Smart Cities: LiDAR-based Traffic Monitoring

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Introduction

Smart cities are urban areas that utilize advanced technology to improve public services such as transportation, healthcare, and safety [1]. Through the deployment of intelligent transport systems and the use of **real-time** data analysis, smart cities can:

- Improve traffic flow by detecting traffic congestion
- Create safer intersections by identifying accidents and near misses
- Reduce travel time by monitoring public transportation

Objective

Online pedestrian and vehicle detection and tracking from 3D LiDAR point clouds.

1. Implement an online object tracking system
2. Test system in real-world environment

LiDAR Sensors

Light Detection and Ranging (LiDAR) sensors use laser beams to measure distances and create high-resolution 3D maps of the surrounding environment. A common type of LiDAR rotates a vertical stack of laser beams to measure thousands of point per scan. Each rotation produces a *point cloud* where the field-of-view (FoV) is dependant on the number of beams and resolution. Figure 1 shows a sensor FoV.

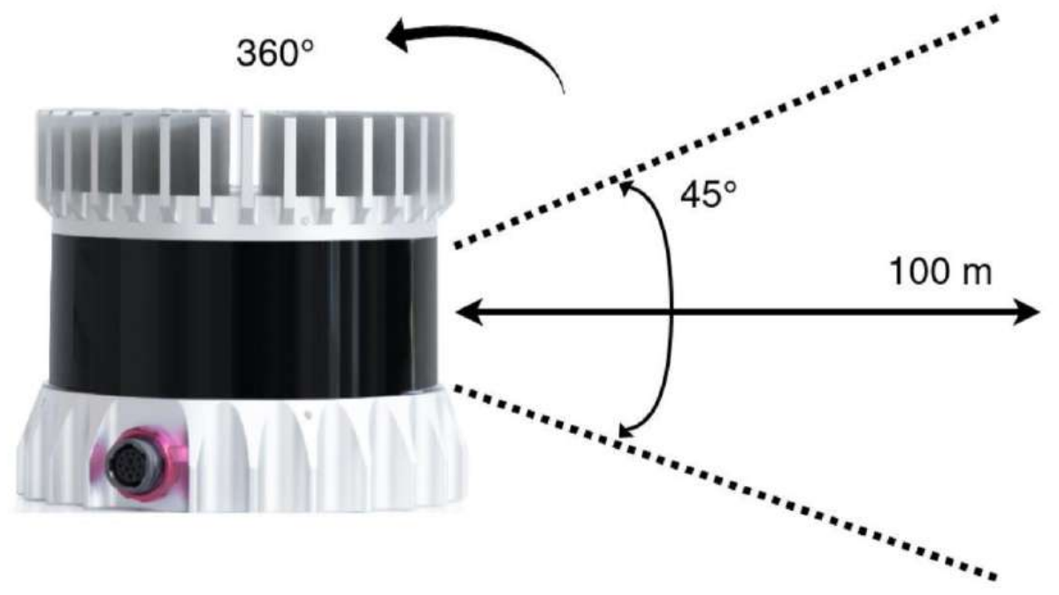


Figure 1. Field of view for a mechanical LiDAR sensor.

The sensor outputs 650,000 points per second, where $p = [x, y, z, I]$ and I is intensity.

Why use LiDAR?

The common sensors used to detect and track objects are found in Figure 2. Often camera and radio detection and ranging (RADAR) are used together because they complement each other. However, LiDAR is strong enough in each category to be used on its own.

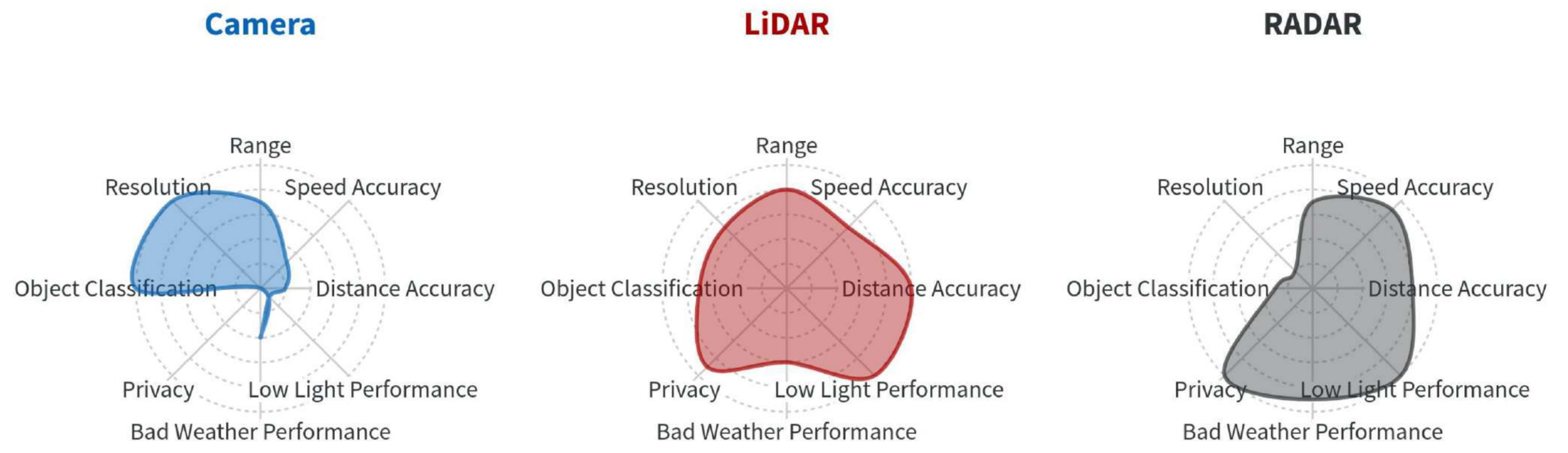


Figure 2. Comparing characteristics of Camera, RADAR, and LiDAR sensors.

Intersection Monitoring System Design

To achieve the objective, the data processing pipeline in Figure 3 is proposed.

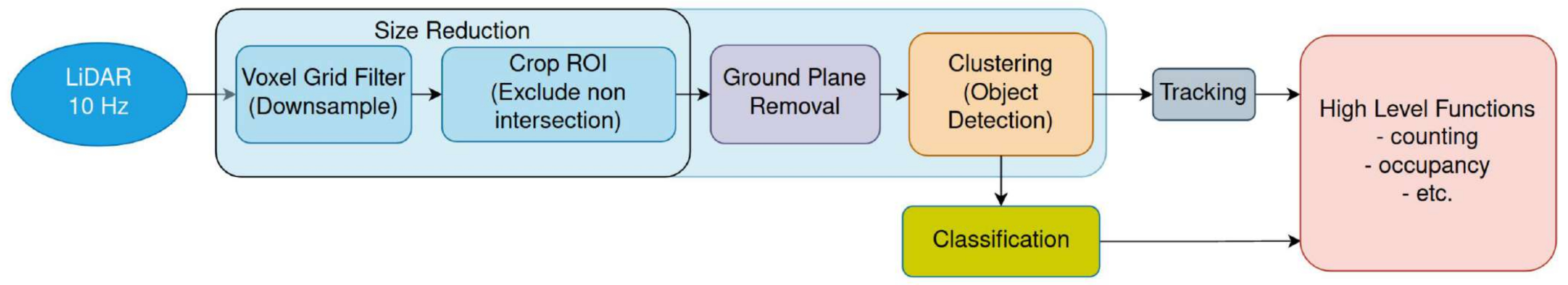
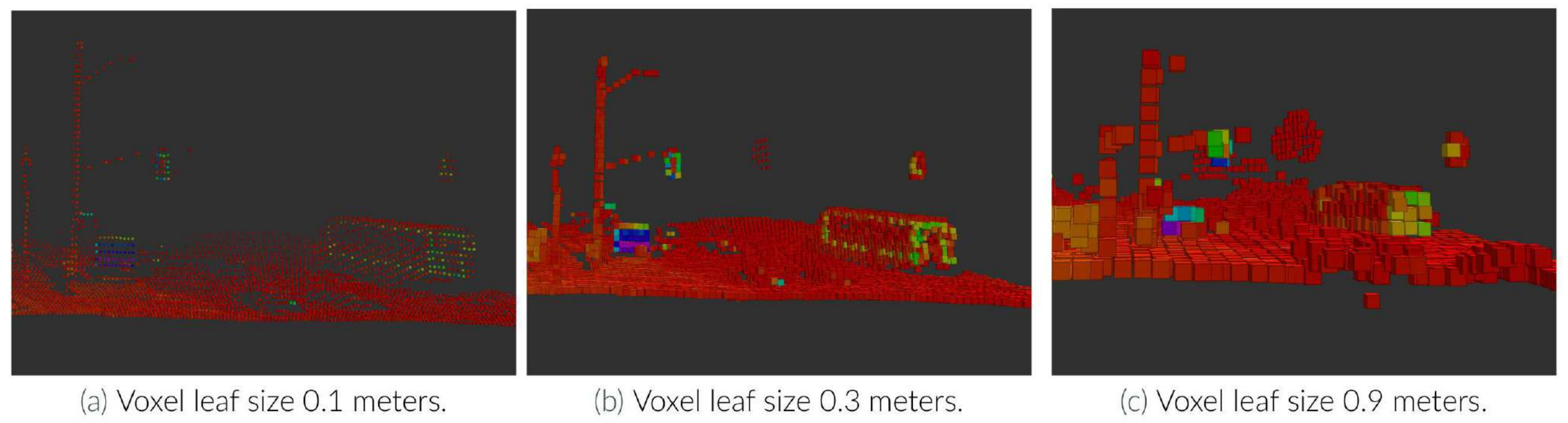


Figure 3. Diagram of the proposed LiDAR Pipeline.

Data Reduction

Voxel grid filtering discretizes the 3D space into cubes called *voxels*. The points within each *voxel* are approximated with their centroid. Figure 4 demonstrates the result of varying the voxel grid filter leaf sizes. Downsampling is critical for online processing.



(a) Voxel leaf size 0.1 meters.
(b) Voxel leaf size 0.3 meters.
(c) Voxel leaf size 0.9 meters.

Figure 4. Effects of voxel grid filter leaf size.

Ground plane removal is important for clustering, since objects touching the ground become disconnected. Assuming the largest plane in the cloud is the road, a **RANSAC**-based approach [2] is used to robustly estimate this plane. Figure 5 shows the result of removing the ground plane.

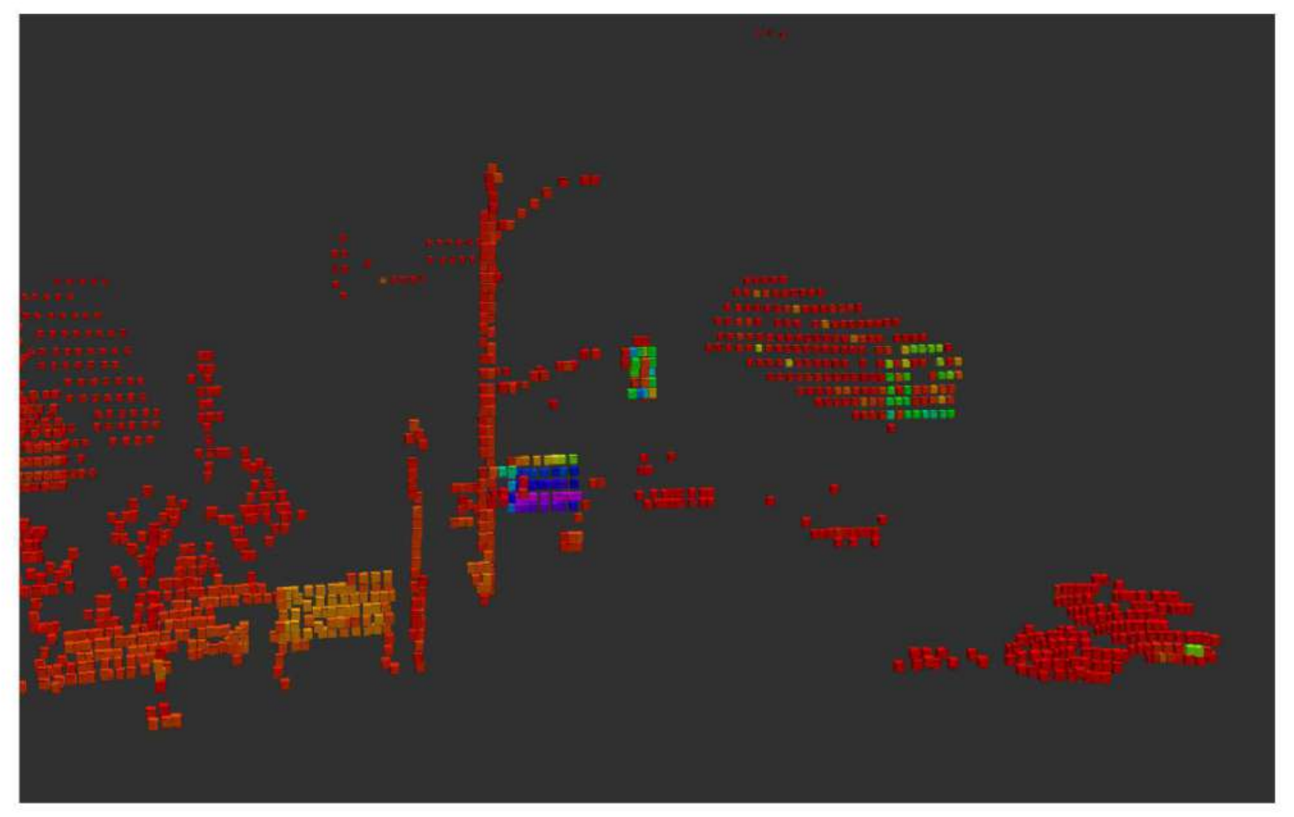


Figure 5. Ground removal result.

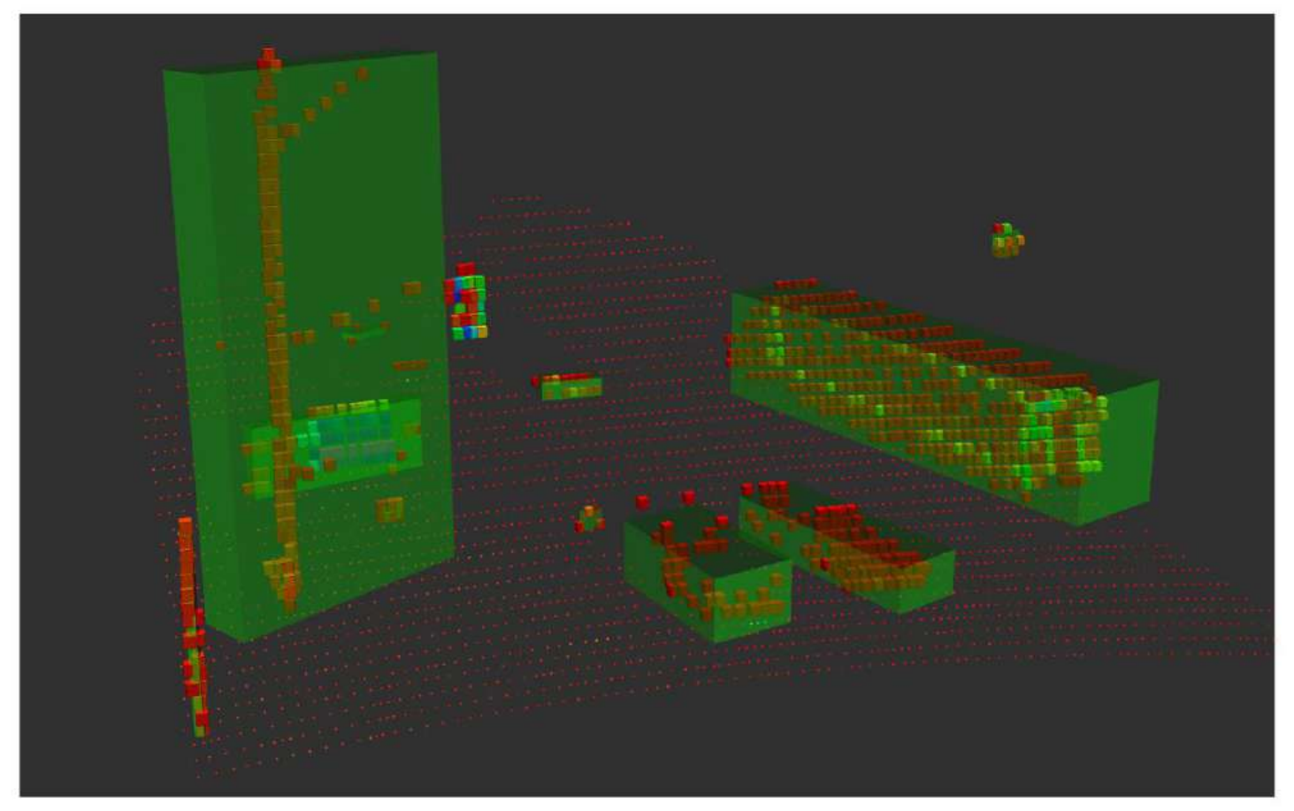


Figure 6. Clustering with OBB result.

Clustering and Tracking

Euclidean clustering groups the points into clusters based on the distance between neighbouring points. Each cluster represents a detected object and is fitted with an oriented bounding box (OBB). An example of the clustering result is shown in Figure 6.

Tracking is used to associate and manage detections (clusters) over time. Figure 8 shows the track identifiers for each object. Input is $z = [x_1, y_1, x_2, y_2]$, where x and y are the min and max points of the 3D bounding box projected onto the ground plane.

Implementation

The Robot Operating System 2 (ROS 2) is used to manage the parallel processes in the pipeline and provide a middleware for inter-process-communication. The system is comprised of modules written in **C++** using the PCL and Eigen libraries and **Python**.

Expiremental Setup

- An *Ouster OS1-64* LiDAR sensor is mounted on a tripod and connected to an Ubuntu laptop via ethernet.
- The system runs at 10 Hz.
- The tripod is placed on a rooftop to simulate its deployed environment.

Figure 7. The *Ouster OS1-64* used for data collection with a synchronized camera for future work.

Results

The system was tested on real-world traffic data. Vehicles are successfully tracked through the intersection assuming there is no occlusion. Further parameter tuning and exploration of more advance methods are necessary.

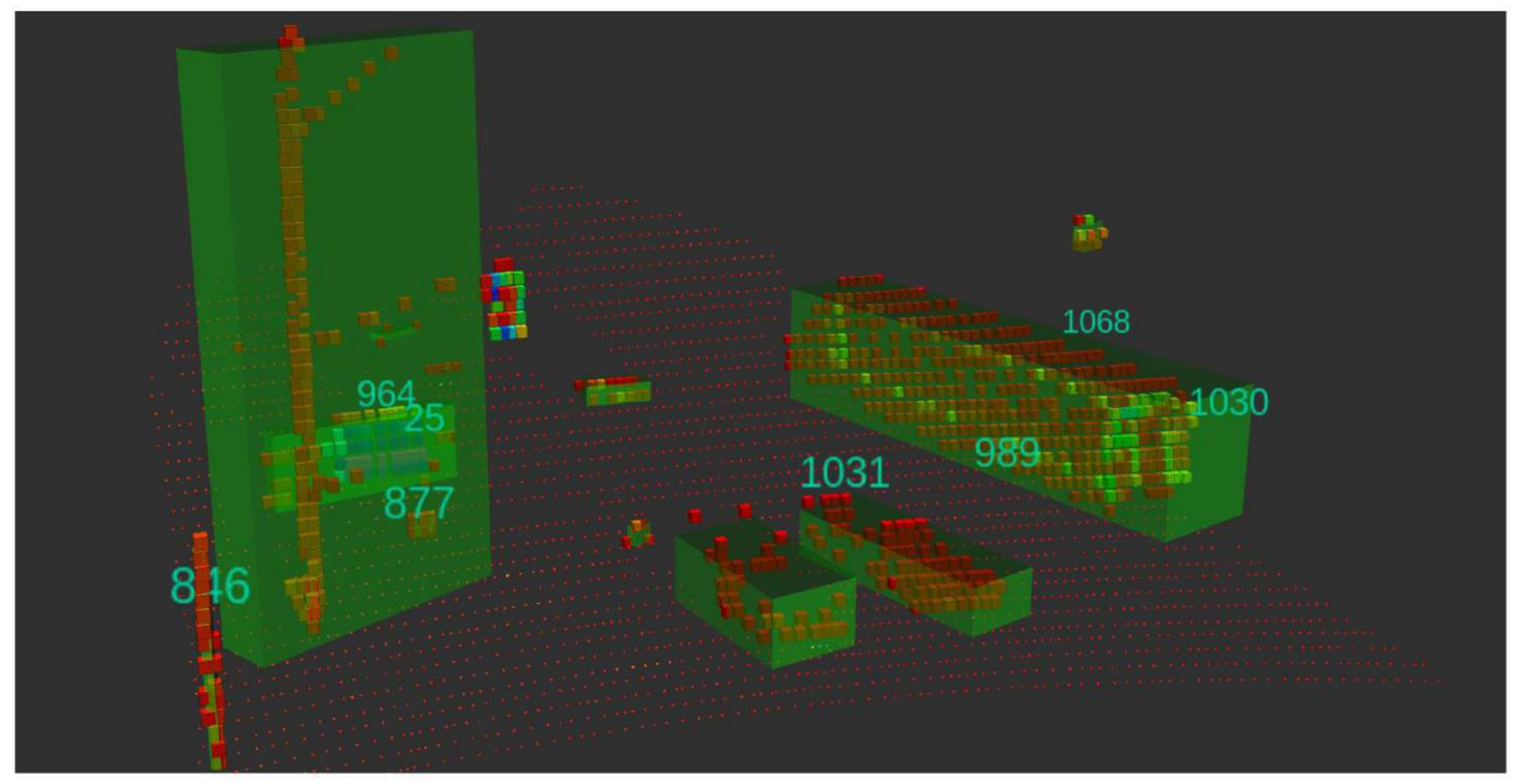


Figure 8. Final LiDAR tracking result showing the track identifiers.

Conclusion

The objective was achieved and a LiDAR object detection and tracking system was successfully implemented. Objects are tracked during daytime and nighttime conditions.

Future Work

- Evaluate accuracy for detection and tracking using MOTA and MOTP metrics
- Integrate more advanced tracking algorithm
- Implement classification using principle component analysis (PCA) and support vector machine (SVM)

References

[1] Eiman Nuaimi, Hind Neyadi, Nader Mohamed, and Jameela Al-Jaroodi. Applications of big data to smart cities. *Journal of Internet Services and Applications*, 6, 08 2015.

[2] Martin A Fischler and Robert C Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6):381–395, 1981.

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Ontario
Research Fund

We acknowledge the support of the Ontario Research Fund: Research Excellence Program.

NSERC
CRSNG

We acknowledge the support of the Natural Sciences and Engineering Council of Canada (NSERC), which invests annually over $1 billion in people, discovery and innovation.