The Brain as a Synergetic and Physical System

Hermann Haken

Center of Synergetics, Institut für Theoretische Physik 1, Universität Stuttgart, Pfaffenwaldring 57, 70550 Stuttgart, Germany
cos@itp1.uni-stuttgart.de
http://itp1.uni-stuttgart.de/institut/arbeitsgruppen/haken

Abstract. This paper presents an outline of our brain theory that we have developed over the past 30 years. Some remarks on the early stages of Synergetics that I initiated some 40 years ago are included. Using basic concepts of Synergetics such as order parameters and the slaving principle, brain functions are modeled both at the macroscopic (order parameter) and the microscopic (neuronal) levels. I deal with movement coordination, psychophysics (ambiguous figures), pattern recognition by the synergetic computer, my "light house model" of a neural net, and give some hints at applications to psychology and psychotherapy ("principle of indirect steering"). Finally, I discuss relations between Synergetics and Complexity Science.

1 The human brain

Our brain is the most complex system we know. It consists of about 100 billion neurons, where a single neuron can be connected with up to 10000 other neurons. This "system" enables our recognition of faces and objects, movement patterns, it serves movement control of our limbs, it produces our thoughts and allows us to express them by speech and gestures, it homes our feelings, just to mention a few characteristic features. But who or what steers the neurons so to produce all these marvelous processes? The famous neurophysiologist Sir John Eccles suggested that the brain is a computer and the mind its programmer. Indeed, the "computer" metaphor is still present in numerous publications (with the "mind" exorcised). In contrast to this picture, some thirty years (in 1982) ago I suggested to treat the brain as a "synergetic" system and jointly with E. Basar, H. Flohr, and A.J. Mandell (Basar et al. [1]), I organized a meeting entitled: "Synergetics of the brain". According to this suggestion, the brain is a self-organizing system, which can be theoretically treated by basic concepts and results of Synergetics.

2 Synergetics: Two examples from physics and a historical remark

I initiated this kind of study by a lecture, jointly with my then coworker Robert Graham in the winter term 1969/70, and continued it in the summer term 1970 (cf. also Haken, Graham [2]). To explain the incentive of our endeavor, I briefly recall my favorate subject of my research at that time:

A. Pelster and G. Wunner (eds.), *Selforganization in Complex Systems: The Past, Present, and Future of Synergetics*, Understanding Complex Systems,
DOI: 10.1007/978-3-319-27635-9_10

2.1 The laser paradigm

A typical example is the ruby laser (first realized by Maiman in 1960 [3]). In a crystal (Al_2O_3) rod, impurity atoms (Cr^+) are embedded. When excited by a "pump" lamp from the outside, the impurity atoms emit light which lends the ruby crystal its typical red color. Two mirrors (one semitransparent) mounted at the rod's end faces serve for a reflection of light waves, emitted in axial direction, so that they can intensely interact with the atoms. By means of stimulated emission (first introduced by Einstein to derive Planck's law of black body radiation), light waves are amplified and, eventually, leave the laser rod in axial direction. What happens, when we increase the pump power of the outer light source? First, light waves (or photons) are spontaneously emitted, which is an entirely *random process*. Even when the waves are enhanced by stimulated emission, which is expressed by the acronym laser (light emission by stimulated emission of radiation) this *randomness* ("Gaussian noise") persists (while the linewidth decreases with increasing pump strength). In the physics community, this line narrowing was considered as *the typical* feature of laser light (besides its high intensity and directionality). In 1964 I showed theoretically, that at a critical pump strength laser light undergoes a dramatic qualitative change (Haken [4]): the noisy output is replaced by a single highly ordered ("coherent") wave. This was the first example of an open (quantum) system far from equilibrium which shows a disorder-order transition actually in close analogy to phase-transitions of systems in thermal quilibrium, based on the Landau theory, as we elaborated later (Graham, Haken 1968,70; also de Giorgio, Scully 1970). But still more important: Here we had an explicit example of a process of *self-organization*!

2.2 A fluid heated from below

In order to bring out some typical features of self-organization which can be clearly visualized ("demonstrare ad oculos") I quote some experimental results (Fig. 1).

In a circular pan, a thin fluid layer (e.g. oil) is heated from below and cooled from above. If the temperature difference Δ between the lower and upper surface is small, heat is conducted microscopically: macroscopically the fluid is at rest. Beyond a critical Δ, a *macroscopic pattern* emerges: a honey comb structure (Bénard [5]). In spite of a completely *homogenous* heating and cooling, a highly ordered structure appears! When, in addition, also the border of the pan is heated uniformly, the structure changes qualitatively: the hexagons are replaced by a spiral (which can be one-or multi-armed) (Bodenschatz et al., experiments [6]; Bestehorn et al., theory [7]).

2.3 A historical remark

While the *laser* provides us with a quantum system away from thermal equilibrium that shows *temporal order*, the fluid exemplifies the formation of *spatially ordered patterns* in a classical non-equilibrium system.

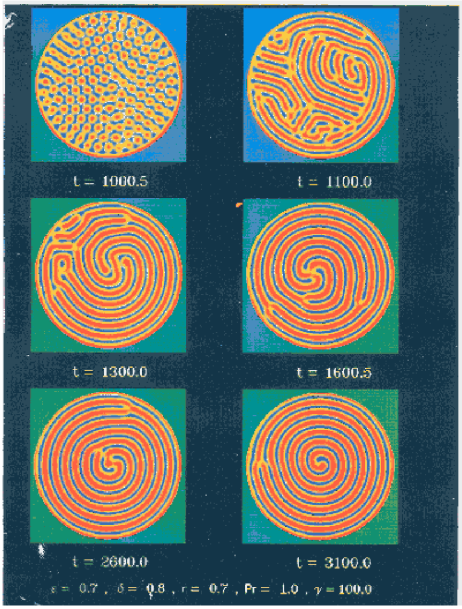

Fig. 1. Fluid layer heated from below.: l.h.s.: formation of hexagons, r.h.s.: formation of spirals when the border is heated in addition. (From Bestehorn, M., Fantz, M., Friedrich, R., Haken, H. [7].)

Are these two cases just two strange singular events (which even seemed to contradict the second law of thermodynamics) or are they just two manifestations of an important new class of phenomena? The attempt to answer such a question lies at the heart of my "Synergetics" endeavor. Historically, the incentive for my approach was – besides the laser paradigm – not the just mentioned example of fluid dynamics, but two phenomena of "phase transitions" in quite other fields, namely Sociology and biological evolution. In 1968 my close colleague Wolfgang Weidlich developed his theory on phase-transitions in the formation of public opinion (Weidlich 1971 [8]), and I learned of Manfred Eigen's work on the evolution of molecular species (Eigen [9]) (see also Eigen, Schuster [10], Weidlich [11]). So my conclusion at that time was: phase-transition-like phenomena must be ubiquitous.

To put this new insight into a broader context, in 1972 I organized a symposium on Synergetics (cf. its proceedings (Haken [12])).

My introduction started with the words "In many disciplines of science we deal with systems composed of many subsystems . . . Very often the properties of the large system cannot be explained by a mere random superposition of actions of the subsystems. Quite on the contrary the subsystems behave in a well organized manner, so that the total system is in an ordered state or shows actions which one might even call purposeful. Furthermore one often observes abrupt changes between disorder and order or transitions between different states of order. Thus the question arises, who are the mysterious demons who tell the subsystems in which way to behave so to create order, or, in a more scientific language, which are the principles by which order is created.” And I concluded my introduction with the statement … “that in spite of the completely different nature of the systems, their behavior is governed, at a well defined level of consideration, by a few very general principles which offers an explanation of the often amazingly similar performance of such systems.”

3 Synergetics: Goal

This interdisciplinary field of research, Synergetics (S.), deals with systems composed of many parts, elements etc. S. distinguishes between the *macroscopic* level and the *microscopic* level by length- and/or time-scale separation. S. studies the spontaneous formation of temporal, spatial, functional structures, i.e. the emergence of new qualities via *self-organization.* S. focusses its attention on *open* systems, i.e. systems subject to an in – and outflow of energy, matter and/or information. The central goal of S. is: *to unearth general principles (or laws) underlying self-organization irrespective of the nature of the individual parts of the considered systems.*

Thus the parts may be, e.g., atoms, photons, molecules, but also neurons or people in society. “It hardly needs to be mentioned that once such common principles are established, they are of an enormous stimulus and help for future research” (quotation from my preface to the proceedings of our first Synergetics meeting in 1972 (Haken [12])).

An important feature of Synergetics has always been to make contact with experiments as closely as possible. For more details cf. Haken [13–16] and the Springer Series in Synergetics.

In the present paper I don’t present the theoretical approaches but rather their verbalization. For lack of space, I must also refrain from discussing the various relationships between S. and general system theory (in the sense of L. von Bertalanffi [17, 18] dynamic systems theory including bifurcation theory, center and inertial manifold theory (e.g. Pliss [19], Kelley [20]), Robinson [21]), Landau theory of phase transitions (Landau, Lifshitz [22]), thermodynamics, statistical physics, quantum field theory, cybernetics and possibly other fields. (In my opinion, the work of myself and my coworkers has given substantial new insights into several of these fields).

4 Synergetics: Basic concepts

4.1 Control parameters

They qualitatively describe the input of energy, matter, information into the considered system. Examples are: power input into the laser, temperature difference in convection experiments.

In brain dynamics: Coffein (blocks Serotonin receptors), Haldol (blocks Dopamin2 receptors), neurotransmitters, neuromodulators, hormones (e.g. oxytocine); the latter acting as internal control parameters.

4.2 Instability

At a critical control parameter value the state of a system tends to disappear and to be replaced by a new one. Critical fluctuations may occur that drive the system into its new state.

4.3 Order parameters

occur close to the instability point. They are new collective variables that serve as macroscopic *descriptors*. They are in general few and obey low dimensional nonlinear dynamics subject to fluctuations.

4.4 Slaving principle

The order parameters determine the behavior of the individual parts (like a puppeteer who lets the puppets dance).

4.5 Circular causality

In contrast to the "puppeteer" metaphor, the puppets – through their cooperation – determine the behavior of the order parameters. This raises far reaching ontological questions. (catchword: mind-body problem) that I will not discuss here.

At any rate: This concept allows us to treat a synergetic (self-organizing) system at two levels:

– macroscopic: order parameters
– microscopic: "consensualization" between parts (elements)

While the second approach requires very many data, the former requires few data ("information compression"). In the following I will elaborate on this distinction in the context of brain dynamics.

5 The phenomenological level I Movement coordination and order parameters

In 1981 Scott Kelso published his experimental results on human movement coordination (Kelso [23]). He instructed subjects to move their index fingers in parallel at a given frequency, ω. While at low frequency the subjects could perform this movement, at an increased, critical frequency ω_c, the movement switched involuntarily to a *symmetric* coordination (Fig. 2). This transition was

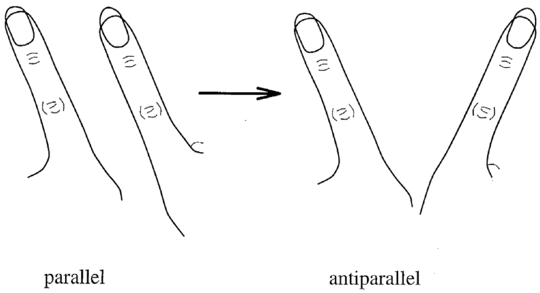

Fig. 2. Kelso Experiment: Change of relative phase in index finger movement

modeled by Haken, Kelso, Bunz (HKB) [24] in the spirit of Synergetics: The pronounced change of the movement pattern occurs at a critical frequency, ω_c. Thus the frequency ω serves as *control parameter*.

The relative position of the index fingers can be mathematically captured by a relative phase ϕ. Because ϕ changes at $\omega = \omega_c$, it may serve as *order parameter*.

As had been elaborated previously in Synergetics, the order parameter dynamics can be modeled by an equation of the form

$$\frac{d\phi}{dt} = \frac{\partial V(\phi)}{\partial \phi} + F(t) \;, \tag{1}$$

where V is a "potential" and $F(t)$ a stochastic force. The crux was to find a suitable $V(\phi)$. Our model V is depicted in Fig. 3. Initially (upper valley) the movement state is characterized by $\phi = \pi$. With increasing ω, the corresponding potential minimum flattens and disappears: The state $\phi = \pi$ undergoes an *instability* and changes into $\phi = 0$.

Now, again in the spirit of Synergetics, a number of important conclusions can be drawn:

1. *hysteresis*: When lowering ω, the "system" will not return from $\phi = 0$ to $\phi = \pi$.
2. a flat potential implies *critical slowing* down and
3. *critical fluctuation* (see Fig. 4).

Kelso and his co-workers were able to experimentally (even quantitatively) verify our predictions. These results lead us to conclude that the brain does not act according to a computer motor program. Rather the features 1-3 are characteristic of self-organization. This is a strong hint at our interpretation that *the brain is a self-organizing system.*

Further beautiful experiments on this issue were performed by Kelso and his group, while theory was carried further by L. Borland, A. Daffertshofer, T. Frank, A. Fuchs, G. Schöner and others, both at Stuttgart and Boca Raton, FA. (For reviews cf. e.g. Kelso [26], Haken [27]). A general conclusion based on these experiments and related ones is: Humans (as well as animals, e.g. quadrupeds)

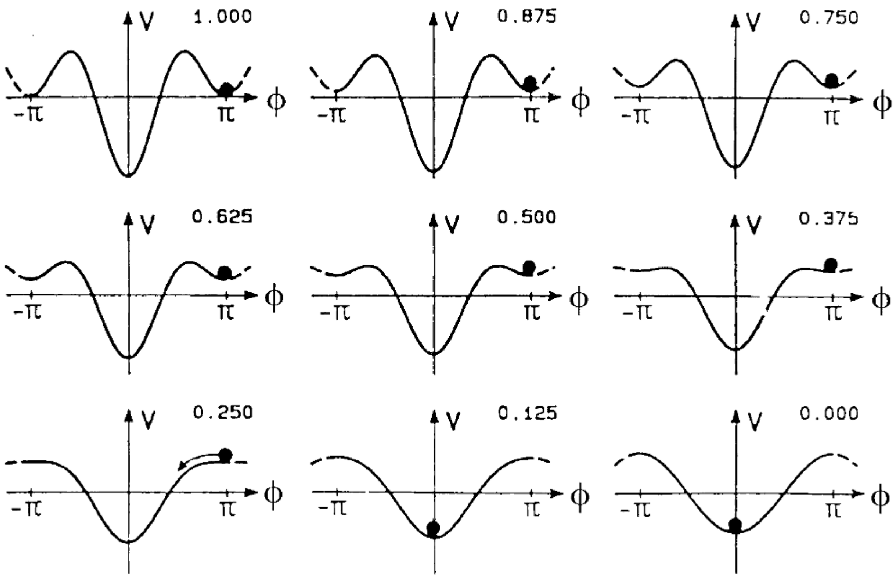

Fig. 3. Change of potential V when frequency ω is increased. Read Fig. from upper left to lower right corner (Haken et al. [24]).

realize only specific movement patterns depending on control parameters, e.g. prescribed speed of performance.

6 The phenomenological level II Psychophysics and order parameters

Our starting point is a typical relation between order parameters and the enslaved parts: While order parameters react to external influences ("perturbations") slowly, parts act on a faster time-scale (time-scale separation). This invites us to the following analogy with brain processes:

While percepts are processed on time scales of 1/10 sec or still longer, neurons function on a time scale of milliseconds.

These facts suggest to establish an analogy (for a review cf. Haken [27])

$$\text{percepts} \leftrightarrow \text{orderparameters}$$
$$\text{neurons} \leftrightarrow \text{parts(elements)}$$

Note the ontological question that lurks behind this analogy!

Nevertheless, let us study a few typical cases of order parameter dynamics with respect to perception. A typical order parameter potential has two valleys indicating two different stable order parameter values, i.e. *bistability*. Which is actually happening in perception (Fig. 5). Do you perceive Einstein's face or?

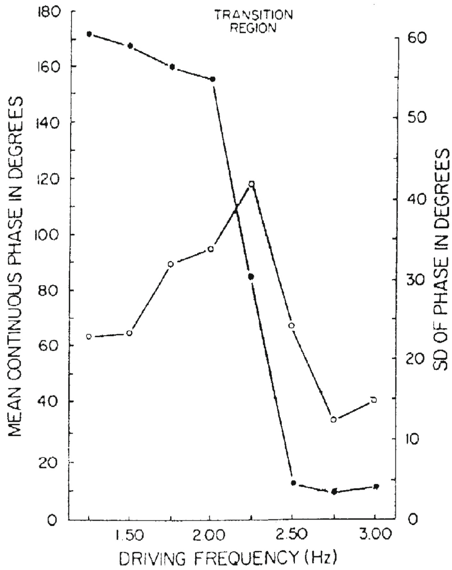

Fig. 4. Fluctuations of relative phase (open circles) and mean phase (solid dots) versus driving frequency (Kelso et al. [25])

Thus, the same picture "induces" two quite different percepts, i.e. "bistability" in perception. Strictly speaking over a somewhat longer time span, oscillations occur (see below). I owe Michael Stadler (Bremen) the hint to oscillations in perception.

A further example is hysteresis, we already came across above in a different context. Hysteresis means that the state of a system depends on history. Fig. 6 provides us with an example from perception: The switching from the perception of a man's face (upper left corner) to that of a kneeling woman (lower right corner) depends on the sequence in which we look at this series of pictures.

In the case of two order parameters, oscillations may occur (limit cycles in the sense of dynamical system theory). In perception such oscillations may be observed when looking at ambiguous figures (Fig. 7). Old or young lady? The dynamics was mathematically modelled under the assumption that each percept is controlled by an "attention" parameter that fades away after that the percept is recognized. As I learned later, Gestaltpsychologist Wolfgang Köhler had made the same suggestion in 1920 [29] (though he didn't model it mathematically). Our model allowed us to establish several relationships between first recognition time, bias, recognition times etc. (Ditzinger, Haken [30]), and to make contact with experimental results (Borsellini et al. [31, 32]).

Fig. 5. Bistability in perception: Einstein's face or three bathing girls?

7 Down to the microscopic level: models Pattern recognition by the synergetic computer

Here, I exploit an analogy between pattern *formation* and pattern *recognition*. This analogy is based on the concepts of order parameters, on the slaving principle, and on circular causality (for a review cf. Haken [33]).

In *pattern formation*, let initially a part of the total system be in an ordered state. This part calls on, in general, several order parameters which then compete among each other. The initially stronger order parameter wins this competition ("principle of winner takes all") and, eventually enslaves the total system, i.e. it establishes a fully ordered pattern. (An example: in the convection instability, initially a single roll is prescribed. Then, by the just described mechanism, a complete system of parallel rolls is formed.)

In pattern *recognition*, the individual parts are features, e.g. grey values of pixels into which a pattern is decomposed. Consider as a concrete example face recognition. Then only some features, e.g. that of a nose, may be given. Those features call upon order parameters which compete among each other, the initially strongest wins and, again via the slaving principle, restores the whole pattern, e.g. face. Cf. Fig. 8: example of stored prototype patterns, and Fig. 9: recognition process, based on the following algorithm, which I formulate, quite in the spirit of Synergetics, both at the microscopic (feature) level and at the macroscopic (order parameter) level.

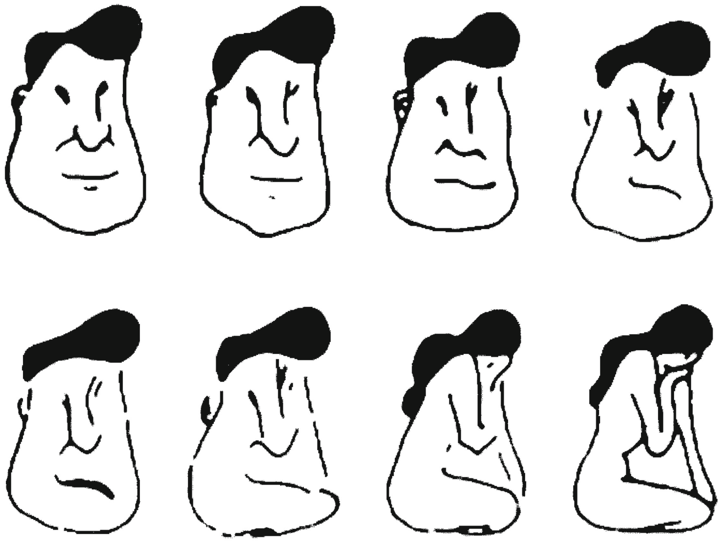

Fig. 6. Hysteresis in perception (cf. text)

At the microscopic level, each pixel $l, l = 1, ...L$, is represented by its grey value q_l, which is mapped onto a neutral net so that q_l is also the excitation level of the model neuron l. Then I introduced evolution equations for the state vector $q = (q_1, ..., q_L)$,

$$\dot{q}(t) = -\mathrm{grad}_q V(q, c) \ , \tag{2}$$

where V is a polynominal of q up to fourth order with coefficients $c = (c_{ll'}, \dots)$ that can be interpreted as synaptic strengths. V describes a hilly landscape which I constructed in such a way that each of its valleys corresponds to one and only one of the prototype patterns: The corresponding values of c can be either inserted "by hand" into the computer or, more importantly, learned by the rule

$$\langle V(q, c) \rangle_q = \min ! \ , \tag{3}$$

where the average $\langle \ \rangle$ refers to a sequence of partially incomplete patterns whose "idealization" is thus achieved. My algorithm was implemented by my former co-worker Armin Fuchs on a serial computer (cf. Figs. 8, 9) (Fuchs, Haken [34]), where recognition has been made invariant against displacements, rotation and scaling. Using attention parameters and their fading away (cf. Sect. 6) our approach was also able to recognize faces in a complex scene. An example is given by Fig. 10. The transition to the macroscopic (order parameter) level is achieved by the transformation of the pixel vector q

$$q(t) = \sum_k \xi_k(t) \nu_k + \mathrm{rest} \ , \quad k = 1, \dots, k \leq L \tag{4}$$

Fig. 7. Oscillations in perception (cf. text)

where $\xi_k(t)$ is the order parameter associated with the prototype pattern vector

$$\nu_k = (\nu_{k1}, \ldots, \nu_{k,L}) \ . \tag{5}$$

The resulting order parameter equations are

$$\dot{\xi}_k = \xi_k \left(\lambda_k + a\xi_k^2 - b \sum_m \xi_m^2 \right) \ , \tag{6}$$

wih $\lambda_k \geq 0$ the attention parameters, and $a, b > 0$.

A comparison with the vast body of pattern recognition procedures developed by other authors can be only sketched.

My procedure belongs to the class of recurrent neural attractor networks. The probably best known example is the Hopfield net (Hopfield [35]). Its disadvantage is the large number of spurious attractor states. To let the dynamical system escape from these unwanted attractors, the laborious procedure of simulated annealing has to be applied. The Grossberg/Carpenter procedure rests on Lyapunov functions (Carpenter, Grossberg [36]) which are less precise than our potential function, however.

8 Down to the physical level of the brain: Coping with the dynamics of "real" neurons

This problem has been dealt with by several members of my former institute, including A. Daffertshofer, T. Frank, V. Jirsa, P. Tass. Of course, there are also approaches by other authors. Here I present my own "light house model" (cf. Haken [37]) which starts from some well known experimental findings. A typical

Fig. 8. Example of stored prototype patterns (after Fuchs, Haken [34])

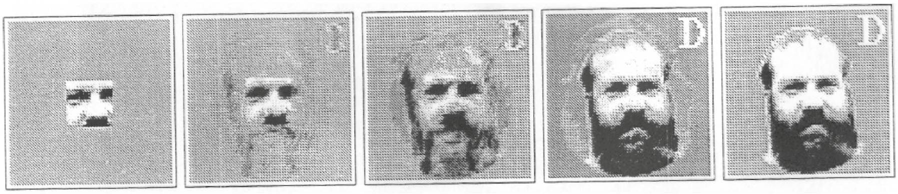

Fig. 9. Example of recognition process (after Fuchs, Haken [34])

neuron emits spike trains into its axon which branches making contact to other neurons. The contact is achieved by synapses which convert spikes into electric currents to the soma of the neuron, which sums them up, and "fires" beyond a threshold, i.e. it emits a spike train. The basic equations of the light house model are:

1. Electric current ψ_m of dendrite m is generated by an axonal pulse from neuron k:
$$\left(\frac{d}{dt}+\gamma\right)^{\alpha}\psi_m = a_{mk}P_k \ . \qquad (7)$$
Here, γ is a damping constant, exponent α with $1 < \alpha < 2$ is a fraction in accordance with experiments, a_{mk} is an experimentally determined transformation rate. (A more general formulation contains a sum over k on the r.h.s.)
2. Pulse production by neuron k, light house analogy:
When the rotating light beam emitted from a light house hits an observer, he or she will notice a series of light flashes ("spikes"). Their time intervals depend on the rotation speed of the beam.
The direction of the beam is described by an angle ϕ. If the beam hits the observer at $\phi = 0$, then (s)he will be hit again and again at times $t_n, n = 1, 2, \ldots$, where $\phi(tn) = 2\pi n$.

Fig. 10. Recognition of a complex scene (after Fuchs, Haken [34])

Thus the rotation speed $\dot{\phi}$ determines the spike emission rate, which, in the case of a neuron, is determined by the incoming dendritic currents. I model this effect by means of the equation

$$\dot{\phi}_k(t) + \Gamma\phi_k(t) \bmod 2\pi = \sum_m C_{km}\psi_m(t) + \sum_{ml} d_{kml}\psi_m(t)\psi_l(t) + p_k \ , \quad (8)$$

where p_k is the incoming signal. I have treated these equations rather extensively (including also time-delays and noise). Here I mention only two special cases: In the case of dense pulse sequence I was able to derive the equations of the synergetic computer [33, 38] so that my equations allow pattern recognition. Under different conditions, my equations describe spike train synchronization where contact can be made with experiments by Gray and Singer [39] as well as by Eckhorn et al. [40] and their respective groups.

9 Further down to the molecular level

In the foregoing I have given a brief sketch of how I had applied basic concepts of Synergetics to different levels of brain functions. In this approach, neurons (somata), axons and dendrites are treated as entities. But these "devices" are, by themselves, complicated systems, composed of molecules. Among the numerous phenomena at this level, the following intrigues me particularly (cf. Alberts et al. [41] for a review).

In an axon, there are microtubuli enbedded, which are long fibers. Along them, biomolecules called kinesin may move by means of movable "heads" (or better "legs"). The kinesin molecules can transport organels that are larger than the kinesin. Powered by ATP, kinesin is an open system – to be treated as a quantum system.

In our recently (September 2012) published book: Haken/Levi: Synergetic Agents [42] we have started to deal with such processes. In a first step we treated a related problem: muscle contraction based on the propagation of myosin molecules on actin fibers by using methods of quantum field theory and quantum statistics of systems far from equilibrium.

10 Back to the phenomenological level: Psychology and psychotherapy

Interestingly, Synergetics, originally quite unexpected, has made its way into psychology and psychotherapy (cf. also the contribution by Günter Schiepek to these proceedings, as well as Haken and Schiepek [43]). Clearly in the present context, a few remarks must suffice here.

Behavioral patterns may be conceived as order parameters. Thus changes of behavioral patterns can be interpreted as phase transitions, often with their typical features, e.g. critical fluctuations. Research in Synergetics has revealed the important role of the *principle of indirect steering*.

This means, the change of a *control parameter* can induce the evolution of a new (behavioral) pattern by means of self-organization. This has fired a discussion on appropriate control parameters in psychotherapy: specific verbal interventions, or specific drugs? Or both?

Eventually, Synergetics cannot escape to try an answer to the eternal mind-body problem (on which I am presently having fascinating discussions with Harald Atmanspacher and Wolfgang Tschacher).

My suggestion is the analogy

$$\begin{aligned} &\text{body} \quad\quad \leftrightarrow \text{parts} \\ &\text{mind} \leftrightarrow \text{orderparameters} \end{aligned}$$

Thus in view of the principle of "circular causality" mind and body are just two sides of the same coin. As I had learned in the meantime, this is just the opinion of Spinoza. Just to conclude this section with a burning question: Will the problem of *qualia* remain an eternal enigma?

11 Concluding remarks and outlook

Out of the vast field of Synergetics with its relations to many scientific disciplines, I have presented a small section.

I have chosen the example of our attempts to model some aspects of brain function to elucidate how basic concepts of Synergetics can be applied to this fascinating field. As our studies (seem to) suggest, the human brain manages to compress the complexity of perception and action time and again into low dimensional dynamics of a rather small number of – in each case appropriately established – order parameters.

Critics may object that this is a too narrow view based on a "Synergetic bias". On the other hand, our brain manages to compress the complexity of our world all the time: e.g. by categorization as witnessed by language. Thus I think that the Synergetics approach may be a useful tool to cut one's way through the jungle of the brain's complexity.

At any rate, this issue brings me to discuss the relation between *Synergetics* and the presently flourishing field of *Complexity Science*. Synergetics is surely one (or even the) forerunner of Complexity Science, both of which share their emphasis on *interdisciplinarity*. But there are also differences that are best explained by looking at the different styles of scientific work:

1. Production of new data (information production)
2. Formulation of principles, laws etc. (information compression)

When I defined the scope of Synergetics I strongly emphasized 2.

Searching for common principles still remains an important goal which has to go along also with 1. This is clearly demonstrated by the various presentations at the Delmenhorst meeting (cf. these proceedings).

Readers interested in Synergetics/Complexity Science are referred to the monograph series edited by H. Haken and S. Kelso (cf. references [14], [28]).

References

1. Basar, E., Flohr, H., Haken, H., Mandell, A.J.: Synergetics of the Brain. Springer Verlag, Berlin (1983)
2. Haken, H., Graham, R.: Synergetik, die Lehre vom Zusammenwirken. Umschau **6**, 191–195 (1971)
3. Maiman, T.H.: Stimulated optical radiation in ruby. Nature **187**, 493–494 (1960)
4. Haken, H.: A Nonlinear Theory of Laser Noise and Coherence. 1. Zeitschrift für Physik **181**, 96–124 (1964)
5. Bénard, H.: Rev. Gen. Sci. Pures Appl. **11** 1261, 1309 (1900)
6. Bodenschatz, E., Cannell, D.S., de Bruyn, J.R., Ecke, R., Hu, Y.-C., Lerman, K., Ahlers, G.: Experiments on three systems with non-variational aspects. Physica D **61**, 77–93 (1992)
7. Bestehorn, M., Fantz, M., Friedrich, R., Haken, H.: Hexagonal and spiral patterns of thermal convection. Phys. Lett. A **174**, 48–52 (1993)
8. Weidlich, W.: The statistical description of polarization phenomena in society. Brit. J. Math. Stat. **24**, 251–266 (1951)
9. Eigen, M.: The self-organization of matter and the evolution of biological macromolecules. Naturwissenschaften **58**, 465–523 (1971)
10. Eigen, M., Schuster, P.: The Hypercycle: A Principle of Natural Self-Organization. Springer, New York (1979)
11. Weidlich, W.: Sociodynamics: A Systematic Approach to Mathematical Modelling in the Social Sciences. Harwood Academic Publishers, Amsterdam (2000)
12. Haken, H. (ed.): Synergetics. Cooperative Phenomena in Multi-Component Systems. B.G. Teubner, Stuttgart (1973)
13. Haken, H.: Synergetics. An Introduction. Nonequilibrium Phase Transitions and Self-Organization in Physics, Chemistry and Biology. Springer, Berlin (1977)
14. Haken, H. (ed.): Springer Series in Synergetics, founded in 1977, now part of the Springer Complexity Program. Springer, Berlin
15. Haken, H.: Advanced Synergetics. Instability Hierarchies of Self-Organizing Systems and Devices. Springer, Berlin (1983)

16. Haken, H.: Synergetics. Introduction and Advanced Topics. Springer, Berlin (2004)
17. Von Bertalanffi, L.: The theory of open systems in physics and biology. Science **111**, 23–29 (1950)
18. Von Bertalanffi, L.: Biophysik des Fließgleichgewichts. Vieweg, Braunschweig (1953)
19. Pliss, V.A.: A reduction principle in the theory of stability of motion. IZV. Akad. Nauk SSSR., Mat. Ser. **28**, 1297 (1964)
20. Kelley, A.: In: Abraham, R., Robbin, J. (eds.) Transversal Mappings and Flows. Benjamin, New York (1967)
21. Robinson, J.C.: Finite-dimensional behavior in dissipative partial differential equations. Chaos **5**, 330–345 (1985)
22. Landau, L.D., Lifshitz, I.M.: Course of Theoretical Physics, vol. 5. Statistical Physics. Pergamon-Press, London (1959)
23. Kelso, J.A.S.: On the oscillatory basis of movements. Bulletin of Psychonomic Society **18**, 63 (1981)
24. Haken, H., Kelso, J.A.S., Bunz, H.: A Theoretical model of phase transitions in human movements. Biol. Cybernetics **51**, 347–356 (1985)
25. Kelso, J.A.S., Scholz, J.P., Schöner, G.: Non-equilibrium phase transitions in coordinated biological motion: Critical fluctuations. Physics Letters A **118**, 279–284 (1986)
26. Kelso, J.A.S.: Dynamic patterns: The self-organization of brain and behavior. MIT Press, Boston (1995)
27. Haken, H.: Principles of Brain Functioning. A Synergetic approach to Brain Activity, Behavior and Cognition. Springer, Berlin (1996)
28. Kelso, S. (ed.), Monograph Series: Understanding Complex Systems, as part of the Springer Complexity Program. Springer, Berlin
29. Köhler, W.: Die physischen Gestalten in Ruhe und im stationären Zustand. Vieweg, Braunschweig (1920)
30. Ditzinger, T., Haken, H.: Oscillations in the perception of ambiguous patterns. Biol. Cybern. **61**, 279–287 (1989)
31. Borsellino, A., deMarco, A., Allazetta, A., Rinesi, S., Bartollini, B.: Reversal time distribution in the perception of visual ambiguous stimuli. Kybernetik **10**, 139–144 (1972)
32. Borsellino, A., Carlini, R., Riani, M., Tuccio, M.T., deMarco, A., Penengo, P., Trabucco, A.: Effects of visual angle on perspective reversal for ambiguous patterns. Perception **11**, 263–273 (1982)
33. Haken, H.: Synergetic computers and cognition. Springer, Berlin (1991)
34. Fuchs, A., Haken, H.: Pattern recognition and associative memory as dynamical process in a synergetic system I+II, Erratum. Biol. Cybern. **60**, 17–22, 107–109, 476 (1988)
35. Hopfield, J.J.: Neural networks andphysical systems with emergent collective computational abilities. Proc. Natl. Acad. Sci. **79**, 2554–2558 (1982)
36. Carpenter, C., Grossberg, S.: The art of adaptive pattern recognition by a self-organizing neural network. Computer, 77–87, March 1980
37. Haken, H.: Brain Dynamics. An Introduction to Models and Simulations. Springer, Berlin (2002/2007)
38. Haken, H.: Synergetic computers for pattern recognition and associative memory. In: Haken, H. (ed.) Computational Systems, Natural and Artificial, pp. 2–22. Springer, Berlin (1987)
39. Gray, C.M., Singer, W.: Stimulus specific neuronal oscillations in orientation columns of cat visual cortex. Proc. Natl. Acad. Sci. USA **86**, 1698–1702 (1987)

40. Eckhorn, R., Bauer, R., Jordan, W., Brosch, M., Kruse, W., Munk, M., Reitblöck, H.J.: Coherent oscillations: a mechanism of feature linking in the visual cortex? Multiple electrode and correlation analyses in the cat. Biol. Cybern. **60**, 121–130 (1988)
41. Alberts, B., Johnson, A., Lewis, J., Raff, M., Roberts, K., Walter, P.: Molecular Biology of the Cell, 5th edn., Garland Science, Part of Taylor and Francis Group LLC (2008)
42. Haken, H., Levi, P.: Synergetic agents. From multi-robot systems to molecular robotics. Wiley, Weinheim (2012)
43. Haken, H., Schiepek, G.: Synergetik in der Psychologie. Hogrefe, Göttingen (2006)