Detection and Tracking of Drone Swarms using LiDAR

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ABSTRACT

This paper introduces *LiSWARM*, a low-cost LiDAR system to detect and track individual drones in a large swarm. *LiSWARM* provides robust and precise localization and recognition of drones in 3D space, which is not possible with state-of-the-art drone tracking systems that rely on radio-frequency (RF), acoustic, or RGB image signatures. It includes (1) an efficient data processing pipeline to process the point clouds, (2) robust priority-aware clustering algorithms to isolate swarm data from the background, (3) a reliable neural network-based algorithm to recognize the drones, and (4) a technique to track the trajectory of every drone in the swarm. We develop the *LiSWARM* prototype and validate it through both in-lab and field experiments. Notably, we measure its performance during two drone light shows involving 150 and 500 drones and confirm that the system achieves up to 98% accuracy in recognizing drones and reliably tracking drone trajectories. To evaluate the scalability of *LiSWARM*, we conduct a thorough analysis to benchmark the system's performance with a swarm consisting of 15,000 drones. The results demonstrate the potential to leverage *LiSWARM* for other applications, such as battlefield operations, errant drone detection, and securing sensitive areas such as airports and prisons.

CCS CONCEPTS

• **Computer systems organization** → **Sensor networks**; *Real-time systems.*

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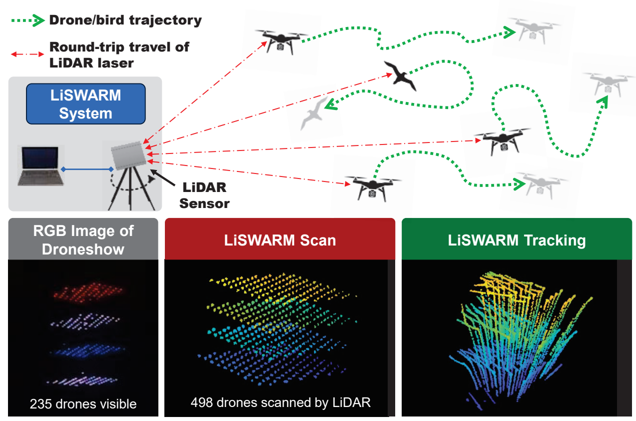


Figure 1: The proposed concept of using low-cost off-the-shelf LiDAR system for drone swarms detection and tracking.

1 INTRODUCTION

Drone swarms have recently exhibited a tremendous growth in importance. First, we have witnessed a significant shift towards replacing traditional fireworks with drone light displays across the globe, driven by a growing focus on sustainability and safety. Drone light shows produce no emissions and do not leave behind chemical residues, making them a far more eco-friendly option [53, 66]. For example, in the U.S., the Fourth of July 2024 celebrations saw the extensive use of drone shows in hundreds of towns, signaling a commitment to more environmentally friendly festivities [88]. In China, the recent festivities were transformed with a synchronized display of up to 14,000 drones [13]. Australia is considering the use of drone shows for New Year's Eve celebrations in Sydney to reduce the risk of bushfires [86]. This global movement illustrates a growing recognition of the benefits of drone displays in offering captivating visual experiences while addressing the ecological and safety challenges posed by traditional pyrotechnics. In addition, drone swarms pose an increasing threat to aviation and ground assets in both commercial and military contexts.

We interviewed four drone-show companies to study the current practices of drone swarm management and obtained a few valuable insights as follows. The most pressing question these companies aim to address is: *How can we perform a comprehensive scan to know what is in the airspace in real-time?* The current practice is to use platforms like Aerial Armor (acquired by Dedrone), which eavesdrop on the RF channel to detect and localize unwanted rogue drones. However, this app often does not pick up all such drones, and the team usually has to manually search for the pilot and ask them to bring the drone down. More importantly, it does not provide a precise understanding of what is in the airspace as non-RF-emitting objects are undetectable.

In addition to policing drone swarms, managing drone swarms presents significant challenges due to their complex behaviors. The interviews revealed that drones fail at the rate of about 6 out of every 1000 drones flying during a drone show, and that the failure modes are such that recovery of the drones is often challenging because the drones stop sending telemetry. Once the drones go missing, it is difficult to estimate where the faulty drones may have flown due to the unpredictability of drone flight behaviors and Byzantine failure modes. Furthermore, drone unpredictability is heightened by being susceptible to jamming attacks [15, 59, 78]. An Inertial Measurement Unit (IMU) sensor can be disrupted using ultrasound jamming [87], while GPS sensors can be easily spoofed using a GPS replay attack with relatively inexpensive equipment [34]. Collisions between drones are another concern, which may arise from factors such as adverse weather conditions, hardware degradation (like worn-out propellers), or human intervention [16]. These collisions can result in unpredictable behaviors, complicating the task of controlling or policing drone swarms effectively.

Detection and tracking of drones have been active research directions with various approaches such as camera-based [18, 85], acoustic-based [9, 32], radar-based [10, 48], RF-based [63, 64], LiDAR-based [29, 39], and multimodality-based systems of these sensing methods extensively studied in both academia and industry. *However, none of the existing approaches have been confirmed to reliably detect and track 3D swarms at long distances.* In particular, camera-based systems leverage advanced computer vision techniques to identify and track drones visually, providing high-resolution data but facing challenges in low-visibility conditions, especially night operation. Acoustic-based systems detect the unique sound signatures of drones, offering a passive detection method but struggle with ambient noise interference. Radar-based systems, widely used in military applications, provide robust detection capabilities over long distances but struggle both with detecting drones made from plastic materials, which are common in commercial and industrial drones today, as well as addressing ground clutter exacerbated by low-flying drones. RF-based systems utilize the radio signals emitted by drones for detection and tracking, offering the potential for long-range monitoring but require the drones to actively transmit signals. When tracking swarm, passive RF-based systems so far are limited to 10 drones with an average spacing of 15m between them [50]. Similarly, camera-based systems to track drone swarms have been confirmed to support up to 30 drones at a very close range of 9m [40]. Current LiDAR-based techniques [1], [30], [19] have only been validated on a couple of drones, do not differentiate between drones and other flying objects like birds, and have not been shown to scale to drone swarms. One of the common LiDAR-based sensing systems is SLAM (Simultaneous Localization and Mapping) [20], which creates a real-time map of the surroundings for autonomous systems indoors and outdoors. However, the performance of SLAM in drone swarm monitoring is unclear. Multimodality-based systems combine these different methods but face complexities in integration and high costs.

To address these limitations, this research investigates the development of a LiDAR-based system, *LiSWARM*, for real-time 3D drone detection and tracking, with the potential to scale up and simultaneously track thousands of drones. *LiSWARM* scales to detect 150–500 real drones and up to 15,000 drones in simulation. *LiSWARM* is designed specifically to track and detect drone formations at large scales to address the performance gaps of previous systems. Key innovations of the *LiSWARM* system include a distance-aware computing strategy, which dynamically downsamples LiDAR point clouds based on the distance to detected objects, thereby significantly improving computational efficiency. *LiSWARM* enables the reconstruction of drone trajectories, allowing for real-time monitoring and detection of malfunctioning drones—vital for applications in military, security, and drone shows. Note that the key distinction between existing SLAM-based methods and *LiSWARM* lies in their respective objectives: SLAM (e.g., LOAM, F-LOAM [92]) is primarily concerned with environmental mapping and self-localization, often for ground-based vehicles or small-scale UAV navigation in structured or predefined environments. In contrast, *LiSWARM* is designed to enable real-time detection and tracking of large, dynamic, fast-moving airborne drone swarms without reliance on predefined maps or landmarks. While traditional SLAM techniques focus on localization and self-positioning, which may limit their capacity for tracking large drone formations, *LiSWARM* focuses explicitly on scalable UAV detection, offering a complementary approach that does not directly compete with SLAM systems but rather addresses the unique challenges posed by drone swarm monitoring.

A critical advantage of *LiSWARM* is its ability to detect both lit and unlit drones, making it highly effective in night-time operations. Unlike vision-based systems, which rely on external lighting conditions, *LiSWARM* leverages LiDAR's active sensing capabilities to monitor drones in low-visibility environments. Furthermore, *LiSWARM*'s scalability allows it to be deployed in large-scale applications such as drone light shows, security monitoring, and aerial traffic management. Figure 1 illustrates the utility of using *LiSWARM* to monitor drone swarms. This snapshot point cloud was obtained via one scan of the *LiSWARM* system at an actual drone light show. The RGB image shows only lit drones, while the full *LiSWARM* scan reveals all drones in the show, where about half of the total are unlit drones. The system enables a drone show operator to continuously monitor the health of all of their drones. It also can be used to identify, track, and recover faulty drones as well as identify and track foreign non-show drones that may interfere with the drone show.

We make the following contributions in this paper:

• We develop a sophisticated signal processing pipeline and neural-network-based algorithms to detect and recognize individual drones in the swarm with up to 98% accuracy.

• We design fast computing methods to achieve real-time drone detection and tracking of a large drone swarm using novel distance-aware computing and CPU-GPU load balancing techniques.

• Through real-world evaluations of drone shows involving 150 and 500 drones at 200m, we demonstrated that our system is able to reliably track drones with delays of only tens of milliseconds. Through our spatial resolution-based disambiguation test, we prove that decimeter-level recognition accuracy is achievable.

• We conduct a comprehensive analysis to validate the system's performance across diverse scenarios, including varying ranges, different drone speeds, and a wide spectrum of lighting conditions, ensuring robust and reliable operation in real-world environments.

• We conduct a thorough scalability analysis, including detailed benchmarking, to evaluate the system's ability to effectively monitor and manage tracking operations involving up to 15,000 drones through simulation to confirm the system's effectiveness. The goal is to assess computational efficiency rather than to precisely replicate the physical behavior of the swarm.

While this study centers on civilian drone shows, we believe that *LiSWARM*'s ability to speedily recognize and track drones day and night could be applicable to many other scenarios, such as battlefield operations [27, 35, 36, 75], errant drone detection, and securing sensitive areas such as airports and prisons. On the battlefield, real-time awareness of the airspace is critical for identifying and neutralizing hostile drones that could endanger troops or disrupt missions. At airports, errant drones—whether flown accidentally by hobbyists or intentionally by malicious actors—pose serious threats to flight operations and have temporarily closed major airports like Gatwick, Dubai and Frankfurt [80]. In prisons, drones are increasingly being used to smuggle contraband, including drugs, weapons, and mobile phones. In 2023, reports from several U.S. correctional facilities highlighted cases where drones were used to deliver illicit items over prison walls under the cover of darkness [62].

2 CHALLENGES

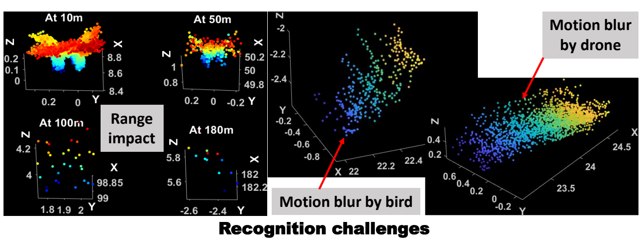


Figure 2: Challenges associated with LiDAR-based recognition and tracking of drones.

We face the following major challenges to show that LiDAR-based detection and tracking of drone swarms is feasible and practical. First, Figure 2 shows that distinguishing drones from other flying objects such as birds is a challenge. We need to train machine learning techniques to find sufficient differentiation between potentially similar point clouds. Further, as the range increases, the reduced number of reflected points from a distant object makes it even more difficult to recognize and classify that object as a drone or other object. Further, due to the finite scanning rate of the LiDAR sensor, pointclouds from complete scans are collected at a slow rate relative to the motion of the drone, resulting in motion blur in the collected pointcloud data from an object that can remove distinguishing features, resulting again in greater difficulty telling apart the smeared pointcloud of a drone from other objects.

Second, the end to end latency of our detection and tracking system must be fast enough to accommodate the different use cases for *LiSWARM*. In cases such as detecting errant drones in airport airspaces, as well as battefield counter-drone interdiction, we need real time detection, localization and tracking of the drone threats. Therefore, while our classifiers must be accurate, the inference must also be nimble enough to provide rapid real time response.

Third, our system must scale to handle monitoring of the airspace for large drone swarms, potentially up to tens of thousands. Therefore, the rate of point of cloud processing of objects must scale so that system performance is able to detect and track drone swarms using optimization techniques such as hardware acceleration and software parallelization.

3 SYSTEM OVERVIEW

To overcome the above challenges, we propose to develop *LiSWARM*, a low-cost LiDAR system to detect and track individual drones in a large swarm in real time as illustrated in Figure 3. *LiSWARM* provides robust, precise and real-time localization and recognition of drones in 3D space, which is not possible with state-of-the-art drone tracking systems that rely on radio-frequency (RF), acoustic, or RGB image signatures. *LiSWARM* consists of three major stages, namely data preprocessing, detection, and tracking.

3.1 Data Preprocessing

Our end-to-end system starts with a data acquisition block which we furnish with LiDAR point cloud data. The system converts the raw point cloud stream into point cloud snapshots or frames. Then, we denoise them by removing outlier points based on reflectivity and spatial location. Next, we remove the ground from the point cloud frames using the random sample consensus (RANSAC) algorithm [25], which implements denoising and filtering operations where ground removal is used to discard ground clutter by iteratively fitting a plane to the ground points and removing the inliers. In this way, the system filters out points from trees, buildings, and other infrastructure considered clutter. Another filter keeps only flying objects by maintaining a Z-axis threshold.

3.2 Detecting Individual Drones in a Swarm

The next segment of our system belongs to the localization of drones, i.e., detection and recognition of individual drones either in scarce or dense swarm scenarios. Since our system deals with unlabeled, unorganized raw pointcloud data, we first use spatial clustering to identify each object separately from the clean and processed pointcloud data generated by the preceding data processing block. After that, all the identified object clusters are also rendered as alphashape objects. An alphashape is a spatial feature that provides a way to model the shape of a set of points in 2D or 3D, capturing both the outer boundary and interior voids. These two types of inputs: *(i) simple pointcloud of each identified object cluster* and *(ii) the associated alphashape objects*, are fed into the recognition block where we use a pre-trained Neural Network (NN)

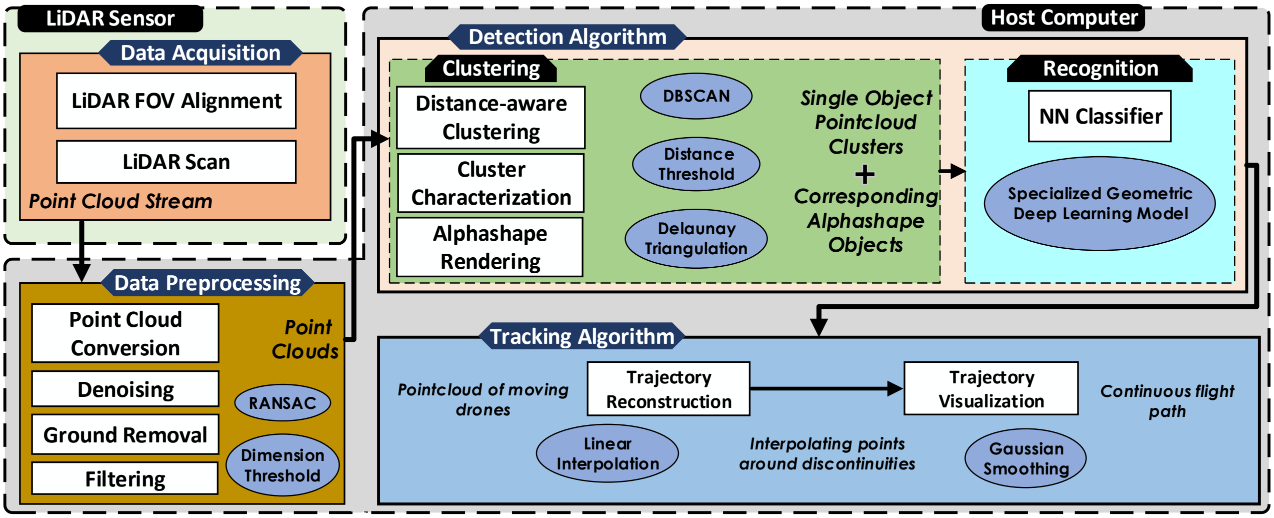


Figure 3: *LiSWARM* system overview.

classifier. This NN finally identifies the object clusters into drone and non-drone (likely birds) classes.

3.2.1 Clustering the swarm.

Spatial Clustering. After preprocessing the point cloud to retain only relevant flying objects (e.g., drones, birds), spatial clustering is applied to isolate each object in 3D space. Each cluster is then processed to extract key features, like centroid and bounding box dimensions, preparing the data for recognition and further analysis.

The system considers the temporal feature of reflected point reception by the LiDAR system based on the spatial characterization, which mimics the "dark adaptation" of the human eye by accumulating light over time. We concatenate single-frame point clouds into sequences of 1, 3, 5, or 10 frames (100ms, 300ms, 500ms, or 1000ms) using a sliding window technique. The number of reflected points is directly proportional to distance, thus according to the cluster centroid distance, it is decided how many consecutive frames will be concatenated to accumulate points just like the light in the eye.

Alphashape. Alphashape, a shape descriptor from computational geometry and generalization of convex hulls, are used for object recognition with Delaunay triangulation as a fundamental step [21]. We use 'alphashape' of each cluster as an additional feature to be used for each cluster during classification. Figure 4 shows the reconstructed 3D convex hulls of UAV2 used in our experiments at 2 different frame times to visualize the impact of frame time in shape recognition.

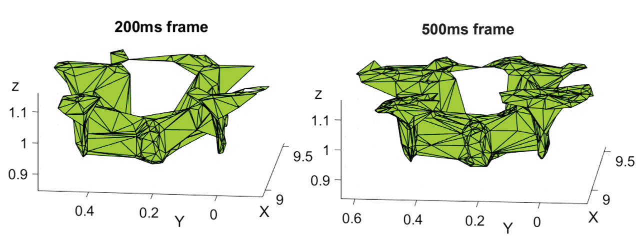


Figure 4: Different Alphashapes of the reconstructed 3D surface models of UAV2 at 2 different frame times

3.2.2 Classification Algorithms. We explore both traditional ML approaches like kNN, SVM, Random Forest, and Neural network (NN) models for recognizing the drones in the detected swarm of pointclouds. While ML approaches offer simplicity and comparatively less computation time, these approaches struggle with scalability and the intricacies of LiDAR data. Again NNs are well-suited for classifying LiDAR data due to their ability to handle high-dimensional inputs and to learn complex spatial relationships.

Deep NN techniques like PointNet [70] could be a great reference to start our implementation. However, after the preliminary studies, we found that PointNet suffered a longer delay than ML methods during the evaluations due to its use of T-Net layers for input and feature transformation to preprocess pointcloud data to handle alignment issues. Since our system pipeline already has data preprocessing and cluster characterization sections prior to the classifier, we remove the T-Net layer from our NN model for faster computation. The key idea is to utilize the reflectivity or intensity value of each point as it carries significant information about any object's outer surface along with the X, Y, Z 3D coordinates and to do that we need to have input layer that accepts data with 4 attributes. While PoinNet input layer size is (nx3), we employ an input layer with size (nx4) which can incorporate the reflectivity attribute. We also modified the feature extractor from shared MLP to Conv1D since tasks with Conv1D can be parallelized and optimized with GPU and hardware.

Validation. We evaluated the different ML algorithms for their recognition accuracy, using real world LiDAR point clouds collected from drones and birds. We employ three quadcopter drones, UAV1, UAV2, and UAV3, as different airborne objects for detection and tracking. We also use the LiDAR sensor to scan birds resting, swimming, and flying while maintaining all safety measures for the wildlife. We conduct experiments for LiDAR scan at various outdoor locations during noon, afternoon, and evening at different places to account for variability in lighting, speed, and range. These experiments covered diverse flight paths and distances at varying speeds. *LiSWARM* was evaluated for scenarios with individual drones or small drone groups (2–3 drones) to distinguish

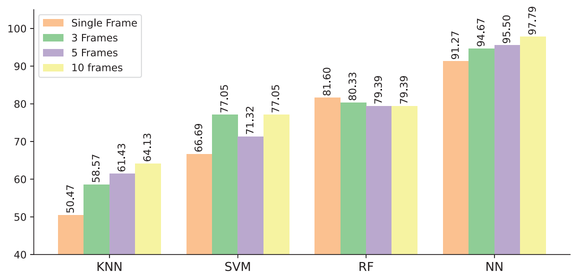


Figure 5: Classification performance on two tested drones.

drones from other flying objects, like birds, and track drones by reconstructing their trajectories. Key factors affecting LiDAR performance include target distance, object speed, lighting conditions, and spatial separation between drones for unique identification.

We detect flying objects across a range of 5m to 300m under varied speeds and lighting conditions. UAV1 and UAV3 are detectable up to 220m, UAV2 up to 180m, and birds up to 180m. After detection, the next step is recognizing drones among other flying objects by classifying point cloud clusters into two categories: drones and other objects. Using kNN, SVM, Random Forest, and a neural network (NN), classifiers are evaluated on a dataset independent of distance, speed, or lighting. The NN classifier achieves the best performance, with 97.79% accuracy for 10 frames and 91.27% for single frames, as shown in Figure 5.

3.3 Tracking Individual Drones in the Swarm

Once point clouds associated with drones are recognized, those point clouds are passed over to the next block in the pipeline: the tracking algorithm. Figure 6 illustrates the problem of discontinuities in the trajectories due to the coarse frame sampling, which is at best once every 100 ms with our chosen LiDAR system. To tackle the discontinuities, we then interpolate points to fill-in the gaps between LiDAR scans caused by fast-moving drones. In this way we reconstruct the continuous flight paths of single/multiple drones. In particular, the continuous stream of points from the merged pointcloud are identified together using neighborhood clustering based on the sequence of 3D spatial location values. This gives us a bounding box of the object, and we then take the centroid of this object and connect it with the closest drone trajectory in a straight line using linear interpolation. This provides us with a piecewise linear trajectory. Since such a path is subject to unrealistic sharp and abrupt changes in direction at each point, creating sharp angular transitions between adjacent points, then we apply Gaussian smoothing. Figure 6b) shows the reconstructed continuous flight paths from their discrete pointcloud counterparts.

4 SYSTEM OPTIMIZATION

While the components described deliver promising detection and tracking accuracy, the process remains limited to offline execution. Achieving real-time (i.e., sub-second delay) detection and tracking requires innovative computer systems techniques. We make multiple directed efforts to optimize the performance of our system by first exploring multiple spatial clustering algorithms and benchmarking them with simulated drone sample data, secondly conditioning the chosen clustering technique with a distance priority-based approach and finally by utilizing the full potential

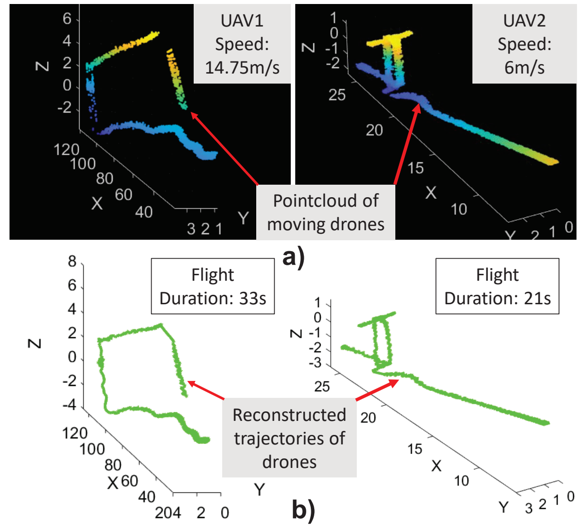


Figure 6: Trajectories reconstructed for 2 different UAVs at different ranges and speed scenarios, a) point clouds of UAV1 and UAV2 in motion 14.75m/s up to 120m and 6m/s up to 26m, b) reconstructed trajectories.

of parallel processing. We implement multi-threading for each of our system blocks described above to balance the high-volume data load of pointclouds between CPU and GPU.

4.1 Prioritized Distance-aware Computing

Traditional clustering methods like: K-Means, hierarchical, etc. clustering cannot support real-time operation as they introduce considerable delays (i.e., 2.19 seconds for 150 real drone clusters and 127.6 seconds for 10000 drone clusters). To address this, we investigate the issue and find out that the spatial clustering algorithm is handling an unusually large amount of data points. And since such clustering algorithms work with all the associated points fed into them as input data to make clustering decisions and this task cannot be distributed among multiple computing nodes, there is a bottleneck in terms of computation time in the case of large pointcloud data. Since the objects located closer to the sensor reflect a large number of points to the sensor receiver compared to far away objects [37], [49], then we opt for downsampling the pointcloud to enable faster processing at the cost of potentially impacting accuracy. As we will show, the impact on accuracy is modest while the improvement in delay is dramatic.

We use the spatial clustering algorithm while applying a distance-aware adaptive downsampling on the input data based on voxel grid filtering which reduces redundant points by dividing the space into smaller, equally sized 3D regions and merging all the points within that voxel grid [81], [54]. To preserve shape information while reducing redundant points, voxel grid sizes are set according to distance range: larger voxel sizes are used for close-range points to downsample aggressively, while smaller sizes are applied to long-range points for finer preservation. Figure 7 depicts this process of distance-aware computing where we use a step function for applying the voxel grid size on UAV1 pointcloud data based on 3 distance ranges: 0 to 100m, 100 to 150m and 150m to beyond. We

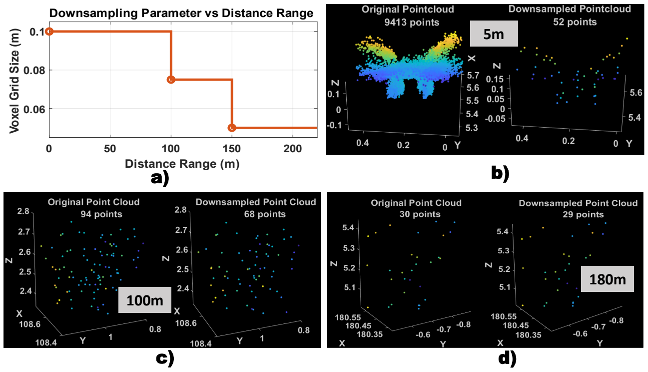


Figure 7: Adaptive downsampling operation based on object distance and its impact on object pointcloud, a) step function used to control voxel grid size, b), c), d) represent actual pointcloud and their downsampled version of UAV1 at 5m, 100m and 180m respectively

select this distance range based on the range sensitivity analysis of the LiDAR sensor in our experiments. For this specific example, we are being able to reduce 9413 reflected points from a drone at 5m away into just 52 points with a voxel grid size of 0.1m while maintaining the shape of the drone. Conversely when UAV1 is at 100m and 180m, the numbers of reflected points are scarce and downsamplings are applied on them with voxel grid size of 0.075m and 0.05m to produce proportional reductions of points.

4.2 CPU-GPU Load Balancing for High-speed Clustering

Clustering takes a significant portion of the time in *LiSWARM*. The challenge is depicted in Figure 8. To prepare for this research, we conducted a series of in-lab and outdoor experiments to assess the feasibility of tracking UAVs using our LiDAR system. In our outdoor experiments, we scanned test drones at various locations with diverse backgrounds under both daytime and nighttime conditions. Figure 8 showcases two examples of raw LiDAR point cloud data collected during these tests. The image depicts two drones approaching the sensor at high speed, with dense trees forming the backdrop. While it is promising to observe how LiDAR accurately captures the drones' locations and trajectories, the scans also indiscriminately record all objects in the scene—drones, ground surfaces, trees, poles, streets, and other infrastructure—producing a dense point cloud. Most of the captured points correspond to irrelevant features such as the ground and background clutter, which do not contribute to the goal of drone detection and tracking.

We explored some cutting-edge clustering algorithms including DBSCAN [22], HDBSCAN [56], OPTICS [6], and KMeans [31] and show their running time as well as the total number of clusters that are distinguished by each of the methods on 10k sample drones in Figure 9. As shown in the figure, DBSCAN achieved the highest accuracy in distinguishing distinct clusters. HDBSCAN and OPTICS are adaptive but slower and less accurate compared to DBSCAN.

Next, to accelerate the clustering phase of drone swarm detection using LiDAR data, we implemented the DBSCAN algorithm on a GPU using CUDA [52]. By parallelizing the neighbor search and distance calculations, critical components of DBSCAN, we leveraged the GPU's ability to handle thousands of threads concurrently,

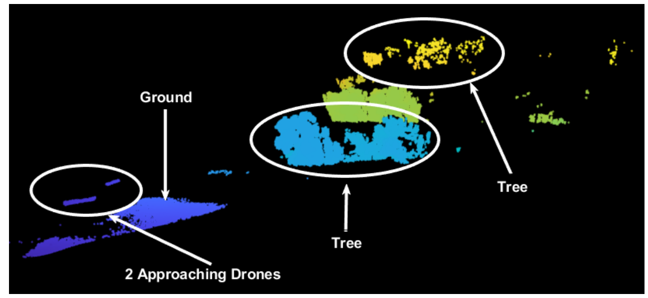


Figure 8: Example clusters of unrecognized objects must be identified by the system

significantly reducing clustering time for large clusters. To maximize the performance on GPU and reduce latency in data transfer between CPU and the GPU, we used pinned memory and asynchronous data transfer via CUDA streams. While pinned memory enables faster data movement between the CPU and GPU by preventing the operating system from swapping memory pages in and out of physical memory, asynchronous data transfer enables overlapping computation with memory transfers by allowing data to be sent and computation to proceed independently. We used brute force for nearest neighbor computations, Euclidean distance as the metric for calculating distances between points.

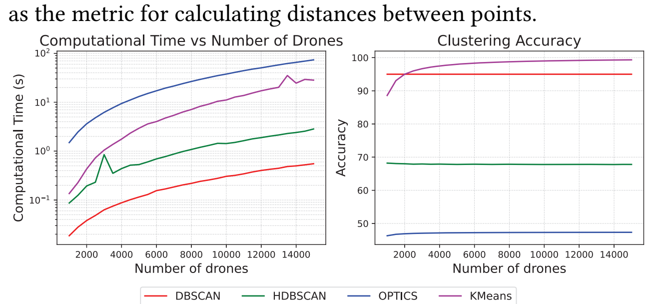


Figure 9: Clustering results with different clustering methods

For cluster characterization, which involves further filtering and analyzing clusters based on geometric properties (e.g., bounding box dimensions and centroids), we utilized multi-threading on the CPU over unique labels identified by DBSCAN. Independent tasks, such as calculating the bounding box dimensions and centroids of individual clusters, were distributed across CPU cores. To avoid stalls caused by synchronization overhead, computation on the CPU was overlapped with GPU processing using streams and concurrent kernel execution. This ensured continuous utilization of both processing units.

This combination of GPU-accelerated DBSCAN and CPU-based parallel cluster characterization reduced overall computation time significantly, enabling real-time analysis of LiDAR data for detecting and recognizing drone swarms. The approach is scalable for large swarms, making it suitable for scenarios involving high-density swarms or expansive environments

5 DETECTION AND TRACKING OF DRONE SWARM SHOWS

5.1 Setup

To validate *LiSWARM*'s performance in real-world swarms, we evaluate it at 2 droneshow events: (*Droneshow1*) with 150 drones &

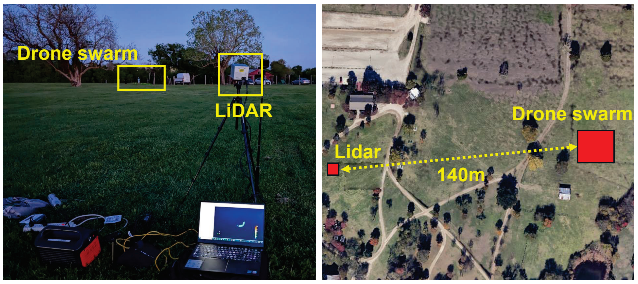
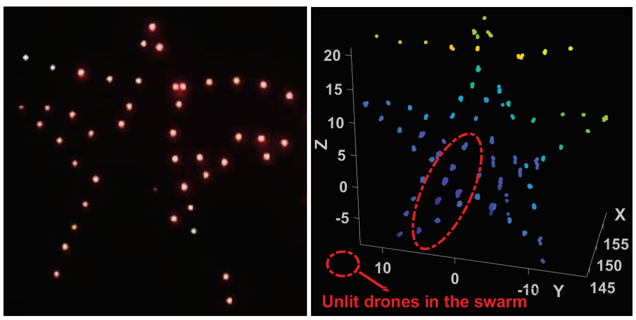


Figure 10: Experimental setup using LiDAR to scan the drone swarm at *Droneshow1*.



a) RGB image of drone swarm formation 1 with both lit and unlit drones

b) LiDAR point cloud frame of drone swarm formation 1, the unlit drones captured by lidar are annotated

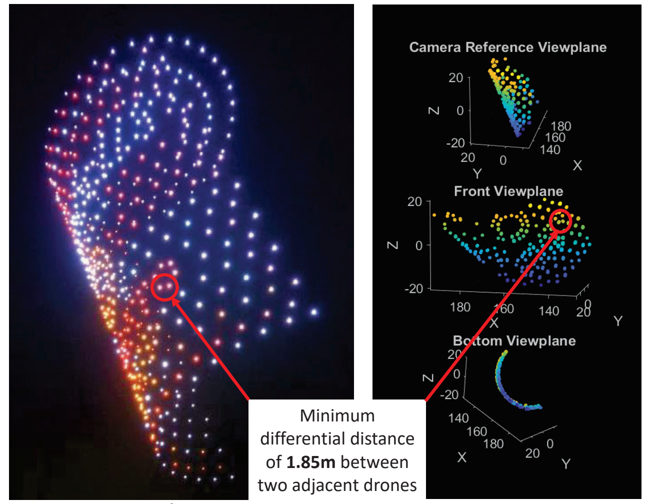
Figure 11: Drone swarm detection with lit and unlit drones.

(*Droneshow2*) with 500 drones, with the experimental setup shown in Figure 10. Since all the drone shows take place during the night and in a secured area, all our LiDAR scans of drone swarms are from the nighttime and from a certain distance outside the secured area. We use LiDAR hardware connected to a Linux-based compute node with one NVIDIA A100 GPU and 16 CPUs cores. Information on the specific model of the hardware and its setup can be obtained by contacting the authors of the paper. The data are processed through Matlab R2023b and CUDA 11.8.

Note that we explored a variety of LiDAR types including mechanical, solid-state, flash, and FMCW. Mechanical LiDAR offers high resolution and range but has wear-prone moving parts [71]. Flash LiDAR provides fast data acquisition but has limited range and resolution [60, 90]. FMCW LiDAR offers high precision and interference immunity but is expensive and complex [76, 96]. Solid-state LiDAR is robust and potentially cheaper but with a shorter range and lower resolution [47, 89]. Our preliminary study identified that solid-state LiDAR, as the most suitable for practical, scalable, low-cost LiDAR-based swarm sensing. The LiDAR had a convenient programmable API, allowing us to set a maximum frame rate of 10 frames/sec (100 ms per frame). The advertised distance is up to 500 m. The Field of View (FOV) is 18 degrees with a rosette pattern.

5.2 Swarm Sensing and Visualization

LiSWARM offers the exciting possibility of being able to sense every drone in 3D within a large drone swarm. Drone light shows are perfect for testing this hypothesis, as they consist of large number of drones tightly packed and typically arranged in a variety of different formations while also transitioning conveniently from formation to formation during the show.



a) b)

Figure 12: a) RGB image frame of a drone swarm formation from a camera placed below, b) LiDAR point cloud frames visualized on three different 3D planes.

5.2.1 Swarm Visualizations. Visualizing the entire swarm, including unlit drones, on a computer offers a complete overview of the airspace activity. To be specific, *LiSWARM* detects unlit drones invisible within the swarm, and provides both location and depth information, allowing the scene to be viewed from any plane, revealing swarm formations or structures not fully perceived from one viewpoint. Consider two instances illustrated in Figure 11 and 12. Figure 11 (a) shows an RGB image and its corresponding point cloud representations (both representations are time-synchronized) of one specific swarm formation from *Droneshow1*. In Figure 11 (b) the annotated elipses mark all the individual drones that were unlit during that specific instance. It is evident if we compare the 'star' formation of *Droneshow1* between its visual RGB and LiDAR representation, drones located at the lower part of the formation are unlit and invisible in the visual RGB image, however, those drones are detected and sensed in the point cloud. Figure 12 exhibits a painting on a cylindrical surface from *Droneshow2* and presents the other aspect of 3D visualization of a swarm at a convenient viewing plane. From the visual point-of-view looking up at the drone cloud, where the sensor was also placed, it is not possible to comprehend the information to its fullest that the formation was trying to convey. However, by using LiDAR and its reflected 3D point cloud, we are able to reconstruct the entire formation, and then rotate it into the most convenient viewing plane to perceive the complete message of the scene.

5.2.2 Swarm Trajectory Visualization. Each drone swarm comprises of many individual drones and during the flight of each such swarm all the individual drones maintain a complicated flight path to recreate diverse 3D shapes, letters or scenes. Therefore, apparently, it seems pretty challenging to reconstruct and visualize the trajectories of individual drones within a swarm. However, using our *LiSWARM* LiDAR-based swarm tracking system which benefits from the superior spatial resolution, we are able to reconstruct drone trajectories within the swarm. In Figure 13 we present

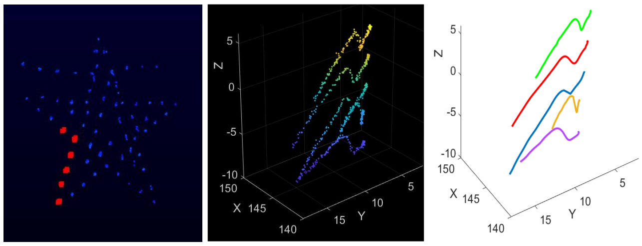


Figure 13: Trajectory monitoring of drone swarm, a) 6 Target drones, b) 12s of point cloud data, c) Reconstructed individual trajectories within drone swarm.

the trajectory visualization of 6 such drones which are part of the 'star' formation of *Droneshow1*. Here, first we select the drones of interest from which we localize their point cloud frames from the complete point cloud stream, then we concatenate point cloud frames of localized drones over a duration (12s in this case) in which we want to visualize their trajectories, and then plot and visualize the 6 individual reconstructed trajectories.

5.3 Recognition Accuracy

We test how well our *LiSWARM* system is capable of identifying objects within a swarm. We obtain recognition accuracy of our system while it is tasked to handle a swarm of objects (both drones and birds). For this purpose we use real drone swarm data collected from *Droneshow2* and then simulated bird swarms at similar locations to the drone swarm. The synthetic bird swarm is created from actual bird point clouds by replicating them in 3D space. Then both the drone swarm and bird swarm are mixed together as shown in Figure 14 to challenge our system to perform recognition tasks and classify the objects in the mixed swarm either as drones or not. Then we evaluate the classification performance using ML classifiers (kNN & SVM) and PointNet-based NN classifier. The accuracy plots and evaluation metrics of the test instance is shown in Figure 15 and the recognition performance establishes the fact that, NN-based classifier performs best with 93.9% test accuracy. We also observe that the precision and recall are both above 90% so that the rate of false positives and false negatives are held low.

To further compare the performance of existing SLAM-based methods and *LiSWARM*, we investigated the use of SLAM-based Fast Point Feature Histograms (FPFH) features [72] within *LiSWARM*'s classification pipeline. Since SLAM and *LiSWARM* differ significantly in their objectives—SLAM focuses on spatial registration and *LiSWARM* on classification—only the feature extraction step from SLAM was considered comparable except the preprocessing phase. We extracted FPFH features from the same dataset and tested classification performance. The results showed that FPFH features led to significantly lower accuracy compared to LiSWARM's shape-based features, with k-NN, SVM and Random Forest classifiers performing at 59.35%, 50.41% and 55.45% test accuracy, respectively. This confirms that FPFH features, primarily designed for point cloud alignment rather than classification, are not well-suited for drone recognition in LiSWARM's framework.

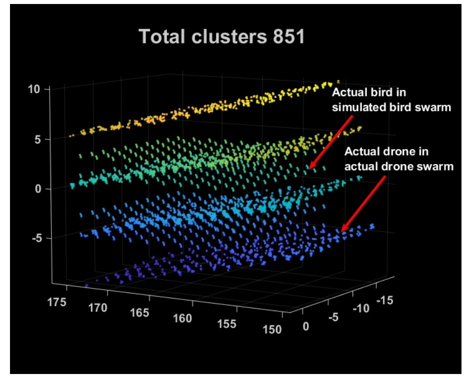
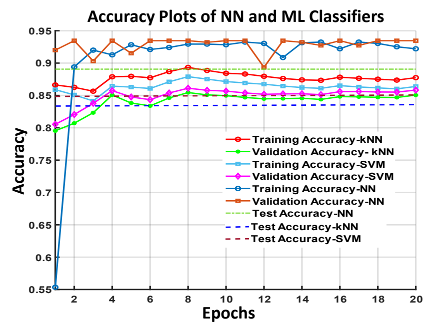


Figure 14: Drone swarm recognition test where an actual drone swarm is mixed with a simulated bird swarm at the same 3D spatial location.



NN Classifier Metrics

Accuracy	93.9%
Precision	95.33%
Recall	93.22%
F1 Score	94.26%

Figure 15: Drone swarm recognition performance with simulated bird swarms: classification accuracy for NN, SVM and kNN classifiers and performance metrics for NN classifier.

5.4 Real-time Performance for the Drone Shows

We present how the different performance optimizations improve the speed and scalability of our system. First, we show how prioritized distance-aware computing can substantially boost speed without sacrificing accuracy. Again, there is a concern about whether we drop so many points for the sake of real-time computation: how it will affect the recognition accuracy of the entire system and whether the shape information utilized by the NN model is maintained properly. We therefore test our entire pipeline with this distance-aware computing in the clustering block and present the comparison of distance-aware recognition accuracy vs recognition accuracy of the system without it. We obtain the classification accuracies using the *Droneshow2* data with both generic and distance-aware computing where the test accuracy for distance-aware computing is 94.06% compared to 97.77% accuracy from the generic approach. The reduction in accuracy is 3.71% in return for reducing the end-to-end system delay dramatically to just 0.17s for 150 real drones and 0.38s for 10000 simulated drones.

Figure 16 illustrates the impact of distance-aware computing alone and then both distance-aware computing with the use of multithreading for the operations associated within the clustering block of the system pipeline. We see how significantly these optimizations improve our system performance. The y axis is logarithmic here. We see how as the number of drones increases, distance-based

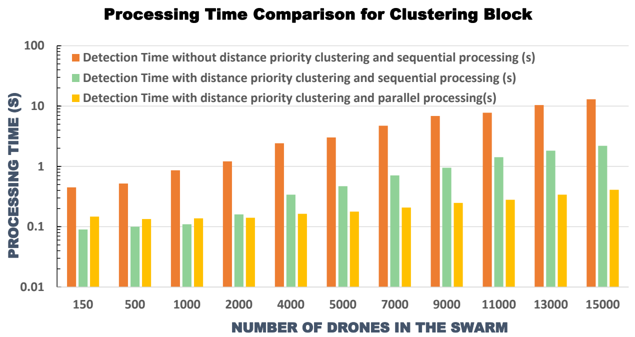


Figure 16: Comparison of computation time taken for the clustering block of system pipeline with and without distance-aware computation and parallel processing

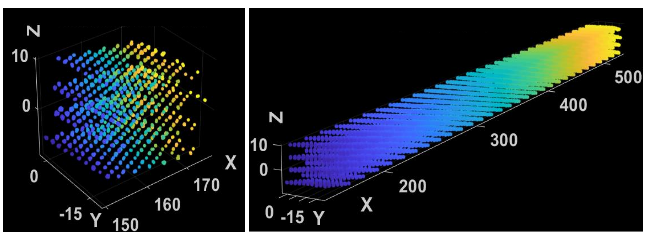


Figure 17: Drone swarm scalability test by replicating drones from actual drone show, a) actual 500 drone swarm point cloud, b) simulated drone swarm that is spatially replicated 30 times to obtain 15000 drones.

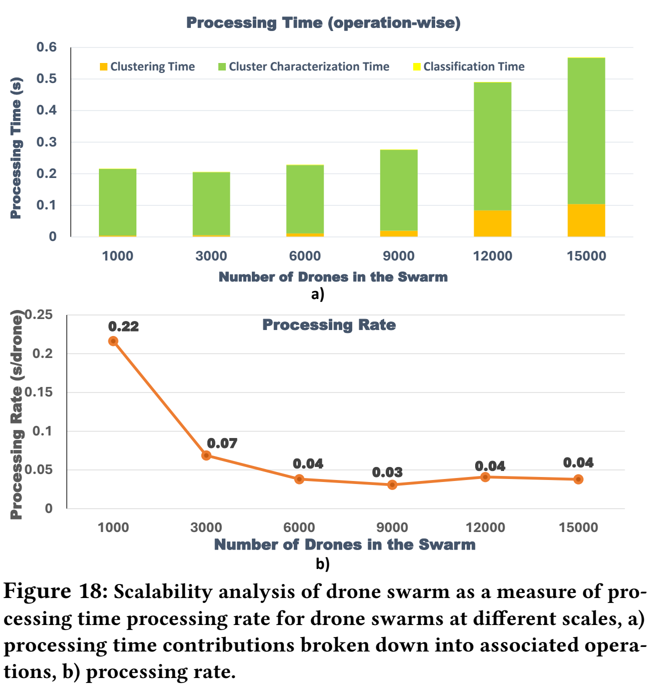


Figure 18: Scalability analysis of drone swarm as a measure of processing time processing rate for drone swarms at different scales, a) processing time contributions broken down into associated operations, b) processing rate.

clustering's gains become less prominent, requiring the need for additional speedup due to parallel processing for large swarms.

5.5 Scalability Analysis on a Swarm of 15,000 Drones

We analyze the scalability of the detection and tracking system with an increasing number of drones in the swarm up to as many as the most recent drone show (~14,000 drones) [13], i.e., how the system will scale up with continuous inclusion of drones in the swarm. We perform this scalability analysis in terms of processing time which includes the spatial clustering, cluster characterization and then recognition task from the mixture of drone and bird swarms. We also investigate the *LiSWARM* system's processing rate to obtain the delay of the system pipeline as a function of the number of drones processed per unit time. In Figure 17a, in order to scale the number of drones, we take *Droneshow2's* 500 drones, and replicate them spatially while maintaining the separation of 1.85m between adjacent drones to create the simulated droneswarm in Figure 17b.

We present the total processing time while showing the time taken at each major operational step as the drone swarm is scaled up in quantity. For each number of drones, the vast majority of the processing time is taken up by the clustering algorithm and detected clusters' spatial characterization, while the inference time due to the classification is quite small. As expected total computational time rises with number of drones in a swarm, but if we look at the normalized rate of computational time per drone in Figure 18b, we see that there is a clear trend towards decreasing latency per drone as the swarm size increases, which is promising for scalability.

6 DETAILED SYSTEM BENCHMARKING

6.1 Detection Sensitivity Analysis

In this section, we evaluate the performance of *LiSWARM* under different settings and environmental conditions to confirm its robustness and usability.

6.1.1 Impact of Distances. The 3 ML and the NN classifier have been trained and tested with datasets segregated into short distance (<50m), medium distance (51-100m), and long distance (>100m). All 4 classifiers' distance-based performance at all 4 available frames is shown in Figure 19. From the test accuracy plots of all 4 classifiers at different frame times, the NN-based classifier has the highest accuracy barring for the 5 frame case at a long distance. The highest accuracies obtained at different scenarios for the NN classifier are 98% for 5 frames and 10 frames at short distances and 97% for 10 frames at both medium and long distances. One trend is evident from these test results: accuracy decreases with an increase in target distance from the sensor, which results from the fact that LiDAR receives fewer reflected points as the target moves further, which was investigated in [1]. This phenomenon impedes classification accuracy at longer distances. For this reason, we decided to mimic the human eye's "*dark adaptation*" technique, which accumulates light over time when it experiences sudden darkness. In our methodology, we concatenated multiple frames to accumulate more reflected points from a target. This approach proves to be working efficiently as we can look into the accuracy plots, so it is evident that classification accuracy, in fact, increases as the number of frames merged together is increased.

6.1.2 Impact of Target Moving Speeds. Since the NN classifier performs best in general over most distances, we selected the NN

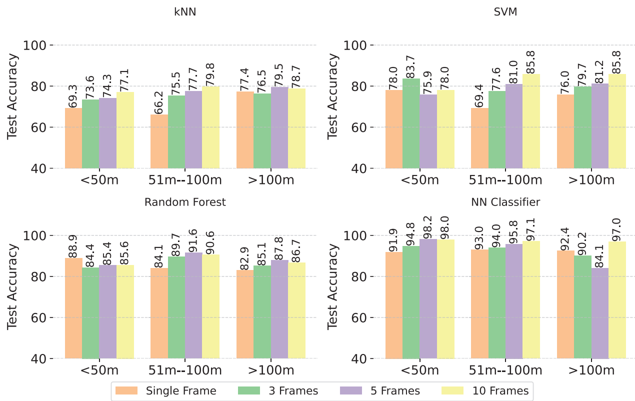


Figure 19: Test accuracy for different range targets.

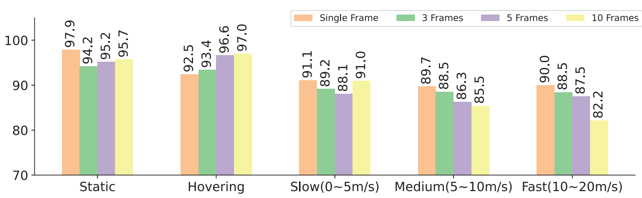


Figure 20: Test accuracy for different target velocities.

classifier to present further performance evaluations. The NN classifier has been trained and tested with a dataset segregated into static targets at the ground, and hovering targets in the sky that are either slow (0-5m/s), medium (5-10m/s), or fast (10-20m/s). Here the dataset is distance-independent which means all speed-based categories contain point clouds from different distances. The NN classifier's velocity-based performance at different frames is shown in Figure 20. The highest accuracies at varied categories obtained are 98% for static targets, 96% for hovering targets, and 90% for three cases of motion. The accuracy plots follow the trend in which accuracy decreases with the increase in target speed across all frames and this trend supports the intuition that a target with higher velocity will incorporate a greater amount of motion blur. And the interesting finding is that contrary to the performance analysis at different ranges, in this case, accuracies are better for fewer frames when the target is in motion.

6.1.3 Impact of Light Conditions - Day/Night Time. The NN classifier has been trained and tested with datasets segregated into daytime and nighttime data where objects were scanned during daylight and at night. The NN classifier's lighting condition-based performance at different frames is shown in Figure 21. The highest accuracies during daytime and nighttime are 89% and 88% respectively. Here accuracies slightly decrease compared to distance-based and speed-based results because we selected long-distance target data for this performance test. In this case, the accuracy plots establish the fact that classifier performance is not significantly impacted by the presence of ambient light.

6.2 Tracking Performance

6.2.1 Spatial Resolution. We perform tests to disambiguate adjacent drones which provide insights on the spatial resolution achievable by LiDAR scan and also to understand how it can be used forntrajectory confusion alleviation. We set to determine how close

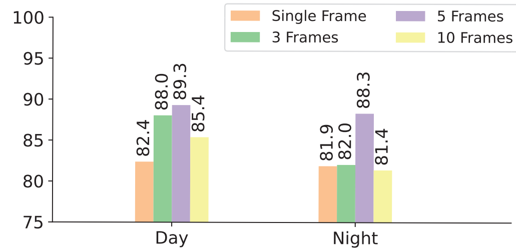


Figure 21: Test accuracy for day and night time data.

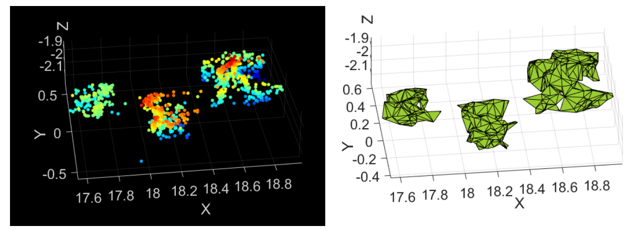


Figure 22: Spatial resolution test with 3 static UAVs, a) point cloud of 3 UAVs at close proximity, b) alphashapes of the 3 UAVs.

2 objects can be in space, and still be identified as distinct objects. While tested with 3 static drones at close proximity, we find this distance to be 30cm and this is shown in Figure 22 using both point cloud data and its alphashape representations. While conducting such tests with drones in flight, we received "Obstacle Detection" notifications in the drone's original flight log whenever flying UAVs at such close proximity that it triggered an obstacle detection warning, which occurred at 300cm or 3m. Even then, the point clouds of the 2 drones were clearly resolved as distinct drones.

6.2.2 Trajectory Reconstruction. We verify the trajectory reconstruction process at various ranges and speed scenarios and also verify the trajectory estimation accuracy by comparing it with the GPS flight data of the drone itself.

Impact of Ranges and Speeds. We conduct experiments with 2 UAVS at 2 different range and speed scenarios and analyze their trajectories for different durations: UAV1 trajectory with 33s duration at a speed of 14.75m/s from distance 20m to 120m, and UAV2 trajectory with 21s duration at a speed of 6m/s from distance 5m to 26m. Figure 6 shows the above-mentioned 2 specific cases.

Comparison against GPS Data. To verify the accuracy of the drone trajectory obtained from *LiSWARM*, we compare the computed values with the baseline. We use the GPS-based location data, extracted from drone flight log files as the baseline for the flight path. The deviation in 3D space is then analyzed by comparing the GPS flight path with the LiDAR-estimated trajectory. Figure 23 shows the 4 main ingredients of this accuracy analysis: original point cloud from LiDAR, reconstructed trajectory from it using our system, GPS flight path, and the deviation of points obtained from 2 modalities. Result shows that both trajectories are overlaid fairly close to each other. The mean deviation of points in the trajectory between 2 modalities is only 3m. Since GPS accuracy itself is not confirmed and can not be considered as absolute ground truth, this experiment proves a basis for applicability of LiDAR as tracking modality with an existing technology. And the result implies that *LiSWARM* localization accuracy is comparable with that of GPS.

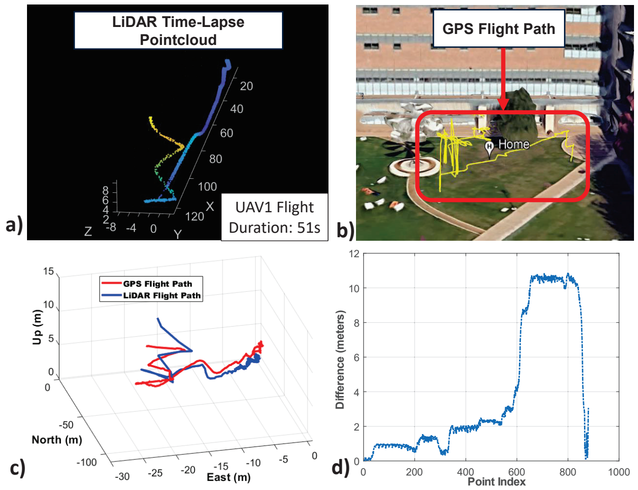


Figure 23: *LiSWARM*'s extracted trajectory vs. GPS data of UAV1, a) LiDAR point cloud, b) GPS flight path, c) LiDAR reconstructed trajectory and GPS flight path overlaid, d) error plot of LiDAR points corresponding to GPS points.

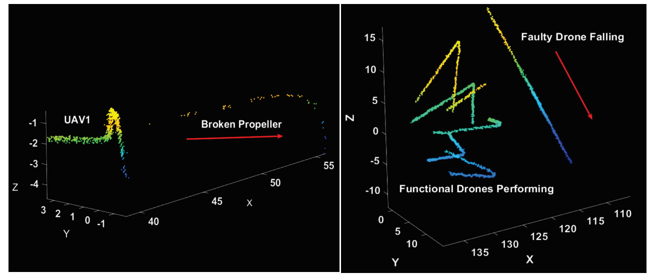
To evaluate the accuracy of LiDAR-based trajectory reconstruction, we conducted an independent validation experiment using a vision-based reference. Instead of relying on GPS, we deployed an overhead drone to record the test drone's flight path from a top-down perspective. This approach provided an alternative ground truth for assessing LiDAR-based tracking performance. The test flight covered a distance range of 30m to 70m from the LiDAR sensor. By comparing the LiDAR-reconstructed 2D trajectory with the vision-based trajectory, we quantified the deviation between both methods. The results showed an average deviation of 15cm and a maximum deviation of 50cm.

By employing a reference independent of GPS enables a more precise assessment of LiDAR-based tracking accuracy. The findings contribute to refining LiSWARM's performance and improving real-time localization strategies for autonomous aerial systems.

6.2.3 Fault Management. LiDAR point clouds can also be used to detect faulty drones in a swarm. During our regular drone flight test, we encountered an irregular incident when one of the propellers of UAV1 broke off and was thrown away during its flight. The drone fell down and we lost the propeller there. However, by analyzing the point cloud stream and the reconstructed trajectory of both the fallen drone and the detached propeller, we were able to find and recover the drone and propeller. Figure 24 presents the incident in terms of the point cloud and the extracted trajectory from it. Further, the figure documents a faulty drone found during drone show 1, whose trajectory is shown. This finding inspires us that LiDAR can be used to detect and manage such anomalous cases to track and recover faulty drones.

7 RELATED WORKS

Studies on anti-drone techniques can be categorized into detecting, tracking, and identifying drones [5, 11, 51]. The critical issue in flying object detection systems is differentiating drones from other



a) Point cloud of UAV1 with broken propeller

b) Point cloud of a faulty drone falling from sky at *Droneshow1*

Figure 24: Recognition of broken propeller in test drone and faulty drone at *Droneshow1*.

flying objects using ground-based static detectors or mobile detection systems [14, 95]. This involves evaluating existing technologies and identifying those that can effectively detect swarms of drones [2, 41, 79, 91].

RF analysis of drone communication signals is popular for detecting single or multiple drones due to its low complexity, ease of implementation, and all-weather operation [7]. However, it struggles with precise positioning, only determining signal direction based on its angle of arrival [23, 57, 65]. Advanced RF technology with software-defined radio platforms can detect small drones up to 75 meters away [17, 61].

The sound from drone motors and propellers, ranging from 20 Hz to 20 kHz, creates a distinct signature allowing acoustic sensors to differentiate drones using fiber-optic acoustic methods [24], machine learning [3], and deep neural networks [84]. This method is effective only in quiet environments and short-range detection. Increasing acoustic sensors and using beam-forming techniques can locate drones with up to 80% success [28, 74]. Optical and thermal cameras use CNN-based algorithms for single and multi-object detection and tracking [4, 26, 45, 55]. However, computer vision technologies struggle with adverse weather, lighting, background conditions, minimal detection range, and detecting small drones [33, 42, 77, 97].

Radar can detect drones by simultaneously analyzing their Doppler signature and echo due to the rotor blades [43, 93]. The system transmits radio waves and detects the reflected signals to accurately determine the target's distance and speed [67]. Radar position adjustments are often required for drone detection during runtime. Multi-agent reinforcement learning can adjust the radar parameters' runtime and the radar platform's position [38]. Unlike RF or acoustic sensing, radar's detection coverage is unaffected by environmental conditions. However, this technology cannot distinguish drones from other flying objects and needs to be combined with other sensing technologies [8, 58].

LiDAR offers precise detection, tracking, and mapping [73]. In one study, a LiDAR system with a peak power of 700 kW extended the detection range to 2 km [39]. Another experiment used a 3D LiDAR system on a vehicle to detect mini drones, showing high success for targets within 30 meters using sensors with a 100-meter range [12, 29]. The LiDAR SLAM method can detect moving objects, and point cloud analysis calculates the confidence level of the initial vehicle model [46, 68, 83]. Enhancing 3D-SLAM accuracy involves using deep-learning-based dynamic object filtering to label dynamic objects in the point cloud automatically [69]. Various SLAM frameworks like Gmapping, Karto, and Hector SLAM can detect moving objects, with advantages depending on the environment and trajectories [94].

Traditional LiDAR-based object recognition algorithms are designed for ground targets, like PV-RCNN for vehicle detection [82], and for general-purpose 3D object recognition, such as PointNet [70] and PointPillars [44] which are not specifically suited for tracking UAV swarms because of their varying 3D formations. While PointNet and PointPillars can detect objects in point clouds, they are primarily optimized for small-scale, static object detection and have limitations in terms of range and scalability when applied to large, dynamic drone swarms.

8 CONCLUSION

This paper presents *LiSWARM*, a new 3D drone swarm detection and tracking system using low-cost LiDAR. We develop techniques for processing point cloud data and adaptively incorporating temporal frames, enabling accurate detection and real-time tracking of hundreds of drones, distinguishing them from other flying objects. The system is shown to be capable of accurately recognizing drones at 94% accuracy using a deep learning neural network. *LiSWARM* is demonstrated on real world drone light show data and is shown to be able to track a drone swarm of size 150 in just 0.17 seconds. Techniques such as prioritized distance-aware computing and GPU/CPU load balancing for high-speed clustering are introduced to optimize system performance. Further, we show that the system scales well to thousands of drones.

9 DISCUSSION

There are a number of limitations to our research. LiDAR itself is limited by rain and fog, so other sensing modalities would need to complement our swarm tracking system in those environments. Our drone show data was only taken at night, while the bird point cloud data was taken during the day, though we also flew individual drones during the day. In the future, we hope to train our classifier on more drone models, more bird species, and other airborne objects like balloons. Our drone swarm analysis was based on two drone shows of 150 and 500 drones each, and in the future we may seek larger shows. LiDAR software prevented real-time streaming of the data into our software pipeline, so we had to record the point cloud data first, then stream it through the pipeline later to calculate scalability performance, but we feel this is a vendor-specific obstacle that will not prevent full end-to-end streaming in a production system. We tested feasibility with one LiDAR COTS model, which advertised up to 500 m range at 50% reflectivity of target, though in practice we found satisfactory point cloud data for drones up to 220m (since getting 50% reflectivity from objects in practical application is unlikely), which we felt was a useful demonstration detection range. In our study, we observed that a 220m detection range was sufficient for capturing drone shows, achieved while operating the COTS LiDAR sensor at its default power setting. This approach ensured compliance with standard eye safety regulations, offering a practical demonstration of the sensor's capability for real-world applications. We believe the range could be substantially extended with custom LiDAR. In future work, we plan to explore customizing the LiDAR system, including using higher-power infrared sensors, to extend the detection range and enhance performance under varying environmental conditions.

In considering the differences between *LiSWARM* and SLAM, it becomes clear that while both systems rely on point cloud data, their primary goals and methodologies diverge significantly. SLAM is geared towards map creation and localization within a static environment, emphasizing the alignment of sequential point clouds and minimizing drift through techniques such as pose graph optimization. In contrast, *LiSWARM* is focused on real-time object detection and classification, with an emphasis on dynamic tracking of UAVs within a drone swarm. This fundamental difference means that while SLAM works to build and refine a global map, *LiSWARM* operates on identifying and tracking individual objects. This distinction also highlights how SLAM traditionally uses handcrafted features like FPFH for feature matching and registration, whereas *LiSWARM* incorporates machine learning techniques for UAV detection and classification, further reinforcing the contrast between map creation and object detection as primary objectives.

In terms of scalability analysis, our motivation and primary objective is to assess computational feasibility rather than precisely simulating LiDAR behavior at extreme densities. Since direct replication in the simulation does not account for the natural reduction in point density with distance, it tends to overrepresent distant points, making our evaluation computationally even more demanding than real-world conditions. In practice, LiDAR loses point density at greater distances due to beam divergence and reduced reflectivity.By maintaining a uniform point density across all drones in our simulation, we effectively tested *LiSWARM* under a worst-case computational load, demonstrating its efficiency even under exaggerated conditions. A more physically accurate LiDAR simulation would involve modeling the gradual loss of reflected points with increasing distance, but the lack of real-world datasets for large-scale drone swarms posed a limitation that can be addressed in future work.

It wasn't clear how best to measure the accuracy of reconstructed drone trajectories since determining what represented ground truth was a challenge. We took GPS measurements as the baseline to compare against, but GPS itself is subject to error. We lacked ground truth for the drone show trajectories, since we were not privy to the pre-programmed trajectories of the drones used in the light shows. Other positioning systems may be expensive to implement, impractical, or imprecise. We will continue to seek solutions for measuring trajectory accuracy. We are also interested in determining how finely we can discriminate one drone trajectory from another. The drone show data always kept the drones far apart, likely for safety reasons to avoid collisions, so we did not have the opportunity to study this matter in more detail.

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