Consensus-based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles*

Raffaele Carli[1 [0000−0001−9184−6017]], Graziana Cavone[1 [0000−0001−7102−4542]], Mario Di Ferdinando[2 [0000−0001−5815−3083]], Nicola Epicoco[2 [0000−0003−0189−8716]]✉, Paolo Scarabaggio[1 [0000−0002−4009−3534]], and Mariagrazia Dotoli[1 [0000−0003−1459−3452]]

[1] Dept. of Electrical and Information Engineering, Polytechnic of Bari, Bari, Italy
{raffaele.carli, graziana.cavone, paolo.scarabaggio, mariagrazia.dotoli}@poliba.it

[2] Center of Excellence DEWS, Dept. of Information Engineering, Computer Science and Mathematics, University of L'Aquila, L'Aquila, Italy
{mario.diferdinando, nicola.epicoco}@univaq.it

Abstract. Multiple Unmanned Aerial Vehicles (multi-UAVs) applications are recently growing in several fields, ranging from military and rescue missions, remote sensing, and environmental surveillance, to meteorology, logistics, and farming. Overcoming the limitations on battery lifespan and on-board processor capabilities, the coordinated use of multi-UAVs is indeed more suitable than employing a single UAV in certain tasks. Hence, the research on swarm of UAVs is receiving increasing attention, including multidisciplinary aspects, such as coordination, aggregation, network communication, path planning, information sensing, and data fusion. The focus of this paper is on defining novel control strategies for the deployment of multi-UAV systems in a distributed time-varying set-up, where UAVs rely on local communication and computation. In particular, modeling the dynamics of each UAV by a discrete-time integrator, we analyze the main swarm intelligence strategies, namely flight formation, swarm tracking, and social foraging. First, we define a distributed control strategy for steering the agents of the swarm towards a collection point. Then, we cope with the formation control, defining a procedure to arrange agents in a family of geometric formations, where the distance between each pair of UAVs is predefined. Subsequently, we focus on swarm tracking, defining a distributed mechanism based on the so-called leader-following consensus to move the entire swarm in accordance with a predefined trajectory. Moreover, we define a social foraging strategy that allows agents to avoid obstacles, by imposing on-line a time-varying formation pattern. Finally, through numerical simulations we show the effectiveness of the proposed algorithms.

Keywords: Unmanned aerial vehicles · Swarm intelligence · Trajectory control.

* This work received funding from the Italian University and Research Ministry under project RAFAEL (National Research Program, contract No. ARS01_00305) and from the European Union's Horizon 2020 programme under project Comp4Drones (ECSEL Joint Undertaking RIA-2018, grant agreement No. 826610).

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

1 Introduction

In the last decade, there has been an increasingly research interest in developing control techniques for Unmanned Aerial Vehicles (UAVs), thanks to their capability to perform complex tasks in dangerous situations where the human intervention is prevented.

UAVs vary in weight, size, type, altitude, payload, and many other factors (see [9]). One of the most common UAV, extensively used in practical applications, is the quadcopter (see, for instance, the work in [10]). Many control strategies have been proposed in the literature concerning the position control of UAVs, and particularly of quadcopters (see, for instance, the earlier contributions in [3], [21], and [13]). In particular, one of the main investigated topics is the path planning strategy, which is often used to implement a collision avoidance behavior (see, for instance, [14], [22], and [11]).

More recently, inspired by the flocking behavior of several animal species (such as birds, fishes, and insects), and thanks to the development of new technologies, many results concerning the formation control of large numbers of UAVs have been provided (see, [6] and the comprehensive introduction in [2]).

The great interest on this topic is mainly due to the fact that the demand for the use of swarms of UAVs is recently growing in several field, such as military and rescue missions, remote sensing and environmental surveillance (including farming applications), logistics, as well as traffic surveillance, civil infrastructure inspection, weather forecasting, hazardous cleanup, etc. In effect, it is well-known that a swarm of agents, in which each agent locally interacts with the other agents and the environment, is able to perform complex tasks which are not achievable by the use of a single agent.

Therefore, the use of multiple UAVs as an organized swarm can significantly increase the performances of the single UAV, as well as of the overall group [10], [1], [7], [23]. Indeed, each agent of the swarm is allowed to make use of the resources and capabilities of other agents through communication and/or coordination, and provide it with extra capabilities. On the other hand, this framework clearly requires the use of more than one sensor, actuator, or payload.

A fundamental coordination problem in swarms of UAVs is the formation control problem, whose objective is to continuously maintain, in the most optimal way, the desired formation while the team motion proceeds. Indeed, in common applications, it is often required that agents are arranged in a suitable shape in order to perform the desired task. In addition, multi-agents perform best when kept in a fixed formation relative to one another, which ensures an intelligent path planning and avoids collisions when the swarm moves from the initial location to a specified destination [17], [26].

Many approaches to the formation control problem of UAVs have been presented in the literature, among which, the most commonly adopted are the following:

- the consensus approach (see, e.g., the contributions in [24], [28], [4], [5], [16], [8], [25], [27], [26], [29]), where each agent updates its state based on the

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

communication with its neighbor agents, and finally achieves the consistency of all agents' states;

- the leader–follower approach (see, e.g., [20] and [31]), whose aim is to select one of the agents as the leader (who tracks the predefined trajectories), while the others agents are the followers (who track the leader according to a given scheme);
- the virtual structure approach (see, for instance, [12] and [30]), which is based on the assumption that agents represent the vertices of a rigid virtual structure, and as such each agent only needs to track the virtual point on this virtual structure. Although this approach can ensure a high precision, it requires high communication and computing power;
- the behavior-based approach (see [15]), which is inspired by the behavior of biological groups, requiring the definition of several basic control behaviors of agents, and the definition of formation control instructions for each agent, defined by a weighted average of the desired behaviors.

It is to be noticed that the leader–follower, the virtual structure, and the behavior-based approaches are particular cases of the consensus approach. Therefore, consensus has received a great attention in the recent years. In effect, it has a distributed nature (which stands out with the aim of achieving a common objective by using local information [19]) and therefore it does not require the acquisition of the entire information on the formation, thus reducing computational costs as well as the required communication bandwidth [18]. Moreover, through a consensus approach, the damage or destruction of individuals has little effect on the overall formation, which makes the consensus algorithm robust, adaptable, and expandable [29].

Among the already recalled contributions on consensus-based formation control of multi-UAVs systems, the work in [24] proposes a consensus-based feedback linearization method to design a leaderless formation control law for quadrotors, such that a desired time-varying formation can be achieved. The consensus problem in the case of time-delay systems is studied in [28], showing that a leader–follower consensus approach can efficiently compensate both delays and disturbances. Experiments concerning the outdoor time-varying formation flight for multi-quadrotor systems are shown in [4]. In [5], second-order multi-agent systems for multi-quadrotors with switching interaction topologies are analyzed for the case where the states of the followers form a predefined time-varying formation while tracking the state of the leader. A distributed linear–quadratic regulator controller based on the consensus approach is proposed in [16] to control heterogeneous multi-agent systems (i.e., quadrotors and two wheeled mobile robots) so that they cooperatively accomplish some tasks. In [26] a decentralized hybrid swarm control mechanism for quadrotor helicopters is presented, showing that, through the decentralized approach, a group of agents is able to successfully achieve the desired formation and follow predefined paths without any collision. Finally, in [29], a distributed control law based on the consensus approach is designed for multi-quadrotor systems.

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

Following the recalled state of the art, in this paper we propose a distributed control strategy for swarms of UAVs based on the leader-following consensus approach under a time-varying topology. More in detail, the dynamics of each UAV is modeled by a discrete-time integrator to analyze the main swarm intelligence strategies in terms of flight formation, swarm tracking, and social foraging. First, we define a distributed control strategy for steering the agents of the swarm towards a collection point. Then, we cope with the formation control defining a procedure to arrange agents in a family of geometric formations, where the distance between each pair of UAVs is predefined. Subsequently, we focus on the swarm tracking defining a distributed mechanism based on the so-called leader-following consensus to move the entire swarm in accordance with a predefined trajectory. Moreover, we define a social foraging strategy that allows agents to avoid obstacles, by imposing on-line a time-varying formation pattern. We finally perform some numerical simulations to show the effectiveness of proposed algorithms.

We highlight that, with respect to the current state of the art in the field of control techniques for multi-UAVs, in this work we address a challenging time-varying distributed set-up characterized by the following features:

- each UAV has limited resources in terms of communication coverage, so that it can only receive information locally from a subset of the swarm;
- the UAVs are required to dynamically avoid obstacles by imposing on-line a time-varying formation pattern;
- both the topology of communication and the configuration of leader and followers are time-varying.

The paper is organized as follows. Section 2 presents some preliminaries on the addressed swarm control problems. In Section 3 we discuss the system model and we present the distributed algorithms for controlling swarms of UAVs. In Section 3 the results obtained from the numerical experiments are illustrated and analyzed. Lastly, conclusions and remarks for future work are presented in Section 4.

2 Preliminaries on Swarm Control Problems

Getting inspiration from the behavior of swarms in nature provides several advantages to researchers that focus on modeling and controlling multi-agent systems, such as multiple UAVs. For example, considering the behavior of animals or insects, these are generally organized such that decisions of an individual depend on the behavior of other members: each individual acts as a data harvester from the surrounding environment, so that the whole swarm can make the right decision. Sometimes it is possible that the whole swarm is dependent on the decisions of a single leader. Several swarming intelligence strategies are indeed adaptable to multi-UAVs applications, while being nowadays characterized by low cost and acceptable implementation complexity. The increasing attention towards mechanisms aimed at enabling a large number of UAVs to operate

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

semi-autonomously is also due to the recent rapid development of communication network infrastructures (e.g., 5G) that allow data exchange in a faster and more efficient way. At the same time, the computational capability in autonomous vehicles has grown too, thus allowing the use of increasingly complex algorithms.

In the sequel we describe the main mechanisms performed by components in a swarm, namely aggregation, flight formation, social foraging, and swarm tracking [1].

- **Aggregation**. Aggregation is the basic mechanism performed by swarms. It corresponds to the ability of a swarm to work and organize itself, moving towards a specific target point, while avoiding collisions among components of the same swarm and obstacles that may be present along the way. From a theoretical point of view, all the components could converge in a single point. Obviously, this is not feasible in real applications, where a safety inter-distance between components must be ensured to avoid collisions.
- **Flight formation**. Flight formation consists in the ability of the components of a swarm to comply with a predefined geometric pattern starting from an initial disordered configuration. In a typical formation task, the scale of the given geometric pattern (i.e., the relative distances between the nodes in the geometric pattern indicating the desired final positions of the swarm components) may or may not be specified. In this work, we address the problem of formation stabilization and achievement of a predefined geometric shape with a-priori known node inter-distances.
- **Swarm tracking**. Swarm tracking consists in the union of aggregation and flight formation. It is the ability of all the components of a swarm to follow a given path, while maintaining the formation configuration. Keeping a swarm formation is an important task for many aspects. For example, squadrons of military planes can save fuel by flying in a V-formation, and migrating birds are supposed to do the same. Furthermore, in several applications it is required to reduce the size of the formation during the flight, and this can only be done by adopting specific geometrical patterns.
- **Social foraging**. Social foraging is aimed at increasing the probability of success for the single components in the swarm. For swarm motion, the emergent behavior is significantly affected by the interactions of the swarm members with their environment. This interaction is commonly modeled by the ability to discriminate favorable and dangerous transit areas in the surrounding environment. From a practical perspective, a favorable region can represent a target to be reached, and a dangerous one can be an obstacle to be avoided. In general, this behaviour is achieved through several mechanisms. For instance, when the so-called leader-following approach is applied, the entire swarm follows a particular member (i.e., the leader), who exactly knows where the favorable area or the target point is located.

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

3 The Proposed Distributed Control Algorithms

In this section we present a set of distributed control algorithms to allow multiple UAVs to perform the basic swarm tasks, namely aggregation, flight formation, social foraging, and swarm tracking. The proposed approach is based on a multi-agent framework, where the leader-following consensus mechanism under a time-varying topology is used to steer all the UAVs strategies to achieve a common goal. More in detail, we assume that each UAV updates its position gathering the information about the position of its own neighbors, that is, a subset of the entire UAVs swarm that is connected to the given UAV. Note that a connection between two UAVs exist if the distance between them is lower than their communication range.

3.1 Model of multi-UAVs

First, we model the swarm of UAVs by a direct graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where $\mathcal{N} = \{1, ..., N\}$ is the set of nodes (or agents) with cardinality $N = |\mathcal{N}|$ representing the UAVs, and $\mathcal{E} \in \mathcal{V} \times \mathcal{N}$ is the set of edges describing the communication link between pairs of UAVs. In the sequel, we refer to agents and edges, putting aside the explicit reference to UAVs and link connections. During the movement of the swarm, the corresponding graph may change. If there is an agent without edges (because it is too far from anyone else in the swarm), the task cannot be successfully completed for the entire swarm. The same happens if the agent positions produce two or more isolated graphs. Therefore, in the sequel we assume that the swarm is represented by a connected graph, meaning that there is always at least a direct path between every pair of agents.

Second, we model the dynamics of each agent as a discrete-time single integrator:

$$x_i(k+1) = x_i(k) + u_i(k), \quad i \in \mathcal{N},\ k \in \mathcal{T}_i \tag{1}$$

where $x_i(k) \in \mathbb{R}^3$ represents the state -in terms of position in a three-dimensional space- of agent i at time k, $u_i(k)$ denotes the control input of agent i at time k, and $\mathcal{T}_i$ is the set of time instants when the state of agent i is updated. In order to satisfy a discrete-time modelling, the following assumption is considered:

$$x_i(k+1) = x_i(k), \quad i \in \mathcal{N},\ k \notin \mathcal{T}_i. \tag{2}$$

In other words, when the position of agent i is not updated, it is considered to be stationary. Moreover, we assume that an agent is represented by a fictitious sphere, whose radius ϵ_r identifies the coverage range of the embedded proximity sensor that is used to detect free path and avoid potential collisions with other agents and obstacles.

3.2 Aggregation Control

A solution to the aggregation problem is found straightforward by the consensus algorithm, which is commonly used in a distributed framework, where each

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

agent is allowed to communicate with a subset of all the remaining ones. The consensus problem deals with achieving an agreement among a group of processes connected by an unreliable communications network. In particular, the consensus is achieved if the differences between the values shared by members of the swarm are as close as possible to a given parameter.

Preliminarily, we respectively denote as $l(k)$ and $\mathcal{N}_f(k) = \mathcal{N} \setminus \{l(k)\}$ the identifier of the leader agent (referred to as leader in the sequel) and the set of follower agents (referred to as followers in the sequel). Given the initial known locations $x_i(0)$ $(i \in \mathcal{N})$ of agents, the position $x_i \in \mathbb{R}^3$ of agent i is updated in accordance with the consensus algorithm for time-varying topologies [19], defined as follows:

$$x_i(k+1) = x_i^*(k+1), \quad i = l(k) \tag{3}$$

$$x_i(k+1) = x_i(k) - \frac{\sum_{j \in \mathcal{M}_i(k)} (x_i(k) - x_j(k))}{|\mathcal{M}_i(k)|}, \quad i \in \mathcal{N}_f(k) \tag{4}$$

where $x_i^*(k)$ denotes the known position of the leader at time k and $\mathcal{M}_i(k)$ is the set of neighbors j related to agent i, which is time-varying according to the topology of the graph at time k. We remark that equations in (3)-(4) represent a simple implementation of the consensus algorithm. Also note that the time-varying graph is not required to be connected at each time instant. Indeed, it can be demonstrated that the consensus iterations are convergent if the union of the time-varying graphs over a finite time horizon is connected [19].

3.3 Formation Control

The flight formation principle relies on defining polynomial potential functions for each agent such that targets and forbidden locations (i.e., obstacles) constitute the zeros of these functions. An iterative algorithm is used to update the position of each follower and impose the predefined distance between each pair of agents (including the leader) based on the negative and positive gradient between the target and obstacle function, respectively. The control of flight formation is composed by three main steps, simultaneously performed by each agent:

- 1) defining the desired position of all the followers related to the neighbors positions, according to the formation geometric pattern;
- 2) defining the target and obstacle polynomial potential functions for all the followers, according to the target and obstacles positions;
- 3) updating the follower position by using Newton's iterative method.

Preliminarily, given the predefined formation pattern, we denote the desired inter-distance between agents i and j as $d_{ij} = ||x_i - x_j||$. The target set for follower i is defined as the set of points whose distance from all the other agents $j \neq i$ (i.e., including the leader) is equal to d_{ij}:

$$\mathcal{H}_i^T(k) = \bigcup_{j \in \mathcal{N} \setminus \{i\}} \mathcal{H}_{ij}^T(k), \quad i \in \mathcal{N}_f(k) \tag{5}$$

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

where $\mathcal{H}_{ij}^T(k)$ is the target set when only agent j is assumed to be present:

$$\mathcal{H}_{ij}^T(k) = \left\{ x_j(k) + d_{ij}\frac{x_i(k) - x_j(k)}{||x_i(k) - x_j(k)||} \right\},\ i \in \mathcal{N}_f(k),\ j \neq i. \tag{6}$$

Given the target set $\mathcal{H}_i^T(k)$ for agent i, the corresponding attraction potential function $F_i^T : \mathbb{R}^3 \to \mathbb{R}^3$ is defined at time k such that the following condition is satisfied:

$$F_i^T(t_i(k)) = 0, \quad t_i(k) \in \mathcal{H}_i^T(k), \quad i \in \mathcal{N}_f(k). \tag{7}$$

For a given agent i it is more convenient to define an attraction potential function $F_{ij}^T(\cdot)$ for each of the other agents $j \neq i$, rather than leveraging only on $F_i^T(\cdot)$ that holistically takes all the target point into account. For the sake of simplicity, we only show the formulation of $F_{ij}^T(\cdot)$ in the case of a two-dimensional space. Assuming that the position of the target and agent i at time k are $t_{ij}(k) = [t_{1j}(k)\ \ t_{2j}(k)]^\top$ and $x_i(k) = [x_{1i}(k)\ \ x_{2i}(k)]^\top$, respectively, the potential attraction function is:

$$F_{ij}^T(x_i(k)) = \begin{cases} x_{1i}(k)x_{2i}(k) - x_{1i}(k)t_{2j}(k) + x_{1i}(k) - x_{2j}(k) \\ x_{2i}(k) - t_{2j}(k) \end{cases}, i \in \mathcal{N}_f, j \neq i. \tag{8}$$

It is apparent that it holds that $F_{ij}^T(x_i(k)) = 0$ if $x_i(k) = t_{ij}(k)$.

Assuming there are no obstacles, the zero of $F_i^T(\cdot)$ can be determined by Newton's method:

$$x_i(k+1) = x_i(k) + \lambda \Delta x_a(k), \quad i \in \mathcal{N}_f(k) \tag{9}$$

where λ is a step size representing the attraction coefficient. The step vector $\Delta x_{ai}(k)$ is computed as follows:

$$\Delta x_{ai}(k) = \sum_{j \in \mathcal{N} \setminus \{i\}} \frac{A_{ij}(k)}{||A_{ij}(k)||}, \quad i \in \mathcal{N}_f(k) \tag{10}$$

where:

$$A_{ij}(k) = -[\nabla F_{ij}^T(x_i(k))]^{-1} F_{ij}^T(x_i(k)),\ i \in \mathcal{N}_f(k),\ j \neq i. \tag{11}$$

Analogous considerations can be used to avoid collisions between agents [6]. Indeed, the avoidance of collisions between agents is guaranteed if agents $j \neq i$ (i.e., including the leader) are considered as obstacles by follower i. Hence, the obstacle set for agent i is defined as follows:

$$\mathcal{H}_i^O(k) = \bigcup_{j \in \mathcal{N} \setminus \{i\}} \mathcal{H}_{ij}^O(k),\ i \in \mathcal{N}_f(k) \tag{12}$$

where $\mathcal{H}_{ij}^O(k)$ contains only agent j as obstacle:

$$\mathcal{H}_{ij}^O(k) = \{x_j(k)\},\ i \in \mathcal{N}_f(k),\ j \neq i. \tag{13}$$

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

Given the target set $\mathcal{H}_i^O(k)$ for agent i, the corresponding repulsion potential function $F_i^O : \mathbb{R}^3 \to \mathbb{R}^3$ is defined to take the position of all other agents $j \neq i$ into account. Similarly to the previous case, it is more convenient to define a repulsion potential function $F_{ij}^O(\cdot)$ for each other agent $j \neq i$. here again, for the sake of simplicity, we show the formulation of $F_{ij}^O(\cdot)$ in the case of a two-dimensional space. Assuming that the position of the obstacle is $o_{ij}(k) = [o_{1j}(k) \;\; o_{2j}(k)]^\top$, the repulsion potential function is:

$$F_{ij}^O(x_i(k)) = \begin{cases} x_{1i}(k)x_{2i}(k) - x_{1i}(k)o_{2j}(k) + x_{1i}(k) - o_{1j}(k) \\ x_{2i}(k) - o_{2j}(k) \end{cases}, \; i \in \mathcal{N}, \; j \neq i. \tag{14}$$

Having defined a repulsion potential function, the computation of the position of follower i in (9) is consequently updated as follows:

$$x_i(k+1) = x_i(k) + \lambda(\Delta x_a(k) + \Delta x_r(k)), \; i \in \mathcal{N}_f(k) \tag{15}$$

where the position variation takes also the repulsion step $\Delta x_{ri}(k)$ into account. This step is computed as summation of terms $\bar{R}_{ij}(k)$ related to the repulsion from single agent $j \neq i$:

$$\Delta x_{ri}(k) = \sum_{j \in \mathcal{N} \setminus \{i\}} \bar{R}_{ij}(k), \; i \in \mathcal{N}_f(k). \tag{16}$$

The repulsion step $\Delta x_{ri}(k)$ related to presence of agent $j \neq i$ is computed as follows:

$$\bar{R}_{ij}(k) = \begin{cases} \frac{1}{(1+(\frac{||R_{ij}(k)||}{C_r})^\mu)||R_{ij}(k)||^3} R_{ij}(k) - \frac{\epsilon_r}{(1+(\frac{\epsilon_r}{C_r})^\mu)\epsilon_r^3}, ||x_i(k) - x_j(k)|| \leq \epsilon_r \\ 0, ||x_i(k) - x_j(k)|| > \epsilon_r \end{cases},$$
$$i \in \mathcal{N}_f(k), \; j \neq i. \tag{17}$$

where C_r and μ are two coefficients of the repulsion component, ϵ_r denotes the safety inter-agent distance and it holds:

$$R_{ij}(k) = +[\nabla F_{ij}^O(x_i(k))]^{-1} F_{ij}^O(x_i(k)), \; i \in \mathcal{N}_f(k), \; j \neq i. \tag{18}$$

In order to improve the convergence of the flight formation mechanism, the step size λ in (15) can be replaced by an adaptive step size $\lambda_i(k)$ at time k for each follower i. By defining the relative error between the desired inter-distance and the actual one at time k:

$$\zeta_i(k) = \frac{\sum_{j \in \mathcal{M}_i(k)} ||d_{ij} - (x_i(k) - x_j(k))||}{|\mathcal{M}_i(k)|}, \; i \in \mathcal{N}_f(k) \tag{19}$$

the adaptive step size shape is defined as:

$$\lambda_i(k) = p\, e^{c_i(k)}, \; i \in \mathcal{N}_f(k) \tag{20}$$

where p is a tuning coefficient and $c(k)$ is the error variation:

$$c_i(k) = \zeta_i(k) - \zeta_i(k-1), \; i \in \mathcal{N}_f(k). \tag{21}$$

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

3.4 Trajectory Tracking and Collision Avoidance

The problems related to the trajectory tracking and collision avoidance can be addressed by leveraging on the concepts shown in the previous sections.

As for trajectory tracking, the first step consists in selecting a leader between the agents and considering the remaining ones as followers. Subsequently, on the one hand the attraction potential function of the leader is set to be coincident with the points of a known trajectory that ends in the destination point:

$$\mathcal{H}_i^T(k) = \{x_i^*(k)\}, \quad i = l(t) \tag{22}$$

Note that the leader is not required to be the same agent through the whole path towards the target. Indeed, it can be demonstrated that the leader-following consensus iterations are convergent even if the leader role switches from one agent to others, which is an important feature from a practical point of view (e.g., in case a failure occurs to the leader).

On the other hand, thanks to (5) all the followers are required to maintain the flight formation until the destination is reached. As for the collision avoidance, this task is simultaneously performed by all the agents. Specifically, all obstacles and no-fly zones are associated with the repulsion function, whilst all the remaining zones are assumed to be free-flight space. This ensures that during the flight path the entire swarm tries to maintain the formation, while this is unavoidably modified due to any obstacles present along the way.

4 Numerical experiments

In this section we show the results of the application of the distributed control technique for aggregation and flight formation, swarm tracking, and social foraging of multi-UAVs to a set of selected numerical experiments. In particular, we consider a fleet of four UAVs, which is a common fleet dimension in multi-UAVs applications, for which the communication system has a connected graph configuration and each UAV can communicate with a set of neighbors of the fleet. Since in this article we use a leader-following based algorithm, only one UAV (i.e., the leader) knows the position of the destination and this information is shared with all the remaining UAVs of the fleet through consensus mechanism.

First, we test the aggregation and flight formation control method by considering three types of geometric formations, i.e., snake, triangular, and square. For all the formation configurations we consider a minimum inter-agent distance between a generic pair of neighboring UAVs equal to $d_{ij} = 2$ ($i \in \mathcal{N}, j \neq i$). The initial coordinates of the UAVs in the xyz-space are randomly generated. The leader is randomly switched between different UAVs along the path of the mission, and, at each change of the leader, the information relating to the target destination is also communicated. Note that this choice relies on the need to keep limited the computational effort. Nonetheless, without loosing in generality, other choices are also possible.

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

In all the configurations the UAVs are imposed to reach a planar formation. As an example, in Fig.1 we report the graphical results in the xyz-space of the aggregation and formation control for the square configuration. The blue stars represent the initial position of the UAVs, and the orange squares their final positions. The trajectory of the four UAVs is represented by dashed colored lines. The shape of the formation is described by the light red square that has the four UAVs at its vertices. In Fig.2 we show the evolution of the mean error of the UAVs positions with respect to the final configuration formation. It can be observed that the error lowers under 20% after 20 iterations and reaches the zero value after 50 iterations.

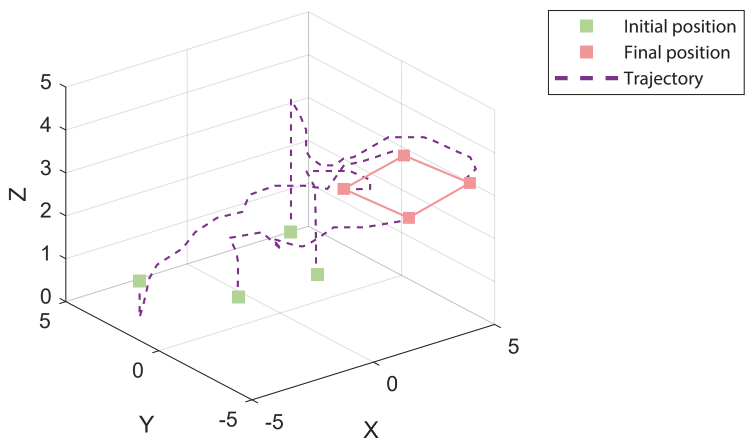

Fig. 1. Aggregation and formation control for a square formation configuration.

The swarm tracking is then tested with various trajectories (i.e., linear, sawtooth, and sinusoidal), which are assigned to the leader of the fleet. In Fig. 3 the trajectory of the controlled fleet in case of a sinusoidal target and a square formation is shown. The four UAVs move from their initial to their final positions following the leader. The initial location of the UAVs is represented by green small squares, while the final position is represented by red green squares, except from the leader, which is identified by a yellow circle. The leader moves along a predefined sinusoidal trajectory, represented by a yellow dashed line, and completes its mission. It is to be noticed that the fleet formation control ensures the four UAVs to keep their square configuration throughout the whole mission. Finally, we show the results of the UAVs control obtained in presence of obstacles along the path of the mission. As shown in Fig. 4, the four UAVs start their mission by reaching the square formation, the initial positions are represented by a yellow square for the leader and green squares for the followers. The leader knows the final target but does not have a predefined trajectory to follow. The UAVs need to pass through a narrow corridor (e.g., a restricted flight

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. **https://doi.org/10.1007/978-3-030-61746-2_7**

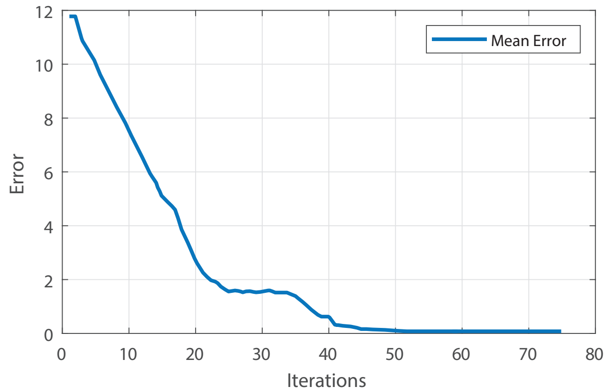

Fig. 2. Evolution of the mean position error of UAVs with respect to the final configuration.

zone) that does not allow to keep the square formation. The distributed control of the fleet allows the avoidance of the obstacle and the achievement of the final target by the leader. Note that, immediately after overcoming the barriers, the fleet returns in a square formation, which further proves the effectiveness of the formation and trajectory control.

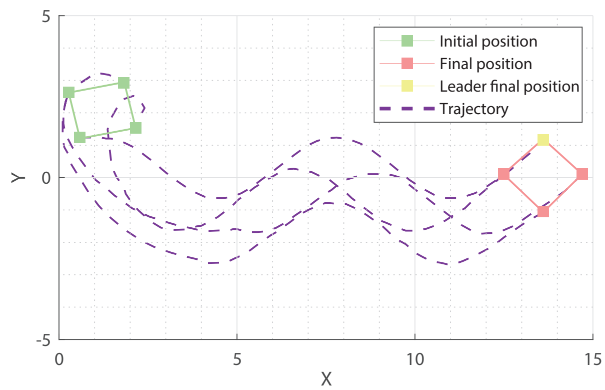

Fig. 3. Control of the UAVs trajectories with a sinusoidal target movement.

5 Conclusions

This work presents a distributed control approaches for the deployment of multi-UAV systems based on the joint application of the leader-following consensus

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

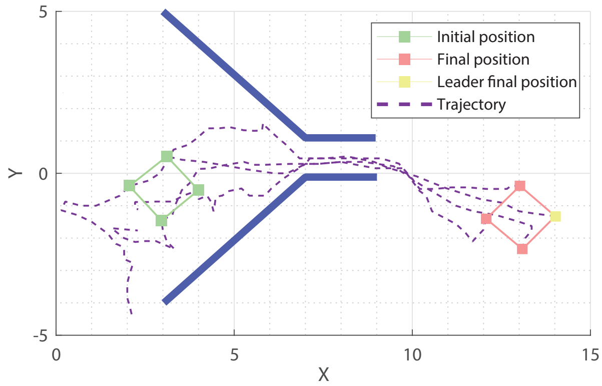

Fig. 4. Control of the UAVs trajectories in a narrow corridor.

theory and swarm intelligence paradigm. On the one hand, the proposed approach fills a gap in the existing literature, where there is a lack of investigations on distributed set-ups where the topology of communication, configuration of leader and followers, and formation pattern are typically time-varying. On the other hand, the application to numerical experiments highlights the effectiveness of the proposed control strategy in solving the main problems related to swarm behaviours, such as aggregation, formation control, swarm tracking, and social foraging under time-varying scenarios.

Future research will be focused on extending the proposed algorithms to agents having a double integrator behavior. We will also integrate additional objective functions and constraints into the system dynamics in order to model UAVs in a more realistic fashion. Finally, future work will be devoted to assessing the scalability of the algorithms in larger-scale scenarios, and modeling uncertainty sources that may affect decision parameters.

References

1. Bandala, A., Dadios, E., Vicerra, R., Lim, L.G.: Swarming algorithm for unmanned aerial vehicle (UAV) quadrotors: Swarm behavior for aggregation, foraging, formation, and tracking. J. Adv. Comput. Intell. Intell. Inform. **18**(5), 745–751 (2014)
2. Barabasi, A.L.: Taming complexity. Nat. Phys. **1**(2), 68–70 (2005)
3. Colorado, J., Barrientos, A., Martinez, A., Lafaverges, B., Valente, J.: Mini-quadrotor attitude control based on Hybrid Backstepping & Frenet-Serret theory. Proc. IEEE Int. Conf. Robot. Autom. (ICRA) (2010)
4. Dong, X., Yu, B., Shi, Z., Zhong, Y.: Time-varying formation control for unmanned aerial vehicles: Theories and applications. IEEE Trans. Contr. Syst. Techn. **23**(1), 340–348 (2015)
5. Dong, X., Zhou, Y., Ren, Z., Zhong, Y.: Time-varying formation tracking for second-order multi-agent systems subjected to switching topologies with application to quadrotor formation flying. IEEE Trans. Ind. Electron. **64**(6), 5014–5024 (2016)

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

6. Gazi, V., Passino, K.: Swarm Stability and Optimization. Springer (2011)
7. Gioioso, G., Franchi, A., Salvietti, G., Scheggi, S., Prattichizzo, D.: The flying hand: A formation of UAVs for cooperative aerial telemanipulation. Proc. IEEE Int. Conf. Robot. Autom. (ICRA) p. 4335–4341 (2014)
8. Gu, Z., Shi, P., Yue, D., Ding, Z.: Decentralized adaptive event-triggered h_∞ filtering for a class of networked nonlinear interconnected systems. IEEE Trans. Cybern. **49**(5), 1570–1579 (2018)
9. Indu, Singh, R.: Trajectory planning and optimization for UAV communication: A review. J. Discret.Math. Sci. Cryptog. **23**(2), 475–483 (2020)
10. Kushleyev, A., Mellinger, D., Powers, C., Kumar, V.: Towards a swarm of agile micro quadrotors. Auton. Robots **35**(4), 287–300 (2013)
11. Lee, H., Kim, H., Kim, H.: Path planning and control of multiple aerial manipulators for a cooperative transportation. Proc. IEEE/RSJ Int. Conf. Intell. Robot Syst. (IROS) (2015)
12. Low, C.: A dynamic virtual structure formation control for fixedwing UAVs. Proc. 9th IEEE Int. Conf. Contr. Autom. (ICCA) p. 627–632 (2011)
13. Magnussen, O., Ottestad, M., Hovland, G.: Experimental validation of a quaternion-based attitude estimation with direct input to a quadcopter control system. Proc. Int. Conf. Unmanned Aircraft Systems (ICUAS) (2013)
14. Mellinger, D., Michael, N., Kumar, V.: Trajectory generation and control for precise aggressive maneuvers with quadrotors. Experimental Robotics **79**, 361–373 (2014)
15. Monteiro, S., Bicho, E.: A dynamical systems approach to behavior-based formation control. Proc. IEEE Int. Conf. Robot. Automa. (ICRA) p. 2606–2611 (2002)
16. Mu, B., Shi, Y.: Distributed LQR consensus control for heterogeneous multiagent systems: Theory and experiments. IEEE/ASME Trans. Mech. **23**(1), 434–443 (2018)
17. Nathan, P., Almurib, H., Kumar, T.: A review of autonomous multi-agent quadrotor control techniques and applications. Proc. 4th Int. Conf. Mechatron. (ICOM) (2011)
18. Pantelimon, G., Tepe, K., Carriveau, R., Ahmed, S.: Survey of multi-agent communication strategies for information exchange and mission control of drone deployments. J. Intell. Robot. Syst. **95**, 779–788 (2019)
19. Ren, W., Beard, R.: Distributed Consensus in Multi-vehicle Cooperative Control - Theory and Applications. Springer (2008)
20. Roldo, V., Cunha, R., Cabecinhas, D., Silvestre, C., Oliveira, P.: A leader-following trajectory generator with application to quadrotor formation flight. Robot. Auton. Syst. **62**(10), 1597–1609 (2014)
21. Sa, I., Corke, P.: Estimation and control for an open-source quadcopter. Proc. Australian Conf. Robot. Autom. (ACRA) (2011)
22. Saska, M., Chudoba, J., Precil, L., Thomas, J., Loianno, G., Tresnak, A., Vonasek, V., Kumar, V.: Autonomous deployment of swarms of micro-aerial vehicles in cooperative surveillance. Proc. Int. Conf. Unmanned Aircraft Systems (ICUAS) (2014)
23. Saska, M., Vakula, J., Preucil, L.: Swarms of micro aerial vehicles stabilized under a visual relative localization. Proc. IEEE Int. Conf. Robot. Autom. (ICRA) p. 3570–3575 (2014)
24. Seo, J., Ahn, C., Kim, Y.: Controller design for UAV formation flight using consensus based decentralized approach. Proc. AIAA Infotech@Aerospace Conf. (2009)
25. Song, Z., Duan, C., Wang, J., Wu, Q.: Chattering-free full-order recursive sliding mode control for finite-time attitude synchronization of rigid spacecraft. J. Franklin Inst. **356**(2), 998–1020 (2019)

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***

26. Toksoz, M., Oguz, S., Gazi, V.: Decentralized formation control of a swarm of quadrotor helicopters. Proc. IEEE 15th Int. Conf. Contr. Autom. (ICCA) (2019)
27. Wang, C., Tnunay, H., Zuo, Z., Lennox, B., Ding, Z.: Fixed-time formation control of multirobot systems: Design and experiments. IEEE Trans. Ind. Electron. **66**(8), 6292–6301 (2019)
28. Wang, C., Zuo, Z., Qi, Z., Ding, Z.: Predictor-based extended-state-observer design for consensus of MASs with delays and disturbances. IEEE Trans. Cybern. **49**(4), 1259–1269 (2009)
29. Wang, J., Zhou, Z., Wang, C., Shan, J.: Multiple quadrotors formation flying control design and experimental verification. Unmanned Syst. **7**(1), 47–54 (2019)
30. Zhao, S.: Affine formation maneuver control of multi-agent systems. IEEE Trans. Autom. Contr. **63**(12), 4140–4155 (2018)
31. Zhao, S., Dimarogonas, D., Sun, Z., Bauso, D.: A general approach to coordination control of mobile agents with motion constraints. IEEE Trans. Automat. Contr. **63**(5), 1509–1516 (2018)

A revised version of this paper has been accepted for publication in 19th International Conference on Ad-Hoc Networks and Wireless. In the following, details concerning the publication are reported:
Carli R., Cavone G., Epicoco N., Di Ferdinando M., Scarabaggio P., Dotoli M. (2020) Consensus-Based Algorithms for Controlling Swarms of Unmanned Aerial Vehicles. In: Grieco L.A., Boggia G., Piro G., Jararweh Y., Campolo C. (eds) Ad-Hoc, Mobile, and Wireless Networks. ADHOC-NOW 2020. Lecture Notes in Computer Science, vol 12338. Springer, Cham. ***https://doi.org/10.1007/978-3-030-61746-2_7***