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Lecture 23: SLAM I - Formulations and Sparsity

based on slides by Kasra Khosoussi
Simultaneous Localization and Mapping

- “Holy grail of mobile robotics”
- Over 30 years of robotic research

H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: part I," in IEEE Robotics & Automation Magazine, vol. 13, no. 2, pp. 99-110, June 2006, doi: 10.1109/MRA.2006.1638022. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see https://ocw.mit.edu/help/faq-fair-use/

C. Cadena et al., "Past, Present, and Future of Simultaneous Localization and Mapping: Toward the Robust-Perception Age," in IEEE Transactions on Robotics, vol. 32, no. 6, pp. 1309-1332, Dec. 2016, doi: 10.1109/TRO.2016.2624754. © IEEE. All rights reserved. This content is excluded from our Creative Commons license. For more information, see https://ocw.mit.edu/help/faq-fair-use/

“The genesis of the probabilistic SLAM problem occurred at the 1986 IEEE Robotics and Automation Conference held in San Francisco. This was a time when probabilistic methods were only just beginning to be introduced into both robotics and AI. A number of researchers had been looking at applying estimation-theoretic methods to mapping and localisation problems; these included Peter Cheeseman, Jim Crowley, and Hugh Durrant-Whyte. Over the course of the conference many paper table cloths and napkins were filled with long discussions about consistent mapping. Along the way, Raja Chatila, Oliver Faugeras, Randal Smith and others also made useful contributions to the conversation.”
Big Picture

Trajectory Planning

Goal

Path planning → Trajectory optimization

desired trajectory

+ -

Controller

control inputs

Robot

robot's state

map and current robot state

>30Hz

Estimator (e.g., Visual Odometry)

Sensors (e.g., cameras)

>30Hz

map and current robot state

~1Hz

SLAM (e.g., pose graph optimization)

Loop closure detection (e.g., place recognition)
“Map”: Environment Representations

- **Sparse:**
  - Landmark-based
  - No explicit representation (pose graph)
  - Geometric primitives

- **Dense:**
  - Point clouds
  - 2D/3D occupancy grids
  - 3D meshes
  - ...

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Pose Graph Optimization

- **Measurements**: odometry + loop closures (i.e., relative pose measurements between non-consecutive poses obtained via place recognition & 2-view geometry, or similar)
- **Variables**: robot poses
Graphical representation of pose graph optimization

pose graph
Graphical representation of pose graph optimization

Incidence Matrix

Laplacian matrix

\[
\begin{bmatrix}
2 & -1 & 0 & 0 & -1 & 0 \\
-1 & 3 & -1 & 0 & -1 & 0 \\
0 & -1 & 2 & -1 & 0 & 0 \\
0 & 0 & -1 & 3 & -1 & -1 \\
-1 & -1 & 0 & -1 & 3 & 0 \\
0 & 0 & 0 & -1 & 0 & 1
\end{bmatrix}
\]
Landmark-based SLAM

- Sequence of robot (camera) poses $T_1, T_2, \ldots, T_t \in SE(d)$
- Robot measures the relative pose between $T_i$ and $T_{i+1}$ (odometry)
- Robot measures the environment (e.g., point landmarks $p_i \in \mathbb{R}^d$)

**Measurements**: odometry + measurements of (projection, range, position, or others) of external landmarks

**Variables**: robot poses and landmark positions
Graphical representation of landmark-based SLAM

- Each variable (robot pose, landmark position/pose) is a node in the graph.
- Each (usually) pairwise measurement denotes an edge between the corresponding two variables (nodes).
Graphical representation of landmark-based SLAM
Some terminology

MAP is maximum \textit{a posteriori} estimation
(MLE if no prior is available ["uninformative" prior])

courtesy of Cadena et al.
