UAV SLAM and Interior Modeling with 3D LiDAR in GNSS-Denied Environments

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ABSTRACT

Small, quadrotor helicopter, or quadcopter, unmanned aerial vehicles (**UAV**s) have unique abilities to map environments, particularly utilizing 3D flash light detection and radar (**LiDAR**) technologies, which yield point cloud data sets. However, the majority of applications to date use global navigation satellite systems (**GNSS**) to determine location in order to stitch together LiDAR frames, which excludes mapping in environments without readily available or reliable GNSS (e.g. inside concrete buildings or underground.) In the context of search and rescue, providing an accurate and extensive model through a UAV could provide emergency personnel critical information on the interior of the structure without risking human lives. Previous projects have been able to confirm the viability of autonomous flight through LiDAR and achieve simultaneous localization and mapping without GNSS. The project presented equipped a quadcopter UAV with a LiDAR sensor and manually navigated through an interior environment to provide navigation and point cloud data, processed in post. With estimates of pose, a virtual mock-up was generated from the point cloud data to provide a comprehensive, 3D representation of the interior. The proposed system was able to create extensive and accurate models of the interior of a building in constrained circumstances. Comprehensive models can be created if the UAV is not actually flying but instead placed on a chair and rotated/translated. Due to the extra weight of the LiDAR and single board computer, the UAV could not fly properly and the data collected in flight was so low quality it could not generate a reasonable model.

TECHNOLOGIES

Flash LiDAR:

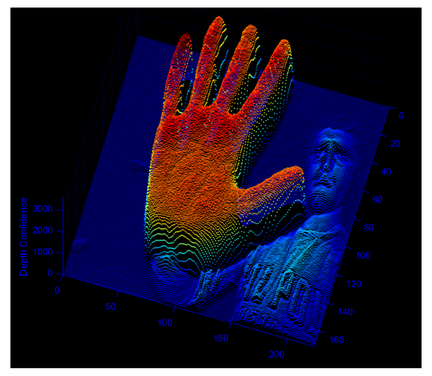


Figure 1: Flash LiDAR Frame

Otherwise called a 3D time of flight (**ToF**) camera, a flash light detection and ranging (**LiDAR**) camera emits light over a two-dimensional area, similar to a camera, and returns the *distance* to each pixel, as demonstrated in Fig. 1. Time of flight is the technique to determine depth by measuring the phase shift of the light reflected back into the camera: like sonar but with light waves. These frames can be converted to point clouds, a collection of points given in Cartesian co-ordinates. Given the difference in space--translation and rotation--between each frame, the point clouds can be merged together into a single, virtual 3D model.

UAVs and Pose Estimation:

Small, quadcopter unmanned aerial vehicles (**UAV**s) are agile and compact enough to navigate indoor environments and as such, provide a unique opportunity to video interiors with lightweight cameras. Often, the Global Navigation Satellite System (**GNSS**), equivalent to GPS, is used to track the location of a UAV. Even when utilizing dead reckoning, GNSS is used extensively to keep bias from accumulating.

OBJECTIVES

- Perform UAV localization without GNSS and utilize pose estimations to determine the transformations between each frame
- Use iterative point cloud **(ICP)** algorithms to determine a separate estimate of the transformations between each frame
- Register LiDAR frames into a single 3D model using aforementioned transforms

METHODS

In order to achieve a 3D model, two technologies, the flash LiDAR and a UAV were manually navigated through the interior of a building to produce two data files: a proprietary .rrf file for the LiDAR and .txt for the navigation data. Considering the computational effort required to properly register point clouds, the processing was done in post in MATLAB on desktop/laptop computers. The navigation data was put through a complementary filter to provide relatively accurate estimations of pose [1][2]. A complementary filter achieves sensor fusion between short and long term stable readings while maintaining physical relevance. The LiDAR data frames were converted into point clouds using MATLAB and then fed through the ICP algorithm. The ICP algorithm takes two point clouds and returns a transform that best matches them. These transformations, when combined with the pose estimations were highly accurate in determining the movement between each frame, providing an initial seed as to how each frame is positioned relative to the first and placing all frames into a single geometric reference. Finally, all frames can be merged and rendered into a clean, 3D model of the environment traversed. A flowchart of the total process is given in Fig. 2. In order to properly map the interior of a building with LiDAR, a small, stable quadcopter is mounted with a powerful single board computer (**SBC**) and a 3D ToF flash camera. The quadcopter is controlled from a stationary laptop while the SBC controls the LiDAR camera.

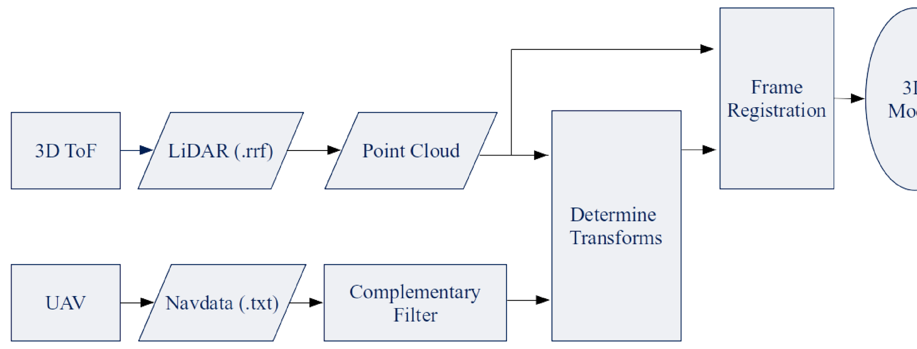
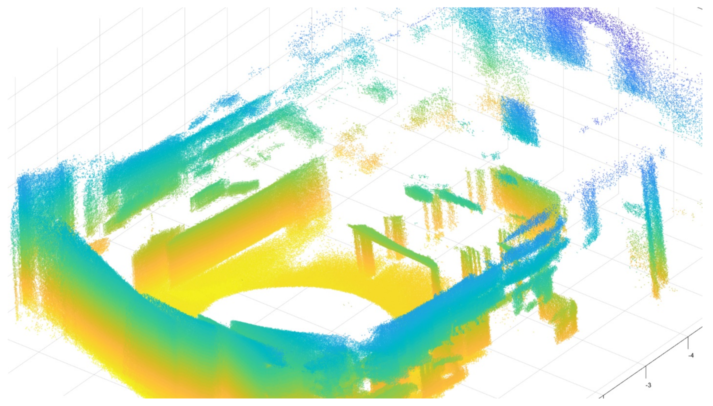


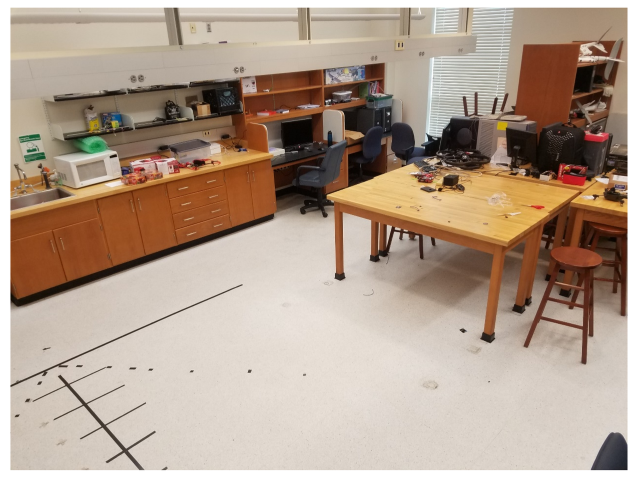
Figure 2: Data and Processes Flowchart

RESULTS

In scans where the flash LiDAR rotated, there were less planes/flat surfaces, or there were more small physical objects, the transforms derived from navigation data proved more accurate. A 360º scan of the workspace was taken by rotating the UAV and flash LiDAR on a chair and gathering the navigation information and frames. The two sets of data were processed in post, weighting more towards the navigation data transforms and the resultant 3D model and a camera image of the workspace are given in Fig. 3(a)(b). Using ICP techniques to determine transforms was significantly more accurate compared to navigation data in scans with many large, flat surfaces and little rotation. The ICP algorithm utilized is best suited for planar features and the pose estimation is highly accurate for rotation but prone to bias over large translations (e.g. a 40m hallway.) A scan of the hallway was taken by putting the UAV on a rolling chair and carting it down the hallway. The resultant LiDAR frames and navigation data was processed, putting more weight on the ICP transforms and the resultant model is given in Fig. 4(a-c). The LiDAR flash camera was fixed to the quadcopter and flown down the same hallway as given in Fig. 4(a-c); however, the resultant 3D model was erroneous. Implementing LiDAR onto a small quadcopter is a physical challenge and is detrimental to the maneuvering ability of the UAV; thus, reducing the LiDAR video quality significantly. The choppy video quality along with position estimation inaccuracies could not be rectified in post-processing.

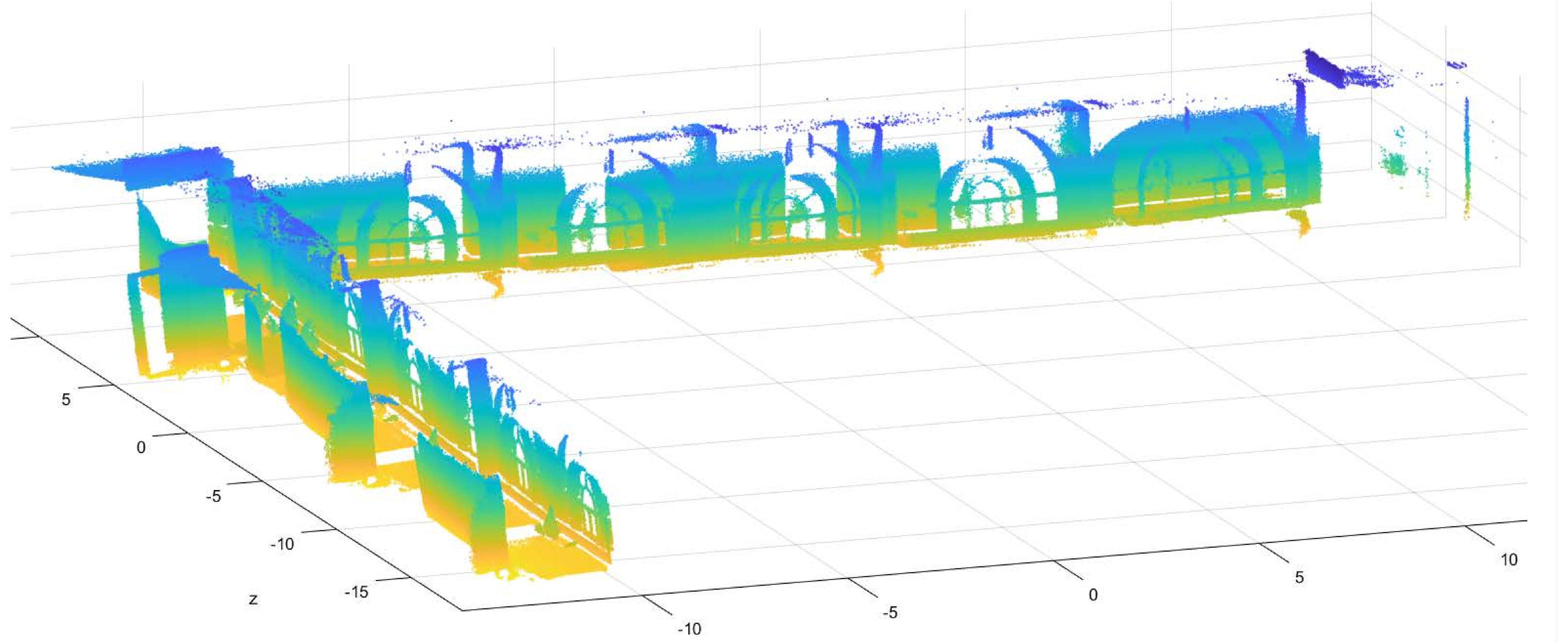


(a) LiDAR Model of Laboratory



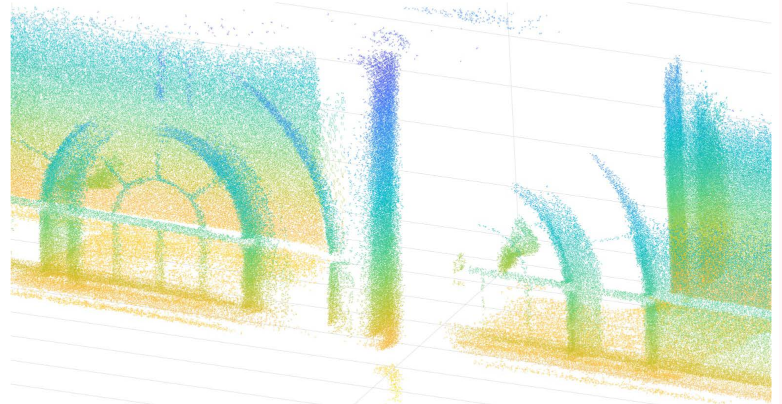
(b) Camera Photo of Laboratory

Figure 3: Rotational LiDAR Model with Corresponding Photo



(a) LiDAR Model of Hallway

(c) Camera Photo of Hallway



(b) LiDAR Model of Hallway Magnified View

Figure 4: Translational LiDAR Model with Corresponding Photo

CONCLUSIONS

Registering a video of LiDAR frames into a single comprehensive model was demonstrated to be viable. The estimation of pose without GNSS was accurate in estimating attitude but inaccurate in estimating position due to accelerometer bias: attitude has long term stable sensors while position requires the long term stable sensor of GNSS. ICP algorithms were able to supplement this inaccuracy in situations with large flat surfaces. Despite reasonable results when the UAV was carted, flying with a 3D ToF camera and SBC did not return a good model. The project still clearly demonstrates the efficacy of LiDAR mapping and provides justification for further research and development in the area. Improved position estimation through a Kalman filter may yield more accurate estimations. Furthermore, kerneling techniques on the point cloud data could significantly improve the transform estimations from the point cloud [3].

REFERENCES

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[3] Y. Tsin and T. Kanade, "A Correlation-Based Approach to Robust Point Set Registration," Proc. European Conf. Computer Vision, pp. 558-569, 2004.

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