

Chapter 12

Social Insects and Swarm Intelligence

12.1 Ants, wasps and bees: The superorganism

Most¹ of the questions on the dynamical behavior of systems of strongly interacting (simple) agents we have posed in previous chapters could be reframed, without any modification, in the context of social insects, since these are, without any doubt, a truly *paradigm* for complex systems.

Social insects have been in our biosphere for more than 100 million years, so nature seems to have already solved our questions about the adaptation ability of collectives of strongly interacting elements. All the ants, some families of wasps and bees and the entire order of *Isoptera* (termites) are what entomologists call *eusocial*. To belong to the class of eusocial species three biological traits should be present: Adults caring for the young, two or more generations of adults living together and a reproductive division of labour. From now on we will restrict our discussion to ants (needless to say that ants are representative enough of *all* kinds of social behaviour in insects). First, we could ask how *rare* is social behaviour in nature, perhaps it has been an evolutive accident surviving only in few places, or an early error being corrected by the introduction of more individual-based species. Fortunately both statements are wrong: Social behaviour evolved from small societies of individuals, that is, ant societies with a huge number of highly cooperative individuals are the youngest, from an evolutionary point of view [45]. With respect to their ubiquity, ant species can be found all over the world, particularly in tropical forests; let us quote [45] concerning estimates of

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diversity and abundance of ants:

“All together, these creatures seem likely to constitute half or more of the insect biomass. Consider the following disproportion: Only 13.500 species of highly social insects are known (9.500 of which are ants) out of a grand total of 750.000 insect species that have been recognized to date by biologists. Thus, more than half the living tissue of insects is made up of just 2 percent of the species, the fraction that live in well-organized colonies.(...) At the risk of oversimplification, we envisage an overall pattern of ants and termites at the ecological center, solitary insects at the periphery.”

So it is quite clear that social behaviour is an advantageous strategy in environments with a certain degree of unpredictability, such as real ecosystems.

There is a large variety of interesting behaviors in ant colonies, behaviours that are attained collectively without central command. The queen, contrary to what is popularly thought, does not control the colony, she has essentially a reproductive function. In fact, queenless colonies are not rare [1] in some ant species. Examples of well-known collective functions performed by ants are task allocation, collective decision, collective sorting, foraging, patrolling and brood care, though there are more surprising behaviours in some ant species, such as propaganda, slavery, decoding, mimicry, Trojan horses (!) and highwaymen [45]. All these striking behaviors are performed by quite simple individuals with no more than 40 “behavioral categories” interacting by means of simple mechanisms, essentially chemical communication (pheromones) and physical contact, though sound may also be used in some species [45].

Chemical communication underlies a remarkable mechanism that plays an essential role in self-organizing collective behavior, besides being, at the time of writing, the main source of inspiration for artificial collective systems, it is called *stigmergy* (name introduced by P.P.Grassé in the 50’s). Following [62] the hypothesis of stigmergy is that

“(...) it is the work already accomplished, rather than direct communication among nest mates, that induces the insects to perform additional labor.”

First of all, it is clear why stigmergy it is interesting for designers of collectives of robots: The problem of communication between agents simply vanishes. So what remains is to build a working individual operating in a common environment with other individuals. There is a plethora of phenomena which can be explained by means of stigmergic mechanisms, such as nest building in termites, collective decision making and collective clustering to cite a few. Artificial systems built according to an underlying stigmergic mechanism are simply most of the systems built up to now.

Stigmergy is also related with the slaving principle (see chapter 3 and [40]), since the work done by individuals acts as a sort of “slow” variable slaving, and

governing, the individual behaviour. Some examples, to be detailed below, may be the clustering phenomenon: Objects forming small clusters induce the individuals to put down objects near the clusters, creating a positive feedback that ends with one or two large clusters; also the example of the Travelling Salesman Problem (TSP) and that of collective decision, the “trail” and the morphogen have “slow” dynamics due to changes in concentrations induced by individual activity, though they also act as a field governing individual behaviour (see below). We see here a *circular causality*, one of the main features of complex systems.

The world of ants is so huge that it is quite likely that the phenomena as yet hidden to us will be far more surprising than those facts already known. Undoubtedly the study of complex systems will benefit from these findings and new design procedures for artificial collective systems will see the light in a near future.

In this chapter we will detail some of the amazing collective behaviors above mentioned. Furthermore, we will speculate a little about a possible trade-off between individual complexity and collective complexity, and the consequences this conjecture could have for a general theory of complex systems. Finally, we will briefly illustrate how engineers have taken the collective behavior of social insects as a source of inspiration to find efficient algorithms for combinatorial optimization problem solving or collective robotics.

12.2 Termite nest building

The first model of social insect behavior, based on a “complex systems” approach, was proposed by Jean-Louis Deneubourg in 1977 [24]. The model was designed to explain the early stages of termite’s nest construction. These nests may be several meters tall, which becomes rather surprising if we consider that their builders are quite small; it is one of the most evident examples of truly collective behavior. Nest construction seems to occur in two phases. Firstly, there is a random deposition of building material. However, it may be that, by chance, one of the deposits became large enough to start a second phase, where ants deposit material on that aggregation preferentially. A pillar or wall begins to grow and an arch may be formed if some other wall also was grown near this one. The model we are going to detail explains in a simple way how these coherent structures may emerge from the apparently random interaction between simple individuals. The model assumes the following hypotheses: The handling of building material by individuals impregnates the material with a certain amount of attractive pheromone. Let $P(r, t)$ be the amount of “active” building material at position r and at time t . The pheromone may be dissociated from the material, so let $H(r, t)$ the concentration of free pheromone. H may diffuse freely in space and its odor attracts termites toward the regions of high H . There is a constant flux Φ of individuals carrying building material, whose concentration we will denote $C(r, t)$. The deposited material is proportional to C , that is, to the density of loaded individuals.

From these assumptions we can build the following rate equations. The first

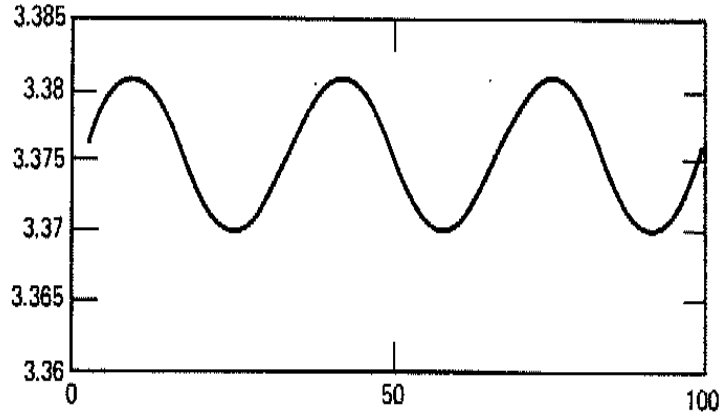


Figure 12.1: After solving eqns. 12.1, 12.2 and 12.3 in a region of instability of the uniform steady state (see text) we can observe a spatial pattern in P . Parameters: $\Phi = 3$, $k_1 = k_2 = k_4 = 0.8888$, $D_c = 0.01$, $D_H = 6.25 \times 10^{-4}$ and $\gamma = -0.4629 \times 10^{-2}$. (after [52])

one tells us that the amount of building material is proportional to the density of carriers:

$$\frac{\partial P(r, t)}{\partial t} = k_1 C - k_2 P \quad (12.1)$$

where k_2 is the amount of pheromone emitted per unit of deposited material per unit time. There is a decay in the amount of free pheromone proportional to its local abundance; also, it passively difuses to nearest locations. However, the amount of free pheromone grows proportionally to active material. Thus, we have the equation

$$\frac{\partial H(r, t)}{\partial t} = k_2 P - k_4 H + D_h \nabla^2 H \quad (12.2)$$

Finally, the equation

$$\frac{\partial C(r, t)}{\partial t} = \Phi - k_1 C + D_c \nabla^2 C + \gamma \nabla \cdot (C \nabla H) \quad (12.3)$$

introduces the spatio-temporal dynamics of carriers. Φ is the flux of insects bringing material into the space where the work is performed, D_c is the coefficient of random dispersion (that is, a random component in movement) and the last term represents the attraction by the odor (γ is the attraction coefficient, also called the chemotactic parameter).

This model allows one to perform a linear stability analysis (according to chapter 10). It admits as a solution the uniform state:

$$(C_s, H_s, P_s) = \left(\frac{\Phi}{k_1}, \frac{\Phi}{k_4}, \frac{\Phi}{k_2} \right)$$

but this solution becomes unstable [24] at

$$\gamma_c = \frac{\left((k_4 D_c)^{\frac{1}{2}} + (k_1 D_h)^{\frac{1}{2}} \right)^2}{\Phi} \quad (12.4)$$

since no perturbation can grow for $\gamma < \gamma_c$. In figure 12.1 we plot P as a function of space (in a one-dimensional version of the model) for $\gamma > \gamma_c$, close to the marginal state. The system converges to a spatially periodic state, making evident the appearance of structure in the spatial distribution of active material. Thus, the “seed” to form pillars and walls appears spontaneously in the form of dominant modes in a steady state solution of the model.

12.3 Collective decision making

Experiments with several ant species have highlighted their collective ability to choose the richest (in saccharose concentration, for example) of several food sources [4]. To measure patterns of source exploitation, two food sources were presented to an ant colony, simultaneously and at the same distance of the nest. Individual ants are unable to locate a food source in the environment and remember its position to report on the colony (at least those of the species in the mentioned experiments), therefore they must rely on some other mechanism to fix the location of food. These mechanisms are based on the deposition of small amounts of pheromones leaving a scent on the ground that other ants are able to follow and reinforce, in such a way that a trail to a specified location is created through a positive feedback. With two equal sources, the response of the colony was to choose one of them, usually the one that was first discovered. If the sources were different and were discovered simultaneously, the richer one was the more exploited, e.g. the number of ants around the richer source, taking food and bringing it to the nest, was quite greater than the number of ants taking food from the poorer source. However, if a source was first discovered, the introduction of a richer source once the trail to the first source is well formed induces distinct behavior depending on ant species. Trail recruiting ants (for example, *Lasius niger*, *Iridomyrmex humilis* or *Pheidole pallidula* [45]) are unable to switch in order to exploit the richer source, while group/trail recruiting ants (for example, *Tetramorium caespitum* [45]) exploit instead the richer source no matter the order of discovery. Thus, if two different sources are discovered simultaneously, the richer one becomes much more exploited. However, a late introduction of the richer source may result in switching, depending on the species’ recruiting strategy. This is because group/trail

recruiting ants do not follow the trail as accurately as trail recruiting ants, so they lose it easily, allowing accidental encounters with other food sources. These findings, are then exploited thanks to the group/trail recruiting strategy. As suggested by the above discussion, it is enough to measure either the number of ants per food source or the quantity of scent left in the trail to a food source to get the picture of the behaviour displayed by the colony.

Beckers *et al.* also propose the following mathematical model for the observed behavior. Assume that we have N foragers of which X_i are at the source $i (= 1, 2)$, E are recruits that have lost the trail, and $N - E - X_1 - X_2$ are in the nest and can be recruited. Recruitment accuracy is expressed by means of the fraction of ants in the nest that will become foragers f_i . The resulting equations of motion are

$$\partial_t X_i = a_i X_i f_i (N - \sum_{i=1}^2 X_i - E) - b X_i + c E \quad (i = 1, 2) \quad (12.5)$$

$$\partial_t E = (N - \sum_{i=1}^2 X_i - E) \sum_{i=1}^2 (a_i X_i (1 - f_i)) - p E - 2c E, \quad (12.6)$$

where the constants have the following meanings. Lost foragers can return to the nest every $1/p$ time units on average or can find one of the two sources every $1/c$ time units on average. $1/b$ is the average number of time units that ants stay at the source. The fraction f_i allows one to take into consideration the differences between recruitment modes across species. Trail recruitment depends on the number of foragers at the source, so it is reasonable to make it depend on X_i . Moreover, because a large number of individuals at the source means that the trail is more reinforced, a monotonic increasing function $f_i = g(X_i)$ is a good choice. Group-trail recruitment has the same features as trail recruitment but a constant term has to be added, because of the recruitment due to direct contact among individuals; thus, $f_i = g(X_i) + k_i$.

The model is able to accurately reproduce the experimental results described above. Trail recruitment and group-trail recruitment both have a term amplifying small differences in initial conditions; that is, source is discovered first. However, the constant term in group-trail recruitment makes a difference when the two sources are different and not simultaneously presented (the richer the last). In this case the model with group-trail recruitment has just one stationary state: i.e. exploiting the richer source. Whereas trail recruitment has several stationary states and which one will be reached depends on initial conditions. Besides recruitment strategies, this model also points out an interesting relation between number of ants and source exploitation, as we can see in figure 12.2. There is a certain number N_c of ants where two solutions appear, depending on which food source ants will be exploited. This is an example of *symmetry breaking* (see chapter 3).

In a related work, another model of this phenomenon was introduced in [47]. Its departure point was the movement of ants along paths where some quantity of

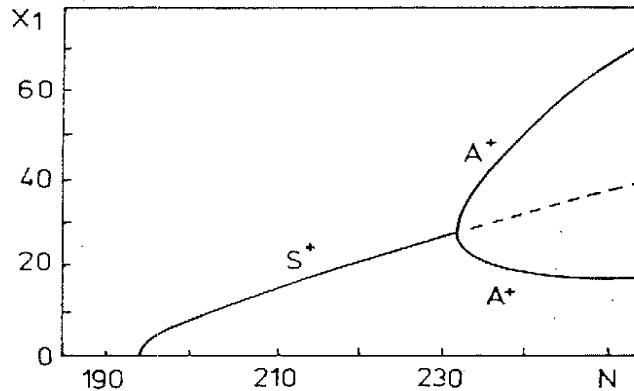


Figure 12.2: Stationary solutions for Beekers *et al.* model. S^+ is the symmetric solution that bifurcates for a certain N_c . Parameters are: $b = 0.1$, $a_1 = a_2 = 0.001$, $p = 0.033$ and $c = 0.018$.

scent was laid, following an experimentally determined probabilistic law to switch at bifurcations [25]. This allows one to define a microscopic dynamics of ants moving on an ant network (a graph where ants travel from vertices to vertices through edges, also called segments) that, under some restrictions of homogeneity and locality, leads to a different model.

Let V_i be the length of the i segment. An ant at a vertex of the network, coming from segment i , will choose segment j to continue its walk with probability $W_{ij} \propto w(\sigma^j)$ depending only on the scent density σ^j present at segment j . This transition probability will be of the form $w(\sigma) = (\alpha + \sigma)^\beta$ where α is a bias in the scent and the role of β will be clarified later. These parameters account for species differences [25]. It is convenient to write this out as $w(\sigma) = e^{-\beta\epsilon(\sigma)}$, where $\epsilon(\sigma) = -\ln(\alpha + \sigma)$; here it is clearly seen that β regulates the steepness of the transition probability as a function of σ . Defining W_{ij} in this way, the following equality holds

$$W_{ij}e^{-\beta\epsilon_i} = W_{ji}e^{-\beta\epsilon_j} . \quad (12.7)$$

this property is called *detailed balance* and is quite useful since it often allows an analytic treatment of the system. The next step is to define an equation for the density s^i of ants at segment i

$$V_i\partial_t s^i = \sum_j w(\sigma^i)s^j - w(\sigma^j)s^i . \quad (12.8)$$

Ants lay scent on the segments according to

$$\partial_t \sigma^i = -\kappa\sigma^i + \eta_i s^i , \quad (12.9)$$

where σ^i is the scent density in segment i , κ is the evaporation rate and η_i is the scent quantity laid by an ant per time step in segment i .

Equations (12.8) and (12.9) determine the dynamics of ants and scents on the network. However, to be able to completely solve these equations, one more assumption has to be made; a separation of time scales. Assume that temporal evolution of scent occurs on a time scale much slower than that of ant density. Thus, we can assume a constant scent in ants temporal evolution. This is called *slaving* after H. Haken [40]. In such a case, ant density relaxes to its equilibrium value before scents change appreciably and s^i can be replaced in Eq. (12.9) by their equilibrium value s_e^i . This can be computed, thanks to the property of detailed balance, and one finds that

$$s_e^i = \frac{N(\alpha + \sigma^i)^\beta}{Z}, \quad (12.10)$$

where N is the number of ants and

$$Z = \sum_i V_i (\alpha + \sigma^i)^\beta \quad (12.11)$$

is a normalization factor. Inserting Eq. (12.10) in Eq. (12.9) a nonlinear evolution equation for scents can be obtained

$$\partial_t \sigma^i = -\kappa \sigma^i + \eta_i \frac{N(\alpha + \sigma^i)^\beta}{Z}. \quad (12.12)$$

The case concerning us, that of a choice among food sources, can be rephrased in terms of this model considering two equal segments, A and B , whose point of departure is the nest, having in their ends food sources. The parameters defining the problem will be η_A and η_B (figure 12.3). This means that ants returning from each food source lay scent at rates according to the quality of the food source, which is in agreement with experiment. Using the parameter $R = (\alpha + \sigma^1)/(\alpha + \sigma^2)$ and some algebraic arrangements, the following dynamical equations are obtained

$$\partial_t \sigma^1 = -\kappa \sigma^1 + \frac{\eta_1 N}{V(1 + R^{-\beta})} \quad (12.13)$$

$$\partial_t \sigma^2 = -\kappa \sigma^2 + \frac{\eta_2 N}{V(1 + R^\beta)}. \quad (12.14)$$

The analysis of this model emphasizes the number of ants N instead of recruitment strategies, as did the previous model (see [47, 48] for details).

On the one hand, let us consider $\eta_A = \eta_B$. In this case, for $N < N_c$ (that is, for N less than a certain *critical* number of ants N_c , to be determined from the equations for σ_1 and σ_2) both sources will be exploited evenly, but a change of behavior occurs at N_c , so that for $N > N_c$ one of the food sources is chosen, depending on random fluctuations in the initial density of ants s^i . On the other

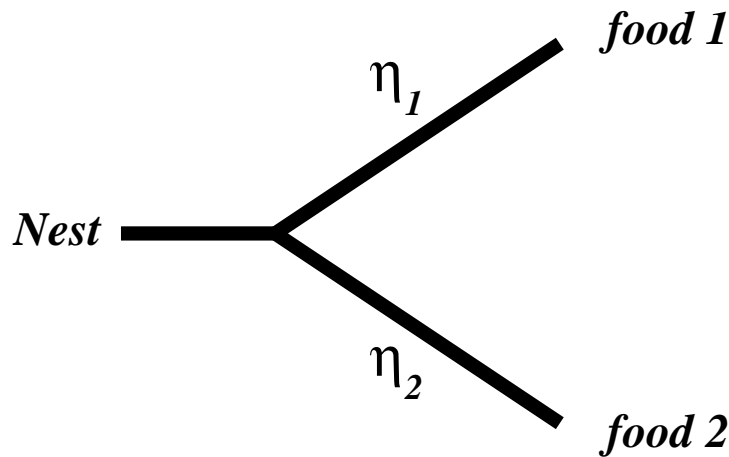


Figure 12.3: Collective decision between two food sources at equal distance from the nest. Scent rates laid by individuals (η_1 and η_2) will depend on the quality of the food source

hand, for $\eta_1 \neq \eta_2$, exploitation of the better food source is a solution for all values of N , although above a certain N_c there will be another solution, i.e. to exploit the poorer food source. However, if the number N of ants grows from zero, as usually happens in experimental situations, the better food source will be always the more exploited.

Thus, we have seen two different models of the same foraging behavior. Each puts emphasis on different aspects, either recruiting strategies or number of individuals. Both models capture one important feature of real ants: The creation of a field of pheromones that guides individual behavior, as we remarked above. The field, represented by σ^i in Millonas' model and by $g(X_i)$ for trail recruitment in Beckers *et al.* model, plays the role of a long-term memory. Information storage here is spatially distributed. Individual ants manipulate this information, either reinforcing or decreasing the field, according to the local information available, that is, the "intensity" of the field on the surroundings of the ant. It is easy to see how information is transmitted, it comes with the local changes of the field, though it can be transmitted also from individual to individual in group/trail recruitment. It's worth also to remark the interplay between the *global* patterns of scent and the *local* variations of pheromone, through depositions of individual ants; in this sense we can consider the trails -the memory- as an *emergent* phenomenon, a global pattern not only emerging from the local activity of individuals, but also directing the behaviour of these individuals.

All of the above discussion can be rephrased in terms of dynamical systems theory. The *state* of our system would be the spatial distribution of pheromone and the location of each ant on the experimental arena; this state would change

with time, in a probabilistic way, towards a *stable attractor*, a stationary state where some food sources are being exploited. These attractors may depend on some features of the colony, such as the number of ants and/or the recruitment strategy, that is, there may be different possible behaviours in our system that appear as some parameters are changed. Furthermore, despite these changes may be purely local (for example different recruitment strategies), their consequences may appear at the global, emergent, level as changes in the *qualitative* nature of the attractor, i.e. different food sources may be exploited.

12.4 Brood sorting

In [27] some experiments are described concerning sorting and clustering in ant colonies. In one of them a large number of ant corpses were placed randomly on a arena. A rapid response of the colony (*Pheidole pallidula*) was observed, sorting the corpses and clustering them. At the end of the process one or two clusters of corpses remained on the arena. The other experiment consisted of larvae sorting. The larvae of a colony of *Leptothorax unifasciatus* were tipped out onto an area. Workers brought back larvae to the nest making some small piles. After a while, one large pile of larvae was observed, with a clear separation between small larvae and large larvae.

In the same paper a model of these phenomena was introduced. It is not a model made out of differential equations, as the models we have seen above, but a discrete model in time and space, a kind of mobile cellular automata. We assume an area of $L_1 \times L_2$ squares, each one containing an individual and/or an object that can be of one of two types, A and B . Individuals are able to move randomly in one of the four directions of the Von Neumann neighborhood, except for the borders of the area. It has, therefore, zero-flux boundary conditions. Each individual can hold an object if he is located at the same place and if he is not holding another object. An individual is also able to put down an object, if he is holding one. An object will be picked up depending on the spatial environment of the object. Each individual has a short memory where he can remember how many objects of type A he has found in the last m steps, and also how many objects of type B . Thus, an individual is able to compute an estimation of the ratio of A objects, f_A^m , and of the ratio of B objects, f_B^m , in the environment of a given object, that located at the same coordinates of the individual at that time step. To pick up an object is done in a probabilistic manner

$$P_{A/B}^{up} = \frac{(K^+)^2}{(K^+ + f_{A/B}^m)^2}$$

where K^+ is a constant. To put down an object we define

$$P_{A/B}^{down} = \frac{(f_{A/B}^m)^2}{(K^- + f_{A/B}^m)^2}$$

where K^- is a constant. As is obvious from the definition of $P_{A/B}^{up}$, the more objects an individual finds of a certain type the less probable is that he picks up one of them, and from the definition of $P_{A/B}^{down}$ we see that an individual will put down an object with a probability that increases with the objects of the same type he finds while walking around. This simple model reproduces the results observed in experimental manipulations, at least qualitatively [27]. In figure 12.4 we can see snapshots of the object locations at different time steps. An increasing clustering according to the type of the objects is observed. Remarkably, this model attains a global result (clustering of objects initially spread out on the lattice) using only local rules, just as did Millonas' model of collective decision.

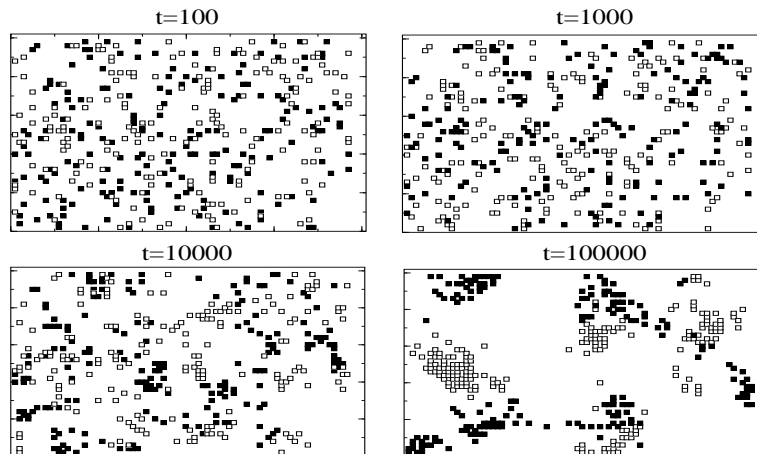


Figure 12.4: Four snapshots of the clustering process in ant-like robots (not shown). Each snapshot shows the object distribution in a 50×80 lattice. The order in time is from top to bottom and from left to right. Parameters: $K^+ = 0.1$, $K^- = 0.3$ and $m = 15$. For a description of the model see text (after [27]).

In this case we deal with a stigmergic process implying that information transmission is performed through the spatial distribution of A and B objects. This turns out to be also the memory used by the collective system to proceed with the clustering task, memory that is modified by individual activity through the picking up and putting down of objects. As the model suggests, the clustering process relies on some fluctuation in the random redistribution of objects that takes place in the initial steps, fluctuation that must be large enough to attract more objects of the same sort. Then, a change in an initially unstructured distribution occurs so that the clustering of equal objects can be initiated. This change in the information storage of our system (a change in structure), how could it be quantified in computational terms? Furthermore, ants gather information from their local neighborhood. Although only local information concerning the types of objects around is available at a given time, there is a certain amount of informa-

tion *stored* in terms of memory. Each ant is able to remember a certain number of past events and this memory is afterwards used in deciding whether or not to pick up/put down an object of a given type. The final outcome is a pattern formation process where the available long-term memory of individuals ants makes possible to cluster the objects properly. As the objects become clustered, the large-scale structure acts somehow as an order parameter. As more and more objects of the same type become clustered, it is more likely for the ant to remember sequences of objects of the same type, thus introducing a further reinforcement into the process. Again, we have a system in which local behaviour induces a global, emergent, phenomenon that is useful for the survival of the colony. In this case the state of the system is the spatial location of each object and the position of the ants, the dynamics is again stochastic, since ants are considered as random walkers on a two dimensional surface, and any state with two large clusters of objects of distinct type has some non-zero probability of being the attractor of the system.

There are some refinements of this model, introduced in [39]. The individuals, as defined up to now, are called “basic” ants; he defines alternative rules for movement, picking up and putting down objects. These ants are called “complexity-seeking” ants. Roughly, these ants are able to measure what Gutowitz calls the local complexity of a square of the lattice. This is a measure of how many consecutive changes of content there are among neighbor cells, i.e., the number of “faces” that separate cells of different type. This determines the direction of the movement and manipulation of objects. Complexity-seeking ants are able to achieve the same results as basic ants, but faster. This is seen in the decreasing rate of the spatial entropy (see [39] for details).

12.5 Army ants

Swarm raid patterns in army ants are among the most astonishing social behaviours one can observe in nature. In a matter of hours, thousands of ants leave their bivouac, forming large columns or swarms, with the only purpose of finding food for the colony. These raids are able to sweep out an area of 1000 m^2 in a single day. The “Huns and Tartars of the insect world” (Wheeler [45, p. 573]) are a beautiful example of decentralised control and self-organised behaviour [11]. The term “Army Ant” (a.k.a. “legionary ants”) refers essentially to the subfamilies *Ecitoninae* and *Dorylinae*, although behaviour patterns characteristic of those mentioned above are also found in the subfamilies *Leptanillinae*, *Ponerinae* and *Myrmicinae* [45]. Such large-scale predatory patterns have been the subject of research by naturalists and myrmecologists since the past century: the structure of the patterns, the relation between division of labour and the raid patterns, their adaptive significance, etc. A sample of the reasons of the scientific interest in raid patterns can be found in [45, chap. 16].

Different species of army ants display different raiding patterns. The column raiding of *Eciton hamatum*, the swarm raiding of *E. burchelli* and the intermediate

pattern –between columns and swarms– characteristic of the monomorphic species *E. rapax* would be good examples of the diversity in raid pattern structure. This diversity was explained by a theoretical model (detailed below, see [26, 25]) which predicted that different patterns were the result of different food distributions and parameter combinations (according to prey preferences), though the underlying mechanism to build raid patterns was the same in all cases. These predictions were successfully tested by means of experiments with *E. burchelli*, whose characteristic swarming pattern changed, when prey distribution was modified, to look like the raiding pattern of *E. rapax* [31]. The mechanism behind raid patterns is a behavioural trait of army ants that has been subject to the forces of natural selection and, as such, it is “partially adaptive and partially an epiphenomenon created by stronger selection occurring on other traits” [53, p. 314].

Following [26], we consider a simple model of army ant raid patterns which involves individual, discrete units moving on a two-dimensional discrete lattice where a pheromone field is created and maintained by the mobile units. More precisely, let $S_k(t)$ be the state of a given ant which will be either $S_k = 1$ or $S_k = 2$ if the ant is searching and moving away from the bivouac or returning back, respectively. Let $\phi(i, j) \geq 0$ be the trail concentration at lattice site (i, j) . When ants are searching, they leave one unit of pheromone, unless the total amount of pheromone already exceeds a threshold value σ_1 . When returning from exploration with a food item (returning ants always carry a food item) they leave q units of pheromone; now the threshold is σ_2 . The pheromone evaporates at a given decay rate δ : at each discrete time step $\phi(i, j) \rightarrow (1 - \delta)\phi(i, j)$.

Movement involves two different rules. These are:

1. Probability of movement. A given ant located at (i, j) will move with a probability P_m by depending on the pheromone field in the three grid points in front of (i, j) . If the ant is leaving the nest, it reads:

$$P_m = \frac{1}{2} \left[1 + \tanh \left(\frac{\phi(i+1, j+1) + \phi(i+1, j) + \phi(i+1, j-1)}{\phi^*} - 1 \right) \right]$$

(and similarly for returning ants but replacing $i+1$ by $i-1$). The parameter ϕ^* represents the concentration of trail pheromone for which the probability of moving per step is 0.5.

2. Once movement is allowed to occur, we have to choose one of the new grid nodes. The nodes with higher pheromone levels are more likely to be chosen. We have three probabilities π_L, π_0 and π_R indicating left, central and right front nodes, respectively. These probabilities are:

$$\pi_L = \frac{1}{C} [\mu + \phi(i+1, j+1)]^2$$

$$\pi_R = \frac{1}{C} [\mu + \phi(i+1, j-1)]^2$$

and obviously $\pi_L = 1 - \pi_R - \pi_0$. Here C is given by

$$C = [\mu + \phi(i + 1, j + 1)]^2 + [\mu + \phi(i + 1, j)]^2 + [\mu + \phi(i + 1, j - 1)]^2$$

This choice of a sigmoidal-like function is based on experiments [31]. The

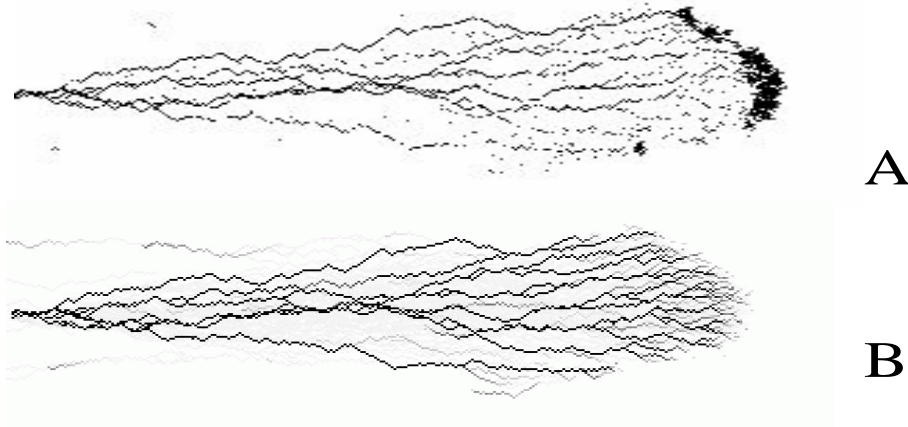


Figure 12.5: Simulation of Deneubourg *et al.* model, as detailed in the text, for a certain set of parameters. We can see in (A) the spatial distribution of individuals and in (B) the associated spatial distribution of pheromone. There is a clear matching between both. Pheromones pattern controls individuals movement though the pattern needs to be reinforced by individuals

parameter μ weights the attractiveness of empty nodes. If the chosen node is such that the total number of ants exceeds a maximum value A_m , then no movement is allowed to occur. Two additional rules are required: (a) lost ants (i. e. those such that they reach the limits of the lattice) are removed from the system; (b) new ants enter from the bivouac, here located at $(1, L/2)$. This is a fixed number but if the bivouac site is already at the limit A_m , no new ants are added.

An example of the amazing raid patterns generated by the model can be seen in figure 12.5. This simple model was able to provide evidence of a common mechanism underlying different foraging patterns in different ant species. Besides, this prediction was verified experimentally, supporting the validity of the model.

Furthermore, an evolutionary study of this model was recently performed, using a variant of a genetic algorithm (chapter 13) to optimize its parameters. The results showed that different optimal patterns, in different conditions, could be obtained with similar values of the parameters, except for the two pheromone saturation parameters, σ_1 and σ_2 . These two parameters may have been the two parameters tuned by evolution to make different species of army ants adapted to

their respective ecological niches, represented here by spatial food distributions. This result is an important addition to Deneubourg *et al.* work: these authors showed that it is in principle possible to obtain the observed patterns with a single set of parameter values but they did not *quantify* the patterns in any way; while the above mentioned study was not able to quantify the spatial patterns *per se*, it was able to quantify their impact on foraging efficiency and did not rely solely on the eye of the beholder. The result of this more accurate quantification of the patterns is that different sets of parameter values are required to generate optimal patterns in different conditions, and we have identified which parameters values should be significantly different.

Assuming that the model reflects indeed what the ants do, which seems to be confirmed to a certain extent by a remarkable set of experiments, this suggests that self-organised raid patterns have been optimised in the course of evolution. Since raid patterns emerge out of relatively simple rules followed by individuals, it means that colony-level selection has shaped the behaviour of individuals in such a way that individuals self-organise to implement optimal foraging strategies. Variation at the level of individual genotypes has been expressed in colony-level patterns through self-organisation.

12.6 Self-synchronization

Ants, refuting popular fables, do not work untiringly all day long. As Sudd [59] pointed out, the proportion of time spent in resting can be high, and the study of Herbers [43] on acts performed by ants of *Leptothorax longispinosus* and *L. ambiguus* species reveals that “(...) ants spent two-thirds of their time apparently doing nothing at all”. These behavioural patterns are by no means exceptional, Franks & Bryant [29] found them in *L. acervorum* and Cole [12] noted that “(...) Time spent quiescent occupies a large fraction of the total time of an ant (on average 55%)” while studying ants of the species *L. allardycei*. A more refined study by Franks *et al.* [30] measured even a 72% of time spent resting for workers inside nests of *L. acervorum*. However, not only patterns of alternate activation have been found in individual ants, these patterns also appear *in whole colonies, showing synchronized patterns of activity*: surprisingly, Franks & Bryant [29], by means of video-recording techniques, were able to get a long enough time series of the activity in whole colonies of *L. acervorum* to show, using spectral analysis, that activity was roughly periodic, with periods between 15 and 30 minutes. This synchronized behaviour has also been found in *L. longispinosus*, *L. ambiguus*, *L. curvispinosus*, *L. allardycei* and *L. muscorum* (see [50, Chap.2]), also in other species such as *Pseudomyrmex elongatus*, *P. pallidus*, *Tapinoma littorale*, *Zacryptocercus varians* and *Crematogaster ashmeadi* [15]. Activity patterns are not just synchronized, but *self-synchronized*: no external signal has been found experimentally as a possible cause of colony synchronization [13]. Furthermore, Cole [14] was able to show evidence of chaotic activity in single ants. So, one important conclu-

sion is already at hand, that is, *self-synchronization is a collective property*, since individual patterns of activation are not periodic.

Two main observations/conclusions emerge from these experiments.

- Randomness is present at the individual level, acting as a source of noise.
- Collective ordered dynamics emerge from the microscopic chaos. The observed oscillations are present in different species and seem to be an intrinsic relevant feature of ant colonies.

There are different mathematical models of self-synchronization in ant colonies. Different approaches based on ordinary differential equations or probabilistic process algebra have been proposed. These models have been criticized on the basis of a lack of testable predictions or dubious assumptions, see [61] for a survey and [5, 23] for some recent work on modelling of collective oscillations. We will detail here the mathematical model known as *Fluid Neural Network* (FNN).

In FNNs the standard approach of neural networks is used [2], but a new set of rules defining local movement and individual activation are also introduced. A set of N automata or “neuron-ants” is used. The state of each automaton (say the i -th one) is described through a continuous state variable $S_i(t) \in \mathbf{R}$, at each time step $t \in \mathbf{N}$. Each element can move on a $L \times L$ two-dimensional lattice

A set of rules is defined:

- *Neural network structure*: Interactions are described as in neural networks by means of a sigmoidal function $\Phi(x)$. If $S_j(t)$ is a given automaton (the spatial dependence is omitted for simplicity), the new states are updated following:

$$S_i(t + \Delta t) = \Phi \left[g \left\{ J_{ii}S_i(t) + \sum_{i \neq j \in B(i)} J_{ij}S_j(t) - \Theta_i \right\} \right] \quad (12.15)$$

where $B(i)$ are the nearest automata, located in the neighborhood defined by the eight nearest lattice sites, and $J_{ii} \neq 0$. For simplicity we use the threshold $\Theta_i = 0$, and we take $\Phi(z) = \tanh(gz)$ with g being a gain parameter.

- *Spontaneous activation*: We have seen above that one of the properties Cole [13] observed in isolated ants was spontaneous activation. In FNNs this has been included in the following way: each automaton can be either *active* or *inactive* and, if active, it moves randomly to one of the eight nearest cells (if no space is available, no movement takes place). In our model a given automaton will be active if $S_i(t) > \theta_{act}$ and inactive otherwise. Once an automaton becomes inactive, it can return to the active state (with an *spontaneous activity level* S_a) with some probability p_a .
- *Coupling matrix*: the coupling matrix \mathbf{J} is not fixed. Connections are local and changing over time as a consequence of movement. They are also state-dependent i.e. J_{ij} will be a simple function of the states of the actually interacting pair (i, j) of automata, i.e. $J_{ij} = f(a_i^t, a_j^t)$, where $a_i^t = \Theta [S_i(t) - \theta_{act}]$

($\Theta[x]$ is the Heaviside step function). In our case, where two basic states are defined, i.e. “active” and “inactive”, the connectivity matrix reduces to the following 2×2 table:

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{10} \\ \lambda_{01} & \lambda_{00} \end{pmatrix}$$

At a given time step, the interaction J_{ij} between the i -th and the j -th elements is equal to $\lambda_{a_i^t a_j^t} \in \Lambda$ by depending on the activity states of the given elements. More precisely, J_{ij} will be equal to: λ_{11} when both ants are active, to $\lambda_{10}, \lambda_{01}$ when one is active and the other inactive and to λ_{00} if both automata are inactive. In this thesis we take for simplicity $\lambda_{a_i^t a_j^t} = 1$. Our choice is based in the observation of ant colonies. Self-interaction and positive feed-back (with local excitability) play an essential role in colony dynamics. The consistency of our choice is fully supported by experimental studies of ant colonies [15].

A technical point is what sort of boundary conditions we use. Though not biologically plausible, we use *periodic* boundary conditions, because we want to verify that ordered temporal behaviour is a consequence of the *intrinsic* dynamics of the system, not a boundary effect. Nevertheless, this turns out to be irrelevant because of the same phenomenology is observed with diverse boundary conditions (periodic and zero-flux).

The collective behaviour we want to measure in FNNs is the mean activity of the system. We have defined above an activity for each individual $S_i(t)$, $a_i^t = \Theta[S_i(t) - \theta_{act}]$, so the mean activity at time t will be

$$\rho_t^+ = \frac{1}{N} \sum_{j=1}^N a_j^t = \frac{1}{N} \sum_{j=1}^N \Theta[S_i(t) - \theta_{act}] \quad (12.16)$$

where $\rho_t^+ \in [0, 1]$. We define also the total density of automata as $\rho = N/L^2$. We can see in figure 12.6 two samples of the temporal behaviour of ρ_t^+ .

FNNs were originally defined to ascertain whether there was a transition between synchronized and non-synchronized behavior, depending on the density ρ . At low ρ we have a very disordered pattern, which becomes more and more ordered as ρ is increased. So, a clear transition from random to ordered, *self-synchronized* temporal behaviour is made evident. Solé *et al.* [57] calculated the Fourier spectrum for FNNs time series and a well defined maximum in the amplitude was found with growing ρ .

Solé & Miramontes [56] showed that a first approach to a quantitative characterization of the transition in the dynamical behavior of the FNN was to measure the *Shannon-Kolmogorov entropy* of the following probability distribution $\{p(j, \rho)\}$: let T_j the number of time steps where exactly j elements were active ($j = 0, 1, \dots, N$); now, if T is the total number of time steps, the relative frequency

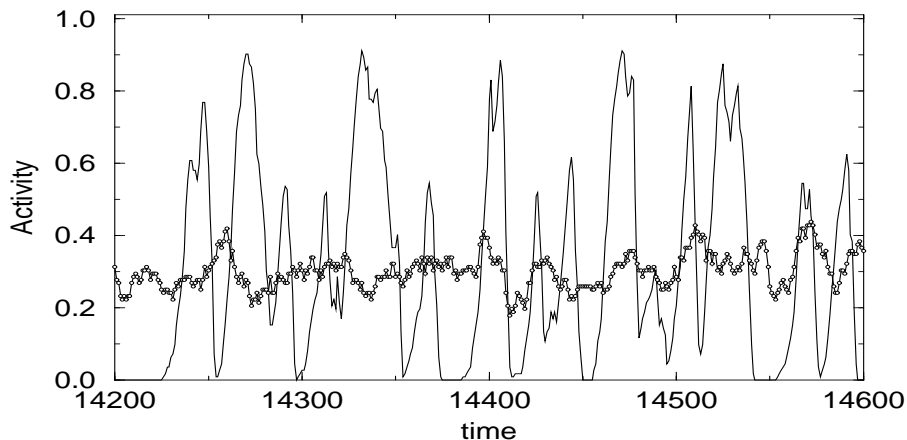


Figure 12.6: Evolution in time of ρ_i^+ . We may get either bursts of synchronized behaviour or non-synchronized behaviour, depending on the set of FNN parameters we choose.

of j simultaneously active elements will be $p(j, \rho) = T_j/T$. The SK entropy is then defined as:

$$S(\rho) = - \sum_{i=0}^N p(i, \rho) \log_2 p(i, \rho)$$

It is expected that SK entropy will provide us with a measure of the diversity of macroscopic states. $S(\rho)$ has an upper and a lower bound: $S(\rho) \in [0, \log_2(N+1)]$. At low densities, $S(\rho)$ will grow until the onset of collective oscillations, where it will decrease due to the highly correlated temporal patterns. So, the transition occurs at a *critical density* ρ_c such that $S(\rho_c)$ is maximum. Using SK entropy, Solé & Miramontes performed an extensive study of the (ρ, g) -space. They found four dynamical domains: random behaviour, chaotic attractors, steady states and periodic oscillations. For high g values the automata collapses to a steady state where all individuals are active. Lower g results in coherent oscillations or disordered behaviour depending on the density ρ . These domains are separated by a maximum in SK entropy.

Thus, a transition from disordered to oscillatory behaviour in FNNs has been characterized numerically as the maxima of SK entropy. Now, how good are FNNs to model the *real* system? In principle the same phenomenology has been observed. However, we observe the onset of oscillations for a critical density $\rho_c \simeq 0.2$, *the same density observed in real ant colonies* [32]. This is clearly a point in favour of FNNs as models of self-synchronized behaviour in *Leptothoracine* ant colonies, besides providing the first evidence of real systems living at the edge of a phase transition [56]. On the other hand, despite having identified a transition,

which kind of transition is it? Non-equilibrium systems (and FNNs are obviously not in equilibrium) may display different types of transitions. In order to get a quantitative theory of a transition phenomenon we have to identify a quantity called *order parameter* (see chapter 7). Focusing on the relation between ρ and p_a we were able to characterize the transition as a *noise-induced* transition [19] by means of a well-defined order parameter. Also, it is possible to simplify the model to get a mean-field theory of FNNs [21]. This simple FNN has the same behavior as the original FNN, though in this case it is possible to obtain analytically the critical density ρ_c , showing a very good agreement with numerically computed critical densities.

FNNs have also been used to obtain some results concerning the adaptive character of self-synchronization [18, 23]. Cole [13] discussed the adaptive significance of short-term activity cycles arguing that it is unlikely that these cycles contribute to the efficiency of the colony. They are “(...) the inevitable outcome of interactions within social groups”. However, at least two functional behaviours in ant colonies have been related to self-synchronized activity: task allocation [55] and mutual exclusion [42].

G.E. Robinson suggested that self-synchronized behavior provides a mechanism for information propagation:

“Sampling behavior that involves social interactions may be facilitated by synchronous bursts of worker activity, which have been observed in ant colonies (...). The decision of which task to perform would be based on the integration of acquired information, coupled with behavioral biases associated with worker, caste, physiological status and prior experience.” [55, pag. 652]

So, according to [55], self-synchronization facilitates the sampling of any information an individual may need from other individuals. Let us try to clarify this point. Assuming that ants cannot be active all the time (which is what is observed in nature, see above), why self-synchronized behavior would be a better (simple) strategy than, say, random (in the sense of “non-synchronized”) activity patterns? We will need further assumptions to answer this question: First, the obvious one of locality (an individual is able to get only local information) and second, the quite reasonable (and biologically plausible [30, 13, 14]) assumption that the unique interaction allowed to an *inactive* individual is to be “awaked” by other(s) individual(s); an inactive individual does not carry any information, namely, it is equivalent to a “slept” individual. Now, in this context, it would be clear why we should obtain an increase of efficiency with synchronized patterns of activity: It would maximize the number of simultaneously *active* neighbours of an *active* individual (let us remind that we are assuming that individuals cannot be active all the time). We took FNNs to model self-synchronization and Finite Threshold Model [9] as a model of task fulfilment to test Robinson’s idea in a formal setting. Our results supported Robinson’s conjecture, showing that self-synchronization enhances task spreading, allowing a more efficient task-solving

process in a spatially distributed colony of simple agents (see [23] for details).

12.7 Task allocation

Division of labor is one of the most explored aspects of behavior in ant colonies. Every instant, active individuals in ant colonies are performing one of the essential tasks for colony upkeep: Foraging, patrolling, nest maintenance or midden work. Every task is done accurately by a certain number of specialized individuals. This specialization is unquestionable in what concerns some tasks such as reproduction, where there are clear differences, morphologically and in reproductive status, among queens, workers and males [45]. The term “caste” was used originally to distinguish among these classes of individuals. However, later on “caste” has been used to distinguish among workers performing different tasks. In polymorphic ant species, where ants morphologically different carry out different tasks, we have “physical” castes (*physical polyethism*) and in monomorphic ant species we have “temporal” castes, where task is age-dependent (*temporal polyethism*). Underlying this notion of caste there is the idea of a *fixed* specialization of individuals, which would determine colony behavior through *caste distribution* [53], caste distribution being a species character subject to evolutionary processes.

This fixed specialization of workers is nowadays controversial, because, as argued by some authors [35], there is a large body of evidence that individuals switch tasks, in both polymorphic and monomorphic ant species. It is interesting that, as Gordon points out, these notions of fixed specialization and caste distributions could have been reinforced by experiments done with small number of colonies in very stable conditions and over short time periods. Concerning task allocation and division of labor, we will assume the ideas unfolded in [35], where a complex dynamical process between the individual level and the collective level is the ultimate reason for the percentage of individuals performing each task. For other current points of view concerning division of labor, see [55].

One of the more interesting properties of task allocation is its *flexibility*. Usually the environment of an ant colony is, to some extent, unpredictable and the colony has to deal with very diverse situations throughout its life. These situations include perturbations in the number of individuals doing some task and task allocation systems should compensate this loss, so that colony upkeep continues as unperturbed as possible. This compensation can take the form of either reassignment of individuals to tasks or activation of inactive individuals or both, involving, among other things, task switching. But this is not so simple. Some experiments [36] show that task switching alone does not account for some colony-level phenomena. The experiments with colonies of Harvester ants (*Pogonomyrmex barbatus*) consisted of marking exterior workers (those either foraging, patrolling, doing nest maintenance or midden work) to compare their behavior in unperturbed colonies with their behavior in colonies where some task has been intensified. Furthermore, colonies of different age were also compared with respect

to task fidelity. Results seemingly suggested some level of task fidelity, although perturbations made workers change task. This change is not independent of the task an individual is performing, since some characteristic trends, such as the tendency of workers to switch task out of nest maintenance and into foraging, were found; see figure 12.7 to sum up the changes among tasks in unperturbed workers. It was also observed that task fidelity is weaker in younger colonies. There are also very interesting results concerning colony-level dynamics suggesting that there is not a simple relation between task switching and number of workers engaged in different tasks. For example, in the perturbation experiments foragers rarely switched tasks to do nest maintenance but perturbations increasing nest maintenance work decreased the number of workers foraging.

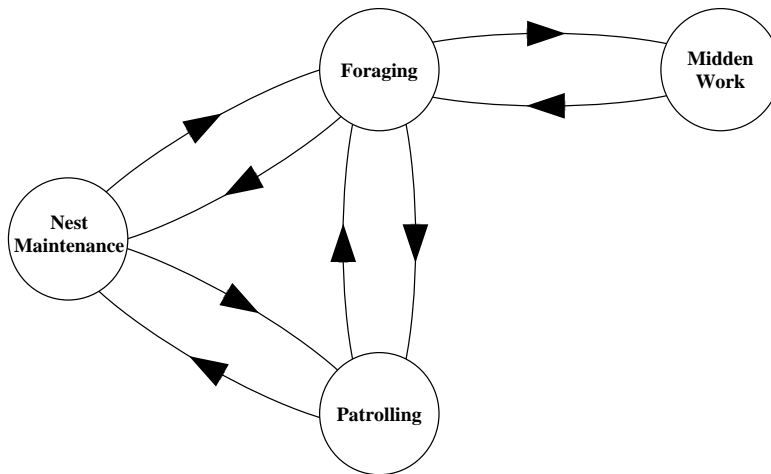


Figure 12.7: Perturbations in *Pogonomyrmex barbatus* colonies induce activity switching (see text). Arrows in the figure show for each activity, to which other activities regular workers will switch; after [36].

From these and other experimental results [35, 36, 45, 55, 62] it is clear that the interplay between the colony and the individual, in what concerns task allocation, cannot be accounted for either by optimization models [53] or by simple linear relationships between numbers of workers engaged in such and such task. Recently some models have been proposed to explain these phenomena, having in common a serious consideration of the complex dynamics underlying these task allocation systems. A model of the above mentioned experiments was suggested in [37] based on attractor neural networks [2]. Individuals are divided into eight categories according to task and activity: Forager, patroller, nest maintenance worker and midden worker, being either active or inactive for each task. A triple $(\pm 1, \pm 1, \pm 1)$ represents each category. Interaction among ants is defined through three matrices α , β and γ , each one representing one binary decision, so that one of the eight

categories can be chosen from the interaction with other ants. These matrices are defined according to some plausible rules of interaction among workers. If we have an ant in a state (a_k^t, b_k^t, c_k^t) , the next state will be given by

$$a_k^{t+1} = \Theta \left[\sum_{j \neq k} \alpha_{kj} a_j^t \right] \quad (12.17)$$

$$b_k^{t+1} = \Theta \left[\sum_{j \neq k} \beta_{kj} b_j^t \right] \quad (12.18)$$

$$c_k^{t+1} = \Theta \left[\sum_{j \neq k} \gamma_{kj} c_j^t \right] \quad (12.19)$$

where $\Theta(x) = 1$ if $x > 0$ and $\Theta(x) = 0$ otherwise. The existence of a global attractor for this system can be demonstrated (see [37] for details) using the energy function

$$E = -\frac{1}{2} \left[\sum \alpha_{jk} a_j a_k + \sum \beta_{jk} b_j b_k + \sum \gamma_{jk} c_j c_k \right] \quad (12.20)$$

Multiple attractors can be obtained with the same system modifying the γ matrix (this can be shown with the same energy function Eq. 12.20). Although the model does not reproduce exactly either the interactions among workers or the structure of these interactions, the type of dynamics proposed reproduces, at least qualitatively, the phenomena to be explained, that is, the non-linear behavior of workers engaged in some tasks with respect to perturbations in workers performing other tasks.

There are other factors, besides that of interaction among workers, affecting allocation of individuals into different tasks. One of these factors is colony size [45]. Recently a model based on ordinary differential equations and stochastic processes has been proposed to account for this phenomenon [54]. Briefly, the model is able to suggest how individuals have to regulate the per capita rate of social interaction in order to keep in balance the acquisition of information through environmental stimuli and social exchanges. Besides, the comparison between deterministic and stochastic versions of the model is useful to see the plausibility of the deterministic model for small groups, perhaps surprisingly due to the collective nature of the phenomenon. Finally, the model is able to show how a very simple mechanistic interaction allows the system to achieve distributions near those that would maximize colony fitness.

Task allocation is a more general problem than those reviewed previously, though myrmecologists have speculated on some aspects of its information processing properties, for example information transmission: Robinson ([55]) suggests that synchronized activity may enhance the sampling of information in individuals, assuming that information is transmitted from individual to individual (see

above), and Bonabeau *et al.* [9] suggest that a “stimulus” associated with each task induces an individual to work in that task in a genetically determined way. The set of individuals with the tasks they are performing would be the state of the system, and the state of the environment will be taken as a sort of boundary conditions. Each individual has also a certain amount of memory since, as we have seen above, task switching depends on the actual task an individual is engaged in. This memory, as [9] points out, is likely to be genetically determined by the thresholds associated to each task. However the collective also needs some sort of global memory, as we have seen in [37], in order to maintain the correct balance of task assignments. This collective memory would be the upkeep status of the colony that individuals perceive locally to decide the next task to perform. In this sense the attractor of the system is a set of states such that the survival of the colony would be guaranteed. Information, in what concerns task allocation, flows within the colony via the stigmergic process of task achievement, that is, through the change of state of the system and the corresponding modification of the global memory, as defined above.

12.8 Individual complexity *vs.* collective complexity

An interesting general problem is that of the capabilities and limitations of collective systems *in general*. Are collective systems restricted to a certain set of possible tasks? Is there some threshold in individual simplicity beyond which any useful task is impossible? or, on the contrary, are non-simple individuals unable to display emergent functional behavior? If we do not restrict the (not formally defined) class of “collective systems” some answers are already at hand, since collective systems such as cellular automata and neural networks are able of universal computation, by means of Turing machines simulation [33] (see also chapter 9). Collectives of concurrent simple agents can also simulate any Turing machine, as was shown with the process algebra CCS in [49]. Furthermore, it is widely believed that some problems are “inherently sequential” (technically, P -complete, see [3]), so it is clear that collective systems are not always more efficient than hierarchical and sequential systems.

However, the topic we want to address now is easy to state: *the more complex a society, the more simple the individual* (Klaus Jaffe, cited in [51]). This sentence, of course, concerns to social insects, among which we will take ants as a main example. We mentioned above that all ants species are eusocial, nevertheless there exist large differences among species, with respect to the number of ants that compose the colony, their collective capabilities and the cognitive skills of individuals. A specific example is that of recruitment strategies: there is a clear correlation between the size of the colony and the behavioral sophistication of individual members [4]. In one extreme we find the more advanced evolutionary grade: mass communication (information that can be transmitted only from one

group of individuals to another group of individuals, according to [45, page 271]). Mass communication is the recruitment strategy used by Army Ants (e.g. *Eciton burchelli*), whose colonies are composed by a huge number of individuals, who are, nevertheless, almost blind and extremely simple in behaviour when isolated. The other extreme is occupied by those ants using individual foraging strategies (e.g. the desert ant *Cataglyphis bicolor*), who displays very complex solitary behaviour. Our interest here is not so much to study this remarkable feature of eusocial insects,

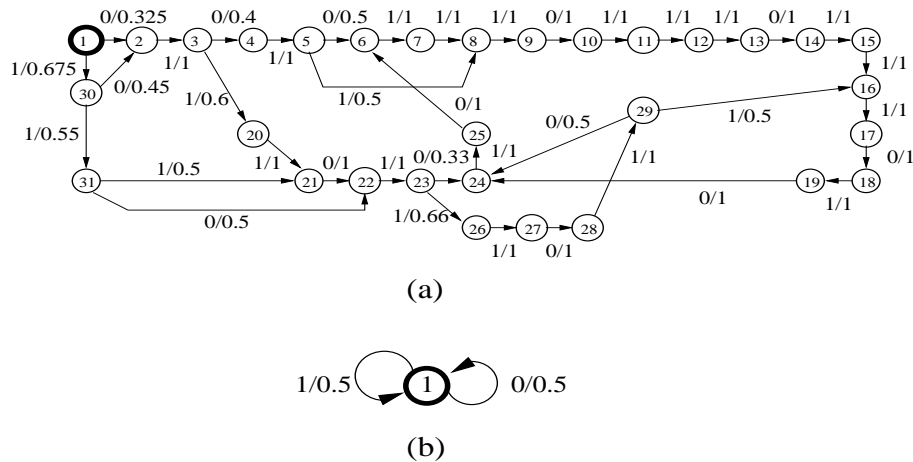


Figure 12.8: DFA with probabilistic labelings resulting from the ϵ -MRA applied to (a) logistic map with $\mu = 1.4$; (b) logistic map with $\mu = 2$. These are the individuals over which we will check if the collective can induce more complex behaviour. As is obvious from the automata, (a) is much more complex than (b) (see text). In all cases the ϵ -MRA parameters are $M = 10^7$, $D = 32$ and $L = 16$. In (a) and (b) the state 1 is the initial state, all other states are accepting states. μ is the dimensionless parameter of the logistic map

as to see if this could be a general trait of collectives of agents. That is, *is there a trade-off between individual complexity and collective behaviour, in such a way that complex emergent properties cannot appear if individuals are too much complex?*

In order to go on with our work, let's start looking thoughtfully at the concept of emergence. According to Hermann Haken [41] and what we have seen in previous chapters, the emergent properties of a system can be studied with the notion of *order parameter* and its associated slaving principle. We can look for an answer in two directions: from the individual to the collective and vice versa. Immediately we can discard the former, because the simplest individuals are those who display collectively the most complex behaviour. So, we can ask now a more concrete question: *what kind of behaviour the collective induces on the otherwise simple individual to attain emergent functional capabilities?* Of course we can answer it

from an evolutionary point of view, arguing that adaptation to the environment is the ultimate reason of those diverse features of ant colonies. This is not the unique answer we can provide [34], because we can also look for relations between the order parameter and the individuals in such a way that, perhaps, complex solitary behaviour imposes severe constraints on the behaviour that a collective would induce on individuals. This would be a structural solution of our problem, and it will be the answer we are seeking.

Now, the collective system we are working on is a Globally Coupled Map (see chapter 3) and our individual will be a randomly chosen logistic map (also, chapter 3) of the system. Our purpose is to see how the collective is (or is not) able to induce more complex behaviour than that the individual is able to show. Here, “complex” refers to Crutchfield’s notion of *statistical complexity*, which will be computed using the ϵ -Machine Reconstruction Algorithm (ϵ -MRA), as seen in chapter 9.

Given a logistic map (our individual) a high statistical complexity is observed for μ close to μ_∞ , i.e. the onset of chaos. There we need a large number of states to model the high periodicity of the orbits. We have chosen $\mu = 1.4$ whose statistical complexity is $C_{1.4} \simeq 4$. As we can see in figure 12.8 (a), this automaton has a large number of states. The next step is to define a GCM with $\mu = 1.4$, and

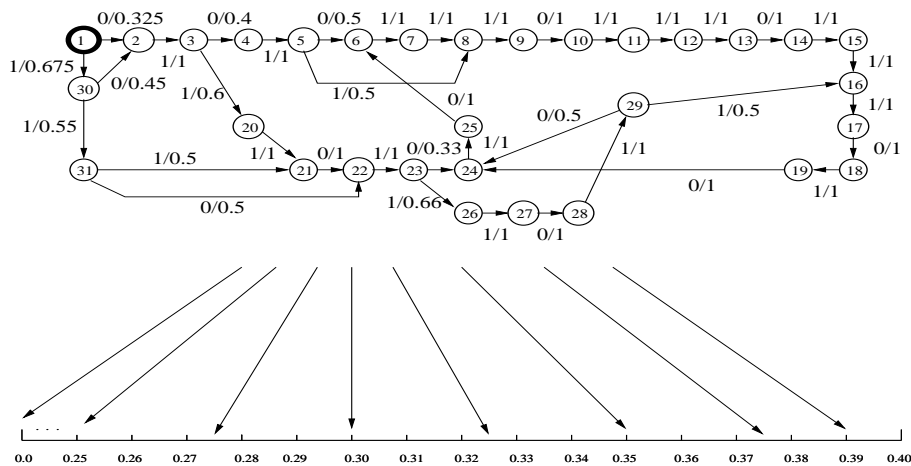


Figure 12.9: If we have a complex individual, no matter how much interaction it receives, its behaviour will not change. The collective cannot induce on the individual any kind of added behaviour. In the figure, the individual possesses the same statistical complexity, for all the values of the coupling parameter. Parameters of the ϵ -MRA: $M = 10^7$, $D = 32$ and $L = 16$. All the automata have 1 as initial state, and all other states are accepting states.

look at the statistical complexity of an individual chosen at random, say, i , as the degree of interaction increases, i.e. we examine $C_{1.4}^i$ as the coupling parameter of

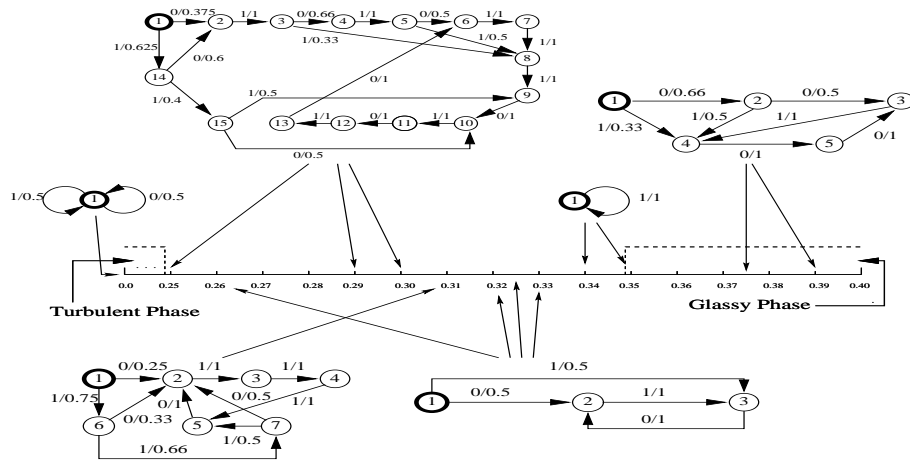


Figure 12.10: With a simple individual like that of $\epsilon = 0$ (in this figure), the collective is able to impose additional behaviour on the individual. We have a decreasing complexity from turbulent phase boundary onwards with increasing ϵ , except in the region of 0.27 (see text). Parameters of the ϵ -MRA: $M = 10^7$, $D = 32$ and $L = 16$. All the automata have 1 as initial state, and all other states are accepting states.

the GCM goes from 0 to 0.4.

The result is simply that there are no changes (as can be seen in figure 12.9). The intrinsic computation of the individual remains to be the same, $C_{1,4}^i \simeq 4$, no matter how large is the interaction with the rest of the system. So, the collective has not been able to induce any kind of added complexity to the individual. In this case there is no emergent behaviour. The collective behavior can be reduced to that of the individuals.

Now, if we take $\mu = 2$ the logistic map has completely chaotic dynamics. It is, in statistical complexity terms, the same as a fair coin toss. So, its automaton has $C_2 = 0$ with just one state (figure 12.8 (b)). We can apply the ϵ -MRA to the symbolic dynamics (i.e. the bit string of length M) of an individual chosen at random among the N that compose the GCM.

Our result is somewhat surprising (figure 12.10), since the individual is able to reach high complexity, If we compare this case with the previous one, we see that simple individual behaviour allows the interaction to create more sophisticated behaviour in the individual, inducing a certain amount of statistical complexity that was not present at the individual level. So, a coordinated behaviour, which the individual is unable to show, emerges from the collective through interaction (details on the relation between the reconstructed automata and GCMs parameter space can be found in [20]).

The ϵ -machine reconstruction of single maps close to the onset of chaos gives us a finite automaton with many states (here 31). So at this point we have a

complex object in terms of computation. Interestingly, the coupling with other units via GCM do not modify this complexity. So entities which are computationally complex in isolation do not change in the presence of coupling: nothing new is induced by the collective. This observation matches the behavior of weakly evolved, primitive ants, where individuals are enough complex to work in isolation and the interactions among them are rather irrelevant.

However, if we start with random, computationally trivial maps and then couple them, the situation turns out to be very different. At $\mu = 2.0$ a fully chaotic map is obtained. The partition of this chaotic attractor defines a Bernoulli sequence and so we have a $C_\mu = 0$ complexity. The coherent motion and the spontaneous emergence of clustering gives birth to well defined ϵ -machines. The coupling starts to control the dynamics of individuals and they behave in a computationally complex way. Nothing except the coupling has been introduced, but it is enough to generate complexity. As in the real ant colonies discussed above, simple isolated individuals can behave in a complex way inside the collective. This is precisely what we have observed. A very important suggestion emerging from this result is that in collectives of simple agents complex behavior is only defined at the level of individuals *inside* the colony and not as isolated entities. In this sense, the observed behavior is the result of an emergent property.

12.9 Conclusion

Finally, after our brief review of Termites nest building, foraging, brood sorting, task allocation and self-synchronization, we can sum up some facts we would like to emphasize:

- Ant colonies display collective, structured, patterns at a macroscopic level (the colony level) like other pattern-forming systems such as Belusov-Zhabotinski reaction or slime mold aggregation (see previous chapters).
- These patterns are *capitalized* by the system in order to get food or maintain the upkeep of the colony, so they are *useful* for the system itself. They are examples of *intrinsic emergence* [17].

Now, let us assume that we, as engineers, can build a collective system with this property of “intrinsic” emergence, but with problem-solving capabilities as a by-product of emergent properties. That is, would we be able to capitalize emergent properties in order to get the solution to some specific problem? This is the “collective of simple agents” approach to problem solving (also called *swarm intelligence*, see the excellent book [8])

As a representative example of the “collective of simple agents” view of problem solving we will detail a collective solution to the Travelling Salesman Problem (TSP [16, 28, 8]) Consider a set of N cities C_1, \dots, C_N and distances between cities $d(C_i, C_j)$ for each pair (C_i, C_j) . A solution to the TSP is a permutation π

of cities such that the quantity

$$\sum_{i=1}^{N-1} d(C_{\pi(i)}, C_{\pi(i+1)}) + d(C_{\pi(N)}, C_{\pi(1)})$$

is minimized. The collective is a set of M agents scattered among the cities, where $b_i(t)$ is the number of agents in the i -th city.

The algorithm is as follows: An agent in city i decides, in the time interval between t and $t + 1$, to go from city i to city j with certain probability $p_{ij}(t)$

$$p_{ij}(t) = \begin{cases} \frac{[s_{ij}(t)]^\alpha d_{ij}^{-\beta}}{\sum_{j \in \text{allowed}} [s_{ij}(t)]^\alpha d_{ij}^{-\beta}} & \text{if } j \in \text{allowed} \\ 0 & \text{otherwise} \end{cases}$$

depending on the distance d_{ij} (whose inverse is called *visibility*) and the *intensity of trail* $s_{ij}(t)$ on edge (i, j) at time t . The *trail* is a kind of evanescent “formal chemical substance” that an agent modifies once it has visited all the cities (see [16], for details on trail dynamics). Each agent is forced to go from a city i to those “allowed” j , that is, those cities not visited in the current tour. Once it has visited all N cities the tour starts again from a “free” state and the trail in each edge (i, j) visited is modified. α and β are parameters that allow the user to control the importance of trail versus visibility. This algorithm is cycled for all agents NC times and at the end the shortest tour found is the solution to the instance of the TSP problem.

The results of this algorithm are quite satisfactory. We only mention that, with the best parameter values, the algorithm finds solutions better than the best found with genetic algorithms and it is very fast in finding good enough (though not optimal) solutions. Furthermore, once found the best parameters (α and β) for problems with a certain dimension, the parameters are little sensitive to increasing the dimension of the problem.

The algorithm makes clear some points already mentioned above. Each agent is simply a stochastic process deciding which city to go from the city where it is. It is not able to perceive a global situation in which to choose the best next city in its tour. In this sense it only uses local information. Besides, information processing capabilities are quite limited, since the only thing it is able to do is to choose randomly a city to go and to remember which cities it has passed during the current tour. It is quite robust since the removing of a certain fraction of agents does not affect the result, though it delays the finding of the solution.

Another instance of collectives of simple interacting agents are groups of robots cooperating to solve some given task (see [8] for a very recent survey on collective robotics). Examples of tasks solved with groups of robots are finding paths to a certain location [38] pushing a box [46] and clustering objects scattered in an

arena [27] In this case there are some added difficulties, due to the physical embodiment of robots (though plenty of collective robotics experiments are performed by means of computer simulations). This embodiment is, in fact, an advantage since some collective behavior is often guided by physical or temporal constraints in the environment, allowing the system to act as if it had some global representation of that environment.

An example of implicit cooperation are the five robots of Kube & Zhang [46] that, without any interaction but with an explicit non-interference command, pushed a box that cannot be pushed by a single robot, due to the weight of the box. To get the task done the robots must locate the box, move toward it without collisions, distribute along a side and push. Each robot was built according to Brooks' subsumption architecture. Using a implicit cooperation strategy, the robots succeeded in pushing the box. Another interesting experiment was to build robots that cluster objects. Initially 81 objects were scattered over an arena and the robots (again built according to Brooks' subsumption architecture) might take some, depending on a microswitch able to detect a certain quantity of objects pushed by the robot. These robots group the objects in little clusters that grow until they cannot be pushed by any robot. When there is no objects in little clusters to be moved by robots the task is done. This is also a case of implicit cooperation [6, pp. 198–201].

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