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Leader-Follower Control and Distributed Communication based UAV Swarm Navigation in GPS-Denied Environment

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Abstract*-- Unmanned Aerial Vehicles (UAVs) have developed rapidly in recent years due to technological advances and UAV technology finds applications in a wide range of fields, including surveillance, search and rescue, and agriculture. The utilization of UAV swarms in these contexts offers numerous advantages, increasing their value across different industries. These advantages include increased efficiency in tasks, enhanced productivity, greater safety, and the higher data quality. The coordination of UAVs becomes particularly crucial during missions in these applications, especially when drones are flying in close proximity as part of a swarm. For instance, if a drone swarm is targeted or needs to navigate through a Global Positioning System (GPS)-denied environment, it may encounter challenges in obtaining the location information typically provided by GPS. This poses a new challenge for the UAV swarms to maintain a reliable formation and successfully complete a given mission. In this article, our objective is to minimize the number of sensors required on each UAV and reduce the amount of information exchanged between UAVs. This approach aims to ensure the reliable maintenance of UAV formations with minimal communication requirements among UAVs while they follow predetermined trajectories during swarm missions. In this paper, we introduce a concept that utilizes extended Kalman filter, leader-follower-based control and a distributed data-sharing scheme to ensure the reliable and safe maintenance of formations and navigation autonomously for UAV swarm missions in GPS-denied environments. The formation control approaches and control strategies for UAV swarms are also discussed.

Keywords -- UAV Swarms, Autonomous Navigation, Formation Control, GPS-denied Environment, Extended Kalman Filter

I. INTRODUCTION

A swarm of drones is a collection of autonomous or remotely controlled aircraft in which the drones maintain some form of internal structure among themselves. Swarms of drones have essential uses in many fields and missions, such as surveillance [1], transportation [2], search and rescue [3], agriculture, and defense [4]. UAVs are low-cost, casualty free, simple to equip, easy to operate, flexible, and reliable. Usually, a single UAV with advanced control strategies can achieve real-time high-precision attitude control and complete trajectory tracking. The success rate and resistance to emergencies of multiple UAVs flying in formation are higher than that of a single UAV. However, the current level of technology still needs to support the autonomous decision-making function of multi-UAV formation in the complete sense of the word. It is almost impossible to achieve a high degree of intelligent clustered mass cooperative formation flight [5]. Therefore, developing UAV trajectory planning, formation control, and positioning technology is of great interest.

In the field of UAV swarm systems, several methods have been investigated to achieve reliable coordinated movement. One commonly utilized approach is leader-follower formation control [6] [7]. In this strategy, a designated leader follows a predetermined path, while followers maintain a specific configuration, matching the leader's speed and direction. This leader can serve as a reference point for tracking. Desai's research team at the University of Pennsylvania [8] has made significant research in advancing both theoretical understanding and practical implementation of this approach

In terms of information interaction within the UAV network, a distributed control method [9] [10] comes into play. Each UAV in the network requires information about its neighboring counterparts, which is illustrated in Fig. 1. Despite its slightly lower accuracy, distributed control requires less information exchange and simpler implementation due to less computational demands [11].

The main goal of this paper is to use a method that copes with GPS-denied environments without incurring the system cost of complex sensor fusion and navigation computations. For a group of UAVs with limited intra-UAV communication and computational resources, there are navigation techniques that can compensate for the lack of GPS-based position feedback. One of the simplest ways to deal with the lack of direct position feedback operation is through application of heading projection techniques. Applying heading projection methods to a swarm of UAVs introduces a new source of error, namely the rapid accumulation of UAV errors due to environmental biases [33].

Considering the above methods and premises, in a 3D environment, when a UAV in a swarm formation loses its GPS signal / localization data, its IMU data is used to predict the position [12] [13] and, through valid communication between UAVs. Thus, its positioning accuracy can be improved.

II. MOTIVATION

The positioning function of UAVs is essential for autonomous navigation. However, it can be challenging to achieve accurate positioning when GPS or indoor positioning systems such as Ultra-Wide Band (UWB) based relative positioning signals are lost. Various localization methods were proposed to address this problem. In recent years, UAV positioning technologies such as visual [14] [15] and anchor-based positioning [16] have made significant progress in both theoretical and practical research, and some of these technologies have even entered the market stage. They have demonstrated good practicality in unique environments. However, there are still many challenges to achieve safe and reliable navigation and positioning tasks for UAVs in outdoor environment, compared to indoor environment for UAVs or mobile robots. There are numerous limitations to UAV positioning in outdoor environments that need to be overcome to achieve reliable and safe navigation.

A UAV must generate sufficient vertical lift to maintain flight, so it has a limited load capacity. Currently, UAVs can be loaded with sensors including cameras, IMUs, and lidars, etc. An onboard controller is required to accomplish the UAV's autonomous positioning task by combination of most of those sensor inputs. Using a lot of sensors on UAV also increases the weight of the load that decreases the flight time and performance accordingly. Reducing the weight of the UAV load and achieving more accurate autonomous positioning has become a vital issue for navigation.

On the other hand, UAV vision localization algorithms require processing image sequences captured by vision sensors, and the image computation is extensive. The processing is required to handle the image data effectively, which may involve tasks like image analysis, manipulation, or enhancement that demand a lot of computational effort. Even a desktop computer with high computational performance requires significant computation time. Currently, the processing performance of airborne devices is far from that of desktop computers. There are high-performance GPU-enabled companion boards available, like NVIDIA Jetson Nano, Xavier NX-Serie, etc. One common approach is to use the ground station to process the visual localization algorithm and transmit the results to the UAV via communication equipment, allowing the UAV to be localized. The outdoor environment is complex, and the performance of the communication equipment will directly affect the real-time performance of the UAV positioning when a large amount of data needs to be transmitted [15].

The fastest flight speed of a quadrotor UAV can reach 8 meters per second. If the visual positioning algorithm cannot achieve real-time positioning, UAV can obtain delayed position information, thus results in the visual positioning function to fail. Positioning delays and positioning errors do not only affect the autonomous navigation, also significantly reduce the safety of the UAV. Therefore, positioning accuracy is also very crucial for UAV autonomous positioning algorithms [17].

In the field of autonomous navigation for UAVs, it is important to explore methods that utilize minimal onboard instruments and can operate in GPS-denied environments. One way to improve positioning accuracy is to utilize a small amount of information exchange between UAVs when they are in formation. An effective formation control method and positioning algorithm can be utilized to achieve this. The main objective of this paper is to improve the positioning accuracy of UAVs in formation by sharing data through valid communication between UAVs and an Extended Kalman Filter [18], while minimizing the need for onboard instrumentation. By developing a method that relies on minimal onboard instruments and can operate in a variety of environments, including those where GPS is not available, it will be possible to improve the autonomous navigation capabilities of UAV swarms.

III. STATE OF THE ART

In this section, the state-of-the-art research includes the following three main aspects:

- Control strategies for UAV swarms,
- Formation control approaches to control and maintain UAV swarm formation,
- Positioning methods used in UAV swarms.

A. Control Strategies for UAV Swarms

UAVs in formation often must keep their relative position in the formation substantially constant due to mission requirements. The general holding strategy is that each UAV in the formation maintains the same relative position to the agreed point in the formation. This holding strategy is called follow-and-hold when this agreed point is the pilot aircraft. In formation keeping, some disturbances may be caused by some disturbing factors. The conflict prevention strategy is to avoid collisions and blockages in information interaction that may occur under the disturbance. To maintain a specific formation shape, the UAV group must have information interaction between them. Control strategies for information interaction are generally centralized [19], distributed [9], and decentralized control [20], each has its unique definition and advantages.

Centralized Control:

In a centralized scheme, a core processing unit is introduced. It can be a base station on the ground or an agent with high computing power in formation. The core unit monitors the coordination of the team to accomplish global tasks based on the information gathered from all remaining agents. All agents must remain in contact with the core unit. The centralized solution introduces some disadvantages, such as poor robustness and wasted energy. Due to the core unit's critical function in monitoring the team's global tasks, a failure of the core unit can bring down the entire formation. The computational power of each agent is not utilized, and the connection links required between the core unit and other members burden the communication resources [19].

Decentralized Control:

In the decentralized scheme, each UAV maintains its close relationship to the agreed points in the queue and does not interact with other UAVs. It has the least effective Control, essentially no interaction of information and the least amount of computation, but the simplest structure [20].

Distributed Control:

In a distributed scheme, the organization does not need a core unit to be organized. As shown in Fig.1, agents in the formation can communicate and share information with other members. The processing unit is available on the agent itself, and decisions are made by the agent based on local observations. Each UAV must interact with information about its position, velocity, attitude, and motion target with the UAVs adjacent to it in the queue. In a distributed control strategy, each UAV needs to know the information of the UAVs adjacent to it. Although the Control is relatively ineffective, there is less information interaction, which significantly reduces the amount of computation, the system is relatively simple to implement, and the bottlenecks in computation and communication of the centralized approach are overcome [9].

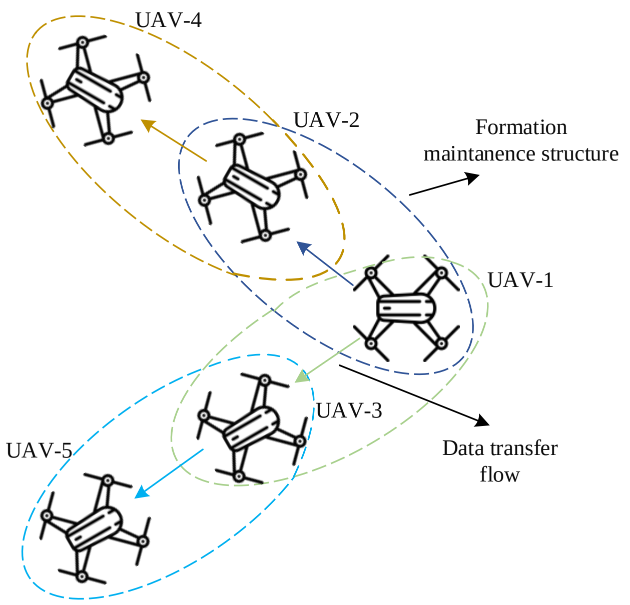

Fig. 1: The distributed control.

B. Formation Control Approaches

Leader-Follower Approach:

The Leader-follower based control method is used in this thesis for the follower with no set path, while the main UAV formation control methods currently available are Leader-follower based Control [6], Behavior-based control method [21], and Virtual structure method [22]. This section explains the reasons for using Leader-follower based Control by comparing the advantages and disadvantages of each method.

The Leader-Follower control method is a strategy that is often used in the control of multi-agent systems, such as a formation of UAVs. In this method, one intelligence is designated as the leader and the rest are followers that track the leader's movement. The followers are able to track the position and direction of the leader using parameters such as distance or speed. Within a multi-intelligence system, there can be one or multiple navigators, but only one navigator is responsible for controlling the shape of the group formation. By setting different position relationships between the navigator and the following intelligence, different network topologies, or formation shapes, can be achieved. The key feature of this method is that the collaboration between the members of the intelligence group is achieved through the sharing of information about the state of the leader intelligence [6].

One advantage of the Leader-Follower control method is that the leader, as the dominant player in controlling the movement of the entire system, can control the behavior of the entire group of intelligence with a given trajectory, which greatly simplifies the control process. This can be particularly useful in scenarios where the leader is able to accurately follow a predefined path and the followers are able to adjust their flight data based on the leader's position, heading, distance, velocity, and angular velocity. However, a disadvantage of this approach is the lack of direct feedback control in the system. If the leader misbehaves, it can directly lead to a disruption in the behavior of the followers, potentially causing the entire system to collapse. For example, if the leader moves faster than the followers can track, the followers will fall out of line [32].

Behavior-based Control Approach:

The main idea of the behavior-based control method is to design the individual behavioral rules and local control schemes of each intelligent body in advance. This is based on the overall behavioral pattern expected to be produced by the control effect on the intelligent body system. It is a movement control method for the first effect and causes. Usually, the behavioral pattern of each intelligent body is stored in the formation controller like a 'library function.' When the system is running, the corresponding behavior is executed according to the environmental information and control instructions, such as avoiding obstacles, forming a particular formation, changing to another formation, moving in the direction of the target, etc. For example, in an obstacle environment, the formation intelligence has to avoid collision with obstacles and other intelligence during their movement. The intelligent body system uses its sensing system to detect changes in the external environment and selects the desired behavior from the behavioral pattern "library function" based on the current system input. This is then used as the system response and output. Unlike the pilot-follower approach, the collaborative role in this method is achieved through sharing information, such as position and state input values, between the intelligence, for which an efficient and stable communication system is indispensable [21].

Virtual Structure Approach:

The idea of the virtual body method is to view the multi-intelligent body formation as a single rigid body structure. The intelligence points at certain fixed positions on this rigid body structure, using their positions in the structure's coordinate system as a reference, and when the intelligence move, i.e., when the multi-intelligent body formation moves, as long as the individual intelligence track their corresponding points in the rigid body structure. In other words, the coordinates of the intelligence in the reference coordinate system remain the same, which means that the relative positions of the intelligence remain unchanged, and the whole multi-intelligence system is always moving in a particular formation [22].

C. Positioning Techniques and Optimization Methods

UAV positioning has various technical details depending on various environments and conditions. As it can be seen in Table I below, that illustrates the lists of some common applications where positioning techniques and optimization methods are used for the localization of UAV swarms at indoor or outdoor environment via communication or vision sensors.

TABLE I. Positioning techniques and optimization methods used for UAV navigation

Reference	**Positioning Techniques**	**Optimization Methods**	**Data**
Xiaoqiang Qi. (2021) [23]	Sensor fusion using onboard IMU and external position measurement	Extended Kalman Filter	Noisy and delayed position data
Zhimin Han et al. (2018) [24]	Distance position measurements -based scheme	Complex Laplacian-based formation control scheme	Distance, velocity, all agents Share: Orientation
Zhiyun Lin et al. (2015) [11]	Relative position measurements-based scheme	Fully distributed localization algorithm	Known anchor node position, other nodes unknown, anchor node positions in a typical global coordinate frame and relative position measurements in local coordinate frames between node pairs
Kexin Guo et al. (2017) [25]	Distance measurements-based scheme	Kalman Filter	Distance, self-displacements
William Power et al. (2020) [26]	Dead reckoning	Multi-Target Gaussian Conditional Random Field (MT-GCRF)	The share of predicted global position between UAVS
Xiaoyang Liu et al. (2018) [27]	Dead reckoning, distance measurements-based scheme, bearing measurements-based scheme	Traditional Federal Kalman Filter	The relative navigation system provides the distance and angle information between the leader and the follower, and the dead reckoning system provides information on the position coordinates and speed of each UAV
Mario Coppola et al. (2018) [28]	Distance measurements-based approach	Discrete-time Extended Kalman Filter (EKF)	The MAVs exchange on-board states (height, velocity orientation) while the signal strength indicates the range
Che Lin et al. (2016) [10]	Bearing measurements-based scheme	Distributed source localization	Bearing angle
Fabian Schilling et al. (2022) [15]	Relative visual localization	Attractive/repulsive flocking algorithm	/
Martin Saska et al. (2017) [17]	Relative visual localization	Algorithm detail is described in [31]	Information from an onboard camera, data from IMU, the altitude and velocities from the intelligent sensor

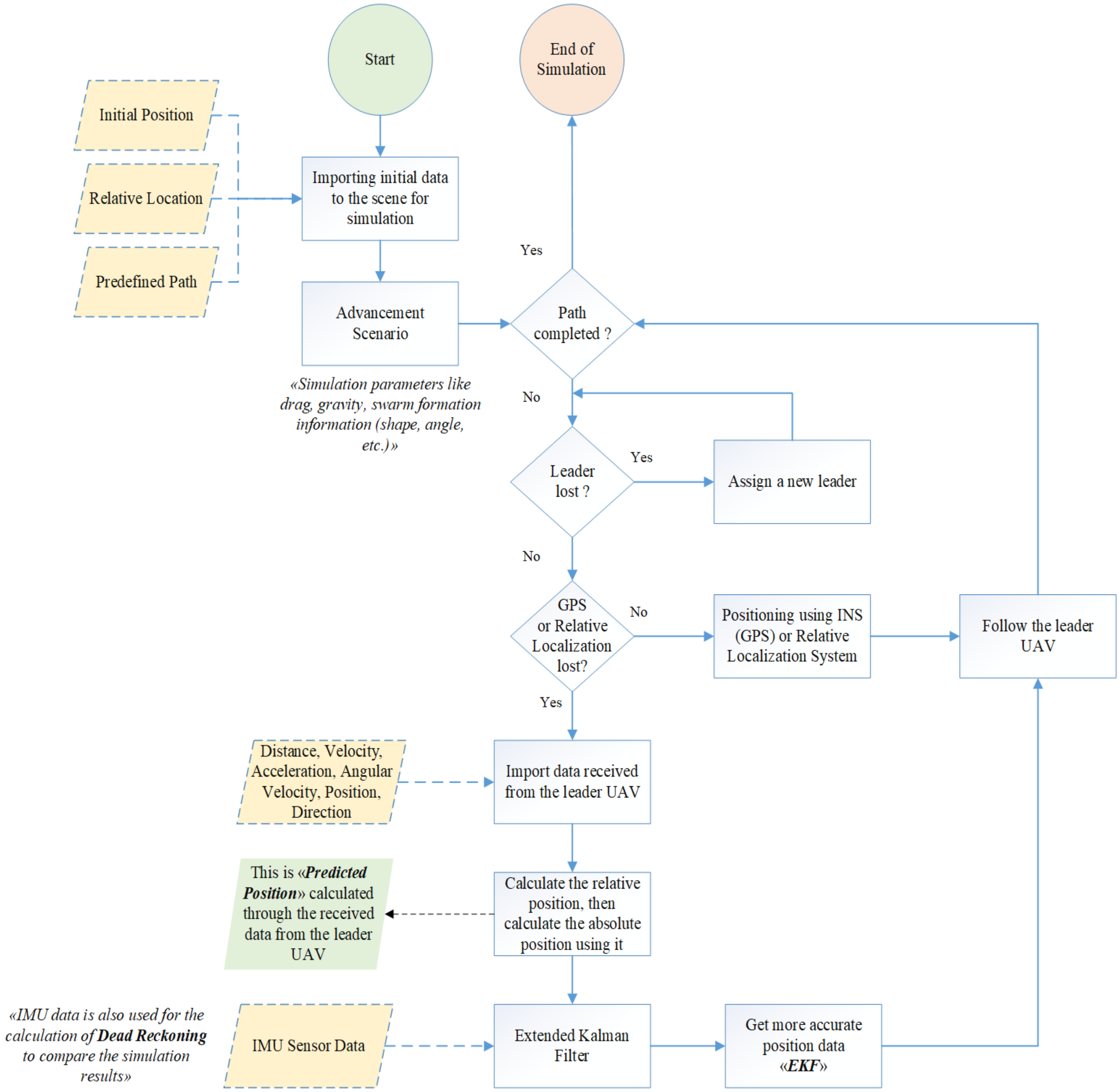

Fig. 2: Flowchart of the control scheme in MATLAB simulation

IV. CONCEPT

This paper presents a control scheme for the UAVs formation. The UAVs use distributed communication, meaning each UAV communicates with and considers one neighbor UAV to be a local leader. Leader-follower approach is employed for formation control. In this approach, the leader UAV follows a predefined path and the other UAVs in the formation determine their flight data based on the leader's position, heading, distance, speed, and angular velocity. Two types of positioning systems are used in the formation: relative positioning systems such as UWB based positioning [29] for indoor environments, and a GPS-aided inertial navigation system (INS) used in MATLAB or GPS [30] for outdoor environments. While UWB positioning tends to have a good accuracy, INS positioning can be less accurate due to the influence of wind and the limitations of GPS positioning at outdoor environment. If most of the UAVs in the formation lose location information, they can still receive positioning information from UAVs that have not lost these capabilities. By combining this relative position information with their own IMU data, they can reduce positioning errors in GPS-denied environments using an EKF. In order to validate the effectiveness of the proposed method in this paper, the following simulation scheme was designed as shown in Fig.2.

In our simulation, firstly the initial and relative positions of the UAV formation are defined, and the predefined paths are given. The flight speed of the drone formation is determined based on the number of path points imported. The initial GPS position / UWB based positioning accuracy are also entered and incorporated these parameters into the simulation scenario. The control flow of the implemented concept is given in Fig.2. If location data from GPS or UWB based positioning is lost, UAV uses the distance, velocity, acceleration, angular velocity, position and direction information from neighbor leader UAV. The absolute position of itself is calculated from this information. The EKF is used to obtain more accurate position information. The calculated new position information is then used to follow the neighboring leader. The fusion process involves combining predicted position data with IMU signals. In this process, the IMU data serves as the basis for state prediction, while the predicted GPS position contributes to filtering correction. Specifically, the predicted GPS position is used in the volume measurement equation, while the IMU measurements are directly integrated into the state prediction equation.

V. RESULTS

Most of the simulation results shown are the trajectory of a UAV randomly selected in a V-shaped formation in a straight path of 350 meters, in order to facilitate visual comparison of trajectories. Other preset paths are also shown at the end of the results. Each UAV is equipped with a GPS and an IMU sensor, and it is assumed that they generate information at the same frequency of 240 Hz. In practice, the GPS usually generates information at a slower frequency than the IMU, but since this paper aims to simulate GPS loss, the same frequency is set here. It is also assumed that each UAV has also a valid communication with other UAVs, i.e., so that neighbor UAVs are able to communicate according to a distributed approach.

The simulation results demonstrate the effectiveness of the proposed control scheme in maintaining the formation of UAVs. The combination of distributed communication, leader-follower control, and EKF localization enables the UAVs to effectively follow a predefined path and maintain their positions relative to one another, even in the presence of GPS loss or high noise. The results show that the EKF can reduce the positioning error and improve the formation's ability to follow the desired path, particularly when at least one UAV has not lost GPS or UWB based positioning data. However, even when all UAVs have lost these capabilities, the EKF is still able to provide better performance than the dead reckoning method alone. The results also demonstrate the effectiveness of the proposed method in adapting to the loss of the leader UAV, with the formation able to smoothly transition to a new leader and continue to follow the desired path. The results for the different preset paths show that the proposed method is flexible and able to handle the paths in varying complexity. Overall, the results of the simulations support the conclusion that the control scheme proposed is effective in maintaining the reliable formation of UAVs in a different of scenarios and environments.

TABLE II. Positioning accuracy setting values for indoor and outdoor

Data	Units	Indoor	Outdoor
Roll, Pitch, Yaw	*deg*	[0.2 0.2 0.2]	[0.2 0.2 0.2]
Position	*m*	[0.15 0.15 0.15]	[1.0 1.0 1.0]
Velocity	*m/s*	0.02	0.05
Acceleration	m/s^2	0.02	0.05
Angular velocity	*deg/s*	0.02	0.05

For the initial accuracy settings as shown in Table II, the accuracy of GPS can be improved, but it is also affected by many factors, including the location and orientation of the antenna, the environment (e.g., buildings, forests, etc.), the quality and functionality of the receiver, and the orbit and signal of the GPS satellite. In general, the accuracy of GPS is around 5 meters. However, by using more advanced receivers, the accuracy of GPS can be improved to about 1 meter. The accuracy of an IMU depends on a variety of factors, including the quality, accuracy, and performance of the sensor, the quality and efficiency of the signal processing algorithm, and the characteristics of the environment in which it is used. In general, IMUs can achieve accuracies in the range of a few centimeters to tens of centimeters. High accuracy IMUs can achieve accuracies of several centimeters, but typically require the use of higher quality sensors. Compared with the actual accuracy, the following accuracy settings are for better simulation and are usually more ideal [34].

A. *Results of Indoor Simulation*

The following results are for the case where there is at least one drone indoors that has not lost positioning data like UWB-based positioning system data. The Fig.3 shows the trajectory of a random drone in a swarm. The red line is the preset path, where a random drone loses GPS or UWB positioning data after about 50 m. In the case of a straight path, the top view on the right clearly shows that the EKF with the green line has an improved position after fusing the predicted position of the blue line with the position of the DR with the yellow line. Compared to DR, the implementation achieves a maximum accuracy improvement of about 40% to 0.25 meters.

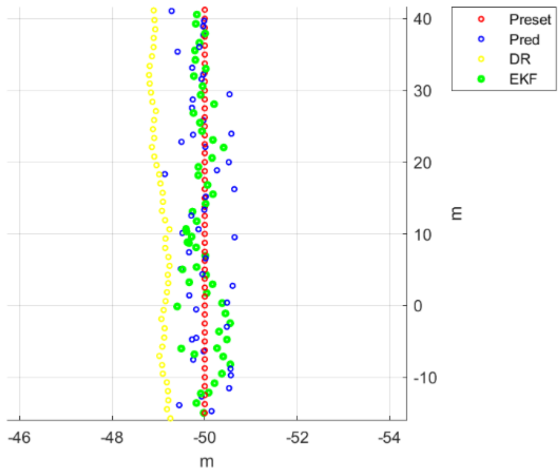

Fig. 3: Simulation result of True path (Preset), predicted position through neighbor UAV's data (Pred), DR positioning using IMU, and positioning result by EKF

The formation can be also maintained while using complex trajectories as shown in Fig. 4 and Fig. 5.

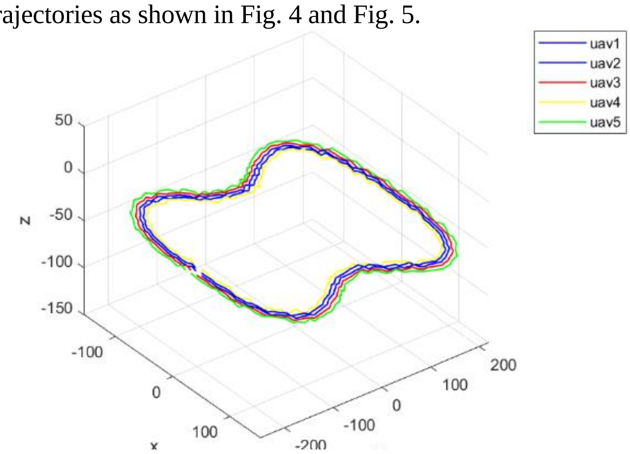

Fig. 4: Trajectory 2 with EKF

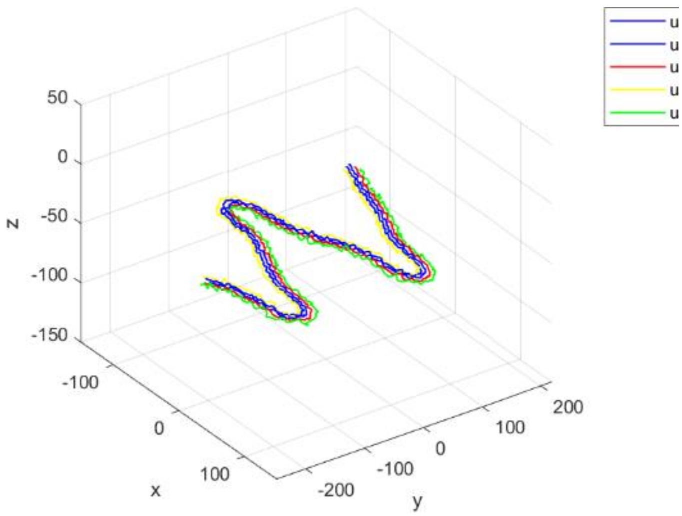

Fig. 5: Trajectory 3 with EKF

The individual UAVs are specifically observed using complex trajectory as shown in Fig. 6. The red line is the predefined path. The EKF "green line" effectively integrates with both the predicted "blue line" and the DR data "yellow line", resulting in the drone closely following its intended path.

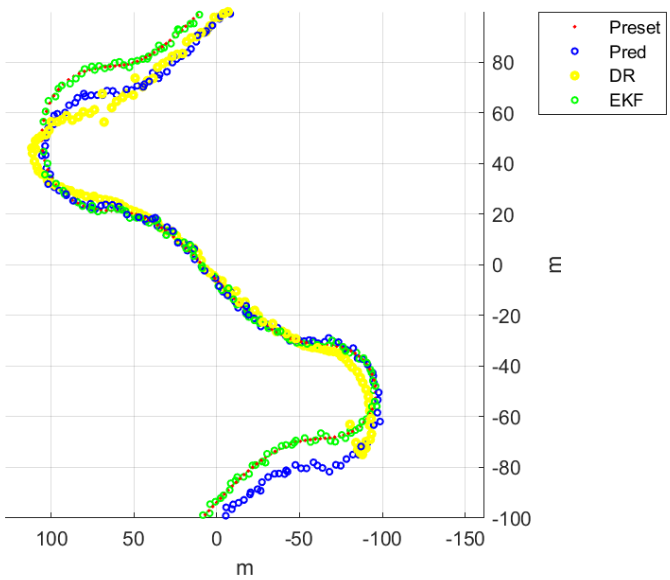

Fig. 6: Comparison of simulation results for a complex trajectory

By observing the Root Mean Squared Error (RMSE) as shown in Fig. 7, it can be clearly seen that, like the expected results, the INS localization (the green line) is better than the EKF localization (the blue line). The EKF localization is better than the GPS of the UAV (the red line) and the DR (the yellow line) from the IMU in the indoor situation.

In an environment where GPS or localization system data is completely lost, as shown in Fig. 8, the accumulated error in the own DR "yellow line" can also be corrected to some extent by the EKF "green line" through the neighbor UAV's DR position "blue line". However, the effect is not obvious. Compared to DR, our implementation achieves a maximum accuracy improvement of about 20% to 1.3m.

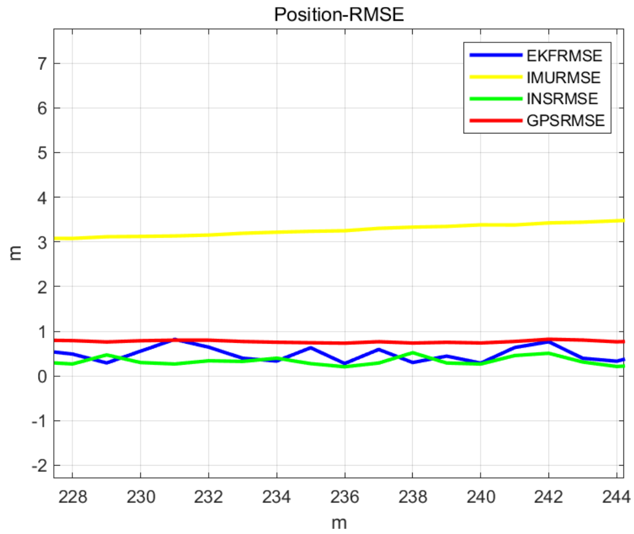

Fig. 7: Comparison of RMSE results after 500 simulations by using proposed concept

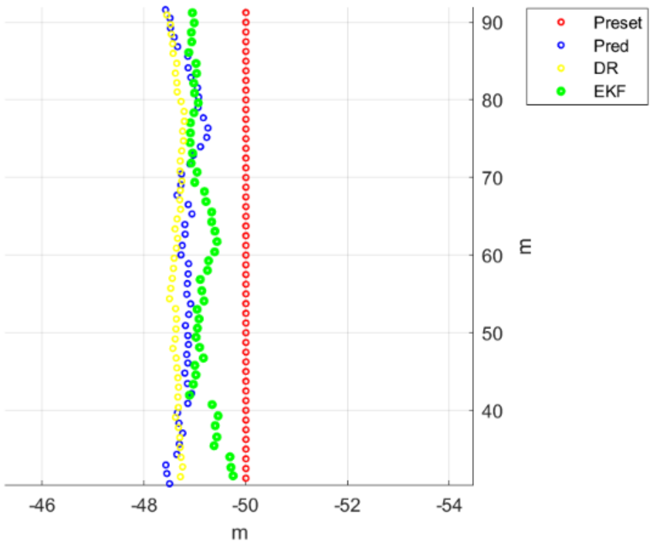

Fig. 8: Simulation results when the UAV swarm completely loses GPS or localization system data

Fig. 9 illustrates V-shape formation used in the tests of Fig. 10. Fig. 10 shows the simulation results that flight formation is not affected in case of losing assigned leader UAV. If UAV-1 fails, UAV-2 will use the pre-stored preset trajectory and UAV3 will assign UAV2 as the new leader. Due to the distributed idea, there is no need to change other settings.

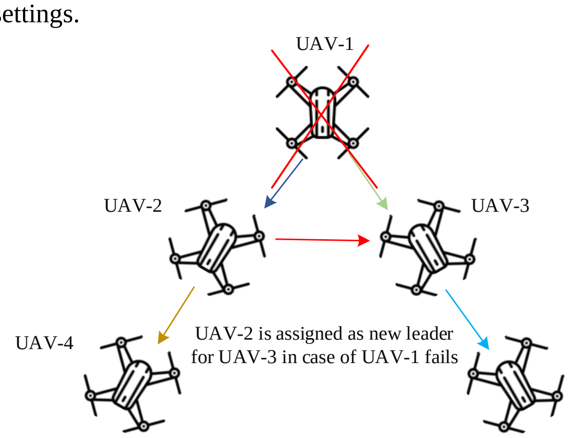

Fig. 9: V-shape formation.

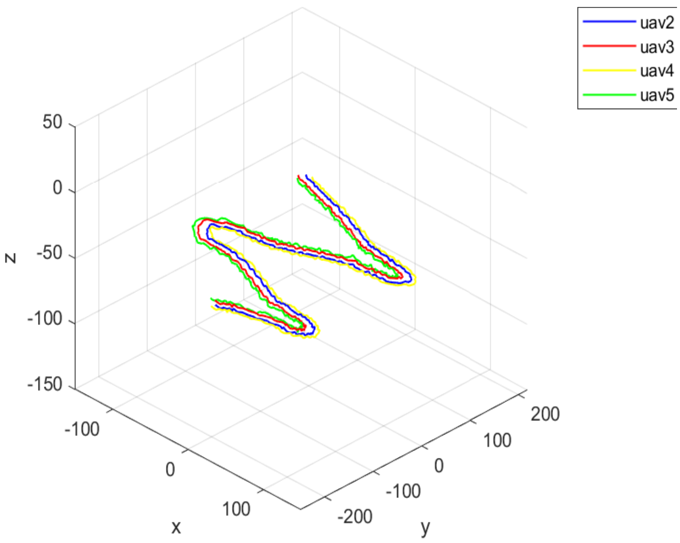

Fig. 10: The swarm loses Leader and assigns a new leader in a V-shape formation

B. Results of Outdoor Simulation

Like the indoor case, the fusion effect of the green line EKF in the outdoor case is more obvious as shown in Fig. 11. This is because the accuracy of IMU is similar no matter indoor and outdoor. Compared to DR, our implementation achieves a maximum accuracy improvement of about 60% to 1.6m.

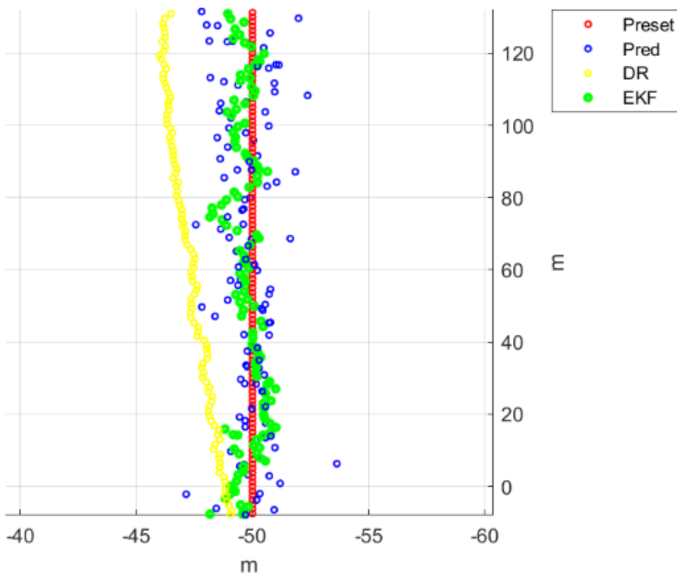

Fig. 11: Simulation results for the configuration outdoor environment given in Table II

VI. CONCLUSION

In this study, a control scheme is proposed for the formation of UAVs. The scheme utilizes distributed communication, where each UAV communicates with neighboring UAVs and treats them as a local leader, and leader-follower control, where the leader UAV stores a predetermined path and the other followers adjust their flight data according to the leader's position, direction, distance, speed, and angular velocity. The reliable formation can be maintained in both indoor and outdoor environments but using localization system with reference points like ultra-wideband based positioning system, which typically has good positioning accuracy in indoor situations. However, the accuracy of (inertial navigation systems) INS positioning can be low due to the limitations of GPS positioning accuracy and other noises like the effect of wind on the UAV, etc. In this paper, to improve the positioning accuracy indoors and outdoors, we proposed that UAVs in formation can receive minimal navigation information from other UAVs (single UAV is sufficient) that have not lost GPS connectivity or indoor localization system capability and use extended Kalman Filter in combination with data from their own inertial measurement units (IMU) to effectively reduce positioning errors in GPS-denied environments at outdoor or where location data cannot be obtained at indoor environment. The final simulation results demonstrate that this scheme can be very effective in reducing the error accumulation caused by its own DR positioning and improving the positioning accuracy when at least one UAV in the UAV fleet has not lost GPS signal or localization system information. Even in the case of that the all UAVs completely lose GPS or localization system information, the proposed control method can improve the positioning accuracy in more than half of the cases and provides safe formation though swarm mission. This paper also conducts simulations using predefined paths of different complexity and different formation shapes to demonstrate the effectiveness of the method.

Furthermore, it's important to note that we operate under the assumption that the relative angles between UAVs remain constant. This assumption is based on the limitations of our sensors in the simulation environment, which are incapable of measuring this parameter. Therefore, we cannot guarantee that the formation will maintain its shape for an extended period after all UAVs lose GPS connectivity. Nevertheless, the UAVs are proficient at consistently maintaining a specified distance from one another. To address this issue, the use of an azimuth sensor can enhance the calculation of relative positions and improve accuracy. Lai et al. [35] conducted research on azimuth-only passive positioning of UAV formations regarding azimuth angle.

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