Simultaneous Localisation and Mapping (SLAM)

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Autonomous Mobile Robots

- The three key questions [Leonard and Durrant-Whyte 1991]
  - Where am I ?
  - Where am I going ?
  - How do I get there ?

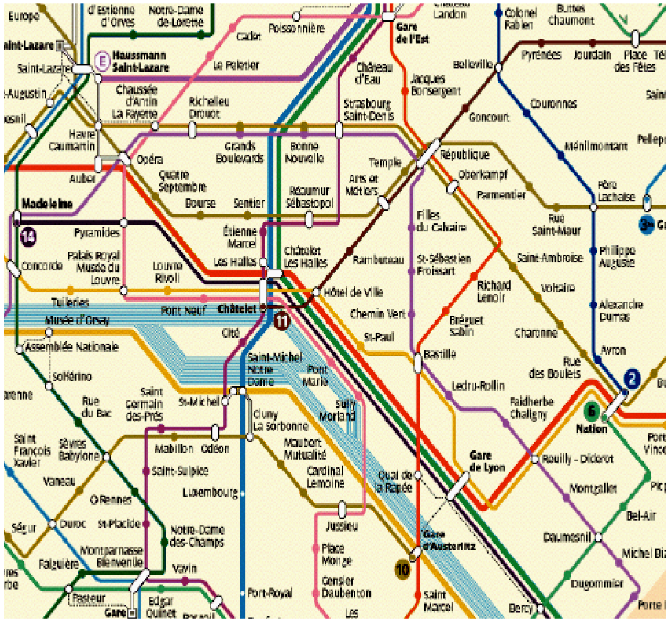
- Robot needs to
  - Know its environment => Mapping.
  - Perceive and analyze the environment => e.g. vision, lidar.
  - Find its position within the environment => Localization.
  - Plan and execute the movement => Path Planning.

Robot Mapping and Localisation

- **Mapping** – modelling the environment.

Geometric map

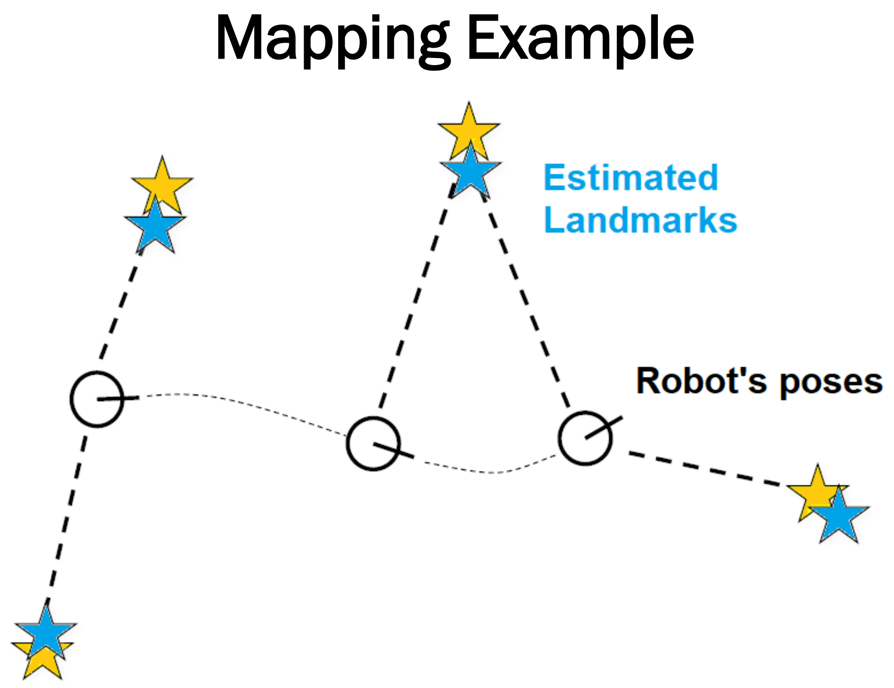
Topological map



- **Localization:** estimating the robot's location.

Courtesy of Wolfram Burgard

Robot Mapping and Localisation

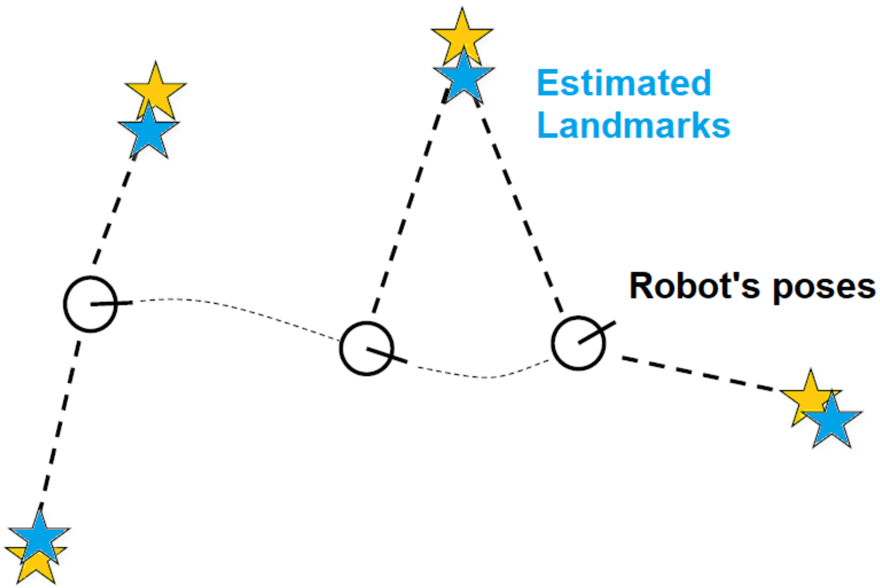


- Robot knows its pose and sees landmarks.
- Robot estimates landmarks on the map
  - to create / update / extend the map.

Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam01-intro.pdf, 2019

Robot Mapping and Localisation

Mapping Example



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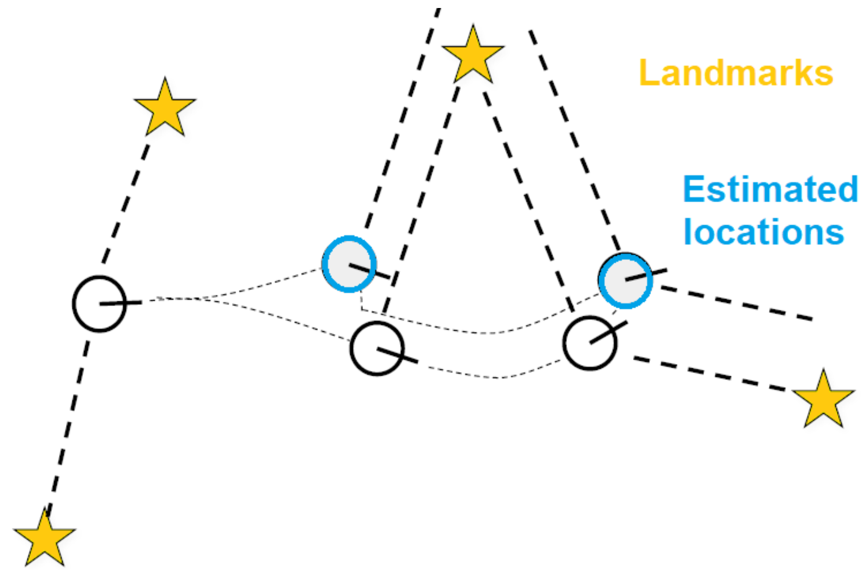
Localisation Example

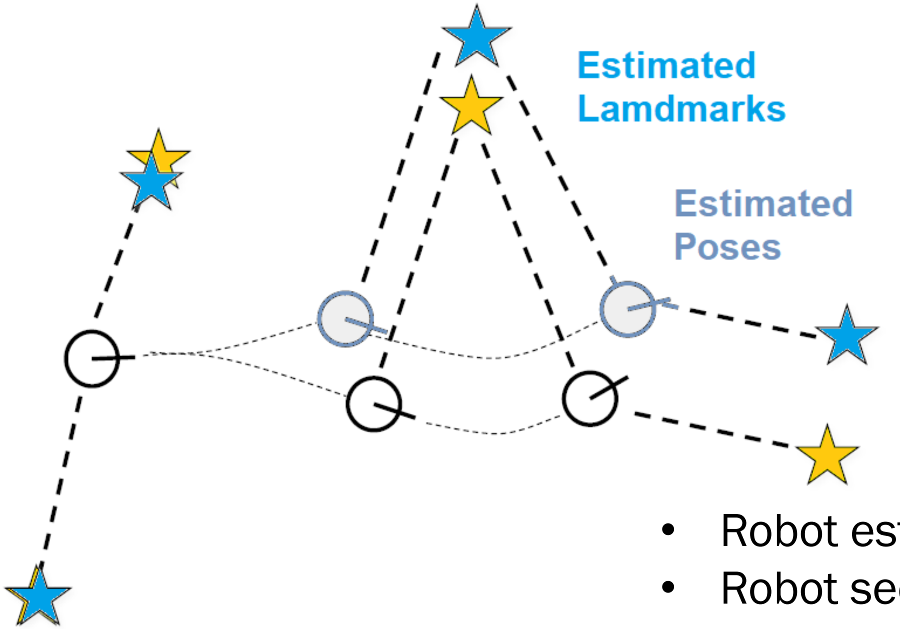


- Robot knows landmarks on map and sees landmarks.
- Robot estimates its pose / location.

Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam01-intro.pdf, 2019

Simultaneous Localisation and Mapping (SLAM)

- Estimate the robot's poses /locations and the landmarks at the same time.
  - building a map and locating the robot simultaneously.



- Robot estimates its pose / location.
- Robot sees landmarks.
- Robot estimates landmarks on the map
  - to create / update / extend the map.

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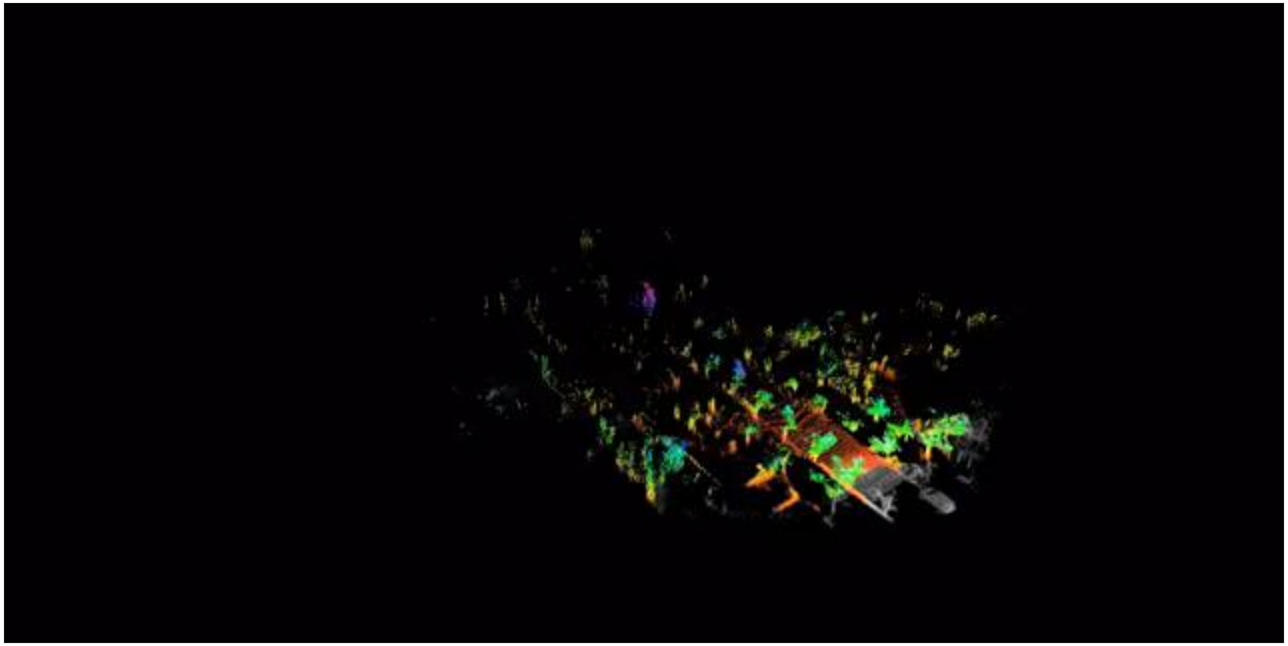
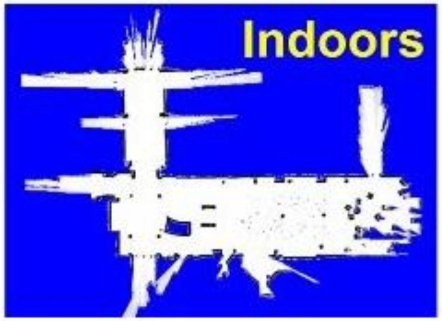


Courtesy https://www.youtube.com/watch?v=1pt3wuQMRDk

SLAM

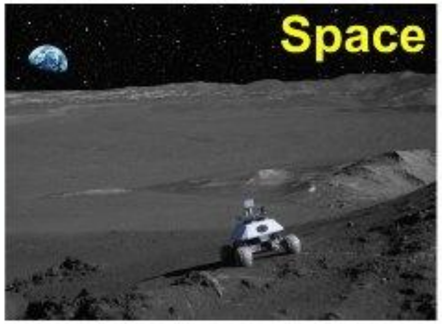
- SLAM is considered as a fundamental problem for autonomous mobile robots.
- It is basis for most navigation systems.
  - building a map of an unknown environment by a mobile robot while at the same time navigating the environment using the map.

- Wide range of applications.
- Highly relevant for all kinds of applications that involve moving robots.



vacuum cleaner

reef monitoring



terrain mapping for localisation

exploration of mines

Courtesy of H. Durrant-Whyte, NASA, S. Thrun

Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam01-intro.pdf, 2019

SLAM in AR/VR

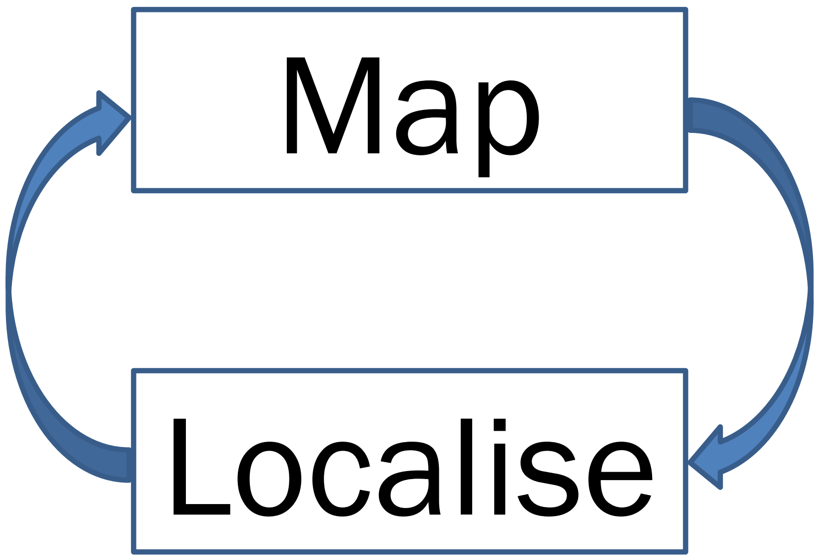
- Project Tango (Google)
- AR/ VR Glasses
  - Hololens (Microsoft)
  - Oculus Rift (Facebook)

- Apple (metaio)
- Oculus (surreal Vision) ..

Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

The SLAM Problem

- SLAM is a chicken-or-egg problem.
  - Map is needed for localisation.
  - Pose estimate is necessary for mapping.



The SLAM Problem

GIVEN

- The robot's controls

$$u_{1:T} = \{u_1, u_2, \dots, u_T\}$$

- Observations

$$z_{1:T} = \{z_1, z_2, \dots, z_T\}$$

Note: The controls and observations are both noisy.

ESTIMATE

- Path of the robot => sequence of poses and locations,

$$x_{0:T} = \{x_0, x_1, x_2, \dots, x_T\}$$

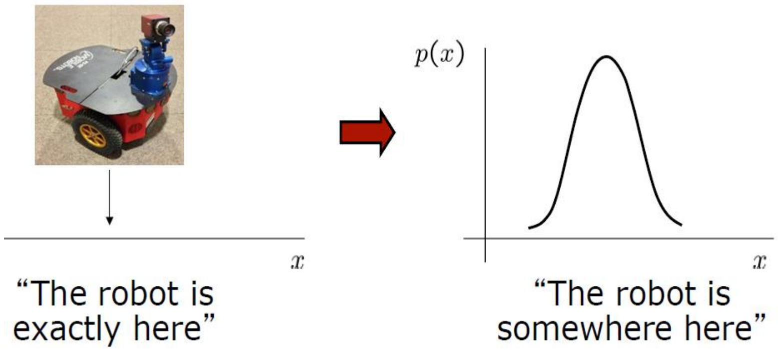
- Map of the environment

$$\boldsymbol{m}$$

Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam01-intro.pdf, 2019

Probabilistic Approaches

- Use the probability theory to explicitly represent the uncertainty.



- **In Probabilistic Terms**
  - Estimate the robot’s path and the map

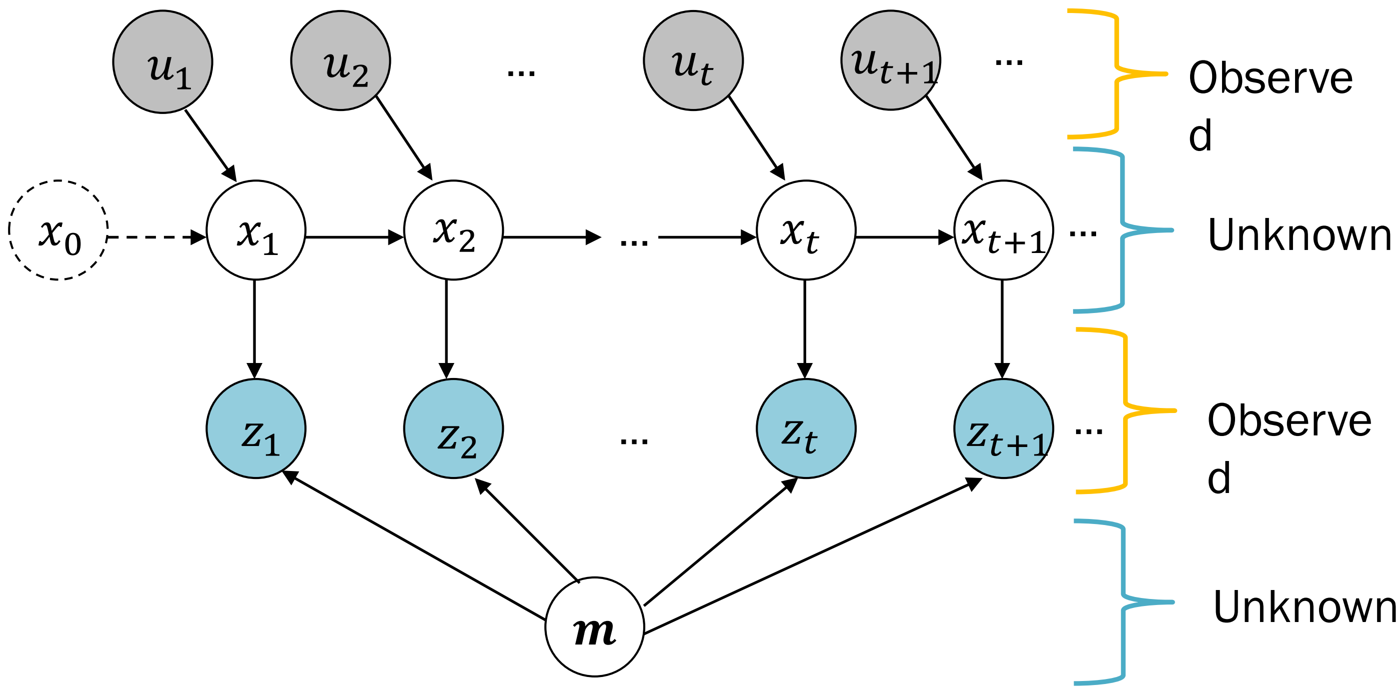
$$p(x_{0:T}, m | z_{1:T}, u_{1:T})$$

distribution path map given observations controls

Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam01-intro.pdf, 2019

Graphical Model

Markov assumption



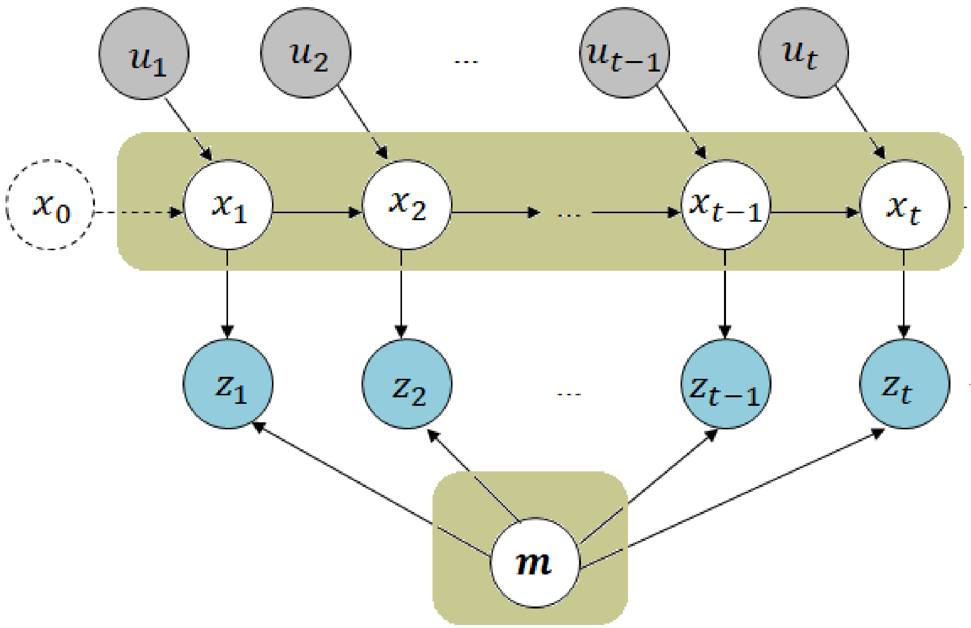
- SLAM as a state estimation Problem
  - Estimate the state of a system given observations and controls. i.e. $p(x|z,u)$

State transition: $p(x_t|x_{t-1},u_t)$ Observation function: $p(z_t|x_t)$

Full SLAM

- Estimates the entire path and map

$$p(x_{0:T}, m | z_{1:T}, u_{1:T})$$



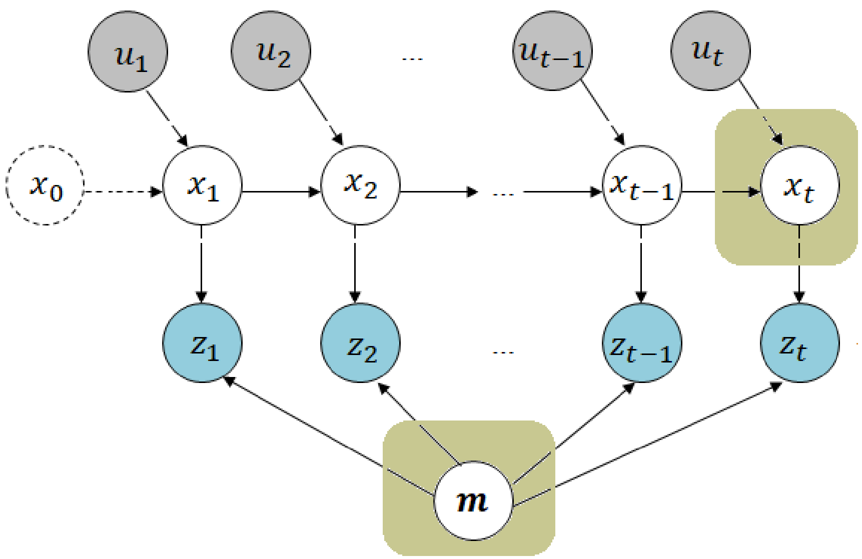
Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam01-intro.pdf, 2019

Online SLAM

- Estimates only the most recent pose and map.

$$p(x_t, m | z_{1:t}, u_{1:t}) = \iint \dots \int p(x_{1:t}, m | z_{1:t}, u_{1:t}) dx_1 dx_2 \dots dt_{t-1}$$

- Integrations typically done recursively, one at a time.



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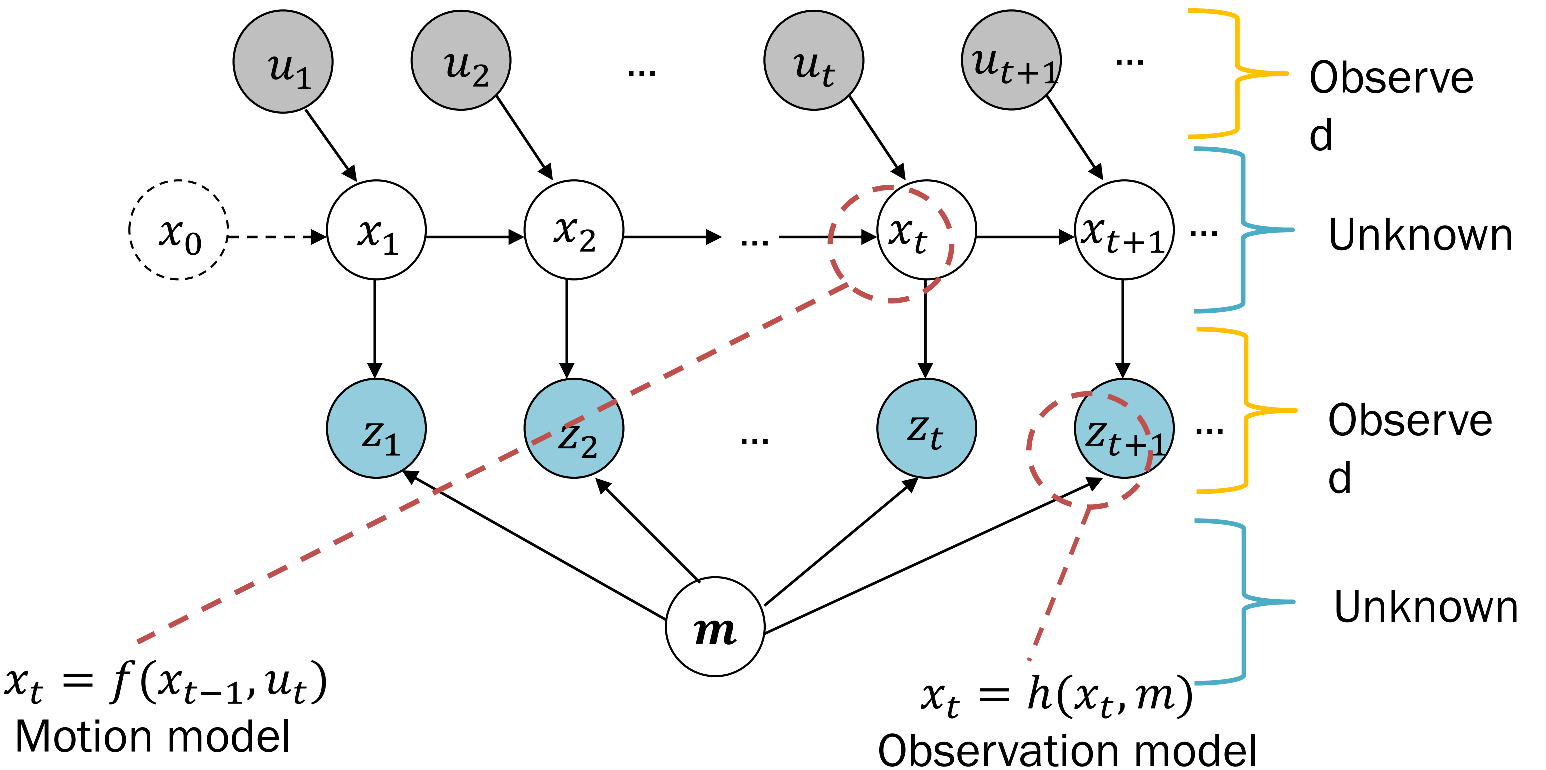
Motion and Observation Model



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  - Estimate the state of a system given observations and controls. i.e. $p(x|z,u)$

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Motion and Observation Model

Motion Model

- describes the relative motion of the robot.

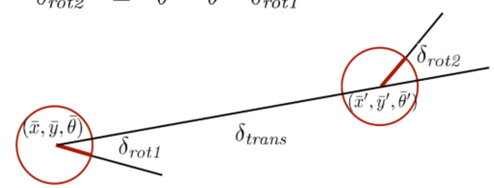
$$p(x_t | x_{t-1}, u_t)$$

distribution new pose given old pose control

Odometry Model

- Robot moves from $(\bar{x}, \bar{y}, \bar{\theta})$ to $(\bar{x}', \bar{y}', \bar{\theta}')$
- Odometry information $u = (\delta_{rot1}, \delta_{trans}, \delta_{rot2})$

$$\begin{aligned}
\delta_{trans} &= \sqrt{(\bar{x}' - \bar{x})^2 + (\bar{y}' - \bar{y})^2} \\
\delta_{rot1} &= \operatorname{atan2}(\bar{y}' - \bar{y}, \bar{x}' - \bar{x}) - \bar{\theta} \\
\delta_{rot2} &= \bar{\theta}' - \bar{\theta} - \delta_{rot1}
\end{aligned}$$



Observation Model

- The observation or sensor model relates measurements with the robot's pose.

$$p(z_t | x_t)$$

distribution observation given pose

Model for Laser Scanners

- Scan z consists of K measurements.

$$z_t = \{z_t^1, \ldots, z_t^k\}$$

- Individual measurements are independent given the robot position

$$p(z_t \mid x_t, m) = \prod_{i=1}^{k} p(z_t^i \mid x_t, m)$$

Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam02-bayes-filter-short.pdf, 2019

Motion and Observation Model

- Sequentially estimate $p(x|z,u)$ and update the map

- Using Bayer's filter
  $bel(x_t) = p(x_t|z_{1:t}, u_{1:t})$ =>belief

Prediction Step

$$\overline{bel}(x_t) = \int \underbrace{\boldsymbol{p}(\boldsymbol{x_t}|\boldsymbol{u_t}, \boldsymbol{x_{t-1}})}_{\text{motion model}} \, bel(x_{t-1}) dx_{t-1}$$

Correction Step

$$bel(x_t) = \eta \underbrace{\boldsymbol{p}(\boldsymbol{z_t}|\boldsymbol{x_t})}_{\text{observation model}} \overline{bel}(x_{t-1})$$

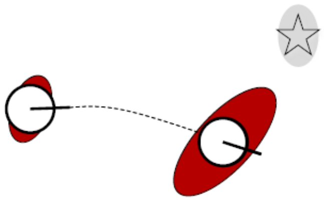
Courtesy of Cyrill Stachniss, Robot Mapping, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam02-bayes-filter-short.pdf, 2019

SLAM

- Kalman Filter => Bayer’s Filter
  - Gaussian distributions and noise
  - Linear motion and observation model.
- Most realistic problems in robotics involve nonlinear functions.
  - The non-linear functions lead to non Gaussian distributions.
- Non-Gaussian Distributions
  - Local linearization by first order Taylor series expansion as in Extended Kalman Filter (EKF).
    - EKF SLAM is the first SLAM solution.
- Non parametric and Arbitrary models
  - Particle Filter based localisation (Monte-Carlo localization)
    - Particle Filters => non-parametric, recursive Bayes filters.

EKF SLAM: Filter Cycle

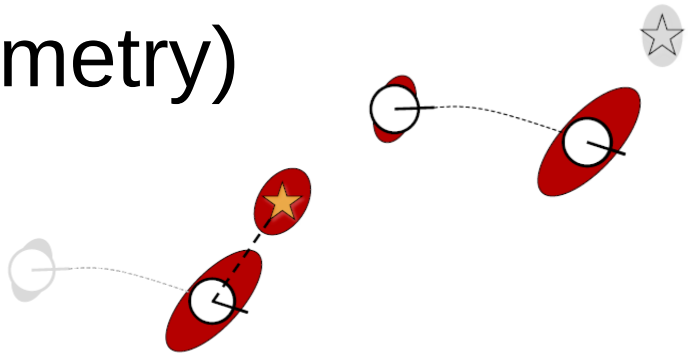
1. State prediction (e.g. odometry)



Courtesy of Cyrill Stachniss, EKF SLAM, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam04-ekf-slam.pdf

EKF SLAM: Filter Cycle

1. State prediction (e.g. odometry)
2. Measurement prediction



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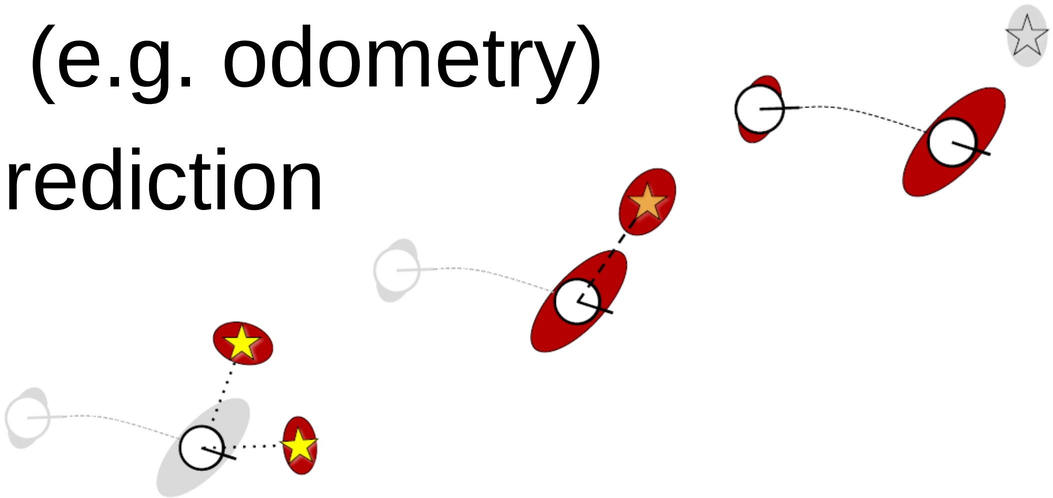

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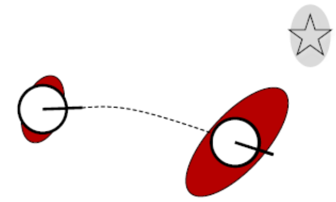

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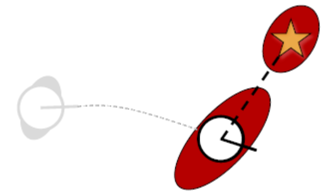
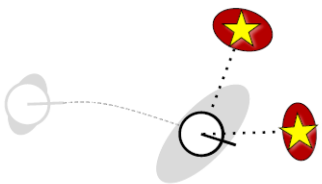
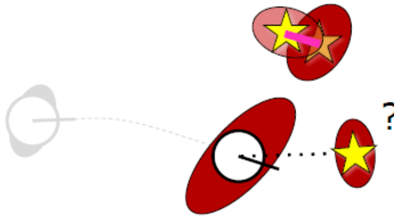




3. Measurement
4. Data association
   - Associates predicted measurements with observation



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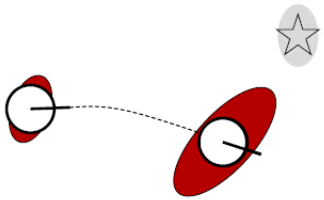

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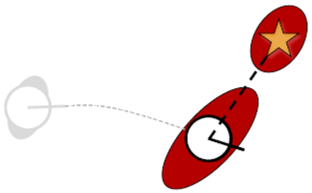

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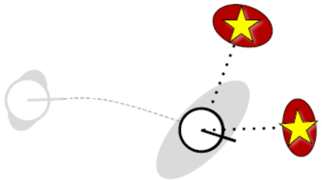

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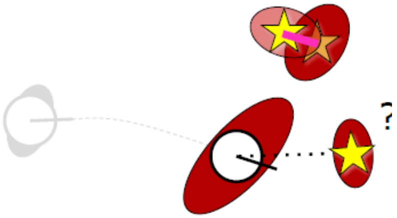
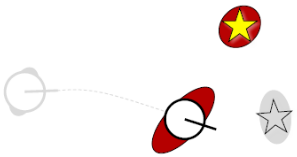


5. Update



Courtesy of Cyrill Stachniss, EKF SLAM, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam04-ekf-slam.pdf

EKF SLAM: Filter Cycle

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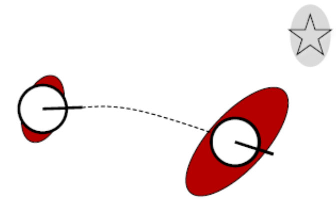

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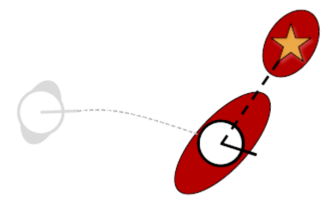

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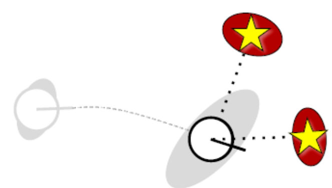

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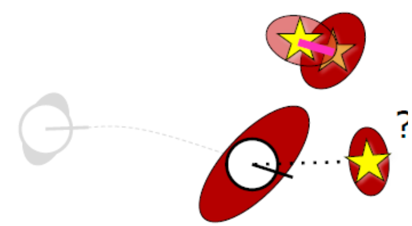

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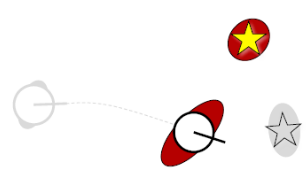
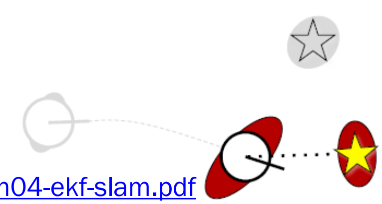


6. Integration of new landmarks



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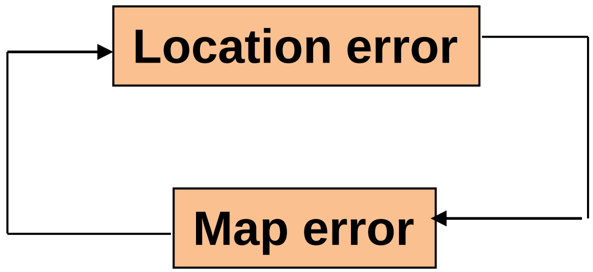
Suggested Readings

- Thrun et al. “Probabilistic Robotics”
- Course: Introduction to Mobile Robotics - SS 2019
- Siciliano et al. “Springer Handbook of Robotics”

Why is SLAM a hard problem?

- Robot path and map are both **unknown.**
- Errors in map and pose estimates correlate.



- The **mapping between observations and the map is unknown.**

- Picking **wrong** data associations can lead to divergence.

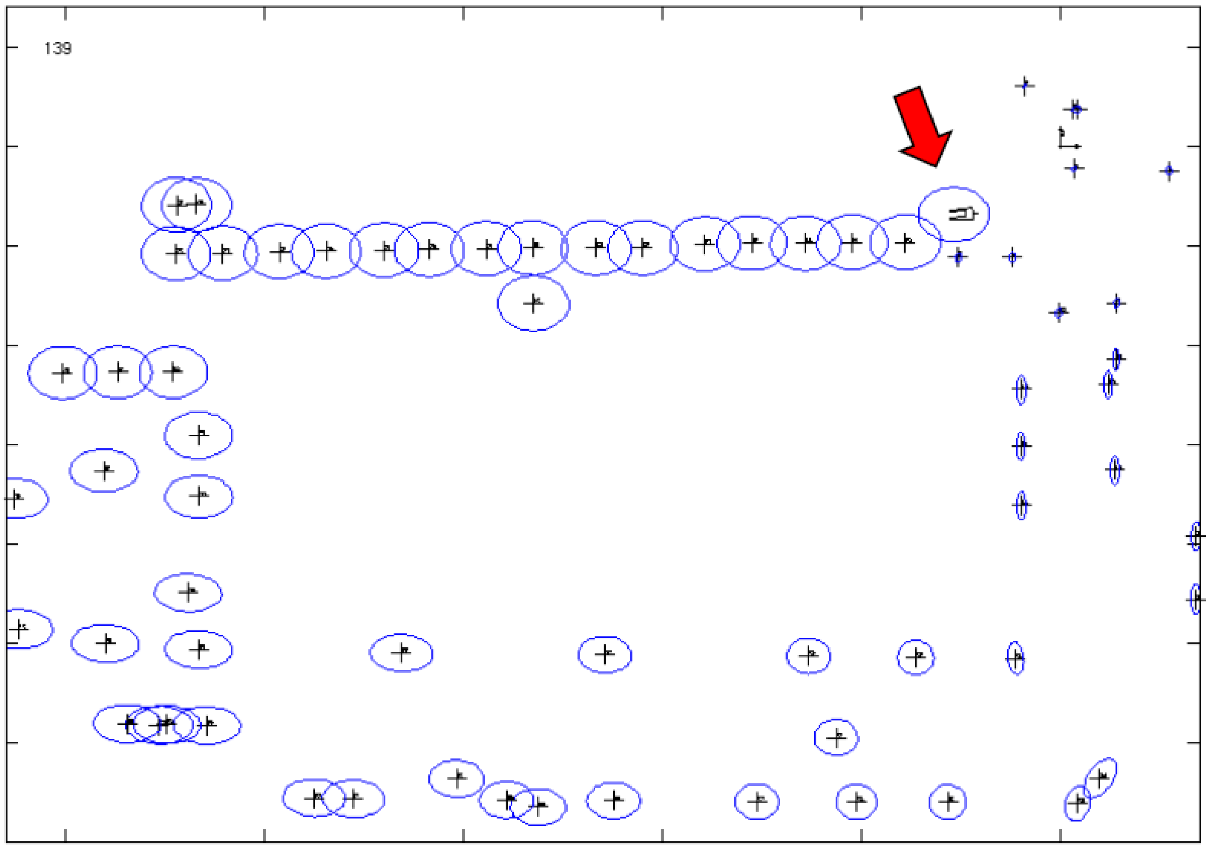
SLAM: Loop Closure

- **Recognizing an already mapped area.**
- By revisiting already mapped areas, uncertainties in robot and landmark estimates can be **reduced.**
- This can be exploited when **exploring** an environment for the sake of better (e.g. more accurate) maps.

Courtesy of Cyrill Stachniss, EKF SLAM, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam04-ekf-slam.pdf

SLAM: Loop Closure

Before loop closure



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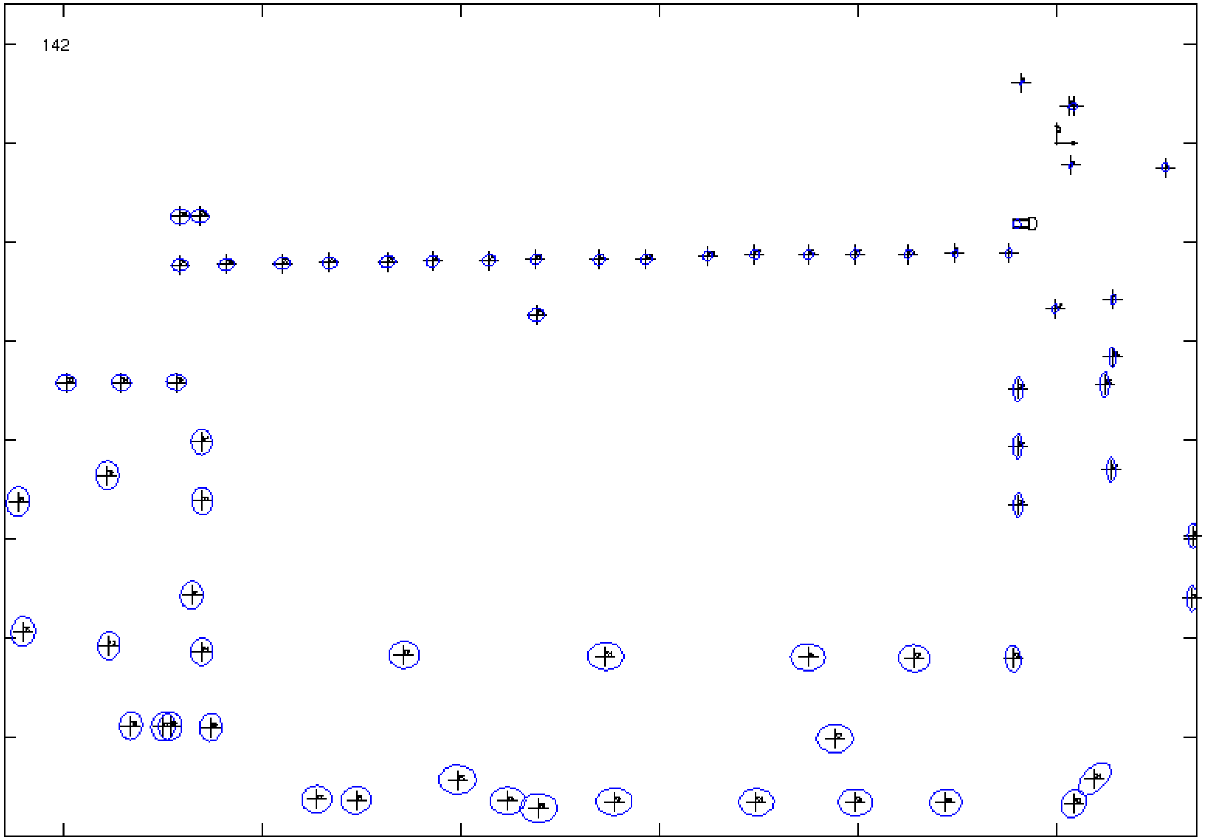
SLAM: Loop Closure

After loop closure



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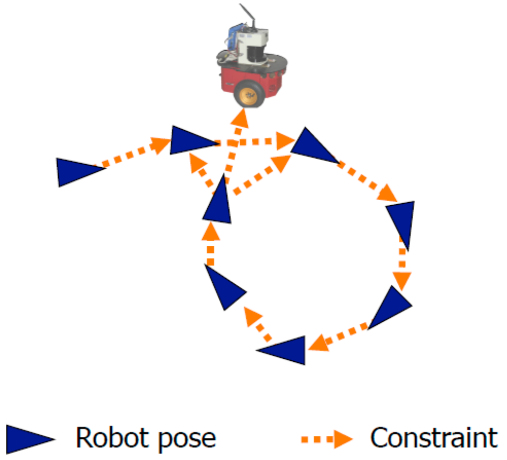
Graph-Based SLAM

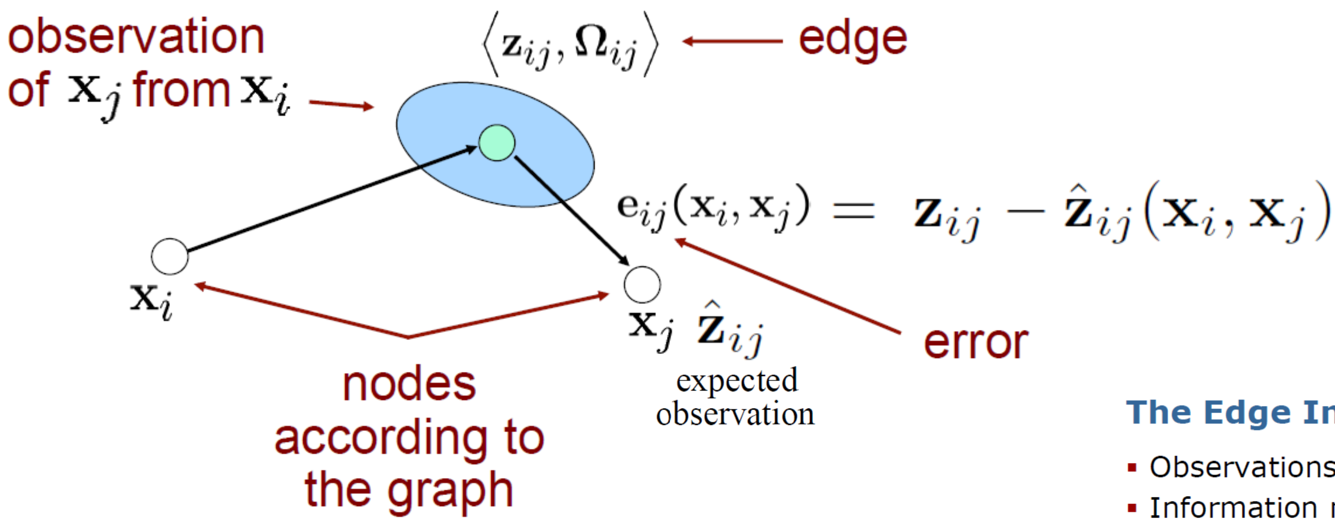
- Use a **graph** to represent the problem .
- Every **node** in the graph corresponds to a **pose of the robot** during mapping.
- Every **edge** between two nodes corresponds to a **spatial constraint** between them.
- **Goal:** Build the graph and find a node configuration that minimize the error introduced by the constraints.
  - Least squares approach to SLAM.



Courtesy of Wolfram Burgard, Graph-Based SLAM, http://ais.informatik.uni-freiburg.de/teaching/ss19/robotics/slides/16-graph-slam.pdf, 2019

Pose Graph

- The problem can be described by a graph.



The Edge Information Matrices

- Observations are affected by noise
- Information matrix Ω_{ij} for each edge to encode its uncertainty
- The "bigger" Ω_{ij}, the more the edge "matters" in the optimization

- Goal

$$x^* = \underset{x}{\operatorname{argmin}} \sum_{ij} e_{ij}^T \Omega_{ij} e_{ij}$$

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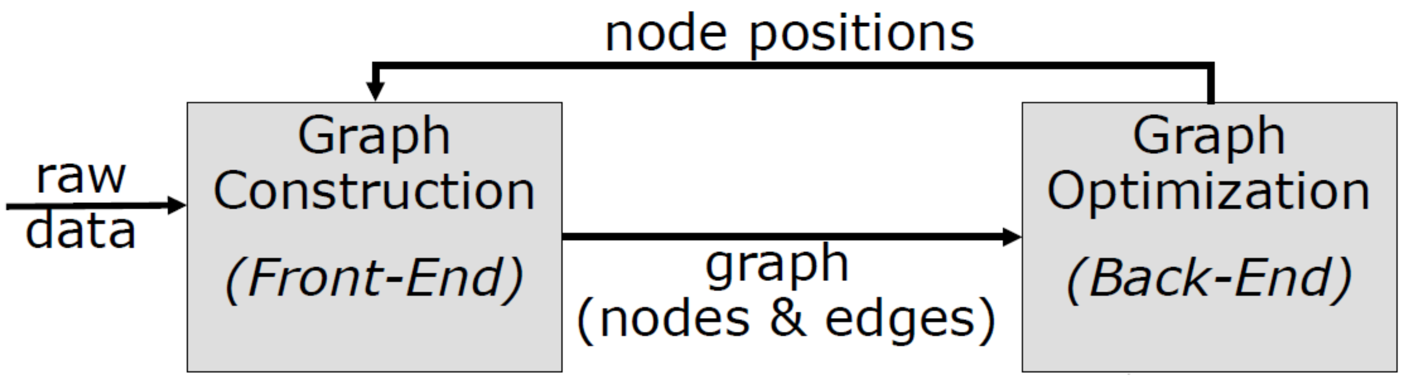
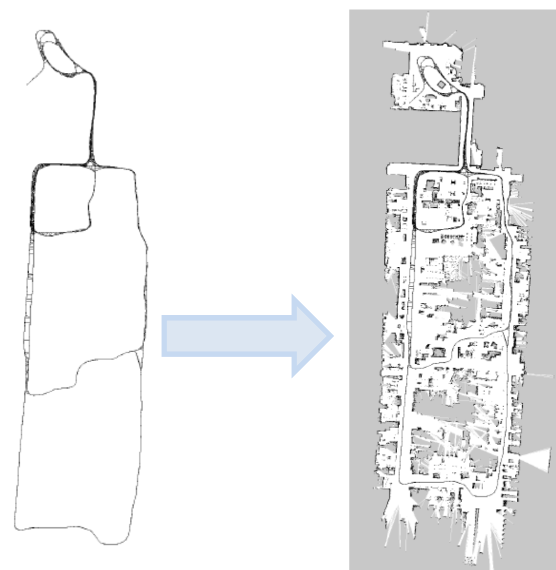
The overall SLAM system



- Once we have the graph, we determine the most likely map by correcting the nodes.

- Then, we can render a map based on the known poses.

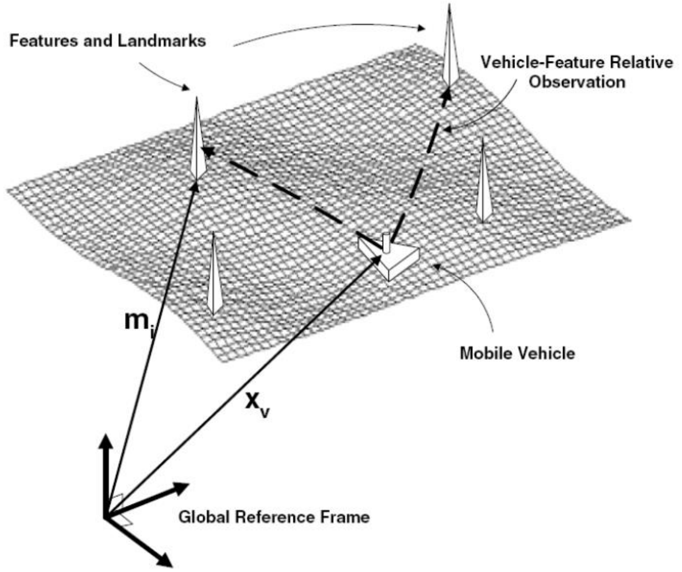


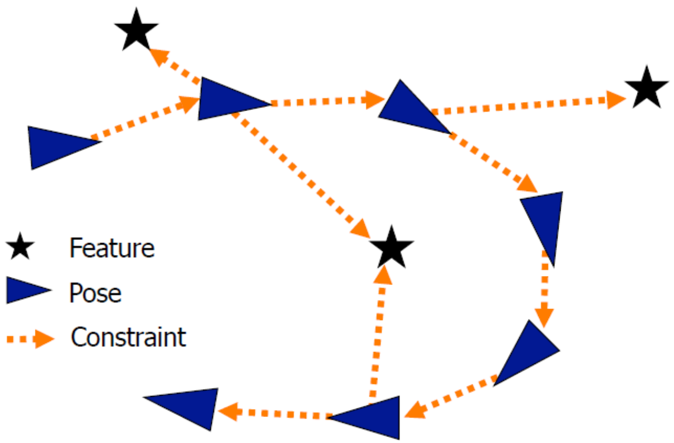
Suggested Reading:
Grisetti, Kümmerle, Stachniss, Burgard:
"A Tutorial on Graph-based SLAM", 2010

Courtesy of Wolfram Burgard, Graph-Based SLAM, http://ais.informatik.uni-freiburg.de/teaching/ss19/robotics/slides/16-graph-slam.pdf, 2019

Graph-Based SLAM 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.



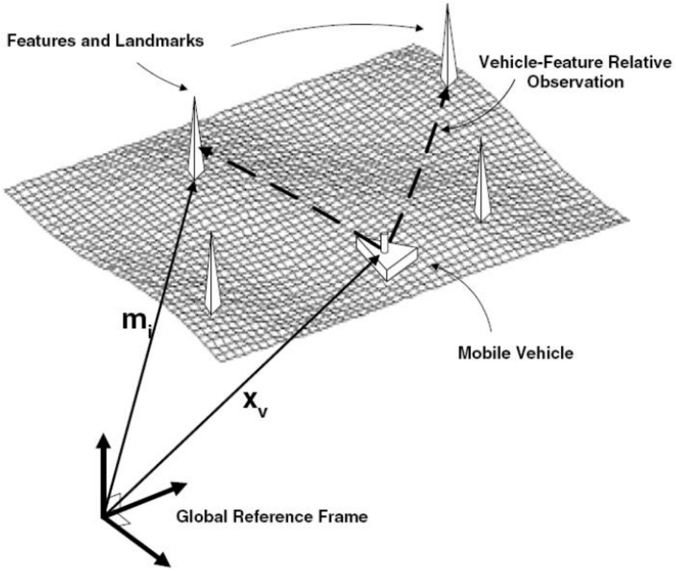


Courtesy of Cyrill Stachniss, Graph-Based SLAM with Landmarks, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam17-ls-landmarks.pdf

Graph-Based SLAM with Landmarks

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

Relative observation in (x, y)



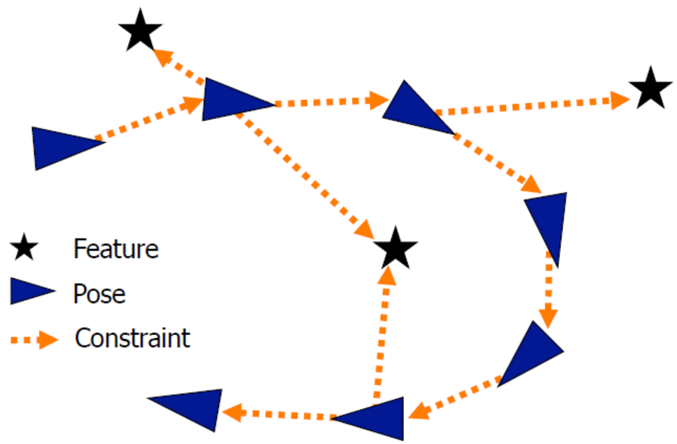
Expected observation (x-y sensor)

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

robot landmark robot translation

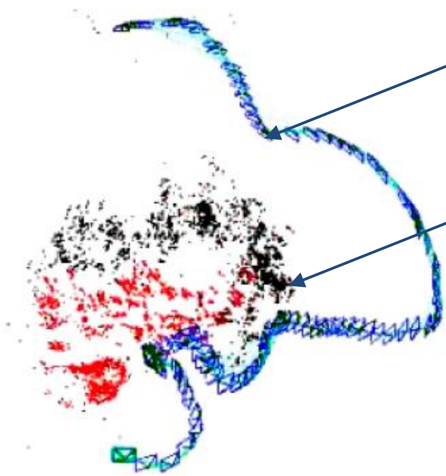
Error function

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



Courtesy of Cyrill Stachniss, Graph-Based SLAM with Landmarks, http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam17-ls-landmarks.pdf

Feature-Based Visual SLAM



States

$\mathbf{T_{iw}} \in \mathbf{SE(3)}$ Pose of Camera **i**

$\mathbf{x_{wj}} \in \mathbb{R}^{\mathbf{3}}$ Coordinates of Point **j**

Measurements

$\mathbf{u_{ij}} = \begin{bmatrix} u_{ij} \\ v_{ij} \end{bmatrix}$ Observation of Point **j** from camera **i**

$$\boldsymbol{T_{iw}} = \begin{cases} \boldsymbol{R_{iw}} \in \mathbf{SO(3)} & \text{Rotation Matrix} \\ \boldsymbol{t_{iw}} \in \mathbb{R}^{\mathbf{3}} & \text{Translation Vector} \end{cases}$$

$\boldsymbol{x_{ij}} = \boldsymbol{R_{iw}}\mathbf{x_{wj}} + \boldsymbol{t_{iw}}$ Coordinates of point **j** wr. t. camera **i**

Reprojection Error

Projection Function

$$\boldsymbol{e_{ij}} = \mathbf{u_{ij}} - \pi_i(\mathbf{T_{iw}} - \mathbf{x_{wj}})$$

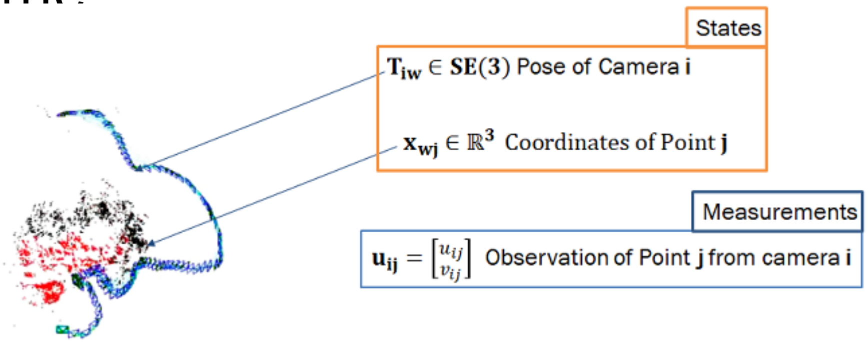
Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

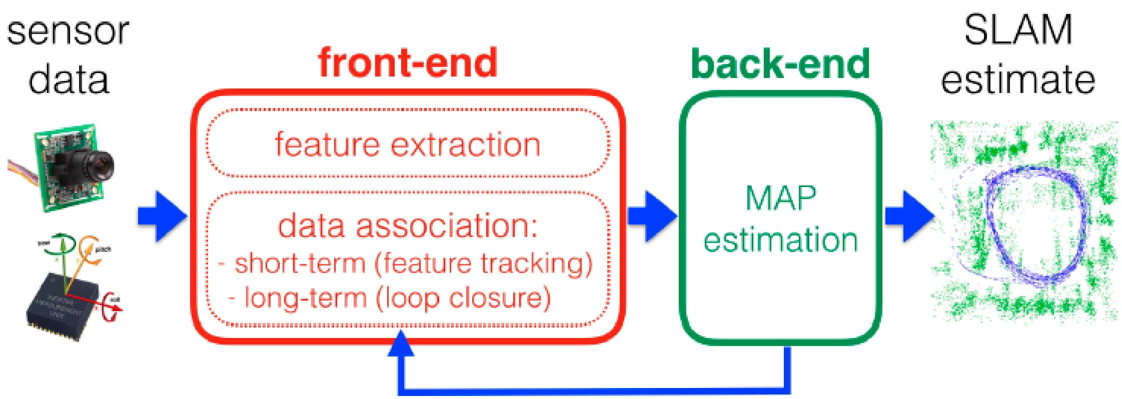
Feature-Based Visual SLAM

- Find the state values minimizing the reprojection error.

$$e_{ij} = \mathbf{u_{ij}} - \pi_i(\mathbf{T_{iw}} - \boldsymbol{x}_{\mathbf{wj}})$$

  - By Bundle Adjustment





Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Data Association (DA)

- Data association is the process of associating uncertain measurements to known tracks.
  - Does the current observation belong to a known landmark or a new landmark needs to be added?

- Why is it difficult?
  - complicated by sensor noise, dynamics, uncertainty in robot motion, static world assumption.
  - correct DA essential for getting correct estimates of landmarks as well as robot motion.

Lowry, Stephanie, et al. "Visual place recognition: A survey." IEEE Transactions on Robotics 32.1 (2016): 1-19

DA in Modern Visual SLAM

- Visual Landmarks
  - Features
    - Corners => Harris, FAST, ORB
    - Blobs like SIFT, SURF
    - Line segment => LSD, ED
  - Feature Descriptors like HoG, DoG, KAZE, BRIEF

- The aim is to track the patch over time
  - Assumption: descriptors vary very little between frames.
  - The scene is static, occlusions are limited, no rapid motion.

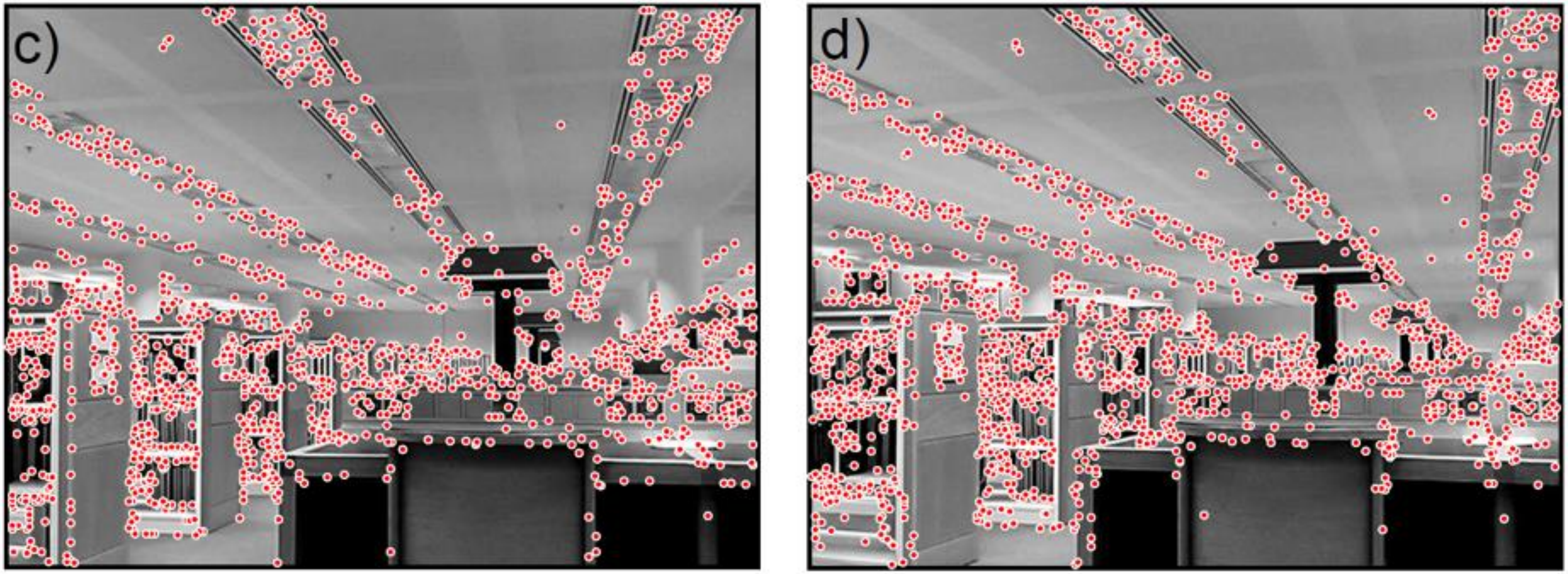
DA in sparse visual SLAM

- Task : Find matches for a reference image in current image.

Courtesy of Simon Lucey, http://16623.courses.cs.cmu.edu/slides/Lecture_18.pdf

DA in sparse visual SLAM

- Find features
  - e.g. using a corner detection algorithm.



Courtesy of Simon Lucey, http://16623.courses.cs.cmu.edu/slides/Lecture_18.pdf

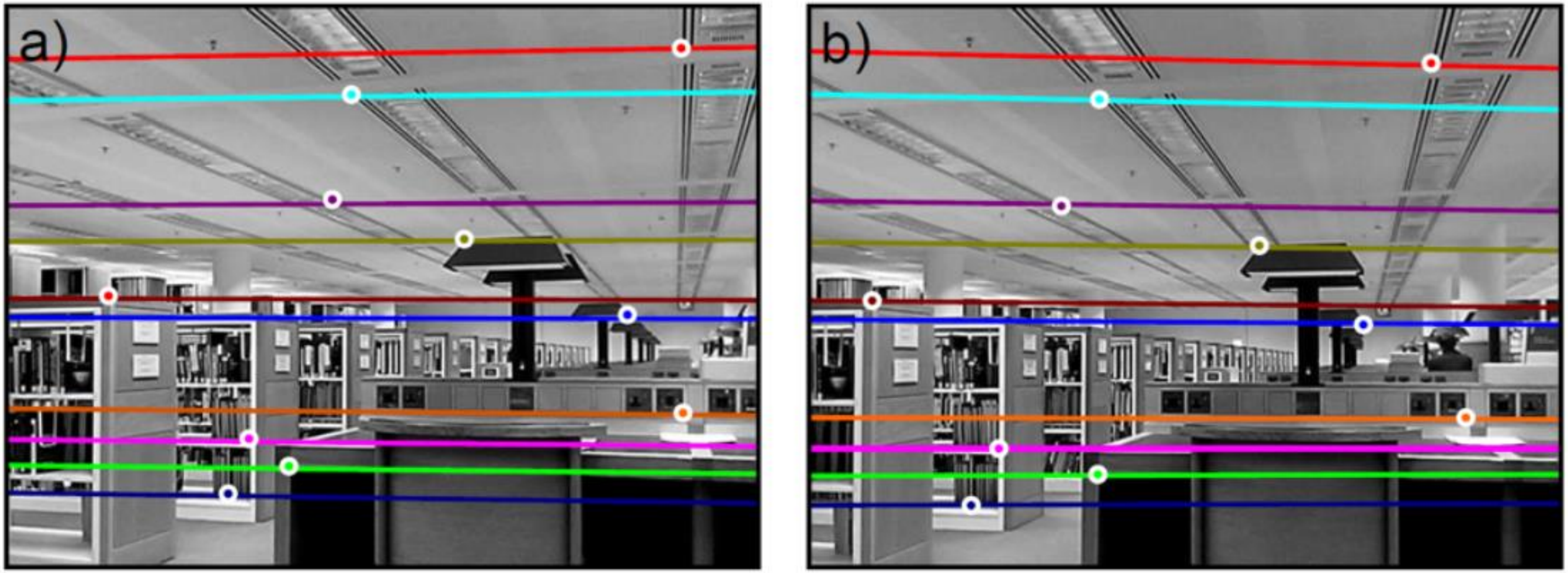
DA in sparse visual SLAM

- Match features.

Courtesy of Simon Lucey, http://16623.courses.cs.cmu.edu/slides/Lecture_18.pdf

DA in sparse visual SLAM

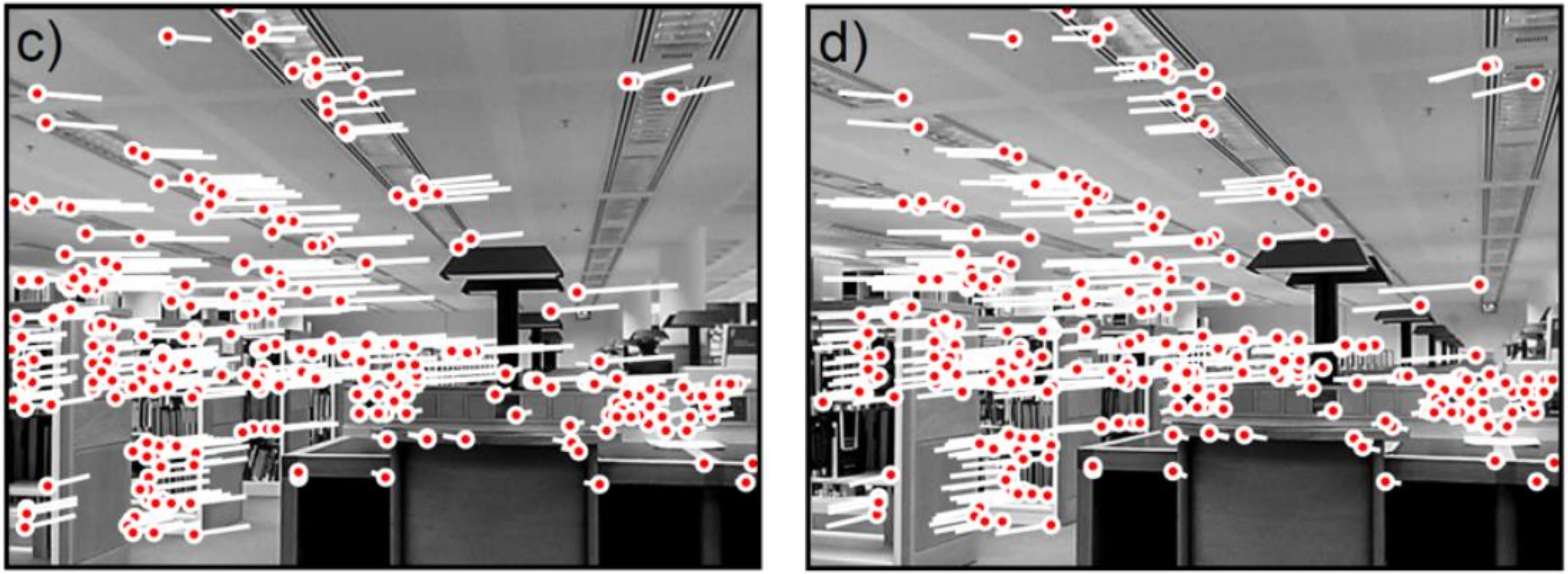
- Remove Outliers
  - Fit fundamental matrix using robust algorithm such as RANSAC



Courtesy of Simon Lucey, http://16623.courses.cs.cmu.edu/slides/Lecture_18.pdf

DA in sparse visual SLAM

- Keep Inliers
  - Find matching points that agree with the fundamental matrix.



Courtesy of Simon Lucey, http://16623.courses.cs.cmu.edu/slides/Lecture_18.pdf

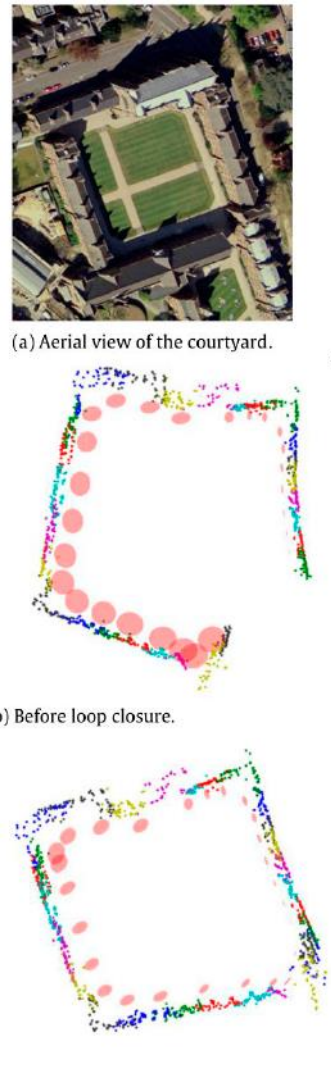
DA in sparse visual SLAM

- Extract essential matrix from fundamental matrix.
- Extract rotation $\boldsymbol{R}$ and translation $\boldsymbol{t}$ from essential matrix.
- Reconstruct the 3D positions $\mathbf{x}$ of points.

$$\lambda\tilde{\mathbf{x}} = \boldsymbol{R}\mathbf{x} + \mathbf{t}$$

Relocation and Loop Closing

- Relocation problem:
  – During SLAM tracking can be lost: occlusions, low texture, quick motions, ...
    - Re-acquire camera pose and continue.
- Loop closing problem
  – SLAM is working, and we come back to a previously mapped area.
    - Loop detection: to avoid map duplication.
    - Loop correction: to compensate the accumulated drift => reduces overall uncertainty.
- In both cases we need a place recognition technique.



(a) Aerial view of the courtyard.

(b) Before loop closure.

(c) After loop closure.

Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Why is loop closing difficult?

- Similar place can look different over time (day/night, weather, construction, etc).

- *Perceptual aliasing*: Different places can “look” similar to the sensor.

Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

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Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

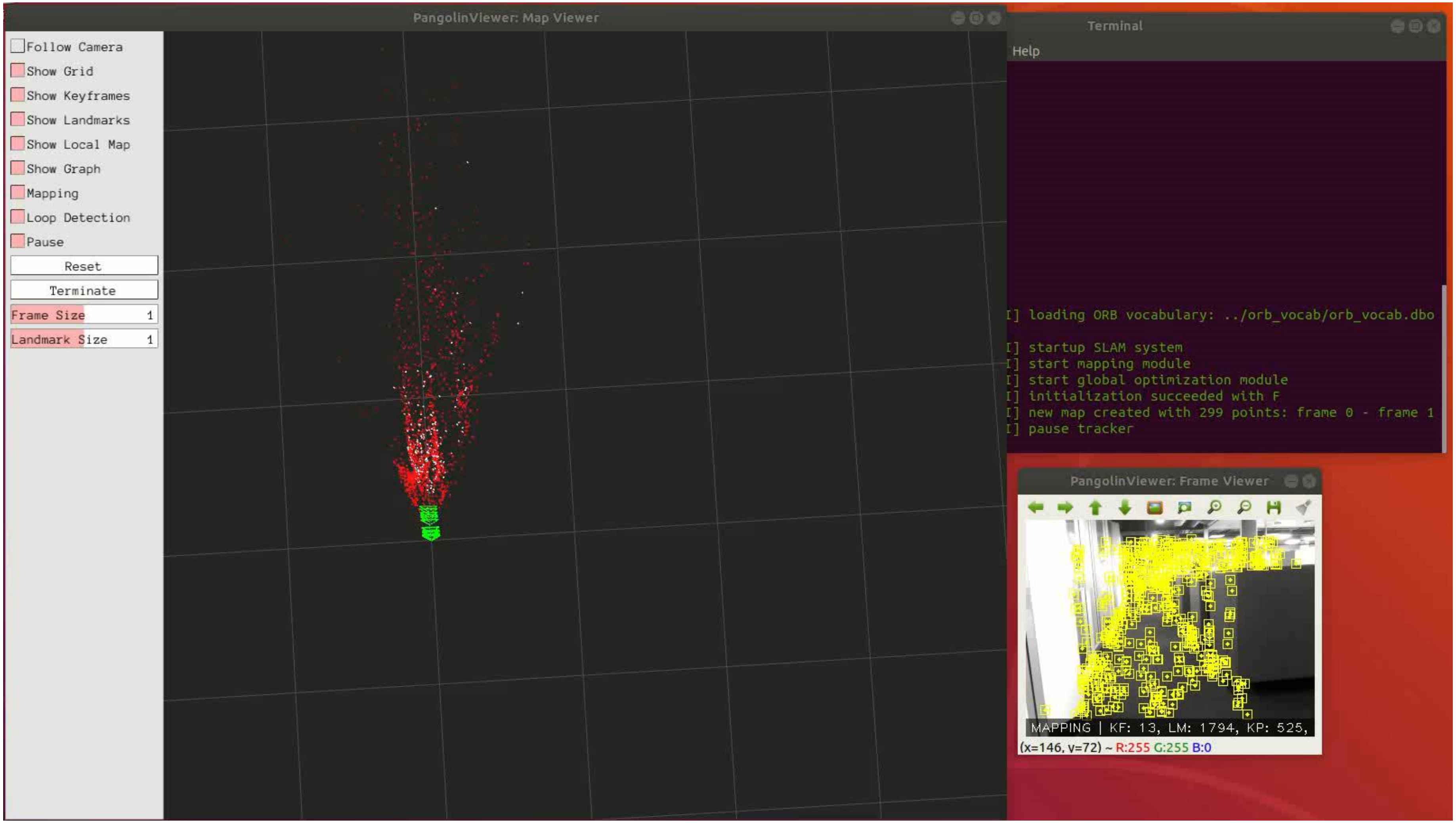
Loop Closing

- Visual similarity can be computed using global image descriptors (GIST descriptors) or local image descriptors (e.g., ORB features).

- Image retrieval is the problem of finding the most similar image of a template image in a database of billion images (image retrieval).

- This can be solved efficiently with Bag of Words.

Loop Closing



ORB-SLAM: **Feature-Based** SLAM

- Use the same features for:
  - Tracking
  - Mapping
  - Loop closing
  - Relocation

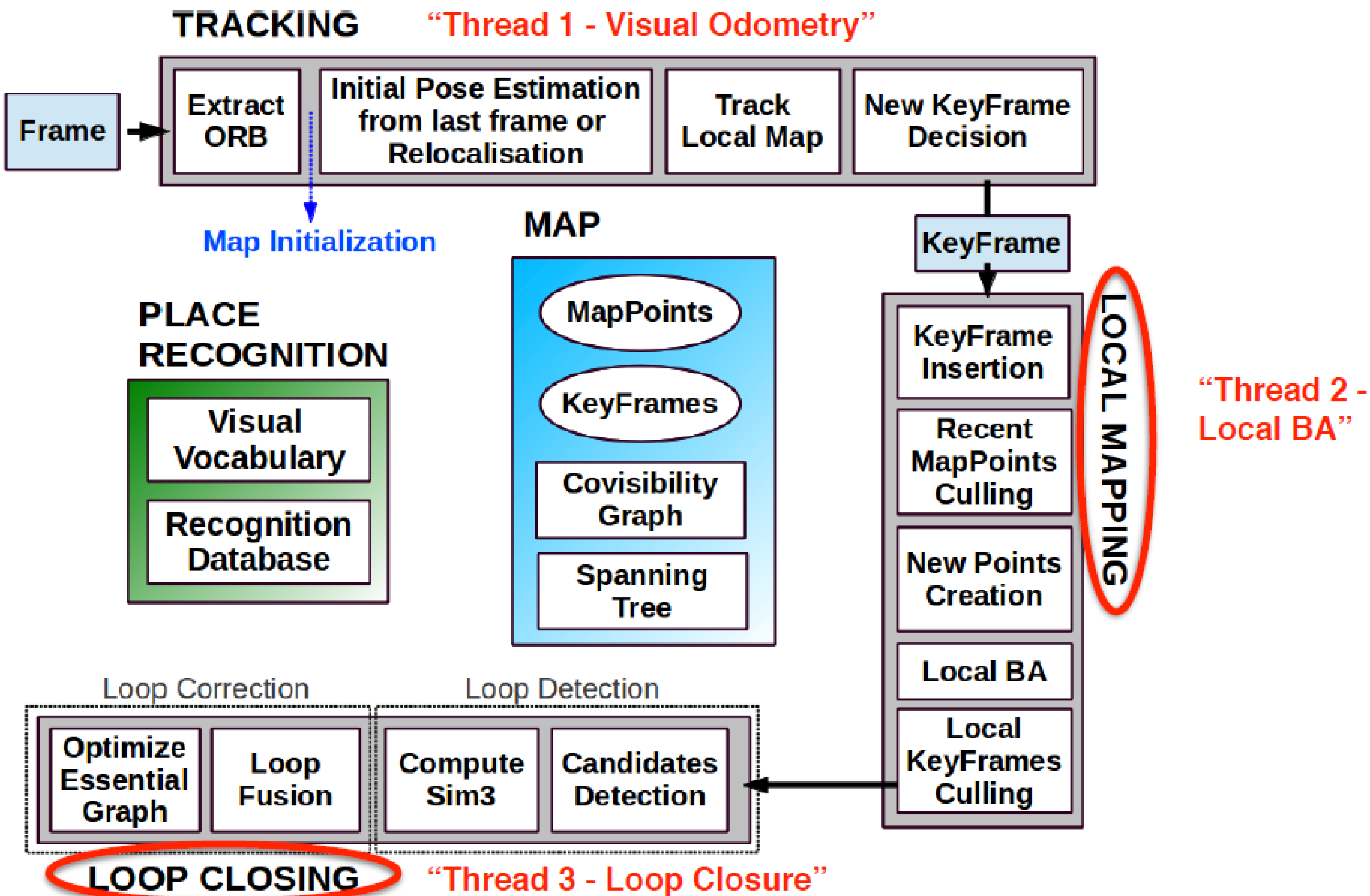
- ORB: FAST corner+ Oriented Rotated Brief descriptor
  - Binary descriptor
  - Very fast to compute and compare

- Real-time, large scale operation

- ORB-SLAM => monocular
- ORB-SLAM2 => for Monocular, Stereo, and RGB-D

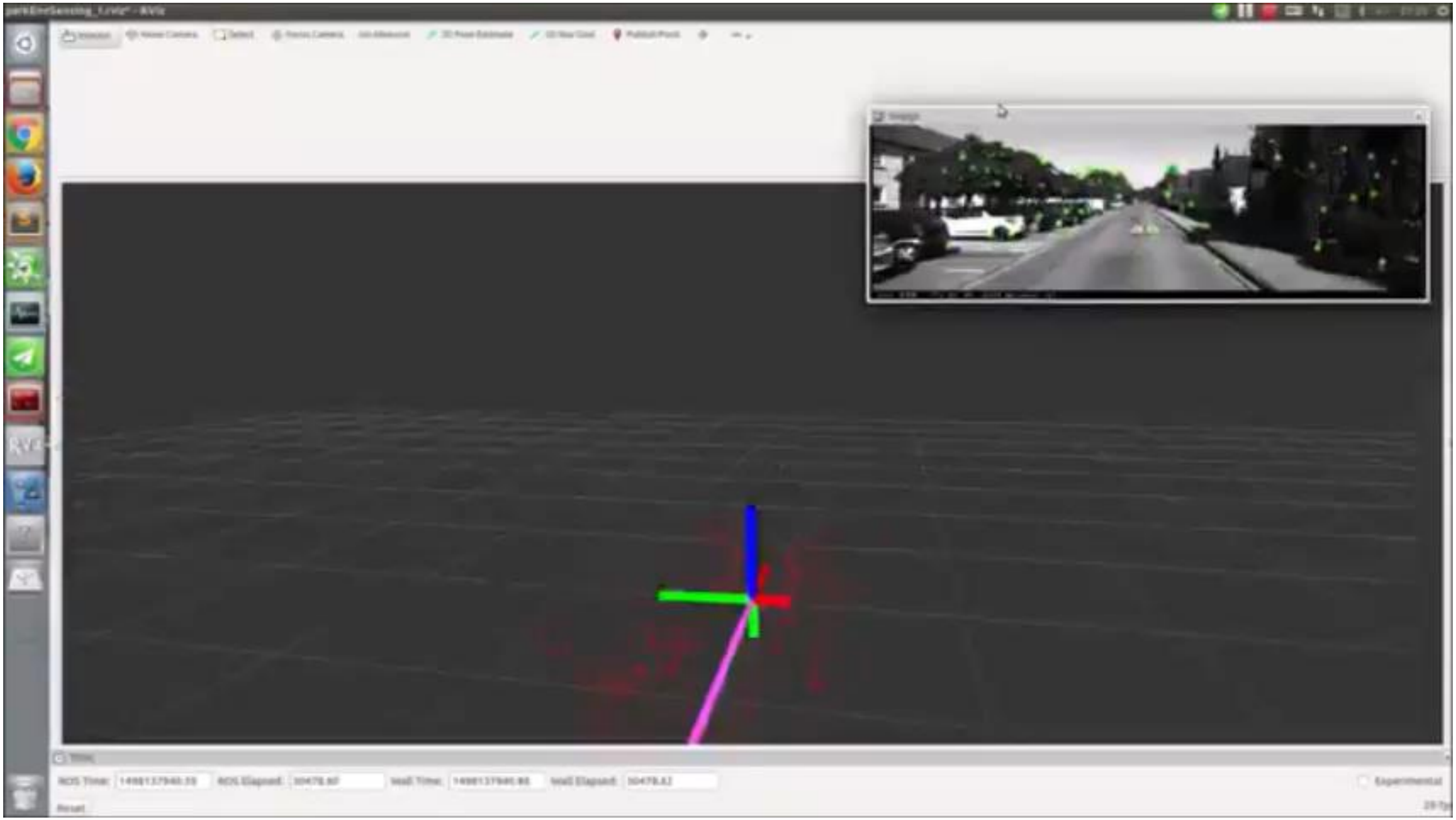
- Raul Mur-Artal, Jose M. M. Montiel and Juan D. Tard6s, ORB-SLAM: A Versatile and Accurate Monocular SLAM System, IEEE Trans. on Robotics 31(5): 1147-1163, Oct 2015
- R. Mur-Artal and J. D. Tardós, "ORB-SLAM2: An Open-Source SLAM System for Monocular, Stereo, and RGB-D Cameras," in *IEEE Transactions on Robotics*, vol. 33, no. 5, pp. 1255-1262, Oct. 2017.
- https://webdiis.unizar.es/~raulmur/orbslam/

ORB-SLAM: Real-Time Monocular SLAM

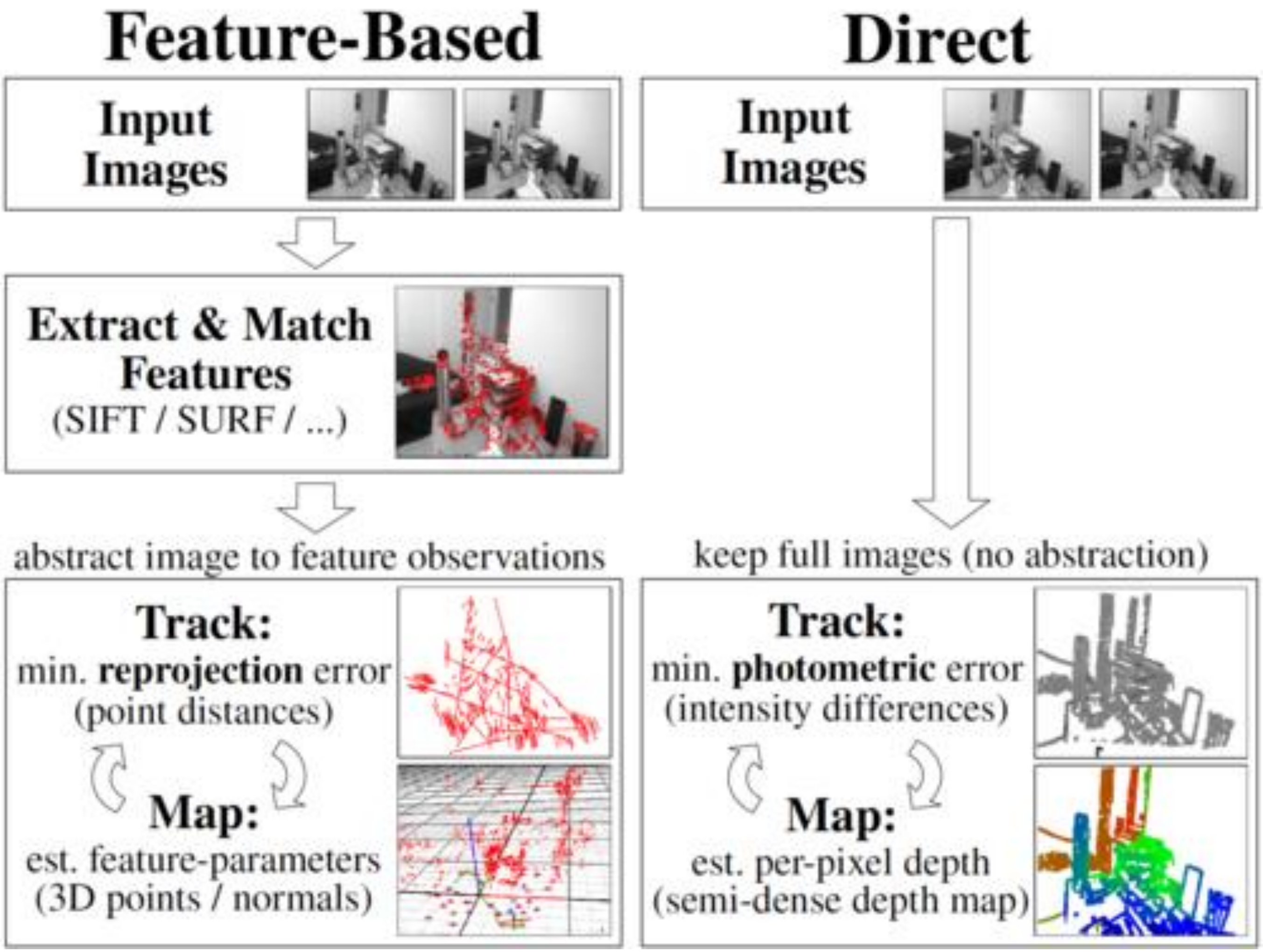


Courtesy of Juan D. Tardos, Feature-Based Visual SLAM, http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

ORB SLAM demo

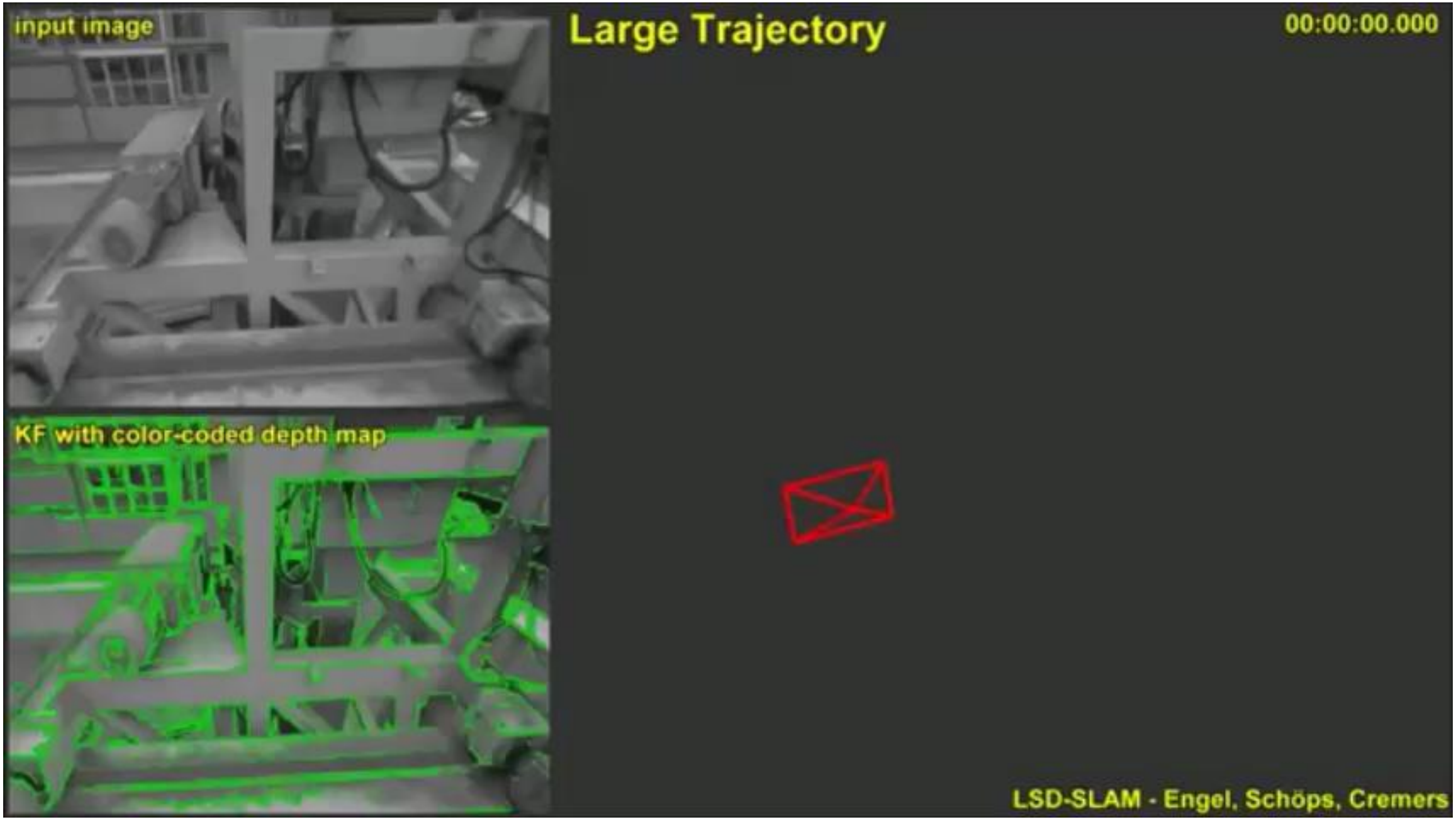


Feature-Based vs Direct SLAM



https://medium.com/@j.zijlmans/lsd-slam-vs-orb-slam2-a-literature-based-comparison-20732df431d

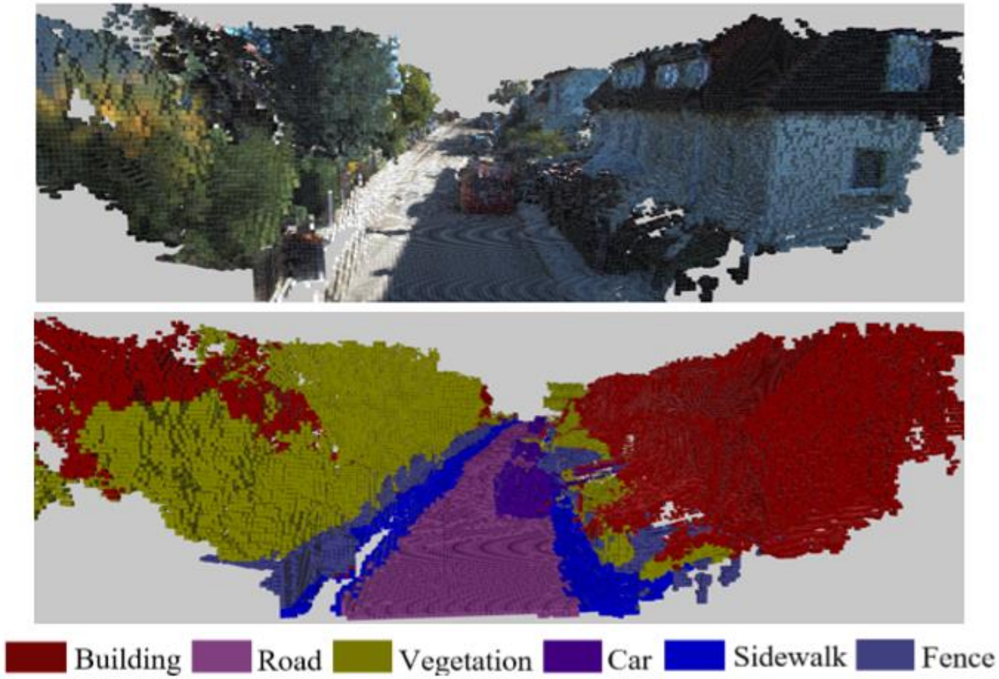
Direct SLAM



https://vision.in.tum.de/research/vslam/lsdslam

Semantic Mapping

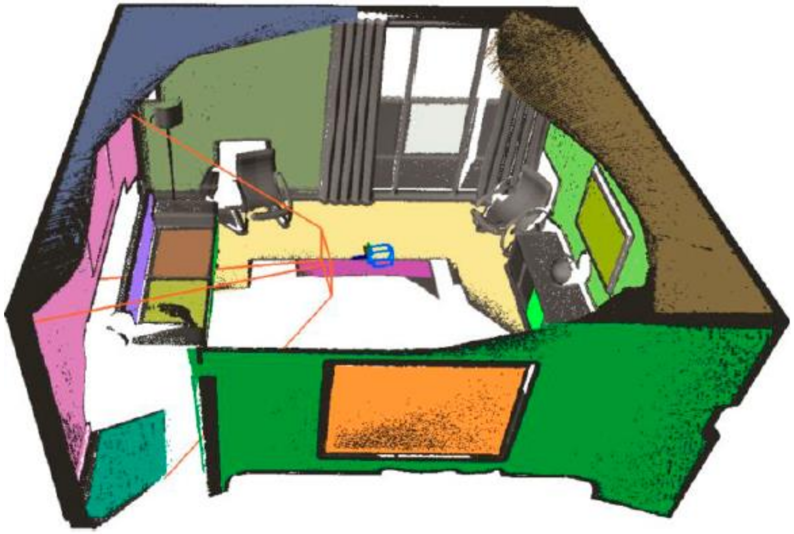
"The goal of semantic mapping is to create maps that include meanings, both to robots and human. Maps that include semantic information make it easier for robots and human to communicate and reason about goals."



Trevor et al. "Tables, Counters, and Shelves: Semantic Mapping of Surfaces in 3D", IROS 2010

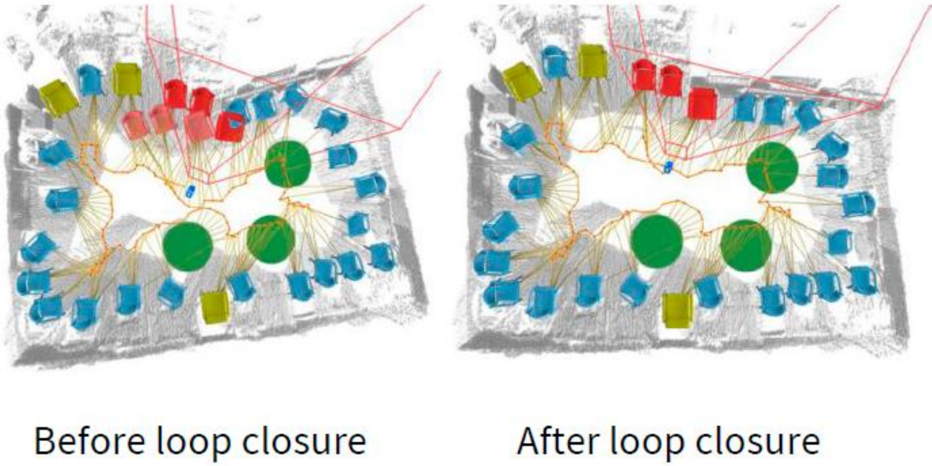
Map Optimisation

- Objects (Semantics) often provide extra constraints that can be used to optimise the map.



Every detected plane imposes constraints on the 3D points lying on the plane. Instead of saying that the 3D points are **independent**, they have to satisfy the plane equation.

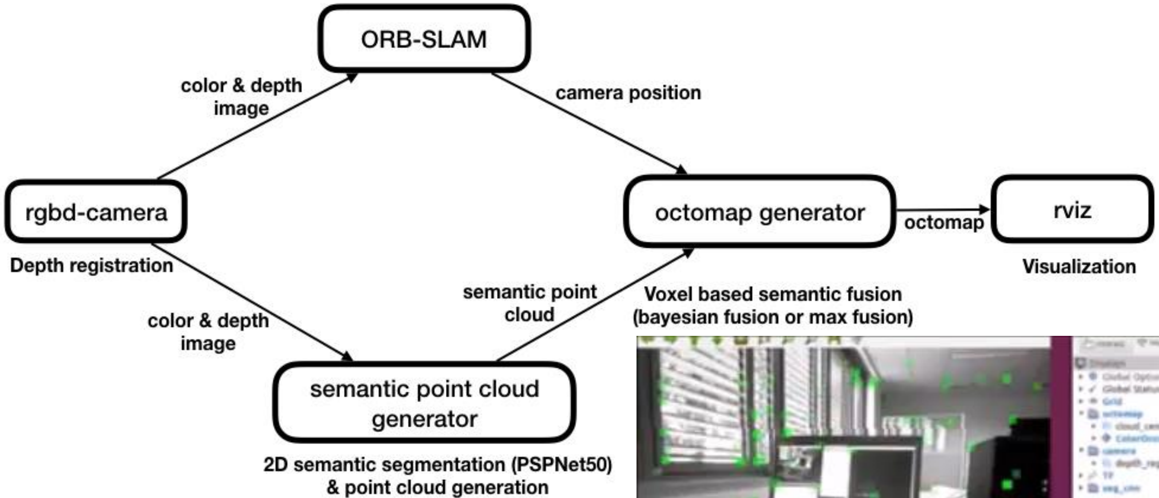
Dense Planar SLAM (Salas-Moreno 2014)

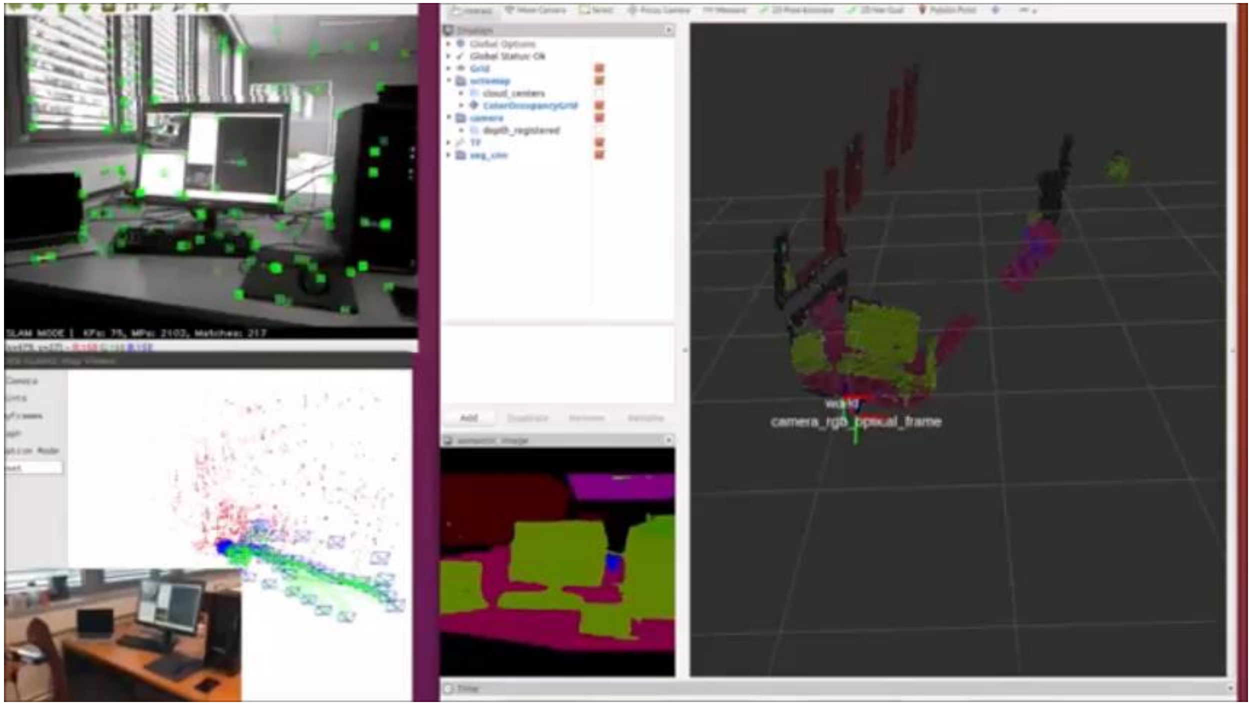


Instead of having a pose graph with edges containing relative camera transformations, have a pose graph with edges containing relative camera and relative object transformations.

SLAM++ (Salas-Moreno et al. 2013)

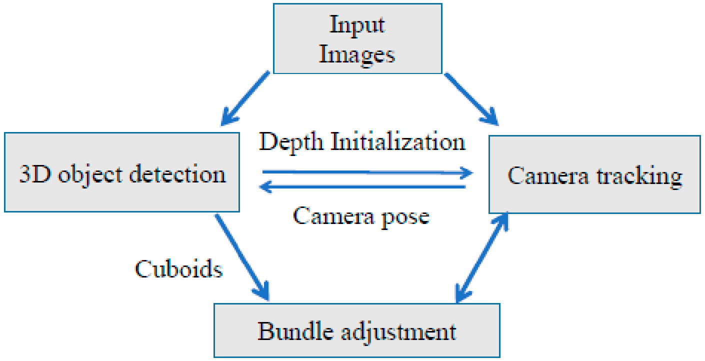
Semantic SLAM





Xuan et al Real-time voxel based 3D semantic mapping with a hand held RGB-D camera, 2018 https://github.com/floatlazer/semantic_slam

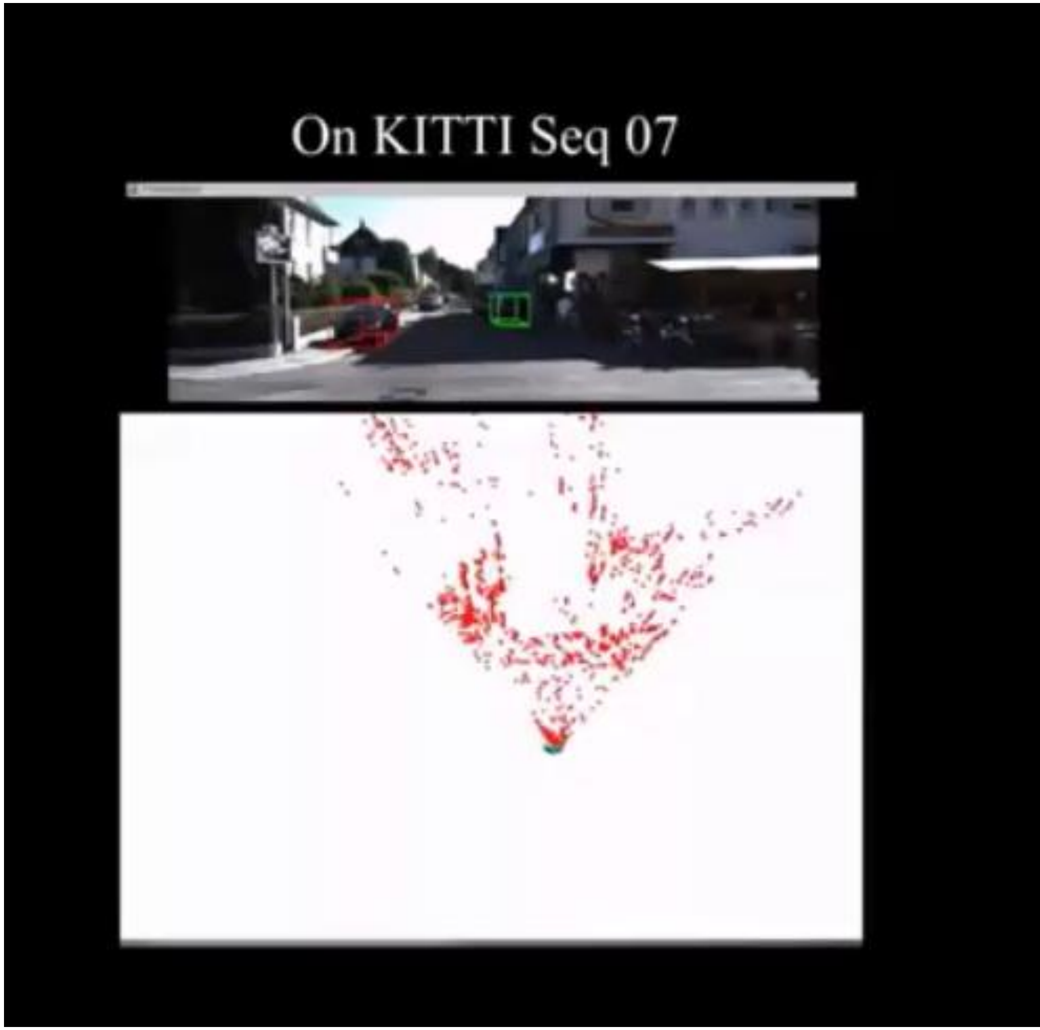
Object SLAM



Single view object detection provides cuboid landmark and depth initialization for SLAM while SLAM can estimate camera pose for more accurate object detection. Object detection and SLAM complements each other.

Yang S, Scherer S. CubeSLAM: Monocular 3-D Object SLAM. IEEE Transactions on Robotics. 2019 May 7.

https://github.com/shichaoy/cube_slam



Open Issues in SLAM

- Dynamic environments.
- Systematically changing environments.
- Seasonal changes.
- Online solutions.
- Life-long operation.
- Resource-constraint systems.
- Failure recovery/zero user intervention.
- Exploiting prior knowledge.
- Robots sharing maps.

http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam21-summary.pdf

Sensor-Related Issues

- Efficient data association.
  - Deep learning can help.

- Sensor-related limitations such as:
  - Poorly structured scenes.
  - Missing light for vision.

- Monocular SLAM (in large environments).

http://ais.informatik.uni-freiburg.de/teaching/ws12/mapping/pdf/slam21-summary.pdf

Resources/ References

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- Taketomi T, Uchiyama H, Ikeda S. Visual SLAM algorithms: a survey from 2010 to 2016. IPSJ Transactions on Computer Vision and Applications. 2017 Dec 1;9(1):16.
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Resources/ References

- https://github.com/ckddls1321/SLAM_Resources
- https://openslam-org.github.io/
- https://pythonrobotics.readthedocs.io/en/latest/
- https://www.mrpt.org/tutorials/slam-algorithms/slam-simultaneous-localization-and-mapping-for-beginners-the-basics/
- https://github.com/xdspacelab/openvslam
- http://www.semanticslam.ai/

- Scene Understanding Challenge
  - https://nikosuenderhauf.github.io/roboticvisionchallenges/scene-understanding
  - https://www.youtube.com/watch?v=xOGzJ6QVVYU

- ROS
  - https://www.ros.org/

- Robot Academy (open online robotics education resource)
  - https://robotacademy.net.au/

Thank you

DEMO: SLAM Map Building with TurtleBot

- http://wiki.ros.org/Robots/TurtleBot

- http://wiki.ros.org/turtlebot_navigation

- Build a map with SLAM
  - You will have live demo

- Autonomously navigate in a known map