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Selforganizology: A science that deals with self-organization

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Abstract
Self-organization is a universe mechanism in nature. In a self-organizing system, the system evolves spontaneously to form an order structure based on some compatible rules. Without external instructions and forces, the self-organizing system arises only from the interactions between the basic components of the system. Although numerous theories and methods were established to describe self-organization, there are still many problems in this area. We still lack of unified theories and thoughts on self-organization. Also, we lack of universal basis of methodology in the modeling and simulation of self-organization. Self-organization is classified into a research area in complexity science. So far it is not an independent science. For this reason, a fundamental science, selforganizology, is proposed for finding and creating theories and methods from self-organization phenomena in nature, simulating and reconstructing self-organization phenomena, exploring mechanisms behind numerous self-organization phenomena, and promoting the applications of self-organization theories methods in science and industry. Existing theories and methods of self-organization are overviewed. Methodological basis of selforganizology is shortly discussed.

Keywords selforganizology; self-organization; theories; methods.

1 Self-organization

1.1 Theories and principles of self-organization

Organization can be characterized to two basic categories, i.e., self-organization and external-organization. The main difference between the two categories of organizations is that whether the organizational instructions/forces come from outside the system or from inside the system. The organization with organizational instructions/forces from inside the system is self-organization. In other words, a system is called self-organizing system if there is any specific intervention from the outside during the system is in the process of evolution (Foerster, 1960; Heyligen, 2002). The stronger a system’s self-organization capacity is, the stronger the system’s ability to generate and maintain new functions.

Self-organizing systems are a kind of systems which can evolve and improve the organization’s behaviors or structure by themselves. Self-organization is a process to describe the system’s global state. In a self-organizing system, the system evolves spontaneously to form an order structure based on some compatible rules. Unlike other organizations, the self-organizing system arises only from the interactions between the basic components of system, without external instructions and forces. In the process of self-organization, several structural components can interact and cooperate to display the behaviors that only a group will have.

The dynamic interactions between low-level components typically include attraction and repulsion, that is, positive and negative feedbacks.

Generally, self-organization arises from the increase in complexity or information. According to the thermodynamic laws, this situation will only occur in the open systems far away from equilibrium. For most systems, this means the energy supply to the system is needed for generating and maintaining a certain mode. In an abstract sense, self-organization is a process that makes the system's entropy increase in the absence of external forces (i.e., a dynamic process that from the disorder to order states) (Glansdorff and Prigogine, 1971; Nicolis and Prigogine, 1977).

From the perspective of systematic theory, self-organization is an irreversible dynamic process. Each component in the system will spontaneously aggregate to form an organic whole without outside instructions. From the view of mathematics and physics, self-organization means the dimensional reduction of state space or the reduction of degrees of freedom, i.e., the system converges spontaneously to one or more steady states (attractors). In such a system, the local interactions between the basic components of the system can change the modes of the system's organization, and the global behaviors of the system cannot be understood intuitively. They cannot be understood by simply observing existing laws and behaviors of between-component interactions (Zhang, 2012). In a word, the global properties of self-organizing systems are not predictable.

Self-organization usually requires to be based on three elements (Bonabeau et al, 1999): (1) strong nonlinear dynamic interactions, even though they do not necessarily correlate to the positive or negative feedbacks; (2) a balance between development and exploration, and (3) complex and diverse interactions.

Self-organization is ubiquitous in nature and human society, covering many fields as physics, chemistry, biology, economics and society. The most obvious examples of self-organization are the nonlinear processes in physics (Glansdorff and Prigogine, 1971; Ansari and Smolin, 2008; Brau et al., 2011). Self-organization is also chemical-related, which is often considered to be synonymous to self-assembly of molecules (Kim et al, 2006; Coleman et al, 2011; Harada, et al 2011). It is also very important to the description of biological systems, whether at sub-cellular level or at ecosystem level (Hess and Mikhailov, 1994; Misteli, 2001; Camazine, 2003; Clyde et al, 2003; Motegi et al., 2011). It can also be found in the mathematical systems, like cellular automata (Zhang, 2012).

1.1.1 Thermodynamic basis of self-organization

The spontaneous formation of new structures, for examples, crystallization process, Bénard phenomenon, Belouzov-Zhabotinsky reaction (Sun and Lin, 2004), etc., are all self-organization processes, i.e., the formation of a structure or a mode does not need to be imposed any external force. It seems that the components of these systems are arranged into a more order pattern by themselves. At first appearance, self-organization violates the second law of thermodynamics. This law holds that the entropy of an independent system can only increase rather than decrease. In other words, the second law of thermodynamics means that an isolated system should evolve in a uniform, simple, difference-eliminating way, which is in fact an evolution to a low-level organization.

In the example of crystallization process, the randomly moving molecules that have been bonded into a crystal structure and thus have been fixed will transmit their kinetic energy to the liquid that they are dissolved. Thus, the reduction in the entropy of crystallization process is just offset by the increase in the entropy of liquid. The entropy of the whole system has actually increased, and therefore it is consistent with the second law of thermodynamics.

For self-organizing systems, which are not in their equilibrium, it is hard to determine whether the second law of thermodynamics is true or not. Prigogine started to study the systems far away from equilibrium states since the 1950s and proposed the theory of dissipative structures (Glansdorff and Prigogine, 1971; Nicolis and Prigogine, 1977), in which the most used models to explain the dynamic self-organization process are Bénard cells and the Brusselator. The theory of dissipative structures tried to address such problems as, under what conditions a system will be able to evolve from the disorder to the order, and form a new, stable, and internally-dynamic structure. Such a structure must be an open system, i.e., there are energy/matter flows in the system; the system will continuously generate entropy, but at the same time the entropy will be actively dissipated from the system or output from the system. Thus, at the cost of environmental disorder, the system will be able to increase order of its own. The system will be able to follow the second law of thermodynamics simply by getting rid of its excess entropy. This dissipation can be mostly found in life systems. Plants and animals obtain energy and matter by absorbing light or food with low entropy, and then output energy and matter by draining the metabolic waste of high entropy. This will reduce its internal entropy to offset the degradation process required by the second law of thermodynamics.

The output of entropy cannot explain why and how self-organization happened. Prigogine held that self-organization would mostly occur in the nonlinear systems far away from equilibrium.

1.1.2 Principles of self-organization

The first symposium on self-organization was held in 1959 in Chicago. In this symposium, British cybernetic expert, Ashby, proposed “the principle of self-organization” (Ashby, 1947). He believed that a dynamic system, ignoring its classification or composition, always tend to move towards an equilibrium, or the “attractor” we are talking about. This theory reduced our uncertainty on the state of system and solved the problem of entropy in systematic science. This is equivalent to self-organization, which finally reaches the equilibrium and the final equilibrium can be considered to be a state of mutually adaptation of all components in the system. Another cybernetic expert, Heinz von Forster, proposed the principle of order from noise (Foerster, 1996). He believed that the larger a system is subject to random interference, paradoxically, the quicker it will perform self-organization (i.e., become more order). This idea is very simple: The larger the state space that a system moves through is, the faster it will reach the attractor. If the system stays at its initial state, it will not reach the attractors, and self-organization will thus not occur (Foerster, 1996). Generally, there are multiple attractors in a nonlinear system. The attractor theory holds that the behavioral trajectories of complex system in the state space can be represented by the dynamic equations. These dynamic equations are always determined by a set of “attractors”. What attractor the system will move towards depends on the attraction domain that the initial state falls into. What attractor the system eventually reaches is uncertain. Small fluctuation of some parametrical values will cause the system to change. Prigogine thus proposed a related principle, i.e., order through fluctuations.

1.1.3 Known theories of self-organization

So far, self-organization theory is generally believed to mainly consist of three parts, the theory of dissipative structures (Glansdorff and Prigogine, 1971; Nicolis and Prigogine, 1977), synergetics (Haken, 1978, 2004), and catastrophe theory (Saunders, 1980). However, the basic thoughts and theoretical kernel of self-organization can be derived entirely by the theory of dissipative structures and synergetics.

(1) The theory of dissipative structures. Prigogine officially proposed the theory of dissipative structures in 1969 in a theoretical physics and biology symposium (Nicolis and Prigogine, 1977). The theory mainly aimed to explain the exchange of matter and energy between the system and the environment and its effect on the self-organizing system. The structure established on the basis of the exchange of matter and energy between the system and the environment is a dissipative structure, such as a city, an organism, etc. Far away from equilibrium, the openness of system, and nonlinear mechanism between different components of system, are three conditions for the formation of a dissipative structure. Far away from equilibrium refers to that the

distribution of matter and energy in different areas of a system is extremely uneven. The theory of dissipative structures is mostly used to discuss the evolution of complex systems. The theory of dissipative structures uses two levels of approaches, i.e., deterministic and stochastic approaches in the discussion of system evolution. Deterministic approach uses macroscopic physical variables to describe system dynamics and features. Stochastic approach treats macroscopic physical variables as the average of corresponding random variables. Analyzing random variables will not only produce the averaged values but also help understand fluctuation characteristics of the system.

(2) Synergetics. Haken first proposed the concept of “synergy” in 1976, and another science on self-organization, synergetics, was thus established (Haken, 1978, 1983, 2004). About synergetics, Haken held that on the one hand, in a system many subsystems interact to produce the structure and function at the macroscopic scale; on the other hand, there are many different scientific disciplines cooperating to explore the general principles for governing self-organizing systems. The order parameters generate and govern subsystems by competition and cooperation between various subsystems. Serving of various subsystems to order parameters reinforces order parameters themselves and further promotes the serving of subsystems to order parameters, so that the system can spontaneously organize by itself (Haken, 1978, 2004). Competition and cooperation between order variables will result in different forms of evolution of self-organization. Synergetics mainly discusses the coordination (synergy) mechanism between internal components of the system studied. It holds that the coordination between various components in the system is the basis of self-organization process. Competition and cooperation between order parameters of the system are direct forces for the formation of new structures. Because of independent evolution of components in the system, various local and collaborative evolution, as well as random inferences by environmental factors, the actual state of system always deviates from the average. The magnitude of such a deviation is called fluctuation. When the system is in its transition from one steady state to another steady state, and if the independence evolution and collaborative evolution between system components move into a balance, any small fluctuation will be amplified, and quickly spread to the whole system. The resultant giant fluctuation will promote the system moving into an order state. In addition, Harken proposed the concept of “functional structure”, i.e., the function and structure are dependent for each other. If the energy or matter flow is cut off, the physical and chemical system will lose their structure, while a biological system is mostly able to maintain a fairly long time. Such biological systems seem to combine non-dissipative and dissipative structures together (Haken, 1978, 2004).

(3) Catastrophe theory. Catastrophe theory was first proposed by the French mathematician, Thom R, in 1969. Since the 1970s, Zeeman and other scientists have further developed catastrophe theory and apply it to various aspects of physics, biology, ecology, medical science, economics and sociology, and produced significant impacts (Zeeman, 1976). This theory was built on the basis of the stability theory. It considers a catastrophe process as a process that transit towards a new steady state through an unsteady state from an original steady state. In mathematical view, this means the changes of values of a set of parameters and mathematical functions that denote the states of the system. Thus it is a theory to describe the phenomena that the continuous change of parameters lead to the discontinuous change of the states of system. It treats with the systems that almost sure structural stability in the state space but there is some structural instability on some point sets of measure 0. The basic characteristics of catastrophe systems include: multiple steady states; reachability; jumping; lagging, and divergence (which reflects the sensitivity of evolutionary trajectory to the path of control parameters). Catastrophe theory holds that different outcomes may occur even if it is the same process that corresponds to the same controlling factors and critical values; different new steady states may be achieved at different probabilities (Saunders, 1980). Generally, catastrophe theory does not reveal the

mechanism to produce catastrophe phenomenon. It provides a reasonable mathematical model to describe the phenomenon of catastrophe in the real world, and classifies various catastrophe types. In ecology, there are a lot of applications on catastrophe theory, such as the sudden outbreak or sudden collapse of biological population.

In addition, there are also other theories on self-organization, for example, Eigen's super circle theory. Super circle theory is a self-organization theory of molecular evolution. However, it is a scientific hypothesis, the impact is still limited.

1.1.4 Properties of self-organization

By interacting with the environment, the self-organizing system can evolve to form new structures and functions. Unlike ordinary mechanical systems, it has its own peculiar properties. Those peculiar properties can be used as part of the definition of self-organizing systems, for example, there is no centralized control, and continuous adaptation to the changing environment, etc.

(1) Local interactions generate global order

the most obvious change in the self-organizing system is the formation of global order. Local interactions follow immediately basic physical processes; any impact from one region to another region must first move through all intermediate regions. When it passes through intermediate regions, all the processes will be disturbed by the turmoil occurred in the intermediate regions. First assume the system is disorder and all components of system evolve randomly. The impact of any passed will be quickly dispersed and ultimately destructed by these random turbulence. The result is thus that, starting at the chaotic state, the distant parts of system is actually independent: they do not affect each other. During self-organization process, all the components of system are closely linked. Understanding of the structure of a regional component will be valuable to know the structure of components of its consecutive regions.

(2) Distributed control

People tend to consider that a highly organized system is instructed and controlled by external or internal forces. This control is called centralized control.

In a self-organizing system, the control on organization is distributed throughout the system. All components contribute to the final arrangement of the states of system. Despite some of the advantages of centralized control with respect to distributed control, on some levels centralized control must be based on distributed control. For example, the function of human brain is dispersed in the network formed by interacting neurons. Different brain regions perform specific functions, but not a neuron or a group of neurons has all the ability to control brain. This is a result of self-organization.

(3) Nonlinearity and feedbacks

Nonlinearity means the whole is not equal to the simple sum of its parts, i.e., superposition principle is not met. Suppose a system is represented by a function: $y=f(x)$. If the following condition is satisfied: $f(\alpha x_1+\beta x_2)=\alpha f(x_1)+\beta f(x_2)$, where $\alpha,\beta\in R$, then it is a linear system, otherwise it is a nonlinear system (Zhang, 2010, 2012). Judging from the mechanical movement, a linear phenomenon is generally manifested as smooth motion in time and space; it can be described by the functions with good performance, and the functions are continuous and differentiable. The nonlinear phenomenon is a movement from regular motion to irregular motion, with obvious jumping and intermitting features. From the view of disturbance and parameter theory, the response of a linear system is smooth and proportional changes, but nonlinear system will exhibit substantial changes in some of the key points because of the small changes in parameters, and form and maintain spatially regular and order structures. Linear relationship is independent of each other, while the nonlinear relationship is an interactive one, which makes it violate superposition principle and produce gain or loss. In nonlinear systems, there are feedbacks between system components; each component affects the others, and other components in turn affect it. The positive feedback plays a role similar to the input so that the system's deviation increases, and the system's oscillation is thus amplified. The negative feedback causes reverse outcome as compared with input's role, so that the system's output error can be reduced and the system is thus stabilized.

In complex self-organizing systems, there are often several chains of positive and negative feedbacks, so a change can be enlarged in a certain direction but suppressed in the other directions. This will result in the very complex behaviors difficult to be predicted.

(4) Far away from equilibrium

Equilibrium is a special state of a system. At this state, the everywhere measurable macroscopic physical properties of system are uniform throughout the system (so that there is not any macroscopic irreversible process inside the system). At the equilibrium state, the system follows the first law of thermodynamics: $d_E = d_Q - pd_V$, i.e., the increment of energy inside system is equal to the absorbed heat subtracting by outward work done by the system. It is also coincident with the second law of thermodynamics: $d_S/d_t \geqslant 0$, that is, the spontaneous evolution of system is always toward the direction of entropy's increase. For the system in equilibrium state, it must abandon its extra energy; it will remain in the minimum energy state without the input of external energy.

A system will likely move to a nonlinear region when it is far away from equilibrium. The system far away from equilibrium is more sensitive and more vulnerable to environmental changes due to its dependence on external energy input. But it is more powerful to respond changes. On the other hand, the surplus of external input energy allows the system to amplify the self-organization process, for example, offsetting small turbulence or maintaining positive feedbacks longer in the aid of strong interactions. This makes the system more vigorous and more adaptive to external changes.

(5) Systematic termination and organizational hierarchy

The interactions between individual components of self-organizing system can be to some extent defined as an order structure. However, the order does not mean organization. Organization is an order structure and can achieve a particular function. In a self-organizing system, this function is to maintain a particular structure under various disturbances. The general characteristics of self-sufficiency can be understood as a closure. A process with causal relationship can be represented as a chain or a sequence: A → B → C → D → ..., where A initiates B, B initiates C, C initiates D, and so on. Overall, this will lead to a continuous change. However, there may be its own termination of a link in the chain, for example, O returns J, so the cycle of the system becomes J, K, L, M, N, O, J, K, L. Thus the corresponding arrangement of system will always be maintained or recycled. In addition, if the loop is placed in a negative feedback region, it is relatively unaffected by the impact of external interference (Foerster, 1960).

In a self-organizing system, it may generate a lot of autonomous and organization-closed subsystems. Those subsystems will interact in a more indirect way. They will also adapt to the structure for termination and determine subsystems at a higher level. New generated subsystems will contain the original subsystems as their components. Each self-organizing system constitutes a series of subsystems. A self-organizing system thus forms a layered structure. Each self-organizing system belongs to the high-level self-organizing system and contains low-level self-organizing systems. It interacts with other self-organizing systems at the same level. Therefore, the hierarchy is a characteristic of self-organizing systems.

1.2 Algorithms of self-organization

1.2.1 Mathematical and computer modeling

Because it is difficult to predict the complex behaviors of self-organizing systems, mathematical modeling and computer simulation have been widely used for theoretical experiments of these systems. They also help people understand how these systems work. A mathematical modeling method for self-organization is to use nonlinear differential equations, and another method is to use cellular automata (Wolfram, 2002; Ballestores and Qiu, 2012; Zhang, 2012).

1.2.2 Intelligence computation

Many complex problems are difficult to be effectively addressed by traditional artificial intelligence technologies. Intelligence computation is a powerful technique to solve more complex problems. In the intelligence computation, computation is intelligent. It can automatically adjust parameters during the process of computation, and thus achieve optimal results (Koza, 1992). Evolutionary computation searches the optimal solution by simulating biological evolution in nature, for example, genetic algorithms, etc. Swarm intelligence algorithms are a kind of new evolutionary algorithms, which are closely related to evolutionary strategies and genetic algorithms.

1.2.2.1 Swarm intelligence algorithms

The concept, swarm intelligence, was first proposed by Hackwood and Beni (1992) in their cellular automata system. Swarm intelligence refers to that a group of unintelligent entities can cooperate to solve problems in a distributed way. They can directly or indirectly communicate by changing the local environment. These unintelligent entities behave intelligently through cooperation (Bonabeau et al, 1999; Hu and of Li, 2008; Zhang, et al., 2008). A significant feature of swarm intelligence is, although the behaviors of an individual are simple, but when they work together, the system will exhibit very complex behaviors. Without centralized control and global model, swarm intelligence provides a solution for distributed problems.

(1) Ant colony algorithm

Ant colony algorithm (ant algorithm) is a method for finding the optimal path in the graph. It is a probabilistic algorithm (Colomi and Maniezzo, 1991; Dorigo et al, 1996). It is proposed by Dorigo in 1992 in his doctoral thesis, inspired by the behaviors of ants found in the process of looking for food path (Colomi and Maniezzo, 1991). Ant colony in nature can cooperate to find the shortest path from the nest to the food, and can change strategy as circumstances change and quickly re-find the shortest path.

Numerous studies found that ant colony algorithm is a self-organization algorithm. At the start of algorithm, a single artificial ant searches for solution in a disorder way. After a period of algorithm evolution, the artificial ants spontaneously tend to find some solutions close to the optimal solution, which is a process from the disorder to the order.

(2) Particle swarm algorithm

Particle swarm algorithm is also called Particle Swarm Optimization (PSO). PSO is an evolutionary computation based on iteration, which is proposed by Kennedy and Eberhart (1995). Particle swarm algorithm was originally a graphical simulation of preying behaviors of a flock of birds. The basic idea is inspired by their early findings on group behaviors of birds, and they thereafter used and improved biological population model. In the particle swarm algorithm, each particle in the particle swarm is equivalent to a bird in the bird flock. They all track the currently optimal particle (which is equivalent to the bird most near the food) in the solution space, and they constantly update their position and velocity. Through continuous iteration, the algorithm reaches the optimal solution (similar to bird finding food) (Shi and Eberhart, 1998; Eberhart and Shi, 2000; the Krink and Løvbjerg, 2002; Clerc, 2004, 2006; Zhang et al. , 2007; Niknam and Amiri, 2010).

(3) Stochastic diffusion search

In 1989, Bishop proposed stochastic diffusion search method in order to solve the problem of incentive equivalence in pattern recognition (Bishop, 1989). Stochastic diffusion search is one of the swarm intelligence algorithms. Unlike most swarm intelligence algorithms, stochastic diffusion search uses direct communication between entities (Beattie and Bishop, 1998; Nasuto et al., 1998; Myatt et al., 2004; Meyer, 2004; Meyer et al., 2006). In stochastic diffusion search, each of the entity holders holds an assumed solution about the problem to be solved, and assesses the solution partially. The successful entity directly communicates with unsuccessful entities to repeatedly test its assumption. Thus a positive feedback mechanism is established, so that the group can quickly converge to the optimal solution in the solution space. In the solution space the regions largely aggregated by entities are considered as candidate solutions. Through the cooperation between the locally-run simple entities, the global solution can be reached in the region with most aggregated entities. The stochastic diffusion search is a truly adaptive algorithm, because even if the optimal solution is found, there are still some entities to explore the solution space, which makes the algorithm adapt to changes in the environment (Nasuto et al., 1998).

1.2.2.2 Genetic algorithms

Genetic algorithms are a kind of stochastic search algorithms that simulate the evolution of organisms (survival of the fittest, genetic mechanism). It was first proposed by Holland (Holland, 1975). It aimed to explain the adaptive processes of natural and artificial systems. Main characteristic of genetic algorithms include, (1) directly operate the structural objects; (2) there is no assumptions on derivative and function continuity, and (3) implicit parallelism and better search performance on global optimization; using probabilistic optimization-searching method which can automatically obtain and guide optimized search space, and adaptively adjust the search direction without determinant rules. These properties make genetic algorithms widely use in combinatorial optimization, machine learning, signal processing, adaptive control and artificial life. Genetic algorithms are considered key technologies that will have significant impacts on the future of computing technology, along with adaptive systems, cellular automata, chaos theory and artificial intelligence.

1.2.3 Other algorithms

In addition to the commonly used algorithms above, a variety of new algorithm have been proposed to study self-organization. Widely recognized algorithms include, fish swarm algorithm (Li, 2003; Grosenick et al, 2007; Chen et al, 2009), bee colony algorithm, co-evolutionary algorithm, Memetic algorithm, hybrid optimization algorithm, bio-inspired algorithm, evolutionary programming, evolutionary strategy, parallel algorithm, etc.

1.3 Case examples of self-organization

(1) Physics

A few categories of physical processes can be considered as self-organization. Such examples include:

(a) Phase transition of structures, spontaneous symmetry breaking. For examples, spontaneously magnetization, crystallization in classical physics, laser in quantum mechanics, superconductivity, and Einstein-Bose condensation.

(b) Formation of structures in the thermodynamic systems far away from equilibrium. The theory of dissipative structures and synergetics are important to theoretically understand these phenomena. Those phenomenon include, structure formation in astrophysics and cosmology (including formation of stars, formation of planetary systems, formation of the Milky Way, etc.), self-similar expansion, diffusion-limited aggregation, infiltration, and reaction-diffusion systems, etc.

(2) Chemistry

Self-organization can be widely found in chemistry. For examples, self-assembly of molecules, oscillatory reactions, autocatalytic networks, Langmuir-Blodgett film, self-assembled monolayer film, B-Z reaction, self-organization of nanomaterials, macroscopic self-assembly under molecular recognition (Kim et al., 2006; Coleman et al., 2011; Harada et al., 2011).

(3) Life sciences

In the field of life sciences, there is a growing emphasis on the phenomena of self-organization in vivo. In biological systems, self-organization is a process at global level. The system is generated only from the interactions between components at the low levels. Implementing the rules of between-component interactions only requires local information rather than global information (Camazine, 2003).

A large number of living systems are self-organization phenomena (Hess and Mikhailov, 1994; Misteli, 2001; Clyde et al, 2003; Motegi et al, 2011), such as, 1) the self-assembly of proteins, as well as the formation of other biological macromolecules and lipid bilayers; 2) homeostasis, which is a self-organization from cell to tissue; 3) pattern formation and morphogenesis, i.e., the growth and differentiation of living organisms; 4) human motion; 5) creation of structures by gregarious animals, such as social insects, bees, ants, etc.; 6) group behaviors (the most typical examples can be found in birds and fish), and 7) in the super cycle theory and autocatalytic theory, life itself is originated from the self-organizing chemical systems.

(4) Cybernetics

Scientists held that the automatic and continuous identification of the black box problems and subsequent replication fitted the properties of self-organization (Machol and Gray, 1964). Self-organization is one of the key steps in self-assembly of molecules. In some sense, cybernetics deals with some of the self-organization problems.

In addition to the above applications, self-organization has also been widely applied to many other fields such as anthropology, economics, linguistics and computer network.

2 Selforganizology

2.1 Problems for self-organization research

Although numerous theories and methods were established to describe self-organization, there are still many problems in this area. We still lack of unified theories and thoughts on self-organization. Also, we lack of universal basis of methodology in the modeling and simulation of self-organization. Self-organization is classified into a research area in complexity science. So far it is not an independent science.

2.2 Selforganizology: a science to deal with self-organization

For the reason mentioned above, here I propose a fundamental science, selforganizology. It is proposed for finding and creating theories and methods from self-organization phenomena in nature, simulating and reconstructing self-organization phenomena, exploring mechanisms behind numerous self-organization phenomena, and promoting the applications of self-organization theories methods in science and industry. Selforganizology is a science that deals with self-organization. Many properties, principles, theories and methods on self-organization hold in this science. The theory of dissipative structures and stability theory are two of the fundamental theories in selforganizology. Some theories and methods should be futher improved. The theory of synergetics should be further improved and innovated to promote selforganizology.

Selforganizology is an interdisplinary science based on systematic theory, computational science, artificial intelligence, mathematics, physics and some other sciences. Evolution-, interaction-, behavior-, organization-, intelligence- and feedback-based theories, such as coevolution theory, coextinction theory, community succession theory, correlation analysis, parrondo’s paradox (Harmer and Abbott, 1999a, b; Toral, 2001, 2002), game theory, neural networks, artificial intelligence, behavioral theory, organization theory and automation theory in various scientific disciplines can be reviewed, revised and introduced to selforganizology.

2.3 Some thoughts on methodological basis of selforganizology

In selforganizology, the self-organization is considered as a universe mechanism in nature. In a sense, all things, from atom to universe, are the products of various self-organization processes. Without external forces and instructions, a dissipative system far away from equilibrium may spontaneuously evolve toward one or more steady states through self-organization process by between-component interactions at different hierarchies. It is thus a self-organizing system. In the self-organizing system, the interactions between components will produce different functions and properties and behaviors from that of components, which leads to a system with certain functional characteristics and purposeful behaviors that different from the nature of components. A self-organizing system is an aggregation of interactive components, and it has a hierarchical structure. A component is an autonomous and organization-closed subsystem. Some components at a hierarchical level will interact and aggregate to form a component at higher hierarchical level, with or without these components in this component. The most basic and inseparable component is the individual (i.e., a person, a bird, a plant). Different components at the same hierarchical level or at different hierarchical levels will most likely have different behaviors. Self-organization is a dynamic and spontaneous process from the low-level to the high-level, from the local to the global and from the micro-level to the macro-level.

Following Macal and North (2005), we may define a component as that satisfies these criteria (Zhang, 2012):

(1) A component is an independent and identifiable individual which possesses a set of attributes and rules that forge its behaviors. A component is self-contained and independent. It has a boundary through which people can easily discern between outside the component and inside the component or shared characteristic.

(2) Each component locates in a certain position and interacts with its adjacent components. A component has a set of protocols that govern its interactions with other components, such as communication protocol, the capability to affect its environment, etc. The component is able to identify and discern the characteristics of other components.

(3) The component is goal-directed. The component behaves to realize some goals.

(4) The component is independent, autonomous and self-guided. At least within a finite range, the component can independently operate in its environment.

(5) The component is flexible. It is capable of adapting the environment and adjusting its behaviors. The component possesses some high-level rules to adjust its low-level behavior rules.

The behaviors of a self-organizing system cannot be described by using deduction, induction, or other formalization methods. However, the behaviors of a component (aggregation behaviors) can be derived from the interactions between components at low hierarchical level. A behavior of an independent component might be a primitive response and decision, or even a complex intelligence. The behavior rules of a component include basic rules and the high-leveled rules that govern basic rules (rule-changing rules) (Casti, 1997; Zhang, 2012). Basic rules define necessary responses to the environment, and rule-changing rules define adaptation. In a specific study, it is necessary to determine a theory on behaviors. A component may use various behavioral models, including if-then rule and threshold rules. Knowledge engineering and participative simulation can be used in defining behaviors. Knowledge engineering includes a series of techniques collected for organizing experts' knowledge (Zhang, 2012).

In a self-organization system, the basic structure of behavior rules includes: IF-THEN-ELSE rule; (2) GO TO rule; (3) DO WHILE rule; (4) SWITCH CASE DO rule; (5) LET rule; (6) RANDOMIZE rule, etc. I think that using these simple rules for all components at all hierarchical levels will probably produce any complex behaviors of the self-organizing system. Simple rules are more useful in exploring mechanisms behind numerous self-organization phenomena. Complex mathematical equations and models can be avoided in the simulation and modeling of self-organization phenomena.

In the sense of systematic simulation, selforganizology may be considered as a science based on self-organization, components, hierarchies, interactions, feedbacks, behaviors and rules.

Some methods, such as agent-based modeling (Topping et al., 2003; Griebeler, 2011; Zhang, 2012) can be considered as the methodological basis of self-organization simulation and modeling. These methods will not only help propose hypothesis on behaviors and mechanism of a self-organizing system but also help propose management strategies on the self-organizing system.

In selforganizology, we can follow some standard protocol, for example, the standard protocol proposed by Grimma et al. (2006) to describe the simulation and modeling of self-organization. The core of the protocol is to structure the information about self-organization simulation and modeling in a sequence. This sequence consists of seven elements, which can be grouped in three blocks: overview, design concepts, and details (Grimma et al., 2006):

(1) The overview consists of three elements including purpose, state variables and scales, process overview and scheduling. It provides an overview of the overall purpose and structure of the model. It includes the declaration of all objects (classes) describing the models entities (different types of components or environments) and the scheduling of the model's processes.

(2) The design concepts describe the general concepts underlying the design of the model. The purpose of this element is to link model design to general concepts identified in the field of self-organizing systems. These concepts include the interaction types between components, whether the components consider predictions about future conditions, or why and how stochasticity is considered.

(3) The details include three elements, i.e., initialization, input, and submodels, which present the details that were omitted in the overview. The sub-models implementing the model's processes are particularly described in detail. All information required to completely re-implement the model and run the baseline simulations should be provided.

The logic behind the protocol sequence is, context and general information is provided first (overview), followed by more strategic considerations (design concepts), and finally more technical details (details).

Main procedures of self-organization simulation and modeling include (Zhang, 2012): (1) determine various types of components and define behaviors of components; (2) identify relations between components, and construct interaction types between components; (3) determine the platforms and environments for self-organization simulation and modeling, and set the strategies for simulation and modeling; (4) acquire necessary data for simulation and modeling; (5) validate the patterns of components' behaviors and system's behaviors, and (6) run the model, and analyze the output from the standpoint of linking the micro-scale behaviors of the components to the macro-scale behaviors of the self-organizing system.

Here I have proposed and presented some ideas for the establishment and development of selforganizology. However, the theories and methods of selforganizology should be continuously revised and improved in the future. Further researches are needed to promote this fundamental science.

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