IoT and Localization

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The Internet of Things: Roadmap to a Connected World

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OUTLINE

Introduction to Localization

Robust Localization

Outdoors Localization

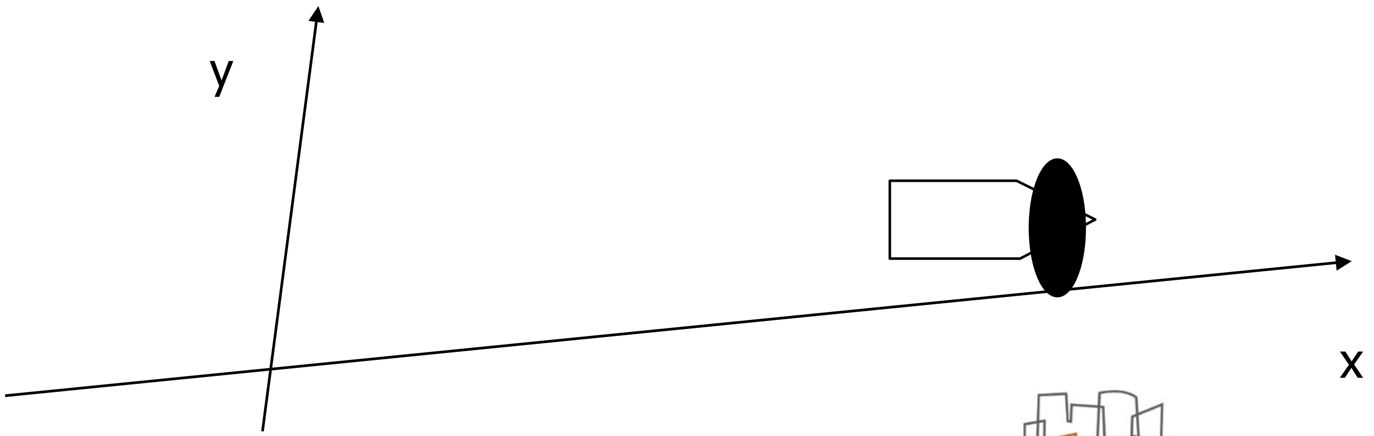
Indoors Localization

LOCALIZATION PROBLEM STATEMENT

Given some representation of the environment, to *localize*, device must, through sensing, determine its pose *with respect to the specified representation*

Pose = (location, heading) wrt external frame

- Global coordinate frame
  - E.g., GPS (Earth) coordinates
- Local coordinate frame
  - Ceiling or floor tiles
  - Mission starting pose
- Environment features
  - E.g., nearby walls, corners, markings



OPEN LOOP POSE ESTIMATION

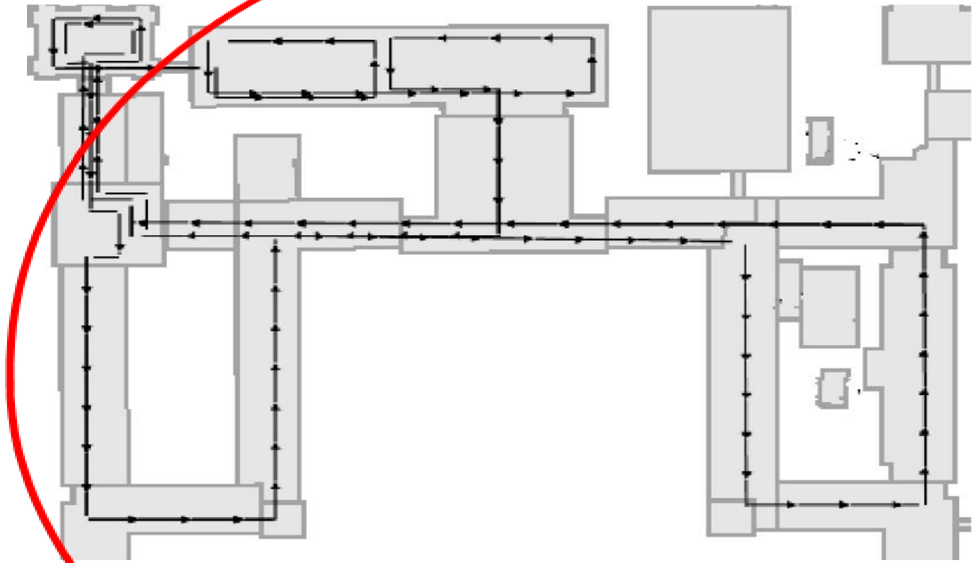
Estimate pose from expected results of motion

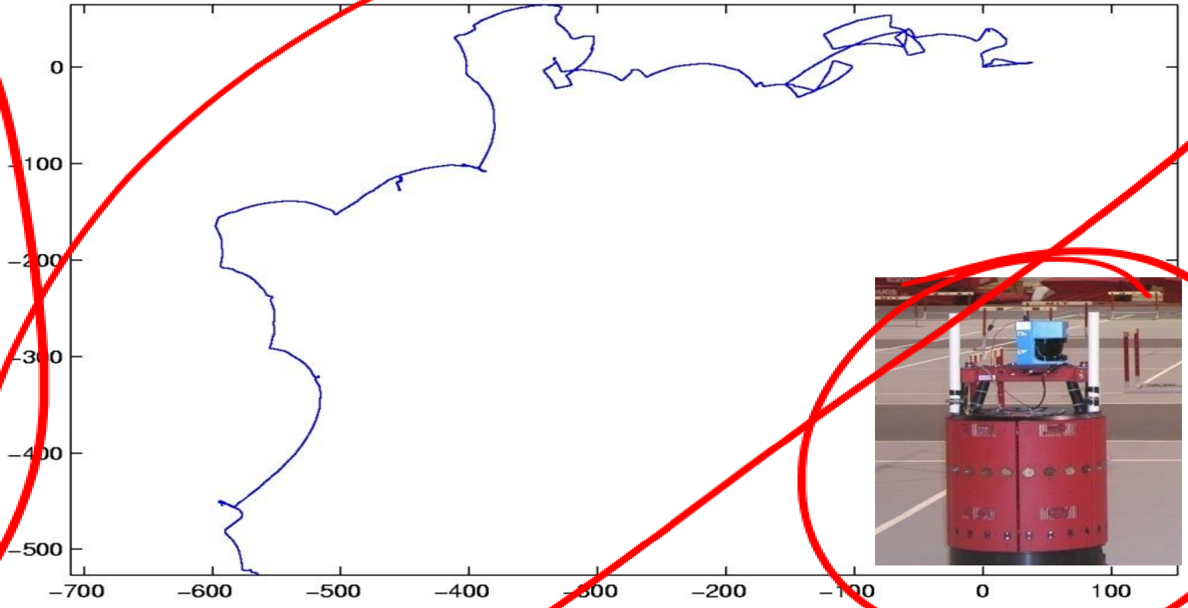
No sensing

Dead reckoning:

- Use odometry to estimate pose w.r.t. *initial* coordinate frame
- Multiple error sources;
- Pose error accumulates with time and motion

OPEN LOOP POSE ESTIMATION

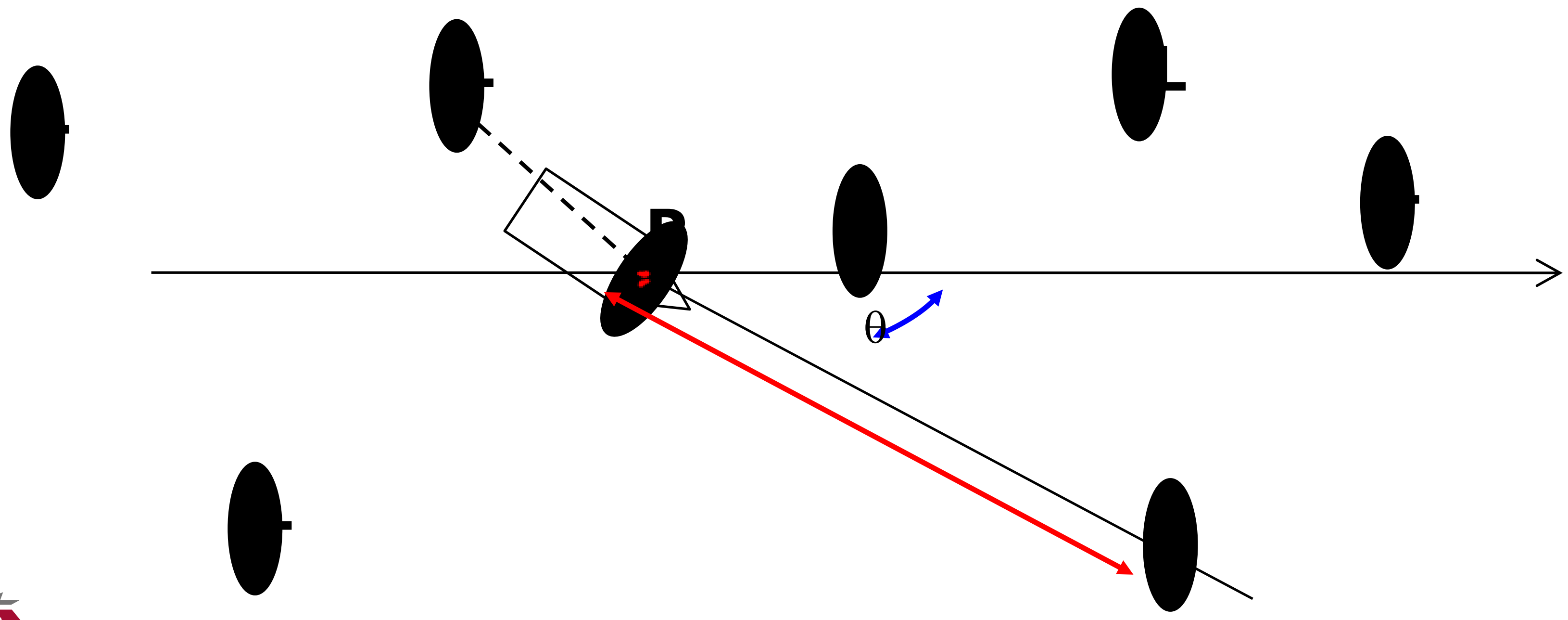




LOCALIZATION SCENARIOS

Estimating location in 2D

- From measured *ranges* (distances)
- From measured *bearings* (directions)



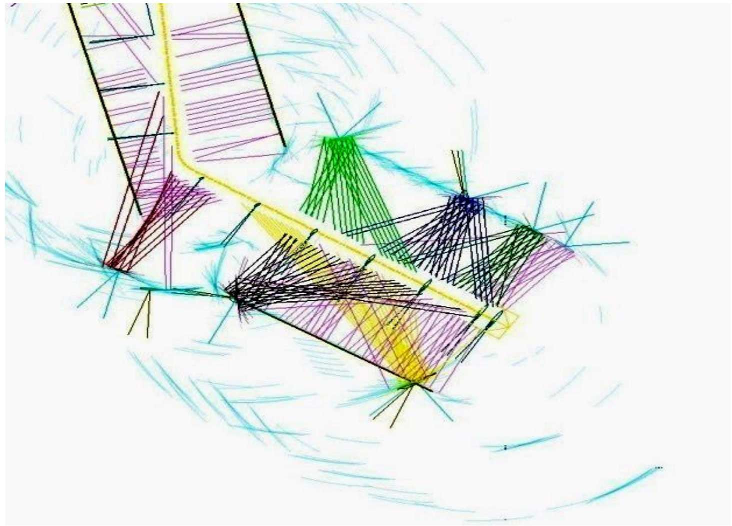
SENSORS AND MEASUREMENTS

Range to surface patch, corner
- Sonar, IR

Bearing (absolute, relative, differential)
- Compass; vision (calibrated camera)

Range to point
- RSS, TOF from RF/acoustic beacon
- TDoA of acoustic & RF pulse

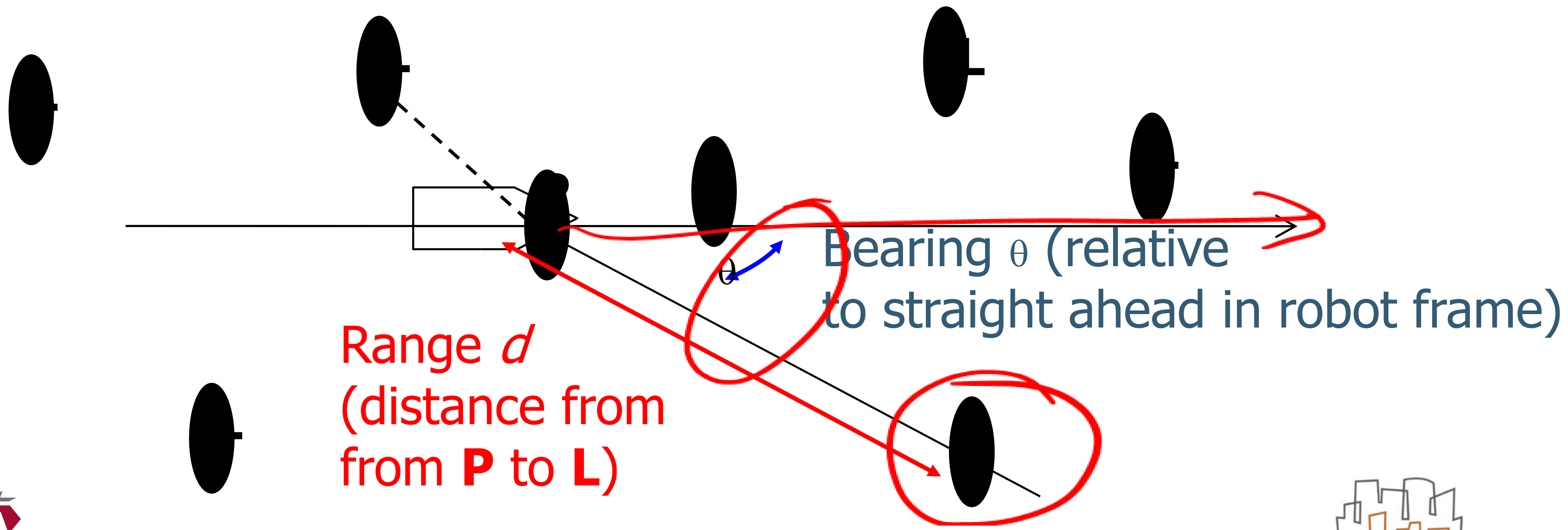
Range and (body-relative) bearing to object
- Radar return
- Laser range scanner return
- Vision (stereo camera rig)



TRIANGULATION

Natural geometry for 2D localization

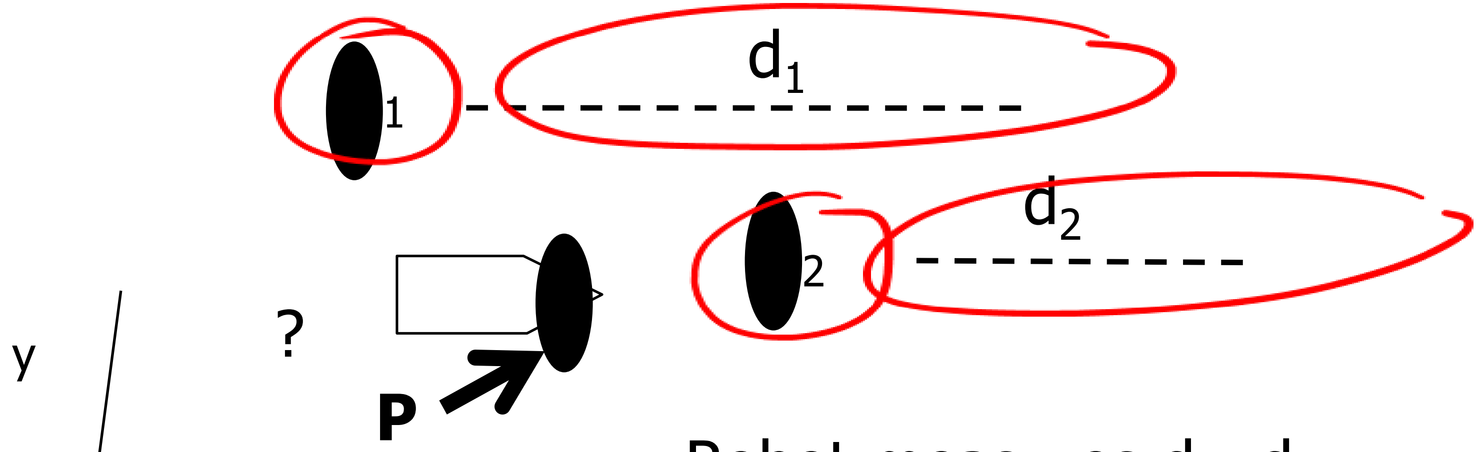
- Simplest framework combining range, bearing
- Used by Egyptians, Romans for engineering



TRIANGULATION FROM RANGE DATA

Device at unknown position **P** measures distances d_1, d_2 to *known* landmarks $\mathbf{L_1}$, $\mathbf{L_2}$

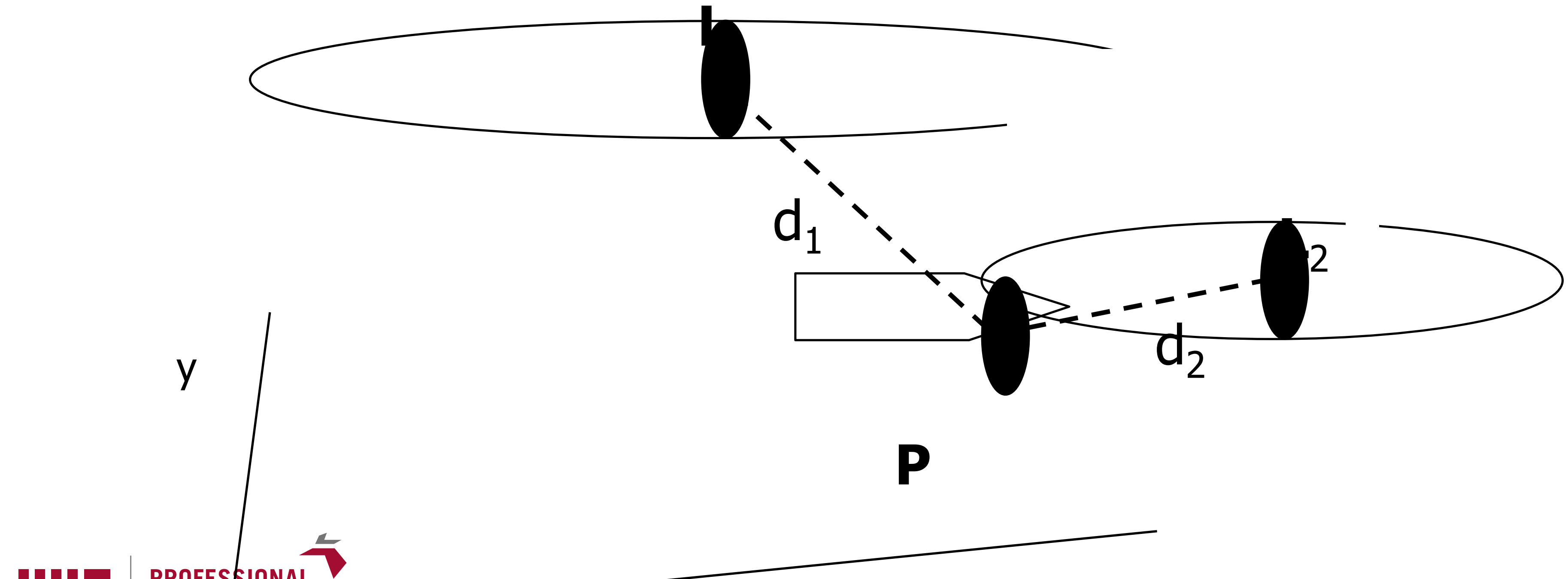
Given d_1, d_2, what are possible values of **P**?



Robot measures d_1, d_2

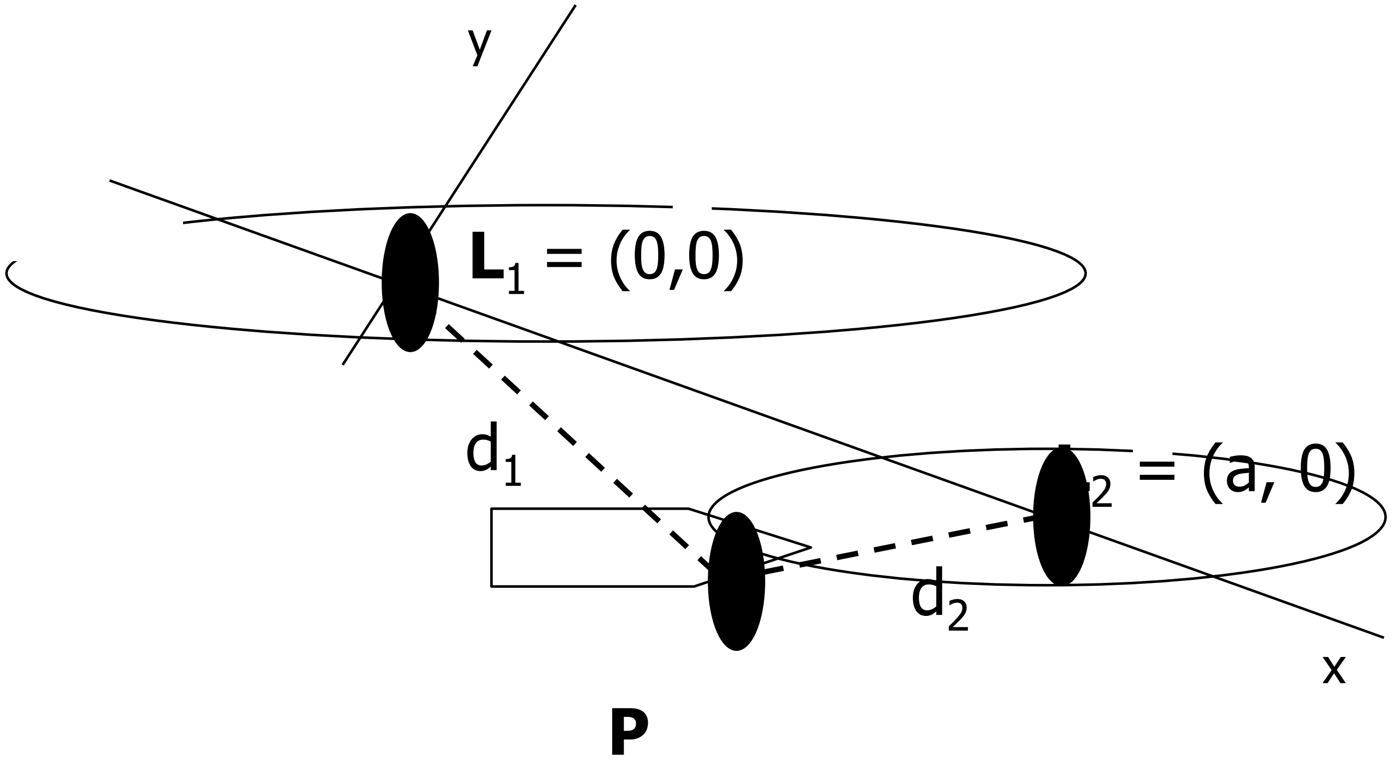
TRIANGULATION FROM RANGE DATA

Device must lie on circles of radius d_1, d_2 centered at $\mathbf{L}_1$, $\mathbf{L}_2$ respectively



TRIANGULATION FROM RANGE DATA

Change basis: put **L**$_1$ at origin, **L**$_2$ at $(a,0)$



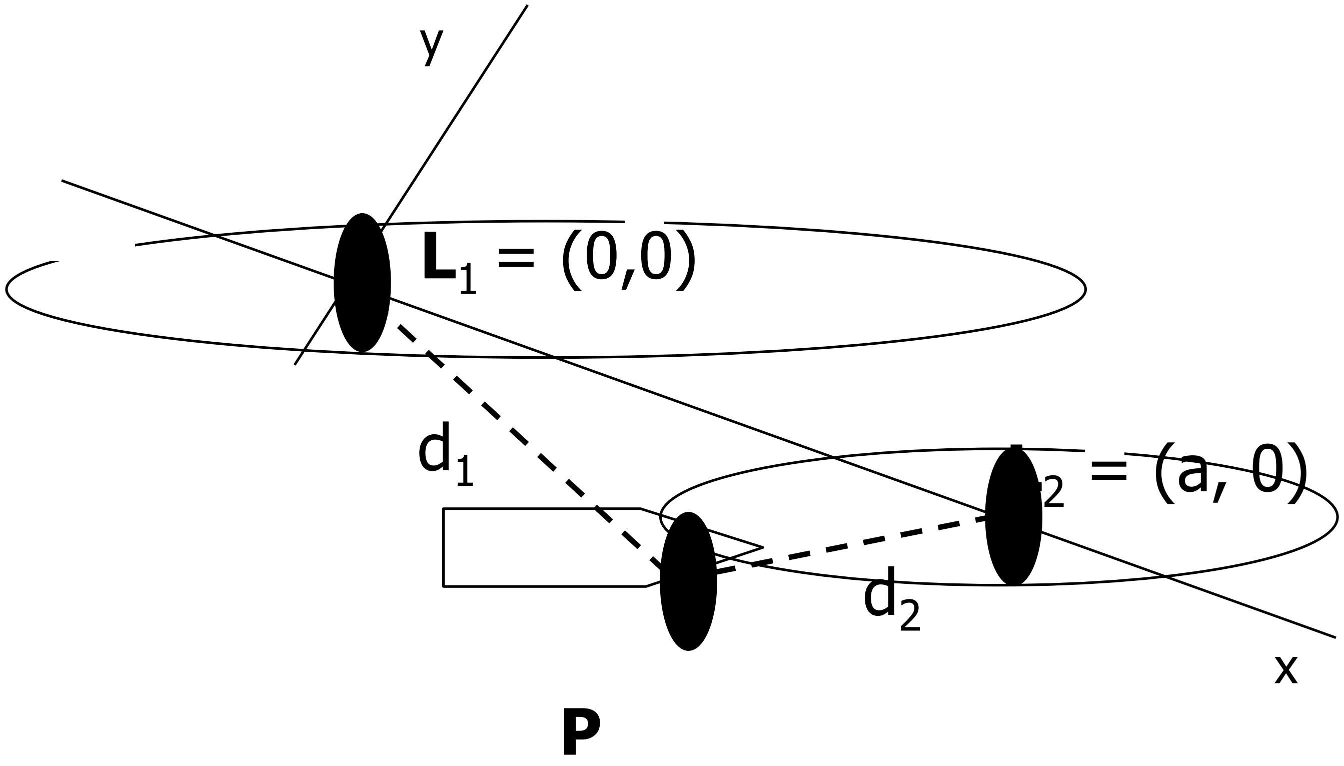
$$x = (a^2 + d_1^2 - d_2^2)/2a$$

$$y = \pm\sqrt{(d_1^2 - x^2)}$$

(Try e.g. setting $d_1 = a$, $d_2 = 0$)

TRIANGULATION FROM RANGE DATA

Change basis: put $\mathbf{L_1}$ at origin, $\mathbf{L_2}$ at $(a,0)$



$$x = (a^2 + d_1^2 - d_2^2)/2a$$

$$y = \pm\sqrt{(d_1^2 - x^2)}$$

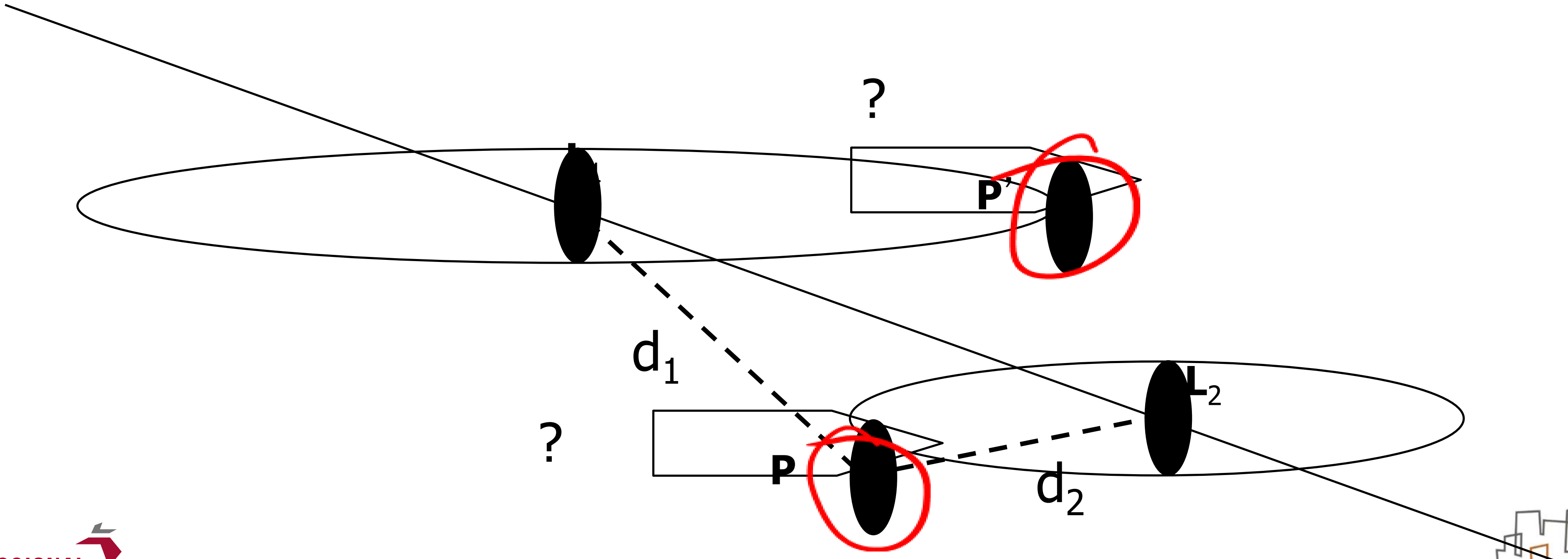
(Try e.g. setting $d_1 = a$, $d_2 = 0$)

Are we done?

TRIANGULATION FROM RANGE DATA

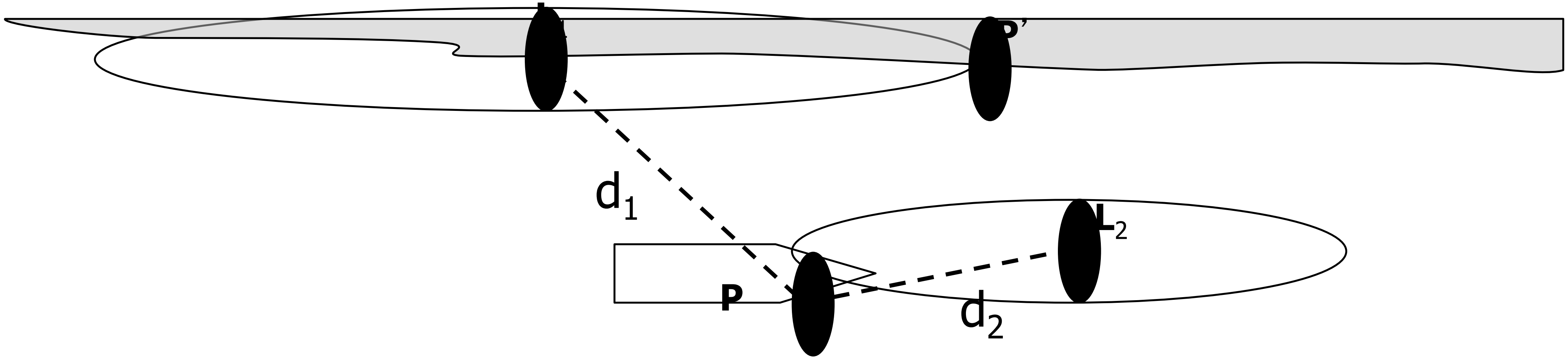
Two solutions in general, P and P'

How to select the correct solution?



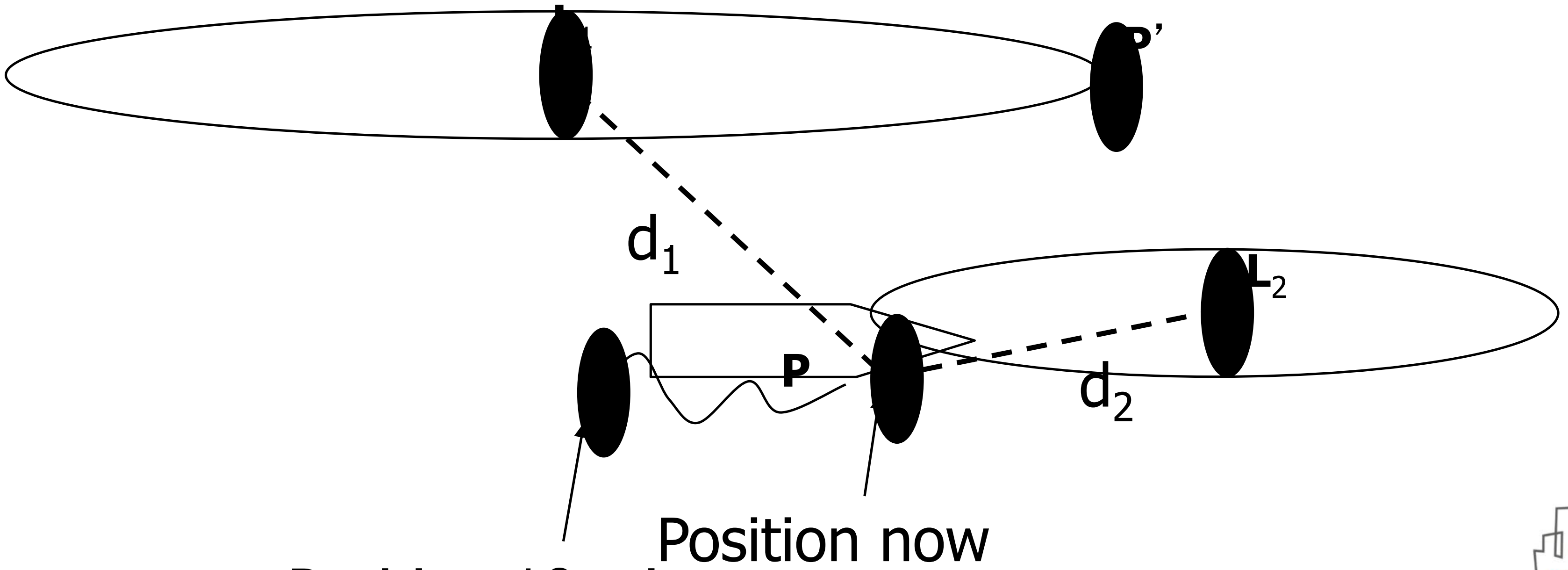
DISAMBIGUATING SOLUTIONS

A priori information (richer map)



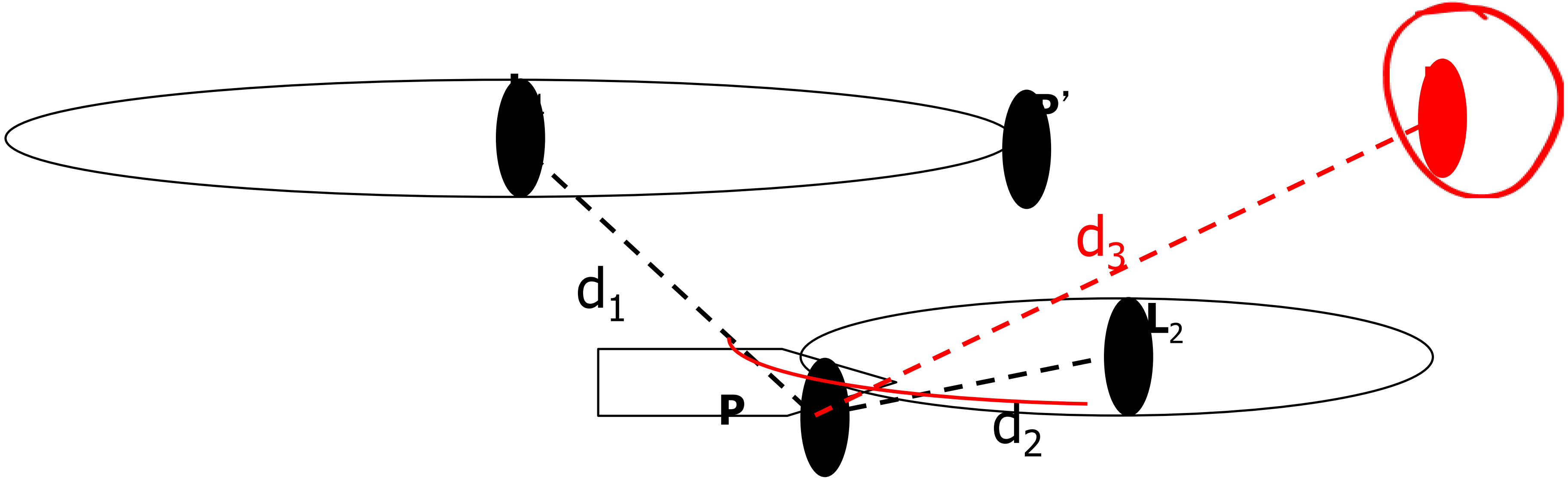
DISAMBIGUATING SOLUTIONS

Continuity (i.e., spatiotemporal information)



DISAMBIGUATING SOLUTIONS

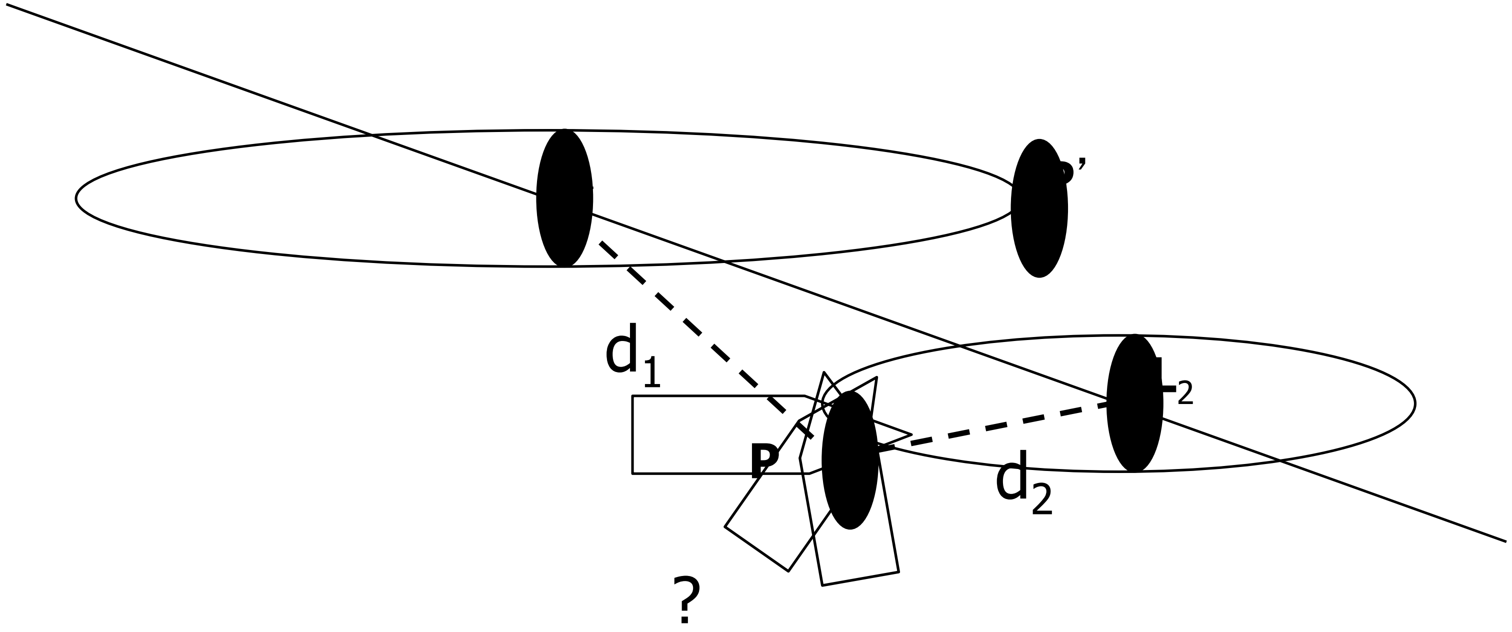
Additional landmarks (redundancy)



TRIANGULATION FROM RANGE DATA

Are we done yet, i.e., is pose fully determined?

No: absolute heading is *not determined*

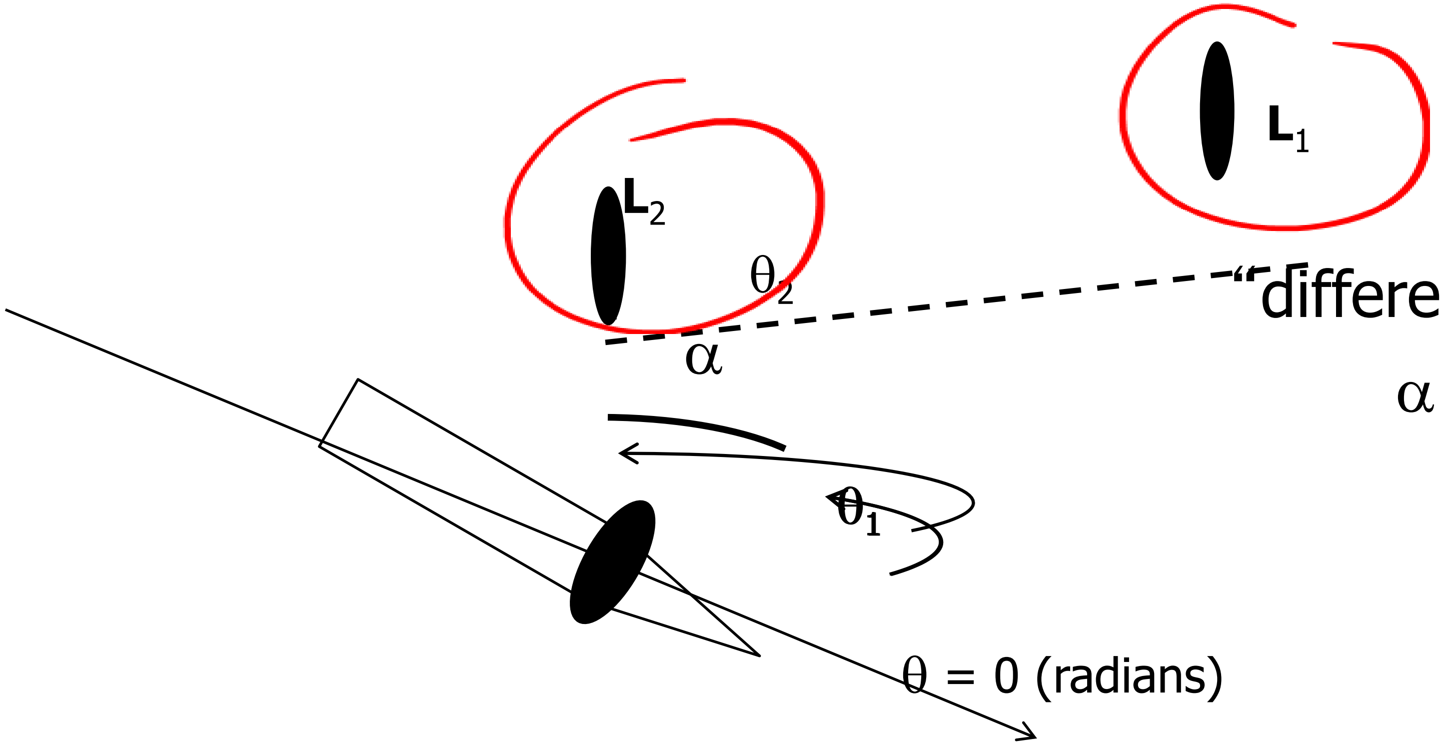


TRIANGULATION FROM BEARING DATA

Body-relative bearings to two landmarks

- Bearings measured relative to "straight ahead"

Robot observes:
L_1 at bearing θ_1
L_2 at bearing θ_2



"differential bearing"

$$\alpha = \theta_2 - \theta_1$$

TRIANGULATION FROM BEARING DATA

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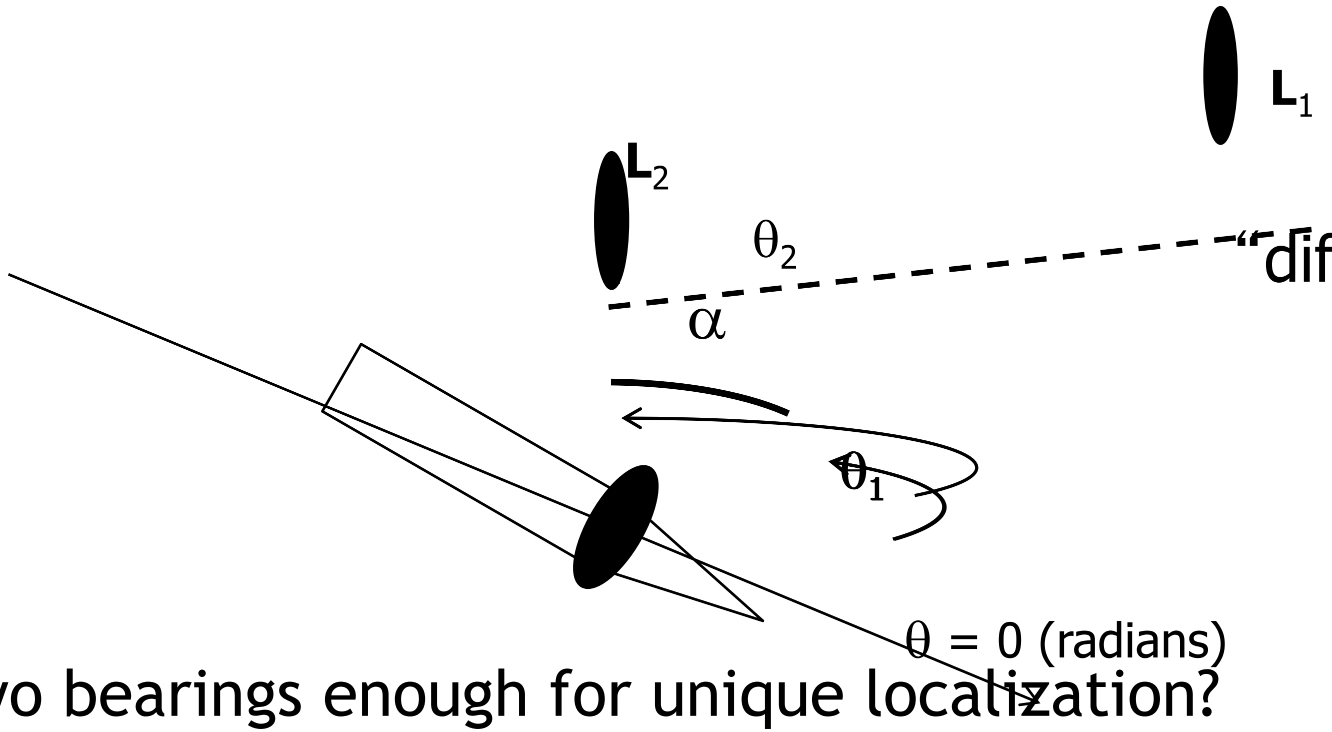
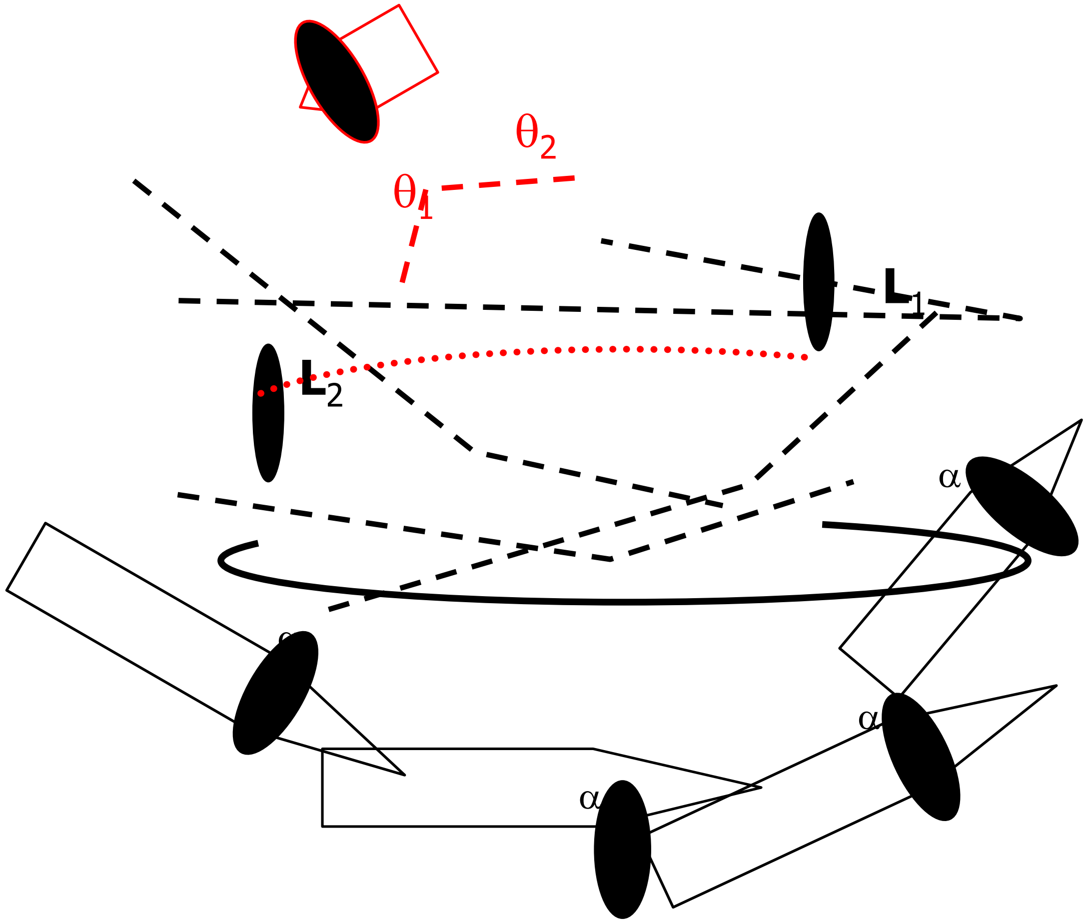


"differential bearing"

$$\alpha = \theta_2 - \theta_1$$

… are two bearings enough for unique localization?

Triangulation from two bearings

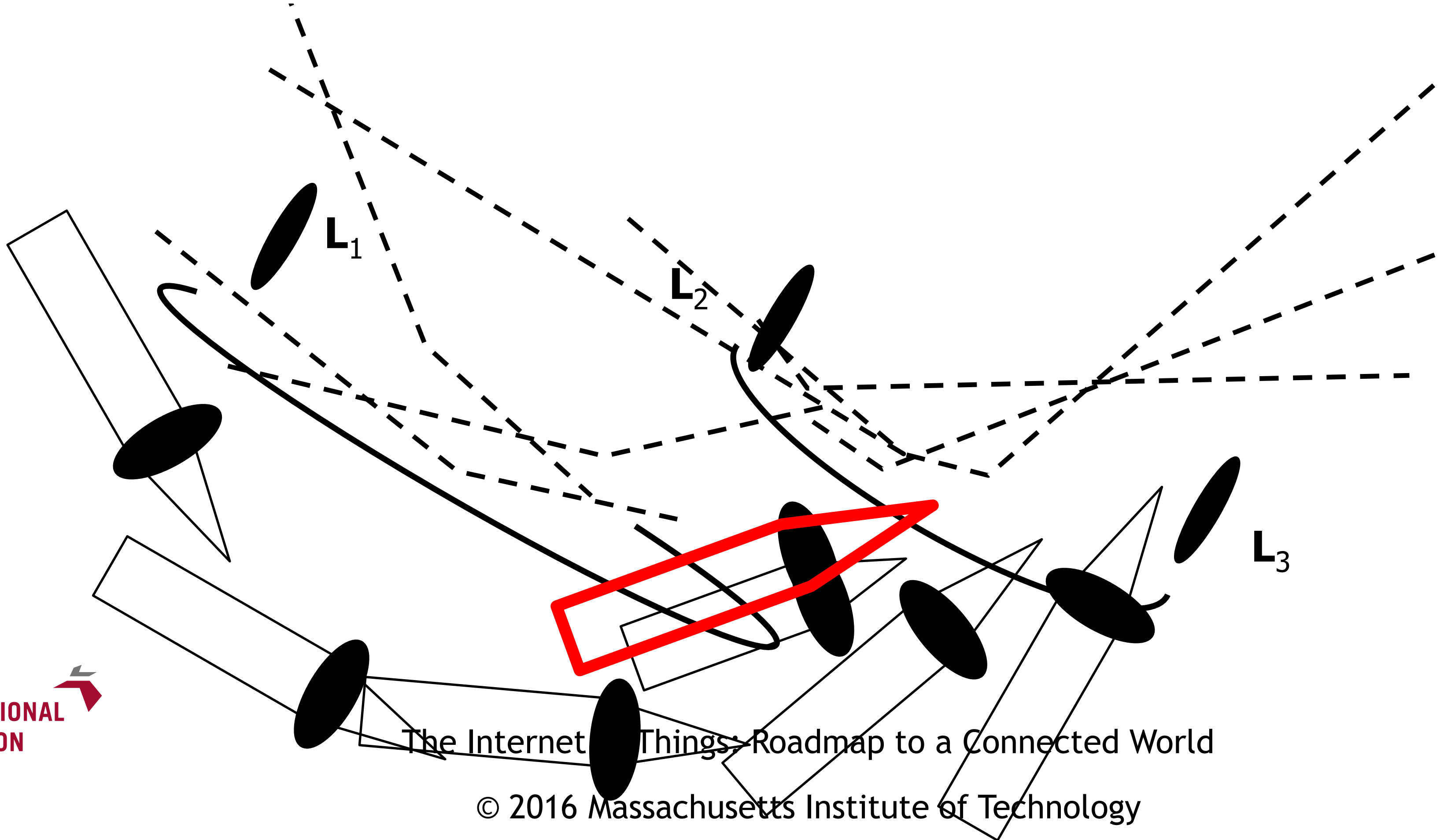


- Device somewhere on black circular arc
- Can it be *anywhere* on circle? (No; ordering constraint)

TRIANGULATION FROM BEARING DATA

Measure bearing to third landmark

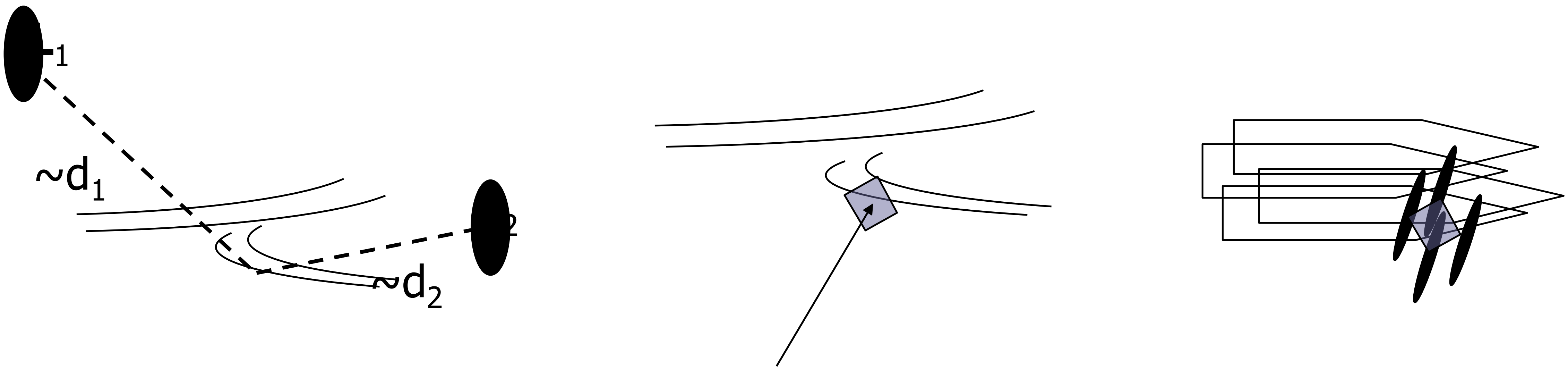
- Yields robot position *and* orientation
- Also called robot *pose* (in this case, 3 DoFs)



MEASUREMENT UNCERTAINTY: RAGES

Ranges, bearings are typically *imprecise*

Range case (estimated ranges ~d_1, ~d_2)



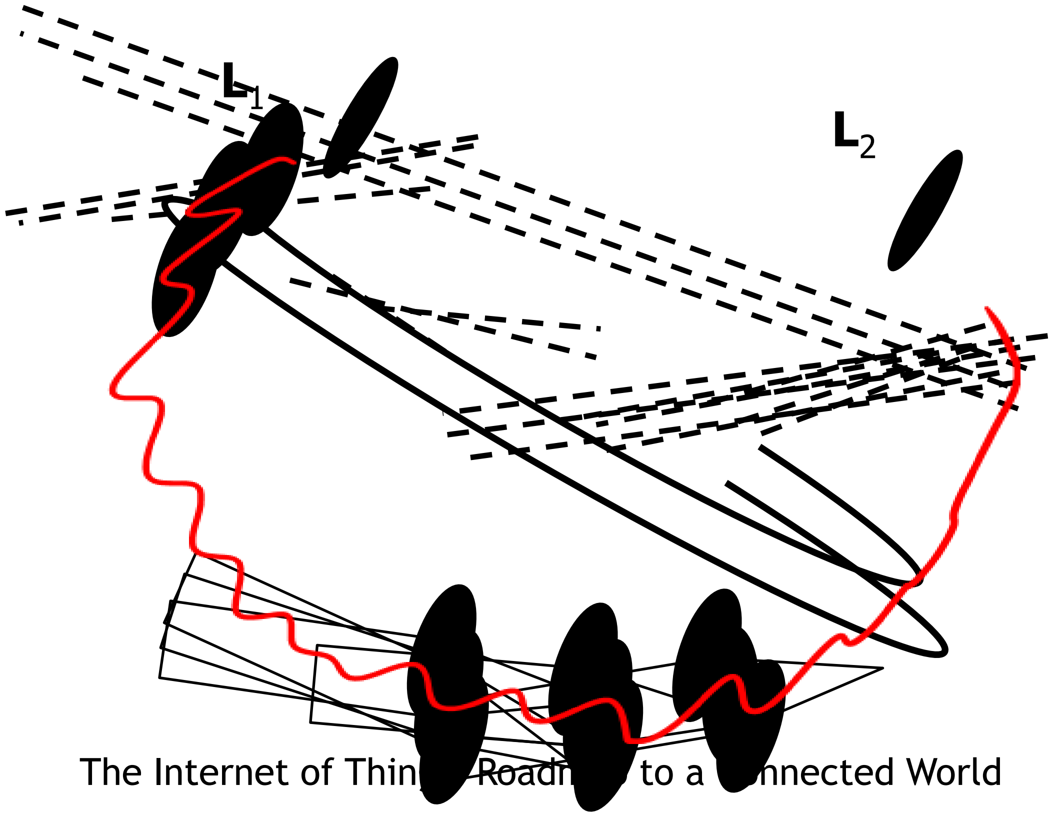
Locus of likely **positions**

MEASUREMENT UNCERTAINTY: BEARING

Two-bearing case (estimated bearings $\sim\theta_1$, $\sim\theta_2$)

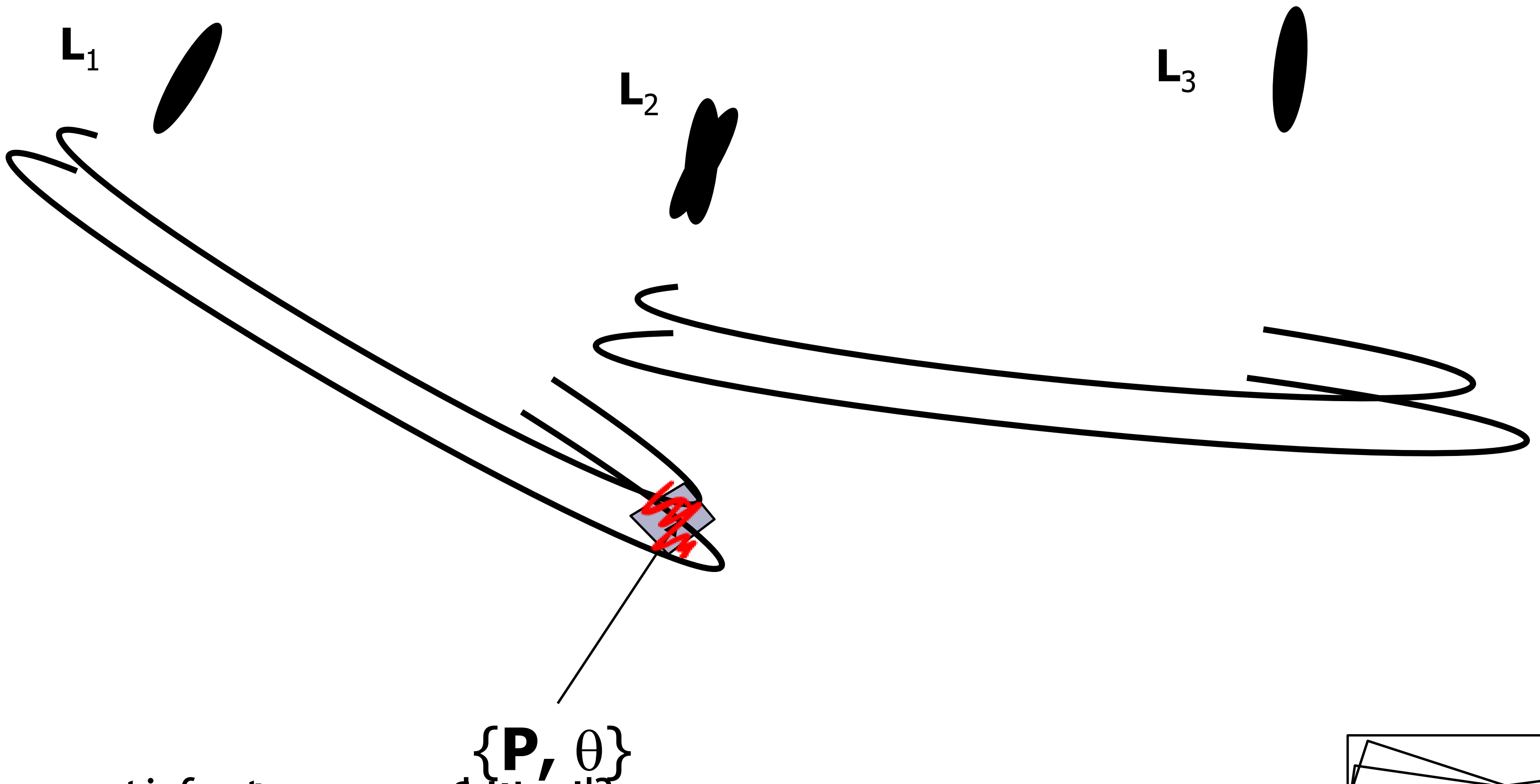
What is *locus* of recovered vehicle poses?

Solve in closed form? Is there an alternative?



MEASUREMENT UNCERTAINTY

Bearing case (measurements ~θ_1, ~θ_2, ~θ_3)



… is this always a satisfactory pose bound?

Locus of likely **poses**

LOCALIZATION SUMMARY

Range – based localization

Bearing – base localization

Uncertainty

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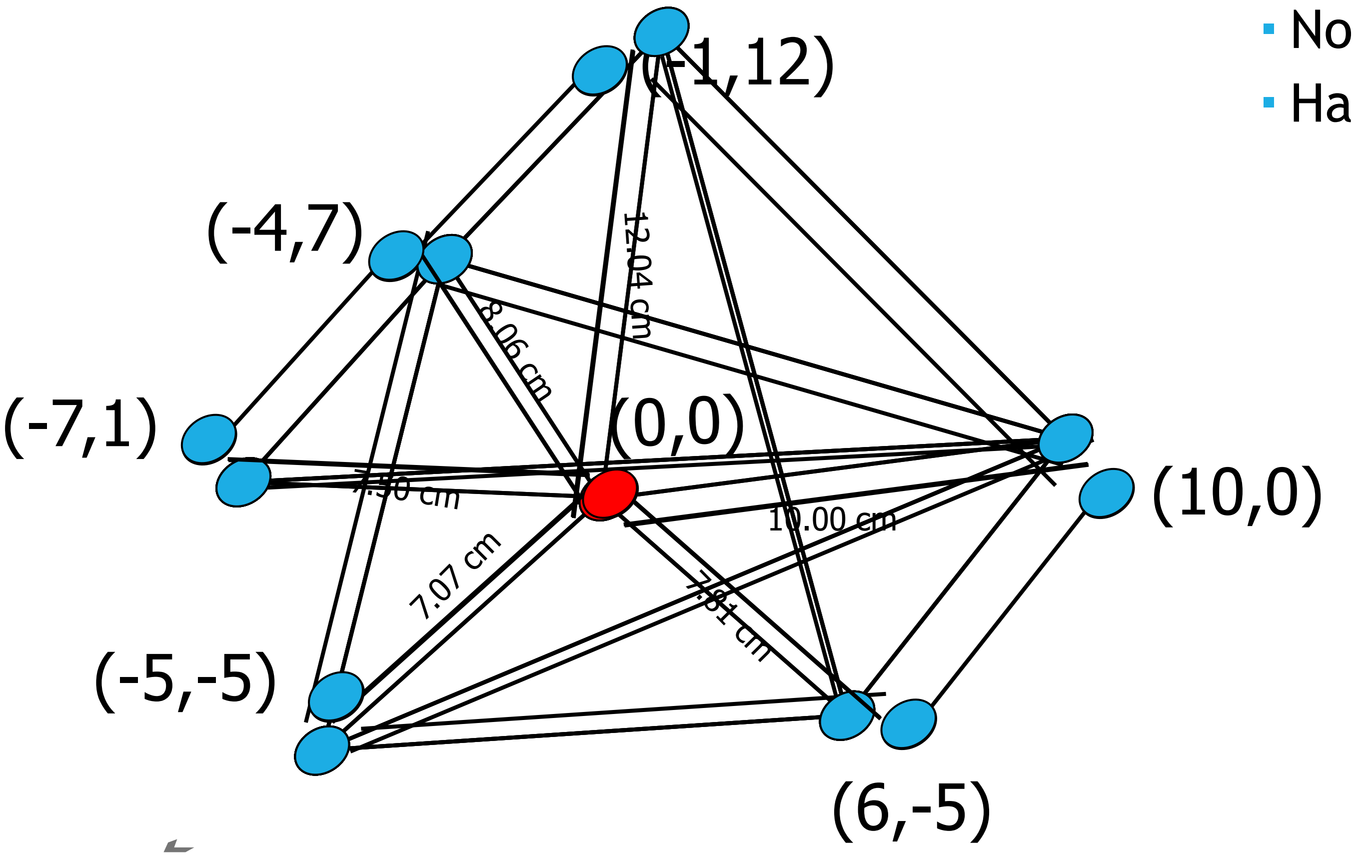
LOCALIZATION WITH NOISY RANGES



Characteristics:

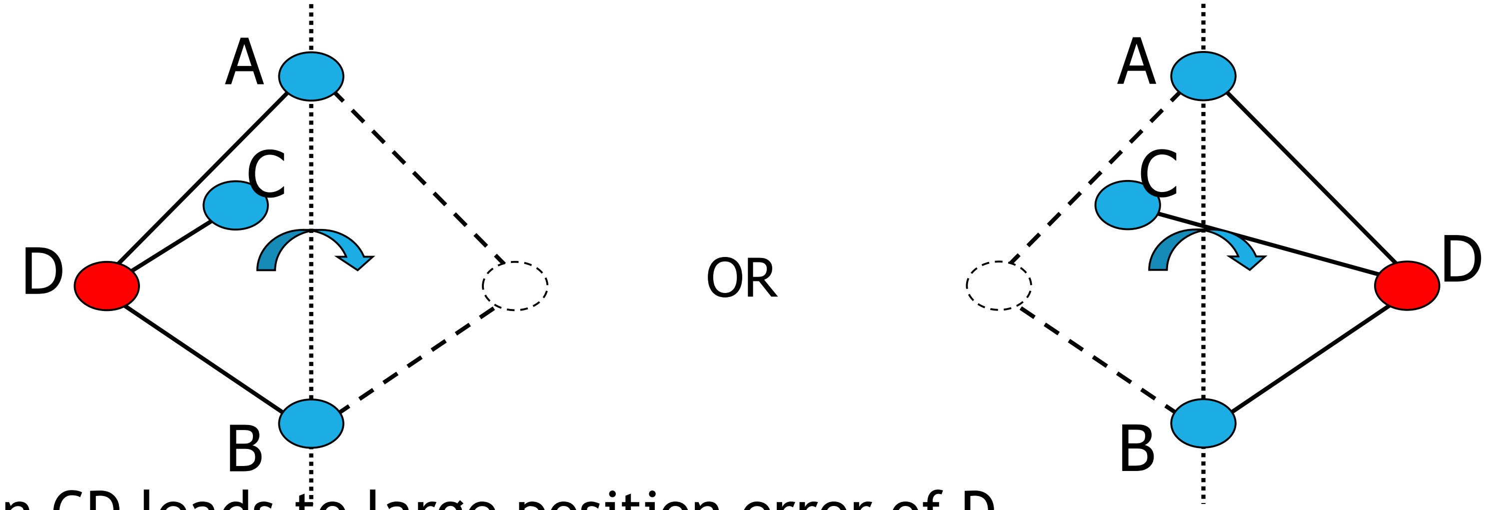
- Robust against noise
- No beacons
- Handles mobility

D. Moore, J. Leonard, D. Rus, S. Teller, Robust distributed network localization with noisy range measurements, Proceedings of the 2004 ACM International Conference on Embedded Networked Sensor Systems (Sensys 2004)

COMPLICATIONS OF NOISE

Small measurement errors due to noise lead to large localization errors

Example: **flip ambiguity** from noise

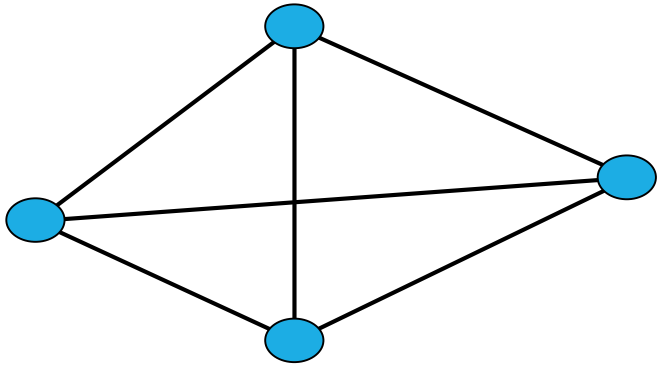


Small error in CD leads to large position error of D

D. Moore, J. Leonard, D. Rus, S. Teller, Robust distributed network localization with noisy range measurements, Proceedings of the 2004 ACM International Conference on Embedded Networked Sensor Systems (Sensys 2004)

THE ROBUST QUADRILATERAL

Consider this graph:



Robustness characteristics:

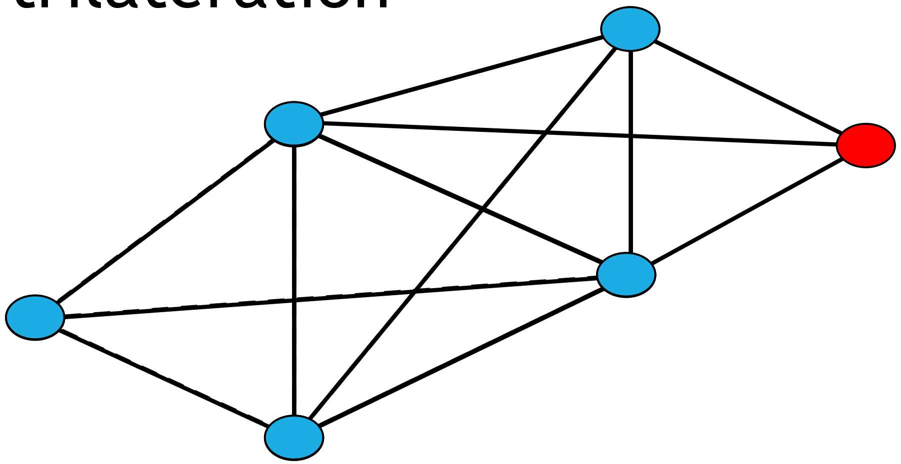
- Rigid (no continuous deformations)
- No discontinuous flex ambiguities (by Laman's Theorem)
- We probabilistically constrain it to minimize the likelihood of a flip ambiguity

We call it a *robust quadrilateral*

A graph constructed from overlapping robust quads will itself possess the robustness characteristics

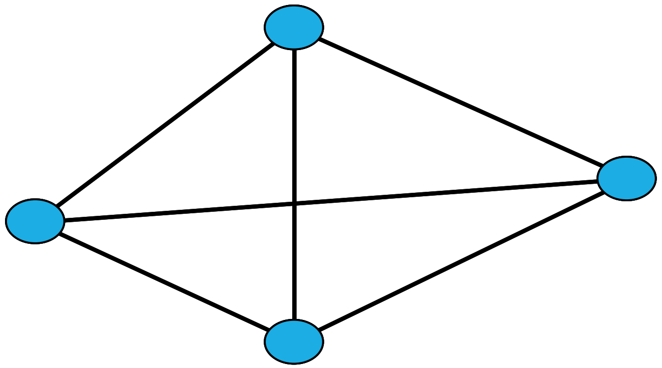
TRILATERATION W/ ROBUST QUADS

If three nodes of a quad have known position, fourth can be computed with trilateration



Quads can be "chained" in this manner

COMPLETE ROBUSTNESS TEST



Test for robust triangle:

Let b = minimum edge length of the triangle

Let θ = minimum angle of the triangle

Then, in worst case: $d_{err} = b \sin^2 \theta$

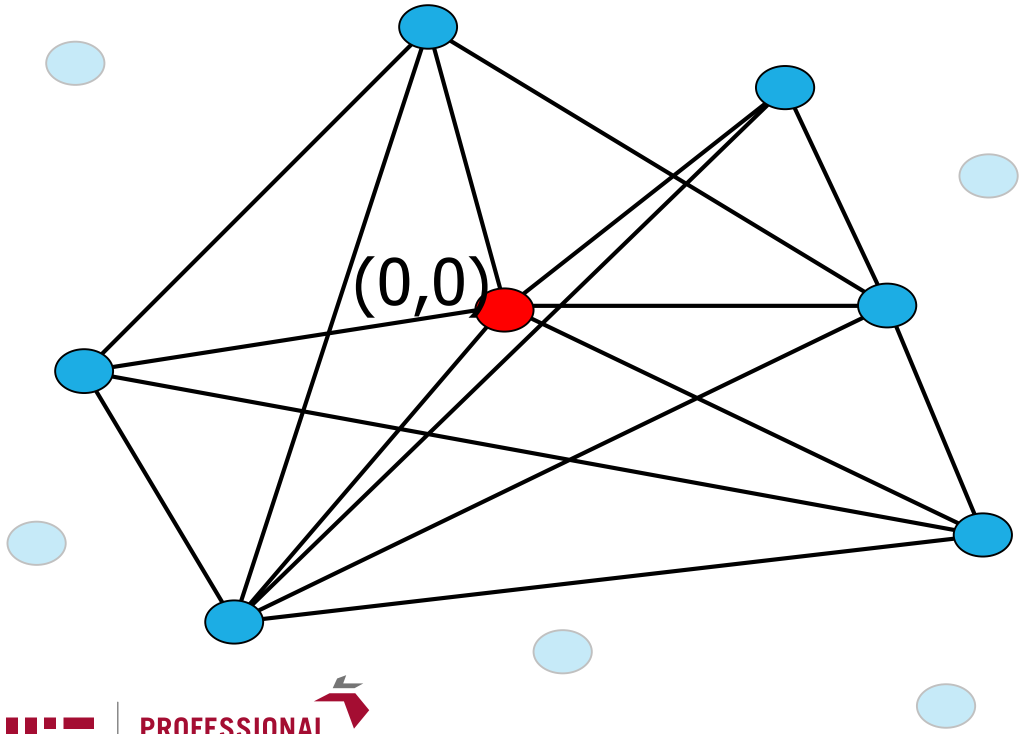
If $b \sin^2 \theta > 3\sigma$ then probability of a flip is less than 1%

Test for robust quadrilateral:

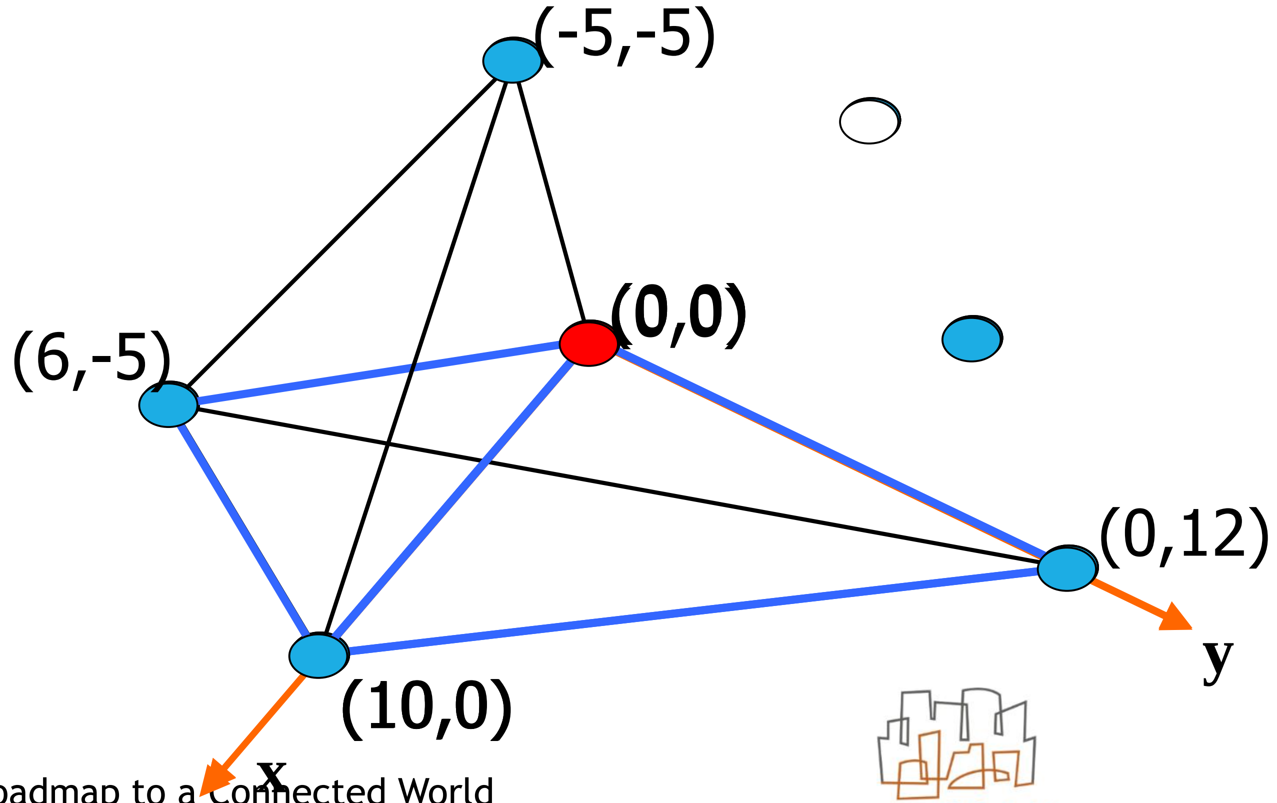
Quad is robust if all four sub-triangles are robust

ALGORITHM

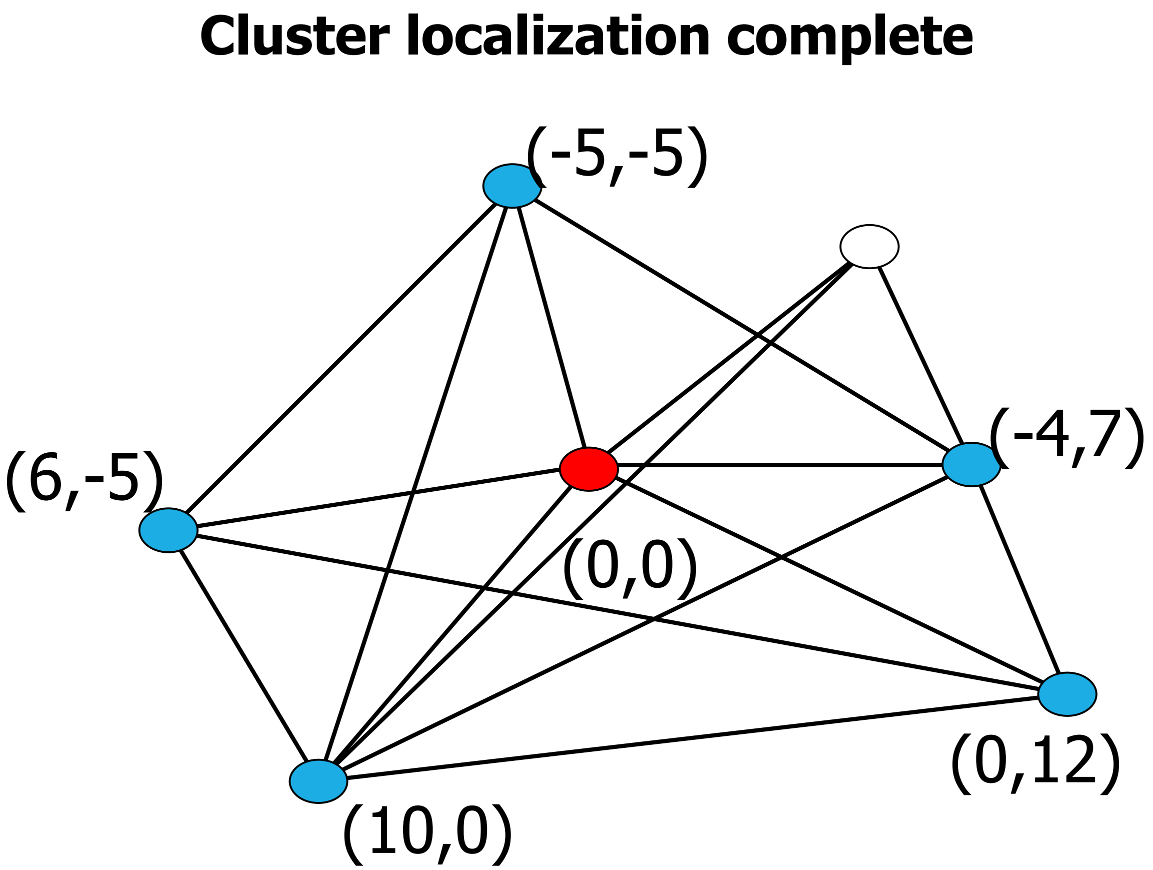
Starting cluster w/ distance measurements



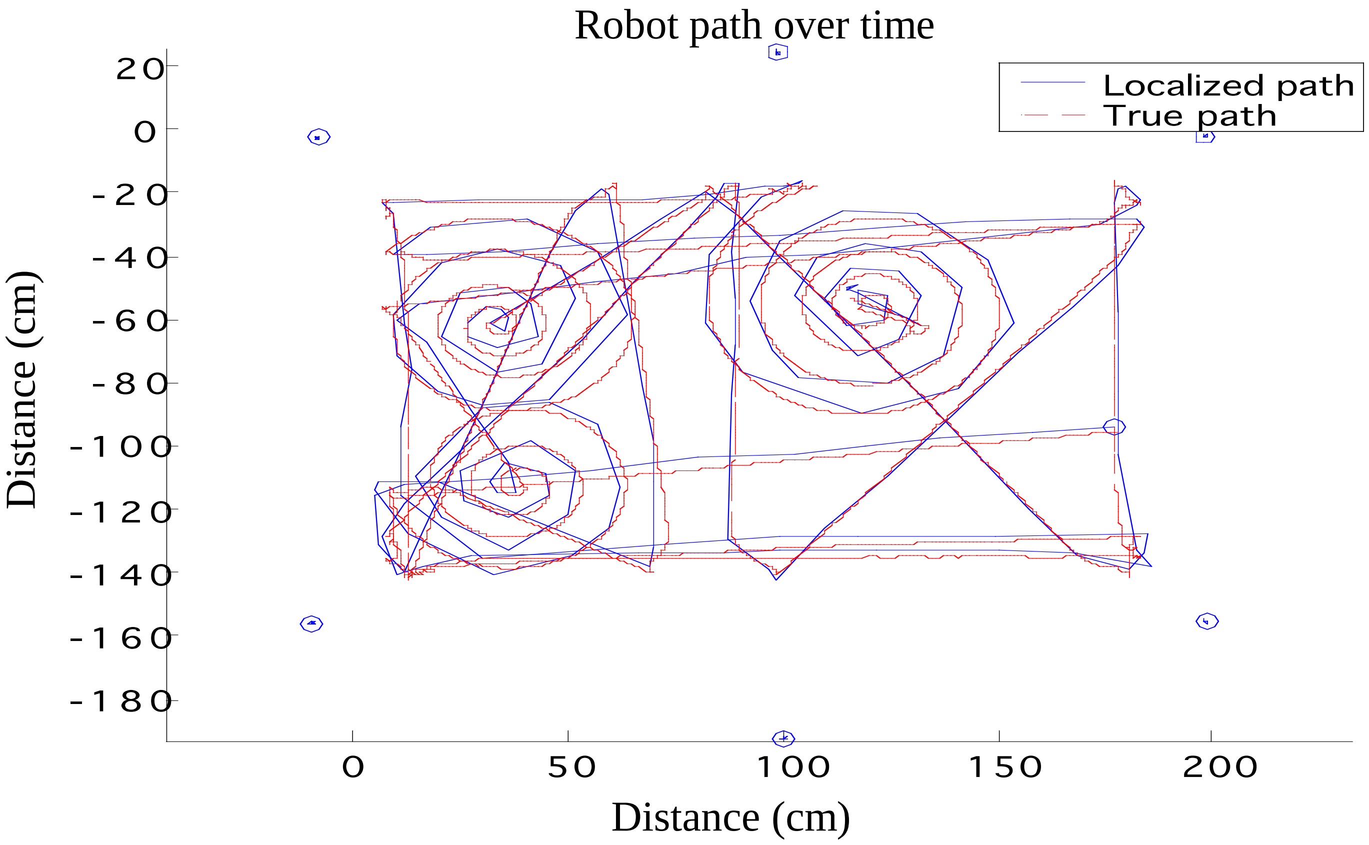
Choose two neighboring nodes for initial robust triangle

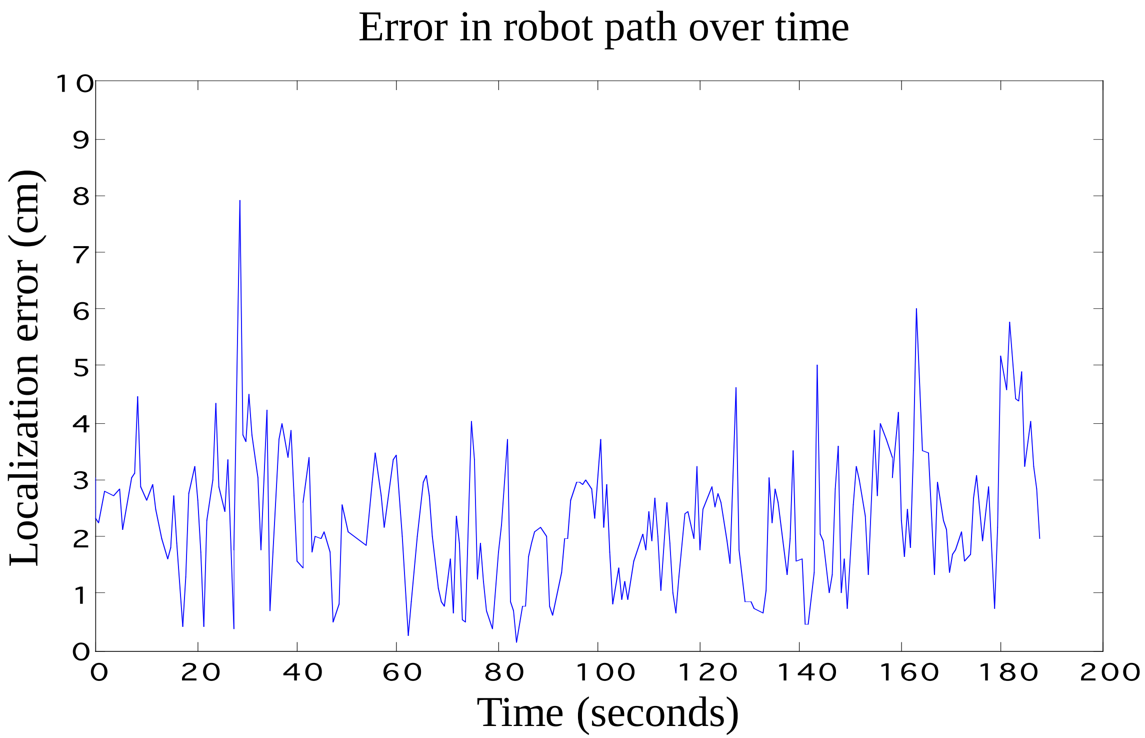


ALGORITHM (CONT.)



EXPERIMENTAL RESULTS





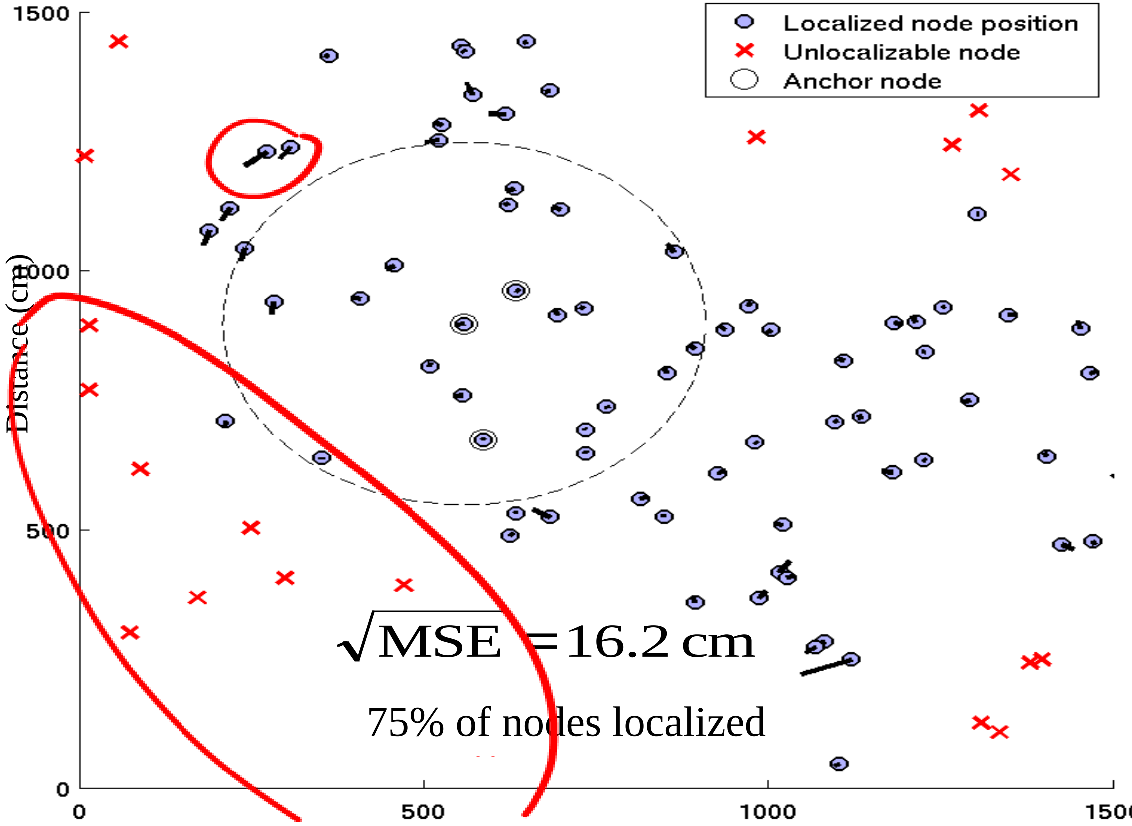
(Ground truth derived from computer vision algorithm applied to captured video)

SIMULATION RESULTS

Noise std. dev.
σ = 5.0 cm

Localized position versus ground truth

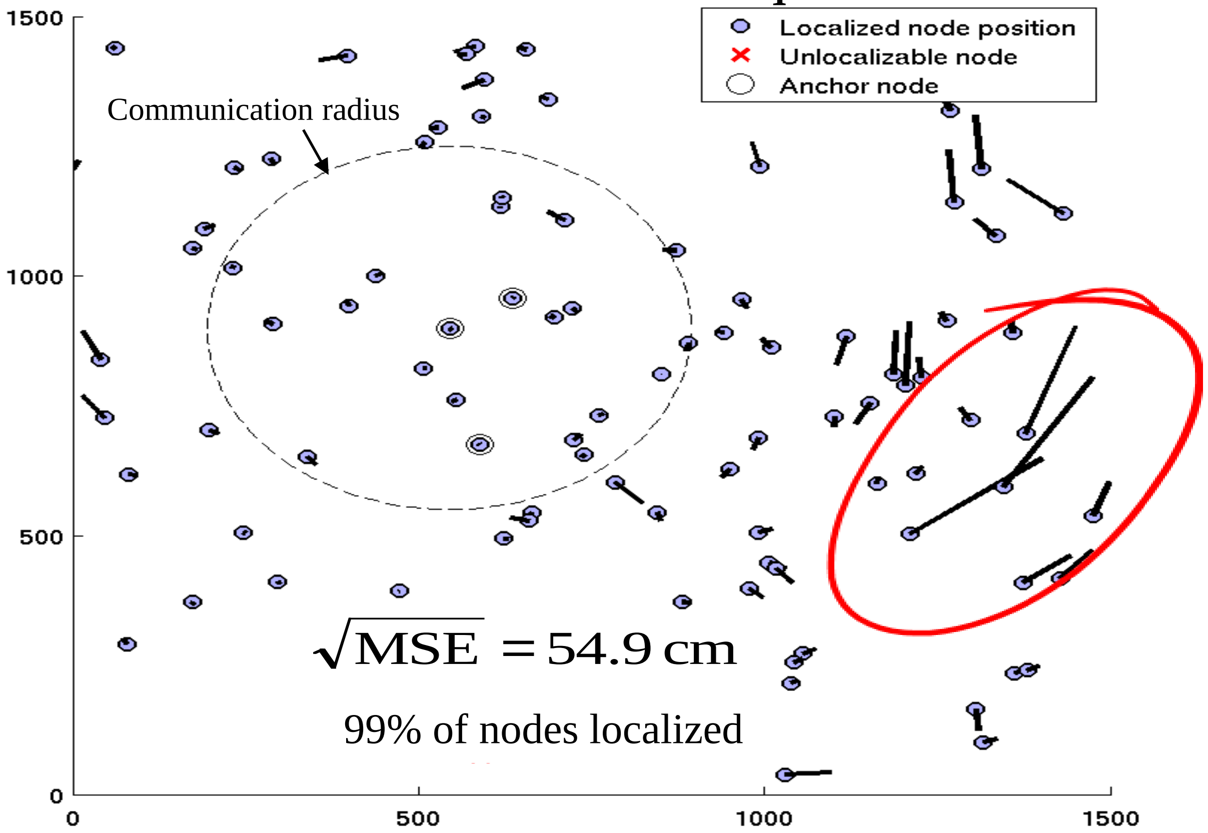
With robust quads



$$\sqrt{\text{MSE}} = 16.2\ \text{cm}$$

75% of nodes localized

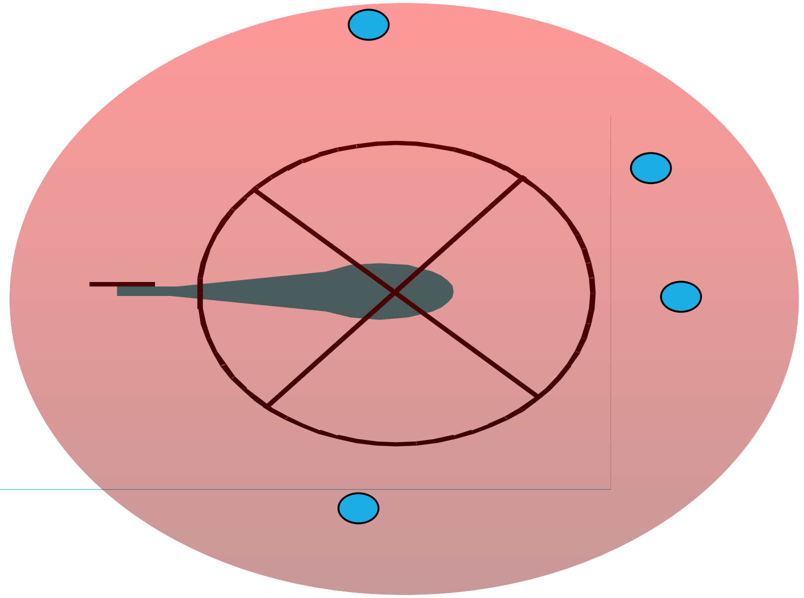
Without robust quads

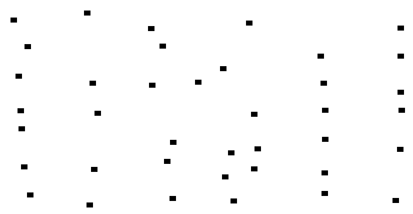


$$\sqrt{\text{MSE}} = 54.9\ \text{cm}$$

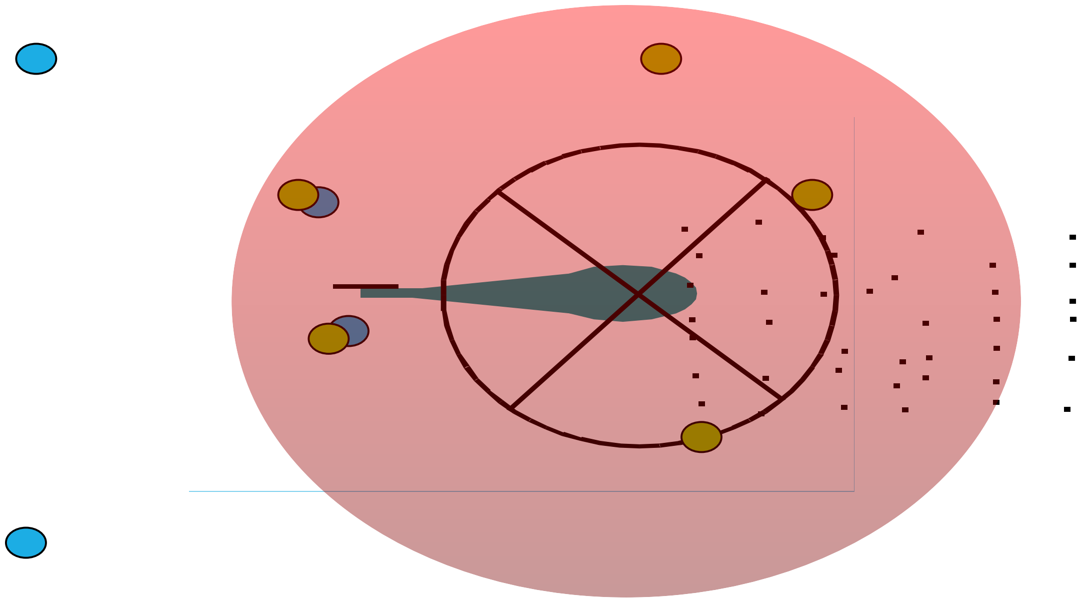
99% of nodes localized

Localizing the “left-over” nodes

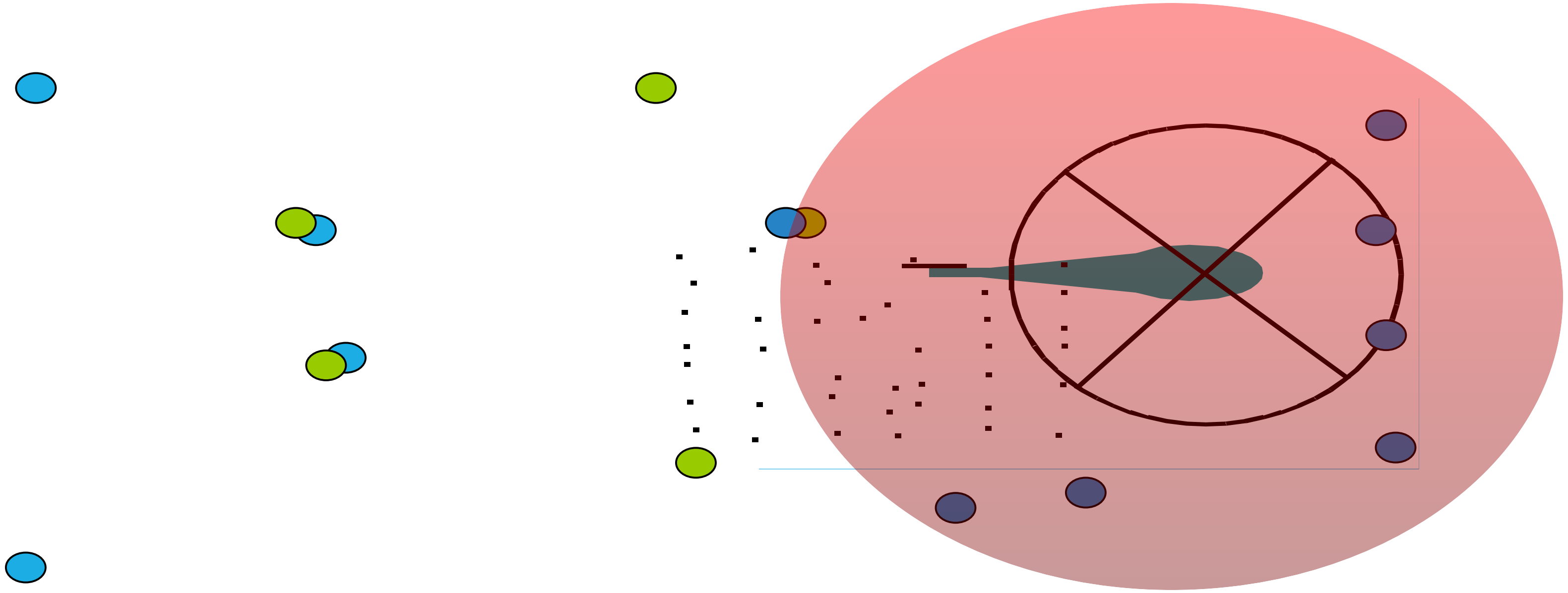




Robot broadcasts locations



Robot broadcasts locations



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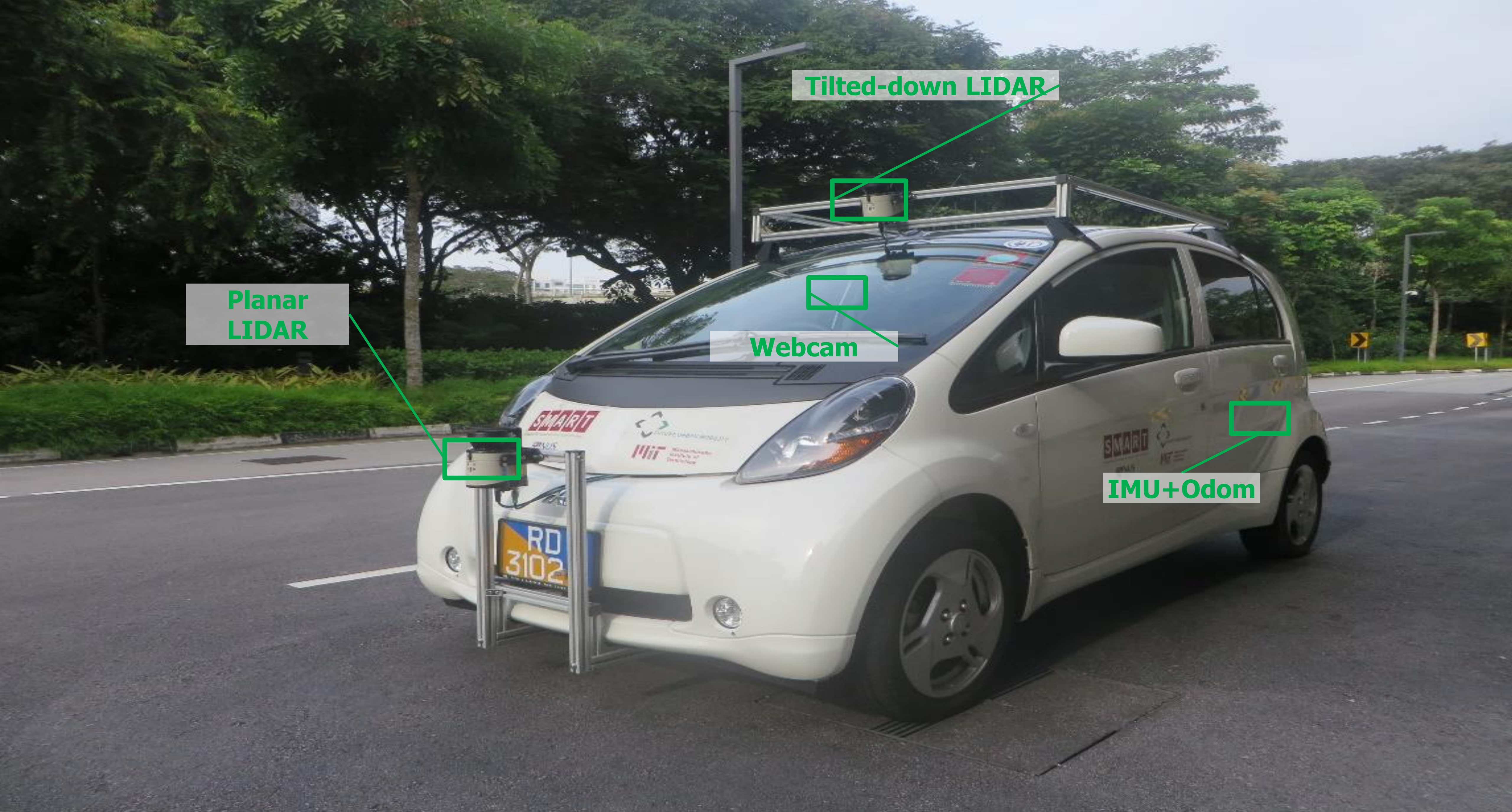
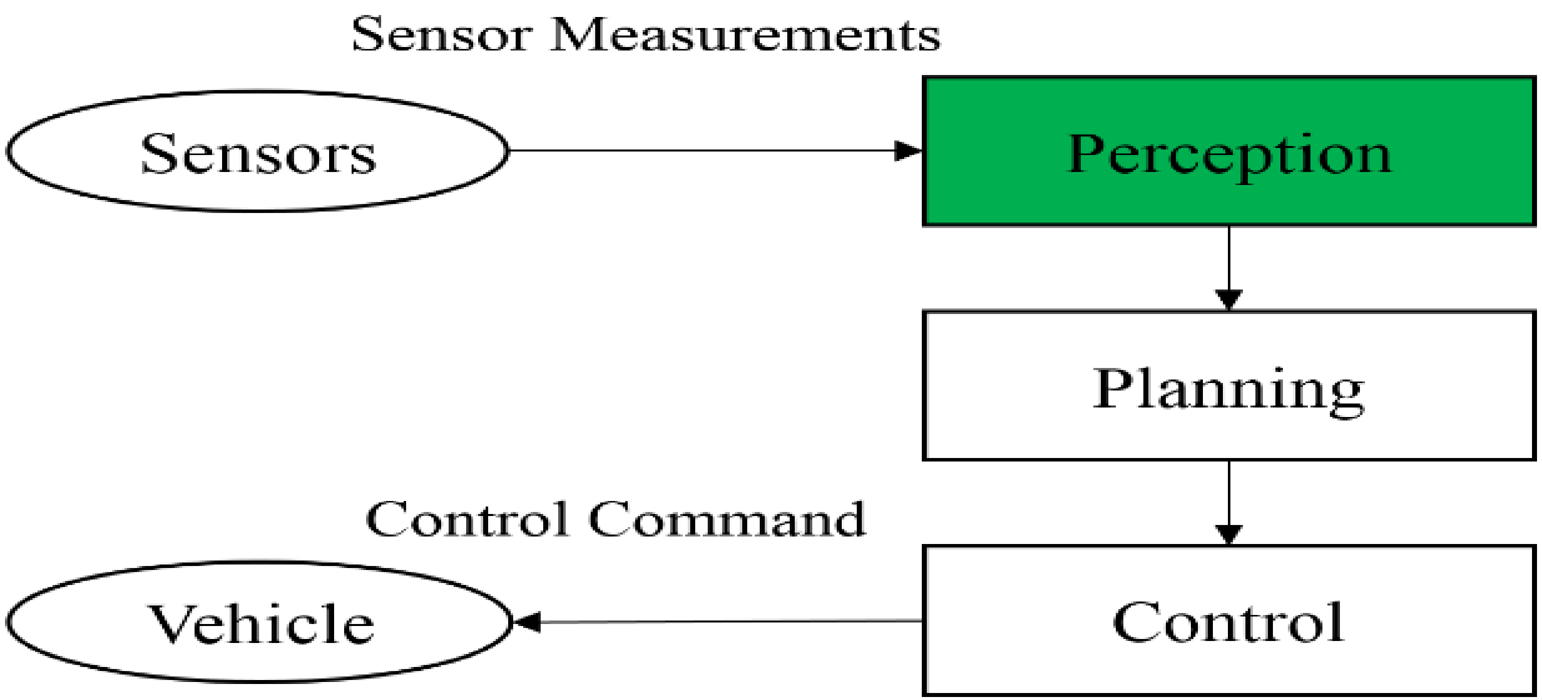
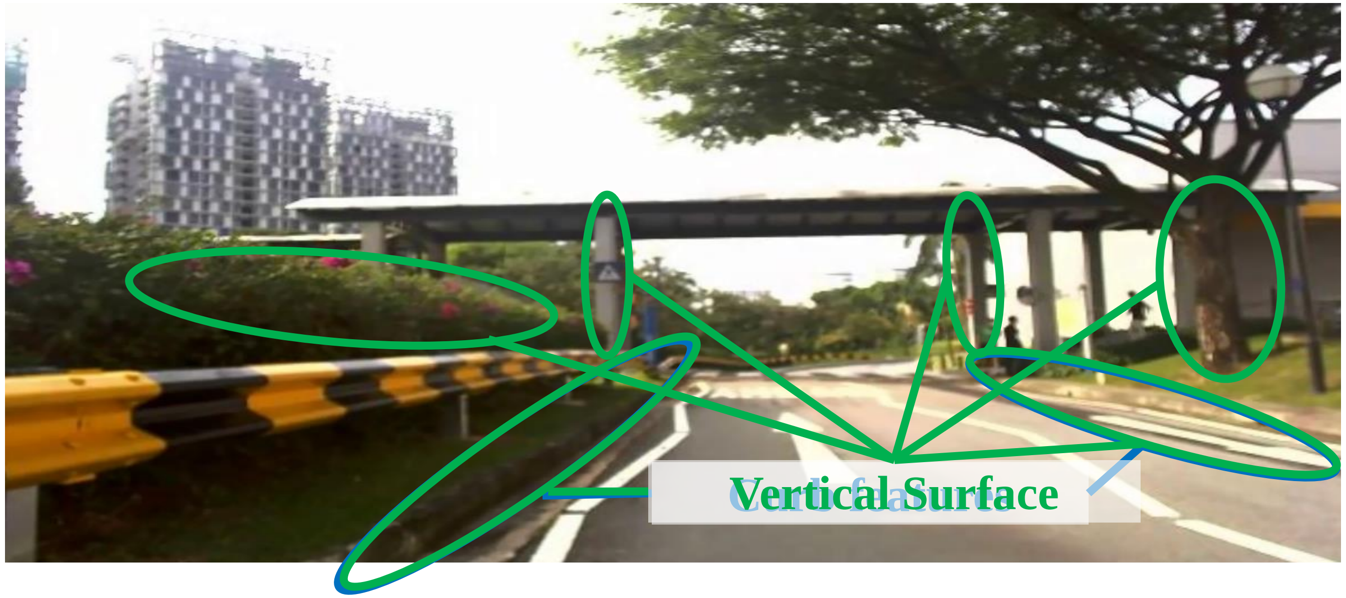
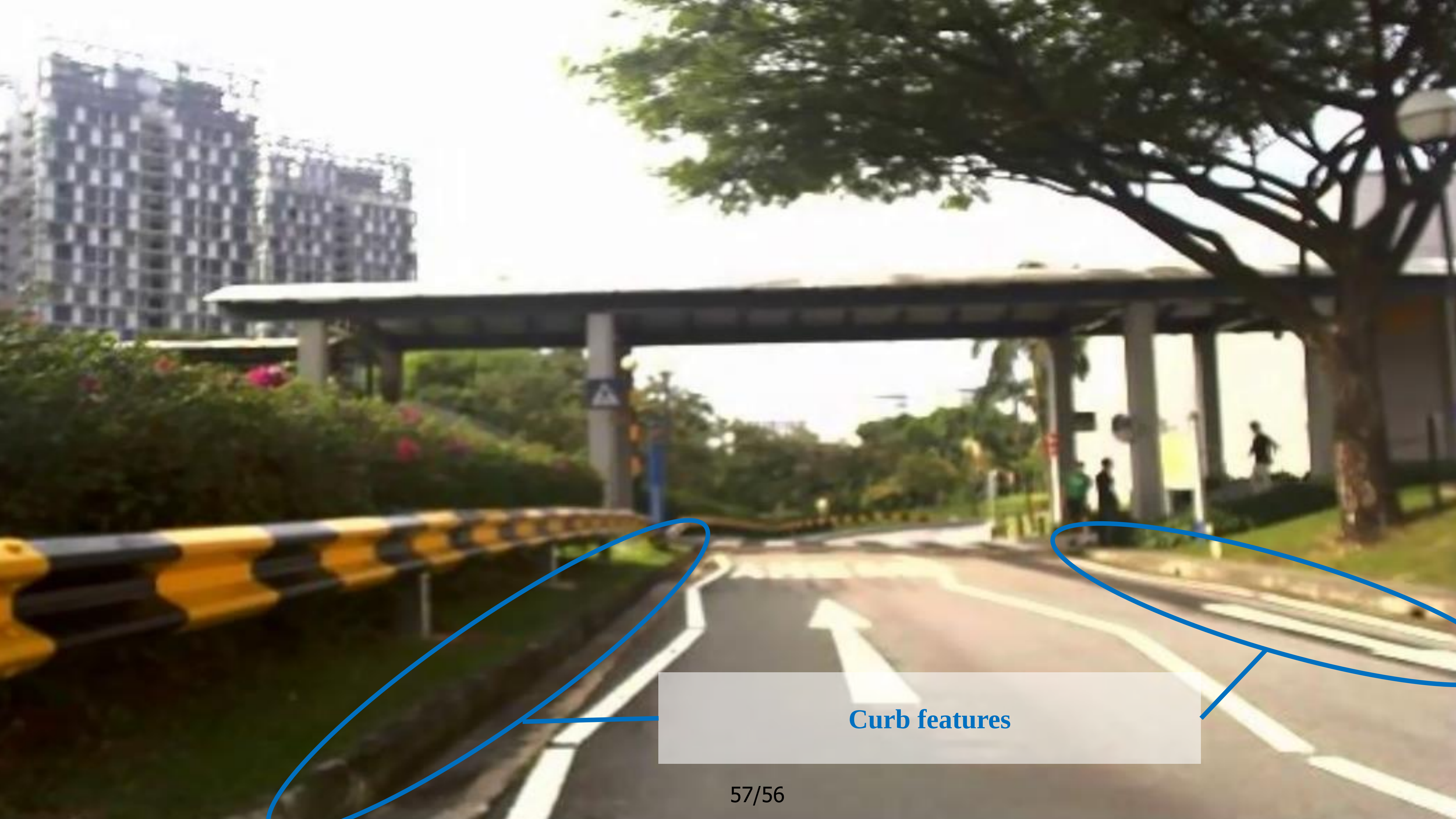
No Landmarks But Map

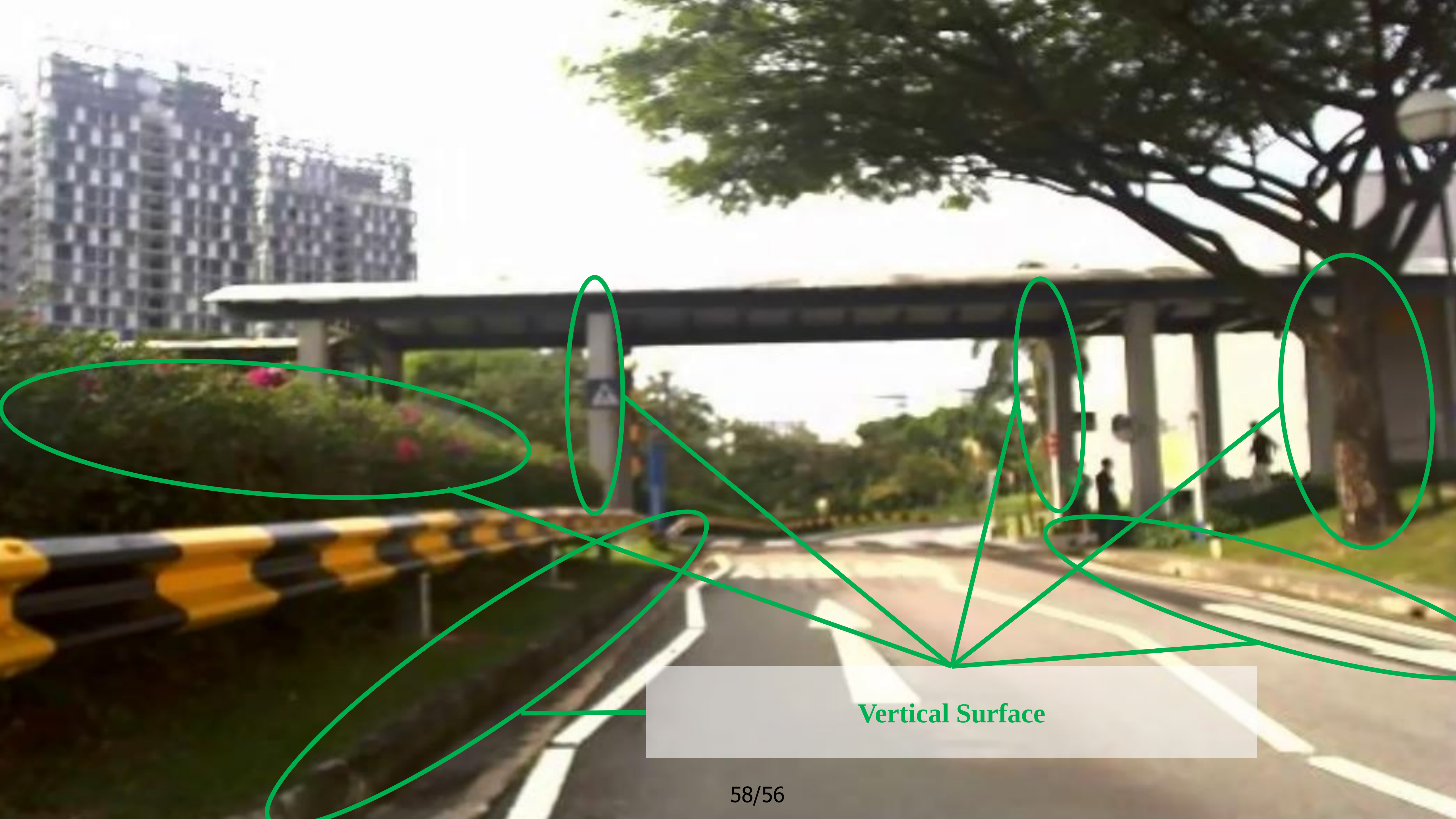
GPS


Tilted-down LIDAR
Planar LIDAR
Webcam
IMU+Odom
RD 3102
SMART

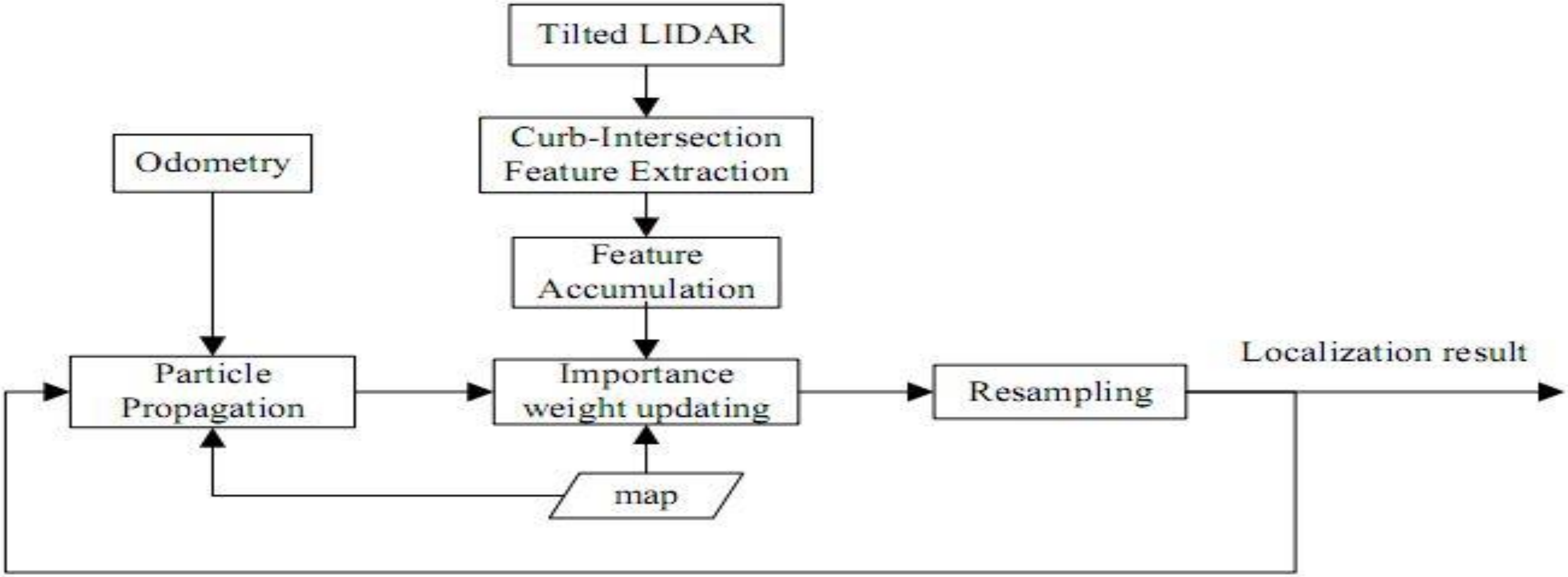

Sensor Measurements
Sensors
Perception
Planning
Control Command
Vehicle
Control


Vertical Surface


Curb features

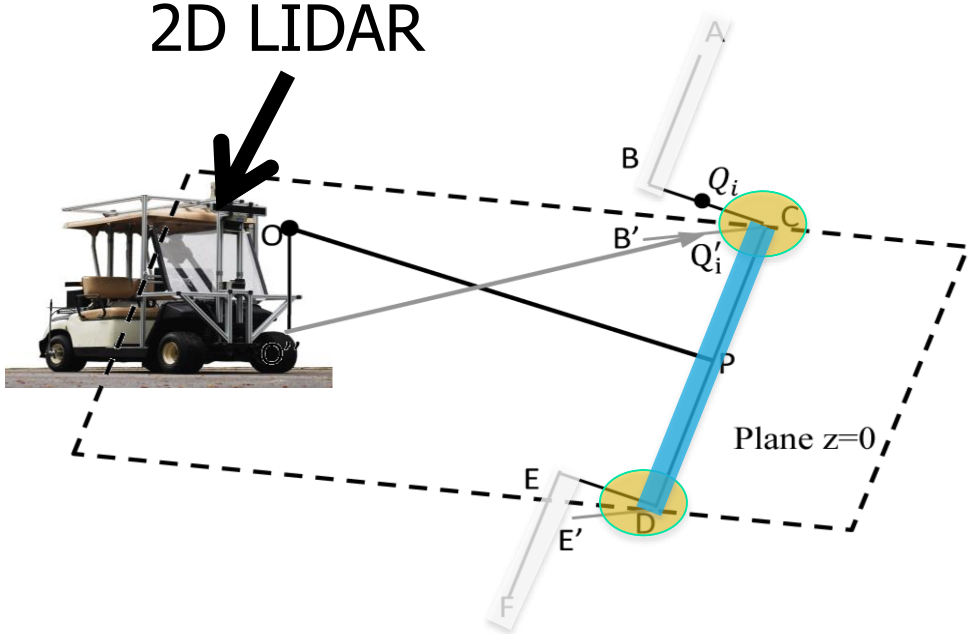

Vertical Surface

MONTE CARLO LOCALIZATION FOR POSE

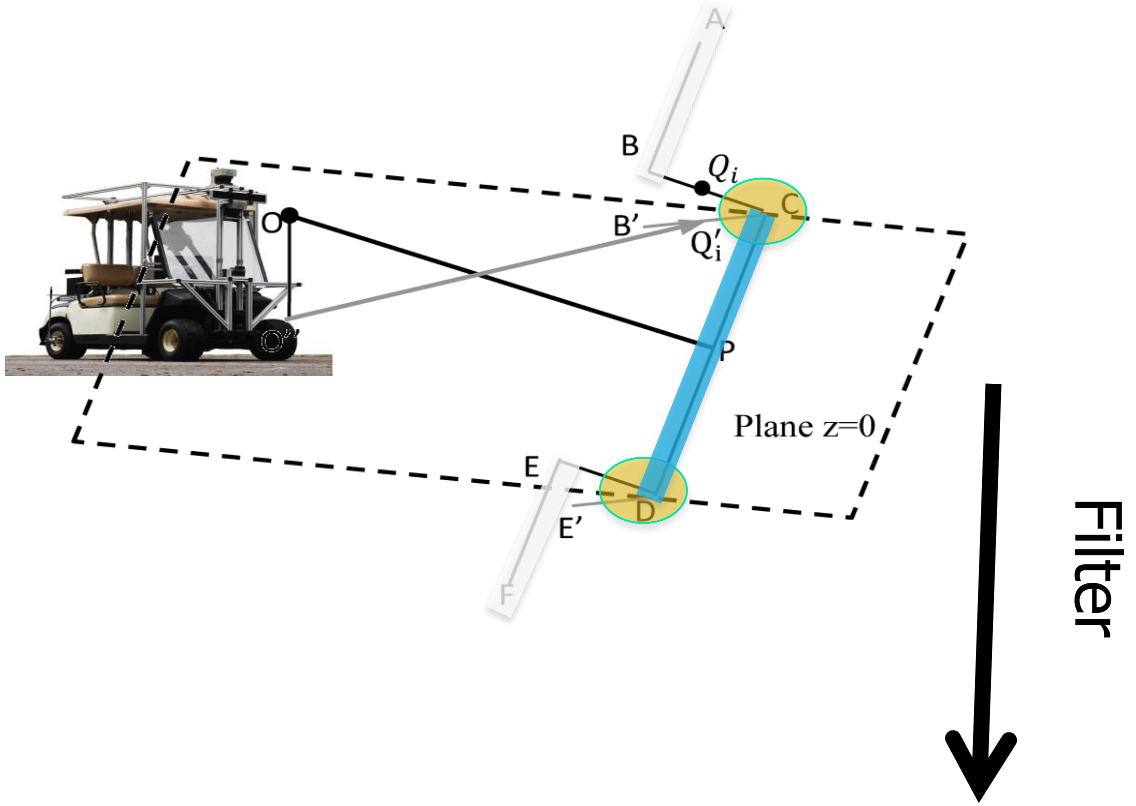


CURB-INTERSECTION FEATURE EXTRACTION

2D LIDAR

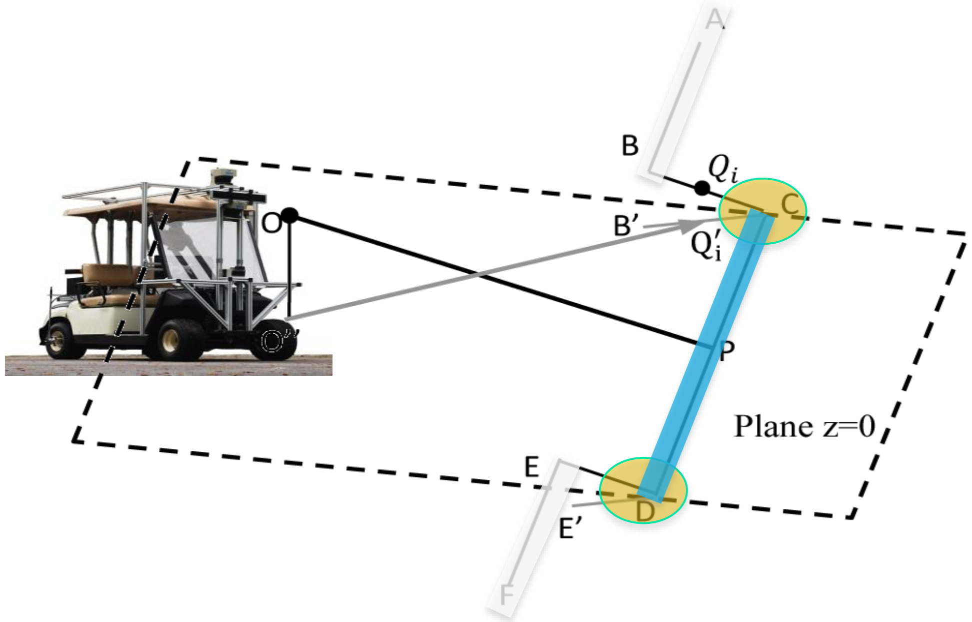


CURB-INTERSECTION FEATURE EXTRACTION

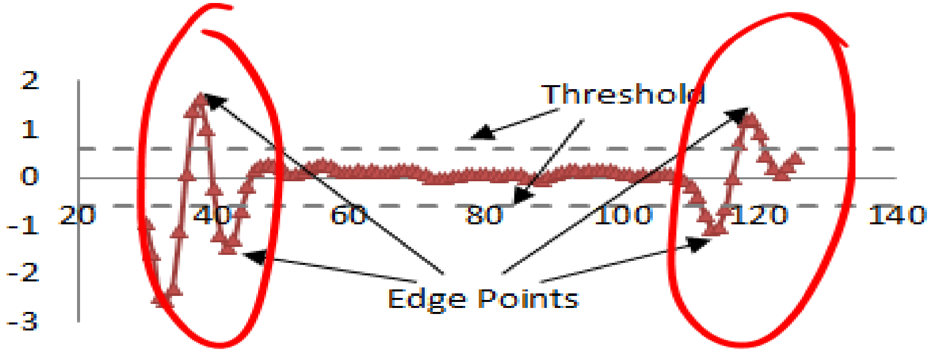


$$r_f(\theta) = \sum_{i=-5}^{i=-3} r\,(\theta + i * \mu) + \sum_{i=3}^{i=5} r\,(\theta + i * \mu) - \sum_{i=-2}^{i=0} r\,(\theta + i * \mu) - \sum_{i=0}^{i=2} r\,(\theta + i * \mu)$$

CURB-INTERSECTION FEATURE EXTRACTION



Filter



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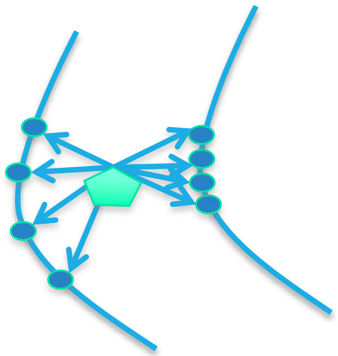
VIRTUAL SENSORS FOR CURB AND INTERSECTION

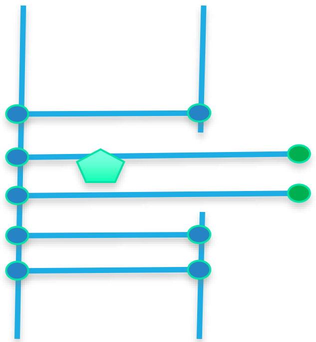
Virtual LIDAR of Curb features (accumulates and fuses points)

Likelihood model



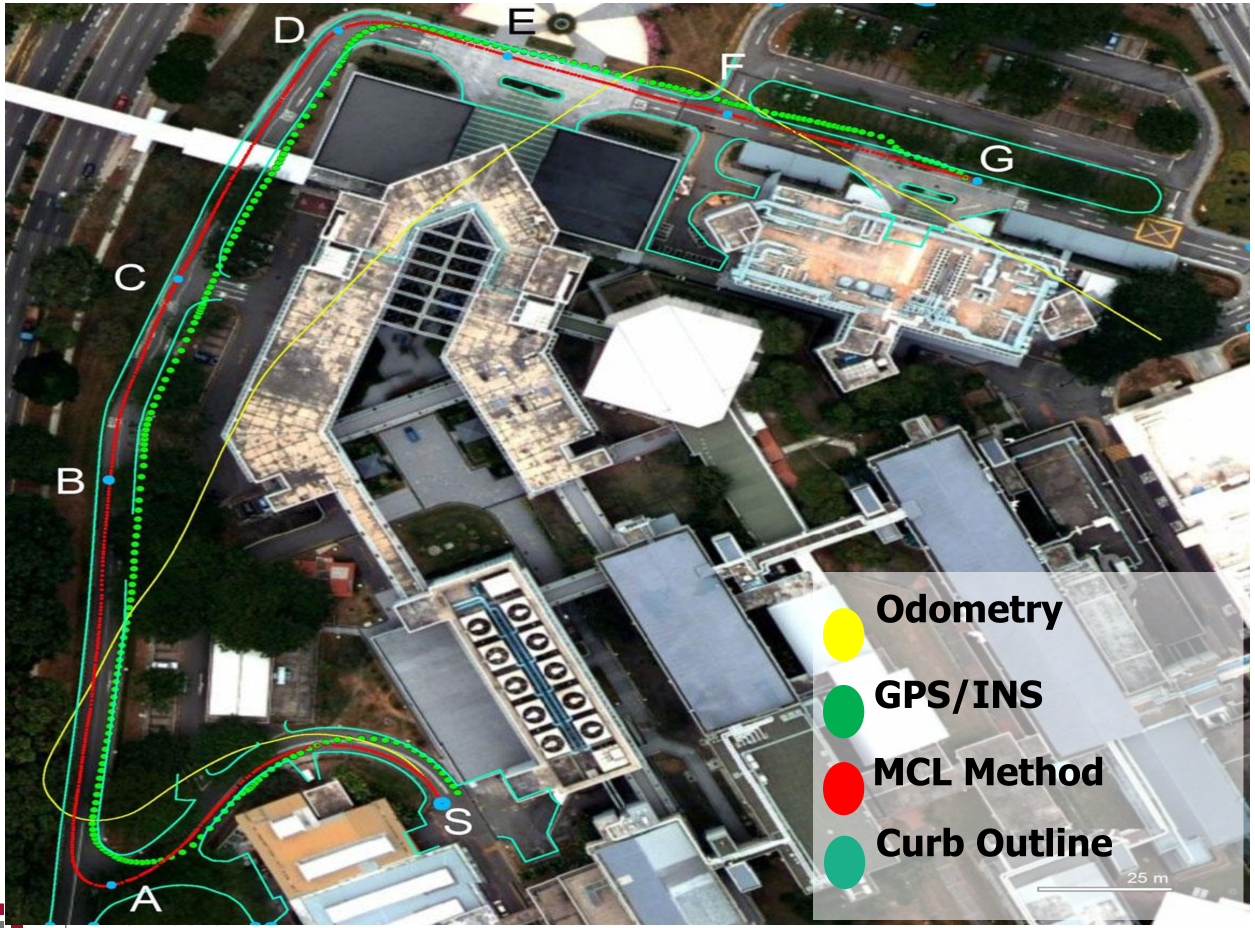
Virtual LIDAR of intersection features (triggered when there are no curb points)

Beam model

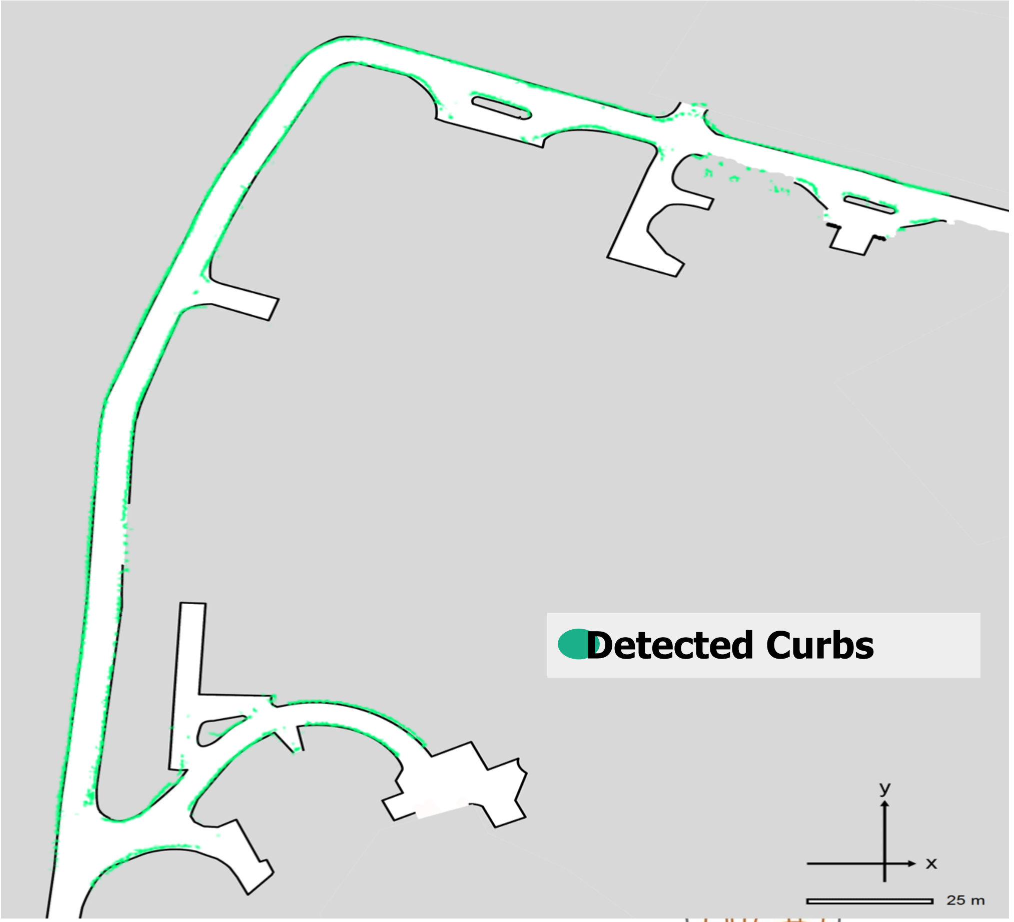


EXPERIMENTAL EVALUATION OF MCL

Localization Results

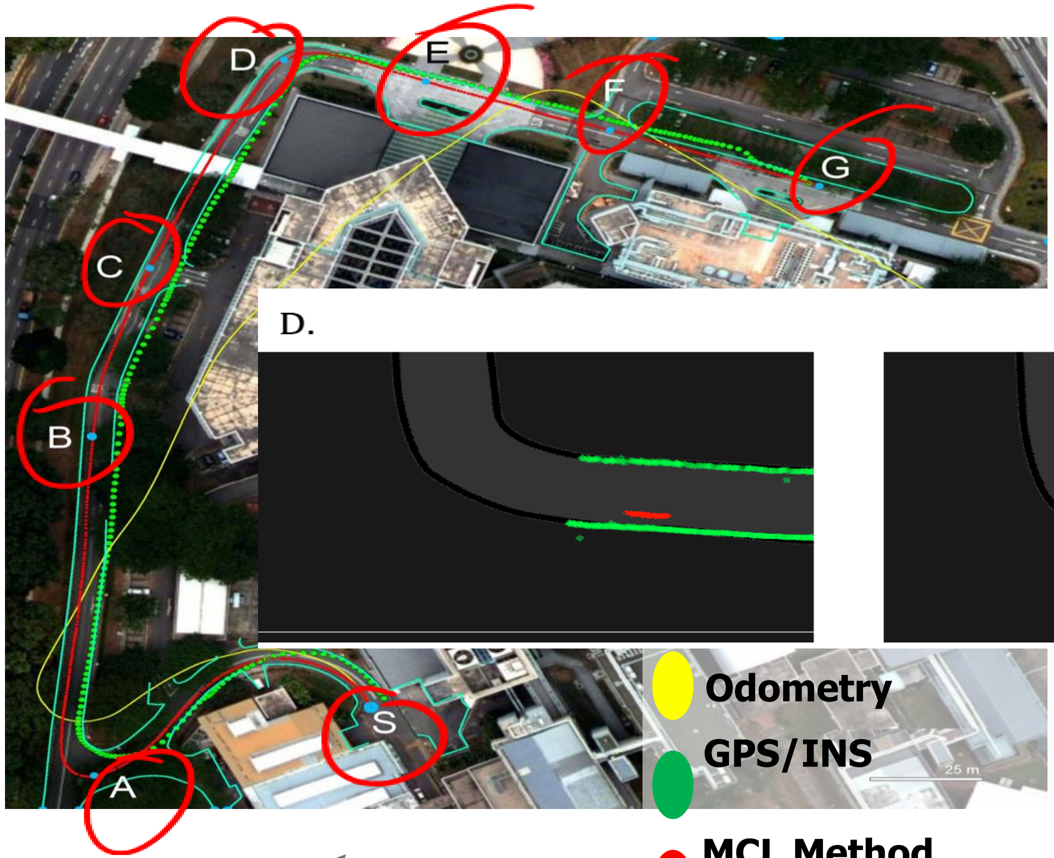


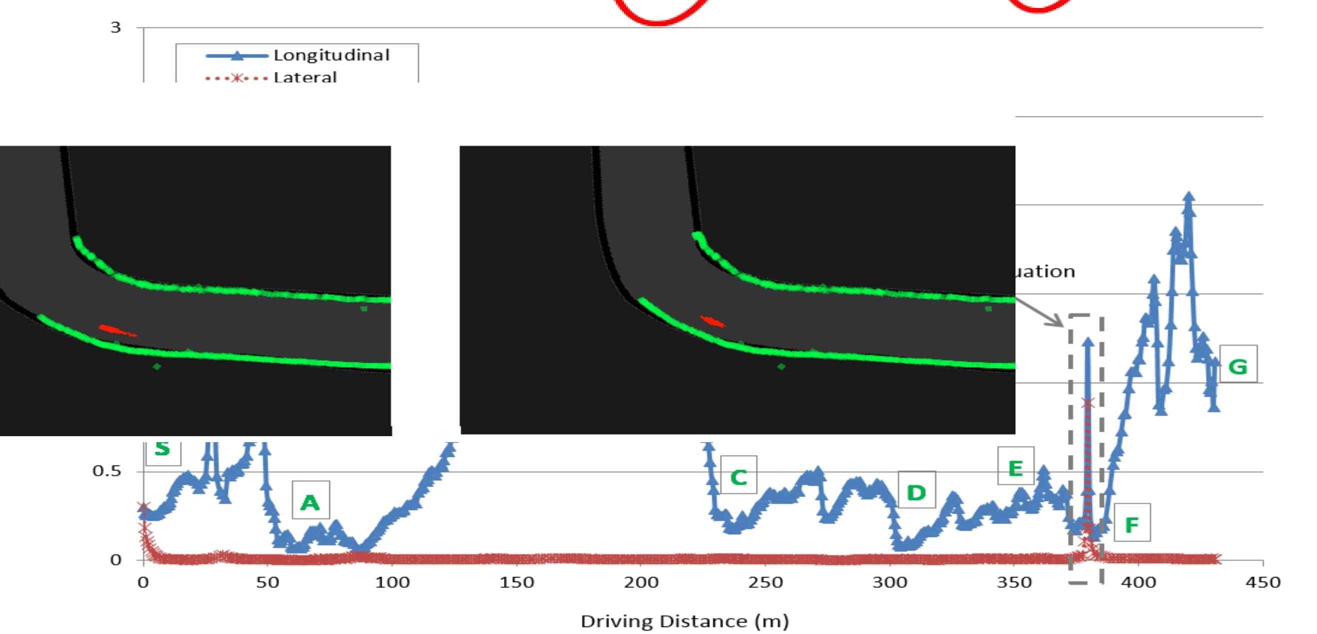
Curb Map



LOCALIZATION ACCURACY

Marked Points	A	B	C	D	E	F	G
Position Error (m)	0.20	0.55	0.06	0.20	0.32	0.06	0.08
Orientation Error (degree)				< 3			



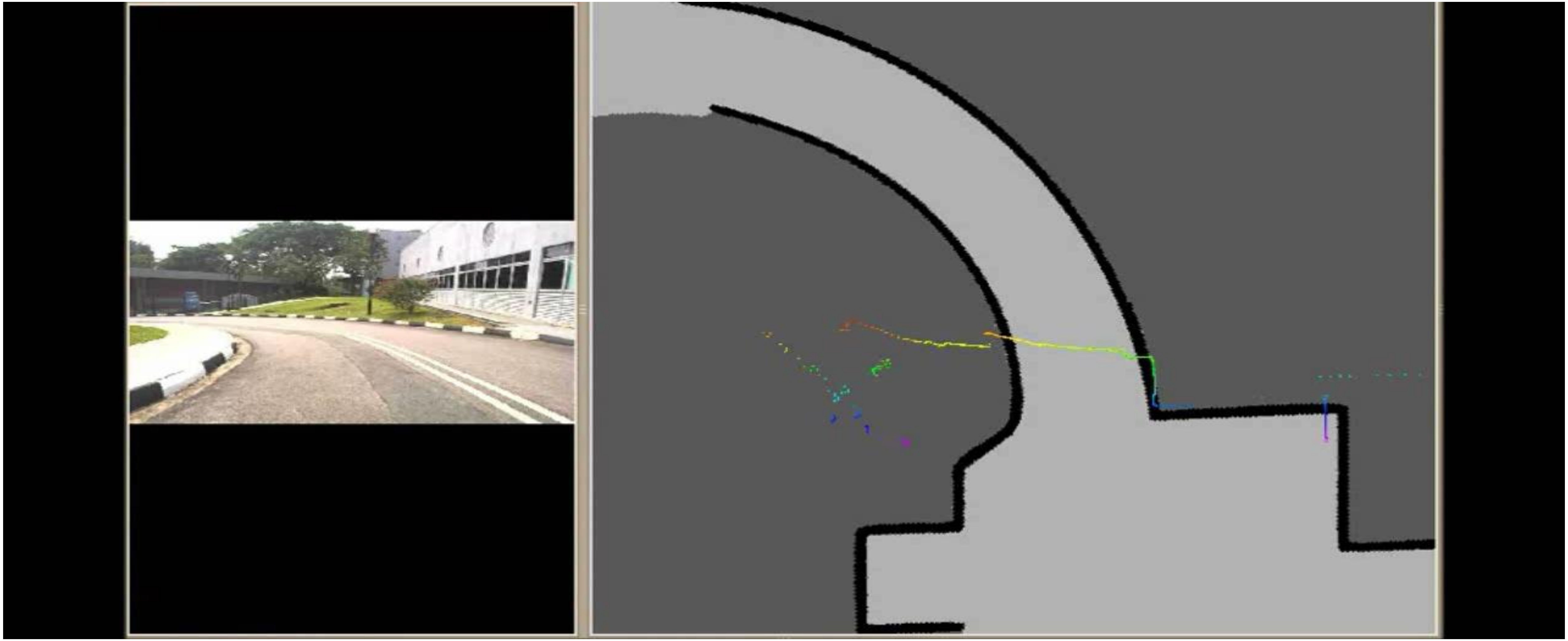


Odometry

GPS/INS

MCL Method

Curb Outline



ZJ Chong, B. Qin, T. Bandyopadhyay, M. Ang, E. Frazzoli, D. Rus, Synthetic 2D LIDAR for Precise Vehicle Localization in 3D Urban Environment, Proceedings of the 2013 Int. Conf. on Robotics and Automation (ICRA), 2013 IEEE International Conference, pp 1554-1559

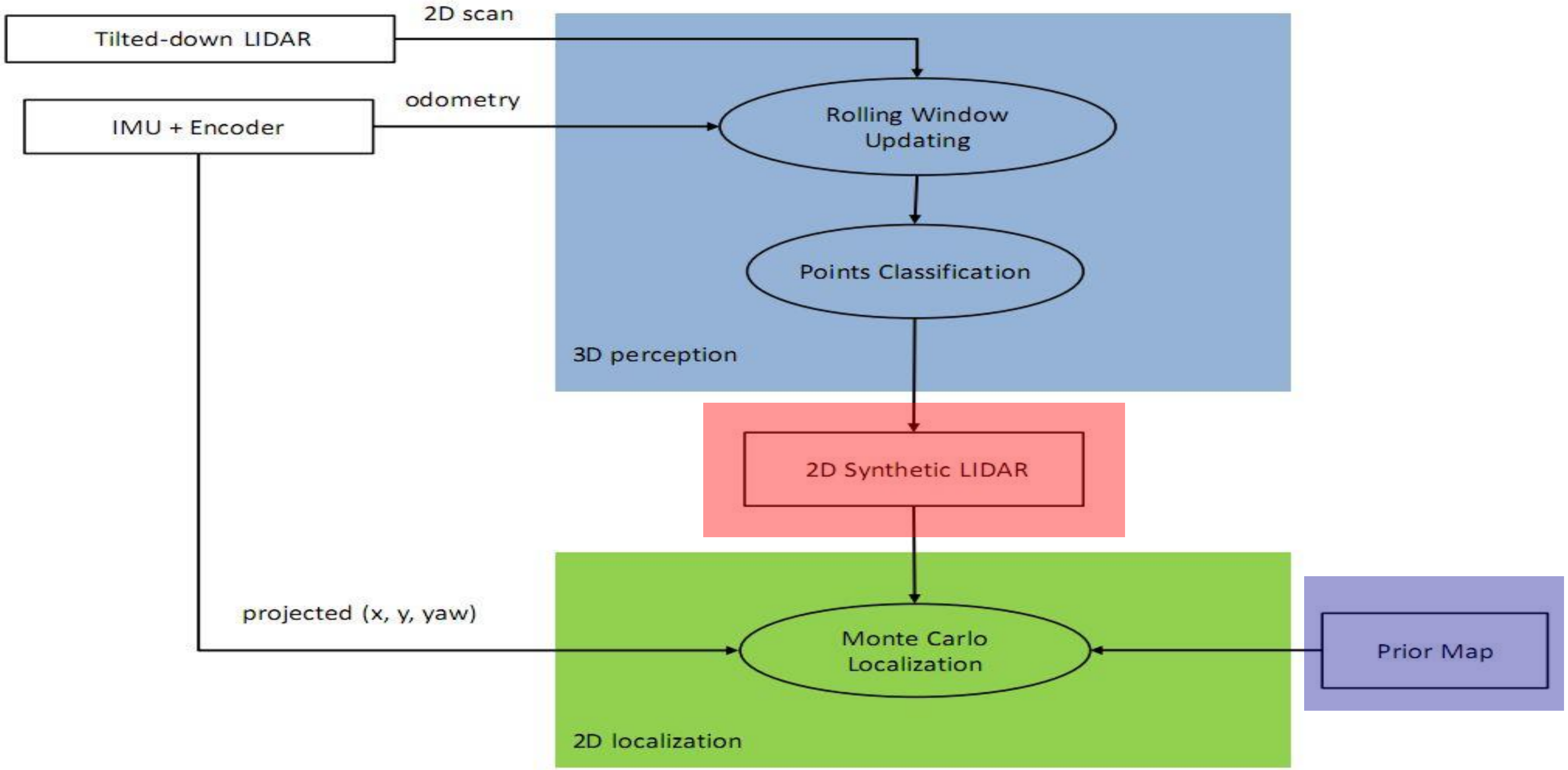
Curb-intersection features exist

Uncertainty on straight segments

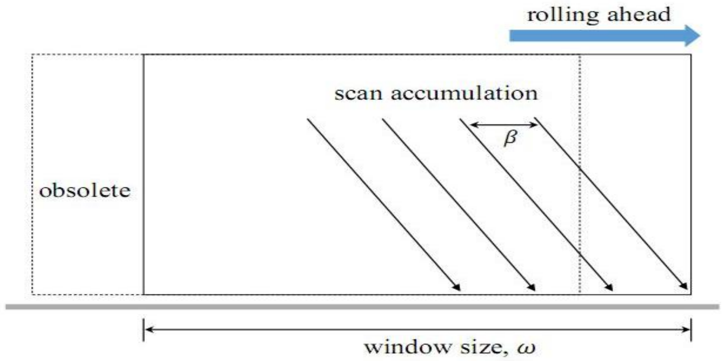
Curb-intersection features exist

Uncertainty on straight segments

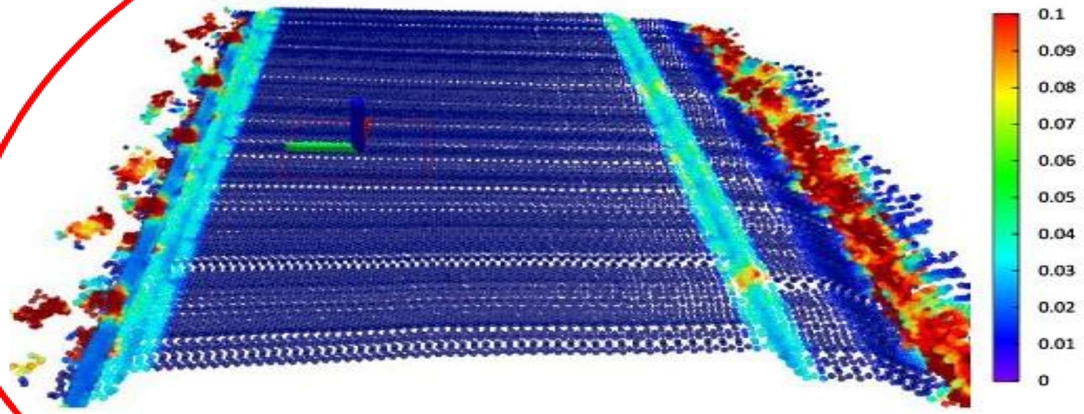
Use Vertical Surfaces

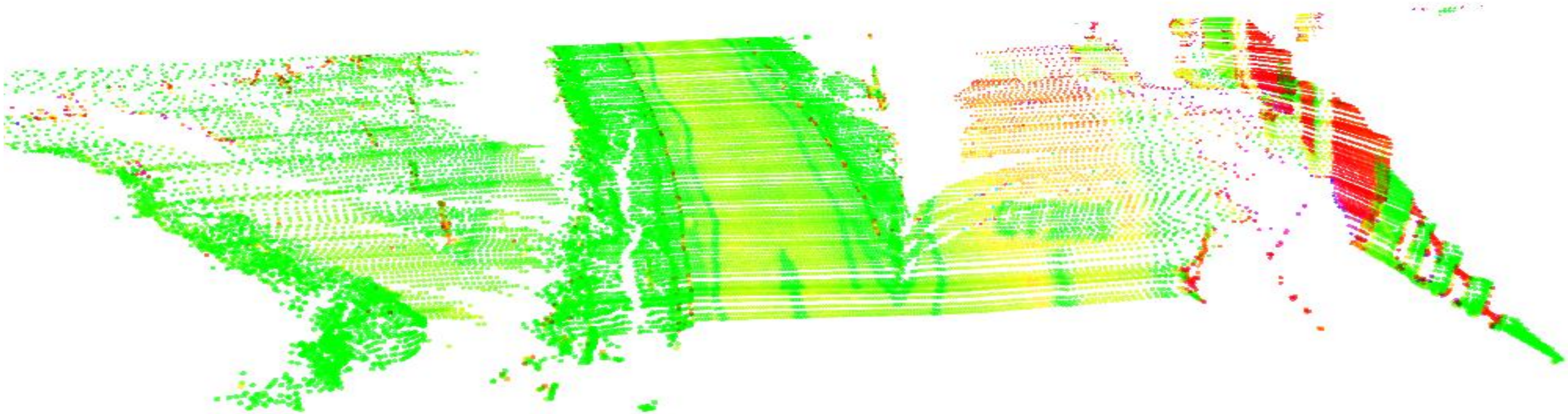

Tilted-down LIDAR
2D scan
IMU + Encoder
odometry
Rolling Window Updating
Points Classification
3D perception
2D Synthetic LIDAR
projected (x, y, yaw)
Monte Carlo Localization
Prior Map
2D localization

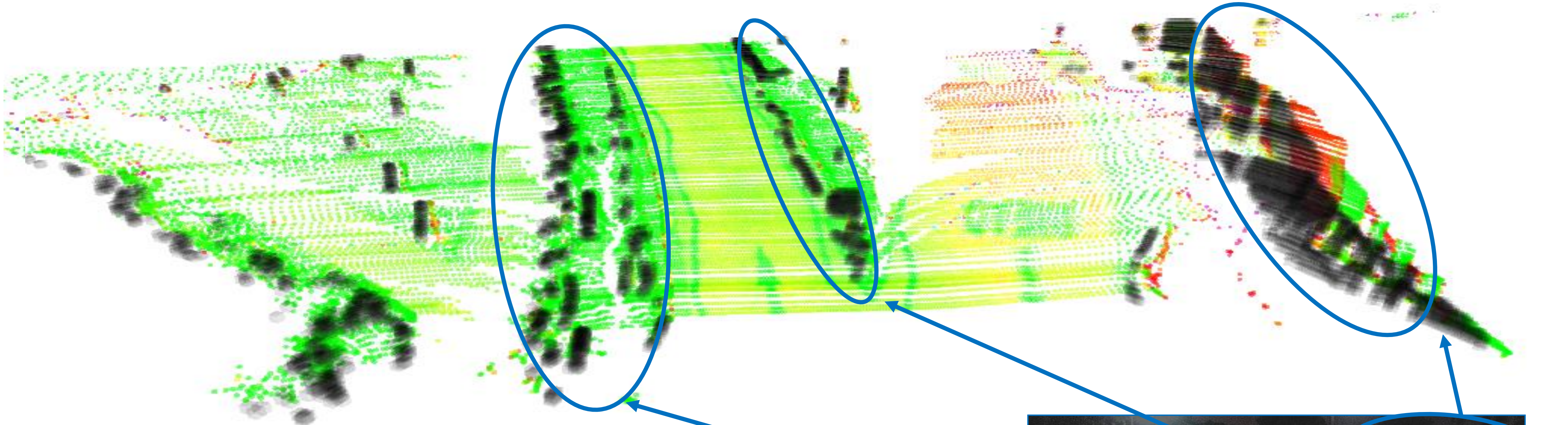
3D ROLLING WINDOW FOR FEATURES

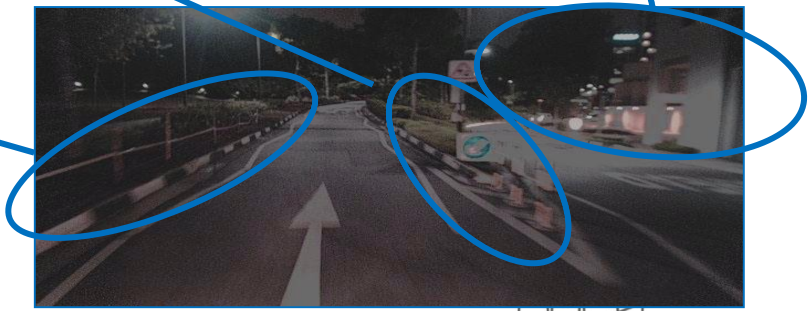


$$P_n = \bigcup_{k=n-\lfloor w/\beta \rfloor} \{p_k, \ldots, p_n\} \quad n > \lfloor w/\beta \rfloor$$

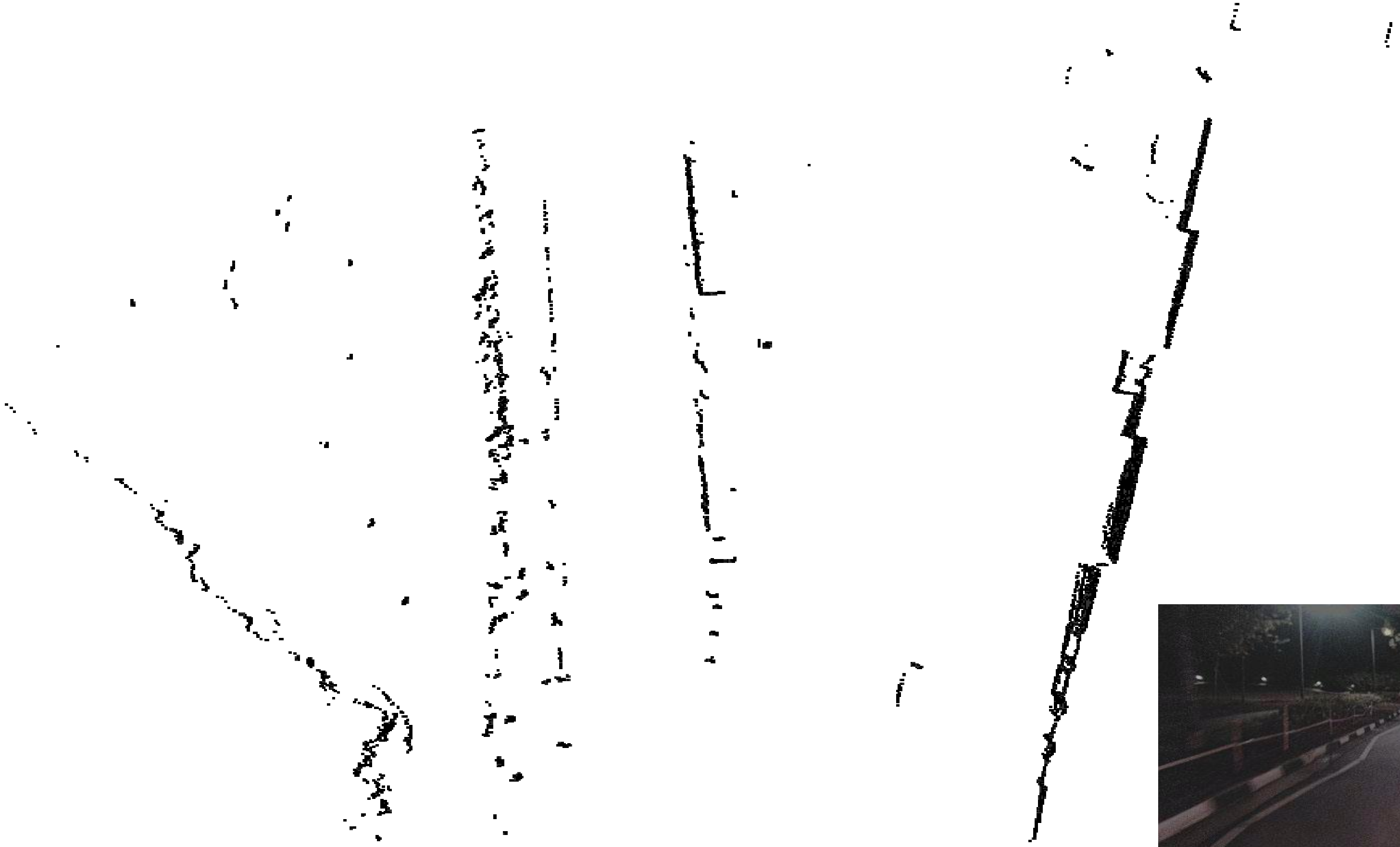






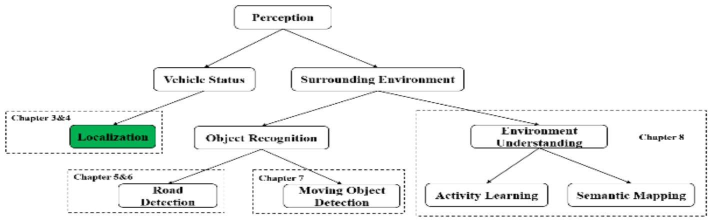


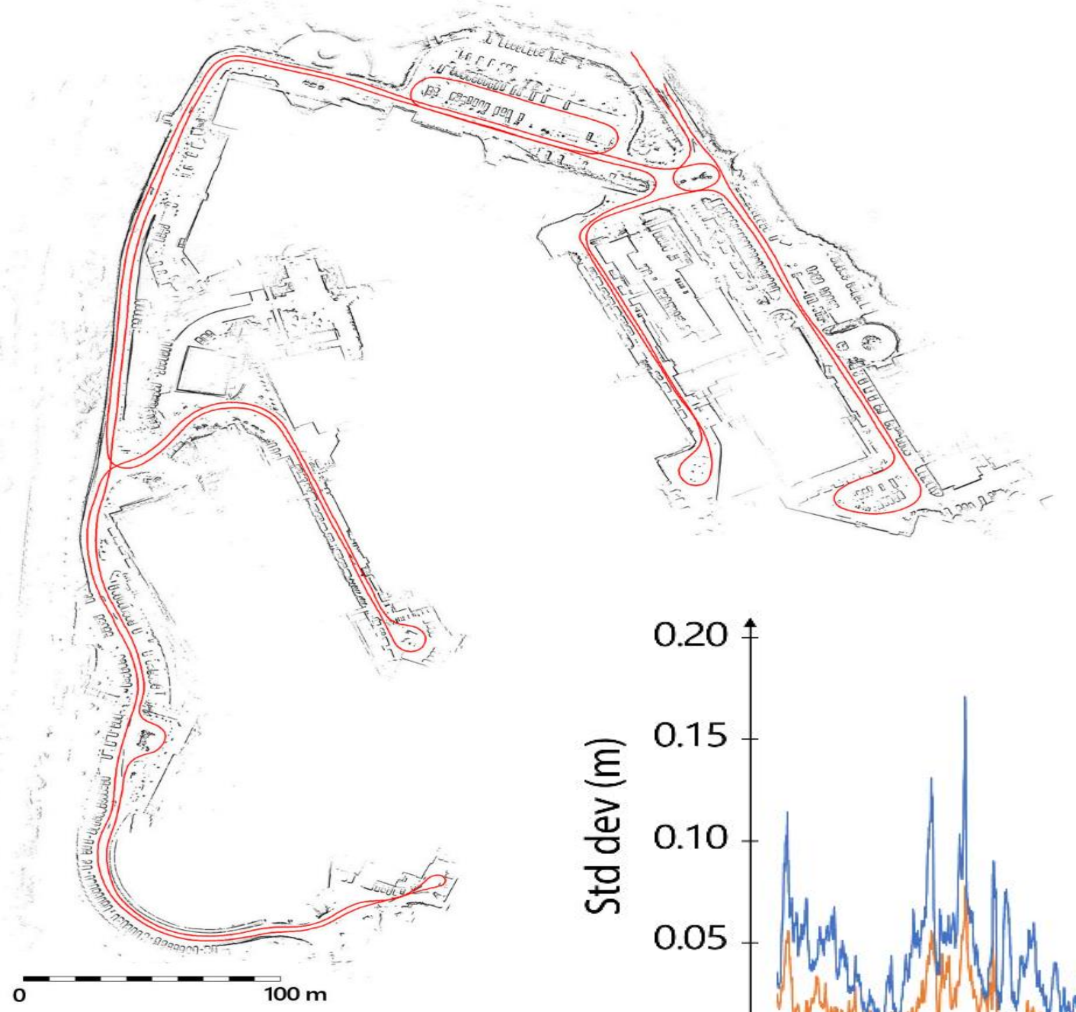
Surface normal
For classification

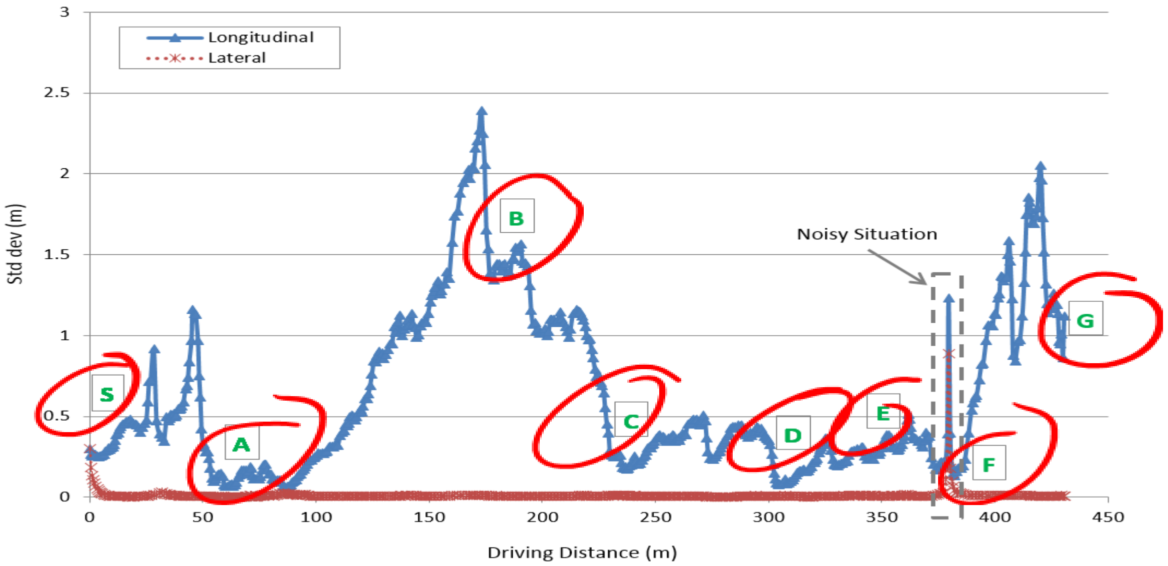


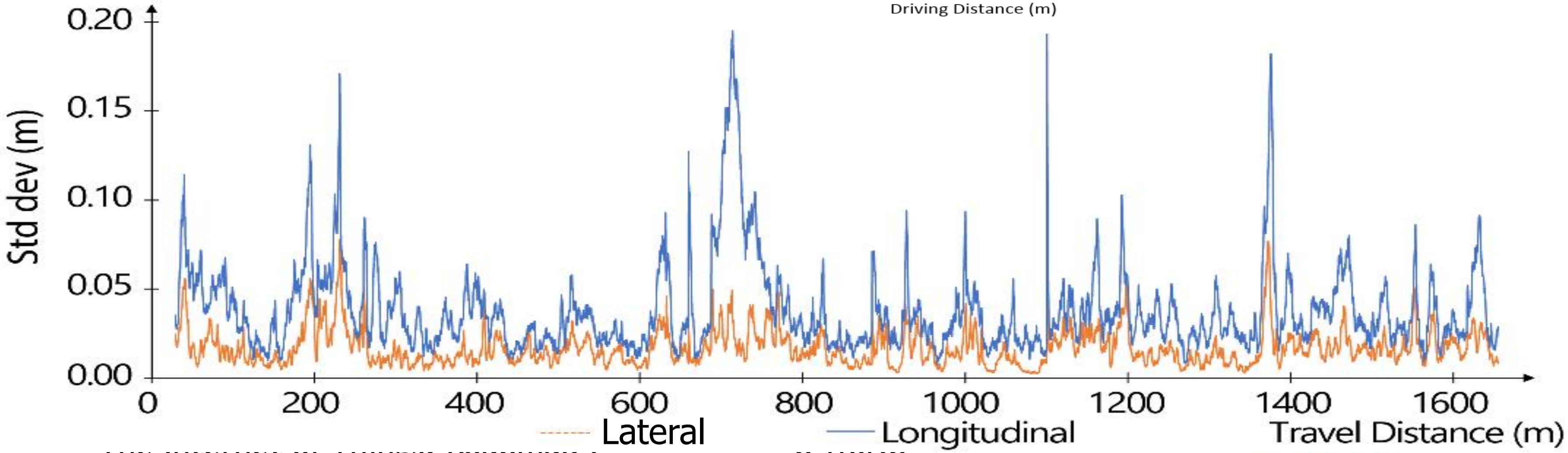

AHEAD

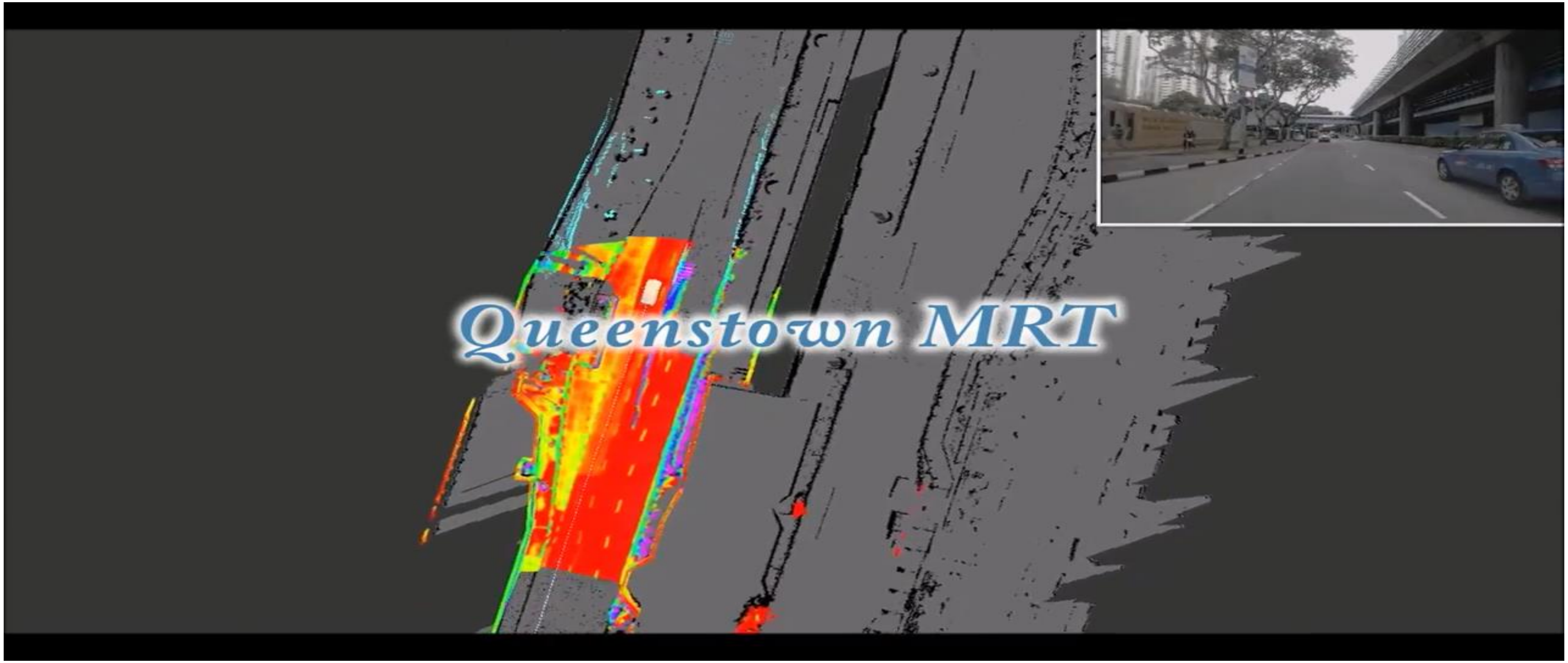
Synthetic LIDAR based localization











ZJ Chong, B. Qin, T. Bandyopadhyay, M. Ang, E. Frazzoli, D. Rus, Synthetic 2D LIDAR for Precise Vehicle Localization in 3D Urban Environment, Proceedings of the 2013 Int. Conf. on Robotics and Automation (ICRA), 2013 IEEE International Conference, pp 1554-1559

OUTLINE

Introduction to Localization

Robust Localization

Outdoors Localization

Indoors Localization

INDOOR GPS TODAY?

Businesses

Research

[RADAR'00], [Cricket'04], [Lease'04], [Horus'05], [PlaceLab'05], [Beepbeep'07], [SrndSense'09], [EZ'10], [Compac'10],[BatPhone'11], [Wigem'11], [Zee '12], [Will'12],[Centaur'12], [Unloc'12], [PinLoc'12], [FootSlm'12], [ArrayTrack'13], [Guoguo'13] , [PinPoint'13],...

S. Kumar, S. Gil, D. Katabi, D. Rus, Accurate Indoor Localization with Zero Startup Cost, Proceedings of Mobicom 2014.

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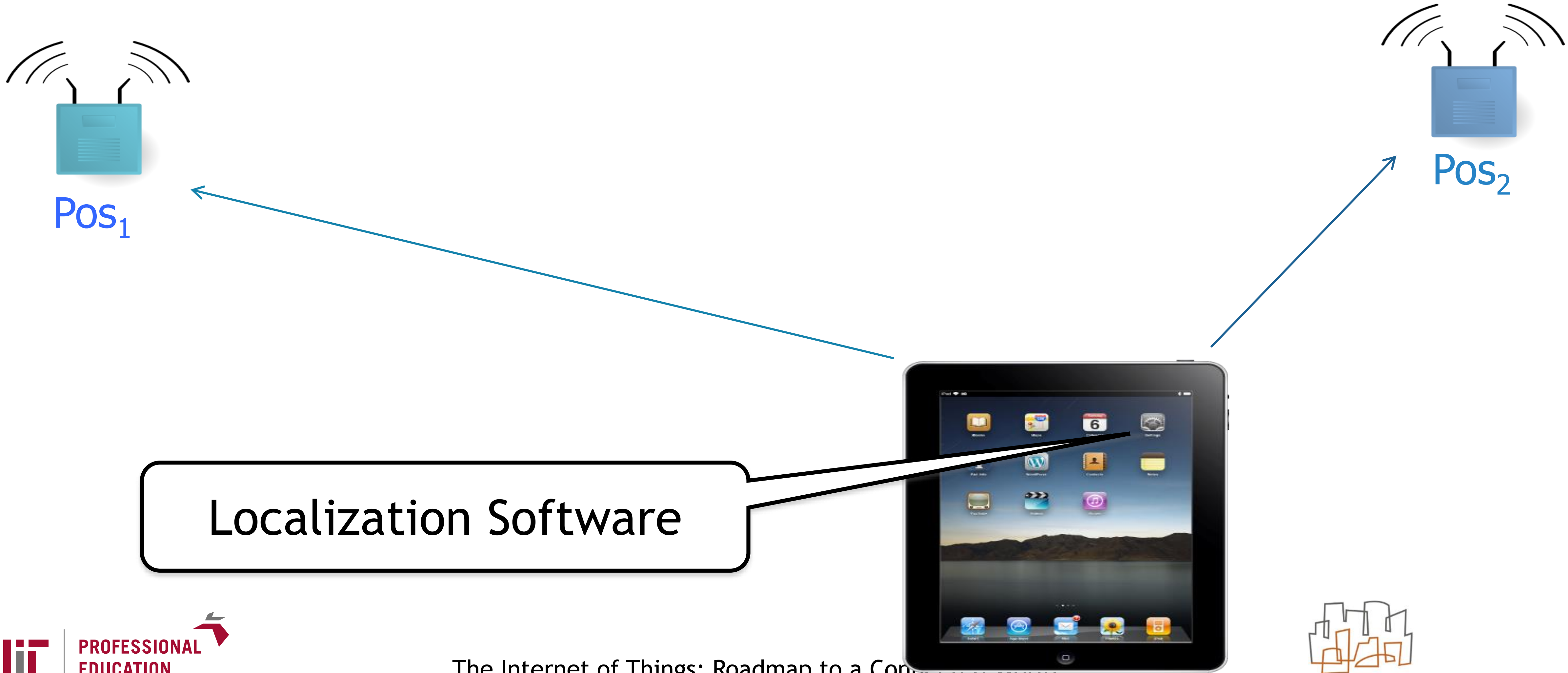
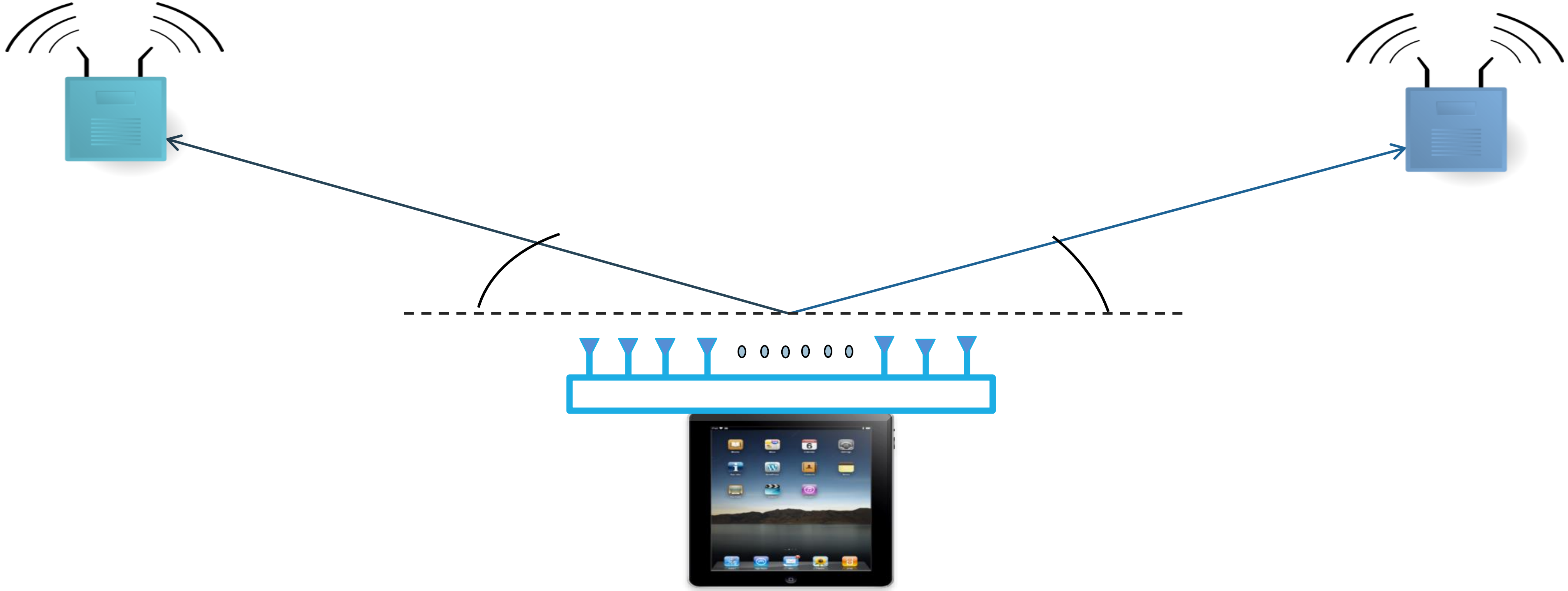


Pos_1
Pos_2
Localization Software

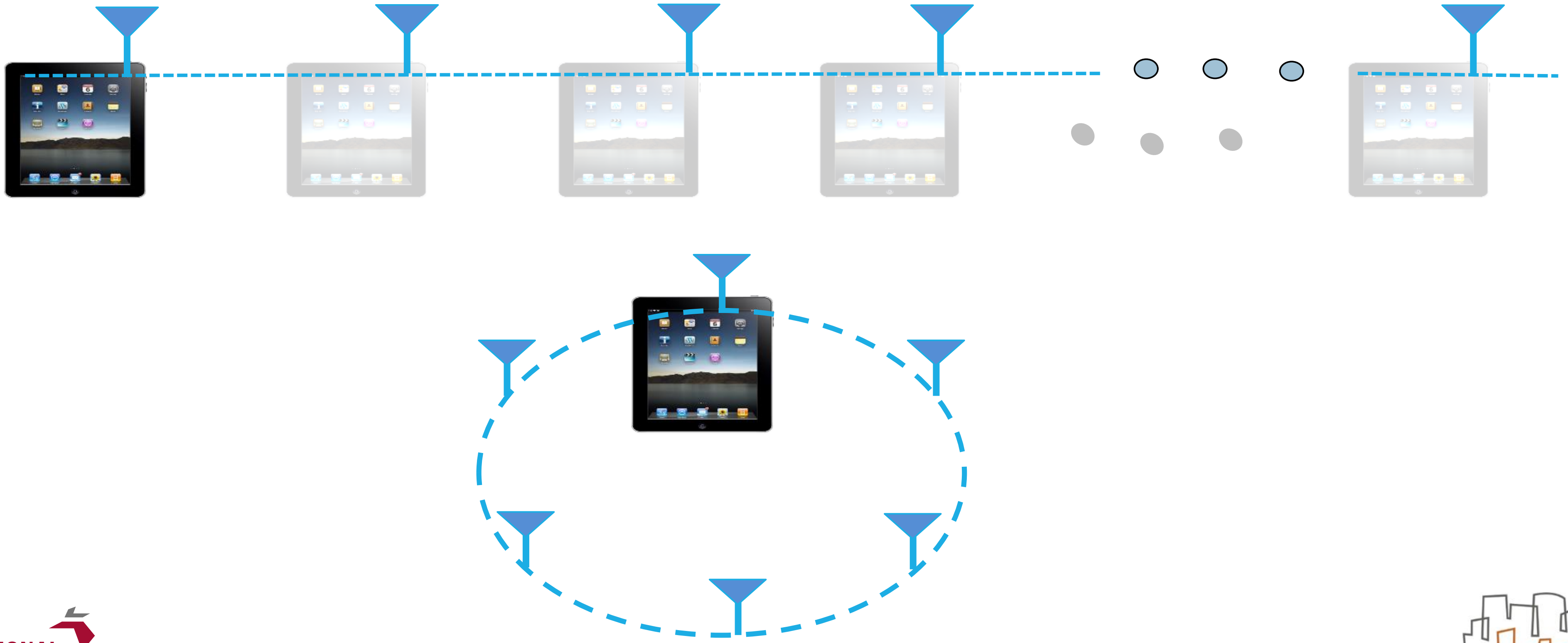
WITH MANY ANTENNAS…



Such a device does not exist!

SYNTHETIC APERTURE RADAR (SAR)

Move device to emulate “antenna array”



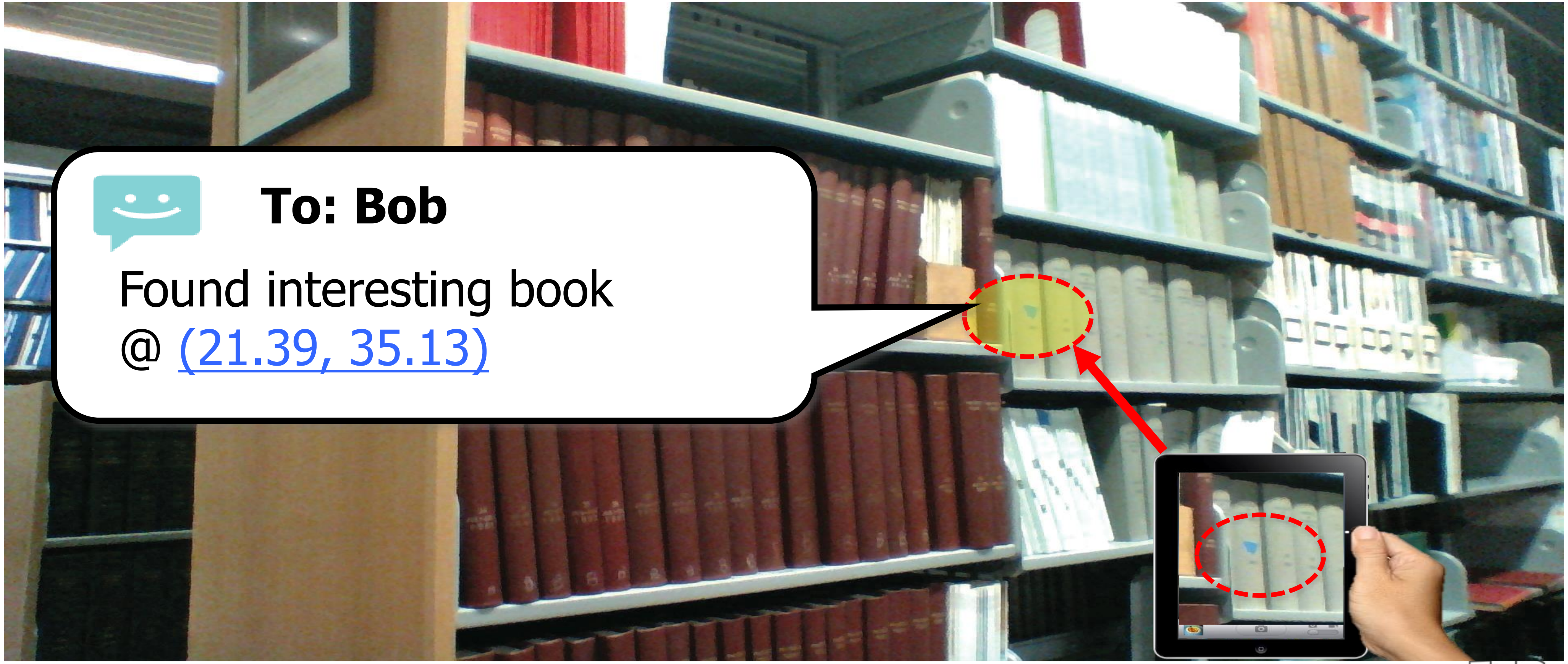
- Users to rotate tablet

- Process signals as circular array

EVALUATION

- Large Library – 5 Access Points
- <u>Baseline:</u> Angle-of-Arrival using 2-Antenna Array

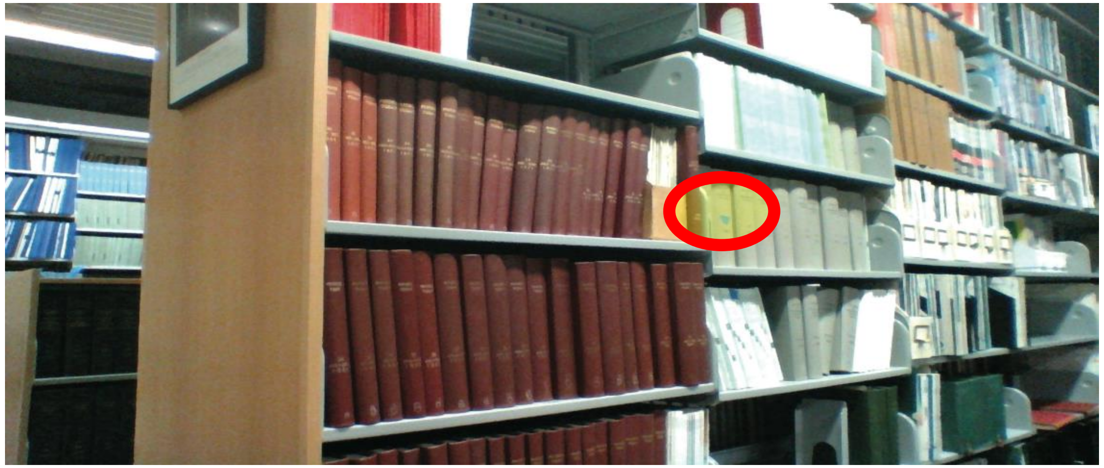
LOCALIZING OBJECTS OF INTEREST AROUND YOU



OBJECT GEO-TAGGING

EVALUATION OF OBJECT GEOTAGGING

- Integrate Ubicarse with VSFM toolkit
- Localize books in the library



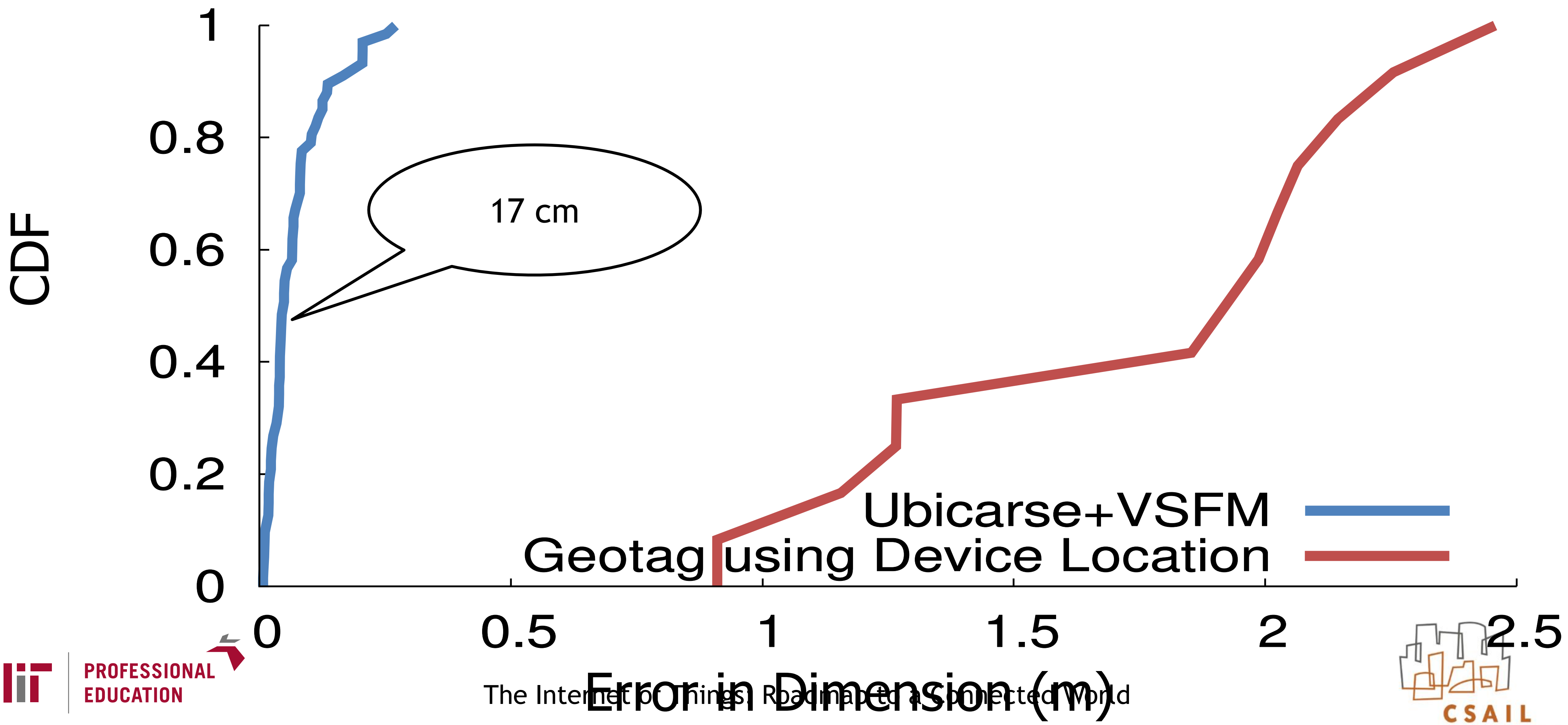
SUMMARY

Localization as pervasive, seamless, instantaneous service

Localized machines will be smarter and more engaged with us

Localized devices will help us know more about us & world

ACCURACY IN GEO-TAGGING



THANK YOU!

Daniela Rus

Andrew (1956) and Erna Viterbi Prof., EECS

Director, CSAIL

Computer Science and Artificial Intelligence Laboratory (CSAIL)
Massachusetts Institute of Technology