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A Unifying Method-based Classification of Robot Swarm Spatial Self-Organisation Behaviours

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SAGE

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Abstract

Self-organisation in robot swarms can produce collective behaviours, particularly through spatial self-organisation. For example, it can be used to ensure that the robots in a swarm move collectively. However, from a designer's point of view, understanding precisely what happens in a swarm that allows these behaviours to emerge at the macroscopic level remains a difficult task. The same behaviour can come from multiple different controllers (i.e. the control algorithm of a robot) and a single controller can give rise to multiple different behaviours, sometimes caused by slight changes in self-organisation. To grasp the causes of these differences, it is necessary to investigate the relationships between the many methods of self-organisation that exist and the various behaviours that can be obtained. The work presented here addresses self-organisation in robot swarms by focusing on the main behaviours that lead to spatial self-organisation of the robots. First, we propose a unified definition of the different behaviours and present an original classification system highlighting ten self-organisation methods that each allow one or more behaviours to be performed. An analysis, based on this classification system, links the identified mechanisms with behaviours that could be considered as obtainable or not. Finally, we discuss some perspectives on this work, notably from the point of view of an operator or designer.

Keywords

Swarm intelligence, Robot swarm, Self-organisation, Aggregation, Flocking, Coverage, Pattern formation, Shape formation

1 Introduction

The field of swarm intelligence studies complex systems composed of agents with low capabilities that reveal a so-called 'intelligent' behaviour once these agents are interacting. These systems have many particularly interesting properties including self-organisation, which is defined by De Wolf and Holvoet as “a dynamical and adaptive process where systems acquire and maintain structure themselves, without external control” (De Wolf & Holvoet, 2004).

Interest in these self-organising systems has led to the emergence of simulations that reproduce the self-organisation present in nature in order to: study and understand their mechanisms (e.g. in biology or physics), reuse them in engineering contexts to solve a precise problem, or even invent new self-organising systems. Swarm robotics is one result of the study of these self-organising systems. It adds new technical constraints to self-organising systems not found in nature but has its own unique benefits and uses, such as aiding in the exploration of dangerous environments (Şahin, 2004).

Self-organisation in robot swarms can produce collective behaviours from the unique actions and interactions of the individual robots. However for designers, understanding what creates these behaviours at the macroscopic level remains a difficult task. On the one hand, very different controllers (i.e. the algorithm that controls the robot) can give rise to the same behaviour. On the other hand, a single controller can cause several different behaviours to emerge: by tuning one parameter, the behaviour of the swarm can change drastically.

The main objective of this work is to review and highlight the methods and mechanisms used in swarm self-organisation in order to offer a new perspective for their analysis. In this document, we define a *mechanism* as a basic element participating in self-organisation, such as an attraction or random movement. A *method* can be defined as a composition of several mechanisms, which can lead to the appearance of one or more collective behaviours. Finally, a collective *behaviour* is a way the swarm organises itself, with identifiable collective properties.

In swarm robotics, objective-based (e.g. flocking, foraging, etc.) and method-based (e.g. virtual forces, artificial evolution, etc.) classifications have been previously proposed (Brambilla et al., 2013; Trianni & Campo, 2015; Bayındır, 2016; Rossi et al., 2018; Nedjah & Junior, 2019; Olaronke et al., 2020; Schranz et al., 2020; Cheraghi et al., 2021). Methods that are identical, but implemented differently or for different objectives, are usually split up into different categories. Similarly, the same method can be implemented in different ways, for example, with finite state machines or virtual forces. Moreover, these different classifications mix behaviours that are at different levels of complexity. In

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fact, some of these behaviours are an assembly of several elementary behaviours. These elementary behaviours can therefore be seen as building blocks, which can be used alone or in association with other building blocks to form complex behaviours (Brambilla et al., 2013). Complex behaviours allow the systems to complete higher-level and less abstract objectives. An example of such complex behaviours is foraging, which could be viewed as an assembly of exploration (Nauta et al., 2020), path formation (Vaughan et al., 2000; Sperati et al., 2011) and sometimes collective transport (Groß & Dorigo, 2009) behaviours.

In this article, we propose an original classification system that brings together methods leading to similar types of self-organisation. Each category combines models and algorithms from past literature using the mechanisms that we identified as necessary for self-organisation. This categorisation does not take into account the type of implementation (virtual force, finite state machines, etc.). Instead, we focus on spatially self-organising systems applied to swarms of robots. Spatially self-organising systems are composed of elements that can organise themselves in space without external control, thus giving rise to static (e.g. an aggregate) and dynamic (e.g. an aggregation) spatial properties at the macroscopic level. In this work, we focus on the four spatial self-organisation behaviours we identified as building blocks based on past literature: aggregation, flocking, coverage and pattern formation. The study of the methods leading to complex behaviours, made up of elementary behaviours, will be the subject of a future paper.

The next section aims to provide a common base by presenting a unified, more specific definition of these reference behaviours, from a historical point of view based on past literature. Then, in section 3, we present our classification system based on the methods that allow these behaviours to appear. Section 4 is based on this classification and proposes to analyse these different methods. From their mechanisms, we investigate the collective behaviours that could be considered as possible or impossible to obtain. In section 5, we discuss the benefits and perspectives of this classification system, and finally present our conclusions in section 6.

2 Definition of behaviours

Earlier definitions of the behaviours studied in this article are sometimes inconsistent across the past literature. The same name can thus be used to qualify multiple different behaviours (e.g. using the term “area coverage” for an exploration behaviour), and behaviours may be defined or interpreted differently by different authors. Therefore, in order to be able to study the methods which lead up to these behaviours, it is necessary to establish their boundaries. As a result, four spatial behaviours of swarms were defined from our analysis: aggregation, flocking, area coverage and pattern formation.

2.1 Aggregation

Aggregation behaviour, observed in nature, has been studied for many years by biologists, especially those studying

ecology, sociology and ethology (fields that analyse and study the societies and organisation of living things).

Allee (1927) defines aggregation among animals as the formation of “groups or clusters, more or less closely associated, in which physical contact may, or may not, occur”. This behaviour allows organisms to facilitate their survival in hostile environments. For example, once aggregated, they are able to act collectively to increase their perceptions of the environment, regulate the temperature of the group, or reproduce. This grouping can occur at specific places of interest, defined by various favourable criteria, such as humidity for cockroaches (Dambach & Goehlen, 1999) or temperature for bees (Schmickl & Hamann, 2011).

In swarm intelligence, aggregation behaviour “constitutes a pre-condition of most collective behaviours” (Şahin, 2004). This has led to the development of multiple solutions for reproducing and using this behaviour by applying it to swarms of agents or robots.

Many definitions of aggregation behaviour are characterised by the process of forming an aggregate, a cluster: “the collecting of units or parts into a mass or whole” (Soysal & Şahin, 2006), “the gathering of spatially distributed robots into a single aggregate” (Arvin et al., 2014), “the gathering of scattered robots to create a single aggregate” (Misir et al., 2020).

Another definition many authors agree on (Brambilla et al., 2013; Trianni & Campo, 2015; Bayındır, 2016; Nedjah & Junior, 2019; Olaronke et al., 2020; Schranz et al., 2020; Cheraghi et al., 2021) states that aggregation is the grouping of agents distributed in the environment so that they are *close enough to interact* with each other. This definition can be seen as more precise than the previous ones because it provides a distance criterion that can be relied upon to qualify an aggregate. The functional capacity of agents to detect and interact with other agents is used as a distance for considering two agents as aggregated.

With such a definition, we can identify two aggregated agents and, by counting groups that match this criterion, obtain the total number of aggregated agents. Nevertheless, other metrics measuring the total distance between agents (Soysal & Şahin, 2005; Misir et al., 2020) can be identified in the literature, with the aim of minimizing this distance. These metrics show that it is sometimes necessary to bring the agents of a swarm closer to each other, in addition to being aggregated.

Allee (1927) proposed a distinction between two types of aggregation. The first corresponds to social aggregations without physical contact, which can be found among birds (Emlen, 1952) and fish (Shaw, 1962). Agents are close enough to interact but do not touch each other. When agents are physically in contact with each other, he uses the term “aggregation by physical contact”. The example used to illustrate the complete expression of this aggregation is that of organisms (such as *Obelia*, (Berrill, 1949)) that grow in dense populations, physically connected to each other throughout their lives. However, there are types of organism that physically aggregate, if only temporarily, such as emperor penguins (Gilbert et al., 2006).

We can thus define aggregation in the domain of swarm intelligence as the grouping of agents spatially distributed in the environment, so that they are at a sufficient distance to

be able to interact. This definition covers specific cases of aggregation such as aggregation by physical contact, or cue-based aggregation requiring agents to be grouped together in a particular location.

Aggregation can be defined as the grouping of agents spatially distributed in the environment, so that they are at an appropriate distance to interact.

2.2 Flocking

According to the Cambridge Dictionary*, to flock is defined as “to move or gather together in large numbers”. This dual meaning has caused an etymological confusion with the use of ‘flock’ and ‘flocking’ in biology (Bajec & Heppner, 2009), and it is interesting to note that the same confusion has remained in ichthyology with the terms ‘school’ and ‘schooling’ (Pavlov & Kasumyan, 2000). For example, what we have just defined as aggregation (section 2.1) can sometimes be expressed semantically by the use of flock (of birds) and school (of fishes) (e.g. in Emlen, 1952). In many cases, however, what is called flocking or schooling refers to the observed capacity of individuals to remain in the group and move in a coordinated and fluid way without any contact (Shaw, 1962). Craig Reynolds (1987) described ‘flocking’ as an aggregate motion, thus making the distinction between *aggregating* birds and *the movement* of aggregated birds.

These biological observations have led to the identification of “social forces” in flocking (Emlen, 1952). An attractive force brings organisms closer together. A repulsive force keeps organisms away from each other, thus maintaining a safe distance to avoid collisions. These two main forces regulate the distance between the organisms in the aggregate. Finally, an additional force allows the organisms to adjust their velocity to that of their close neighbours.

Reynolds proposed the first realistic flocking model (Reynolds, 1987), using agents called “Boids” and “social forces” stated as rules (see section 3.2). This first model opened a new branch of study of swarm intelligence. The properties present in swarms of birds or schools of fishes, for example, allow one to move a large number of autonomous agents without losing any. A swarm can do this despite obstacles on the way that may affect each unit differently. As there are multiple biological inspirations, this behaviour is often called “coordinated motion” (Brambilla et al., 2013; Trianni & Campo, 2015; Schranz et al., 2020) or “coordinated movement” (Nedjah & Junior, 2019; Cheraghi et al., 2021). However, the term ‘flocking’ is still mostly used in swarm intelligence (e.g. Hanada et al., 2007; Su et al., 2009; Xiang et al., 2009; Liu et al., 2021b; Bezcioglu et al., 2021), and represents the collective motion behaviours of agents.

Flocking or coordinated motion can be defined as the coordinated movement (i.e. similar speed and direction) of an **aggregate** of autonomous agents.

According to Reynolds’ use of ‘flocking’, this definition does not include the aggregation behaviour but focuses on already aggregated individuals moving in a coordinated way.

2.3 Coverage

Area coverage is a behaviour that takes advantage of the properties of agent swarms, with the objective of spatially covering an area. Using several agents allows the swarm to cover a larger area than a single agent could cover alone.

The area coverage of a swarm of robots can thus be used in many applications such as searching for victims (Cardona & Calderon, 2019), detecting intruders (Gage, 1992), or simply exploring areas that are dangerous or difficult to access (Şahin, 2004).

Gage (1992) defines area coverage as the implementation of a spatial organisation adapting to its environment. In his study this allowed him to increase the chances of detecting intruders. He proposes three types of area coverage; “Blanket coverage” allowing robots to be dispersed in the environment in a static way so that they cover the largest possible area, “Barrier coverage” allowing robots to be aligned like a barrier, and “Sweep coverage” allowing agents to move across an area to cover it, similar to a mobile barrier.

Other authors (Ugur et al., 2007; Mathews et al., 2012; Panerati et al., 2018; Bayert & Khorbotly, 2019; Nedjah & Junior, 2019; Olaronke et al., 2020) define area coverage as the dispersion of a swarm of agents in the environment with the objective of covering the largest possible area without losing the communication link with the rest of the group. This definition has the advantage of including the properties of the aggregation behaviour that aims to maintain social contact between the agents composing the swarm while keeping the agents as far away as possible from each other. However, some authors (Howard et al., 2002; Rutishauser et al., 2009a) do not mention the need to maintain contact between agents. Instead they focus mainly on maximising the area covered, which leads to the loss of collective behaviour. Consequently, the definition that involves maintaining the communication link between agents seems more appropriate as it keeps the notion of collective behaviour in the swarm.

Coverage can be defined as the maximum expansion of an aggregate of autonomous agents.

This definition is distinct from the aggregation behaviour, just as the previous definition, and focuses on already aggregated individuals distancing themselves from one another.

2.4 Pattern formation

Among aggregation behaviours, there are spatial organisation behaviours (observable in nature in bacteria, (Ben-Jacob, 2003) or crystals, (Langer, 1980) for example) that lead to the emergence of a global form identifiable by the organisation of the different elements composing it. In bacteria and crystals, this organisation is structured and regular since a repeating geometric pattern can be observed.

In swarm intelligence, this type of behaviour is called ‘pattern formation’. This type of formation can also be found in other more complex behaviours such as “morphogenesis” (O’Grady et al., 2009; O’Grady et al., 2012), and allows agents of a swarm capable of ‘self-assembly’ (i.e. they are able to cooperate physically and

* <https://dictionary.cambridge.org/dictionary/english/flock>

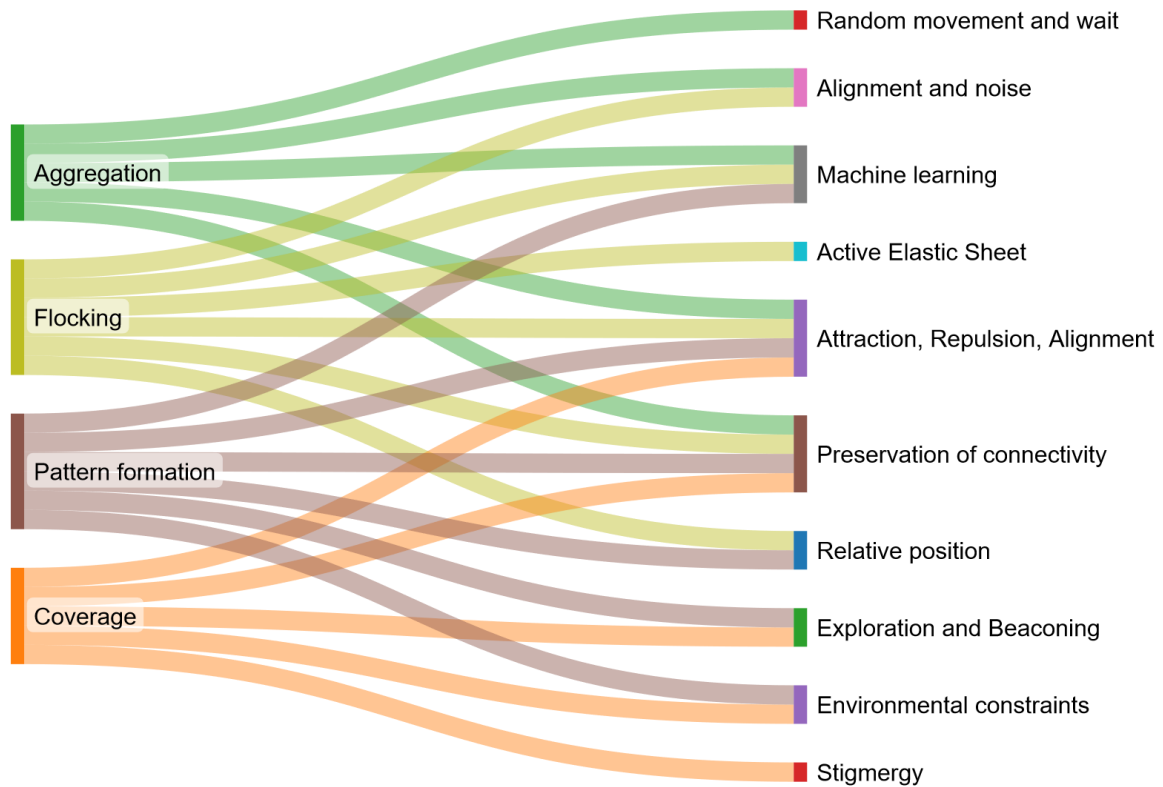


Figure 1. Sankey diagram of four emergent robot swarms' spatial behaviours (left) that can be obtained through the use of self-organisation methods (right)

assemble themselves) to adopt a particular group structure ultimately forming a single entity. This is inspired by the behaviour with the same name observed in nature.

Brambilla et al. (2013) define pattern formation as the deployment of agents in a regular and repeated manner to form the desired pattern. Schranz et al. (2020) define pattern formation as the formation of an identifiable shape by observing the swarm from a global perspective. Nedjah and Junior (2019) define pattern formation as the emergence of an identifiable overall shape from the organisation of agents to form a regular and repeated structure.

In the swarm robotics literature, overall shape either emerges from the local organisation of robots (Spears et al., 2004), or is predefined and guides their behaviour (Rubenstein et al., 2014; Dong & Sitti, 2020; Li et al., 2019).

We can thus define a pattern as being a regular and repeated spatial structure between the agents, resulting in a global shape at the swarm level.

Pattern formation can be defined as the establishment of a regular and repeated spatial structure between agents, forming an overall shape.

With the behaviours and their limits now defined, the algorithms for obtaining them can be identified and classified according to the self-organisation they generate in a swarm. The main mechanisms used by the algorithms will allow us to identify the ten reference methods we present in the next section.

3 Self-organisation methods

The existing classifications for the self-organisation mechanisms of robot swarms do not allow a fine-scaled analysis of their behaviours. For example, Brambilla et al. (2013) propose two approaches: a classification based on design methods and a classification based on collective behaviour. These types of classifications group together methods that exhibit similar behaviours but do this in different ways. For example, current classifications group all flocking algorithms using virtual forces within the same category. However, there are different methods of flocking with virtual forces, and different underlying mechanisms. The well-known Reynolds' Boids model (Reynolds, 1987) uses attraction and repulsion mechanisms, which the Vicsek's model (Vicsek et al., 1995) does not. Yet, they both lead to a flocking behaviour (see sections 3.2 and 3.4). In the same way, the Reynolds' Boids model, initially intended for flocking, can be used for area coverage (Mathews et al., 2012) by correctly adjusting the weight of the rules, thus placing it in at least two separate categories. Hence, these classifications do not have the necessary level of detail to allow for this type of analysis.

As a result, a new classification system based on self-organisation methods is required. To establish the different categories, we grouped together the controllers and models that use the same mechanisms. We identified ten different categories of methods that lead to the previously defined spatial behaviours of robot swarms (see Figure 1).

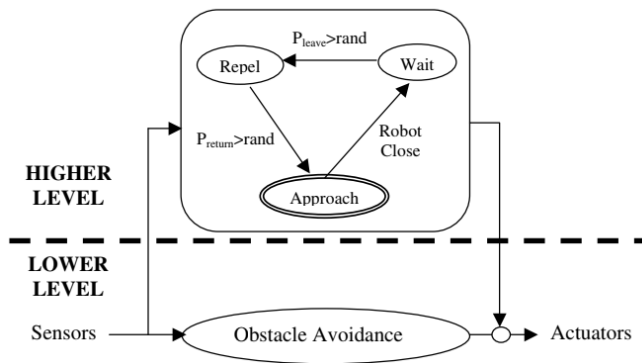


Figure 2. Diagram of the probabilistic finite state machine of aggregation behaviour from (Soysal & Sahin, 2005).

3.1 Random movement and wait

Behaviours: *aggregation*

Implementation: *finite state machine, fuzzy logic*

Starting from an initial state where agents are out of interaction range from each other, they then move randomly through the environment. When an agent encounters another agent, it stops and waits for a time related to a given probability, the absence or the presence of detected neighbours and/or their number. (Bayindir & Sahin, 2009) (see Figure 2). After a while, the agents end up forming an aggregate.

Extensions to this basic strategy aim to speed up and reinforce the aggregation. For example, an agent's probability of waiting or moving again can be determined by the number of close neighbours (Correll & Martinoli, 2007), reinforcing a positive feedback loop that favours waiting over the more numerous groups. If the agents react to and emit sounds proportional to the number of agents aggregated, grouping can be facilitated (Soysal & Sahin, 2005). Rather than navigating randomly, the agents will locate the largest sound source, which is made up of several agents each emitting a sound, and then move towards it. In addition, the behaviour can be optimised using artificial evolution and a neural network connected to the sensors and actuators (Soysal et al., 2007).

When a cue-based aggregation is required, extensions add the constraint of waiting at a specific location. This location can be symbolised in a variety of ways; for example, by a colour on the ground (Garnier et al., 2005; Firat et al., 2018). Finally, rather than using probabilities, the 'Hop-Count' strategy or 'Trophallaxis-inspired' strategy (Schmickl et al., 2006) can use agent's internal or external perceptions as conditions to decide either to keep waiting or leave. These strategies necessitate the use of inter-agent communication. Simply put, agents have an internal value that varies depending on the circumstances and the agent's location. The agent can then choose whether or not to move and in which direction, or to remain stationary, based on this value. The 'Hop-Count' and 'Trophallaxis-inspired' strategies can be distinguished via the process of obtaining, propagating and using the internal value.

Another popular model called Beeclust (Kernbach et al., 2009; Schmickl & Hamann, 2011) falls within this category. It is based on the temperature regulation behaviour of

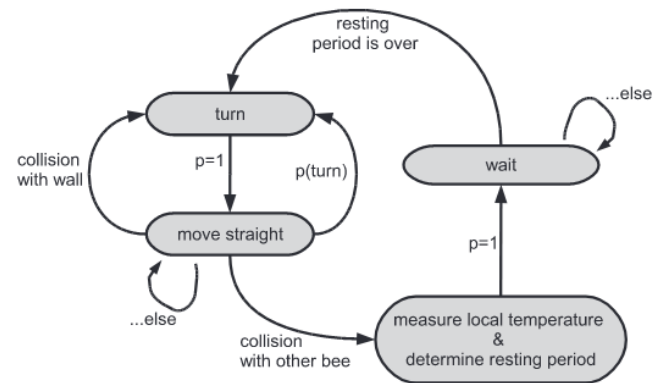


Figure 3. Diagram of the Finite state machine of the aggregation behaviour of Beeclust from (Kernbach et al., 2009).

bees that leads to a cue-based aggregation. Beeclust allows agents to aggregate at a location of interest characterised by luminance, representing the ideal temperature for bees. Agents move in a straight line while checking for the presence of another agent or an obstacle ahead. If an agent encounters another agent, it will measure the local luminance and wait. The higher the luminance, the longer the agent will wait. Once the wait is over, the agent turns around and goes straight ahead once more. When the agent encounters an obstacle, it will also turn around and go straight ahead (see Figure 3).

Beeclust has extensions to facilitate aggregation. For example, landmarks in the environment can be used to help agents orient themselves (Amjadi et al., 2021). By giving the agents a temporary memory and communication capacity, they become able to compare past values of measured luminance with each other. Thus, they can obtain an overall perception of luminance in the environment (Wahby et al., 2019). It is also possible to modify the waiting time of a stationary agent according to the density of neighbours it perceives (Wahby et al., 2019). By adding pheromones that agents release when they are in a waiting state (in combination with the method presented in section 3.8), they are able to attract other agents that encounter these pheromones (Arvin et al., 2018). Sound can also be used to attract agents in a similar way (Arvin et al., 2014). Finally, some variants of Beeclust propose adding a group of deviant agents preferring darkness (Bodi et al., 2012), testing several light zones (Ramroop et al., 2018), or implementing Beeclust using fuzzy logic (Mısır et al., 2020; Arvin et al., 2014).

3.2 Attraction, Alignment and Repulsion

Behaviours: *flocking, coverage, aggregation, pattern formation*

Implementation: *virtual forces, finite state machine*

Craig Reynolds is known to have created the first computer-animated, realistic simulation of a flock of birds (Reynolds, 1987). Inspired by biologists' observations of bird flocks and schools of fish, his Boids (A 'Boid' is the name given to the agents in Craig Reynolds' flocking simulation) are directed by three elementary rules modifying their behaviour according to their close neighbours in a set area of scope (without taking into account Boids in their blind spot). The attraction rule of a Boid brings it closer to

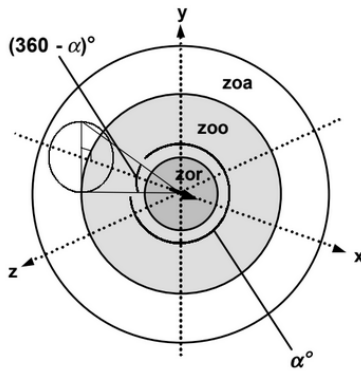


Figure 4. Diagram of the flocking model from Couzin et al. (2002) applying the three rules on three distinct zones: 'zor' repulsion zone, 'zoo' orientation zone and 'zoa' attraction zone.

the average position of the Boids in a set area, allowing it to form a group. The alignment rule brings the Boid's velocity (containing information about the speed and orientation of the Boid) closer to the average velocity of its neighbours, allowing the Boids to move in the same direction and at the same speed. Finally, the repulsion rule keeps the Boid away from all the Boids in a set area, thus maintaining a minimum distance between Boids.

These three rules are the mechanisms necessary for self-organisation to appear. Combined with random movement, they allow the Boids in the simulation to encounter each other and stay in contact, leading to **aggregation** behaviour, before moving in a coordinated manner and causing **flocking** to emerge. An extra rule can be added to allow agents to move in environments with obstacles, allowing them to bypass obstructions in their path. Using these three mechanisms can even provide area **coverage** (Mathews et al., 2012). Here, repulsion keeps agents away from each other, while attraction maintains contact.

Some controllers do not apply these three rules to all nearby agents. There are algorithms (Fetcau, 2011; Yasuda et al., 2014; Cheraghi et al., 2020) using the three successive detection zones from the controller of Couzin et al.'s. (2002) work. Such algorithms can also be found in the controller simulating a school of fish in Aoki's simulation (1982). Each of the three zones corresponds to one of the three rules. The rules then apply only to the agents present in the corresponding zone (see Figure 4). Similarly, these three rules may be implemented while using finite state machines instead of virtual forces. Thus, the rules will then be called upon according to the information obtained by the sensors if they meet certain conditions corresponding to the three zones for the three rules (Wilensky, 1998; Moeslinger et al., 2009; Moeslinger et al., 2010).

Extensions can then be added to this method. For example, the use of a leader (Leonard & Fiorelli, 2001; Fierro et al., 2001; Payton et al., 2001), or informed agents (Ferrante et al., 2012) can be incorporated to guide the direction of the swarm. The work of Payton et al. (2001) seems to be inspired by the Reynolds model, where only the attraction and repulsion mechanisms are used to allow the flock to be guided by a single leader. The leader has a greater repulsive force than the other agents, which forces it to distance itself from the group. However, the other agents have a weaker

repulsion force and are, therefore, attracted to the leader when it moves away, which will then force the leader to move away again. This is how movement is created.

By adding collective decision making, agents can also consult each other to choose the direction to follow (Ferrante et al., 2014). It is also possible to strengthen the group against environments with obstacles disrupting communication between agents (Bonnefond et al., 2021), or to have agents not aligning themselves with others (Stranieri et al., 2011).

The different rules, implemented using virtual forces, have weights that allow their intensity to be modified. For example, by increasing the weight of the attraction rule, attraction between neighbours is strengthened. Different techniques can, therefore, be used for choosing the value of the weights. The first is to arbitrarily choose the different weights to obtain the desired behaviour. Another solution is to use optimisation techniques such as reinforcement learning (Hahn et al., 2019) or artificial evolution (Wood & Ackland, 2007; Vásárhelyi et al., 2018; Ramos et al., 2019) to obtain the optimal weights that best meet the desired optimisation function. The last solution allows the weights of the rules to be adapted during the simulation. For example, they can be adjusted to identify the priority rule depending on the number of elements detected in the environment (Hoang et al., 2021).

Finally, Couzin et al. (2002) have shown that a torus can be formed by modifying the radii of the different zones of repulsion, orientation and alignment. If we consider the torus as a pattern, it is then legitimate to consider that a limited **pattern formation** behaviour can be obtained with the 'Attraction, Alignment and Repulsion' method.

3.3 Preservation of connectivity

Behaviours: *flocking, coverage, aggregation, pattern formation*

Implementation: *graph theory, virtual forces, fuzzy logic*

Some emerging behaviours are explicitly based on connectivity preservation mechanisms (Tanner et al., 2003b; Tanner et al., 2003a). The creation of a virtual graph allows a swarm's various agents to define their relations to each other. The agents will then adjust their behaviour based on where their neighbours are in the graph. Two rules, which are the two mechanisms of this method, are applied to these agents. The first alignment rule is similar to the one in the 'Attraction, Alignment and Repulsion' method (section 3.2). The second rule combines the attraction and repulsion mechanisms into a single potential function that precisely controls the distance between the agents. The force generated by this rule is proportional to the difference between the desired distance and the distance between two agents. Unlike the 'Attraction, Alignment and Repulsion' method, where the distance between agents is determined by the equilibrium of attraction and repulsion, this rule keeps the distance between agents stable over time. We can see that attraction is applied to each of the neighbours, not just on their centre of mass. This is done by dissecting the potential function and comparing it to the attraction and repulsion of the 'Attraction, Alignment and Repulsion' method. Moreover, attraction will be stronger if the neighbour is far away, and almost null if it is close. Finally, the agent will get

closer to the distant agents more easily. The repulsion rule is then applied to each neighbour, just as in the ‘Attraction, Alignment and Repulsion’ method. The distance between the agent and its neighbour is taken into account in this case and, consequently, if the agent is too close, it will be repelled exponentially. However, if it is far away, the intensity of the repulsion will be almost zero. As a result, the agent will prioritise moving away from agents too close to them, reducing the risk of collision. The swarm’s movement differs from that observed in nature and in the ‘Attraction, Alignment and Repulsion’ method because the distance between agents remains stable and the risk of collision and swarm fracture is reduced (Tanner et al., 2003a).

The graph representing the relationships in the swarm can be static (Tanner et al., 2003b) and defined at the start, but this increases the risk of collisions because two agents that are not directly linked in the graph can collide. It is, therefore, necessary that all agents are linked to each other. Consequently, the majority of controllers use dynamic graphs (Tanner et al., 2003a; Olfati-Saber, 2006; Tanner et al., 2007; Zavlanos et al., 2007; McCook & Esposito, 2007; Su et al., 2009; Wen et al., 2012; Ning et al., 2017; Dai et al., 2019), modifying the relations between the agents of the swarm according to their actual neighbours, as for the ‘Attraction, alignment and repulsion’ method. Initially implemented with virtual forces, this method can also be implemented with fuzzy logic (Gu & Hu, 2008; Yu et al., 2010).

Notably used for **flocking** behaviours, this method can also be found in certain controllers that allow **coverage** and **pattern formation**. The agents are able to move away from each other without losing sight of each other and thus disperse in the environment by maintaining a structure among them that has the form of a communication graph (McLurkin & Smith, 2004; De Silva et al., 2005; Ugur et al., 2007; Panerati et al., 2018). The method can be used to create patterns such as hexagons (Spears et al., 2004), or to **aggregate** the agents of the swarm (Khaldi et al., 2018; Khaldi et al., 2020; Berlinger et al., 2021). This aggregation is facilitated by making the intensity of the rules between agents dependent on the density of agents surrounding an agent’s neighbour (Distance Weighted-K Nearest Neighbour algorithm). Thus, an agent will apply its potential function only on the first K agents with the highest densities.

3.4 Alignment and noise

Behaviours: *flocking, aggregation*

Implementation: *virtual forces*

This method, whose historical model is based on Vicsek’s work (Vicsek et al., 1995), is another method of self-organisation based on alignment and noise mechanisms. Thus, this method allows agents to move in dynamic aggregates, as for the **flocking** behaviour. Here, agents move at a constant speed and update their direction according to the average direction of the agents in their neighbouring area, with the addition of a noise factor corresponding to a random direction from a predefined interval. When a single agent encounters a group (or another single agent), it will align with the group, while also possibly influencing said group slightly, and thus join the aggregate. Consequently, this

method is able to show **aggregation** behaviour. The distance between the agents in the aggregate changes slightly because there is no attraction or repulsion mechanism. However, the constant noise that each agent experiences can cause changes in the direction of the group. Without this constant noise, the grouped agents would always move straight forward.

Extensions for this approach exist for anticipating the change of direction of the neighbours according to their current spin direction (Morin et al., 2015) and using adaptive rules to accelerate the convergence of the direction of the agents (Xiao et al., 2020; Liu et al., 2021a). Long-range perception allows agents to observe distant agents in order to adapt their behaviour. This seems to lead to longer navigation before the group scatters (Zumaya et al., 2018). This solution was applied to the Vicsek model, but can also be applied to the Couzin et al. model (Couzin et al., 2002) and probably to any other method that adapts the behaviour of agents according to their neighbours.

3.5 Active Elastic Sheet

Behaviours: *flocking*

Implementation: *virtual forces*

The Active Elastic Sheet (AES) method provides **coordinated motion** behaviour in a swarm. Unlike the ‘Alignment and noise’ method (section 3.4), which relies solely on an alignment mechanism, this method employs both attraction and repulsion mechanisms, but no explicit alignment mechanism.

The different agents of the swarm are self-propelled forward and connected by virtual elastic links, forming a kind of stretchable membrane (Ferrante et al., 2013; Ban et al., 2020; Liu et al., 2021b). Connections and distances between agents are static and defined at initialisation according to the position of the agents in relation to each other. These connections do not break, no matter how much tension the swarm may experience. These elastic links allow a certain distance to be maintained between agents, pushing away agents that are too close and attracting agents that are too far. In the same way, unlike the ‘Preservation of connectivity’ method in section 3.3, the rotation of an agent will cause tension attracting or repelling the connected agents. This maintains a consistent distance and alignment in the swarm. Thus, the swarm will move and rotate like a solid body around a barycentre. As a result of the distance separating them from the barycentre, agents close to it must slow, allowing agents further away to accelerate and cover a greater distance. Reinforcement learning can also be used to improve the behaviour of the agents that implement this method (Bezzioglu et al., 2021).

3.6 Exploration and Beaconing

Behaviours: *coverage, pattern formation*

Implementation: *gradient*

The ‘Exploration and Beaconing’ (Payton et al., 2001; Ludwig & Gini, 2006; Hoff et al., 2010; Bayert & Khorbotly, 2019) method mainly allows a swarm of agents to disperse and explore an unknown environment while maintaining communication with the rest of the group, resulting in a **coverage** behaviour.

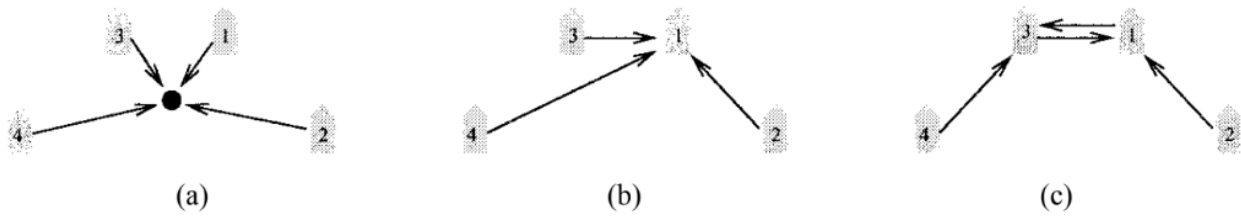


Figure 5. Diagram describing various positioning techniques: (a) unit-center, (b) leader and (c) neighbour from (Balch & Arkin, 1998).

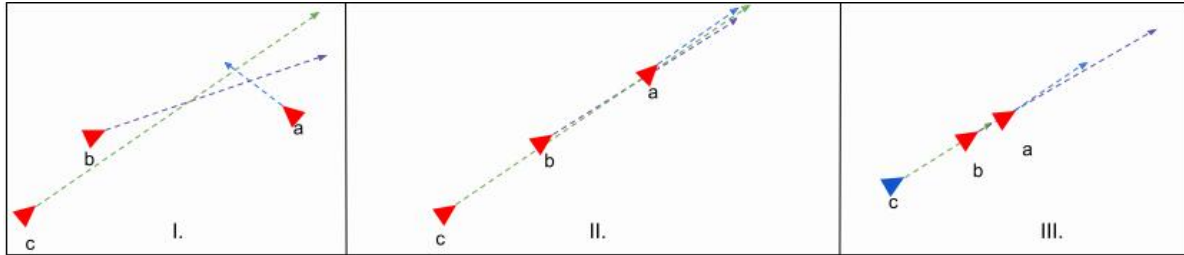


Figure 6. Diagram describing how flocking can emerge with *Heroes and Cowards* model. (I) All agents are **cowards**. Agent *a* wants to avoid *c* hiding behind *b*. Agent *b* wants to avoid *c* hiding behind *a*. Agent *c* wants to avoid *b* hiding behind *a*. (II) The agents end up aligning themselves. Each one wants to go ahead of the others at the same speed, so they end up going in a straight line. (III) Another example of a potential flocking situation, with a **hero** agent (agent *c*), wanting to stand between the other two agents, who are already moving in a straight line to avoid agent *c*.

The different agents in the swarm have two roles: beacons and explorers. Beacons are immobile agents positioned in the environment. They are used as landmarks to allow the explorers to orient themselves. Thus, the explorers try to get as far away from the beacons as they can without losing communication. When an explorer has moved far enough away from the beacons, and therefore recognises that it has reached a correct position, it stops and becomes a beacon itself. By becoming a beacon, the agent then obtains a gradient value that all beacons have. This value represents the distance separating the beacon from the origin of the swarm and is dependent on the values of the neighbouring beacons. The explorers can orient themselves and move away in the right direction using the values communicated by the beacons.

This mechanism can also be found in **pattern formation** controllers, where agents have a gradient value and rely on the gradient values of their stationary neighbours to move and stop at the right moment. The computation of each gradient value is determined by the predefined shape. This method has been implemented by Kilobots (Rubenstein et al., 2014), which are robots that only perceive other robots when they are in contact with them. The pattern formation proceeds as follows: four robots are initially placed forming the origin of the shape and providing a reference frame (x,y). The other robots will then move in turn along the other robots in a clockwise direction. A robot stops and integrates into the shape depending on one of two conditions: either it reaches an edge of the shape, or it meets a neighbour having the same gradient value as its own. There is an extension (Wang & Zhang, 2021) that can accelerate the formation of the shape by using several starting groups. An older version of this method can also be found using cellular automata to form three-dimensional shapes (Støy, 2003). Pattern formation can also be obtained by proposing patterns

based on circles (Mamei et al., 2004). Here, all the agents are explorers, except for those called barycentres. These agents propagate a gradient value through the swarm. By reading its gradient value, an agent is able to estimate whether it is too far from the barycentre or not and then move closer accordingly.

3.7 Relative position

Behaviours: *pattern formation, flocking*

Implementation: *graph theory, virtual forces*

It is possible to obtain different shapes in the swarm and thus perform **pattern formation** by precisely positioning the agents in relation to one another. In this approach, it is sufficient to tell each agent just its graph neighbours' positions, as well as its relative position and orientation with respect to them, once the predefined final form has been converted into a graph whose nodes represent the swarm's agents. The agents will search for their partners and correctly position themselves in relation to them (Desai et al., 2001; Shiell & Vardy, 2016; Li et al., 2017; Li et al., 2019). It is also possible to define the position of close neighbours without defining agents specifically. Thus, the agents will try to arrange themselves with respect to their neighbours' conditions (Coppola et al., 2019) or their polarities (Poulton et al., 2004). One can even obtain similar results by positioning the agents relative to the centre of mass of the group or to a leader (see Figure 5) rather than to predefined neighbours (Balch & Arkin, 1998; Güzel et al., 2017). Pattern formation can also be obtained by allowing each agent to choose several nearby agents and maintain a predefined position with respect to them in order to form patterns like repeating triangles (Hanada et al., 2007; Xiang et al., 2009). This approach allows the swarm to move in a structured way to reach a goal position (Ge

& Fua, 2005; Hanada et al., 2007; Xiang et al., 2009) as a **flocking** behaviour without prior establishment of any particular relationship between the agents.

This method is used in the ‘Heroes and Cowards’ (Wilensky & Rand, 2015) model, which positions each agent in a specific manner in relation to the positions of two other agents chosen at initialisation. One will be considered a friend, and the other an enemy. If the agent plays the role of hero, it will place itself between its friend and its enemy. If the agent plays the role of coward, it will place itself behind its friend relative to its enemy. Thus, aggregation, flocking (see Figure 6) and several other behaviours can be observed. However, these behaviours are not systematic because they are dependent on the perception capacities of the agents and on their initial state (i.e. their position, their role and their choice of agents).

3.8 Stigmergy

Behaviours: *coverage*

Implementation: *finite state machine*

Stigmergy is an indirect coordination mechanism through an environment. An agent leaves a trace in the environment that will impact the actions of other agents upon discovering the trace. This mechanism can be observed in nature, notably the recruitment mechanism of ants that explore the environment in search of food by leaving pheromones on the path between the food and the nest and attracting other ants thus forming a chain. This is also known as foraging (Bonabeau et al., 1999).

It is possible to achieve **area coverage** using this method. While moving, agents lay virtual pheromones and avoid the pheromones of other agents. The agents can move randomly (Hunt et al., 2019) or by making circles with their direction changing if the agent comes into contact with a virtual pheromone (Ranjbar-Sahraei et al., 2012). As agents try to permanently avoid the pheromones released by the other agents, the swarm will end up dispersing. This allows the swarm to accomplish several goals, e.g. dynamically covering an area or exploring. However, with random movement (Hunt et al., 2019), the agents end up dispersing without remaining in a group, which is contrary to the definition of coverage in section 2.3. In contrast, when agents form circles, they move away from each other in a predefined manner and stop moving when they no longer encounter pheromones. Thus, the agents thus remain at the edge of their neighbours’ perception, keeping them grouped together.

3.9 Machine learning

Behaviours: *flocking, aggregation, pattern formation*

Implementation: *neural network, artificial evolution, deep reinforcement learning*

Machine learning is a field with many techniques for optimising and/or generating solutions automatically, thus simplifying the obtention of certain collective behaviours. Several examples use neural networks associated with artificial evolution or deep reinforcement learning to induce self-organisation in a swarm, allowing the desired behaviour to appear.

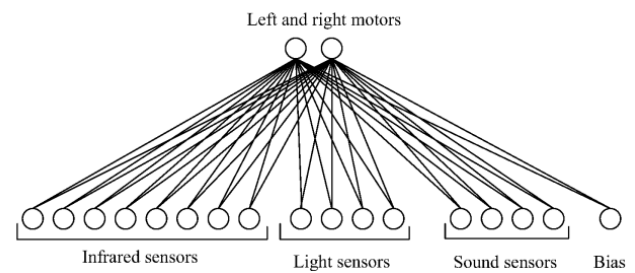


Figure 7. Diagram describing a neural network connecting the robot’s sensors and actuators, from Baldassarre et al. (2003).

Using this approach, the neural network of an agent receives input values from the sensors and generates an output value for the actuators (see Figure 7). Thus, the agent’s perceptions will modify its behaviour. However, in order for the behaviour to be coherent, and to generate the desired collective behaviour, it is necessary to carry out an artificial evolution or a deep reinforcement learning process (Bäck & Schwefel, 1993).

The artificial evolution process involves a fitness function, determined beforehand, that represents the quality of the expected behaviour. For example, the quality of aggregation may be measured with the number of aggregated agents, or the time needed to obtain one aggregate. A fitness function can focus on the quality of flocking by measuring whether the agents are aligned or the number of groups. Once the fitness function has been determined, the neural network will evolve through a process of mutation and selection until the desired result is achieved. For this reason, this process may be used to obtain **aggregation** (Trianni et al., 2003; Bahgeçi & Sahin, 2005; Gauci et al., 2014) or **flocking** (Baldassarre et al., 2003; La et al., 2010) behaviours.

The deep reinforcement learning process combines reinforcement learning and deep learning (Azar et al., 2021). Thus, it involves rewards usually generated by the environment, that each robot tries to maximize by adapting its behaviour through trial and error. Deep learning is used to help the robot find the best policy by representing this policy with a neural network of which the weights are adjusted through time. **Flocking** (Salimi & Pasquier, 2021) and **pattern formation** (Sharma et al., 2022) are two examples of collective behaviours that can be obtained with this method and process.

With this method, however, even if the behaviours at the swarm level are identifiable, the behaviour of the agents is like a black box, making it difficult to identify the mechanisms.

3.10 Environmental constraints

Behaviours: *coverage, pattern formation*

Implementation: *virtual forces, Voronoi, graph theory*

The ‘Environmental constraints’ method uses the evolving environment to add new constraints to the agents. These constraints then influence the agents’ behaviour, which will lead to changes in the self-organisation of the swarm and, thus, create a new organisation. The environment is not modified by the agents in this section, as could be done using the ‘Stigmergy method’ in section 3.8. Here, the environment

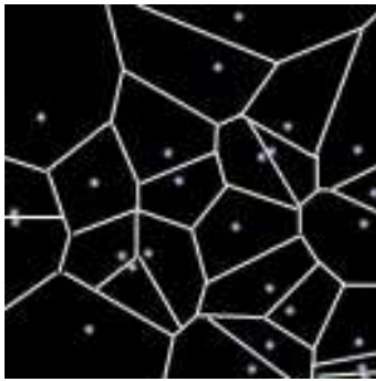


Figure 8. Diagram of the decomposition of an area into Voronoi cells, from Yang et al. (2015). Each point is an agent allocated to a cell.

is modified by an external control, but the organisation of the system remains autonomous.

Using this approach, the behaviour of a swarm may be influenced through the environment. For example by taking inspiration from sea currents, the earth's topography, or the wind. Thus, it is possible to **cover** the environment with virtual forces, usually exerted by an external control. An agent moving in the environment will experience a force that modifies its trajectory. This force has a direction and an intensity, and changes according to the position of the agent in the environment. Then, by drawing an overall shape in the environment using virtual forces, the agents will be attracted into the shape or its outline, making a solid or hollow shape emerge, respectively (Mong-ying & Kumar, 2006; Hsieh et al., 2008; Barnes, 2008; Dong & Sitti, 2020). In the same way, these forces can be used to avoid obstacles, repelling agents that approach them (Howard et al., 2002). Further examples of the application of environmental virtual forces on particles can be found in the amorphous computing programming paradigm (Kolling et al., 2015; Bachrach et al., 2010), which requires a high density of particles to be effective.

Furthermore, by using knowledge of the environment, different breakdowns of an environment can be used to assign a position to the agents. The breakdowns provided by Voronoi cells (Aurenhammer, 1991) make it possible to divide an area into several smaller zones allocated to the agents of the swarm (Yang et al., 2015) (see Figure 8). The agents can then move freely in the zone that was allocated to them, or simply remain stationary.

Moreover, by exploring an environment, a swarm of agents can break it down and represent it in the form of a graph, formed as a result of each agent's contribution. The agents will then disperse into the environment by spreading out on this virtual graph and moving along the links between the nodes (Rutishauser et al., 2009a). Breaking down a predefined shape rather than the environment can also allow the agents to position themselves into a **pattern formation** (Spletzer & Fierro, 2005; Turpin et al., 2013). This breakdown can be done with Voronoi cells (Alonso-Mora et al., 2011) or with a graph (Liu & Shell, 2014).

4 Analysis

In section 3, we presented different self-organisation methods, each leading to one or several reference spatial behaviours. The aim of this section is to identify any associations between mechanisms and collective behaviours, as we have defined these in section 2, which have been asserted from our methods. On the one hand, connections that may be considered impossible due to the intrinsic principles of the mechanisms: for example, the wait mechanism of the 'Random movement and wait' method seems to prevent the formation of a coordinated movement of aggregated agents. On the other hand, to the best of our knowledge, there are methods that have not yet been proposed in the literature for obtaining specific collective behaviours, despite the fact that they may be suited to it.

Each of the methods identified in this article is examined in this section and summarised in Table 1, which also includes past articles studied in relation to the methods and used to outline specific emergent behaviours. This section and Table 1 pave the way for the production of a future 'design guide', useful to any designer looking for a specific behaviour, stating the different existing solutions for obtaining this behaviour, and presenting the constraints for each solution. In addition, this section and Table 1 can be used as a starting point for investigating solutions that have not yet been studied. We discuss this point further in section 5.

4.1 Random movement and wait

As seen in past literature, the 'Random movement and wait' method can be used for the aggregation (Bayindir & Sahin, 2009) of agents distributed in an environment. Flocking should not be possible with this method because agents move randomly and synchronise with other agents by forming an immobile aggregate. It is critical that agents move in groups in order for flocking to occur. Here, when the agents are grouped together, they are immobile. Moreover, when they move, it is individually and randomly. Pattern formation should be possible within a cue-based aggregation, where the shape projected on the environment (e.g. with light) guides the agents. The mechanisms of this method do not seem to prevent the formation of a coverage behaviour. However, the only article we found in the literature mentioning coverage, and using a similar version of this method, applies to a very specific environment and does not seem to fit our definition of coverage (Rutishauser et al., 2009b).

4.2 Attraction, Alignment and Repulsion / Alignment and noise

As shown in the literature, the 'Attraction, Alignment and Repulsion' method can be used for flocking (Reynolds, 1987), aggregation (Reynolds, 1987) and coverage (Mathews et al., 2012). Meanwhile, the 'Alignment and noise' method allows flocking and aggregation (Vicsek et al., 1995). Unlike the 'Attraction, Alignment and Repulsion' method, the 'Alignment and noise' method lacks a mechanism for adjusting the distance between agents, meaning that they cannot be moved further apart for area coverage or moved precisely relatively to each other for pattern formation.

4.3 Preservation of connectivity

From the literature we can see that the ‘Preservation of connectivity’ method can be used for aggregation (Khalidi et al., 2018), flocking (Tanner et al., 2003a), area coverage (McLurkin & Smith, 2004) and pattern formation (Spears et al., 2004) where the shape emerges from the interactions between robots. Given the strength of the links between agents and the fact that the swarm can be represented as a graph, it should also be possible to predefine a shape and break it down to be represented by a graph where each node is represented by an agent. When the agents begin to move to their corresponding node positions, they should form the shape. However, one drawback of this method is the problem presented by Tanner et al. (2003b), involving collisions between agents that are not direct neighbours in the static graph. It can be hypothesised that a new rule could be applied to these agents to solve this issue.

4.4 Active Elastic Sheet

The ‘AES’ method mechanisms consist in relatively strong attraction and repulsion, carried by static virtual links created in the initial state. Adding self-propulsion of agents allows flocking (Ferrante et al., 2013). These mechanisms alone lead to an immutable structure, thus preventing the integration of isolated agents, the increase of distance between them to cover an area, and the emergence of a pattern.

However, if the length of the virtual links were modifiable at any time, this method could perform coverage and pattern formation. One could imagine that increasing the length of all the links to the perception limit of each agent would lead to coverage. If the agents are placed in a particular pattern in the initial state, they should be able to maintain that pattern. On the contrary, to obtain an emergent pattern, one could take inspiration from the ‘Relative position’ method and use the distances between linked agents to place them. This would require making each virtual link modifiable by the agents independently of the other link lengths.

4.5 Exploration and Beaconing

The ‘Exploration and Beaconing’ method can be used for area coverage (Ludwig & Gini, 2006) and pattern formation (Rubenstein et al., 2014). It is conceivable that a pattern could eventually be obtained, as the agents are placed at homogeneous distances from each other. However, flocking may not be possible because the agents eventually stop and do not move in groups. Meanwhile, even though most algorithms start from an initial state where the agents are aggregated, it should be possible to achieve aggregation if the agents are scattered beforehand. The random movement mechanism (a priori present in the method) should allow agents to explore the environment until they encounter a beacon. They should then be expected to maintain contact with these beacons.

4.6 Relative position

The ‘Relative position’ method can be used for pattern formation (Hanada et al., 2007; Desai et al., 2001) and flocking (Ge & Fua, 2005). By increasing the distance

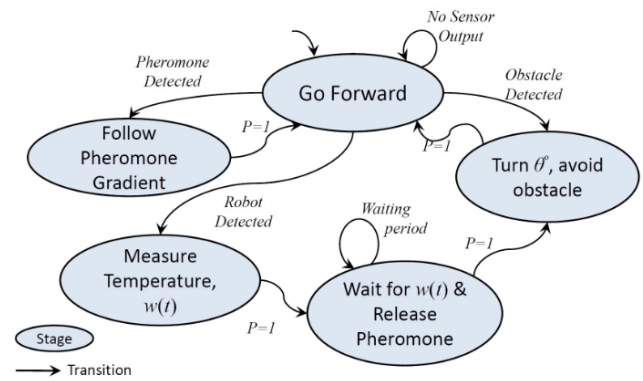


Figure 9. Finite state machine of an agent’s behaviour with the combination of the ‘Random movement and wait’ method and ‘Stigmergy’ method, from Arvin et al. (2018).

between the agents of an aggregate, it is even possible to perform area coverage. Finally, the method allows contact between agents to be maintained. Thus, when encountering a group, agents are able to join it. Except in particular cases where agents are only linked to a set group of other agents, this means they are able to form an aggregate.

4.7 Stigmergy

The ‘Stigmergy’ method is mostly used to attract or repel agents, depending on the information carried by the pheromones. As such, it can be used for coverage (Ranjbar-Sahraei et al., 2012), when pheromones repel other agents. When the agents release pheromones that attract other agents, it becomes possible to facilitate the gathering of the swarm. In this way, Arvin et al. (2018) have shown that combining this method with the ‘Random movement and wait’ method leads to a (faster) aggregation: the agents follow the pheromone gradient when they are detected, guiding their random movement, and drop pheromone when they wait (see Figure 9).

However, to the best of our knowledge, in the literature the ‘Stigmergy’ method *alone* has not been proved to be a successful way to obtain aggregation. Likewise, we could not find any articles demonstrating the use of this method to obtain flocking or pattern formation. Because agents communicate through their environment, it is not impossible to imagine a strategy for coordinating agents so that they can perform these behaviours.

4.8 Machine learning

The ‘Machine learning’ method can be used for aggregation (Trianni et al., 2003), flocking (Baldassarre et al., 2003; Salimi & Pasquier, 2021) and pattern formation (Sharma et al., 2022). It is reasonable to assume that the other behaviours can be obtained with the right fitness function or the correct reward mechanism. Several difficulties remain to be overcome, including finding the right fitness function or decomposing the overall reward into individual rewards (Brambilla et al., 2013). Additionally, there is no guarantee that the artificial evolution will converge to a solution, despite its computational cost.

Table 1. Summary table of self-organisation methods leading to the apparition of collective behaviour. The symbol ‘?’ indicates that the behaviour may be conceivable with this method, whereas the symbol ‘ø’ indicates that the behaviour does not seem to be obtainable, based on the analysis of methods in section 4.

Self-organisation methods	Aggregation	Flocking	Coverage	Pattern formation
Random movement and wait	(Bayindir & Sahin, 2009; Correll & Martinoli, 2007; Soysal & Sahin, 2005; Soysal et al., 2007; Garnier et al., 2005; Firat et al., 2018; Schmickl et al., 2006; Kernbach et al., 2009; Schmickl & Hamann, 2011; Amjadi et al., 2021; Wahby et al., 2019; Arvin et al., 2018; Arvin et al., 2014; Bodi et al., 2012; Ramroop et al., 2018; Mısıř et al., 2020)	ø	?	?
Attraction, Alignment and Repulsion	(Reynolds, 1987)	(Reynolds, 1987; Fetecau, 2011; Yasuda et al., 2014; Cheraghi et al., 2020; Couzin et al., 2002; Aoki, 1982; Wilensky, 1998; Moeslinger et al., 2009; Moeslinger et al., 2010; Leonard & Fiorelli, 2001; Fierro et al., 2001; Ferrante et al., 2012; Ferrante et al., 2014; Bonnefond et al., 2021; Stranieri et al., 2011; Hahn et al., 2019; Wood & Ackland, 2007; Vásárhelyi et al., 2018; Ramos et al., 2019; Hoang et al., 2021)	(Mathews et al., 2012)	(Couzin et al., 2002)
Preservation of connectivity	(Khaldi et al., 2018; Khaldi et al., 2020; Berlinger et al., 2021)	(Tanner et al., 2003b; Tanner et al., 2003a; Olfati-Saber, 2006; Tanner et al., 2007; Zavlanos et al., 2007; McCook & Esposito, 2007; Su et al., 2009; Wen et al., 2012; Ning et al., 2017; Dai et al., 2019; Gu & Hu, 2008; Yu et al., 2010)	(McLurkin & Smith, 2004; De Silva et al., 2005; Ugur et al., 2007; Panerati et al., 2018)	(Spears et al., 2004)
Alignment and noise	(Vicsek et al., 1995)	(Vicsek et al., 1995; Morin et al., 2015; Zumaya et al., 2018; Xiao et al., 2020; Liu et al., 2021a)	ø	ø
AES	?	(Ferrante et al., 2013; Ban et al., 2020; Liu et al., 2021b; Bezcioglu et al., 2021)	?	ø
Exploration and Beaconing	?	ø	(Ludwig & Gini, 2006; Hoff et al., 2010; Bayert & Khorbotly, 2019; Payton et al., 2001)	(Rubenstein et al., 2014; Wang & Zhang, 2021; Mamei et al., 2004; Støy, 2003)
Relative position	?	(Ge & Fua, 2005; Hanada et al., 2007; Xiang et al., 2009)	?	(Hanada et al., 2007; Xiang et al., 2009; Desai et al., 2001; Shiell & Vardy, 2016; Poulton et al., 2004; Balch & Arkin, 1998; Güzel et al., 2017; Li et al., 2017; Li et al., 2019; Coppola et al., 2019)
Stigmergy	?	?	(Ranjbar-Sahraei et al., 2012; Hunt et al., 2019)	?
Machine learning	(Trianni et al., 2003; Bahgeçi & Sahin, 2005; Gauci et al., 2014)	(Baldassarre et al., 2003; La et al., 2010)	?	(Sharma et al., 2022)
Environmental constraints	?	?	(Howard et al., 2002; Yang et al., 2015; Rutishauser et al., 2009a)	(Mong-ying & Kumar, 2006; Hsieh et al., 2008; Barnes, 2008; Dong & Sitti, 2020; Spletzer & Fierro, 2005; Turpin et al., 2013; Alonso-Mora et al., 2011; Liu & Shell, 2014)

4.9 Environmental constraints

The ‘Environmental constraints’ method can be used for pattern formation (Mong-ying & Kumar, 2006) and coverage (Howard et al., 2002). However, as this method’s inspirations come from sea currents or topology, one could imagine that flocking and aggregation could be obtained. One of the difficulties lies in correctly designing the environment for the external control that will be applied on the autonomous robots. This can be seen as a top-down-like approach, with all the implied uncertainties arising from the complex nature of swarms.

5 Discussion

This classification system presented in section 3 highlights the unique aspects of each method, showing their differences and their specificities. One of the outcomes of the analysis of the methods in section 4 is the identification of those methods that have not yet been used to obtain a specific collective behaviour. This opens up the possibility to explore potential solutions, represented with a ‘?’ in Table 1, such as the use of the ‘Stigmergy’ and ‘Environmental constraints’ methods to obtain flocking. The same approach could be used to further explore the capabilities of existing methods.

Taking the ‘Active Elastic Sheet’ method as an example, this method is known to be capable of generating flocking behaviour. It would be interesting to further explore the identified potential behaviours this method could produce based on Table 1, such as aggregation or coverage.

We also believe that this classification system facilitates the comprehension of the mechanisms of the studied methods. This comprehension and the resulting analysis should make it easier to imagine the methods that could be combined in order to obtain a specific collective behaviour. For example, the mechanisms of the ‘Stigmergy’ or the ‘Environmental constraints’ method could be used as additions to other methods since they allow information to be communicated to agents via the environment, and can influence the behaviour of an agent without necessarily replacing it. In fact, such combination already exists and can be observed, for example, in the work of Arvin et al. (2018) where the robot’s behaviour based on the ‘Random movement and wait’ method is extended with the use of pheromones (‘Stigmergy’ method) to facilitate aggregation, as detailed in section 4.7.

The production of a future ‘design guide’ is one of the direct perspectives of this work. A formal study with a systemic approach, for example, could help to confirm the behaviours that can or cannot be obtained by each method. To illustrate the role of such a guide, let us imagine a hypothetical use case where a designer must achieve a pattern formation behaviour in a swarm simulating a flock of birds. Using the guide based on Table 1, six solutions can be easily and quickly identified for pattern formation. However, there are not many methods that can simulate realistic bird flight behaviour. Consequently, the designer decides to use a model based on the ‘Attraction, Alignment and Repulsion’ method such as Reynolds’ Boids model or the Couzin model, which are known for their ability to realistically simulate bird flight. Another use case could be a designer seeking to achieve a flocking behaviour with a swarm of UAVs. The guide based on Table 1 would state that six different methods can lead to flocking. However, this swarm must maintain a stable formation and avoid collisions among its agents. Based on the description of each method in section 3, the designer could quickly see which methods could be used and which methods to dismiss. As an example, a relevant choice could be to implement the ‘Preservation of connectivity’ (see 3.3) method, which would meet the requirements given.

In addition, this document showcases different studied behaviours according to their self-organisation methods. We found that a single method can be used to generate many different behaviours, sometimes just by changing a single parameter. Because of such factors, it is difficult to predict which behaviour a method will produce, or if a collective behaviour will appear at all (Gravagne & Marks, 2007). Moreover, even if the desired behaviour is obtained, there is no guarantee that it will remain consistent. Depending on the circumstances, the behaviour could display a change in its properties or result in a completely new behaviour altogether. From these revelations, the questions arise of how we could predict the evolving behaviour of a swarm and how we could assist the operator in understanding it.

From the definitions presented in section 2, it is possible to break down the various behaviours studied into simple

properties by which they can be characterised. This can enable us to sort these basic properties with metrics and represent them quantitatively. For example, flocking is defined by the property “agents move in the same direction”. The ‘Order’ metric (Vicsek et al., 1995) is often used in the literature to evaluate this property. Thus, when this metric gives a value close to one, the group moves in the same direction. On the contrary, when it is close to zero, the agents go in different directions. Moreover, since this metric is not binary, it can offer a fairly precise characterisation of the swarm’s current state. By reproducing this approach for the different properties of each studied behaviour, we can then obtain a set of indicators to characterise the state of the swarm.

Finally, facilitating the comprehension of the mechanisms of the studied methods should also provide a greater understanding of their dynamics. It is, thus, possible to imagine future designers or operators being able to analyse a swarm’s dynamics in real time by combining the various data collected here. This analysis could then be used to propose indicators for an observer, for identifying the essential information needed to create a *mental model* of the swarm and communicating it effectively and simply to others. As a result, the observer could build a mental model that would allow them to interpret changes in the swarm without having to observe the swarm’s agents one by one (Kolling et al., 2015). These indicators could, for example, convey the stability of the swarm, or the risks that the swarm is facing, such as the splitting up of an aggregate.

6 Conclusion

In swarm intelligence, it is difficult to understand how self-organisation leads to the emergence of collective behaviours. The classification system proposed in this document offers a new perspective by highlighting the methods of self-organisation of a robot swarm. This new perspective led us to perform an analysis to better understand the mechanisms that give rise to different elementary spatial behaviours. Complex behaviours, made up of elementary behaviours, will be the subject of a future classification and analysis. The presented cross-analysis also paves the way for defining metrics that allow external observers to better understand the underlying mechanisms of self-organisation, thus aiding further development of self-organised systems.

Declaration of conflicting interests

The Authors declare that there is no conflict of interest.

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