COLLECTIVELY SELF-SOLVING PROBLEMS

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INTRODUCTION

Observing insect societies, we are deeply impressed by their capacity to build structures and solve problems, and it is not really surprising that popular litterature is full of anthropomorphic explanations stressing the capacities of individual ants. In such blueprints, however, a central unit manages the whole system, and to achieve this it must collect all the data needed. The algorithms to treat these data are necessarily complex and therefore highly specific. They can tolerate neither internal errors, inexact or incomplete information, nor changes in the problem which is assumed to be stable. The consequences of this type of organisation are such that each solution must be constantly monitored and overhauled to cope with unforeseen events, leading to a spiral of mutually increasing complexity and fragility.

The solution chosen by insect societies is in many respects diametrically opposed to the above caricature. Rather than one solitary central control unit, that is both complex and omniscient and which has its solutions programmed into it, the social insects constitute a team of simple, random units that are only locally "informed" and are not hierarchically organised. Despite this individual "ignorance", the society as a whole is able to exhibit a collective "intelligence", as illustrated by their building behaviour, their sorting, or the synchronisation of the castes' activities (See e.g. Seeley, 1985; Hölldobler and Wilson, 1990).

What are the rules governing such systems, and how can our technology benefit from understanding their mechanisms? We shall start by answering the first question, and then discuss some possible applications to illustrate the second point.
THE BLUEPRINT OF AN INSECT SOCIETY

Insect societies have been frequently qualified as a superorganisms, but it is important to remark that these superorganisms have no brain and, moreover, that their members are spatially dispersed in their local environments. In order to exploit the information gathered by the different individuals, the insect societies have developed a decision making system that functions without symbolic representation by using the communication between the individuals and the physical constraints of the system.

Much of the communication or interaction between the members of insect societies has a positive feedback character. For example if an ant recruits a nest-mate to a food source by means of a chemical trail, the recruit will in its turn reinforce the trail and recruit other nest-mates, and so on.

Such feedback between the "units" allows not only the amplification of local information found by one or a few of them, but also the competition of different informations and the selection of one of them. To give an example that will be treated in more detail below, if one chemical trail leads to a nearby food source and another to a more distant one, the first will be amplified faster because of the physical constraints of the system. In this case the time needed to come back and recruit to a nearer source is less than that needed for a more distant one. The result of the two trails' competition for recruits at the nest will be that the nearer nearly always dominates.

Thus coordinated, the team's collective reaction to local signals is in a sense the solution to a problem which must be solved by the society, such as the selection of the closest food source. While no one individual is aware of all the alternatives possible, and no one individual contains an explicitly programmed solution, together they reach an "unconscious" decision.

We term this process of problem-solving through the interplay between environment and communication "functional self-organisation" or, following G. Beni (University of California, Santa Barbara) and A. Meystel (Drexel University) : "swarm intelligence".

The social insects offer a complete range of contrast between the individual and collective levels of intelligence and complexity. At one extreme there are species whose societies are composed of a huge number of individuals, characterised by the simplicity of their behavioural repertoire, their lack of individuality, their limited capacity for orientation and learning and their highly developed pheromone based mass communication (Beckers et al., 1990a). At the other extreme there are species whose societies are composed of small numbers of individuals, each with a high capacity for orientation and learning, and which lack mass communication, (Deneubourg et al., 1987; Theraulaz et al., 1991; Corbara et al., in prep.). Between these two
extremes, there are many number of species that combine in various degrees both characteristics.

Because of this, insect societies are a particularly good material through which to approach the following problem: "Where should a group place its intelligence and complexity?". In other words to what extent should a group place its intelligence within each unit and to what extent in the interactions between units? How does this balance simultaneously influence efficiency, reliability, flexibility and fault tolerance?

Different examples of this decentralized and collective intelligence have been discussed, including building behaviour, collective choice, the formation of trail networks, sorting, collective exploration and foraging, dynamical division of labour, synchronisation and the generation of temporal and spatio-temporal oscillations (see e.g. Deneubourg, 1977; Belic et al., 1986; Pasteels et al. 1987; Wilson and Hölldobler 1988; Deneubourg et al., 1989; Goss and Deneubourg, 1989; Beckers et al., 1990b; Camazine, 1990; Camazine and Sneyd, 1990; Camazine et al., 1990; Deneubourg and Goss, 1990; Seeley et al., 1990; Skarka et al., 1990).

Since many years, social insect specialists have emphasized the problem-solving capacity of their societies and have developed analogies with the brain. So it is not really surprising to find analogies between insect societies and neural networks or with algorithms such as the elastic net. There are, however, some important differences. Most artificial intelligence algorithms refer to a central information processing unit, "out" the problem and calculating a priori.

In insects societies, the problems appear to solve themselves, in real time, in the sense that the interactions between the environment and the actors give birth to the solution. A second difference is that our insects are mobile, and exhibit complex behaviour and an autonomy of decision which evidently doesn't exist in a nerve cell.

A SIMPLE EXAMPLE : THE EXPLOITATION OF THE CLOSEST FOOD-SOURCE

Most of the social insects use food recruitment, which can be described very generally as follows. When a scout discovers the food source i, it becomes an informed animal (Xi) and returns to the nest. There Xi invites waiting nestmates (Y) and guides them towards its discovery. These recruits become recruiters themselves after having been at the food source. The time-evolution of the population at food source i can be given approximately as:

\[
\frac{dX_i}{dt} = a_i X_i Y - b X_i
\]

\[(i = 1, \ldots, k \text{ where } k \text{ is the number of food sources } ; Y = N - X_1 - \ldots - X_k \text{ where } N \text{ is the total number of ants}).\]
The term \( a_i \) \( X_i \) \( Y \) is the flux of recruitment towards the food source \( i \). \( a_i \) is the rate of "reproduction" of the information and is the mean number of nest-mates that a recruiter recruits per unit of time and per nest-mate. The farther the food source is from the nest, the smaller \( a_i \), which is more or less inversely proportional to the time needed to travel between the food source and the nest and to recruit.

\( b X_i \) is the term describing the departure from the food source, \( b \) being the inverse the the average time spent at the food source. The set of \( i \) equations (1) (with \( i > 1 \)) shows that if we have a competition between different informations, in this case the location of different sources, it is the food source charactized with the greater \( a_i \), i.e. the closest food source, which is the source selected. The others are "forgotten". This solution is independent of both the number of food sources and the sequence of discovery.

In this case, we have no measurement of the distances and no modulation of the communication, i.e. no difference in the recruitment behaviour as a function of the distance. The "natural selection" of one food source is a direct by-product of the physical constraints, i.e. the distance between the nest and the food source, and the recruitment mechanism. The selection is a collective process and not the result of a decision made by one or more individuals. Another example in which an insect society selects the shortest path between \( n \) points is given in Goss et al. (1989) and Aron et al. (1991). A similar logic is also used by ants and bees to select the richer of two or more food sources (Beckers et al., 1990b; Camazine and Sneyd, 1990; Seeley et al., 1990).

TECHNICAL APPLICATIONS

An insect society is a strikingly efficient, robust and flexible machine, and yet is built with simple components. We have been investigating the possibility for some years now (Deneubourg et al., 1984) of "exporting" their blueprint to other fields such as robotics. This field is a little bit in a situation similar to those of the evolution when it invented insects societies with simple insects. A clever team of cheap and simple robots could well be an appropriate solution for a number of problems, and in many cases a valid alternative to making a complex and expensive robot (with on-board computer, artificial intelligence programs manipulating symbolic representations of the world, vision analysis, etc). This is especially true as cheap and simple robots are starting to appear on the market today.

Many of the problems that are self-solved in insect societies, such as building, synchronisation or sorting, are also classical engineering problems. Moreover, a number of technical systems, as for example a railway company, are like insect societies in that they consist of a large number of autonomous units interacting together and spatially distributed. However the analogy goes no further as most of
these systems are governed by a central unit that is more or less perfectly informed. The recent development of automation and of microelectronics nevertheless encourages us to ask if it is not possible to rethink the organisation of such systems along the blueprint of swarm intelligence.

What should then be the rules governing the units' behaviour and communication, and how should they be tuned to generate different and efficient collective solutions? To start with, the units should only perceive and act on information from their immediate environment or from other nearby units, and their internal decisions should not be based on any calculation or representation. In this way our swarm intelligence systems are spared the problems of data accumulation and processing which can form bottle-necks, particularly when the actors are numerous as in a transportation system.

We are actually studying different particular cases which represent a large class of situations, and we shall now present two of them. The "satisfactory" rules are empirically selected from tests by computer simulation and/or by the development of prototypes.

THE A.N.T. PROJECT (AUTONOMOUS NAVIGATION AND TRANSPORTATION)

Collective Exploration

A number of technical activities can be defined as the synchronized movement of vehicles in a heterogeneous and unpredictable environment. These vehicles collect information (cartography, scientific survey, border control, security patrols, ...) or objects (mining, cleaning, fishing, ...), or fight against something such as fire or enemy vehicles. Let us consider a simple case in which our swarm of robot vehicles must find their way in an unpredictable environment in which it is not easy to move.

The vehicles are distributed in space, searching an easy path. At the individual level, if a robot progresses easily, it doesn't change of direction, whereas if blocked, it turns left or right searching for a zone of easy progression. We now add communication between the vehicles, such that each vehicle emits a signal attracting that attracts others (see Sandini and Dario, 1989; Deneubourg et al., 1990, for the description of such a design). The signal strength is correlated to the vehicle's speed, the higher its speed, the higher the strength. The quality of the local environment thus modulates the emission.

What spatial distribution does such a group adopt? Firstly, and this is not surprising, the vehicles cluster in a number of chains in zones of easy progression. However if the speed of a chain decreases its atractivity declines and its members begin to disperse and explore the immediate environment. When one discovers a new path of easy
progression, it increases its speed and attracts other vehicles, and a new chains is formed.

This case, for which a prototype is in preparation, is easy to simulate, and shows how a simple link between "perception" and communication can modulate the development of a collective and synchronized movement which can shift towards individual exploration when needed.

Transportation: Shift Between Different Modes.

The interplay between collective behaviour (e.g. synchronized movement) and individual movement (e.g. exploration) as we have just discussed, is found in transport. Is it possible for a fleet of vehicles - without a central coordinating unit - to transport objects efficiently between a number of different points, avoiding collisions and adapting to a variable "supply and demand" of objects to be transported?

In such a system, a number of short and long range interactions between these units are required to organise the traffic. This differentiating it from the more classical system one of urban traffic, in which the interactions are few and limited. Urban traffic is typically a mixture of a large number of players with weak interactions, obeying the decisions of a central controller (e.g. traffic lights). For the last thirty years or so, most traffic-controllers dream of a large and perfectly informed computer directing urban traffic. Very few of the envisage increasing the communication between vehicles.

Take the case of the reduction of collisions and the optimal use of a transport network. A solution frequently proposed in transportation and robotics (see e.g. Fukuda and Kawauchi, 1989) - some prototypes having been tested - envisage vehicles tagging on after others going in the same direction so as to form "trains". This reduces both crowding and the overall probability of collision. Note that joining and leaving a train of vehicles is linked to the problem of a vehicle perceiving who is going where, and thus with who to link and when.

This problem of train formation (which is only one of the different forms of cooperation between vehicles that can be imagined) leads us to consider another classical problem, that of the mode choice. Transport can be achieved by different modes which are locally in competition (e.g. car versus bus). Each mode attracts users, and their choice modifies the pattern of the transportation network. With the introduction of automated systems and different interactions between vehicles, such trains formation, the competition and separation between modes loses its meaning. In future transportation systems, vehicles will be simultaneously a "module" of a large collective vehicle and an independant vehicle, with the supply and demand governing the user density and thus the pattern of the transportation systems.
As supply and demand for transport inevitably vary, other related problems appears such as how to generate an emergent time-table. Each point-source of objet to be transported needs to be serviced by an appropriate number of transporters, according to the varying number of objects (or people) it "produces". These demands typically fluctuate and the system must react appropriately, for example changing from an occasional to a regular service of a point. Such transport problems in fact imply scheduling, planning and synchronising the activities of the different units.

We present here a simple system of equations describing a large fleet of AGV (automated guided vehicles), and shall see how with vehicles possessing only local perception, the transport system can shift from an individual to a collective mode to assure traffic fluidity.

These mobile robots are capable of avoiding obstacles and each other and of performing a few "cooperative behaviour". For example, each vehicle is able to form a train with other vehicles, and to wait at a crossroad to join in a train. Without giving a too detailed description (e.g. we neglect in the model the explicit destination), we shall discuss the behavioural rules which allow the AGVs to change behaviour and their influence on the pattern of the transport system. The model derives from a set of models developed by D. Kahn of the D.O.T and co-workers to describe competition between different transport modes (Deneubourg et al., 1979; Kahn et al., 1981, 1983, 1985).

An AGV can be in two-states : X corresponds to an individualist behaviour (like a car), the second Y corresponds to a cooperative behaviour (e.g. a member of a train). The equations (2) give us the mean number of AGVs at any moment in the state X and Y. Each AGV emits a long range signal, giving its position and speed, and from these signals each AGV is able to estimate the vehicles' spatial distribution and speed distribution. As a function of these estimates and its behavioural rules, the vehicle changes from state X to Y or vice-versa. This is expressed by the terms G(X,Y) and F(X,Y).

\[
\frac{dX}{dt} = - G(X,Y)X + F(X,Y)Y + INX - OUTX \tag{2.1}
\]

\[
\frac{dY}{dt} = G(X,Y)X - F(X,Y)Y + INY - OUTY \tag{2.2}
\]

The terms INX, INY, OUTX and OUTY reflect the arrivals and the departure of new vehicles in the network, both of which vary in time. We suppose here that these terms are null, then total number of vehicles remains constant. If we take for example that \( G(X,Y) = (a + Y)^n \) and \( F(X,Y) = (V(K-X)^n. \) The first term \( G \) expresses a "cooperative-logic" : the higher the Y density, the more efficient the cooperative strategy (more ready to join a train, the more important the train with respect to an individual vehicle, ...). The term F reflects the individual logic: the higher the vehicle density, the lower the efficiency of this strategy and the lower the attraction of this solution.
With such behavioural rules, the model shows that without any central controller, the system is able to modify its configuration as a function of the density of vehicles, to assume an efficient fluidity of transport. At low density, more or less all the vehicles exhibit an individualist behaviour. If the density is high, the vehicles adopt a cooperative strategy. Between these extremes, different situations are observed such as multiple stationary states, i.e. for the same value of parameters, different configurations are possible and the network adopts one as a function of the system's history (a detailed description of such a system is in prep.).

DISCUSSION

Our goal is to explore a blue-print which could be both complementary and an alternative to "knowledge-based" blue-prints. We have described how insects societies solve problems and how some technical systems could be organized in a similar manner. What are the benefits for such solutions?

The solutions our swarms generate are necessarily less efficient than optimally tailored ones. However this short term sacrifice can be outweighed by other long term benefits, the first being reliability. The more decentralised and less omniscient the unit, the simpler it can be. The simpler the units, the easier it is to program them and the less likely they are to "break down". Working as a team of generalists implies that even if many the units fail, the rest continue. Note that it is not always possible for all the members of a swarm to be, and in these cases the swarm can include sub-populations of physically specialized units (e.g. soldiers/minors, lorries/cars, builders/carriers). This does not change the basic principles described earlier.

The second benefit is flexibility. As no solution is explicitly imposed, the decentralised units can react to environmental heterogeneities, either temporal or spatial. Indeed as the units are intimately mixed with the problem and its environment, these heterogeneities contribute to the solution, allowing the team to cope with unforeseen and unforeseeable circumstances.

The third benefit is fault tolerance. Individual simplicity implies a high degree of randomness and error. The positive feedback interactions allow this and easily coordinate random individuals into an efficient team. Far from being undesirable, individual randomness offers an escape route to individuals caught in a maze, and can help the team to reach collective solutions that would otherwise be out of reach.

The trade off between these somewhat overlapping and interwoven benefits and efficiency is especially revealing in situations where positive feedback can block a team in a sub-optimal solution. To escape from the sub-optimal solution to a better one it can be necessary to increase the
individual complexity or randomness, at the risk of reducing the benefits of a collective organisation (Deneubourg et al., 1983; Deneubourg et al., 1982; Pasteels et al., 1987). In societies, randomness in decision and communication contributes to their "imagination".

We have very briefly discussed the role of "individual complexity", such as described by Seeley (1985) for bee scouts searching for a new nest-site, or Lumsden and Hölldobler (1983) for the estimation of enemy number in ritualized combats in ants. What are the benefits of increasing the complexity of units? This is part of the general question we have been discussing.

A very wide spectrum of applications are actually envisaged. The management of a potentially large number of spatially distributed units is an ideal application. Beni and co-workers, with the concept of cellular robotics, have treated the problem extensively and proposed a number of applications (Beni, 1988; Wang and Beni, 1988; Hackwood and Wang, 1988).

Apart from the problems discussed, other applications are actually under study, such as the management of a very large set of floating solar captors (Brenig et al., in prep.), sorting (Deneubourg et al., 1990), digging, building, and so on. Working in extreme conditions and in unpredictable environments seems a second group of applications. Some authors envisage spatial exploration (see Brooks et al., 1990 who have imagined a wide range of applications, or Steels, 1990).

Hackwood and Wang (1988) have proposed a system of fire-security and rapid evacuation (see also Wang and Beni, 1988). These last examples lead us to envisage rebuilding some machines in which currently the physical components are completely separated from a "central unit" controlling the behaviour. A new design, could be closer to a bee swarm. The bees locally modify their behaviour as a function of what they perceive, and so for example the swarm can change form and thereby regulate their temperature.

Most of these projects can appear as dreams, but they are testable dreams.

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