

Collecting and Processing Point Cloud Data for Snow Depth and Density Measurement

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Project: Integrating a LiDAR Sensor into a low-cost Weather Station

Purpose: Collect and process point cloud data into useful snow measurements under computational and storage constraints.

Approach: Parallel collection and analysis of point cloud measurements using Raspberry Pi.

- **Measuring snow is important**
 - Climate modeling/forecasting
 - Water management
- **Measuring snow is difficult**
 - Poorly measured
 - Expensive
- **Our goal is measuring snow with high precision at low cost.**



Background - Hardware

- Livox Mid-70 3D automotive LiDAR sensor
- 100k or 200k measurements per second
- \$1099



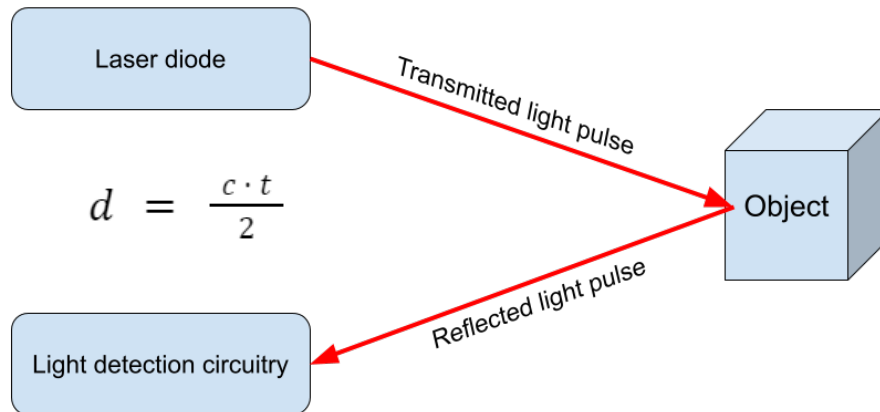
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- Raspberry Pi 3 model B+ single-board computer
- SoC 64-bit quad-core processor at 1 GHz
- \$30-\$40

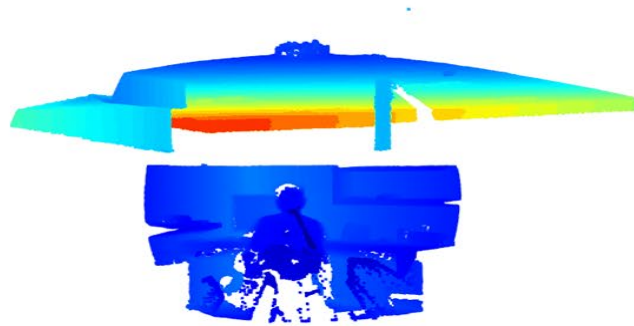


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Background - LiDARs and Point Clouds



- Unstructured data array containing x,y,z coordinates, reflectivity, timestamp, and status code
- Ordered (mostly) in the sequence of capture determined by sensor manufacturer



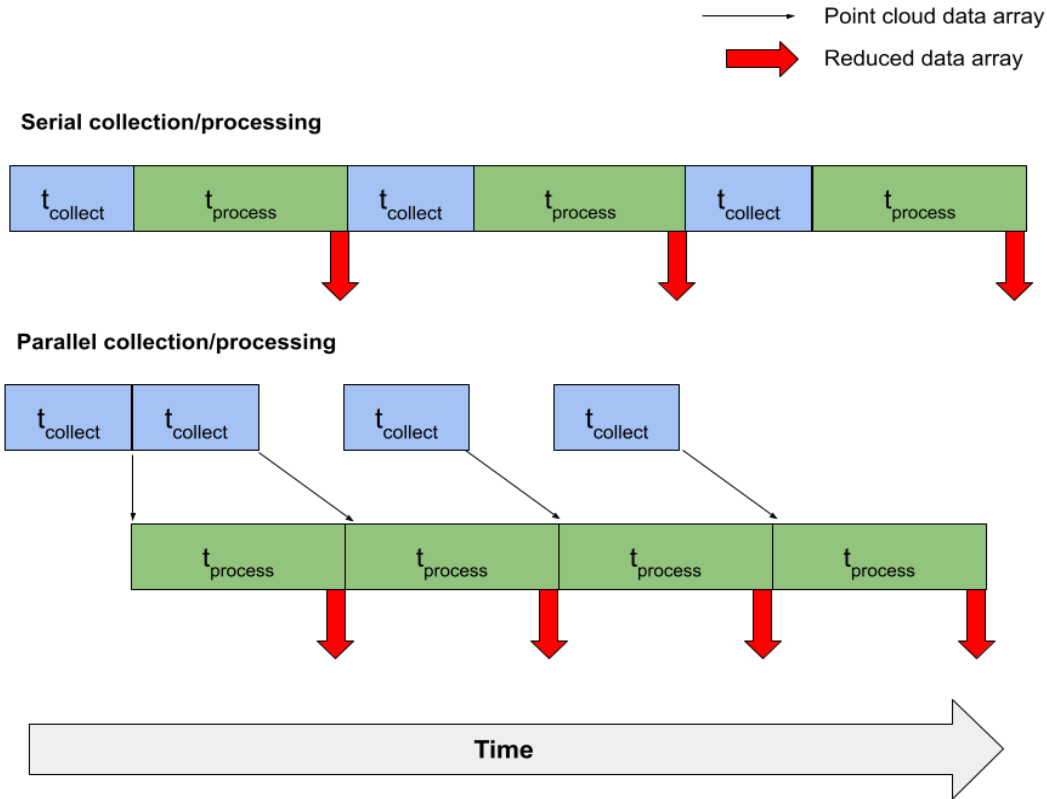
Example visualization of point cloud

- **Point cloud collection with LiDAR**
 - Update existing device driver to keep point cloud data in memory for processing.
- **Point cloud analysis**
 - Preliminary point cloud processing algorithms to estimate snowpack depth on the ground and snowflake density in the air.
 - Extract key measurements from large data in the interest of disk storage savings.
- **Interplay**
 - Process level parallelism to allow simultaneous data collection and processing/downsizing.

Methods - Why Process in Real -Time?

- Each point requires 12 bytes - one 4 byte integer for each coordinate.
- At collection rate of 100,000 points/sec, it takes **14.91 minutes to fill 1 GB** .
- Intended for deployment in remote locations
- Strategy: collect and process point clouds simultaneously

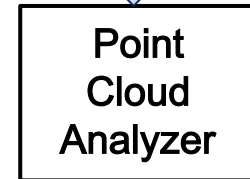
Methods - Multiprocessing



Processes



Communicates with LiDAR, records point cloud.



Access point cloud, processes data, and saves to disk.

Results - Data Storage

For a recording session of 3 point clouds of 3 seconds each:

	Raw Data File Size	Ground Height Array Size	In Air Point Cloud Size	Total Storage
Without processing	12.8 MB	X	X	12.8 MB
With processing	X	1.88 MB	2.86 MB	4.74 MB

Only 37% of storage is required and most information is retained!

However, this is an arbitrary benchmark.

Methods - Snowpack Height Measurement

Motivation:

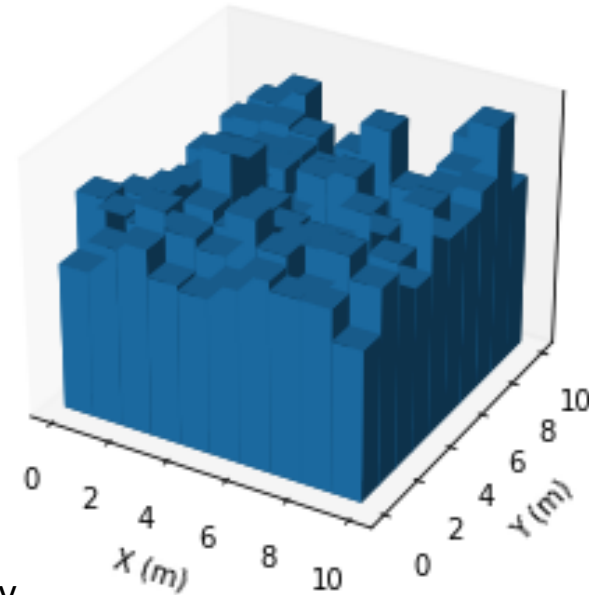
Measure the volume of snowpack over a specified ground area.

Algorithm:

1. First separate points on the ground from points in the air.
 - For each bin, find point with lowest z coordinate value
1. Approximate height of ground in each bin
 - Take average of all points within a threshold of minimum value.

Output:

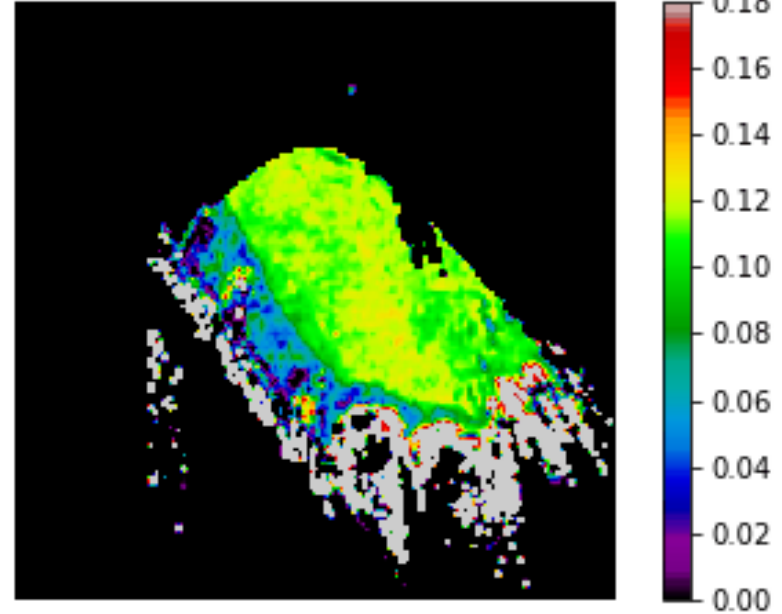
A 2D array of ground height values in equally size bins in the x,y plane.



Results - Snowpack Height Measurement



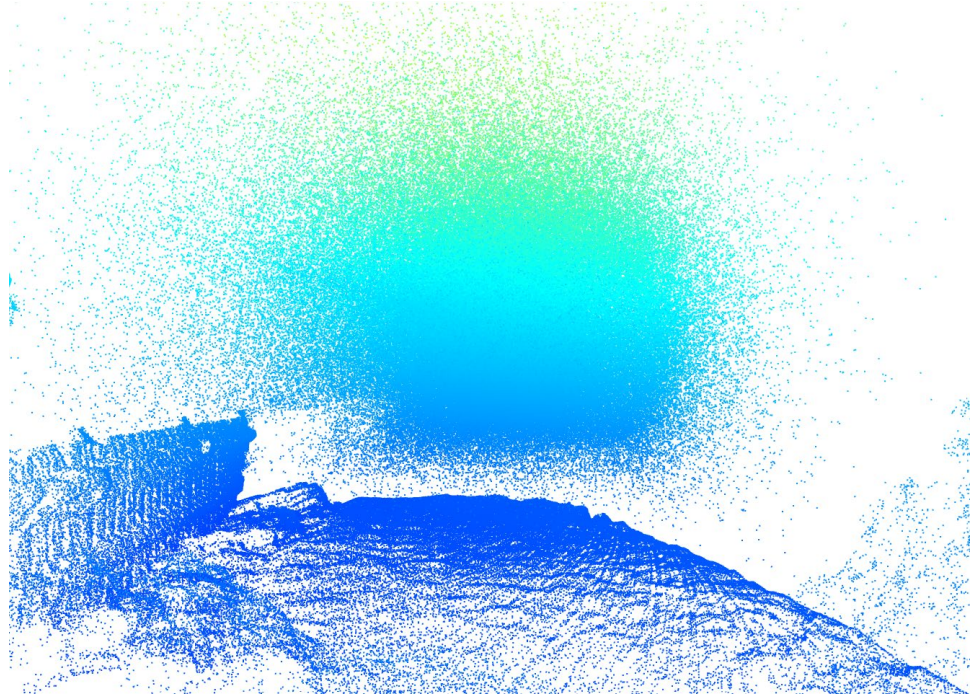
LiDAR test environment



Snowpack height map over time series of point clouds

Methods - Snowflake Density

- Extracting useful observations of snow in the air from point cloud data proves more difficult.
- Use a 3D histogram to visualize the density of points in the air.
- Visualization may help lend insight into limitations of LiDAR and possible measurements to investigate.



Motivation:

Calculate the density of snowflakes in the air as a 3D histogram

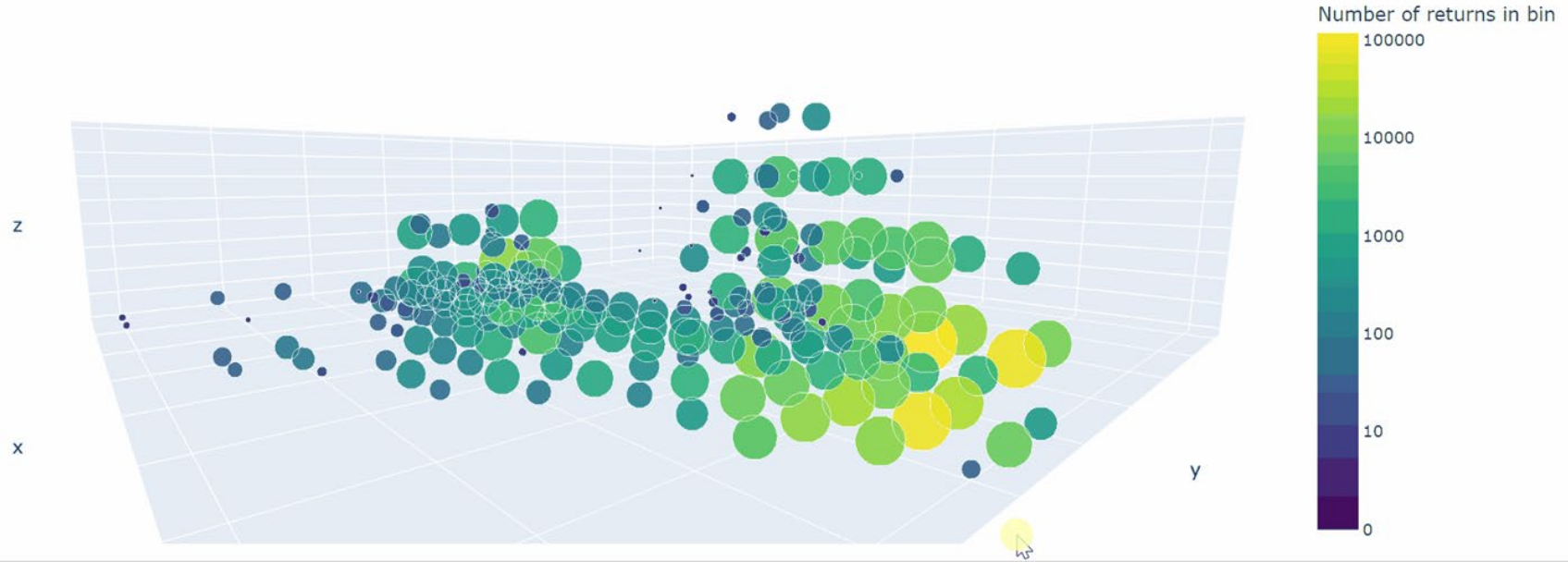
Algorithm:

1. Create a grid structure which separates the 3D space into equally sized bins.
 - The size of bins and area of interest are configurable.
1. For every point in the point cloud, add 1 to its respective bin.

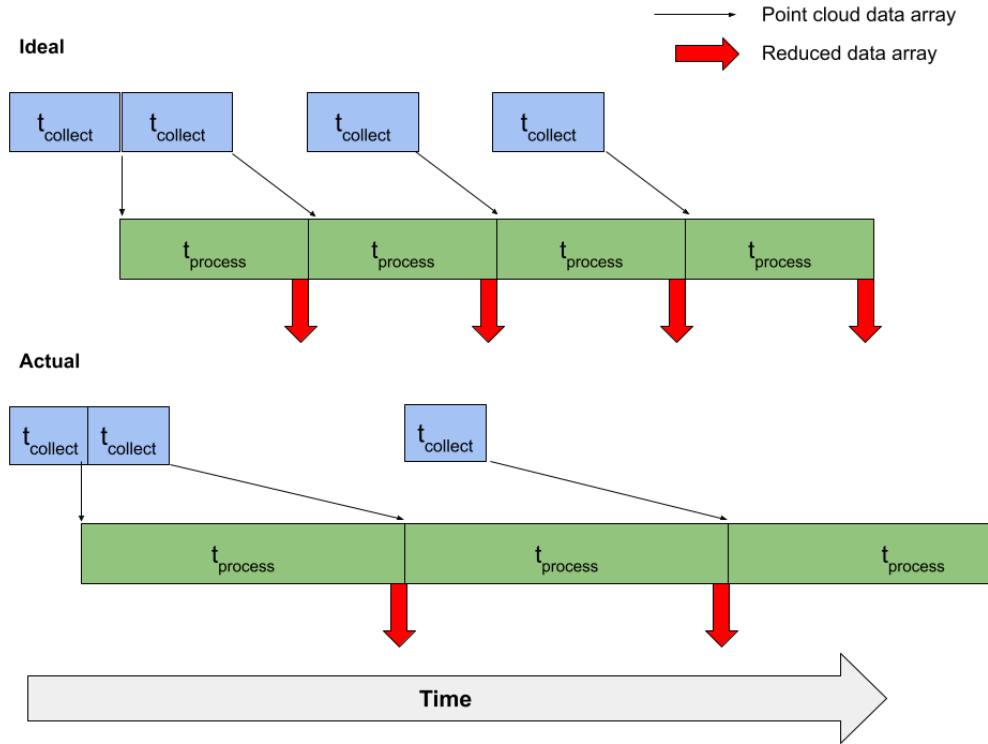
Output:

A 3D array with each element containing the number of snowflake returns in the bin location.

Results - Snowflake Density Visualization



Discussion - Timing



- **Speedup?** Only about 5%.
- Ground height computation is costly.
- Snowflake density is highly optimized.
- Ideal scenario has a better balance.

Conclusion

- Multiprocessing implemented to parallelize point cloud collection and processing.
- Preliminary algorithms developed to extract key observations from point clouds.
- Significant downsizing of memory requirements - less frequent data offloading.

Future Work

- Extensive testing during upcoming winter.
- Optimization of current processing routines.
- Development of new processing routines (dependent on larger dataset for guidance).
- Investigation of data buffers/further multiprocessing to improve data throughput with timing imbalance.

Thank You

Questions?

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