TR-H-278

Self-Organization of Mind in CBM-like Environments.

Andrzej BULLER (ATR-HIP/Tech. Univ. Gdansk)

1999.12.8

ATR人間情報通信研究所
〒619-0288 京都府相楽郡精華町光台2-2 TEL: 0774-95-1011

ATR Human Information Processing Research Laboratories
2-2, Hikaridai, Seika-cho, Soraku-gun, Kyoto 619-0288, Japan
Telephone: +81-774-95-1011
Fax : +81-774-95-1008

Self-Organization of Mind in CBM-like Environments

Andrzej Buller

ATR Human Information Processing Research Laboratories
2-2 Hikaridai, Seika-cho, Soraku-gun, Kyoto 619-02 Japan
abuller@hip.atr.co.jp
&
Technical University of Gdańsk
Faculty of Electronics, Telecommunications & Informatics
ul. G.Narutowicza 11/12, 80-952 Gdańsk, Poland
buller@pg.gda.pl

December 7, 1999

Abstract: In this essay-like report I argue that **self-organization of mind** can take place even in a hardware neural environment with **unchangeable synapses**, provided the environment supports a sufficient number of state variables (ATR's CBM belongs to this class of hardware). The discussion is preceded by an introduction to the field of discrete dynamic systems. A novel interpretation of the notions of *state* and *complexity* is proposed.

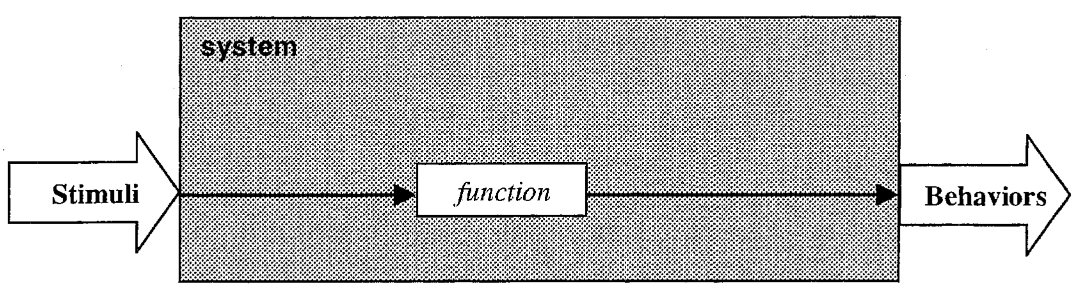
Self-Organization of Mind in CBM-like Environments

> We see that human creativity and innovation can be understood as the amplification of laws of nature present in physics and chemistry[1].
>
> —ILYA PRIGOGINE
> Nobel Prize winner in chemistry

The field of dynamical systems emerged from mathematics and control theory. Introducing the study of chaotic systems it has been hailed as one of the important breakthroughs in science in this century[2]. The notion *system* refers to a collection of related elements that we consider as a single entity. The word *dynamics* refers to the way a system behaves as time passes[3]. Since in physical world everything changes, we can recognize everything as dynamical systems, however, such radical view is a bit impractical, especially when an analysis of a system refers to a particular period of time in which changes in the system are negligible.

Functions and states

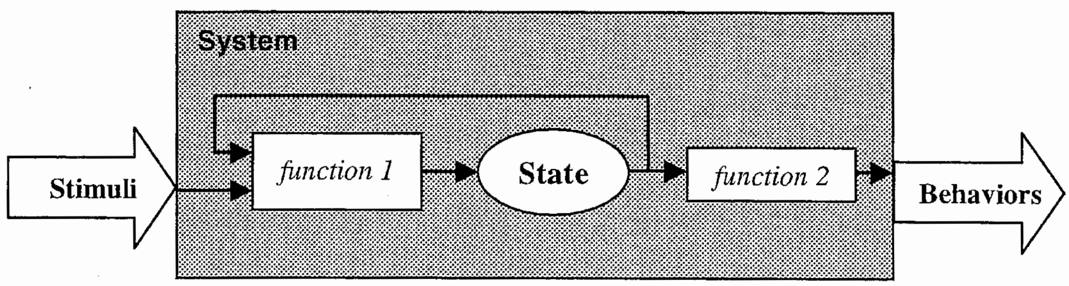
A diagrammatic representation of any system is showed below.



[1] Prigogine (1997: 71).
[2] Devaney (1989).
[3] Norton (1995).

As it can be noted, this diagram fits everything physically existing, from an electron to a galaxy, from a single bacterium to the mankind. For a particular system, any consistent description of the *function* and the variables it maps is a model of the system. In simple cases, a collection of numerical variables representing stimuli and behaviors plus a simple mathematical formula is sufficient. In some cases, with the same numerical variables, a transition table describing the function is helpful. Sometimes the function may be given in the form of a multi-step algorithm. In of very sophisticated behaviors the stimuli and reactions may be described verbally. In such case also the function must be described verbally, as, for example, a rule set. If through the entire time we are interested in a system the same constant stimulus implies the same constant set values describing its behavior, we do not need to call such system dynamic one.

When a system that reacted to a given stimulus in a particular way, next time reacts to the same stimulus in different way, this means that the *function* changes in time. One (inefficient) way to cope with such situation is to assume that when speaking about a stimulus we mean the full record of stimuli that took place from the beginning of the system's existence. In such case the *function* could map all possible histories of stimuli to all possible histories of its behavior. Another way is to assume that the *function* may change as time passes and provide rules describing the way the *function* changes. Yet another method of system description—the most useful of all methods known so far, is to view the *function* as two unchanging functions and a collection of internal variables, called *state*. Let it be assumed that a current stimulus and current state are mapped by the *function 1* onto speed and direction of the change of the state, while the state is mapped by the *function 2* onto the system behavior, as it is showed in the below diagram.



It has been stated as a kind of theorem that a state-based system description exists for practically any behavior[4]. Using the notion of state has two major advantages. First, the history of stimuli is not required to deduct the system's behavior. Second, several even surprisingly sophisticated behaviors can be explained using relatively simple *function 1* and *function 2* and a small collection of variables considered as a state. It can also be noted, that owing to the notion of state the difference between behaviorism and cognitivism disappears[5]. Let, therefore, the view of system represented by the above diagram be a framework for further discussion about mind—the thing supposed to be a dynamical system.

Sampling and Control Parameters

In order to make the things simpler, let us assume that the state of a system is sampled at fixed time intervals. With this assumption the system is called *discrete dynamical system*. The state sampling is common practice in research of real objects. For example, measuring body temperature every 6 to 8 hours is the standard practice. A number of man-made systems change their states in regular periods of time. For example, every next change of the state of a digital electronic device takes place only when a clock sends next control pulse. A discrete system can be a model of a real continuous object. For every real object there is maximum length of the period between two consecutive samples with which the approximation remains sufficiently accurate. In a discrete system the vague notion 'speed and direction of the state change' is replaced with the simple notions: *current state* and *next state*. Indeed, the difference between the next state and the current state is a counterpart of the speed and direction of the state of the continuous system. For discrete systems it is assumed that the *function 1* maps all possible pairs ⟨*current state*, *current stimulus*⟩ onto the set of adequate *next states*. The *behavior* may be considered as a series of consecutive values returning by the *function 2* for selected variables from among those constituting the state.

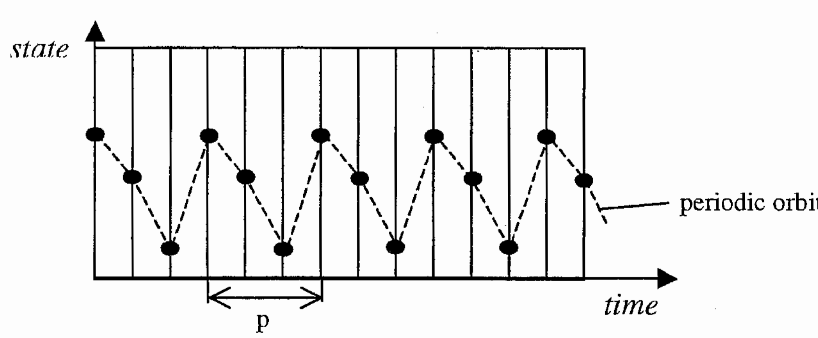
---

[4] Kalman, Falb & Arbib (1969).
[5] Kampis (1991: 11).

Also in order to make things simpler, let us assume that we discuss the cases when the analyzed behavior is a result of constant stimulus. This way we put aside a lot of interesting topics explored by classic control theory, but (i) there are systems that even for constant stimulus demonstrate amazingly sophisticated behaviors, and (ii) when we investigate a psychological phenomenon, sometimes it is important to know whether a change in subject's behavior is caused by a change of stimulus or it is a consequence of internal dynamics of subject's mind. In any case, even with the constant-state assumption dynamical systems remain interesting topic. Dynamic-system theorists call constant stimulus a set of *control parameters*.

Orbits and Attractors

Such domain-specific concepts, as, for example, strange attractor, bifurcation, and fractal, has been popularized in the media. The concepts let us, in a convenient way, compare systems, analyze their behaviors, and, to certain extent, predict their behaviors even when we do not know the present state of a given system[6]. Let us introduce some of them to facilitate further discussion.

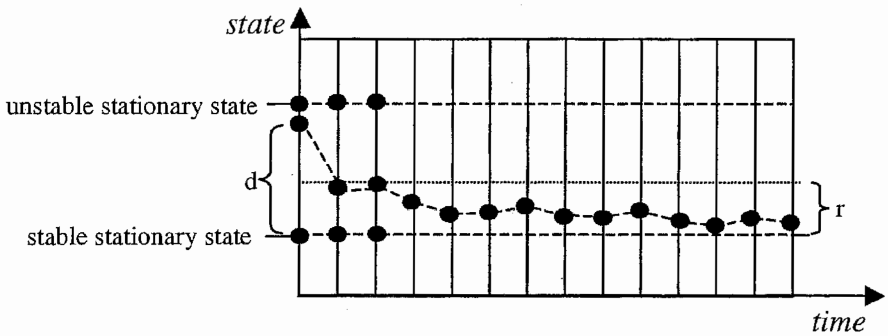


Let a series of consecutive states of a given system be called an *orbit*. The orbit is called *periodic* of period p when every p samples the state is the same, as it takes place in the above example.

If a current state of a given system is equal to its next state, then the current state is called a *stationary state* or a *fixed point*. A fixed point is called *stable* if for every r>0 there exist d>0 such that if the distance between an initial state and the point is not

[6] see Nowak, Vallacher & Levenstein (1994).

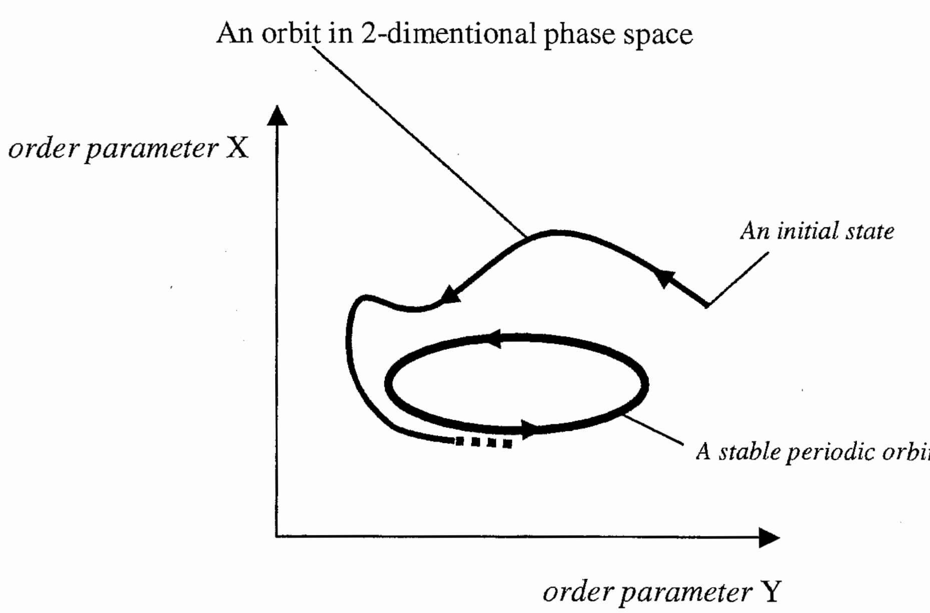
greater than d, then the distances between all next states and the point are not greater than r[7]. In other words, if we have chosen how close the state of system must remain to the fixed point in the future, we can find how close the initial state must be to the point. Analogically the notion of stability can refer to periodic orbits.



In several cases one cannot analyze system behavior using only a single numerical variable. Having, say, two or three state variables we can use two plots, however such an image may be not too informative. The recommended solution is to resign from time coordinate and assign all available coordinates to state variables. In case of dense sampling, the orbit becomes practically a continuous curve. A hypothetical space having as many dimensions as the number of variables needed to specify a state of a given dynamical system theorists call *phase space*. When a state of a system is specified by more than three variables is difficult to visualize the system's phase space. Since without a visualization it may be difficult to predict or discover the most interesting system behaviors, a good solution is to aggregate some state variables onto so called *order parameter* which itself is also a state variable. In case of a large number of state variables, for example, when one want to model the dynamics of gas molecules in a container, instead of coping with positions and velocities of billions molecule, those can introduce only two collective variables – pressure and temperature[8]. Finding a proper set of order parameters is a kind of art.

[7] Adapted from Martelli (1999: 16-18).
[8] Example taken from Nowak & Lewenstein (1994).

If, after a theoretical or experimental investigation of a system, we know its stationary states or orbits and its initial state, we can say a lot about future behavior of the system. If the initial state is close to a stable point, we can suppose the system will remain near the stable state. If the initial state is perfectly in an unstable point, the system will keep in this state until an external force changes its state to even a little distance off the initial point. Then the state will dramatically escape towards a stable point if such exists. This is not the same as a perfect prediction of the state in particular time, but it is far more than to know nothing about the system's future behavior. Sometimes, however, an orbit seems to neither tend to a stable state nor look periodic. Such an orbit can be called chaotic. But not everything what is chaotic must be completely unpredictable, especially if it is describable in terms of attractors.



A fixed point x_s is said to be an *attractor* if there exist r>0 such that for any initial state x_0 which are at distance less than or equal to r from x_s the further states tend toward x_s, when time goes to infinity. Also a periodic orbit as a whole can be said to be an attractor, when each of its points is an attractor[9]. It has been observed, that sometimes an

[9] Adapted from Martelli (1999: 61-62).

orbit can converge to an unstable point[10]. This counterintuitive observation led to a formal definition of an attractor in reference to states assumed as q-dimensional numerical variables: Let U be a subset of q-dimensional space of real numbers and let *function 1* map U onto U; a closed and bounded set A, being a subset of U is an attractor if the *function 1* for A returns A and there exists r>0 such that for any initial state x_0 the distance between x_0 and A not less than r implies that the distance between n-th state and A tends to zero as n goes to infinity[11]. In other words, an attractor is a limit set that is not contained in any larger limit set, and from which no orbits emanate[12]. If, therefore, we can divide a phase space of a given system onto attractor basins, we are able to predict, to certain extent, long-term behaviors of the system. However, the more sophisticated shape of an attractor, the smaller precision of the predictions. But even imprecise prediction is more than nothing.

Deterministic chaos

Let us assume, that there is an orbit that comes closer and closer to a fixed point. Such an orbit is called *asymptotic*. What will happen if an initial state of the same system is very close to an asymptotic orbit? The intuitive answer is that the orbit emanating from the initial state will be also asymptotic. This is true for a number of classes of dynamical systems. However, it was observed, that there are systems for which there are orbits demonstrating so called *sensitive dependence*. This means that for a given orbit most other orbits that pass close to it at some point do not remain close to it as time advances. In such situation it is hardly to say that the system's behavior is predictable since from two very close initial states it can go completely different ways. If for a dynamical system most orbits demonstrate sensitive dependence we can call such system fully *chaotic*. When some special orbits are nonperiodic but most are periodic or almost periodic, we can call such system *limitedly chaotic* and predict at least certain features of its behavior patterns[13].

---

[10] Martelli (1999: 202).
[11] Martelli (1999: 203). The distance between a state and a set can be formally defined in several ways.
[12] Lorenz (1995: 206).
[13] Lorenz (1995: 206-212).

Maybe the most spectacular example of limited chaos is *Lorenz attractor.* In 1963, Edward Lorenz, the MIT meteorologist, formulated a system of differential equations with three state variables as a crude model of atmospheric behavior. By selecting realistic values of three control parameters and solving the system numerically, he noticed that very minor changes in the initial conditions could produce significantly different outcomes. Since the distance between corresponding states of initially very close orbits could oscillate aperiodically, Lorenz suggested that this discovery implied that no long-range prediction of atmospheric changes would be ever possible[14]. Regardless the truth of the suggestion, the Lorenz's discovery was the beginning of amazing career of deterministic chaos. There is no contradiction between 'deterministic' and 'chaotic'. As it has been showed, the chaotic behavior is demonstrated by a system described using simple and completely deterministic mathematical formulas. In 1971 sets of such kind as this obtained by Lorenz for the first time was called *strange attractor*[15], which, as Mario Martelli states, is an expression well-suited for describing these astonishing and poorly understood objects[16]. The phenomenon consisting in sudden shift of a system's state to a distant region of a phase space caused by a small disturbance making a minute deviation from a sensitive dependent orbit has been called the *Butterfly Effect.* The name came from the jocular "example" how Lorenz attractor works: a butterfly flapping its wings today in Brazil can jiggle the atmosphere so as to cause a snowstorm in Alaska tomorrow[17]. Coincidentally, a colored projection of Lorenz attractor onto a 2-dimedsional surface really resembles a butterfly[18].

Self-organization

When a thin layer of silicone oil is heated carefully from below, the initial featureless uniformity of the liquid suddenly gives away to an array of hexagonal convection cells, forming a honeycomb pattern[19]. This amazing phenomenon, known as

[14] Lorenz (1963); quoted from Martelli (1999: 205-206).
[15] Ruelle F, Takens F (1971) On the nature of turbulence, *Commun. Math. Phys., 20,* 167-192.
[16] Martelli (1999: 203).
[17] Casti (1994: 89).
[18] see Gleick (1988)
[19] Platten and Legros (1984: 318); quoted from Coveney & Highfield (1995: 155).

Raileigh-Bénard cells, is easily explainable using dynamic-systems concepts. If a given orbit is stable but also sensitive dependent, a small deviation from it may cause sudden escape of a system's state from the orbit. Sometimes the new orbit may be completely chaotic. Let temperature be a control parameter, while a shape of convection pattern let be an order parameter. For a certain range of temperatures the shape is honeycomb-like and stable, i.e. although one can observe small movements of the cells' borders, they remain honeycomb-like and keep their average size. Even if the oil is shaken, which may be interpreted as a setting of a new initial state, the convection cells will appear again, which means that the orbit went to a stable quasi-periodic orbit (atractor). This works this way until the temperature is above certain threshold. Below this threshold all possible orbits are chaotic.

Half century ago Boris Pavlowitch Belousov devised a cocktail of chemicals and with a surprise noted that the mixture oscillated, with clockwork regularity, between being colorless and having a yellow hue. In subsequent investigations he also observed the formation of spatial patterns. Unfortunately, the reaction was so peculiar that it's discoverer had a great trouble in convincing the scientific establishment that it was real. No editor wanted to publish his manuscript. But the research was continued by Anatoly Zhabotinski—a Belousov's student. Testimonials to the importance of the discovered phenomenon were sought from scientists worldwide in 1979—nine years after Belousov's death[20]. Todays, both Raileigh-Bénard cells and Belousov-Zhabotinski reaction are quoted as the most impressive examples supported the notion of self-organization.

Self-organization is such a process that in a dynamical system a new quality emerges with no external information about the target pattern and with no external control towards the target pattern. Neither Belousov-Zhabotinski reaction nor Raileigh-Bénard cells were designed. Moreover, both of them neither were nor could be predicted. Indeed, even for several simple theoretical systems (i.e. described by relatively simple mathematical formulas) nobody knows other way of prediction of a given system's state a dozen or more samples ahead but as to calculate all consecutive states taking each time

[20] Coveney & Highfield (1995: 175-176).

a previous state as a data for the next state calculation. The results of the process of self-organization are, therefore, unpredictable. However, this conclusion applies only to the situation when perfect predictions are required, which, if took place, would be an unrealistic requirement. In real life, based on reasoning by analogy, or after experimental estimation of a given system states' attractors, we can try to anticipate whether the phenomenon of self-organization will take place or not, and if so, to estimate more or less probable directions of the process. The most important conditions for self-organization are as follows:

1. Patterns can arise spontaneously as the result of large numbers of interacting components; if there are not enough components or they are prevented from interacting, neither pattern emergence nor evolution will be seen.
2. The system must be dissipative and far from equilibrium; dissipation is equivalent to a kind of attraction that may take several forms, from stable points or orbits to those more or less chaotic; in other words, due to nonlinear interactions in the system, heat or other form of energy does not diffuse uniformly but is concentrated into structural flows that transport the energy (dissipate it) more efficiently; many of the system's degrees of freedom is suppressed and only a few (represented by order parameters) contribute to the behavior[21].

The general scheme of self-organizing dynamic system constitutes grounds for deeper understanding a number of phenomena apart from physics/chemistry investigated in the field of biology[22] and social sciences[23]. Several sorts of self-organizing processes have been utilized in extraordinary engineer's constructions, as for example, cellular automata[24], artificial neural networks[25] and evolutionary systems[26] (all three ideas

[21] Summarized from Kelso (1995: 16-17).
[22] It is suggested that a complex biological cell emerged from the coevolution of bacteria (de Duve 1996; Stewart & Cohen 1997: 23). Hameroff (1997) investigates a possibility of emergence of consciousness from interactions of tubulins constituting cytoskeleton.
[23] Axelrod R (1986); Nowak A, Szamrej J & Latané B (1990); Axelrod R & Bennet DS (1993); Nowak, Lewenstein M & Szamrej J (1993); Nowak & Vallacher (1998ab)
[24] Toffoli & Margolus (1987); Toffoli (1995).
[25] Rumelhart, NcClelland & PDP Research Group (1986); Schalkoff (1997); Heikkonen & Koikkalainen (1997); Moravec (1999: 40-49).
[26] Goldberg (1989); Michalewicz (1992); Man, Tan & Kwong (1999).

implemented also as hardware[27]) where ingeniously framed energy dissipation inside electronic circuits leads to an emergence of useful computation. Scientists attempt to explain the biggest mysteries of existence—origins of life and species evolution—in terms of self-organization in extremely complex systems[28]. It was shown that in analogical terms one can analyze brain and mind functioning[29], however, dynamical approach in psychology still remains rather an idea than a routine methodology. Nevertheless, the small dynamical-system-theoretic implant seemingly is not going to be rejected by psychology. Some serious tokens of its presence can be observed, as for example the resurrection of Gestaltists' ideas[30].

Conclusions

A structure of a dynamical system provided in this chapter is commonly accepted, but the non-standard way of presentation and the interpretation of some of its elements have been invented to facilitate further discussion. In the framework of the proposed way of thinking the self-organization may be considered as a given system's behavior resulting in a growth of the system's complexity, where the complexity is interpreted as a minimum number of elementary relationships between elementary variables representing efficiently the state of the system and explaining its behavior. Owing to this intellectual trick we can keep the simple view of the system transition *function* as an aggregate of a changeable state and unchangeable *function 1* and *function 2*. The functions can be assumed to be fixed but capable of processing a great number of variables from which only a small part is initially non-zero. Indeed, the model in which *function* becomes more and more sophisticated may demonstrate the same behaviors as the model in which new variables become active and start influence the system's behavior making it more sophisticated. Why not to consider a case, where *function 1* and *function 2* are represented by a fixed hardware, while the entire state is equivalent to an informational

---

[27] Korkin, de Garis, Nawa & Rieken (1999); Glesner & Pöhlmüller (1994); Stoica, Keymeulen & Lohn (1999).
[28] Eigen & Schuster (1979);
[29] Keeler (1990); Kelso (1995: 257-285); Haken (1996); Cerf , El Ouasdad & El Amri (1999); Haken (1999); Uhl & Friedrich (1999).
[30] Epstein & Hatfield (1994).

content of a random access memory? The emerging conclusion is that a hardware simulating **a very large-scale neural network can serve as an environment of self-organizing mind even if it has unchangeable synapses**[31].

Pieces of pure information also can interact. Hence, one can imagine a great number of purely informational entities, which, interacting, results in an emergence of higher mental functions. The energy to be dissipated does not need to be physical. As we learned from the Hopfield model[32], also energy can be a stipulated entity existing as pure information. In order to be able to interact the entities must exist in an environment facilitating their interactions. Today we know no other such environments but nervous system or electronic hardware. If higher mental phenomena may emerge from interactions in a large number of informational entities, maybe this way a complete personality can organize itself. If so, why it had to be possible exclusively in a protein-based facility? These speculations cause a strong drive and give a promising direction for research towards a computational model of self-organizing mind.

Belousov's discovery had to wait for almost 30 years for being noted by scientific establishment and, finally, recognized as Mona Lisa of the gallery of curios the complex-system science maintains and develops. Knowing this one should not be surprised having noted that psychologists so far seldom try to explain the mind as a whole in terms of states, attractors, or self-organization. Seemingly lot of those who try to use connectionist networks for modeling of particular mental phenomena, utilize self-organization unconsciously, as researchers usually concentrate on similarity between values provided by their models and the values characterizing behaviors of examined people or animals, putting aside the essentials of the behaviors of the models themselves[33]. Yet it seems to be obvious that since similar phenomena, explainable in terms of dynamical system theory, are noted in a number of various physical, chemical, biological systems, as well as in designed artifacts, this means that the theory of dynamical systems tries to fathom a still poorly noted law of nature—the law supposedly equally important and omnipresent

[31] The CBM (Cellular [Automata-based] Brain Machine) developed it Genobyte Inc. can simulate a system consisting on over 75,000,000 neurons with unchangeable synapses (see Korkin, de Garis, Nawa & Rieken 1999; Buller, Chodakowski, Hemmi & Shimohara 1999).
[32] Schalkoff (1997: 256).
[33] See Reed & Miller (1998).

as the law of conservation of energy or the law of gravity. It would be a groundless speculation to consider a possibility that human psyche is beyond the law's reach. Perhaps one day students of psychology will learn the dynamical-systemic toolbox as eagerly as they learn chi-square test today. Indeed, as this chapter seems to show, the states, orbits, phase spaces, attractors, or self-organization—the notions so useful in mental phenomena modeling—can be discussed without discouraging mathematics.

References

1. Axelrod R (1986) An evolutionary approach to norms, *Am. Political Sci. Rev.*, 80.
2. Axelrod R & Bennet DS (1993) A landscape theory of aggregation, *British Journal of Political Science, 23*, 211-233.
3. Århem P, Liljenström H & Svedin U (Eds.) (1997) *Matter Matters: On the Material Basis of the Cognitive Activity of Mind*, Berlin: Springer.
4. Buller A, Chodakowski T, Hemmi H & Shimohara K (1999) CoDi Technique: Cellular Automata-Based Neural Networks, *Technical Report TR-H-277, ATR Human Information Processing Research Laboratories, Kyoto*.
5. Casti JL (1994) *Complexification : Explaining a Paradoxical World Through the Science of Surprise*, HarperCollins: New York. 1995.
6. Cerf R, El Ouasdad & El Amri M (1999) EEE-Detected Episodes of Low-Dimensional Self-Organized Cortical Activity and the Concept of a Brain Attractor, In: Uhl, 126-144.
7. Coveney P & Highfield R (1995) *Frontiers of Complexity: The Search for Order in a Chaotic World*, New York: Fawcett Columbine.
8. de Duve C (1996) The birth of complex cells, *Scientific American, April*, 38-45.
9. Devaney RK (1989) An Introduction to Chaotic Dynamical Systems, Reading, MA: Addison-Wesley.
10. Eigen M & Schuster P (1979) *The Hypercycle – A Principle of natural Self-Organization*, Heidelberg: Springer.
11. Epstein W & Hatfield G (1994) Gestalt psychology and the philosophy of mind, *Philosophical Psychology, 7*, 163-181.

12. Forest S (Ed.) (1990) *Emergent Computation*, Cambridge, Mass., London: A Bradford Book/The MIT Press.

13. Gleick J (1988) Chaos: making a New Science, New York: Viking.

14. Glesner & Pöhlmüller (1994) Neurocomputers: An Overview of Neural networks in VLSI, London: Chapman & Hall.

15. Goldberg DE (1989) Genetic algorithms in search, optimization, and machine learning, Addison-Wesley: New York.

16. Haken H (1996) *Principles of Brain Functioning: A Synergetic Approach to Brain Activity, Behavior and Cognition*, Springer: Berlin.

17. Haken H (1999) What Can Synergetics Contribute to the Understanding of Brain Functioning? In: Uhl, 7-40.

18. Hameroff S (1997) Quantum Automata in Cytoskeletal Microtubules: A Nanoscale Substrate of Cognition, In: Århem, Liljenström & Svedin, 61-106.

19. Heikkonen J & Koikkalainen P (1997) Self-Organization and Autonomous Robots, In: Omidvar & Van der Smagt, 297-337.

20. Kalman R, Falb P & Arbib M (1969) *Topics in Mathematical System Theory*, New York: McGraw-Hill.

21. Kampis G (1991) *Self-Modyfying Systems in Biology and Cognitive Science*, Oxford: Pergamon Press.

22. Keeler JD (1990) A Dynamical System View of Cerebral Function, In: Forest (Ed.) 396-410.

23. Kelso JAS (1995) *Dynamic Patterns: The Self-Organization of Brain and Behavior*, Cambridge, Mass, London: A Bradford Book/The MIT Press.

24. Korkin M, de Garis H, Nawa NE & Rieken WD (1999) ATR's Artificial Brain Project: CAM-Brain Machine (CBM) and Robot Kitten (Robokoneko) Issues, in: Dobnikar A, Steele NC, Pearson DW & Albrecht R (Eds.) *Artificial Neural Nets and Genetic Algorithms*, Springer: Wien, 107-110.

25. Lorenz E (1963) Deterministic nonperiodic flow, *J. Atmos. Sci., 20*, 130-141.

26. Lorenz E (1995) *The Essence of Chaos*, Seattle: Univ. of Washington Press.

27. Man KF, Tang KS & Kwong S (1999) *Genetic Algorithms: Concepts and Designs*, London: Springer.

28. Martelli M (1999) *Introduction to Discrete Dynamical Systems and Chaos*, New York: J. Wiley.

29. Medin DL, Goldstone RL & Gentner D (1993) Respects for similarity, *Psychological Review, 100*, 254-278.

30. Michalewicz Z (1992) *Genetic Algorithms + Data Structures = Evolution Programs*, Berlin: Springer.

31. Moravec H (1999) *Robot: Mere machine to Transcendent Mind*, New York: Oxford University Press.

32. Norton A (1995) Dynamics: An Introduction, In: Port & van Gelder, 45-68.

33. Nowak A & Lewenstein M (1994) Dynamical Systems: A Tool for Social Psychology, In: Vallacher & Nowak, 17-53.

34. Nowak A, Lewenstein M & Szamrej J (1993) Bąble modelem przemian społecznych, *Świat Nauki, 12*, 16- 25.

35. Nowak A, Szamrej A & Latané B (1990) From private attitude to public opinion: A dynamic theory of social impact, *Psychological Review, 97*, 362-376.

36. Nowak A & Vallacher RA (1998a) *Dynamical Social Psychology*, Guilford Press.

37. Nowak A & Vallacher R (1998b) Toward Computational Social Psychology: Cellular Automata and Neural Network Models of Interpersonal Dynamics, In: Read & Miller, 277-311.

38. Nowak A, Vallacher RA & Lewnstein M (1994) Toward a Dynamical Social Psychology, In: Vallacher & Nowak, 279-293.

39. Omidavar O & Van der Smagt P (Eds.) (1997) *Neural Systems for Robotics*, San Diego: Academic Press.

40. Platten JK & Legros JC (1984) *Convection in Liquids*, Berlin: Springer.

41. Port RF & van Gelder T (Eds.) (1995) *Mind as Motion: Explorations in the Dynamics of Cognition*, Cambridge, Mass., London: A Bradford Book/The MIT Press.

42. Prigogine I (1996) The End of Certainty. Time, chaos, and the New Laws of Nature, New York: The Free Press.

43. Read SJ & Miller LC (Eds.) (1998) *Connectionist Models of Social Reasoning and Social Behavior*, Mahwah, NJ: Erlbaum.

44. Ruelle F, Takens F (1971) On the nature of turbulence, *Commun. Math. Phys., 20*, 167-192.

45. Rumelhart DE, McClelland & PDP Research Group (Eds.) (1986) *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Vol.1. Foundations*, The MIT Press: Cambridge, Mass.

46. Schalkoff RJ (1997) *Artificial Neural Networks*, New York: McGraw-Hill.

47. Stewart I & Cohen J (1997) *Figments of Reality. The Evolution of the Curious Mind*, Cambridge: Cambridge University Press.

48. Stoica A, Keymeulen D & Lohn J (Eds.) (1999) *Proceedings of the First NASA/DoD Workshop on Evolvable Hardware*, Los Alamitos: IEEE Computer Society.

49. Toffoli T (1995) Cellular Automata, In: Arbib (1995a), 166-169.

50. Toffoli T & Margolus N (1987) *Cellular Automata Machines*, The MIT Press: Cambridge, Mass.

51. Uhl C (Ed.) (1999) *Analysis of Neurophysiological Brain Functioning*, Berlin: Springer.

52. Uhl C & Friedrich R (1999) Spatio-Temporal Modeling Based on Dynamical Systems Theory, In: Uhl, 274-305.

53. Vallacher RA & Nowak A (Eds.) (1994) *Dynamical Systems in Social psychology*, San Diego: Academic Press.

* * *