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Bio-inspired self-organising multi-robot pattern formation: A review

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HIGHLIGHTS

- Up-to-date review of advances in self-organising multi-robot pattern formation.
- Pattern formation inspired from macroscopic or microscopic biological mechanisms.
- Challenges in pattern formation using large-scale real robots.
- Guided self-organisation of swarm robotic system.

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ABSTRACT

Self-organised emergent patterns can be widely seen in natural and man-made complex systems generated by interactions among local components without external or global control. This paper presents a survey of recent research advances in self-organising pattern formation in mobile multi-robot (or swarm robotic) systems. Relevant pattern formation methods are reviewed with a special focus on biologically-inspired self-organising approaches inspired from macroscopic collective behaviours or microscopic multicellular developing mechanisms. As the ultimate goal of this review is to provide insight into pattern formation using real robots, limitations and considerations on dealing with a large number of robots are discussed. In addition, guided self-organisation is also discussed as a design strategy where the swarm robotic system may be endowed with local rules for generating desired global patterns.

1. Introduction

Multi-robot or swarm robotic systems consist of a large number of small and simple autonomous robots, each having limited communication/sensing capability and computational resources. Developing self-organising collective multi-robot systems has become an active research area in recent decades due to their attractive properties such as robustness to faults and damages, adaptability to unknown environments and cost efficiency [1–3]. Recent advances in robotics make it possible to build and operate a large number of inexpensive robots for various tasks beyond the scope of any single robots. Collaborative robot modelling and operations have been comprehensively explored in [4]. Others have taken the idea of using collaborative robots to find and track coherent structures in fluid which is a difficult problem since these structures are inherently unstable [5–9]. In addition, theoretical work on the use of collaborative robots in path planning has been investigated in [10,11]. Specific applications for these multi-robot systems under consideration include, but are not limited to, collaborative search and rescue [12,13], collective transportation and construction [14,15], remote terrain/space exploration and mapping [16], deployment of sensor networks [17] and formation flying of micro-UAVs [18] and small satellites [19].

In particular, considerable interests have been paid to pattern formation allowing multi-robots to move in a loose or tight formation as a basic function for accomplishing a given mission. The pattern formation problem in multi-robot systems represents the coordination of a group of robots to generate and maintain a formation with a certain shape, in which the shape can be either a pre-defined pattern or adaptively formed in a self-organised way through local interactions with neighbouring robots and with the environment. In the former case of using pre-defined patterns, a group of autonomous robots shall follow a predefined trajectory while keeping a pre-specified spatial pattern and individual robots should maintain a specific relative orientation and distance between each other. In this pattern formation process, different control methodologies can be applied depending on the objectives. Leaders of the group may be selected to perform a higher level mission while the others follow the leaders in a specified way, or an entire group can be governed by a desired set of behaviours. Centralised pattern formation is possible when coordination is

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performed by a centralised unit that can overlook the entire group and control the individual robots accordingly. However, as robots generally have a limited communication and computation ability, global information is often not available to each robot, which makes the system less robust to failures and poorly scalable. Thus, when a large number of agents are involved, the design of the controller should be based on local information only, which is the main concept in decentralised and distributed systems.

Distributed self-organising systems are considered to be more robust to failures of individual robots in the group for the following reasons. Distributed multi-robot systems have an inherent redundancy since the same role is given to all individual robots without the explicit use of any pre-specified individuals. If some robots fail to perform their tasks well, get damaged or even become completely defect, their neighbours can compensate their roles [20–22]. On top of the above, self-organising robotic systems are more adaptable to environmental changes since each robot not only has its own sensors but also receives information from its neighbours. Another advantage is computational scalability [23,24]. Since individual robots do not need global interactions, increasing the number of robots and scaling up the system hardly affect the computational complexity of the controller of individual robots.

For self-organised adaptive pattern formation, global patterns should emerge resulting from local interactions between individual robots. This sort of emergent patterns can be often seen in ecosystems such as patterning in seashells and fishes [25], and bird flocking, ant colony and fish schooling [26–29]. Also, it can be observed in biological findings about how cells self-organise into global patterns, for example, animal pigmentation. A key to understanding the emergence of complex pattern formation system is self-organisation. Self-organisation is a spontaneous process in which some form of global order or coordination emerges from local interactions between components in a fully decentralised or distributed way [2,30]. Thanks to some important properties of self-organised systems (e.g., flexibility, scalability and robustness), self-organisation in nature has become one of the primary inspiration sources for self-organising mobile multi-robot systems [31].

In this review, we deal with the problem of self-organising pattern formation in the context of mobile swarm robotics. By pattern formation, we mean both pattern generation and pattern maintenance. The pattern formation process is illustrated in Fig. 1 where the robots first need to flock to a certain location, then they have to self-organise into a spatial pattern, and finally they display a specific graphical pattern (or differentiate into robots responsible for different functionalities). Note that, flocking and swarming which describe a collective behaviour of a group of interacting agents with a common objective such as aggregation, segregation or sorting is regarded as the part of pattern formation in a wide sense as it is a necessary process to form a pattern from an initially dispersed configuration (i.e. going from (i) to (ii) of the pattern formation process in Fig. 1).

Existing pattern formation algorithms for multi-agent/robotic systems can be categorised into many different ways in terms of control methodologies, movement constraints or sources of its inspiration, as suggested in [32–34]. Among others, this paper particularly focuses on bio-inspired algorithms, as nature provides rich and excellent examples of distributed self-organising systems for adaptive pattern formation. For instance, cooperative behaviours of animals in a flock, school or swarm often lead to formation of interesting patterns [28]. It is also known that complex organisms grow into desired patterns in the body of living beings without any centralised control starting from a core of identical biological cells.

Considering above inspirations, this paper divides the relevant bio-inspired pattern formation algorithms into two groups: (1) macroscopic collective behaviour-inspired and (2) microscopic multicellular organism-inspired pattern formation. In general, macroscopic algorithms are related with (ii) flocking (aggregation) and (iii) spatial patterning of the pattern formation process in Fig. 1. Microscopic ones cover from (ii) to (iv) complex patterning, and in many cases, these three pattern formation steps occur concurrently rather than step by step by a certain bio-inspired algorithm. Note that, research work concerned only with pattern generation using the concept of biological morphogenesis, which involves differentiation, growth or division of the cell with little or no movement of agents (e.g. amorphous computing [35]), is not considered in great detail in this review. As this review aims to provide insight into pattern formation using real multiple robots, limitations and consideration on dealing with a large number of swarm robots with respect to communication, computation, sensing and hardware cost are also discussed.

The remaining part of this paper is organised as follows. Different formation control strategies using macroscopic collective behaviour-inspired pattern formation are given in Section 2. Then, Section 3 presents microscopic multicellular-mechanism-inspired pattern formations. Considerations in dealing with a large number of robots are presented in terms of physical hardware constraints in real-world environments, followed by perspectives on the future research direction of pattern formation in Section 4. Concluding remarks of this review are provided in Section 5.

2. Macroscopic collective behaviour-inspired pattern formation

Aggregation, which can be seen as a process to form a particular pattern, is a very common behaviour in nature, for example, bird flocking, fish schooling and ant colony in maintaining their society [36]. This section presents bio-inspired pattern formation algorithms inspired from these animal aggregation behaviours (i.e. at a macroscopic level), which are a conventional approach in robotics and control-oriented research. As not all global information is available for each robot, usually a centralised controller is not assumed to exist. There are many issues needed to be considered when designing a decentralised and distributed controller for pattern formation with a swarm of robots, such as the stability of the formation, controllability of different patterns, safety and uncertainties in formations. Many control strategies have been put forward to achieve successful pattern formation.

Multi-robot pattern formation inspired from animal aggregation behaviours can largely be categorised into a structured approach and a behavioural approach. A structured approach, in which the leader or a virtual structure is first identified and the followers follow the leader or the structure with rigid or relaxed formation constraints, is mainly used to maintain pre-defined patterns. One may argue that the structured approach is man-made rather than explicitly related to nature or biology, however, in a broad sense, we see that the structure itself is often inspired from observations of natural phenomenon such as the V-shaped formation of a bird flock led by a leader to improve aerodynamic efficiency and save energy [37]. The structured approach requires the full states of the leader or virtual structure information (e.g., the trajectory of corresponding points) to be communicated with the entire formation group. By contrast, a behavioural approach, in which a desired set of behaviours with relative importance is implemented onto individual robots, can be used for maintenance of pre-defined patterns as well as control of flocking behaviour leading to self-organising patterns in a decentralised way with significantly less communication.

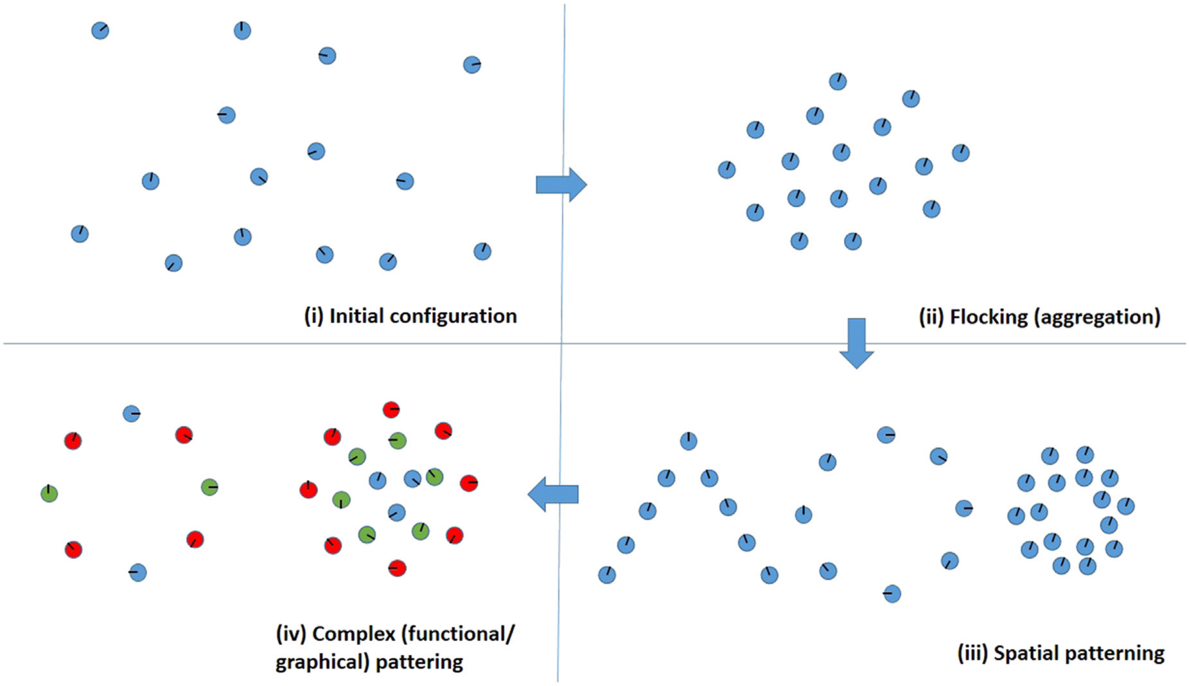


Fig. 1. Illustration of a pattern formation process.

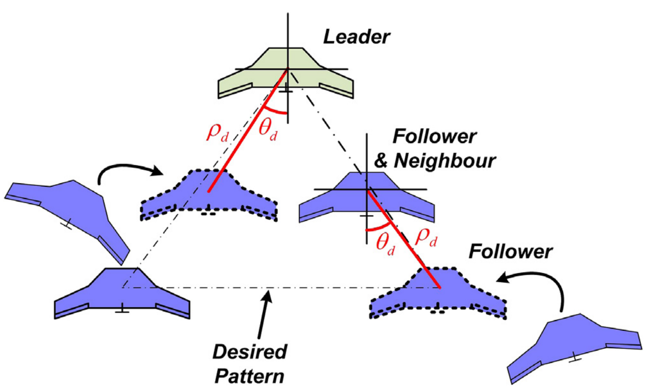


Fig. 2. Illustration of a leader–follower structure for pattern formation. ρ_d and θ_d represent a desired relative distance and an angle to the corresponding leader, respectively. Followers are controlled to the desired pattern.

2.1. Structured approach

2.1.1. Leader–follower structure

In a leader–follower structure, the leaders are first specified or identified, and the followers keep relative position with respect to the leader as illustrated in Fig. 2.

Alur et al. [38] developed a framework and architecture for multi-robot cooperative operations. In this work, leader-following is realised by linear feedback control where a leader follows a desired trajectory and followers maintain prescribed separation and bearing to the neighbouring robot. A real experiment is performed using two car-like robots with a single omnidirectional camera and image processing techniques to obtain range and angle information locally. Similarly, Tahk et al. [39] addressed a formation flight guidance problem using a line-of-sight angle to other vehicles measured by visual sensors or radars, which does not require data communication between the vehicles. The algorithm is tested in numerical simulations. Koo and Shahruz [40] proposed a path-panning approach to autonomously operate multiple UAVs in a desired formation, based on the simulation study. The path for each UAV is obtained by a leader UAV having cameras and sensors, which is more capable than others. The other UAVs receive trajectories they should track from the leader. Edwards et al. [41] adopted the leader–follower algorithm to operate multiple autonomous underwater vehicles. Real experiments were performed with two vehicles in a semi-autonomous way which involves human driver to follow the desired commands generated by the formation algorithm. Gautam and Mohan [42] proposed a leader–follower approach wherein the leader guides the followers to their respective positions on the circle circumference. Panagou and Kumar [43] addressed a motion coordination and control strategy for leader–follower formations of nonholonomic vehicles, under visibility and communication constraints in known obstacle environments.

Despite the significant theoretical formalisation of this approach in the literature, this structure has a substantial limitation in that formation is rigid, which is a hard constraint difficult to be achieved in uncertain and dynamic environments. In addition, this requires identification (ID) and order of the robots in the formation, which makes the team behaviour vulnerable to failures. For instance, a failure of the leader may result in the failure of the entire group mission. Several attempts have been made to address these limitations.

In Consolini et al. [44], the follower position is made flexible along a circular arc centred at the leader position, however the distance between the leader and follower still remains fixed. In Dimarogonas et al. [45] and Ji et al. [46], several leaders are first commanded to reach a desired formation independent of followers, and the followers are then converges to the convex hull generated by the final position of leaders. In [47], the authors investigate how to accomplish global-level formation coordination with only local sensing and communication (i.e. without global knowledge of others). The leader is determined by the number of robots and desired pattern, and the followers maintain a desired distance and angle relative to local leaders. They addressed robustness to group size changes and switching between formations along with stability analysis and obstacle avoidance. Numerical simulations

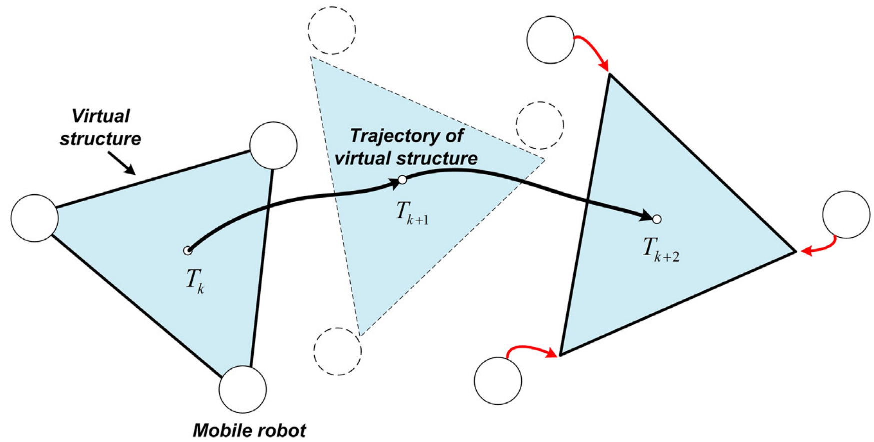


Fig. 3. Illustration of a virtual structure approach for dynamic pattern formation where robots are controlled to follow trajectories defined by the virtual structure.

and real experiments using four ground robots are performed to form several geometric shapes. Morgan and Schwartz [48] proposed the local controller in the Frenet–Serret frame for leader following behaviour. In this work, a leader follows an explicit steering program and followers pursue a leader while interacting with their neighbours and a leader via long-range attractive and shot-range repulsive interactions. So, this combines the leader–follower approach with the local interaction rule, behavioural approach, which will be explained in the Section 2.2.

2.1.2. Virtual structure

To further tackle the above weaknesses of the leader–follower structure, the virtual structure method was proposed where the whole formation is regarded as a single entity and the desired position or motion for the group is allocated to the structure, as illustrated in Fig. 3.

The concept of a virtual structure for multi-robot formation was first presented in [49,50]. In this work, control methods are developed to force an ensemble of robots to behave as if they were particles embedded in a rigid structure while moving in formation. Numerical simulations and real experiment with three robots show that the proposed control algorithm can provide a high level of precision for moving towards a target while maintaining formation, and maintain a desired virtual structure even if some robots in the group fail. Later, Giulietti et al. [51] adopted the concept of virtual structure to autonomous formation flying, addressing the problem of maintaining formation in the presence of communication failure in some vehicles in the group. A formation management structure was developed using a decentralised approach and the Dijkstra algorithm [52]. Oh et al. [53] addressed the circular formation of multiple UAVs with both leader–follower and virtual structure to track a moving target while maintaining the desired distance between UAVs and the target and separation angle to improve estimation accuracy. Askari et al. [54] also proposed formation flying approach for multiple UAVs based on virtual structure.

Similar to the leader–follower structure, the formation in this approach should be rigid as the geometric relationship amongst the robots needs to be strictly maintained during the formation and transition period. However, this approach can cope with leader failure and disturbance residing in the leader–follower approach by removing physical leader's role or hierarchy in the formation. Note that the virtual structure method is achieved at the cost of high communication and computation capabilities required to synthesise the virtual leader and exchange its position in real time to the other vehicles. Thus, it could be easier to analyse the convergence and stability of the formation structure mathematically, but may not be well suited for handling a large number of robots, since the constraint interdependence among robots will become more complicated with the increasing number of robots in the group.

2.2. Behavioural approach

Biological research on insects, ants and birds in nature revealed that the coordination problem involving a large number of such animals can be efficiently solved by using swarm behaviours without any central coordination [55]. Inspired by these findings, much work has been performed in the swarm robotics area. Doctor et al. [56] and Pugh and Martinoli [12] proposed efficient search algorithms for swarm robots based on the principles of particle swarm optimisation which simulates the behaviour of bird flocking or fish schooling, in order to find a target in an efficient way. Wilson et al. [57] designed decentralised robot control policies that mimic certain microscopic and macroscopic behaviours of ants performing collective transport tasks. The key point here is that swarm behaviours can be triggered autonomously by relatively simple rules followed by individuals. The basic idea of the behaviour-based method is to combine the outputs of multiple controllers designed for achieving different and possibly competing behaviours [58]. Possible behaviours include collision avoidance, obstacle avoidance, goal seeking, and formation keeping [59] among many others.

In [60,61], authors provide a comprehensive overview of various versions of the flocking algorithm. Most notably, Reynolds introduced three heuristic (behavioural) rules which aim to mimic a bird flocking behaviour [28]. There are three types of flocking rules: (1) cohesion — flock centring that attempts to stay close to nearby flock mates; (2) separation — collision avoidance with nearby flock mates; and (3) alignment — velocity alignment that matches velocity with nearby flock mates, as illustrated in Fig. 4. Similarly, Vicsek et al. [62] explains the heading synchronisation phenomenon of self-driven agents moving a constant speed by updating each agent's heading with the mean heading direction of local neighbours. The importance and contribution of above work is that it successfully shows the emergence of a global group behaviour only by local interactions of each agent with close neighbours and local environment.

These local interaction rules have inspired various behaviour-based control algorithms later on. Importantly, Balch and Arkin [63] initiated a behaviour-based approach to robot formation-keeping with similar philosophy to the Reynolds' flocking rules but focusing on a specific geometric formation rather than flocking. The behaviours are implemented and tested in simulation and real robotic testbed. In [64], a behaviour-based formation control

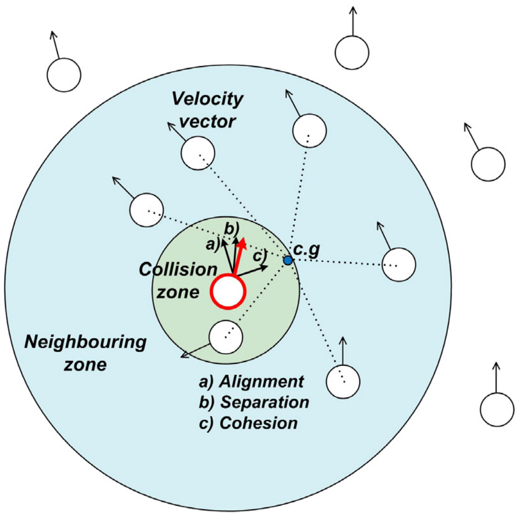


Fig. 4. Illustration of Reynolds behavioural rules including alignment of velocity vector, separation between neighbouring agents, and cohesion towards the centre of neighbouring flock mates. The red arrow represents the net direction to move. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

strategy is proposed focusing on formation keeping during the transition from one pattern to the other with three real wheeled robots. Fine and Shell [61] implemented the Local Crowd Horizon (LCH) rule [65], in which each agent uses the density of the group to determine its next move, on a real robotic platform while investigating differences between the use of position and heading information. Xu [66] proposed a behaviour-based control design approach, in which a classification-based searching method was used to generate large scale robot formation in order to reduce the computational complexity and speed up the initial formation process for any desired formation, and the behaviour-based method was applied for the formation control of swarm robotic systems when navigating in an unknown environment having obstacles. Chen et al. [67] proposed medium-range interactions to control splitting of flocking behaviour along with long-range attractive and short-range repulsive interactions for aggregation.

As the behaviour-based approach is typically decentralised and thus can be implemented with significantly less communication compared to the others, it has been the most common choice to date for swarm robotics applications [68]. However, it does not provide any guideline to define what the individual robot should do so that the given swarm-level specifications are met; this becomes the core design problem that one faces in swarm robotics [69]. Since the significant portion of behavioural-based swarm robotics research is performed by using potential field and/or consensus-based control methods, the following section briefly explains them, followed by delay issues in flocking and examples of real swarm robotics experiments using this approach.

2.2.1. Potential field

The basic idea of the potential field methods is that each robot moves according to the direction of a gradient of the potential fields, generated by the sum of virtual attractive and repulsive forces. In general, it is difficult to form a desired shape using this potential function approach since the robots are guided to stay close together only within the group and avoid collision amongst them [70,71].

To address this issue, Belta and Kumar [72] proposed a control method for a large number of agents based on an abstraction of the team to a smaller dimensional manifold independent of the number of robots. In this work, a target shape is adaptable to environmental changes by spanning the shape, as demonstrated in a numerical simulation with a narrow tunnel passing scenario. However, they considered only two simple shapes: rectangle and ellipsoid, and the resulting formation is just loosely distributed in the shaped area. Pimenta et al. [73] proposed the use of the analogy of fluids in electrostatic fields for multi-robot pattern formation. They model a group of robots as an incompressible fluid, and generate an electrostatic field which provides external forces to the fluid (and controller), where the field is attracted into the geometric pattern and repelled from the obstacles and environment constraints. Simulation studies are presented with a large number of robotic agents for geometric shape formation scenarios with static obstacle avoidance. This study is beneficial in the sense that it uses a fully decentralised control structure and can handle generic obstacle shapes. However, it is difficult to be used for dynamic and unknown environments due to a complex electrostatic field generation process relying on a finite element method which is computationally burdensome.

To better deal with a large number of robots, Hou et al. [33,74] have introduced a region-based pattern formation control for a large number of agents based on potential field, where each agent in the group stays within a moving region while maintaining a specified minimum distance from each other. Region-reaching control and minimum distance keeping is accomplished by defining potential energy function P_a which attracts agents to the desired region and P_r which repels robots within the minimum distance between each other, respectively. P_a and P_r can be described in the following:

$$P_a^i(\mathbf{X}) = \sum_{k=1}^{N_k} \frac{k_a}{2}[\max(0, f_k(\mathbf{X}))]^2, \tag{1}$$

$$P_r^i(\mathbf{X}) = \sum_{j=1}^{N_j} \frac{k_r}{2}\left[\max(0, r^2 - \|\Delta\mathbf{X}_{ij}\|^2)\right]^2, \tag{2}$$

where k_a and k_r is a positive constant, N_k is the number of inequality functions f_k forming a desired region shape. N_j is the number of neighbouring agents within the communication range of the ith agent, $\|\Delta\mathbf{X}_{ij}\|$ is the distance between agent i and j, and r is the minimum distance between the two agents. Partial differentiation of the potential energy function gives the force direction for the agents as illustrated in Fig. 5. This work presents the rigorous convergence analysis of multi-agents systems and considered various shapes (e.g., circle, ring, star) of the desired region as a combination of inequality functions. Haghighi and Cheah extended their work on the shape control by adding a new mutual interactive force between agents for better swarm aggregation property (i.e. moving as a group) during movement towards the desired shape [75]. This is done by dividing environments of each agent into four areas: separation (for minimum distance), neutral (for flexibility of movement), attractive (for swarm aggregation), and inactive areas. Besides, in [76], with the same framework as above, a dynamic compound shape control is addressed by combining several basic shapes (such as circle, rectangular and triangle) with multiplicative potential energy function. In this work, they also considered dynamic changes of orientation and size of the shape during the course of movement by using a time-varying transformation (scaling and rotation) of shape inequality functions. Similarly, in [77], Haghighi and Cheah proposed a multi-group coordination control concept for pattern formation by formulating the problem into two parts: (i) inter-group (between groups consisting of a complex shape) formation using a hierarchical leader–follower structure and inter-group interactions, and (ii) intra-group formation for the members of each group to form the corresponding desired shape. Note that all region-based pattern formation studies presented above are performed in numerical simulations with a simple 2-D kinematic model of the robot only.

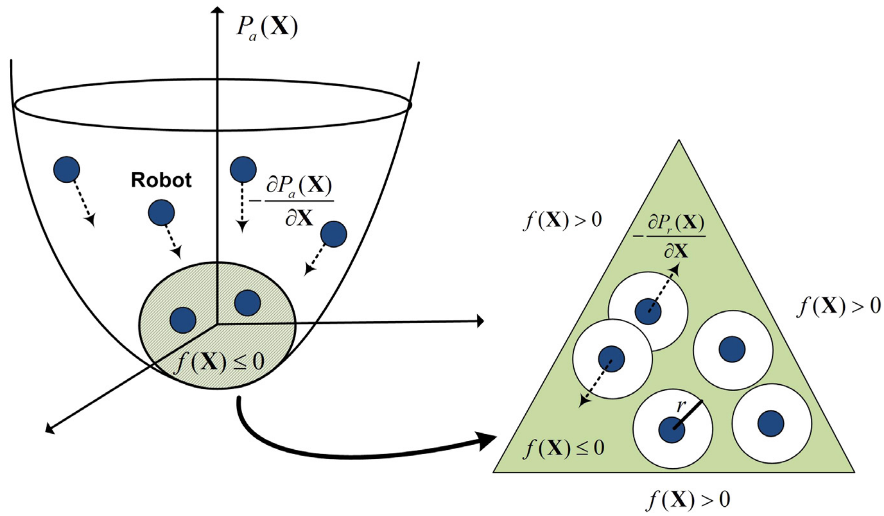


Fig. 5. Illustration of the potential energy function for region based shape control [33,74]. Robots are first guided into the defined region by following a gradient direction from the potential energy function and then self-organise within the region to avoid collisions and to be evenly distributed.

2.2.2. Consensus-based control

Inspired by the Reynolds flocking rule [28] and Vicsek model [62] mentioned before, consensus-based control has been widely studied for cooperative control of multi-agent systems, where the agents make use of information exchange between them to reach a common value (known as a consensus) on velocities or headings for cohesive movement as a group [78,79]. A general discrete-time consensus protocol between agents can be expressed as:

$$x_i[k+1] = x_i[k] + \sum_{j=1}^{N} \alpha_{ij}[k] g_{ij}[k] (x_j[k] - x_i[k]) \tag{3}$$

where x_i represents the information of agent i, N denotes the number of neighbours, α_{ij} represents relative confidence on information of agent i to agent j, and g_{ij} represents communication network connectivity between agents, so if connected, then it is one, otherwise zero. Fig. 6 shows an example of an information consensus process between six agents having different initial conditions depending on the communication structure by using Eq. (3). Compared to the traditional consensus [80] or agreement [81] problems in computer sciences concerning a fault tolerance aspect, consensus-based control algorithms in multi-agent coordination focus more on the convergence based on a control theory [82]. Jadbabaie et al. [84] initiated a theoretical analysis of a multi-agent consensus problem using bearing-only information for dynamically changing communication topologies based on bidirectional information exchange. Ren and Beard [78] extended the result of [84] for the case of directional information exchange and considered the relative weighting factors (accounting for the relative importance or reliability of the information) in an information update process. In addition, in [82], Cao et al. established various fundamental properties which are helpful to understand the consensus phenomenon and presented a condition for a group of agents to reach a consensus in the graph-theoretic approach. A detailed review of consensus control for multi-agent coordination can be found in [78].

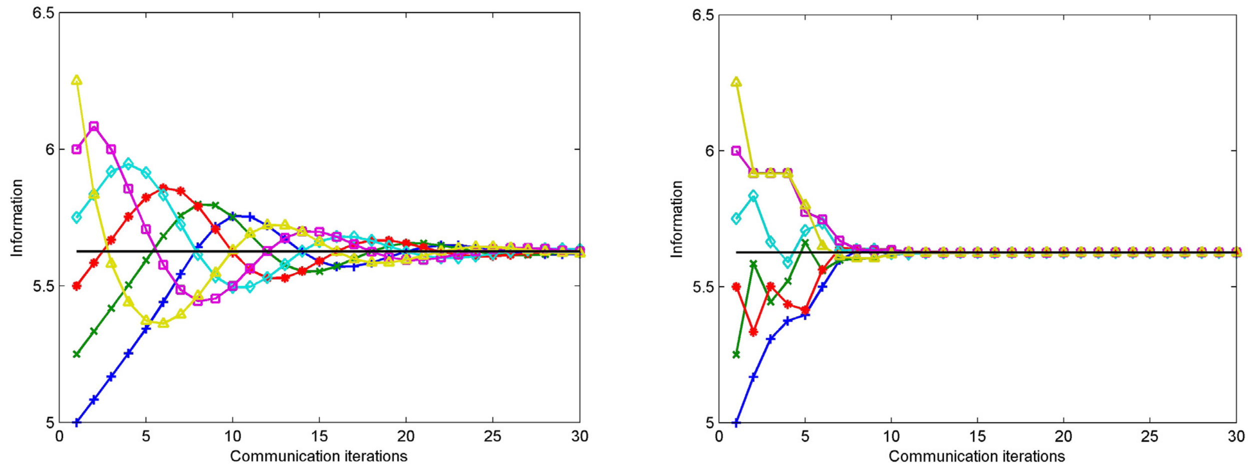
Note that many of consensus-based control methods for pattern formation are combined with a potential field method for the guidance of agents. Reif and Wang [85] did early simulation work on pattern formation using a consensus-based control scheme. They proposed simple artificial force laws using attraction and repulsion between robots or robot groups, where the force laws are determined by reflecting the social relations among robots. Notably, this paper suggested the term of very large scale robotic (VLSR) systems for describing systems with a large-scale autonomous robot swarm. They discussed several problems for future studies including convergence and local-minima problem, robustness and efficiency, loss of information when simplifying the state of the system, and restriction for defining force laws considering dynamic equilibrium.

Tanner et al. [86–88] proposed a decentralised synchronisation (consensus) strategy with artificial potential fields and graph theory for a group of nonholonomic agents. The group is able to cluster to a tight formation under fixed [87] and switching [88] topologies by aligning headings of all agents to the same value and stabilising the pairwise relative speeds. The collision avoidance is done by a local potential function regarding relative distance between agents. The convergence (of agent speed) is shown to be closely related to the degree of algebraic connectivity of the graph (which represents agent interconnection) in the numerical simulation study. Similarly, Olfati-Saber [89] presented distributed flocking algorithms based on velocity consensus among the agents and graph theory while focusing on the fragmentation or flocking of the group and obstacle avoidance. The author conducted numerical simulations using up to 150 agents for 2-D and 3-D flocking and split/rejoin/squeezing manoeuvre.

In [90], Fax and Murray investigated the effect of different communication or information flow topologies on stability and performance of formation control using a graph-theoretic framework. They proposed a decentralised information exchange law for the agent in the group to reach consensus on the centre of formation as a common reference of cooperative movement. Numerical simulations showed robustness of the proposed law to the changes in the graph, which allows accurate control of formation even with limitations in the communication among agents. Similar approaches using an information flow law are reported while considering stochastic loss and disturbances in the communication graph [91].

2.2.3. Delay in networks

Delay in networks used in many flocking and swarming models is an important issue to be addressed, thus it has received a significant attention recently [92–98]. Delay shows up in communication across a network as well as in actuation times and coding errors. In addition, large spatial spread of swarms means that information transmitted across large scales through a network will be delayed. In particular, some patterns can only occur in the presence of communication delay where populations are homogeneous;



(a) Communication with the minimum number of links.

(b) Communication with randomly selected one other agent.

Fig. 6. Information exchange and consensus process between six agents with different communication topologies [83]. Initially, each agent has a different information/value but it converges to an agreed/averaged value by the communication.

e.g., [99–101]. Other issues with delay include communications with distributions of delay, which results in very complex stability diagrams [94] in which stability of the rotational dynamic patterns depend not only on the mean of the delay distribution, but also on all moments of the distribution. In other work, it is also shown that mean field behaviour, when the number of agents is very large, fails to predict the existence of bi-stable patterns, which means higher order moments must be included in the dynamic models [95]. This is important since many controllers which are global in nature, need to use simplified low dimensional models to stabilise certain patterns. However, if one ignores certain high-order moments, one misses relevant correction terms which might cause control to be in error. Others have examined noise induced pattern switching in delay coupled systems [93].

2.2.4. Real swarm robotics experiments

There are several recent attempts to implement the Reynolds flocking behaviour in real flying vehicles. Hauber et al. investigated the effect of the communication range and vehicle dynamic constraints (a maximum turn rate) when implementing Reynolds rules, and presented a numerical simulation as well as real flight experiment with ten small fixed-wing UAVs [102]. Vasarhelyi et al. [103] also successfully performed a flight test for flocking and formation flight with up to ten quadrotor UAVs based on their theoretical work [104] dealing with instability issues due to general deficiencies of real robotic systems such as time delay, short range local communication and inaccuracy of sensors, a GPS device in this paper.

Besides, very fine experiments have been done, which tests and validates the stability of patterns in dynamic swarm patterns with delay [101,105]. Mijalkov et al. proposed the idea of using the sensorial delay between the time of sensing and reacting to signals as a parameter to control collective behaviours [101]. Three phototactic robots are used to demonstrate that they exhibit the aggregation and segregation behaviour depending on the sign (i.e. positive or negative) of the sensorial delay. Szwaykowska et al. used four real two-wheeled robots and 46 virtual agents to validate the emergent swarm pattern (ring state in this case) of delay-coupled agents where there is a communication time delay and global communication/coupling between agents is not guaranteed [105].

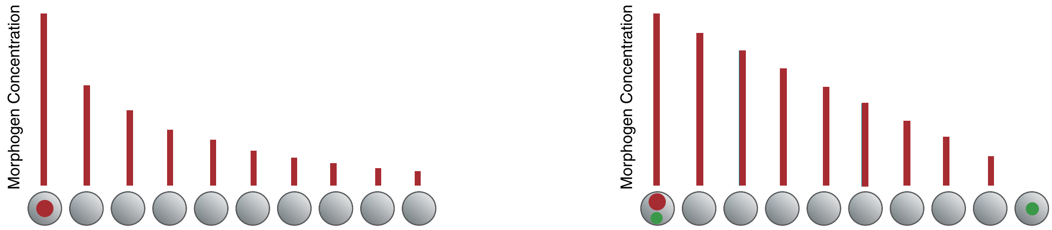
There are other pieces of work directly inspired from a certain animal behaviour. Kernbach et al. [106] proposed an aggregation algorithm for a swarm of robots inspired by the thermotactic aggregation behaviour of honeybees, where honeybees form a big cluster close to an area with optimal temperature. Garnier et al. [107] modelled the behaviour of cockroaches and applied it to a group of micro-robots, named Alice, for the simulation of aggregation behaviours.

3. Multicellular mechanism-inspired pattern formation

In addition to animal collective behaviours, pattern formation phenomenons at cellular level can be also found in biology, for example, the spatial disposition of bacterial colonies and the chromatic patterns on some animal's fur [108]. Biologists have carried out many studies to understand the mechanism for forming pattern and structures during embryonic development and cell growth [109–114]. In silico experiments have also been performed to build up computational models to simulate the microscopic level of swarm behaviours. In addition, mathematical models have been proposed to interpret the mechanisms of developmental patterns in biological systems [25,115–119], most of which are based on the Turing model for biological pattern formation [120] and reaction–diffusion mechanisms.

There are a large body of research on simulation and modelling of developing arbitrary shapes from artificial cells [121–126]. In these algorithms, the development of a shape is initiated with one cell, and the process continues with cell duplication and differentiation. Cell to cell adhesion and chemotaxis, which are usually parts of the process of biological pattern formation, have been modelled for simulation of aggregation and sorting of agents [127].

Multi-robotic systems are suited for implementing these bio-inspired algorithms if robots are considered as cells that cooperate to form pre-defined or adaptive patterns. However, simple robots used in multi-robot systems usually have very limited capabilities [128], and many cell actions are not applicable to robots directly. For instance, a normal robot cannot duplicate itself or is not able to change its shape into an arbitrary shape as a cell does. Hence, the biological pattern formation mechanisms such as morphogenesis, chemotaxis, gene regulatory network (GRN) and pheromone have been introduced into bio-inspired multi-robot systems in a conceptual way only. In this section, we review and discuss the application of these multicellular mechanisms in self-organising pattern formation of multi-robot systems, and show how researchers have borrowed the ideas and concepts, simplified and made them applicable to self-organisation of swarms of robots.



(a) Exponential morphogen gradient. (b) Linear morphogen gradient.

Fig. 7. Comparing the concentration pattern of two type of diffusion mechanisms. The height of the bars represents morphogen concentration. The red circles indicate the morphogen sources, and green circles indicate the morphogen sinks [130]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.1. Morphogen diffusion

In biology, morphogens represent signalling molecules that are diffused into the developing tissues during embryonic stages. The concentration of a morphogen becomes lower by going further away from its source and forms a corresponding gradient. Cells obtain a relative understanding of their position with respect to this gradient and adjust their behaviours and reactions accordingly. Cell growth, cell differentiation, cell movement, production or repression of other genes and morphogens are examples of these actions [129].

In a swarm of robots without directional sensing and global position, morphogen-like signals can provide robots with information of their relative locations. Morphogen can diffuse through robots using following equation:

$$\frac{\Delta C_{bi}}{\Delta t} = D_i \sum_{b'=1}^{N_b} \frac{(C_{bi} - C_{b'i})}{n_i d_{bb'}} - r_i C_{bi} \tag{4}$$

where C_{bi} is the concentration of morphogen i in robot b, D_i represents diffusion rate, r_i is degradation rate, $d_{bb'}$ is the distance between robots b and b' and N_b is the number of the robots which are connected to robot i. Having a source of morphogen in one robot which degrades and diffuses through the other robots following Eq. (4), an exponentially decreasing morphogen gradient is generated as shown in Fig. 7(a). The grey circles represent individual agents and the bars indicate the concentration level of morphogen. For this kind of diffusion, the slope of the concentration gradient near the source is steep, and for the agents far away from the source, the gradient's slope is quite shallow. The low slope of the gradient makes it sensitive to noise and disturbance. To address this, Werfel [130] discussed the merit of having a morphogen gradient produced by two morphogens deposited in both ends of a row of agents (Fig. 7(b)). The first morphogen, indicated in red colour, does not degrade on its own but only diffuses through the agents. The second morphogen, indicated in green, is non-diffusible and acts as a sink for the first morphogen. By putting a small morphogen at the left end, two morphogens reach equilibrium status, and this kind of diffusion results in producing a linear concentration gradient of the first morphogen. This can be a potentially useful process robust to noise and disturbance.

A pioneer study on morphogenesis solution for pattern formation in swarm robotics have been reported by Mamei et al. [131]. They showed how diffusion of three morphogens can be applied to finding the centre of a swarm of simulated robots, forming a ring shaped pattern and growing some lobes on the ring to achieve polygonal pattern formation. A few years later, Yeom [132] adapted a mechanical interaction model to this algorithm to have more control of the agents' movement and validated his model via a simulation. One of the ideas represented in Mamei's work is 'selective propagation' which is inhibition of the diffusion of a morphogen by a group of agents. For instance, consider a morphogen which controls the size of the swarm. If this morphogen is inhibited by a group of agents in one side of the swarm, it leads to asymmetric growth of the swarm. In the other method, when the concentration of a morphogen reaches a specific amount, the agents inhibit the diffusion of a morphogen or start to diffuse another morphogen. Region selection can be achieved by this method.

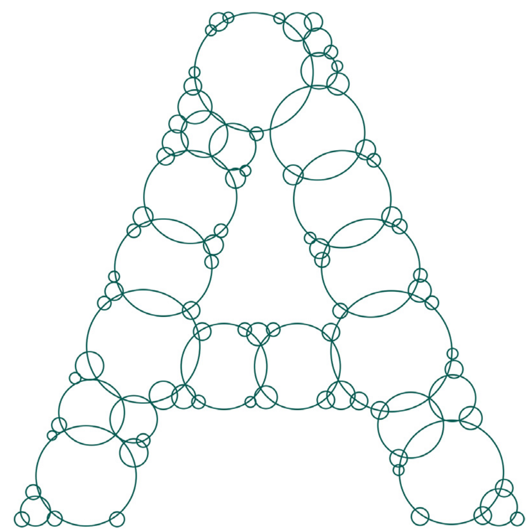


Fig. 8. A two-dimension arbitrary shape, here an A-shape area, is approximated by discs with various sizes [133].

Combining morphogens and geometry, Kondacs [133,134] developed an algorithm to simulate the self-organising generation of two-dimensional arbitrary shapes. The agents which constitute the pattern do not move but replicate themselves to a close position. At the first stage, a predefined shape is covered with a large number of discs in various sizes. These discs approximate the predefined shape as shown in Fig. 8. Then, replication starts from one agent, and each new offspring has a copy of the discs map in its memory. In the beginning, the agents do not have global position information, but they can find out their relative position using the morphogen gradients they receive from reference points. Each disc has several reference points including the centres of discs, intersection points of discs' boundaries and four more points evenly located on the boundary. By using morphogens, geometric proportions and local interactions, an agent can find out whether it is near to one of these reference points or not. The proposed algorithm was conducted through a simulation method. Once an agent realises that it is located in a reference point, it starts to emit morphogen to guide other agents. One might say that this algorithm is not applicable to swarm robotics simply because

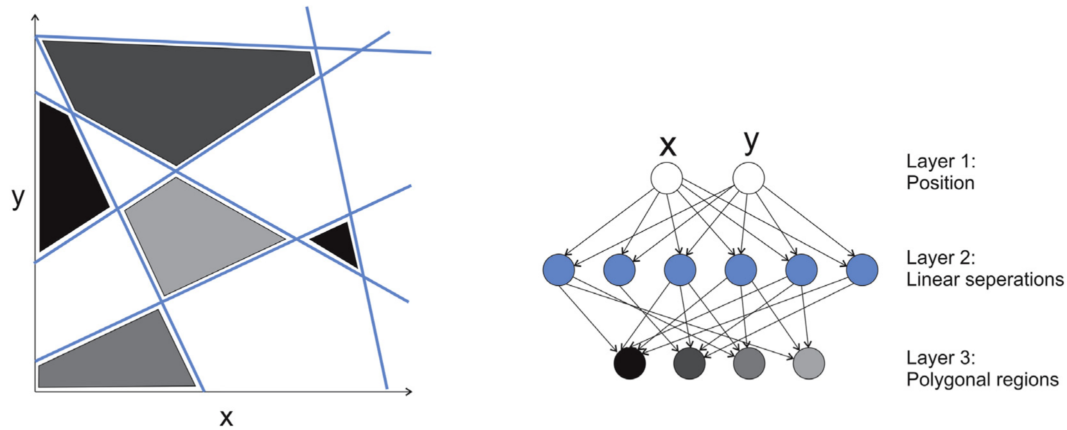


Fig. 9. A multilayer perceptron neural network (right) creates a two-dimensional pattern (left) [135]. Each output of the neural network is associated by a grey area in the pattern with the same greyscale. The number of neurons in the second layer is equal to the number of blue dividing lines in the left which determine the shape of the pattern. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

robots cannot duplicate themselves. However, some solutions can be considered to cope with this problem. For instance, free robots which are not yet involved in the pattern can be recruited. Once a robot needs to duplicate itself, it can instead recruit one of the free robots nearby and copy its memory and genome on this newly recruited robot.

There are more morphogen-inspired pattern formation algorithms which are not directly applied in swarm robotics but contain potential compatible ideas. Doursat [135] proposed an algorithm to create patterns that are similar to stained glass segmentation, inspired by morphogenesis and perceptron neural networks as shown in Fig. 9. The morphogens provide positional information for the agents and a multilayer perceptron network uses this position as its input. The second layer in the network splits the two-dimensional space into half-planes by several straight lines. Eventually, the output layer combines these half-plane to define polygonal regions. The effectiveness of the algorithm was tested by conducting a simulation. The generation of smoother regions can be made possible by adding more hidden layers to the neural network. Moreover, for each region, another neural network can be applied to create a specific division on that region to achieve more complex patterns.

Yeom and Park [136] proposed an evolutionary morphogenetic system to form two-dimensional shapes using square-shaped cells, in such way that the simulation looks like a bitmap graphics. In their algorithm, each signal is produced and spread by a specific diffuser. The cells which contain these diffusers can emit signals. The level of a signal in a cell that has the corresponding diffuser is always at the highest amount. Once a cell receives a signal, it records the value of that signal and never changes it. Moreover, individual signals do not affect each other. According to signal values in each cell, a function will be assigned to the cell that defines the cellular behaviour. The genetic algorithm is applied to define the location of diffusers in the swarm and the thresholds for signal values that activate a function in a cell.

Bhattacharyya [137] combines the concept of stabilising signal and morphogenesis in his study. In the algorithm, after the growth of some random cytoskeleton-like structures from the centre of a ring shaped swarm towards its boundary, those structures that receive the stabilising signal become stabilised while the others decay gradually. Therefore, cytoskeleton-like structures are bound to grow in all regions, but they will shrink ultimately unless they receive a stabilising signal. This makes it possible to have a control of the structure by using a single signal rather than manipulation of the growth mechanism.

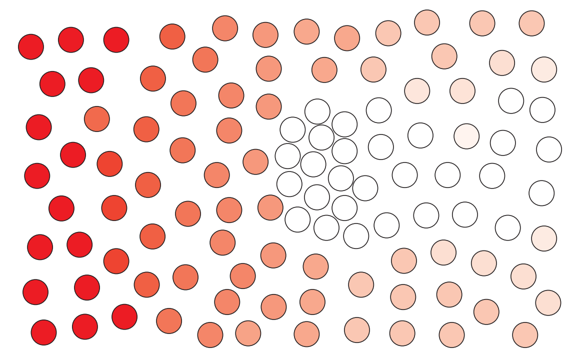


Fig. 10. Interaction of density of agents and morphogen diffusion. A dense region in the swarm inhibits the morphogen diffusion. Circles represent agents and the intensity of the red colour denotes the morphogens concentration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

One area that deserves additional study is the interaction between the density of robots and morphogens' diffusion. The density of the robots can be included in the diffusion equation and affect a morphogen expression and diffusion process. For example, whenever the density of robots in a region goes above a threshold, the robots in that region can inhibit the diffusion of the morphogen or any changes in density can activate the expression of a specific morphogen (Fig. 10).

3.2. Reaction–diffusion model

When several morphogens in a cell start to react with morphogens in other neighbouring cells, they are able to create interesting patterns [115,129]. Adding the reaction term into the Eq. (4), we have:

$$\frac{\Delta C_{bi}}{\Delta t} = \sum_{j} w_{ij} f_{ij}(C_{bi}, C_{bj}) + D_i \sum_{b'=1}^{N_b} \frac{(C_{bi} - C_{b'i})}{n_i d_{bb'}} - r_i C_{bi} \tag{5}$$

where w_{ij} is the element of an interaction matrix and f_{ij} is the update function that is usually a sigmoid function. Turing did his pioneering work showing that by using two morphogens it is possible to generate complex patterns [120], where one morphogen serves as an activator and activates both itself and the other one, while the second morphogen, called inhibitor, inhibits the expression of activator. To generate stable periodic pattern, the diffusion rate of the inhibitor needs to be larger than that of the activator.

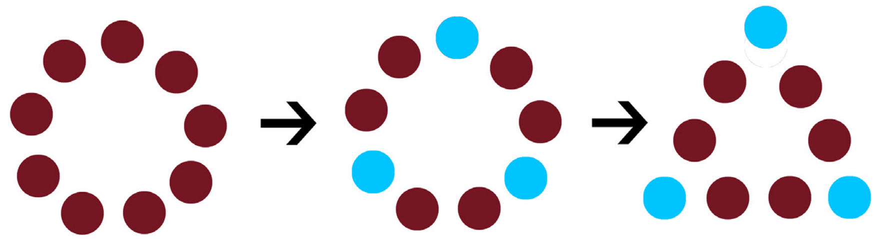


Fig. 11. Generation of polygonal pattern formation from a circle pattern produced by Turing reaction–diffusion mechanism. Each coloured circle represents an individual agents connected locally with its adjacent neighbours. Blue circles denote agents with higher morphogen concentration after Turing reaction–diffusion mechanism [141]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The Turing reaction–diffusion model aroused considerable interests in the field of pattern formation and self-organising systems [138,139]. Shen et al. [140] proposed a simple distributed control algorithm based on Turing reaction–diffusion model. Two hormones, an activator and an inhibitor, are distributed between agents, which are assumed to be locally connected via short range wireless communication. The agents can measure the distance and direction of other agents in their sensing range. The sum of these two hormones is interpreted as a repulsion or attraction force. They implemented pattern formation using these two hormones and other implementation like searching and seizing a target and self-repairing. They ran a simulation as a proof of concept for the proposed algorithm.

Ikemoto et al. [141] generated polygonal patterns such as triangle, quadrangle and hexagon by applying the Turing theory using a group of robots. In their algorithm, once a circle pattern is formed by the robots, two morphogen-like signals exchange between the robots and interact with each other through a set of reaction–diffusion differential equations. Eventually, a discrete Turing pattern is generated on the circle. In Fig. 11, robots with maximum concentration are depicted in blue and by moving the position of these robots slightly inside or outside of the circle according to their signal values, several polygonal patterns can be generated. The algorithm has been validated using up to twelve autonomous mobile robots, named MK-01.

The capability of Turing pattern in swarm robotic pattern generation has not been explored thoroughly. Fig. 12 illustrates the generation of strip pattern in a swarm using Turing pattern. Consider that the attraction and repulsion forces between the robots are a function of the morphogen concentration. In this manner, this strip pattern can lead to the generation of a wave shaped swarm pattern autonomously without using any pre-existing positional information from random initial conditions. However, the difficulty of using Turing pattern with one activator and one inhibitor is that the pattern is not precisely controllable. Moreover, patterns which are generated with the same parameters are not exactly the same through the different iterations/generations. Adding more morphogens can increase the reliability and the precision of generated patterns [142].

3.3. Gene regulatory network

By introducing more morphogens into a system, the complexity of the control of the expression and the regulation of morphogens increases rapidly. In biological organisms, the regulation of interactions between genes, proteins and morphogens is encoded into the genome of organism's cells. In a multi-cellular organism, all cells have the same genome, but changes in the arrangement of activated and silenced genes differentiate the behaviour and the functionality of each cell and regulate the expression of genes. Activation of genes can trigger cell actions such as cell migration, differentiation, division, realising proteins and chemical signals, programmed cell death and so on [129,143]. Proteins also are products of genes and are responsible for signalling, sensing, actuation, bounding and so forth. This process is known to be governed by gene regulatory networks (GRNs), models of genes and the interaction of gene products that describe the gene expression rate dynamics [144], where coupled differential equations in Eq. (5) can be used as one type of GRN model. However, note that real GRNs are much more complex and contain many units other than genes. More realistic GRNs have been analysed by several methods such as probabilistic Boolean networks [145] and emergence of negative feedback [146].

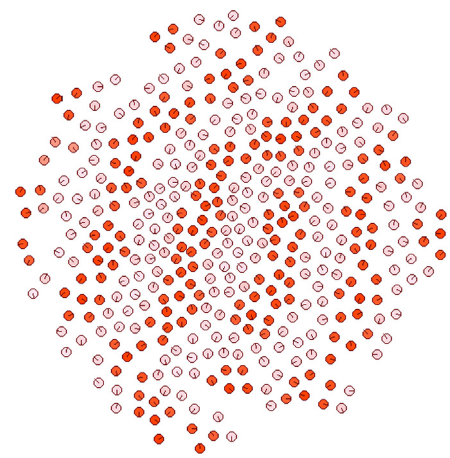
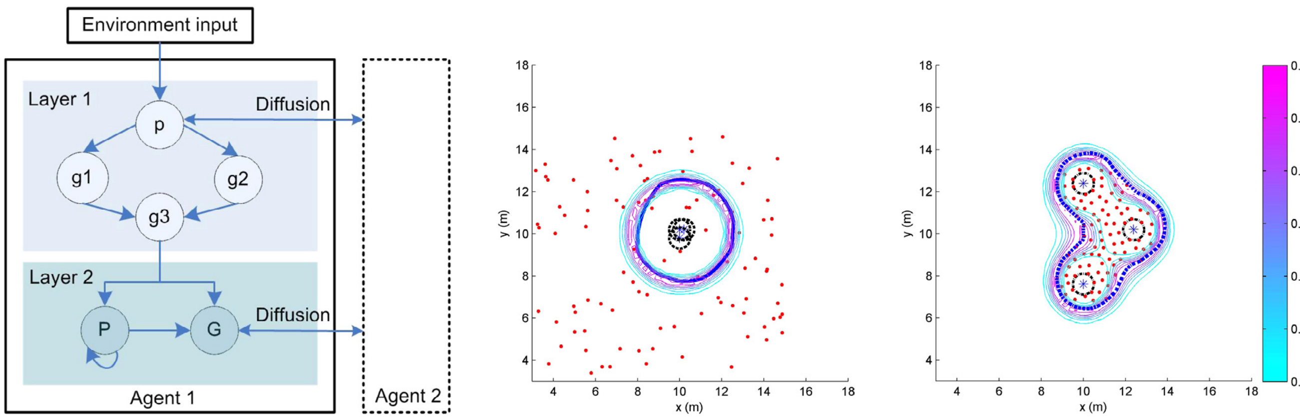


Fig. 12. Creation of a strip-like pattern in a circular swarm using Eq. (5). The circles represent the simulated robots and the saturation of red colour denotes the activator's concentration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Implementation of GRNs in swarm robotics is an emerging field that has received increased attention in recent years [147–149]. Taylor et al. [150] combined a GRN and a cell adhesion model (CAM) and introduced a new control method GRN–CAM to control a group of underwater spherical robots called Hydrons. Hydrons can propel themselves horizontally by impelling and ejecting water, and vertically using a buoyancy control system. They simulated the controller performance for 2-D case of clustering and task differentiation and compared it with a GRN-only controller. They observed that the GRN–CAM controller is more efficient to produce complex patterns.

Guo et al. [151,152] applied GRNs to multi-robot pattern formation. In their algorithm, each agent has a GRN containing two genes that produce two proteins which control x and y directions of the agent. Moreover, to avoid collision, the agents and the obstacles secrete proteins into the environment that can be sensed by other agents. These proteins, produced by the GRN, drive the agents to the boundary of a desired shape in order to evenly distribute them over the boundary and prevent them from colliding with each other or with obstacles in the environment. The gene expression is controlled by a function that is defined by the desired shape.



(a) Block diagram of a H-GRN structure. (b) Initial configuration. (c) Final configuration.

Fig. 13. A hierarchical-GRN manipulates gene expression and controls robots movement to entrap the target [32,154]. Layer 1 is responsible for pattern generation and the layer 2 controls robot movement. The stars denote the positions of the targets and the dots represent the robots. The morphogens concentration is indicated by the contours.

They also optimised the regulation parameters considering agents' travel time and distance from their initial position to the final positions on the desired shape using multi-objective evolutionary optimisation. In simulations, they showed that GRN-based method for swarm robot pattern formation is insensitive to the parameter settings and robust to partial failures in the system and to environmental changes.

For a real swarm composed of robots with limited capabilities, access to a global coordinate system is challenging. To deal with this issue, Guo et al. [153] proposed a multi-robot pattern formation based on a GRN, where the robots find their way by establishing a local coordinate system. One robot is selected as a reference robot by competing each other. Then, the other robots form the pattern in a local coordinate system, where its origin is the position of the reference robot. The shape of the pattern is represented by a non-uniform rational B-spline (NURBS) and stored in robots' memory. Integrating pattern generation and navigation control, Jin et al. [32] introduced a two-layer GRN for multi-robot pattern formation to entrap targets in a dynamic environment as shown in Fig. 13. This hierarchical GRN structure was extended by Oh and Jin [154] to realise region coverage instead of boundary coverage. The first layer of the GRN regulates three genes in term of the proteins from targets, which generates the entrapping pattern (Fig. 13(b)) to be covered. The second layer inputs are output of the first layer in terms of protein concentrations and the proteins secreted from nearby robots. This layer regulates genes which determine the robots'location and internal states. In this study, moving targets and obstacles diffuse proteins-like signals into the environment. The robots follow the protein gradient to entrap the targets, where the shape of the pattern is adapted to the location of the targets. Moreover, robots themselves diffuse proteins in order to detect and follow each other and avoid collisions. It also helps the robots distribute evenly on the pattern's boundary or region as shown in Fig. 13(c). This algorithm has successfully been applied in a group of eight e-puck robots. Subsequently, Oh et al. [155] proposed an evolving GRN framework, called EH-GRN, in order to improve the flexibility of the pattern generation. The obstacles are introduced as one of environment input sources along with the targets in the EH-GRN, which addressed the weakness of H-GRN whose pattern is not able to be adaptable to obstacles.

Determining the GRN structure and the coefficients of differential equations is very challenging. Meng and Guo [156] studied an evolving GRN where an evolutionary algorithm determines the structure and coefficients of GRN by using frequently-recurring regulation patterns known as network motifs. However, all of these GRN frameworks left the question unanswered that how different structures affect the efficiency of pattern formation and how the coefficients will change the robots' behaviour.

Although morphogenesis is known to be able to generate highly complex organs in living beings, so far the patterns that can be achieved in morphogenetic robotics remain more or less simple. This raises the following questions: (i) how can more complex patterns emerge from a swarm of robots using morphogenesis? (ii) how can a multi-robot system dynamically switch between different patterns in a changing environment? (iii) and how can a swarm manoeuvre in the environment without losing its predefined pattern? To answer these questions, more advanced morphogenetic systems are needed where many morphogens react with each other according to certain local interaction rules and regulations. The relationship between genes can be expressed via a complex network which regulates these morphogens or gene relations. In the next session, we discuss this gene regulatory network approach.

3.4. Chemotaxis

Chemotaxis is a mechanism that guides cell movements, where cells release chemicals to their surrounding environment and other cells react to that by moving towards or away from it [157]. It plays an important role in the self-organising biological systems. Cell movement, aggregation and sorting which are important phenomena in pattern formation can be achieved by chemotaxis [158]. Fates and Vlassopoulos applied chemotaxis to a group of robots, named ALICE Robots, to generate aggregation behaviour in a dynamic environment [159]. Eyiyurekli et al. [160] used chemotaxis to separate two mixed types of agents in a simulation, so that eventually the agents form an aggregation in which the second type surrounds the first type of agents as shown in Fig. 14. In this algorithm, the first type of agents, which are depicted in red, secretes two artificial chemicals into the environment. The blue agents do not secrete any artificial chemicals but just react to chemicals secreted by the red agents with a delay to allow the red agents to aggregate at the centre. As can be seen in Fig. 14, it appears that some of the red agents are not surrounded by the blue ones. Changing the parameters used in the simulation can improve the separation property of agents in the sorted aggregation. To optimise these parameters, Bai et al. [161] introduced a metric to measure the quality of the aggregation formation and conducted a parametric study on this sorting algorithm.

It has been shown that chemotaxis is able to generate more complex patterns. Bai and Breen [162] designed an algorithm inspired by chemotaxis for a self-organising swarm of identical

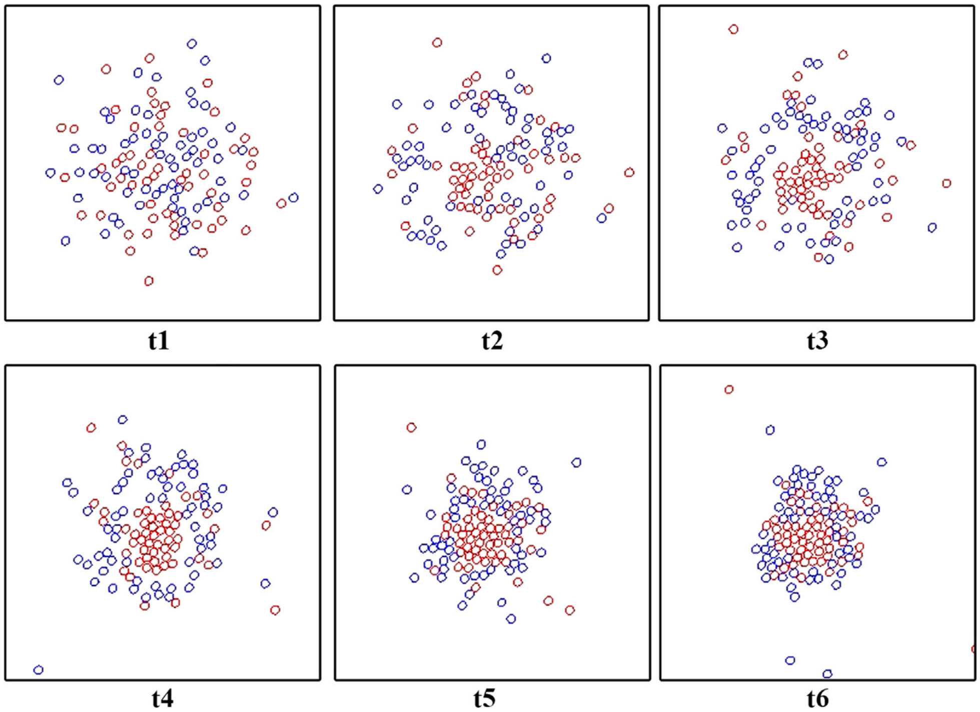


Fig. 14. Radial separation of two different types of agents using a chemotaxis inspired algorithm. At the first step, the red agents attract each other by emitting a chemical. At next step, the red agents emit a chemical that attracts blue agents. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

disc shape simulated agents. Each agent emits and detects chemo-attractant chemicals and changes its internal state according to them. They are capable of directional sensing using eight receptors, which are evenly placed around them. The agents can also detect their close neighbours' orientation and align themselves with them. There is no leader, seed or special region, and agents do not need to have knowledge about the shape which should be formed. The system works in two stages: at the first stage, information related to the desired shape is transformed to the local behaviours of the agents, and at the second stage, these local behaviours will create an aggregate compared with the desired shape. To accomplish the target of the first stage, the authors used an evolutionary method that takes the desired shape as an input and returns a field function that surrounds agents and directs them to form the desired shape. At each iteration of the optimisation, the similarity between aggregate and desired shape is evaluated to generate the next population of variables. The problem in this algorithm is that the field functions cannot always generate their associated desired shape and sometimes end up with unexpected shapes. The success ratio of the pattern generation is not reported in the paper.

Sayama [163] proposed Swarm Chemistry that is inspired from the chemical reactions amongst living cells. The author used Swarm Chemistry for a self-organising swarm of simple homogeneous agents, which means that the agents do not change and differentiate their types. The simulated agents can sense velocity, orientation and position of their neighbouring agents and perform simple actions such as steering towards the centre of the group of agents' or changing orientation to align themselves with others. In the simulation, the author studied a swarm composed of two or more different types of interactive agents that move and form patterns. Sayama, in his later works [22,164], included some other bio-inspired features to Swarm Chemistry including cell differentiation, self-repairing and recipe exchange. A recipe is a sort of record for all active and non-active sets of parameters which define the agent behaviour. In this way, a recipe is comparable with genome residing in the cell. When agents collide with each other, recipes are exchanged between them leading to a type differentiation. There is a competition function that defines which agent transmits its recipe and recruits the other agent. Mutation is also considered during the recipe transmissions.

4. Challenges and perspectives

4.1. Real world issues

Pattern formation algorithms in swarm robotic systems presented in the literature are developed primarily to be operated on collectives of a large number of robots. In reality, due to the constraints of the real world operation such as cost, time, and complexity of building and testing hardware systems, most research work has been performed in simulations only with an approximated model of sensors and robots, or experiments with a relatively small number of robots with few exceptions [165], where over 1000 kilobots have been used in experiments. Nevertheless, the robots move in a sequential order in these experiments, which alleviated the challenges to a certain degree. In general, the current simulation based approaches suffer from several issues.

First, it might be difficult to precisely model robot's interaction with each other and with the environments in simulations. For instance, where the robots are densely populated in the environment for swarm behaviours, physical action–reaction amongst robots combined with surface friction of the environment is hard to predict. Secondly, unknown robotic dynamics linked with an actuation system, sensing noise and disturbance from environments may seriously degrade the performance in experiments. In particular, as sensors typically provide uncertain and noisy measurements even in a stable condition, precise sensor modelling with a stochastic process as well as advanced signal processing such as the Kalman filtering and sensor/data fusion [24,166] techniques are necessary for many cases. In addition, computation capability of a simple autonomous robot having a limited memory capacity can be a bottleneck to run the developed algorithm based only on numerical simulations in a hardware in real time.

Second, in most multi-robot pattern formation systems, some form of wireless communication network is required for the local agents to obtain neighbours' information for the group formation and surrounding environments. In this networked system, an intrinsic problem is that the network structure and properties can affect the performance of formation, and even make the system unstable while forming a pattern due to communication delay, packet loss, inconsistent connection with other robots' communication nodes, or other noise sources [167]. col Although some work has been done on performance analysis of pattern formation to mitigate networking issues considering such kind of adverse conditions as in [168,169] and those mentioned in Section 2.2, the performance evaluation of pattern formation control has hardly been addressed with real robots and network environments [167]. The design methods for swarm pattern formation and network systems have to be combined to provide more realistic algorithms and results.

Finally, experimenting bio-inspired algorithms designed for swarm behaviours using only a small number of robots may not be sufficient as it could contain scaling issues, which can be realised in only a large-scale collective system [128]. Thus, to rigorously examine swarm pattern formation algorithms, it would be essential to test them on a larger scale of real robotic systems. As mentioned above [165], interesting experimental results involving over 1000 kilobots have been reported, which is a great step forward towards large-scale swarm robot systems. This does not mean, however, the challenges of experimenting with a large number of real robots have been addressed. More discussions about large-scale swarm robotic systems will be provided below.

4.2. Robotic platforms suited for large-scale swarm systems

Regarding real swarm robotic test-beds, the e-puck robots are one of the most widely used and also commercially available options [170]. An e-puck robot contains eight infrared communication sensors (with a maximum sensing range of 25 cm at a maximum rate of 30 bytes per second when using a *liblrcom* library) and a colour camera built around a Microchip dsPIC (a combination of a micro-processor and a digital signal processor) allowing the implementation of sophisticated self-organising algorithms. However, as it costs over 600 pounds, only a few tens of robot are used in a research project [171–173]. In addition, there is no scalability in charging or programming the robots, which means that each robot should be turned on and off or programmed one by one, requiring a considerable preparation time.

Jasmine robot [106] may be suited for pattern formation with their relatively cheap cost and essential sensing and communication (maximal and minimal ranges of 20 cm and 10 cm, respectively, at a rate of one kilobit per second) abilities such as distance, bearing and light colour with reasonable computation power (with two micro-controllers). Despite not being commercially available, it is developed as an open source project (for both hardware and software) allowing users to create a simple but cost-effective robotics system [174].

In the Kilobot project [165,175], Rubenstein et al. addressed the issue of system size, pointing out that for technical reasons of hardware cost and complexity, most robotic swarms contain a few tens of robots at most. To reach higher numbers, they designed robot units made of cheap parts that are easy to assemble. This made it possible to test swarm algorithms using collectives of robots of an order larger than that of existing systems. More importantly, to make the system scalable to the large number of robots, an overhead infrared transmitter is developed to be programmable so that the power can be switched on and off and the program can be uploaded in a batch of tens of robots simultaneously. However, the capability of the robot platform is quite limited. For example, the kilobots doe not have the capability of self-localisation and directional sensing. In addition, the kilibots have range sensing only and communication range of the kilobots is 7 cm at rates up to 30 kilobits per second. Finally, kilobots can move only slowly and inaccurately due to vibration motor control without a wheel mechanism. They also need a lot of space to make a turn.

The droplet [176], an open-source swarm robotic platform is developed, which falls in size, cost and capability between aforementioned Kilobot and the e-Puck. Similar to Kilobot, it uses three vibration motors which allow omnidirectional motions. Six emitters and receivers (leading to a 6 by 6 matrix of pairwise intensity measurements) are used to provide the accurate range and bearing sensing even for robots within close proximity. Besides, this platform solves the problem of charging a large number of robots using a powered floor that is equipped with alternating stripes of positive charge and ground providing continuous power during the experiment.

Further information on a wide range of other existing mobile swarm robots can be found in [170,175,177]. Table 1 shows the comparison amongst some of swarm robotics test-beds in which the structure of the table is borrowed from [175]. As there exist obvious trade-offs between the cost and the capability of the robot platform such as movement and sensing capability, an adequate robotic test-bed needs to be carefully determined depending on the requirement of a specific pattern formation algorithm.

4.3. Guided or programmable self-organisation

It is worthwhile to point out that some emergent behaviours can be unpredictable and may be undesirable in self-organising systems. For instance, in Swarm Chemistry framework [22], arbitrary patterns arise as emergent self-organising phenomenon from interactions between swarm particles rather than being able to generate task-driven or desired complex shapes. As a design strategy, it is useful to endow system components or each agent with local rules intended to yield desired global pattern formation. Here, the new challenge is how the agent's local-rules can be inferred from the systems' global objectives. This will be answered by directing the decentralisation, in turn, finding out the conditions favourable to a non-random, reliable self-organisation of a highly distributed system. This is termed as programmable [183] or guided self-organisation (GSO) [184].

GSO aims to achieve design or planning processes with predictable results, whereas the pure self-organisation may result in non-deterministic and spontaneous dynamics with emergent behaviours. Including and controlling constraints on self-organisation is one possibility to guide the swarm system by applying constrains on the scope of the self-organising structures and functions. Utilising the specified rate of the internal dynamics or selecting a certain subset of all possible trajectories that the dynamics may provide would be alternatives. In the same context, Doursat et al. [183] introduced openness and solution-rich space of meta-design towards not building an entire system directly but shaping its building blocks in such a way that these blocks can build the system by themselves, which could result in unexpected yet innovative systems that have never been imagined by users.

Recently, several ideas have been proposed for achieving GSO within the context of information theory and dynamical systems, such as universal utility function [185], information driven evolution [186], recurrent neural networks [187], robust overdesign [188], reinforcement-driven homeokinesis [189], and predictive information [190], just to name a few. Among them, only a few were applied to robotic swarm systems. Martius and Herrmann [191] uses GSO for designing robot controllers by combining

Table 1
Comparison of swarm robotics test-beds.

Robot	Cost (GBP)	Scalable operation	Sensing	Locomotion	Size (cm)	Battery (h)
Alice [178]	30[a]	None	Distance	Wheel, 1 cm/s	2	3.5–10
Kilobot [175]	10[a]/80[b]	Charge, power, program	Distance, ambient light	Vibration, 1 cm/s	3	3–24
Formica [179]	15[a]	None	Ambient light	Wheel	3	1.5
Jasmine [106]	90[a]	Charge	Distance, bearing, light colour	Wheel	3	1–2
E-puck [170]	450[a]/600[b]	None	Camera, distance, bearing, IR proximity, acc, encoders	Wheel, 13 cm/s	7.5	1–10
R-one [180]	150[a]	None	Visible light, accel/gyro, IR sensors, encoders	Wheel, 30 cm/s	10	6
Droplets [176]	25[a]	Charge	Distance, bearing, ambient light, RGB colour	Vibration	4.4	–
iRobot [181]	–	Charge, power, program	Camera, distance, bearing, bump	Wheel, 50 cm/s	12.7	3
Swarm-Bot [182]	–	None	Camera, distanc, bearing, proximity, accel/gyro	Treel	17	4–7

[a] Part cost only.
[b] Selling price.

goal-oriented learning and developmental self-organisation. They introduced three mechanisms of GSO using: (i) online external rewards to shape the emerging behaviour, (ii) a problem-specific error function with supervised leaning signals (termed teaching signal), and (iii) assumptions about the symmetries of the desire behaviours with cross-motor teaching. It is shown that the teaching signal is an effective way to provide useful constraints to facilitate the unsupervised development of specific behaviours. Ay et al. [190] considered predictive information in sensor space as a measure for the behaviour complexity of a two-wheel robot, and used it as an objective function for the self-organisation of robot behaviour. Rodriguez [192] introduced hybrid control to guide the self-organisation process allowing the global behaviour of the system to be partially directed in a more predictable manner without resorting to actual global behaviour. This hybrid control is done with a layered architecture: the bottom layer is reactive controllers which produce global self-organising through local interactions between groups of agents, and the top layer comprises an abstract representation of the problem, necessary actions or sub-goals, and is capable of adjusting the bottom layer according to these goals. More recently, it has shown that in the presence of delay, network topology can be used to create novel dynamic pattern forming swarms [193]. The new states are combinations of many of the states observed in swarming and flocking systems. The application using network topology as a control of pattern formation, density for surveillance, and the ability to switch between many patterns is enormous. However, it is still difficult to find many examples of GSO designed specially for pattern formation, which remains as future work.

5. Concluding remarks

This paper provides a review of bio-inspired pattern formation algorithms within the context of mobile multi-robot systems. The basic idea behind most bio-inspired algorithms is that complex behaviours can be achieved by simple interactions between agents with limited capabilities and information. Agents do not need global awareness such as the status of all other agents or their global position, and there is no need for centralised control to allocate tasks to individual robots. In such systems, robots behave simply based upon local information and interaction with their neighbours.

Despite abundant research work on bio-inspired pattern formation problems with their benefits, there are also limitations and unresolved issues. A deep understanding of self-organising systems that can allow us to design a guided self-organising system to yield desired global pattern formation, is still missing. In addition, it is difficult to rigorously analyse stability or convergence of the entire swarm patterning system using bio-inspired algorithms since they are a heuristic approach inspired by the observation of animal behaviours or cellular mechanisms, which has many unexplored or hidden parts in the end. Some self-organising patterning based on reaction–diffusion or GRNs might require a significant computation effort to optimise the relevant parameters in complex and coupled differential equations.

As future work, one interesting problem in decentralised self-organising swarm robotic systems would be human–swarm interaction on how a user can change the functionality of a swarm while it is still running. Another problem of interest is the designing a feedback loop in a self-organising swarm so that a swarm can obtain a global knowledge of the group itself and individuals can adjust their behaviour according to the feedback. In addition, verification of the performance of self-organisation algorithms in real experiments rather than only numerical simulations and application of the algorithms in a large-scale (over a hundreds or even thousands) multi-robotic system remain as future work.

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