Towards Robust Lidar-based 3D Detection and Tracking of UAVs

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ABSTRACT

In this paper, we study the robustness of lidar-based 3D detection & tracking of UAVs. We investigate the effective detection ranges of different UAVs based on their construction materials and the effective range & 3D detection performance of a specific UAV at different atmospheric visibility conditions. Further, we examine to what extent lidar-based systems can track a drone's trajectories via real-world experiments and point cloud data processing. Using a COTS lidar-based system (Livox Mid-40), we confirm that we can track UAVs in a fine-grained manner at up to 80m distance under various environmental conditions (i.e., morning, afternoon, and night).

CCS CONCEPTS

• **Computer systems organization** → **Real-time system architecture**.

KEYWORDS

Lidar-based detection, UAV detection and tracking, Target reflectivity, Light robustness

1 INTRODUCTION

Drones are becoming an increasing reality, both in terms of massive holiday light shows with over a thousand drones [13] and also on the modern battlefield [7]. We expect the trend to grow dramatically as new applications popularize the mass use of drones, such as commercial package delivery to businesses and homes [2, 3, 8]

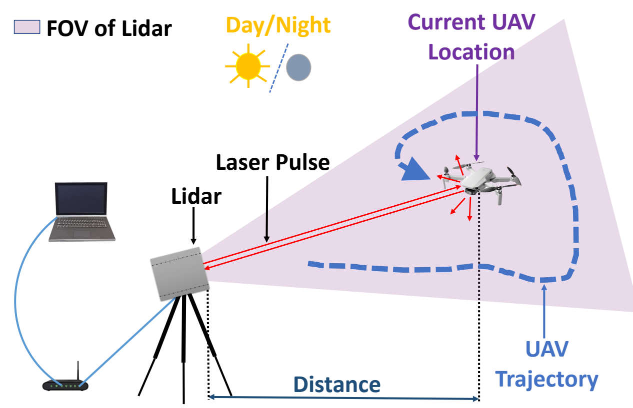

Figure 1: Robustness analysis and localization concept for lidar-based drone monitoring

and autonomous monitoring of critical infrastructure such as roads, buildings, and transmission lines, leading to crowded air spaces in urban environments. Such drones pose a risk to sensitive airspaces such as around airports [14], so it is important to have accurate, robust, and low-cost technology capable of scalably detecting, localizing, and tracking drones in real-time. Conventional approaches for detecting & tracking airborne vehicles such as radar [23] are not well suited for drones due to the low radar cross section (RCS) of drones, which are often small and consist of many non-metallic components, as well as the low altitude at which most drones fly, making the drones difficult to distinguish from the ground clutter. Passive radio frequency (RF) sensing systems [17, 18]) can detect and localize a single drone, but have not shown an ability to scale and rely on the drone to constantly transmit. Video-based sensing systems have also been investigated, for example the camera-based small flying object detection which is robust with the change in object appearence & background [20] and the low complexity UAV to UAV detection & tracking scheme using autonomous see & avoid system [15]. However, all video-based systems perform poorly in darkness, inclement and foggy weather. Acoustic-based drone monitoring performs poorly in high acoustic noise environments

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such as cities, airports, or factories. Also, since the UAVs generate sounds at similar frequency ranges and amplitudes, separating the sound of individual UAVs for reliable swarm monitoring is an unsolved challenge and the emergence of silent drones makes the acoustic-based drone detection even more challenging. Most of the variety of RF, video, and audio techniques for drone tracking summarized in [19] focus on monitoring a single or a few drones but not yet a reliable drone swarm tracking system [21].

In this paper, we characterize the performance of a lidar-based (Light Detection And Ranging) system for drone detection, and tracking, focusing on robustness of range estimation to different drone models & robustness to different lighting conditions. Figure 1 illustrates our lidar-based 3D detection and tracking system for drones. While there has been limited prior work beginning to explore the feasibility of using lidar for drone detection and tracking [1, 5, 9], the literature is largely lacking in a more detailed study and understanding of the robustness and practical utility of such systems under a variety of different real-world conditions, such as different models that may affect range estimation, and varying lighting conditions that may affect point cloud gathering and tracking of drones. As a result, the main contributions of this paper are summarized as follows:

- We explore the effective range of lidar-based drone 3D localization with different UAV models.
- We investigate the robustness of UAV detection during different environmental lighting conditions by examining reflectivity across different ranges.
- We present drone tracking & trajectory measurements at different lighting conditions using 3D point cloud.

2 FUNDAMENTALS OF LIDAR DETECTION AND RELATED WORK

We describe the parameters affecting the performance of lidar-based solution and plan to conduct real-world experiments to analyze those impacts along with the limitations of existing lidar-based systems.

2.1 Lidar Fundamentals

Lidar is a remote sensing technology that uses laser pulses to measure the distance to a target object or surface and used in topographical mapping, atmospheric sensing [10], and object detection and tracking. The round-trip time (τ) of the laser pulses is used to calculate the range (R) of the target based on the speed of light in a vacuum (c) and the average group refractive index of the optical path between the lidar system and the target (η), then $R = (c/2\eta)$. However, the range that a lidar system can effectively operate at is influenced by two main factors: (1) the sensitivity of its photoreceiver and (2) the strength of the optical signal that is returned based on the distance of the target. The factors that affect the strength of the signal return are examined, which include the energy of the laser pulses, the conditions of the atmosphere, and the characteristics of the target such as its size, orientation, and surface properties.

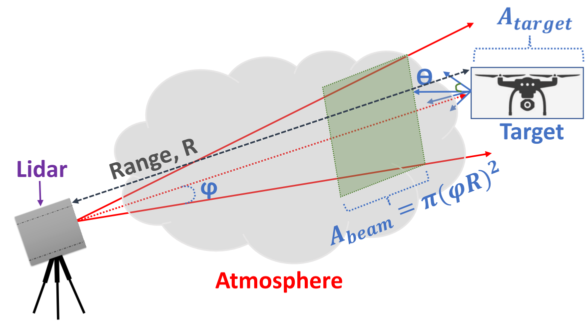

Figure 2: Fundamentals of lidar scan of target object

Atmospheric conditions play a vital role in the lidar performance which eventually depends on visibility or lighting conditions, spreading and scattering effect of the environment, rain, fog, etc. The external factors that control the amount of distortion and attenuation are the distance through the atmosphere, and environmental factors like *visibility*, *temperature*, and *turbulence*.

The optical power of laser pulses is affected by both absorption and scattering, which can be described by the attenuation coefficient (σ) measured in m^{-1}. The optical energy of the laser beam within its cross-sectional area (A_{beam}) at a distance (R) can be estimated using this equation which incorporates all the defining factors:

$$\begin{aligned} E_{opt} &= (E_{Tx.}/A_{beam})exp(-\sigma R) \\ &= (E_{Tx.}/\pi(\phi R)^2)exp(-\sigma R) \end{aligned} \quad (1)$$

Here $E_{Tx.}$ is the transmitted laser power and ϕ is half of the divergence angle of the laser beam. Therefore, the effective range is directly dependent on optical energy used $E_{Tx.}$, environmental impact termed as attenuation σ, and the laser beam quality or collimation ϕ. The lidar detection mechanism and effective range is demonstrated in Figure 2.

2.2 Lidar Applications and Related Works

Lidar technology provides highly accurate and detailed 3D data, making it valuable for various applications. These include 3D object detection for autonomous driving [16], creating detailed seafloor maps [12], monitoring urban flooding [22], forest inventory estimation for carbon sequestration [4], and archaeological research [10].

There are few works using lidar to localize UAVs or other intrusions, including a technique for monitoring

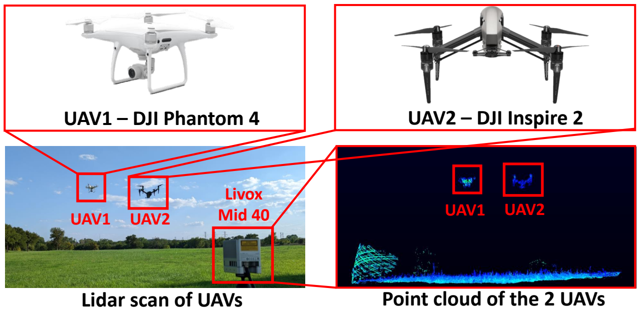

Figure 3: Lidar scan of UAVs for point cloud analysis using Livox Mid-40

the trajectory of drones using lidar [1], a method to detect targets in a complex background through relative state estimation [6], and identifying drones from the cross-polarization ratio analysis of the optical echo [24].

In particular, using lidar, a single drone can be detected up to 35 m using a Velodyne HDL-64 lidar [9] while another work shows that ground-based aerial target detection detecting drones with sparse detection methods & active tracking [5]. A lidar-based drone trajectory monitoring technique has also been proposed and evaluated [1]. While these approaches are promising, they lacked a detailed range analysis across different UAV models, and also no consideration was made about the lidar range performance when the atmosphere, visibility, or light environment is changed. In addition, no attempt was made to compare UAV tracking & trajectory analysis at different lighting conditions. We address these limitations in this work.

3 RANGE ESTIMATION ANALYSIS

This section discusses the feasibility and robustness of the lidar-based system in detecting UAVs flying at distances via a series of outdoor and real-world experiments. These experiments are designed to answer the following questions: (1) *What is the detection range of UAVs using a lidar-based monitoring system?*, (2) *Does drone type and shape affect the lidar-based system performance?*, (3) *What factors limit the detection range?*

3.1 Study Design

In this study, we place a Livox Mid-40 lidar in an open field and fly two UAVs (DJI Phantom 4 (white) and DJI Inspire 2 (black)) in the Field of View (FOV) of the Livox device at distances ranging from 5m to 200m as shown in Figure 3, we designate them as UAV1 & UAV2 respectively for the sake of discussion through the entire paper. We are able to detect UAV1 and UAV2 at distances up to 80m and 50m, respectively. All the lidar scan experiments are done with a 1s frame rate,

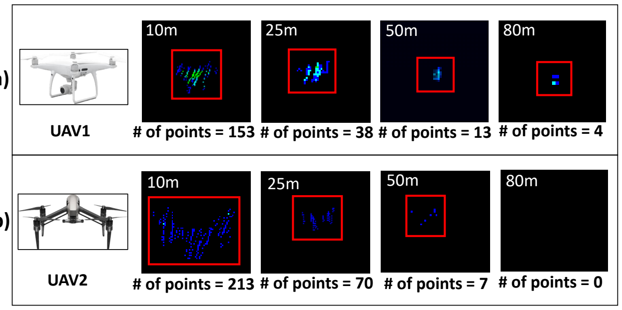

Figure 4: Detection range estimation of lidar using point clouds of a) UAV1 & b) UAV2

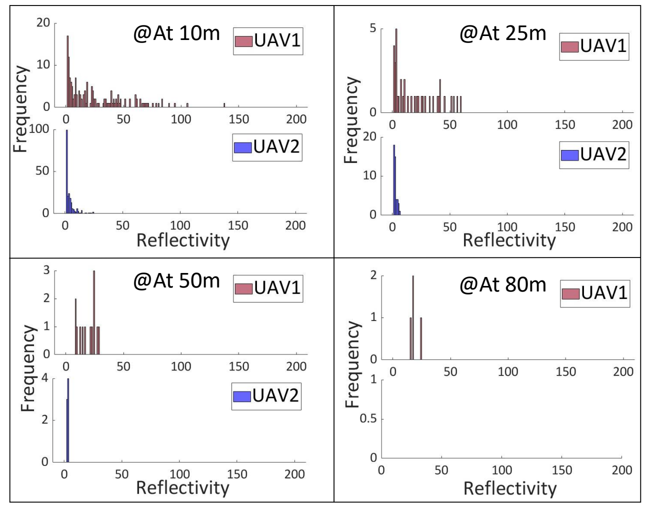

Figure 5: Reflectivity histograms of UAV1 & UAV2 with varying distances

which is chosen to have a tradeoff between point cloud density & tracking of moving UAVs.

3.2 Preliminary Results

The measurements we received from the outdoor lidar scan of the 2 UAVs are accumulated in terms of point cloud analysis, the number of reflected points from each UAV, and the histogram of reflectivity of each UAV. In Figure 4 it can be seen that UAV1 can be detected up to 80m while UAV2 is detected up to 50m. Note that despite UAV2 being significantly larger than UAV1, the detection range of UAV2 is much shorter than UAV1. And this can be explained and analyzed in terms of the reflectivity of each UAV where white UAV1 has much more reflectivity, R_I, than black UAV2. The reflectivity distribution, the number of reflected points & individual average reflectivity is shown in Figure 5 & Table 1 which are being obtained for the segmented point clouds of UAV1 & UAV in Figure 4. From the histograms of the 2 UAVs in Figure 5, it is evident that the reflectivity of UAV1 is much higher than UAV2 which results in a higher effective range for UAV1. *This result conforms*

	UAV 1		UAV 2	
Distance	Reflected Points Count	Average Reflectivity	Reflected Points Count	Average Reflectivity
10m	153	25.21	213	3.68
25m	38	19.45	45	2.16
50m	13	18.24	7	2.57
80m	4	18.25	0	0

Table 1: Number of reflected points and average reflectivity of UAV1 & UAV2 during afternoon with 1s frame.

with the theory that reflectivity is related to laser fluence or optical energy in Equation 1.

The reflectivity of a material can be affected by various factors, including its optical properties, surface roughness, and the wavelength and intensity of the incident laser light. When a laser beam interacts with a material, it can be absorbed, transmitted, or reflected, depending on the characteristics of the material and the laser parameters. Therefore, the effective range of a UAV or any other target object depends on its reflectivity, physical material, or atmospheric impacts. The atmospheric impact will be discussed in the next section whereas the impact of physical material & reflectivity on optical energy is analyzed in this section. Table 1 shows the number of reflected points and mean reflectivity value of the 2 UAV's physical material. It suggests that since UAV2 is larger in dimension it will have a greater number of reflected points at close proximity than UAV1 but since it has a very low average reflectivity value, the optical energy attenuation with distance is more severe on it than in UAV1. This in turn, limits the detection range of UAV2 up to 50 m.

4 VISIBILITY ROBUSTNESS OF LIDAR

This section discusses the impact of the atmosphere on UAV detection in terms of visibility & lighting environment. This time we conduct lidar scan experiments only with UAV1 (since it has greater range than UAV2) during morning, afternoon, and night at the same place and with the same background to analyze the effect of different lighting conditions on the UAV detection. We choose these 3 different time periods of a day to allow us to conduct at 3 different visibility conditions, where the morning had the highest visibility, then during the afternoon the natural light faded and during the night no sunlight was available.

4.1 Impact of Environmental Conditions on Lidar Performance

From Equation 1, it can be seen that the attenuation factor (σ) encompasses all the environmental impacts, including visibility due to different natural light, weather conditions, and other factors. Since visibility plays a vital role in determining the effective range of lidar while scanning for UAVs or other aerial intrusions, the robustness analysis of lidar at different lighting conditions can shed light on an important design aspect of any integrated intrusion detection & localization system.

4.2 Robustness Analysis at Different Lighting Conditions

Here, we present the robust performance of lidar in detecting & localizing UAVs irrespective of different lighting conditions. In Figure 6, the point clouds of UAV1 from each lidar scan during morning, afternoon & night at different distances are shown with the surrounding background with trees and the segmented version of only the UAV. From the point clouds, it is observed that detectability & range at all 3 different lighting conditions do not vary much, however, the background clutter is less visible at night. This can be explained by the fact that during the night there is very low ambient light which makes it difficult for the trees or other natural clutters here to reflect enough optical energy to pass the object identification threshold of lidar.

We then analyze the point clouds in terms of the reflectivity parameter of the target object which is UAV1 from the segmented point clouds and present in terms of reflectivity histogram at different lighting conditions with varied distance in Figure 7. The number of reflected points and the mean reflectivity of UAV1 is shown in Table 2. There is a trend across all lighting conditions that as the distance increases, both the number of collected points and the mean value of the reflectivity decrease. However, at the most extreme distances, the mean reflectivity actually increases. This effect could arise because the reflection point cloud is dominated only by the shiniest most reflective parts of the UAV at great distances.

	Morning		Afternoon		Night	
Distance	Reflected Points Count	Average Reflec-tivity	Reflected Points Count	Average Reflec-tivity	Reflected Points Count	Average Reflec-tivity
10m	847	23.1	153	25.21	491	41.52
25m	95	19.47	38	19.45	38	23.84
50m	25	16.92	13	18.24	7	19.71
80m	7	17.85	4	18.25	1	25

Table 2: Number of reflected points and average reflectivity of UAV1 at different environments with 1s frame.

5 3D UAV TRACKING

This section explores the performance of UAV tracking using lidar scans. We perform continuous lidar scans during morning, afternoon & night to observe the motion sequence of UAV1 and estimate its trajectory within the scan time.

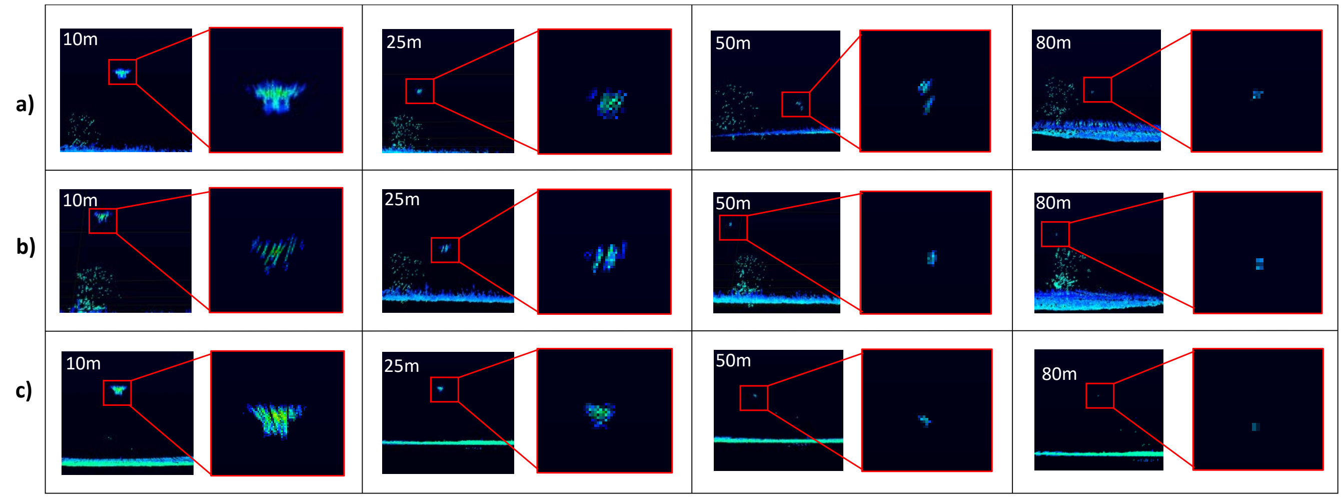

Figure 6: Point cloud analysis of UAV1 with varying distances at different natural light: a) morning, b) afternoon, c) night

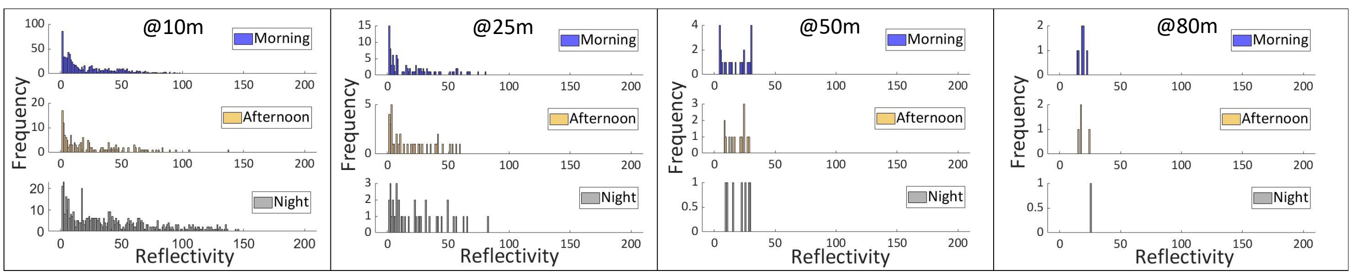

Figure 7: Reflectivity histogram of UAV1 with varying distances at different natural light

5.1 UAV Motion Tracking

Tracking by utilizing lidar point cloud data analysis requires a tradeoff between frame time control and point cloud density because the point cloud is denser with a higher frame rate but a higher frame rate also fails to capture the UAV motion. Hence, we choose 1 second as the frame rate for our experiments so that there is not a significant discontinuity between reflected points from the UAV when it is at the designated speed set by our experiment (DJI Phantom 4 average speed: 31mph in P-mode). Using the point cloud obtained from the lidar scan we can follow the UAV motion and ultimately track it by using single frames or snapshots from the lidar scan. Figure 8 shows a UAV1 point cloud sequence of single frames for a specific instance of time and distance of 10m from the lidar where the UAV is hovering and then moving with varying speeds between 0 to 20 mph. Since the lidar point cloud is 3D, we analyze the UAV motion in all 6 degrees-of-fredom but to maintain brevity only upward-downward & left-right single frame analysis are shown here at a fixed distance for motion tracking. From this single-frame analysis, we observe that target motion and movements can be tracked efficiently within the field of view.

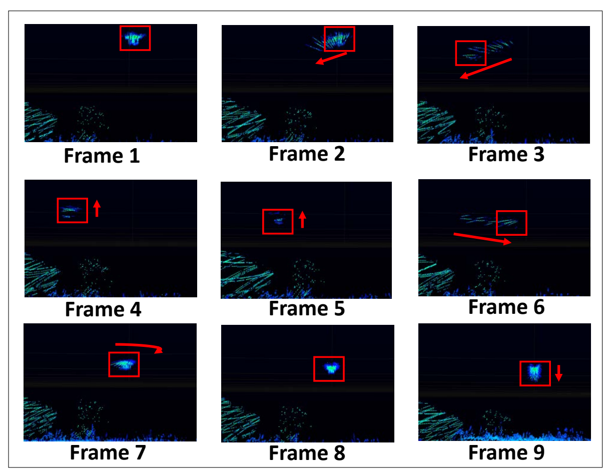

Figure 8: 3D tracking of UAV motion at 10m away from a sequence of frames

5.2 UAV Trajectory Monitoring using Multiple Frame Point Clouds

We perform lidar scan experiments with UAV1 for about 3 minutes continuously so that we can estimate a sizable trajectory of the UAV. After data acquisition and modifications using the Livox Viewer 0.11.0 software and

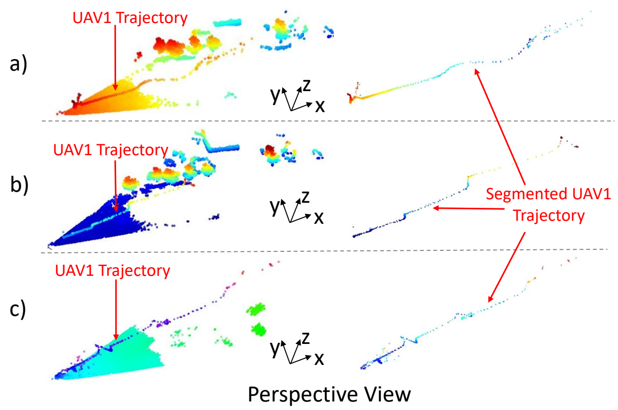

Figure 9: 3D trajectory measurement of UAV from lidar scan during a) Morning, b) Afternoon, and c) Night.

processing & computations using Matlab [11] and the Lidar Viewer app, we illustrate a time-lapse point cloud that merges all the single frame point clouds within the scan duration. As shown in Figure 9, we show the trajectory of UAV1 over experiments during the morning, afternoon & night to observe whether the UAV trajectory measurement is robust for all lighting conditions. First, we present the UAV point cloud data with the background data & then present the segmented UAV-only point cloud data, and in both cases, the trajectory of UAV1 is clearly visible. From these trajectory measurements, the movements & motion of the UAV can be analyzed and processed. Our focus was on visualizing the trajectories so we used a variety of post-processing to compute and plot the trajectories, making the process non-real-time. If we strip out the visualization and conversions between different software vendors and instead build a custom implementation, we feel that real-time tracking should be feasible and leave this for future work. Next, to provide a more fine-grained analysis of the ability of 3D lidar tracking to follow the trajectories of the UAV, we present a more detailed study of the frame-by-frame point cloud statistics. We present the results in Table 3. In the experiment, we vary the trajectory and range of the UAV and calculate this statistical location data for all 3 continuous lidar scans in the morning, afternoon & night. Still, for the sake of brevity, we show only a sample frame group of 10 frames selected from an afternoon lidar scan between 7s to 16s, with a frame time of 1s. We see from the table the computed distances traveled by the UAV between frames d_{frame} as well as the corresponding speeds. The maximum distance traveled is 4.8m, corresponding to a UAV speed of 20.17 mph. This shows the ability of lidar to track drones over a wide range of speeds.

	Sample Frame Group	
Frame No.	$d_{frame}(m)$	Speed(mph)
1	-	-
2	0.88	4.62
3	2.74	16.76
4	4.80	20.17
5	3.20	20.96
6	2.4	14.23
7	0.53	3.09
8	0.10	0.08
9	0.15	0.14
10	0.02	0.03

Table 3: Statistical analysis of multi-frame UAV location.

6 CONCLUSION AND FUTURE WORK

This paper explored lidar performance in terms of detection range, robustness with different visibility conditions for the localization of UAVs and potential for UAV tracking regardless of lighting conditions. This paper found that the color of the UAV significantly affected its reflectivity and hence the range of detection, with a smaller white UAV being detectable at a further range than a larger black UAV despite the latter's advantage in size. Another important finding is that UAV localization is robust even in low light conditions, without losing detection range. This shows the usefulness of lidar in detecting UAVs in darkness which might be useful for intrusion detection at night near airports, power stations, or secured prison systems. In addition, the experiments show that lidar-based tracking of drone trajectories is also largely unaffected by lighting conditions and can track a variety of different speeds of drones, which reveals the potential of robust drone tracking using lidar.

These preliminary studies suggest the promise of applying 3D lidar for robust detection, localization & tracking of UAVs, but also suggest promising future directions of research. We plan to employ a sophisticated zoom mechanism to extend the detection range to reach at least 200m without increasing the laser power. While we are currently working on a mobile UAV tracking system with the ability to track higher-speed drones without losing the point cloud density,we also plan to implement a real-time system that can employ AI and machine learning algorithms to recognize and track drones with different shape, material & reflectivity. Our current project goal also encompasses the detection & tracking of drone swarms in 3D and testing the robustness of lidar detection with inclement weather conditions (e.g. snow, fog, rain, etc.).

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