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On Formal Constraints in Swarm Dynamics

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Abstract

This paper deals with distributed problem solving in social insect colonies. We show that different processes used by social insects could be implemented in artificial swarm systems to solve different categories of problems. After reviewing these problems and defining some basic concepts of Swarm Intelligence we examine through the example of building behavior in termite and wasp colonies how different types of constraints operate both on individual behavior and on swarm dynamics.

1. Introduction

A profound change is seen in the organization of individual behavior with the transition from solitary to social life. In social insects, these modifications generally include an increase in the direct and indirect interactions between individuals. Indeed, any individual's activity must be integrated at each moment to the overall activity of the group to which it belongs. What then are the mechanisms by which a society is able to coordinate individual activities and to become functionally self-organized ? What kinds of behavioral algorithms govern the individuals and what are the parameters governing the time evolution of such systems ? These are some of the questions tackled in the analysis of social insects' dynamics. With such a way of functioning, based on the properties of the interactions taking place between individuals and between individuals and their local near environment one can possibly design a collective and minimalist robotic system (see in particular [1], [2], [3], [4], [5], [6]). Our objective is first to show that some categories of problems are particularly suited for such distributed solving ; and on the other hand, our analysis of the functioning of social insect colonies provides us with a range of information as to the different processes that could be implemented in artificial swarm systems to solve such problems. In this paper we classify the different categories of problems which can be solved by swarms and we show through the example of building behavior in wasp colonies how different types of constraints operate both on individual behavior and on the swarm's dynamics.

2. Insect societies as biological models for collective problem solving

These last years, the interest in the adaptability of social systems in insects has been renewed (see [7] for an overview). Indeed, these non-linear systems can display a large variety of rich and even very complex behaviors, even though the constituent individual behavior is paradoxically very simple and has a strong random component. Local constraints and informations control the behavior of each individual, which is mixed with the material components of the environment where it is moving about. The collective performance is the integration of the myriads of individuals' activities, with each individual both processing information produced by the activities of others and stimulating and informing them in their turn. One particular approach is to analyze the performance of the social group as a form of collective problem solving. In this kind of analysis, the question is to determine what are the characteristics at the level of the different elements which govern the efficiency of the solving process and how the environmental factors regulate the form of the solution adopted by the colony. To do this, our studies combine a detailed biological analysis of individual behavior with numerical simulations to link this level with the colony's global behavior. In the next section we define some basic concepts of Swarm Intelligence, and examine the elementary behavioral rules of individuals in a swarm and the main constraints governing the swarm's dynamic properties.

3. Basic concepts and fundamental properties in swarm intelligence

3.1. Swarm

A swarm is defined as a set of (mobile) agents which are liable to communicate directly or indirectly (by acting on their local environment) with each other, and which collectively carry out a distributed problem solving [8, 9]. In this sense we refer to emergent functionality [10, 11] or functional self-organization [12] since this emerges from swarm's internal dynamics and its interaction with the environment (see also [2] for special references with cellular robotics). The swarm functioning induces both the geneses of functional collective patterns which caracterize the differentiation and spatio-temporal organization of the agents of the swarm and also the parallel organization of the material elements in the environment upon which each agent has an action. We will see that close connections exist between these different patterns and the specific categories of problem which are able to solved by a swarm.

3.2. Problem and collective problem solving

In the framework of swarm functioning the concept of a problem can be defined as a kind of description of the position of a biological or artificial agent, where a functional outcome is described as a goal even though some parameters having the possibility to evolve with time are described as constraints. One can consider the problem to be set when the goal, the constraints and the lawful procedure to move from an initial state S_0 to a final state S_f taking into account the swarm and the environment in which the swarm is scattered. It is worth noting that this definition not only applies to a swarm but also to a single agent. The swarm is characterized by the collective resolution of the problem. Depending on whether an artificial or biological system is considered, the description of the problem to be solved will take a different look :

- when we consider an artificial system, the problem can be conceived before the design of the swarm whose local elementary behavioral rules will bring the system to solve this problem in a given environment ;
- but when we consider a biological system, the specification of the problem is equivalent to identifying a specific biological function (e.g. : the building behavior, the task assignment, ...).

The solution of the problem can be considered in both cases as a particular state of the swarm environment system through which the functional outcome looked for is reached. As a general rule, a number of solutions exist for a given problem, meaning that a given goal is compatible with several states of the system constituted by the swarm and its environment. Thus the "collective resolution of the problem" lies in the structural coevolutionary process between the swarm and its environment in which the functional outcome described as a goal is reached.

Taking an anthill as an example ; observation shows different elements constituting the brood (eggs, larvae and pupae) are sorted and aggregated into piles of the same type by the workers. The sorting can be smaller and discriminate several larval instars. In this example the goal is sorting the different elements which constitute the brood ; the problem is how to achieve this ? The variation in the final number of aggregates we obtain : such as three (eggs, larvae, pupae), four (eggs, small larvae, big larvae, pupae) or more, represents different solutions to the problem. The resolution is the process by which the swarm reaches one of these solutions (see [4, 5] for further information about a particular example of sorting algorithm).

3.3. What the kinds of problems can be solved by a swarm ?

Solving a problem with a swarm amounts to a morphogenetic process leading to a form which is the solution of the problem. Such a process involves both a structuring of the group of agents and the environment in which the swarm moves. If one specifies the different kind of problems a swarm is able to solve, one identifies the elements this structuring process is acting on. Indeed, in a swarm the structure of the environment and the organization of the group of agents molding each other. Both make up the double sides of the same structuring process. The problem to be solved may still turn on one face or the other : organizing the environment or specifying and organizing in space and time the individual activities of each agent.

Numerous studies have dealt with these two classes of problems (see references in section 8). When the problem turns on the structuring of the environment, the swarm changes the structure characterizing a set of objects spread over the environment with handling operations. Different algorithms have been elaborated to enable an artificial swarm to sort different types of objects. One of the algorithm was inspired from the processes used in ant colonies to sort their brood [4, 5]. When we simulate a swarm of robots with simple elementary and reshaping properties reproducing the behavior of ants, the swarm's activity is coordinated and we obtain the sorting of two or more classes of objects. But the problem may also turn on the structuring of the behavioral units of the swarm to realize a spatio-temporal distribution [13, 14, 15, 16, 17] or a functional specialization in the agents' activities [6, 8, 18, 19].

4. The bases of the swarm's functional logic

4.1. Characteristics of individuals' interactions

Insect societies have elaborated collective decision making (CDM) systems which don't require symbolic representation but take advantage of the physical constraints of the milieu where the colony lives. Moreover, these CDM systems primarily use communications between individuals either directly when they meet or indirectly using the environment as a communication channel. One of the main features of these communications is randomness and positive feed-back. A standard example is given by food recruitment in ant colonies (see fig.1). When a new food source is discovered by an ant, it lays down a transient chemical trail. This pheromonal marking promotes in an indirect manner the other ants of the colony to follow this trail towards the place where the food was discovered. These ants, after feeding at the source, will reinforce the trail when they return to the nest. In so doing they themselves

Fig. 1 : The exploitation of the closest food source S_1, S_2, S_3 are the food sources ; the thickness of the curves is a function of the stream of individuals following the trail.

change from recruits to recruiters. The amplification of a discovery but also the selection of an information through the competition which might exist between several discoveries, is enabled by this kind of communication. Indeed, with the help of this autocatalytic logic and the use of spatial constraints, the strength of the "near source" signal increases faster than the strength of the "far source" signal. The latter will be eliminated afterwards. In this way a food source close to the nest will be selected more rapidly than a food source far away from the nest. This collective response of the society, showing in this special case a temporal structuring of the individuals' activity, is the solution to the problem in hand : in this example the exploitation of the closest food-source. Through this example we put in place all the elements which give the collective problem solving in insect societies its original features. Even though none of the individuals in the colony is informed of all the possible ways to find a solution, and none have an explicitly preprogrammed solution, the colony as a whole converges towards an adaptive solution. We can thus see that without any particular spatial coding the colony solves the problem using only an autocatalytic logic and the geometrical and physical constraints of the environment in which it moves.

4.2 From the solitary to the collective state : the organization of individual behavioral rules

The behavior of solitary insects is mainly based on a motor program of the sequential type which we call program with internal reference (see fig.2). This kind of program brings in the state of the animal at a given state (E_I) and a particular configuration of external stimuli (C_I) to which it responds by executing a specific response (R_I). Furthermore, the animal's activity becomes integrated into a fixed action pattern which could be for instance : $R_A \rightarrow R_B \rightarrow R_C$. The motor program enforces the animal to execute a succession of actions according to a well defined order which remain always the same (ABCABCABC...). The behavior of the animal unfolds according to an internal kinesthetic image that takes into account the individual's past actions and governs its present behavior. The result of this behavior on the outside world acts as a physical constraint, since it must exist to enable the animal to finish the sequence it is engaged in. This type of algorithm is particularly well suited for a solitary animal because it allows it to build by

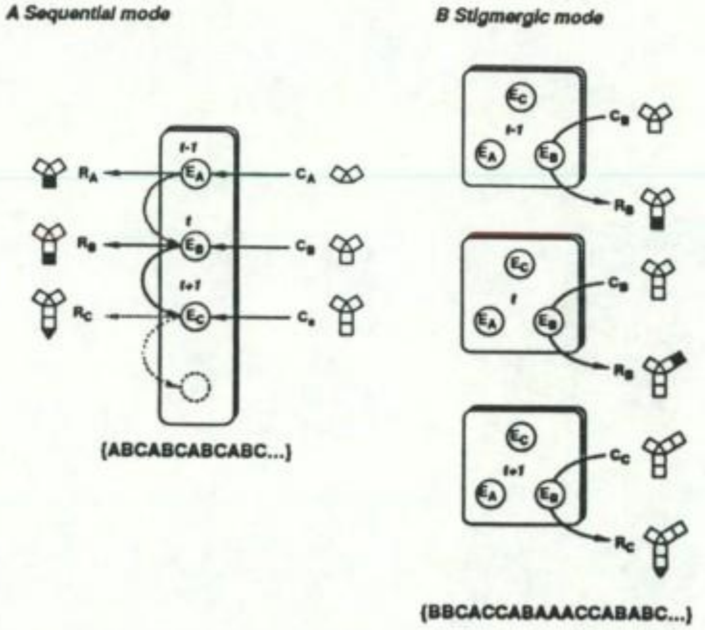

Fig. 2 : Sequential and stigmergic behavioural algorithms (see text for details).

itself within the framework of a nesting cycle for example.

Such an algorithm can only be used with difficulty to collective behavior. Indeed, when several individuals cooperate in order to do a global task which requires a scheduling to be realized, each of them must operate directly without the constraints to be engaged in a behavioral sequence. So, when the transition from a solitary to a social mode of functioning occurs, each of the preceding actions, initially integrated into a sequence and displayed by the same individual, are now uncoupled and achieved independently by the whole swarm. Individual behavior is then based on a motor program of stigmergic type which we call a program with an external reference. In this mode of functioning the environmental structure is perceived locally by each individual, plays a deciding role in the control of individual activity. However in opposition to that which we observe in the sequential mode, each individual does here what there is to do when it meets a releasing configuration (C_I) in the world without being assigned by any internal constraint. This implies that the structure generated, such as a particular nest architecture must be compatible with this mode of functioning while preserving a similar functionality. Indeed, in the sequential mode, the unfolding of the algorithm in a predifined order was enough by itself to obtain a precise structure, and which is always the same. In the stigmergic mode, however, the evolving structure realized by the swarm governs at each moment the individuals' activities, and must play a similar role to the sequential constraint. In so doing we shift from an internal referential in the sequential case to an external referential where the evolving form of the structure to be generated gains more and more importance. So in both cases one could imagine that the resulting form will reflect the interplay between the type of algorithm that governs individual behavior and the size of the colony.

We will examine these two parameters in the next sections. In wasp colonies, this explains why the nest shapes realized by solitary individuals and those realized by colonies are so different. We saw that in the stigmergic algorithm, each individual is a kind of generalist (AACABBBCACABCAC... is a particular succession of actions realized by a single individual). When learning processes are introduced, a single individual could be specialized to some particular action or particular zone of a workspace. Then, when a kind of response R_I to a given external configuration C_I is displayed by an animal, the probability $p(R_I)$ of responding again to this configuration is increased. This process allows the swarm functioning to adapt to the needs of the colony, which will change with time and space as the structure is elaborated. This is in particular what happens with the dynamic task assignment in wasps' colonies we studied elsewhere [6, 19].

5. The evolving swarm and controls parameters

The establishment of a link between the rules governing the units' behavior (including interactions between these units) and the system's behavior is common to numerous scientific activities. In behavioral science, computer science and all the sciences related to the problem of organization, traditionally the hierarchical blueprint was privileged. Recently, an alternative was offered by the self-organization concept (which is far from new in physics and chemistry, see [20, 21]. We see today the development and the analysis of multi-agent systems such as eco-problem-solving [22], emergent functionality [10, 11], computational ecology [23] or cellular robotics [1, 24]. The self-organization blueprint shows that rather simple and decentralized units with strong interactions (e.g. with positive feed-back) are able to produce complex patterns and solve problems.

But after an initial fascination, we quickly became unsatisfied and some questions appear:

- What are the links between the behavioral program and the structure produced ?
- How complex should the individual (behavioral) program be to produce global patterns ? By complexity, we refer here essentially to the number of factors (and their interplay) which influence the insect's behavior.
- The animal evolves in an environment What are the components which must be behaviorally coded and what can be obtained as a byproduct of the physical constraints exploited by the program ?
- What are the constraints introduced on the program by the type of environment, the material manipulated (silk, mud,...) or the tasks done (digging, weaving,...).

These questions are not specific to swarms or colonies, they are shared with all builders. However we shall see that the behavioral program for the same problem (e.g. digging) will depend on whether the builder is solitary or social and how the size of the society interacts with the program.

Comparisons between solitary and social workers building similar structures in similar environments can provide information on the number of blueprints actually at work. The difference can appear for example at the level of the complexity needed to produce the right structure. However complexity is not the only characteristic of the behavioral program. Indeed these programs can be classified in different families such as stigmergy or the sequential (see the definitions below). So, for the same tasks, are some families of rules more adapted to solitary or to social agents ?

This is the link between the number of agents and the type of behavioral programs which shall be discussed here, from a theoretical point of view, with the help of mathematical models.

6. Must a solitary worker's rules be different from a social worker's, with digging as first example

6.1. A stigmergic script

This script is inspired by different biological observations and our first goal with such a model is to examine the power and the limit of given rules, rather than to fit theoretical and experimental results.

Grassé introduced the concept of stigmergy [25]. The basic idea is that no direct interactions are necessary to coordinate the work of a group, but that the interactions between the nest and the workers are enough. The working termites modify their environment, providing new stimuli. These new stimuli induce new behavioral responses which in their turn modify the environment. With this succession of stimulus-reaction, the society is able to produce a structure. It is the work itself which assumes the coordination of the workers' activities.

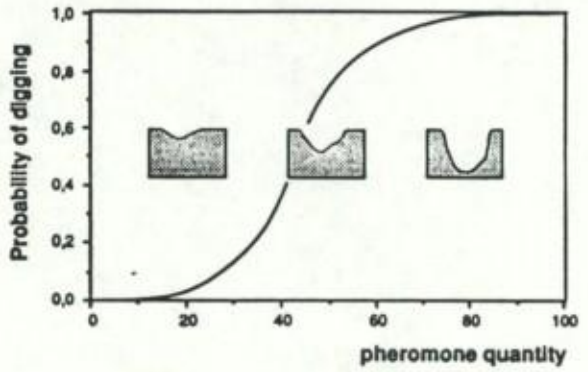

Fig. 3 : Probability of digging as a function of chemical marking

The termites in the present script "use" a particular stigmergic mechanism which is an amplification. The termites move randomly in their nest and at each time-step, each termite is characterized by a probability P of digging and of extracting a soil particle. The model assumes that when a termite extracts a soil particle, it marks the neighboring ground with a pheromone, or with a trail, and the probability of digging increases. This chemical marking stimulates the nestmates to dig (the probability of digging increases) at the same place or just in its neighborhood (see fig.3). So the probability of digging is only determined by the local conditions.

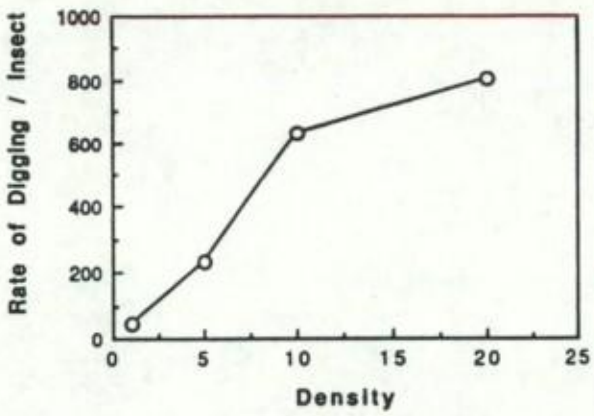

Fig. 4 : Digging rate per individual as a function of the colony' size

The figure 4 shows that the digging rate per termite grows as the group's size (density) increases. In other words, the individual level of activity increases as the group increases.

6.2. Regulation of the nest volume

In a natural system, as the nest population grows, the digging activity increases to adapt the nest size to the total population. The algorithm described earlier doesn't contain any explicit instructions for "switch" the insects to digging (or non-digging) when the density reaches a certain threshold. However the algorithm does provide such regulation. Indeed, coupling the model with a slow population increase, the group is able to modulate the digging activities and to adapt the nest size to the population.

Different dynamics can be produced. We describe here only two extremes. The first and most intuitive is a continuous digging activity, producing a continuous increase in nest size. The second corresponds to a pulsatile growth of the nest size : brief periods of a high rate of digging, with long periods of negligible digging between (c.f. fig. 5).

This behavior is finally rather simple to understand. At low density, the digging activity is weak (see fig.5). As the population increases, the density increases and a high level of activity is produced. This digging activity abruptly increases the nest size, but during this period the

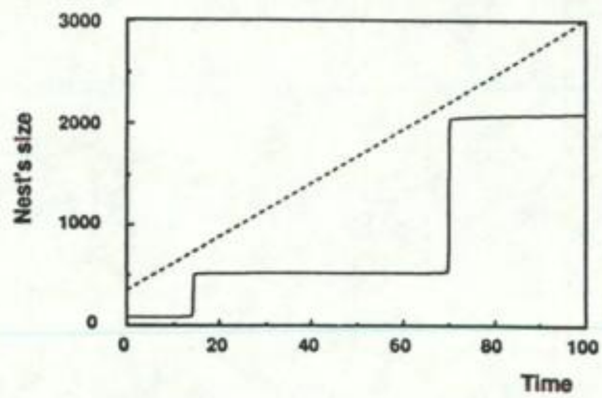

Fig. 5 : Time evolution of the nest size. The doted curve corresponds to the population growth.

population doesn't really change. The consequence is that the termites' density falls and the rate of digging became negligible until the density reaches again a high density. So without any explicit coding between nest size and colony population, a regulation is produced simply as a byproduct of the rules used and the physical characteristics of the environment.

6.3. Selection of one site

The nest can be surrounded by heterogeneous material : for example one soft part easy to dig and one hard, more difficult to dig. The model simply assumes that when a termite tries to extract a soil particle in the soft part the probability of success is higher, and it is only when the extraction is successful that pheromone is laid down. The environment's hardness-softness don't appear explicitly. Examining the decision as a function of the colony size (e.g. a group compared to a solitary individual), it appears

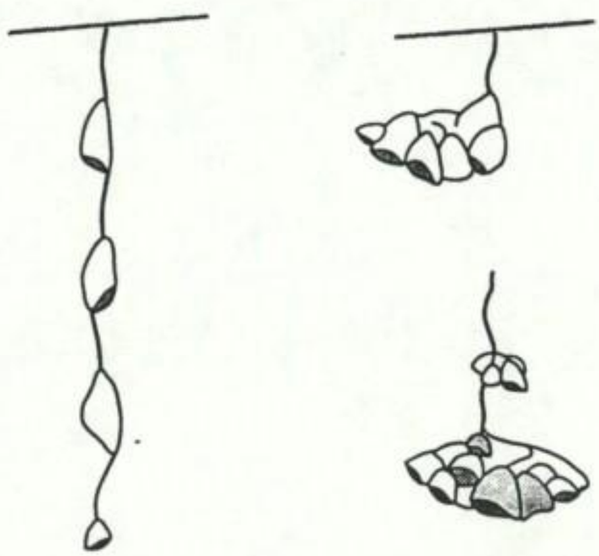

Fig. 6 Some aspects of the diversity of wasp nest architecture.

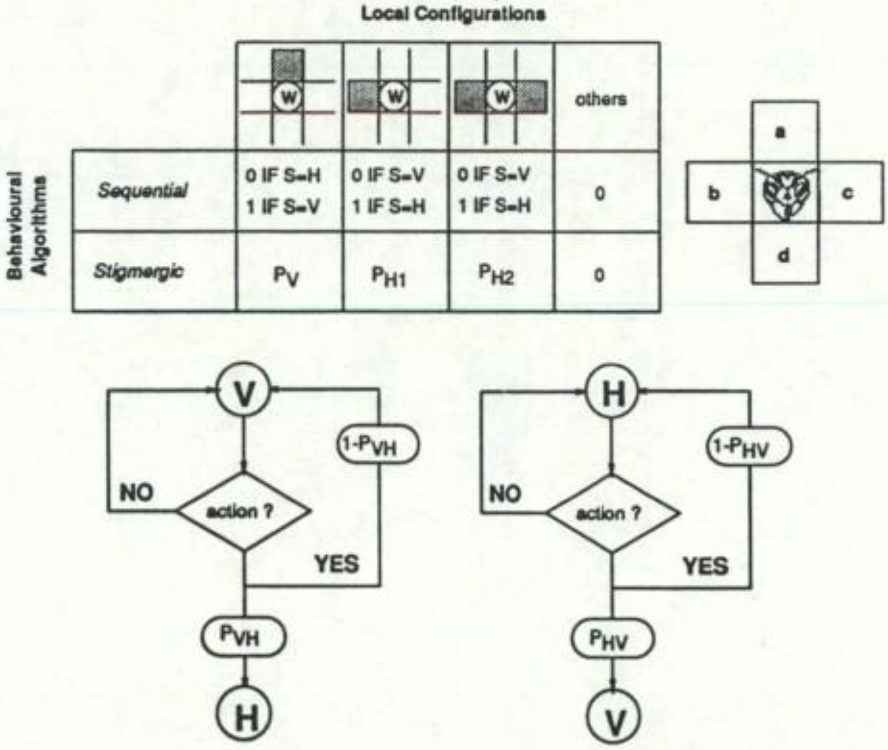

Fig. 7 : Definition of the behavioural algorithms used by artificial wasps.

that group is able to concentrate its activity on the soft part, neglecting the hard part, while the solitary cannot. Decreasing the strength of the positive feed-back, the group remains selective and the solitary individual increases its selectivity, but in this case its level of activity remains very low.

These examples show the power of such simple rules : regulation, selection of favorable sites, and roughly works for a solitary or social animal. However this example stresses the limit of a rule as a function of the number of agents : this rule appears much more powerful for a group than for a solitary worker, and so suggests the search of complexification or modification to produce a more efficient program for solitary builders.

The second case, discussed now, explores the limit of a stigmergic and of a sequential program as a function of the colony size.

7. Wasp builders

Figure 6 shows some aspects of the great diversity of nest architecture we observe in wasps. The variation of nest design extends from one cell per comb with an elongate form (a) to larger single combs (b) and multiple stacked combs with a varying number of cells per comb (c). Combs are suspended either to the substrate or from the rim of the cells of the upper comb. One question we approach in this paper is why do these structures have the form they have ?

7.1. The scripts

The environment is a lattice divided in n x m cells which can be empty (0) or full (1). The wasps move randomly on the nest and in its neighborhood.

The stigmergic algorithm

In the case of the stigmergic script, as in the precedent case, only the local configuration met by the wasp determines its behavior, which is here reduced to fill or not the corresponding cells. From the 16 possible configurations, only three configurations stimulate the filling of the cell (see fig. 7). Two correspond to the horizontal mode and one to a vertical mode. Each mode is characterized by a probability P_{H1}, P_{H2} and P_V of filling the corresponding cell met by the wasp.

The sequential algorithm

In this case, the past activities of a wasp affect its building activity. The local configuration does not play a stimulating role, but only authorizes the wasp to fill, or not, the cell. It is the state of the wasp which controls its activity. At time t the wasps can be in the state "horizontal" or "vertical filling". The wasp in the state horizontal (vertical) can only fill a cell in the configuration "horizontal filling" ("vertical filling"). Having exhibited a vertical (horizontal) filling, the animal has a probability P_{VH} (P_{HV}) of becoming a horizontal (vertical) builder.

Comparing the rate of building per insect for different colony sizes, the sequential algorithm shows a decrease of efficiency. The stigmergic mechanism generally shows an increase as in the digging model.

Moreover, the form produced is much more stable (the same form is usually produced) in the sequential case than in the stigmergic one (see fig.8). However increasing the number of agents, the sequential algorithm produces forms that are increasingly variable.

In the first example with our termites, we see that a stigmergic mechanism is more adapted to a colony than to a solitary insect. In the case of wasps, the sequential program is more adapted to a solitary individual or a small group than to large numbers.

5. Discussion

To the questions, "How they are able to build such structure", we intuitively suggest mechanisms which are generally more complex than necessary. Both examples discussed show that simple mechanisms are able to solve problems and generally these mechanisms are much more powerful than we might imagine. Moreover, we saw that for the same tasks, different behavioral rules are able to produce (rather) similar structures. However, in relation with the number of agents, some algorithms are more adapted than others.

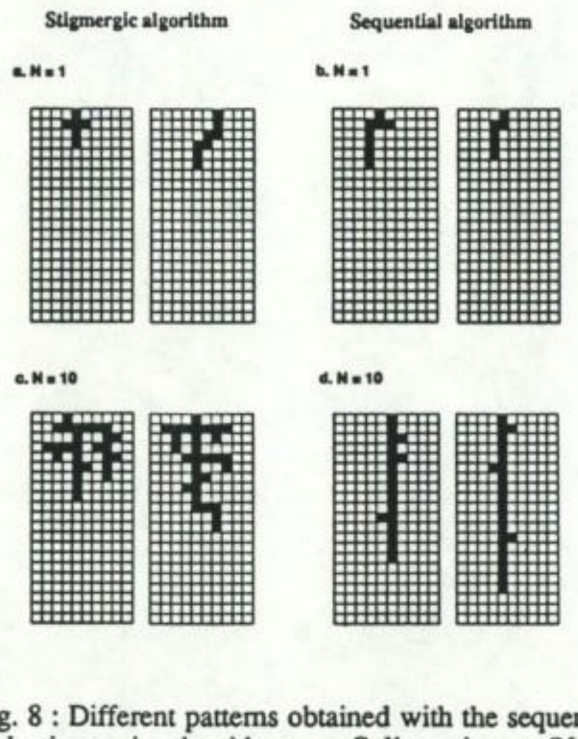

Fig. 8 : Different patterns obtained with the sequential and stigmergic algorithms. a. Solitary insect (N=1), sequential algorithm, $P_{VH} = 0.8$; $P_{HV} = 0.2$. b. Solitary insect (N=1), stigmergic algorithm, $P_V = 0.8$; $P_{H1} = 0.2$; $P_{H2} = 0.4$. c. Idem as a], but the structure is obtained with N=10 individuals. d. Idem as b], but the structure is obtained with N=10 individuals.

This lead us to ask ourselves the specificity of the rules or the number of differents rules able to solve the same problem. It is possible that these exists a finite (small) number of different blueprints, the number of ways to do this being itself large.

Inversely, the same algorithm is able to produce a diversity of structures. However this diversity is not always desirable and moreover can be strongly related to the type of program and the environment. The previous discuss was essentially related to a homogeneous environment.

To cope with the environmental heterogeneities, two extreme blueprints can be designed. The first is careful about any heterogeneity and is able to amplify fluctuations and exploit opportunities. Such systems, exploiting randomness, inevitably show a wide diversity of structures. Exploiting randomness, they are particularly adapted to swarms and can be made by rather simple programs. Indeed by sending scouts in different "directions" over a large area, they increase their randomness [26]. The scouts, discovering new sites, are able with the right communications, to amplify the discoveries and the competition between the informations leads to the selection of one of them. This was illustrated by the choice problem between the hard and soft part in the digging model. Inversely, the structure's invariance is desirable or necessary in different environments. This problem seems to require more complex behavioral programs than the previous blueprint, and is more easily achieved by a solitary builder than by a group.

In this context of invariance and swarm, the influence of the number of agents is particularly interesting. A social insect colony increases its number of individuals, must it therefore modify its nest structure ? With a simple structure such as "a hole", it is only the size which increases. With a more elaborate structure different options must be considered as the size of each component increases, the addition of new modules (e.g. the number of rooms), or a change of form. Clearly, these different solutions described can be produced by rather different algorithms. Some being more or less complex. However it is interesting to see that for each category, it is possible to find a set of rules able to produce the right structure and the right dynamics without an explicit use of a map and a system for counting the population.

And what about human architecture ? For example, the different classifications proposed here seems to integrate numerous aspects and problems of human architecture. With the development of microelectronics, the conception and development of artificial creatures with an economical goal and able to "build", is no longer an idle dream [27]. The analyses of such systems lead us to imagine how these artificial creatures could be programmed as a function of the goal wished.

Building behavior must be seen here, not only for itself, but also as a model. Numerous other problems such as task allocation, coordination, collecting material inspired by social insects or other social groups can support similar discussions and speculations. Different examples of this decentralized and collective intelligence have been discussed, including building behaviour [28, 29, 30], collective choice [13, 31, 32, 33], the formation of trail networks [12], sorting [5, 34, 35], collective exploration [14, 36, 37], dynamical division of labour [6, 38, 39] and synchronisation and the generation of oscillations [16, 40, 41]. Such reflexions clearly lead us to imagine the development of new engineering systems such as new transportations systems, new building monitoring,...

It is moving, from the point of view of nature lovers and admirers of technology, to imagine that the next robots could be the nephews of modest animals that have been on the earth for millions of years.

Acknowledgements

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