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# How to Grasp the Complexity of Self-Organised Robot Swarms?

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**Abstract** Robot swarms consist of large numbers of autonomous robots, whose behaviour has been greatly inspired by existing complex biological, physical or chemical systems. This is especially the case for behaviours that involve mechanisms leading to spatial self-organisation of robots. The complex nature of these behaviours prevents a human operator from keeping a mental model of them, which makes it difficult to interact with them, even though this is necessary in certain cases: prediction of a loss of stability, detection of blocking situations, etc. How to allow an operator to grasp the complexity of self-organised robot swarms? This article aims at providing leads to answer this question, by investigating what humans are capable of perceiving of a complex system, and what additional information could be needed to enable them to understand its dynamics and state, and to predict the effects of their control. We first present what an operator is able to perceive from a large number of agents, self-organised or not, through a state of the art of existing works in cognitive sciences, vision and swarm robotics. Secondly, we identify in the literature the different types of information on robot swarms that are transmitted to the operator, with the aim of facilitating his perception and improving his understanding. Finally, we discuss what could be the information needed to build a mental model of the operator, the avenues being explored and the possible challenges to be taken into account.

**Keywords** Robot Swarm · Self-Organisation · Perception · Interaction

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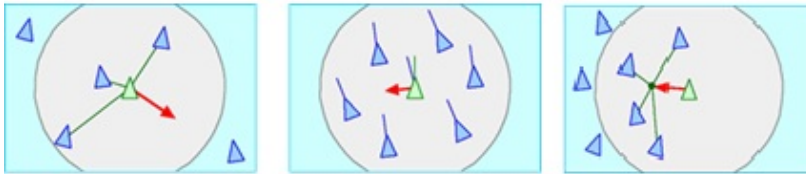
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## 1 Introduction

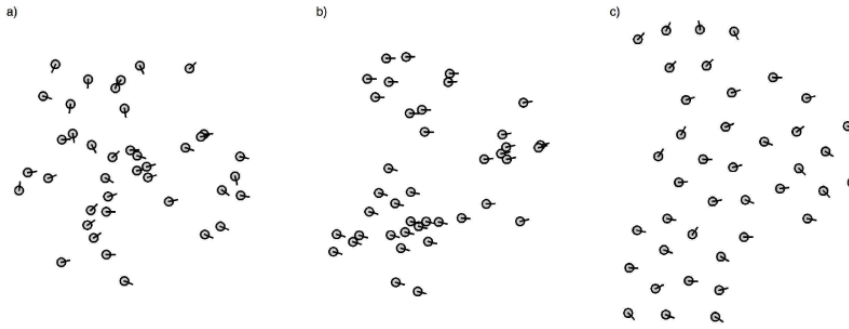
Robot swarms are decentralised systems composed of a large number of small, autonomous robots capable of collectively exploring a space, coordinating their movements, or dynamically self-allocating tasks [25,4]. These capacities come from algorithms and models inspired by complex biological, physical or chemical systems, that define the behaviour of a robot according to its state at time  $t$  and its perception and action capabilities [25]. The overall behaviour of the swarm emerges from local interactions between these robots. One of the most widely used model is the Reynolds model [22], that allows robots to move in a coordinated way, as flocks of birds or some fish species, through the use of three simple social forces stated as rules: repulsion, attraction and alignment (cf. Figure 1). This coordinated movement (also known as *flocking*) is one of the elementary behaviours of robot swarms, as well as aggregation, pattern formation and area coverage [25, 4]. These elementary behaviours can be identified as the building blocks used to construct higher-level behaviours such as collective exploration, target tracking or surveillance of an area of interest.



**Fig. 1** The three rules of the Reynolds model [22]. From left to right: avoid collision with too close neighbours (repulsion), match heading and speed with neighbours (orientation), stay close to neighbours (attraction).

By their nature, swarms of robots exhibit properties of robustness, self-adaptation, resilience, and scalability that are very useful, but make visualisation, understanding and control by a human operator very difficult [19], especially when the robot's behaviour is unknown, but not only. The very source of these properties, the emergence of the swarm's behaviour through the interactions between the robots, has been preventing the operator from keeping a *mental model* of the swarm behaviour over time [19,23].

A mental model is defined in cognitive sciences as an internal and simplified representation of reality, and is dynamically constructed from observations of this reality [17]. To effectively control a dynamic process, an operator must base his actions on the mental model of this process that allows him to describe, explain and predict its form, function and state [17]. The example of the *Neglect Benevolence* [33], highlighted in robot swarms, is a good illustration of this need: in order to get a swarm to carry out a task as efficiently as possible, it is sometimes necessary to wait until the self-organisation has stabilised *before* exercising control. Figure 2 illustrates this counter-intuitive phenomenon: it is only after the robots have self-organised to the same orientation (b) that sending a coordinated motion command will be most effective in finding targets (c).



**Fig. 2** Robot swarm simulation used in the evaluation of *Neglect Benevolence* (from [33]). At the initial state (a), each robot follows its own randomly generated heading. The middle section (b) shows the robots after they have self-organised to follow the same direction. Section (c) shows the robots after the reception of the operator’s command to coordinate their movement.

When interacting with a complex system such as swarms of self-organising robots, however, humans are able to perceive a number of properties exhibited by a set of moving agents, that help them to build mental models. In the following section, we thus start by presenting a state of the art of human perception of swarms in cognitive science, vision and swarm robotics. Section 3 reviews the literature in the field of human-swarm interactions (HSI) to present the different types of information that are transmitted to the operator, in order to enable him to better perceive, understand and even predict the swarm’s dynamics. Finally, we discuss in section 4 the information that we believe is necessary to communicate to an operator to enable him to understand and correctly predict the complex dynamics of robot swarms.

## 2 Human perception of swarms

One of the first properties of human perception that can be highlighted is the ability to identify the movement of one or more discrete elements (agents) in a noisy environment. Thus, humans observing a set of moving agents are able to quickly identify an agent moving in a fixed direction among a set of agents going in random directions [34]. According to the cognitive notion of *visual inertia* [1], human perception seems to prefer to see movement in one direction, rather than movements that change direction abruptly.

Human perception also automatically constructs groupings of agents that form coherent sets. This ability depends on a certain number of properties carried by the agents, that were introduced by the Gestalt theory [35] in cognitive sciences. Among these agent properties that influence this ability to perceive groups, a few are particularly interesting in the context of the perception of dynamic systems (see [29] for more details):

- proximity, *i.e.* the agents that are closest to each other
- similarity, *i.e.* the agents that are more similar to each other (in terms of size, colour, orientation, movement etc.), relatively to other elements of the system

- common fate, *i.e.* the moving agents that are heading toward the same point
- synchrony, *i.e.* the agents that exhibit simultaneously changes (in a broad sense).

All these properties are more or less present in the observed system, and seem to combine in a synergistic way in perception: humans will unconsciously use these cues in such a way as to form groups. This process may go so far as to *abstract* the individual elements of the system from the perception [29].

These properties are particularly interesting because they can be carried by the agents of a complex system, self-organising in space, as robots in swarms. Humans, when interacting with such systems, seem to be able to perceive the swarm (or several swarms) as a *coherent* set of grouped agents, as stated by Seiffert et al. [26]. The authors have shown that humans are able to discriminate more effectively between agents moving in a coordinated way as a school of fish, and agents whose movement lacks the coherence of biological movement, even in the presence of noise in both cases. According to the authors, the human perception of biological flocking is more efficient because it benefits from a more coherent organisation of agents among themselves. In flocking, we clearly find the properties of common fate, similarity and proximity which help in the perception of groups. It is also interesting to note that one result of this study is that individual movements of agents are abstracted by cognitive processes to be replaced by a single global movement of an entity seen as coherent, the swarm [26]. Another study, in the area of robot swarms, was conducted to identify the properties influencing the human perception of a robot swarm cohesion and stability [27]. The results agree with the previous conclusions, and have shown that the perceived cohesion of a swarm of Zooids robots[20] depends on three parameters: the tendencies of the robots to synchronise their movements, to stay in a group, and to follow one of their number. In this study, the robots' behaviour is a coordinated movement of flocking.

To resume, humans are therefore able to perceive one or more groups of agents, acting coherently, within a noisy environment. According to several previous works, humans are also able to categorise different self-organised behaviours of robot swarms, quickly, in the presence of noise or occlusion of part of the swarm members. Thus, Walker et al. [31] have shown that humans are able to identify and differentiate between flocking, aggregation and dispersion behaviours in the presence of noise, in a swarm of 2048 simulated robots. Furthermore, with maximum noise (*i.e.* agents that do not take in account other agents in their behaviour), humans are able to identify that there is no self-organisation in the swarm. Feedback from participants shows that they rely on properties directly related to Gestalt theory, such as proximity and similarities in orientation and speed, to identify those behaviours. Another work by Harvey et al. [13] studied the perception of different behaviours generated by a simulation of the Reynolds model when one or more rules are omitted. The aim of this study was to evaluate the links between the perception of common direction, the perception of grouping and the perception of a biologically realistic flocking. The results show that the perception of realistic flocking is more often present when the members of the swarm are judged to be grouped but not oriented in the same direction. Moreover, flocking is perceived and

identified as such in the majority of cases, showing the ability of the participants to correctly categorise different behaviours.

### 3 Augmented Perception through Improved Transparency

If humans are able to perceive and categorise self-organised swarm behaviour, nothing in the literature, to our knowledge, has shown that they are able to explain complex behaviour, or to predict its evolution. These natural perceptions alone are therefore not sufficient to build a mental model that could enable an effective control of swarm.

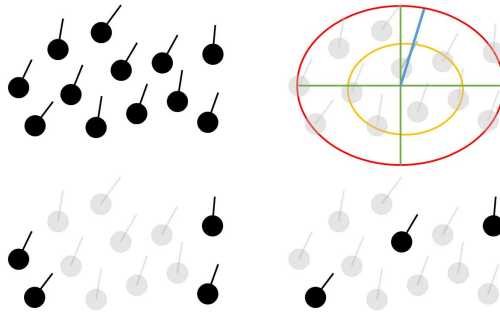
In order to build a mental model, one of the solutions to bring more knowledge and information to humans is based on learning. The three following learning approaches can be identified [14]. The first approach is model exploration. It consists in implementing the control algorithm oneself and testing the influence of each parameter on the outcome behaviour. Model exploration is time consuming but can lead to the creation of an effective mental model. Bottom-up understanding is the second approach, and involves considering the swarm as a black box that must be analysed. To do this, one must first study the behaviour of one single agent, then add a second agent and study their interactions, then increase the number of agents until the entire swarm can be obtained. Finally, the last approach is *embracing complexity*: interacting directly with the swarm in its entirety and allowing time for the human to experiment, proceed by trial and error to control it, and study its various reactions. Learning is a relevant and essential method for obtaining knowledge about a dynamical system and evolving its mental model [17]. However, the learning process can be too long, incomplete, and has to be started over again with another system.

Another solution to improve the quality, accuracy and quickness of the establishment of a mental model is to improve the system *transparency*. Transparency can be broadly defined as the means of conveying additional *relevant information* about the system to human [23]. Finding the right level of transparency is challenging: too much transparency, for example, can overload the operator with information, and have negative effects on the usability and understanding of the system. This is particularly true when the system is a swarm made up of several dozen, or even hundreds, of robots (Human Capability Limitations), whose behaviour emerges from the interactions between these robots (Emergent Behaviour), and has limited communication abilities [23].

In the swarm robotics literature, what types of additional information are provided to the operator? First, most works have focused on the transmission of certain atomic information to the operator. Displaying the direction of each agent [6,32,23] makes it possible to visually represent their movement, especially when their speed is too low for their movement to be perceptible. This is usually done by adding an arrow or a line on each agent pointing towards its direction, as in Figure 2, or on each real robot through the use of Augmented Reality [6]. Other atomic information can concern the state of the robots (*e.g.* id, position, type / role [2]) or inter-robot communication (*e.g.* messages sent / received, communica-

tion links [18] or textual information such as individual logs [10]).

Global information about the swarm can also be communicated to the operator. This type of information is most often computed from atomic information about the robots, such as the average direction of the swarm or its centre of mass. In [32], the authors evaluate the effects of visualising atomic or global information (see Figure 3), in a task where participants had to predict the final position in space of a robot swarm. The results showed that participants obtained similar low average accuracies, between 38% and 45%, when predicting the final position of flocking or aggregating swarms, independently of the type of information conveyed. The prediction accuracy was better, between 62% and 65%, when the swarm was exhibiting a dispersion behaviour. Both the *centroid* (global information) and the *full information* (atomic information) displays were found significantly better than the two other displays. However, it would have been interesting from our article’s perspective to compare these results with the prediction accuracy of participants when non additional information is communicated.



**Fig. 3** The display types of the swarm (from [32]): in the top left, the *full information* display, *i.e.* each agent’s direction; in the top right, the swarm’s centroid (at the intersection of the green cross), along with a bounding ellipse (in red) and another ellipse (in yellow) representing the robot positions median; and in the bottom left and right, only some leaders’ direction.

Other examples can be found in the field of teleoperation, where the operator controls the movements of a leader robot to influence the speed and direction of an autonomous swarm (able to avoid obstacles, maintain a formation, etc.). Thus, in [21,9], two global information about the swarm are communicated to the operator: the difference in velocity between the leader robot and the position desired by the operator, and the proximity of obstacles expressed by means of an average of repulsive forces. This information is provided by simple haptic feedback, *i.e.* forces applied to the joystick used by the operator.

In general, such global information can therefore enable the operator to better perceive characteristics of the group as a whole, such as speed, direction, spatial distribution, and so on. Global information can also focus on the swarm dynamic behaviour state. For example, Haas et al. [12] proposed to convey to the operator four indicators about this state, which they called “health”: the swarm speed, strength, capability, and dispersion (see Figure 4). It is not specified how these indicators are constructed, but several of them seem to be related to the potential field approach used to implement the swarm behaviour. These indicators are

nonetheless interesting, because they communicate certain dynamic aspects of the state of the swarm.



**Fig. 4** Control and supervision display for an operator, from [12]. The four indicators of the swarm’s health are in the bottom left. Their value is conveyed by status lights (green, yellow, red).

Finally, an important role of a mental model is the ability to predict, in the more or less short term, the evolution of the system. As detailed above, Walker et al. [32] have studied the effect of different types of visualisation on the prediction accuracy. In another article [33], these authors also proposed to display, as an additional information, the future position of agents, and to evaluate this display efficiency in the context of *Neglect benevolence*. The future position of each agent corresponds to its position twenty seconds later: it is automatically calculated from its orientation and speed, to be displayed by transparency in the interface. This display has been shown to be useful to counterbalance the potential latency of the control transmitted by the operator. However, the effects of direct interactions between agents do not seem to be taken into account in the calculation of their future position, and this type of visualisation does not seem to be generalisable, especially in real situations.

## 4 Discussion

To summarise, in the literature, two types of information are communicated to the operator in order to improve the swarm transparency: atomic, local information, coming from the robots composing the swarm, and global information, concerning the characteristics of the swarm. Information at these two levels is in our opinion

not sufficient to complete the perception of an operator in order to allow him to create a mental model of the swarm’s behaviour.

In this section, we discuss the following hypothesis, already put forward by Kolling et al. [19] in 2016, but that has been not much taken up to our knowledge:

**H1:** *The swarm models (e.g. bio-inspired models) may offer suitable metaphors to facilitate the understanding of swarm dynamics as well as the impact of control inputs.*

This hypothesis means in our view that the relevant type of information to be communicated to the operator is on the level of the swarm behaviour self-organisation mechanisms, *i.e.* the basic elements participating in self-organisation, such as attraction or random movement.

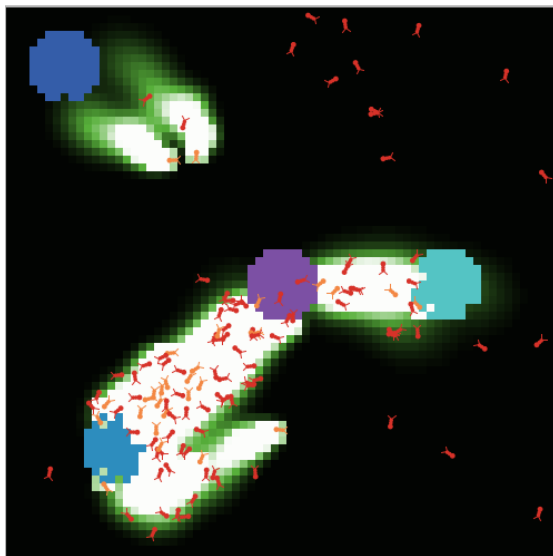
Let us take the famous example of ants and their ability to self-organise to efficiently bring back resources to the nest by communicating through the environment with pheromones (stigmergy). With the right perspective (typically a view from above, as in many multi-agent simulation platforms), humans should be able to perceive and identify the movements of groups of ants between the food and the nest, and by completion the paths and patterns formed by the movements of these groups. Occasionally, they could also be able to account for the dynamics of these paths at time  $t$ , based on the past evolution of the number of ants travelling on them. However, without prior knowledge on stigmergy and pheromones, it should be difficult to *explain* how groups are formed and how patterns appear, and to *predict* the evolution of these dynamics: the disappearance or enlargement of a path, its stability, the emergence of a new path between the nest and a food source, etc.

The aforementioned hypothesis H1 could take the form, in this particular example, of displaying the pheromones deposited by the ants, to obtain additional information that could allow a faster and more complete construction of the observer’s mental model. Indeed, the paths that human perception completed based on the movements of ants are now explicitly visible thanks to the visualisation of pheromones, as shown by Figure 5. For the prediction of the path dynamics, it also becomes possible to observe the increase / decrease of the quantity of pheromones *before* the appearance / disappearance of the ant column. Finally, in this specific case, the role of pheromones in self-organisation, highlighted by the visualisation and inferred from the mental model, could allow the operator to consider their use as a mean of control: depositing pheromones in the environment to influence the formation of paths to designated food sources, for example.

With robot swarms exhibiting spatial self-organising behaviour, following H1 requires:

1. to identify the self-organisation mechanisms in each elementary behaviour;
2. to convey to the operator their dynamics during the behaviour execution of the robots.

With regard to the first point, Brambilla et al. [4] have listed for each of the elementary behaviours their source of inspiration, as well as the models used to implement them. These inspirations are real biological (*e.g.* colonies of bees, ants, birds, fish), physical or chemical (*e.g.* forces, crystal patterns, molecules)



**Fig. 5** Screen capture of a simulation run of the NetLogo Ants model. The pheromone concentration is shown in a green-to-white gradient, from a top view.

systems that all have the particularity of being complex: composed of a large number of simple interacting parts, with limited communication between these parts, and with no central control or leader, they show emergent capacities for self-organisation and self-adaptation. These capacities come from mechanisms that are abstracted by the concrete implementation of these behaviours, mainly based on finite state machines or virtual forces [4].

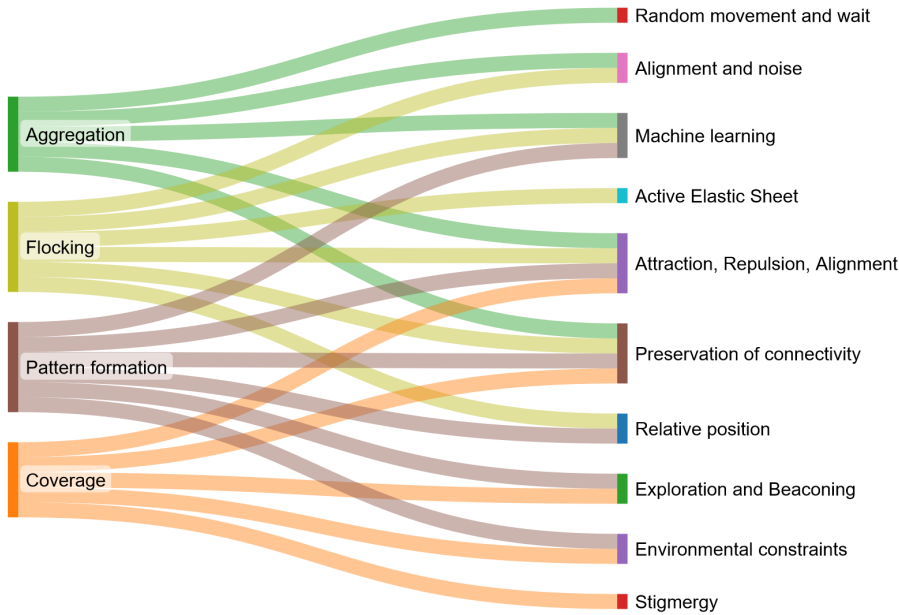
A preliminary work [15] allowed us to identify the spatial self-organisation mechanisms of these behaviours, based on direct interactions between individuals [11] and involving positive and negative feedback loops [28,16,3]. Different mechanisms, used together, form several self-organisation methods. One method can lead to the appearance of one or more collective behaviours, and one behaviour can be obtained through one or more method. The Sankey diagram in Figure 6 summarises these relations between methods and behaviours.

For example, the Reynolds model [22] is based on the “Attraction, Alignment and Repulsion” method, whose main self-organisation mechanisms are:

- attraction and repulsion, that form two feedback loops balancing the distance between agents and allowing them to remain aggregated;
- the alignment of speeds and directions of aggregated agents;
- and random movement, that allows the agents to encounter each other by exploring the space, and that gives the direction followed by the swarm when the agents are aggregated.

This method not only can lead to coordinated movement, but also to aggregation, area coverage and pattern formation.

Regarding the second point, constructing indicators of these mechanism dynamics and finding suitable metaphors to visualise them would constitute an im-



**Fig. 6** Sankey diagram of four emergent robot swarms’ elementary behaviours (left) that can be obtained through the use of self-organisation methods (right). From [15].

portant challenge. The data communicated by the robots in real time (mainly coming from their interactions and behaviour) are the basis for the construction of these indicators: we can only follow the evolution of the mechanisms if we know what is happening at the *micro* level. The challenges linked to the recovery of these data and their communication concern [19,10]:

- the possible incompleteness of the received data (bandwidth, latency, sensor errors);
- a risk of cognitive overload for the operator;
- the need to relate this information to the swarm collective.

On these issues, the main conclusion of the literature is that it may be necessary to summarise in the display the state of the swarm from aggregated, merged and noise-reduced local information. Thus, one solution could be to collect, through communication with the robots and their tracking, data from the *micro* level, and to pass these data through a process of aggregation, fusion and noise reduction, with the aim of giving the operator intuitive real-time information on the behaviour of the swarm in terms of mechanisms and interactions. The concept of “Macroscope”, proposed by de Rosnay [7], was already built on this principle: “the Macroscope filters the details, amplifies what connects, brings out what brings together, to observe the infinitely complex”.

Another solution could be inspired by, for example, the work of Escobedo et al. [8]: identify and characterise the interactions between individual robots from these data, and develop a mathematical model of the mechanisms. Finding ways

to convey indicators of these mechanisms in real-time, through an intuitive visualisation, remains an open challenge.

The proposal developed in this discussion, to identify the complex mechanisms of self-organisation, and then to retrieve from the *micro* level their state in real time to update a visualisation of these mechanisms, is still at an embryonic stage. Its purpose is first of all to initiate a reflection and a discussion on its soundness, the expected challenges and outcomes. This proposal is made here in the context of swarm robotics, but it goes beyond this framework and could be generalised to many complex artificial systems of human design.

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