ELEC 3210
Introduction to Mobile Robotics
Lecture 11

(Machine Learning and Infomation Processing for Robotics)

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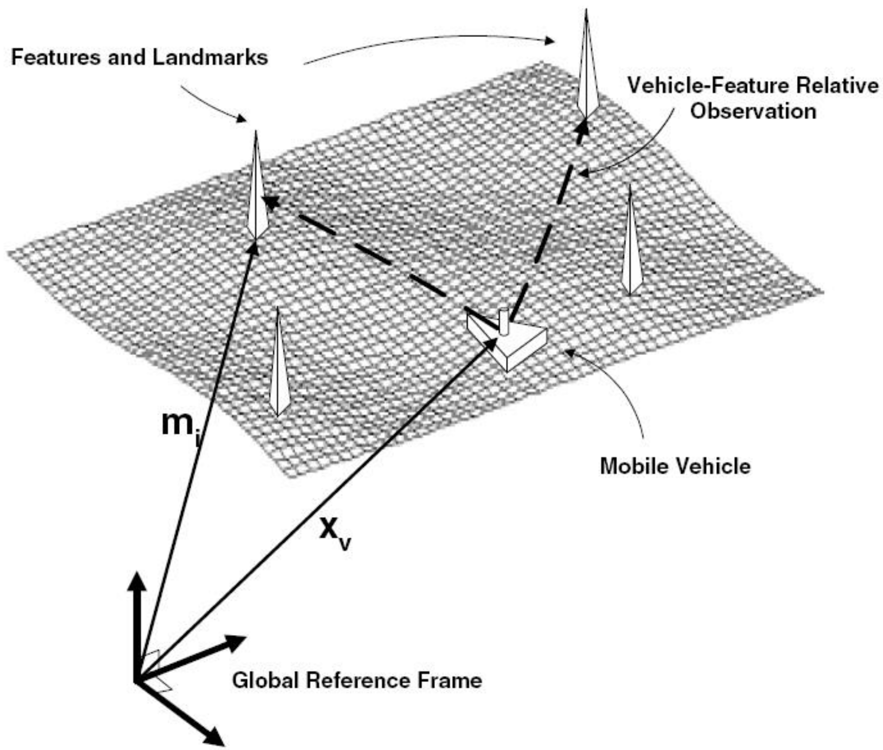
Recap L10 - EKF SLAM

- Extended Kalman Filter-based Simultaneous Localization and Mapping (EKF SLAM)
- Obtain both **feature (landmark) map** and **robot poses** in **real time**



Recap L10 - EKF SLAM

- Velocity-based Motion
- Range-Bearing Observation

1: **Extended_Kalman_filter**$(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t)$**:**

2: $\bar{\mu}_t = g(u_t, \mu_{t-1})$

3: $\bar{\Sigma}_t = G_t\, \Sigma_{t-1}\, G_t^T + R_t$

4: $K_t = \bar{\Sigma}_t\, H_t^T (H_t\, \bar{\Sigma}_t\, H_t^T + Q_t)^{-1}$

5: $\mu_t = \bar{\mu}_t + K_t(z_t - h(\bar{\mu}_t))$

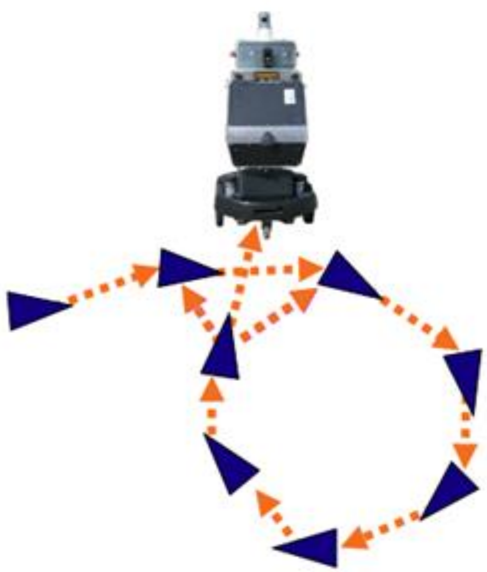
6: $\Sigma_t = (I - K_t\, H_t)\, \bar{\Sigma}_t$

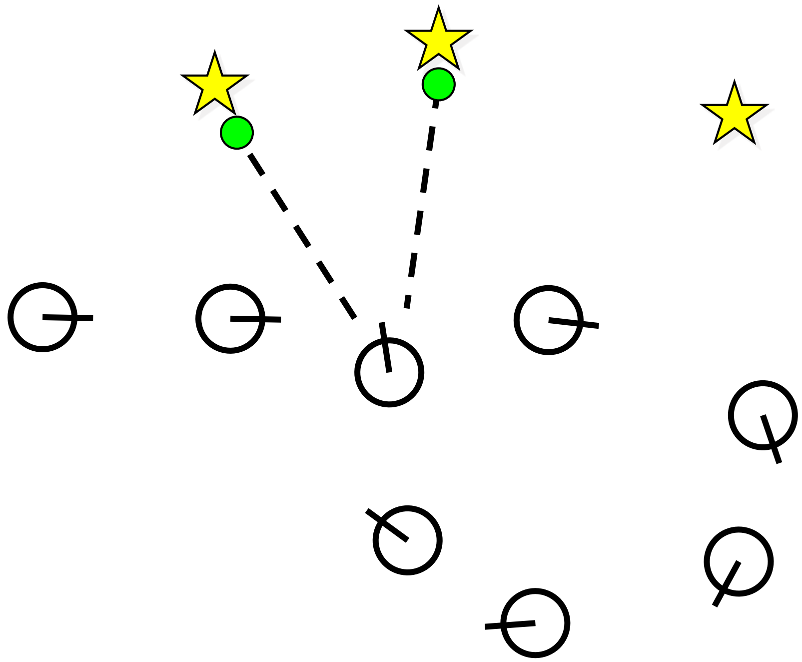
7: return μ_t, Σ_t

Courtesy: Cyrill Stachniss

Loop Closing in SLAM

- What if the robot travels a place that it has been before?
- In EKF SLAM, the loop closure could be achieved by landmark data association (or on a nearest-neighbor basis)

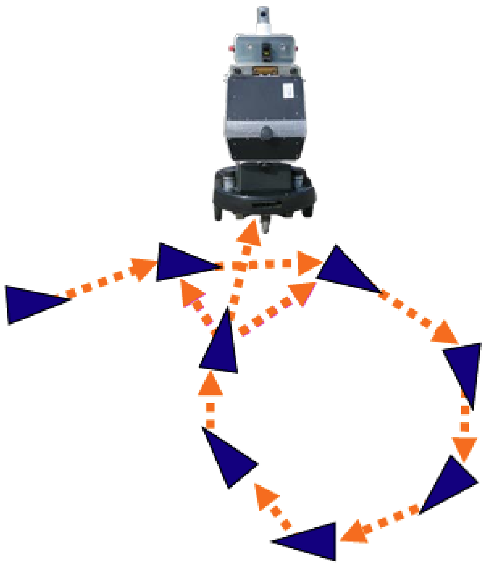




Loop Closing for EKF SLAM

Loop Closing

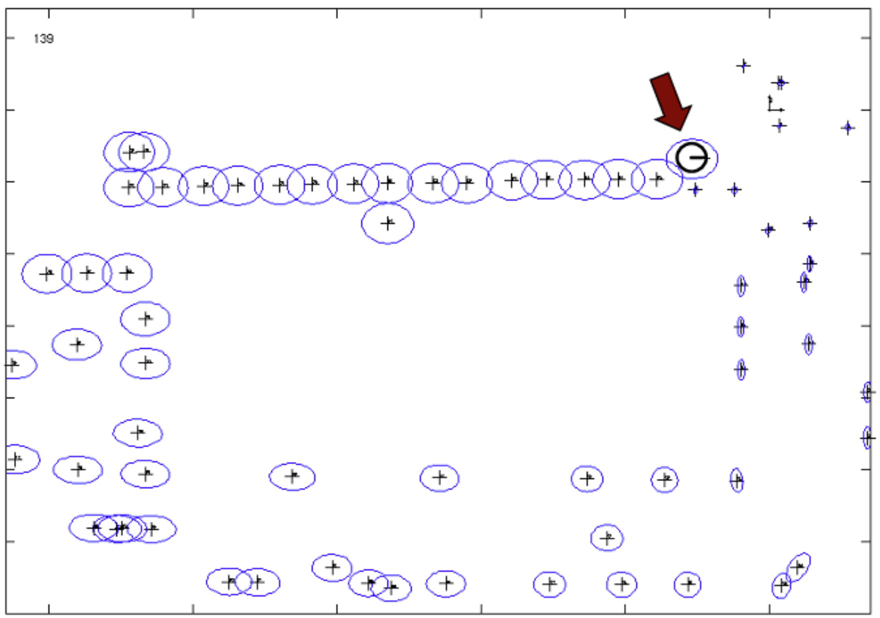
- Loop closing means recognizing an already mapped area
- Data association under
  - high ambiguity
  - possible environment symmetries
- Uncertainties collapse after a loop closure (whether the closure was correct or not)



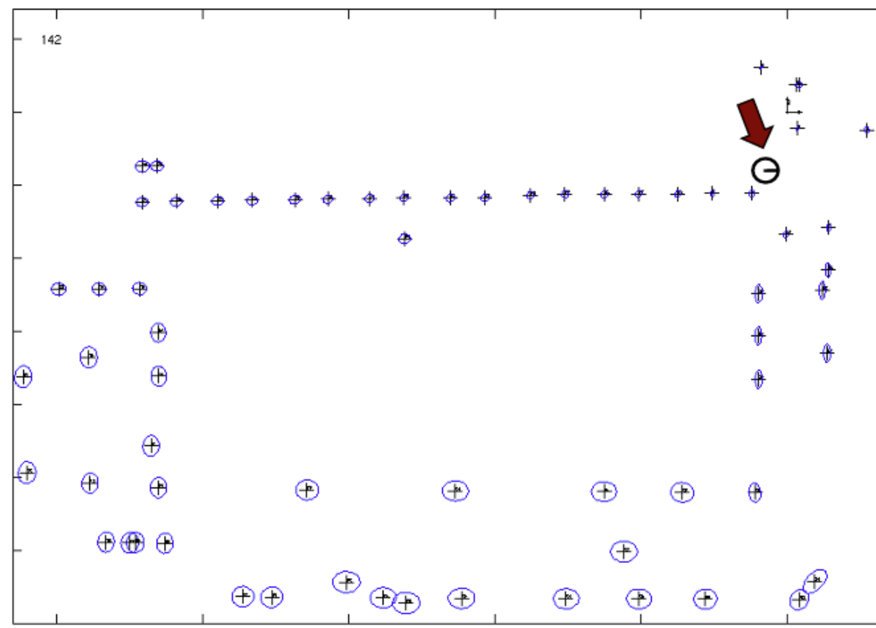
Courtesy: Cyrill Stachniss

Loop Closing

- Loop closing reduces the uncertainty in robot and landmark estimates
- This can be exploited when exploring an environment for the sake of better (more accurate) maps
- Wrong loop closures lead to filter divergence



Before Loop Closing

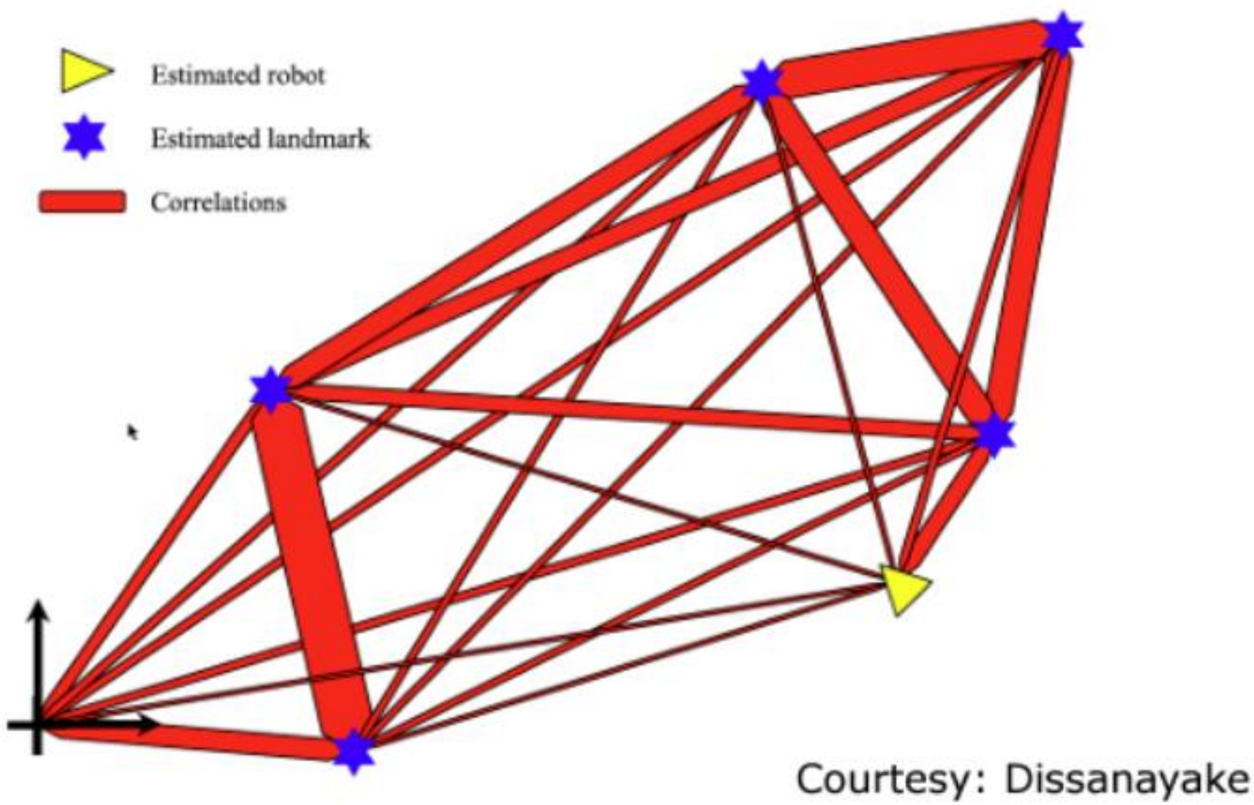


After Loop Closing

Courtesy: Cyrill Stachniss and K. Arras

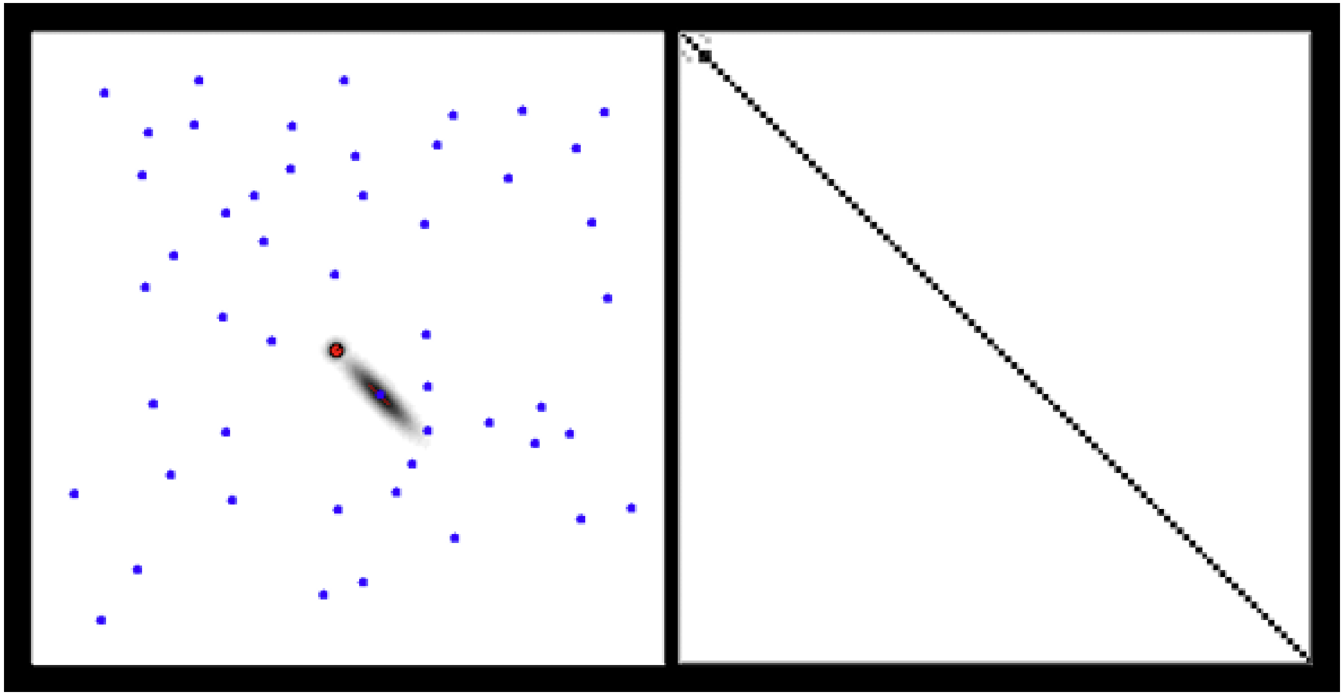
EKF SLAM Correlations

- In the limited, the landmark estimates become fully correlated



Courtesy:

EKF SLAM Correlations



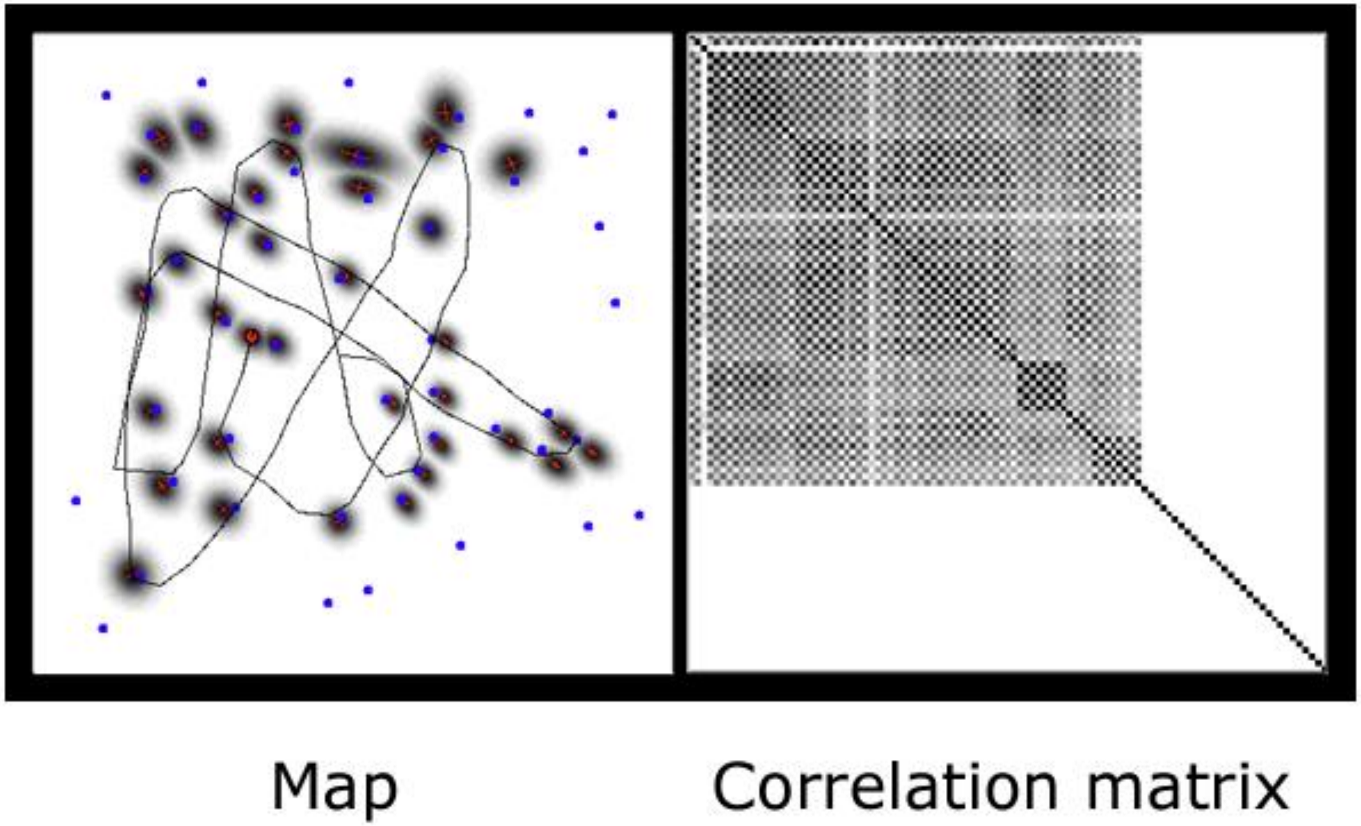
Map

Correlation matrix

(normalized covariance matrix)

Courtesy: M. Montemerlo

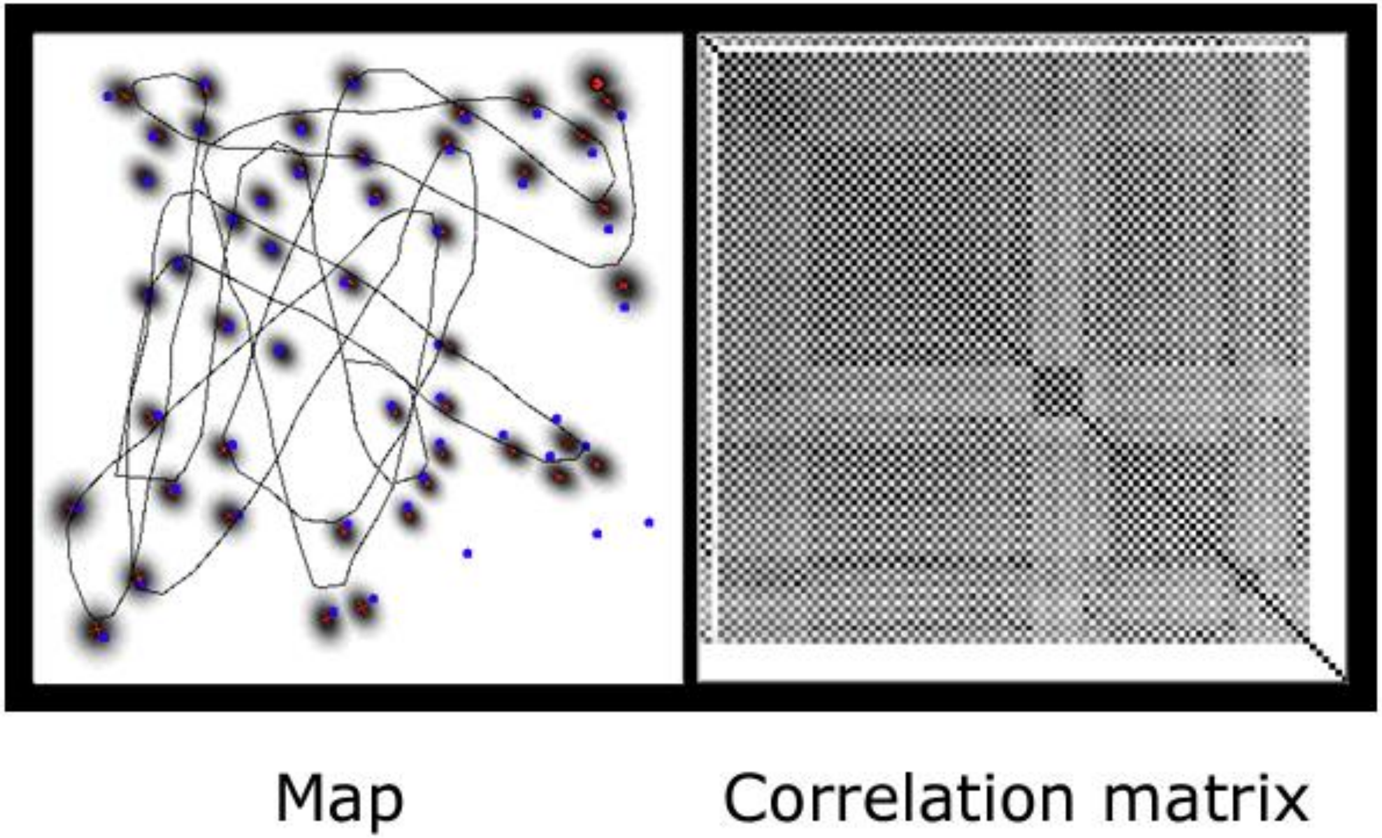
EKF SLAM Correlations



Courtesy: M. Montemerlo

EKF SLAM Correlations

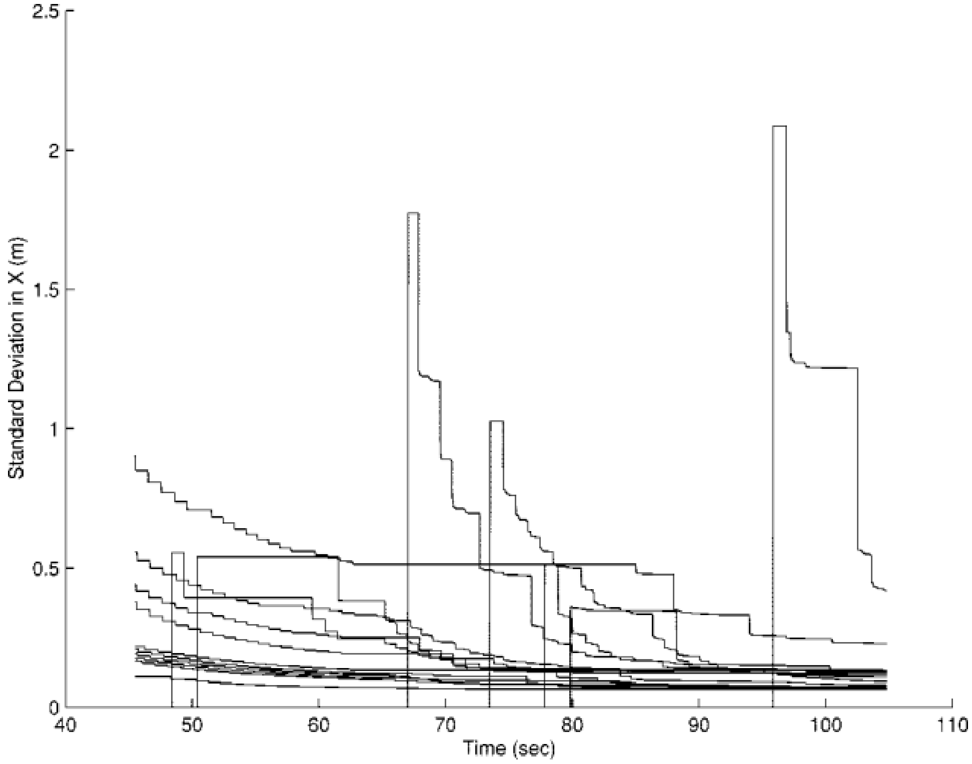
- What if I fix a location of one landmark?



Courtesy: M. Montemerlo

EKF SLAM Uncertainties

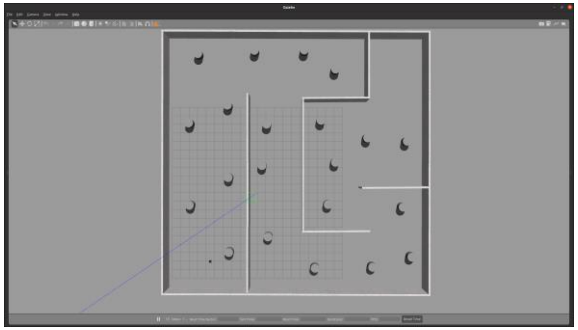
- The determinant of any sub-matrix of the map covariance matrix decreases monotonically
- New landmarks are initialized with maximum uncertainty

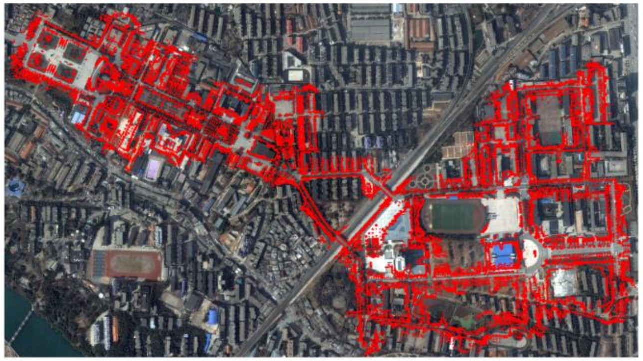


Courtesy: Gamini Dissanayake, Cyrill Stachniss

How to Close Loops in Urbans?

- What are the differences?




Place Recognition

- From **small/medium-scale** environments to **large-scale**
- From **short-term** operation to **long-term**
- From **global sparse landmark** to **topological dense representations,** Lecture 6 Map Representations and Organization
- Place Recognition Today
  - LiDAR Place Recognition - Scan Context
  - Visual Place Recognition

LiDAR Place Recognition

Recap L4 - Sensors

- LiDAR - Light Detection and Ranging
- Compared to 2D Laser Scanner
  - 3D Data
  - More expensive

3 Years Ago

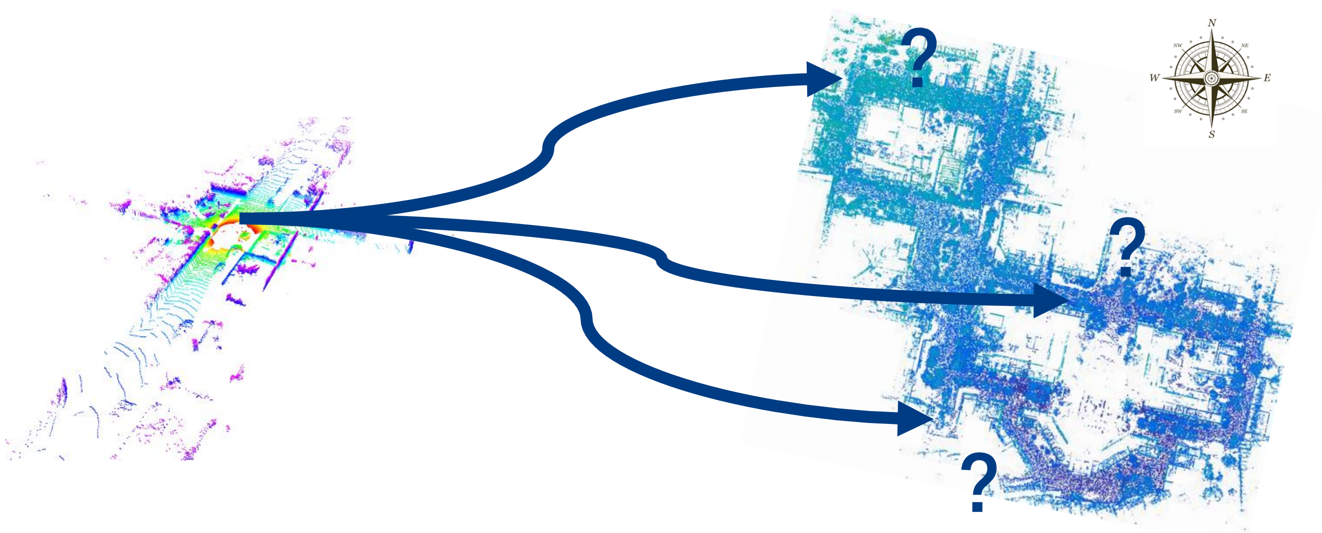
LiDAR Place Recognition

Robotics

- Has the robot been to this place before?
- Which point clouds were taken around the same location?

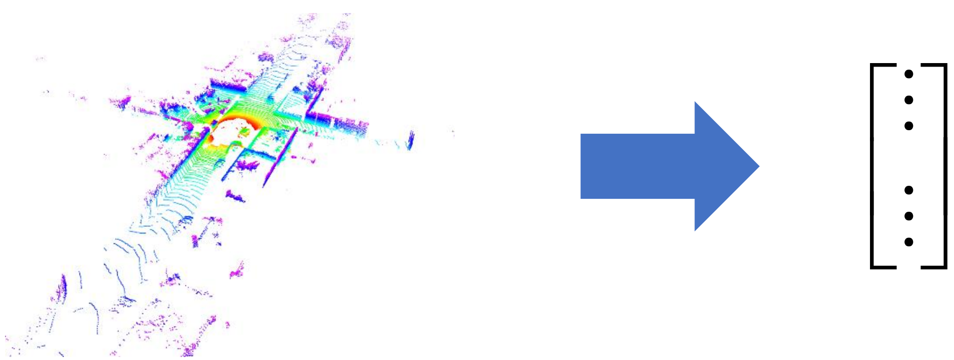
LiDAR Point Cloud Retrieval Problem

- Have I seen this point cloud before?
- Which LiDAR scan or submap in my map databse look similar to it?



Key Points

- Need descripotors
  - discriminative
  - low-dimension
- Need retrieval scheme
  - need similarity design
  - high efficiency
  - better provides orientation



LiDAR Point Cloud **Descriptor**

LiDAR Place Recognition

- Many approaches in recent years
- Kim G, Kim A. **Scan context: Egocentric spatial descriptor for place recognition within 3d point cloud map**. In2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2018 Oct 1 (pp. 4802-4809). IEEE.

2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
Madrid, Spain, October 1-5, 2018

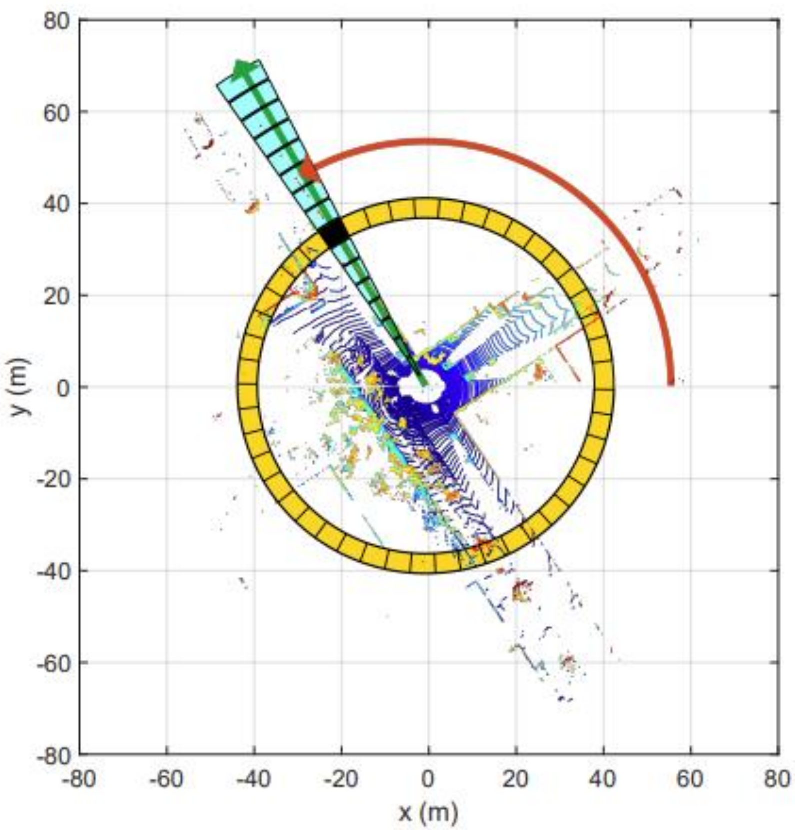
Scan Context: Egocentric Spatial Descriptor for Place Recognition within 3D Point Cloud Map

Giseop Kim[1] and Ayoung Kim[1*]

Courtesy: Scan Context by Kim

Describe a LiDAR Point Cloud

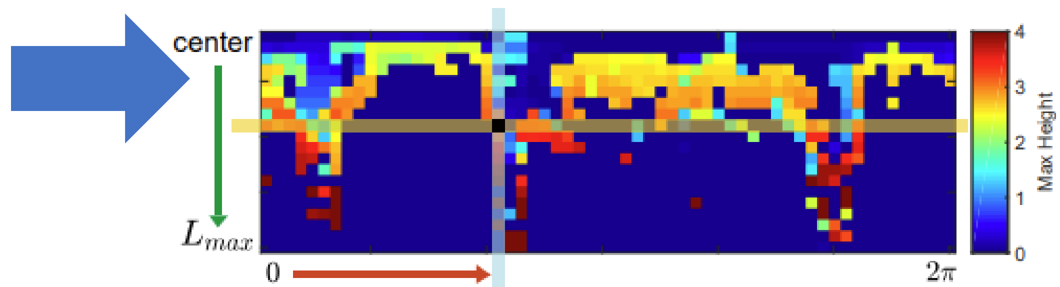
- Encodes the highest z-value in each context pixel



Bin division along azimuthal and radial directions

$$\phi\left(\mathcal{P}_{ij}\right) = \max_{\mathbf{p} \in \mathcal{P}_{ij}} z(\mathbf{p})$$

$$I = (a_{ij}) \in \mathbb{R}^{N_r \times N_s}, a_{ij} = \phi\left(\mathcal{P}_{ij}\right)$$

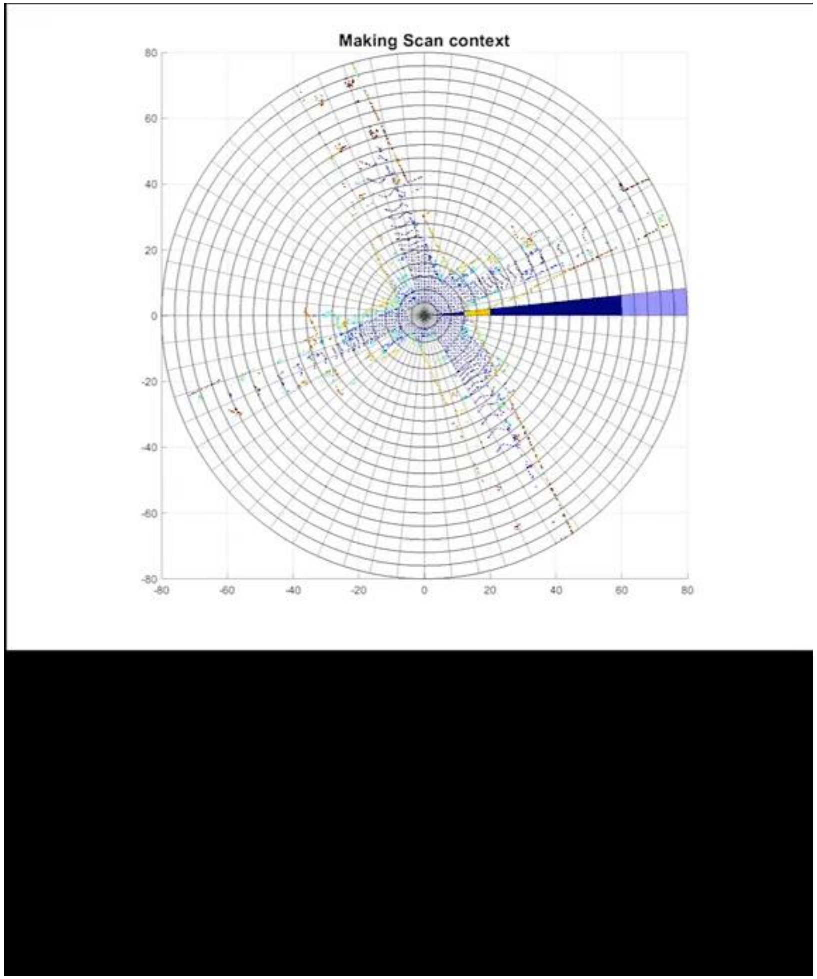


Scan Context

Courtesy: Scan Context by Kim

Describe a LiDAR Point Cloud

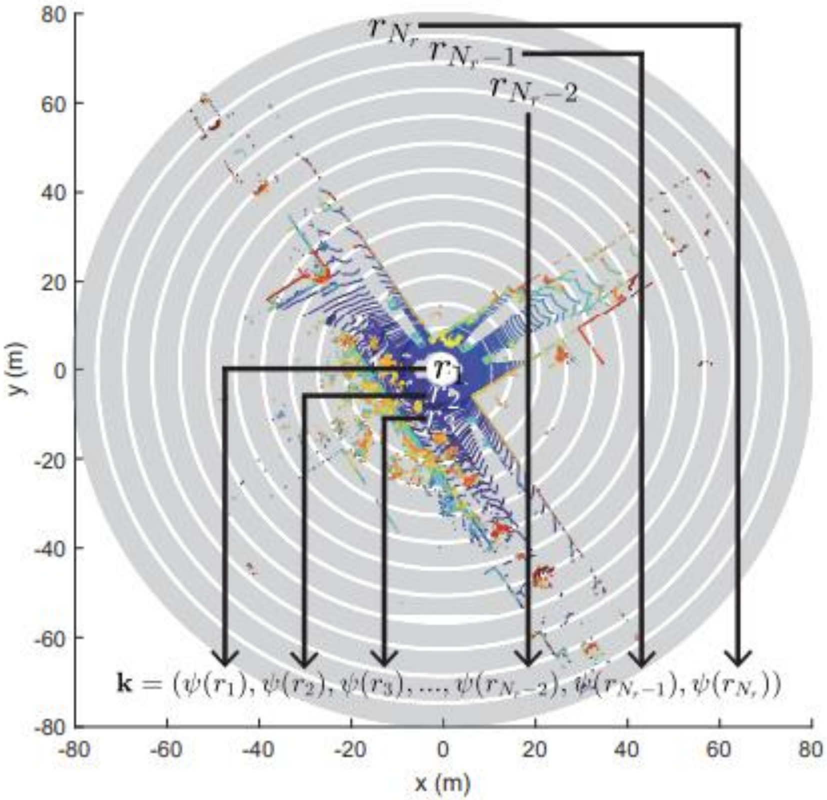
- From the scan to the context



Courtesy: Scan Context by Kim

Ring Key for Fast Retrieval

- From 2-Dimension to 1-Dimension
- Occupy ratio of each ring



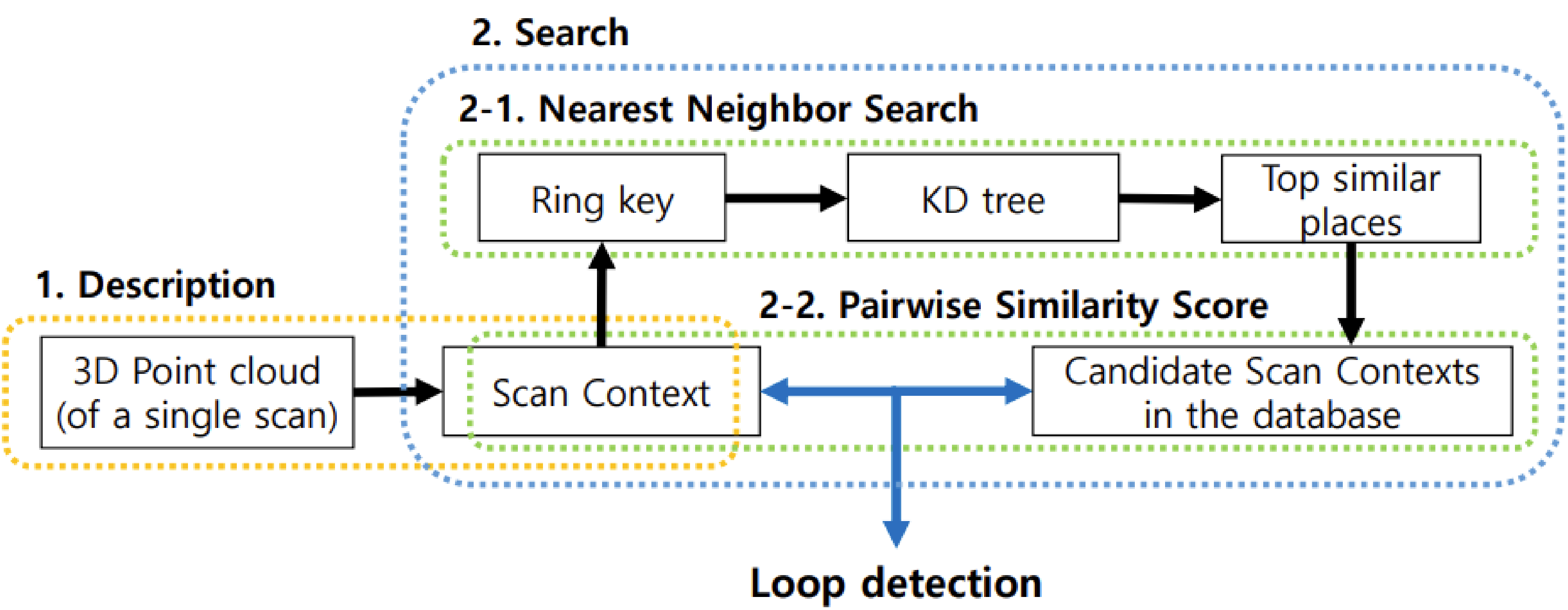
$$\mathbf{k} = \left(\psi\left(r_1\right), \ldots, \psi\left(r_{N_r}\right)\right)$$

$$\psi\left(r_i\right) = \frac{\|r_i\|_0}{N_s}$$

Courtesy: Scan Context by Kim

Scan Context Framework

- First Describe, Then Search
- Framework



Courtesy: Scan Context by Kim

Similarity Score

For a candidate, the similarity score is by

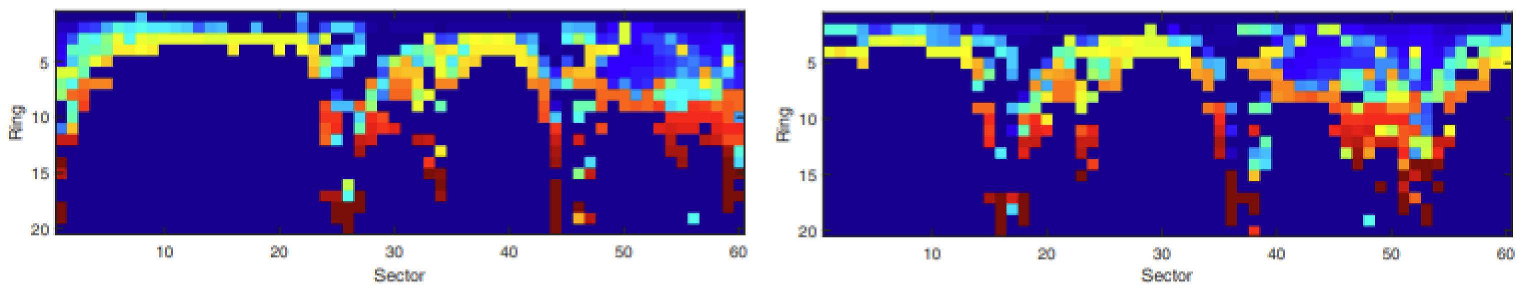
- Cosine Distance of each column in the xontext

$$d\left(I^q, I^c\right) = \frac{1}{N_s} \sum_{j=1}^{N_s} \left(1 - \frac{c_j^q \cdot c_j^c}{\left\|c_j^q\right\| \left\|c_j^c\right\|}\right)$$

- Exhaustive search on the columns and find the “best” alignment

$$D\left(I^q, I^c\right) = \min_{n \in [N_s]} d\left(I^q, I_n^c\right),$$

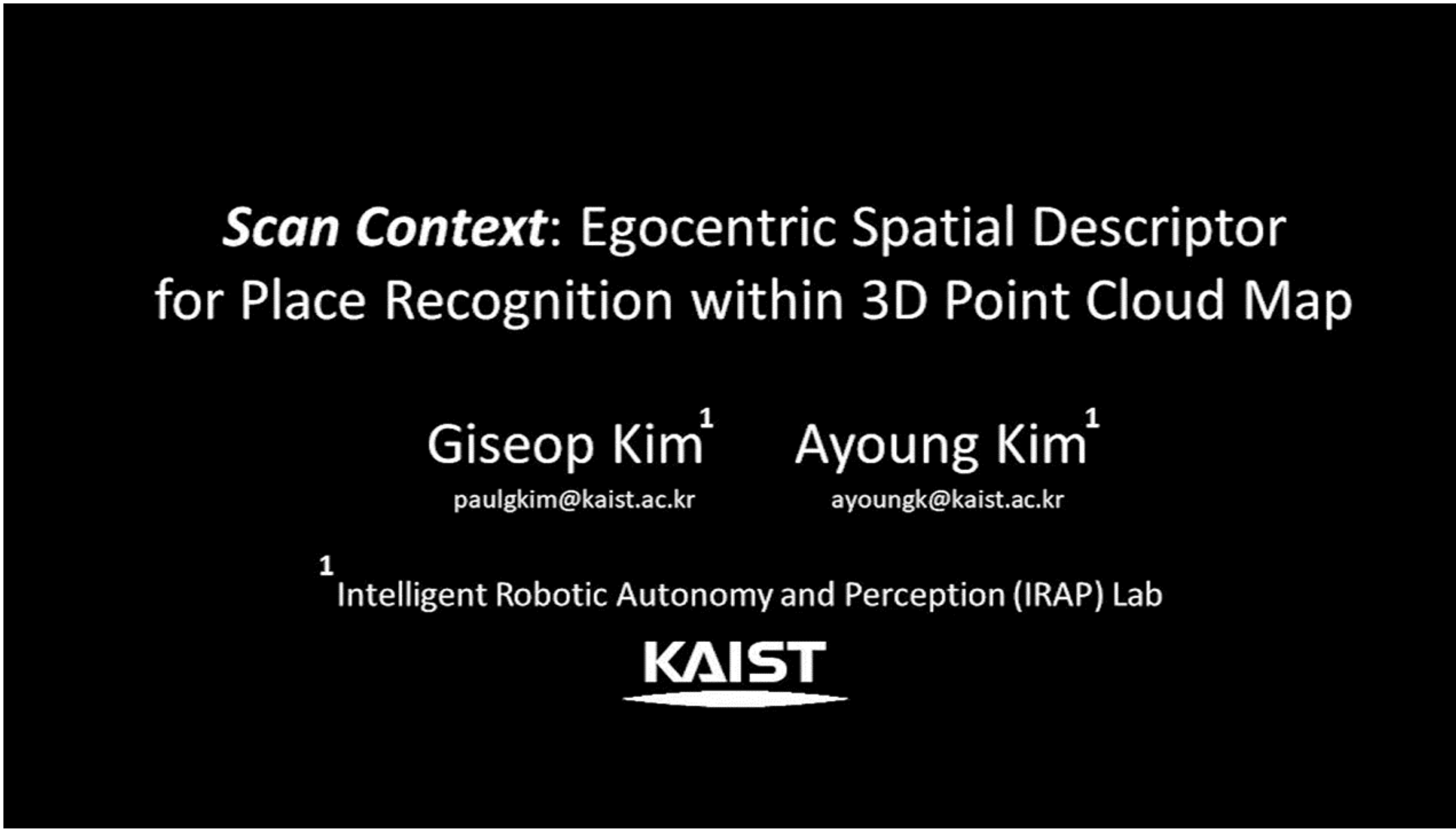
$$n^* = \text{argmin}_{n \in [N_s]}^{\text{argmin}} d\left(I^q, I_n^c\right).$$



Contexts at the same location but with different orientation

Courtesy: Scan Context by Kim

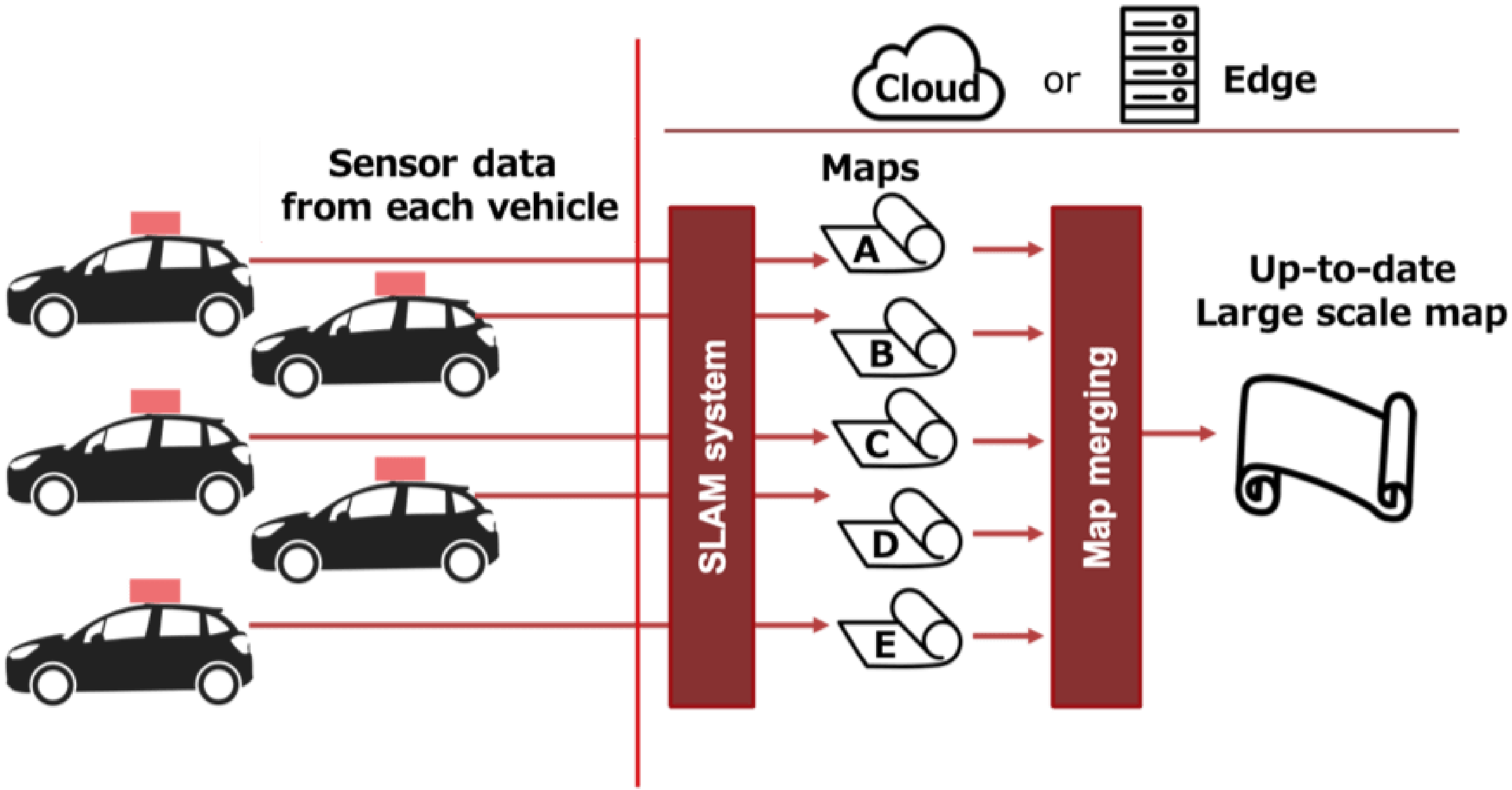
Scan Context



Courtesy: Scan Context by Kim

Application of the LiDAR PR

- Large-scale LiDAR mapping in cities



Courtesy: Kudan 3D-Lidar SLAM

Our Work on LiDAR PR

HKUST

- Yu Z, Qiao Z, Qiu L, Yin H, Shen S. Multi-Session, Localization-oriented and Lightweight LiDAR Mapping Using Semantic Lines and Planes. arXiv preprint arXiv:2307.07126. 2023 Jul 14.

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Ri 香港科大機器人研究所 ROBOTICS INSTITUTE

Multi-Session, Localization-oriented and Lightweight LiDAR Mapping Using Semantic Lines and Planes

Zehuan Yu, Zhijian Qiao, Liuyang Qiu, Huan Yin and Shaojie Shen

Visual Place Recognition

Visual Place Recognition

Robotics

- Has the robot been to this place before?
- Which ~~point clouds~~ images were taken around the same location?

LiDAR Point Cloud Retrieval Problem

- Have I seen this ~~point cloud~~ image before?
- Which ~~LiDAR scan or submap~~ image in my map databse look similar to it?

Why so challenging?

- Much more difficult than LiDAR place recognition
  - information-rich data -> high dimensional descriptors
  - illumination change
  - view change
  - others

Two images at the same place

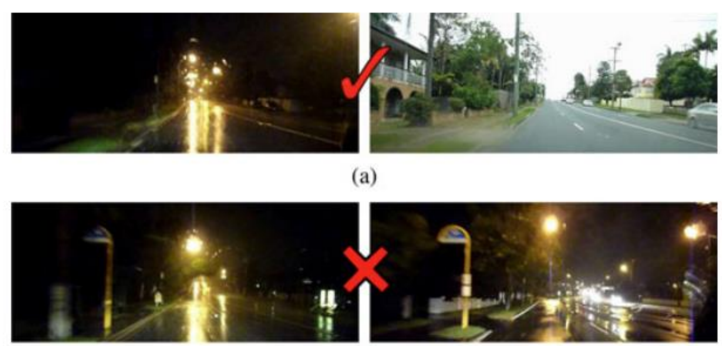
Visual Place Recognition Survey

- Many many many approaches for VPR
- Lowry S, Sünderhauf N, Newman P, Leonard JJ, Cox D, Corke P, Milford MJ. **Visual place recognition: A survey.** ieee transactions on robotics. 2015 Nov 26;32(1):1-9.

Visual Place Recognition: A Survey

Stephanie Lowry, Niko Sünderhauf, Paul Newman, *Fellow, IEEE*, John J. Leonard, *Fellow, IEEE*, David Cox, Peter Corke, *Fellow, IEEE*, and Michael J. Milford, *Member, IEEE*

***Abstract*—Visual place recognition is a challenging problem due to the vast range of ways in which the appearance of real-world places can vary. In recent years, improvements in visual sensing capabilities, an ever-increasing focus on long-term mobile robot autonomy, and the ability to draw on state-of-the-art research in other disciplines—particularly recognition in computer vision and animal navigation in neuroscience—have all contributed to significant advances in visual place recognition systems. This paper presents a survey of the visual place recognition research landscape. We start by introducing the concepts behind place recognition—the role of place recognition in the animal kingdom, how a "place" is defined in a robotics context, and the major components of a place recognition system. Long-term robot operations have revealed that changing**



(a)

(b)

FAB Map

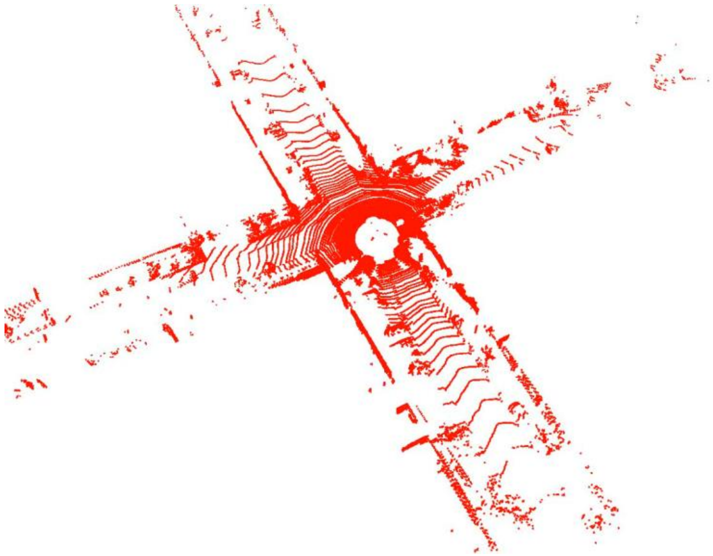
Courtesy: FAB Map 2.0

Summary of Place Recognition

- Place recognition is a data retrieval problem
- Scan Context could handle most LiDAR place recognition cases
- Many issues for information-rich visual place recognition

For the SLAM problem

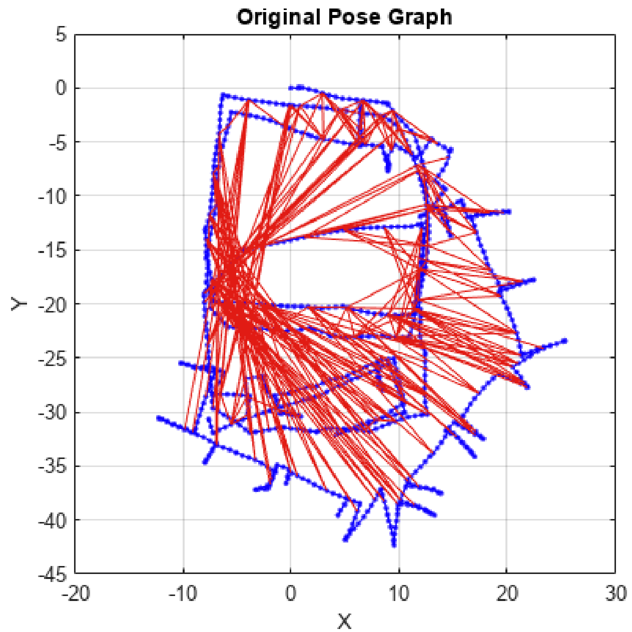
- In medium/large-scale environments, **place recognition and pose estimation** provides a constraint for robot poses



Pose Estimation by ICP

Constraint

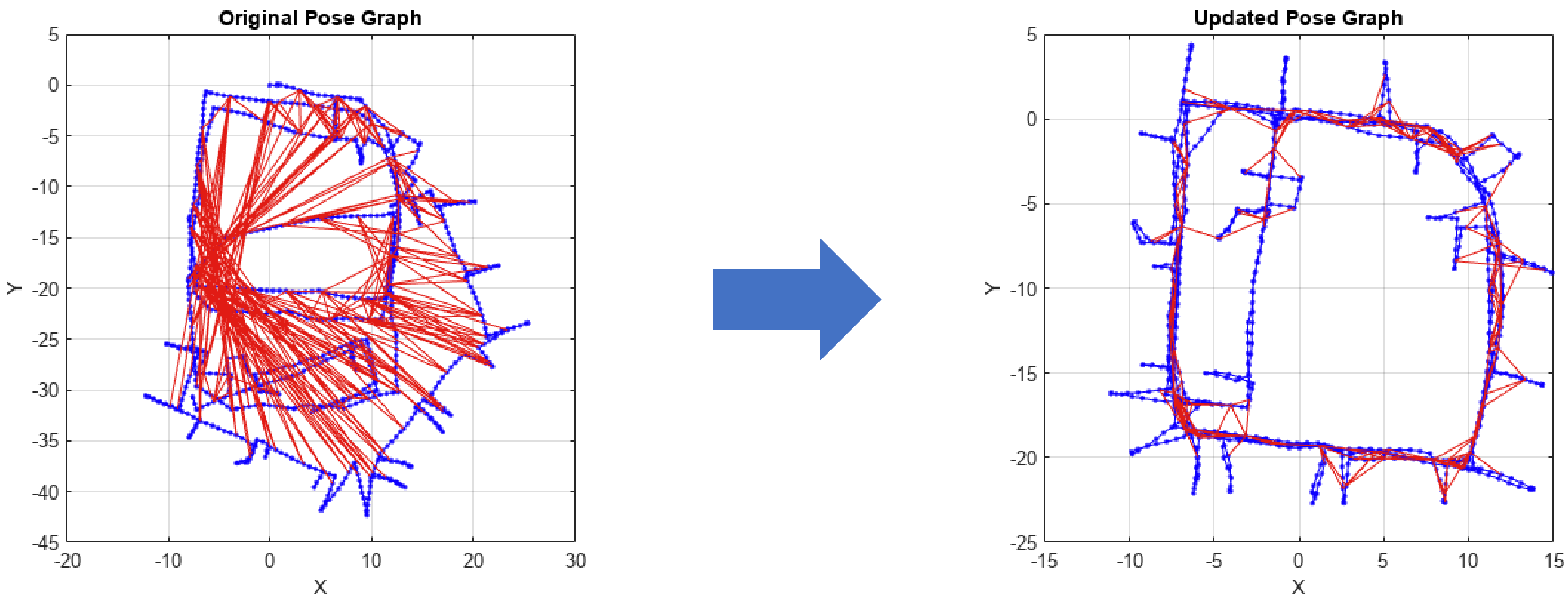
- A constraint is a relative transformation between two poses
- Can we refine the global mapping results from ICP odometry and EKF SLAM (w/o loop closing) with more constraints? (For high-precision mapping)



Courtesy: MATLAB

Next Lecture

- Pose Graph SLAM
  - one of the state-of-the-art mapping frameworks
  - not recursive filter, a batch processing approach
  - we study a 2D dense laser-based case



Courtesy: MATLAB