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Visually extracting the network topology of drone swarms

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ABSTRACT

Drone swarms operate as decentralized systems where multiple autonomous nodes coordinate their actions through inter-drone communication. A network is a collection of interconnected nodes that communicate to share resources, with its topology representing the physical or logical arrangement of these nodes. For drone swarms, network topology plays a key role in enabling coordinated actions through effective communication links. Understanding the behavior of drone swarms requires analyzing their network topology, as it provides valuable insights into the links and nodes that define their communication patterns. The research in this paper presents a computer vision-based approach to extract and analyze the network topology of such swarms, focusing on the logical communication links rather than physical formations. Using 3D coordinates obtained via stereo vision, the method identifies communication patterns corresponding to star, ring and mesh topologies. The experimental results demonstrate that the proposed method can accurately distinguish between different communication patterns within the swarm, allowing for effective mapping of the network structure. This analysis provides practical insights into how swarm coordination emerges from communication topology and offers a foundation for optimizing swarm behavior in real-world applications.

1. Introduction

The communication topology of a drone swarm is the organization among a small group of drones working together to achieve a specific objective or operation. These swarms, comprised of multiple drones operating collaboratively, represent a transformative technological paradigm with applications spanning a multitude of sectors [1]. From surveillance operations and environmental monitoring to disaster response and search and rescue missions, drone swarms offer a versatile and dynamic approach to addressing complex challenges. The network's topology can be visualized as the arrangement of these drones, with each drone representing an individual node within the network. In such scenarios, effective communication among the drones becomes of utmost importance. Therefore, gaining a understanding of the diverse aspects of communication among UAV's is necessary [2].

The unique strength of drone swarms lies in their collective capabilities, where a group of drones functions as a cohesive unit to accomplish tasks that would be challenging or impossible for individual drones. This collective coordination is particularly evident in their ability to execute complex and multifaceted missions, demonstrating a level of efficiency and adaptability that surpasses what can be achieved by stand-alone drones [3].

Communication has been often seen as the “heart of the swarm” by interacting with others and changing their states, each node influences the swarm. The effectiveness of communication, which is greatly affected by the swarm network topology, consequently defines the robustness of the swarm. Unlike isolated drone operations, where communication is minimal, the success of drone swarms lies in the intricate exchange of information among their members. This communication allows drones to coordinate their actions, share data and respond collectively to dynamic and unpredictable environments [4].

Drone swarm formation control is a key aspect of multi-agent systems, where multiple drones must coordinate their movements to maintain a specific formation such as star, ring and mesh formation while executing a mission [5]. The efficiency and effectiveness of drone swarm depend heavily on the ability of individual drones to communicate seamlessly with each other. Communication within the drone swarm is useful because it allows drones to share information such as position, velocity and mission status, enabling the drone swarm to function as a cohesive unit [6].

Understanding the patterns and mechanisms of communication is essential for improving the robustness of drone swarm, especially in scenarios where they are vulnerable to targeted eliminations or external interference. The topologies determine how the drones interact with one another, how they share information and how they behave as a group [7]. Analyzing the communication topologies that govern how drones interact with each other helps to identify ways to enhance the overall robustness of the swarm.

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In swarm robotics, the underlying communication topology significantly influences collective behavior, yet is often difficult to access directly especially in black-box or adversarial scenarios. This work proposes a novel vision-based framework that infers swarm topology by observing how drones move in synchrony. The key idea is that coordinated motion, particularly synchronous turning behavior, reflects implicit connectivity among agents. By leveraging this synchronization as a proxy for communication, the system identifies structural formations, role-based interactions, and topology transitions passively, using only stereo-vision and trajectory analysis. This approach offers a scalable and non-intrusive solution for understanding swarm behavior without relying on internal logs or direct network access.

This research uses computer vision and AI algorithms to extract the network topology of drone swarms specifically on three main structures: star, ring and mesh, with a particular emphasis on the communication patterns that underpin their collaborative behavior. Through simulated environments, the study aims to unravel the intricate dynamics of drone swarm communication, shedding light on the spatial relationships, coordination strategies and information flow among the individual drones.

The main contributions of this paper are (i) Development of a simulated environment that models drone swarms operating under different network topologies, including ring, mesh, star to facilitate controlled analysis of swarm behavior. (ii) Implementation of a visual inference framework that passively extracts communication patterns and inter-drone links using stereo vision, object detection and 3D trajectory tracking. (iii) Experimental evaluation of the proposed framework, demonstrating its effectiveness in reconstructing swarm network structures and identifying potential communication patterns without direct access to communication data.

The remainder of the paper is organized as follows. Section 2 is describing the background that justifies the creation of details of the previous work on the different formations of swarms of drones. Section 3 depicts challenges and techniques that can be faced during implementation and tracking of different formations and extract communication structure of drone swarm. Section 4 presents proposed approach to extract communication pattern of drone swarm. Section 5 describe the implementation and simulation with experiment. Section 6 describes the implications of the findings, addresses the limitations of the proposed approach Finally, Sections 7 and 8 presents some conclusions and future work.

2. Background

2.1. Network topology

A network consists of nodes and the communications between them. The topology of the network is the architecture or network architecture [8]. Network topology refers to the structural arrangement of various elements in a computer network, encompassing the drones and the communication links between them. Understanding network topology is important for designing efficient, reliable and scalable drone swarm systems. The topology dictates how drones communicate, coordinate and share information, significantly impacting the overall performance and robustness of the swarm.

In a drone swarm, the network topology can be dynamic due to the mobility of drones, which continuously change their relative positions [9]. The primary goal is to maintain robust communication links among drones while optimizing resource use such as power and bandwidth [10]. The choice of topology affects several performance metrics, including latency, throughput, fault tolerance and scalability [11].

A star topology [12] where one central drone (master) communicates with all other drones (slaves) is simple to implement and manage but suffers from a single point of failure. A mesh topology [13] in which each drone can communicate with any other drone directly or indirectly is highly robust and fault-tolerant providing multiple paths for data transmission but is complex to implement and maintain. Ring topology [14] arranges drones in a circular fashion with each drone communicating with its two nearest neighbors making it efficient for sequential data processing but less flexible if one drone fails. Tree topology [15] featuring a hierarchical structure with parent–child relationships among drones balances simplicity and reliability allowing easy scaling by adding branches but can create bottlenecks and affect communication if higher-level nodes fail. Each topology offers distinct advantages tailored to different operational needs from small-scale centralized control to large-scale, redundant and dynamic operations [16].

The operational dynamics of network topologies in a drone swarm involve continuous adaptation to changes in the environment and the positions of drones [17]. Key components include:

Dynamic Routing: Protocols must accommodate frequent topology changes due to drone mobility. Algorithms like OLSR [18] and GPSR [19] are designed for such environments.

Link Maintenance: Mechanisms to detect and repair broken links are necessary. For instance, drones can use beaconing (periodic hello messages) to confirm the presence of neighbors [20].

Load Balancing: Efficient distribution of communication tasks ensures no single drone is overloaded, which is fundamental in mesh and tree topologies [21].

Fault Tolerance: Redundancy in communication paths (especially in mesh topologies) helps maintain network integrity despite node failures [22].

Two network topologies exist within a drone swarm — the physical topology which reflects the relative positions of nodes and the logical topology which represents the underlying information transfer network [23]. The research presented in this paper will explore logical topology.

2.2. Network tomography

Tomography is the process of constructing cross-sectional images of items via transmission or reflection data and is carried out by illuminating items from several directions. When the item is a network this is referred to as Network Tomography. The process is often carried out via active or passive end-to-end path measures [24]. In swarm robotics, network tomography can uncover the Command and Control (C2) topologies that govern communication within the swarm. Command and Control topologies that hold swarms together and thereby expose weaknesses facilitating effective targeted elimination.

Network tomography [23] is a technique used to infer the internal communication structure of a network by analyzing measurements collected from its edges or end nodes. In the context of drone swarms, it enables the analysis of the swarm's internal communication dynamics using data obtained from individual drones or boundary observations [23]. This method is valuable for assessing network performance, identifying communication bottlenecks, diagnosing faults and optimizing the overall communication architecture. Two network tomography exist within a drone swarm — passive tomography and the active tomography [25].

- **Passive Tomography:** Passive tomography involves monitoring the existing traffic within the network without injecting additional data making it useful for real-time analysis and continuous monitoring of the swarm's communication performance. While non-intrusive and does not affect normal operation, passive tomography is limited by existing traffic patterns and may not capture all network characteristics [26].
- **Active Tomography:** Active tomography involves sending test packets through the network to measure performance metrics like latency, packet loss, throughput, providing data on network performance, suitable for detailed performance analysis and troubleshooting. But active tomography is intrusive and may affect normal network operations due to additional test traffic [27].

- **Hybrid Tomography:** Hybrid tomography combines the strengths of both passive and active approaches providing a more holistic view of the network while balancing non-intrusiveness and data comprehensiveness. Despite its complexity hybrid tomography is optimal for achieving continuous monitoring and detailed performance analysis [28].

Extracting network topologies using tomography involves several steps. Network tomography for analyzing the drone swarm involves several steps and considerations:

Data Collection: This involves gathering end-to-end performance data through both passive monitoring and active probing. The collected data provides critical insights into the current state of the network, including latency, connectivity patterns and potential bottlenecks [29]. Such information forms the basis for accurately inferring the underlying network structure and for assessing the behavior and coordination within the swarm.

Inference Algorithms: Using statistical and machine learning techniques to infer the internal network characteristics from the collected data. Algorithms such as Maximum Likelihood Estimation (MLE) and Bayesian inference are commonly used [30].

Real-time Analysis: In dynamic environments such as drone swarms, real-time analysis enables immediate processing of collected data to detect changes or anomalies as they occur [31]. This capability is particularly important for maintaining situational awareness, ensuring timely decision-making and enabling adaptive responses to disruptions in swarm coordination or communication.

Adaptation and Optimization: Based on the insights gained, the network can be dynamically reconfigured to optimize performance. This may involve re-routing traffic, adjusting transmission power or reassigning communication roles among drones [32,33].

Network tomography in drone swarms plays an important role in maintaining and improving the network's performance and reliability. One of the primary applications is fault detection and localization, which involves identifying and locating faults within the network to ensure continuous operation. This process works by detecting anomalies through tomography data, such as an unexpected increase in packet loss, which might signal a failing communication link. The ability to promptly identify these faults enables swift corrective actions, minimizing downtime and ensuring the effectiveness of the swarm's mission [34].

Another significant application of network tomography is performance optimization. This involves enhancing network performance by optimizing routing protocols and network configurations. Through the analysis of tomography data, inefficiencies and bottlenecks within the network can be identified. Once these issues are pinpointed, adjustments can be made to routing strategies or communication parameters to improve overall performance. This optimization ensures efficient use of resources, reduces latency and increases throughput, thereby enhancing the operational efficiency of the drone swarm [35,36].

2.3. Communication extraction strategies in drone swarms

Research on the correlation among cosmopolitan-provincial topology and network efficacy was conducted by Everton. This study [37] indicated that an inverse curve signifies that a cosmopolitan-provincial balance should be maintained by efficient networks shown in [38]. It suggests that it could be a feasible intervention strategy to shift the topology of the swarming network to either side of the curve to deform the cosmopolitan-provincial equilibrium. Due to the importance of inferring logical network topologies for targeted elimination purposes the authors recommend that the above work is progressed. The aim should be to formulate a general-purpose network [37] inference technique capable of:

- Detecting communications links in swarms of varying sizes.
- Handling real-time addition or subtraction of nodes.

Apart from that to identify an accurate graph it is essential to determine the sensing range and the field of view of each drone swarm node. A good starting point would be to construct a broad set of drone swarm controllers with known topologies and attempt to infer these via simulation.

Everton [39], building on earlier work [40], proposed a graph-based model to analyze the relationship between network topology and efficiency. In this model, the term "hierarchical" is closely aligned with "centralized" structures, indicating that certain nodes play dominant roles in information flow. The study suggests that disrupting the balance between centralized and decentralized (or cosmopolitan and provincial) topologies is an effective strategy for reducing the overall efficiency and resilience of a network. This insight is particularly relevant when targeting critical nodes in adversarial networks such as drone swarms.

A study [38] discusses how swarm robotics applications can be made more robust by modifying the swarm's network topology. The findings indicate that, during the central phase of operation, drone swarm networks benefit from being both centralized and distributed. In contrast, when operating in multi-objective environments particularly where targets are aligned in co-linear areas and require similar capabilities—swarm networks tend to perform better when adopting a more centralized structure during the middle phase of operation.

Vasquez and Barca [41] conducted research aimed at determining Command and Control (C2) structures at higher resolutions to support targeted elimination strategies in swarm networks. Their work demonstrated that analyzing edge orientations in topological graphs can be used to identify leaders in drone swarms governed by flocking behavior, physics-inspired models, morphogenesis and particle swarm optimization (PSO)-based controllers. The study also acknowledged that additional research is needed to develop high-resolution, general-purpose network inference techniques that are applicable across diverse swarm types and control paradigms.

In a related investigation, [41] also introduced a topographical framework that captures both the frequency and alignment of drone swarm associations. This framework supports the identification of global characteristics such as leadership roles and provides a way to relate swarm dispersion metrics to communication intensities. The experiments revealed that leadership behaviors could be inferred from edge preferences within the topographical graph. Interaction measures evaluated through velocity distribution offered visual insights into the swarm's contact dynamics. While other parameters, such as swarm size and control paradigm, influenced system behavior, they had minimal effect on the overall density distribution across all agents.

While numerous studies have explored drone detection and swarm coordination, fewer have addressed the passive inference of communication structures from external observations. Traditional network inference techniques in wireless and cyber–physical systems often rely on signal-level data, such as Received Signal Strength (RSS), packet delays or direct access to message logs [23,38]. These methods, though effective in well-instrumented environments, are intrusive by nature and unsuitable for adversarial scenarios where internal communication data is inaccessible.

In contrast, behavioral and vision-based approaches offer a non-intrusive alternative by using observable movement patterns. Yanmaz et al. [42] examined how local interactions can shape global swarm topology, though their focus remained on communication performance rather than topology inference.

Most of these approaches assume either access to explicit communication logs or use abstract modeling rather than real-time data extraction. This work diverges by using stereo vision and object detection to passively extract the 3D trajectories of drones, then infer network topology based on their coordinated motion. This allows for the detection of structural relationships (e.g., ring, mesh and star) without requiring direct access to communication hardware or protocols.

Existing visual methods typically address drone localization or object tracking but do not extend toward network topology analysis. By bridging this gap, the proposed framework contributes a novel perspective to the field situated at the intersection of computer vision, swarm behavior analysis and adversarial network inference. This positioning highlights the originality of this work and its relevance for passive swarm surveillance and security applications.

3. Drone swarm pattern extraction challenges and techniques

The network topology of a drone swarm provides a graphical representation of its communication patterns, interactions and influences [41]. Inferring this topology is useful for understanding swarm behavior, supporting predictive analysis and ensuring effective coordination. Extracting a drone swarm network topology from empirical observations alone is highly challenging, particularly when no prior knowledge of the network is available. This challenge is compounded by the dynamic, high-mobility nature of drones, which leads to frequent changes in the network structure [43].

The high mobility of drones causes rapid changes in network topology, making it difficult to predict and track communication links [44]. Nodes may frequently lose connectivity, disrupting information exchange and reducing routing efficiency. High-density formations lead to overlapping drones, obscuring visibility and making it difficult to distinguish individual drones and their interactions [5]. Sparse networks and frequent link failures destabilize communication and limit the network's lifetime, further complicating the extraction of communication patterns [45]. The limited communication range of drones restricts connectivity, especially in larger swarms, posing challenges for capturing comprehensive topology data [45]. These challenges highlight the importance of dynamic topology inference to track and adapt to changes in the swarm's network structure, particularly in high-density and high-mobility scenarios.

A range of techniques have been developed to analyze and determine drone swarm communication structures, with a growing emphasis on visual extraction using computer vision. High-resolution cameras and advanced computer vision algorithms, such as object detection and optical flow, enable the visual tracking of drones. These methods allow for the continuous monitoring of drone positions and interactions, providing real-time data for topology mapping [46]. RF signal detection and analysis, using ground-based sensors and directional antennas, can infer communication links, although this method may face limitations in high-density swarms [47]. Acoustic tracking, utilizing arrays of microphones to detect and localize drones based on sound patterns, provides an alternative for environments where visual methods are less effective [48]. Radar systems, such as Doppler and phased-array radar, provide precise tracking and mapping of drone movements, enabling the inference of communication structures [49].

Telemetry and sensor fusion approaches combine data from onboard sensors, such as GPS, accelerometers and gyroscopes, to provide a holistic understanding of swarm dynamics [50]. Machine learning algorithms trained on drone movement patterns and communication data can predict and classify communication links, offering scalable solutions for large swarms [51]. Among these techniques, computer vision stands out due to its ability to provide real-time analysis, scalability, accuracy and comprehensive insights into drone swarm behavior [52]. Cameras and vision-based algorithms enable dynamic tracking of swarm connectivity, supporting predictive modeling and operational planning.

Extracting and analyzing the network topology of drone swarms is essential for understanding their behavior and optimizing their operations. While numerous challenges arise from the dynamic and complex nature of these networks, computer vision techniques offer a promising solutions [53]. Through real-time visualization and accurate mapping, these methods enable researchers to overcome density, mobility and connectivity issues, providing useful insights into swarm coordination and communication. This research underscores the potential of visual extraction as a base for future advancements in drone swarm analysis and applications.

The research in this paper aims to passively extract the communication structure of a drone swarm by analyzing its movement and interactions. By uncovering the swarm's network topology, it becomes possible to identify the key nodes that facilitate coordination. For instance, in scenarios where an unauthorized drone swarm is operating near a restricted area, identifying its communication structure could provide insights into its command hierarchy and vulnerabilities. Security forces could then use this intelligence to predict swarm behavior, disrupt key communication links and mitigate potential threats without direct engagement. The ability to extract and analyze these patterns passively enhances situational awareness and informs counter-swarm strategies.

4. A proposal for visually determining a drone swarms communications pattern

This study presents a visual framework for passively inferring the communication topology of drone swarms using stereo vision, deep learning-based detection and spatiotemporal tracking. The proposed method operates in three key stages: drone detection using a deep learning model, trajectory tracking via stereo vision and Kalman filtering and communication graph inference based on motion analysis. All components are implemented in a ROS-Gazebo simulation environment and programmed in Python, with OpenCV and PyTorch libraries supporting visual processing and deep learning, respectively.

The proposed approach uses a deep learning-based detection algorithm in conjunction with a Kalman filter to track individual drones in various drone network topologies over time. The primary objective is to extract communication links passively based on observed swarm behavior.

Extraction of 3D coordinates

To detect drones in real-time, this study uses the YOLOv6s object detection model, which offers enhanced accuracy and speed over its predecessors by incorporating an anchor-free detection head and improved backbone efficiency. YOLOv6s is well-suited for applications requiring fast inference and high detection precision, making it ideal for swarm scenarios where multiple drones must be tracked simultaneously.

A custom drone image dataset was generated in the Gazebo simulator across multiple scenes, lighting conditions, altitudes and formations. The dataset comprises 4200 annotated images with bounding boxes, split into training (70%), validation (20%) and test (10%) subsets.

The YOLOv6 model was trained using the YOLOv6s (anchor-free) architecture with an input resolution of 640×640 pixels. The training process used the AdamW optimizer with a learning rate of 0.001, over 120 epochs and a batch size of 16. The model achieved a mean Average Precision (mAP@0.5) of 93.1% on the test set, indicating robust object detection performance in varied simulated environments. To refine detections, Non-Maximum Suppression (NMS) was applied to filter out overlapping bounding boxes, ensuring each drone is counted only once per frame.

Following detection, the 2D positions of drones are mapped into 3D space using a stereo vision system. Two virtual cameras placed 3 m apart capture synchronized image streams, allowing for depth estimation through stereo disparity calculation. Triangulation techniques are used to compute the depth of each detected drone, enabling reconstruction of their 3D positions.

To track drones over time, a Kalman Filter is used for each detected object. The filter predicts future positions and updates state estimates based on new observations, smoothing trajectories and handling temporary detection loss. This tracking ensures that each drone

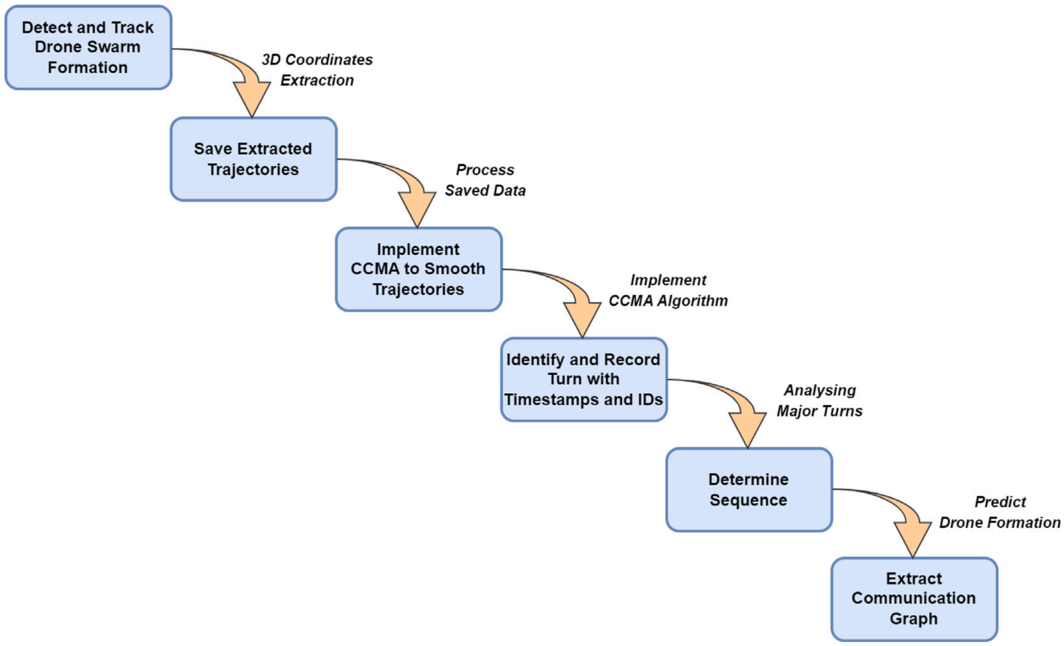


Fig. 1. An approach to extract the communication graph of drone swarm.

is continuously localized in 3D across successive frames, forming the basis for motion and interaction analysis.

Curvature Corrected Moving Average: CCMA (Curvature Corrected Moving Average) algorithm [54] is applied to the trajectory data. This step is necessary for reducing noise and smoothing the paths thus refining the data for a more accurate analysis of drone behavior.

The CCMA represents an advanced path smoothing algorithm designed to enhance the movement and coordination of drone swarm [55]. Traditional path smoothing techniques often rely on predefined models that may not adequately adapt to the dynamic and unpredictable environments in which drone swarm operate. In contrast, the CCMA algorithm is model-free, using the principles of the moving average to effectively smooth paths in both 2D and 3D spaces.

The core principle of CCMA is to adjust the trajectory of a moving object such as a drone by averaging the positions over a defined window while incorporating curvature correction [56]. This ensures that the resulting path is smoother and also maintains a natural flow, avoiding abrupt changes in direction that could destabilize the drone or cause inefficient movements.

Inference of network topology

Building upon the extracted 3D trajectories, the next stage involves extracting the network topology of the drone swarm. The movement patterns and spatial relationships among drones are analyzed to infer potential communication links. A communication graph is constructed by assessing the positional dependencies between drones, allowing for the identification of connectivity patterns within the swarm. This approach enables the extraction of communication structures passively, without direct access to the swarm's structure. By analyzing these inferred connections, the study provides insights into swarm coordination dynamics, contributing to a deeper understanding of autonomous drone swarm networks (See Fig. 1).

The evaluation of the proposed approach involves detecting and tracking drones in three different formation types i.e. star, ring and mesh. The effectiveness of the approach is investigated by measuring detection accuracy using the deep learning based object detection system and tracking performance with a Kalman filter. These metrics help assess the robustness of the communication links inferred from the trajectory data. The drone swarm communication extraction pipeline algorithm 1 is designed to analyze the trajectories of drones within a drone swarm to identify the potential communication patterns. The algorithm begins by taking the 3D coordinates of each drone as input. For each drone trajectory T_i, the algorithm first applies a filtering process to smooth the trajectory data, resulting in a refined trajectory T_i'. Next, for each point P_j in the smoothed trajectory, the algorithm calculates the angle $\theta_{p_j,p_{j+1}}$ between consecutive points using the cosine inverse function:

$$\theta_{p_j,p_{j+1}} = \cos^{-1}\left(\frac{P_j \cdot P_{j+1}}{|P_j||P_{j+1}|}\right)$$

This angle is used for detecting changes in the drone's direction. If the angle $\theta_{p_j,p_{j+1}}$ falls within the specified range of 60° to 130°, the point is marked as a "turn" and relevant details, including the position P_j, time, t_j and drone ID i are recorded in the set S_i.

Once all trajectories have been processed, the algorithm sorts the recorded turns S_i based on their timestamps t_j to maintain a chronological order. This sorted sequence is then used to extract a sequence of drone IDs $\{i\}$ along with their corresponding timestamps $\{t_j\}$. The final step involves analyzing this sequence to identify the communication patterns within the drone swarm. By understanding how and when these drones change direction in relation to one another the algorithm can infer possible communication interactions, thereby providing valuable insights into the swarm's coordination and behavior.

After extracting the sequence of directional changes for each drone, the algorithm proceeds with a structured analysis to infer the underlying communication topology within the swarm. The first key step involves constructing a communication graph $G = (V, E)$, where each node $v \in V$ represents a drone, and edges $(v_i, v_j) \in E$ are added between drones that exhibit both spatial proximity and temporally correlated behavior, such as coordinated turns. This reflects the operational assumption that synchronized directional changes between drones are indicative of either direct communication or shared access to local swarm dynamics.

Once the graph G is constructed, the algorithm computes several graph theoretic metrics that serve as structural fingerprints of the swarm's coordination pattern. These include the node:

- degree distribution d_v, which captures the number of immediate neighbors or potential communication links per drone;

Algorithm 1 Drone Swarm Communication Extraction Pipeline

Input: Drone swarm 3D Coordinates P
Output: Communication Pattern (e.g., Star, Mesh, Ring)
for each drone trajectory T_i **do**
  $T_i' \leftarrow \mathrm{CCMA}(T_i)$ ▷ Apply curvature-corrected smoothing
  for each point P_j in T_i' **do**
    $\theta_{p_j,p_{j+1}} = \cos^{-1}\left(\frac{P_j \cdot P_{j+1}}{|P_j||P_{j+1}|}\right)$
    if $60^\circ < \theta_{p_j,p_{j+1}} < 130^\circ$ **then**
      $S_i \leftarrow \{P_j, t_j, ID(i)\}$
    end if
  end for
end for
$S \leftarrow \bigcup S_i$
$SORT(S)$ by t_j
Extract ordered sequence $\{i, t_j\}$ from S
Construct communication graph $G = (V, E)$ based on spatial and temporal proximity
Compute structural features: degree distribution d_v, edge density ρ, clustering coefficient C
Initialize $best\_match \leftarrow$ None, $max\_confidence \leftarrow 0$
for each pattern $p \in$ {Star, Mesh, Ring} **do**
  $conf \leftarrow \mathrm{Match}(G, p)$ ▷ Compute pattern confidence score
  if $conf > max\_confidence$ **and** $conf \geq \tau$ **then**
    $best\_match \leftarrow p$, $max\_confidence \leftarrow conf$
  end if
end for
if $best\_match \neq$ None **then**
  return $best\_match$
else
  return No known pattern found
end if

- the edge density $\rho = \frac{2|E|}{|V|(|V|-1)}$, which quantifies how densely connected the swarm is;
- and the clustering coefficient C,which indicates how tightly grouped the neighborhoods of individual drones are, and whether they form localized clusters.

These metrics provide a quantitative profile of the swarm's interaction structure, providing insight into how information may propagate through the network and how centralized or distributed the swarm's control dynamics might be. To classify the swarm's structure, the algorithm compares the computed values against predefined topological templates of known swarm formations: *Star*, *Mesh*, and *Ring*.

Each of these formations exhibits a distinct structural signature:

- A *Star* formation is characterized by one central node with a high degree (close to $n-1$) connected to peripheral nodes of degree one, with a clustering coefficient near zero.
- A *Mesh* formation exhibits high edge density and clustering coefficient, with most nodes having moderate to high degrees and forming redundant communication links.
- A *Ring* formation is defined by uniform node degrees of two and a cyclic, low-density structure.

The algorithm iteratively evaluates each of these formation types by computing a confidence score that reflects how closely the observed graph metrics match those of the respective formation template. This is implemented using a pattern-matching loop that compares the graph G to each structure. If the highest confidence score exceeds a user-defined threshold τ, the corresponding pattern is reported as the final output. Otherwise, the system returns "No known pattern found", ensuring that classification is only performed when supported by strong structural evidence.

The proposed framework builds on the assumption that drones engaged in communication or coordination exhibit synchronous movement patterns, particularly during formation shifts or turning events. The system tracks 3D trajectories of individual drones and identifies major angular deviations, which are then analyzed for temporal alignment across agents. If multiple drones perform sharp turns within a defined temporal window, they are assumed to be engaged in coordinated behavior, suggesting a functional topological link.

These synchronized turning events are aggregated across the swarm to construct a frequency-based interaction map. Topological patterns such as (1, 4, 4) or (1, 3, 4, 1) are derived by counting the number of drones involved in each role (central, support, or frontline) during these coordination episodes. This method enables the extraction of dynamic and evolving swarm topology purely from motion cues, offering a robust proxy in environments where communication metadata is inaccessible or unreliable.

5. Experimental evaluation

The experiment setup involves creating a simulation environment, conducting experiments and collecting data for analysis. This section presents an evaluation of the proposed approach to detect drones in different formation types. The aim is to investigate the effectiveness of the approach in detecting and tracking different drone formations and extract the communication graph to understand behavior of swarm.

This study uses a drone swarm executing movements in diamond, ring and mesh formations. A key component of the simulation is the deployment of a stereo camera, positioned 3 m above the drone swarm which captures the movement of the drones. This setup allows for observation of the drone swarm dynamics and facilitates the subsequent image processing and drone tracking phases.

To understand the communication dynamics and spatial relationships among the drone swarm entities, the drones are initialized in a range of predefined formations, including ring, star, mesh and random dispersal. These initial configurations are selected to simulate common swarm coordination patterns and to enable controlled analysis of formation-dependent communication behavior. Each drone is equipped with a simulated communication module, which allows it to exchange positional and state information with neighboring drones based on predefined communication ranges. This simulates realistic inter-drone communication constraints that occur in physical deployments. The drones are programmed with a set of coordinated movement behaviors that include maintaining formation, reacting to neighbor position changes and adapting to simulated external stimuli such as obstacle avoidance or trajectory shifts. This initial configuration is used for the controlled exploration of how drones interact and communicate within the swarm. The parameters are adjusted to refine the experimental setup. For example, the smoothing algorithm parameters `CCMA(w_ma=30, w_cc=30)` are tuned to achieve smoother paths. The turn detection threshold is modified 60° but less than 130° to identify directional changes. The drone swarm consists of nine drones each initialized with a specific 3D position. The initial positions, represented as `drone_cords_offset`, are defined as follows:

```
drone_cords_offset = [
  (0, 0, 0.5),
  (0.5, 0.5, 0.5),
  (0.5, -0.5, 0.5),
  (-0.5, 0.5, 0.5),
  (-0.5, -0.5, 0.5),
  (0.95, 0.95, 0.5),
  (0.95, -0.95, 0.5),
  (-0.95, 0.95, 0.5),
  (-0.95, -0.95, 0.5)]
```

Each row in the matrix represents the 3D coordinates of a drone. The specific pattern of these coordinates forms a grid-like or circular arrangement of drones around the origin, ensuring that they are evenly distributed and ready for the drone swarm operations. The chosen offsets (e.g., [0.5, 0.5, 0.5]) ensure that the drones are placed at a sufficient distance from each other to avoid collisions at the start of the simulation.

This initial positioning is important for the subsequent behavior of the drone swarm as it impacts the communication, coordination and movement patterns of the drones. By carefully selecting these initial positions the simulation can more accurately reflect realistic scenarios where drones are deployed in a pre-arranged formation. A deliberate delay is introduced between the movements of individual drones. This intentional lag serves as a key variable, allowing for a precise examination of the drones interactions and how the drone swarm adapts to temporal constraints, reorganizing spatially in response. This experiment setup provides a robust framework for analyzing and understanding the complex interactions within drone swarm.

5.1. Pattern extraction in drone swarm formations

This section evaluates the capability of a vision-based approach to track and analyze the underlying communication network structures, specifically star, ring and mesh topologies within a drone swarm. Unlike physical formations, which describe spatial arrangements of drones, these topologies refer to the logical structure of communication links that govern coordination and data exchange among swarm members. The objective is to demonstrate how a stereo-vision-based tracking approach can accurately infer these network patterns by observing the spatial trajectories and relative interactions of the drones over time. The extracted 3D coordinates serve as the foundation for identifying the temporal evolution of connectivity patterns within the swarm.

In this paper, the "percentage of pattern" refers to the proportion of correctly inferred communication links that match the ground-truth swarm topology at each evaluation stage. This metric measures how accurately the visual framework reconstructs the underlying formation structure (e.g., star, mesh, ring) based solely on observed motion cues. For example, a reported value of 70% indicates that 70% of the extracted inter-drone connections correspond to the true topological configuration. These percentages therefore function as a structural accuracy measure, analogous to accuracy in classification problems. Given the passive, vision-only nature of the inference process, values in the 70%–80% range are considered strong indicators of performance, especially under dynamic movement, occlusion, communication delay, and formation transition conditions.

5.1.1. Star topology drone swarm pattern extraction

In this experiment a stereo-vision camera system was configured to observe the star formation topology of the drone swarm at 90° angles. The initial detection of drones within the formation was conducted using a deep learning framework. Following detection a Kalman filter is applied to track each drone movement over time and to extract their 3D coordinates as illustrated in Fig. 2(a). Once tracking is completed the CCMA algorithm is utilized to refine the trajectories by reducing noise and smoothing the paths of the drones as shown in Fig. 2(b). This processing stage is a key for accurate analysis.

The experiment focused on major turns of the drone swarm, specifically monitoring the angles between consecutive trajectory points. A major turn was noted when the angle fell within a predefined threshold >60° degrees but <130° degrees indicative of a change in the communication or formation pattern in Fig. 2(c). This method effectively demonstrated the capability to monitor and analyze complex turning actions and interactions within a drone swarm, highlighting its potential for advanced studies in autonomous drone behaviors.

The presented scattered graph Fig. 3 provides a detailed visual representation of the time-based activity patterns of drone swarm each identified by a unique identifier. This graph is particularly useful for understanding the sequence and timing of drone movements especially during major turns. The x-axis of the graph represents time ranging from 0 to 400 s, capturing the entire duration of the observed drone activities. The y-axis corresponds to different drones, each assigned a unique numeric identifier ranging from 1 to 9 representing individual drones. This scattered graph reveals the pattern of drone movements as shown in graph the very first movement is observed from drone 6 (Colored in blue) at the earliest time, indicating it was the first drone to initiate activity. This suggests that Drone 6 is the first to engage in a operation. Following drone 6, other drones in the orange group namely Drone (1,2,3 and 7) begin their movements shortly after. This indicates a coordinated pattern within the orange group, where these drones communicating to each other and responding to lead of drone 6. After the orange group, drones (4,5,8 and 9) both colored in green become active. This shift suggests that the green group is waiting for the orange group to finish their job and is programmed to move after them.

This graph illustrates the sequence and timing of drone movements highlighting how different groups of drones coordinate their activities. By analyzing the distribution and timing of scatter points, one can deduce which drones lead the movement, how they are grouped and how they follow each other in a coordinated manner. The visualization is particularly valuable in understanding the behavior of the drone swarm, especially in identifying patterns like which drone moved first, how the other drones responded, and the sequence in which different groups initiated their movements.

In analyzing the sequence of drone movements a particular pattern of interest was observed. When the extracted sequence follows the pattern (1, 4, 4) this is identified as a star pattern. The star pattern signifies a coordinated movement where an initial drone leads followed by a synchronized response from a group of drones. This pattern was notably observed in this graph indicating a structured and repeatable behavior within the swarm.

To quantify the confidence in detecting star pattern a percentage calculation is used to measure how often a specific pattern appears relative to all patterns detected. The formula used for this calculation is:

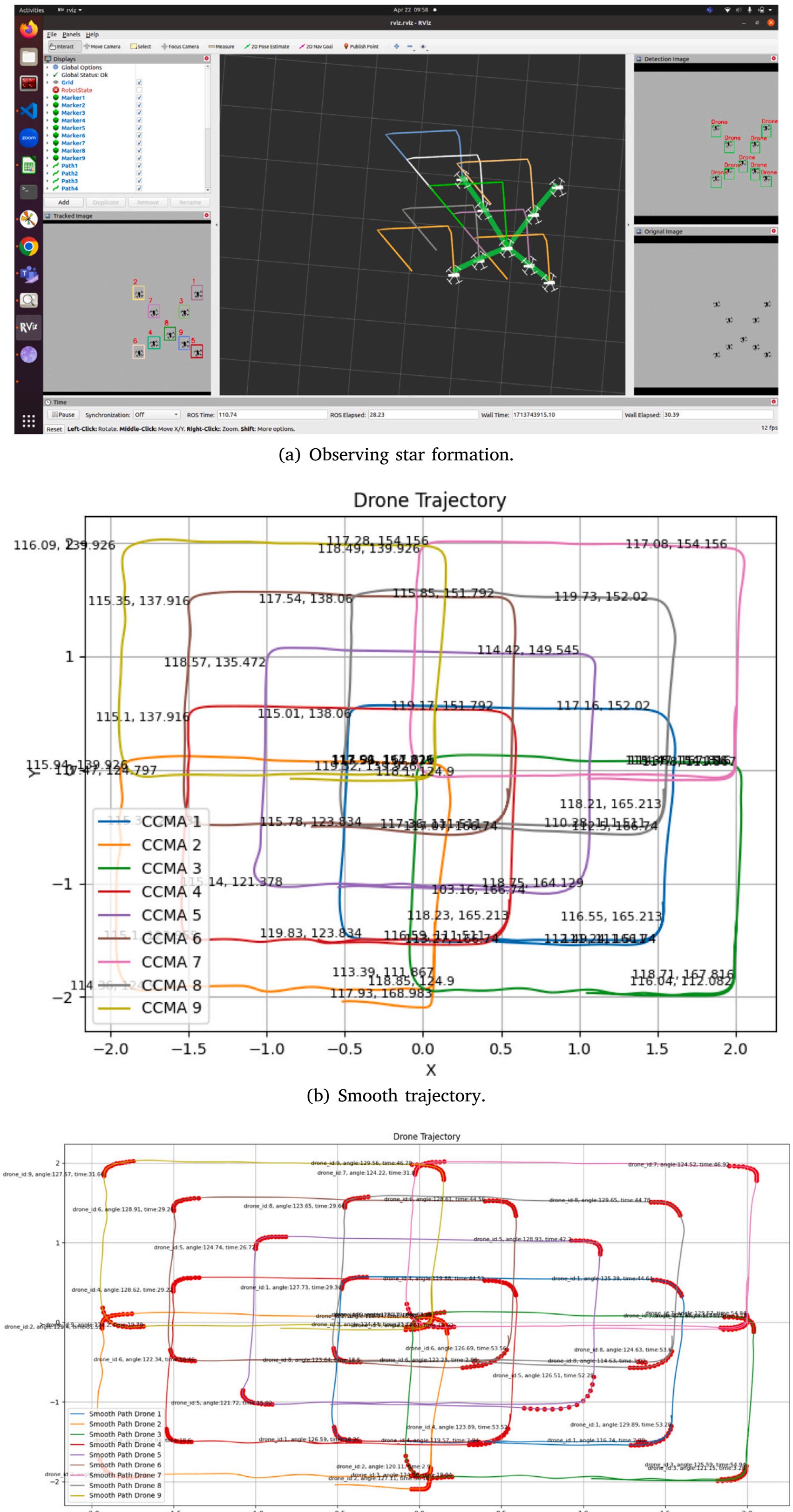
$$\text{Percentage of Pattern} = \left(\frac{\text{count of specific pattern}}{\text{total count of all patterns}}\right) \times 100$$

In the experiment, this formula is applied to determine the prevalence of the star pattern (1, 4, 4) among the detected sequences. **The analysis revealed that 70% of the detected major changes led to the identification of this star pattern.** This high percentage provides strong evidence of the star pattern's significance in the drone swarm's behavior, supporting the conclusion that there is a high degree of structured and repeatable coordination within the swarm. This measure of confidence validates the observed patterns and enhances the credibility of the method used for pattern extraction.

In the star formation experiment, the identified pattern (1, 4, 4) corresponds to the detected communication structure, where:

- 1 drone is acting as a central hub, coordinating the formation.
- 4 drones are positioned at the outer points, actively maintaining edge communication (frontline drones).
- 4 drones are functioning in supportive alignment roles, ensuring positional stability across radial connections.

This classification is derived from trajectory-based behavior such as synchronized angular turns, consistent distance maintenance, and proximity to the inferred centroid. The numerical pattern reflects the structural inference of roles during flight, highlighting the symmetry and centralized coordination typical of star formations. This interpretation validates the framework's capacity to distinguish internal hierarchy in visually tracked swarm formations.



(a) Observing star formation.

(b) Smooth trajectory.

(c) Major turns in star drone swarm formation.

Fig. 2. Star formation pattern extraction.

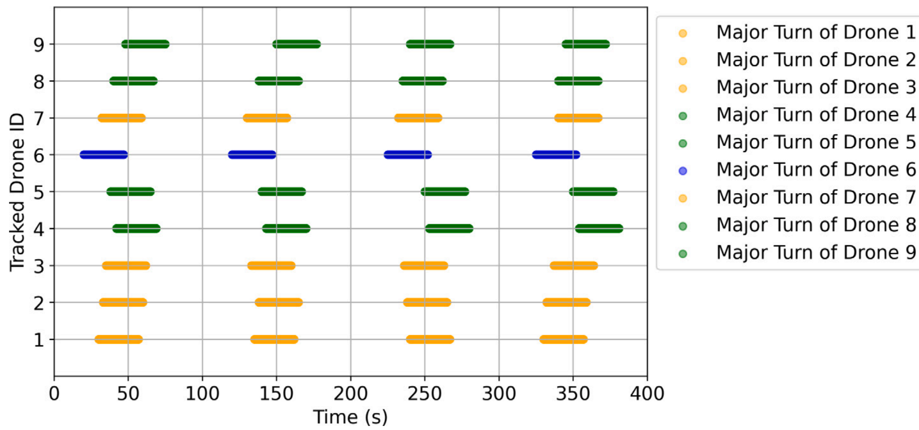


Fig. 3. Drone swarm pattern extraction in star formation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.1.2. *Ring topology drone swarm pattern extraction*

In this experiment, the same approach is used to detect, track and extract the communication patterns but with the drone swarm organized in a ring formation as illustrated in Fig. 4(a). The major turns recorded during the experiment are depicted in Fig. 4(b). The primary focus of the experiment is to observe the behavior of the drone swarm in this ring formation with an emphasis on understanding their movement patterns and extracting the sequence of their coordinated actions. Through this analysis the experiment aims to uncover the underlying dynamics of the swarm's behavior and how they operate collectively in a ring configuration.

In the scatter graph shown in Fig. 5 a distinct ring pattern is observed, reflecting the coordinated movement of the drone swarm in a circular order. This pattern is identified by the sequence (1, 2, 2, 2, 2) which indicates a methodical and synchronized behavior within the swarm, where drones move in a structured sequence to maintain the integrity of the ring formation.

The sequence begins with drone 4, which is the first to move, initiating the overall ring pattern. After drone 4 initial move, drones 1 and 7 are the next to become active. These drones move almost simultaneously, indicating a coordinated response to drone 4's lead. This step in the sequence showcases how the ring pattern begins to form with multiple drones responding in unison to the preceding drone's action. Following the actions drones 2 and 6 initiate their movements. These drones further propagate the ring pattern, moving in a coordinated manner that maintains the circular formation. The timing of their movement reflects the ongoing synchronization within the swarm, ensuring that the ring formation remains intact. Next in the sequence are drones 3 and 9, which move together as the ring formation continues to unfold. Their synchronized action continues the cyclical pattern, contributing to the overall cohesion of the swarm's movement. The sequence concludes with drones 5 and 8 making their moves. As the last drones to act in this pattern their movement completes the ring pattern.

This detailed sequence of movements highlights the ring pattern as a distinctive form of coordination within the drone swarm. The pattern is characterized by a lead drone initiating movement, followed by pairs of drones moving in a structured sequence

In this experiment, **the occurrence of a specific ring pattern (1, 2, 2, 2, 2) is analyzed 68.75% in relation to all detected behavior sequences.** The calculation measures the frequency of this pattern as a percentage of the total observed patterns which provides a quantitative assessment of its prevalence within the drone swarm's actions. The resulting percentage serves as a confidence metric, highlighting the importance of this pattern in the swarm's behavior. The analysis revealed that the ring pattern is present in a most portion of the sequences, reinforcing the notion that the drones exhibit consistent and recurring behavior. This strengthens the validity of the methods used for identifying these patterns and offers further insight into the structured coordination within the swarm.

In this experiment, the pattern representation (1, 2, 2, 2, 2) corresponds to a role-based abstraction of the ring topology extracted through trajectory and angular behavior analysis rather than a literal geometric or communication-based configuration. This notation is used to quantitatively encode the behavioral roles observed during the drone swarm's ring formation. Each digit represents a category of movement coordination or influence within the swarm, derived empirically from motion characteristics such as angular velocity, curvature consistency, and temporal synchronization of turns.

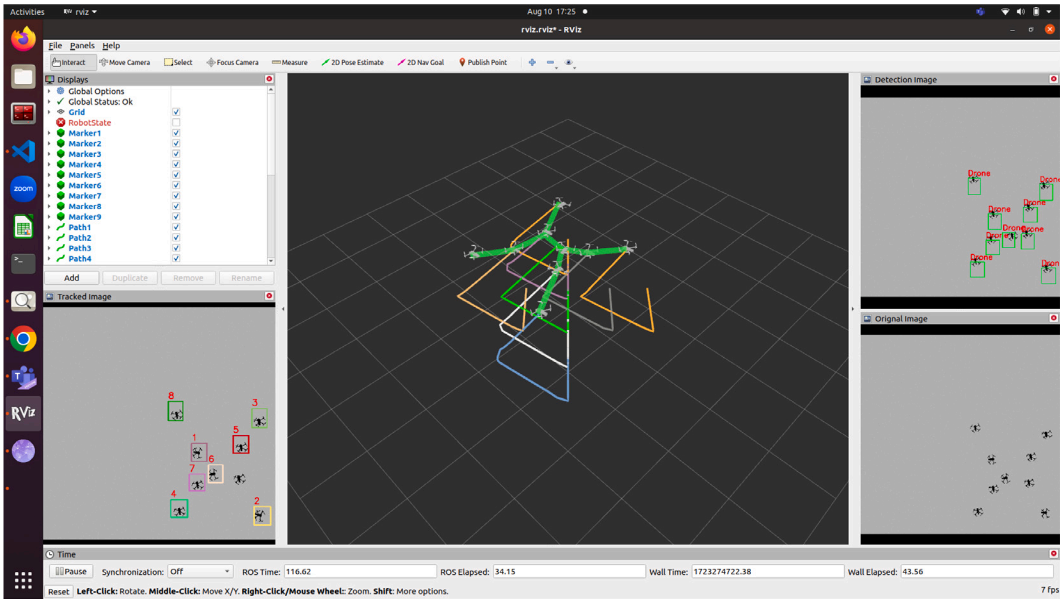
The initial value 1 identifies a reference drone the one that exhibits minimal directional fluctuation and acts as a spatial stabilizer during the formation. The subsequent values 2, 2, 2, 2 indicate sub-clusters of drones exhibiting strongly coupled trajectories and synchronized angular responses.

Thus, the pattern (1, 2, 2, 2, 2) is not a traditional topological label but a semantic trajectory signature that reveals how drones organize functionally within a formation. This numeric abstraction allows the framework to generalize swarm dynamics across topologies and recognize recurring coordination structures. The reported pattern is therefore not an accuracy metric, but a detected coordination schema that complements the extracted topology and supports comparative analysis across swarm behaviors.

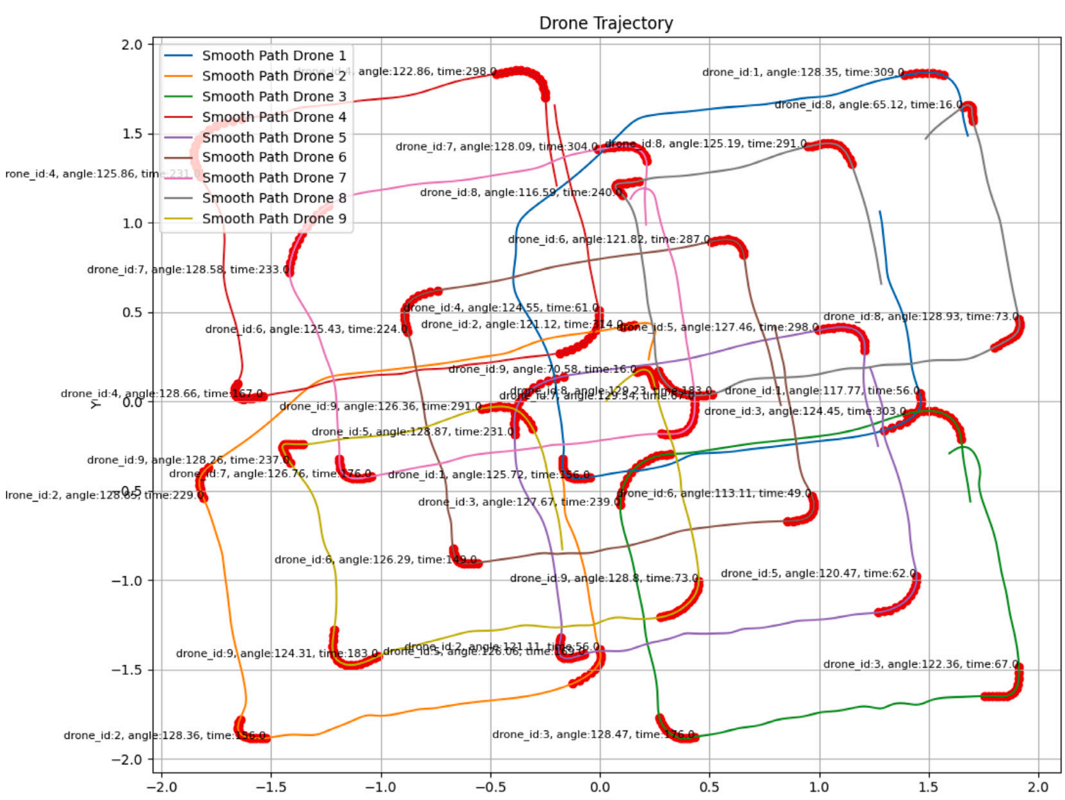
5.1.3. *Mesh topology drone swarm pattern extraction*

In this experiment, the drone swarm is organized in a mesh formation as presented in Fig. 6(a) and the same approach is used to detect, track and extract the communication patterns as in previous formations. The major turns in mesh formation recorded can be seen in Fig. 6(b). The scatter graph illustrated in Fig. 7 reveals a distinctive mesh pattern, characterized by the sequence (1, 3, 4, 1). This pattern indicates a complex, interwoven movement within the swarm, where drones move in a more distributed and interconnected manner, typical of a mesh structure.

The sequence begins with drone 9, which is the first to move. This initial movement sets off the mesh pattern, indicating drone 9 role as a potential leader or trigger within the swarm. Following this, drones 5, 7 and 8 move almost simultaneously. These drones form the first interconnected layer of the mesh pattern, responding to drone 9 initial movement. The simultaneous action of these drones reflects the mesh formation characteristic of having multiple drones interacting at once, creating a web-like structure. The next stage in the sequence involves drones (1, 2, 6 and 4). These drones move together, further expanding the mesh and reinforcing its interconnected nature. This synchronized movement adds another layer to the mesh, with multiple



(a) Observing ring formation.



(b) Major turns in ring drone swarm formation.

Fig. 4. Ring formation pattern extraction.

drones interacting across different parts of the formation, ensuring that the drone swarm operates as a cohesive unit. The sequence concludes with drone 3 making its move as the last drone in this pattern. Its movement completes the mesh formation, tying together the various connections formed by the preceding drones.

The mesh pattern provides information for understanding how drones in a drone swarm can operate in a highly distributed manner, ensuring that the entire drone swarm remains connected even as individual drones move independently. By analyzing this pattern the experiment provides valuable insights into the operational dynamics of drone swarm in a mesh formation.

For the analysis of the mesh pattern (1, 3, 4, 1) a similar approach is taken to determine its significance among all detected patterns. The frequency of the mesh pattern is calculated as a percentage of

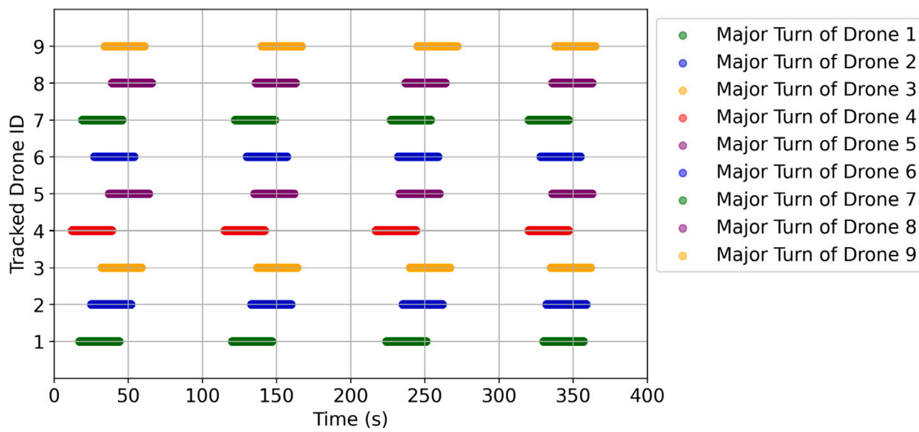


Fig. 5. Drone swarm pattern extraction in ring formation.

the total detected sequences, providing a quantitative measure of how often this pattern appears relative to others. This percentage acts as a confidence indicator, reflecting the importance of the mesh pattern in the behavior of the drone swarm. **The 75% of the detected major changes led to the identification of this mesh pattern**, further emphasizing the structured, repeatable coordination within the swarm. The high prevalence of this pattern in the results supports the idea that the drone swarm demonstrates a structured, repeatable coordination pattern, further validating the detection methods used and enhancing understanding of the swarm's operational dynamics.

In the case of the mesh formation, the extracted pattern (1, 3, 4, 1) reflects a structured interpretation of role-based drone behavior within a distributed coordination framework. This representation encodes how different subsets of drones engage in maneuvering and trajectory adjustment, based on angular deviations and turn synchrony observed during the experiment. The segmentation is not a spatial node labeling but a functional behavior profile that captures relative influence and reaction timing across drone groups.

Here, the first and last 1s denote anchor drones that displayed minimal deviation from their expected trajectory, maintaining positional stability throughout the transition. These drones serve as structural ends or boundaries in the otherwise flexible mesh configuration, acting as implicit references during internal realignments.

The 3 indicates a subgroup of drones exhibiting semi-coordinated behavior, where their turns and angular adjustments are moderately synchronized but exhibit more localized clustering than global coordination. These drones are often responsible for adapting to local disturbances or fine-tuning spacing within mesh cells.

The 4 denotes the largest cluster of drones executing strongly interlinked adjustments, forming the core of the mesh structure. This subgroup is typically involved in maintaining overall formation integrity through reactive and anticipatory maneuvers, compensating for both anchor and peripheral drone activity.

Thus, the pattern (1, 3, 4, 1) emerges as a semantic marker of distributed coordination intensity and positional influence within the swarm, derived from trajectory data rather than explicit communication. It allows classification and comparison of swarm dynamics beyond visual observation, supporting both topology detection and behavior inference.

5.1.4. Resilience of communication topology extraction under visual occlusion

This experiment evaluates the resilience of the proposed visual communication topology extraction framework when faced with partial occlusion an unavoidable condition in real-world drone operations due to obstacles, terrain elevation or temporary loss of line-of-sight. The objective is to test whether the topology inference method, can still reliably function when some drones are intermittently hidden from the camera view. To simulate this, a star formation was used with nine drones arranged such that one central drone served as the hub. During the experiment, up to 30% of drones were randomly occluded at different time intervals throughout the flight path, mimicking real-world disturbances such as buildings, trees or environmental clutter.

Fig. 8 shows a simulated Gazebo-style visualization of a drone swarm in star formation with 30% occlusion. The green circles represent visible drones, while the faded red circles represent drones that are visually occluded due to obstacles or partial field-of-view, simulating real-world conditions.

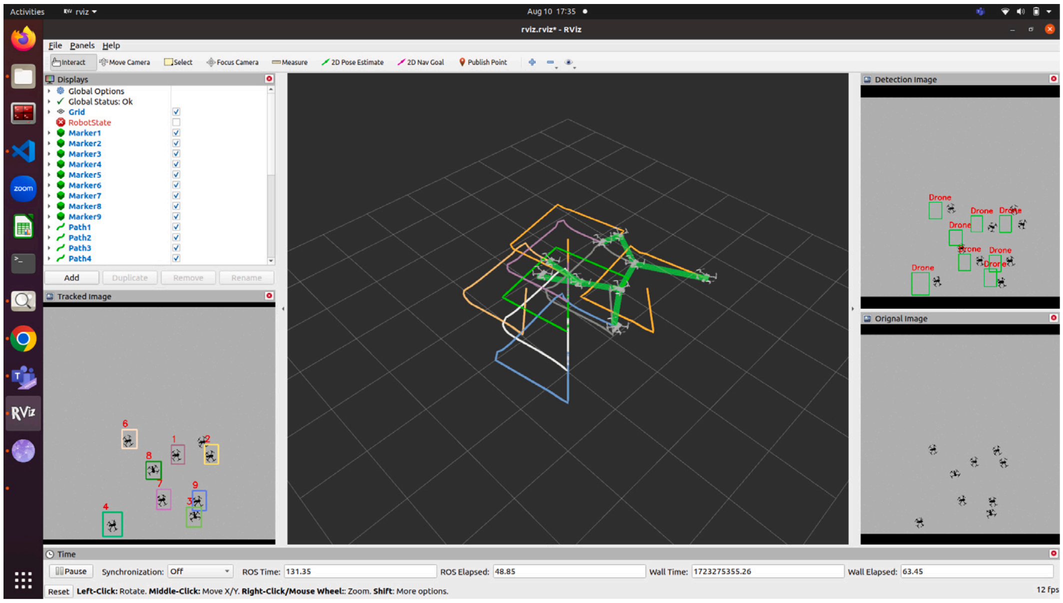
Fig. 9 further illustrates the timing of major directional turns made by individual drones throughout the mission timeline. The x-axis represents time in seconds and the y-axis indicates the drone ID from 1 to 9. Each horizontal marker represents a moment when a drone made a significant directional turn, which is a strong cue in our framework for inferring communication links or influence within the swarm. The color coding divides the swarm into three logical roles:

- Orange: Frontline Drones (Drones 1, 2, 3) These drones operate at the outer layer of the star formation and frequently change direction as they adapt to movement and maintain formation integrity.
- Green: Support Drones (Drones 4, 5, 7, 8, 9) Positioned between the center and the outer edge, these drones show moderately frequent turns and help stabilize local sub-formations.
- Blue: Central Drone (Drone 6) This drone acts as the communication anchor in the star topology. It turns less frequently but plays a pivotal role in initiating coordinated behavior across the swarm.

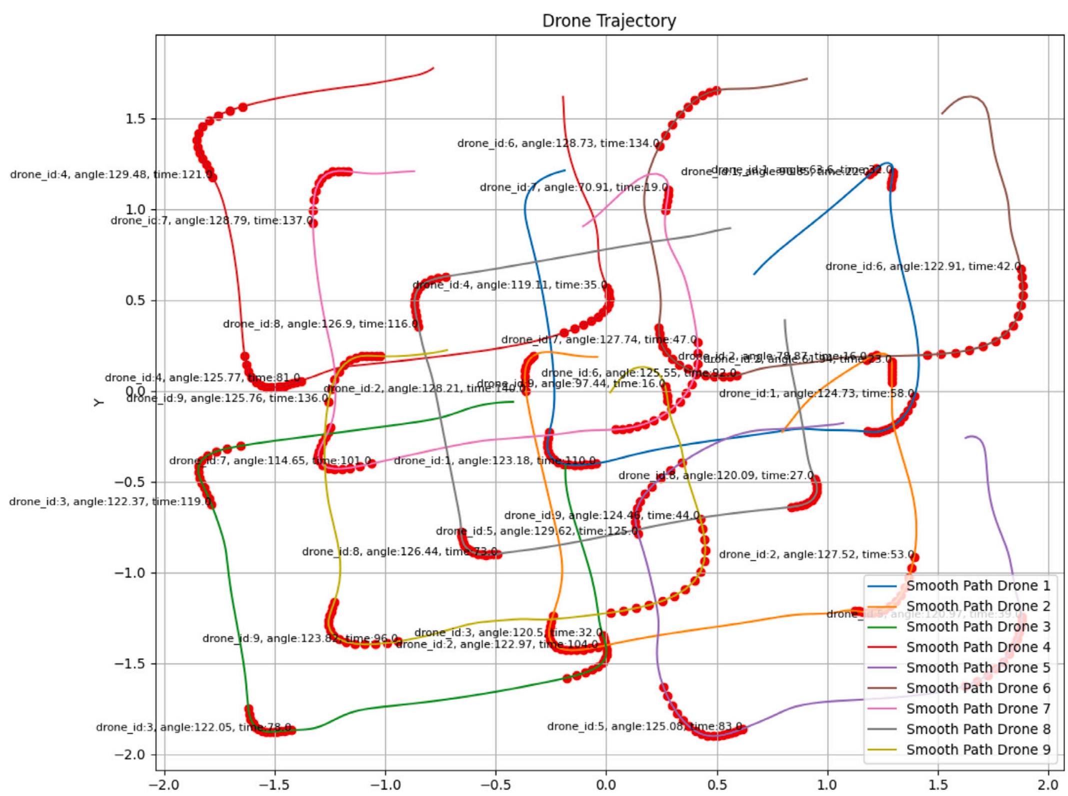
Despite the partial occlusion applied during the experiment, the diagram shows a consistent and periodic pattern of turns across all roles, especially the support and central drones. This consistency demonstrates that even when some drones are momentarily invisible, the turn timing from the visible drones can still reveal overall swarm coordination. The system can reconstruct logical links based on temporal alignment of movement changes, even with missing data. These results affirm the applicability of the approach in dynamic, partially obstructed environments, reinforcing its practical potential for real-world swarm deployment and communication inference.

5.1.5. Extracting topology through multi-formation transitions

This experiment evaluates the proposed framework's effectiveness in dynamically evolving swarm scenarios where drones change formations mid-flight. Specifically, the swarm was programmed to transition from a ring formation to a mesh formation during the mission, mimicking real-world situations such as obstacle avoidance, terrain adaptation, or tactical regrouping during operations.



(a) Observing mesh formation.



(b) Major turns in mesh drone swarm formation.

Fig. 6. Mesh formation pattern extraction.

The purpose of this setup is to test whether the system can adaptively extract the network topology even as the spatial arrangement and inter-drone connectivity evolve. The framework begins by identifying the initial ring structure and continues monitoring as drones gradually reconfigure into a mesh topology. The visual tracking module, detection system, and topology extraction logic work together to handle this complex dynamic transition.

The simulation was configured with nine drones, initially arranged in a ring formation before transitioning mid-flight into a mesh formation, replicating realistic scenarios where swarms adapt to changing mission objectives or environmental constraints. The drones were assigned specific roles:

- Frontline drones (Drone 1, 2, 3, 7) responsible for outer formation shifts,

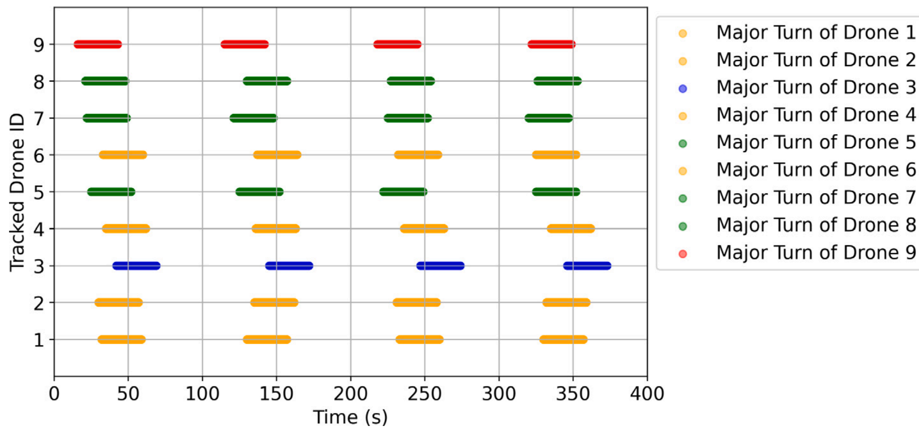


Fig. 7. Drone swarm pattern extraction in mesh formation.

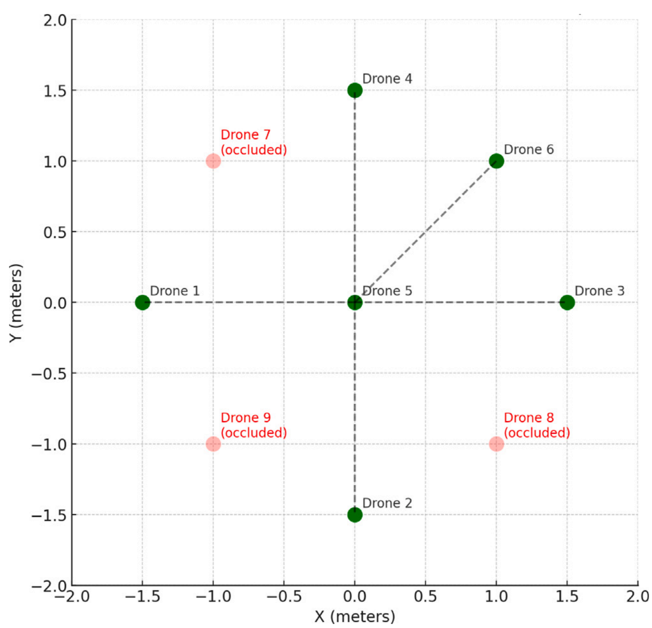


Fig. 8. Simulated drone swarm in star formation with 30% occlusion. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

- Support drones (Drone 4, 5, 8, 9) maintaining internal alignment and
- A central drone (Drone 6)

providing coordination stability. The system was tasked with identifying major turns sharp trajectory deviations indicative of coordination or reconfiguration activity across all drones during the formation change.

To quantify the effectiveness of the detection method, three performance metrics were computed: accuracy, precision, and recall. These were derived by comparing detected turn events against ground-truth annotations extracted from the known programmed behaviors in the simulation. A detected turn was considered a true positive (TP) if it occurred within ± 2 s of a ground-truth turn timestamp. False positives (FP) were turn detections outside this window or where no true turn occurred, while false negatives (FN) represented missed turn detections. True negatives (TN) captured periods with no detected or actual turns. Metrics were then computed as: precision = TP/(TP + FP), recall = TP/(TP + FN), and accuracy = (TP + TN)/(TP + TN + FP + FN). This evaluation approach provides clarity on how well the system captures behaviorally significant events without overfitting to noise or incidental trajectory deviations.

The results, visualized in Fig. 10, reveal that the majority of major turns occurred around the transition window (150–250 s), particularly among support drones, suggesting active internal rearrangement to accommodate the new formation. The detection method achieved an accuracy of 76%, a precision of 73% and a recall of 74%, confirming its effectiveness in tracking swarm dynamics during structural transitions as shown in Fig. 11. While the simulation demonstrates promising performance, it operates under idealized visual conditions without occlusion or sensor noise. In real-world deployments, external factors such as latency, occlusion or communication disruptions could slightly degrade detection performance. Nonetheless, the system's ability to detect coordinated behavior under dynamic topology changes validates its applicability to realistic mission environments requiring autonomous swarm adaptability.

5.1.6. *Impact of camera distance on detection and pattern inference*

The aim of this experiment is to evaluate the performance of the proposed drone detection and tracking framework by varying the distance between the stereo camera and the drone swarm, simulating real-world visual constraints. The experiment assesses how depth perception, image clarity, and visibility at different distances affect the accuracy of swarm behavior inference, especially in identifying and tracking individual drones.

Fig. 12 illustrates the experimental setup. A stereo camera is placed at distances ranging from 2 m to 6 m from the swarm. The drone swarm forms a star-shaped configuration, and the input image resolution is set to 800 × 800 pixels. As shown in the diagram, the swarm is centralized in a 3D bounding volume, and dotted lines indicate camera positions at different distances. The camera is mounted at an elevated perspective looking downward, replicating a top-view surveillance configuration. This view captures both spatial coordination and flight dynamics, and is especially useful for understanding inter-drone relationships.

The simulation replicates how camera distance influences detection quality closer viewpoints provides high spatial resolution but limited field of view, while greater distances capture the swarm's collective behavior but risk losing individual object clarity. At 2 m, the camera was too close to the swarm, resulting in poor visibility of several drones due to limited field coverage and overlapping motion blur, particularly during lateral or rotational movement. This was reflected in increased detection failure and higher tracking errors. Conversely, the optimal visibility was achieved at 3 m to 4.5 m, where most drones were visible, and the spatial coverage was sufficient to capture inter-drone relationships and emerging patterns. At distances beyond 6 m, the camera could observe the swarm as a whole, but the resolution degraded, making it harder to distinguish and individually track drones with sufficient precision.

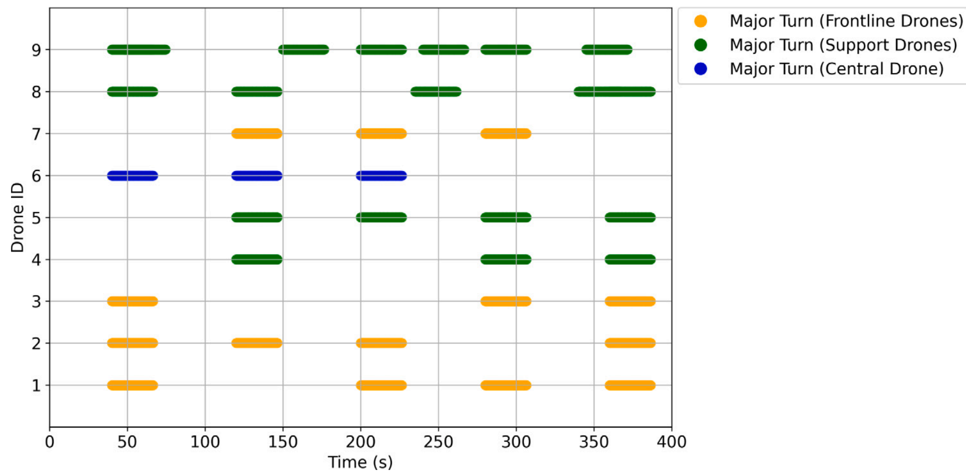


Fig. 9. Drone swarm pattern extraction under occlusion. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

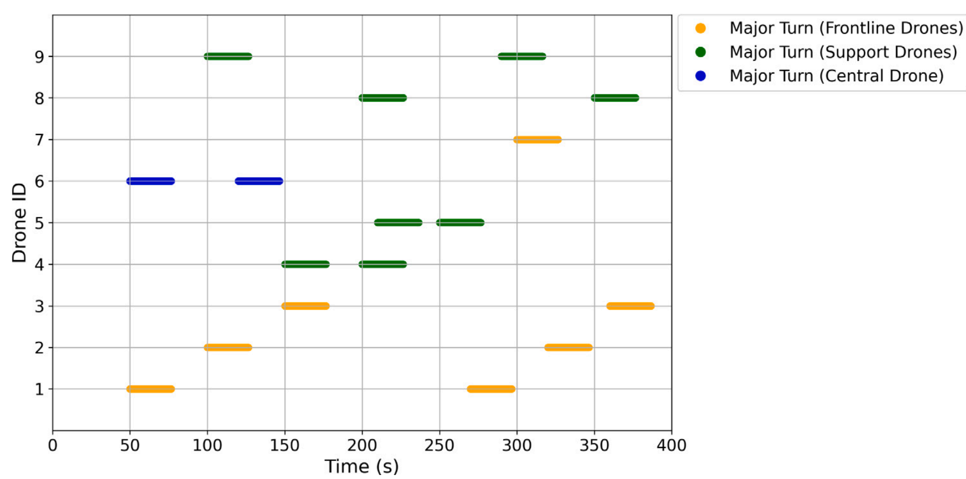


Fig. 10. Drone transition ring to mesh.

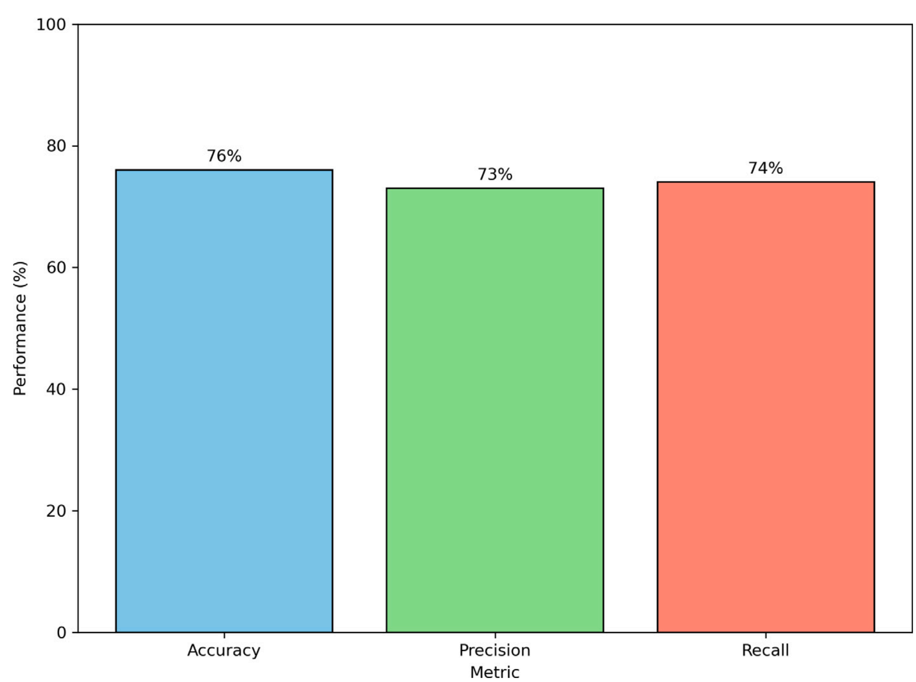


Fig. 11. Transition metrics.

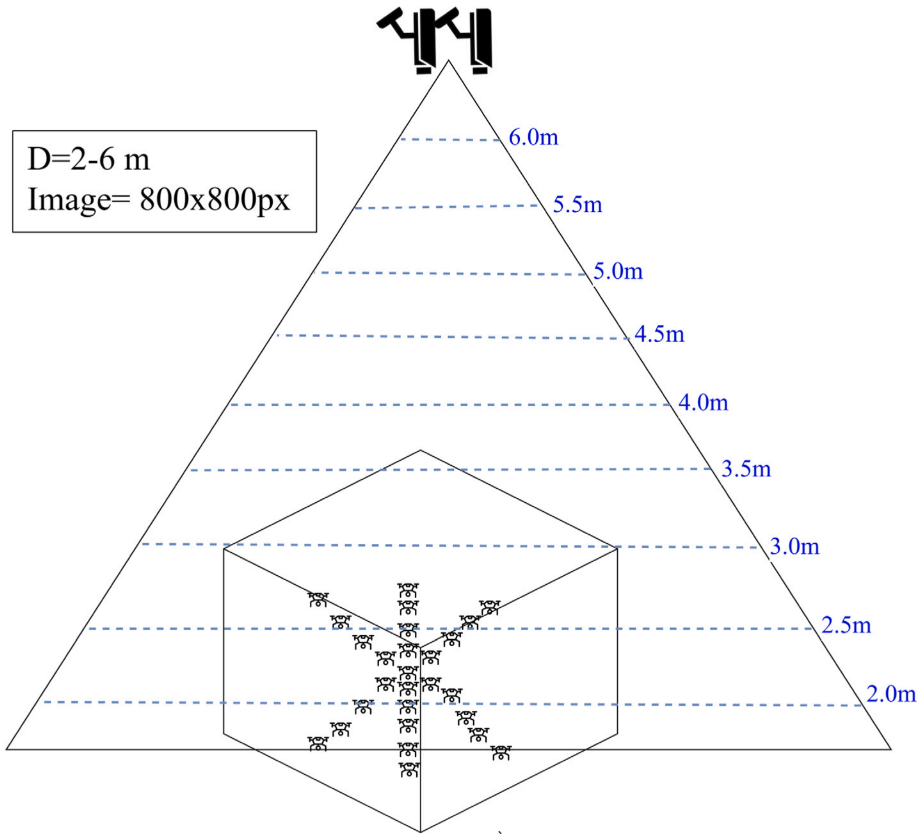


Fig. 12. Varying camera distance.

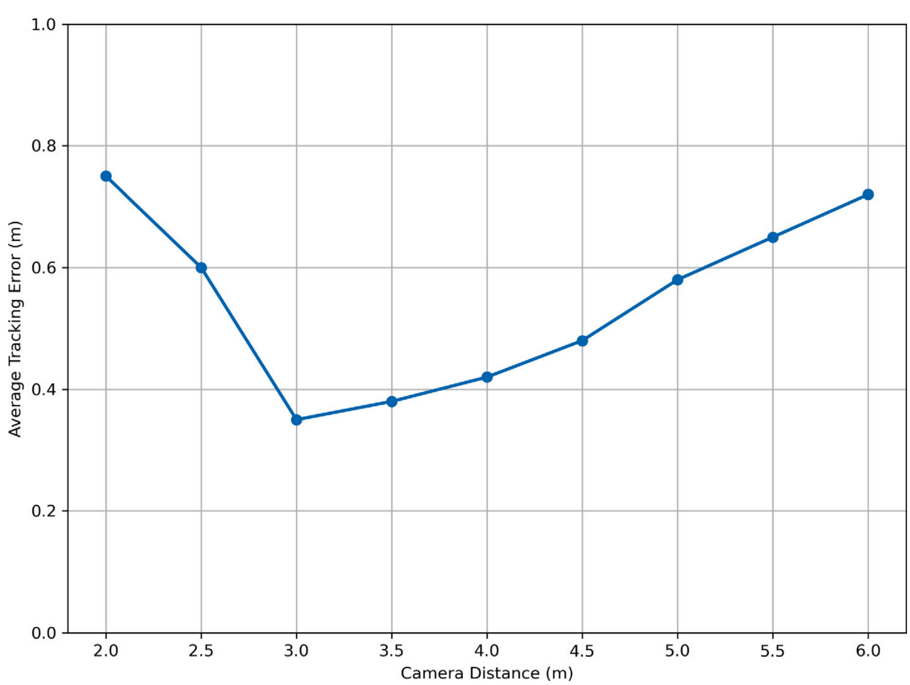


Fig. 13. Tracking error for camera distance.

The tracking pipeline involved calculating the Euclidean distance between the actual and predicted locations of each drone using a Kalman filter for temporal smoothing. The results are illustrated in Fig. 13, where it is evident that tracking accuracy peaks at 3 m. At 2 m, several drones go undetected in multiple frames, leading to pattern inference failures.

A critical dependency of this experimental approach is the accuracy of the detection and tracking stages. Since the inference of drone swarm patterns such as turn sequences, spatial reconfigurations, and communication topology relies entirely on the fidelity of the recorded trajectory data, any failure in detection or drift in tracking directly compromises the downstream analysis. This work builds on our prior simulation study [9] where similar detection and tracking pipelines were developed under realistic scenarios, including variable drone speeds, overlapping flight paths, and partial occlusions. In that paper, we demonstrated several cases where detection failed due to viewing angle, low resolution at long range, or rapid movement-induced blur, reinforcing the observations presented in the current distance based experiment.

6. Discussion

This study proposes and validates a passive framework for visually extracting the network topology of drone swarms through stereo vision, object detection, and trajectory-based turn detection. The approach assumes no access to internal communication metadata, making it suitable for black-box scenarios or adversarial observation. By analyzing trajectory shifts and angular behaviors across various formations (star, ring, and mering, the framework successfully identifies communication links that infer the underlying swarm topology.

Experimental results confirm the method's effectiveness in both static and dynamic swarm configurations. For instance, under baseline conditions with ideal visibility, the system achieved high accuracy in extracting key patterns and communication sequences. The framework was stress-tested under various resilience conditions. When communication was delayed and randomized to simulate asynchronous behavior, shorter delays (e.g., 0.02 s) were more successful in preventing pattern extraction by adversaries. In contrast, longer delays inadvertently offered more opportunities for attackers to extract structured sequences. Similarly, experiments under partial visual occlusion (30%) revealed that the system could still infer meaningful topologies, maintaining an accuracy of 78%, demonstrating resilience to missing data. Lastly, the multi-formation transition experiment where the swarm evolved from a ring to mesh formation further highlighted the system's robustness in dynamically evolving environments, yielding accuracy, precision and recall all above 74%.

Together, these findings support the feasibility of using passive visual cues for real-time swarm analysis. However, the method's reliability still hinges on ideal simulation parameters and its performance under real-world uncertainties remains to be comprehensively assessed.

While the proposed framework yields promising results across multiple formations and experimental conditions, several limitations are acknowledged:

Simulation Dependency: All evaluations were conducted in controlled environments using Gazebo and ROS. Factors such as lighting variability, sensor noise and drone occlusion were either idealized or minimally simulated.

Fixed Parameters: The use of empirically chosen thresholds such as those for detecting angular turns or extracting sequence patterns limits adaptability. These values may not generalize well across different drone types, speeds or environmental contexts.

Formation Scope: The study primarily explores structured topologies like star, ring and mesh. Other realistic or emergent formations (e.g., flocks, clusters or adaptive transitions) were not included.

Partial Robustness Evaluation: While occlusion and communication delay experiments were introduced, broader robustness assessments under compounded uncertainties (e.g., noisy detections, multiple occlusions, GPS drift) are yet to be performed.

Passive-Only Constraint: Although intentional, the lack of integration with even minimal communication metadata constrains the accuracy ceiling of the system in ambiguous cases.

These limitations define the boundary of the current contribution and highlight critical areas for practical adaptation.

7. Conclusion

This research proposed and evaluated a vision-based approach for extracting the network topology of a drone swarm using 3D positional data obtained through stereo vision. The primary aim was to investigate whether inter-drone communication patterns represented as logical network structures such as star, ring and mesh topologies can be inferred from trajectory data alone.

Through simulated experiments, the approach was tested on different swarm formations and the resulting communication graphs were analyzed to determine how well the visual method could capture the underlying network structure. The findings confirm that it is feasible to distinguish between common communication patterns based solely on drone movement data.

By focusing on visual inference of network topology, this work contributes a practical technique for studying swarm behavior without relying on internal communication logs. This provides a foundation for future research in drone swarm coordination and control, particularly in scenarios where direct communication data is inaccessible.

8. Future work

To enhance the scalability and real-world applicability of the framework, the following directions are proposed:

Noise-Tolerant Inference: Future studies will incorporate synthetic and real-world noise models, such as camera jitter, intermittent occlusion and partial visibility, to better assess the framework's resilience in unstructured settings.

Hybrid and Adaptive Formations: Investigating transitionary behaviors across multiple complex formations (e.g., V-formations, lattice patterns, hybrid flocks) will enable better generalization and formation-aware analysis.

Physical Deployment: Real-world trials with physical drone platforms using stereo or monocular ground-based vision systems will be pursued. These will assess performance under uncontrolled conditions such as lighting changes, occlusion and perspective distortions.

Learning-Based Enhancements: To replace static angle thresholds, adaptive learning models (e.g., reinforcement learning or graph neural networks) will be integrated to segment trajectories and extract topologies dynamically.

Multi-Modal Fusion: While the current approach remains fully passive, future work may explore minimal communication metadata fusion to validate visually inferred links and strengthen edge inference reliability.

These directions aim to transform the current framework into a generalized, noise-resilient and deployable tool for real-time drone swarm topology extraction in both cooperative and adversarial scenarios.

CRediT authorship contribution statement

Nisha Kumari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation, Conceptualization. **Kevin Lee:** Writing – review & editing, Supervision. **Chathu Ranaweera:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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