MT Robot Reading Group

Past, Present, (and Future) of Simultaneous Localization and Mapping:

Toward the Robust-Perception Age

by Cesar Cadena, Luca Carlone, Henry Carrillo, Yasir Latif, Davide Scaramuzza, Jose Neira, Ian Reid, and John J, Leonard

T-RO 2016

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1. Introduction

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2. SLAM problem formulation

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3. Anatomy of a modern SLAM system
    - Front end
    - Back end

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Introduction

- Simultaneous Localization and Mapping (SLAM):

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  - Simultaneous estimation of the state of a robot

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- Simultaneous Localization and Mapping (SLAM):
    - Simultaneous estimation of the state of a robot
    - Construction of a model of the environment

ORB-SLAM2: an Open-Source SLAM for Monocular, Stereo and RGB-D Cameras

Introduction

- Map

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- Map
  - Can be used for navigation & planning

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  - Can be used to counteract drift in the estimation

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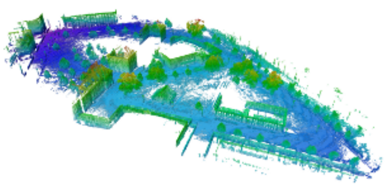
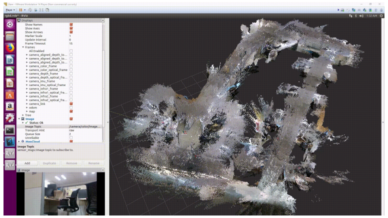
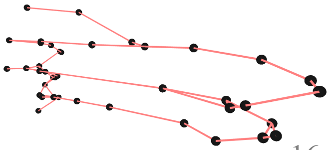
Voxels



Point clouds



Topological maps

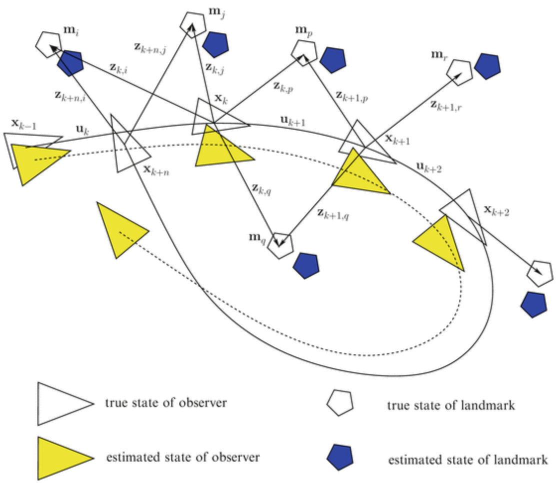


Introduction

Three periods of SLAM

- The classical age (1986-2004)
- Algorithmic-Analysis age (2004-2015)
- Robust-Perception age (2015-present)

SLAM problem formulation



$x_k, m_k \in \mathcal{X}$: Trajectory and landmarks

$u_k, z_k \in Z$: Measurements

Goal: $\mathcal{X}^\star \doteq \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(\mathcal{X}|Z)$

SLAM problem formulation

- A maximum a posteriori estimation problem

$$\mathcal{X}^\star \doteq \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(\mathcal{X}|Z) = \underset{\mathcal{X}}{\operatorname{argmax}} \frac{\mathrm{p}(Z|\mathcal{X})\mathrm{p}(\mathcal{X})}{\mathrm{p}(Z)} = \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(Z|\mathcal{X})\mathrm{p}(\mathcal{X})$$

- where $\mathcal{X}$ typically includes the trajectory and the landmarks
- $Z = z_k : k = 1, \ldots, m$ are a set of measurements
  - $z_k = h_k(\mathcal{X}_k) + \epsilon_k$ with known $h_k(\cdot)$

SLAM problem formulation

- Assuming the measurements Z are independent
  - Noises are uncorrelated

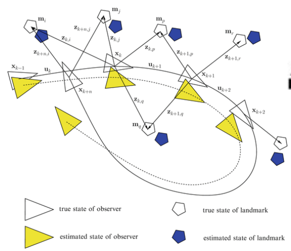
$$\mathcal{X}^\star = \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(Z|\mathcal{X})\mathrm{p}(\mathcal{X})$$

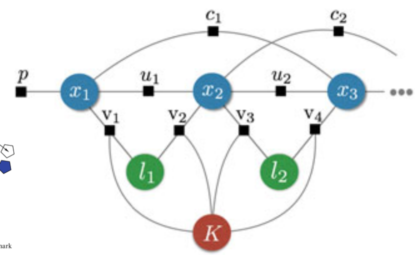
becomes

$$\mathcal{X}^\star = \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(\mathcal{X}) \prod_{k=1}^{m} \mathrm{p}\left(z_k|\mathcal{X}_k\right)$$

SLAM problem formulation

- SLAM interpreted as inference over a factor graph





- The variables correspond to nodes in the factor graph
- The terms $\mathrm{p}\left(z_k|\mathcal{X}_k\right)$ and the prior $\mathrm{p}(\mathcal{X})$ are called *factors*
  - they encode probabilistic constraints

SLAM problem formulation

More explicit

- Assuming measurement noise to be zero-mean Gaussian noise with information matrix Ω_k

SLAM problem formulation

More explicit

- Assuming measurement noise to be zero-mean Gaussian noise with information matrix Ω_k
- Measurement likelihood becomes:

$$\mathrm{p}\left(z_k|\mathcal{X}_k\right) \propto \exp\left(-\frac{1}{2}\|h_k\left(\mathcal{X}_k\right) - z_k\|^2_{\Omega_k}\right)$$

- with $\|e\|^2_{\Omega} = e^\top \Omega e$

SLAM problem formulation

More explicit

- Assuming the prior can be written as:

$$\mathrm{p}(\mathcal{X}) \propto \exp\left(-\frac{1}{2}\|h_0(\mathcal{X}) - z_0\|^2_{\Omega_0}\right)$$

- with prior mean z_0, and information matrix Ω_0

SLAM problem formulation

More explicit

Maximizing the posterior: $\mathcal{X}^{\star} = \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(\mathcal{X}) \prod_{k=1}^{m} \mathrm{p}\left(z_k | \mathcal{X}_k\right)$

SLAM problem formulation

More explicit

Maximizing the posterior: $\mathcal{X}^\star = \underset{\mathcal{X}}{\operatorname{argmax}}\, \mathrm{p}(\mathcal{X}) \prod_{k=1}^{m} \mathrm{p}\left(z_k | \mathcal{X}_k\right)$

... is the same as minimizing the *negative log-posterior*:

SLAM problem formulation

More explicit

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... is the same as minimizing the *negative log-posterior*:

$$\begin{aligned}
\mathcal{X}^{\star} &= \underset{\mathcal{X}}{\operatorname{argmin}} - \log\left(\mathrm{p}(\mathcal{X}) \prod_{k=1}^{m} \mathrm{p}\left(z_k | \mathcal{X}_k\right)\right) \\
&= \underset{\mathcal{X}}{\operatorname{argmin}} \sum_{k=0}^{m} \left\| h_k\left(\mathcal{X}_k\right) - z_k \right\|_{\Omega_k}^{2}
\end{aligned}$$

SLAM problem formulation

Minimizing the *negative log-posterior*:

$$
\begin{aligned}
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SLAM problem formulation

Minimizing the *negative log-posterior*:

$$\begin{aligned}\mathcal{X}^\star &= \underset{\mathcal{X}}{\operatorname{argmin}} -\log\left(\mathrm{p}(\mathcal{X})\prod_{k=1}^{m}\mathrm{p}\left(z_k|\mathcal{X}_k\right)\right)\\ &= \underset{\mathcal{X}}{\operatorname{argmin}}\sum_{k=0}^{m}\left\|h_k\left(\mathcal{X}_k\right)-z_k\right\|^2_{\Omega_k}\end{aligned}$$

... is a nonlinear least squares problem

SLAM problem formulation

Minimizing the *negative log-posterior*:

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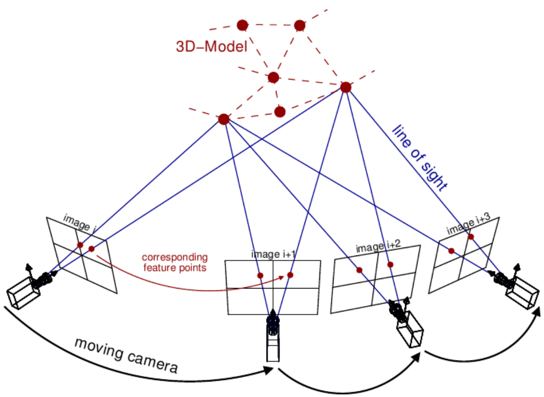
\end{aligned}
$$

... is a nonlinear least squares problem

- Similar to *bundle adjustment* known from Computer Vision

SLAM problem formulation

Bundle adjustment



SLAM problem formulation

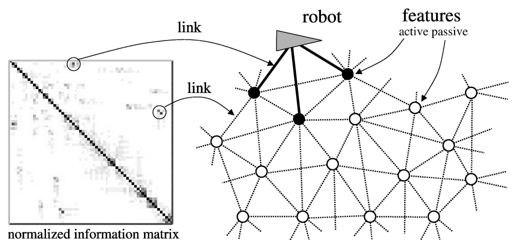
Solving the nonlinear least squares problem

- Solved via successive linearization
  - e.g. Gauss-Newton or Levenberg-Marquardt

SLAM problem formulation

Solving the nonlinear least squares problem

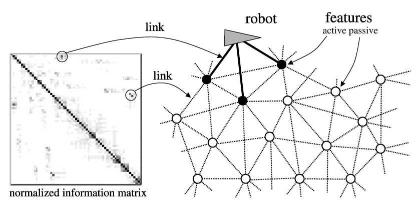
- Matrix appearing in the linearized problem is sparse



SLAM problem formulation

Solving the nonlinear least squares problem

- Matrix appearing in the linearized problem is sparse
  - Enables the use of fast linear solvers
  - Current SLAM libraries solve problems with tens of thousands of variables in a few seconds



SLAM problem formulation

- Early SLAM systems were based on nonlinear filtering

SLAM problem formulation

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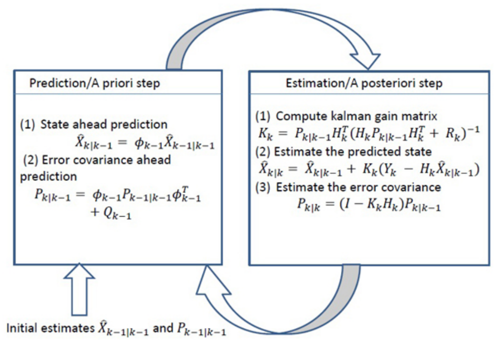
  - e.g. (Extended) Kalman Filter, particle filter



SLAM problem formulation

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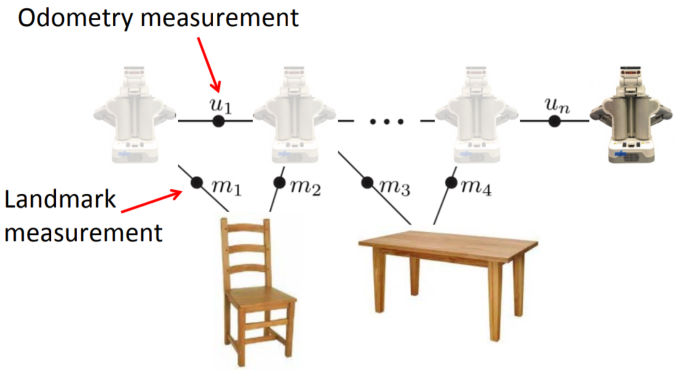

SLAM problem formulation

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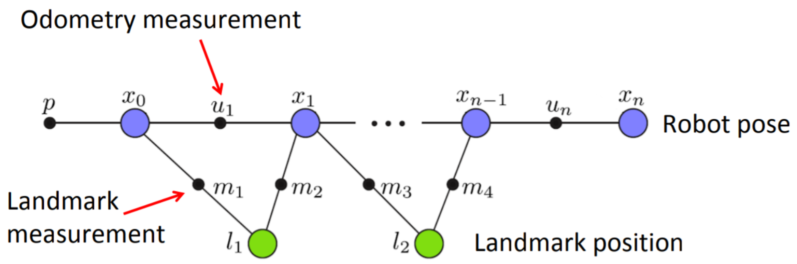
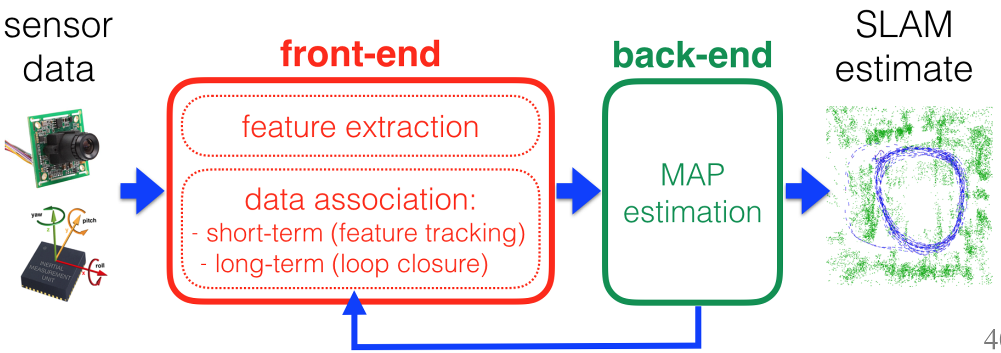


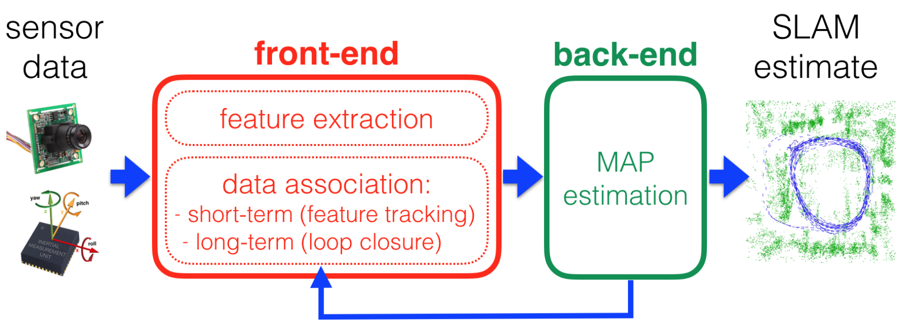
Anatomy of a modern SLAM system

- Front end: Abstracts sensor data into a models
- Back end: Performs inference on the abstracted data



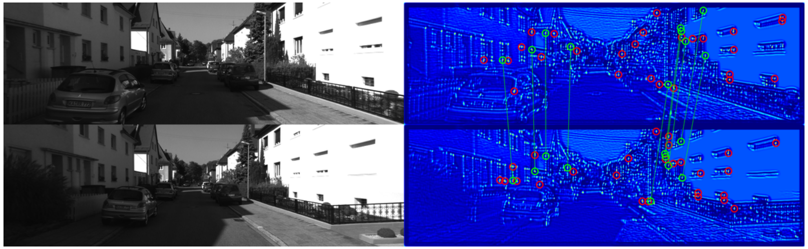
SLAM front-end

- Hard to write the sensor measurements directly as an analytic function of the states
  - as required in maximum a posteriori estimation



SLAM front-end

Short-term data association



SLAM front-end

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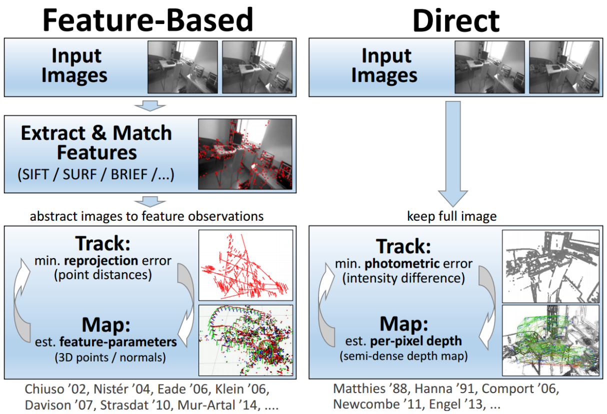
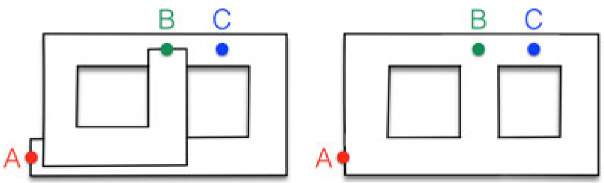


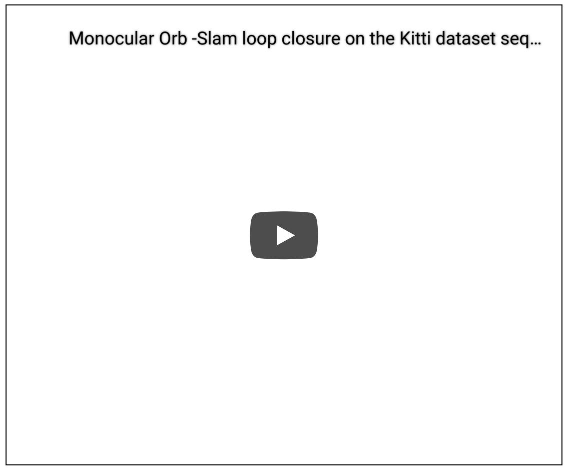
SLAM front-end

Long-term data association (or loop-closure)

- With information provided by the back-end



Long-term data association (or loop-closure)

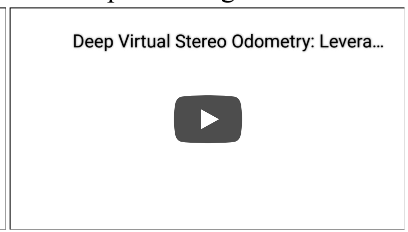


Further directions

Further directions

Event based cameras

Deep Learning & SLAM

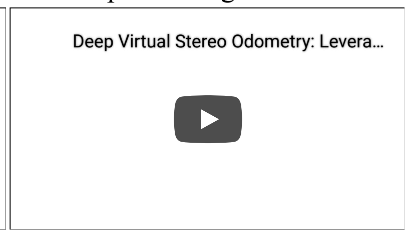


Semantic SLAM

Further directions

Event based cameras

Deep Learning & SLAM



Semantic SLAM

Further directions

Event based cameras

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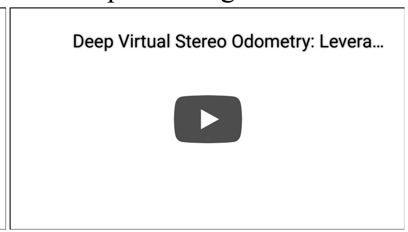

Semantic SLAM

Available systems

- Back ends:
  - gtsam (iSAM, iSAM2) (BSD License)
  - g2o (BSD License)
  - Google Ceres (New BSD License)
- SLAM systems:
  - Google Cartographer (Apache 2.0 License)
  - Maplab (Apache 2.0 License)
  - VINS-Fusion (GNU GPL v3.0)
  - RTAB-Map (BSD License)

Demo

Questions & Discussion