

Antichaos in ants: the excitability metaphor at two hierarchical levels

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Abstract

We discuss the excitable media metaphor in the context of the social behaviour of ants. Each individual ant has a neural network that generates chaotic signals for spontaneous locomotor activity. Ants are able to move and interact among them, this process of movement-interaction generates periodic pulses of activity in the colony context. Activity spreads among the ants as if they were particles of an excitable fluid. This phenomenon is antichaotic in the sense that the system self-organize to give spatio-temporal order out from the chaotic social units.

1 Introduction

Mobility is a characteristic of all adult insects. It allows them to move in order to perform a range of vital activities such as feeding, dispersal, mating, defense, etc. and it has been suggested that the success of insects as terrestrial animals may be in part due to their high degree of mobility (Chapman, 1991). In the case of ants, as in all other groups of social insects, mobility of individuals is fundamental for the adequate coordination and maintenance of their social organization: mobility ensures widespread information diffusion, correct task allocation and an efficient dynamics of interactions among the individuals.

It is now well established that the temporal patterns of movement and activity in ants reveal some degree of discontinuity suggesting that individuals spend an important

portion of their time in a state of quiescence (eg. Sudd, 1967; Herbers, 1983). Recently, it has been reported that temporal patterns of movement inside the nest of *Leptothorax* ants show periodic cycles of activity alternated with periods of inactivity (Franks et al, 1987; Franks et al, 1990; Cole, 1991a). The initiation of a cycle of movement is due to the spontaneous activation of a few -or just a single- individuals and subsequent activation of the motionless by interaction with the active ones. Detailed studies of single isolated workers show that the pattern of individual spontaneous activation is chaotic and that chaotic behaviour tends to vanish when the ants are allowed to interact in the colony context (Cole, 1991b). This means a transition from a chaotic disordered temporal regime into a periodic ordered one, in other words, *antichaos* generated by a process of interactions among the social units.

Antichaos is a novel concept in the sciences of complexity that refers to those initially disordered systems that "spontaneously crystalize into a high degree of order" (Kauffman, 1991). Antichaos is thought to be present in many of the process where pattern formation exist and biological examples must be many, if not the general rule, from the autocatalytic biomolecular level to the global dynamics of interacting populations. In the present study we review the case of an antichaotic phenomena in an example of insect societies through the development of an artificial self-organized society of interacting automata. We would like to suggest that some aspects of what we call *social behaviour* may be inevitable properties of interacting synergetic collectives of individuals and thus are robust and independent of their material substrata or particular designs.

The specific phenomenon we are interested in has been modeled in the past using a variety of formalisms (Goss et al, 1988; Hemerick et al, 1990; Tofts et al, 1992; Cole 1992; Miramontes et al, 1993; Solé et al, 1993a,b). We will use the formalism of mobile cellular automata as in Miramontes et al (1993) and Solé et al (1993a,b) but with the innovation that spontaneous activations at the individual level are produced by a chaotic neural network. Before introducing the model, we would discuss some relevant aspects of the biology of the *Leptothorax* ants.

2 The basic biology of *Leptothorax* ants

350 worldwide-distributed named taxa compose the Hymenoptera genus *Leptothorax*. They are quite small in size and their natural colonies rarely exceeds a few hundred individuals, the typical size being of around one hundred. The colonies of these ants

are very compact and the individuals live in close proximity to each other. *Leptothorax* commonly nest in small preformed cavities like hollow seeds, cracks on rocks or under stones. Colonies may have one or multiple queens but queenless colonies are also common in nature suggesting that the queen has no other role but reproduction and that the colony is not centrally ruled by a single individual (Miramontes, 1992).

The ants in this genus are monomorphic and no castes exist on their societies except by some degree of labor specialization that develops with age, nevertheless the individuals are quite homogeneous and can easily switch and engage in tasks not belonging normally to their specific age groups. Being compact and living in close proximity suggests that communications are mostly short-ranged and in fact the most used form is direct contact through antennation (Herbers, 1983).

Cole (1991b) has established that the process of spontaneous activations in *Leptothorax* ants involves low dimensional chaos and has suggested that this may have considerable consequences for the study of social behaviour since movement is correlated with the ants activity as social beings. Hence the study of locomotion and the central nervous system in ants must be of relevance as well.

2.1 Locomotion and the central nervous system in ants

Locomotor activity in all animals is under direct control of the central nervous system (CNS). Motion results after muscles receive signals from the motorneurons that innerve them. Motorneurons in turn, are coupled via axons to neurons situated in the nervous ganglia, the nervous cord or the brain, depending of the anatomic and physiological details of the animal in question.

Physiological rhythms, that are translated into motor activity through activation of specific motor programs, can be generated by single cells or by networks of coupled cells that are part of the central nervous system and are named central pattern generators (CPG). CPGs are involved in many important processes involving muscular activity like cardiac pulses, breathing, intestinal contractions, swimming, escape movements, flight etc.

One of the most well known CPGs in invertebrates is the R15 neuron of the *Aplysia* mollusc. The R15 is a single cell with the ability of endogenously rhythmic activity but subject to modulation by synaptic input and hormonal influence. Another single cell CPG exist in the mollusc *Tritonia*. In this case, three different cells are know for they property of endogenous rhythmic firing patterns. In *Tritonia*, these CPGs are know to

be involved in locomotor control of swimming patterns.

A number of CPGs are formed by only a few interconnected neurons via electrical synapses. The simplest of these cell aggregates are those formed by only two single neurons. An example is known to exist in the snail *Lymnaea stagnalis* where the neural oscillator (known as VD1/RPD2) is a pair of electrically coupled peptidergic cells that fire in close synchrony. The VD1/RPD2 system is connected externally by means of excitatory and inhibitory inputs but their rhythms are endogenous to the coupled pair.

Many neural circuits are known to generate electrical activity without any external input from the sensory organs and rhythmic patterns can arise from the network architecture only (Glass et al, 1988 and ref. therein) and this seems to be the case in ants that can spontaneously show motor activity without any external stimulus.

The nervous system in ants is organized as a network of interconnected ganglia that are located in specific regions along the body and with direct connection with the brain. The brain is located inside the head and it is the largest conglomeration of neural tissue with direct connections with the eyes and the sense organs in the antennae, being for this reason involved in complex information processing and control tasks.

Apart from the basic anatomy, the CNS in ants is very poorly understood. This is due to the obvious difficulty posed by the size of an ant and by the fact that any experiment involving surgical manipulation that intends to observe the resulting behaviour will be impossibilized by the fact that any "misbehaved" or impaired ant is quickly disposed by its colony fellows. Another reason has to do with the generalized belief that ants are capable of only quite simple individual behaviour due to the simplicity of their nervous system (typically formed by about 100,000 neurons). It is widely accepted, yet not rigorously probed, that ants seem to have very limited neural plasticity and that, probably, most of its behaviour is stereotyped and fixed pre-programmed.

That the ant's nervous system section that deals with locomotion may be partially organized in a neural network is not a remote hypothesis. At least evidence exists that some nervous regions have the typical parallel-distributed-system feature of being robust or fault-tolerant. It is known that ants have a number of special innervated regions that are involved in orientation and locomotion and experimental damage to them causes disorientation only after a number of them are impaired. Disabling of only a few does not cause any noticeable loss of orientation (Dumpert, 1981).

As we already said, the patterns of spontaneous activations in some of the species of *Leptothorax* ants exhibit low dimensional chaos (it is unknown at the present time whether this phenomenon is universal for the genus). We would like to model this

individual behaviour by means of a simple neural network. This will be accomplished by choosing a simple neural circuit that can generate low dimensional chaos.

3 Collective behaviour in artificial societies

An ant colony is a highly integrated structure and this colony-level order comes out as the result of coordinated massive individual interactions that are facilitated by the existence of effective communication links among them. In some degree, social behaviour must be regarded as the inevitable outcome of interconnected structures and must be regarded as a robust generic property of natural and artificial self-organized complex systems. Social behaviour can not be reduced to the individual behaviour in the sense that isolated individuals can not generate alone the variety and richness of the global collective behaviour present in their society. Social behaviour is thus holistic or synergetic and is only produced by the existence of more than one interacting organism. Social behaviour only exist if the interacting individuals can communicate and modify their individual behaviour as a consequence of such acts.

We will use here the term "artificial society" in the narrow sense of a collection of individuals (the mobile cellular automata) that can interact and modify their individual behaviour because of the interactions. The coupled collective will be able to exhibit global dynamics and in the case reviewed here will be able to mimic the antichaotic phenomena of disorder-order transition observed in real ants.

3.1 A neural network model for individual chaotic activation

Neural networks of only a few elements may exhibit very complex dynamical behaviour and models of four, two and even one single element able to generate chaos have been studied elsewhere (Das II et al, 1991; Wang, 1991; Chay, 1985; Aihara et al, 1990; Kurten et al, 1986; among others). For simplicity, we will use a two-neurons full interconnected NN without external inputs. One neuron is excitatory and the other inhibitory. The network is a discrete time two-dimensional coupled map with a sigmoid function. Wang (1991) has studied exactly in a very elegant way an equivalent network and has shown that this quite simple cellular arrangement of two interacting elements exhibits period-doubling route to chaos.

Consider the network formed by neuron x and neuron y as is shown in figure 1. The time evolution of the system is given by the following parametric map:

$$\begin{aligned}x(t+1) &= F_{\mu}(w_{11}x(t) + w_{12}y(t)) \\y(t+1) &= F_{\mu}(w_{21}x(t) + w_{22}y(t))\end{aligned}\quad (1)$$

where

$$F_{\mu}(z) = \tanh(\mu z) \quad (2)$$

μ is the *neuron gain*, and the w coefficients are the entries of the interaction matrix \mathbf{W} that codifies the strength of the neuron's connections. Following Wang (1991), the network shows chaos for a suitable value of μ and when the entries of \mathbf{W} are of the form:

$$\mathbf{W} = \begin{pmatrix} -a & a \\ -b & b \end{pmatrix}$$

Each neuron in the network exhibits chaotic motion in its temporal evolution and the bifurcation diagram can be easily constructed taking μ as the bifurcation parameter. Here we will use the absolute value of the difference of the two neurons' states as the signal for locomotion activation and the resulting bifurcation diagram appears in figure 2. A signal for spontaneous chaotic activation will be passed to an hypothetic motor program only if this absolute difference exceeds a given threshold value ϵ (that is, the signal is produced depending on the degree of the network synchrony):

$$|x(t) - y(t)| > \epsilon \quad (3)$$

The use of this convention allows fine control of the firing rate probability in the network.

3.2 Interactions and global dynamics

The colony-level dynamics is implemented here by means of an interacting set of *mobile cellular automata* that have a range of features that capture closely the basic biology of the ants: (1) a set of identical elements reflecting the fact that *Leptothorax* ants are monomorphic and casteless; (2) there are not "privileged" individuals dictating the dynamics to follow (no queens ruling centrally); (3) first neighbor interactions that capture the known fact that interaction among the ants are based on direct antennations (information is transmitted locally but globally distributed in space by interactions as in an excitable medium); (4) the automata can change their activity-movement status because of the interactions; (5) isolated individuals can activate spontaneously and

the activation process is chaotic (the signal triggering activation is generated by the individual's own neural network).

3.3 Mobile cellular automata

Mobile cellular automata are space-extended discrete dynamical systems with mobile elements (Miramontes et al, 1993). In the particular case discussed here, the automata are two-dimensional and interactions are restricted to the first neighbors in the nine-cells square around each automaton. The movement pattern of the automata (objects) are random walks with two constraints: two objects cannot be at the same place at the same time and new positions are selected only among the first-neighborhood square. The objects perform a maximum of six searching attempts until a free cell is found. In case of not available space being found, the objects remain still.

The activity state S_i of each object a_i is given by a function that couples the object's own activity with that of the others objects in the first neighborhood:

$$S_i(t+1) = \tanh \left\{ g \left(\left(\sum_{j=1}^k J_{ij} S_j^t \right) + J_{ii} S_i^t \right) \right\} \quad (4)$$

where J_{ij} are coupling coefficients taken from the colony interaction matrix \mathbf{C} and k is the number of neighbors of a_i . Note that term $J_{ii} S_i^t$ represents the contribution of the self-interaction. \mathbf{C} is the square interaction matrix defined as follows:

$$\mathbf{C} = \begin{pmatrix} c_1 & c_2 \\ c_3 & c_4 \end{pmatrix}$$

c_1 represents active-active interactions, c_3 and c_2 represent active-inactive and inactive-active interactions, while c_4 represents inactive-inactive interactions. The activity value of the i and j elements are considered together. For instance, if $S_i > 0$ and $S_j > 0$ then the interaction is of the active-active type and $J_{ij} = c_1$.

The parameter g (gain) controls the slope of the hyperbolic tangent function and determine the rate of activation and deactivation of the mobile objects. If the activity of a given object is greater than zero then it is regarded as active and able to move, otherwise it will be inactive and motionless.

Because the mathematical equivalence between equations (2) governing the dynamics of the individuals and (4) that governs the dynamics at the colony level, it seems appropriate to consider the system above defined as an excitable media at two hierarchical levels. Also it seems appropriate to consider our mobile cellular automata as a

sort of mobile neural network where processing units are not embedded in any fixed spatiotemporal architecture.

An isolated inactive object will remain so until activated by one of the two following processes: (1) it is spontaneously activated by a signal coming from its neural network and when this happens S_i is assigned with a fixed positive initial value (in all our simulations this value was arbitrarily taken as 0.1); (2) activated after contacted by an already active object.

Consider a given lattice with a single isolated object on it. This automaton will activate spontaneously and will keep moving for an interval of time, as long as the S_i keeps greater than zero (S_i as defined in (4) is monotonically decreasing to zero for an adequate choice of g , see Miramontes et al, 1993). We can plot the time series of the activations we got with this system (see figure 4(a)). The time intervals between successive peaks is chaotic and it is possible to apply a linear transform to this series in order to show, in another way, that single isolated automata are chaotic. The transform is quite simple and consists in the following: we take the time difference Δt_i between two successive activation peaks over a given time interval. The maximum of these Δt_i intervals is found (Δt_{max}) and the Δt_i are normalized to Δt_{max} . A new time series is reconstructed with this normalized data as successive points. One of this series (200 chaotic activations out of an original 10,000 time steps long series) is shown in figure 3 together with the chaotic attractor in two and three dimensions. We compare the qualitative aspect of the series with the data for real ants as in Cole (1991b) and we found a good agreement.

After performing the experiment of adding more and more objects to the lattice, we observe the same transition phenomena reported by Cole (1991a, b) in ant colonies and the same dynamic behaviour reported for random-activated objects (Miramontes et al, 1993). In the present study, we found that the transition is exhibited by chaotically-activated objects as is shown in the graphs that appear in figure 4. A transition from chaos into periodic cycles of activity is reached at densities of around 0.2. In order to show this in a more explicit way, we calculate the Fourier transform and produced the graphs shown in figure 5 where the existence of clear peaks in the power spectrum amplitude signals the presence of periodic motion as a function of lattice density (objects/lattice cells).

We confirm the hypothesis that coupling of elements reduce the randomness of the activations: as density is increased the number of chaotic activations per object decreases (figure 6) meaning that the proportion of activations produced by interaction

with another objects has increased. This process is non-linear suggesting that in this simple model emergence of coherent collective behaviour is synergetic: the activity budget of two interacting automata is greater than the sum of the time budgets of two isolated objects (Miramontes, 1992).

4 Discussion

A number of models have been presented to attempt the simulation of periodic oscillations in *Leptothorax* (Goss, et.al., 1988; Hemerick et.al., 1989; Tofts, et.al., 1992; Solé et.al., 1992). All of them differ markedly in the assumption of the origin of the cycles and in their degree of biological realism and predictive ability (see Tofts, et.al. (1992) for a review of most of them). The model presented here match quite well the observed phenomena in real ants and cellular automata capture quite well the essence of the biology involved: (1) Single individuals are chaotic in their spontaneous activations. (2) Activations occur by interactions among the objects and this process is clearly synergetic. (3) There is a transition from chaos into periodic cycles in the global dynamics of the colony as more individuals are allowed to interact. (4) Chaotic activations per object tend to decrease as a function of density. (5) Period length follow an exponential decay for low densities but increases slightly for higher densities (Miramontes, 1992). (6) Spatial distribution of activity seems to follow concentric symetries over the nest space (Miramontes et al, 1993).

Aggrement with real data confirm the power of the formalism here used and the correctness of interpreting the ants as excitable interacting units that compose an excitable fluid with emergent collective dynamics: the social behaviour.

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6 Figure captions

[Figure 1] Connection diagram of the neural network model used for generation of chaotic signals. The NN is a two-neurons discrete-time coupled map.

[Figure 2] Bifurcation diagram of $|x(t) - y(t)|$ and μ as a bifurcation parameter. The system shows constant, periodic and chaotic motion. System parameters are: $x(0) = 0.9$, $y(0) = 0.6$, $w_{11} = -3$, $w_{12} = 3$, $w_{21} = -6$, $w_{22} = 6$.

[Figure 3] (a) Reconstructed chaotic time serie for a single isolated object. Lattice size 10×10 , $g = 0.05$, C matrix entries all one. $\mu = 3$, $\epsilon = 0.3$, the rest of the NN parameters as in figure 2. (b) First return map of the serie shown in (a). (c) 3D reconstruction of the same serie, x-axis: $\text{data}(t)$; y-axis: $\text{data}(t+1)$; z-axis: $\text{data}(t+3)$. Note the qualitative similarity of the data and atractors with those in Cole (1991b) for real ants.

[Figure 4] Global dynamics of the MCA as a function of density. The graphs show the number of active objects for different densities. The patterns are chaotic but transform into periodic cycles when density is greater than around 0.2. Density values are: (a) 0.01, (b) 0.1, (c) 0.2, (d) 0.4, (e) 0.6, (f) 0.8, (g) 1.0. System parameters as in figure 3.

[Figure 5] Power spectrum (Fourier transform) of four series generated for different density values: (a) 0.1, (b) 0.4, (c) 0.6, (d) 1.0. Note the development of peaks that reveal the periodic nature of the data when density is high. System parameters as in figure 3.

[Figure 6] Number of chaotic activations per object as a function of the density. The activations decrease in a non-linear way showing the decrease of the system randomness. The original time serie was 100,000 steps long. System parameters as in figure 3.

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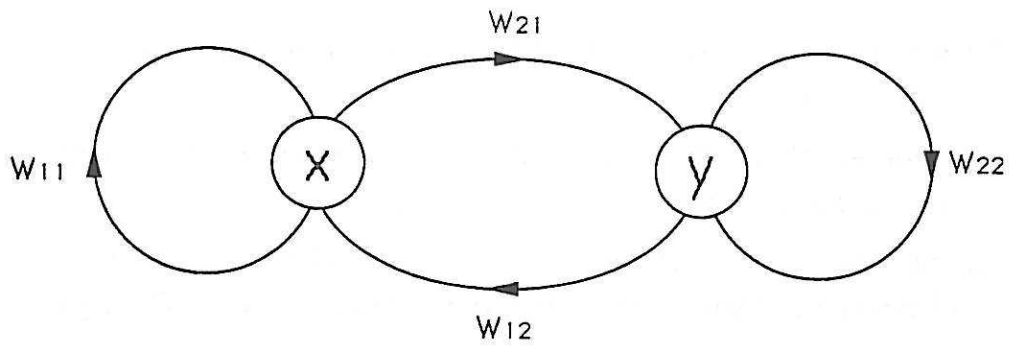
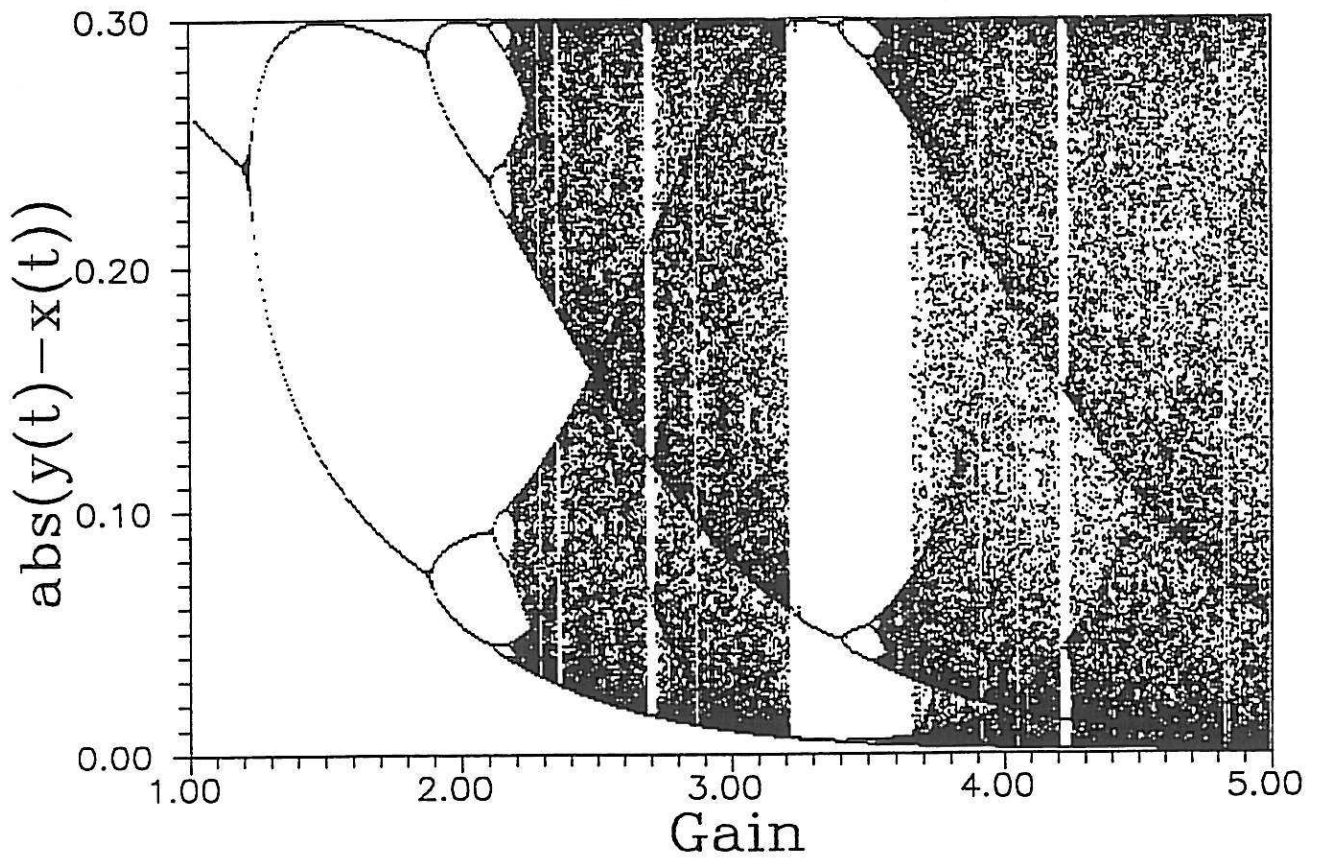
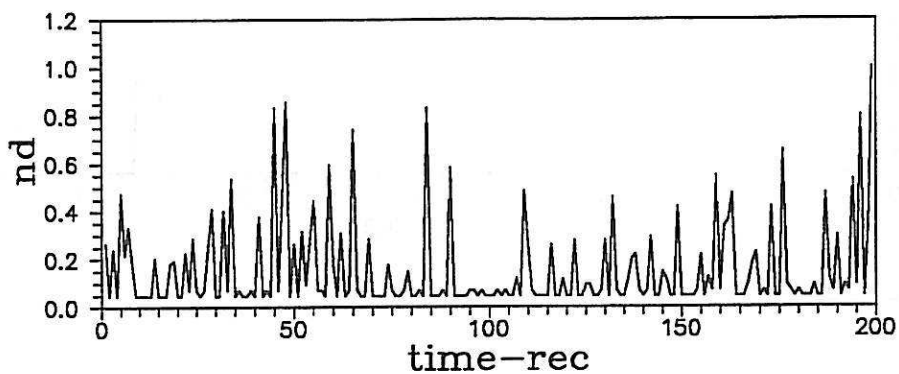
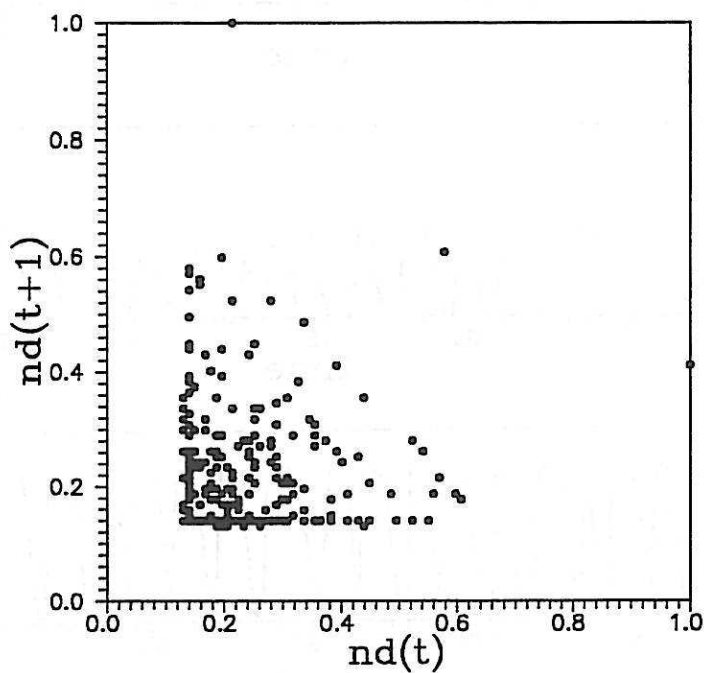


Fig 2

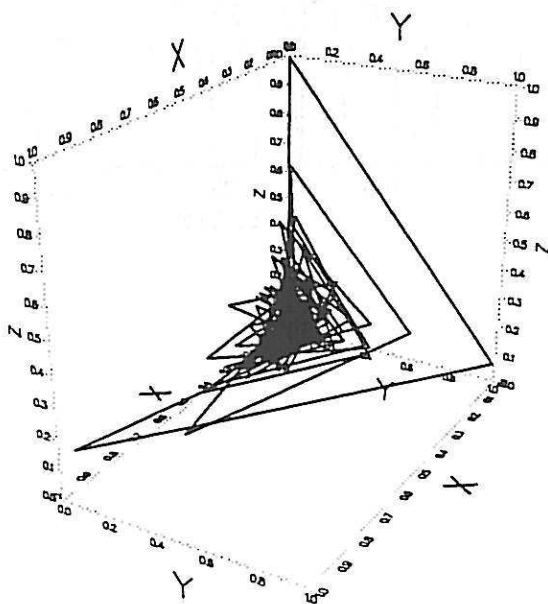




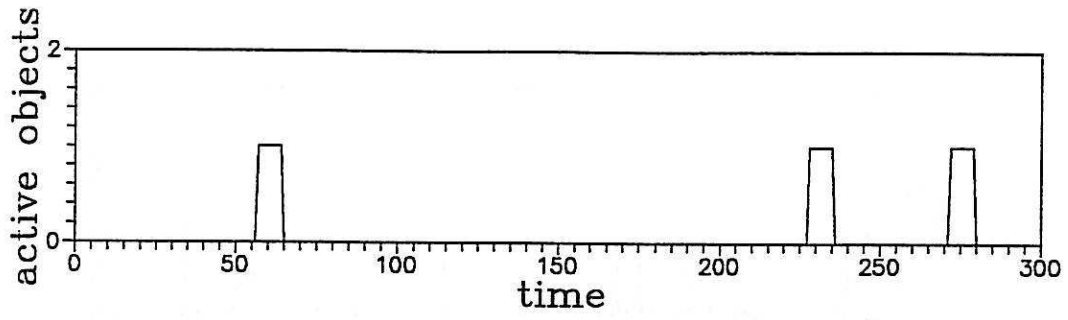
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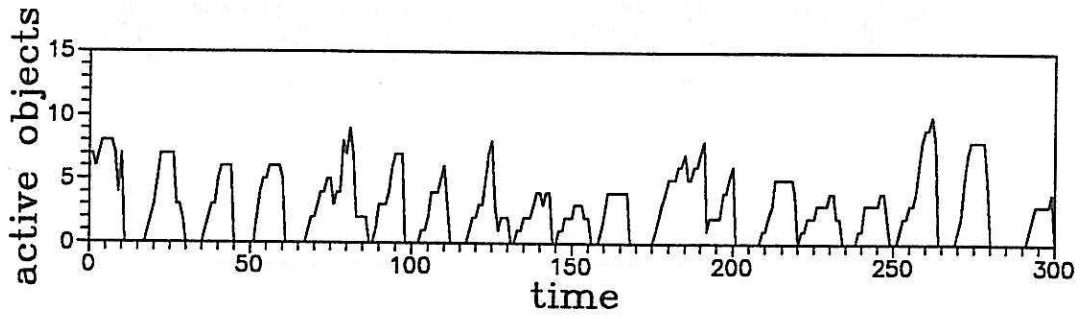
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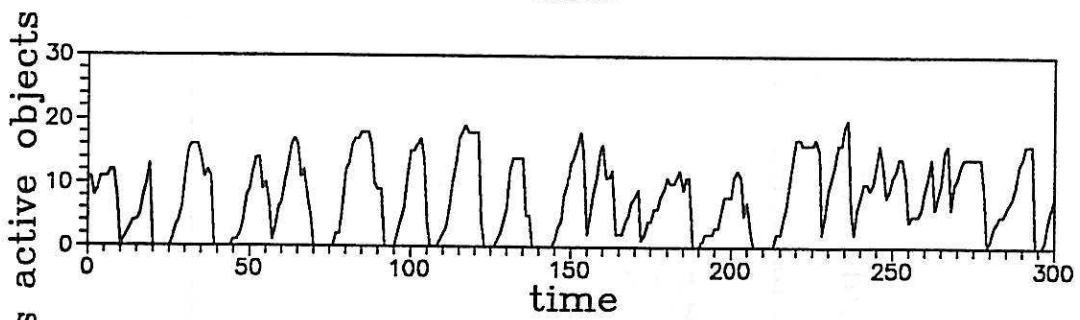
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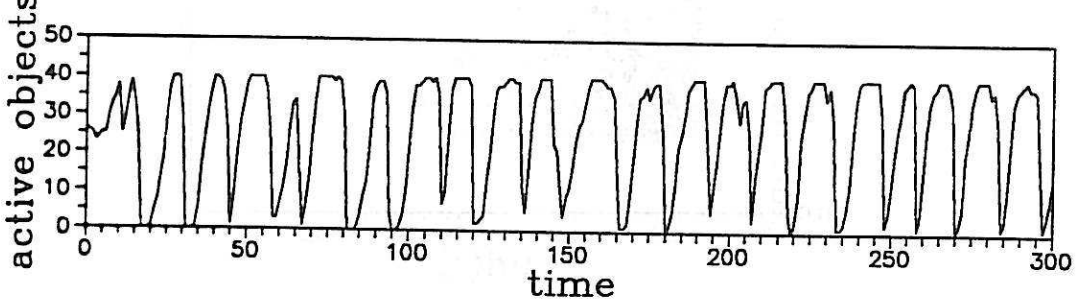
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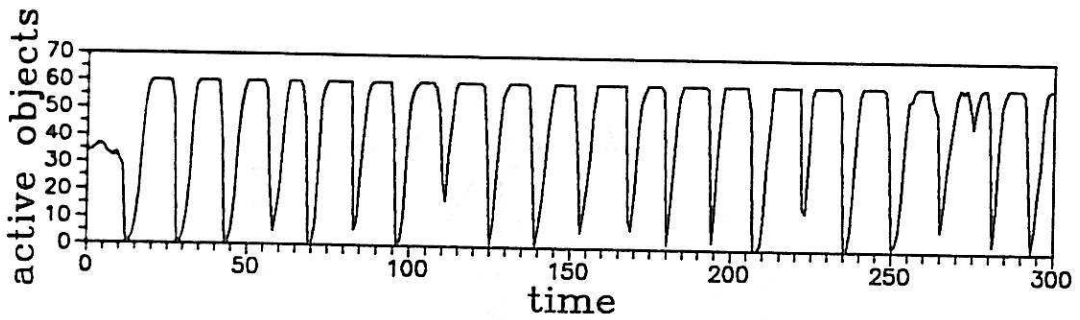
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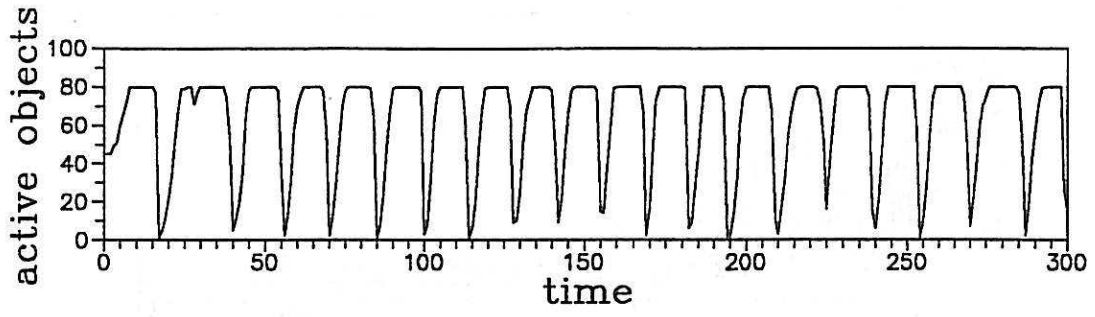
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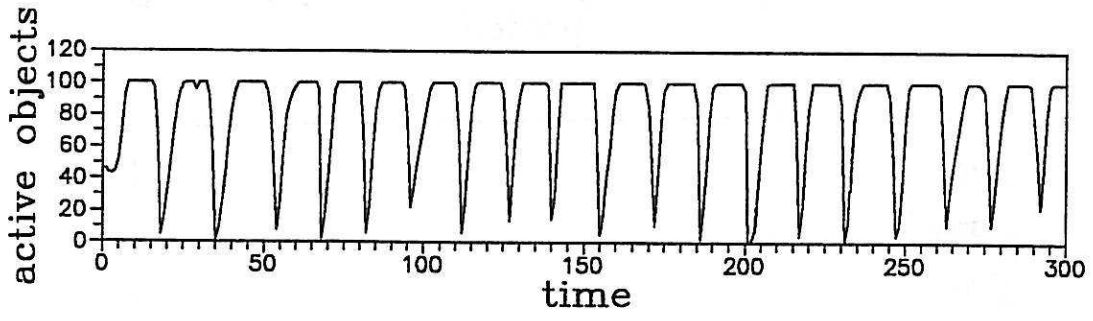
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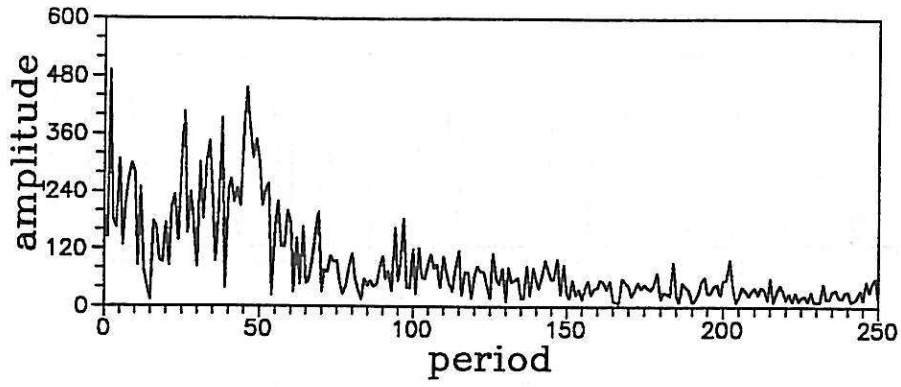
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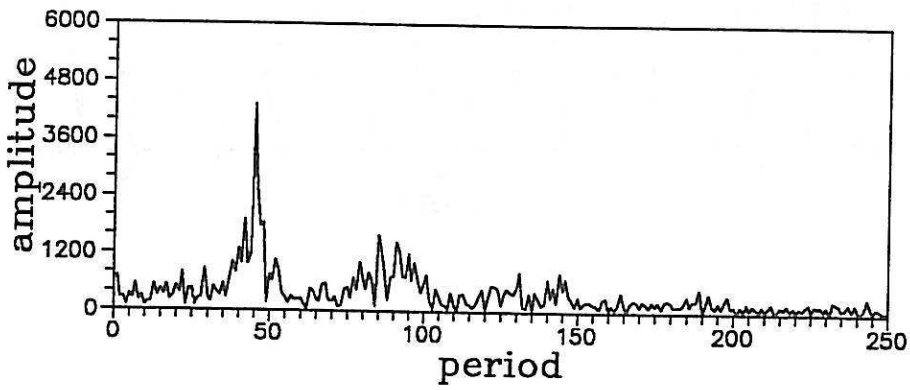
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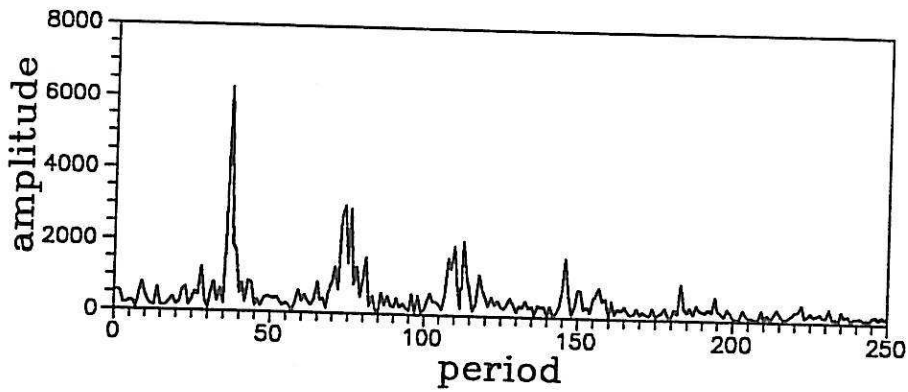
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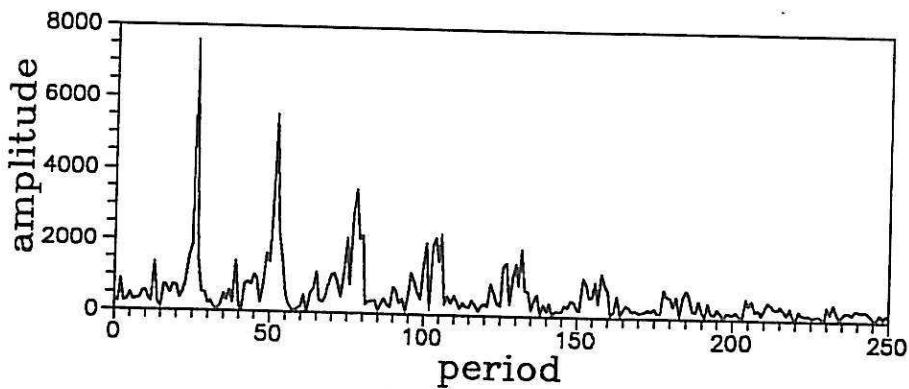
(a)



(b)



(c)



(d)

