Attention-locked computation with chaotic neural nets

Carlos Lourenço[*]

Computer Science Department, Faculty of Sciences, Lisbon University,
Campo Grande, 1749-016 Lisboa, Portugal

and

Center for Logic and Computation, Mathematics Department,
Instituto Superior Técnico, Av. Rovisco Pais, 1049-001 Lisboa, Portugal

To appear in the
International Journal of Bifurcation and Chaos, Vol. 14, No. 2 (2004)

---

[*] e-mail: csl@di.fc.ul.pt
http://www.di.fc.ul.pt/~csl/
Postal address: Faculdade de Ciências da Universidade de Lisboa,
Departamento de Informática, Campo Grande, 1749-016 Lisboa, Portugal

Attention-locked computation with chaotic neural nets

Abstract

We review a neural network model based on chaotic dynamics [Babloyantz & Lourenço, 1994, 1996] and provide a detailed discussion of its biological and computational relevance. Chaos can be viewed as a "reservoir" containing an infinite number of unstable periodic orbits. In our approach, the periodic orbits are used as coding devices. By considering a large enough number of them, one can in principle expand the information processing capacity of small or moderate-size networks. The system is most of the time in an undetermined state characterized by a chaotic attractor. Depending on the type of an external stimulus, the dynamics is stabilized into one of the available periodic orbits, and the system is then ready to process information. This corresponds to the system being driven into an "attentive" state. We show that, apart from static pattern processing, the model is capable of dealing with moving stimuli. We especially consider in this paper the case of transient visual stimuli, which has a clear biological relevance. The advantages of chaos over more regular regimes are discussed.

Keywords: Chaos; Computation; Attention; Spatiotemporal Dynamics; Neural Networks; Cortical Layers; Processing of Changing Visual Stimuli

1 Introduction

Never quiet, the brain oscillates. The electroencephalogram (EEG) and the measurement of local field potentials (LFPs) provide notable examples of oscillations in electrical activity. Most relevant to cognitive sciences are the observed correlations of electrical activity with information processing tasks. The spatial dimension of electrical oscillations in the brain has revealed additional structure not present in global measurements of a scalar variable. In a much cited example [Eckhorn et al., 1988; Gray & Singer, 1989], functional subunits in separate regions of the cortex synchronize in response to a visual stimulus. Thus the regions are linked by a mechanism of phase coherence. The synchronization mechanism is a much more general and powerful one, in that it can amplify small individual effects via collective organization. More complex spatiotemporal modes of oscillation, other than synchronous activity, may also be considered. Although these modes are difficult to deal with experimentally, researchers at the laboratory have revealed their nature over the last decade. Lachaux et al. [1997], for instance, advocate that single-channel EEG reconstruction of brain dynamics is misleading and does not reliably quantify spatial aspects of the dynamics as well as multi-channel techniques do. Further evidence along these lines prompts us to include spatial features in cognitive modeling *ab initio*. In our more theoretical work we propose and explore abstract models of cognitive processes. Such models feature a spatiotemporal dynamics and general layout that aim to reproduce some of the intricacies of the real brain. As in every operational model, just about the right level of detail is retained so that the essence of the targeted phenomenon is captured. Our modeling does not try to avoid the complexity that may unfold from a full spatiotemporal nonlinear dynamics, but instead incorporates that complexity to the advantage of performance in computational and cognitive tasks. In this paper we consider the modulator role of attention in the complex dynamical regimes of spatially distributed neural networks, and the resulting enhancement of stimulus processing capabilities. We review a specific computational model capable of stimulus processing [Babloyantz & Lourenço, 1994, 1996], but precede the presentation of the mathematical part of the model with an original discussion of its biological relevance. We further elaborate on the case where the stimuli themselves are dynamic, or even transient. The latter is of course a most relevant case in biological terms.

Sections 2 to 5 present the biological motivation of our model. Actually the main features of the model are introduced in those sections along with a review of the most relevant findings and open issues in biology. The computational model itself is presented in detail in Sec. 6, whereas Sec. 7 demonstrates the type of stimulus processing that it is capable of. The last section summarizes the main results and adds to the biological relevance of the abstract model in view of Secs. 6 and 7.

2 Complexity and Chaos in the Brain

The first models of biological cycles produced extremely regular, periodic, time-series. Yet, this regularity was often overruled by experiments. Complex patterns of oscillation were revealed, escaping the predictions of simple models. This happened at all levels, from the single neuron to entire cortical and subcortical regions. During the last years, the theory of nonlinear dynamical systems provided a new framework in which to study complex phenomena in brain. The notion of deterministic chaos is an important cornerstone of the new approach. It allows that randomness and complexity embrace determinism and underlying structure.

The tools of nonlinear analysis have been fruitful in two directions. They enabled the identification of underlying order in seemingly random biological time-series such as the EEG. They also helped propose qualitative and quantitative models of brain processes, including those that generate the experimental time-series. Nonlinearity arises at the level of internal dynamics of units, or through the interactions between coupled units. Below we cite some important results in the domains of data analysis and modeling. Another salient feature of the nonlinear approach is the explanation of how bifurcations and self-organization can arise in complex systems. Interestingly, these provide an elegant setting where a quantitative and a qualitative view of dynamics come to merge.

In 1985 Babloyantz et al., using the tools of nonlinear time-series analysis, could show that several behavioral states of the brain, as measured from EEGs, exhibit deterministic chaos. This study made a comparative analysis of different sleep as well as awake stages, in human subjects. The assessment of chaos was done by measuring correlation dimensions and positive Lyapunov exponents of reconstructed attractors of the dynamics. In the same year, chaotic activity was detected in the monkey neurons by Rapp et al. [1985]. These seminal papers gave rise to a vast literature which is still expanding. Early examples include *e.g.* the unveiling of deterministic chaos in petit-mal epilepsy [Babloyantz & Destexhe, 1986] and in cat olfactory bulb [Skarda & Freeman, 1987]. Other dynamical quantities have been measured, such as generalized dimensions, Kolmogorov-Sinai entropy and power spectra. Apart from the EEG, the magnetoencephalogram (MEG) has also provided time-series for dimension evaluation. In each case, the ensemble activity of large populations of neurons is monitored. Meanwhile, deterministic chaos has also been detected in the dynamics of isolated neurons [Elbert et al., 1994]. All these studies share a new view of what was previously described as "random effect of internal noise sources". The system dynamics is perceived as a relatively low-dimensional process, in contrast to the great number of degrees of freedom of purely random noise or fully developed turbulence. Although the numerical accuracy of certain measurements has been a matter of debate, it became clear that some form of determinism underlies the time-series. In a sense, the brain could be viewed as operating at the "edge of chaos".

Interestingly, chaos was initially believed to be a sign of illness. The term "dynamical disease" was even adopted in 1977 [Elbert et al., 1994]. Although the most obvious demonstrations of low-dimensional chaos are provided by pathological states, such as epilepsy [Babloyantz & Destexhe, 1986] and Creutzfeld-Jacob coma [Babloyantz & Destexhe, 1987], other (behavioral) states allowed the measurement of moderate correlation dimensions, indicating determinism [Elbert et al., 1994]. It has been proposed that chaos could serve cognitive functions that cannot be described in a linear fashion, such as searching in memory for some concept, or finding a creative solution to a problem. Chaos would also underly the brain's ability to respond flexibly to external stimuli. A too regular behavior could even be maladaptive in many circumstances. In addition, chaos provides a model for the transition between regular and irregular behavior in a single system. Such transitions are observed in biological time-series, either spontaneously or in response to some stimulus.

Chaos is a consequence of internal mechanisms of the brain. The most evident demonstrations of brain dynamics are our everyday actions and thoughts. This fact inspired a number of experiments on the chaotic nature of human perception and behavior. In [Richards et al., 1994], a low fractal dimension is obtained from a time-series that reflects the outcome of a perceptual task. Another interesting approach is one that relates chaos in the internal electromagnetic state of the brain, with behavior. Kelso and colleagues have performed a series of experiments where MEGs or EEGs are recorded during sensorimotor coordination tasks. The measured signals include simple time-series as well as the amplitudes of entire spatial modes of electrical activity. By varying a behavioral parameter, critical instabilities giving rise to non-equilibrium phase transitions are detected in both the psychophysical data and brain activity [Fuchs et al., 1992; Kelso et al., 1992; Wallenstein et al., 1995]. In MEG experiments reported in [Kelso & Fuchs, 1995], the time-varying amplitude of spatial modes displays a task-dependent phase-space geometry characteristic of Šil'nikov chaos. The geometry changes qualitatively at a phase transition. For a recent account of correlating spatiotemporal brain signals with behavior, see [Jirsa, this issue].

If one accepts that brain dynamics is of a spatiotemporal chaotic nature, then it may be investigated how this relates to biological information processing in concrete ways. How can chaotic operation modes actually enhance the processing capabilities of the system? This question lead us to propose a model neural network featuring chaotic spatiotemporal dynamics [Babloyantz & Lourenço, 1994, 1996]. Along this paper we shall point out the model features more directly inspired in biology.

In modeling, details of individual units, neurons, axons, synapses, can sometimes be overlooked with respect to the dynamical function that they support. This has led *e.g.* to the modeling of the thalamo-cortical system as abstract coupled oscillators, or modernly to the description of cortical activity in terms of chaotic differential equations based on generic biological data. In our work we follow this conceptual view.

Observing the microscopic activity of neurons is a natural starting point in a "bottom-up" approach. However this *démarche* is not exclusive. For instance, in the experiments of Kelso *et al.* (see above), the measurements have a macroscopic nature. One monitors the electromagnetic field generated by neuronal activity. In that case, the physiology and behavior of individual neurons need not be known exactly. Overall, a two-level or multi-level approach to brain seems necessary, considering functional units at different scales.

For the purpose of the present paper, we actually consider individual units consisting in oscillators, having a phase and amplitude as relevant variables. These are coupled within a so-called neural network, giving rise to cooperative phenomena through mutual forcing of the units. These can adequately be viewed as sub-populations of neurons (which could then be of a more realistic type). With a large enough number of units, massively parallel computation becomes possible.

3 Single-cell versus Population Coding

The issue of cooperative behavior relates to a debate among the neurobiology community, on the relative merits of single-unit versus population coding. A strong motivation to the single-unit approach was provided by Hubel and Wiesel's experiments starting in the late 1950's [Hubel, 1982]. They established that individual cortical cells could respond selectively to a feature of visual stimuli, such as the orientation angle of simple bars. This can be viewed as a "quantum" of knowledge, but it may be argued that correct assessment of a complex object can only be obtained through the activity of an entire array of such cells, and also of different cells responding to other features of the input. A modern stream of research seeks to evaluate the information content of spike trains from single neurons [Strehler & Lestienne, 1986]. In a typical experiment, the animal performs the same sensory or motor task on different occasions. Simultaneously, spikes are recorded from individual cortical cells. Although the data are very noisy, well-defined temporal patterns appear repeatedly in individual spike trains, denoting deterministic response to a stimulus or preparation of motor action. However, the profound implications of such results for cognition have not yet been clarified. The situation would be somewhat like looking at a single pixel on a TV screen, and trying to deduce the features of a moving image from it [Deadwyler & Hampson, 1995].

This goes in pair with the discussion of the "grandmother cell". The latter is a single cell, sitting at the top of some hierarchy, and which after presentation of visual input and a few more computational steps would answer yes or no to the question "is that grandmother's face?". Hence the debate is: Is grandmother coded in a single cell, or in the distributed activity of a neuronal population? We believe that both levels of coding must coexist in brain. Let us also mention an experiment involving a wide-field, movement-sensitive visual neuron in the brain of the locust [Hatsopoulos et al., 1995]. Visual stimuli consisted in approaching, receding and translating objects. The neuron's responses could be described by multiplying the velocity of the image edge with an exponential function of the object's size on the retina. The authors argue that the neuron receives distinct inputs about image velocity and size, and hence the dendritic tree of a single neuron may work as a biophysical device performing the multiplication of two independent input signals. In [Single & Borst, 1998], dendritic integration is observed in single motion-sensitive cells of the fly, giving rise to axonal signals coding for image velocity. Reports of information processing by individual neurons, however, do not exclude that entire neural populations may be working at a "pre-processing" stage to provide the individual neuron with relevant signals.

Meanwhile, the evidence of coding by neuronal populations has become quite sizable. We cite but a few examples. In [Wu et al., 1994], the active neuronal populations in the *Aplysia* abdominal ganglion during different behaviors are compared via multineuronal optical measurements. The populations activated during distinct behaviors, spontaneous or evoked, may overlap by more than 90%. However, the activity patterns are different for each behavior. Furthermore, if a gill withdrawal reflex is elicited a few seconds after a respiratory pumping episode, the evoked neuronal activity is clearly altered for the majority of neurons. Thus it appears that different behaviors are generated by altered activities of a single, extended network, and not by small dedicated circuits. The experiments of Freeman and co-workers (see [Freeman, 1991, 1994] and references therein) have demonstrated a similar phenomenon, while providing further coding evidence. Here the spatial and temporal distributions of neuronal activity were measured in the olfactory bulb of different species of mammals, most often rabbit. The animal's task consisted in sniffing different odors, some known beforehand, others not. It was found that each odor is coded by a particular spatial pattern of amplitude modulation (AM) of common carrier oscillations that are self-organized within the neuronal population. Interestingly, the detailed form of an AM pattern may change in the course of learning, denoting structural reorganization. Nicolelis et al. [1993] have provided clear evidence that the ventral posterior medial thalamus (VPM) of the rat displays a dynamical and distributed representation of the animal's face. Their experiments involved vibromechanical stimulation of single facial whiskers. Previously it was believed that the map of the face in the VPM was static and highly discrete. It would be based on small, robust, and non-overlapping receptive fields (RFs) of the neurons. However, quantitative analysis proved that the RFs in the VPM are large and overlapping. Moreover, they tend to shift as a function of post-stimulus time. This suggests that nontrivial spatial and temporal coding of stimulus information is occurring. Shortly after, Nicolelis et al. [1995] have measured widespread 7 to 12 Hz synchronous oscillations at multiple sites of the trigeminal somatosensory system of rat. The measurements involved up to 48 cortical, thalamic and brainstem neurons. The oscillations began during attentive immobility and reliably predicted the onset of whisker twitching. The pattern of activity consisted in traveling waves propagating from the cortex to the thalamus and to the spinal trigeminal brainstem complex. Direct neuronal response to tactile stimulation also displayed spatiotemporal structure, as previously demonstrated for VPM neurons [Nicolelis et al., 1993].

A different set of experiments provides coding evidence of a more quantitative nature. The so-called neuronal population vector [Georgopoulos et al., 1989] is a weighted vector sum of contributions or "votes" of neurons tuned to direction. Each neuron is assumed to contribute along its preferred direction with a strength that depends on how much the neuron's activity changes for the movement considered. The cognitive operation of mental rotation is tested with a trained rhesus monkey. The animal must move its arm in a direction at a fixed angle from a visual stimulus that changes from trial to trial. By measuring arrays of cells in motor cortex, the authors find that accomplishing this task involves the creation and mental rotation of a population vector from the direction of the stimulus to the direction of the movement. The speed of mental rotation is estimated at 732° per second. It should be emphasized that each neuron is broadly tuned to movement direction, and only the ensemble activity of the population has meaningful quantitative value. In fact, a neuron has a graded activity level with respect to direction. This implies that the same neuron may participate ("vote") in the coding of different directions. The notion of population vector has also been useful in interpreting the results of a more recent experiment [Young & Yamane, 1992]. Here, the activity of the population codes faces instead of directions of movement. Macaque monkeys are presented with photographs of different men in full face. Measurements in the anterior inferotemporal cortex indicate a selective response to physical properties of face stimuli. The responses in the superior temporal polysensory area correlate with other aspects of faces, such as familiarity. Each neuron has a graded response to the combined features of the stimuli. The authors report that there is often sufficient information in small neuronal populations to identify particular faces. In both studies [Georgopoulos et al., 1989; Young & Yamane, 1992], the neurons whose individual activities are captured by the electrodes represent only a tiny fraction of the total neuronal population. Yet there is often enough information in those activities to predict the properties of some stimulus or motor action. Thus there is a form of sparse coding, most likely redundant and therefore with high survival value. A note should be made on the mechanism of cooperation. Dynamical entrainment within the same population arises through synaptic connections, whose strengths may be viewed as parameters conditioning the observed patterns of activity. Yet the pattern of synaptic linking is rarely discussed in the context of the above studies. *A priori*, the connectivity pattern conditioning the population vector in the monkey's motor cortex may be quite different from, say, the one featured in the rabbit's olfactory bulb. Hence, functional connectivity among neurons forming a pattern of activity must still be elucidated.

4 Cortical Layers and Retinotopy

Our model mimics a fully parallel type of biological computation in continuous time, via a recurrent neural network with sparse connectivity of a local type inducing a natural topology. Parallelism is a crucial feature of brain dynamics, allowing increased processing speed and fault tolerance due to redundancy. Likewise, topological ordering has been identified in neuroanatomic studies of sensory and motor processing, at several stages [Sereno, 1995]. Another essential feature of the model is the existence of different interconnected layers. A strong biological motivation comes from the multilayer structure of cerebral cortex, with specific interconnections between different layers [Kandel et al., 1999; Churchland & Sejnowski, 1989]. Each layer is a network of densely connected neurons. Different layers are thought to have functional specificities in the processing of information, and it is widely assumed that information transmission is mediated by the links or synapses joining the neurons.

In the following we concentrate on visual-type processing, for which our model is most adequate. Vision is a major capability of most animals. In higher primates, including humans, over 50% of the cortex is dedicated to visual processing [Sereno, 1995]. In sighted people, it constitutes the most important interface with the external world, providing fast and accurate information about the surrounding environment. In humans, the most distinct visual area is V1 of primary visual cortex. There is evidence that human areas V1 and V2 are laid out similarly to those of other primates [Burkhalter & Bernardo, 1989]. In non-human primates, cortical electrical activity is measured arbitrarily close to its sources, via arrays of electrodes. These multi-electrode measurements can be correlated to sensory-evoked potentials (SEPs) and event-related potentials (ERPs) [Kandel et al., 1999]. Both types of potentials constitute changes in the standard electroencephalogram (EEG), and can therefore be studied also in humans, in diverse behavioral states. The measurement of cortical electrical activity by these procedures remains as one of the most convenient ways of monitoring the dynamical states of the brain. It provides a wealth of data that prompt dynamical models of brain function and also question their validity.

It was initially thought that the visual information pathways, from the eyes up to the highest cortical processing areas, are arranged in a single chain of areas. A successively higher level of analysis would be present at each stage, receiving an image from the previous stage and feeding a transformed version of it to the next stage. At present, it has been established that several serial pathways run in parallel, each of them specialized to a large degree in some function [Honavar & Uhr, 1989]. This can be for example the analysis of form, color, motion, or partial aspects thereof. One then speaks of heterarchies rather than a simple hierarchy. Our modeling makes no claims of such functional completeness, but rather concentrates on specific processing capabilities of a dynamical device, that do not exclude concurrent treatment of the image in the visual field. Furthermore, biological details are incorporated in a highly schematic manner.

Let us briefly review biological vision. The images of the external world are projected onto the retina, which is made up of sensitive cells arranged in a two-dimensional array. Outside of the fovea, a number of neuronal layers pre-treat the information that is then supplied to the optical nerve. The visual signal is then oriented to the primary visual cortex, situated in the occipital lobe, via the lateral geniculate nucleus of the thalamus. Several distinct sub-areas are found in the primary visual cortex, namely, areas V1 to V5. The most thoroughly studied is certainly area V1. As most sensory cortices, the visual cortex displays a structure with several layers of neurons, numbered from I to VI. The complete sheet, with a thickness no larger than 2 mm, forms the gray matter. The layers are structurally and functionally distinct. Although the patterns of intra- and inter-connectivity are somehow involved and include several feedback loops, we may summarize the main pathway as follows. Input to the sensory cortices, via the thalamus, terminates predominantly in layer IV. The neurons in this layer, in turn, distribute the information to other layers. Typically, the output functions are conveyed by neurons in layers II, III, V, and VI [Kandel et al., 1999]. Processes that connect cells in different layers, within the same area, run perpendicularly to the surface of the cortex. Within the same layer, most lateral processes are of short range [Honavar & Uhr, 1989].

Retinotopy is a fundamental property of visual information processing. It consists in a point-to-point mapping, from the sensitive cells of the retina to the neuronal layers at several stages of the processing. A high degree of topological order is preserved, such that the images of the external world are "reproduced" in an oriented manner along the visual pathways. Retinotopy is most marked in area V1, and becomes less precise at higher visual areas [Sereno, 1995]. Detailed neuroanatomic studies in mammals (*e.g.*, the galago [Sereno, 1995] and the wallaby [Ding & Marotte, 1994]) as well as in insects (*e.g.*, *Drosophila* [Kunes et al., 1993]) have demonstrated that this is a rather general property in the animal world. In experiments with behaving monkeys [Tootell et al., 1988], a pattern seen by the animal elicits neuronal activity in one of the layers of primary visual cortex. The spatial distribution of activity closely resembles the form of the visual pattern. For humans, it has been pointed out that retinotopy (or its analogue) may also be an important element in speech processing, by an adequate transformation between time and space [Edelman, 1994]. This is supported by growing evidence that visual areas in humans participate in specifically linguistic functions. For an interpretation based on the study of cerebral lesions, see [Sereno, 1995].

Retinotopy is also an important pre-requisite of our abstract model, where it is present in the simplest form: each "cell" in a two-dimensional array detects the presence or the absence of visual stimulus at the corresponding position in an image of the visual field. We should however note a number of simplifications that are present in the model. In area V1, for example, the entire visual field is represented via a polar coordinate map according to a complex logarithm law [Girod et al., 1994]. Here, we dispense with the complications of polar coordinates and adopt a simple Cartesian arrangement of the units in a regular network. Likewise, we implement a basic "visual projection" that ignores such pathways as those from V1 to V2, then to V4, and eventually to parietal and temporal cortices [Honavar & Uhr, 1989]. We consider two layers, instead of the usual five or six in a typical region of cortex. We evaluate the dynamical influence of one layer over the other, mediated by specificities of the external input. By isolating two layers in this manner, we avoid having to consider a much more complex, global pathway. We demonstrate, however, that a two-layer device already possesses a fair degree of visual pattern processing capability. Finer details, such as the distinction between cones (color sensitive) and rods (sensing position and intensity) in the retina, are not incorporated into the model. We note that a cortical organization into columns of cells grouped by, *e.g.*, ocular dominance and orientation selectivity criteria [Hubel, 1982], is not in conflict with a retinotopic organization such as the one featured in the model. For further details, see for example [Hubel, 1982; von der Malsburg & Singer, 1988; Honavar & Uhr, 1989]. Overall, it should still be said that the connectivity in the model can only be related to biology in a very abstract way.

5 Attentiveness and Performance

It has been noted that animal and human responses to relevant, attended events, can show marked improvement when compared to the case where no attentional mechanism is present [Mangun & Heinze, 1995]. Spatial selective attention is of particular importance, given its functional role and the extent of the neuronal regions involved. Some of these neuronal mechanisms have been elucidated in humans, by a combined study of ERPs (via noninvasive electrophysiological approaches), and neuroimaging data, obtained with positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) [Mangun & Heinze, 1995]. The complete mechanism is quite complex and still on its way to being revealed. Evidence reported in the above reference and references therein does suggest, however, the presence of an attentional process that gives input from selected regions of the visual field a preferential access to higher systems of stimulus identification. This can be viewed as a modulation of the external input. In another example of such modulation, Fries et al. [2001] recorded neurons in cortical area V4 of macaque monkeys while the animals attended to relevant stimuli. The animals were also conditioned to ignore distracter stimuli. Neurons activated by the attended stimulus displayed increased synchronization in the gamma frequency band (35 to 90 Hz) but reduced low-frequency synchronization (<17 Hz) when compared with nearby neurons activated by distracters. Those authors suggest that local changes in synchronization may serve to amplify relevant signals upward in cortical processing.

In our model, there is a *dynamical* modulation of the input, associated with a so-called state of attentiveness. The important feature is that the details of the modulator mechanism selected are dependent on gross features of the input, or on the visual task to be performed. In a way, the global quality of the input prompts the activation of a certain type of modulation. In the presence of this modulation, the device then fine-tunes the evaluation of the visual pattern presented externally.

The pattern recognition system can therefore select an internal state best suited to process a given type of input. The biological correlate of this property is not necessarily associated with a deliberate will. We speak of attentiveness in a more general, operational, sense. Emphasis is put on the dynamical modulation of the input, and not on the biological mechanism creating or sustaining that modulation. In particular, we do not concern ourselves with the relation between automatic and controlled processing of the stimuli, as discussed *e.g.* in [Schneider et al., 1995]. In other words, the degree of conscious attentiveness is not specified here. Hillyard & Picton [1979] helped fix the nomenclature, as summarized in [Başar et al., 1989]:

> [They] used the term "selective attention" or simply "attention" as a construct which has a rather broad but circumscribed set of meanings, being clearly distinguished from nonselective central nervous system (CNS) processes such as arousal or alertness. Attentional processes are those CNS functions which enable perceptual or motor responses to be made selectively to one stimulus category or dimension in preference to others. Irrelevant stimuli that are not being attended are either partially or completely rejected from perceptual experience, entry into long-term memory, and control over behavior. Furthermore, these authors state that attention refers to selective aspects of sensory processing. Accordingly all experimental demonstrations of attention must measure the responsiveness of the organism to more than one category of stimulus.

Attentional processes are well characterized in a large psychophysical literature. As indicated above, their traces can also be found in electrophysiological and neuroimaging experiments with behaving subjects. A remarkable series of experiments was performed by Rougeul-Buser and colleagues in the 1970s and 1980s [Rougeul et al., 1974; Rougeul-Buser et al., 1978, 1983]. These experiments include electrocorticographic (ECoG) exploration, which is a form of invasive electrophysiology. An array of electrodes is implanted over the sensorimotor and proximal parietal cortices in cats and monkeys, in an arrangement providing good spatial resolution. It is found that the electrical activity of brain shows different frequency and amplitude according to the behavioral state of the subject. Furthermore, the cortical regions showing these characteristic frequencies, are well localized and differentiated from the remaining cortex, that provides a background of "desynchronized" activity. This indicates that these rhythms are to be distinguished from the classical alpha waves [Andersen & Andersson, 1968], found in EEG and associated with a state of relaxed wakefulness. The latter have a more global nature, lacking a strict spatial localization. Taking *e.g.* the cat, two distinct situations are studied, within waking immobility [Rougeul-Buser et al., 1983]. In one case ("expectancy/quiet waking"), the cat watches a hole in a wall, from which a mouse may come out at any moment. This originates a focal rhythm close to 14 Hz. In another situation ("watching prey/focused attention/hypervigilance"), a mouse is inside a perspex box; the cat can see it, but not catch it. A frequency of around 36 Hz is measured. In both cases, the animal is motionless, displaying only occasional movements of the eyes or tail. One can, therefore, associate the measured electrical rhythms primarily with visual stimulus processing; eventually, the visual information will serve to guide motor action. Occasional trains of 36 Hz activities are also observed when the animal displays an exploratory behavior at an unfamiliar place. In analogy with human EEG, the 14 Hz and 36 Hz rhythms have been called mu and beta, respectively. These electrical activities are clearly distinct from the 7 Hz signals (in the cat) accompanying drowsiness, or the slow waves and spindles of slow sleep [Rougeul-Buser et al., 1978]. Do the synchronized oscillations, in behaving situations, possess a definite functional role? Or are they an epiphenomenon? The answer to this question is not known yet. By way of the abstract model in the present paper, we will show how a synchronized oscillatory state, stabilized out of a chaotic dynamics, can be a key factor in visual information processing.

6 Chaotic Categorizer

Our modeling stems from the observation that, in all sensory processing, the first task is to become receptive to incoming information. Once such an attentive state is reached, the information to be treated can flow through the specific pathways. In the model system, switching to one of the alternative attentive states is achieved by stabilizing a corresponding unstable periodic orbit (UPO) in the dynamics of one of the layers. Let us note that each layer of the neural network will be in a chaotic dynamical regime if left uncontrolled. When controlled, a layer will show a sudden increase in spatiotemporal order. Only one layer is stabilized, and this will be called the attentiveness layer. Each attentive state corresponding to a given UPO is more suitable to handle a certain class of information processing tasks. From a dynamics point of view, it is known that an infinity of UPOs may coexist in a chaotic regime [Ruelle, 1978; Takens, 1980; Auerbach et al., 1987; Ott, 1993]. In the case of extended systems, such as the network we consider, these UPOs may show different spatial and temporal symmetries, thus allowing great operational flexibility. This flexibility is further enhanced by the great sensitivity and small response times of chaos to small perturbations.

6.1 The model

The chaotic categorizer is based on a device developed by Babloyantz, Sepulchre and Lourenço (see [Babloyantz & Lourenço, 1994, 1996]) and featured in preliminary form in the PhD thesis of Sepulchre [1993]. It is made of two interconnected layers (see Fig. 1). Each layer comprises $N \times N$ oscillating elements. The elements of the two layers are connected in a one-to-one correspondence via links that are active and represent a given pattern only if an external stimulus activates the first layer [Babloyantz & Lourenço, 1994, 1996]. The details of this process will become apparent in the sequel.

A “pacemaker” P sends micropulses only to layer I, as shown in Fig. 1. In the absence of external stimuli, the activities of the two layers are independent and both show spatiotemporal chaotic behavior [Babloyantz et al., 1995]. The device is described by the following differential equations.

$$
\begin{aligned}
\frac{dZ_{jk}}{d\,t} &= Z_{jk} - (1 + i\,\beta)|Z_{jk}|^2 Z_{jk} + (1 + i\,\alpha)\,D \sum_{l,m} C_{jklm} Z_{lm} + P_{jk}(t) \qquad (1)\\
\frac{dW_{jk}}{d\,t} &= W_{jk} - (1 + i\,\beta)|W_{jk}|^2 W_{jk} + (1 + i\,\alpha)\,D \sum_{l,m} C_{jklm} W_{lm} + \gamma I_{jk}(Z_{jk} - W_{jk})
\end{aligned}
$$

$$(j, k, l, m = 1, \ldots, N).$$

The variables Z_{jk} are the complex amplitudes describing the oscillators in layer I, whereas the W_{jk} refer to the corresponding variables in layer II. At a mathematical level, Eqs. (1) can be related to the complex Ginzburg-Landau equation describing oscillating reaction-diffusion systems. If we ignore the P_{jk} and $\gamma I_{jk}(Z_{jk} - W_{jk})$ terms, what remains in Eqs. (1) corresponds exactly to the discretization of the complex Ginzburg-Landau equation on each of the layers (taking into account the choice in Eqs. (2)). Let us note that the evolution equation for each of the complex variables can effectively be decoupled into two equations for two real variables. The first two terms, a linear and a cubic one, provide a simple description of periodic oscillations of a single oscillator. The summation terms describe a diffusion coupling, in the form of a discretized Laplacian. Equations (1) are generic as they constitute the normal form of an oscillatory network near a supercritical Hopf bifurcation. Other models can describe certain aspects of cortical dynamics in finer detail. That is the case of the well-known FitzHugh-Nagumo model for excitable neurons [FitzHugh, 1961, 1969], which also features diffusive coupling. Both the Ginzburg-Landau and the FitzHugh-Nagumo equations provide local oscillations via the first (non-coupling) terms. However, the oscillations displayed by the Ginzburg-Landau equation are not akin to the ones featured by the FitzHugh-Nagumo equation in the usual dynamical region of interest of the latter. Our use of the Ginzburg-Landau equation should be viewed as describing neuronal population oscillations in a very broad sense, without the aim of uncovering the actual mechanisms that sustain local oscillations.

The terms $P_{jk}(t)$ represent the influence of the pacemaker P on each oscillator of layer I, whereas the terms proportional to γ take into account the forcing of layer II by layer I. We consider only first-neighbor interactions, defined by

$$\sum_{l,m} C_{jklm} Z_{lm} = Z_{j(k+1)} + Z_{j(k-1)} + Z_{(j+1)k} + Z_{(j-1)k} - 4Z_{jk} \; . \qquad (2)$$

The parameters α, β, D and γ are real-valued. α and D reflect the coupling strength between units. The complete list of fixed parameter values is: $N = 9$, $\alpha = -10$, $\beta = 2$ and $D = 1.3$. The value of γ is dependent on the particular experiment. The boundary conditions are of the zero-flux type.

The information to be processed is sent to the device via a binary matrix I_{jk}. If $I_{jk} = 0$ then the connection between elements jk of the two layers is nonexistent. However, if $I_{jk} = 1$ then the two layers are connected via elements jk, and γ describes the strength of the binding. Moreover, in this model if $P_{jk}(t) \equiv 0$ then $\gamma = 0$. Thus, it is only when the pacemaker P is active, and therefore a periodic orbit has been stabilized in layer I, that there is entrainment of the second layer by the first layer. The entrainment can be total if all $I_{jk} = 1$, and it is partial if only some of the I_{jk} are nonzero. Moreover, the dynamics of the second layer is critically dependent on the parameter γ. If $\gamma = 0$ then the two layers have independent dynamics, whereas large values of γ with a large number of "on" links representing incoming information, can synchronize the activities of the two layers.

If $P_{jk}(t) = 0$, $\gamma = 0$, $N = 9$, $\alpha = -10$, $\beta = 2$ and $D = 1.3$, then both layers follow spatiotemporal chaotic activity. The dynamics of each network separately could be viewed as evolving on a chaotic attractor embedded in a $2(N \times N)$-dimensional space. The nature of this spatiotemporal chaotic regime is elucidated namely in [Babloyantz et al., 1995]. In the same article, it is shown how a number of UPOs can be stabilized from the chaotic attractor. In this case, the process consists in an extension of the well-known Ott-Grebogi-Yorke control algorithm [Ott et al., 1990] to high dimension. Under this type of control, the chaotic system is acted upon by only small-sized perturbations. Four orbits are stabilized, displaying different spatiotemporal symmetries. Here, control of chaos is symbolized by the pacemaker P applying micropulses to layer I of the device. Hence, the nature of the stabilized orbit is a function of the action performed by P.

6.2 Attentive states

Three different orbits, exhibiting spatiotemporal structure, are displayed in Fig. 2. Another orbit, $\mathcal{C}_0$, could also be stabilized but is not represented in the figure. It corresponds to the bulk oscillation of the network, where all the oscillators are in phase. Its period is $T = \pi$. Let us summarize the main features of the depicted orbits. Although the orbits $\mathcal{C}_1$, $\mathcal{C}_2$ and $\mathcal{C}_3$ are periodic at the level of the $2N^2$-dimensional dynamics, when viewed at the network level they exhibit spatiotemporal structure. Phase differences are seen between individual oscillators of the network. The orbit $\mathcal{C}_1$, with T=13.66, shows a rotating wave activity of the amplitude of individual units around the central unit of the network. The amplitude of the latter is zero; that is, we are in the presence of a "phase defect". In this case, the rotation is clockwise. The orbits $\mathcal{C}_2$ and $\mathcal{C}_3$ show stationary waves of different symmetries. Orbit $\mathcal{C}_2$ shows a polar structure. At a given moment, the amplitude is higher on one side of the network and lower on the opposite side; the amplitude distribution then reverses. The complete alternation has a period T=15.38. In $\mathcal{C}_2$, the activity is antisymmetric with respect to the reflection around a median and constant along any direction parallel to that median. Due to the square geometry of the network, a similar solution exists with a symmetry axis perpendicular to the one seen in Fig. 2. In orbit $\mathcal{C}_3$, spatiotemporal phenomena show a different structure. The activity is high in units along one of the diagonals and near the corners of the network, whereas the oscillators on the other diagonal show lower activity close to the corners. Again, the situation changes periodically. Here, the period is T=2.25. This orbit shows an invariance with respect to reflection around the two diagonal axes of the square. In principle, an infinite number of other periodic orbits might be found in this system.

Let us go back to the device as shown in Fig. 1, and describe how it can process information. The total input into the system is divided into two parts: the pacemaker P, which emits the appropriate micropulses, and the input representing the pattern to be processed. Thus, the information is captured on the first layer and on the links relating the latter to the second layer. The response of the second layer defines the output of the system. The pacemaker P, according to the nature of the information to be processed, stabilizes the first layer into one of the orbits described in Fig. 2. Let us recall the analogy with sensory processing in the brain, where the first act is to become attentive to an external input. In accordance, these orbits correspond to the so-called attentive states of the device. Now the device is ready for processing the input. The latter is imprinted in the links I_{jk}, which are nonzero only if they represent an active portion of the input. The attentive state, associated with a well-defined spatiotemporal structure, entrains the output layer according to the number and location of "on" links in the device. Thus, each input pattern generates a specific spatiotemporal activity in the second layer. The resulting notion of information processing is not far from the one presented by Jirsa [this issue], who argues that input information becomes relevant when it alters qualitatively a given dynamical state of the system. Such qualitative changes are indeed observed in our model.

6.3 Output functions

The dynamics of the output layer can remain chaotic, or become periodic or at least more regular. In order to discriminate between various inputs, we need to quantify the spatiotemporal activity of the response layer. We are interested in the differential change in the network coherence of layer II as a result of the input. To assess it, a global evaluation of the activity of that layer is performed. Finer details of the full spatiotemporal activity obtained in layer II might also be relevant, but they were not judged necessary for the present purposes. Indeed, a balance must be obtained when choosing the level of detail of the observables, in view of both desired pattern discrimination and information compression capacities. In our case, the amount of information compression when reading a global variable as output does not compromise performance in terms of pattern categorization. We consider most often the average value of the squared amplitude of the forced layer $\langle |W|^2 \rangle(t)$ as the output function. Here, the brackets $\langle\ \rangle$ denote a space average over the entire network, and not a time average. We have also computed other quantities such as the mean value of the real part of W over the network. The time evolution of the cross-correlation function between the two layers was also computed. It is defined as

$$C(t) = \mathrm{Re}\, \frac{\sum_{j,k} \overline{Z_{jk}}(t)\, W_{jk}(t)}{\left(\sum_{j,k} |Z_{jk}(t)|^2\right)^{1/2} \left(\sum_{j,k} |W_{jk}(t)|^2\right)^{1/2}} \,. \tag{3}$$

In our simulations, the function $\langle |W|^2 \rangle(t)$ seemed in general more appropriate for static pattern classification and circular motion discrimination than the other output functions. Notwithstanding, in our work the cross-correlation function (3) was useful in the evaluation of linear motion.

7 Pattern Processing

The chaotic categorizer of Fig. 1 can be used as a pattern recognition device as well as a motion detector. The ability of the device to perform a given task is a function of the attentive state that is generated by the device under the action of the input to be processed. Visual processing tasks could be grouped by their symmetries, into different possible classes.

In general terms, with the categorizer the orbits $\mathcal{C}_2$ and $\mathcal{C}_3$ are suitable for pattern recognition and also for detection of linear motion. As will be seen in the sequel, however, $\mathcal{C}_2$ and $\mathcal{C}_3$ do not perform equally well with all possible patterns. $\mathcal{C}_3$ may be totally inoperative in a task correctly handled by $\mathcal{C}_2$. On the other hand, orbit $\mathcal{C}_1$ leads to detection of clockwise and counterclockwise motion.

7.1 Static pattern discrimination

Basic orientation task

We start with the device in the attentive state $\mathcal{C}_2$. In this state, the stabilized orbit in the first layer shows a polarity that oscillates in time. At a given time one may see a high activity at the right-hand side of the network while the activity is at its lowest level at the left-hand side. The situation reverses periodically. In this attentive state, the device is presented with a bar that activates the nine middle links between the two layers and is parallel to the direction of polarity of orbit $\mathcal{C}_2$ (see Fig. 3 (a)). When these links are "on", there follows an entrainment of layer II by layer I. The value of the space average $\langle|W|^2\rangle$ is a measure of this entrainment and is shown in Fig. 4. One sees a constant value of 0.68. In another experiment, the bar is presented again to the middle links of the network but perpendicularly to the polarity of $\mathcal{C}_2$ (shown in Fig. 3 (b)). The response of the system as seen in Fig. 4 is irregular, with high amplitude and a decreased mean value. If the bar is presented along the diagonal (as in Fig. 3 (c)), the response is periodic with a time averaged value of 0.53 (see also Fig. 4). Hence, the device when in the attentive state $\mathcal{C}_2$ can discriminate between different orientations on the plane.

If the same type of experiment is conducted in the attentive state $\mathcal{C}_3$, the device can only discriminate between a bar perpendicular to the side of the network and one presented along the diagonal. This property stems from the fact that orbit $\mathcal{C}_3$ has a reflection symmetry with respect to the two diagonals and therefore the two bars perpendicular to the side of the network entrain layer II in the same manner. Because of the quasi-circular symmetry of orbit $\mathcal{C}_1$, the corresponding attentive state is not suitable for the type of pattern processing mentioned above.

Symbol discrimination

We consider two different patterns, + and × (see Fig. 5). Figure 6 shows the output of layer II when these two patterns are presented to the system, when it is in the attentive state $\mathcal{C}_2$. We see that the two patterns are discriminated by the system. The same is true for the attentive state $\mathcal{C}_3$ (see also Fig. 6). However, we notice that the form and the amplitude of responses for a given pattern are not identical for the two attentive states. Figure 7 shows a longer plot of the network's response to pattern × when in the attentive state $\mathcal{C}_2$ (same color coding of the time-series as in Fig. 6). It reveals bimodal oscillating behavior, not strictly periodic but nonetheless with a major periodicity. Such a large time-window as in Fig. 7 might be too long for pattern processing in a real-time setting. We have actually been considering smaller time-windows (with 120 time units) for pattern discrimination. Nevertheless, we note that the response to pattern × when in the attentive state $\mathcal{C}_2$ is markedly different from all other responses on any finite time-scale. Thus, pattern discrimination remains effective.

Let us now perform another simple experiment, that illustrates the role of symmetries in finding the adequate attentive state for a given task. We consider a new pair of patterns, N and Z (see Fig. 8). The first letter can be recovered by a 90° rotation of the second. From symmetry considerations and the result of experiments with single bars, we expect that the attentive state $\mathcal{C}_2$ will discriminate between patterns N and Z, whereas the state $\mathcal{C}_3$ will give the same answer for both patterns. Our simulations confirmed these conjectures. We present only the result of the N/Z discrimination with the attentive state $\mathcal{C}_2$. Each of these patterns originates its own response, as displayed in Fig. 9.

7.2 Motion detection

Circular motion

The device of Fig. 1 is able to discriminate between clockwise and counterclockwise rotation. To this end we assume that the attentive state of the system is achieved by the stabilization of the first layer into orbit $\mathcal{C}_1$, which shows a phase rotation of period T=13.66 (see Fig. 2). As we have stated already, in this example the phase motion of the stabilized orbit is clockwise. Because of the phase rotation of the orbit, the attentive state $\mathcal{C}_1$ is able to discriminate between clockwise and counterclockwise motion of a pattern presented to the system.

To see this, let us consider the motion of a small object that activates three links at a time. In this experiment, $\gamma = 30$. As the object moves, at each step only the next neighboring link is activated and one of the previous "on" links is deactivated. Thus, the successive activation and deactivation of links represents a circular motion. Figure 10 illustrates this motion. In our example, the diameter of the circular trajectory spans over five network units and the rotation period of the object varies from $T = 6$ to $T = 25$.

In a first experiment, when in the attentive state $\mathcal{C}_1$, the device perceives the clockwise motion of the object which is imprinted in the links. The response of layer II is shown in Fig. 11 for a period of rotation of the object of $T = 18.96$. The value of the space average of the squared amplitude $\langle |W|^2 \rangle = 0.65$ is almost constant in time. However, at very fine resolution, small amplitude oscillations are seen around this value (not apparent in Fig. 11). The same response is seen for all values of the rotation periods considered. Thus, in the attentive state $\mathcal{C}_1$, the device is not sensitive to the speed of clockwise motion of the object.

Presently we reverse the direction of rotation of the object, and keep all other conditions as above. The response of layer II to counterclockwise motion is very different and is sensitive to the rotation speed. For $T = 6$, the motion generates a chaotic response $\langle |W|^2 \rangle$ around a time-averaged value of 0.5. As the speed decreases, the time behavior of the response becomes less and less chaotic and gradually a periodic output function appears. Figure 11 shows the responses associated with the counterclockwise motions of periods $T = 12.48$ and $T = 18.96$. The corresponding time-averaged values of $\langle |W|^2 \rangle$ are 0.54 and 0.57, respectively. For the range of T considered, the value of $\langle |W|^2 \rangle$ corresponding to counterclockwise motion is always smaller than that for clockwise motion. The time-averaged value and the shape of the response in the case of counterclockwise motion are sensitive to the speed of rotation. If we restrict the range of T to $12 < T < 25$, we observe that the time-averaged value of $\langle |W|^2 \rangle$ is an increasing function of T. This function is plotted in Fig. 12. Thus, in this range not only the device discriminates between clockwise and counterclockwise motion, but it also evaluates the speed of counterclockwise motion.

For slow motions, $T > 26$, and very fast motions, $T < 0.5$, the response to clockwise and counterclockwise rotation is practically identical. A difference may be seen only in the fine structure of the $\langle |W|^2 \rangle$ output function. Thus, for these velocities the device is “blind” with respect to the direction of rotation. The responses in these ranges are similar to the response to clockwise rotation for $6 < T < 25$ (see Fig. 11). For values of $0.5 < T < 6$, the response of the system does not follow the smooth change that was described above.

A static object could be considered as rotating with period $T \to \infty$ and thus it is perceived in the same manner as other objects rotating with long periods — that is, $T > 26$.

Linear motion

Motion detection is not limited to orbit $\mathcal{C}_1$. The attentive states corresponding to orbits $\mathcal{C}_2$ and $\mathcal{C}_3$ are able to perceive a moving object and discriminate between “perpendicular” and “diagonal” motions.

Let us consider the attentive state $\mathcal{C}_3$ and a moving object that activates only one link at a time. In one case, the motion starts from the middle of the boundary of the device and continues along a straight line perpendicular to that boundary (see Fig. 13 (a)). In the other case, the motion is along the diagonal (represented in Fig. 13 (b)). Contrarily to Fig. 10, where the rotating pattern settles in a permanent motion, here the object performs a single passage through the visual field. Therefore, the features of the object (size, direction, speed) must be apprehended quickly by the device. Although the system's response depends also on the object's size and speed, for the purpose of this discussion we consider only the direction dependence. In this experiment, we choose the cross-correlation function $C(t)$ defined in Eq. (3) for monitoring. The response of the system is markedly different for each of the two cases displayed above. Figure 14 provides a comparison between the two responses. We see that the perpendicular motion provokes a "lasting impression", whereas, for the diagonal motion, there is a faster return to a high-variance signal. The difference can also be appreciated with a plot of the (running) variance of $C(t)$, as in Fig. 15. Although these are transient responses, we verified that their form is reproduced in a consistent manner, for several independent numerical simulations. As expected, opposite directions of motion, along any one of the paths in Fig. 13, cannot be distinguished. With orbit $\mathcal{C}_3$ the two perpendicular orientations cannot be distinguished, and the same happens regarding the two diagonal ones. The distinction between the two perpendicular orientations is possible only if the device is in the attentive state $\mathcal{C}_2$. The latter is also unable to discriminate between the two opposite directions along any one of the two diagonals as well as along each of the two perpendicular axes. We note the importance of the time-scales involved. The choice of the UPO to stabilize, for a given processing task, must depend on spatial symmetries but also on temporal resolution. For instance, in the linear motion detection that we have been discussing, the spatial distribution of the activity of orbit $\mathcal{C}_3$ oscillates $99 \div 2.25 = 44$ times during the crossing of the visual field by the moving object. For the same speed of the object, orbit $\mathcal{C}_2$ will only "flap" $99 \div 15.38 = 6.4$ times during pattern presentation. This may imply considering the relative phase between the moving object and the stabilized orbit, and its influence on the form of the output functions. This problem disappears whenever the frequency of the orbit stabilized in layer I is high enough, compared to the speed of the dynamical pattern. In this manner, the forcing of layer II by layer I can appear as an averaged process at the slower time-scale of the moving object. The experiment of Figs. 13 to 15 was performed in these conditions.

8 Discussion

We have shown that a simple device, made of two interconnected layers of oscillators and featuring spatiotemporal chaotic dynamics, is capable of pattern selection and motion detection. UPOs are stabilized from the chaotic attractor, placing the system into a state of attentiveness. The system is then ready for pattern processing. The attentive state selected depends on general features of the visual pattern presented, or on the symmetry class of the processing task to be performed. For a given task, the periodic orbit that is stabilized is the one with the most adequate spatiotemporal symmetry.

The two-layer architecture and neural connectivity in the model are reminiscent of brain anatomy, although largely simplified. Here, we mean to bring out essential dynamical features, and not to produce a detailed model of visual processing in the brain. An attentive state is encoded in the activity of layer I, where an UPO is stabilized. The patterns to be processed are encoded in the links between layers. A response or output is measured from the activity of layer II. For the same UPO stabilized in layer I, different visual patterns modulate the forcing of layer II by layer I in different manners, thus originating different responses at the level of layer II. This allows that the patterns be discriminated. We can take the alternative view: for the same pattern presented to the system, different UPOs stabilized in layer I modulate the action of that pattern, on layer II, in distinct ways. From the ensemble of UPOs available, a symmetry evaluation reveals the orbit that enhances certain features of the visual pattern. The processing of the pattern can then performed by measuring some observable of the forced dynamics of layer II. That is, the gross features of the input and processing task constrain the type of modulation. Following that, fine-tuning of the response may take place.

Especially interesting is the case of motion evaluation. Circular motion detection and angular velocity measurement within our model might ultimately be considered a stationary process (after transient periods have elapsed), or at least time-periodic. However, in the case of linear motion with a single passage through the visual field, the transient *is* the process (see Figs. 13 to 15). Thus, a fast and reliable judgment must be made about a moving stimulus under far from optimal conditions. Such type of judgment is of great survival value if one is to consider biological implications. We observe that the model contains an operation mode capable of this type of processing.

We focused on general symmetry considerations in our discussion of pattern evaluation. This does not preclude that further detailed analytical study of the mathematical model, *e.g.* regarding the response dynamics of layer II, be performed. At this point, however, such a study was not essential to the main cognitive and computational aspects of the modeling.

The UPOs were stabilized with the help of an algorithm similar to the one proposed by Ott, Grebogi, & Yorke [1990]. This algorithm can become quite involved, for a spatially extended system such as the one considered [Babloyantz et al., 1995]. To keep numerical integrations at an affordable level, in this example only three orbits with spatiotemporal structure and the bulk oscillation were stabilized in the first layer. Yet, in principle there is an infinite number of UPOs in a chaotic attractor that could be stabilized. With the stabilization of higher-order orbits one would expect more intricate symmetries or more complex spatiotemporal phenomena, especially if larger networks are considered. Thus, one would think that such a chaotic device could process a great variety of information relative to static as well as moving objects. This “reservoir” of behaviors, featured by chaotic dynamics, could be viewed as a form of dynamic operational memory. The system stores, in the form of links or synapses between oscillators or neurons, the “algorithm” from which the different spatiotemporal activities are generated. The activities themselves need not be stored. This results in an economy of processes that may also be advantageous biologically.

Due to this mixture of behaviors found in a chaotic attractor, the instantaneous state of the system is never too far from a desired behavior. Furthermore, a targeting procedure [Shinbrot et al., 1992; Kostelich et al., 1993], taking advantage of the sensibility of chaotic dynamics to small perturbations, can drive the system very rapidly into a desired orbit. Acting upon the system via small perturbations can also represent a technological or biological advantage. The gross physical or biochemical parameters of the system need not be altered. Let us consider the brain once more. If the change of state was based on synaptic change (via *e.g.* protein synthesis or degradation), it would be energetically costly, and often not fast enough for the required processing.

The high flexibility of chaotic dynamics manifests itself on the easy switching of the attentive state, and also on the wide range of responses of the output layer, layer II. The latter features a dynamics that, when unperturbed, shows a chaotic regime similar to the one of the up-most layer (but mutually independent, in the absence of stimuli). Upon encoding of a stimulus in their mutual links, layer II gets forced by layer I. The ensemble of possible responses of layer II is used to discriminate between different stimuli. If the unperturbed dynamics of layer II consisted in, say, a stable limit cycle, a relatively strong forcing would be required to provoke a noticeable change in the response dynamics.

Information is processed under the form of complex spatiotemporal activities, making our approach divergent from classical neural network theory. Furthermore, global observables of the dynamics are measured, making for a collective computation. The device presents a high level of parallelism. Apart from increasing processing speed, this enhances fault tolerance and pattern completion. The failure of individual processing units has a reduced effect on the ensemble activity of the network. On the other hand, small variations of the pattern presented to the device do not alter the system’s response qualitatively. One can speak of an “analog” type of processing, as opposed to a “digital” one. These aspects are most important to biological systems. The latter are built upon processing elements that are not fully reliable individually. In addition, they often have to deal with corrupted or ambiguous input, which prevents a direct comparison with a “library” of template patterns. The volume of the memory required to encompass all possible configurations of the presented stimuli, would have to be exceedingly large. There is therefore an advantage in grouping the stimuli into adequate classes with respect to a number of features (orientation, size, or more complex properties). In our study of the model, we tested the effects of small to moderate distortions of an “ideal” input pattern. The stronger distortions included totally deleting a (reduced) number of active units from the pattern, and perturbing the position or orientation of bars in the visual field. With the present setting, we found that the system only allows small perturbations of the pattern, in order to maintain the same qualitative response. We recall that this response is a one-dimensional signal that has itself several distinct features, all of which must be consistently preserved: average value, amplitude, frequency spectrum, and other statistical quantities if the response itself turns out to be chaotic. Upon perturbation of a pattern, the features of the response signal are not all altered in the same proportion. This allows generalization over a class of patterns that, although differing moderately in some feature of the response that they elicit, are very close with respect to some other feature of that response. We believe that a modest tolerance capacity with respect to pixel corruption or distortion, found in the device, is caused by the smallness of the network that was investigated numerically. The visual field is covered by only 9×9 sensitive “cells”, which originates a discretization error. We expect that larger networks will allow more graceful degradation.

The dynamical character of the computation makes pattern evaluation a robust process. In addition, dynamical computation of this type is most suitable for handling patterns that are themselves dynamic. Under our proposed paradigm, a common neuronal population participates in multiple activities, that is, provides the substrate for different dynamical regimes that are suitable for different types of stimulus processing; switching from one dynamical regime to another is fast and requires but minimal perturbation of the system. This is to be contrasted with the case where one would have several “dedicated circuits”, each dealing with its own class of stimuli. We propose that a dynamical modulation of input patterns, by spatiotemporal cortical activity, need not be restricted to visual processing. Due to the ever-changing nature of the external world perceived by the different sensory modalities, such a modulation may often be essential for stimulus processing. Indeed, information processing can only occur if the basic regularities of the stimuli are first extracted or even anticipated. As noted, these regularities must also be extracted from dynamic stimuli.

In recent years, several researchers have reported the presence of chaos in the brain. This is based on the evaluation of time-series of electrophysiological activity, obtained with EEGs and other methods [Babloyantz et al., 1985; Babloyantz & Destexhe, 1986; Babloyantz, 1991; Gallez & Babloyantz, 1991; Rapp et al., 1986; Röschke & Başar, 1988]. In addition, deterministic chaotic models of cortex originate patterns of activity akin to the ones observed physiologically [Destexhe & Babloyantz, 1991; Lourenço & Babloyantz, 1994]. The degree of determinism observed in the biological time-series, however, remains an open question. There is also an ongoing discussion as to the stationarity of the measured time-series. It is clear that the time-scale of most brain processes is a short one. Nonetheless, it must be accepted that the brain is able to modulate its degree of temporal stationarity, according, *e.g.*, to the sleep-wake cycle or eventual requirements of information processing. The picture of a single dynamical attractor must eventually be abandoned, in favor of a multiplicity of attractors related in an intricate manner. Regardless of how it is understood, chaos may be a normal operating mode in the brain, with the advantages discussed above.

We focused on the importance of bringing the system into a state of attentiveness. This is a necessary condition for information processing to take place. Yet, we did not engage in the discussion of awareness and conscious attentiveness. Indeed, we discuss visual stimulus processing that might happen at a very primary stage, say, in area V1 or one of the areas close to it. It has been argued that the neuronal activity in V1 does not provoke any direct feeling of awareness [Crick & Koch, 1995]. If this is confirmed, then the placing of V1 in a dynamical state adequate for stimulus processing might not be apprehended immediately at a higher, "conscious", level. This does not preclude "top-down" influences over early processing stages, conscious or otherwise. These influences might result in the type of dynamical modulation discussed above. The attentive state can be prompted by external or internal cues. Brain states with different levels of dynamical coherence are detected in physiological time-series. Episodes of neuronal coherence can originate the so-called sensory-evoked and event-related potentials (SEPs and ERPs, respectively). These can appear, for instance, in EEG, MEG, and ECoG. These potentials arise from a background of desynchronized activity, that corresponds to a signal of low amplitude and high frequency. In the model that we investigated, the "desynchronized" state is given by the dynamics of the chaotic attractor. Based on evidence from experimental studies [Rougeul et al., 1974; Rougeul-Buser et al., 1978, 1983], the coherent episodes are associated with states of attentiveness. In a study involving different sensory modalities [Başar et al., 1989] (not restricted to vision), the authors report on phase-ordered rhythmic patterns in human EEG, with frequencies close to 10 Hz, during periods of attended visual or auditory stimuli. The location of the rhythmic foci is well determined, and depends on the sensory modality. These patterns are highly reproducible and are denoted as "quasi-deterministic EEG". Furthermore, the authors associate them with "cognitive microstates" of the brain. Such states can be reached very rapidly. We proposed that some sort of chaos control may act to stabilize the dynamics of the brain into one of the synchronized states required for stimulus processing and mechanical action guidance. We do not specify the physical or biological mechanism responsible for the control. One could suspect that thalamo-cortical interactions are involved in some degree, due to the double role of "relay" and "pacemaker" attributed to the thalamus. However, this remains a speculative issue. Chaos control happening in the brain may not be as sharp a process as the one achieved in physical devices and theoretical models. SEPs and ERPs are not permanently locked processes. In the model, the synchronized states also have a finite time span, if thermal noise is included into the system. We note that there is no harm in the system abandoning the vicinity of a stabilized orbit, if it has stayed close to the orbit long enough for information processing to take place. In the brain, such "cognitive microstates" (cf. [Başar et al., 1989]), corresponding to Lehmann's momentary "electric landscapes" [Lehmann, 1989], could last from 20 to about 500 msec.

Synchronization in the model happens in an architectonically distinct part, layer I. Layer II may then respond by becoming also coherent, or by showing diverse irregular behaviors, depending on features of the stimuli. Experiments with behaving cats and monkeys also show that synchronization arises in cortical areas that are precisely localized in space, functionally and anatomically [Rougeul-Buser et al., 1978, 1983]. It would be interesting to assess the influence of these areas over the ones that are closest to them, in the visual information processing pathways. This could help confirm the existence of the dynamical modulation of the activity of a neuronal population, by the activity of another population. As has been suggested, it is possible that this interaction is laid out in a topographically oriented manner, preserving properties of the visible scene deep inside cortical pathways. Experimental research could also bring out biological mechanisms that permit the encoding of spatiotemporal patterns in the links between layers, via *e.g.* local synaptic enhancement. We remark that no plastic change need actually take place at synapses or axons, which would eventually make the stimulus reading process too slow to be effective. Rather, something like a controlled gate might be present at each link site. If we view this as a sort of logical AND operation (more precisely an analog product), then one argument for the AND would correspond to external stimulus conveyed by a sensory cell whereas another argument would come from the so-called layer I and would be combined via a simple summation (with the correct signs) with the activity of layer II. All these operations, including the AND, are known to be within the reach of biological neurons.

The model that we investigated leaves out a number of important properties of neuronal populations. Neurons are not oscillators. However, groups of neurons can show oscillating electrical activity, sustained by the exchange of excitation and inhibition. Actually, in some cases, single neurons have been reported to display auto-oscillating properties [Llinás, 1988]. These are associated with the rhythmic firing of action potentials independently of synaptic input. However, at the level of description of, say, the post-synaptic potential, this may not even correspond to a clear oscillation. In any case, the neuronal rhythmic dynamics is only grossly approximated by the Ginzburg-Landau oscillator.

Neuronal coupling is far from the simple linear connectivity considered in this paper. Lourenço & Babloyantz [1994] have shown that control of spatiotemporal chaos is also possible with models describing more adequately the cortical tissue, incorporating excitatory and inhibitory neurons. In that study, passive and active membrane properties were considered, as well as a highly nonlinear coupling and delays in signal transmission between neurons. However, only rather homogeneous behavior could be stabilized in the network. In a forthcoming paper, we shall deploy more sophisticated methods to show that spatiotemporal dynamics with more subtle symmetries can also be stabilized in these networks which have a stronger biological appeal.

Acknowledgments

This work was partially supported by FCT and FEDER under POCTI and POSI and namely via project ConTComp (POCTI/MAT/45978/2002).

References

Andersen, P. & Andersson, S. [1968] Physiological Basis of the Alpha Rhythm. (Appleton-Century-Croft New York).

Auerbach, D., Cvitanović, P., Eckmann, J. P., Gunaratne, G., & Procaccia, I. [1987] "Exploring chaotic motion through periodic orbits" *Physical Review Letters* **58**, 2387–2389.

Babloyantz, A. [1991] "Evidence for slow brain waves: a dynamical approach" *Electroencephalography and Clinical Neurophysiology* **78**, 402–405.

Babloyantz, A. & Destexhe, A. [1986] "Low-dimensional chaos in an instance of epilepsy" *Proceedings of the National Academy of Sciences USA* **83**, 3513–3517.

Babloyantz, A. & Destexhe, A. [1987] "The Creutzfeld-Jacob disease in the hierarchy of chaotic attractors" in: M. Markus, S. Müller, & G. Nicolis, eds., *From Chemical to Biological Organization* pp. 307–316 (Springer-Verlag Berlin).

Babloyantz, A. & Lourenço, C. [1994] "Computation with chaos: A paradigm for cortical activity" *Proceedings of the National Academy of Sciences USA* **91**, 9027–9031.

Babloyantz, A. & Lourenço, C. [1996] "Brain chaos and computation" *International Journal of Neural Systems* **7**, 461–471.

Babloyantz, A., Lourenço, C., & Sepulchre, J.-A. [1995] "Control of chaos in delay differential equations, in a network of oscillators and in model cortex" *Physica D* **86**, 274–283.

Babloyantz, A., Salazar, J., & Nicolis, C. [1985] "Evidence of chaotic dynamics of brain activity during the sleep cycle" *Physics Letters A* **111**, 152–156.

Başar, E., Başar-Eroglu, C., Röschke, J., & Schütt, A. [1989] "The EEG is a quasi-deterministic signal anticipating sensory-cognitive tasks" in: E. Başar & T. Bullock, eds., *Brain Dynamics* vol. 2 of *Springer Series in Brain Dynamics* pp. 43–71 (Springer-Verlag Berlin).

Burkhalter, A. & Bernardo, K. [1989] "Organization of corticocortical connections in human visual cortex" *Proceedings of the National Academy of Sciences USA* **86**, 1071–1075.

Churchland, P. & Sejnowski, T. [1989] The Computational Brain. (MIT Press Cambridge, MA).

Crick, F. & Koch, C. [1995] "Are we aware of neural activity in primary visual cortex?" *Nature* **375**, 121–123.

Deadwyler, S. & Hampson, R. [1995] "Ensemble activity and behavior: What's the code?" *Science* **270**, 1316–1318.

Destexhe, A. & Babloyantz, A. [1991] "Pacemaker-induced coherence in cortical networks" *Neural Computation* **3**, 145–154.

Ding, Y. & Marotte, L. [1994] "Retinotopy in the developing optic nerve of the wallaby (Macropus eugenii)" Communicated at the Australian Neuroscience Society Meeting, Sidney, February 1994.

Eckhorn, R., Bauer, R., Jordan, W., Brosch, M., Kruse, W., Munk, M., & H., R. [1988] "Coherent oscillations: A mechanism of feature linking in the visual cortex?" *Biological Cybernetics* **60**, 121–130.

Edelman, S. [1994] "Biological constraints and the representation of structure in vision and language" PSYCOLOQUY 5 (46), language-network.3.edelman.

Elbert, T., Ray, W., Kowalik, Z., Skinner, J., Graf, K., & Birbaumer, N. [1994] "Chaos in physiology: Deterministic chaos in excitable cell assemblies" *Physiological Reviews* **74**, 1–47.

FitzHugh, R. [1961] "Impulses and physiological states in models of nerve membrane" *Biophysics Journal* **1**, 445–466.

FitzHugh, R. [1969] "Mathematical models of excitation and propagation in nerve" in: H. Schwan, ed., *Biological Engineering* pp. 1–85 (McGraw-Hill New York).

Freeman, W. [1991] "The physiology of perception" *Scientific American* **264**, 78–85.

Freeman, W. [1994] "Chaos in the CNS: Theory and practice" in: F. Ventriglia, ed., *Neural Modeling and Neural Networks* pp. 185–216 (Pergamon Press New York).

Fries, P., Reynolds, J., Rorie, A., & Desimone, R. [2001] "Modulation of oscillatory neuronal synchronization by selective visual attention" *Science* **291**, 1560–1563.

Fuchs, A., Kelso, J., & Haken, H. [1992] "Phase transitions in the human brain: Spatial mode dynamics" *International Journal of Bifurcation and Chaos* **2**, 917–939.

Gallez, D. & Babloyantz, A. [1991] "Predictability of human EEG: a dynamical approach" *Biological Cybernetics* **64**, 381–391.

Georgopoulos, A., Lurito, J., Petrides, M., Schwartz, A., & Massey, J. [1989] "Mental rotation of the neuronal population vector" *Science* **243**, 234–236.

Girod, J., Martin, G., Heit, B., & Bremont, J. [1994] "Image segmentation by the modelisation of the biological visual system" in: *Proceedings of the IEEE International Conference on Neural Networks, Orlando, Florida, 28 June-2 July 1994* pp. 2233–2238 (IEEE Press Piscataway, New Jersey).

Gray, C. & Singer, W. [1989] "Stimulus-specific neuronal oscillations in orientation columns of cat visual cortex" *Proceedings of the National Academy of Sciences USA* **86**, 1698–1702.

Hatsopoulos, N., Gabbiani, F., & Laurent, G. [1995] "Elementary computation of object approach by a wide-field visual neuron" *Science* **270**, 1000–1003.

Hillyard, S. & Picton, T. [1979] "Event-related brain potentials and selective information processing in man" in: J. Desmedt, ed., *Cognitive Components in Cerebral Event-related Potentials and Selective Attention* vol. 6 of *Progress in Clinical Neurophysiology* pp. 1–52.

Honavar, V. & Uhr, L. [1989] "Brain-structured connectionist networks that perceive and learn" *Connection Science* **1**, 139–159.

Hubel, D. [1982] "Exploration of the primary visual cortex, 1955-1978" *Nature* **299**, 515–524.

Jirsa, V. K. [this issue] "Information processing in brain and behavior displayed in large-scale scalp topographies such as EEG and MEG" *International Journal of Bifurcation and Chaos*.

Kandel, E., Schwartz, J., & Jessel, T., eds. [1999] Principles of Neural Science. (Appleton and Lange) fourth edn.

Kelso, J., Bressler, S., Buchanan, S., DeGuzman, G., Ding, M., Fuchs, A., & Holroyd, T. [1992] "A phase transition in human brain and behavior" *Physics Letters A* **169**, 134–144.

Kelso, J. & Fuchs, A. [1995] "Self-organizing dynamics of the human brain: Critical instabilities and šil'nikov chaos" *Chaos* **5**, 64–69.

Kostelich, E., Grebogi, C., Ott, E., & Yorke, J. [1993] "Higher-dimensional targeting" *Physical Review E* **47**, 305–310.

Kunes, S., Wilson, C., & Steller, H. [1993] "Independent guidance of retinal axons in the developing visual system of Drosophyla" *The Journal of Neuroscience* **13**, 752–767.

Lachaux, J.-P., Pezard, L., Garnero, L., Pelte, C., Renault, B., Varela, F., & Martinerie, J. [1997] "Spatial extension of brain activity fools the single-channel reconstruction of EEG dynamics" *Human Brain Mapping* **5**, 26–47.

Lehmann, D. [1989] "Microstates of the brain in EEG and ERP mapping studies" in: E. Başar & T. Bullock, eds., *Brain Dynamics* vol. 2 of *Springer Series in Brain Dynamics* pp. 72–83 (Springer-Verlag Berlin).

Llinás, R. [1988] "The intrinsic electrophysiological properties of mammalian neurons: Insights into central nervous system function" *Science* **242**, 1654–1664.

Lourenço, C. & Babloyantz, A. [1994] "Control of chaos in networks with delay: A model for synchronization of cortical tissue" *Neural Computation* **6**, 1141–1154.

Mangun, G. & Heinze, H.-J. [1995] "Combining electrophysiology with neuroimaging in the study of human cognition" in: H. Herrmann, D. Wolf, & Pöppel, eds., *Workshop on Supercomputing and Brain Research: From Tomography to Neural Networks, HLRZ, KFA Jülich, Germany, 21-23 November 1994* pp. 61–74 (World Scientific Singapore).

Nicolelis, M., Baccala, L., Lin, R., & Chapin, J. [1995] "Sensorimotor encoding by synchronous neural ensemble activity at multiple levels of the somatosensory system" *Science* **268**, 1353–1358.

Nicolelis, M., Lin, R., Woodward, D., & Chapin, J. [1993] "Dynamic and distributed properties of many-neuron ensembles in the ventral posterior medial thalamus of awake rats" *Proceedings of the National Academy of Sciences USA* **90**, 2212–2216.

Ott, E. [1993] Chaos in Dynamical Systems. (Cambridge University Press).

Ott, E., Grebogi, C., & Yorke, J. [1990] "Controlling chaos" *Physical Review Letters* **64**, 1196–1199.

Rapp, P., Zimmerman, I., Albano, A., de Guzman, G., & Greenbaun, N. [1985] "Dynamics of spontaneous neural activity in the simian motor cortex: The dimension of chaotic neurons" *Physics Letters A* **110**, 335–338.

Rapp, P., Zimmerman, I., Albano, A., de Guzman, G., Greenbaun, N., & Bashore, T. [1986] "Experimental studies of chaotic neural behavior: cellular activity and electroencephalographic signals" in: H. Othmer, ed., *Nonlinear Oscillations in Biology and Chemistry* vol. 66 of *Lecture Notes in Biomathematics* pp. 366–381 (Springer-Verlag Berlin).

Richards, W., Wilson, H., & Sommer, M. [1994] "Chaos in percepts?" *Biological Cybernetics* **70**, 345–349.

Röschke, J. & Başar, E. [1988] "The EEG is not a simple noise: strange attractors in intracranial structures" in: E. Başar, ed., *Dynamics of Sensory and Cognitive Processing by the Brain* vol. 1 of *Springer Series in Brain Dynamics* pp. 203–216 (Springer-Verlag Berlin).

Rougeul, A., Corvisier, J., & Letalle, A. [1974] "Rythmes electrocorticaux caracteristiques de l'instalation du sommeil naturel chez le chat. Leurs rapports avec le comportement moteur" *Electroencephalography and Clinical Neurophysiology* **37**, 41–57.

Rougeul-Buser, A., Bouyer, J., & Buser, P. [1978] "Transitional states of awareness and short-term fluctuations of selective attention: Neurophysiological correlates and hypotheses" in: P. Buser & A. Rougeul-Buser, eds., *Cerebral Correlates of Conscious Experience, INSERM Symposium No. 6* (Elsevier/North-Holland Biomedical Press).

Rougeul-Buser, A., Bouyer, J., Montaron, M., & Buser, P. [1983] "Patterns of activities in the ventrobasal thalamus and somatic cortex SI during behavioral immobility in the awake cat: Focal waking rhythms" in: *Experimental Brain Research, Suppl. 7* (Springer-Verlag Berlin).

Ruelle, D. [1978] Thermodynamic Formalism. (Addison-Wesley Reading, MA).

Schneider, W., Pimm-Smith, M., & Worden, M. [1995] “Neurobiology of attention and automaticity” *Current Opinion in Biology – Cognitive neuroscience* pp. 177–182.

Sepulchre, J.-A. [1993] Phénomènes Spatio-temporels dans des Réseaux d’Oscillateurs – Applications au Traitement d’Information. Ph.D. thesis Université Libre de Bruxelles.

Sereno, M. [1995] “Language and the primate brain” Center for Research in Neurolanguage, Newsletter, Article 4-4 (University of California at San Diego).

Shinbrot, T., Ditto, W., Grebogi, C., Ott, E., Spano, M., & Yorke, J. [1992] “Using the sensitive dependence of chaos (the “butterfly effect”) to direct trajectories in an experimental chaotic system” *Physical Review Letters* **68**, 2863–2866.

Single, S. & Borst, A. [1998] “Dendritic integration and its role in computing image velocity” *Science* **281**, 1848–1850.

Skarda, C. & Freeman, W. [1987] “How brains make chaos in order to make sense of the world” *Behavioral and Brain Sciences* **10**, 161–195.

Strehler, B. & Lestienne, R. [1986] “Evidence on precise time-coded symbols and memory of patterns in monkey cortical neuronal spike trains” *Proceedings of the National Academy of Sciences USA* **83**, 9812–9816.

Takens, F. [1980] “Detecting strange attractors in turbulence” in: D. Rand & L.-S. Young, eds., *Dynamical Systems and Turbulence* vol. 898 of *Springer Lecture Notes in Mathematics* pp. 366–381 (Springer-Verlag New York, Heidelberg, Berlin).

Tootell, R., Switkes, E., Silverman, M., & Hamilton, S. [1988] “Functional anatomy of macaque striate cortex. II. Retinotopic organization” *The Journal of Neuroscience* **8**, 1531–1568.

von der Malsburg, C. & Singer, W. [1988] “Principles of cortical network organization” in: P. Rakić & W. Singer, eds., *Neurobiology of Neocortex* pp. 69–99 (Wiley).

Wallenstein, G., Kelso, J., & Bressler, S. [1995] “Phase transitions in spatiotemporal patterns of brain activity and behavior” *Physica D* **84**, 626–634.

Wu, J.-Y., Cohen, L., & Falk, C. [1994] “Neuronal activity during different behaviors in *Aplysia*: A distributed organization?” *Science* **263**, 820–823.

Young, M. & Yamane, S. [1992] “Sparse population coding of faces in the inferotemporal cortex” *Science* **256**, 1327–1331.

Figures

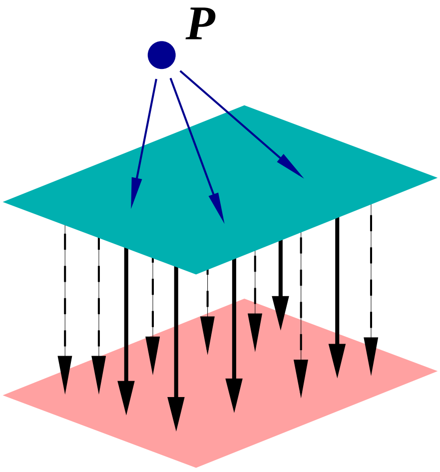


Figure 1: Chaotic categorizer. The pacemaker P sends micropulses to layer I, thus stabilizing one of the unstable periodic orbits. The oscillators of layers I and II are connected with a one-to-one correspondence. The distribution of active links (solid arrows) and inactive ones (dashed arrows) is determined by a pattern to be processed. A response is measured from output layer II.

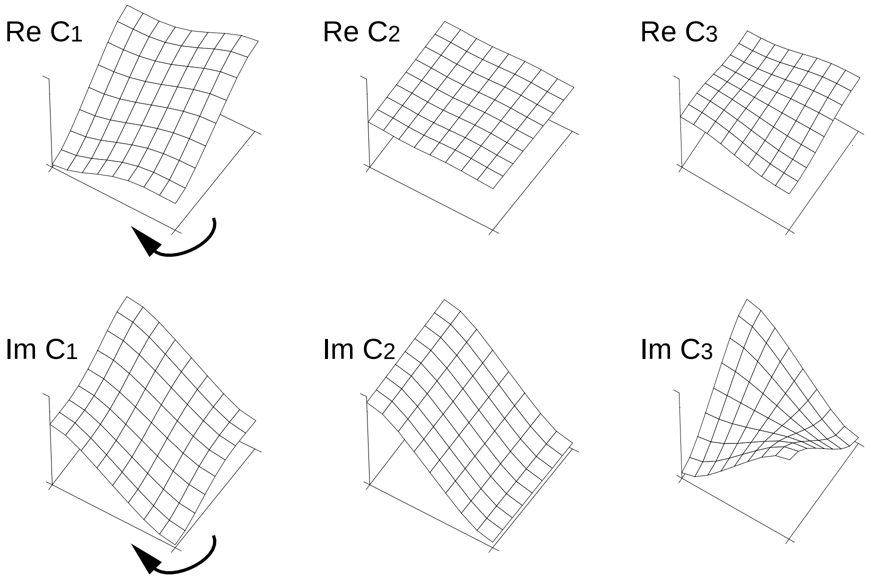


Figure 2: Snapshots of network activity Z corresponding to the unstable periodic orbits $\mathcal{C}_1$, $\mathcal{C}_2$ and $\mathcal{C}_3$ with periods $T = 13.66$, 15.38 and 2.25, respectively. The vertical axes span the interval $[-1.2, 1.2]$. Parameter values are $N = 9$, $\alpha = -10$, $\beta = 2$ and $D = 1.3$. For orbit $\mathcal{C}_1$, arrows show the direction of rotation of the wave of activity.

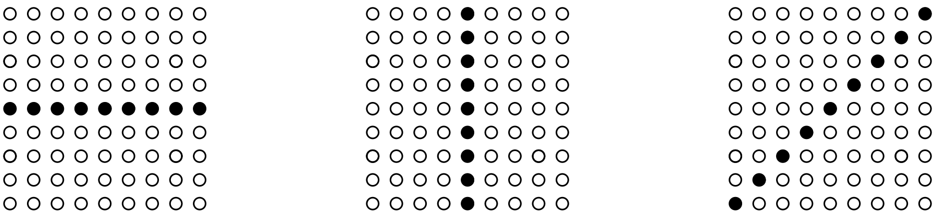

(a) (b) (c)

Figure 3: Three different orientations for a spatial pattern consisting in a straight bar. The device can discriminate between these orientations.

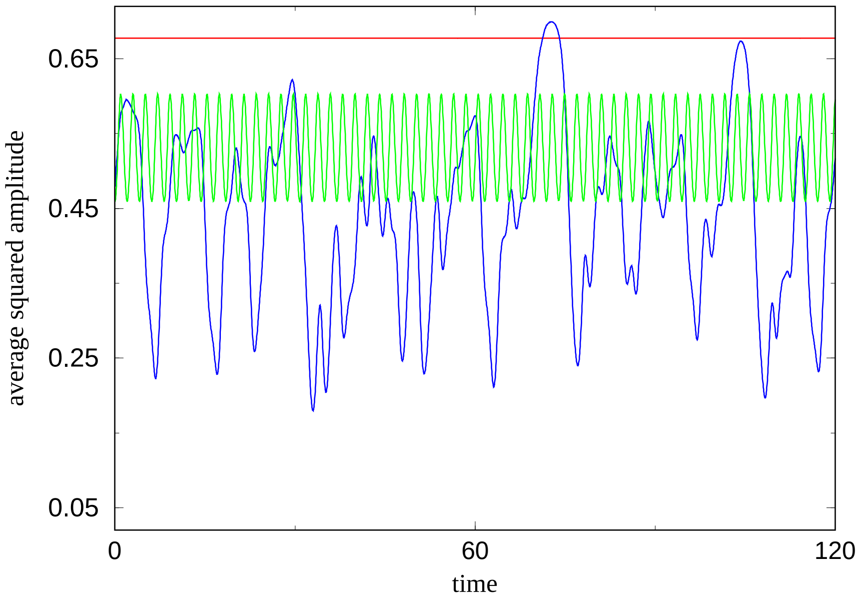


Figure 4: Space average of the squared amplitude, $\langle |W|^2 \rangle$, measured from layer II. Orbit $\mathcal{C}_2$ is stabilized in layer I. The three patterns of Fig. 3 are presented to the device, respectively: (a) a bar activating the nine middle links and parallel to the direction of polarity of $\mathcal{C}_2$ (red line); (b) a bar activating nine links perpendicularly to the direction of polarity (blue line); (c) a bar activating nine links along one of the diagonals of the network (green line). $\gamma = 2.44$ and all other parameters are as in Fig. 2.

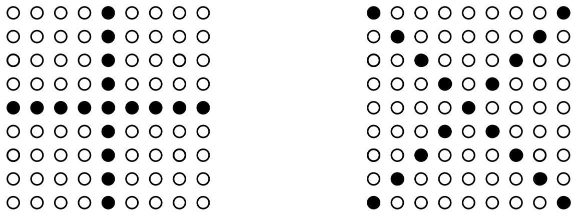


Figure 5: A pair of symbol patterns to be discriminated by the categorizer.

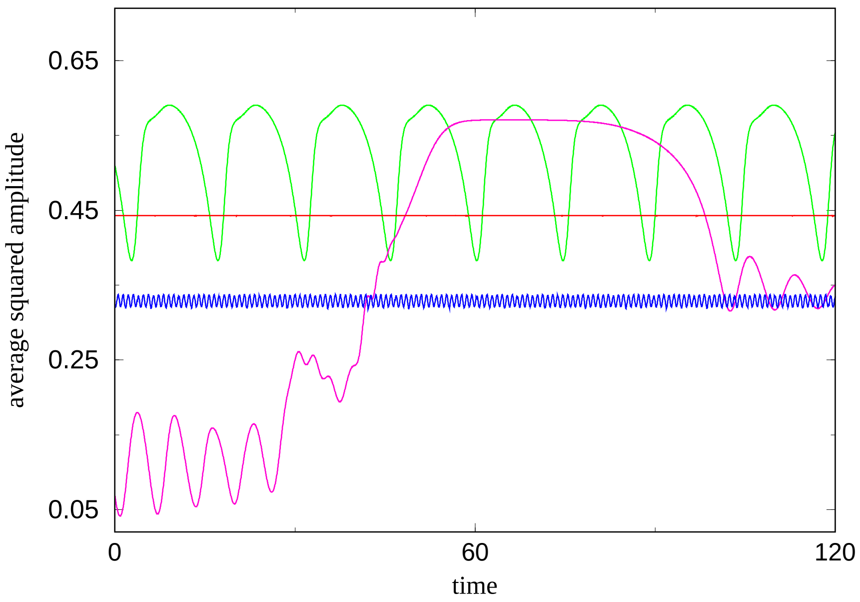


Figure 6: Responses $\langle |W|^2 \rangle (t)$ of the output layer in the presence of the patterns + and ×. With orbit $\mathcal{C}_2$ the response is shown as a green line for pattern + and a magenta line for pattern ×. When orbit $\mathcal{C}_3$ is used, the response corresponding to the pattern + is shown as a red line, whereas the blue line is obtained with the pattern ×. Parameter values are as in Fig. 4.

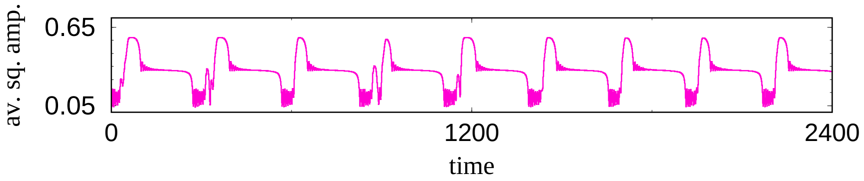


Figure 7: Plot of $\langle |W|^2 \rangle (t)$ of the output layer in attentive state $\mathcal{C}_2$ and in the presence of pattern × (same color as in Fig. 6), but with a longer time-span than in Fig. 6. Parameter values are as in Fig. 4.

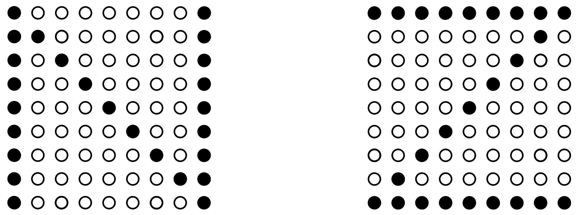


Figure 8: Another pair of symbol patterns to be processed.

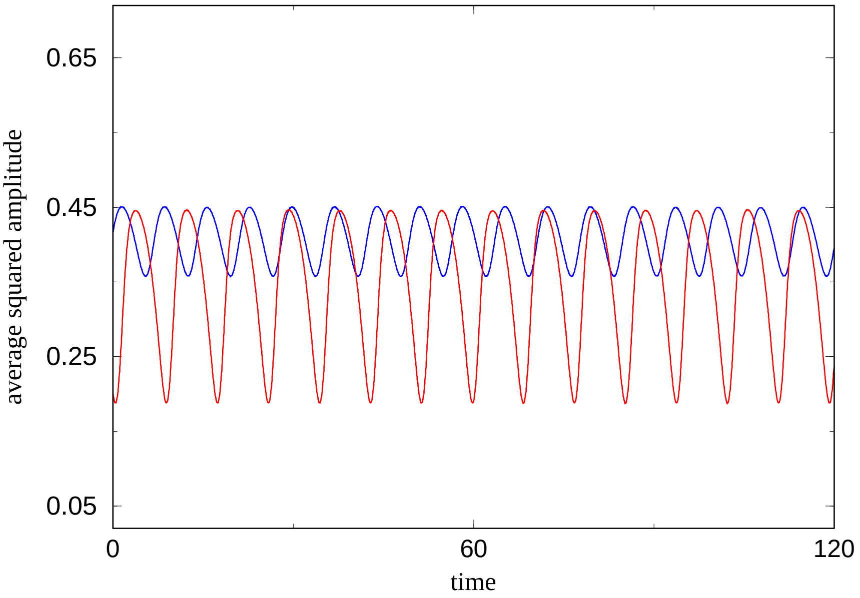


Figure 9: Responses $\langle|W|^2\rangle(t)$ showing a discrimination between patterns N (blue line) and Z (red line). Orbit $\mathcal{C}_2$ is stabilized in layer I. Parameter values are as in Fig. 4.

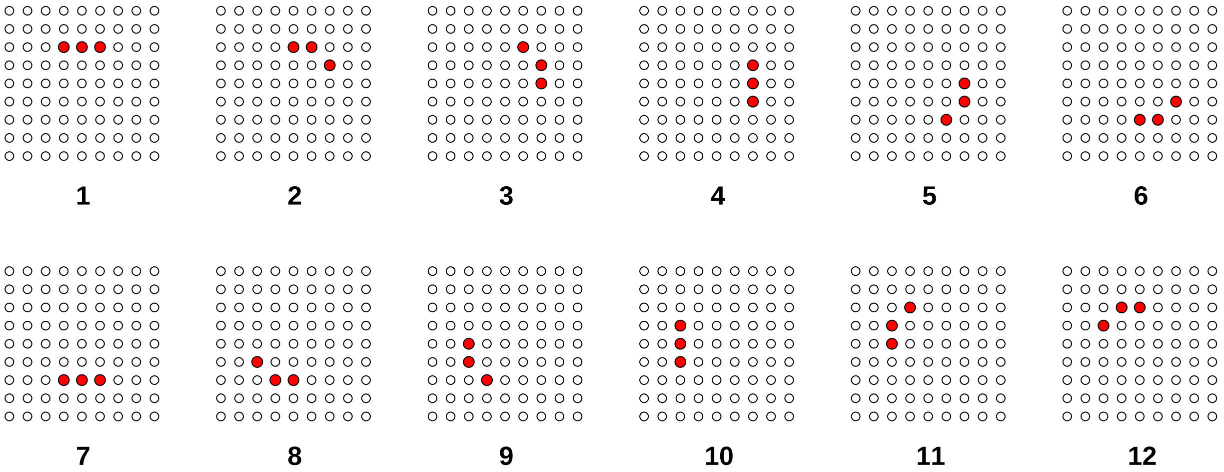


Figure 10: "Motion picture" showing the successive positions occupied by the active units of a moving pattern. After frame 12, the motion continues at frame 1, originating a continuous loop. The result is a circular motion. The period of rotation is varied according to the needs of each experiment. Both directions of rotation are considered, but the present figure shows only the clockwise direction.

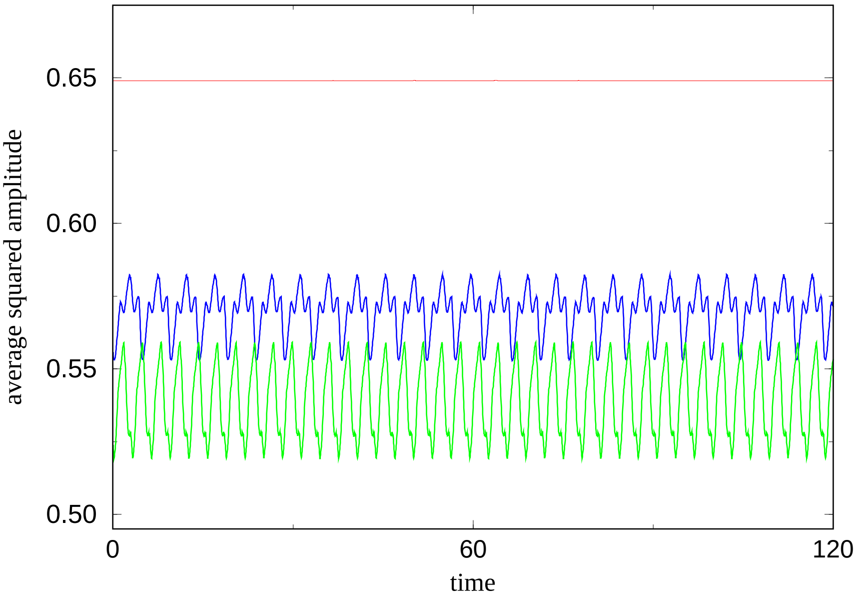


Figure 11: $\langle|W|^2\rangle(t)$ computed in the attentive state $\mathcal{C}_1$ for a clockwise (red line) and a counterclockwise rotating pattern (blue line), with period of rotation $T = 18.96$. If the object rotates in the counterclockwise direction with a period $T = 12.48$ (green line), a higher amplitude response with a lower time-average value is seen. $\gamma = 30$; other parameters are as in Fig. 2.

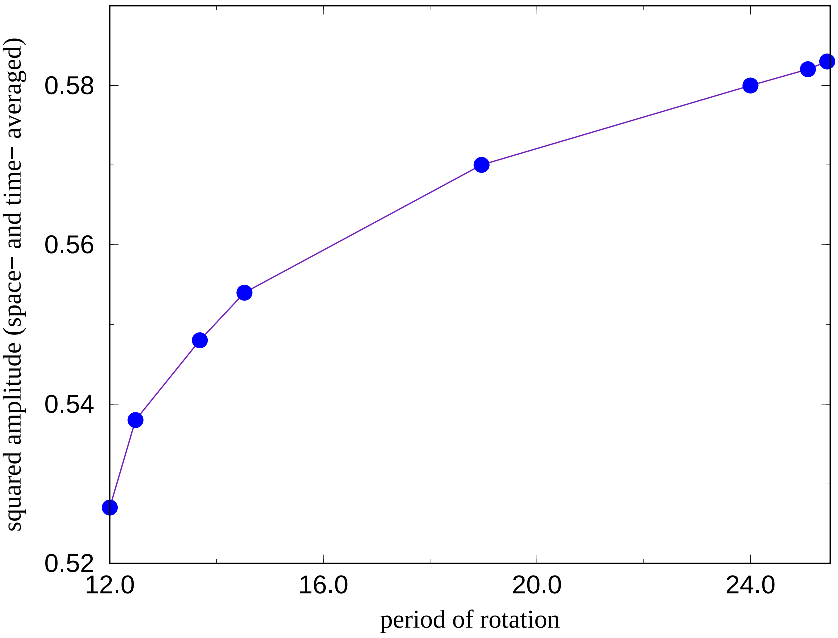


Figure 12: Dependence of the average $(1/t)\int_{\text{o}}^{t}\langle|W|^2\rangle(\tau)\,d\tau$ on the period of rotation T of the pattern. The device operates in the attentive state $\mathcal{C}_1$. Here, the direction of rotation of the object is counterclockwise. The clockwise motion does not display this dependence. See text for the details.

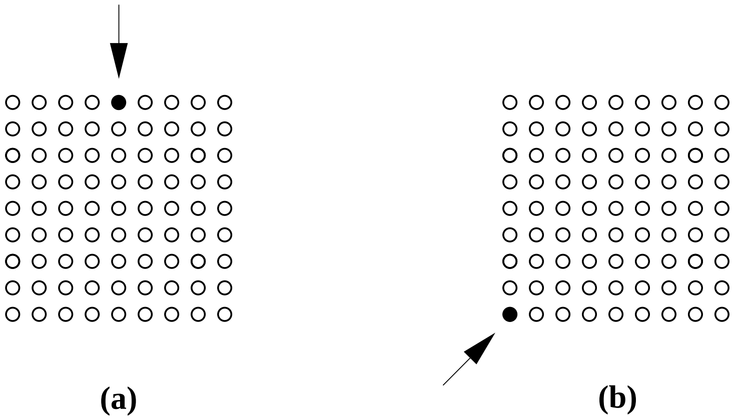
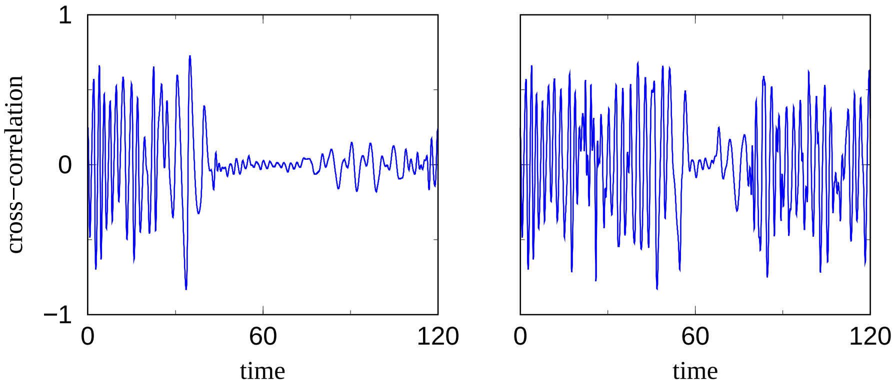
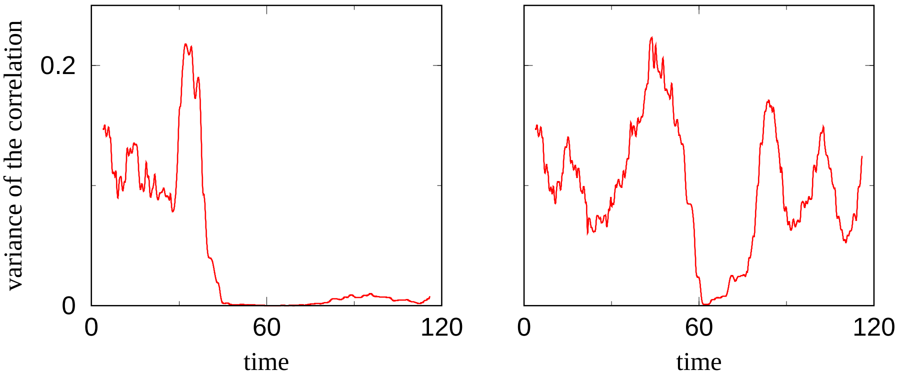


Figure 13: Patterns of motion along straight lines, in two different directions. The arrows indicate the point of entry of the moving object in the visual field, and also the direction of the motion. Each link is activated during eleven time units. Therefore, in both cases, the object remains inside the visual field during 11 × 9 = 99 time units.



(a) (b)

Figure 14: Discrimination between two different directions of linear motion. Shown is the time-variation of the cross-correlation $C(t)$, given by Eq. (3), for the two cases illustrated in Fig. 13. The device operates in the attentive state $\mathcal{C}_3$. (a) and (b) correspond to Fig. 13 (a) and Fig. 13 (b), respectively. In both cases, the time-window of observation is larger than the period that the moving object spends inside the visual field: the object enters the scene at $t = 11$ and leaves it at $t = 110$. $\gamma = 25$; other parameters are as before.



(a) (b)

Figure 15: Running variance of the time-series in Fig. 14, distinguishing between two different directions of linear motion. (a) and (b) correspond to perpendicular and diagonal motions, respectively. The variance is evaluated within a running time-window measuring eight time units.