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Springer-Verlag

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With 71 Figures

Springer-Verlag Berlin Heidelberg New York
London Paris Tokyo Hong Kong

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The *cover picture* shows a ganglion cell, part of the retina of the eye of a rabbit, enlarged about 5000 diameters. The cell responds to the movement in one direction of an object in the field of view by sending electrical impulses to the brain, and ignores motion in the opposite direction. The cell was identified and stained by Frank R. Amthor, Clyde W. Oyster and Ellen S. Takahashi at the University of Alabama.

CR Subject Classification (1987): I.2, G.0, C.1, F.1

ISBN 3-540-51393-0 Springer-Verlag Berlin Heidelberg New York
ISBN 0-387-51393-0 Springer-Verlag New York Berlin Heidelberg

Library of Congress Cataloging-in-Publication Data
Serra, Roberto, 1952–
Complex systems and cognitive processes / Roberto Serra, Gianni Zanarini.
p. cm. Includes bibliographical references.
ISBN 0-387-51393-0
1. Artificial intelligence. 2. Neural computers. I. Zanarini, Gianni, 1940–. II. Title.
Q335.S435 1990 006.3-dc20 89-26096 CIP

Printed in Germany

Media conversion: EDV-Beratung Mattes, Heidelberg
2145/3140-543210 - Printed on acid-free paper

To

Francesca, Eleonora, Elisabetta,
Lorenzo and Gabriele

Preface

This volume describes our intellectual path from the physics of complex systems to the science of artificial cognitive systems. It was exciting to discover that many of the concepts and methods which succeed in describing the self-organizing phenomena of the physical world are relevant also for understanding cognitive processes. Several nonlinear physicists have felt the fascination of such discovery in recent years.

In this volume, we will limit our discussion to artificial cognitive systems, without attempting to model either the cognitive behaviour or the nervous structure of humans or animals. On the one hand, such artificial systems are important *per se*; on the other hand, it can be expected that their study will shed light on some general principles which are relevant also to biological cognitive systems.

The main purpose of this volume is to show that nonlinear dynamical systems have several properties which make them particularly attractive for reaching some of the goals of artificial intelligence.

The enthusiasm which was mentioned above must however be qualified by a critical consideration of the limitations of the dynamical systems approach. Understanding cognitive processes is a tremendous scientific challenge, and the achievements reached so far allow no single method to claim that it is the only valid one. In particular, the approach based upon nonlinear dynamical systems, which is our main topic, is still in an early stage of development.

The human brain evolved by adopting an "opportunistic" strategy, and artificial cognitive systems should in an analogous way evolve towards an integration of different paradigms, in particular towards a coupling of dynamical systems with classical AI techniques.

The structure of this book reflects these beliefs. The most successful and most thoroughly studied dynamical cognitive systems are connectionist models: therefore much attention is given to neural network models. Indeed the volume can also be used as an introductory textbook about connectionism.

However, the most attractive features of connectionist models are shared by a wider class of dynamical systems. In our view, emphasis should be placed upon these properties of dynamical systems rather than on the fact that the latter could be interpreted as networks of highly simplified neurons. Therefore, room is left also for dynamical cognitive systems different from neural networks.

Classifier systems are given much emphasis, since they can provide a link between the dynamical and the inferential approach to AI.

The presentation given here is by no means complete. The literature in this field is large and rapidly growing: the emphasis placed upon the different models reflects reasons of scientific interest, historical importance, personal taste and, as in every human affair, randomness. Our choice was to treat, first and foremost, some models which allowed us to illustrate, as clearly as possible, what we believe to be the most significant characteristics of the dynamical approach to artificial intelligence. We do not mean that the space given to the different models is a measure of their scientific or applicative importance.

Moreover, this volume is concerned essentially with ideas, methods and techniques. We did not feel it appropriate to include a detailed account of work on applications, since this would soon become old, while we hope that at least some of the ideas presented here may have a longer decay constant.

This volume is the result of the joint work by both of us; however, the major influence in Chaps. 1, 3 and 5 was by GZ, and in Chaps. 2, 4, 6 and 7, by RS.

We wish to acknowledge here the support of the University of Bologna, Enidata and Tema to our work. Such support was not only financial, but also scientific and cultural. Particular thanks are due to Vincenzo Gervasio, Francesco Zambon, Silvio Serbassi and Paolo Verrecchia.

The development of the ideas presented here has been made possible by the stimulating collaboration with some friends and colleagues: Mario Compiani, Daniele Montanari and Gianfranco Valastro. Most of the results presented here have been obtained by working with them on specific research projects.

The contribution of some bright students (Franco Fasano, Paolo Simonini and Luciana Malferrari) has also been very important.

We have also enjoyed the benefit of deep and fruitful discussions with Marco Vanneschi and Fabrizio Baiardi about the relationship between dynamical networks and parallel computation, with Tito Arecchi and Gianfranco Basti about the role of chaos in neural models, with Francoise Fogelman about layered feedforward networks and with Luc Steels about non-neural dynamical systems for AI and about genetic algorithms. On this latter topic, also fruitful discussions with John Holland and Heinz Muehlenbein are gratefully acknowledged. Rick Riolo kindly provided us with the CFS-C software package for classifier systems. We also benefited from a stimulating discussion with Edoardo Caianiello about the past and the future of neural networks.

Thanks are due also to Derek Jones, who carried out a careful English translation of our work.

We finally wish to express our gratitude to Hans Wössner and to his staff at Springer-Verlag for their interest and their support to our book, and for their friendly and careful editorial work.

Bologna, January 1990

Roberto Serra
Gianni Zanarini

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1. Introductory Concepts

1.1 Complex Systems and Self-organization

Observing many natural phenomena (such as a flame, a smoke-ring, a procession of clouds) we are often surprised by their regularity, their organization, their dynamical order. The science of complex systems has undertaken the study of these aspects of simplicity which emerge from interactions amongst a myriad of elementary "objects". It has stepped forward to answer the questions which present themselves when we observe more closely, with greater attention, many systems with which we have become acquainted from daily experience.

This order, which we often observe over a certain space-time scale, how does it arise? From where do the individual elementary objects get the information necessary for them to conform to the global order? Furthermore, it is an order which relates to a completely different space-time scale from any meaningful one at the level of the individual elements themselves. Where does the design for this emergent order lie? From where is it controlled?

The answer provided by the science of complexity centres upon the development of the concept of "self-organization", which expresses precisely this possibility of highly organized behaviour even in the absence of a pre-ordained design (Haken, 1978; Nicolis and Prigogine, 1977; Serra et al., 1986).

As an example, in order to clarify the genesis of a self-organized situation in a physical system, we will refer to a particularly interesting system: the laser. To a first approximation, one can consider this system as being composed of a volume of "active material" placed between two mirrors and of a suitable external energy source. The atoms of the active material function as "oscillators": once promoted to an excited state, they can emit electromagnetic radiation of a characteristic frequency; they can also absorb incident radiation of the same frequency. Emission, in particular, can take place either spontaneously or through a kind of "resonance" with the incident radiation ("stimulated emission").

Usually, in response to an external excitation, a system of this type shows an "uncorrelated" emission, such as that giving rise to light emission in a normal electric lamp. However, under particular conditions, defined by the geometry of the system and by the intensity of the external radiation, the oscillators get synchronized and operate in a cooperative mode, supplying a highly coherent emission of radiation. In this case, the light waves produced by the cooperative behaviour of the individual atoms act as "messengers of a possible order" towards the individual atoms themselves, whose behaviour they condition.

In this example (although its illustration has been greatly simplified for reasons of brevity) we can see the development of a self-organization which is a consequence of the collective behaviour of a large number of atoms. This self-organization, however, can be recognized and is meaningful only over a space-time scale which is different from that of the atoms, being much more aggregate.

Even within physics, one can find many other self-organization phenomena, so many that we begin to think that we may be changing our way of looking at the world: we observe today, with great attention and wonder, ordered dynamical structures which in the past we took for granted, or considered as being not particularly interesting.

Let us recall another case: the thermo-hydrodynamic instabilities in a fluid close to its boiling point. It is well-known that, under the action of a thermal gradient, produced and maintained externally, convection currents develop within the fluid. As in the case of laser, under suitable experimental conditions, these currents take shape according to regular structures of a characteristic "beehive" form (Bénard cells), which indicate the presence of a high level of molecular cooperation (Haken, 1978).

One striking aspect of these physical examples is the fact that the establishment of a self-organized behaviour depends upon parameters with quite a meagre information content about the characteristics of the self-organization. The geometrical structure and the radiation intensity in a laser, like the physical dimensions and the thermal gradient in thermo-hydrodynamical instabilities, "know nothing" of the self-organization which emerges in the system, just as the atoms of the active material or the molecules of the fluid know nothing of it.

As we shall see in Chap. 3, this observation can be reformulated in mathematical terms, because the cooperative effects and the corresponding self-organization processes may be described by means of nonlinear equations which usually allow multiple asymptotic solutions; the variation of suitable parameters can alter the stability characteristics of the solutions, so inducing transitions from one to another.

At this point, however, a cautionary note is necessary. These allusions to the themes of self-organization might seem to suggest that, in all cases, a greater order and a greater simplicity emerge at the more aggregated levels. In many cases, however, on aggregate space-time scales, highly complex situations may be observed which can be characterized in terms of "deterministic chaos" (Arecchi, 1986; Serra et al., 1986). This theme will be taken up again in Chap. 3.

1.2 Self-organization in Artificial Systems

It might seem that the above considerations refer exclusively to natural systems. But, if we reflect for a moment, we realize that this is not true. Take, for example, the laser: it is a system which, while being based upon natural processes and showing an effect which in some cases may be found in nature, is normally built and operated according to a design. Can we then say that what is observed in a laser is an example of "designed self-organization"?

The laser lies in an intermediate position between natural and artificial systems. Its designer, in fact, can neither foresee nor control the behaviour of the single elements (in this case, the atoms of the active material). The design essentially regards the control parameters which affect the system's behaviour.

A completely artificial system is one which does not critically depend upon a material support. The best examples of completely artificial systems are abstract mathematical and logical systems. Even though an abstract system is made up of a large number of elements, every one of them can be defined a priori. Therefore, we must clarify the meaning of self-organization in artificial systems.

In order to enlarge upon this point, we will briefly examine a particular class of artificial systems, which will be dealt with in detail in Chap. 3: one-dimensional cellular automata (Wolfram, 1986). Consider a large number of binary elements (i.e. which can only take the values 0 or 1) and suppose that these elements are placed in a regular fashion along a line, each being connected to its two "nearest neighbours" (next left and next right). At any discrete point in time, the state of each element is defined by a function of the states of the element itself and of its two nearest neighbours at the preceding time-step. For simplicity, we will assume that this function is the same for all the elements. To avoid boundary problems, we also assume that the system closes upon itself to form a circle.

A detailed examination of the various types of automata and their classification is given in Chap. 3. For the moment, we will show that cellular automata, although extremely simple from the point of view of their "elementary laws", may exhibit unexpected and complex behaviours which can be considered as self-organized.

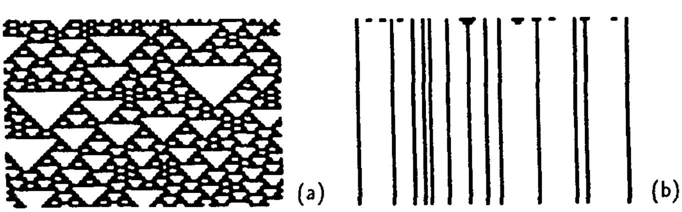

Fig. 1.1a,b. Two examples of one-dimensional cellular automata. Time evolution is from top to bottom of figure

To illustrate this statement, let us first of all consider the automaton in Fig. 1.1a, and follow its time evolution starting from randomly defined initial conditions. Black dots represent 1's, while white dots represent 0's. Time evolution is from the top to the bottom of the figure. As seen in the figure, the system shows a behaviour which is both ordered and predictable: in the space-time plane, in fact, we can see the appearance and the disappearance of triangular structures of various dimensions. From an undifferentiated initial state (that is, with the same probability of having one or the other of the two possible values at any position) the system moves on to a multiplicity of well-differentiated domains which evolve over time. Another ordered system is shown in Fig. 1.1b. In this case, after a short initial transient, the system behaves in an extremely regular manner, giving rise to a time-independent configuration. The detailed structure of this configuration (number of "lines" and distance between "lines") depends upon the initial conditions.

We can then say that, in these systems, a kind of spontaneous self-organization takes place, which brings them closer to the physical systems mentioned above. Their organization, in fact, does not derive directly from an external design: the design does not regard the whole system, but only the individual elements, whose interaction gives rise to an overall regularity (whether it be time-dependent, as in the case of the "triangles" in Fig. 1.1a, or time-independent, as in the case of the "lines" in Fig. 1.1b).

Self-organization, therefore, may arise not only from the interaction between unknown microscopic dynamics, but also from the practical impossibility of foreseeing all possible kinds of collective behaviour which can emerge from the interactions between microscopic elements.

This leads to an extremely important consequence: in a more radical way than in the case of natural systems, self-organization in abstract systems is not an observer-independent concept.

In order to describe the emergence of self-organized behaviours in cellular automata we have adopted a particular space-time scale: that is, we have considered to be meaningful a spatial dimension of the order of the whole network (unlike that which is meaningful for a single element, of the order of the distance between elements) and we have adopted an aggregate time scale (unlike that which is meaningful for the individual elements, whose memory is limited to a single time-step). It is from this particular point of view that the evolution of the automata in Fig. 1.1 may be described as an emergence of self-organization, i.e. of an overall order resulting from a large number of elementary interactions.

This emergence of order can be considered to be associated with a reduction in redundancy, with an elimination of the excess of data which characterizes the initial condition. In a global framework, in fact, the specific distribution of 1's and 0's in the initial condition is merely one of the many possible microscopic realizations of the characteristic randomness of the initial condition itself. In this sense, a detailed knowledge of the initial condition may be considered to be redundant.

On the other hand, if we observe the system by concentrating upon the space-time scales which are characteristic of the individual elements (that is, from a microscopic point of view), nothing important changes with time: neither the possible states, nor the number of nearest neighbours, nor the transition function. From this point of view, the state of the system at any time appears to be completely determined by the law of transformation and by the initial conditions. But this is not all: surprisingly, an observer adopting this microscopic point of view might even notice that the evolution of the system carries with it a reduction, an impoverishment of the initial information. The observer may explain this by the fact that the transformations produced by the transition functions in some cases compress the richness of the initial state into a repetitive homogeneity (as, for example, in the case shown in Fig. 1.1b).

But why does that which is seen from an overall viewpoint as a useless redundancy of the initial conditions now become a wealth of information which is destroyed over time? Precisely because the attention of a microscopic observer is not focussed upon the random nature of the initial distribution, but rather upon its detailed structure.

These two different approaches in considering the characteristics of the initial conditions are confirmed by posing the question in terms of the complexity of the algorithm necessary for defining them. Here, for complexity of an algorithm we mean, following Kolmogorov and Chaitin (Chaitin, 1975), the minimum length of the program necessary to carry out the required task. It can then immediately be seen that the algorithm required to obtain a string of random numbers is, from the overall viewpoint, quite simple, whereas, from the microscopic viewpoint, it is the most complex algorithm that one can imagine, because there is no way in which the corresponding program can be made shorter than the description of the string of numbers which constitutes the output (Atlan, 1987).

To summarize, it can be said that, from the macroscopic viewpoint only, that which emerges is meaningful, distinguishing itself from the insignificant redundancy of the microscopic level, whereas at the microscopic level, not only are the transition functions and the interconnections important, but also the detailed information about initial conditions.

Therefore, if we find ourselves in either of these two points of observation, that which is important for the other may lose its importance. These brief reflections confirm the relevance, the central role of the observer in the analysis of systems and, in particular, in the identification of their self-organization characteristics.

1.3 Cognitive Processes in Artificial Systems

We would now like to further extend our considerations about the centrality of the observer in the identification and in the description of self-organization processes. As we shall see, in fact, it is the adoption of a specific viewpoint which allows the recognition and the description of cognitive processes (Ceruti, 1986; Varela, 1986) in a system.

Let us first of all take the viewpoint of an observer external to the system, which studies its interaction with an environment which is, a priori, endowed with a meaning: the "design and control" point of view. Then one has to see if and how the system, at least partially, recognizes the meaning of the input.

In this light, for example, Fig. 1.1b may be interpreted in the sense that the system "responds" to the initial conditions with a behaviour (which can be detected externally through the time sequence shown in the figure) which "recognizes", in the initial conditions, particular spatial sequences of 1's and 0's.

On the other hand, by taking up a point of view "internal to the system" (however vague this expression may be in the case of systems which are not capable of self-consciousness), attention will be focussed upon its properties of autonomy, that is, upon its autonomous "creation of meaning" for the experience of the external environment: an experience which, in the case of the example in Fig. 1.1b, consists only of the initial conditions.

This change of viewpoint leads to consider the environmental influences as having, a priori, no meaning for the system. In other words, in this latter case it is not assumed that an "absolute" meaning is given for the external environment, but rather a creation of meaning is observed by the system itself (Varela, 1986).

The previous example of cellular automata does not allow a more detailed examination of the differences between the two approaches towards cognitive processes in artificial systems mentioned above. In fact, in order to observe an effective creation of meaning, a building of representations, a recognition of configurations, a learning from the external environment, it is necessary to consider systems which can change. We will take up these arguments again in the following chapters, where learning in artificial systems is discussed.

One can, however, speak of cognitive behaviour in artificial systems both from a "control" perspective and from an "internal" viewpoint. Thus, it is not a question of choosing once and for all between the two points of view which have been briefly outlined here. It would be much better to recognize their complementary nature, and to adopt one or the other according to the objectives set.

For example, it is clear that if cellular automata are to be studied as the first example of complex artificial systems capable of cognitive behaviours (such as the recognition and learning of "patterns" which are meaningful to an external observer) then the adoption of a "control-centred" approach is certainly an adequate one. If, on the other hand, the reference to cellular automata has the function of favouring the comprehension of concepts which are central to the description of biological systems (such as, for instance, the creation of meaning), then the adoption of a "control-centred" approach may turn out to be misleading and trivializing, and an "internal" perspective seems a more adequate one when our attention is directed towards the emergent cognitive dimensions.

1.4 Metaphors of the Cognitive Sciences

We have presented so far some examples and reflections which may help the reader to appreciate the richness and the fascination (scientific and epistemological, besides aesthetic) of the science of complex systems, and its potential application to the study of cognitive systems. At this point, however, some historical aspects are worth mentioning, in order to better appreciate the novelty and the effectiveness of the complex systems approach towards the study of cognitive processes, whilst succeeding, at the same time, to understand its roots. This theme will be taken up in more detail in the next chapter.

Cognitive processes are the object of research in various disciplines which, over the last 50 years, have experienced varied and continually changing interrelationships: neuroscience, psychology and information science (Parisi, 1989).

It is quite difficult to summarize the differences in the various approaches, without running the risk of being over-schematic. It may be stated, however, that neuroscience studies the neurocerebral system as a physical apparatus which shows computational properties (in the etymological meaning of analysis and evaluation of different pieces of information): input recognition, reasoning, learning, etc. Neuroscience essentially focusses upon the microscopic level, attempting to explain the working of the brain at an overall level by reducing it to elementary processes.

Psychology, on the other hand, deals more with the mind than with the brain, i.e., it deals with cognitive behaviours manifested by living organisms having a neuro-cerebral apparatus. Even when the prevalence of a reductionist approach has emphasized the expectation of a definitive explanation of the working of the mind on the basis of the underlying biochemical processes, psychology has always maintained an approach centred on high levels of aggregation.

Information science, unlike the previous ones, is not characterized by a precise option about the level of aggregation for the study of its own objects. On the contrary, it is possible (at least schematically) to distinguish in its history various phases corresponding to different approaches, and therefore also to different relationships with the other disciplines cited above. Moreover, information science, precisely because of its greater variety of different viewpoints, may constitute an important reference for a better articulation between aggregate and microscopic approaches in the cognitive sciences as a whole.

When information science, under the name of cybernetics, began the formal study of mental functions, it was characterized by a tendentially microscopic approach. It could not, in fact, be otherwise, as one of the objectives of cybernetics was that of building machines capable of cognitive behaviours: its aim was not only to explain, but to explain operationally, achieving high-level functions starting from very simple elementary cognitive mechanisms. This particular orientation of cybernetics, as may be expected, favoured the development of close links with neuroscience.

For various reasons (some of which will be examined below), this approach had limited success, and the informatics community thus created the expression "artificial intelligence" to indicate a new direction of information science: the high level approach, in which cognitive functions began to be studied independently of their physical implementation. Increasingly, the "artificial minds" moved away from the "electronic brains" which supported them, rendering themselves autonomous. This transition, abandoning the hypothesis that artificial cognitive systems could reap advantage and inspiration from the study of the physical characteristics of the brain, led information science further away from neuroscience but closer to psychology.

This allows the understanding of the birth of a whole new line of psychological research (cognitive psychology) inspired by the analogy between symbolic computing by the mind and the operation of computers (in their high-level characteristics, and no longer in their micro-organization). In particular, within the field of cognitive psychology, the drafting of computer programs in high level languages has increasingly taken on the function of simulating mental processes, although with the awareness that complete reduction is not possible.

Some of the problems currently facing artificial intelligence will be examined in the following chapters, together with its undeniable successes. We will limit ourselves here to recalling the difficulties and the costs associated with the storage of knowledge in the form of rules, the problem of managing contradictions and uncertainties, and the fragility of artificial intelligence systems. These difficulties force to reflect more deeply upon the convenience, and even the possibility, of completely separating the "artificial mind" from the "physical machine" supporting it.

It is true, in fact, that many high level cognitive functions can be implemented upon a multiplicity of different substrates. But it is also true that a particular organization of a substrate (i.e., its microscopic structure) may give rise, through self-organization processes, to high level primitives whose implementation would, perhaps, otherwise not even have been attempted.

The development of a science of complex systems, which stresses the importance of self-organization processes, can give a decisive contribution in overcoming many of the difficulties faced by artificial intelligence, showing the potentialities of "connectionist" architectures, that is of structures made up of an enormous number of identical and mutually interconnected elements. Moreover, also the developments of neuroscience have contributed to the re-launching of the cybernetic approach.

At the same time, cognitive psychology has come up against the increasingly evident limits of the approach adopted. The "commonsense reasoning", the spontaneous generalizations, the learning by examples instead of by rules (to cite only a few points), that is, the simplest cognitive capabilities of a young child, appear to be rather difficult to include within the framework of the "metaphor" of the symbolic processing of information which inspires cognitive psychology. Thus, even psychology has been compelled to search for new reference models which could, at least, complement the preceding ones where these latter fail. The new "neurally inspired" (not purely "mind inspired") information science increasingly constitutes, in this sense, a promising "workshop" for the construction of models capable of interconnecting the various levels of analysis and of emulating cognitive behaviour.

In a sense, a historical circle has been closed, and information science is today "revisiting" the cultural environment in which it was born. But its history is not one of lurchings and waverings: it is rather the history of a relationship between a complex system (the mind-brain system) and a complex task (the development of artificial systems with cognitive capabilities).