Leveraging Clustering Techniques for Enhanced Drone Monitoring and Position Estimation

Abstract

Drone tracking and localization are essential for various applications, including managing drone formations and implementing anti-drone strategies. Pinpointing and monitoring drones in three-dimensional space is difficult, particularly when trying to capture the subtle movements of small drones during rapid maneuvers. This involves extracting faint signals from varied flight settings and maintaining alignment despite swift actions. Typically, cameras and LiDAR systems are used to record the paths of drones. However, they encounter challenges in categorizing drones and estimating their positions accurately. This report provides an overview of an approach named CL-Det. It uses a clustering-based learning detection strategy to track and estimate the position of drones using data from two types of LiDAR sensors: Livox Avia and LiDAR 360. This method merges data from both LiDAR sources to accurately determine the drone's location in three dimensions. The method begins by synchronizing the time codes of the data from the two sensors and then isolates the point cloud data for the objects of interest (OOIs) from the environmental data. A Density-Based Spatial Clustering of Applications with Noise (DBSCAN) method is applied to cluster the OOI point cloud data, and the center point of the most prominent cluster is taken as the drone's location. The technique also incorporates past position estimates to compensate for any missing information.

1 Introduction

Unmanned aerial vehicles (UAVs), commonly referred to as drones, have gained prominence and significantly influence areas like logistics, imaging, and emergency response, offering substantial advantages to society. However, the broad adoption and sophisticated features of compact, off-the-shelf drones have created intricate security issues that extend beyond conventional risks.

Recent years have witnessed a surge in research on anti-UAV systems. Present anti-UAV methods predominantly utilize visual, radar, and radio frequency (RF) technologies. Despite these strides, recognizing drones poses a considerable hurdle for sensors like cameras, particularly when drones are at significant altitudes or in challenging visual environments. These methods usually fail to spot small drones because of their minimal size, which leads to a decreased radar cross-section and a less noticeable visual presence. Furthermore, current anti-UAV studies primarily focus on detecting objects and tracking them in two dimensions, overlooking the crucial element of estimating their 3D paths. This omission significantly restricts the effectiveness of anti-UAV systems in practical, real-world contexts.

Our proposed solution, a detection method based on clustering learning (CL-Det), uses the strengths of both Livox Avia and LiDAR 360 to improve the tracking and position estimation of UAVs. Initially, the timestamps from the Livox Avia and LiDAR 360 data are aligned to maintain temporal consistency. By examining the LiDAR data, which contains the spatial coordinates of objects at specific times, and comparing these to the actual recorded positions of the drone at those times, the drone's location within the LiDAR point cloud data is effectively pinpointed. The point cloud for

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objects of interest (OOIs) is then isolated from the environmental data. The point cloud of the OOIs is grouped using the DBSCAN algorithm, and the central point of the largest cluster is designated as the UAV's position. Moreover, radar data also faces significant challenges due to missing information. To mitigate potential data deficiencies, past estimations are employed to supplement missing data, thereby maintaining the consistency and precision of UAV tracking.

2 Methodology

This section details the methodology employed to ascertain the drone's spatial position utilizing information from LiDAR 360 and Livox Avia sensors. The strategy integrates data from both sensor types to achieve precise position calculations.

2.1 Data Sources

The following modalities of data were utilized:

- Double fisheye camera visual images
- Livox Mid-360 (LiDAR 360) 3D point cloud data
- Livox Avia 3D point cloud data
- Millimeter-wave radar 3D point cloud data

Only 14 out of 59 test sequences have non-zero radar values; therefore, the radar dataset is excluded from this work due to data availability issues. Two primary sensor types are employed: LiDAR 360 and Livox Avia, both of which supply 3D point cloud data crucial for identifying the drone's location. The detailed data descriptions are outlined as follows:

- LiDAR 360 offers a complete 360-degree view with 3D point cloud data. This dataset encompasses environmental details and other observable objects.
- Livox Avia delivers focused 3D point cloud data at specific timestamps, typically indicating the origin point or the drone's position.

2.2 Algorithm

For every sequence, corresponding positions are recorded at specific timestamps. The procedure gives precedence to LiDAR 360 data, using Livox Avia data as a backup if the former is not available. If neither source is accessible, the position is estimated using historical averages.

2.2.1 LiDAR 360 Data Processing

- **Separation of Points:** The LiDAR 360 data is visually examined to classify areas into two zones: environment and non-environment zones.
- **Removal of Environment Points:** All points within the environment zone are deemed part of the surroundings and are thus excluded from the dataset. After removing environment points, it is observed that the remaining non-environment points imply the drone position.
- **Clustering:** The DBSCAN clustering algorithm is applied to the remaining points to discern distinct clusters.
- **Cluster Selection:** The most extensive non-environment cluster is chosen as the representative group of points that correspond to the drone.
- **Mean Position Calculation:** The drone's position is determined by calculating the mean of the selected cluster, represented by (x, y, z) coordinates.

2.2.2 Livox Avia Data Processing

- **Removal of Noise:** Points with coordinates (0, 0, 0) are eliminated as they are regarded as noise.
- **Mean Position Calculation:** The mean of the residual points is computed to ascertain the drone's position in (x, y, z) coordinates.

2.2.3 Fallback Method

When neither LiDAR 360 nor Livox Avia data is available, the average location of the drone derived from training datasets is used. The average ground truth position (x, y, z) from all training datasets estimates the drone ground truth position, which is (0.734, -9.739, 33.353).

2.3 Implementation Details

The program fetches LiDAR 360 or Livox Avia data from the nearest timestamp for each sequence, as indicated in the test dataset. Clustering is executed using the DBSCAN algorithm with appropriate parameters to guarantee strong clustering. Visual inspection is employed for the preliminary separation of points, ensuring an accurate categorization of environment points.

The implementation was conducted on a Lenovo IdeaPad Slim 5 Pro (16") running Windows 11 with an AMD Ryzen 7 5800H CPU and 16GB DDR4 RAM. The analysis was carried out in a Jupyter Notebook environment using Python 3.10. For clustering, the DBSCAN algorithm from the Scikit-Learn library was utilized. The DBSCAN algorithm was configured with an epsilon (eps) value of 2 and a minimum number of points (minPts) set to 1.

3 Results

The algorithm achieved a pose MSE loss of 120.215 and a classification accuracy of 0.322. Table 1 presents the evaluation results compared to other teams.

Table 1: Evaluation results on the leaderboard

Team	ID	Pose MSE (↓)	Accuracy (↑)
SDUCZS	58198	2.21375	0.8136
Gaofen Lab	57978	7.299575	0.3220
sysutlt	57843	24.50694	0.3220
casetrous	58233	56.880267	0.2542
NTU-ICG (ours)	58268	120.215107	0.3220
MTC	58180	189.669428	0.2724
gzist	56936	417.396317	0.2302

4 Conclusions

This paper introduces a clustering-based learning method, CL-Det, which employs advanced clustering techniques such as K-Means and DBSCAN for drone detection and position estimation using LiDAR data. The approach guarantees dependable and precise drone position estimation by utilizing multi-sensor data and robust clustering methods. Fallback mechanisms are in place to ensure continuous position estimation even when primary sensor data is absent. Through thorough parameter optimization and comparative assessment, the proposed method's effective performance in drone tracking and position estimation is demonstrated.