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Consensus-based virtual leader tracking algorithm for flight formation control of swarm UAVs

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Abstract: Technological developments in industrial areas also impact unmanned aerial vehicles (UAVs). Recent improvements in both software and hardware have significantly increased the use of many UAVs in social and military fields. In particular, the widespread use of these vehicles in social areas such as entertainment, shipping, transportation, and delivery and military areas such as surveillance, tracking, and offensive measures has accelerated the research on swarm systems. This study examined the previous investigations on swarm UAVs and aimed to create a more efficient algorithm. The effectiveness of the proposed algorithm was compared with other leader-based applications. A swarm consisting of 5 UAVs scattered throughout the environment was directed to a fixed altitude using a gathering algorithm. Afterward, a virtual leader was added to the swarm and moved toward the target point by maintaining the flight formation with the consensus-based virtual leader tracking algorithm (CBVLTA). Unlike leader-based applications, where leader or member failure is not taken into account, here, in the event that a random number of UAVs crash and their communication is broken in different scenarios, a new formation shape is created and a flight is made to the target point. The swarm performs the determined formation flight with an error rate below 2% throughout its movement. If the error rate equals or exceeds 2%, push-and-pull functions are applied between members and the error is reduced below 2%. Thus, the results show that the proposed algorithm allows robust and flexible swarm structures against the distortions in topology caused by external factors. In this way, swarm applications such as area coverage, target tracking or detection, collision avoidance, and defense or attack can be performed.

Key words: Collision avoidance, formation control, target detection, unmanned aerial vehicle swarm

1. Introduction

In swarm robotics studies, the concepts of cooperation, coordination, and communication among many robots come to the fore [1]. Many robots working simultaneously can perform tasks with complex structures much faster than a single robot [2]. Having a distributed control mechanism among swarm members that is not managed from a single center can eliminate the impact of mechanical failures on the system [3]. Thus, task errors due to defective members can be reduced with the help of other swarm members. Besides mobile robots, unmanned aerial vehicles (UAVs) have become very popular in civil, commercial, and military fields. In particular, UAVs do not cause air pollution by using their electric fans and can use the 3D airspace very efficiently by vertical landings/take-offs, which are essential advantages. Therefore, greater mobility compared to mobile and other types of robots makes UAVs highly efficient for swarm robotics. When an unmanned and autonomous system [4–

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8] is designed under the control of such air robots, convenient applications can be realized in science, technology, and society. On the other hand, the control of UAVs can be more challenging compared to other types of robots, considering the dynamic environmental conditions. Therefore, an intelligent route control mechanism for a coordinated and communicating collective UAV swarm will provide significant advantages in many applications, mainly in numerous civilian, commercial, and military areas.

In recent years, swarm UAV studies have gained momentum thanks to distributed control methods that make it easier for multirobot systems to adapt to real-time applications [9]. The robots working in a swarm must have consensus on a piece of information to act cooperatively. In addition, this information should be shared with all members over the network topology. For this shared information to form the final herd decision, consensus-based algorithms have been developed based on distributed control methods [10]. In consensus-based applications, where it is assumed that each robot communicates with only robots in its immediate neighborhood, a communication topology is created between close swarm members. This formation network is a system in which continuous communication is maintained throughout the movement [11]. Data about obstacles are collected from each swarm member, a decision mechanism is formed, and nonlinear optimization methods can determine the optimum unobstructed route [10, 11]. Although geometric and optimization-based applications are adapted to consensus-based algorithms [10–12], formation disruptions due to changes in the number of swarm members and communication gaps are not considered. This should not be ignored as it is a problem that may be encountered in real-time applications.

Swarm robotic behaviors based on collective mechanisms and consensus are similar to social behaviors occurring spontaneously and not in a specific order [3]. Therefore, the ability of the system to work despite the failure of some members [13], the ability to adapt the internal parameters of the swarm members to the environment against dynamic environmental changes [14], and the ability of the swarm to work with different numbers of submembers of its system [15] are the features expected from robotic systems in swarms. Although various studies have been conducted in the literature on topics relevant to swarming UAVs, such as aggregation [16], formation [17, 18], tracking [19], surveillance [20], and foraging [21], there are still problems due to real-time application constraints and system design without robustness and flexibility [22]. This highlights the need to use an intelligent control system for movement in a swarm.

Considering all these points, in this study, scattered UAVs in the environment were brought together according to specific formation shapes. A path-planning algorithm was then developed to reach the target without hitting the UAVs in the swarm or obstacles in the environment. This work stands out because robustness and flexibility capabilities, which are essential for the swarm topology and were not considered in previous studies [17–21, 25, 28, 29], are provided to the swarm system with a consensus-based virtual leader algorithm. In addition, using only the location vector makes this application easily adaptable to many systems.

The contributions of this work are as follows:

- Robust swarm topology is provided, whereby, if for some reason members fail or lose communication during flight, the remaining swarm members perform the minimum completion of the mission description.
- Flexible swarm topology is provided, whereby swarm members can update their internal parameters to form new flight formations in response to a swarm flight formation that is disrupted for any reason.

In Section 2 of this paper, related studies are presented. Section 3 details the methodology, the problem formulation, the model framework, and the algorithms. Simulations and results supporting the proposed algorithms are described in Section 4 and the results are interpreted. Finally, Section 5 emphasizes the conclusions, the importance of the study, and areas for improvement.

2. Related works

UAVs can be used widely thanks to their vertical take-off and maneuvering capabilities. However, studies and improvements for swarm applications are still in progress. Studies are being carried out on subtopics such as aggregation, flight formation control [16–18], object and target tracking, surveillance, and monitoring for swarm UAVs [19–22]. Formation control, which is one of the leading swarm applications, is a problem that must be overcome, especially in cargo delivery, traffic monitoring, and highway or bridge inspection applications encountered in urban environments [9]. In studies conducted on specific tasks [10, 11, 17, 22, 23], it has been suggested that formation be provided by a displacement-based consensus algorithm processing the location data. Petit performed formation protection modeling for flocking quadcopters under the name of cooperative control systems [23]. First, a traditional consensus algorithm was used to create a formation among quadcopters [17]. In this way, a swarm with a specific formation shape could acquire a standard view of its environment. Feedback consisting of data related to the maximum dimensions of the formation shape was then given to this formation control system [23]. In simulations performed within the scope of that study, formation controls with and without feedback were compared. It was demonstrated that the formation shape was preserved more efficiently with the proposed feedback control [23]. An important limitation in these cases is that each member's proposed algorithm [18] requires a global position measurement system. Therefore, while it is more efficient in indoor environments, the situation becomes more difficult in outdoor environments. Additionally, it is assumed that there is no data loss [23]. Here, it is understood that the formation shape can be arranged before starting the movement. However, since complications that may occur during movement are ignored, it is vulnerable to malfunctions and communication breakdowns. As can be seen from this situation, robust and flexible structures [22] should be developed for more productive swarm systems.

Besides specific tasks, applications that involve many subtasks, such as gathering, formation control, and target attainment, in which the movements of a swarm are thoroughly planned, have become popular lately. In these practices, sometimes a leader is selected from the swarm and all system dynamics are shaped according to this leader. In another study with a consensus-based algorithm [28], which included leader tracking, the swarm gathered at a specific point from the determined formation shape, which was formed by a distributed directed graph. It then performed the flight in this formation and followed the appropriate trajectory to reach the target without swarm members hitting obstacles or each other with a foraging algorithm [28]. However, leader tracking was inefficient for large-scale applications, being similar to a centralized herd system. Therefore, area coverage with maximum efficiency is an increasingly important problem in target-oriented studies with swarm UAVs. In particular, it can cause failure in the tracking missions of spy UAVs. To overcome this problem and to measure the changing dynamics of UAVs during autonomous movement, a consensus-based algorithm including asymptotically stable but nonlinear control laws (Lyapunov's direct method and the modified invariance principle) was proposed in another study [29]. In this way, the formation area formed by fixed-wing aircraft adopting decentralized aircraft–aircraft interaction architecture was preserved [29]. At the same time, the communication topology was maintained under consensus architecture, and malfunctions and communication breakdowns of the fixed-wing leader UAV or other follower UAVs were ignored. Such a situation is vulnerable to coordination problems related to the leader [29].

Moreover, when it comes to saving time and energy during the target-oriented movement of UAV swarms, their formation patterns should be broken down and reconstructed. The Lyapunov theory and linear matrix inequality (LMI) method have been proposed against the distributed cooperative control problem for the reconfiguration of the formation of a system with a consensus communication topology [30]. However, the effect of swarm capacity on the system was neglected. The size of the swarm is another problem. Controlling swarms of large numbers of UAVs with basic consensus algorithms can be challenging. In a study addressing such a problem [31], a potential function-based multilayer consensus control structure was proposed. Thanks to the multilayer graph structure, the UAVs were randomly distributed over a fixed working area and moved toward the determined formation when the forces between the layers were at the same level [31]. Otherwise, the UAVs formed the first layer of the topology within a series of subgroups, and then the neighboring UAVs within the group were determined according to the targeted formation [31]. These neighboring UAVs formed the bottom-layer topologies. Until the swarm reached the desired formation, efforts were made to include the lower layers in the upper layers by updating their positions [31]. Although the proposed practice showed positive results for large-scale swarm formation, the loss of members due to collision, which is especially common in large swarms, was not considered. In large-scale swarm structures, loss of members due to communication breakdown is common, and the swarm must be robust enough to continue to maintain formation control.

One of the main problems of swarm robots in a dynamic environment is to update the system parameters flexibly to be compatible with the external environment. The control parameters of a swarm system are susceptible to changes in the number of swarm members and the size of the environment. To solve such problems, the improved consensus algorithm (ICA) was applied for formation state control and configuration control of UAVs using the minimum tuning strategy, and the ICA-particle swarm optimization (PSO) and model predictive control (MPC)-PSO algorithms were used to deal with static and dynamic obstacles [32]. Although the proposed algorithm was flexible enough to switch to different flight formations according to different initial states depending on the obstacles in the environment, it was weak against the member losses that may occur during flight [32]. This situation was ignored.

When the studies mentioned above are examined, it is an essential problem that the swarm be robust against loss of members during movement and be flexible enough to remodel its flight formation in ordinary situations such as loss of communication. In the present study, UAVs scattered throughout an environment are gathered at the same altitude according to specific formation shapes. Next, a path-planning algorithm is proposed to prevent swarm members from hitting each other or surrounding obstacles. The feature that makes this study stand out compared to similar studies [22–28] is that, thanks to the virtual leader-based algorithm, the system is robust enough to protect its formation against the failures that may occur among members and flexible enough to create new formations according to the changes in the number of swarm members.

3. Methodology

3.1. Swarm topology

The communication topology of UAVs in swarms can be created using a directed graph, where instant location data can be processed and information can be easily shared. In this application, the swarm communication based on location data is expressed with the distributed directed graph (DDG) [33] structure $G_i = (M_i, E_{ij})$. Here, M_i denotes the node set (the members of the swarm), while E_{ij} denotes the set of edges, which is the distance d between members i and neighboring j. A DDG is a structure in which each member can directly communicate with other members of its subset. The most important reason this is preferred is that there is holistic communication between the members, and it can make the system control more efficient by providing an information flow to the communication topology of each member. The basic DDG structure in question is shown in Figure 1.

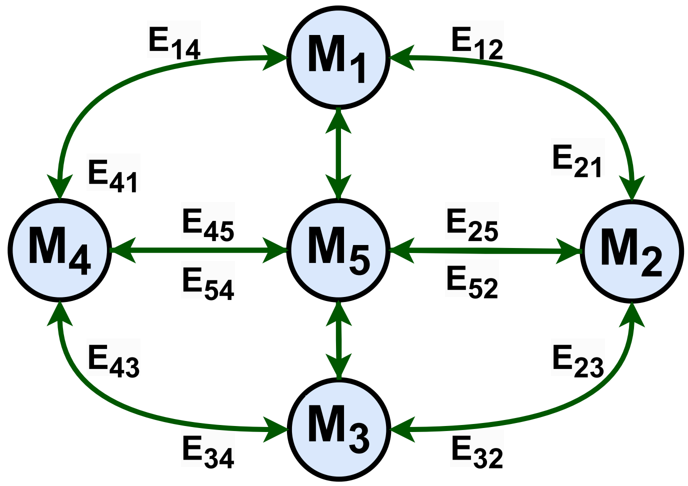


Figure 1. Distributed directed graph (DDG).

Position, velocity, and acceleration dynamics can be used in the dynamic modeling of swarm UAVs. Since the dynamic structures of UAVs are expressed with complex and lengthy mathematical models, a discrete-time single-integrator model [34], namely the position-dependent dynamic modeling given in Eq. (1), is taken into account to control the system in its simplest form within the scope of this application.

$$x_1(t+1) = x_i(t) + u_i(t), i \in M, M = \{1, 2, 3, ..m\} \tag{1}$$

Here, the position of the ith UAV in 3D space at time t is $x_i(t)$ and the control input is $u_i(t)$. The next position of the ith UAV is $x_i(t+1)$. The M (members) cluster expresses the size of the UAV swarm in the environment. Each swarm member is assumed to have a spherical sensor field with radius ε_r to avoid collisions with other swarm members or obstacles.

3.2. Consensus-based virtual leader tracking algorithm (CBVLTA)

3.2.1. Discrete-time consensus algorithm

In consensus-based swarm systems, the discrete-time single-integrator model in Eq. (1) shares data in discrete packets [34]. Thus, updating the collaborative knowledge can be done as shown in Eq. (2) [11].

$$C_i(t+1) = \sum_{i \in M_i} d_{ij} C_i(t) \tag{2}$$

Here, d_{ij} is an element of the row stochastic matrix D. If information flows from i to j, $d_{ij} > 0$. Otherwise, $d_{ij} = 0$, meaning that there is no information flow. In the case of $d_{ij} > 0$, where the information flow is maintained, the updated consensus data constitute the weighted average of the current state of the member itself and the members in its neighborhood M_i. In this case, $C_i(t+1)$ can be expressed as in Eq. (3) [11].

$$C_i(t+1) = D \times C_i(t) \tag{3}$$

The row stochastic matrix D has an eigenvector 1_m equal to 1 in all cases [35, 36]. This matrix has an eigenvalue of 1 when associated with the DDG structure G. All remaining eigenvalues are within the unit circle. As expected, when t approaches ∞, $C(t)$ converges to $D \times C(0)$, where $D = 1_m \mu^T$ and μ is the left unit eigenvector of D [35]. As a result, it is seen that each $C_i(t)$ value tends to a common value given by $\sum_{i=1}^{m} \mu_i C_i(0)$ and the system reaches consensus [35].

3.2.2. Gathering and formation control algorithm

The information data that the swarm members share within the proposed topology constitute the Euclidean distance between them. Swarm members gather according to geometric formation connections or pile up in a cluster at particular points that define the formation connection. The points where the swarm will gather are kept in the D matrix associated with the graph theory. This matrix is created as a distance matrix (square matrix) with 0 diagonals and is constantly updated to maintain the proposed formation shape. In this case, d_{ij} is the expected formation distance between member i and its neighborhood j, as given in Eq. (4) [28].

$$d_{ij} = \|x_i - x_j\| \tag{4}$$

For the swarm members to react more quickly to the environmental conditions and to adapt to the swarm control in a shorter time, the members gather at a fixed altitude, and this altitude is tried to be maintained in each subsequent movement update. This can provide the fastest and easiest path for the swarm system. First, a set of leaders and followers is generated. With $l(t)$ being the leader, the follower set is determined as $M_f(t) = M(t) - l(t)$. The average distance z_{ia} of each UAV to the follower on the z-axis is calculated with Eq. (5) [35]. The calculated values are subtracted from the instantaneous positions of the UAVs, and their new positions on the z-axis are found with Eq. (6). When the obtained position coincides with the leader UAV's target position, as expressed in Eq. (7), all the swarm members will be gathered at a certain altitude. Here, the set $N_i(t)$ consists of members located in the neighborhood of member i at time t.

$$z_{ia}(t) = \frac{\sum_{j=1}^{|N_i(t)|} [z_i(t) - z_j(t)]}{|N_i(t)}, i \in M_f(t) \tag{5}$$

$$z_i(t+1) = z_i(t) - z_{ia}(t), i \in M_f(t) \tag{6}$$

$$z_i(t+1) = z_i^*(t+1), i = l(t) \tag{7}$$

After maintaining a fixed altitude between the swarm members, a formation connection is formed on the $x-y$ plane, adapted to a specific geometric shape. Target and obstacle sets are created so that the swarm members can maintain their formation distance while moving. The target set consists of directional magnitudes depending on the formation distance added to the instantaneous position of the members so that the distance between each member remains constant. When the elements of target set $T_{ij}(t)$, given in Eq. (8), are collected in a cluster, then the target set assigned in Eq. (9) is expressed as $T_i(t)$ [28].

$$T_{ij}(t) = \{x_j(t) + d_{ij} \frac{x_i(t) - x_j(t)}{\|x_i(t) - x_j(t)\|}\}, i \in M_f(t) \wedge i \neq j \tag{8}$$

$$T_i(t) = \bigcup_{j \in N-\{i\}} T_{ij}(t) \tag{9}$$

Collision between members is also prevented when each swarm member accepts the location of other members as an obstacle. The obstacle set $O_i(t)$, which consists of the instantaneous positions of the swarm members in formation, is formed as in Eqs. (10) and (11) [28].

$$O_{ij}(t) = x_j(t), i \in M_f(t) \wedge i \neq j \tag{10}$$

$$O_i(t) = \bigcup_{j \in N-\{i\}} O_{ij}(t) \tag{11}$$

To maintain the formation distance of the swarm members, instant push-and-pull forces are applied according to their instantaneous positions. Suppose the close distance d between the members is greater than or equal to the desired formation distance ε_r. In that case, this distance is included in the target set and the pull function is applied between the members. Within the scope of this application, since the altitude is constant in the z-axis, the potential pull function can be written as in Eq. (13) when the instantaneous elements in target set $T_i(t)$ are defined as in Eq. (12) [28].

$$T_{ij}(t) = \begin{bmatrix} T_{1j}(t) \\ T_{2j}(t) \end{bmatrix} \tag{12}$$

$$F_{ij}(t)^T = \begin{Bmatrix} x_{1i}(t)x_{2i}(t) - x_{1i}(t)T_{2j}(t) + x_{1i}(t) - T_{1j}(t) \\ x_{2i}(t) - T_{2j}(t) \end{Bmatrix}, i \in M_f(t) \wedge i \neq j \tag{13}$$

If swarm member i has reached the target point, $x_i(t) = T_{ij}(t)$, and so $F_{ij}^T(x_i(t)) = 0$. This indicates that the pull force is 0 and the formation is completed. If the instant distance d between the members is less than the desired ε_r, the members are too close to each other and in a position to create an obstacle. In this case, the instantaneous distance between the members is in the obstacle set and the push function is applied between the members. The potential push function can then be written as in Eq. (14) when the instantaneous elements in the obstacle set $O_i(t)$ are defined as in Eq. (15) [28].

$$O_{ij}(t) = \begin{bmatrix} O_{1j}(t) \\ O_{2j}(t) \end{bmatrix} \tag{14}$$

$$F_{ij}(t)^O = \begin{Bmatrix} x_{1i}(t)x_{2i}(t) - x_{1i}(t)O_{2j}(t) + x_{1i}(t) - O_{1j}(t) \\ x_{2i}(t) - O_{2j}(t) \end{Bmatrix}, i \in M_f(t) \wedge i \neq j \tag{15}$$

Within the scope of this application, the time-dependent Newton iteration method [28] is used to update the instantaneous member positions specified in the potential push-and-pull functions.

3.2.3. Time-dependent Newton iteration method

The stable formation is formed by setting the push-and-pull functions $F_{ij}^T(x_i(t))$ and $F_{ij}^O(x_i(t))$ among the swarm members to 0. Thus, the dynamic modeling equation $x_i(t+1) = x_i(t)$ is achieved. Therefore, the control input $u_i(t)$ of the discrete-time single-integrator model given in Eq. (1) should be minimized depending on the push-and-pull functions. The model defined within the scope of this application is as in Eq. (16) [28].

$$x_i(t+1) = x_i(t) + \lambda(\Delta x_{pull}(t) + \Delta x_{push}(t)), i \in M_f(t) \tag{16}$$

Here, $\Delta x_{pull}(t)$ is the step vector generated by the potential pull function, while $\Delta x_{push}(t)$ is the step vector generated by the potential push function. λ is a step coefficient. The equations for the pull step vector and the push step vector are given in Eqs. (17), (18), (19), (20), and (21) [28].

$$\Delta x_{pull}(t) = \sum_{j \in \{N-\{i\}\}} \frac{A_{ij}(t)}{\|A_{ij}(t)\|} \tag{17}$$

$$A_{ij}(t) = -[\nabla F_{ij}^T(x_i(t))]^{-1} \cdot F_{ij}^T(x_i(t) \tag{18}$$

$$\Delta x_{push}(t) = \sum_{j \in \{N-\{i\}\}} R_{ij}^*(t) \tag{19}$$

$$R_{ij}^*(t) = \{\frac{R_{ij}(t)}{[1+(\frac{\|R_{ij}(t)\|}{C_r})^{\mu} \cdot \|R_{ij}(t)\|^3]} - \frac{\varepsilon_r}{[(1+(\frac{\varepsilon_r}{C_r})^{\mu}) \cdot (\varepsilon_r)^3]}\}, d_{ij} \le \varepsilon_r \tag{20}$$

$$R_{ij}(t) = +[\nabla F_{ij}^O(x_i(t))]^{-1} \cdot F_{ij}^O(x_i(t) \tag{21}$$

In the equations above, C_r and μ are the push coefficients. These coefficients can be selected according to the sensitivity of the environment in which the swarm is located. ε_r is the desired formation distance between the previously mentioned members. In addition, the step coefficient λ given in Eq. (16) can be defined as an adaptive step size $\lambda_i(t)$ to minimize the formation error. The formation error $\phi_i(t)$ is defined as in Eq. (22) [28].

$$\phi_i(t) = \frac{\sum_{j \in N_i(t)} \|d_{ij} - [x_i(t) - x_j(t)]\|}{|N_i(t)|} \tag{22}$$

From this point of view, the difference between two consecutive formation errors can be defined as $S_i(t)$ as in Eq. (23) [28].

$$S_i(t) = \phi_i(t) - \phi_i(t-1) \tag{23}$$

The adaptive step size $\lambda_i(t)$ was created using this error variation as in Eq. (24) [28].

$$\lambda_i(t) = \rho \cdot e^{S_i(t)}, i \in M_f \tag{24}$$

3.2.4. Virtual leader tracking algorithm

After the formation, the members of the swarm should be able to move without hitting the obstacles in the environment while moving toward a specific target. The leader tracking method was applied in a previous study using these algorithms. With this method, the potential attraction function of the leader is adjusted to coincide with the targeted destination, as expressed in Eq. (25) [28]. Thus, trajectory tracking is performed depending on the leader.

$$T_{ij}(t) = \{x_i^*(t)\}, i = l(t) \tag{25}$$

For obstacle avoidance, all obstacles are defined as obstacles associated with the push function, as given in Eq. (26) [28].

$$O_{ij}(t) = O^{nofly}(t), i = l(t) \tag{26}$$

Many robotic systems used in swarms may be subject to internal or external interventions during real-time applications. Therefore, the swarm should be able to show robustness [14] and flexibility [15] against such situations. However, the leader's follow-up [22, 28, 35] ignores the deterioration of the formation and the losses in flight dynamics when an obstacle is encountered. We recommend the consensus-based virtual leader tracking algorithm (CBVLTA) to bring these skills to the UAV swarm system. A formation protection algorithm is applied for the virtual leader and all swarm members. Each swarm member rechecks the formation distance after updating the position, and the formation error is calculated continuously. Thanks to this algorithm, the swarm system can successfully fulfill its intended task by updating its internal parameters despite communication breakdown or malfunctions among the members. The graph structure developed based on the virtual leader can be defined as $G_{VL} = (N, E) \cup \{V_L\}$. Graph structures of the created virtual leader tracking-based swarm topology are shown in Figure 2.

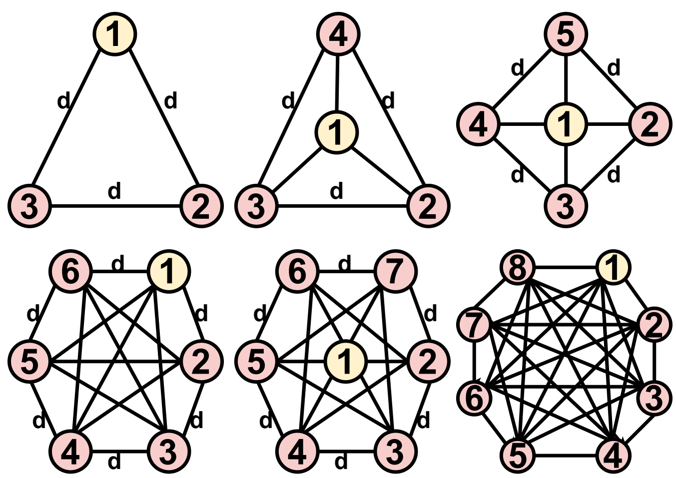


Figure 2. Virtual leader-based DDG.

To follow the virtual leader, the potential pull force is rearranged to be $i = V_L(t)$, as given in Eq. (27).

$$F_{Lj}^T(V_L(t)) = \begin{Bmatrix} V_{1L}(t)V_{2L}(t) - V_{1L}(t)T_{2j}(t) + V_{1L}(t) - T_{1j}(t) \\ V_{2L}(t) - T_{2j}(t) \end{Bmatrix}, i = V_L(t) \wedge i \in N \tag{27}$$

The flowchart created from the algorithms given in the methodology section throughout the swarm movement is shown in Figure 3.

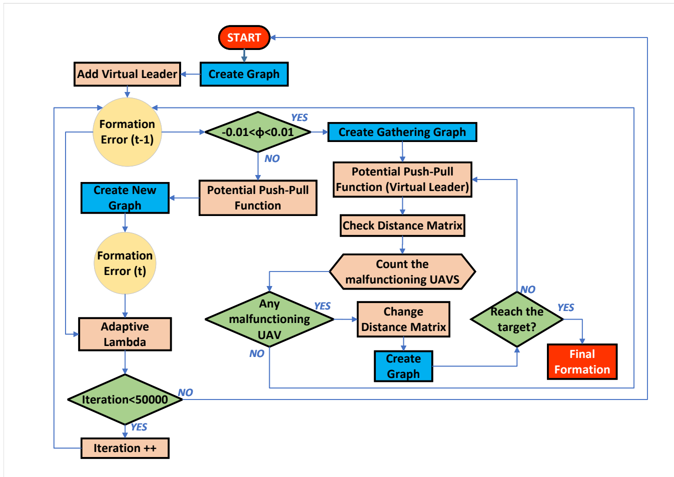


Figure 3. Flowchart of consensus-based virtual leader tracking algorithm (CBVLTA).

4. Simulation and results

Within the scope of this application, we compare the consensus-based leader tracking algorithm and the CBVLTA. The algorithms proposed in this study are modeled in the MATLAB simulation environment.

For applicability and ease of observation, we make a set of assumptions as follows:

- UAVs are processed as point data. ε_r, defined as the safe or formation distance, is also accepted as the sensor radius.
- During the simulations, it is assumed that the locations of the UAVs, obstacles, and target points are known in advance. The locations of the swarm member UAVs can be obtained from GPS and IMU sensors, which are widely used in UAV applications. Obstacle locations can be detected from the infrared, ultrasonic, radar, or LiDAR sensors on the UAVs, depending on their current locations.
- Every quadrotor must have a connection with each other in the network, which must be a bidirectional connection between the quadrotors.

In the first algorithm, it is possible to detect a specific target or to attack that target by following the leader in an environment with and without obstacles like in other works [28, 35]. In the applications made with leader tracking, the same altitude aggregation algorithm was applied first by using the location data of 3 UAVs randomly distributed in the environment. Afterward, a triangle formation was formed between swarm members coming to the concentric altitude. After establishing the formation connection, a specific target was reached by following the predetermined leader UAV. After achieving the target, the triangle formation started again. The algorithms applied in previous studies [28, 35] gave outstanding results against small and scattered environmental obstacles. However, when enormous obstacles cover the environment, it is difficult for the swarm to determine how to reach the target. For this reason, the algorithms used in previous studies [28, 35] were further developed and their behavior against enormous obstacles was tested. Moreover, the extended algorithm was applied for formation protection and field scanning by keeping the constant formation shape in the presence of obstacles. With the second algorithm, simulations were made using the virtual leader tracking algorithm and results were compared with those of the previous algorithm. Finally, the robustness and flexibility solutions that the proposed virtual leader-based algorithm brings to the swarm system were determined. The parameter values used during the simulations conducted with the MATLAB program are given in Table 1.

Table 1. Simulation parameters.

Parameters	Values
λ (step coefficient)	0.1
C_r (push function coefficient)	0.1
μ (push function coefficient)	1
ε_r (formation distance)	1.5

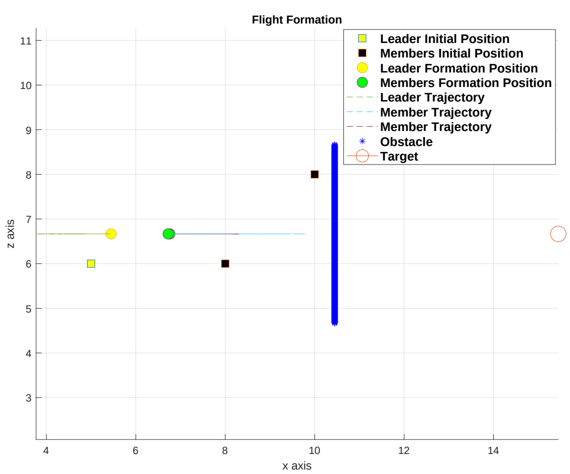
4.1. Leader tracking and formation control simulations

The leader tracking method connects the entire communication topology to the leader UAV. This is efficient for narrow spaces and target-oriented applications. However, in some applications with swarm UAVs, it is crucial to scan the area by maintaining the flight form besides reaching the target point. Providing formation control using common data between swarm members during the flight provides movement and control capability in more areas. The simulations of triangular formation control carried out within the scope of this application are given in Figure 4. Here, as in the leader tracking application, the same altitude and triangular formation were created among the randomly distributed UAVs. In the figures, the black dots are the positions where the swarm members are randomly distributed at the beginning of the simulation. The yellow dot is the position of the leader UAV. First, UAVs at different altitudes are positioned at the same altitude, as in Figure 4a. The flight formation is then created according to the number of UAVs in the environment with the proposed formation algorithm as in Figure 4b. Here, the green circles represent the members, the yellow circle represents the leader UAV, and the dashes represent the trajectories. The swarm with the location-based topology is able to reach the target point, as seen in Figure 4c. Afterward, the target point is reached by preserving the formation shape during the swarm movement as given in Figure 4d.

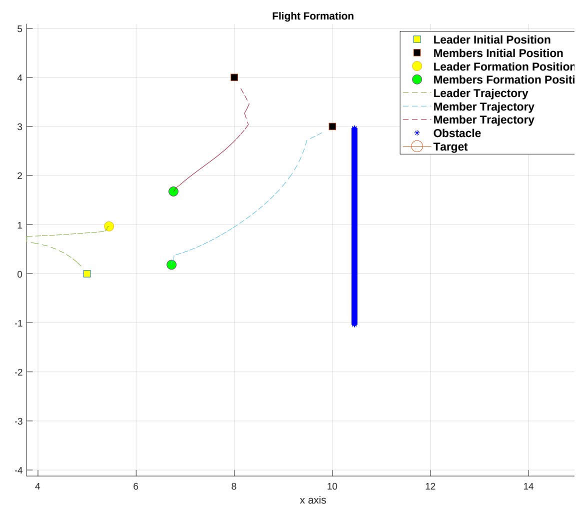
Swarm members share location data during the movement toward the target point. In addition, this is a swarm topology that is more resistant to external effects, as the leader does not need to be a pioneer, as in leader follow-up. Therefore, swarm applications such as field scanning or target tracking can be performed with this formation control algorithm. However, failures and losses among swarm members, frequently seen in real-time applications, have been ignored. In particular, the slightest malfunction or communication gap that may occur in the leader UAV can put the entire system in a difficult situation. Therefore, a virtual leader-based consensus algorithm has been developed to prevent these problems.

4.2. Virtual leader tracking and formation control simulations

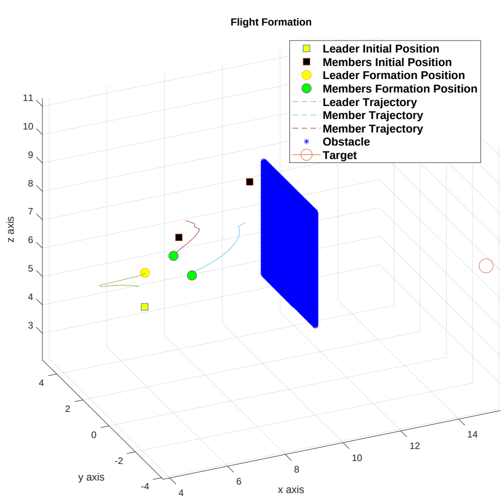
UAVs in swarm duty should be capable of performing the desired task even if malfunctions occur due to technical or external causes. Swarm members should also be able to update their internal parameters against dynamic environmental changes. We propose a virtual leader tracking algorithm to solve these problems. The proposed algorithm is able to regulate the internal parameters against external influences by preserving the flight formation despite the swarm members' failures and ensuring the swarm's task completion. When there is a communication gap affecting more than one swarm member, the remaining members can act on the task definition by creating a new formation without being affected. Therefore, it can be said that the proposed DDG-based consensus structure, including a virtual leader, has Byzantine fault tolerance. Additionally, the swarm performs the determined formation flight within the error range of 2% throughout its movement. When the error rate increases to 2% or above, the error is reduced by applying push-and-pull functions. The next location update step starts when it drops below 2%. After the number and location information of the UAVs in the environment is obtained, the virtual leader is added to the swarm and the formation shape is created. Follower UAVs take their positions according to the position of the virtual leader within the variable graph structure. Formation shapes of graph structures made according to the virtual leader-based swarm topology are given in Figure 2. Here, the DDG structure is reshaped according to the virtual leader's position to reduce the geometric calculation density. For the swarm with 3 UAVs, the virtual leader is assigned to the center of the triangle formation. Similarly, a virtual leader is assigned to the center for the herd consisting of 4 UAVs. A swarm topology with 5 or more members is arranged according to whether the elements are odd or even in number. The virtual leader is assigned to the top to form the double-sided polygon if odd. If it is even, it is assigned to the center of the resulting double-sided polygon. The simulation based on the virtual leader tracking algorithm is presented in Figure 5.



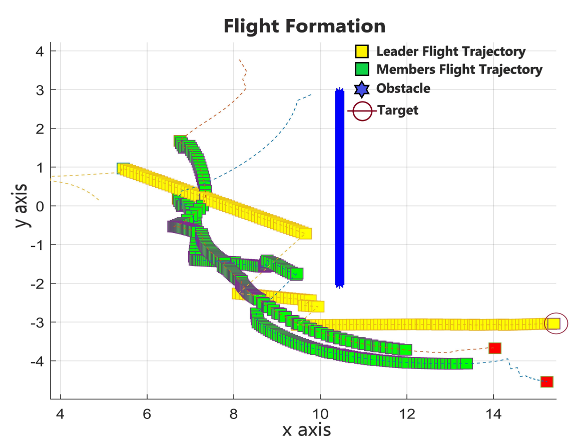
(a) Position at the same altitude



(b) Gathering formation

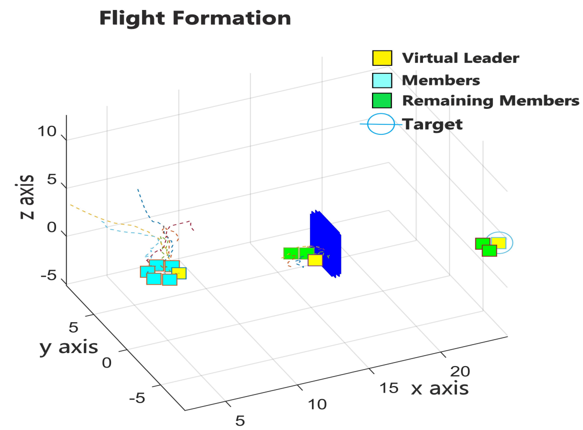


(c) Location-based topology in 3D

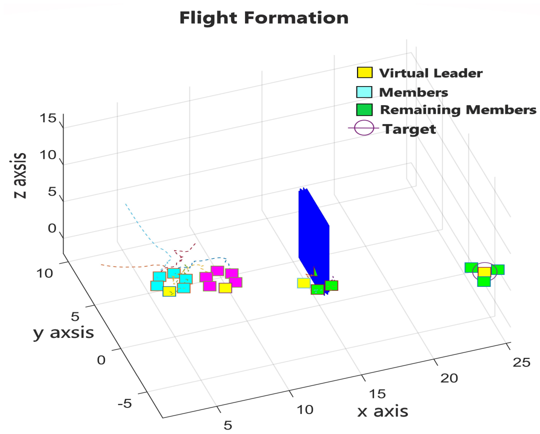


(d) Flight formation

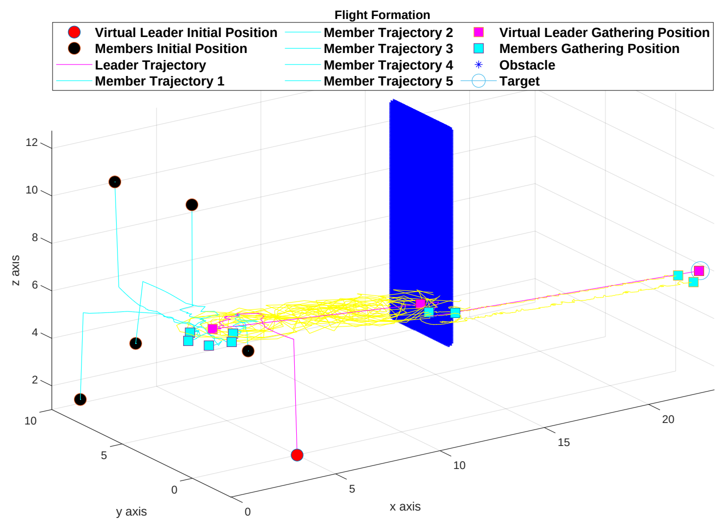
Figure 4. Leader tracking target detection and formation control in a 3D obstacle environment.



(a) Remaining 3 followers



(b) Remaining 2 followers



(c) Simulation image including all steps

Figure 5. Virtual leader tracking target detection and formation control in a 3D obstacle environment.

In the first application shown in Figure 5a, 3 drones were downed and the swarm updated its internal parameters against this dynamic change and formed a new triangle formation. In the second application, 2 drones were downed and the swarm switched to a virtual leader-centered triangle formation, as seen in Figure 5b. A simulation picture including all steps is also given in Figure 5c. In the simulations, thanks to the algorithm based on the virtual leader, the remaining swarm members created a new formation to follow the virtual leader. With the new swarm formation, the target point was reached without breaking the swarm's connection or hitting an obstacle. Thus, a more robust and flexible swarm algorithm was created.

4.3. Performance criteria

The performances of the virtual leader and leader-following algorithms according to the time in which they reached the target point, the number of iterations, the length of the route, and the size of the swarm are given in Table 2 according to the simulation results.

Table 2. Simulation performances.

Formation	Parameters	3 UAVs	6 UAVs 3 down	6 UAVs 2 down
Gathering formation	Time (s)	48	56	58
	Iteration	83	102	105
	Trajectory 1 (unit)	1.50	1.30	4.10
	Trajectory 2	4.80	7.90	5.20
	Trajectory 3	4.10	8.50	10.5
	Trajectory 4	None	8.00	10.1
	Trajectory 5	None	5.40	6.20
	Trajectory 6	None	6.00	6.10
Flight formation	Time (min)	11	17	19
	Iteration	1230	1866	2055
	Trajectory 1 (unit)	15.3	20.6	21.2
	Trajectory 2	10.5	19.8	20.8
	Trajectory 3	13.2	21.0	18.7
	Trajectory 4	None	8.70	10.2
	Trajectory 5	None	8.20	21.1
	Trajectory 6	None	8.50	9.70

First of all, when the performance values of the randomly dispersed UAVs during the gathering formation are examined, it is seen that the swarm size is directly proportional to the flight time and the number of iterations. The trajectories of the randomly distributed swarm members are quickly collected at the same altitude, thanks to the formulas given in Eqs. (5), (6), and (7). The flight formation shape is then taken with the push-and-pull functions applied. Therefore, the difference in gathering formation time between applications is relatively small. The times recorded for the flight formations until reaching the target point are similarly proportional to swarm size. Moreover, it can be said that this is inversely proportional to the number of members that collide with obstacles or each other or lose communication in virtual leader-based applications. It can be said that the target is reached in a shorter time by creating a more straightforward trajectory in the leader-following application. However, it is vulnerable to failures or communication breaks in the swarm system. The only condition for the remaining members to be able to reform is that the leader UAV should not experience any problems. Therefore, some tolerance for flight formation time can be shown for a more efficient, robust, and flexible swarm system.

5. Conclusion

UAVs are technological tools in demand in many areas today, and it is crucial to deploy them in flocks. However, it can be challenging to use them in a swarm due to the dynamic structure. In particular, malfunctions in swarm members and sudden changes due to external factors can cause significant problems. In this study, a gathering algorithm has been applied for UAVs distributed inside or outside the environment of interest. A path-planning algorithm has been developed based on virtual leader tracking that can reach the target without interruption in communication or collisions involving the swarm member UAVs or obstacles in the environment. A communication topology was created by providing consensus-based formation control among the swarm members during their flight. Here, swarm members share their instant locations. It is straightforward to implement as only location information is processed.

In the simulations, it was seen that the swarm system protects its internal parameters against external influences by using the virtual leader algorithm and it completes the task despite the failure of its members. Therefore, thanks to the intelligent path control developed for UAVs, efficient results were obtained against swarm problems. In addition, system performance can be measured by testing on real-time applications. On the other hand, it has limited efficiency in terms of time and cost for swarm systems with dozens or even hundreds of UAVs. A linearized dynamic model in which only position data are processed may be insufficient. In order to overcome this problem in the future, the main swarm should be divided into subswarms, and potential dynamics such as velocity acceleration may also need to be included in the system. The system can perform the expected task by creating a hierarchical swarm structure. Another limitation of the application is that there are too many alternative routes to reach the target point due to increases in map size. For this problem, the optimum route can be determined by developing an offline path-planning algorithm before the flight.

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