

Robot Mapping

Graph-Based SLAM with Landmarks

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Graph-Based SLAM (Chap. 15)

- Use a **graph** to represent the problem
- 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
- **Graph-Based SLAM:** Build the graph and find a node configuration that minimize the error introduced by the constraints

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The Graph

So far:

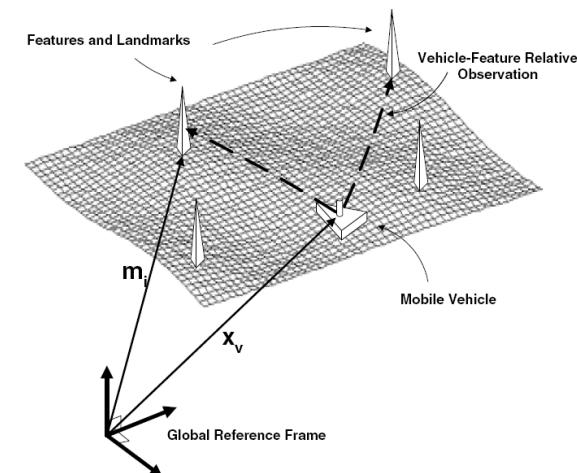
- Vertices for robot poses (x, y, θ)
- Edges for virtual observations (transformations) between robot poses

Topic today:

- How to deal with landmarks

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Landmark-Based SLAM



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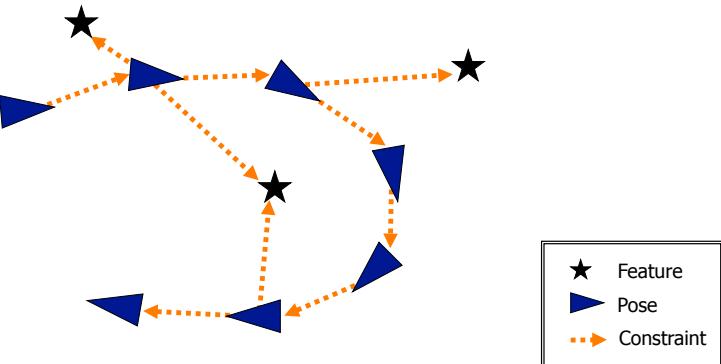
Real Landmark Map Example



Image courtesy: E. Nebot

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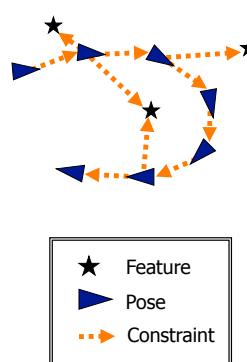
The Graph with Landmarks



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The Graph with Landmarks

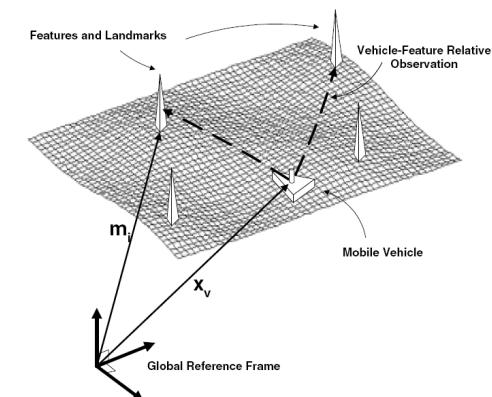
- **Nodes** can represent:
 - Robot poses
 - Landmark locations
- **Edges** can represent:
 - Landmark observations
 - Odometry measurements
- The minimization optimizes the landmark locations and robot poses



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2D Landmarks

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



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Landmarks Observation

- Expected observation (x-y sensor)

$$\hat{z}_{ij}(x_i, x_j) = R_i^T(x_j - t_i)$$

robot ↑ landmark ↑ robot translation ↑

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Bearing Only Observations

- A landmark is still a 2D point
- The robot observe only the bearing towards the landmark
- Observation function

$$\hat{z}_{ij}(x_i, x_j) = \text{atan} \frac{(x_j - t_i).y}{(x_j - t_i).x} - \theta_i$$

robot ↑ landmark ↑ robot-landmark angle ↑ robot orientation ↑

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Bearing Only Observations

- Observation function

$$\hat{z}_{ij}(x_i, x_j) = \text{atan} \frac{(x_j - t_i).y}{(x_j - t_i).x} - \theta_i$$

robot ↑ landmark ↑ robot-landmark angle ↑ robot orientation ↑

- Error function

$$e_{ij}(x_i, x_j) = \text{atan} \frac{(x_j - t_i).y}{(x_j - t_i).x} - \theta_i - z_j$$

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The Rank of the Matrix H

- What is the rank of H_{ij} for a 2D landmark-pose constraint?

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The Rank of the Matrix H

- What is the rank of H_{ij} for a 2D landmark-pose constraint?
 - The blocks of J_{ij} are a 2×3 matrices
 - H_{ij} cannot have more than rank 2
 $\text{rank}(A^T A) = \text{rank}(A^T) = \text{rank}(A)$

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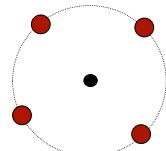
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 $\text{rank}(A^T A) = \text{rank}(A^T) = \text{rank}(A)$
- What is the rank of H_{ij} for a bearing-only constraint?
 - The blocks of J_{ij} are a 1×3 matrices
 - H_{ij} has rank 1

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Where is the Robot?

- Robot observes one landmark (x,y)
- Where can the robot be relative to the landmark?



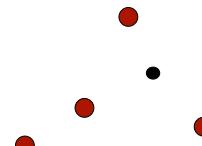
The robot can be somewhere on a circle around the landmark

It is a 1D solution space (constrained by the distance and the robot's orientation)

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Where is the Robot?

- Robot observes one landmark (bearing-only)
- Where can the robot be relative to the landmark?



The robot can be anywhere in the x-y plane

It is a 2D solution space (constrained by the robot's orientation)

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Rank

- In landmark-based SLAM, the system can be under-determined
- The rank of 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**

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Questions

- The rank of 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**
- **Questions:**
 - 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?

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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

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

What is the effect of that?

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

- Damping factor for \mathbf{H}
- $(\mathbf{H} + \lambda \mathbf{I})\Delta\mathbf{x} = -\mathbf{b}$
- The damping factor $\lambda \mathbf{I}$ makes the system positive definite
- Weighted sum of Gauss Newton and Steepest Descent

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Simplified Levenberg Marquardt

- Damping to regulate the convergence using backup/restore actions

```
x: the initial guess
while (! converged)
    λ = λinit
    <H,b> = buildLinearSystem(x);
    E = error(x);
    xold = x;
    Δx = solveSparse( (H + λ I) Δx = -b );
    x += Δx;
    If (E < error(x)) {
        x = xold;
        λ *= 2;
    } else { λ /= 2; }
```

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Bundle Adjustment

- 3D reconstruction based on images taken at different viewpoints
- Minimizes the reprojection error
- Often Levenberg Marquardt
- Developed in photogrammetry during the 1950ies

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Summary

- Graph-Based SLAM for landmarks
- The rank of \mathbf{H} matters
- Levenberg Marquardt for optimization

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Literature

Bundle Adjustment:

- Triggs et al. "Bundle Adjustment — A Modern Synthesis"

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