

# **Complexity and emergence of meaning: the fundamental level of neurophysics(\*)**

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## Outline

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### Abstract

The central issue of cognitive science is how a large collection of coupled neurons does not limit to automatic responses to environmental inputs, as done by brainless lower animals, but combines external data with internal memories into new coherent patterns of meaning.

Based on recent laboratory investigations of homoclinic chaotic systems, and how they mutually synchronize by weak coupling, a novel conjecture on the dynamics of the single neuron is formulated. Homoclinic chaos appears as the easiest way to code information in time by a code consisting of trains of equal spikes occurring at erratic times; synchronization of trains of different individual neurons is the basis of a coherent perception.

The percept space P can be given a metric structure by introducing a distance measure. The distance in P space is conjugate to the duration time in the sense that a quantum uncertainty relation in percept space is associated with time limited perceptions.

(+) Presentato al Workshop “Determinismo, Olismo e Complessità” , Arcidosso (GR), 3-8 Settembre 2001.

## Introduction

In a debate on “Complexity and emergence”, we should first of all provide clear definitions for these terms, in order to ascertain how much of what we say depends on our cultural bias, is an artifact of our linguistic tools, and how much corresponds to hard facts, to our embedding in an open environment, whose features, even though actively elaborated by our semantic memory, can not be taken as sheer “autopoiesis”, but are grounded on an ontology.

This inquiry is done from the point of view of a physicist who has been active for decades in investigating the formation of collective or coherent processes out of a large amount of otherwise separate individuals, pointing out the critical appearance (emergence) of new world configurations and the elements of novelty of this emergence, which make this phenomenon complex. By complex we do not mean the trivial fact that the computational cost of their description is high (in such a case I would rather call them complicate) but the fact that available knowledge stored in well established models is not sufficient to predict reliably the emergence, and one must integrate the deductive chains with extra information which introduces a historical flavour into the scientific procedure.

This presentation is organized as follows.

The core of the paper goes to the very ground of perceptive processes. If we accept – as proper of complex systems – to organize our knowledge as different and mutually irreducible hierarchical levels, each one with its own rules and language, then the most fundamental one in cognitive processes is the physical description of how external stimuli (light, sound, pressure, chemicals) are transformed into sensorial perceptions.

Without entering those levels which for a physicist are meta-levels rather foreign to his/her competence, already at the neurodynamical level, we come across a quantum limitation, here presented explicitly for the first time, which forbids the brain operations to be fully simulated by a universal computing machine. By purpose, I said “brain” since I do not wish to enter the debates on “mind”, “consciousness” etc.

I have called “neurophysics” the combination of neurodynamical facts, whereby neurons are treated as physical objects to be compared to lasers or other nonlinear dynamical systems, and the quantum limitation emerging from the peculiar spike synchronization strategy selected in course of the natural evolution as the optimal strategy to elaborate information into relevant cognitive processes.

As for the Reference list, I have often replaced the specific mention of an article or a book by a Web site, where one can conveniently browse for a more satisfactory answer. I think that time is ripe to consider this reference tool as a standard one.

### 1. What is neurophysics

It is by now firmly established that a holistic perception emerges, out of separate stimuli entering different receptive fields, by synchronizing the corresponding spike trains of neural action potentials [Von der Malsburg, Singer].

We recall that action potentials play a crucial role for communication between neurons [Izhikevich]. They are steep variations in the electric potential across a cell’s membrane, and they propagate in essentially constant shape from the soma (neuron’s body) along axons toward synaptic connections with other neurons. At the synapses they release an amount of neurotransmitter molecules

depending upon the temporal sequences of spikes, thus transforming the electrical into a chemical carrier.

As a fact, neural communication is based on a temporal code whereby different cortical areas which have to contribute to the same percept  $P$  synchronize their spikes. Spike emission from a nonlinear threshold dynamical system results as a trade off between bottom-up stimuli to the higher cortical regions (arriving through the LGN (lateral geniculate nucleus) from the sensory detectors, video or audio) and threshold modulation due to top-down readjustment mediated by glial cells [Parpura and Haydon].

It is then plausible to hypothesize, as in ART (adaptive resonance theory [Grossberg1995a]) or other computational models of perception [Edelman and Tononi] that a stable cortical pattern is the result of a Darwinian competition among different percepts with different strength. The winning pattern must be confirmed by some matching procedures between bottom-up and top-down signals. It is the aim of this Section to present two fundamental aspects of percept formation, namely,

- i) The neurodynamics of spike formation
- ii) A quantum limitation in information encoding/decoding through spike trains

As for the first aspect, a saddle point instability separates in parameter space an *excitable* region, where axons are silent, from a *periodic* region, where the spike train is periodic (equal interspike intervals). If a control parameter is tuned at the saddle point, the corresponding dynamical behavior (homoclinic chaos) consists of a frequent return to the instability [Allaria]. This manifests as a train of geometrical identical spikes, which however occur at erratic times (chaotic interspike intervals). Around the saddle point the system displays a large susceptibility to an external stimulus, hence it is easily adjustable and prone to respond to an input, provided this is at sufficiently low frequencies; this means that such a system is robust against broadband noise as discussed later.

As for the second aspect, the temporal coding requires a sufficiently long sequence of synchronized spikes, in order to realize a specific percept. If the sequence is interrupted by the arrival of new uncorrelated stimuli, then a fundamental uncertainty  $\Delta P$  emerges in the percept space  $P$ . This is related to the finite duration  $\Delta T$  allotted for the code processing by a fundamental uncertainty relation

$$\Delta P \cdot \Delta T \geq C$$

where  $C$  is a positive dimensional quantity whose non zero value represents a quantum constraint on the coding. This constraint implies that the percepts are not set-theoretical objects, that is, objects belonging to separate domains, but there are overlap regions where it is impossible to discriminate one percept from another. We will discuss later the occurrence of this new class of time dependent perceptual illusions.

We call “neurophysics” the combination of i) and ii), by analogy with “econophysics” which as extracted some general physical from economic phenomena [Mantegna].

Neurophysics is distinct from neurodynamics, which is the investigation of dynamical models of neuron behaviors, as well from neurophysiology, which explores the coupling of different brain areas. Neurophysics is restricted to the two above items, and it is rather model-independent, so that it provides a general ground upon which different models can be built and compared.

## 2. Neurodynamics

The neurodynamic aspect has been dealt with in a preliminary series of reports, that here I recapitulate as the following chain of linked facts.

- 1) A single spike in a 3D dynamics corresponds to a quasi-homoclinic trajectory around a saddle point (fixed point with 1 (2) stable direction and 2 (1) unstable ones); the trajectory leaves the saddle and returns to it (Fig.1).

- 2) A train of spike corresponds to the sequential return to, and escape from, the saddle point. A control parameter can be set at a value  $B_C$  for which this return is erratic (chaotic interspike interval) even though there is a finite average frequency. As the control parameter is set above or below  $B_C$ , the system moves from *excitable* (single spike triggered by an input signal) to *periodic* (yielding a regular sequence of spikes without need for an input), with a frequency monotonically increasing with the separation  $\Delta B$  from  $B_C$  (Fig.2) [Meucci].
- 3) Around the saddle point the dynamical system has a high susceptibility. This means that a tiny disturbance applied there provides a large response. Thus the homoclinic spike trains can be synchronized by a periodic sequence of small disturbances (Fig. 3). However each disturbance has to be applied for a minimal time, below which it is no longer effective; this means that the system is insensitive to broadband noise, which is a random collection of fast positive and negative signals.
- 4) The above considerations lay the floor for the use of mutual synchronization as the most convenient way to let different neurons respond coherently to the same stimulus, organizing as a space pattern. In the case of a single dynamical system, it can be fed back by its own delayed signal. As the delay is long enough the system is decorrelated with itself and this is equivalent to feeding an independent system. This process allows to store meaningful sequences of spikes as necessary for a long term memory [Arecchi et al.2001].

### 3. The role of synchronization in neural communications

The role of elementary feature detectors has been extensively studied in the past decades. Let us refer to the visual system [Hubel]; by now we know that some neurons are specialized in detecting exclusively vertical or horizontal bars, a specific luminance contrast, etc. However the problem arises: how elementary detectors contribute to a holistic (Gestalt) perception? A hint is provided by Fig.4 [Singer]. Both the woman and the cat are made of the same visual elements, horizontal and vertical contour bars, different degrees of luminance, etc. What are then the neural correlates of the identification of separate individual objects? We have one million fibers connecting the retina to the visual cortex, through the LGN. Each fiber results from the merging of approximately 100 retinal detectors (rods and cones) and as a result it has its own receptive field which is about 3.5 angular degrees wide. Each receptive field isolate a specific detail of an object (e.g. a vertical bar). We thus split an image into a mosaic of adjacent receptive fields, as indicated in the figure by white circles for the woman and black circles for the cat.

Now the “feature binding” hypothesis consists of assuming that all the neurons whose receptive fields are pointing to a specific object (either the woman or the cat) synchronize the spikes as shown in the right of the figure. Here each vertical bar, of duration 1 millisecc, correspond to a single spike, and there are two distinct spike trains for the two objects.

Direct experimental evidence of this synchronization is obtained by insertion of microelectrodes in the cortical tissue of animals just sensing the single neuron [Singer]. Indirect evidence of synchronization has been reached for human beings as well, by processing the EEG (electroencephalo-gram) data [Rodriguez et al.].

The advantage of such a temporal coding scheme, as compared to traditional rate based codes, which are sensitive to the average pulse rate over a time interval and which have been exploited in communication engineering, has been discussed in a recent paper [Softky].

Based on the neurodynamical facts reported above, we can understand how this occurs [Grossberg 1995a, Julesz]. In Fig.5 the central cloud represents the higher cortical stages where synchronization takes place. It has two inputs. One (bottom-up) comes from the sensory detectors via the early stages which classify elementary features. This single input is insufficient, because it would provide the same signal for e.g. horizontal bars belonging indifferently to the woman or to the cat. However, as we said already, each neuron is a nonlinear system passing close to a saddle point, and the

application to a suitable perturbation can stretch or shrink the interval of time spent around, and thus lengthen or shorten the interspike interval. The perturbation consists of top-down signals corresponding to conjecture made by the semantic memory.

In other words, the perception process is not like the passive imprinting of a camera film, but it is an active process whereby the external stimuli are interpreted in terms of past memories. A focal attention mechanism assures that a matching is eventually reached. This matching consists of resonant or coherent behavior between bottom-up and top-down signals; that is why it has received the name ART as introduced by Grossberg (1976) and later specified in term of synchronization of the spike positions by Von der Malsburg has tested by Singer and his school. If matching does not occur, different memories are tried, until the matching is realized. In presence of a fully new image without memorized correlates, then the brain has to accept the fact that it is exposed to a new experience.

Notice the advantage of this time dependent use of neurons, which become available to be active in different perceptions at different times, as compared to the computer paradigm of fixed memory elements which store a specific object and are not available for others (the so called “grandmother neuron” hypothesis).

#### 4. The self-organizing character of synchronized patterns

We have presented above qualitative reasons why the degree of synchronization represents the perceptual salience of an object. Synchronization of neurons located even far away from each other yields a space pattern on the sensory cortex, which can be as wide as a few millimeter-square, involving one million neurons. The winning pattern is determined by dynamic competition (the so-called “winner takes all” dynamics).

This model has an early formulation in ART and has been later substantiated by the synchronization mechanisms. Perceptual knowledge appears as a complex self-organizing process. We show how this approach overcomes earlier approaches of A.I. (Artificial Intelligence) and PDP (Parallel Distributed Processing) models.

Classical accounts of knowing and learning, influenced by the information processing paradigm, hold that procedural and declarative knowledge reside as information in long-term memory and are assembled during problem solving to produce appropriate solution. The underlying assumption is that any cognitive agent possesses some language-like sign system to represent the world; cognition is said to occur when these sign systems are manipulated according to rules with IF....THEN.... structure [Anderson].

This classical approach to cognition, which posits some sign system as the necessary and sufficient condition for any cognitive agent to exhibit intelligence, is known as the physical symbol system hypothesis [Newell and Simon]. However, this approach, in which learning is conceived of as the rule-governed updating of a system of sentences encountered numerous failures to account for empirical data as [Churchland and Sejnowski]:

- the preanalytic human judgements of credibility which is the basis of any account of large scale conceptual change as the acceptance of a new scientific paradigm;
- the perceptual discriminations;
- the connections between conceptual and material practices which are the basis of manual activities;
- the speed with which human beings construct appropriate frames relevant to explanatory problems (the so-called “frame problem”).

In the PDP models the connectivity is realized by three layers consisting of input, hidden and output units (fig.6).

In contrast with the traditional computer models such networks are not programmed to contain procedural and declarative knowledge but are trained to do specific things [Churchland and Sejnowski]. The network is exposed to a large set of examples. Each time the output is compared to the “correct” answer, the difference is used to readjust the connection weights through the network.

This is a form of training known as “back propagation”. However, a strong criticism [Grossberg 1995b] is that connections are fixed apriori and there is no self-organizing behavior as instead it occurs in the dynamical formation of a synchronized pattern.

A possible model for a patterned coupling of neurons across the sensorial cortex has been suggested by Calvin [Calvin] in analogy with the pattern formation at the top of a fluid layer heated from below. In both cases if the excitation range is fixed (in our case by the axon length), then the most likely configuration is an equilateral triangle, since each vertex confirms the other two. But each vertex can also be coupled to other equilateral triangles, yielding an overall mosaic pattern which looks as a floor of connected hexagons.

### 5. A metric in percept space

We discuss two proposal of metrics of spike trains. The first one that we call class A [Victor and Purpura] considers each spike as very short, almost like a Dirac delta-function and each coincidence as an instantaneous event with no time uncertainty. The metric spans a large, yet discrete, space and it can be programmed on a standard computer.

A more recent proposal [Rossum] accounts for the physical fact that each spike is spread in time by filtering process, hence the overlap takes a time breadth  $t_c$  and any coincidence is a smooth process. Indeed, as discussed above, in neurodynamics the high sensitivity region around the saddle point has a finite time width (unpublished results of my research group). We call B the class of smooth metrics.

The discrete metrics A satisfy a set-theoretical expectation and are programmable in a computer. The continuous metrics B fit better neurodynamical facts; they however imply a quantum limitation which then seems to be intrinsic of cognitive processes.

#### Class A metrics

Victor and Purpura [Victor and Purpura] have introduced several families of metrics between spike trains as a tool to study the nature and precision of temporal coding. Each metric defines the distance between two spike trains as the minimal "cost" required to transform one spike train into the other via a sequence of allowed elementary steps, such as inserting or deleting a spike, shifting a spike in time, or changing an interspike interval length.

The geometries corresponding to these metrics are in general not Euclidean, and distinct families of cost-based metrics typically correspond to distinct topologies on the space of spike trains. Each metric, in essence, represents a candidate temporal code in which similar stimuli produce responses which are close and dissimilar stimuli produce responses which are more distant.

Spike trains are considered to be points in an abstract topological space. A spike train metric is a rule which assigns a non-negative number  $D(S_a, S_b)$  to pairs of spike trains  $S_a$  and  $S_b$  which expresses how dissimilar they are.

A metric  $D$  is essentially an abstract distance. By definition, metrics have the following properties:

- $D(S_a, S_a) = 0$
- Symmetry:  $D(S_a, S_b) = D(S_b, S_a)$
- Triangle inequality:  $D(S_a, S_c) \leq D(S_a, S_b) + D(S_b, S_c)$
- Non-negativity:  $D(S_a, S_b) > 0$  unless  $S_a = S_b$ ,

The metrics may be used in a variety of ways -- for example, one can construct a neural response space via multidimensional scaling of the pairwise distances, and one can assess coding characteristics via comparison of stimulus-dependent clustering across a range of metrics.

#### *Cost-based metrics*

Cost-based metrics fulfill the general definition of a metric, and are constructed with the following ingredients:

- a list of allowed elementary steps (allowed transformations of spike trains)

- an assignment of non-negative costs to each elementary step

For any such set of choices one can define a metric  $D(S_a, S_b)$  as the least total cost of any allowed transformation from  $S_a$  to  $S_b$  via any sequence of spike trains  $S_a, S_1, S_2, \dots, S_n, S_b$ .

#### *The spike count distance $D^{count}$*

This is a cost-based metric in which the elementary steps and associated costs are:

- insert a spike: cost = 1
- delete a spike: cost = 1
- shift a spike in time: cost = 0

The distance between two spike trains is the difference in the number of spikes, independent of when they occur. That is, this metric formalizes the notion that the only significant aspect of a spike train is the number of spikes it contains.

#### *The spike time distance $D^{spike}[q]$*

This is a family of cost-based metrics, parametrized by a "cost per unit time"  $q$  (units of 1/sec). The elementary steps and associated costs are:

- insert a spike: cost = 1
- delete a spike: cost = 1
- shift a spike by an amount of time  $t$ : cost =  $qt$

If  $q$  is very small, this becomes the spike count distance. If  $q$  is very large, all spike trains are far apart from each other, unless they are nearly identical. For intermediate values of  $q$ , the distance between two spike trains is small if they have a similar number of spikes, occurring at similar times. The motivation for this construction is that neurons which act like coincidence detectors should care about this metric. The value of  $q$  corresponds to the temporal precision  $1/q$  of the coincidence detector.

This distance can be calculated efficiently by a dynamic programming algorithm.

#### *The spike interval distance $D^{interval}[q]$*

In this family of cost-based metrics, the elementary steps and associated costs are:

- insert a spike (along with an interspike interval): cost = 1
- delete a spike (along with an interspike interval): cost = 1
- change an interspike interval by an amount of time  $t$ : cost =  $qt$

If  $q$  is very small, this becomes the spike count distance. If  $q$  is very large, all spike trains are far apart from each other, unless they are nearly identical. For intermediate values of  $q$ , the distance between two spike trains is small if they have a similar number of spikes, occurring with similar intervals.

Although this method has been applied successfully [MacLeod et al.], the calculation of the full cost function is quite involved. The reason is that it is not always clear where a displaced spike came from, and if the number of spikes in the trains is unequal, it can be difficult to determine which spike was inserted/deleted.

#### A class B metric

Rossum has introduced an Euclidean distance measure that computes the dissimilarity between two spike trains [Rossum]. First of all, filter both spikes trains giving to each spike a duration  $t_c$ . In our language, this would be the time extension of the saddle point region of high susceptibility, where perturbations are effective. To calculate the distance, evaluate the integrated squared difference of the two trains. The simplicity of the distance allows for an analytical treatment of simple cases. Numerical implementation is straightforward and fast.

The distance interpolates between, on the one hand, counting non-coincident spikes and, on the other hand, counting the squared difference in total spike count. In order to compare spike trains

with different rates, total spike count can be used (large  $t_c$ ). However, for spike trains with similar rates, the difference in total spike number is not useful and coincidence detection is sensitive to noise.

The distance uses a convolution with the exponential function. This has an interpretation in physiological terms.

As an alternative measure, one could convolve the spikes with a square window. In that case the situation becomes somewhat similar to binning followed by calculating the Euclidean distance between the number of spikes in the bins. But in standard binning the bins are fixed on the time axis, therefore two different spike trains yield identical binning patterns as long as spikes fall in the same bin. However, with the proposed distance (convolving with either square or exponential) this does not happen; the distance is zero only if the two spike trains are fully identical (assuming  $t_c$  is finite).

The distance is loosely related to the distance measure introduced by Victor and Purpura. The distance introduced here is explicitly embedded in Euclidean space, which makes it less general but easier to analyze than the class A distance.

Interestingly, the distance is related to stimulus reconstruction techniques, where convolving the spike train with the spike triggered average yields a first order reconstruction of the stimulus [Rieke et al.]. Here the exponential corresponds roughly to the spike triggered average and the filtered spike trains correspond to the stimulus. The distance thus approximately measures the difference in the reconstructed stimuli. This might well explain the linearity of the measure for intermediate  $t_c$ .

## 6. Role of duration T in perceptual definition: a quantum aspect

How does a synchronized pattern of neuronal action potentials become a relevant perception? This is an active area of investigation which may be split into many hierarchical levels. At the present level of knowledge, we think that not only the different receptive fields of the visual system, but also other sensory channels as auditory, olfactory, etc. integrate via feature binding into a holistic perception. Its meaning is “decided” in the PCF (pre frontal cortex) which is a kind of arrival station from the sensory areas and departure for signals going to the motor areas. On the basis of the perceived information, actions are started, including linguistic utterances.

Sticking to the neurodynamical level, which is the most fundamental one, and leaving to other sciences, from neurophysiology to psychophysics, the investigation of what goes on at higher levels of organization, we stress here a fundamental temporal limitation.

Taking into account that each spike lasts about 1 msec, that the minimal interspike separation is 3 msec, and that the average decision time at the PCF level is about  $T=240$  msec, we can split  $T$  into  $240/3 = 80$  bins of 3 msec duration, which are designated by 1 or 0 depending whether they have a spike or not. Thus the total number of messages which can be transmitted is

$$2^{80} \approx 10^{27}$$

that is, well beyond the information capacity of present computers. Even though this number is large, we are still within a finitistic realm. Provided we have time enough to ascertain which one of the  $10^{27}$  different messages we are dealing with, we can classify it with the accuracy of a digital processor, without residual error.

But suppose we expose the cognitive agent to fast changing scenes, for instance by presenting in sequence unrelated video frames with a time separation less than 240 msec. While small gradual changes induce the sense of motion as in movies, big differences imply completely different subsequent spike trains. Here any spike train gets interrupted after a duration  $\Delta T$  less than the canonical  $T$ . This means that the PCF cannot decide among all perceptions coded by the neural systems and having the same structure up to  $\Delta T$ , but different afterwards. How many are they: the remaining time is  $\tau = T - \Delta T$ . To make a numerical example, take a time separation of the video frames  $\Delta T = T/2$ , then  $\tau = T/2$ . Thus in spike space an interval  $\Delta P$  comprising

$$2^{\tau/3} \approx 2^{40} \approx 10^{13}$$

different perceptual patterns is uncertain.

As we increase  $\Delta T$ ,  $\Delta P$  reduces, thus we have an uncertainty principle

$$\Delta P \Delta T \geq C$$

If we adopt the Victor Purpura metrics, with the distances measured by costs in nondimensional units, than  $C$  has the dimensions of a time.

If we adopt the Rossum metric then the distance  $\Delta P$  is the square of a voltage and therefore an energy, so that  $C$  has the dimensions of an action, as Planck's constant in the quantum energy-time uncertainty relation.

The problem faced thus far in the scientific literature, of an abstract comparison of two spike trains without accounting for the available time for such a comparison, is rather unrealistic. A finite available time  $\Delta T$  places a crucial role in any decision, either if we are trying to identify an object within a fast sequence of different perceptions or if we are scanning through memorized patterns in order to decide about an action.

As a result the perceptual space  $P$  per se is meaningless. What is relevant for cognition is the joint  $(P,T)$  space, since "in vivo" we have always to face a limited time  $\Delta T$  which may truncate the whole spike sequence upon which a given perception has been coded. Only "in vitro" we allot to each perception all the time necessary to classify it.

A limited  $\Delta T$  is not only due to the temporal crowding of sequential images, as reported clinically in behavioral disturbances in teenagers exposed to fast video games, but also to sequential conjectures that the semantic memory essays via different top-down signals. Thus in the metrical space  $(P,T)$ , while the isolated localization of a percept  $P$  (however long is  $T$ ) or of a time  $T$  (however spread is the perceptual interval  $\Delta P$ ) have a sense, a joint localization both in percept and time has an ultimate limit when the corresponding domain is less than the quantum area  $C$ .

Let us consider the following thought experiment. Take two percepts  $P_1$  e  $P_2$  which for long processing times appear as the two stable states of a bistable optical illusion, e.g the Necker cube. If we let only a limited observation time  $\Delta T$  then the two uncertainty areas overlap. The contours drawn in Fig.7 have only a qualitative meaning. The situation is logically equivalent to the non commutative coordinate-momentum space of a single quantum particle. In this case it is well known [Zurek] that the quasiprobability Wigner function has strong non classical oscillations in the overlap region. We cannot split the coordinate-momentum space into two disjoint domains (sets) to which we can apply a Boolean logic or a classical Kolmogorov probability. This is the reason why the Bell inequalities are violated in an experiment dealing with such a situation [Omnès]. The Wigner function formalism derives from a Schroedinger wavefunction treatment for pure state, and corresponding density matrix for mixed states.

In the perceptual  $(P,T)$  space no Schroedinger treatment is yet available, but we can apply a reverse logical path as follows.

The uncertainty relation  $\Delta P \Delta T \geq C$  forbids a partition of the  $(P,T)$  space into sets. Therefore the  $(P,T)$  space is non commutative. Thus it must be susceptible of a Wigner function treatment and we can consider the contours of Fig.7 as fully equivalent to isolevel cuts of a Wigner function. Hence we can introduce Schroedinger cat states and violations of Bell inequalities exactly as in quantum physics but with a reverse logical process, as illustrated in Fig.8.

The equivalent of a superposition state should be a bistable situation observed for a time shorter than whole decision time. An experimental test is in preparation in my research group. Such a test should provide an estimation of the  $C$  value, which plausibly changes from individual to individual, and for a single one may be age and motivation dependent.

Thus in neurophysics time occurs under two completely different meanings, that is, as the ordering parameter to classify the position of successive events and as the useful duration of a relevant spike sequence, that is the duration of a synchronized train. In the second meaning, time  $T$  is a variable conjugate to perception  $P$ .

The quantum character has emerged as a necessity from the analysis of an interrupted spike train in a perceptual process. It follows that the (P,T) space cannot be partitioned into disjoint sets to which a Boolean yes/not relation is applicable and hence where ensembles obeying a classical probability can be considered. A set-theoretical partition is the condition to apply the Church-Turing thesis, which establishes the equivalence between recursive functions on a set and operations of a universal computer machine.

The evidence of quantum entanglement of overlapping perceptions should rule out in principle a finitistic character of the perceptual processes. This should be the negative answer to the Turing 1950 question whether the mental processes can be simulated by a universal computer [Turing].

Among other things, the characterization of the “concept” or “category” as the limit of a recursive operation on a sequence of individual related perceptions gets rather shaky, since recursive relations imply a set structure.

Quantum limitations were also put forward by Penrose [Penrose] but on a completely different basis. In his proposal, the quantum character was attributed to the physical behavior of the “microtubules” which are microscopic components of the neurons playing a central role in the synaptic activity. However, speaking of quantum coherence in biological processes is very hard to accept, if one accounts for the extreme vulnerability of any quantum system due to “decoherence” processes, which make quantum superposition effects observable only in extremely controlled laboratory situations.

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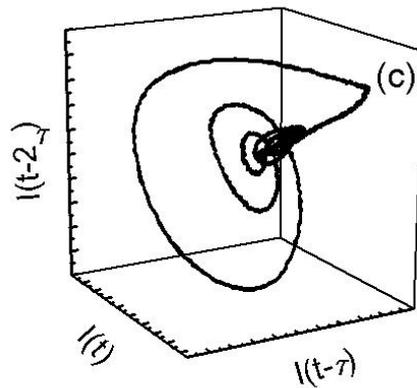
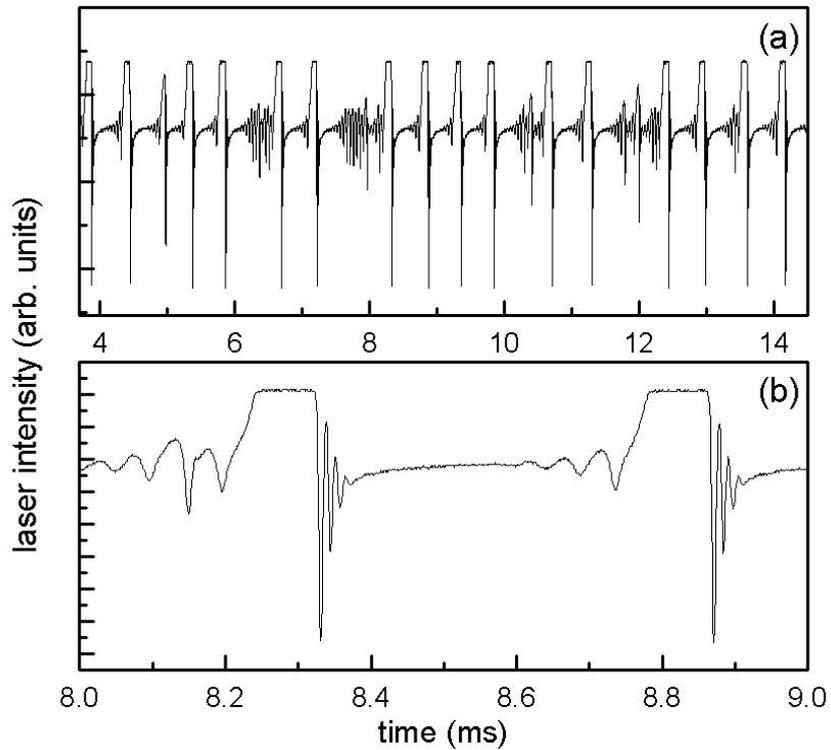


Fig. 1 : (a) Experimental time series of the laser intensity for a CO<sub>2</sub> laser with feedback in the regime of homoclinic chaos. (b) Time expansion of a single orbit. (c) Phase space trajectory built by an embedding technique with appropriate delays [from Allaria et al.].

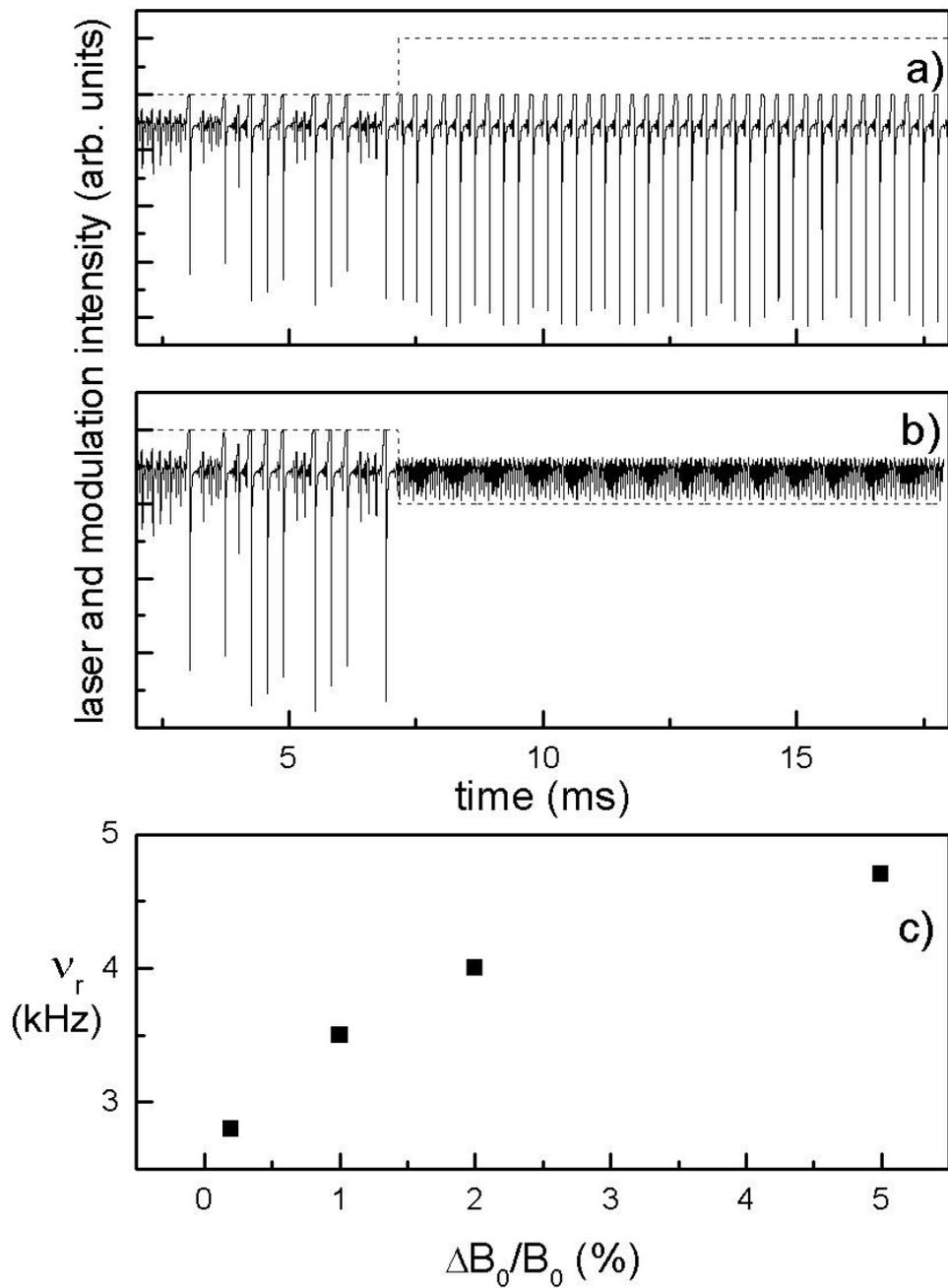


Fig.2 : Stepwise increase a) and decrease b) of control parameter  $B_0$  by  $\pm 1\%$  brings the system from homoclinic to periodic or excitable behavior. c) In case a) the frequency  $\nu_r$  of the spikes increases monotonically with  $\Delta B_0$  [from Meucci et al.].

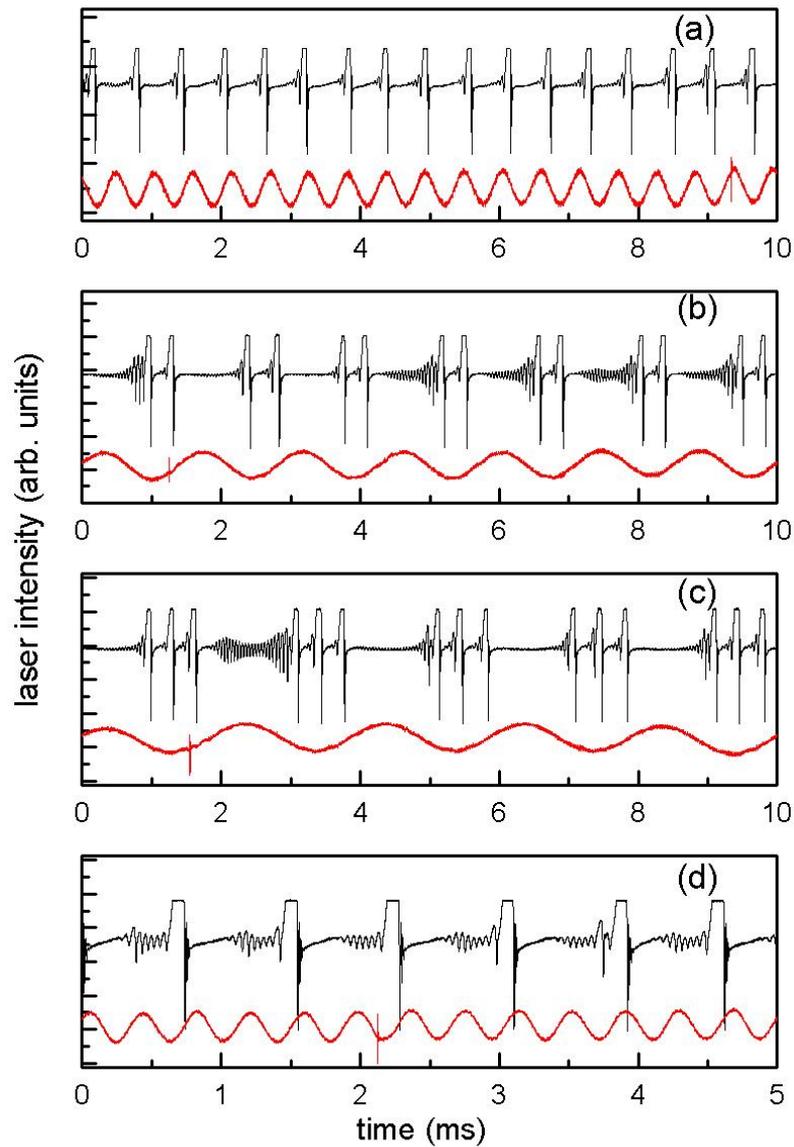


Fig. 3: Experimental time series for different synchronization induced by periodic changes of the control parameter. (a) 1:1 locking, (b) 1:2, (c) 1:3, (d) 2:1 [from Allaria et al.].

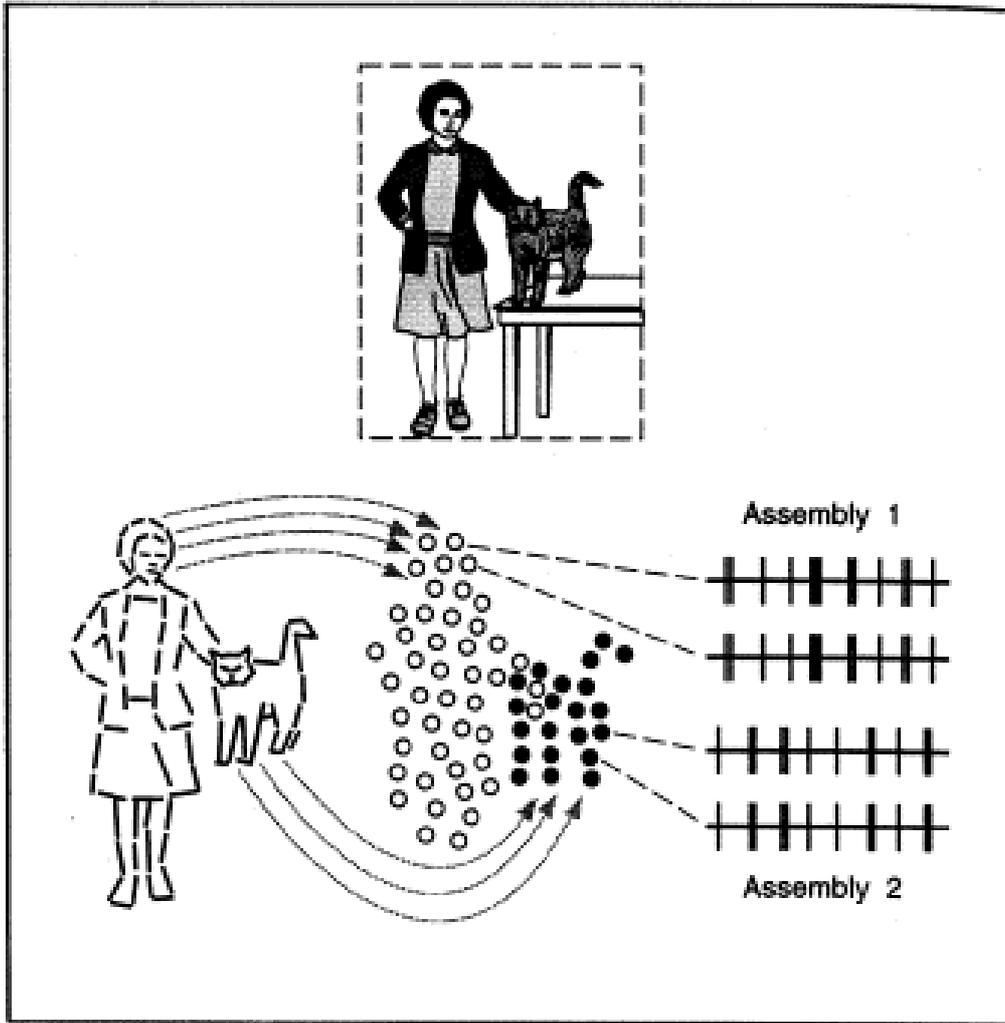
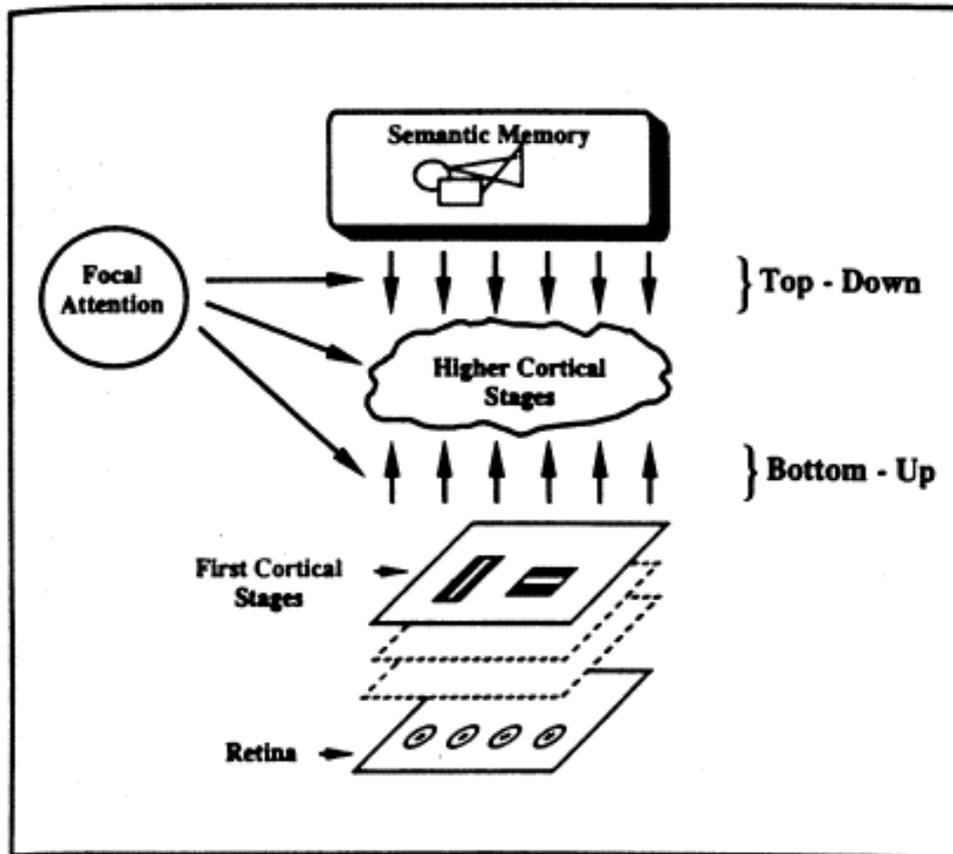


Fig. 4 : Feature binding: the lady and the cat are respectively represented by the mosaic of empty and filled circles, each one representing the receptive field of a neuron group in the visual cortex. Within each circle the processing refers to a specific detail (e.g. contour orientation). The relations between details are coded by the temporal correlation among neurons, as shown by the same sequences of electrical pulses for two filled circles or two empty circles. Neurons referring to the same individual (e.g. the cat) have synchronous discharges, whereas their spikes are uncorrelated with those referring to another individual (the lady) [from Singer].



**Fig.5** ART = Adaptive Resonance Theory. Role of bottom-up stimuli from the early visual stages and top-down signals due to expectations formulated by the semantic memory. The focal attention assures the matching (resonance) between the two streams [from Julesz].

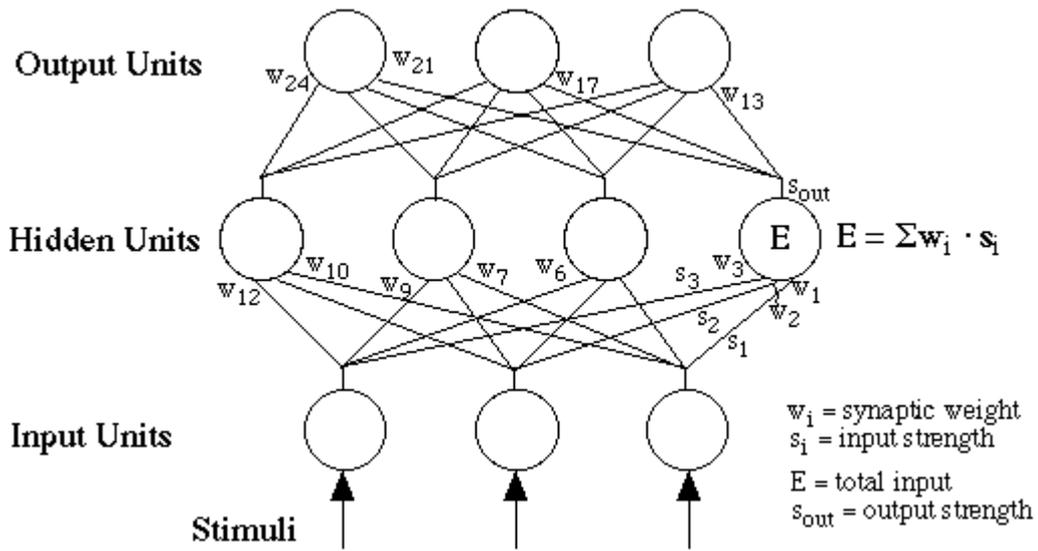


Fig.6 A simple network including one example of a neuronlike processing unit. The state of each neural unit is calculated as the sum of the weighted inputs from all neural units at a lower level that connect to it.

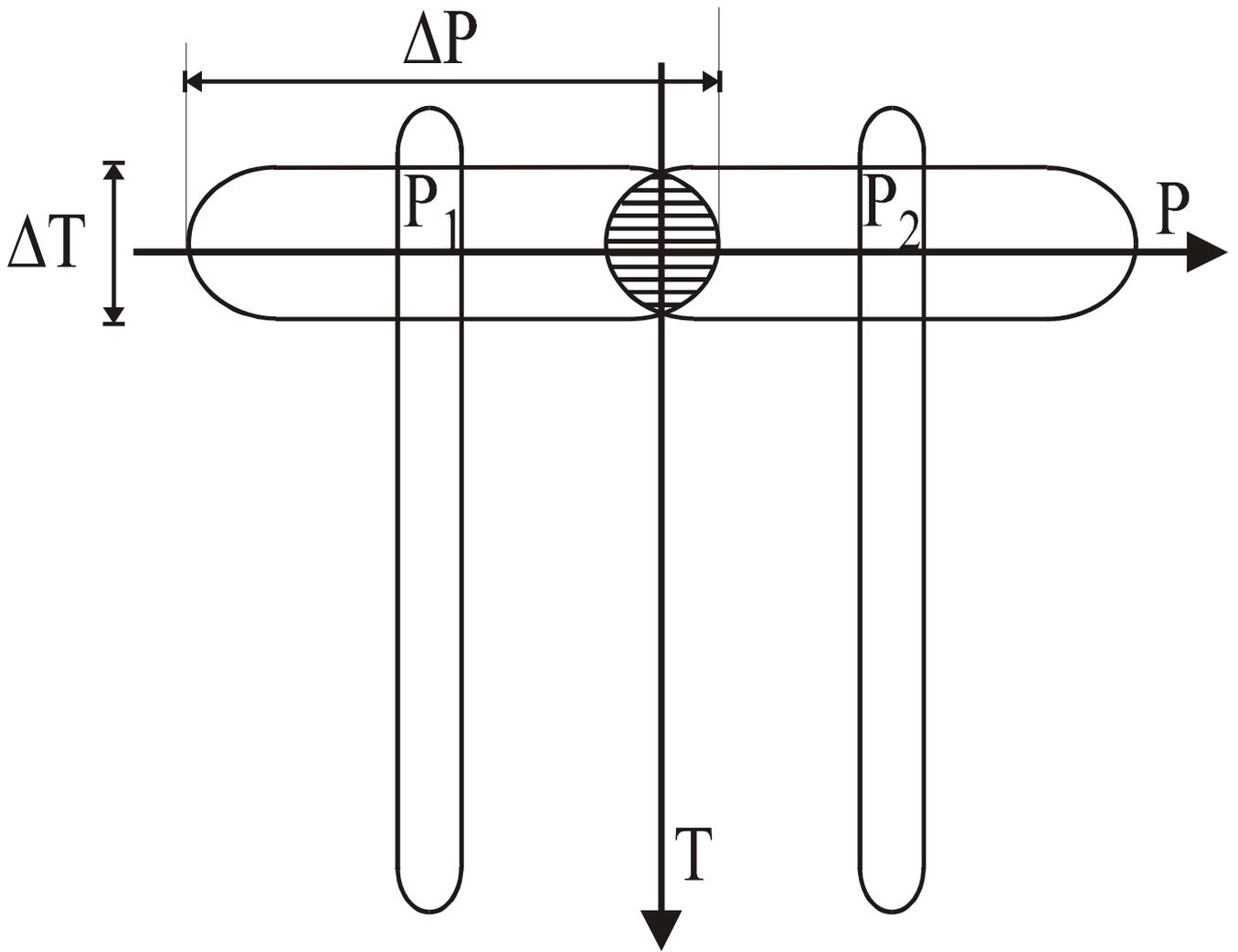


Fig.7 Uncertainty areas of two perceptions  $P_1$  and  $P_2$  for two different durations of the spike trains. In the case of short  $\Delta T$ , the overlap region is represented by a Wigner function with strong positive and negative oscillations which go as  $\cos \frac{\Delta P}{C} T$  along the  $T$  axis; therefore with a frequency given by the ratio of the percept separation  $\Delta P = P_2 - P_1$  to the perceptual “Planck’s constant”  $C$ .

**Quantum  
Mechanics**

**Time limited  
perception**

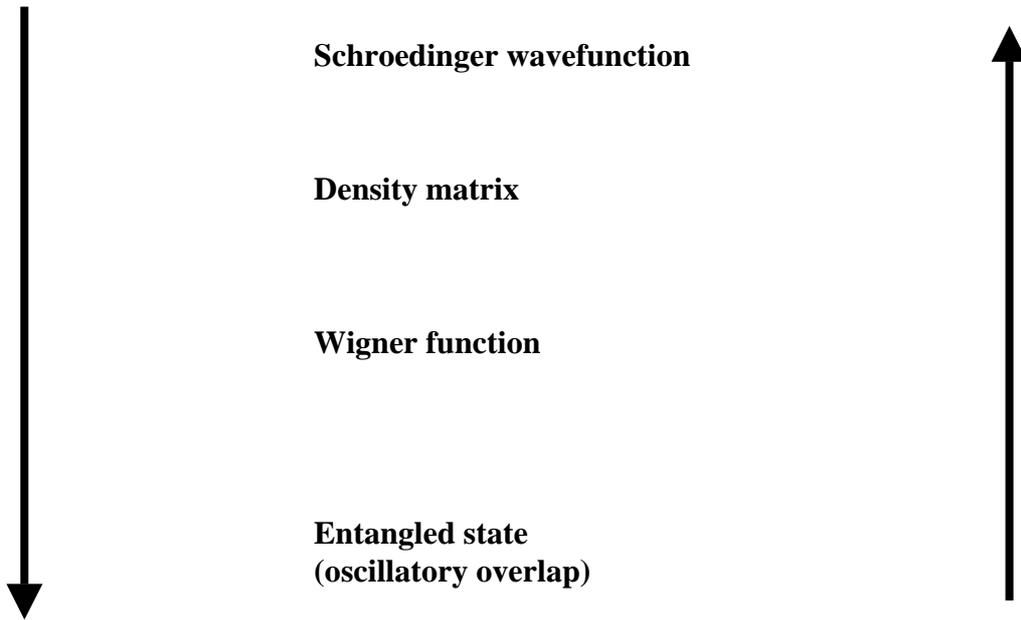


Fig.8 Direction of the logical processes which lead from wavefunction to entangled states or viceversa