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29 March 2023

REVIEW PAPER

A Review of Consensus-based Multi-agent UAV Implementations

Fausto Francesco Lizzio[1] [ID] **· Elisa Capello[2] · Giorgio Guglieri[2]**

Abstract
In this paper, a survey on distributed control applications for multi Unmanned Aerial Vehicles (UAVs) systems is proposed. The focus is on consensus-based control, and both rotary-wing and fixed-wing UAVs are considered. On one side, the latest experimental configurations for the implementation of formation flight are analysed and compared for multirotor UAVs. On the other hand, the control frameworks taking into account the mobility of the fixed-wing UAVs performing target tracking are considered. This approach can be helpful to assess and compare the solutions for practical applications of consensus in UAV swarms.

Keywords Consensus · Distributed control · UAV · Swarm · Multi-agent

1 Introduction

The application of distributed control methods to real systems has been gaining momentum in recent years due to the advantages that a multi-agent framework can provide with respect to a single operating unit. Multiple Unmanned Aerial Vehicles (UAVs) applications represent one of the most promising areas of interest of distributed control, as the typical weakness of a single-UAV mission can be overcome by employing a swarm of drones.

This paper is a follow-up to a previous overview on consensus-based control in multi-agent UAV systems conducted by the authors in [1]. Consensus is a distributed control method aiming at reaching an "agreement" among the agents of a system on a given variable of interest, exploiting only local information exchange among neighbors [2].

The previous work [1] aimed at categorizing the literature focusing on one side on the application of formation control through consensus in rotary-wing UAVs, and on the other hand on the application of distributed target tracking through consensus in fixed-wing UAVs.

The reason for such classification is that rotary-wing UAVs are generally deployed in confined and dense areas, such as indoor and urban environments since they can provide hovering flight and vertical take-off and landing, although yielding limited endurance [3]. Thus, a swarm of multirotor UAVs requires a collaborative formation control framework linked to an obstacle and collision avoidance strategy.

On the other hand, due to their considerable endurance and high minimum airspeed, fixed-wing UAVs are suitable to perform missions as patrolling, surveillance, or data gathering over vast regions [4]. Employing multiple drones to perform such tasks requires an efficient framework for distributed information fusion to enhance the accuracy of target detection and tracking.

However, implementing a theoretic distributed control model in a real swarm introduces new challenges related to the technical limitations of a UAV platform, for instance, limited computational power available onboard, poor sensing capabilities, and finite communication range. In the recent literature, many studies attempted to test and validate distributed methods through some experimental implementations or to bring the simulations closer to the real setup.

For this reason, in this paper the applications reviewed in [1] are addressed from a more practical point of view. In particular, several studies implementing consensus-based

✉ Fausto Francesco Lizzio
  fausto.lizzio@polito.it

  Elisa Capello
  elisa.capello@polito.it

  Giorgio Guglieri
  giorgio.guglieri@polito.it

[1] Department of Mechanical and Aerospace Engineering, Politecnico di Torino, Torino, Italy

[2] Department of Mechanical and Aerospace Engineering, Politecnico di Torino, CNR-IEIIT, Torino, Italy

formation control on a real swarm of multirotor UAVs are analyzed and compared according to criterion as the selected hardware and platform or the communication infrastructure of the swarm.

Instead, regarding distributed target tracking through consensus, we review the works taking into account also the mobility of the sensing UAVs. In particular, the coupling between target estimation and the motion of the swarm is examined in the view of the selected path following method, to highlight the inter-dependency between the two tasks.

This approach to classifying the literature could assist researchers in the first phase of the experimental setup design for testing multirotor consensus-based formation strategies. On the other hand, it could help to compare the most suitable control frameworks to implement distributed target tracking through fixed-wing UAVs.

The rest of the paper is organized as follows. In Section 2, some preliminaries on graph theory and consensus control are provided. In Section 3, we review the latest attempts to implement consensus control on rotary-wing UAV swarms. Section 4 focuses on the coupling between target tracking and motion control of a swarm. Finally, concluding remarks are provided in Section 5.

2 Preliminaries

In this section, we will briefly recap the most significant results regarding consensus theory. Some relevant surveys for a more comprehensive analysis can be found in the literature [2, 5, 6].

2.1 Graph Theory

In the scenario of inter-agents communication in a multi-vehicle system, the exchange of information among n drones can be modelled as a graph $\mathcal{G}$. A graph is defined by a non-empty set of n nodes $\mathcal{V}$ connected by a set of edges $\mathcal{E}$, with $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$.

The communication flowing among multiple vehicles can be either directed or undirected. Given two agents, in a directed graph, information can flow from an agent to another one, but not necessarily vice versa. The undirected graph considers only bidirectional communication, in which both agents send and receive information to each other simultaneously [1].

If $(i,j) \in \mathcal{E}$, the two nodes are said to be connected or neighbors. A directed graph is said to be strongly connected if there is an ordered sequence of edges in the set $\mathcal{E}$ from every node i to every other node j. An undirected graph is said to be connected if there is a sequence of edges in the set $\mathcal{E}$ between any two nodes in $\mathcal{G}$ [7].

Given a graph $\mathcal{G}$ it is possible to define the adjacency matrix $\mathcal{A} \in \mathbb{R}^{n \times n}$, such that $a_{ij} > 0$ if node i receives information from node j, while $a_{ij} = 0$ otherwise. The parameter a_{ij} is a positive weight usually set equal to a decreasing function of the inter-agent distance. The matrix $\mathcal{A}$ is symmetrical for an undirected graph. Starting from $\mathcal{A}$, it is possible to define the Laplacian matrix $\mathscr{L}$, such that:

$$l_{ii} = \sum_{j=1, j \neq i}^{n} a_{ij}, \quad l_{ij} = -a_{ij} \quad \text{for } i,j = 1, ..., n \tag{1}$$

Notice that $\mathscr{L}$ has zero row sum [8]. The multiplication of each row of $\mathscr{L}$ for the vector of ones $\mathbf{1}_n$ is always equal to 0. This means that the Laplacian matrix always has at least one null eigenvalue, associated with the eigenvector $\mathbf{1}_n$.

2.2 Consensus Algorithm for Continuous Time Systems

If the communication between neighbors allows continuous information sharing, or if the communication bandwidth is large enough, the system could be modelled as a continuous time one [2].

Given a generic variable x_i with $i = 1,...,n$ (n is the number of drones), consensus aims to obtain the convergence of x_i to a common value, only exploiting local information exchange. Let $\mathcal{N}_i$ be the set of neighbors of a node i. The traditional form of consensus algorithm for a continuous first-order dynamic system is:

$$\dot{x}_i(t) = - \sum_{j \in \mathcal{N}_i} a_{ij}[x_i(t) - x_j(t)]. \tag{2}$$

The value of the variable of interest x_i is driven towards the values of the variables of interest of its neighbors, i.e. $\|x_i(t) - x_j(t)\| \to 0$ as $t \to \infty$ [9, 10]. It is straightforward to notice how applying locally (2) is equivalent to apply globally

$$\dot{\mathbf{x}}(t) = -\mathcal{L}\,\mathbf{x}(t), \tag{3}$$

where $\mathbf{x}(t) = [x_1(t),...,x_n(t)]^T$. This means that the distributed multi-agent system behaves as a linear dynamic system where $\mathbf{x}(t)$ is the state vector and $-\mathscr{L}$ is the state matrix. The stability properties of such a system depend on the spectrum of the state matrix. Since matrix $-\mathscr{L}$ always has at least one null eigenvalue, the system is not asymptotically stable. Still, the system could be internally stable if 0 is the only null eigenvalue of the spectrum, and the other eigenvalues have negative real parts.

In [2] it is shown that such conditions on $-\mathscr{L}$ hold if a directed (undirected) graph contains a directed spanning tree (is connected). This means that the system is internally

stable, and its state variables $x_i(t)$ remain bounded for any initial condition $x_i(0)$.

From algebraic control theory [11], the equilibrium state of such a linear system is only affected by its kernel, i.e., the eigenvectors associated to the null eigenvalue.

In particular, $\mathbf{x}(t) \to (\mathbf{1}_n \nu^T)\mathbf{x}(0)$ as $t \to \infty$, where ν is the unit left eigenvector of $\mathscr{L}$ associated to the eigenvalue 0. Since $(\mathbf{1}_n \nu^T)$ is a matrix with identical rows, it is clear how each x_i tends to a common value given by a weighted average $\sum_{i=1}^{n} \nu_i x_i(0)$ of the initial states, meaning that the system reaches consensus [2].

Similar results can be found for second-order dynamic systems in [12] and discrete-time systems in [1, 2].

3 Formation Control and Collision Avoidance

Several applications employing multi-rotor UAVs as delivery services, bridge inspection, and traffic monitoring are deployed in urban environments, where an adequate safety level must be maintained [13]. A crucial requirement in such conditions is the capability of generating a formation while avoiding collisions between members of the swarm and crashes with external obstacles [14].

One of the most investigated issues in this field is consensus-based formation control [15–17]. Consensus is a displacement-based control methodology [18], meaning that, to achieve the desired formation, the agents only need the relative positions (displacements) of their neighbors with respect to a local reference system aligned to a global one.

Displacement-based formation control is usually categorized in three main strategies that can be realized through a second-order consensus protocol: leader-follower (LF), behaviour-based (BB) and virtual structure (VS), [5].

However, the basic formation algorithms do not consider the collision between agents that could occur while trying to reach the desired positions.

This is why collision/obstacle avoidance methodologies have been developed along with formation strategies. Most of the collision-free approaches through consensus fall into the optimization-based or force-field categories [1, 19].

As pointed out in [1], force-fields are more suitable to operate in dynamic environments and present a higher number of experimental validation in the recent literature. Instead, optimization approaches prevent the occurrence of local minima at the price of a higher computational cost.

In a completely distributed experimental setup that aims at validating a formation strategy, a drone runs on-board the consensus algorithm (Guidance layer), is able to estimate its position (Navigation layer) and share it with its neighbors, while tracking its desired trajectory through commands computed on-board (Control layer). However, researchers tried to

overcome the difficulties of putting together such a considerably distributed setup by deploying centralized solutions in certain layers. Keeping this in mind, the studies are classified in the view of an increasing level of decentralization.

Table 1 clarifies the differences among the implementations described in the following Sections 3.1, 3.2 and 3.3. It reports where the control and guidance layers are performed, and where the navigation information of agent i is sent for further processing. The term "*ground*" in Table 1 denotes a centralized computing unit, e.g. a Ground Control Station (GCS).

The focus is kept on the hardware solutions chosen in the studies to validate the swarming procedure, on the control and sensing frequencies proven to be sufficient for the outcome, and on the differences between simulation expectations and experimental results.

3.1 Guidance Performed on Ground

In this subsection, we report the studies in which only the inner (attitude) loop of the control layer is performed on-board. The observation of the pose of the UAVs is performed by a centralized motion capture system and later sent to the GCS. Here, this information is used to execute both the guidance algorithm and the outer (position) loop of the control layer. The desired attitude is transmitted, through some user-defined protocol (UDP), to the drones that run on-board their inner loop to achieve it. This kind of setup is quite centralized and it is usually employed to test the performance of the guidance layer and to validate its assumptions.

In [20], consensus is employed to change the formation shape of 4 quadrotor UAVs. A receding-horizon optimization minimizes a cost function in which the derivatives of the formation errors add up. Collision avoidance during formation change is performed through a reassignment strategy, assuming a first-order kinematic model for the drones. Two UAVs trade trajectories if their relative position before and after a formation change switches orientation. A Vicon system observes the position of the UAVs at $150Hz$. The authors adopted Matlab to compute first the trajectory commands and later the desired attitude. This is sent, through a Zigbee network at $50Hz$, to each drone, running the inner loop at $1kHz$. The study simulated a distributed navigation layer by

Table 1 Implementation features of the reported studies

	Control Layer	Guidance Layer	Navigation Info of UAV i
Section 3.1	position on ground, attitude on-board	on ground	to ground
Section 3.2	on-board	on-board	to all UAVs
Section 3.3	on-board	on-board	to UAV i

varying the neighborhood range of the UAVs, showing how greater sensing radii lead to faster consensus, as expected. The authors also performed a high speed formation test to push the limit of their kinematic assumption, observing a degradation of the performance in terms of position errors.

A similar implementation framework is provided in [21] for a Crazyfile nano quadrotor swarm. The poses of the UAVs are observed by an Optitrack system at $100Hz$. The study considers a general distributed guidance layer whose output is a reference trajectory tracked by the position control layer running in Simulink at $100Hz$. The desired attitude and thrust are sent, through a specific Client, to each UAV, tracking them at $250Hz$. It is possible to notice how the frequencies of the guidance loop and of the position information update are very similar to the previous study [20].

This configuration is adopted by the authors in [22] to test a formation algorithm based on an artificial potential function. The aim of this guidance layer is to aggregate several UAVs from random initial positions to a safe formation. The authors investigated the effects of increasing the number of UAVs in a real swarm, observing that a larger swarm yields a slightly higher formation error.

3.2 Guidance on-board and no Inter-agent Communication

In this subsection, we describe the works in which the guidance algorithm runs on a companion computer, and the control layer runs entirely on-board. A centralized motion capture system provides the absolute position information of all the drones to each agent, so that the relative positions are computed on-board. This kind of setup is employed to test the feasibility of running the Guidance and Control layers on the on-board hardware.

In [23], the authors tested on a swarm of Crazyfile UAVs a formation algorithm whose protocol weights several behaviours. First, it aims at generating a V-shape formation through consensus. It then uses a repulsive potential to avoid collision and a feedforward PD controller to track the desired position of the centroid of the swarm. Moreover, the study suggests a method for achieving a smooth rotation of the entire swarm to avoid sudden formation errors during maneuvers. The drones are localized by a BitCraze system. The authors proved the validity of their approach regarding formation rotation, observing smooth trajectories even during a 180 degree swarm rotation.

Another behaviour-based approach can be found in [24], where a swarm of ArDrone2 was employed to generate an α-lattice, i.e., a formation in which each drone keeps a fixed separation distance with respect to its neighbors. This is a well-known formation algorithm developed in [15]. The authors employed an Optitrack system to send at $100Hz$ the position information of each agent to every drone. The

experimental results showed two significant differences with respect to simulations: the presence of a steady state error in the inter-agent distances, and the occurrence of oscillations once the desired relative distance was reached. The authors were able to attenuate both these unintended behaviours by adding a distributed integral action on the inter-agent distance error and by appropriately tuning the gains in the consensus protocol, respectively.

3.3 Guidance on-board and Inter-agent Communication

This subsection is devoted to the analysis of those studies in which both the Guidance and Control layers run on-board. Additionally, each drone only receives its own position information by the centralized motion capture system or, in the case of outdoor applications, by a Global Navigation Satellite System (GNSS). This means that the agents will have to share with the other members of the swarm their own position through some ad hoc wireless network for the deployment of the mission. This kind of experimental setup is very decentralized, and it aims at evaluating the effects of inter-agent communication on the performance of the formation strategy.

The authors in [25] designed a formation strategy and tested it on a swarm of four quad-copters UAVs. The guidance algorithm is a retraction-balancing procedure, in which the agents deploy themselves toward an evenly spaced geometric configuration as a circle or a convex polygon. The resulting desired linear velocity is passed to a distributed MPC, that encodes it as the terminal velocity reference. The optimal input is then transformed into a desired thrust and attitude, tracked by a backstepping controller. A Vicon system captures at $100Hz$ the motion of each UAV, that forwards this information to all of its neighbors. All the computations are performed on-board as it was shown how the MPC position controller could be executed at $50Hz$ on a low-power companion computer. The experimental results showed the occurrence of a slight drift of about $5cm$ in the hovering positions due to external disturbances, delay on the transfer of control commands, or on wireless communication. For a communication delay between agents greater than $5ms$, the authors noted the occurrence of oscillations and an increase of the hovering position error of about 30%.

A virtual structure formation algorithm for outdoor environments was tested in [26]. The UAVs reach consensus on their deviation vectors, so that a geometric shape is preserved during maneuvers. Since the test is performed outdoors, each drone uses a GPS module with an accuracy of $1.2m$ to get its own position and velocity at $10Hz$. This information is spread across the swarm through a Zigbee network. The UAVs' companion computers execute the formation algorithm at $5Hz$, while the inner attitude controller

runs at $500Hz$. The experimental outcomes were very similar to the simulation results, so that the authors adopted an analogous setup to validate a more elaborate guidance algorithm.

Indeed, in [27], the implementation of a formation containment problem through consensus was investigated. In such control framework, the designated leaders of the swarm deploy themselves in a geometric formation through the strategy described in [26]. Moreover, several followers employ the containment protocol to keep a formation specified by the convex combination of the states of the leaders. Eventually, this will yield a swarm behaviour such that the follower UAVs converge inside the geometric shape deployed by the leaders, and their velocities will coincide. In the experimental setup, the authors used 3 leaders generating a triangular formation and 2 followers converging inside it. The formation containment was realized despite the presence of wind, that resulted in a slight drift in the position of the UAVs. Hence, the accuracy of $1.2m$ provided by the GPS was adequate for a triangular formation whose edges were about $17m$.

A tighter formation based on GPS positioning can be found in [28], where an Artificial Potential Function (APF) method was tested outdoors. The interaction scheme is highly hierarchical and draws inspiration from pidgeon flocks. Thanks to this communication topology, each UAV only needs to broadcast its position and velocity information to 3 members of the swarm to maintain the relative positions of the entire swarm fixed. This procedure alleviates communication cost especially in large swarms. The authors performed flight tests with 4 quadcoptes. A GPS module was employed by each agent to get its own position and velocity information that was shared through Xbee modules. The guidance algorithm was executed on-board at $20Hz$. The experimental setup specified a diamond formation with a side length of $3m$. Also in this case, the accuracy provided by the GPS was enough to make the system reach consensus despite the presence of external disturbances.

Another outdoor experimental test was conducted in [29], where the authors proposed a formation strategy based on Voronoi partition. The agents are able to distributively compute their task regions, and to switch trajectories whether an agent has to pass through another one's region to reach its target position. The authors adopted an Ultra Wide Band (UWB) localization system instead of the GPS even though the experimental tests were performed outside. This is due to the higher accuracy of the UWB system, that is able to reach a maximum positioning error of less than $10cm$. Each one of the five drones in the experiment receives its position information at $50Hz$ and executes the formation algorithm at $25Hz$. The results showed good convergence of the swarm to the desired formation with no collisions. However the speed of the UAVs was kept under $0.5m/s$. For higher speeds or for a greater number of drones in the swarm, the authors warned

that the UWB would not be appropriate due to its limited sensing range, while the GPS would not be accurate enough.

3.4 Discussion

In this section, several studies performing experimental implementation of consensus-based formation were discussed. The level of decentralization in the described configurations increases over the years, with the most recent studies deploying quite distributed hardware solutions. The comparison of the outlined methods was performed in terms of how the authors tried to decentralized the Guidance, Navigation and Control layers of the mission.

The increased computational capabilities of the recently developed companion computers allow the on-board deployment of both the Guidance and Control layers. This is due to the fact that relatively low control frequencies, in the range of $20 – 50\ Hz$, were proven to be sufficient for updating the commands of the swarming algorithm in the Guidance layer.

A distributed Navigation layer regarding position tracking of the UAVs in the swarm is a crucial feature in a consensus strategy. In outdoor environments, the on-board GPS module is frequently used to get position and velocity information. However, GPS accuracy could not be high enough for more elaborate formation strategies. Centralized motion capture systems have been used in indoor GPS-denied environments, or to get more precise information in outdoor tests. However, these schemes require fixed anchors or cameras deployed in the test area, thus confining their application to experimental tests. Some recent studies about relative sensing of the inter-agent distance have been emerging [30–32] and could represent a starting point to actually decentralize the Navigation layer. Note that a relative position update frequency of about $50 – 100Hz$ has proven to be sufficient for the successful deployment of many of the discussed methods.

It is worth noticing how most of the works reported satisfactory outcomes of the experiments, with the major discrepancy between simulation and real tests being the occurrence of oscillations once the formation is achieved, especially in potential field-based methods. These oscillations are generally caused by bad tuning of the control parameters, or by communication delay between agents. In this sense, some recent studies are trying to attenuate this unintended effect, [33, 34].

4 Distributed Target Tracking

Fixed-wing UAVs are frequently employed in operations as patrolling, surveillance or data collection in outdoor environments, where the target tracking task plays a crucial role [4]. Deploying a network of n mobile sensors can drastically

reduce the measurement noise of an observed process with respect to the performance of a single drone [35, 36].

Given a dynamic target such:

$$\mathbf{x}(k+1) = \mathbf{A}(k)\mathbf{x}(k) + \mathbf{B}(k)\mathbf{w}(k) \tag{4}$$

where $\mathbf{x}(k) \in \mathbb{R}^m$ and $\mathbf{w}(k) \in \mathbb{R}^m$ are the state and the input noise of the process, and a sensing model such:

$$\mathbf{z}_i(k) = \mathbf{H}_i(k)\mathbf{x}(k) + \mathbf{v}_i(k) \tag{5}$$

where $\mathbf{z}_i(k) \in \mathbb{R}^p$ and $\mathbf{v}_i(k) \in \mathbb{R}^p$ are the measured output of sensor i and the measurement noise affecting it, distributed target tracking consists in generating a distributed filter such that the estimation error covariances of the local estimates $\hat{\mathbf{x}}_i$, for all $i = 1, \ldots, n$ are bounded.

The aim of the whole process is to reduce the uncertainty related to the estimation of the target, i.e., to minimize the covariance of the estimation error.

Kalman-like filters are widely used for this purpose and can be classified into consensus on measurements (CM), estimates (CE), and information matrices (CI), depending on the quantity the filter reaches consensus on [37, 38].

As indicated in [1], CE and CI provide more cohesive local estimates with respect to CM. Moreover, CI can limit the computational time of the estimation since it functions even with a single consensus step per iteration, and it is directly linked with the concept of the information value of an observation. This is why CI and hybrid methods based on it are relevant for real implementations.

According to information theory [39], the variance of an unbiased estimator, i.e., the uncertainty related to the estimated state of a target, is bounded below by the inverse of the Fisher information matrix. This is a measure of the information value provided by an observation [40]. Thus, minimizing the covariance is equivalent to maximize the information value of a measurement.

Since the observations are performed by the UAVs, it is clear how the estimation task and the motion of the swarm constitute a cascade structure: the state of a moving target is estimated through some consensus-based filtering process, and the swarm moves toward the target employing some path following algorithm to increase the information value of their observations. This cascade framework is also known as information-driven mobility [41].

While in our previous work the main focus was solely on the distributed estimation process, here also the motion of the swarm is taken into account.

In this context, in the next subsections the studies are classified in the view of the path following algorithm the UAVs employ to maximize their information value. Complying with the categories described in [42], three kinds of path following algorithms are considered here: artificial potential field (APF), optimization-based and geometric methods.

The focus is maintained on the sensor model used in the simulations, on the type of consensus strategy employed for target estimation, and on the path following algorithm adopted for chasing the target.

4.1 APF Path Following

The Artificial Potential Field is a well-known method for path planning consisting in the formulation of attractive and repulsive potentials either between agents of the swarm, with respect to external obstacles or target positions [1]. The input commands for the mobile agents are usually provided by the gradient of the potential so that the swarm is driven towards low potential equilibrium points.

The concept of information-driven mobility was first investigated in relation to multi-agent APF in [41]. The authors considered a swarm of double-integrator particles tracking a target moving in $\mathbb{R}^2$ through a range sensor model. This kind of sensor measures the relative distance (range) ρ_i with respect to the target, providing a noisy version of its position. The covariance of the measurements decreases as the sensing agents move closer to the target, i.e., the information value I_i of an observation is a decreasing function of the range, such that $I_i = f(\rho_i)$. With this in mind, the authors designed a consensus protocol equal to the gradient of the weighted sum of two potential functions: a collective potential and an agent-target interaction potential. The first one has a minimum in the desired separation distance between the sensing agents. The second one drives the UAVs toward the estimated target, and it is equal to $I_\gamma = \sum_{i=1}^{n}(f^{-1}(I_i))^2 = \sum_{i=1}^{n}\rho_i^2$. It is straightforward to notice how minimizing the potential leads to the reduction of the individual target ranges, and to the preservation of a safe distance between agents. This motion behaviour is also known as *flocking*, [15].

In [43, 44], the authors coupled the *flocking* behavior with the estimation process introducing a cascade structure. In particular, they broke up the entire dynamics into three subsystems: structural dynamics Σ_s, translational dynamics Σ_t and error dynamics Σ_e. The first one describes the motion of the agents with respect to the center of mass of the swarm, while the second one refers to the motion of the center of mass. The last system Σ_e describes the evolution of the collective estimation error and is based on the consensus on estimates filtering approach. The authors ultimately proved that the agents are able to generate a flock chasing a target, with all the sensing agents asymptotically reaching a consensus on the state estimates of the target (if zero noise is considered in the error dynamics).

The stability analysis of the cascade structure was further extended in [45]. In particular, the input noise was considered as an acceleration input in the error dynamics Σ_e, and the authors proved the stability of the whole system given

bounded input and measurement noise. Again, consensus on estimates was chosen as the distributed filtering algorithm.

The same cascade framework was analysed also in [46], where the authors studied the optimal observation configuration problem for a swarm of double integrator agents. This means to find the best relative position of the swarm with respect to the target, so that the information value of the measurements is maximized. With respect to [41], the authors considered a range-bearing sensor model, so that the information value is a function of both the range ρ_i and the azimuth θ_i with respect to the target. By employing the determinant of the information matrix as a measure of the quality of the observations, it was found that the optimal configuration requires the agents to be located in an evenly spaced manner on the circumference of radius r_{min} centered at the target position. Here, r_{min} is the minimum effective observation distance of the sensors with respect to the target.

To deal with the presence of m multiple targets, an interesting approach called *semi-flocking* was developed in [47]. The n mobile sensors (with $n \gg m$) are driven towards the targets that are currently being chased by fewer drones, so that eventually each target will be tracked by a number of UAVs roughly equal to $\frac{n}{m}$. The authors did not address the estimation Σ_e subsystem, assuming that the positions of the m targets were already known. However, such an approach could be the starting point to formulate a cascade structure for multi-target tracking applications.

Another study worth mentioning as a starting point for future application is [48]. Indeed, the authors performed the experimental validation of a collaborative target tracking mission on a real swarm of fixed-wing UAVs. The drones track a collaborative target, that is a multi-rotor UAV broadcasting its position and velocity to the entire swarm through Xbee modules. Hence, also in this case no distributed estimation Σ_e is performed as every agent already knows the state of the target. However, the study could provide interesting insights for the implementation of path following through potential-based algorithms to real fixed-wing UAVs. The aim of the swarm is to drive its centroid toward the position of the target, and later to remain inside a bounded region centered at it. For the experiments, the authors employed three fixed-wing aircraft flying at different altitudes to avoid collisions. The target broadcasts its position at $5Hz$, while the agents share at $10Hz$ with all the other members of the swarm their own GPS position, to compute the centroid state. The flight tests provided satisfactory results, despite the presence of a noticeable wind ($3m/s$) and recurrent communication loss between UAVs.

4.2 Optimization-based Path Following

Optimization-based methods encode the path following problem into a cost function to be minimized under several constraints. A popular optimization technique is the Model Predictive Control (MPC), that predicts the state of the system up to a certain time instant and applies the first computed optimal input. A typical drawback of applying MPC to distributed systems is given by its considerable computational load.

This is why a faster version of the decentralized MPC was developed in [49]. The mobile agents are simulated through the fixed-wing UAV two-dimensional kinematic model, and carry an onboard radar able to provide the relative distance, azimuth, and pitch angle with respect to the target. Its position is derived in a distributed fashion through a hybrid CM/CI approach and then plugged in the cost function of the MPC. Indeed, the authors proposed a cost function minimizing both the relative distance of the UAV with respect to the target and the drone's angular and linear velocities. Collision avoidance between agents is ensured by a nonlinear inequality constraint. The MPC framework is first linearized and then, through the use of Lagrangian multipliers, transformed into an unconstrained optimization problem, that is much faster to solve distributively.

A decentralized version of the MPC was used also in [50], but the authors opted to directly maximize the information value of the measurements in the cost function, instead of minimizing the relative distance with the target. The kinematic model of the UAVs is the same as in [49], while the sensor model is able to provide the range ρ_i and the azimuth θ_i. The filtering approach is based on a novel consensus on information, in which also the communication noise between agents is taken into account. The authors suggested that it can be treated as an additive observation noise affecting the information value coming from neighbour agents. In this way, maximizing the collective information in the cost function leads the swarm to reach a compromise between observation and communication. Indeed, communication degrades as the distance between agents increases, while collective observations acquire greater value when performed by farther points of view. Interestingly, the best trade-off is reached through the configuration found in [46], i.e., evenly spaced points in a circumference.

4.3 Geometric Path Following

Geometric algorithms for path following are based on the online computation and manipulation of several geometric quantities as the relative distance with respect to the desired trajectory, known as cross-track error, or the desired heading angle, [42].

The authors in [51] developed a road-map assisted target tracking mission. This kind of application for ground moving targets requires an *a priori* approximation of the road, treated as a sequence of constant curvature segments. This additional information is considered as a pseudo-measurement that augments the real sensor measurement model,

already providing the cross-track error and the azimuth of the target. The authors adopted a two-dimensional fixed-wing kinematic model and consensus on information as the filtering algorithm. Once the target position is estimated, a vector-field path following algorithm is employed, It consists in computing the desired heading angle needed to reach the proximity of the target and to loiter above it afterward. To achieve an even inter-agent angular separation during loiter, a velocity control based on the relative angular position is employed, so that the circular observation configuration described in [46, 50] is achieved likewise.

4.4 Discussion

In this section, the coupling between the distributed target tracking performed by a swarm of fixed-wing UAVs and its motion control was analysed. The concept of collective information value of the swarm's observations was introduced, highlighting how it affects the motion of the UAVs.

Artificial potential fields represent a largely adopted solution for path planning when it comes to distributed motion control. The intuitiveness of this approach as well as the ease of the stability proofs make it suitable to be employed in cascade with the estimation process.

The main filtering strategy adopted to achieve distributed target tracking is based on consensus on information, or on hybrid methods related to it. This may be because the information form of the distributed Kalman filter is directly linked to the information value of an observation. Indeed, in this kind of framework, the update step fusing the information coming from local and neighbors' measurements is just a trivial sum.

The experimental validations regarding estimation tracking methods for multi-UAV systems are still very limited in the literature. Some studies started to validate their distributed path following algorithm tracking a collaborative target. However, the performance of the estimation process plays a crucial role in the stability of the cascade structure. This is why future research should focus on the experimental validation of the coupling between motion and estimation.

5 Conclusions

This work provides an overview of consensus-based methodologies applied to multi-UAV systems.

Regarding the implementation of formation control for multi-rotor platforms, we compared the adopted hardware solutions and the necessary update frequencies of the algorithms, highlighting the discrepancies between simulations and experimental tests. In recent years, the research is moving towards increasing levels of decentralization in the inter-agent communication and in the on-board computation. Instead, in GPS-denied environments, the localization

of the UAVs is still centralized. Among the solutions for the inter-agent communication network, WiFi and Zigbee represent the most commonly adopted wireless protocols in the outlined studies. All of the indoor experiments described here need a motion capture system to obtain the position of the UAVs. Generally, Optitrack and Vicon are used for this purpose. The flight tests analysed in this review showed that although being a much lower cost solution, Optitrack provides sufficient accuracy (millimeter level) and sampling frequency (about $100Hz$) for the outcome of the tests. Finally, it is worth noticing how the companion computers employed in the studies for the on-board computation of the Guidance algorithms are available off-the-shelf at very affordable prices (less than 200 USD).

Regarding distributed target tracking, we emphasized the coupling between the estimation process and the motion control of a swarm of fixed-wing UAVs. The focus was kept on the studies applying a distributed filtering algorithm in cascade with a path following strategy. This analysis suggests that the best control framework to adopt is constituted by a consensus on information-based estimation process coupled with an artificial potential field method for following the target. This is due to the simplicity of performing simultaneously data fusion and swarm aggregation through the application of information theory. Regarding the choice of the measurement sensors needed for the collection of the data, the most frequently adopted solution in the studies is given by direction-finding sensors. They are made up of the combination of a photoelectric/infrared imaging sensor and an ultrasonic/laser radar, which are able to provide both the range and azimuth of the target.

The outlined approach to classify the literature could help researchers on one side to choose the most suitable framework for the validation of consensus-based formation strategies, and on the other hand to select a convenient path following algorithm for distributed target tracking.

Declarations

References

1. Lizzio, F.F., Capello, E., Guglieri, G.: A review of consensus-based multi-agent UAV applications. In: 2021 International Conference on Unmanned Aircraft Systems (ICUAS), pp 1548–1557 (2021). https://doi.org/10.1109/ICUAS51884.2021.9476858

2. Ren, W., Beard, R.W.: Distributed Consensus in Multi-vehicle Cooperative Control. Springer-Verlag, London Limited (2008)

3. Baek, D, Chen, Y, Bocca, A, Macii, A, Macii, E, Poncino, M: Battery-aware energy model of drone delivery tasks. In: SLPED '18: Proceedings of the International Symposium on Low Power Electronics and Design, vol. 49, pp 1–6 (2018)

4. Hassanalian, M., Abdelkefi, A: Classifications, applications, and design challenges of drones: A review. In: Progress in Aerospace Sciences, vol. 91, pp 99–131 (2017)

5. Ren, W: Consensus strategies for cooperative control of vehicle formations. In: IET Control Theory and Applications 1, vol. 2, pp 505–512 (2007)

6. Proskurnikov, AV, Ming, C: Consensus in multi-agent systems. In: Webster, J. (ed.) Wiley Encyclopedia of Electrical and Electronics EngineeringPublisher. Wiley (2016)

7. Godsil, C., Royle, G.: Algebraic graph theory. In: Graduate Texts in Mathematics, vol. 207. Berlin, Germany, Springer-Verlag (2001)

8. Merris, R.: Laplacian matrices of a graph: A survey. In: Linear Algebra its Applications, vol. 197, pp 143–176 (1994)

9. Wu, C.W.: Agreement and consensus problems in groups of autonomous agents with linear dynamics. In: 2005 IEEE International Symposium on Circuits and Systems, vol. 1, pp 292–295. Kobe (2005)

10. Ren, W, Beard, R.W., McLain, T.W.: Coordination variables and consensus building in multiple vehicle systems. In: Kumar, V., Leonard, N.E., Morse, A.S. (eds.) Cooperative Control, volume 309 of Lecture Notes in Control and Information Sciences, pp 171–188 (2005)

11. Mirzaev, I., Gunawardena, J.: Laplacian dynamics on general graphs. Bull. Math. Biol. **75**(11) (2013)

12. Ren, W.: Consensus strategies for cooperative control of vehicle formations. IET Control Theory Appl. **1**(2), 505–512 (2007)

13. Shakhatreh, H., et al.: Unmanned Aerial Vehicles (UAVs): A survey on civil applications and key research challenges. IEEE Access **7**, 48572–48634 (2019)

14. Liu, H, Liu, H.H.T., Chi, C., Zhai, Y, Zhan, X.: Navigation information augmented artificial potential field algorithm for collision avoidance in UAV formation flight. Aerosp. Syst. **3**, 229–241 (2020)

15. Olfati-Saber, R.: Flocking for multi-agent dynamic systems: algorithms and theory. IEEE Trans. Autom. Control **51**(3), 401–420 (2006)

16. Zhang, J., Wang, W., Zhang, Z., Luo, K., Liu, J.: Cooperative control of UAV cluster formation based on distributed consensus. In: 2019 IEEE 15th International Conference on Control and Automation (ICCA), Edinburgh, United Kingdom, 2019, pp 788–793 (2019)

17. Mukherjee, S., Namuduri, K.: Formation control of UAVs for connectivity maintenance and collision avoidance. In: 2019 IEEE National Aerospace and Electronics Conference (NAECON), pp 126–130, Dayton, OH, USA (2019)

18. Oh, K., Park, M., Ahn, H.: A survey of multi-agent formation control. Automatica **53**, 424–440 (2015)

19. Yasin, J.N., Mohamed, S.A.S., Haghbayan, M., Heikkonen, J., Tenhunen, H., Plosila, J.: Unmanned Aerial Vehicles (UAVs): Collision avoidance systems and approaches, vol. 8, pp 105139–105155 (2020)

20. Turpin, M., Michael, N., Kumar, V.: Decentralized formation control with variable shapes for aerial robots. In: 2012 IEEE International Conference on Robotics and Automation, pp 23–30 (2012). https://doi.org/10.1109/ICRA.2012.6225196

21. Furci, M., Casadei, G., Naldi, R., Sanfelice, R.G., Marconi, L.: An open-source architecture for control and coordination of a swarm of micro-quadrotors. In: 2015 International Conference on Unmanned Aircraft Systems (ICUAS), pp 139–146 (2015). https://doi.org/10.1109/ICUAS.2015.7152285

22. Faelden, G.E., Maningo, J.M., Nakano, R.C., Bandala, A., Vicerra, R.R., Dadios, E.: Implementation of swarm aggregation in quadrotor swarms using an artificial potential function model. In: 2016 IEEE Region 10 Conference (TENCON), pp 2021–2026 (2016). https://doi.org/10.1109/TENCON.2016.7848380

23. Toksöz, M.A., Oğuz, S., Gazi, V.: Decentralized Formation Control of a Swarm of Quadrotor Helicopters. In: 2019 IEEE 15th International Conference on Control and Automation (ICCA), pp 1006–1013 (2019). https://doi.org/10.1109/ICCA.2019.8899628

24. Saif, O, Fantoni, I., Zavala, A.: Distributed integral control of multiple UAVs, Precise flocking and navigation. IET Control Theory & Appl. 13 (2019). https://doi.org/10.1049/iet-cta.2018.5684

25. Liu, Y., et al: A distributed control approach to formation balancing and maneuvering of multiple multirotor UAVs. IEEE Trans. Robot. **34**(4), 870–882 (2018). https://doi.org/10.1109/TRO.2018.2853606

26. Yu, B, Dong, X., Shi, Z., Zhong, Y.: Formation control for quadrotor swarm systems: Algorithms and experiments. In: Proceedings of the 32nd Chinese Control Conference, pp 7099–7104 (2013)

27. Dong, X., Hua, Y., Zhou, Y., Ren, Z., Zhong, Y.: Theory and experiment on formation-containment control of multiple multirotor unmanned aerial vehicle systems. IEEE Trans. Autom. Sci. Eng. **16**(1), 229–240 (2019). https://doi.org/10.1109/TASE.2018.2792327

28. Cao, S., Lee, C., Duan, H., Zhu, J., Yuan, S., Song, W.: Quadrotor swarm flight experimentation inspired by pigeon flock topology. In: 2019 IEEE 15th International Conference on Control and Automation (ICCA), pp 657–662 (2019). https://doi.org/10.1109/ICCA.2019.8899745

29. Hu, J., Zhang, H., Liu, L., Zhu, X., Zhao, C., Pan, Q.: Convergent multiagent formation control with collision avoidance. IEEE Trans. Robot. **36**(6), 1805–1818 (2020). https://doi.org/10.1109/TRO.2020.2998766

30. Zhao, H., Wu, S.: A method to estimate relative position and attitude of cooperative UAVs based on monocular vision. In: 2018 IEEE CSAA Guidance, Navigation and Control Conference (CGNCC), pp 1–6 (2018). https://doi.org/10.1109/GNCC42960.2018.9018876

31. Guo, K., Li, X., Xie, L.: Ultra-wideband and odometry-based cooperative relative localization with application to multi-UAV formation control. IEEE Trans. Cybern. **50**(6), 2590–2603 (2020). https://doi.org/10.1109/TCYB.2019.2905570

32. Shen, H., Zong, Q., Lu, H., Zhang, X., Tian, B., He, L.: A distributed approach for lidar-based relative state estimation of multi-UAV in GPS-denied environments. Chin. J. Aeronaut. 2021, ISSN 1000-9361. https://doi.org/10.1016/j.cja.2021.04.021

33. Ma, P., Ji, J., Sui, J., Lei, M.: Research on cooperative formation flight control of multi-UAV with communication time delay. In: 2021 International Conference on Control Science and Electric Power Systems (CSEPS), pp 54–58 (2021). https://doi.org/10.1109/CSEPS53726.2021.00017

34. Vazquez Trejo, J.A., et al: Robust formation control based on leader-following consensus in multi-agent systems with faults in the information exchange: application in a fleet of unmanned aerial vehicles. IEEE Access 9, 104940–104949 (2021). https://doi.org/10.1109/ACCESS.2021.3098303

35. Olfati-Saber, R., Shamma, J.S.: Consensus filters for sensor networks and distributed sensor fusion. In: Proceedings of the 44th IEEE Conference on Decision and Control, pp 6698–6703, Seville, Spain (2005)

36. Olfati-Saber, R.: Distributed Kalman filter with embedded consensus filters. In: Proceedings of the 44th IEEE Conference on Decision and Control, pp 8179–8184, Seville, Spain (2005)

37. Li, W., Wang, Z., Wei, G., Ma, L., Hu, J., Ding, D.: A survey on multisensor fusion and consensus filtering for sensor networks. Discret. Dyn. Nat. Soc. 2015(Article ID 683701), 12 (2015)

38. Olfati-Saber, R.: Distributed Kalman filtering for sensor networks. In: 2007 46th IEEE Conference on Decision and Control, pp 5492–5498, New Orleans, LA, USA (2007)

39. Grocholsky, B.: Information-Theoretic Control of Multiple Sensor Platforms (2002)

40. Esmailifar, S.M., Saghafi, F.: Cooperative localization of marine targets by UAVs. Mech. Syst. Sig. Process. 87, 23–42 (2017)

41. Olfati-Saber, R.: Distributed tracking for mobile sensor networks with information-driven mobility. In: 2007 American Control Conference, pp 4606–4612 (2007). https://doi.org/10.1109/ACC.2007.4282261

42. Sujit, P.B., Saripalli, S., Sousa, J.B.: Unmanned aerial vehicle path following: A survey and analysis of algorithms for fixed-wing unmanned aerial vehicless. IEEE Control Syst. Mag. 34(1), 42–59 (2014). https://doi.org/10.1109/MCS.2013.2287568

43. Olfati-Saber, R., Jalalkamali, P.: Collaborative target tracking using distributed Kalman filtering on mobile sensor networks. In: Proceedings of the 2011 American Control Conference, pp 1100–1105 (2011). https://doi.org/10.1109/ACC.2011.5990979

44. Olfati-Saber, R., Jalalkamali, P.: Coupled distributed estimation and control for mobile sensor networks. IEEE Trans. Autom. Control 57(10), 2609–2614 (2012). https://doi.org/10.1109/TAC.2012.2190184

45. Zhou, R., Feng, Y., Di, B., et al: Multi- UAV cooperative target tracking with bounded noise for connectivity preservation. Front. Inform. Technol. Electron. Eng. 21, 1494–1503 (2020). https://doi.org/10.1631/FITEE.1900617

46. Dong, Z., Liu, Y.: Optimal observation configuration method for multi-UAV distributed cooperative target tracking. In: 2018 IEEE CSAA Guidance, Navigation and Control Conference (CGNCC), pp 1–6 (2018). https://doi.org/10.1109/GNCC42960.2018.9018658

47. Semnani, S.H., Basir, O.A.: Semi-flocking algorithm for motion control of mobile sensors in large-scale surveillance systems. IEEE Trans. Cybern. 45(1), 129–137 (2015). https://doi.org/10.1109/TCYB.2014.2328659

48. Sun, Z., Garcia de Marina, H., Anderson, B.D.O., Yu, C.: Collaborative target-tracking control using multiple fixed-wing unmanned aerial vehicles with constant speeds. J. Guid. Control Dyn. 44(2), 238–250 (2021). https://doi.org/10.2514/1.G005092

49. Hu, C., Zhang, Z., Tao, Y., Wang, N.: Decentralized real-time estimation and tracking for unknown ground moving target using UAVs. IEEE Access 7, 1808–1817 (2019). https://doi.org/10.1109/ACCESS.2018.2885776

50. Fu, X., Liu, K., Gao, X.: Multi-UAVs communication-aware cooperative target tracking. Appl. Sci. 8(6), 870 (2018)

51. Oh, H., Kim, S., Tsourdos, A., White, B.: Decentralised roadmap assisted ground target tracking using a team of UAVs. In: 9th IET Data Fusion and Target Tracking Conference (DF&TT 2012): Algorithms and Applications, pp 1–6 (2012). https://doi.org/10.1049/cp.2012.0407

Fausto Francesco Lizzio is a Ph.D. candidate at Politecnico di Torino in the Department of Mechanical and Aerospace Engineering. He received the B.S. degree in Aerospace Engineering in 2017 and the M.S. degree in Mechatronic Engineering in 2019 both from Politecnico di Torino. He has been a visiting student at Universidad Politecnica de Madrid in 2017, at California State University Los Angeles in 2019,and at Osaka University in 2022. He started his Ph.D. in late 2020. His research interests mainly focus on distributed control of Unmanned Aerial Vehicles (UAVs), consensus theory, formation flight, collision avoidance, target estimation, and delayed networks.

Elisa Capello is Associate Professor of Flight Mechanics at Politecnico di Torino, Department of Mechanical and Aerospace Engineering. She is research associate at the Istituto di Elettronica e di Ingegneria dell'Informazione edelle Telecomunicazioni (IEIIT) of the Italian National Research Council (CNR), in the Systems Modeling and Control group (http://www.sct.ieiit.cnr.it) since 2012. She is a member of The Institute of Electrical and Electronics Engineers, Member (IEEE), Control Systems Society since 2014. She is a member of the IEEE Technical Committ eein Aerospace Control since 2016. She has the national qualification as Full Professor (Professor e di Prima Fascia) since 2022.

Giorgio Guglieri is Full Professor of flight mechanics at Politecnico di Torino, Italy. He is member of the steer in board of the Ph.D. Program in Aerospace Engineering and he carries out teaching activities in the Aerospace Engineering degree program of Politecnico di Torino. He is a senior member of American Institute of Aeronautics and Astronautics (AIAA) and American Helicopter Society (AHS). Author of several articles published in international journals and conferences of the following sectors: aerospace engineering, control, automation and robotics.

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