香 港 浸 会 大 学 HONG KONG BAPTIST UNIVERSITY

计 算 机 科 学 系 Department of Computer Science

Usage	Date & Time	Author
AAMAS/AOC Research Group Meeting	7-Jun-2004	Hu Bingcheng

1 Complex System

In a few papers I read about complex systems, I have known CA can have ordered, complex, and chaotic state. However, none of them gave quantitative measurement for distinguishing these states but some qualitative properties. Fortunately [2] gives some quantitative methods to examine the complexity in 1-d Cellular Automata. We can see from Fig. 1, only when the complex dynamics exhibits high variance of entropy. The entropy is defined here in Eq. 1. Where Q_i^t is the look up frequency of neighborhood i at time t. k is the neighborhood size and n is the system size, namely the number of cell in the 1-d CA.

Prokopenko applies this idea to the domain of RoboCup in [3]. He use Eq. 2 to calculate the behavior entropy of a single player. Where m is the number of rules player has at his disposal. B_i^k is the look up frequency of rule i during game k. The author claims that the diversity (measured by its behavior entropy) of a single player will be different when the team competes with teams of different competitive ability. In addition, he conjectures that a player will have a more diverse behavior (higher entropy) when facing easier opponents while a player will exhibit a more narrowed/constraint (low entropy) when facing strong opponents. His conjecture is validated by experimental results shown in Fig. 2. From complex system theory, there should be phase transitions when the system evolves from ordered state to chaotic states. This theory was supported by experimental results shown in Fig. 3. However, I think these phase transitions look rather strange. There should be a sudden increase/transition not a sudden decrease when the entropy changes from low to high. In addition, the author gives a experimental result shown in Fig. 4, which further strength his theory. This result is quite similar with (b) in Fig. 1, which indicates the a player is in a complex state when the score difference is close to zero in terms of behavior entropy.

$$S^t = -\sum_{i=1}^{2^k} (\frac{Q_i^t}{n} \times \log(\frac{Q_i^t}{n})) \tag{1}$$

$$E^k = -\sum_{i=1}^{m} (\frac{B_i^k}{n} \times \log(\frac{B_i^k}{n})) \tag{2}$$

2 Coordination

In [4], prokopenko argues and proves by experiments that the joint belief of players is related to the coordination of a team. A belief $K(A, B)$ refers to player A sends a message about object B. The object can be a player, the ball, or other things. The joint belief is defined as a sequence of individual beliefs. Then the author defined selfish agreements, transitively-selfish agreements, and non transitively-selfish agreements (mixed). Then a simple shannon entropy is defined over a probability distribution $P = \{p_1; p_2; ...; p_m\}$, where p_i is the probability of ith individual belief exists in a joint belief after a synchronization period. The author defines the

Usage	Date & Time	Author
AAMAS/AOC Research Group Meeting	7-Jun-2004	Hu Bingcheng

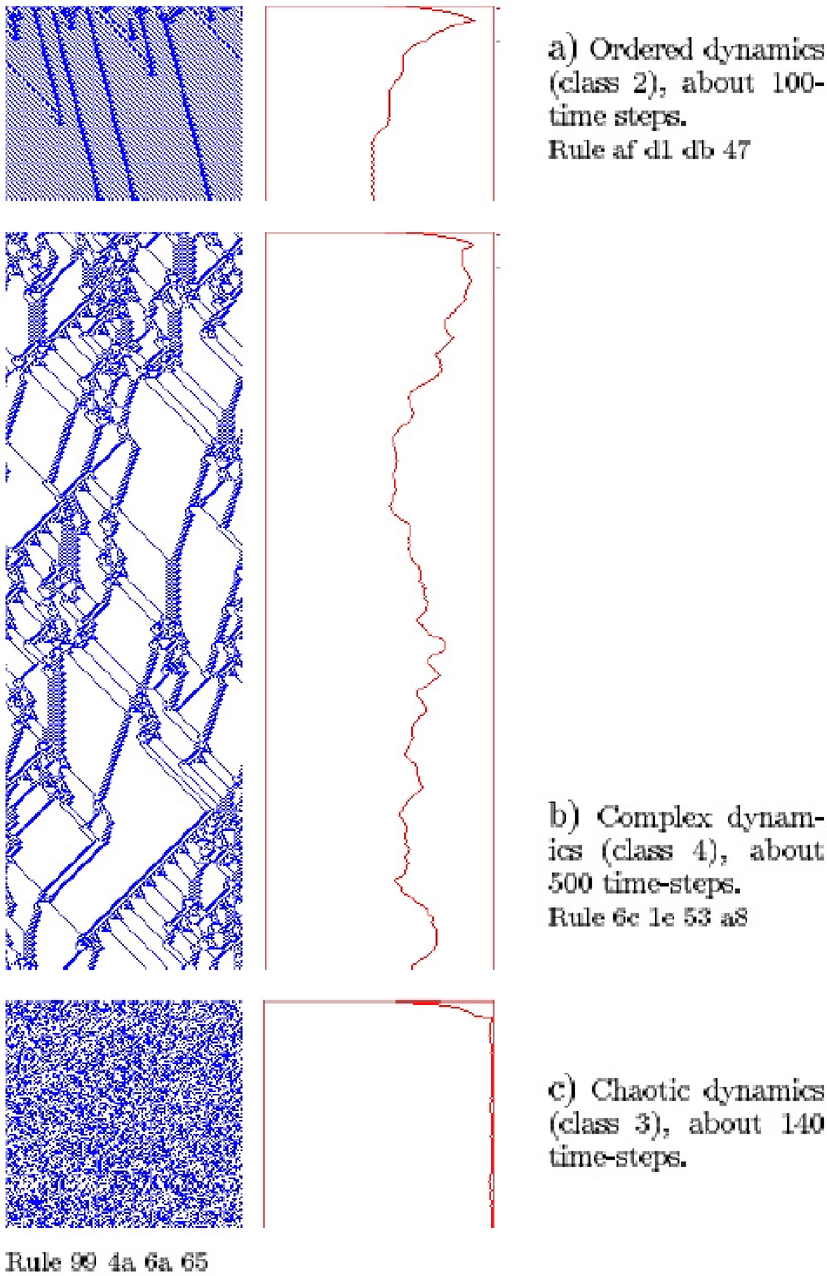

Figure 1: Typical 1-d CA space-time patterns showing ordered, complex, and chaotic dynamics. Time proceeds from top to down.

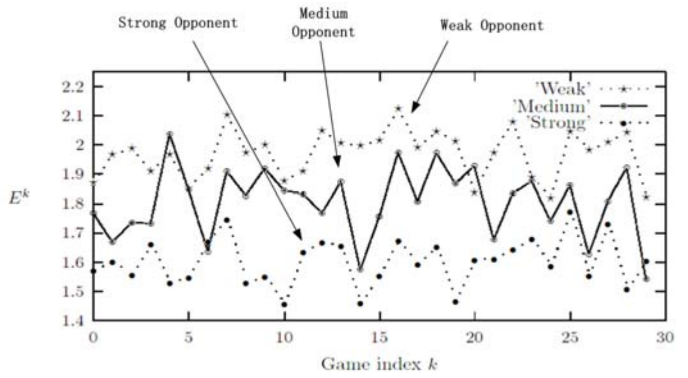

Figure 2: The behavior entropy of the left-middle player when facing easy, medium, and tough opponents

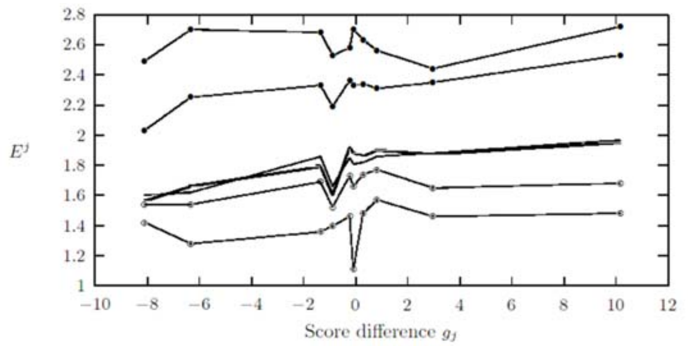

Figure 3: The phase transition of behavior entropy of six players in the test team.

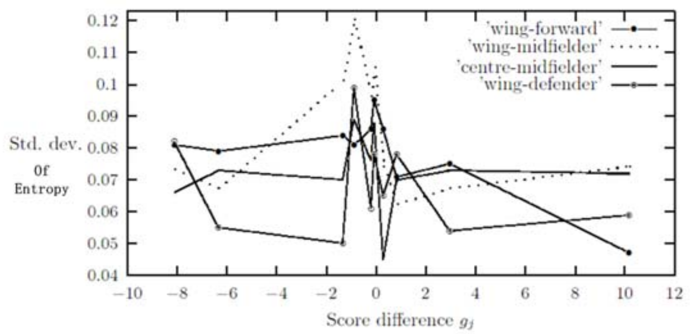

Figure 4: The stand deviation of behavior entropy.

agreement and has some theoretical analysis on them (Definition 1 and Theorem 1 in [4]). The coordination is measured by the team's performance, since the author claims the coordination is hard to evaluate.

Team vs "A"	Goals	Points	$\gamma(3)$	$M(1)$	$\xi(3,1)$	Team vs "B"	Goals	Points	$\gamma(3)$	$M(1)$	$\xi(3,1)$
Press	31–91	65	0.553	0.067	0.12	Press	105–70	152	0.533	0.070	0.13
Zonal	18–107	50	0.657	0.224	0.34	Zonal	114–53	180	0.641	0.217	0.34
Mix	30–127	63	0.522	0.068	0.13	Mix	118–65	172	0.495	0.071	0.14

Figure 5: Entrpy v.s. Coordination

Explanations:

- Each set experiment uses different communication agreements but leaves other things the same. A is a strong opponent and B is a weak opponent.
- Press adopts transitively selfish communication agreement and it exhibits high macro entropy but low micro entropy.
- Zonal adopts selfish communication agreement and it exhibits low macro entropy but high micro entropy.
- Mix adopts mix communication agreement. Both of macro and micro entropy lie in between of Press and Zonal.

From Fig. 5, we can observe the dependence of entropy and coordination (evaluated by performance), although the performance also depends on the power of opponents.

A question: the author claims "transitively selfish agreement, with very local coordination" and "selfish agreement, with very global coordination". How is this claim based? The author does not provide any evidence for it.

3 Diversity

Shannon's entropy is definitely a good way to measure diversity. However, the entropy itself is a single value, thus omitting a lot of other information, such as spatial characteristics. Balch in [6] provides a hierarchical social entropy to solve this problem. Balch investigates the diversity in two applications, roboCup and robot foraging. In order to calculate the diversity, the behavior differences are needed prior. He provides a methods defined as:

$$D(r_a, r_b) = \sum_i \frac{p_a^i + p_b^i}{2} \left|\pi_a(i) - \pi_b(i)\right| \tag{3}$$

In the roboCup experiment, Balch uses locally-reinforced methods and globally-reinforced methods. He finds that local-reinforced method leads to fully homogeneous behaviors while globally -reinforced method leads to more diverse/heterogeneous behaviors. For robot foraging, the author have done similar experiment and similar results. The difference lies in the correlation of diversity and performance in two application is different. The roboCup favors diversity while the robot foraging does not.

4 Future Work

What I would like to do is as follows:

- We have some belief defined in our model, although it is different with the belief often used in the literature. I think there should be some dependence between the distribution of these beliefs and the coordination potential of the whole team. I think we can do some observation on it. I would call it emergence of coordination.
- I think the Eq. 3 is simply not good enough. This formula only applies to state-based action selection mechanism, such as reinforcement learning. But it seems not directly applicable to a utility-based methods, such as BDI model and our model as well. We need new measurement.
- This summation only adds up pieces of local difference but ignores the global behaviors of robots. We can record some statistical information for a team and serves as a measurement. For example, how far is a ball usually be shot? In Which angle would the ball be shot? Which player will does the shooting often? Who will give the final pass to facilitate the shooting?
- The author considers reinforcement learning only on applications. I think I may consider a wider domain, such as rationality and emotion [7] of agents. The question is under what conditions will diversity emerge? For example, I can use a parameter to control the degree of agent's rationality and investigate how it is related to diversity.
- We can consider rationality and emotion as two extreme of player action selection mechanism. It may be similar to ordered and chaotic dynamics in CA. Then what left to us is to find a complex state in our domain as well as phase transitions.

References

[1] H.V.D. Parunak and S. Brueckner, Entropy and Self-Organization in Multi-Agent Systems, *in International Conference on Autonomous Agents,* 2001.

[2] A. Wuensche, Classifying Cellular Automata Automatically, *Complexity*, Vol.4, no.3, 47 - 66, 1999.

[3] M. ProkopenKo and P. Wang, Relating the Entropy of Joint Beliefs to Multi-Agent Coordination, *in Proceedings of the 6th International Symposium on RoboCup*, 2002.

[4] M. ProkopenKo and P. Wang, Evaluating Team Performance at the Edge of Chaos, *in Proceedings of the 7th RoboCup-2003 Symposium*, Padua, July 2003.

[5] F. Dylla, A. Ferrein, G. Lakemeyer, J. Murray, O. Obst, T. Röst, F. Stolzenburg, U. Visser, and T. Wagner Towards a League-Independent Qualitative Soccer Theory for RoboCup, *in: 8th International Workshop on RoboCup 2004 (Robot World Cup Soccer Games and Conferences), Lecture Notes in Artificial Intelligence. Springer, to appear*, 2005.

[6] T. Balch, Hierarchic Social Entropy: An Information Theoretic Measure of Robot Group Diversity, *Autonomous Robots, vol 8, no 3*, July, 2000.

[7] S. Marsella, A Step Towards Irrationality: Using Emotion to Change Belief, *in the First International Joint Conference on Autonomous Agents and Multi Agent Systems*, Bologna, Italy, 2002.