a successful shot. Hence, the correlation between the ball control time and the score is relatively large. On the contrary, attack patterns of rationale agents are of high diversity and are thus highly unpredictable. Rationale agents require an interval of varied length, and thus the ball control time and the score are not strongly correlated.

Table 9. The correlation between the ball control time and the score in the three experiments

	Team A	Team B
Experiment 1	0.4888	0.1870
Experiment 2	0.1623	0.0776
Experiment 3	–0.0525	–0.1452

Table 10. Correlation between the cooperative motivation and the score in three experiments

	Team A	Team B
Experiment 1	0.3617	–0.1995
Experiment 2	0.0036	–0.0715
Experiment 3	–0.2419	–0.3185

3. The relationship between the cooperative motivation and the score varies according to different situations. From Table 10, we can see that only for team A (simple reactive agents) in experiment 1, the correlation value is significantly greater than zero. It means that more simple reactive agents involved in attacks result in better performance. For simple reactive agents, more agents involved in attacks infer an increasing diversity of attack patterns and thus better performance because individual agents do not exhibit diverse attack patterns. On the contrary, four out of five correlation values for rationale agents are negative. It means that more rationale agents involved in attacks lead to poorer performance. For rationale agents, more agents involved in attacks do not necessarily improve the diversity of attack patterns as well as the performance because individual agents already exhibit diverse attack patterns. In addition, frequently passing the ball to a teammate is risky (e.g., the ball could be caught by opponents).

4. The diversity of attack patterns of a single team varies when competing with teams with different defense strategies. Intuitively, we may imagine that a strong team will be more diverse than a weak team in terms of tactics and strategies. Diverse tactics and strategies of teams will certainly lead to diverse attack patterns. However, it is important to point out that the difference between a strong team and a weak team should be reasonably small. Otherwise, the diversity of a strong team could be low because it does not need diverse attack patterns to win against an extremely weak team. For example, agents in team A do not move at all, and so agents in team B only need to take the same route to attack. Thus, team B can win easily, even though the diversity of agents in team B is extremely low. Table 11 presents the score area entropy and the score entropy of the team of rationale agents with a greedy defense strategy competing against different opponents. We can find out that both the score area entropy and the score entropy decrease when the opponent team gets stronger. The results validate our conjecture about the diversity evolution of attack patterns of a single team competing against teams adopting different defense strategies.

Table 11. The diversities of the team of rationale agents with the greedy defense

	Score Area Entropy		Score Entropy	
	Mean	Standard Deviation	Mean	Standard Deviation
Simple reactive agents	1.66	0.34	1.76	0.31
Rationale agents with fixed mark defense	1.63	0.44	1.62	0.41
Rationale agents with adaptive mark defense	1.47	0.38	1.60	0.36

Validation Efforts. We have validated the experimental results in this article. All three experiments used 60 time-averaged results. From Tables 3, 5, and 7, we can see small standard deviations for all global performance measurements except those of the stamina remaining, which should be compared with initial stamina (3000) subtracted by the stamina remaining. Therefore, we were able to obtain quite stable data for global performance. From Tables 6 and 8, we can see that the data are quite close for the two teams, whereas in Table 4, the data are rather different for the two. This is reasonable since only decision-making mechanisms induce great influence on the entropies.

Parameters. The parameters in RoboNBA and players are illustrated in Tables 1 and 2. Parameter values in Table 1 are chosen to ensure that they are consistent with real basketball matches. On the other hand, parameter values in Table 2 are chosen so that players can perform well. In addition, these values can be flexible in certain ranges. For example, if κ and λ are in the range of [0.5, 2] and [–2, –0.5], respectively, the performance of the team will only be changed slightly. In addition, we have tried the range of [0.5, 1] for σ; the results still remain stable. Note that if κ, λ, and σ are extremely large or small, the results of the matches can be undesirable.

Further Remarks. We believe that our research work can be beneficial to other research domains, such as RoboCup, multiagent pursuit and evasion games [25], and military applications [26]. In these domains, a high diversity of attack patterns should increase the chances to win. In

Robocup, we expect a similar relationship between global performance and global patterns. For multiagent pursuit and evasion games, it should be favorable for pursuers to take advantage of varieties of pursuing strategies. In simulated warfare games, attacking from different directions certainly will contribute to winning the battle because it makes the defense more difficult and more vulnerable. For more interesting results on characterizing global behavior in a generalized MAS (including player ability changes), readers are recommended to consult Hu and Liu [27].

6. Conclusions

In this article, we reviewed the previous work on the relationship between local behaviors of agents and global characteristics of MAS. In light of limitations in the previous work, we studied the relationship in a more complex environment, RoboNBA. We formulated two sources of different agent local behaviors, including decision-making mechanisms and agent strategies. In addition, global performance and global patterns were defined in the domain of RoboNBA. Furthermore, the diversity of global patterns can capture the dynamic processes of RoboNBA matches, such as attack routes of a team. Thereafter, through experiments and analyses, we discovered that local behaviors of agents have great influence on the global performance as well as the global patterns of MAS. From the experimental results, we observed that the rationale agent team has significantly better performance than the simple reactive agent team. Moreover, the rationale agent team is more diverse in terms of attack patterns than the simple reactive agent team. We believe that this higher diversity is an emergent property of rationale agents because we cannot infer this directly from the decision-making mechanisms of rationale agents. Finally, we compared teams of rationale agents with different defense strategies. We found out that the fixed mark defense strategy is slightly superior to the greedy defense strategy in terms of performance as well as diversity of attack patterns. Besides, the adaptive mark defense significantly outperforms the greedy defense.

7. Acknowledgments

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