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Review of flocking organization strategies for robot swarms

Revisión de las estrategias de organización en bandadas para enjambres de robots

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Robotics promises great benefits for human beings, both at the industrial level and concerning personal services. This has led to the continuous development and research in different problems, including control, manipulation, human-machine interaction, and of course, autonomous navigation. Robot swarm systems promise an alternative solution to the classic high-performance platforms, particularly in applications that require task distribution. Among these systems, flocking navigation schemes are currently attracting high attention. To establish a frame of reference, a general review of the literature to date related to flocking behavior, in particular, optimized schemes with some guarantee of safety, is presented. In most of the cases presented, the characteristics of these systems, such as minimal computational and communication requirements, and event-driven planning, are maintained.

Keywords: Emergence, flocking, multi-agent systems, path planning, swarm systems

La robótica promete grandes beneficios para el ser humano, tanto a nivel industrial como con respecto a servicios personales. Esto ha incidido en el continuo desarrollo e investigación en diferentes problemas, entre ellos el control, la manipulación, la interacción hombre-máquina, y por supuesto, la navegación autónoma. Los sistemas de enjambres de robots prometen una alternativa de solución frente a las clásicas plataformas de alto de desempeño, particularmente en aplicaciones que requieren distribución de tareas. Entre estos sistemas, llama la atención los esquemas de navegación en bandada, los cuales tiene actualmente una alta atención. Para establecer un marco de referencia, se presenta una revisión general de la literatura a la fecha relacionada con comportamientos en bandada, en particular esquemas optimizados y con alguna garantía de seguridad. En la mayoría de los casos presentados se mantienen las características de estos sistemas, como son requisitos mínimos de computación y comunicación, y la planificación basada en eventos.

Palabras clave: Bandada, emergencia, planificación de trayectorias, sistemas de enjambre, sistemas multiagentes

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Introduction

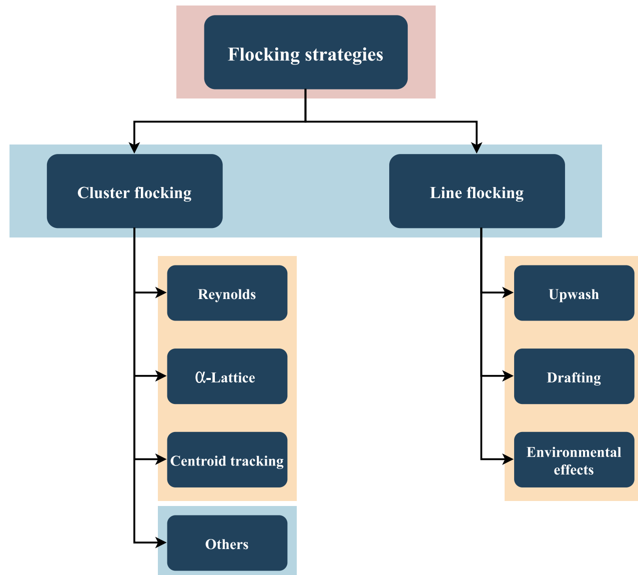
It can be stated that the study of swarm behavior in multi-agent systems started from the three heuristic rules proposed by Reynolds in 1987 (Reynolds, 1987). This model is known as Reynolds' classical behavior and is based on two measures of the multi-agent swarm, the area of the group and the polarization. From these measures, the model proposes the design of applications, and it is possible to observe the variation in the behavior of the system by varying the individual values of these parameters. From these ideas, initially simulated by computer, several applications of robotic flocking involving coordinated delivery, reconnaissance, surveillance, and mobile sensor networks have been proposed (Martínez & Delgado, 2012; Semnani & Basir, 2017; Xiao et al., 2018; W. Yuan et al., 2020). These ideas have been able to take advantage of the most recent advances in processing power and low energy consumption to implement robotic swarm applications with high adaptability, scalability, and robustness (Martínez et al., 2018; Oh et al., 2017). Even so, research in this field remains an open engineering problem due to the constraints imposed by a large swarm, both in control and cost. A robot, or agent, in a multi-agent system, must be endowed with limited sensing, communication, actuation, memory, and computational capabilities. Size concerning the environment and the task is also very important, and everything must fit together with optimized power consumption schemes.

Flocking behavior emerges as a consequence of specific rules executed individually by each agent. In this sense, many researchers have proposed decentralized control alternatives that lead to flocking behavior (Barve & Nene, 2013; Bayındır, 2016; Zhu et al., 2016). Much of the early work in this direction was proposed to demonstrate the functionality of the system, without considering optimal operating conditions. It was normal at the time to consider the self-organization problem and the optimal performance problem as two independent problems (Fine & Shell, 2013). More recent design approaches consider the two problems as simultaneous design objectives, thus requiring a single design scheme (Beaver et al., 2020; Wilson et al., 2020).

If we think of a way to classify the different flock control schemes, it is correct to refer to the very characteristics of this behavior in biological systems, the initial source of inspiration. From this point of view, it is possible to separate the behavioral models into two categories. The first category is characterized by group flocking, or cluster flocking, as observed, for example, in the movement of sparrows. The second category has different grouping rules and resembles more the movement on a line, known as line flocking, for example in the movement of geese (Fig. 1). This same classification is used in this paper to characterize the different schemes found in the literature. As in different groups of birds, different flocking behaviors have different applications, and of course, different behavioral rules and implementation. Even so, engineering schemes can be much richer in options and implementations than those found in nature.

Figure 1

Flocking strategies according to clustering form (Beaver & Malikopoulos, 2021).



Our research focuses more on cluster approaches, yet this review presents the two flocking models as an important starting background. There are also limitations of technical content in the compilation due to the restricted space available. In any case, the details and fundamental concepts of each case are presented, and the future development of this field of research is projected.

Problem statement

A robot swarm is a multi-agent system whose behavior emerges as a consequence of simple rules executed by each agent in response to events or stimuli detected in the environment. This system is composed of $N \in \mathbb{N}$ agents from a finite population indexed by the set $\mathcal{A} = \{1, 2, 3, \cdots, N\}$. Each of these agents is assigned position and velocity properties in the navigation environment $\mathcal{W} \subset \mathbb{R}^2$. The position of the agent i is defined by the vector $\boldsymbol{p}_i(t)$, and its velocity by the vector $\boldsymbol{v}_i(t)$, both parameters defined in the interval $t \in \mathbb{R}_{\geq 0}$. The environment $\mathcal{W}$ is compact and planar, with a limiting boundary $\partial\mathcal{W}$ that restricts the motion of the agents. The agents are small concerning $\mathcal{W}$, so they are modeled as points with specific kinematics. The state of

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each agent is defined by the state vector $\boldsymbol{x}_i(t)$, so the state of the system is set by Eq. 1.

$$\boldsymbol{x}(t) = \left[\boldsymbol{x}_1^T(t), \boldsymbol{x}_2^T(t), \cdots, \boldsymbol{x}_N^T(t)\right]^T \tag{1}$$

The state of each agent is not explicitly controlled, which is why it is not important to measure its state precisely. Instead, the coordination of the system is relegated to the fact that the agents satisfy a trajectory that follows some high-level property. For any region, $R \in \mathcal{W}$ it is assumed that each agent moves on a trajectory according to the behavior of the neighborhood of robots $N_i(t) \subseteq \mathcal{A}$ to which it belongs. This neighborhood is formed by all agents near agent i that agent i can sense and/or establish communication with, including agent i. Consequently, the neighborhood can be defined in different ways according to the coordination strategy of the system, which includes distance between agents, information radiated by the agents, k-nearest neighbors, geometric partitions of the environment, or specific landmarks in the environment. The neighborhood of an agent is in general a fraction of the system but can encompass all agents depending on the specific topology.

The obstacle set $\mathcal{O}$ consists of a finite number of inaccessible regions in $\mathcal{W}$. These regions are enumerable, closed, and share the same properties as $\partial\mathcal{W}$ in that they limit the movement of agents. The free space through which the agents can navigate is defined as $E = \mathcal{W} - \mathcal{O}$. The control of the agent i is developed during the evolution of the system according to a policy. State feedback is not performed in general, instead, information feedback is performed using filters. A filter is a mapping of the form $\phi : \mathcal{I} \longrightarrow Y$ where $\mathcal{I}$ corresponds to the information space that is designed for the task (Bobadilla et al., 2012), and is defined with each observation Y of the agent.

Clusters and swarms

In biology, the movement of small birds in groups is known as cluster flocking (Sankey & Portugal, 2019). Among the advantages of this type of joint movement, it is postulated that it facilitates predator avoidance by extending the sensing range and rapid group communication of the swarm. It is also believed to serve the system to estimate population size and coordinate collective actions. These hypotheses are under investigation, as well as whether or not this type of navigation requires a leader (hierarchical flocking). All these cases are considered equally in this review.

A group of continuously moving agents forms a flocking cluster if there is a finite distance between any pair of agents in the swarm for an instant and all agents in the swarm. The fact that the agents remain within a defined diameter is what defines the cohesion parameter of the swarm. In addition, the agents must converge continuously over time, but without explicit formation. Each agent in the system can detect some other neighboring agents at a certain instant of time, according to its sensing and communication capacity (partial observation). From this information, it must establish its relative location in the system and its movement strategy. Consequently, most cluster flocking strategies simulate the continuous update of the control policies of each agent, while evaluating the overall cost of the system (energy and task time) (Martínez et al., 2012).

Undoubtedly, the cluster flocking scheme with the largest number of implementations in the specialized literature is the one that seeks to replicate Reynolds' basic behavioral rules (Reynolds, 1987): collision avoidance, velocity matching, and flock centering. The simplest way to implement these rules is to apply a cost function J to each agent consisting of two parts, a first one in charge of collision avoidance, and a second one with the task of guaranteeing the velocity alignment of the agent. If the relative position between two agents of the system $i, j \in \mathcal{A}$ is defined as (Eq. 2):

$$\boldsymbol{s}_{ij}(t) = \boldsymbol{p}_i(t) - \boldsymbol{p}_j(t) \tag{2}$$

Then, the cost function for agent $i \in \mathcal{A}$ with respect to agent $j \in N_i(t)$ (the neighborhood of agent i at instant t), can be defined in general form as follows (Eq. 3):

$$J_i = V\left(\left\|\boldsymbol{s}_{ij}(t)\right\|\right) + \sum_{j \in N_i(t)} \left\|\dot{\boldsymbol{s}_{ij}}(t)\right\|^2 \tag{3}$$

Since V is in charge of avoiding collisions, this function is configured as a potential field that defines local attraction-repulsion forces for agent i with respect to its neighborhood $N_i(t)$. Eq. 3 allows defining the motion strategy of agent i from the instantaneous location of the neighboring agents (Fig. 2).

One such group behavior scheme is α-lattice (Olfati-Saber, 2006). In this algorithm it is proposed to use a distance d that minimizes the potential field defined by V, and which is set as the distance that any agent $i \in \mathcal{A}$ must satisfy concerning its neighbors $j \in N_i(t)$, that is (Eq. 4):

$$\left\|\boldsymbol{s}_{ij}(t)\right\| = d \tag{4}$$

Since this definition coincides with the global minimum of the cost function J, it is widely used in many schemes to define the flocking rules in multi-agent systems, differentiating each strategy in the motion planning algorithms. In this sense, two approaches can be differentiated, those with reactive behavior without prior knowledge of the environment, and planning approaches that use some a priori information from the environment. In the first group, agents consider local information, including the behavior of their neighbors, to establish a movement strategy while respecting the basic rules of flocking (Morihiro et al., 2006a, 2006b). This local information usually comes from the state detected in the neighbors, which is continuously

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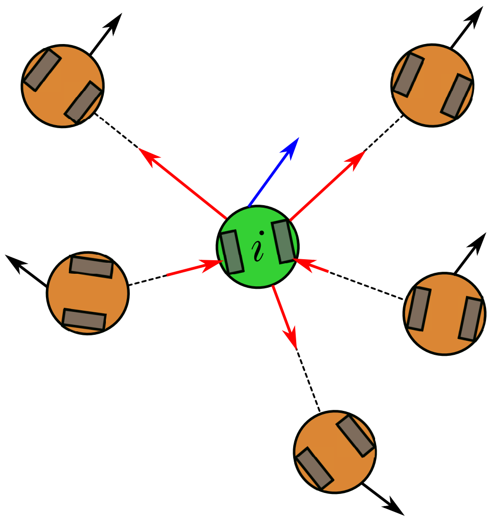
Figure 2

Definition of the movement strategy of agent i based on the behavior of its neighboring agents.



updated, but in other schemes predator information is included as additional populations to force movement or global references in the environment (C. Wang et al., 2018) to avoid sub-groups of agents in the system (Camperi et al., 2012; Fine & Shell, 2013).

In these reactive strategies, considerable work has been done on the problem of optimal Reynolds rule-following. In this sense, schemes have been proposed with constraints on the system states (Qiu & Duan, 2020), estimation of the possible optimal states of the agents from models based on neural networks (Navarro et al., 2015), constraints on the control inputs (Celikkanat, 2008), and constraints on the environment and the agents (Vásárhelyi et al., 2018). In the vast majority of these investigations, navigation is ensured by avoiding collisions based on the computation of potential field strengths. However, this strategy has widely known convergence problems, which brings this problem back to the research field in schemes in which the agent's motion is restricted to safe trajectories that minimize its energy consumption (constraint-driven approach) (Egerstedt et al., 2018; Ibuki et al., 2020).

As an alternative to reactive strategies, there are also planning approaches in which each agent plans an optimal trajectory based on the information it already possesses from the environment and its neighbors. In general terms, this type of strategy presents a better behavior of the agent in terms of performance (convergence and movement), but at a high computational cost, which poses much higher requirements for the design of each agent. It is also important to note that these schemes, by concept, do not have a central control system, so the update of the system information along the agents is very complex, opting for state estimation schemes (Dave & Malikopoulos, 2020; Nayyar et al., 2013). These problems are solved in some cases by establishing communication links between nearby agents (Morgan et al., 2016), limiting planning to only a few agents in the system among which information is shared (Dave & Malikopoulos, 2019), and applying predictive models in which agents recalculate their strategy each time they obtain new information from the system (Jafari et al., 2020; Xu & Carrillo, 2017; Q. Yuan et al., 2017; Zhang et al., 2008).

Within optimal control research, the center-of-mass tracking problem has become popular. This is a general approach to many engineering problems, but in the specific case of cluster flocking it seeks to define the center of mass of the swarm (virtual leader), which must follow the reference trajectory, and whose state is always known to all agents. This design concept is addressed by including a term in Eq. 3 that allows for the reference's state to be followed and thus can be solved using both reactive and planned schemes. As a result, the general Reynolds flocking rules hold, i.e., each agent only handles the information of its neighborhood, so the virtual leader tracking problem becomes an optimization problem because no agent handles the state information of the entire system globally (Hayes & Dormiani-Tabatabaei, 2002; La et al., 2015; La et al., 2009).

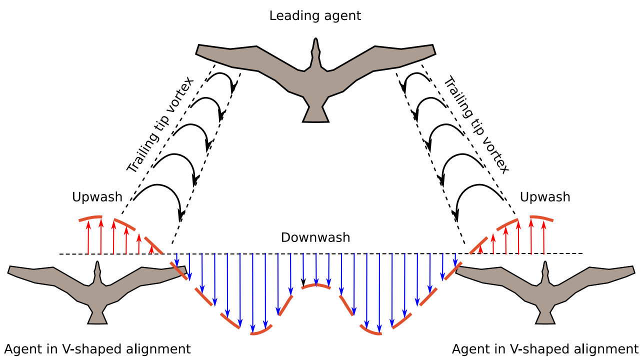
Line flocking

Line flocks are behaviors observed in certain birds, such as geese, in which agents travel in a V-shape, not in an unshaped cluster of agents. This behavior is observed in some large birds in migratory processes and has been determined to have large energy savings for individuals when traveling long distances (Gatt et al., 2020; Kölzsch et al., 2020). This energetic characteristic is what makes it interesting for multi-agent systems in the development of tasks that require large displacements, and the inability to recharge along the way. The advantage in birds lies in the possibility of suspending themselves in the ascending winds caused by the leading bird, reducing their energy consumption (Fig. 3). Similar advantages are found in other types of displacements such as terrestrial and underwater, such as the possibility of taking advantage of the low-pressure wake that the leading agent leaves behind it to reduce the force required by the other agents in the system (Beaumont et al., 2017; Ouvrard et al., 2018).

To reach line flocking in an artificial system, the shape of the swarm is more important than the distance to its neighbors. To achieve this simply, it is common to define formation points based on the characteristics of the system, i.e., the wake that each agent produces when moving in the environment for which it has been designed (Nathan & Barbosa, 2008). This is a new control problem, in which

Figure 3

Low-pressure effect on the line flock. The flock leader induces upwash and downwash in its wake with its wings and tail, which are used by the other birds to sustain themselves and reduce energy costs.



the important thing is that each agent reaches its formation point in the time defined for it (in most cases, the shortest possible time) (Mirzaeinia et al., 2019). This type of control is complex to perform autonomously by each agent, which in general changes the control structure to a centralized one (W. Wang et al., 2020; Yang et al., 2018). Moreover, in the biological model, birds consider the particular characteristics of each agent to establish its position in the flock, such as age and size, elements that become meaningless in the artificial approach, since in principle all agents are identical, so in general their position in the flock is fixed. Schemes of reconfiguration of the agents in ways other than V-formation are outside the focus of this research and are therefore not documented. It is worth noting, however, that there is a variant of line flocking that also seeks energy savings in agent displacement while taking into account the aerodynamic and hydrodynamic interactions between the agents (Bedruz et al., 2019). This criterion can be used to define an agent's ideal distance from its neighbors, and thus a flock structure that meets the requirements of line flocking.

Interestingly, however, some works show that line flocking emerges as a consequence of simple rules executed by each agent, as occurs in cluster flocking (Yang et al., 2016). For this behavior to emerge, it is necessary to adjust the direction and velocity of each agent according to the upwash vectors, while minimizing the occlusion of the sensing field of each agent by the agents producing the low pressure. This approach somehow achieves a meeting point between the cluster and line schemes, showing that the difference between them lies in the objectives to be maximized in the self-organization policies of the system. Following this same principle, it is possible to adjust the agent's movement rules to respond to environmental conditions of wind and turbulence (Song et al., 2017). When the environment is particularly hostile and changing, moving against the current results in higher energy consumption, whereas taking advantage of these flows, even when it means changing the direction of travel slightly, can result in considerable energy and time savings in the end (Alam et al., 2018).

Other cluster flocking

This section is devoted to a set of approaches that have demonstrated flocking behavior without strictly following the basic Reynolds behavior rules. We have already discussed that line flocking can come to be considered a particular case of cluster flocking, but in the investigations described here similar behavior to cluster flocking is achieved (hence its location in Fig. 1) without using the same design approach. This is the case of a system that uses local measurements not directly related to neighboring agents to estimate the movement strategy of each agent to maximize the speed of the virtual leader (Vatankhah et al., 2009). Another case with a similar approach worth mentioning uses the anisotropy in the angle between neighbors as a flock structure estimation parameter (Makiguchi & Inoue, 2010).

Another approach proposes deriving each agent's movement from the ergodic trajectories defined by the other agents, which is equivalent to a mass vector of the system over time, and using this information to estimate which positions in the environment the system has visited (Veitch et al., 2019). This, however, does not guarantee flock behavior, which is why they supplement the scheme by limiting the agents' positions to the interior of a circle. There are also approaches in which the force driving the movement of the agents comes from somewhere other than the environment or other agents (Genter, 2017).

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Conclusion

The last two decades have shown a great deal of research activity related to multi-agent systems with flocking behavior. Much of this work is derived from the basic control rules postulated by Reynolds, with variations that seek to improve the behavior of the system throughout a task, optimize its displacement, energy consumption, and even its cost through the use of hardware of smaller computational capacity and size. Although centralized control schemes

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exist, the original idea derived from the biological model prevails, in which each agent autonomously defines its movement strategy based on its readings and control rules. Although it is possible to categorize the different proposals for flocking schemes, the fact is that they all respond to specific control rules based on the information that the agent gathers from its neighborhood, the environment, or external elements. This is true even for schemes that do not strictly follow Reynolds' behaviors. This remains an area of great research interest, but there are still unsolved problems regarding the information required for control, its processing, availability, and performance in terms of time and energy.

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