Article

Selforganizology: A more detailed description

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Abstract

Selforganizology is a science on self-organization. It was first proposed by the author in 2013. Theories and methods of selforganizology should be continuously revised and improved. More details on selforganizology were described in present report as compared to the original study.

Keywords selforganizology; self-organization.

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1 Introduction

As described earlier (Zhang, 2013a; Zhao and Zhang, 2013), the organization with organizational instructions/forces from inside the system is called self-organization. Self-organizing systems are those systems which can evolve and improve the organization's behaviors or structure by themselves. In a self-organizing system, the system evolves spontaneously to form an order structure based on some compatible rules. That is, a system is called self-organizing system if there is not any specific intervention from the outside during the system is in the process of evolution. The stronger a system's self-organization capacity is, the stronger the system's ability to generate and maintain new functions.

Self-organization is a process that some form of global order or coordination arises out of the local interactions between the components of an initially disordered system. This process is spontaneous, i.e., it is not directed or controlled by any agent or subsystem inside or outside of the system; however, the laws followed by the process and its initial conditions may have been chosen or caused by an agent. It is often triggered by random fluctuations that are amplified by positive feedback. The resulting organization is wholly decentralized or distributed over all the components of the system. As such it is typically very robust and able to survive and self-repair substantial damage or perturbations (Zhang, 2013a, b; Wikipedia, 2014).

Unlike other organizations, the self-organizing system arises only from the interactions between the basic components of system, without external instructions and forces. During the process of self-organization, some 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 from thermodynamic 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 dynamic process that makes an open system change from the disorder to order states and thus reduces system's entropy by absorbing "negative entropy" from outside the system (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 entity 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, i.e., 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, 2013a, b). In a word, the global properties of self-organizing systems are not predictable.

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

Prigogine believed that conditions for self-organization include: (1) the system must be an open and dissipative system, where a dissipative system is a thermodynamically open system, which is operating out of, and often far from thermodynamic equilibrium in an environment with which it exchanges matter/energy (Wikipedia: http://en.wikipedia.org/wiki/Dissipative_system); (2) the system is far from thermodynamic equilibrium, which allows for entering the non-linear zone; (3) nonlinear interactions exist between components, and (4) some parameters fluctuate and if fluctuations reach some thresholds, the system will change to unstable from steady state, catastrophe will occur and the system may thus exhibit a highly ordered state. For example, we often try to put sand dune higher, but to a certain height, the addition of a little amount of sand will cause landslide of a large amount of sand in the sand dune, and the sand dune cannot be further piled higher. In fact, before landslide occurs, sand dune has reached a critical state (threshold), and thus small perturbations can lead to instability.

2 Existing Algorithms of Self-organization

Because it is hard to predict the complex behaviors of self-organizing systems, sometimes we use mathematical modeling and computer simulation to describe these systems. They also help people understand how these systems work. A mathematical modeling method for self-organization is to use differential equations, and another method is to use cellular automata (Wolfram, 2002; Ballestores and Qiu, 2012; Zhang and Gu, 2001; Zhang et al., 2011; Zhang, 2012, 2013a).

Many optimization algorithms can be considered as a self-organization system because optimization aims to find the optimal solution to a problem. If the solution is considered as a state of the iterative system, the optimal solution is essentially the selected, converged state or structure of the system, driven by the algorithm based on the system landscape (Yang et al., 2013; Yang, 2014). In fact, we can view an optimization algorithm as a self-organization system.

In the sense of optimization, existing algorithms of self-organization can be classified into four hierarchies, Monte Carlo method, heuristic method, meta-heuristic method and hyper-heuristic method (Mirjalili et al., 2014; Zhao, 2014).

2.1 Monte Carlo method

Monte Carlo method tries to obtain deterministic solution by using random numbers. Monte Carlo method is used to test the statistical characteristics, approximate the distribution of statistic with asymptotic approximation, estimate the variance and test statistical significance, and compute the expectation of function of random variables (Manly, 1997; Zhang and Shoenly, 1999a, b; Zhang and Schoenly, 2001; Ferrarini, 2011; Zhang, 2010, 2012; Zhang, 2011a, b, c; Zhang and Zheng, 2012).

2.2 Heuristic methods

Heuristic methods use the heuristic information contained in the problem itself to guide search process. This information is usually localized, limited, and incomplete. Heuristic methods use some simple heuristic rules to search for solution in a limited search space, which can greatly reduce the attempts and quickly reach the solution even although the search process is occasionally failed. The key of the methods is how to design simple and effective heuristic rules.

The greedy algorithm is a typical heuristic method. A greedy algorithm is an algorithm that follows the problem solving heuristic of making the locally optimal choice at each stage with the hope of finding a global optimum (Cormen et al., 1990). A greedy strategy does not in general produce an optimal solution, but it may yield locally optimal solutions that approximate a global optimal solution in a reasonable time (Wikipedia: http://en.wikipedia.org/wiki/Greedy_ algorithm).

In addition, gradient-based algorithms such as Newton's method, conjugate gradient method, etc., can be called heuristic methods using different levels of heuristic information.

Generally, the efficiency of a heuristic method depends on the available amount of heuristic information that a problem can provide. For example, Newton's method uses the heuristic information in Hessian matrix to solve problem in the local area to achieve quadratic convergence rate. Thus, Newton's method is highly efficient and specialized. However a general creedy algorithm with limited heuristic information is inefficient but it may be widely applicable.

2.3 Meta-heuristic methods

Roughly speaking, meta-heuristic methods can be viewed as the population-based heuristic methods with some stochastic characteristic. It tries to have both speciality and high-efficiency of heuristic methods and simplicity of Monte Carlo method. Nevertheless, the two requirements are contradictive for each other. How to avoid its disadvantages is extremely important.

Meta-heuristic methods can be generally divided into three categories, evolutionary, physics-based, and swarm intelligence algorithms. Sometimes meta-heuristic methods are also equivalent to population-based optimization algorithm, natural computation, computational intelligence, intelligence computation (the later three methods can be viewed evolutionary algorithms also), etc. Many complex problems are hard to be addressed by conventional artificial intelligence technologies. Intelligence computation is a powerful technique to address 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 (swarm intelligence can be viewed as the population-based optimization with population size 1), which are closely related to evolutionary strategies and genetic algorithms.

2.3.1 Evolution- and population-based method

The fundamental rule for the development of these algorithms is Darwinian natural selection, survival of fittest (Chen et al., 2014). Main operations of algorithms include recombination/crossover, mutation, selection and other operations. Driving and evolution of agents are achieved by using these operations. They are also called evolutionary algorithms, evolutionary computation, bio-inspired computing, etc. In a narrow sense, these algorithms include genetic algorithm (GA), evolution strategy (ES), evolutionary programming (EP), and genetic programming (GP). Broadly speaking, in addition to these algorithms (GA, ES, EP, and GP), further expansion include immune optimization algorithm (IOA), differential evolution (DE), biogeography-based optimizer (BBO), and memetic algorithm, etc. Among these IOA also include four algorithms, clonal selection algorithm (CSA), artificial immune network (AIN), and negative selection algorithm (NSA).

Genetic algorithm is 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 characteristics of genetic algorithm 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 algorithm widely use in combinatorial optimization, machine learning, signal processing, adaptive control and artificial life. Genetic algorithm is considered key technology that will significantly impact the future of computing technology, along with adaptive systems, cellular automata, chaos theory, and artificial intelligence, etc.

2.3.2 Physics-based method

The mechanism of these algorithms is different from the genetic mechanism. They construct the population-based optimization algorithm according to some physical laws. By using some rules inspired by physical laws, agents can mutually exchange information and move in the search space, and finally the population solution is achieved. They include simulated annealing (SA), gravitational search algorithm (GSA), chemical reaction optimization algorithm (CRO), gravitational local search (GLSA), Big-Bang Big-Crunch (BBBC), Central Force Optimization (CFO), charged system search (CSS), black hole (BH) algorithm, ray optimization (RO) algorithm, small-world optimization algorithm (SWOA), galaxy-based search algorithm (GbSA), curved space optimization (CSO), Tabu search algorithm (Tabu Search, TS), etc.

2.3.3 Swarm Intelligence (SI)-based method

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.

Swarm intelligence simulates population search, collaborative behavior and emergency phenomenon of biological population to achieve population-based intelligence search behavior that cannot be achieved by a single individual. Through group collaboration, information exchange and social intelligence, the optimal solution can be achieved. Swarm intelligence computation includes particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony optimization (ABC), bat-inspired algorithm (BA), artificial fish-swarm algorithm (AFSA) (Li, 2003; Grosenick et al, 2007; Chen et al, 2009), grey wolf optimizer (GWO), weed optimization algorithm (WOA), firefly algorithm (FA), fruit fly optimization algorithm (FOA), etc.

Ant colony optimization 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.

Ant colony optimization 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.

Particle swarm optimization (PSO) is an evolutionary computation based on iteration, which is proposed by Kennedy and Eberhart (1995). PSO 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; Krink and Løvbjerg, 2002; Clerc, 2004, 2006; Zhang et al., 2007; Niknam and Amiri, 2010).

Stochastic diffusion search was proposed by Bishop (1989) to solve the problem of incentive equivalence in pattern recognition. Stochastic diffusion search is one of the swarm intelligence optimization algorithms. Unlike most swarm intelligence optimization 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).

2.3.4 Hyper-heuristic method

Hyper-heuristic method can be roughly understood as the heuristic method to find the heuristic algorithms (Jiang, 2011). Hyper-heuristic method provides a high-level heuristic method, which produces a new heuristic algorithm by managing or manipulating a series of low-level heuristic algorithms. Hyper-heuristic method runs in the search space consisting of heuristic algorithms. Each vertex in the search space represents the combination of a series of low-level heuristic algorithms. It runs to achieve one or more optimal heuristic algorithms. Roughly speaking, hyper-heuristic method is to find an optimal heuristic algorithm in the search space of (meta-) heuristic algorithms.

2.4 Further explanation of computation/algorithm

In detail, Denning (2003, 2007, 2010) have discussed the definition of computing/computation/algorithm in a series of his papers. Representation is defined as a pattern of symbols that stands for something. The association between a representation and what it stands for can be treated as a link in a table/database, or as a memory in human brain. A representation has two important aspects, syntax and stuff. Syntax is the rules for constructing patterns. It allows us to distinguish patterns that stand for something from patterns that do not. Stuff is the measurable physical states of the world that hold representations (e.g., in media or signals)

(Denning, 2010). A machine can be built to detect when a valid pattern is present. Denning stated that a representation which stands for a method of evaluating a function is called an algorithm, and a representation that stands for values is called data. An algorithm controls the transformation of an input data representation to an output data representation when it is implemented by a machine. The algorithm representation controls the transformation of data representations. According to these definitions, however, there is no algorithm for finding the shortest possible representation of something (Chaitin, 2006).

In the sense of a machine, an implementation is a computation. An information process is a sequence of (changing) representations. A computation is an information process in which the transitions from one element of the sequence to the next are controlled by a representation (Denining, 2010). Strictly, computations are logical orderings of strings in abstract languages. Denning held that implementable representations are the basis of scientific approach to computation.

Computation and its implementation schemes were first defined and discussed as early as in 1930's by Kurt Godel, Alonzo Church, Emil Post and Alan Turing. In their definition, computation means the mechanical steps followed to evaluate mathematical functions (Denning, 2003, 2007, 2010). By the 1980s, computing included a series of related fields, computer science, computational science, computer engineering, software engineering, information technology, etc. By 1990, computing had become the standard for referring to these disciplines. Since then, computing was treated as not only a tool for science, but also a new method of thought and discovery in science (Hazen, 2007). So far there is not recognized and uniform definition on computing. Some treat it as a branch of applied mathematics and some refer to a branch of computational oriented science. Since 1990s, people wonder whether all natural information processes are produced by algorithms (Hazen, 2007). If it is true, traditional view that algorithms are at the heart of computing will be challenged. Under such situation, Information processes may be more fundamental than algorithms (Denining, 2010). Actually, Wolfram (2002) has argued that information processes underlie every natural process in the universe. This leads to a conclusion that computing is the study of natural and artificial information processes, just as stated by Denining (2010): “To think computationally is to interpret a problem as an information process and then seek to discover an algorithmic solution”. As a consequence, Denining (2003, 2007, 2010), and Denning and Freeman (2009) developed a set of principles computing framework, which fall into seven categories: computation, communication, coordination, recollection, automation, evaluation and design.

Self-organization can be treated as an information process and a computation. How to find algorithmic solution is a focus in self-organization studies.

3 Case Examples of Self-organization

Self-organization is popular in nature and human society, covering many fields as physics, chemistry, biology, economics and society.

3.1 Physics

Some physical processes can be treated as self-organization (Glansdorff and Prigogine, 1971). Such examples include structure formation in astrophysics and cosmology (formation of stars, formation of planetary systems, formation of the Milky Way, etc.), phase transition of structures, self-similar expansion, diffusion-limited aggregation, infiltration, reaction-diffusion systems, crystallization, spontaneously magnetization, laser, superconductivity, Einstein-Bose condensation, and spontaneous symmetry breaking, etc.

A phase transition is the transformation of a thermodynamic system from one phase of matter to another phase. The measurement of the external conditions that leads to the transformation is called phase transition. During a phase transition of a given system, induced by certain external condition, some properties of the system change (often abruptly). For example, a liquid may become gas when it has been heated to the boiling point, which results in an abrupt change in volume. (Wikipedia: http://en.wikipedia.org/wiki/Phase_transition).

Diffusion-limited aggregation (e.g., electrodeposition, Hele-Shaw flow, mineral deposits, and dielectric breakdown) is a process in which the random walking particles due to Brownian motion aggregate together to form clusters of these particles (Witten and Sander, 1981).

Dendrite growth is a complex nonlinear self-organization process: (1) non-linearity. The partial differential equation used to simulate dendrite growth is non-linear. In particular, both the phase-field parameters and the second-order derivative terms in the phase-field equations are non-linear. (2) Self-organization. Dendrite growth is a self-organization process, that is, given initial and boundary conditions and assume no more imposition of certain external conditions, it will spotaneuously form an ordered structure. This is just a dissipative structure. (3) Complexity. Dendritic growth is a self-organization, so it is much sensitive to the initial and boundary conditions.

Laser is a time-ordered self-organization. In the Helium-Neon laser-generating mechanism, the laser generator is an open system. Energy is supplied to the laser generator from the external by a pump. When the power supply is little, the laser generator emits random and weak natural light only, because the frequency, phase and vibration direction of light emitted by every Neon atoms are different. When the power supply increases to a certain value, the system mutates and self-organization occurs for large number of atoms; and they will emit highly coherent light beam, i.e., laser, with the same frequency, phase and direction.

Spontaneous symmetry breaking is the realization of symmetry breaking in a physical system (Weinberg, 2011). In spontaneous symmetry breaking, the basic laws are invariant under a symmetry transformation, but the system as a whole changes under such transformations, which is in contrast to explicit symmetry breaking. Spontaneous symmetry breaking is a spontaneous process by which a system in a symmetrical state ends up in an asymmetrical state (Wikipedia: http://en.wikipedia.org/wiki/Spontaneous_symmetry_breaking).

3.2 Chemistry

Self-organization is widely found in chemical processes, for example, molecular self-assembly, self-assembled monolayer film, Langmuir-Blodgett film, B-Z reaction, self-organization of nanomaterials, macroscopic self-assembly under molecular recognition, oscillatory chemical reactions, and autocatalytic networks, etc (Kim et al., 2006; Pokroy et al., 2009; Coleman et al., 2011; Harada et al., 2011).

Molecular self-assembly (intramolecular self-assembly and intermolecular self-assembly) is the process by which molecules follow a pre-defined arrangement without external commands. Formation of micelles, vesicles, liquid crystal phases, and Langmuir monolayers by surfactant molecules fall in this category. Assembly of molecules in such systems is directed through noncovalent interactions (e.g., hydrogen bonding, metal coordination, hydrophobic forces, van der Waals forces, π-π interactions, and/or electrostatic) and electromagnetic interactions (Lehn, 1988, 1990; Wikipedia: http://en.wikipedia.org/wiki/Molecular_self-assembly). It was proved that molecular self-assembly can produce different shapes and sizes (Katsuhiko et al., 2008).

3.3 Life sciences

Self-organization is very popular in 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).

Self-organization of ecosystems is a fundamental theory in ecology. The essential difference between ecosystems and non-biological systems is its ability in self-organization. The evaluation of self-organizing capacity of ecosystems has become one of the most important methods to reveal the complexity and uncertainty of ecosystems.

In the field of life sciences, there is a rapid 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). Increasing evidences are proving that many biological systems are close to what's called a critical point: they sit on a knife-edge, precariously poised between order and disorder. This strategy is believed to increase the flexibility to deal with a complex and unpredictable environment (Ball, 2014).

Almost all biological systems are self-organizing systems (Hess and Mikhailov, 1994; Misteli, 2001; Clyde et al, 2003; Motegi et al, 2011), for example, (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; the interface between two different types of cell will trigger the formation of a third kind of cell at their boundary; an embryo can construct complex tissues this way, with different cell types in all the right places (Davies, 2014); (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.

Phase transitions often occur in biological systems. For example, the lipid bilayer formation, the coil-globule transition in protein folding and DNA melting, liquid crystal-like transitions in DNA condensation, and cooperative ligand binding to DNA and proteins with the character of phase transition (Lando and Teif, 2000).

Gel to liquid crystalline phase transitions is critical in physiological role of biomembranes. Due to low fluidity of membrane lipid fatty-acyl chains, in gel phase, membrane proteins have restricted movement and are restrained. Plants depend on photosynthesis by chloroplast thylakoid membranes exposed to cold environmental temperatures. Thylakoid membranes retain innate fluidity even at relatively low temperatures, due to high degree of fatty-acyl disorder allowed by their high content of linolenic acid (YashRoy, 1987).

Molecular self-assembly is the fundamental for constructing macromolecules in cells of the living organism, including the self-assembly of lipids to form the membrane, the formation of double helical DNA through hydrogen bonding of the individual strands, and the self-assembly of proteins to form quaternary structures. Molecular self-assembly of nanoscale structures is important in the growth of β-keratin lamellae/setae/spatulae structures which are used to endow geckos the ability to climb walls and adhere to ceilings and rock overhangs (Daniel et al., 2007; Min et al., 2008; Wikipedia: http://en.wikipedia.org/ wiki/ Molecular_self-assembly).

In biology, we know a famous experiment, Miller experiment. It proved that the thundering and lightning in the primitive Earth's atmosphere produced organic compounds (especially amino acids), which demonstrated the chemical evolution of the origin of life. In this experiment, the mixture of of hydrogen gas (H_2), helium (He), methane (CH_4), ammonia (NH_3) and other inorganic composition can generate 17 kinds of amino acids after the spark discharging was implemented. This process (simple inorganic matters become complex organic compounds when high energy is supplied) is a typical phenomenon of self-organization. In the self-organization, the supply of high energy leads to a more ordered matters, and the amino acids of high enery are maintained at the excitation state, and a new state of equilibrium of more ordered is thus achieved.

In recent years, some scientists have attempted to interpret the origin of life from the view of self-organization. Scientists use a set of biomolecules to show a way in which life might have started. They hold that different chemicals come together due to many forces that act on them and become a molecular machine capable of even more complex tasks. Each living cell is full of these molecular machines. These molecular machines haven’t done much on their own. When they add fatty chemicals, which form a primitive cell membrane, it got the chemicals close enough to react in a highly specific manner. Molecules and cells interact according to simple rules, creating a whole that is greater than the sum of its parts (Davies, 2014). This form of self-organization may be popular for the origine of life on both earth and other planets.

To interpret the origin of life, Stano and his colleagues chose an assembly that consists of 83 different molecules including DNA, which was programmed to produce a special green fluorescent protein (GFP) that could be observed under a confocal microscope (Lehn, 1988, 1990). The assembly can only produce proteins when its molecules are close enough together to react with each other. When the assembly is diluted with water, they can no longer react. This can explain why the cell is so compact: to allow the chemicals to work.

In order to recreate this molecular crowding, Stano added a fatty molecule, POPC, to the dilute water solution and these molecules then automatically form liposomes that have a very similar structure to the membranes of living cells. They found that many of these liposomes trapped some molecules of the assembly. Five in every 1000 liposomes had all 83 of the molecules needed to produce a protein. These liposomes produced large amount of GFP and glowed green under a microscope. Surprisingly, computer calculations reveal that even by chance, five liposomes in 1000 could not have trapped all 83 molecules of the assembly. The calculated probability for even one such liposome to form is essentially zero. This means some quite unique mechanism behind it, and self-organization is one of the reasons.

Davies (2014) even showed how from these interactions we can deduce "rules" of embryo development. For example, cells communicate with each other and tweak their behaviour in response to changes in their environments. This is what puts the "adaptive" into adaptive self-organisation, ensuring that development can cope with noise or disruption. An example is the way tiny blood vessels called capillaries manage to cater to different kinds of tissue, even while these tissues are moving and growing (Davies, 2014). A feedback loop exists between oxygen and a cell protein called HIF-1-alpha. Oxygen normally causes HIF-1-alpha to be destroyed. If a tissue lacks oxygen, HIF-1-alpha levels rise, triggering a cellular signal encouraging capillaries to grow. This brings in oxygen, which shuts down HIF-1-alpha and halts capillary development. Should the tissue then grow, oxygen levels will fall again, and the loop is set in motion once more.

3.4 Self-organization in socialogy

Self-organization is also called spontaneous order theory in socialogy. Complex behaviors, such as herd behaviour, groupthink, critical mass, etc., are found to follow some mathematical laws, e.g., Zipf's law, power law, and Pareto principle, which are self-organizing behaviors (Wikipedia, 2014).

Self-referentiality is a social self-organization that can describe the evolution of society and its subsytems (Luhmann, 1991). In a social system, all elements are self-producing communications, that is, a communication will produce more communications and the system can thus reproduce itself given there is dynamic communication (Luhmann, 1991; Wikipedia, 2014).

Self-organization may result in a decentralized, distributed, self-healing system in the human network. By limiting each individual’s scope of knowledge on entire, it can protect the individuals’ security (Wikipedia, 2014).

3.5 Self-organization in cybernetics

As early as in 1960s, Machol and Gray held that the automatic and continuous identification of the black box problems and subsequent replication fitted the properties of self-organization. In a sense, cybernetics deals with some of the self-organization problems.

3.6 Self-organization in networks

Self-organization is an important mechanism to establish networks (Wikipedia, 2014). Such mechanisms are also referred to as self-organizing networks. It should be noted that only certain kinds of networks are self-organizing. They are known as small-world networks, or scale-free networks. These networks emerge from bottom-up interactions, and appear to be limitless in size. In contrast, there are top-down hierarchical networks, which are not self-organizing. These are typical of organizations, and have severe size limits (Wikipedia, 2014).

3.7 Self-organization in mathematics and computer science

As mentioned above, phenomena from mathematics and computer science such as cellular automata, random graphs, and some instances of evolutionary computation and artificial life exhibit features of self-organization. In swarm robotics, self-organization is used to produce emergent behaviors. In particular the theory of random graphs has been used as a justification for self-organization as a general principle of complex systems. In the field of multi-agent systems, understanding how to engineer systems that are capable of presenting self-organized behavior is a very active research area.

4 Selforganizology

4.1 Problems for self-organization research

Although a lot of theories and methods were established to describe self-organization, there are still many problems in this area. Self-organization is a universe phenomenon. Nevertheless, we still lack of unified theories and thoughts on self-organization. We lack of universal basis of methodology in the modeling and simulation of self-organization. Self-organization is categorized as a research area in complexity science. So far it is not an independent science (Zhang, 2013a, b).

4.2 Selforganizology: A science on self-organization

For the reason mentioned above, I proposed a fundamental science, selforganizology (Zhang 2013a). It was proposed for finding and creating theories and methods from self-organization phenomena in nature, simulating and reconstructing self-organization phenomena, exploring and synthesing mechanisms behind numerous self-organization phenomena, and promoting the applications of self-organization theories and 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, stability theory (e.g., bifurcation theory, singularity theory, catastrophe theory), topology, etc., are fundamental theories in selforganizology. Some theories and methods should be futher improved.

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, automation and control theory in various scientific disciplines can be reviewed, revised and introduced to selforganizology.

4.3 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 results of various self-organization processes. Without external forces and instructions, a dissipative system far from thermodynamic equilibrium may spontaneuously evolve towards one or more steady states through between-component interactions at different hierarchies in self-organization process. It is thus a self-organizing system. In the self-organizing system, the interactions between components produce different functions and properties and behaviors from that of components, which lead to a system with certain functional characteristics and purposeful behaviors 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 defined a component as that satisfies these criteria (Zhang, 2012, 2013a):

(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 rules, threshold rules, and other equation/model based 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; (7) other equation-, model-, or algorithm-based rules, etc. I think that using these 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. Also, mathematical equations and models (e.g., differential equations) can be used in the simulation and modeling of self-organization phenomena. It is expected that many existing self-organization algorithms, such as Swarm Intelligence algorithms, can be rewrited into simple rules based algorithms.

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

Some methods, in particular 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.

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

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