Lidar and Scan Matching

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-with ideas carried over from lectures by
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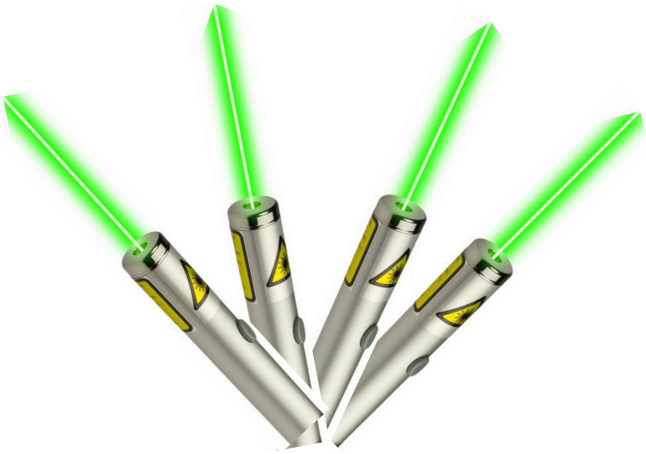
Topics to cover

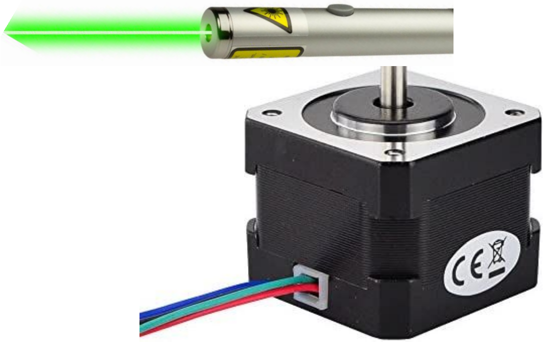
- Popular scanners and Theory
- ICP Scan Matching
    - Correlation
    - Optimization
    - Error Rejection
- Information Theory in regards to error rejection

Popular scanners and Theory

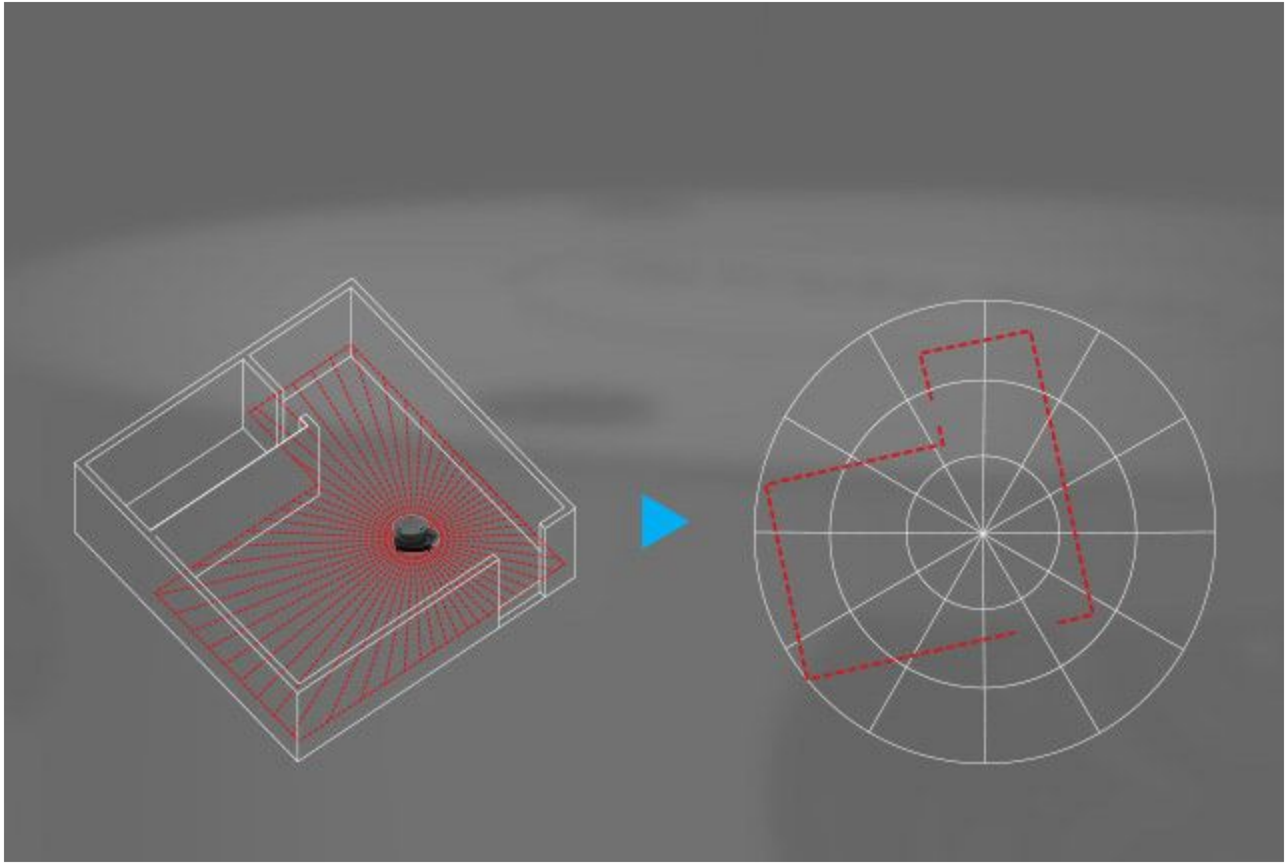
Instead of a laser array, let's attach one laser to a motor and spin it!



Measure range via time of flight and pair with motor position



Popular scanners and Theory



Popular scanners and Theory

SICK LiDars

- Industrial safety
- 180 samples, 1 degree spacing, 75Hz
- Resolution ~1cm, ~0.25 deg.
- Interlacing
- Max range: “80m” 30m fairly reliable
- Intensity
- $4500

Popular scanners and Theory

SLAMTEC RPLIDARS

A1:

- $99
- 12m range
- 8,000 samples
- 5.5 HZ

A3:

- $600
- 25m range
- 16,000 samples
- 15 HZ

Popular scanners and Theory

3D lidar scanners

Much more complicated than a 2D Lidar.

Gives a lot more data

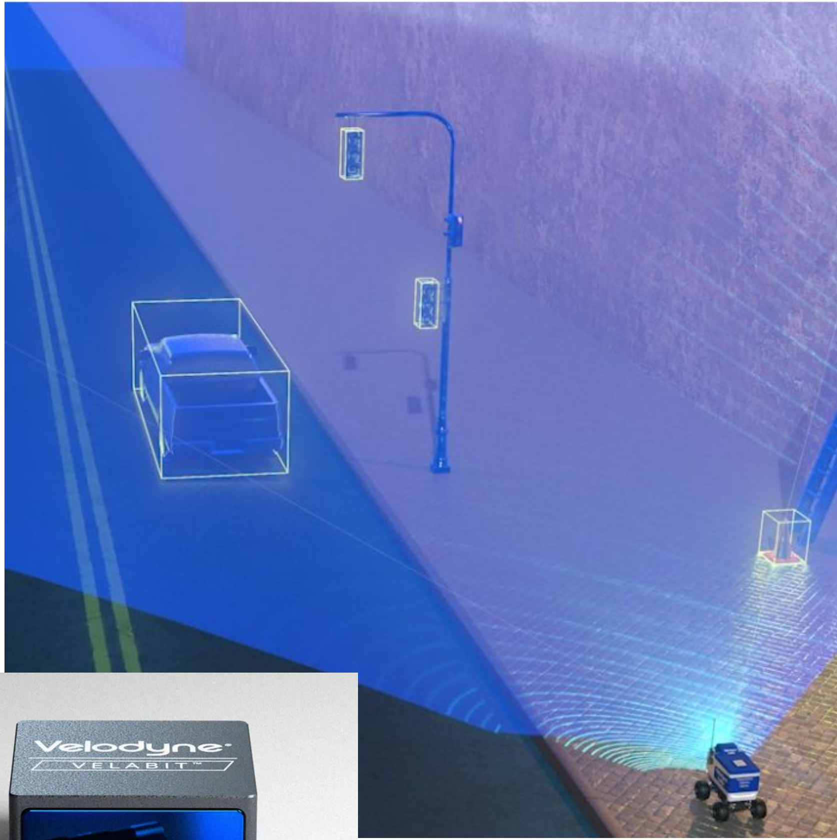
Obviously more expensive

Beware of the dead zones near the sensor

Popular scanners and Theory

Velodyne Velabit: $99

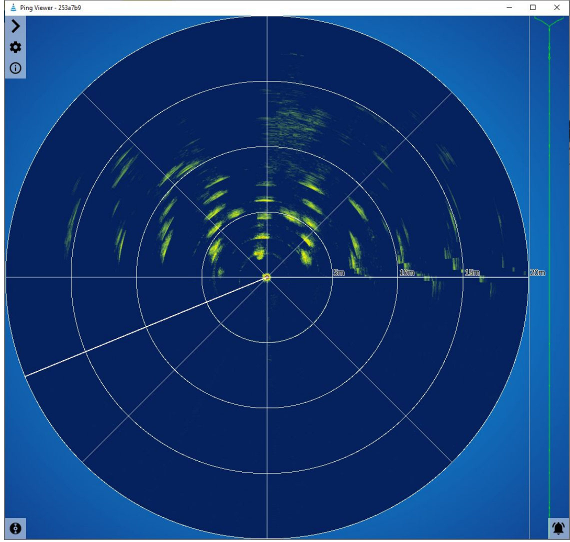
- horizontal (90°) and vertical (70°) field of view
- Small form factor: lightweight (125g) and compact (2.4” x 2.4” x 1.38”) with integrated processing
- Range of up to 100 meters
- Low power consumption (3-6W)
- Expected to release Q1 2023



Popular scanners and Theory

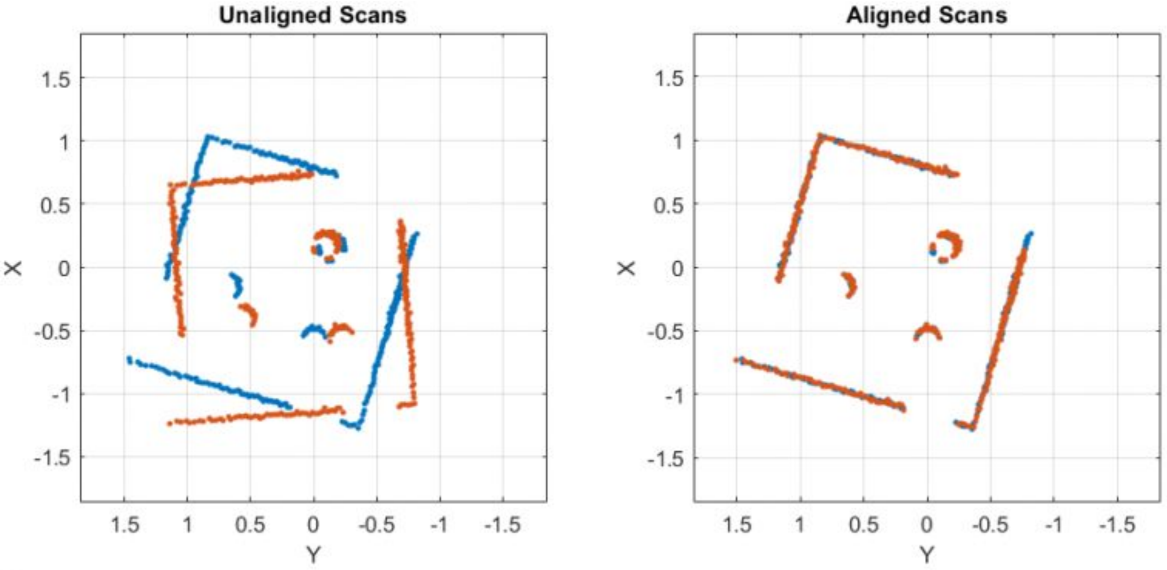
Ping 360 Scanning imaging sonar

- Shameless underwater robotics tie-in
- $2,500
- 50m range
- Scan frequency dependent on desired scan distance (sound is slow)
- Scan speed
  - @2m: 9 secs/rotation
  - @50m: 35 secs/rotation



ICP Scan Matching: Purpose

- We can compute relative translation between scans
  - Replaces odometry
- Loop closing while running SLAM



ICP Scan Matching: Approach Overview

Two approaches:

- Feature based alignment

- Featureless based, correspondence alignment

ICP Scan Matching: Feature Extraction Approach

- Extract features from two scans
- Match features
- Computer Rigid body transformation

Possible Features

- Lines
- Corners
- Discontinuities

Intuition: Data compression by using features instead of every point makes optimization easier

ICP Scan Matching: Feature Extraction Approach

Issues:

- Difficult to implement
- Can be dependent on order of received points
- Computationally intensive

Tradeoffs between robustness and simplicity (including computationally)

ICP Scan Matching: Aligning scans without features:

Correlation-based scan matching

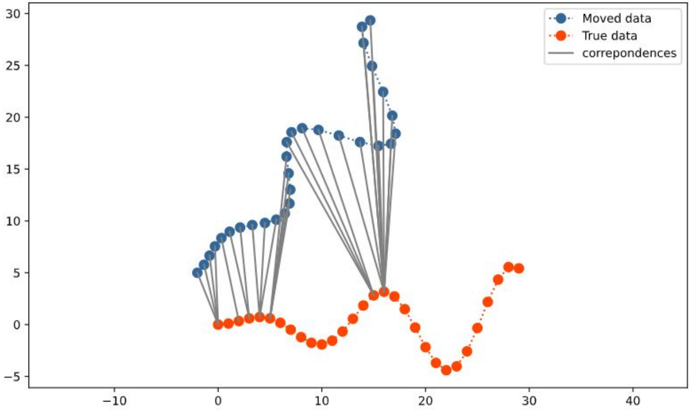
Iterative closest point (ICP)

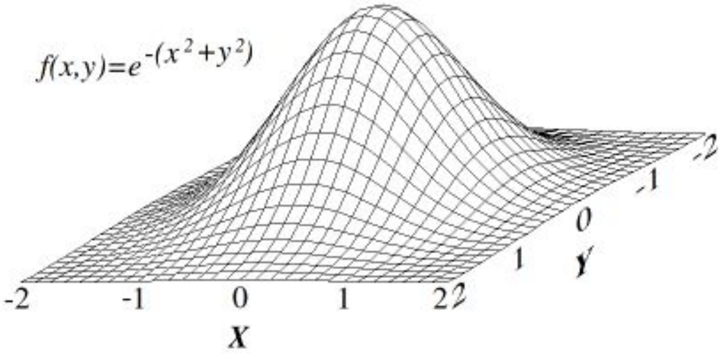
“How well do the scans match up?”

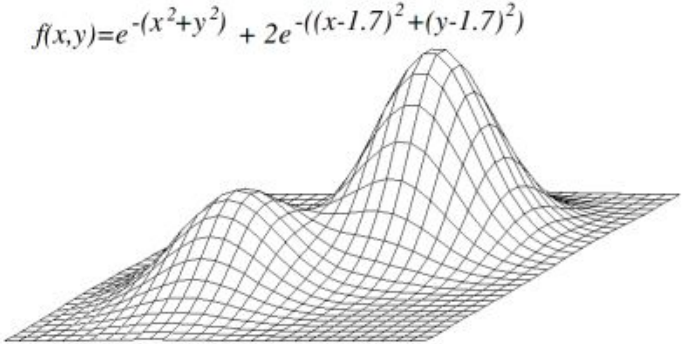
Find the rotation/translation that lines the two scans up the best

ICP Scan Matching: Correspondence Overview

- Compute scan correspondence
- Some form of iterative alignment
  - ICP based on SVD
  - Non linear Least Squares based ICP
  - Point to plane metric with Least Squares ICP
- Outlier rejection and information theory

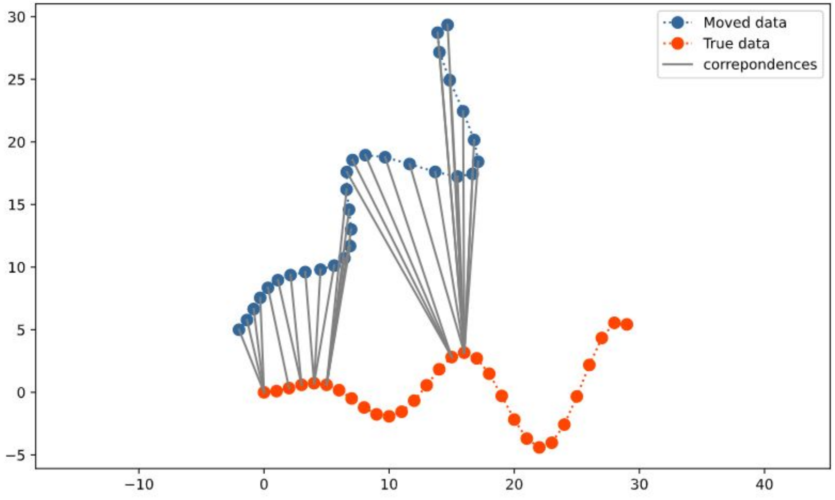


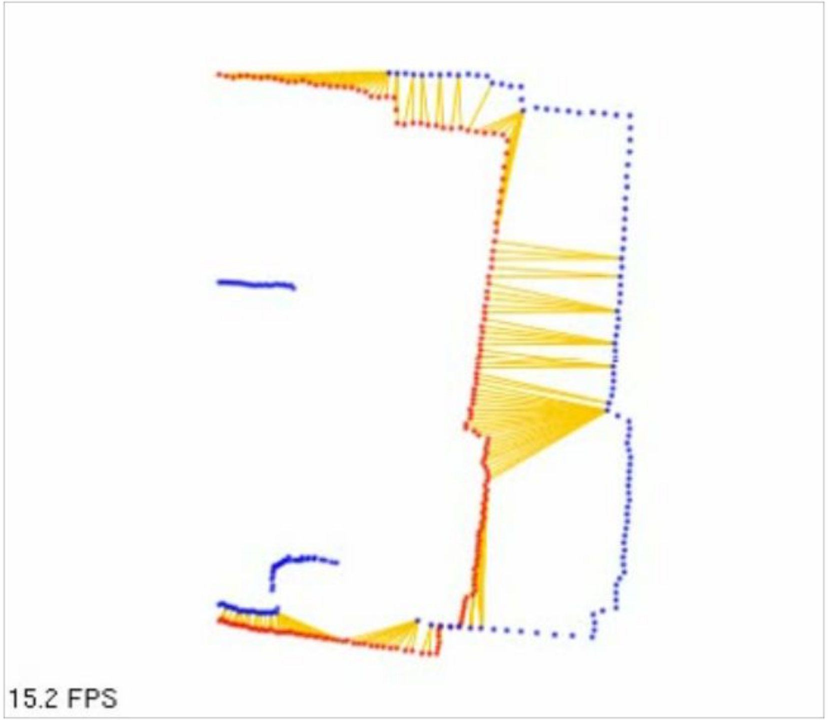




ICP Scan Matching: Example Jupyter notebook

https://nbviewer.org/github/niosus/notebooks/blob/master/icp.ipynb





ICP Scan Matching: Issues?

- Local minima
  - Use closer, incremental scans to avoid this issue
- Lidar scans points arbitrary
  - Solution: Iterative closest line, or plane, instead of point
- Sensitive to outliers
- O(m*n)
  - M, N are number of points in scans A and B

ICP Scan Matching: (ICL) Iterative Closest Line

Lidars sample points at arbitrary space

- Exact points sampled in A may not be sampled in B
- Solution: interpolate lines between points in Scan B, find closest *line* instead of closest *point*
- Same can be done with planes in 3D

ICP Scan Matching: Dealing with Outliers

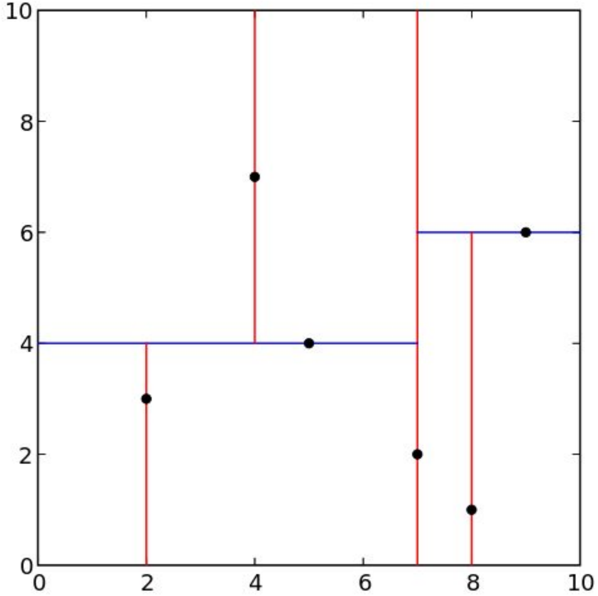
- Review literature for current methods
- Simplistic methods
  - Outlier removal based on threshold
  - Weighting points
- Modified K-D Tree

ICP Scan Matching: Simplifying Correspondences

- To compute correspondences, currently each point of scan 2 has to check distance with every point of scan 1 ~O(N^2)
  - Not impossible with small lidars only calculating 300 points a scan
  - Velodyne Lidar provides ~300k-700k+ points a second
- Solution: Preprocess data before each scan
  - K-D Trees

ICP Scan Matching: K-D Trees

- Process of partitioning data into a tree structure with 2 leaves per node.
- Starts with centered point (methods to estimated center point) to ensure balanced tree



k-d decomposition of points

Points

:

(2,3),

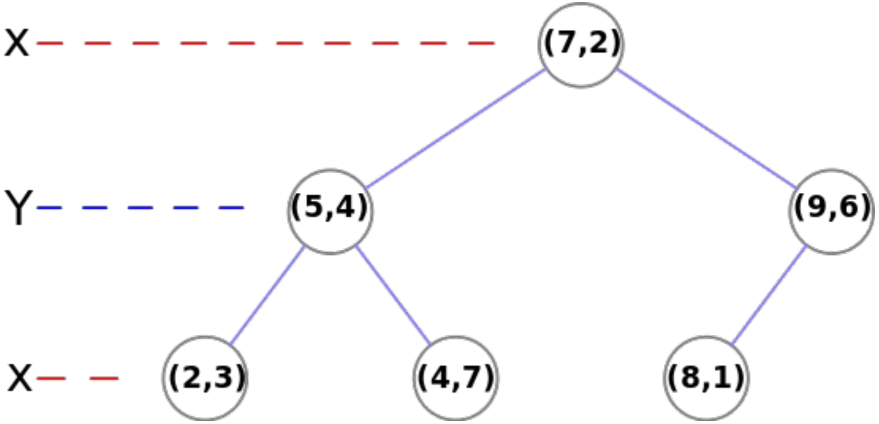
(5,4),

(9,6),

(4,7),

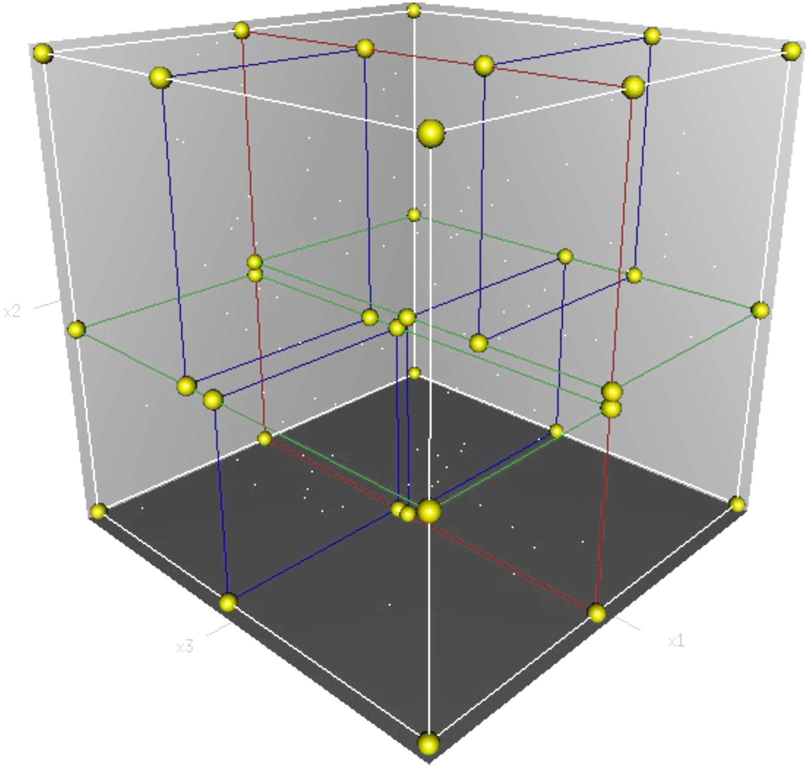
(8,1),

(7,2)

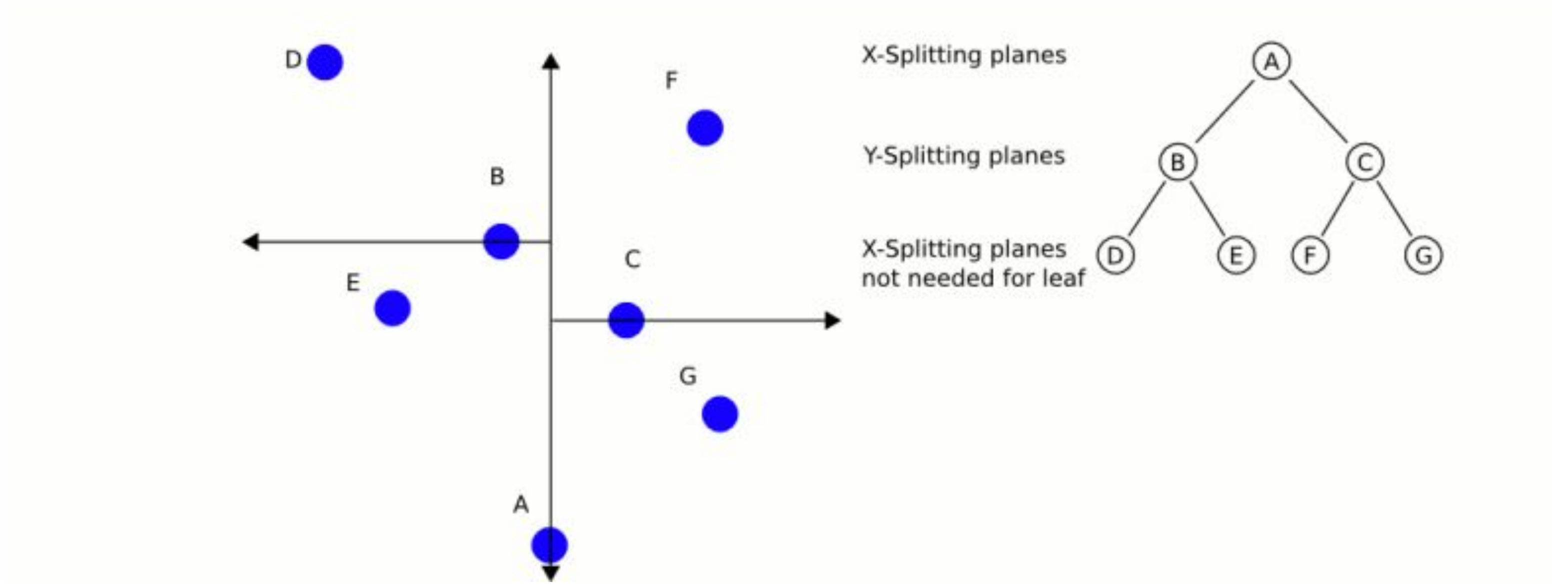


Resulting k-d tree

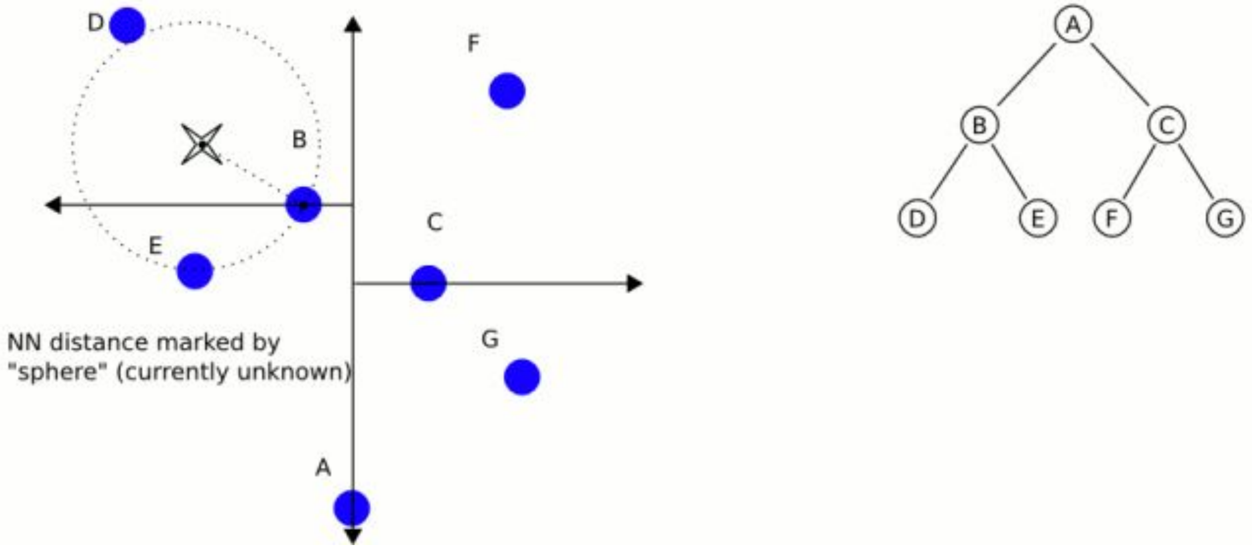
K-D tree in 3 dimensions



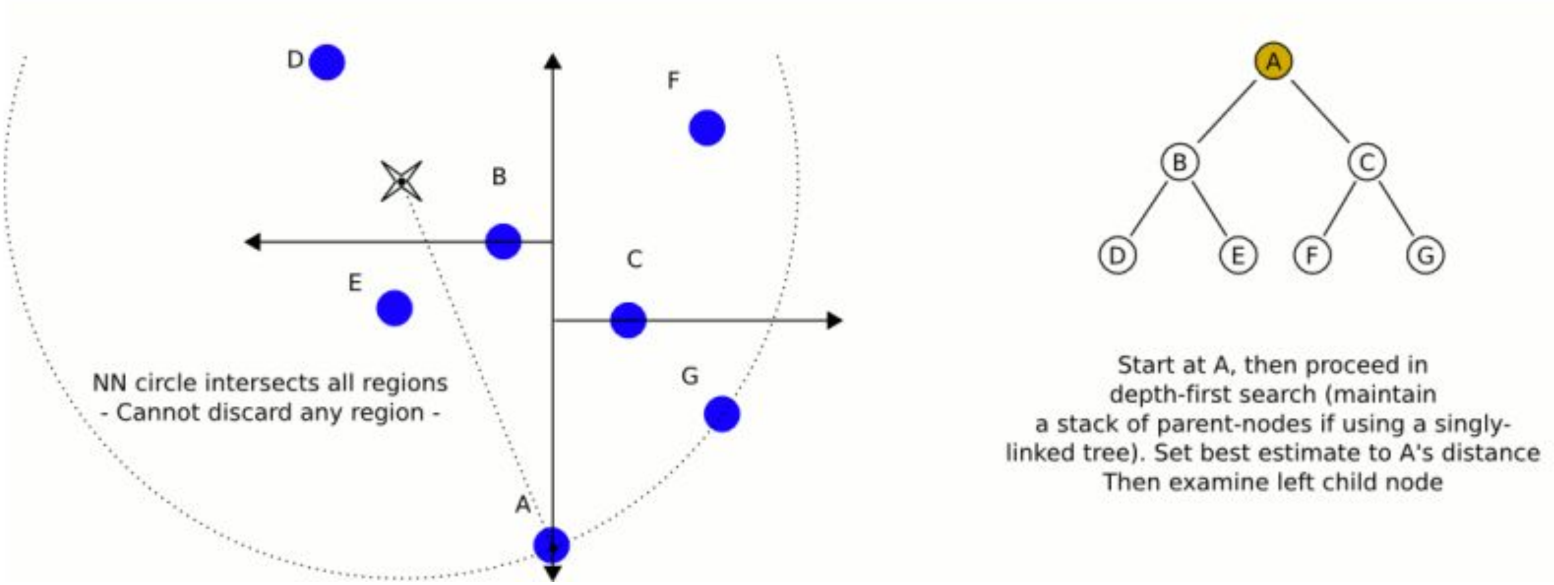
Nearest Neighbor Search



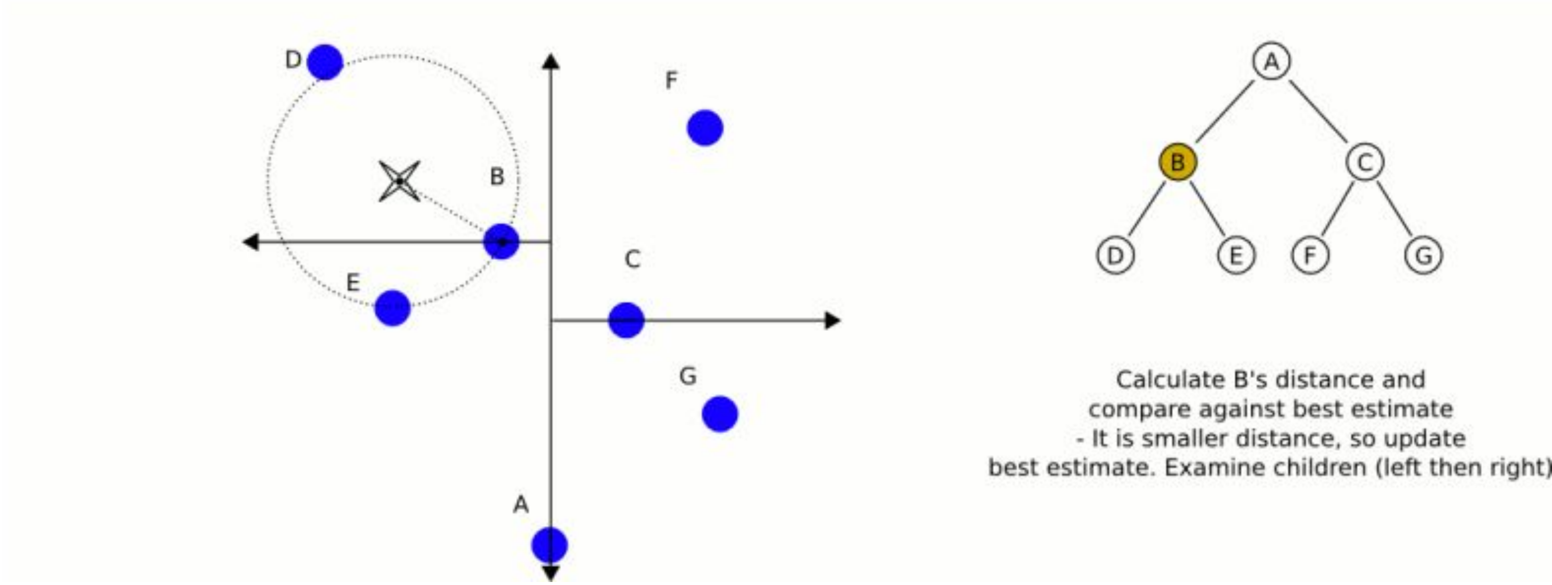
Nearest Neighbor Search



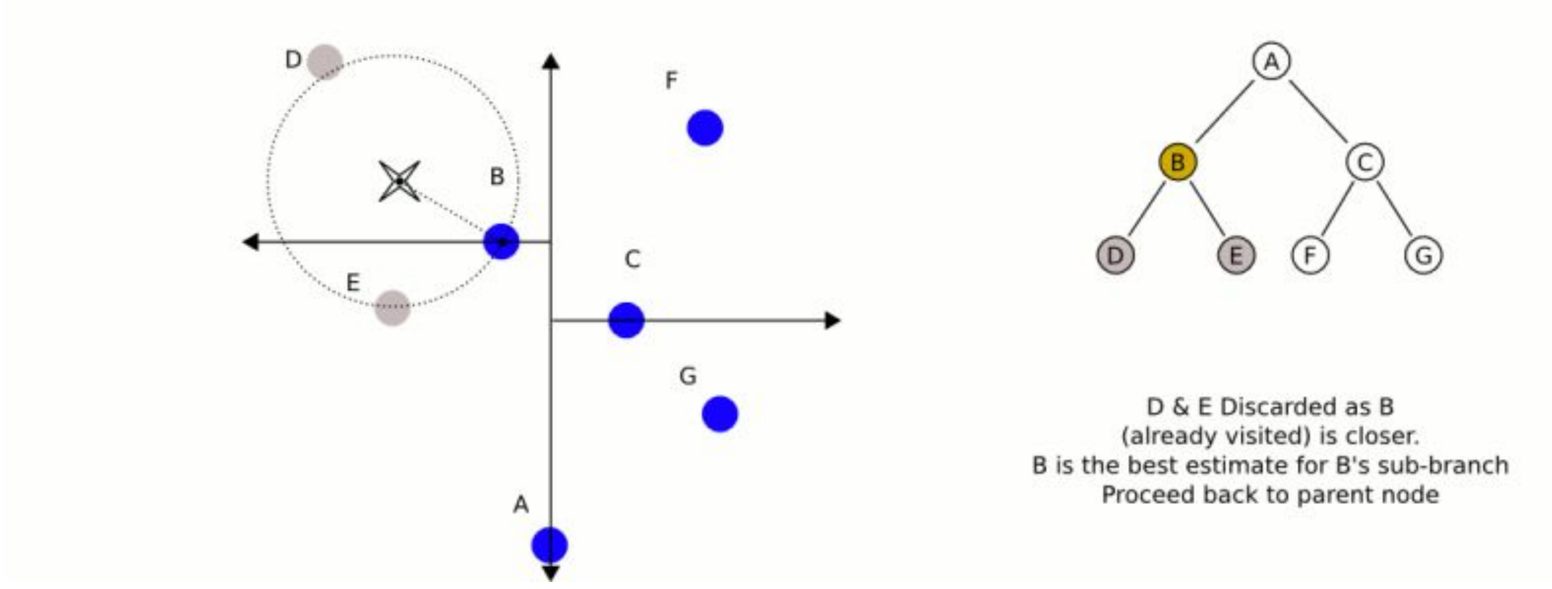
Nearest Neighbor Search



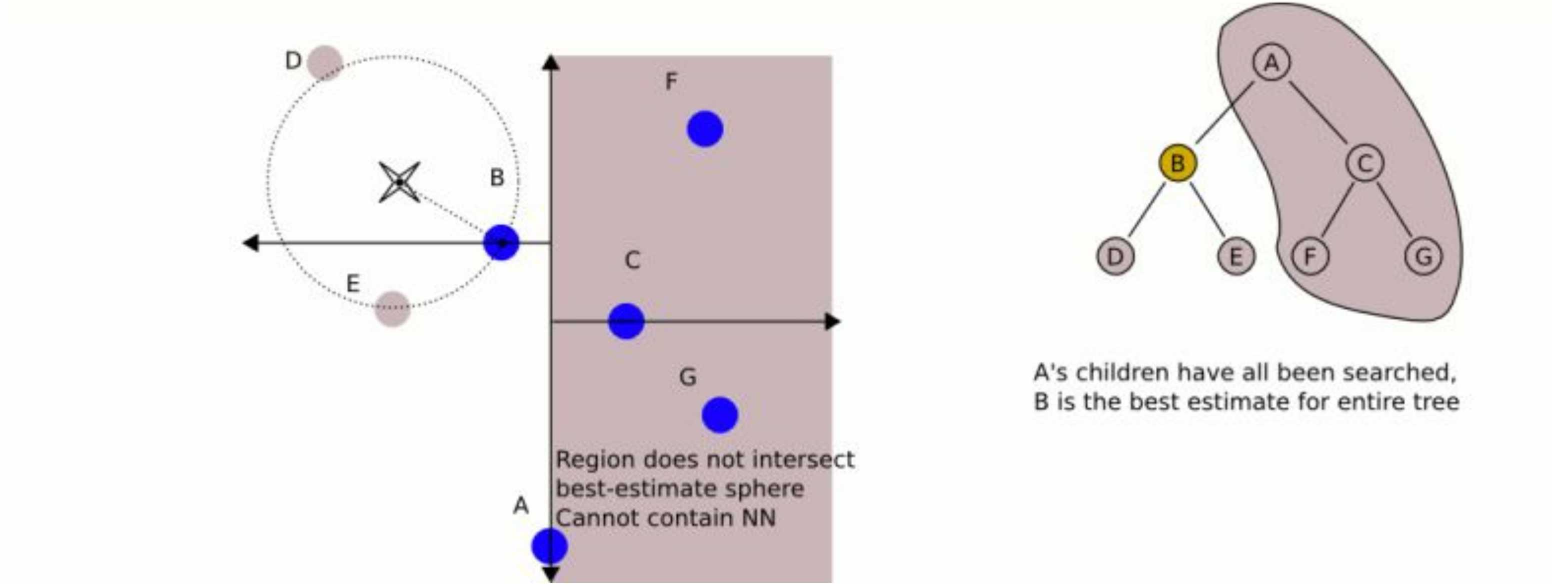
Nearest Neighbor Search



Nearest Neighbor Search

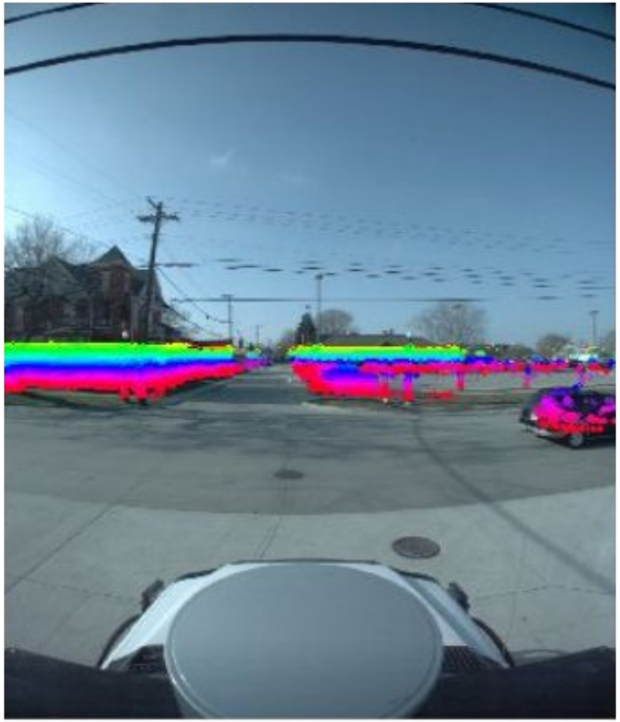


Nearest Neighbor Search

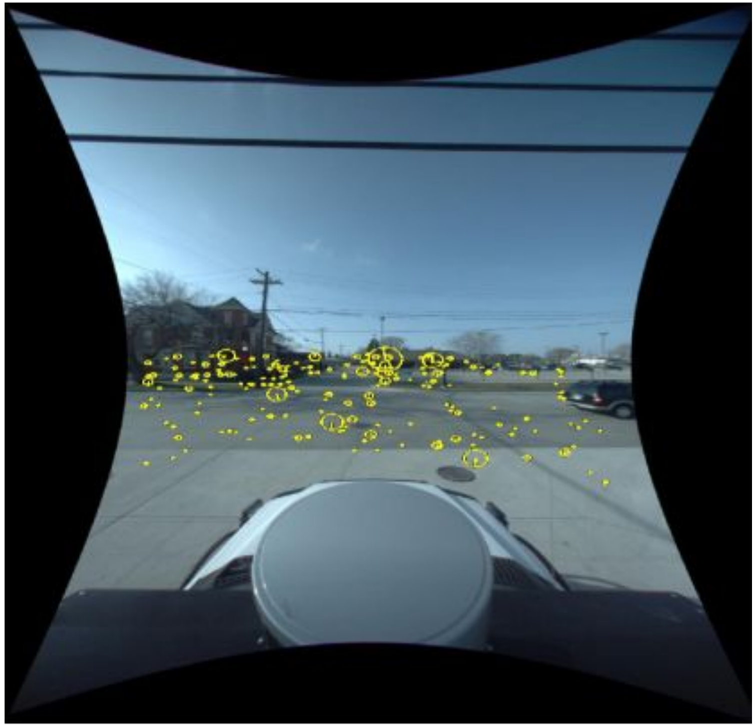


Camera+ICP Fused Algorithm

Assign SIFT descriptors to the 3-D LIDAR for robust point-cloud matching



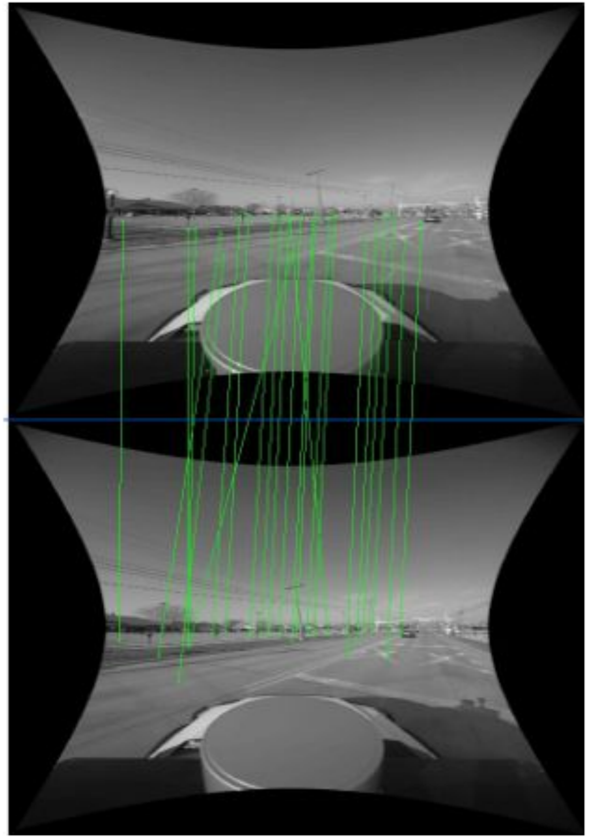
LIDAR projected into imagery
(ground-plane not rendered for visual clarity)



SIFT camera feature detections
(coincident with LIDAR data)

Camera+ICP Fused Algorithm

RANSAC algorithm that uses SIFT matches to seed ICP registration, resulting in faster and more robust point-cloud registration



Frame to frame SIFT matching

Visually bootstraped ICP Algorithm:

Extract SIFT features and re-project onto to lidar

Assign putative lidar correspondences based upon visual similarity

While (# trials)

  Draw 3 random putative correspondence pairs

  Fit rigid body transform, RBT

  Test for model consensus

  Keep RBT model with best consensus

endWhile

Refine RBT using generalized ICP

This algorithm generates more robust results with less spatial data

Visually Bootstrapped ICP Results

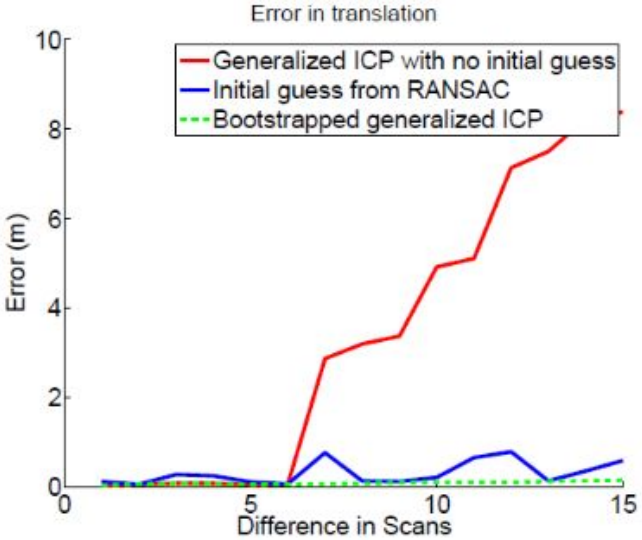


TABLE I

THIS TABLE SUMMARIZES THE ERROR IN SCAN ALIGNMENT. WE SHOW HERE THE TRANSLATION AND ROTATIONAL ERROR BETWEEN SCAN PAIRS {1-2, 1-5, 1-10, 1-15} OBTAINED AT DIFFERENT LOCATIONS. HERE WE HAVE USED THE POSE OF THE VEHICLE OBTAINED FROM A HIGH END IMU AS GROUND TRUTH TO CALCULATE ALL THE ERRORS.

	Generalized ICP with no initial guess						Initial guess from RANSAC						Bootstrapped generalized ICP					
Scans	T (m)		Ax (degrees)		An (degrees)		T (m)		Ax (degrees)		An (degrees)		T (m)		Ax (degrees)		An (degrees)	
	Err	Std	Err	Std	Err	Std	Err	Std	Err	Std	Err	Std	Err	Std	Err	Std	Err	Std
1-2	.047	.011	0	0	.05	.02	.15	.02	0	0	.223	.0003	.04	.010	0	0	.057	.110
1-5	.546	.173	.570	.20	1.15	.344	.20	.03	.43	.15	.230	.0001	.084	.010	.025	.090	.058	.006
1-10	6.37	.868	.710	.25	1.72	.573	.51	.09	.59	.01	.745	.0044	.145	.015	.030	.010	.057	.012
1-15	10.34	.834	1.86	.13	2.86	.057	1.02	.02	1.35	.54	1.15	.0021	.220	.008	.042	.015	.070	.017

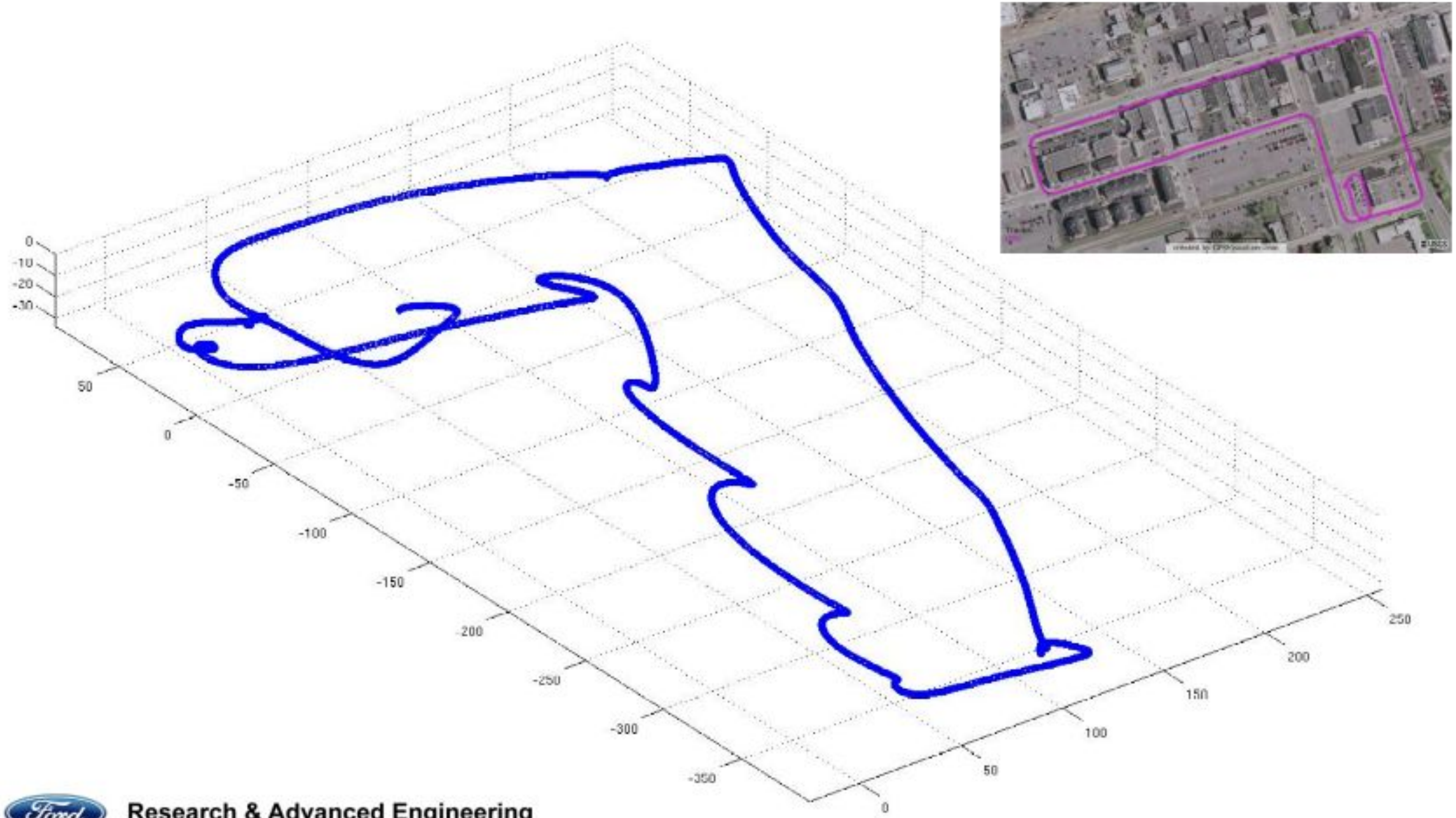
T = Error in translation (meters); Ax = Error in rotation axis (degrees); An = Error in rotation angle (degrees)
Err = Average Error; Std = Standard Deviation

SLAM GPS-Denied Demonstration

OmniSTAR HP GPS ground-truth and Applanix POS-LV IMU
1.6 km loop around Dearborn

Dead Reckoning

No GPS Reception – Velocity Integration of MEMs-based XSENS MTi-G IMU Data



SLAM Demonstration

Ground Truth vs. Laser Odometry

No GPS Reception – Intra-frame Motion Compensated by XSENS MTi-G IMU

Summary:
Feature vs. non-feature matching

- Features (pros)
  - Data reduction
  - Noise filtering
  - Extraction + Matching is often fast
  - Can handle from large prior uncertainties.

- Non-Feature Matching (pros)
  - General purpose: don't require world to contain our features
  - ICP/ICL:
    - Very fast, easy to implement. Local maxima problems.
  - Correlation
    - Fast enough, very robust