Analysis of Decision-making Behavior Based on Complex Adaptive System

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Abstract: - This paper focuses on the decision-making behavior based on the complex adaptive system. Firstly, the paper reviewed the related work of the complex adaptive system and the edge of chaos in complex systems in different fields. Secondly, a general decision model of an agent is established and the condition that an agent is just at the edge of chaos is defined. Thirdly, making use of Langton's coefficient widely used in the research on cellular automata, the paper defines the edge of chaos that describes the decision behavior of agent. Finally, the paper conducts an evolutionary artificial life experiment. Then the connection between the behavior at the edge of chaos and the individual adaptability is illustrated.

Key-Words: - Decision-making, Complex adaptive system, Edge of chaos, Agent.

1 Introduction

The theory of complex adaptive system has received more and more attention in the past few years. As a theory on change, adaptation and self-organization, it has made some achievements in the way it deals with decision-making problems, i.e. in the point of view of dynamic evolution and emergence [1-3].

The concept of the edge of chaos was proposed by Langton when he studied a special kind of complex system [4]. It refers to the state that the system stays at the edge between the rigid orders and the chaos without any rules. In this situation the system will evolve into a more complex one gradually. Moreover, there must emerge some new orders and modes step by step.

The concept of the edge of chaos emphasizes the condition on which the self-organization of a system happens and is applicable to the natural, social and artificial systems. Therefore, it has been applied to various fields during the past few years. Arntzen discusses the adaptive software development approach based on the edge of chaos [5]. Daryl and Feng explore how the leaders go on with their administration at the edge of chaos when an enterprise is in a changing environment [6][7]. Richard examines the way the successful managers make their decisions on business at the edge of chaos [8]. Cohen examines the behaviors at the edge of chaos in financial market [9]. All the literatures above show that the concept of the edge of chaos is very important and is applicable in a great many fields. However, most of the existing researches make use of qualitative methods to describe the concept of the edge of chaos in an economic or management system. Therefore, the quantitative models are necessary and required to describe the concept more exactly than before.

In the aspect of modeling, Stuart et al. presents the random network model and defines the concept of the edge of chaos [10]. Nils studies the problem of the edge of chaos in the neural network model [11]. Mikhail examines the phenomenon that the Multi-agent system of football robot evolved towards the edge of chaos [12]. On the basis of the above research, this paper establishes the decision-making model based on agent and focuses on the decision-making behaviors of the agents. Although Mikhail gives the condition of the information entropy when the agent evolves towards the edge of chaos, the condition strongly relies on the specific behavior rules of the agent. In fact, people could hardly be aware of the internal structure of the agent in analysis.

The remaining parts of this paper are organized as follows. The second section adopts the decision-making model of an agent, reviews the concept research literature on the edge of chaos, and explores the conditions for the decision-making behaviors of the agents at the edge of chaos. After that the decision-making behavior based on the edge of chaos is analyzed. Then an evolutionary artificial life experiment is conducted. Few literatures have analyzed the relationship between the behaviors at the edge of chaos and the individual adaptiveness. This research proposes that the decision-making agent is able to get adapted to the changing environment only when the individual or organizational decision-making is at the edge of chaos between the rigid orders and the chaos without any rules.

2 The Basic Theory

2.1 The Complex Adaptive Systems

Complexity science has long been used to describe and explain behaviour in natural and biological systems, characterised by nonlinear dynamics and emergent properties based on diverse populations of individuals interacting with each other and capable of undergoing spontaneous self-organisation [13]. Recent research in organisational management, behavior and psychology indicate that human systems also behave in a complex fashion [14].

The operational model of complexity science is Complex Adaptive Systems (CAS). CAS theory provides a different way of thinking about decision science and systems.

A CAS is “a collection of individual agents who have the freedom to act in ways that are not always totally predictable, and whose actions are interconnected such that one agent’s actions change the context for other agents” [15]. Thus CAS are defined in terms of their component parts, the behaviour of those parts, the relationships between the parts and the behaviours (or properties) of the whole [3] [16].

Agents are connected to and exchange information with others in the system through a complex web of relationships. These interactions and the interconnections that facilitate them are the most important aspect of a CAS [17][18]. CAS relationships have been described as massively entangled [19] because the component parts of the system and the variables describing those parts are large in number and interrelated in complex ways. The diversity, extent, intricacy and strength of the relationships influence the system’s ability to adapt. There can be too much connectivity, as well as too little.

Agents respond to their environment using internalized ‘short lists of simple rules’ that drive action and generate behaviour. The rules need not be shared, explicit, or even logical when viewed by others, but they nonetheless contribute to patterns and bring coherence to behaviours in complex systems. Deliberately exposing and changing underlying simple rules leads directly to innovative ideas. In addition, short lists can be used proactively. When a new system is being instituted, a short list of simple rules (or minimum specifications) may be the most effective way to bring about change. They set the parameters and provide both focus and freedom for system activities. Over-prescription is counter-productive because it stifles creativity and innovation.

Together agents, their behaviours and their connections create a system that has a number of CAS defining properties.

A CAS is dynamic, which refers to “the continual presence of multiple interactions and their accompanying surprises, challenges and responses both within the system and between the system and its environment” [20]. Change is influenced by the number of agents, their rules of behaviour and the strengths and diversity of the relationships between them. Change is also discontinuous, with periods of stability and periods of change - the latter occurring at different rates at different times. The state of the system at a given time is a nonlinear function of the state of the system at some previous time. At no time does the system come to a natural equilibrium or stopping point.

2.2 The Decision-making Model

The automotive agent model is adopted from Ronon to study the decision-making behaviors. A decision-maker can be modeled as an agent [21] [22] [23]. The environment this agent stays in is a discrete state set E of which e is an element. Generally speaking, the environment an agent can sense is limited. Here the environment is noted as I. The possible sensible environment for an agent is noted as:

$$I = \{i_1, i_2 \cdots, i_n\} \tag{1}$$

All the possible internal states of an agent comprise the internal state set shown as

$$S = \{s_1, s_2, \cdots, s_m\} \tag{2}$$

An agent may have the behaviors as its output to change its environment and put an influence on it meanwhile. In this paper, it is supposed that the possible output behavior set is

$$O = \{o_1, o_2, \cdots, o_p\} \tag{3}$$

Then, at the time t, the decision of an agent is made according to the sensed environment $i^t \in I$ and the present internal state $s^t \in S$. The result of the decision is to choose one behavior output from the set O and change its internal state. Therefore, a decision is a function as

$$\begin{aligned} &\Delta : I \times S \to O \times S \\ &\forall i^t \in I, s^t \in S, \Delta(i^t, s^t) = (o^{t+1}, s^{t+1}) \end{aligned} \tag{4}$$

in which, $o^{t+1} \in O, s^{t+1} \in S$. Moreover, the decision of an agent affects the whole environment. That is, for the environment state, suppose that an agent stays at the state e^t at time t, and then it stays at state e^{t+1} at time *t+1*. It is also shown as

$$\begin{aligned} &\Phi O \times E \to E \\ &\forall o^{t+1} \in O, e^t \in E, \Phi(o^{t+1}, e^t) = e^{t+1} \end{aligned} \tag{5}$$

in which, $e^{t+1} \in E$. Each behavior of an agent can change its environment. The change of the environment affects the decision-making behavior of the agent because of its sensitivity.

Since it is not related to the complex internal structure of the agent, the decision model is simple. However, the model is universal as it is the same as a touring machine in its computing ability. The decision-making process of an agent is the computing process of a touring machine. Therefore, the decision-making of an agent is essentially computing through changing the decision-making rules [24] [25].

2.3 Related Research on the Edge of Chaos

Cellular automata are dynamical systems in which space, time, and the states of the system are discrete. Each cell in a regular lattice changes its state with time according to a rule which is local and deterministic. All cells on the lattice obey the same rule. This class of dynamical systems has been extensively studied as a model of natural systems in which large numbers of simple individuals interact locally so as to give rise to globally complex dynamics.

Study of cellular automata has given rise to the “edge of chaos” hypothesis. In its basic form, this is the hypothesis that in the space of dynamical systems of a given type, there will generically exist regions in which systems with simple behavior are likely to be found, and other regions in which systems with chaotic behavior are to be found. Near the boundaries of these regions more interesting behavior, neither simple nor chaotic, may be expected.

Early evidence for the existence of an edge of chaos has been reported by Langton [26, 27] and Packard [28]. Langton based his conclusion on data gathered from a parameterized survey of cellular automaton behavior. Packard, on the other hand, used a genetic algorithm [29] to evolve a particular class of complex rules. He found that as evolution proceeded the population of rules tended to cluster near the critical region identified by Langton.

The validity of some of these results have been called into question by Mitchell, Crutchfield, and coworkers [30][31]. These authors performed experiments in the spirit of Packard's. They found that while their genetic algorithm indeed produced increasingly complex rules, the cellular automata generated could not be considered to reside at a separatrix between simple and chaotic dynamical regimes.

The edge of chaos is a stimulating idea in that it promises to provide a framework in which to relate methods and results originating in biology, physics, and computer science[32]. Yet the very generality and cross-disciplinary nature of the edge of chaos concept has lead to enormous difficulties of communication between workers from different background attempting to make these intuitions rigorous by the standards of their discipline.

In this paper we clarify a subset of the issues surrounding the edge of chaos theme. We restrict ourselves to study of the edge of chaos in the context of cellular automata. A cellular automation is a discrete dynamic system. This research takes the One-dimensional Cellular Automata as an example. It supposes that there are a number of grids in a row. Each grid has a unique state. The state of each grid at the next moment depends on its own state and the states of its neighbors. Suppose that the values of all the possible states of the grids are from $\sum$ and that the state of the grid *i* at the moment *t* is s_i^t. The state combination of its neighbors at the moment *t* is N^t, then the state of grid *i* at the next moment is

$$S_i^{t+1} = f(N_t, s_i^t), N^t \in \textstyle\sum^r, s \in \sum \tag{6}$$

in which, *r* is the number of the grids; different transfer function *f* corresponds to different behavior of the whole cellular automata. Wolfram examined hundreds of cellular automata and discovered that their behaviors can be divided into four categories that are fixed valued behaviors, circular behaviors, chaotic random behaviors and complex behaviors. The last type obtained people’s attention most as they create many ordered structures. These structures are approximately chaotic and not completely random. Therefore, they are complex. The behaviors of the four types of cellular automata are deeply related to each other. Langtong discovered the coefficient λ which is defined as the rule coefficient at the edge of the chaos.

Definition 1 Rules Coefficient a state q_0 is chosen from the state set $\sum$ which is called the static state. Then, for the rule f of the cellular automata, there are K^{r+1} elements among which $K = |\sum|$. Among these elements, if there are n_q elements at the state of q_0, then the rule coefficient λ of the rule f is defined as follows:

$$\lambda = \left(K^{r+1} - n_q\right) / K^{r+1} \tag{7}$$

As a result, the cellular automaton with different rules corresponds to different coefficient λ. Through the experiment, Langton discovered that the values of λ correspond to the types of the cellular automata approximately. Specifically speaking, λ corresponds to the fixed valued behavior type when $0<\lambda<0.2$, while it corresponds to the circular type when $0.2<\lambda<0.4$. It corresponds to the complex type when $0.4<\lambda<0.6$, while it corresponds to the chaotic type when >0.6. According to the change of λ, complex cellular automata is a state between the chaos and the rigid order. Therefore, it is called the edge of chaos by Langton.

Although the concept of the edge of chaos is proposed in the research of cellular automata, it is meaningful universally. For instance, the transformation area of the edge of chaos in random network is discussed in literature [10]. The edge of chaos in neural network is explored in literature [11]. The edge of chaos reveals the common feature of all self-organizational complex systems. Namely, a large-scaled complex transformation of the whole system will happen and a new order and structure will emerge when the individual moves and is at the edge of chaos.

3 The Analysis of Decision-making Behavior Based on the Edge of Chaos

3.1 The Framework of Decision Agent

In the real world, the abstract view of an agent illustrated in Fig.1, it obtains the inputs from the environment and produces the output to the environment. The black box in the middle refers to the cognition, learning, reaction or autonomous decision making components of the agent. In a dynamic environment inputs change with time and the agent has to decide the required autonomous decision for the current status of the environment.

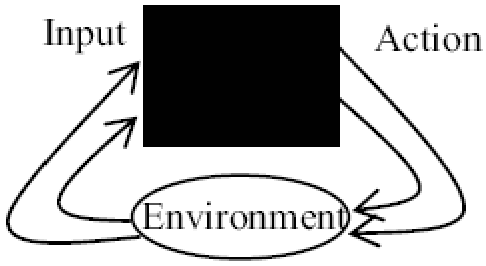

Fig.1. the abstract view of an agent

The layered conceptual framework of the decision agent, which can replace the black box in Fig.1, is shown in Fig. 2. It comprises of four layers: inheritance (Ψ_i), training (Ψ_t), experience (Ψ_e) and unexpected (Ψ_u).

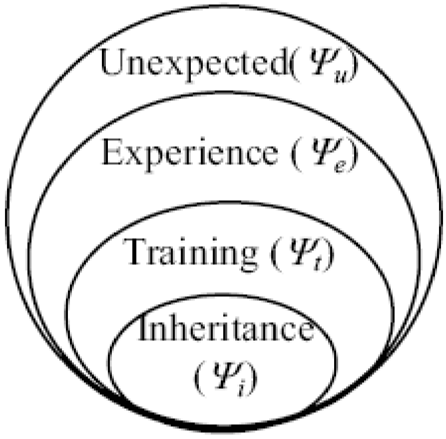

Fig.2. The layered conceptual framework of decision agent

In the proposed four-layered conceptual framework, each layer corresponds to the behavioral cycle of a human being giving a human oriented architecture to the agent to make autonomous decisions in a dynamic environment.

Generally the primitive actions taken for survival come as pre wired neurons and this phenomenon is captured by Ψ_i in the proposed architecture. The Ψ_t builds on top of Ψ_i provides solidness to the brittleness of inheritance layer. What is learnt by a human being either through education or training programs is mapped to the Ψ_e. This is synonymous to the job related training that humans get prior to being assigned to work. It is said that the evolution of the brain is achieved through genetically defined information as well as learning, and therefore,

Ψ_i and Ψ_t are used to model the actual evolution process of the brain. With maturity, humans gain experience on top of training which allows him/her with more suitable methods of handling a situation. This is denoted by the Ψ_e and experience makes an agent more adaptive to the environment. Once the agent has Ψ_i, Ψ_t and Ψ_e, ultimately it will become capable of reacting to the "unexpected" nature of a dynamic environment. This capability is mapped to the Ψ_u in the proposed architecture. With time this layer can be absorbed into Ψ_e.

3.2 The Analysis of Agent's Behavior Based on the Edge of Chaos

This section focuses on the introduction of the edge of chaos, especially Langton's coefficients, into the general model of decision agent. The edge of chaos refers to the state at the edge that the decision-making behavior is not totally fixed or over-random, but between them. In fact, when people observe a decision agent from outside, i.e. from the aspect of behavior, they can only observe the output behavior. Its input information or internal state is unknown. If the decision agent takes values randomly from all the possible output space, then a judgment can be made that the decision agent is at a chaotic state. On the contrary, if the behavior of the agent is always fixed at a given output state, then the agent shows too much order. Only when the behavior of the agent remains at a comparatively stable output order and make mistakes at a low probability, the agent is just at the edge of chaos. In the following part, a coefficient that makes judgment about whether the decision behavior of an agent stays at the edge of chaos is proposed just like the coefficient λ given by Langton.

Definition 2 The coefficient of decision behavior (i.e. decision coefficient). For each agent, the output behavior obtained through its decision rule Δ during a certain fixed period of time for observation is in accordance with the probability distribution *F* on the set *O*. Specifically, for $\forall o \in O, F(o) = p$, in which *p* stands for the probability of the output *o* of the agent, i.e. *p* implies the possibility that the agent select *o* as its output. Obviously, each element of *O* corresponds to a probability. Then, there is the maximum $p_{\max}$. Suppose $F(o_{\max}) = p_{\max}$, then the definition of λ is

$$\lambda = \frac{\sum_{o \in O} p_o - p_{\max}}{\sum_{o \in O} p_o} = 1 - p_{\max} \qquad (8)$$

in which $\sum_{o \in O} p_o$ refers to the probabilities that all the elements of set *O* correspond to and is obviously equal to 1. The output behavior $o_{\max}$ that corresponds to the maximum probability $p_{\max}$ is defined as the main behavior of the agent in this period of time. When λ takes a very low value, the possibility that the system takes a certain value is high. When λ takes a very high value, it implies that the behavior of the agent is random. When λ is in an ideal interval, the decision of the agent is at the state of the edge of chaos. At this time, the value of λ depends on the specific condition.

4 Decision Behavior and the Adaptability

4.1 Experiment of Artificial Life

People have to face various external environments and make decisions in real life. However, what kind of decision behavior improves the adaptability of the decision agent to the changing environment? The answer is that the decision at the edge of chaos can improve it. That is, only if λ takes a value from a certain interval, the adaptability of the agent is possible to be improved. According to the research of artificial life, the life system stimulated by computer highly resembles the real world [33]. Therefore, people can study the concepts and rules in the real world by means of computer models [34].

In the following section, an experiment on artificial life is designed to illustrate the relationship between the decision at the edge of chaos and its adaptability. In the experiment, the world is a limited grid area with a periodical boundary. Various food and agents are scattered in this area. A possible distribution of this world is shown in Fig. 1.

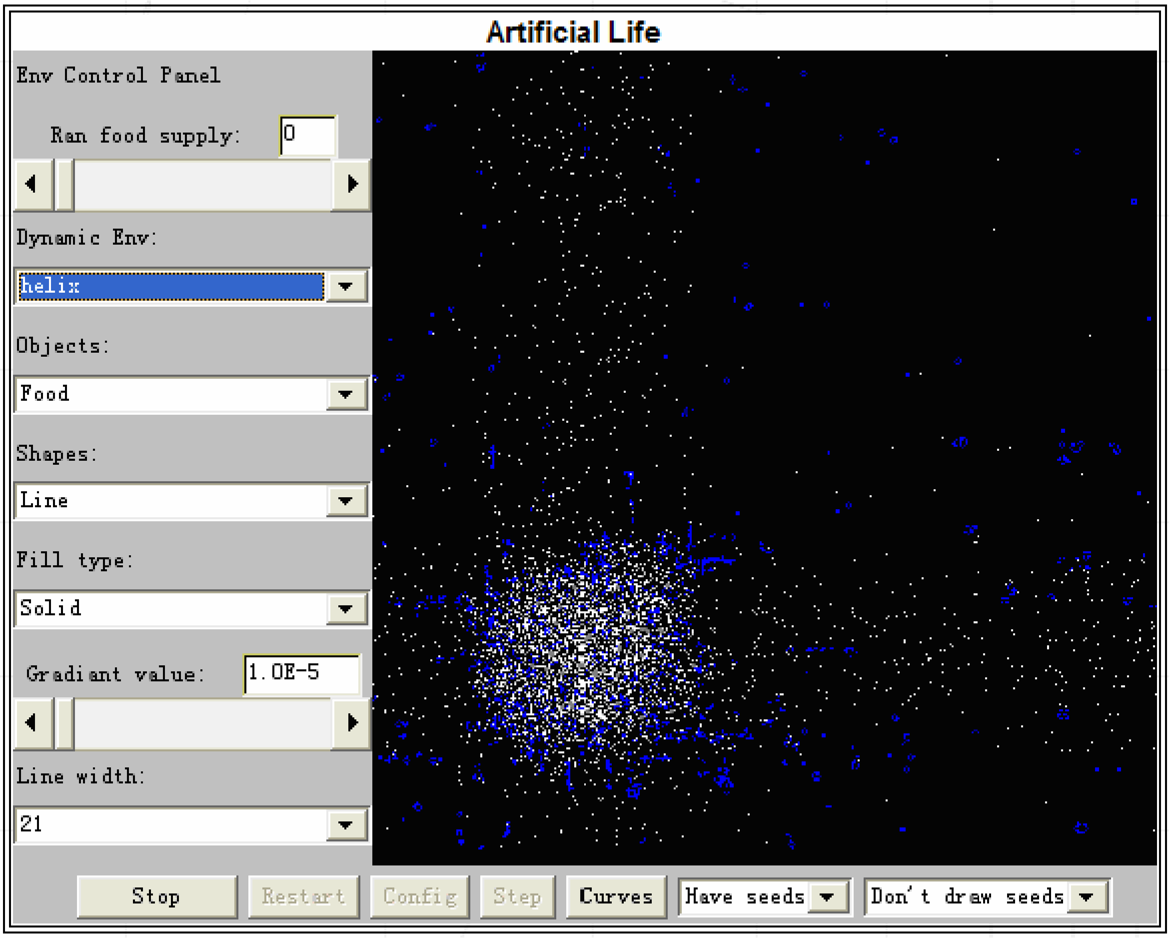

Fig.1. the experiment of artificial life

In Figure 1, the blue spots stand for agents and the white ones stand for various kinds of food. Each agent is an intelligent agent that makes decisions. In each stimulation cycle, the agent faces one direction among upwardness, downwardness, left and right (i.e. an agent is likely to face its upward side, downward side, left side, right side and so on). Suppose the agent can only observe the conditions in the three grids it faces as shown in Fig. 2.

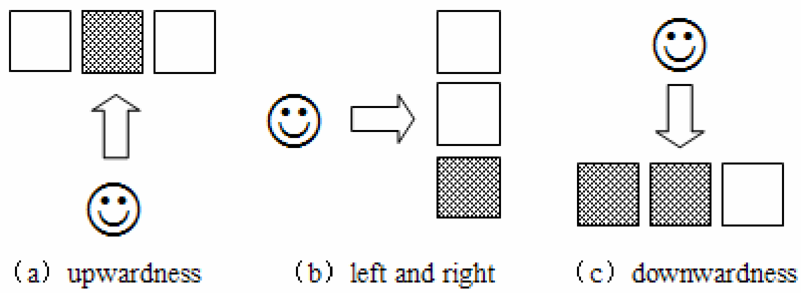

Fig.2. the directions of an agent face

As a result, at any time the environment the agent exists in is the combination of the states of the three grids. If the grid with food is noted as 1 and the grid without food is noted as 0, then, according to the discussion in section 2, the input set is

$$I = \{0,1\} \times \{0,1\} \times \{0,1\} \tag{9}$$

This set is a combination of different rows of 0 and 1. The eight possible combinations are 000, 001, 010, 011, 100, 101 and 111. Any one of the combinations is a row with 3 characters of 0 and 1. For instance, the input rows corresponding to the three conditions shown in Figure 2 are respectively

010, 001 and 011. Moreover, the three characters of each row are arranged in the same direction as the rotating hands of a clock. Suppose the internal state set of the agent is $S = \{1, 2, \cdots, 10\}$, i.e. there are 10 internal states. Then, the output behavior set is $O = \{0, 1, 2\}$. There, 0 stands for one step forward, 1 stands for turning left, 2 stands for turning right. Each agent can select one of the three possible behavior states at any time, i.e. it can go directly forward into the next grid, or turn left and move into the next grid, or turn right and move into the next grid. The decision rule Δ of an agent can be shown in a table (see Table 1). It instructs the agent to select different outputs and the internal state at the next moment in different conditions and at different internal states. For instance, as shown in Table 1, the first term shows that if the internal state of the agent is 1 while its input is 000, then it turns left and changes its internal state into 2. Obviously, different tables correspond to different decision rules. When the agent makes a decision, it selects a behavior as the output. The environment will then update itself according to the behavior of the agent. Suppose there is a grid with food in front of the agent, while its present output is 0 (i.e. going one step forward), then the agent is considered to eat the food. Consequently, the state of the present grid changes from 1 into 0. The specific update rules of the environment (Ø) are not shown here.

Table 1. The Decision Rule Table

No.	Input *e*	Internal-state *s*	Output *o*	Inter-state *s'*
1	000	1	1	2
2	010	3	0	1
3	100	2	2	3
⋮	⋮	⋮	⋮	⋮

In the following section, a group of 50 agents is selected and their decision rules are randomly produced. Then their decision rule tables are disposed with the approach of genetic evolution. This group of agent is called the first generation population. Each population goes through 10 different environments (i.e. the densities of the food distribution are different). Furthermore, in the 10 different environments each agent goes through 1000 stimulation cycles. The average value of the total amount of the food the agent eats in different environments is taken as its adaptiveness. Then, the next generation will be obtained after an operation of the genetic algorithm. The agents will be more and more intelligent in their digital environments. They gradually learn to get adapted to various environments. Meanwhile, their average adaptiveness is improving.

4.2 The Result of the Experiment

It is not very difficult to obtain λ that makes judgments on whether each agent is at the state of the edge of chaos. The average values of λ of the agent population of each generation and the population of the present generation in evolution are put in the same coordinate area (see Fig. 3). In the figure, the horizontal axis shows the serial number of the generation; the vertical axis shows the average values of λ in each generation; the dark spots show the values of λ of each agent in each generation. The light line shows the average values of λ in each generation. From Fig. 3, the values of λ become stable gradually with the operation of the genetic algorithm. The stable interval is approximately between 0.2 and 0.4. Therefore, the whole agent population is evolving towards the state of the edge of chaos.

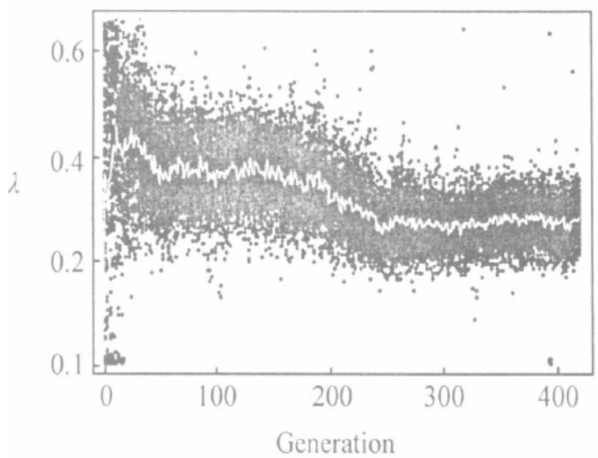

Fig. 3. the relationship between decision behavior coefficient and the evolutionary generation of agent

In order to discover the relationship between the value of λ and the adaptiveness, the values of λ in different intervals and the comparative average adaptiveness of the agent in these intervals (i.e. the adaptiveness of this agent is divided by the maximum adaptiveness) are put into the same coordinate area in this research (see Fig. 4). It is easy to discover that there is a convex in the curved line of the average adaptiveness. Moreover, the convex has its maximum value when λ is about 0.3. It implies that when λ is between 0.2 and 0.4, the adaptiveness increases. If λ is outside the interval, the adaptiveness decreases. According to the above discussion, a too high value of λ means that the decision behavior of the agent is too chaotic, while a too low value of λ means that the decision behavior of the agent is too rigid. When λ is between them, the decision of the agent is at the edge of chaos. In this experiment, when λ is in the interval of [0.2, 0.4], the agent is at the edge of chaos. Only the agents at the edge of chaos have a high adaptiveness.

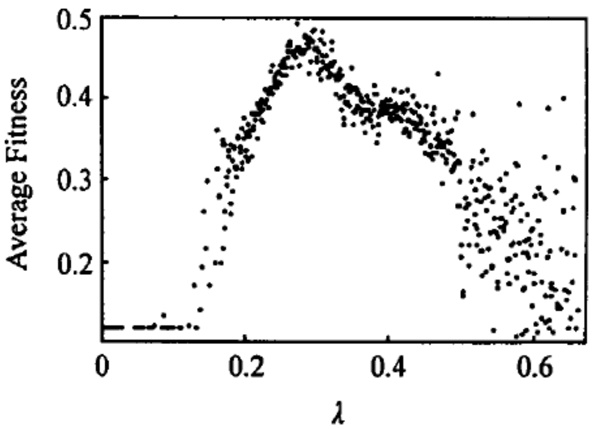

Fig. 4. the distribution of the comparative average adaptiveness of decision behavior coefficient

Although this computer experiment analyzes the evolution process of the virtual digital life in computer and the relationship between their decision behaviors and the adaptiveness, it is a metaphor of the human decision-making. In this experiment, each agent is equivalent to a decision-maker in real world. It can only sense the limited and randomly distributed food, which implies that the decision individual faces a completely unpredictable complex environment. However, each agent obeys its own decision rules, which is equivalent to the rules people obey in their decisions. In real world there are not decision rules that are proved right in advance. Each agent can only learn from its errors and make improvements from time to time in the complex changing environment, which is equivalent to the evolution of the agent. Generally speaking, the agent evolves to be more and more adaptive to the environment. As the evolution goes on, what kind of decision rules will be kept and what kind of decision rules will be eliminated? It depends on whether the rules are helpful for controlling the decision agent and pushing it to the edge of chaos. The experiment shows that the behavior of the agent has the tendency towards the edge of chaos as the evolution goes on. In the area of the edge of chaos, the agent is likely to lean and evolve its own decision rules further. This is a metaphor of the human decision problem, i.e. when people are facing a complex varying environment, only their behavior at the edge of chaos is helpful for the improvement of people's adaptability.

5 Conclusions

At present, the environment in which people make decisions is changing all the time and complex. How to make effective decisions in this kind of environment has become a significant problem. As a general idea on complex system, the concept of the edge of chaos has been applied to many subjects. Therefore, it can be applied to the analysis of individual decision behavior. This research reviews the concept of the edge of chaos at first. Then the coefficient for the measurement of the decision agent staying at the edge of chaos is defined by means of agent decision model. With the stimulation of artificial life, the adaptiveness of different decision rules is researched. The result of the experiment shows that only when the agent stays at the edge of chaos it can improve its adaptiveness.

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