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Animal–robots collective intelligence

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In this paper we try to define – as ethologists – the easiest ways for creating such a synergy around a common project: mixed groups of interacting animals and robots. The following aspects are explored.

(1) During this century, ethology has accumulated numerous results showing that animals' interactions could be rather simple signals and it is possible to interact with animals not only by mimicking their behaviors but also by making specially designed and often simple artifacts.
(2) The theory of self-organization in animal societies shows that very simple, but numerous, interactions taking place between individuals may ensure complex performances and produce Collective Intelligence (CI) at the level of the group. This context is the most interesting to develop mixed animal–robots interactions.
(3) An experiment using an artifact interacting within a CI system in the wild (gull flocks) is developed.
(4) Cases of robots making CI on their own have been developed.
(5) Considering (4) and (5), what are the expected difficulties to mix robots and animals in CI systems.
(6) Why develop such mixed societies?

The control of interactions between artificial systems and living organisms is a key aspect in the design of artificial systems, as well as in many agricultural, medical, scientific and technical fields. Such developments refer generally to human–robots interactions, leading to further complexity of the behavior and algorithms of robots. However, complex performances do not always require complex individual behavior and interesting developments may also refer to simpler interactions. As far as we know, experiments studying animal–robots interactions are rather anecdotal, with a naïve point of view on animal behavior and are often published in non-scientific journals.

However, we are very convinced that robotics has much to learn from ethology while robotics in turn may surely help ethology to explore animal behavior.

1. One simple interaction

1.1. Stimulus–response

Niko Tinbergen made the following strange observation: a male three-spined stickleback (a small territorial fish) exhibited a specified sequence of territorial display, every day at the same hour, just as if another male was in the aquarium challenging his territory. But there was no other male. Tinbergen, one of the founders of ethology, realized that the "other male" was in fact the post truck, passing every day at the same hour in front of the lab window. This is probably one of the first scientifically documented examples of interaction between an animal and a complex human-made machine.

How could a male stickleback confuse a post truck with a male stickleback? Niko Tinbergen proposed an answer: the post truck is red. Male sticklebacks displays a red belly during the courtship season differentiating them from the females. Experiments using decoys plunged into aquariums with territorial male sticklebacks confirmed this explanation [37]. A decoy perfectly shaped as a male stickleback, except that the belly was not red, elicited very few reactions from territorial males. In contrast, very crude models of various rough shapes, hardly resembling a fish, but with red undersides elicited vigorous reactions from the male sticklebacks (figure 1).

A lot of similar results are known in social insects [26]. Experiments using a mechanical model of a dancing honey bee have been performed by Axel Michelsen and his colleagues to investigate the role of various stimuli emitted during the wagging dance in the transfer of information about a nectar source to follower bees inside the hive [31]. The decoy used in their experiments carried some floral scent, had an acoustic near-field similar to that of live dancers and its movements were controlled by a computer in such a way that several components of the dance were easily manipulated independently. Using this device it was possible to show that the figure-of-eight dance path did not convey any information alone, and that both sound and wagging had to be present in the dance to correctly lead the follower bees towards the position of the nectar source indicated by the decoy.

In ants, numerous experiments show that the interaction between nestmates may be reproduced only using the pheromone involved in the communication (see, e.g., [42], for group recruitment in ants).

The principle of such experiments, one of the cornerstone of ethology, is to isolate the stimulus inducing a behavior – here, the red color – from the others features of the interacting animal. To isolate the stimulus, artificial patterns have to be made and their ability to induce the behavior tested. Ethological literature provides numerous experiments based on this principle (see, e.g., [30]). A large number of results shows that, as in the case of the sticklebacks or the social insects, the signals are rather simple. However, such simple interactions do not mean that the physiology or the cognitive processes needed to produce and to react to these signals is simple [8].

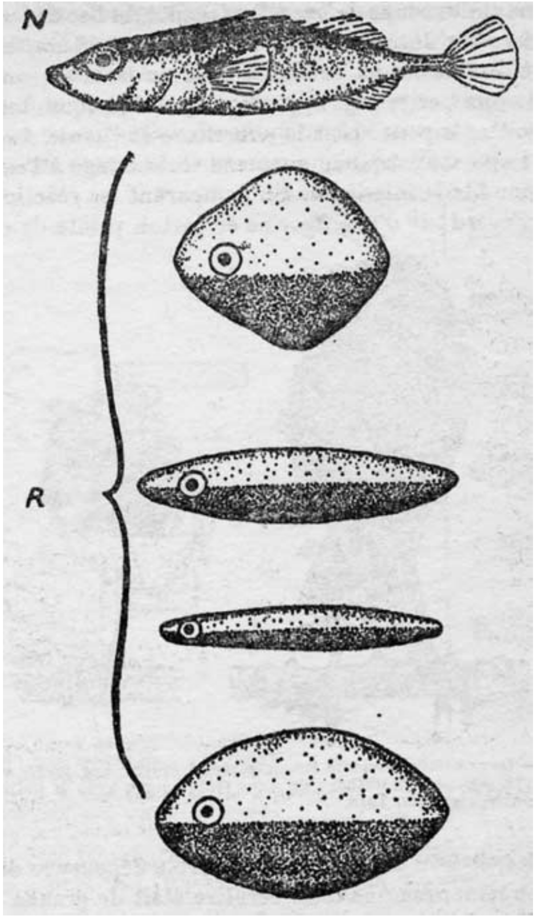

Figure 1. Models of male sticklebacks. A dead male lacking red underside does not elicit particular reaction from other males (N). Very crude models with red underside provide reaction of attack (R). (From [37].)

1.2. Supernormal stimulus

As shown by the unrealistic sticklebacks (figure 1), it is possible to induce a reaction from an animal even if not mimicking the animal entirely. The study of the begging behavior of herring gulls chicks [39] has shown that it is even possible to be more efficient when not mimicking.

An herring gull's chick begs food from a parent by pecking on the parents' bill, inducing a regurgitation. The bill of an adult breeding herring gull is yellow with a bright red spot at the gonys. Tinbergen and his students presented various cardboard models of a gull's head and bill to newly hatched herring gulls chicks in colonies of the Frison Islands. Dozens of models were used during these experiments totaling more than 16,000 pecks. Various stimuli were tested: color of the gonys spot, contrast between spot and bill, bill color, presence of a spot, head color, location of the spot, head shape,

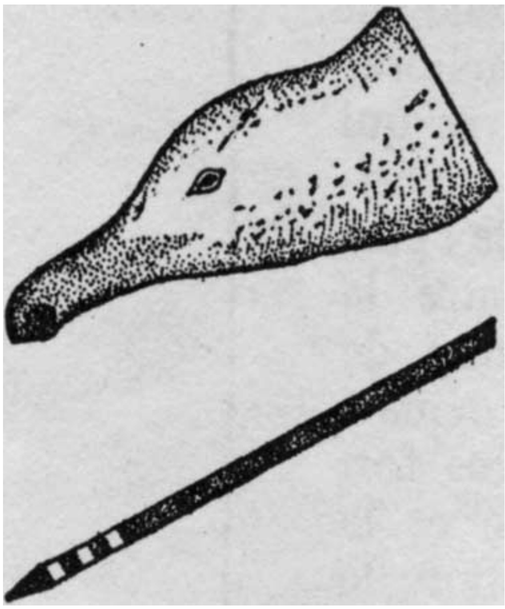

Figure 2. A thin red stick with three white stripes elicits more begging response (1.26 times more reactions) than a perfect model of an adult head (from [38]).

presence of a head, bill shape, location of bill on the head, height or proximity of bill to chick, orientation of the bill, etc. As a result of these experiments, it was possible to design a "supernormal stimulus", an artifact which was more efficient in inducing a reaction from the chick than a close copy of an adult head and bill. This very efficient artifact is actually a simple red stick with three white strips (see figure 2).

Hunters and fishers have known the use of lures and decoys for a long time. Some closely resemble the animal, while others are in fact supernormal stimuli. For instances, artificial flies used in fly-fishing are not meant to be close copies of natural flies. They empirically select the lure features that have been the most efficient in attracting fishes. As a result, artificial flies do not closely resemble the natural ones but they are actually more attractive – in fact, natural flies do not try to be eaten.

To summarize these classical results: (1) the signals used – and needed – by the animal to interact could be more simpler that one could imagine; (2) it is possible and relatively simple to interact with animals, not only by mimicking reality but also by making specially designed and often simple artifacts.

2. Multiple interactions

2.1. More than one interaction

Lures and decoys are man-made objects "interacting" with animals. However, once the selected behavior has been performed by the animal, the interaction stops because the lure cannot reply to the animal. Post trucks do not intend to get territories inside aquariums, cardboard do not regurgitate food to chicks and artificial flies do not try to escape fishes. A key step in interacting with animals would require being able to reply, control or manage several related interactions. Robots acting as decoys able to "respond" to the animal and adapt their behavior to the animals they interact with is an interesting perspective for ethology as well as robotics.

Interactions may be "related" in different ways. Two extreme cases are, on one hand, a linear sequence of successive interactions between two animals, each interaction being triggered by the previous one as a kind of reply; on the other hand, a large number of animals interacting simultaneously with each other. Territorial or courtship displays are examples of the first case [19] while flocks, schools and insect colonies are extreme example of the second [8].

In the first case, any behavioral changes occuring in an animal, depend on the result of the previous interaction. For instance, the chick starts to eat if its parent regurgitates but continues to beg if it does not. Similarly, a male stickleback trying to convince a female to lay eggs in its nest performs a complete sequence of successive displays responding to those performed by the female. In most cases, after several interactions, the proper behavior has to be selected within a large set of possible behaviors, including intermediates combining different ones in different ways. A decoy or robot programmed to interact in such a context will have to be extremely complex and it will have actually very few chances of being efficient in most cases. In this way, we are convinced that most animal behavioral sequences are probably too subtle for robots and irreducible to program algorithm.

At the other extreme, numerous individuals may interact simultaneously, exhibiting the same continuous behavior. Inside a group of animals like a flock or a school, or an insect society, multiple simple direct or indirect interactions between animals lead the whole group to adopt a specific spatial (and/or temporal) configuration [1,6,27]. In such cases, only the parameters of the behavior can change (such as the probability to be performed, the duration, the orientation, etc.) depending on the other interacting individuals. These multiple interactions (including imitation [20]) – amplified and/or constrained by each other – result in a kind of pattern generation. Such a pattern allows the group to carry out tasks [4,8,17,18,21,22]. It may lead to remarkable performances such as the selection of the best food source and shortest path to the food source, thermoregulation, task allocation or nest building [4,8,17]. Such kinds of systems are commonly called "Collective Intelligence" (CI) Systems or "Swarm Intelligence Systems" [5].

2.2. *Collective Intelligence*

A classical instance of CI is given by trail recruitment in ants. An ant finds an interesting food source and encourages his nestmates to exploit it by recruiting them using chemical signals (laying pheromone trails; figure 3). The recruited ants examine the site and recruit other nestmates in the same way. This recruitment amplifies the discovery and allows selection to take place between competing sites. In this context, more distant

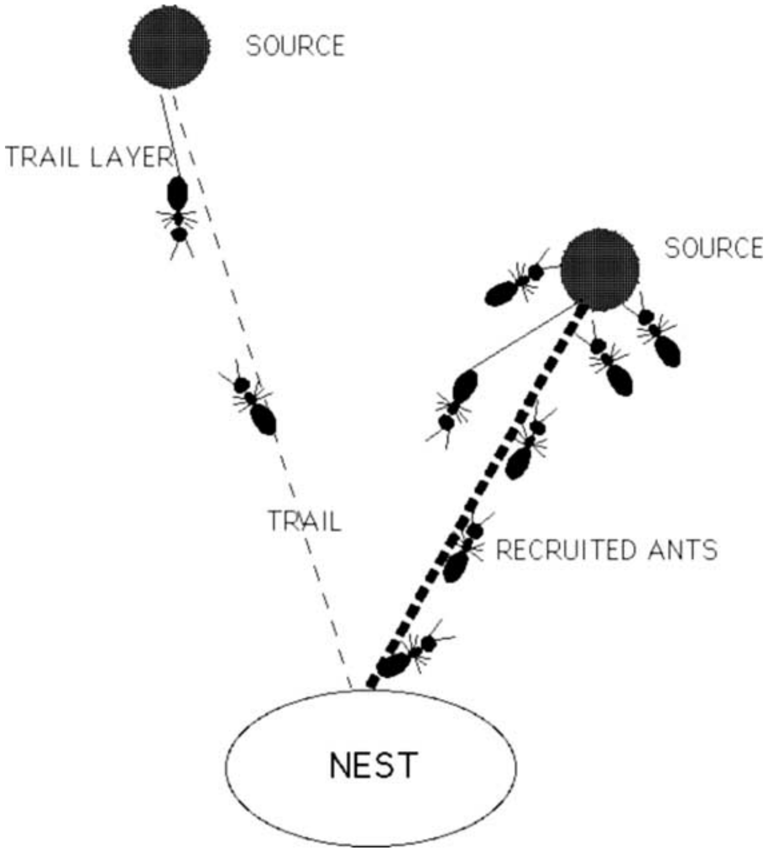

Figure 3. Competition between two identical food sources at different distances.

sites, for example, will be neglected due to the delay involved in recruiting nestmates. No explicit coding of the distance is needed for such a selection of the nearest food source. This selection is effective even if only one simple behavior, laying and following a pheromone trail, is performed in the same way by all the individuals at all the food sources. No one individual is aware of all the alternatives, nor is the solution preprogrammed (e.g., [18]). The response is collective, characterized by a spatio-temporal structuring of the individuals' movements which constitutes the solution or the "decision" reached by the group.

Many aspects of animal societies are based on such a decentralized organization, on the cooperation and competition of separate, simple and somewhat random units, distributed in the environment and having only access to local information. In such systems, problems are collectively solved. In most cases, the collective decisions and patterns arise as a result of competition between different sources of information which can be amplified in different ways. Usually, positive feedbacks are the repetition of a simple behavior. In contrast negative feedback often arises "automatically" as a result of the limits or constraints in the system, for example, food exhaustion. In such systems, the same behavioral rule may produce different patterns depending on the parameters' values or the environmental constraints (see, e.g., [13,32]).

2.3. Some interesting features of Collective Intelligence

Such Collective Intelligence systems are of great interest for implementing robots within animal groups. The behavior to be performed by the robot is simple and the animal behavior to which it has to respond to is simple as well. Despite this simplicity, the emerging collective pattern may be of remarkable interest [12].

2.3.1. The signal is the information

One key point of simplification in such systems comes from the fact that for the interacting individuals, the signal (e.g., the trail) itself constitutes the information rather than being the physical support for an exchange of information. The individual behavior accommodates to the signal itself and not to its possible content of information.

Modulations of the signal may be due to modification of the behavioral parameters but it may also be influenced by the environment. For instance, the way in which a signal weakens with distance can determine how the group responds or not to a signal, and can, for example, form the basis of a collective selection of closer sites of interest [2,6,36], or influence the degree of aggregation (e.g., [15]).

2.3.2. The usefulness of randomness

In such a context, communication has a distinctly random element, signals can be blocked or can interfere with each other. In the example of trail following, the antennae can be pointing in the "wrong direction" and can give varying responses to the same stimulus. Individual simplicity implies a high degree of randomness and error. 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 overlooked. Positive feedback interactions allow for this and easily coordinate random individuals into an efficient team. One of the strengths of collective intelligence comes from its tolerance to this type of error, and the use of such randomness helps the group to solve problems, especially in situations where the team is blocked in a sub-optimal solution [11,16,34].

2.3.3. Reliability

In Collective Intelligent Systems, interactions between units are both simple and numerous while the collective performance may be complex and sophisticated. Interacting units may thus be very simple. The simpler the units, the easier they are programmed and the less likely they are to "break down".

At the collective level, the reliability of the collective performance is also less sensible to the malfunction of the units. As each unit is similar, none of them is indispensable, so some may break down without greatly affecting the performance of the group.

3. Could artifact interact within Collective Intelligence Systems?

We are convinced that in most cases, it is not very difficult to mix robots and animals within Collective Intelligence Systems, even in the wild. In this section we describe one example referring to a very simple remote-controlled artifact interacting with birds in the wild, inside a Collective Intelligent process.

At first glance, it is not easy to build a robot of the size of an ant, able to lay a pheromone trail back to the colony, as soon as it detect a food source. Despite documented instances of Collective Intelligence referring to social insects, other cases start to be documented.

Schools, flocks, swarms or herds are large groups of animals (up to tens of thousands individuals) within which all the (numerous) individuals move together as if they were each one cell of one larger unique superorganism. Mathematical models [1,25,27,33] and empirical evidence [35] have suggested that a simple behavioral rule *"move as your neighbors do"* may governs the dynamics of most of these large groups. We tested this in the field on flocks of gulls roosting on water (De Schutter et al., submitted). Observational data showed that the gulls engage in collective movements preferentially when their inter-individual distance (IID) is reduced (figure 4(a)). This may suggest that the movement of one individual may induce its neighbors to move in the same way if the IID is reduced. Such an induction would be able to prompt a collective movement if amplified from one individual to the next.

This was tested by moving a stuffed gull attached to a small remote-controlled boat inside groups of gull at rest. It was moved straight for about seven seconds throughout the group. At short IID, this actually induced nearby gulls to move in the same way. Gulls situated beside, in front or behind the stuffed one were induced to move as well. The number of birds induced to move is directly related to the IID existing within the group before movement of the stuffed gull (figure 4(b)) which is similar to the observation recorded about spontaneous collective movement (compare figure 4(a) to 4(b)). Furthermore, if the remote controlled gull is turned, all the induced birds turn in same way, including those that are outside the turn.

It was shown as well that these movements act as collective decision-making processes controling the departure or stay of the gulls (De Schutter et al., submitted). Eventually, these decisions allow gulls to accommodate local period food depletion (the week-end closure of a dump site) which they were even able to anticipate (De Schutter et al., submitted). It is one of the first documented example of collective intelligence in vertebrates.

In this experiment, animals reacted to a moving lure manipulated by an observer. An autonomous lure programmed to react to neighbors movements would allow further experiments. Additionally, it would open large opportunities to control the dynamic and the distribution of animals. Developing robot–animal interactions in such a context would be of key interest especially when the goal is to control the animals' behavior to achieve a useful task. For example, the Robot Sheepdog Project where an automated

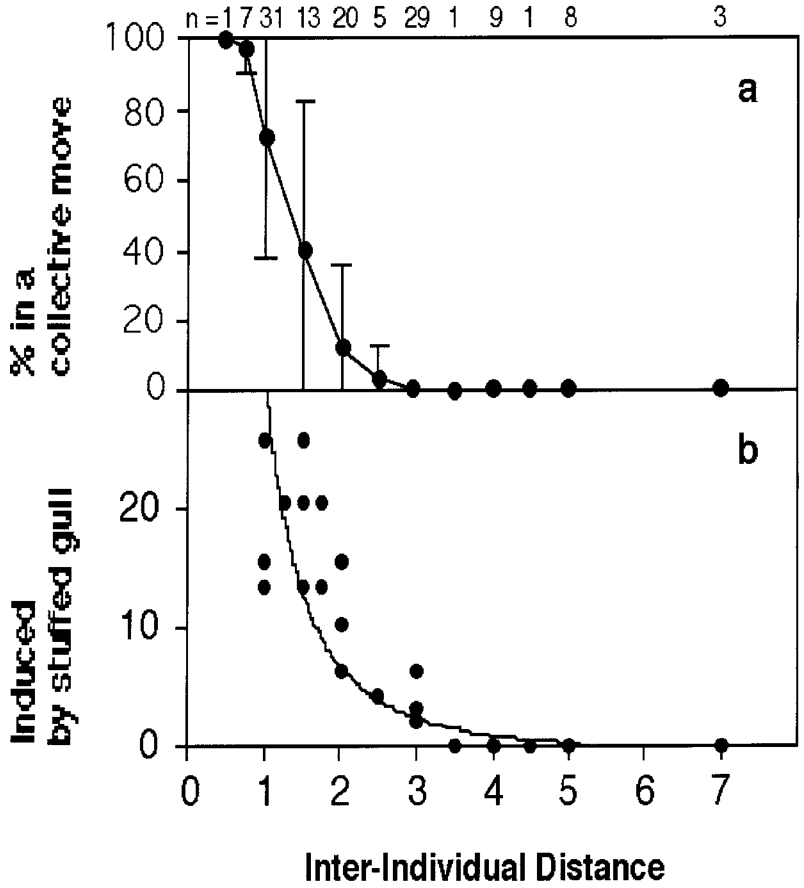

Figure 4. Relationship between inter-individual distance (IID) and collective movements. (a) Inter-individual distance in groups of gulls at rest in relation to the proportion of those engaged in a collective movement within the next 15 minutes ($n = 128$, detailed in the top of the figure). The IID unit is one black-headed gull body-length (~35 cm). The line is not fitted but joins the means. The proportion of birds in a collective movement decreases as the IID increases. (b) Inter-individual distance in a roosting group at rest and the number of gulls induced to move by the remote controlled stuffed gull in motion during seven seconds. The number of birds induced by the stuffed one decreases as the IID increases ($n = 22$, linear regression on log-log values: $r2 = 0.832$, $F = 109.18$, $p < 0.0005$).

mobile robot was designed to gather a flock of ducks to maneuver them safely to a specified goal position [40,41].

4. Robots making Collective Intelligence

Natural collective intelligence has been a source of inspiration for robotics [4,5,28, 29]. Today's automata have all the capabilities required for collective intelligence (see, for example, the Khepera and Alice micro-robots family (figure 6) developed at EPFL in Lausanne [9]; more information is available at `http://www.k-team.com`; and

Figure 5. S. Goss leading a column of vehicle (see text). ©Deneubourg and Theraulaz.

`http://dmtwww.epfl.ch/isr/asl/projects/alice_pj.html`). Numerous researches involving "colonies" of robots mimicking more or less the behavior of animals have been conducted [4]. Rather than one solitary central control unit that is specific, complex and omniscient, a group of simple robots is self-organized through a multitude of direct interactions or through the modifications they induce in their environment. Each robot emits signals and has receptors. Its decision, position and movement thus affect the decision, position and movement of others and vice versa. Very often, these interactions lead to a cooperative behavior or to positive feed-backs. Basically, each robot obeys the rule which determines how it reacts as a function of the signals received from other robots or from the environment, eventually modified by other robots. While no group behavior is programmed explicitly, a number of collective movement patterns readily emerge from these interactions.

Beckers et al. [3] conducted a series of experiments where a group of mobile robots gather randomly distributed objects and cluster them in one pile. This group mimics the clustering and building behavior of social insects. Coordination of the agents' movement is achieved through stigmergy (incitement to work by the products of previous work [24]). This principle allows indirect communication between agents through sensing and modification of the local environment which determines the agent's behavior. The basic behavior of the robots leads to amplification and grouping of the objects. To summarize, the robot is able to push one or two objects. If the robot pushes three or more pucks, a microswitch is activated. This triggers the puck-dropping behavior. This basic behavior and the indirect communications lead to the grouping of the objects. These groups of robots mimic mechanically the clustering behavior of ants [7,14].

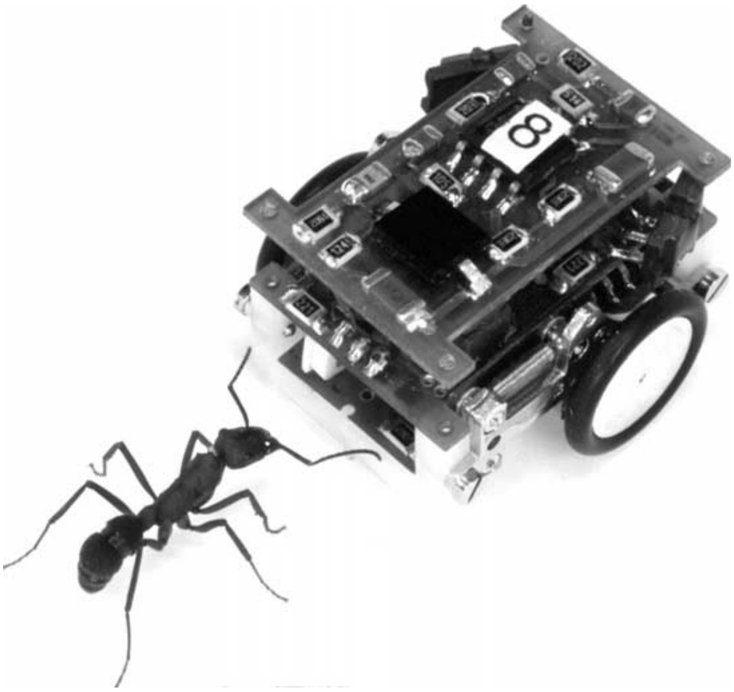

Figure 6. A micro-robot “Alice” facing a ponerine ant of the species *Ectatomma opaciventris*. ©Theraulaz.

Another group of robots (constructed by Beckers and King), were used to move collectively. Their decentralized algorithms using non coded information may allow robots to make collective patterns. Moreover, these simple interactions were used by human to lead the group. Each robot emits an omni-directional infra-red signal, and has two overlapping receptors facing ahead left and ahead right. All the robots were programmed identically to turn left if a signal was received by the left “eye” and right if a signal was received by the right “eye”, and to continue in a straight line if a signal was received by both “eyes” or neither “eye”. This was sufficient to allow one vehicle to home in on the signal from another. However, as the signals were being sent by moving vehicles, with more or less the same speed, the overall result was that the group spontaneously and regularly formed follow-the-leader columns. In each case, the leader of the column did not know it was a leader, but as no-one was ahead of it, it carried on in a straight line. The other vehicle either homed in on its signal or homed in on the signal of a vehicle following the leader, thereby forming the columns. Every so often, the presence of walls or obstacles elicited obstacle-avoidance reaction, causing the column to break up for a time before reforming behind a new leader and with a new direction [23].

Moreover, these interactions may be used by a human to coordinate and pilot the movement of a group of simple robots. In figure 5, a human leader is carrying an infra-red emitter that emits the same signal that of the other vehicle, and uses it to lead the column about once he managed to establish himself as the leader. The Leadership has often been invoked to explain the organized activities of animal groups, especially in those groups where it seems that one group member has more experience or is better informed than other individuals. One pattern which evidently does arise through leadership is the classical example of queuing behavior by ducklings or chicks, following each other and following their mother, who in turn makes sure that each duckling is following her. This example shows that such a leadership emerges automatically from the elementary rules that control the robot's behavior.

5. Mixing robots and animals in Collective Intelligence Systems

We have shown that robots may interact with each other to produce collective intelligent behaviors (section 4) and that simple animated artifacts may also interact within an animal group or colony in the wild (section 3). We are therefore not far from having the conditions for an animal-robot Collective Intelligence.

What are the rules which must govern the behavior of such robots and how should these rules be tuned to generate different patterns and efficient solutions? How may the robot modify the organization of the group which leads to new patterns?

Each robot emits signals and has receptors. Basically, each robot obeys a simple rule which determines how it reacts as a function of the signals it receives from the other robots or animals. Its decision, position and movement thus affect the decision, position and movement of other members of the group, be they animals or robots.

Considering the robots, we are confronted with the development of algorithms to be implemented. As the behavioral rules used by animals in CI systems are simple, the algorithms to be implemented in their artificial partners may be as simple.

The main problem in animal–robots interactions is that the signal emitted by animals has to be detected by the robot and the robot has to be able to emit signals detected by animals. So it is important to choose situations in which communications are not only simple, but also that the signals used to communicate are easily detected by the robots' artificial sensors. This is one of the limiting steps of this project.

However, in many animal groups that display collective intelligence, the signal – which is the information itself, as was said above – remains relatively simple to detect, being, for instance, movement (flocks, herds, schools), position of the body, light emission (see, e.g., the synchronization of the fireflies, for a review see [8]). These are at least among the simplest animal signals.

6. Why such mixed societies? Or the future of experimental ethology and robotics

6.1. *Experimental ethology*

From the ethological point-of-view, a first goal in developing such mixed colonies is to understand how animal societies work. One of the main questions in social biology is to understand the link between individual and collective behavior [8]. An elegant way to identify individual behaviors consist of replacing some animals in a group by robots and searching for behavioral algorithms for which we do not see any differences in the collective responses between the "mixed" and "natural" group.

6.2. *Animal management*

Breeding domestic animals and managing wild populations is another field concerned with such mixed groups. Most of the species that we are breeding, hunting or fishing are social (80% of the fish species we are fishing are gregarious, Dagorn, Pers. com.). Mixed groups of animal and robots may probably offer new ranges of applications in such domains.

Most problems appearing in animal societies have a strong self-organized component: synchronization of activities, aggregation, sorting, etc. As most self-organized systems are very sensitive to small changes at the individual level or of a small fraction of the population [2], it is very credible that a few number of robots interacting within the group might be the source of small differences inducing the whole group to escape from some sub-optimal solution. This gives the opportunity to introduce new collective behaviors and/or to "push" the group towards new patterns and, in this way, to improve breeding conditions, animal welfare, pests management and so on.

The control of the behavior of domestic fowl and other birds of poultry farming gathered in very large number is one example. Social imitation plays a key role in these species [10] and most of their collective patterns results from positive feed-back. For instance, collective panic movements may induce high mortality in some species. The snowball effect of positive feedback takes an initial change in a system and reinforces that change in the *same* direction as the original deviation. Is a robot (or a group of robots) able to induce a snowball effect in another way and modify the organization of the group, leading to an increase of activity or preventing collective panic? The different problems to solve and the potential benefits that can be gained with such systems are sufficiently important to initiate and develop researches in this direction.

6.3. *Pest management*

Animal pest like rats, locusts, Queleas, starlings, etc. are nearly always highly social species. One example of pest management refers to birds roosting by thousands, or even millions, in a given place that might be the source of various problems for local inhabitants and environment. We have shown in the case of roosting gulls (see section 3), that leaving the roost depended on a collective decision emerging from the interactions between individuals. In such a context, a control of these interactions by the way of relatively simple robot-gulls, inducing movements as the remote-controlled gull would be able to control for the spatial distribution of these wild animals. In general, methods of management inferring into the social behavior will be much more efficent than the usual destructive methods.

6.4. Managing endangered and invasive species

A similar example would be the management of the distribution and behavior of endangered species with sophisticated lures allowing for the management of their distribution and behavior. In the other way, invasive species in now recognized to be one main thread for biodiversity. Most of these species are highly social. Limiting or constraining the distribution of such invasive species could be of great interest.

6.5. Developments of robots

The control of the interactions between artificial systems and living organisms most often refer to human–robots interactions, leading to further complexity of the robots behavior and algorithm. However, using animals rather than humans as models for robots presents various advantages:

1. Wild animals leave in a context of selection towards efficiency and survival. Their behaviors are strongly selected toward efficiency in ensuring tasks. Developments based on animal behavior will be among the most efficient.
2. Behavioral interactions are generally more simple in animals than in humans.
3. From amoebae to great apes, passing by ants and birds, the great number and variety of animals exhibit an extremely large range of systems, of levels of complexity and of solutions to an extremely large number of problems.
4. Humans evolved from animals so that the behaviors exhibited by to similar principles of functioning. Artificial systems developed in interaction with animal behaviors are more susceptible to fit human behaviors than systems developed only in the context of robotics and mimicking superficially the human behavior.

We are very convinced that robotics has much to learn from ethology while robotics may surely help ethology to explore animal behavior. Our main goal was to show that: (1) complex collective responses may emerge with individual simplicity and simple signals; (2) a lot of experiments using decoy mimicking these simple signals are able to modify the group behavior; (3) the state-of the art of robotics is such that, today, we are able to design robots able to interact with animals, “synthetise” mixed groups of animals and robots, and develop a fundamental and applied scientific program in this field.

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References

[1] I. Aoki, Internal dynamics of fish schools in relation to inter-fish distance, Bulletin of the Japanese Society Sci. Fisher 50 (1984) 751–758.

[2] R. Beckers, J.L. Deneubourg, S. Goss and J.M. Pasteels, Collective decision making through food recruitment, Insectes Sociaux 37 (1990) 258–267.

[3] R. Beckers, O.E. Holland and J.L. Deneubourg, From local actions to global tasks: stigmergy and collective robotics, in: *Proceedings of ALIFE IV*, eds. R.A. Brooks and P. Maes (MIT Press/Bradford Books, Cambridge, MA, 1994).

[4] E. Bonabeau, M. Dorigo and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems* (Oxford University Press, Oxford, 1999).

[5] E. Bonabeau and G. Theraulaz, Swarm smarts, Scientific American 282 (2000) 72–79.

[6] E. Bonabeau, G. Theraulaz, J.L. Deneubourg, S. Aron and S. Camazine, Self-organisation in social insects, Trends in Ecology and Evolution 12 (1997) 188–193.

[7] E. Bonabeau, G. Theraulaz, V. Fourcassié and J.L. Deneubourg, Phase-ordering kinetics of cemetery organization in ants, Physical Review E 57 (1998) 4568–4571.

[8] S. Camazine, J.L. Deneubourg, N.R. Franks, J. Sneyd, G. Theraulaz and E. Bonabeau, *Self-Organization in Biological Systems* (Princeton University Press, Princeton, 2001).

[9] G. Caprari, P. Balmer, R. Piguet and R. Siegwart, The autonomous microrobot "Alice": a platform for scientific and commercial applications, in: *MHS'98, Proceedings of the 9th International Symposium on Micromechatronics and Human Science*, Nagoya, Japan (1998) pp. 231–235.

[10] D.A. Clayton, Socially facilitated behavior, The Quartely Review of Biology 53 (1978) 373–392.

[11] J.L. Deneubourg, S. Aron, S. Goss, J.M. Pasteels and G. Duerinck, Random behavior, amplification processes and number of participants: how they contribute to the foraging properties of ants, Physica D 22 (1986) 176–186.

[12] J.L. Deneubourg, S. Camazine and Cl. Detrain, Self-organization or individual complexity: a false dilemma or a true complementarity?, in: *Information Processing in Social Insects*, eds. Cl. Detrain, J.L. Deneubourg and J.M. Pasteels (Birkhäuser, Basel, 1999) pp. 401–407.

[13] J.L. Deneubourg and S. Goss, Collective patterns and decision-making, Ethology, Ecology and Evolution 1 (1989) 295–311.

[14] J.L. Deneubourg, S. Goss, N.R. Franks, A. Sendova-Franks, C. Detrain and L. Chretien, The dynamics of collective sorting: Robot-like ant and ant-like robot, in: *Simulation of Adaptive Behavior: From Animals to Animats*, eds. J.A. Meyer and S.W. Wilson (MIT Press/Bradford Books, Cambridge, MA, 1991) pp. 356–365.

[15] J.-L. Deneubourg, J.-C. Grégoire and E. Le Fort, Kinetics of larval gregarious behavior in the bark beetle *Dendroctonus micans* (Coleoptera: Scolytidae), Journal of Insect Behavior 3 (1990) 169–182.

[16] J.L. Deneubourg, J.M. Pasteels and J.C. Verhaeghe, Probabilistic behavior in ants: a strategy of errors?, Journal of Theoretical Biology 105 (1983) 259–271.

[17] Cl. Detrain, J.L. Deneubourg and J.M. Pasteels (eds.), *Information Processing in Social Insects* (Birkhäuser, Basel, 1999).

[18] Cl. Detrain, J.L. Deneubourg and J.M. Pasteels, Decision-making in foraging by social insects, in: *Information Processing in Social Insects*, eds. Cl. Detrain, J.L. Deneubourg and J.M. Pasteels (Birkhäuser, Basel, 1999) pp. 331–354.

[19] I. Eibl-Eibesfeldt, *Ethology: The Biology of Behavior* (Holt Rinehard and Winston, New York, 1970).

[20] B.G. Galef, Imitation in animals: history, definition, and interpretation of data from the psychological laboratory, in: *Social Learning Psychological and Biological Perspectives*, eds. T.R. Zentall and B.G. Galef (Lawrence Erlbaum Associates, Hillsdale, NJ, 1988) pp. 3–28.

[21] D.M. Gordon, The organization of work in social insects colonies, Nature 380 (1996) 121–124.

[22] D.M. Gordon, *Ants at Work* (The Free Press, New York, 1999).

[23] S. Goss, J.L. Deneubourg, R. Beckers and J.L. Henrotte, Recipes for collective movement, in: *Proceedings of ECAL 93*, Bruxelles (1993).

[24] P.P. Grassé, La reconstruction du nid et les coordinations inter-individuelles chez *Bellicositermes natalensis et Cubitermes* sp. La théorie de la stigmergie: Essai d'interprétation du comportement des termites constructeurs, Insectes Sociaux 6 (1959) 41–84.

[25] S. Gueron and S.A. Levin, Self-organisation of front patterns in large wildebeest herds, Journal of Theoretical Biology 165 (1993) 541–552.

[26] B. Hölldobler and E.O. Wilson, *The Ants* (Harvard University Press, Cambridge, MA, 1990).

[27] A. Huth and C. Wissel, The simulation of the movements of fish schools, Journal of Theoretical Biology 156 (1992) 365–385.

[28] A. Martinoli, E. Franzi and O. Matthey, Toward a reliable set-up for bio-inspired collectiv experiments with real robots, in: *Proceedings of the Fifth International Symposium on Experimental Robotics*, Barcelona, Spain, June 1997, eds. A. Casals and A.T. de Almeida, Lectures Notes in Control and Information Sciences (Springer, Berlin, 1997) pp. 597–608.

[29] A. Martinoli, A.J. Ijspeert and F. Mondada, Understanding collective aggregation mechanisms: From probabilistic modeling to experiments with real robots, Robotics and Autonomous Systems 29 (1999) 51–63.

[30] D. McFarland, *Animal Behavior* (Longman, Harlow, 1985).

[31] A. Michelsen, B. Bach Andersen, J. Storm, W.H. Kirchner and M. Lindauer, How honeybees perceive communication dances, studied by means of a mechanical model, Behavioral Ecology and Sociobiology 30 (1992) 143–150.

[32] S.C. Nicolis and J.L. Deneubourg, Emerging patterns and food recruitment in ants: an analytical study, Journal of Theoretical Biology 198 (1999) 575–592.

[33] J.K. Parish and L. Edelstein-Keshet, Complexity, pattern, and evolutionary trade-offs in animal aggregation, Science 284 (1999) 99–101.

[34] J.M. Pasteels, J.L. Deneubourg and S. Goss, Self-organization mechanisms in ant societies (I): trail recruitment to newly discovered food sources, in: *From Individual to Collective Behavior in Social Insects*, eds. J.M. Pasteels and J.L. Deneubourg, Experientia Supplementum, Vol. 54 (Birkhaüser, Basel, 1987) pp. 155–175.

[35] H. Pomeroy and F. Heppner, Structure of turning in airborne rock dove *Columba livia* flocks, The Auk 109 (1992) 256–267.

[36] T.D. Seeley, S. Camazine and J. Sneyd, Collective decision-making in honey bees: how colonies choose among nectar sources, Behavioral Ecology and Sociobiology 28 (1991) 277–290.

[37] N. Tinbergen, *The Study of Instinct* (Oxford University Press, Oxford, 1951).

[38] N. Tinbergen, *The Herring Gull's World* (Collins, London, 1953).

[39] N. Tinbergen and A.C. Perdeck, On the stimulus situation realising the begging response in the newly hatched herring gull chick, Behavior 3 (1950) 1–38.

[40] R. Vaughan, J. Henderson and N. Stumpter, Introducing the robot sheepdog project, in: *Proceedings of the International Workshop on Robotics and Automated Machinery for BioProductions*, eds. F. Juste, G. Andreu, J.M. Valiente and J.V. Benlloch (1997).

[41] R. Vaughan, N. Stumpter, A. Frost and S. Cameron, Robot sheepdog project achieve automatic animal control, in: *From Animals to Animats 5: Proceedings of the Fifth International Conference on the Simulation of Adaptive Behavior* (1998).

[42] J.C. Verhaeghe, Food recruitment in *Tetramorium impurum* (Hymenoptera: Formicidae), Insectes Sociaux 29 (1982) 65–85.