

# **ELEC 3210**

# **Introduction to Mobile Robotics**

## **Lecture 13**

**(Machine Learning and Information Processing for Robotics)**

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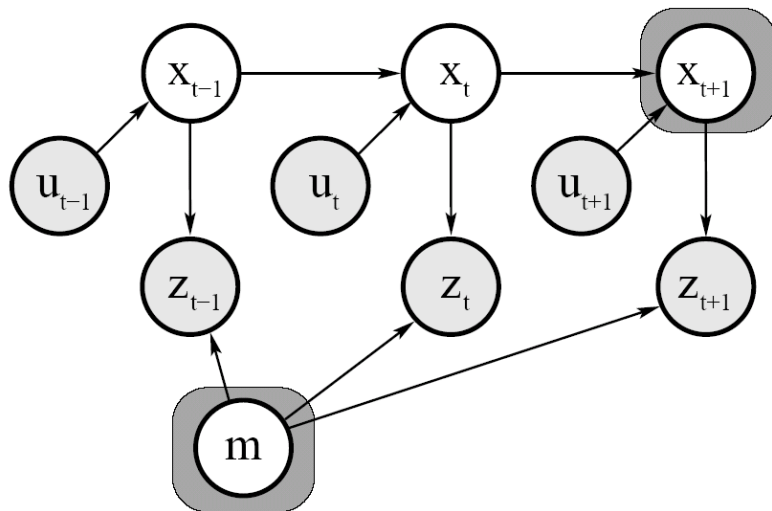
[eehyin@ust.hk](mailto:eehyin@ust.hk)



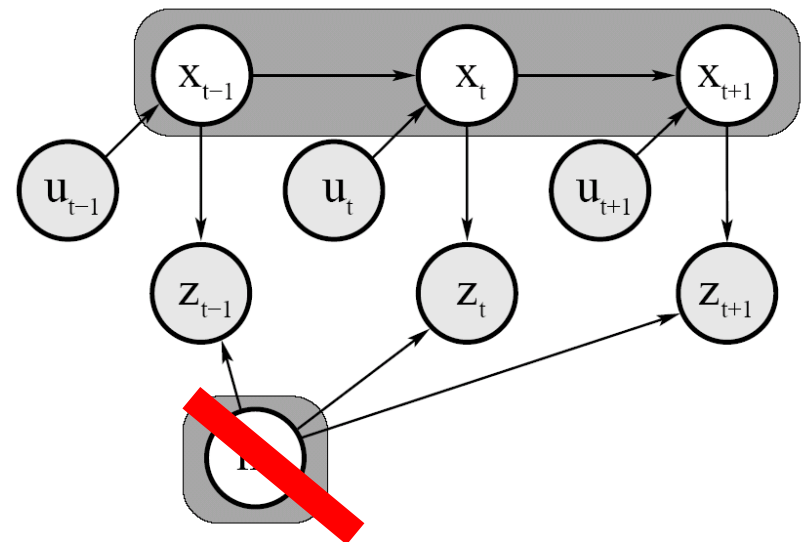
# Recap 12 - Pose Graph SLAM

- Achieve global consistent mapping with loops
- From recursive filter to batch processing

$$p(x_t, m \mid z_{1:t}, u_{1:t})$$

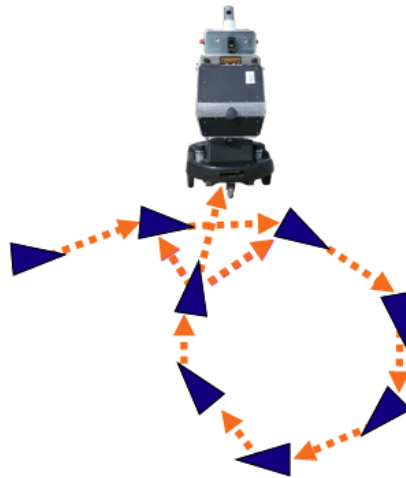


$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t})$$



# Recap L12 - Pose Graph SLAM

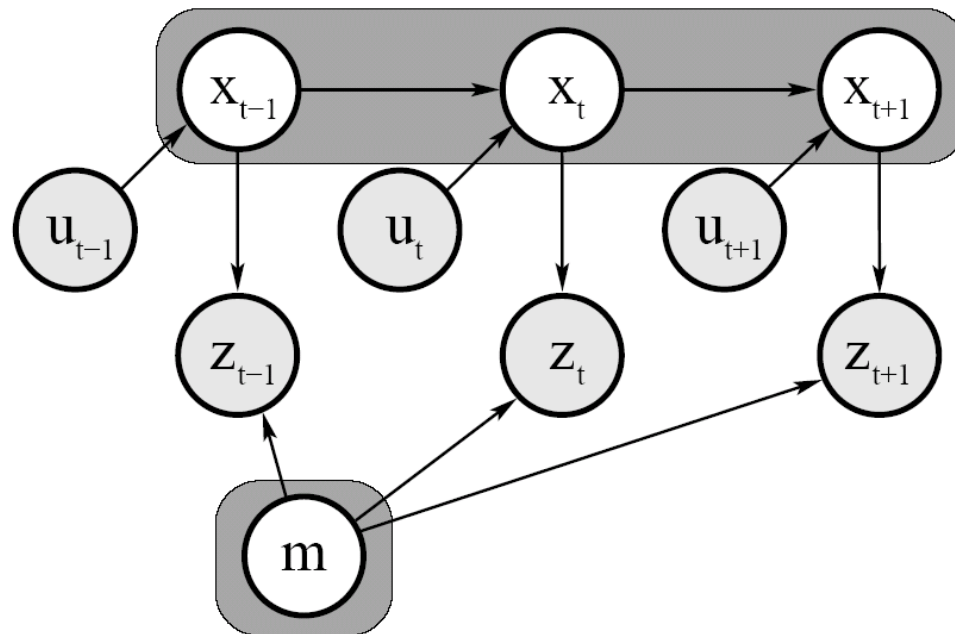
- Every **node** in the graph corresponds to a pose of the robot during mapping
- Every **edge** between two nodes corresponds to a spatial constraint between them
- Build the graph and find a node configuration that **minimize** the error introduced by the constraints



# Topic Today

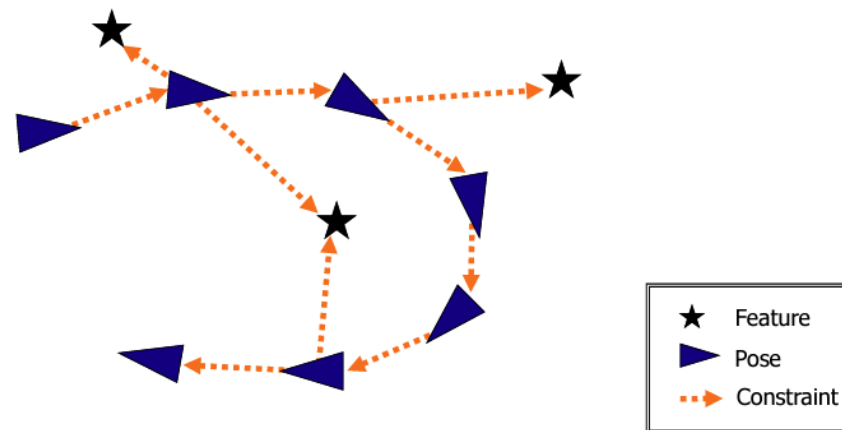
- Graph SLAM with Landmarks
- Estimate both landmark map and robot poses

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t})$$



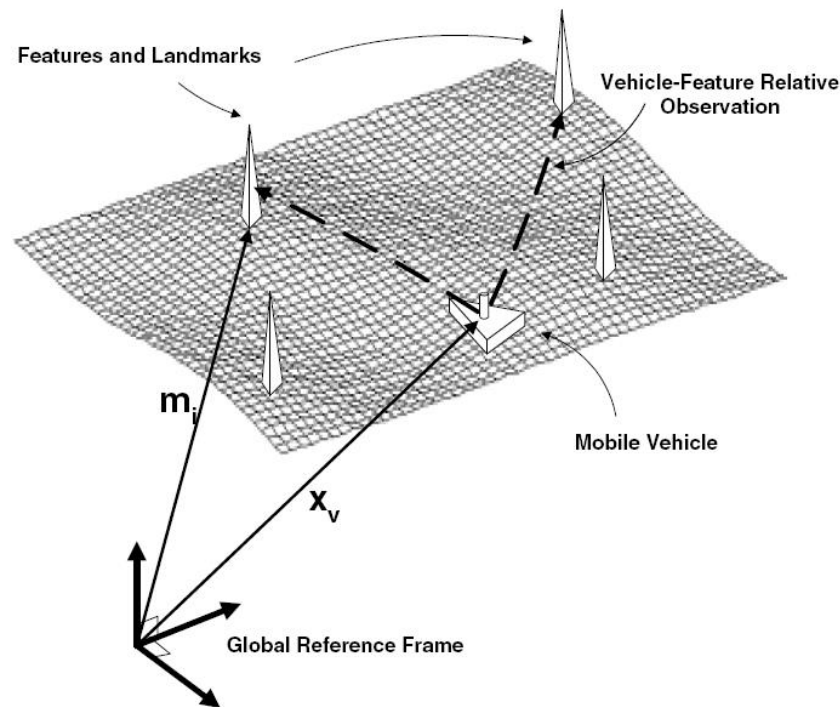
# Graph with Landmarks

- Nodes can represent:
  - Robot poses
  - Landmark locations
- Edges can represent:
  - Landmark observations
  - Odometry measurements
- Today we mainly focus on error function design for the graph



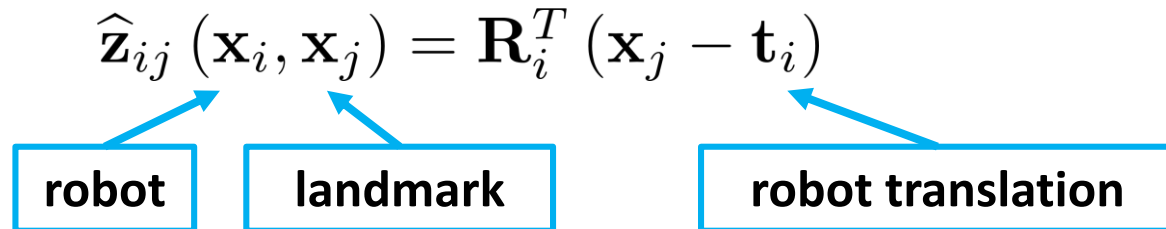
# Deal with 2D Landmarks

- Landmark is a  $(x,y)$  - point in the world
- Relative observation in  $(x,y)$



# Landmarks Observation

- Expected observation (x-y sensor)

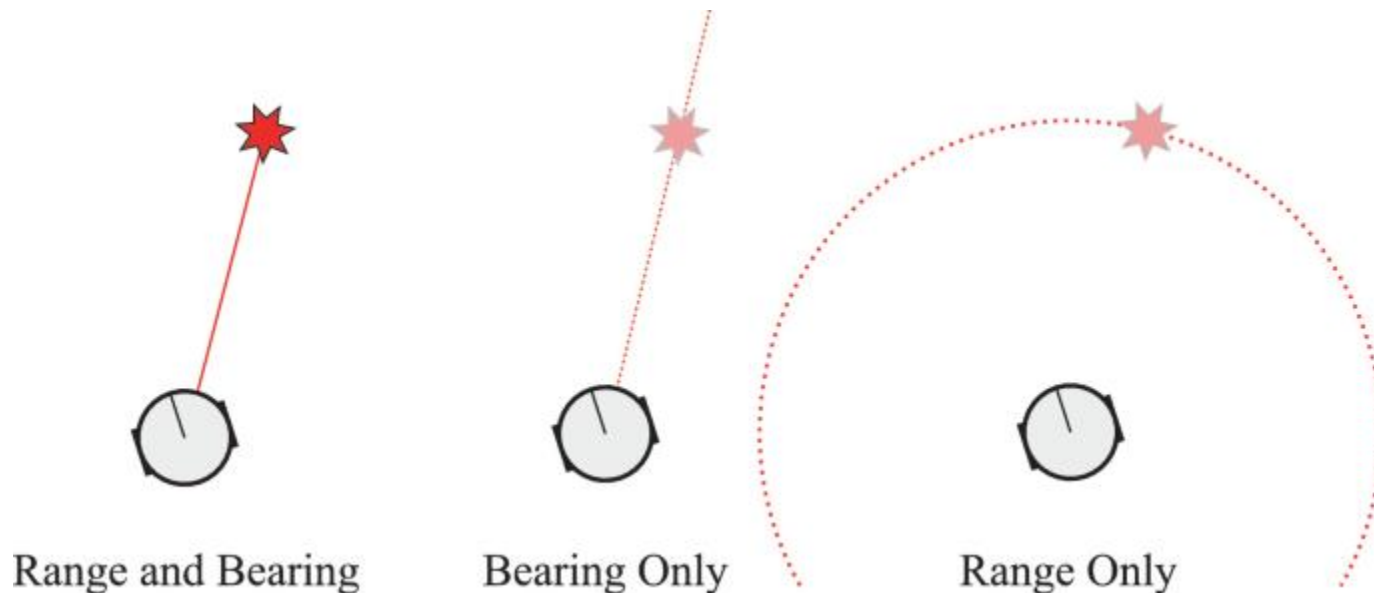
$$\hat{\mathbf{z}}_{ij}(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{R}_i^T (\mathbf{x}_j - \mathbf{t}_i)$$


- Error function

$$\begin{aligned} \mathbf{e}_{ij}(\mathbf{x}_i, \mathbf{x}_j) &= \hat{\mathbf{z}}_{ij} - \mathbf{z}_{ij} \\ &= \mathbf{R}_i^T (\mathbf{x}_j - \mathbf{t}_i) - \mathbf{z}_{ij} \end{aligned}$$

# Recap L10 - EKF SLAM

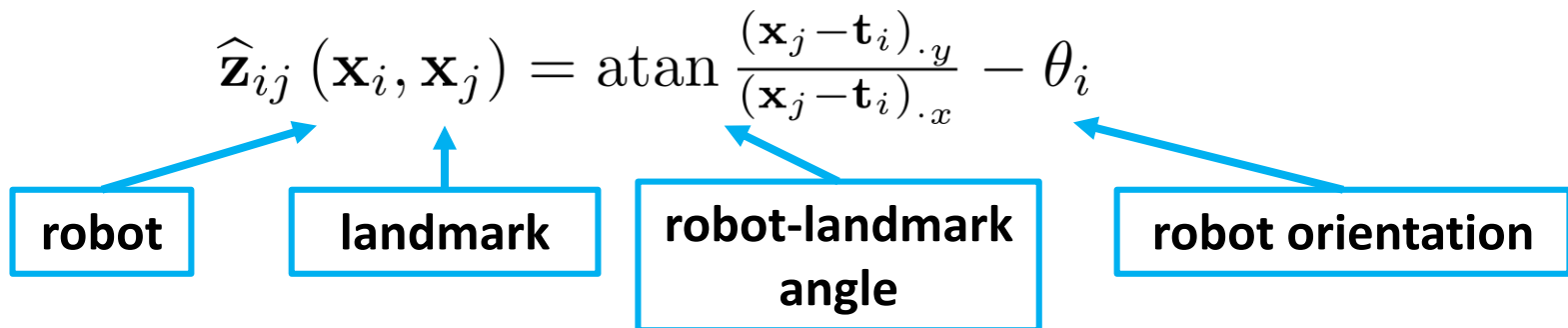
- Range-Bearing Observation
- Detect a landmark with the laser scan
  - like clustering the laser points and detect with a classifier
- Range (meter) and orientation (degree/rad) respected to the robot
- What if we have bearing-only observation?





# Bearing-Only Observations

- Bearing Only Observations
- The robot observe only the bearing (orientation towards the landmark)
- Observation function

$$\hat{\mathbf{z}}_{ij}(\mathbf{x}_i, \mathbf{x}_j) = \text{atan} \frac{(\mathbf{x}_j - \mathbf{t}_i) \cdot \mathbf{y}}{(\mathbf{x}_j - \mathbf{t}_i) \cdot \mathbf{x}} - \theta_i$$


- Error function

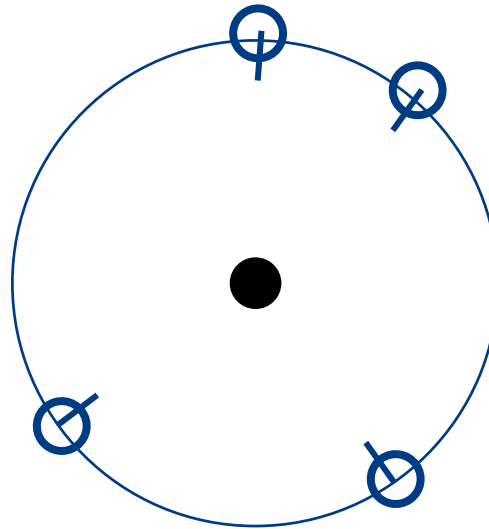
$$\mathbf{e}_{ij}(\mathbf{x}_i, \mathbf{x}_j) = \text{atan} \frac{(\mathbf{x}_j - \mathbf{t}_i) \cdot \mathbf{y}}{(\mathbf{x}_j - \mathbf{t}_i) \cdot \mathbf{x}} - \theta_i - \mathbf{z}_j$$

# The Rank of the Matrix $\mathbf{H}$

- What is the rank of  $\mathbf{H}_{ij}$  for a 2D landmark-pose constraint?
  - The blocks of  $\mathbf{J}_{ij}$  are a  $2 \times 3$  matrices
  - $\mathbf{H}_{ij}$  cannot have more than rank 2
$$\text{rank}(\mathbf{J}^T \mathbf{J}) = \text{rank}(\mathbf{J}^T) = \text{rank}(\mathbf{J})$$
- What is the rank of  $\mathbf{H}_{ij}$  for a bearing-only constraint?
  - The blocks of  $\mathbf{J}_{ij}$  are a  $1 \times 3$  matrices
  - $\mathbf{H}_{ij}$  has rank 1

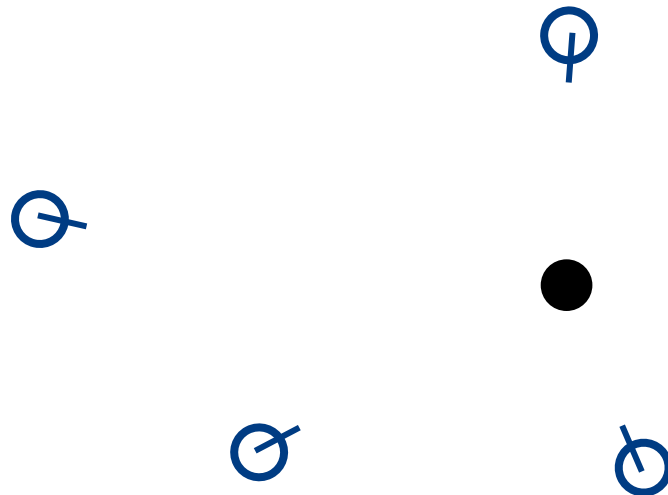
# Where is the Robot?

- Robot observes one landmark  $(x,y)$
- Where can the robot be?
  - The robot can be somewhere on a circle around the landmark
  - It is a 1D solution space (constrained by the distance and the robot's orientation)



# Where is the Robot?

- Robot observes one landmark with bearing-only
- Where can the robot be?
  - The robot can be anywhere in the x-y plane
  - It is a 2D solution space (constrained by the robot's orientation)



- In landmark-based SLAM, the system can be under-determined
- The rank of  $\mathbf{H}$  is less or equal to the sum of the ranks of the constraints
- To determine a unique solution, the system must have full rank
- **Question**
  - How many 2D landmark observations are needed to resolve for a robot pose?
  - How many bearing-only observations are needed to resolve for a robot pose?

# Under-Determined Systems

- No guarantee for a full rank system
  - Landmarks may be observed only once
  - Robot might have no odometry
- We can still deal with these situations by adding a “damping” factor to  $\mathbf{H}$
- Instead of solving  $\mathbf{H}\Delta\mathbf{x} = -\mathbf{b}$  we solve

$$(\mathbf{H} + \lambda\mathbf{I})\Delta\mathbf{x} = -\mathbf{b}$$

- The damping factor  $\lambda\mathbf{I}$  makes the system positive definite
- It adds an additional constraints that “drag” the increments towards 0
- Wighted sum of Gauss Newton and Steepest Descent

# Simplified Levenberg Marquardt

- Damping to regulate the convergence using backup/restore actions

```
x: the initial guess
while (! converged)
     $\lambda = \lambda_{init}$ 
    <H,b> = buildLinearSystem(x);
    E = error(x)
    xold = x;
     $\Delta x$  = solveSparse( (H +  $\lambda$  I)  $\Delta x$  = -b);
    x +=  $\Delta x$ ;
    If (E < error(x)) {
        x = xold;
         $\lambda$  *= 2;
    } else {  $\lambda$  /= 2; }
```

# Bundle Adjustment

- Often Levenberg Marquardt
- No notation of odometry (pose-pose)
- An offline pose graph with landmarks problem
  - SLAM is an online problem
- 3D reconstruction based on images taken at different views
  - LiDAR Bundle Adjustment is also popular in recent years
- Minimizes the projection error in the 2D image plane
- Developed in photogrammetry during 1950s



# Visual Bundle Adjustment



Parallax Bundle Adjustment with Improved Convergence

Liyang Liu, Teng Zhang, Yi Liu, Liang Zhao, Shoudong Huang and Gamini Dissanayake

# LiDAR Bundle Adjustment

Large-Scale LiDAR Consistent Mapping using Hierarchical LiDAR Bundle Adjustment

## Large-Scale LiDAR Consistent Mapping using Hierarchical LiDAR Bundle Adjustment

Xiyuan Liu, Zheng Liu, Fanze Kong and Fu Zhang



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MARS LAB

0:00 / 7:20

# Next Lecture

- Visual Perception 1
  - Feature Detection and Matching

