Chapter 9
Self-organization

If biologists have ignored self-organization, it is not because self-ordering is not pervasive and profound. It is because we biologists have yet to understand how to think about systems governed by two sources of order. We have to see that we are the natural expression of a deeper order…

Stuart Kauffman

As a philosopher I am interested in all kinds of phenomena of self-organization, from the wind patterns that have regulated human life for a long time to the self-organizing patterns within our bodies, to the self-organizing processes in the economy, to the self-organizing process that is the Internet.

Manuel De Landa

Abstract Self-organization is an inherent process of life and society that refers to the capability of biological, natural, and society systems to change their structure by their own during their operation, such as to show more order or pattern without the help of external agents. This chapter starts with the ontological question "what is self-organization" and provides representative alternative answers given by eminent workers and thinkers in the field. It continues by discussing the four fundamental mechanisms of self-organization observed in nature viz. synergetics, export of entropy, positive/negative feedback interplay, and selective retention, followed by an examination of the concept of self-organized criticality (edge of chaos). Then, this chapter discusses the contribution of cybernetics to the study of self-organization, and the relation of self-organization with "complex adaptive systems (CAS)" providing a description of five self-organization features that are transferred to CASs. This chapter continues with the presentation of six examples of natural and artificial self-organizing systems, namely ecological systems, magnetization, convective instability cells, linguistic systems, knowledge networks, and self-organizing neural network maps. The conclusions provide some additional remarks about complexity and the future of man-made self-organizing systems.

Keywords Self-organization (S-O) · Natural S-O · S-O mechanisms
Synergy · Entropy export · Positive/negative feedback interplay
Requisite variety · Interdependence · Selective retention · Self-organized criticality
Complex adaptive system (CAS) · Society vertical/horizontal S-O

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Bifurcation · Pitchfork bifurcations · Stationary bifurcations · Ecological S-O
Robotic S-O · Self-organizing map

9.1 Introduction

Self-organization is a concept that refers to the capability of biological, natural, and society systems to change their structure by themselves during their interaction process with the environment. This means that self-organization is not environment determined but self-determined and self-adaptive. In other words, one can say that a system is self-organizing if it tends to become more organized on its own, i.e., if it shows more structure or order or pattern without the help or influence of an external agent. Clearly, the self-organization concept is one of the most useful concepts in science and society, but at the same time a very vague concept, because all terms used to define it, viz., organization, structure, order, pattern, etc., are not uniquely defined or interpreted. In some cases, self-organization is interpreted as emergence, but this is not correct because we can have self-organization without emergence and emergence without self-organization, although both of them are features of complex adaptive systems (see Fig. 8.1). The idea that natural systems have a tendency to become more orderly without external intervention was first stated by the philosopher Descartes who argued that "ordinary laws of nature tend to produce organization" (see his "Discourse on Method"). Also, Kant argued that "the principle of unity of nature is a regulative principle according to which nature is constructed so as to correspond to our needs for order" (see his "Critique for Judgment"). Many authors have used other terms for defining self-organization, which sometimes are related to human behavior. One of these terms is *autopoiesis* coined by *Humberto Maturama* and *Francisco Varela* [1]. The term autopoiesis comes from the Greek composite word αυτο-ποίηση (autopoiesis = self-making/self-creating). Another term is extropy, which is the opposite of entropy. If we adopt the entropy interpretation of Boltzmann as disorganization (disorder), then extropy means organization (order). A general field where self-organization has been extensively studied is cybernetics. More information on this is provided in Sect. 9.5. Another new technological field closely related to self-organization is "Artificial Life" (ALife) [2, 3].

The purpose of this chapter is:

- To investigate the question "what is self-organization?" and present a set of definitions given by eminent researchers in the field.
- To outline and discuss the four fundamental mechanisms of self-organization observed in nature (synergy, entropy export, positive/negative feedback interplay, and selective retention).
- To examine the concept of "self-organized criticality", a term equivalent to the "edge of chaos".
- To discuss the contribution of cybernetics to the study of self-organization via a listing of well-known cyberneticists and their major results.

- To study the relation of self-organization with "complex adaptive systems" (CAS) providing a description of the five self-organization features that are shared with CAS.
- To present six representative examples of natural and artificial self-organizing systems, namely: ecological systems, magnetization, heated liquids (convective instability cells), linguistic systems, knowledge networks, and self-organizing maps.

9.2 What Is Self-organization?

Self-organization is inherent in life, nature, and society. However, only after the 1950s has the scientific study of self-organization assumed concrete shape. According to the Longman Dictionary, the word organization has three linguistic meanings [4]:

- The way in which different parts of a system are arranged and work together.
- Planning and arranging something so that it is successful or effective.
- A group such as a club or business that has formed for a particular purpose.

These meanings are used in our current scientific, information, technological, cultural, and economic society, and cover both cases: external and internal organization of a system. In general, all these definitions imply that organization is some kind of order and excludes randomness produced by any cause at any level. The alternative definitions presented here are the following.

9.2.1 Definition of W. Ross Ashby

In modern times, the term "self-organizing" was first used in 1947 by W. Ross Ashby, a cybernetician (psychiatrist, neuroscientist, and mathematician) [5–7]. According to him "a system shows self-organization if its behavior shows increasing redundancy with increasing length of the protocol" Ashby used the term *redundancy* (R) in the Shannon's sense, i.e.,:

$$R = 1 - H/H_{\max}$$

where H is the actual uncertainty (entropy) and $H_{\max}$ the maximum uncertainty of the system. He argued that: "Since redundancy R can only increase if either H is decreasing or $H_{\max}$ is increasing, and since $\mathrm{H}_{\max}$ can only change by redefining the system (i.e., by externally changing the number of states), one can say that a system is *self-organizing*, only if the increase in the redundancy R is the outcome of a corresponding decrease in the randomness H." This essentially means that non-utilized, potential, channel bandwidth provides a measure of self-organization.

Ashby used Shannon's *Tenth Theorem* which states: "If an error correction channel has capacity C, then equivocation of amount C can be removed, but no more," to formulate his "*Law of Requisite Variety*", which states: "Any quantity K of appropriate selection demands the transmission or processing of quantity K of information. There is no getting of selection for nothing." Shannon's theorem was developed in the context of telephone and other similar communication channels, regarding a case with a lot of "message" and little "error". In biology, we face the case where the "message" is small, but the disturbing errors are many and large.

Both "Shannon's Tenth Theorem" and Ashby's "Law of Requisite Variety" are applicable to regulatory biological systems, such as the brain, through the fact that "the amount of regulatory or selective action that the brain can achieve is absolutely bounded by its capacity as a channel."

9.2.2 Definition of Francis Heylinghen

According to Heylinghen: "Self-organization is the spontaneous emergence of global structure out of local interactions" [8]. "*Spontaneous*" here means that no internal or external agent is in control of the process; for a sufficiently large system, any individual agent can be removed or replaced without any effect on the resulting structure. The self-organization process is fully parallel and distributed over all the agents, i.e., it is truly collective. This implies that the organization that is achieved is inherently robust to faults and perturbations.

9.2.3 Definition of Chris Lucas

He stated that: "Self-organization is the evolution of a system into an organized form in the absence of external constraints. It is a move from a large region of state space to a persistent smaller one, under the control of the system itself" [9]. Here, the term "organized form" is meant in the sense described before (i.e., nonrandom form).

9.2.4 Definition of Scott Camazine

According to him "Self-organization in biological systems is a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower level components of the system, and the rules that specify interactions, among system components, are executed using local information, without reference to the global pattern" [10]. This definition implies that the pattern is an emergent property of the system and not a property imposed on the system by an external ordering influence.

9.2.5 Definition of A.N. Whitehead

He stated that: "Self-organization of society depends on commonly diffused symbols evoking commonly diffused ideas, and at the same time indicating commonly understood action" [11]. He argued that the human mind is functioning symbolically when some components of its experience elicit consciousness, beliefs, emotions, and usages, respecting other components of its experience. The former set of components involves the "symbols", and the latter set constitutes the "meaning" of the symbols. He remarks that "symbolism plays a dominant part in the way in which all higher organisms conduct their lives. It is the cause of progress and the cause of error."

9.2.6 Definition of M. B. L Dempster

Dempster studied the distinction between *autopoietic* (self-producing) and *sympoietic* (collectively producing) systems. These two contrasting lenses offer alternatives views of the world, forcing recognition of system properties frequently neglected. Taking into account Andrew's remark that it is difficult, probably impossible, to find a precise definition of what is understood by a self-organizing system, he did not attempt to give such a precise definition, while stating that: "On an intuitive level, self-organization refers to exactly what is suggested: systems that appear to organize themselves without external direction, manipulation, or control" [12].

Self-organization in human society occurs at various levels (vertical self-organization) and various activities or processes (horizontal self-organization). From top level to bottom level, vertical self-organization involves [7]:

- Human–non-human environments
- Society establishment
- Groups and communities
- Individuals.

On the horizontal dimension, we have:

• Culture • Ideology • Politics • Religion	• Economy • Industry • Agriculture • Education, etc

All processes are interdependent and influence each other. This implies that coevolution occurs within and between vertical and horizontal processes.

According to *Takatoshi Imada* [13], in the 1960s attempts were made to develop a theory based on the logic of a system and its control. Contrary to this view of a societal system as the aggregate of individuals where self-organization is the sum of the practices of a system driven by control, or self-control in particular, in the 1980s a new view gained popularity, adopted based on the logic of creative individuals and fluctuations. This new view looks at the practices of individuals departing from the standard logic of a system, making the existing system fluctuate and transforming its structure. In [13], Imada integrated these two antithetical approaches into a structure of the self and through self-reflection. This opened new ways for designing planning and control actions and developing a spontaneously performative action theory. More information on society self-organization and societal complex adaptive systems will be given in Chap. 13.

9.3 Mechanisms of Self-organization

The fundamental natural mechanisms by which self-organization is achieved are the following:

- Synergetics
- Export of entropy
- Positive/negative feedback interplay
- Selective retention.

The *synergetics* mechanism (from the Greek συν-έργεια = synergia = act together) was discovered by the German physicist *Hermann Haken* [14], who studied lasers and other similar phenomena and was surprised by the apparent cooperation (synergy) between the interacting components. The elements (agents, components) of a complex system at the beginning interact only locally (i.e., with their close neighbors), but, due to the direct or indirect connection and interaction of the agents, the changes gradually propagate to faraway regions, leading finally to an obvious synergy at the system level. Examples of such collective patterns resulting from many interacting components include (besides lasers), chemical reactions, molecular self-assembly, crystal formations, spontaneous magnetization, etc. This synergy in laser-light production is explained as follows. When atoms or molecules receive an energy input, they emit the surplus energy as “photons” at random times and directions. This leads to *diffuse light*. But under certain conditions, the atoms can be synchronized and emit photons at the same time in the same direction, with the outcome of a highly coherent and *focused beam of laser light* [15].

The achievement of a *synergetic state* is, in general, a “trial-and-error” or “mutual adaptation” process. System’s components (agents, etc.) handle permissible or plausible actions (or sometimes select them randomly) and maintain or repeat those actions that bring them nearer to their goals. This process is actually a natural-selection process, but it differs from Darwinian evolution since the system agents are functioning simultaneously until they mutually fit, i.e., they *coevolve* (mutually adapted) so as to minimize friction and maximize synergy.

The mechanism for the *export of entropy* self-organization was revealed by Prigogine and Nicolis [16]. They developed and promoted the theory of *dissipative structures* (i.e., systems that continuously decrease their entropy). Dissipation (i.e., entropy export) is the mechanism that leads to self-organization. This means that a self-organizing system imports high-quality (usable) energy from the environment and exports entropy back to it. Prigogine formulated a new worldview. He saw the world as an irreversible "becoming", which produces novelty without end. This is the opposite of the Newtonian reduction to a static framework, i.e., to the "being" view. This point of view is compactly expressed by *Prigogine's* quote: "The irreversibility of time is the mechanism that brings order out of chaos". Speaking about chaos, *James Gleick* [17] wrote that "Where chaos begins, classical science stops". In other words, this means that chaos is our third great revolution in physical sciences after relativity and quantum mechanics.

Prigogine and Stengers [18] state that "order creation" at the macro-level is a way of dissipating (exporting) entropy caused by energy flux at the micro-level. For example, a whirlpool is formed spontaneously in a draining bathtub because in this way the potential energy of the standing water is dissipated better than a laminar (smooth) or turbulent (chaotic) flow [19].

As we have seen in Sect. 8.8, a nonlinear system has, in general, a multiplicity of attractors. Each one of these attractors corresponds to a self-organized configuration. Therefore, the study of self-organization is equivalent to the study of the system attractors' properties and dynamics. If the system starts out in a basin state, it will settle down to the corresponding attractor, but, if it starts between different "*basins*", it has the freedom to choose the basin and the attractor in which it will end up. This depends on the unpredictable fluctuations that may exist. The self-organized configuration is, of course, more stable than the configuration from which the system started. We call this phenomenon "*order from noise*" [20], but thermodynamicists [18] call it "*order through fluctuations*" or "*order out of chaos*".

The "*interplay between positive and negative feedback*, i.e., the self-organization mechanism, works in the same way as described in the previous chapter in connection with *adaptability* to the environment. Here, however, this constitutes an internal (esoteric) business of the system aiming at (and leading to) increased organization and order. Actually, self-organization takes place via existing feedback loops between system components (elements) and between components and the structures that are formed at the higher hierarchical levels. A necessary condition for this to occur is that the system is "nonlinear", as happens in living organisms, biochemistry (autocatalysis), and the behavioral systems in human society. Typically, self-organization starts with positive feedback. An initial fluctuation towards organization (order) is amplified and spreads quickly, until it affects the entire system. Once all elements of the system have "*aligned*" their behavior with the configuration created by the initial fluctuation, and the system has reached an equilibrium state, further growth of self-organization is not possible. This is because at this stage only changes that weaken the self-organized (dominant) configuration are possible, and the same mechanisms that reinforced that configuration will suppress the deviation (i.e., they will apply negative feedback) and return the system to its stable configuration. In more complex situations, there may exist several interlocking positive- and negative-feedback loops, i.e., changes in some directions are reinforced, and changes in other directions are suppressed. The final result of this process is very difficult to predict.

The *selective-retention* mechanism of self-organization ensures that the outcome of the interactions of the system components is not arbitrary but shows a "preference" for certain situations over others [8]. This is analogous to Darwinian evolution, which is based on the assumption that the environment acts on a population of organisms that compete for resources (in order to survive). The winners of this competition (those that most fit to obtain the resources) will be selected, the others are eliminated.

The second assumption of Darwinian evolution is that selection is carried out by the common environment of the competing organisms. However, in selective retention, there is no need to have a population of competing organisms (configurations). It works well even in "population-of-one" situations. A configuration (state) can be chosen or eliminated no matter if other candidate configurations are present. A single system can happen via a sequence of states or configurations. Some of them are selected (retained), while others are eliminated. Actually, the competition in selective retention is taking place between subsequent states of the same system, and more importantly, there is no need to assume the existence of an environment external to the state(s) under selection. Selective retention can occur in both living and nonliving systems. For example, a stone "prefers" to be in a stable state at the foot of a hill, instead of being in an unstable state on the top. A "cloud" of gas molecules in a vacuum will spontaneously diffuse, but a crystal in the same vacuum will maintain its crystalline form. The first configuration (i.e., the cloud) disappears; the second (i.e., the crystalline structure) is retained. An animal in an ecosystem prefers a situation that assures more food or minimizes the risk of being attacked by a predator.

9.4 Self-organized Criticality

Self-organized criticality (SOC) is an alternative name for the capability of complex systems to maintain a balance between "*order and disorder*", which is also called "*the edge of chaos*" (see Sect. 8.9). It is a common property of living beings to live at such an edge of chaos via self-organization. Our purpose in this section is to discuss a little more this feature of self-organized systems. Throughout the years, many biologists, nonlinear-systems researchers, and cyberneticians have attempted to explain the phenomenon of self-organized criticality and especially why and how a system moves on its own to such a state existing in the order-chaos spectrum.

Criticality, in general, is a state at which the properties of a system change suddenly, e.g., the critical gain in a control system determines the boundary (edge) of the stable region; higher gain leads the system to the unstable region. Another example of criticality is the case in which a structure moves from non-percolating to percolating or vice versa (where the system is subject to phase change). Percolation is a structure (or matrix) of parts in which a property appears that connects the opposite sides of a disconnecting structure by developing a path or disconnecting them into a fully connected structure by introducing an obstruction (non-percolation). The edge at which this percolation/non-percolation change occurs is exactly the edge to which a self-organized system goes and obeys a *power distribution* law of effects, i.e., the smaller the effect, the more frequently it is occurring. This is actually the typical *self-similarity property* of all self-organized systems.

Examples of natural systems with self-organized criticality include: floods caused by interconnected valleys, forest fires in areas susceptible to lightning bolts, snow avalanches occurring on snowy hillsides, etc. Three such examples are illustrated in Fig. 9.1(a–c).

Self-organized criticality is the capability of a system to work in a manner by which it can approach closely to a critical point and then sustain itself at that point. Actually, there exist many alternative theories for explaining this movement of natural and biological systems to a self-organized critical state. Three of them are the following [19]:

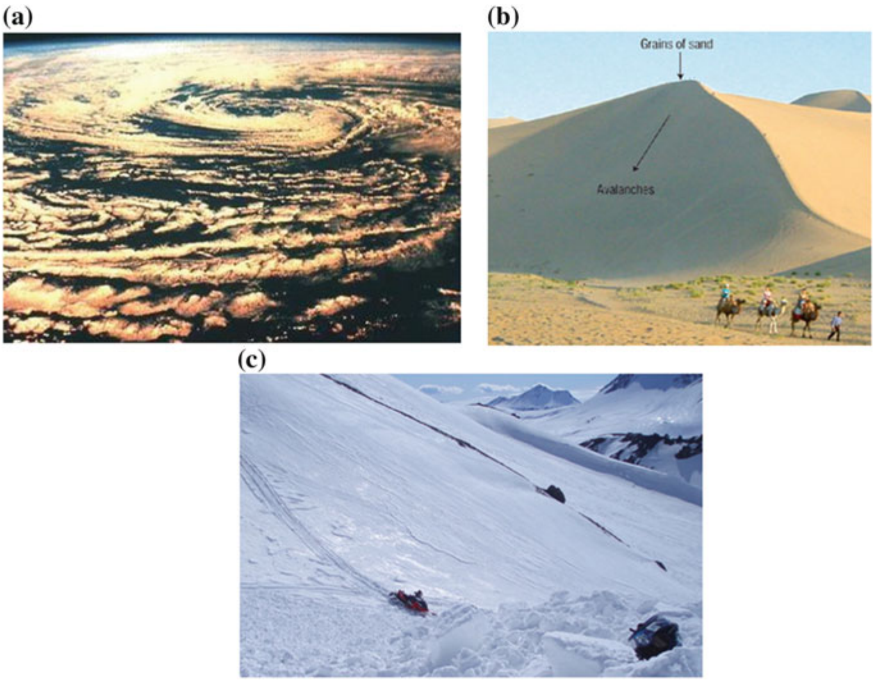


Fig. 9.1 Three natural examples of self-organized criticality: **a** cyclone, **b** sand dune, **c** snow avalanche (http://www.newciv.org/pic/nl/artpic/10/1929/cyclone.jpg; http://www.nature.com/nmat/journal/v4/n6/images/nmat1405-f1.jpg; http://en.vedur.is/media/ofanflod/myndasafn/frodleikur/medium/P1010396%5B1%5D.JPG). The reader is informed that Web figures and references were collected at the time of writing the book. So some of them may no longer be valid due to change or removal by their creators

- **Stuart Kauffman** His explanation is based on the so-called "*coupled-fitness landscape*" which is a Boolean network of N cells, each one having S states with an overall of C possible connection paths to other cells [21, 22]. This N-cell system is mapped into a C-dimensional "landscape" that involves (topographically) all possible system states. According to Kauffman, the connectivity C is an index of how *orderly* or *chaotic* is a system. When C is very small, the system is "stuck" in its present state, and if C is very large, the system has chaotic behavior. If C has just the right size, the system can go to very high fitness peaks and achieve very good proficiency. The C-dimensional landscape may represent a genome, a population, etc.
- **Rod Swenson** His explanation is based on the law of maximum entropy production as explained in Sect. 8.3, which implies that ordered flow produces entropy faster than disordered flow.
- **P. Bak** He and his colleagues argued that a system self-organizes to a critical state without any "fine-tuning" process, but via a driving and dissipating process. Self-organized criticality seems to be the underlying concept for temporal and spatial scaling in dissipative nonequilibrium systems [23, 24]. Bak and colleagues explained that "power law distributions of phenomena" exhibit a self-organizing criticality performance. They studied several examples of systems in which this occurs. For example, they simulated the "sandpile" model which consists of sand poured on a table continuously until the occurrence of "mini avalanches". Similar results on the self-organized criticality have been derived by many other researchers (e.g., [25–27]).

9.5 Self-organization and Cybernetics

Self-organization was a topic of study in cybernetics right from its beginning. The term *cybernetics* comes from the Greek world "κυβερνώ/κυβερνήτης" (kyverno/kyvernitis = govern/governor). The founder of Cybernetics was *Norbert Wiener,* who defined it as follows: "*Cybernetics is control and communication in the animal and the machine*" (1947) [28]. The initial work of Wiener was related to the control of anti-aircraft fire. The gun should aim not at the present position of the aircraft, but at the point to which the aircraft will move during the flight time of the shell. He estimated this new position of the aircraft by collecting data about the discrepancies between predicted position and actual measured position and then feeding it back to the predictor. The result of his study is the celebrated *Wiener filter/predictor*. The field of cybernetics has attracted interdisciplinary interest. Scientists and engineers from a multitude of fields (physics, mathematics, operational research, biology, medicine, environment, psychology, anthropology, management, neurology, economics, sociology, ecology, computers, control, etc.), either individually or in multidisciplinary research groups, have derived important results in many directions. A comprehensive list of cybernetics and systems thinkers (cyberneticists or cyberneticians) who have made substantial contributions to the field is provided in [29], and historical remarks about their role in [30]. Among them, in addition to *Norbert Wiener*, the father of cybernetics, those who have studied self-organization and closely related topics are the following:

- **W. Ross Ashby** One of the founders of cybernetics. He developed homeostasis, requisite variety law, and the self-organization principle [6, 31].
- **Henri Atlan** He studied self-organization in cells and networks and developed the theory of *random organization* according to which, at the birth of the universe, there was an order/disorder/organization dialogic triggered by calorific turbulence (disorder), in which under certain conditions (random encounters) organizing principles made possible the creation of nuclei, atoms, galaxies, and stars. The dialogue between order, disorder, and organization exists in a wide variety of forms, and via countless feedback processes is constantly in action in the physical, biological, and human worlds [32]. He contributed substantially to the development of *Biocentric Culture* governed by the "Vital Unconscious and Biocentric Principle".
- **Warren McCulloch** He developed mathematical models of learning and self-organizing neural networks. Together with *Walter Pitts,* he proposed the first model of a neural network, composed of functioning elements (neurons) and synaptic weights. This "artificial neuron" is known as McCulloch–Pitts neuron and is the foundation of most modern types of artificial neural networks [33].
- **Ilya Prigogine** He studied the thermodynamical approach to self-organization and coined the concepts of irreversibility and dissipative structures [16, 18, 34] discussed at many points in this book.
- **Heinz von Foerster** One of the founders of cybernetics. He was the first to study self-organization and self-reference and was the creator of second-order cybernetics [20, 25].
- **Humberto Maturana** He developed, together with *Francisco Varela*, the theory of *autopoiesis* and substantially contributed to complex systems theory [1].
- **Nikolas Luhmann** He applied the theory of autopoiesis to social systems [35].
- **Herbert A. Simon** He made major contributions to management, cognitive psychology, and complex systems theory [36]. Three important quotes of Simon are the following:

  – "I don't care how big and fast computers are; they are not as big and fast as the world."
  – "Learning is any change in a system that produces a more or less permanent change in its capacity for adapting to its environment."
  – "The social sciences, I thought, needed the same kind of trigger and the same mathematical underpinnings that had made the "hard" sciences so brilliantly successful."

- **Francis Heylinghen** He made important contributions to adaptation and self-organization [8, 37–39].
- **James Gleick** He reintroduced and reformulated chaos theory and contributed to the growth of interest in the modern science of complexity [17].

- **H. Haken** He studied physical phenomena that exhibit self-organization and revealed the synergetics mechanism between interacting components that leads to global patterns [14, 40].
- **Manfred Eigen** He studied the origin of life, including chemical self-organization and biological evolution. He was particularly interested in extremely fast chemical reactions induced in response to very short pulses of energy. The concept of "*hypercube*", i.e., an autocatalytic chemical cycle involving other cycles, as an explanation for the self-organization of prebiotic systems, was coined by him in 1971 in cooperation with *Peter Schuster* [41].
- **Gregory Bateson** He studied the parallelism between mind and natural evolution and developed the "double-bind" theory of the complexity of communication [42]. Some relevant statements of Bateson are the following:

  – "Logic is a poor model of cause and effect."
  – "Logic can often be reversed, but the effect does not precede the cause.
  – "It is impossible, in principle, to explain any pattern by invoking a single quantity."
  – "We do not know enough how the present will lead into the future."

- **Benoit Mandelbrot** He was the founder of *fractal geometry*, which, as we have seen in Sect. 8.8, describes the emergence of similar shapes or patterns at different scales that obey the power law of distributions of self-similarity [43] (see also: [44]).

To summarize the above aspects, we give in Fig. 9.2 the four main areas involved in the concept of self-organization.

Figure 9.3 shows two examples of self-organized crystal formation and an example of dissipative structure.

(a) Barium carbonate crystals (http://www.nanowerk.com/spotlight/id646.jpg),
(b) Crystals on cadmium (http://www.natureasia.com/asia-materials/article_images/227.jpg),
(c) Dissipative structures (http://www.filefestival.org/SITE_2007/RESOURCES/CONTENT/ILYA02.JPG).

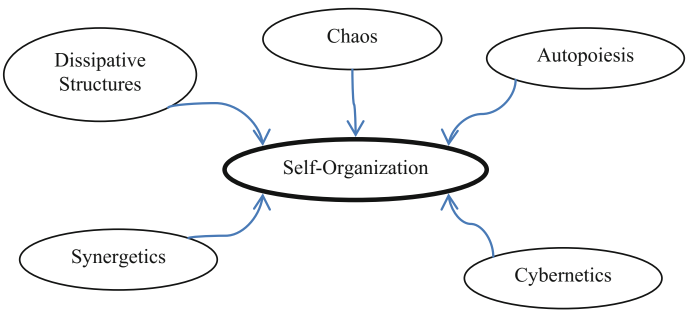


Fig. 9.2 The basic areas of self-organization

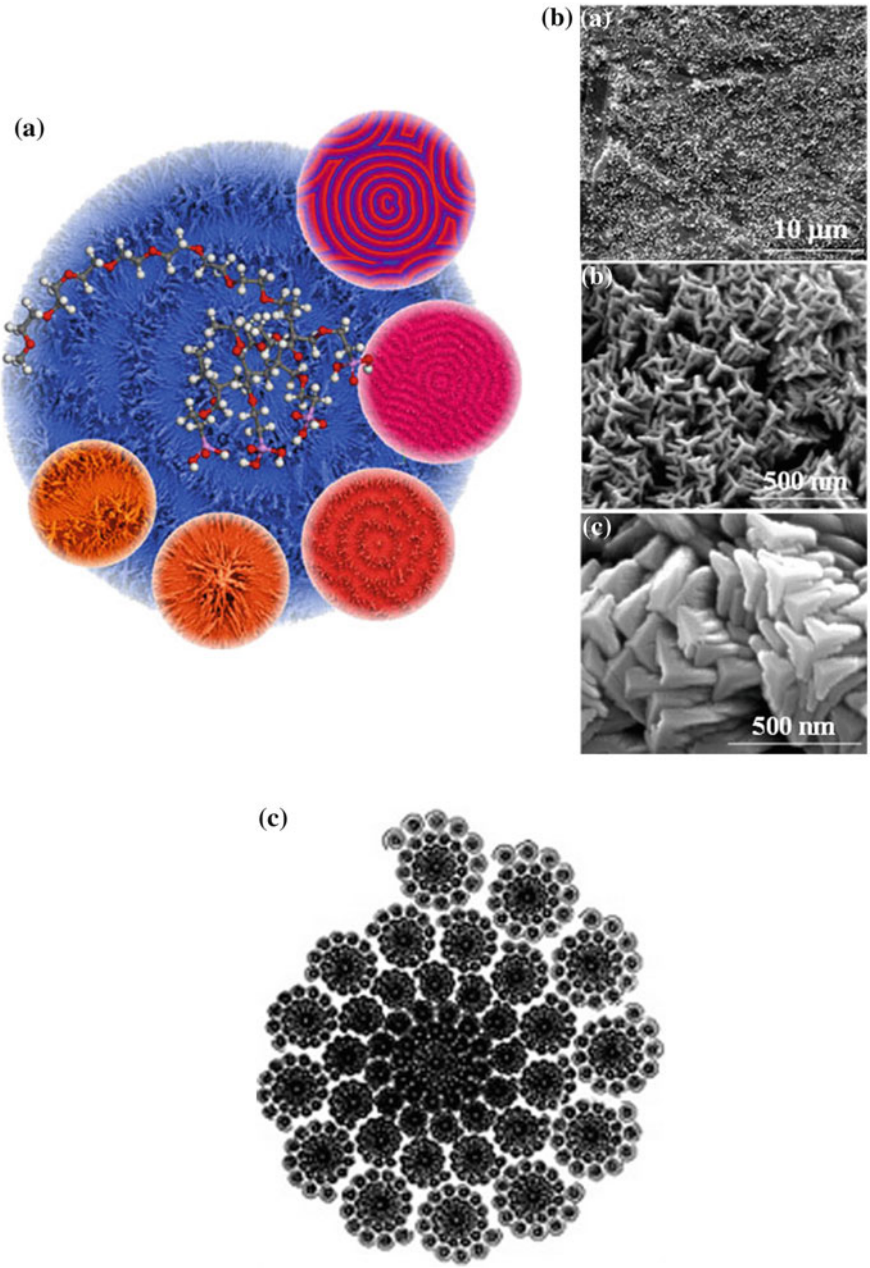


Fig. 9.3 Natural self-organizing systems

9.6 Self-organization in Complex Adaptive Systems

Looking at the properties complex adaptive systems listed in most definitions available in the literature (see Chap. 8) one can verify that self-organization is one of the most fundamental common features of CASs together with adaptation, emergence, and complexity. The self-similarity property is a property of self-organization that is transferred to CASs. Other properties of self-organization that are transferred to CASs are the following:

- Interdependence
- Interaction
- Selective variety
- Modularity
- Clustering.

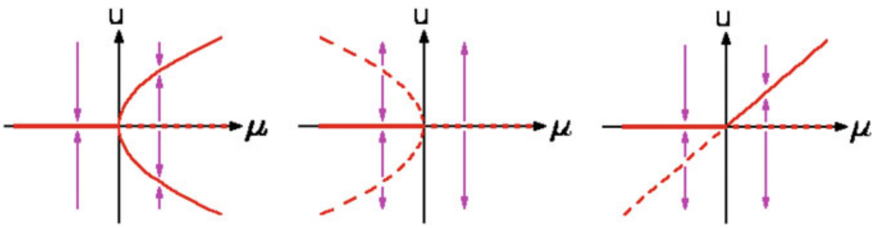
A short discussion of them follows.

Interdependence This is a term indicating that the elements (parts, components, agents) of a complex system are related by interdependence relationships obeying the physical, biological, informational, systemic, psychological, economic, ecological laws, etc., depending on the scale and nature of them. Examples of such elements are molecules cells, systems states, animals, circuit elements, trees, human, etc.

Two elements that cooperate with each other are interdependent and interconnected. Complete dependence (as, e.g., in a crystal where the state of one molecule determines the states of all the others) may imply *full order*. Complete independence (like the molecules of a gas) implies *full disorder,* in which case the state of a molecule cannot give any information about the states of the other molecules. Interdependence is a concept very common in human societies, enterprises, economies, and countries interconnected to achieve common goals. It should be noted that to achieve self-organization, a system must be neither too loosely interconnected (in which case most elements are independent), nor too strongly interconnected (in which case most elements influence one another). For example, in Boolean networks, the optimum self-organization is obtained when there are two connections per element (unit) [9].

Interaction This is a property closely connected (but not identical) to the interdependence of two or more elements (objects, agents) that are acting so as to have an effect upon one another. These interactive actions, when combined and integrated, produce very important emergent outcomes. The interaction is usually a purposeful process aiming at maximizing the fitness, utility, and productivity of both the individual elements and the entire system or organism. Even if no specific purpose exists, the elements of the system act according to the input excitation that is received from the environment. This perception-action (causal) process (or rule) is effected initially by some type of elements, but then through the interdependence and interaction that is extended to other element types utilizing some learning or evolutionary variation. The interaction process is implemented through communication and feedback among the system elements. Examples of interactions taking place in self-organized systems include: interaction of drugs in medications (pharmacodynamic or pharmacokinetic interactions), physical interactions (elementary particles' interactions via exchanging gauge bosons, interactions of charged particles via electromagnetic-field mediation, gravitational interactions), sociocultural interactions between individual persons, groups or larger societies and populations and genetic interactions (combined mutations affecting or not affecting the genotype), etc. [45, 46].

Selective variety This is the self-organization principle according to which the wider the repertoire of configurations a system has available for selection, the higher the probability that one or more of them will be selectively retained. This principle is the theoretical expression of the "selective-retention" mechanism discussed in Sect. 9.3. It implies that to increase the probability of achieving self-organization (and speed-up the process), a larger variety of configurations should be available for the system to pass through. After self-organization, one configuration dominates all others, which means that the system symmetry existing in the disorganized situation is lost. Of course, it must be noted that there does not exist well-known criteria for the preference of one stable configuration over another. Thus, it appears that the system has made an arbitrary decision via which it has changed the repertoire of possibilities. Actually, it is this unpredictability that (in some sense) produces the observed novelty. This selectivity phenomenon is also called a *bifurcation* (or *branching*) in the possible configuration. When a control parameter μ (called "*bifurcation parameter*" or "*order-parameter*") increases to a certain critical value μ_c, there are two possible outcomes for the dependent variables u, i.e., to go upwards or downwards. In general, a bifurcation is a change in the number of candidate operating conditions of a nonlinear system that occurs as μ is quasi-statically varied. The depiction of the equilibrium points and limit cycles of a system plotted against the bifurcation parameter is known as the "bifurcation diagram". A bifurcation can be *super-critical*, *sub-critical,* or *trans-critical* depending on the direction of bifurcation, as shown in Fig. 9.4 [47]. The trans-critical bifurcation appears when, in the combined space of phase space and bifurcation



(**a**) Super-critical (**b**) Sub-critical (**c**) Trans-critical

Fig. 9.4 Pitchfork bifurcations: **a** Supercritical, **b** Sub-critical, **c** Trans-critical. (https://elmer.unibas.ch/pendulum/pbif.gif) parameter space, two different manifolds of fixed points cross each other. At the crossing point, the unstable fixed point becomes stable, and, vice versa, the stable fixed point becomes unstable.

It is noted that a trans-critical bifurcation is unlikely to occur in a space higher than two-dimensional (because in such a space two lines are unlikely to cross each other). When the nominal operating point exists, both before and after the critical parameter value, we say that a stationary bifurcation occurs "from a known solution". If the nominal solution disappears beyond the critical parameter value, we say that a stationary bifurcation occurs "from an unknown solution". The former is usually called simply a "*stationary bifurcation*".

To illustrate how a bifurcation occurs, we consider the following simple nonlinear system:

$$\dot{u} = \mu u - u^3$$

where μ is the bifurcation parameter. Clearly, the origin $u_0 = 0$ is an equilibrium point for any value of μ. But, as μ increases from $\mu = 0$, the origin loses stability, since, at $\mu = \mu_c = 0$, a bifurcation occurs, and two more equilibrium points are possible. This pair of equilibrium points is found by solving the equation $(\mu - u^2)u = 0$ for $u \neq 0$, i.e., they are $u_1 = +\sqrt{\mu}$ and $u_2 = -\sqrt{\mu}$. We say that this pair of equilibrium points is bifurcated (branched) from the origin for the critical value $\mu_c = 0$ of μ (i.e., the equilibrium point "breaks"), as shown in Fig. 9.4a. If the nonlinear system under consideration is

$$\dot{u} = \mu u + u^3,$$

the direction of bifurcation is reversed resulting in the subcritical bifurcation shown in Fig. 9.4b.

In complex systems, there may be more than two alternatives solutions (configurations) for selection at the bifurcation point. The increase in the number of possible configurations that follows the increase in the order parameter μ can be regarded as an increase in general variability, which facilitates the self-organization process. This is a special case of "order-from-noise" or "order-out-of chaos" processes [8, 37, 39].

Modularity This is a general principle for managing complexity. That is, to manage a large number of systemic interconnections, a complex system is broken into discrete subassemblies which communicate with one another via standard channels within a standardized structure or architecture. Modularity is an inherent feature of many living organisms, but today it is extensively used in man-made complex systems and social systems. According to *F.A. Hayek* [48]: "Complexity is a function of the minimum number of elements of which an instance of the pattern must consist in order to exhibit all the characteristic attributes of the class of patterns in question." According to *Herbert Simon* [36]: "A complex system is one made up of a large number of parts that interact in a non-simple way," and so complexity is a matter of both the number of distinct parts contained in the system and the nature of the interconnection or interdependencies between these parts. *Simon* states that the *criterion of decomposability* (i.e., of grouping the system's elements in a smaller number of subsystems) in modular design can be provided by a person or drawn from the systems available (ready- made) in nature. In a non-decomposed system, the correct working of a given part depends on the performance of other parts with high probability, but in a decomposed system, this effect occurs with much lower probability. Therefore, a decomposable system may continue to work (of course, suboptimally) even if some subsystems are damaged or are incomplete. In other words, decomposable systems have the important feature of *fault/failure tolerance* and *robustness*.

In engineering and societal systems, the interaction between the parts can be considered to be an issue of information exchange or communication. For example, in computer systems, the decomposition of a system into modules can be done through partitioning of information into *visible design rules* and *hidden design rules* [49, 50].

- **Visible design rules** These rules consist of three parts, viz.,: *architecture* (identify the modules/functions/structure of the system), *interfaces* (ways of interaction and communication and fitting of modules), and *standard test* (conformity of modules to design rules and measure of relative performance of modules).
- **Hidden design rules** These rules are embedded within the modules without the need of being communicated to other modules, but only within the boundaries of the module.

According to *Richard Langlois* [50], the three parts (architecture, interfaces, standard test) are collectively called "*modularization*". Regarding modularity in social systems, the design rules of interaction are the so-called "*social institutions*", which (among others) determine how much a society is a modular system [51]. Modularity in social systems has been a topic of study since the 1960s. For example, *Adam Smith* [52] coined a decentralized concept which, he believed, would lead to economic growth enforced by learning, evolution, and further division of labor. Smith stated that his decentralized system is "the obvious and simple system of natural liberty."

Clustering This is a concept similar to modularization and has been developed in the field of complex networks (electrical networks, social networks, political networks, etc.). A *cluster* is a group of elements (components, agents, etc.) that are interacting and usually have similar goals, beliefs, values, etc. Clustering means that, if the element A is connected to B and B to C, then there is a high probability that A is also connected to C (this probability is always higher than the corresponding probability in a random (non-clustered) network. To understand better the concept of clustering, we consider the case of social networks (groups, societies, etc.). Here, clustering can be interpreted as, e.g., "the friends of my friends are (likely to be) my friends" [8]. Expressing this type of clustering in another way, we have a social cluster or community if, e.g., everyone knows everyone, because when one meets regularly his/her friends, he/she has the chance to meet their friends as well. In general, if an entity A interacts frequently with an entity B, and B interacts with C, then with high probability A will interact (sooner or later) with C as well. If A and B have similar (or identical) goals, it is quite likely to act in a synergetic way, and the same is true for B and C, and consequently, between A and C. Scientific societies and worker syndicates operate in this cluster-wise manner.

9.7 Examples of Self-organization

It is generally accepted, on the basis of deep studies and extensive experiments, that most natural systems are self-organizing systems. Therefore, in their effort to understand how these self-organizing systems work, and what is their performance, scientists and engineers have designed and built appropriate computer-based models and simulators that involve embedded multiple agents, local interactions, multiple connections, positive and negative feedback loops, and synergetic features. The states and outputs of these simulators are monitored, analyzed, and evaluated over time using suitable human–machine interfaces. Therefore, these models and simulators provide the technological tools for the qualitative and quantitative study of self-organized systems. Some examples of such models and simulators include flocks, herds, swarms, plant communities, predator–prey interactions, plant-herbivore communities, social-insect colonies, fractal river basins, salmon propagation in rivers, immune systems, cellular automata, etc. [19, 53–62]. Especially, Holland's *ECHO* (ecological) CAS Model [59] has found great utility and many applications [60, 63].

Our purpose in this section is to provide a brief outline of a few natural and man-made self-organizing systems, namely:

- Ecological systems
- Magnetization
- Heated liquids
- Linguistic systems
- Knowledge networks
- Self-organizing maps.

Ecological systems This example illustrates very well the difference between the classical "*top-down*" from the "*bottom-up*" (self-organizing) modeling of life in ecological systems [19]. In the top-down methodology, the phenomena are studied using parameters from the higher hierarchical levels. For example, predators are studied as homogeneous populations that uniformly impact homogenous prey population. Trees are not studied individually but as *patches of trees*. This top-down approach violates two of the basic aspects of biology, namely, *individuality* and *locality,* which implies that population evolution is the result of activity at the level of the individual and the range of locality. Actually, individual members in a population have clear differences (e.g., body size, reproduction rate, etc.) that may have cascading and amplifying effects at higher levels. Tree gaps that result when a tree falls in the tropics may produce severe ecological changes in the region of the gap (due, e.g., to a gap in the canopy). Clearly, seeds of the forest do not have an equal chance of germinating in the gap. Ignoring this fact (i.e., locality) may mask the factors that affect spatial and temporal ecological dynamics. For example, seeding found in a high-rainfall region may have better-growing conditions than those that exist in the dry soil. The possibility of increased moisture-detention is very high, which may result in the creation of new landscape patterns. This is an example of the validity of the ecological principle that "*pattern affects process*", which is one of the self-organization mechanisms in ecological systems [64, 65].

Magnetization This is a simple self-organizing system used by many authors to illustrate the basic physical mechanism of self-organization [37]. Consider a potential magnetic material (e.g., a piece of iron), which consists of a huge number of microscopic magnetic "dipoles" (known as "spins"). At high temperatures, these ferromagnetic dipoles move quite randomly (i.e., they are disordered), and the orientations of their magnetic fields are random and cancel each other, resulting in a non-magnetized overall configuration (state) of the material (see Fig. 9.5a). But, if the temperature is lowered, the "spins" are spontaneously aligned and point in the same direction (Fig. 9.5b). The outcome of this alignment is that now the magnetic fields add up, producing a strong, overall magnetic field.

This preference of the spins is due to the fact that dipoles pointing in the same direction attract each other (the north pole of one magnetic dipole attracts the south pole of another dipole), while dipoles with opposite direction repel each other. This spontaneous alignment (magnetization) process shows that "self-organization" is occurring. In other cases, such as "crystallization", the self-organization involves not only the orientations but also the positions of the molecules which are evenly arranged.

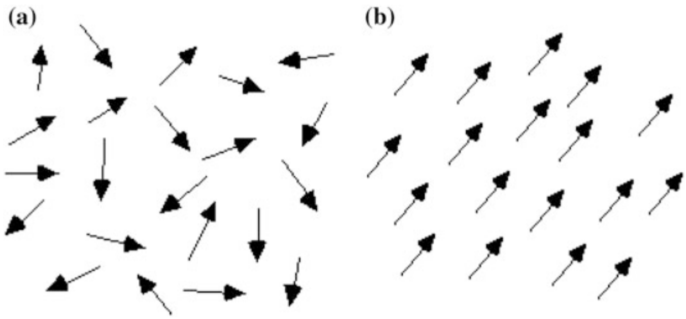


Fig. 9.5 Self-organization leading to magnetization **a** disordered spins, **b** ordered spins

Heated Liquids A liquid contained in an open container is heated evenly from below (via a hot plate) [37]. Hot liquid is lighter than cold liquid, and so it tends to move upwards. Similarly, the cold liquid tries to sink to the bottom (convective instability). These two opposite movements take place in a self-organized way in the form of parallel "rolls" with an upward flow on one side of the roll and a downward flow on the other side. Initially, the molecules of the liquid have a random movement, but finally, all "hot" molecules are moving upward on the one side of the roll and "cool" molecules are moving downward on the other side as shown in Fig. 9.6.

This self-organizing process was first observed by *Bénard* and is known as the "*Bénard phenomenon*". In this example, the molecules after self-organization keep in perpetual motion, whereas the magnetic dipoles, in the magnetization example, after self-organization, do not move (the spins are "frozen").

9.7.1 Linguistic Self-organization

Here again, a super macro-global structure is the result of local interactions. Self-organizing issues in linguistics include [66]:

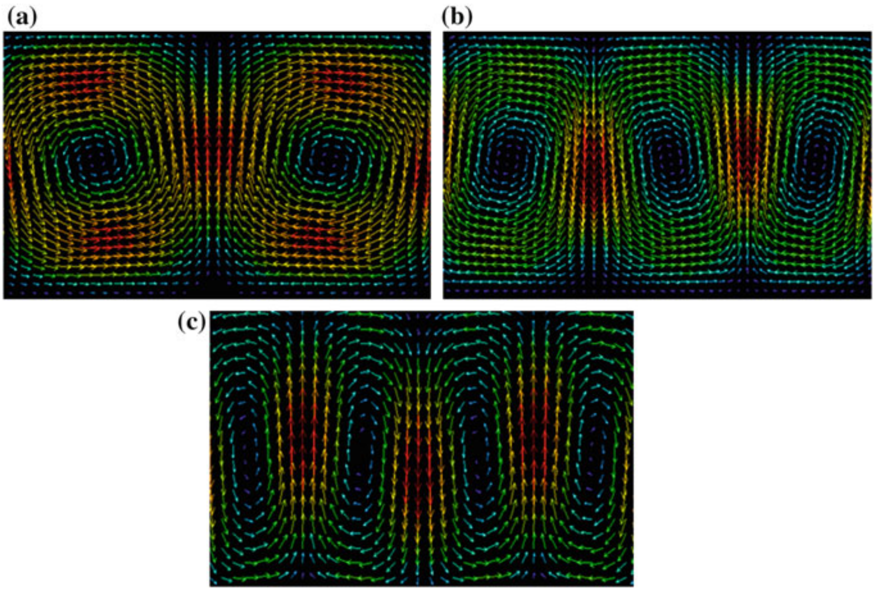


Fig. 9.6 Three steps in the self-organization movement process of the liquid molecules: **a** Rayleigh number: $R_a = 2084$, **b** $R_a = 2603$, **c** $R_a = 9215$ (http://hmf.enseeiht.fr/travaux/CD0001/travaux/optmfn/hi/01pa/hyb72/rb/rb.htm)

- Decentralized generation of lexical and semantic conventions in populations of agents.
- Formation of conventionalized syntactic structures.
- Conditions for selection of systematic reuse.
- Shared inventories of vowels or syllables in groups of agents.

To study how self-organization takes place in linguistics, suitable operational models are constructed that explicitly involve the set of assumptions and show how their consequences (conclusions) are calculated.

Self-organization in linguistics occurs in the following [66]:

- **In the emergence of language** (information senders and receivers, compositionality, the ability to sustain cultural progress cumulatively).
- **In language acquisition** (through the ability to see others as intentional agents, or through joint attention of actions).
- **In articulatory phonology** (speech production via a coordinated set of gestures known as "constellations").
- **In diachrony and synchrony** (dynamic or self-organizing models of language evolution).

9.7.2 Knowledge Networks

Knowledge networks [8] belong to the area of *information science* (see Sect. 5.2) and refer to the documentation items in libraries and databases worldwide. Documents (papers, books, reports) are typically produced by authors and researchers working in defined fields and building further on the result of other authors. This knowledge-producing system is actually a self-organized system, because it is not controlled centrally, but is generated spontaneously by local interactions of the individuals or groups that produce the new knowledge. The networks are formed by the researchers, the concepts used, and the publications linked directly or indirectly by corresponding relations (e.g., citations, collaboration, and information exchange). The new knowledge (patterns) are generated via the nonlinear interactions of multiple autonomous agents (scientists, groups, organizations), and the overall system is a "*heterogeneous network*" involving three different kinds of nodes, viz.: *agents* (individual scientists, groups, organizations), *containers* (documents, papers, etc.), and *concepts* (keywords, abstract knowledge items). Knowledge networks can be viewed as complex adaptive systems and can be designed and operated by CASs techniques.

9.7.3 Self-organizing Maps

Self-organizing maps(**SOMs**) [67, 68] represent a special class of artificial neural networks that are based on competitive learning, in which the network's output neurons compete among themselves to be fired or activated such that only one output neuron is activated (on) at each time. The name self-organizing map is due to the fact that the impact patterns are mapped on a topographical map where the spatial locations (coordinates) of the neurons indicate the various inherent features of the input patterns. An SOM transforms an input signal pattern of arbitrary dimension into a one-or two-dimensional discrete map and performs this transformation in a topologically adaptive way. The topographical mapping of the input patterns can be done as suggested by Kohonen and shown in Figs. 9.7, 9.8. This mapping is known as a Kohonen SOM or Kohonen model. It is clear that each neuron has a set of neighbors.

Each input pattern consists of a localized region or "spot" of activity against a quiet background. Since the location and nature of "spots" are different from one input pattern to another, to ensure that the self-organization process will be properly established, all neurons must receive a sufficient number of different realizations of the input pattern. The formation of the SOM starts by initializing the network's synaptic weights randomly, with small values provided by a random-number generator. After this random initialization, the SOM formation is formed via three basic processes:

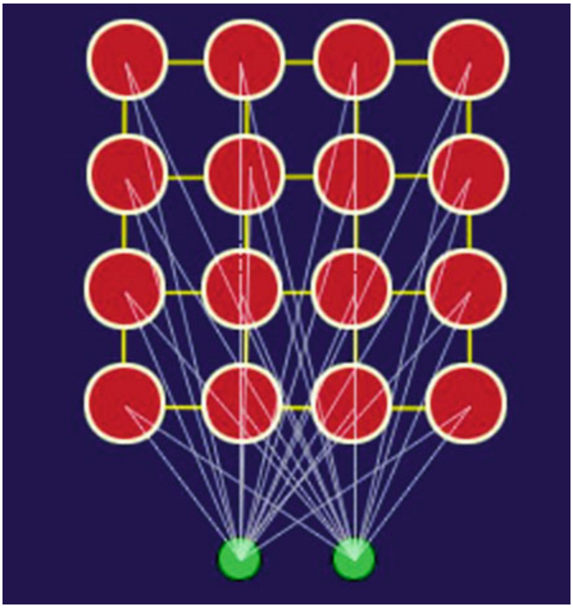


Fig. 9.7 A first representation of a Kohonen self-organizing map. (http://www.ai-junkie.com/ann/som/som1.html)

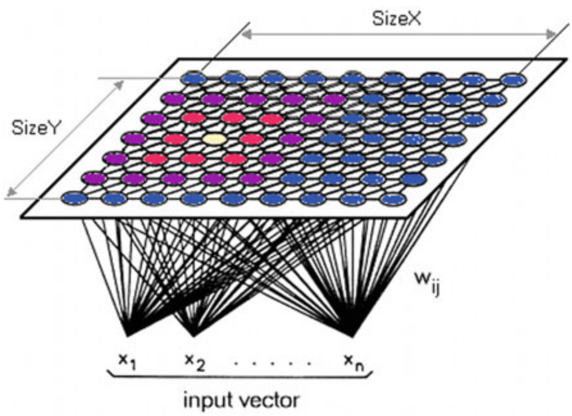


Fig. 9.8 The winning node is the pink one (http://www.ai-junkie.com/ann/som/som1.html http://www.lohninger.com/comimg/kohonen1.gif)

- **Competition** A fitness (discriminant) function is computed for each input pattern by the neurons. The neuron with the largest fitness value is declared the winner of the competition.
- **Cooperation** The winning neuron specifies the location of a neighborhood of fired neurons, which are allowed to cooperate.
- **Synaptic adaptation** The excited neurons increase the value of the fitness function through suitable adjustments of their synaptic weights. In this way, the winning neuron enhances its response to similar patterns subsequently entered into the neural network/SOM.

The SOM starts from a completely disordered initial state and leads to an organized representation of activation patterns drawn from the input space. Kohonen [67, 68], pointed out that this is performed in these two phases:

- Ordering (self-organizing) phase
- Convergence phase.

Mathematical details of Kohonen's SOM algorithm can be found in standard textbooks on neural networks (e.g., [69–71].

9.8 Concluding Remarks

In this chapter, we have provided a tour to the basic concepts and principles of self-organization, which occurs in natural, biological, and societal systems. Self-organization is performed (and needed) in complex systems and, together with adaptation, in complex adaptive systems. We have seen that the mechanisms by which self-organization is realized are synergy, entropy export, positive/negative feedback interplay, and selective retention. Other self-organizational properties that are also possessed by complex adaptive systems are interdependence, interaction, selective variety, modularity, and clustering.

Complexity implies a lack of symmetry which exists in both full disorder and full order, but the midpoint between order and disorder which specifies the complexity depends on the level of representation. Something that appears to be complex in one representation may not seem complex in a representation on another scale [72]. A fractal is self-similar, i.e., its shape is independent of scale, something which is not valid in the case of a simple system like a building which, to an outside observer, is seen to be different at several scales: the entire building, the doors/windows, the rooms, and the bricks represent four different scales. Typically, an observer picks up those distinctions (features) that are in some sense the most important and creates categories of similar processes (neglecting the existing differences among the members of each category). Thus, the increase or decrease of complexity depends on which distinctions the observer is introducing [5, 6, 38].

We have seen that an increase in variety (which is called *differentiation*), or an increase in the *connectivity* (which is called *integration*) of a complex system facilitates and speeds-up the process of self-organization. Evolution and adaptation are based on (and produce) differentiation and integration along with several dimensions, viz., space, spatial scale, time, and timescale, leading to the so-called structural, hierarchical, functional, and functional hierarchical differentiation/integration, respectively [8, 37, 39].

To recapitulate, a self-organizing system has the following (surely not exhaustive) features:

- Autonomy (absence of external ordering or controlling agent).
- Self-configuration (autonomous arrangement of system's constituent past).
- Dynamic performance (time-evolving operation).
- Spontaneous order (emerging from local interactions).
- Synergy (mutual coevolution adaptation of local agents).
- Perturbations (noise/fluctuations, order-from-noise).
- Complexity ("*paradox*" *phenomena*).
- Nonlinearity (multiple "attractors", bifurcations).
- Dissipation (far from equilibrium, extropy).
- Self-organized criticality (edge-of-chaos operation).
- Selectively variety (selective retention).
- Positive/negative feedback interplay.
- Self-similarity (power-law distribution).
- Commonly understood action (at all levels).
- Redundancy (robustness to faults and damages).
- Self-maintenance (reproduction/repair).
- Symmetry-breaking (heterogeneity).
- Differentiation and integration.
- Modularity and clustering.
- Self-reference (the system's behavior is evaluated with respect to the system itself).

We close our discussion by noting that self-organization is typically achieved through distributed (non-centralized) control. This means that there is not a unique external or internal controller that drives the system towards self-organization. Rather, all parts of the system contribute smoothly to the resulting self-organized configuration.

Today, most industrial and other man-made controllers are centralized, and those which are decentralized or distributed work in a deterministic (reductive/cause-effect) way. But as *Jim Pinto* argues [73], drawing from [17], the advent of self-organizing industrial controllers (i.e., controllers working with mechanisms and principles of natural-like self-organization) will mark the end of deterministic and centralized controllers. The main reason for this is the fact that conventional centralized or decentralized controllers and DCSs cannot be sealed (i.e., they do not have the necessary self-similarity property). Therefore new peer-to-peer I/O-based self-organizing controls are the controls of the future. In these controllers and systems, the overall behavior must be the result of the interactions of the individual elements (components, agents, computer programs), which both decompose and integrate the control/performance problem. This means that all man-made self-organizing systems should have *autonomy* (partly or fully) and be able to operate successfully without the need for an external designer. Examples of such man-made (engineered), self-organizing systems (with features like the ones of natural systems) include many robotic systems such as *robot swarms* and *robot groups* [74], etc. These systems are characterized by prediction (anticipatory control), adaptation (adaptive control), robustness (robust control), and general intelligence (intelligent control) as described in Chap. 7. *Artificial-life* (**Alife**) systems form a class of man-made systems that exhibit properties and behaviors characteristic of living organisms, i.e., they synthesize life-like behaviors within computer and control science and engineering. As the founder of Alife, *Chris Langton* stated [2]: "by extending the empirical foundation upon which biology is based *beyond* the carbon-chain life that has evolved on Earth, Artificial Life can contribute to theoretical biology by locating "*life-as-we-know-it*" within the larger picture of "*life-as-it-could-be*"… Only when we are able to view *life-as-we-know-it* in the larger context of *life-as-it-could-be* we will really understand the nature of the beast."

Thus, *Alife* is a relatively new field employing a synthetic approach to the study of life-as-it-could-be. Alife differs substantially from artificial intelligence. The most important philosophical aspects of this area are coming from biology, not from psychology, and it complements traditional/theoretical biology in two ways, namely: (i) it deals with the synthesis of life-like behavior (further to the analysis of biological processes for which biology is concerned), and (ii) it aims at exploring the possibilities of life-as-it-could-be. That is, Alife explores and studies the total range of mechanisms that can aid such a synthesis, independently of their similarity or not of what we see in the actual biosphere. An important reference work on Alife is [3]. Two references on self-organization available on the Web are [75, 76]. Some references on history, principles, simulation, and global patterns of self-organization are [77–81].

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