Graph SLAM

slam_toolbox

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1 Pose graph SLAM

Credit

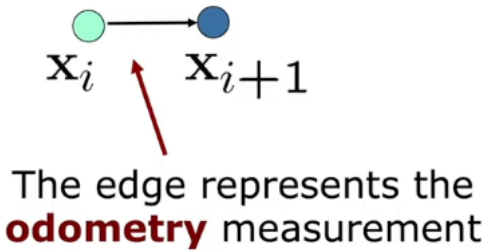
Wolfram Burgard, Giorgio Grisetti, and Cyrill Stachniss: http://ais.informatik.uni-freiburg.de/teaching/ws11/robotics2/pdfs/ls-slam-tutorial.pdf

The pose graph

- It consistants of n nodes $x = x_{1:n}$
- Each x_i is a robot pose (at time t_i)
- We create an edge between nodes x_i and x_j if and only if...

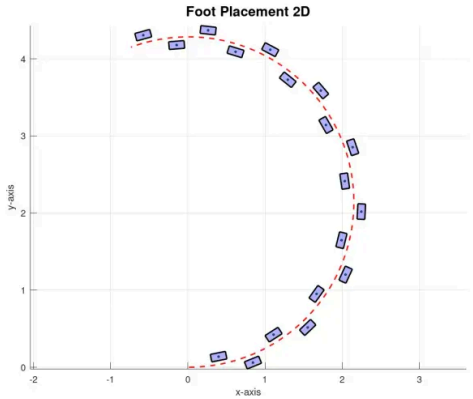
Create an Edge If... (1)

- ...The robot moves from x_i to x_{i+1}
- Edge corresponds to odometry data



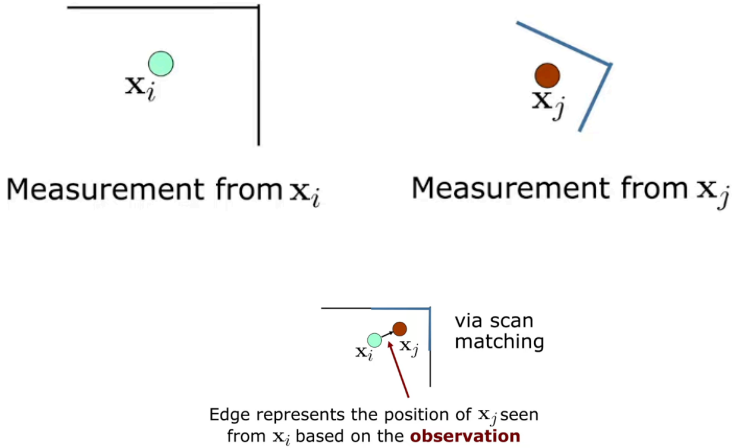
Odometry

- Constraints connect the poses of the robot while it is moving using odometry
- Constraints are inherently uncertain



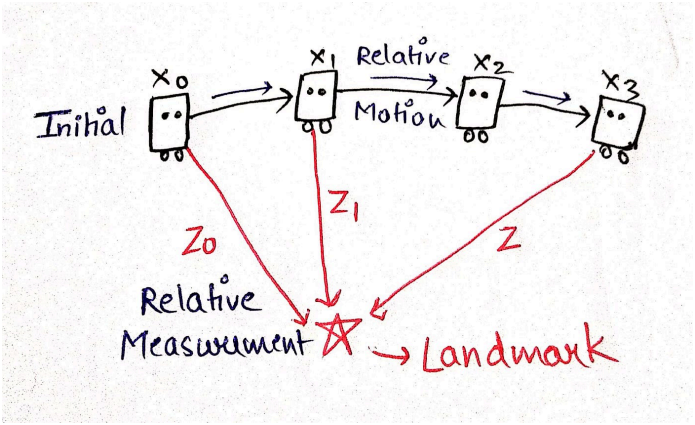
Create an Edge If... (2)

- The robot observes the same part of the environment in both x_i and x_j.



Lidar

- Observing previously seen areas generates new constraints



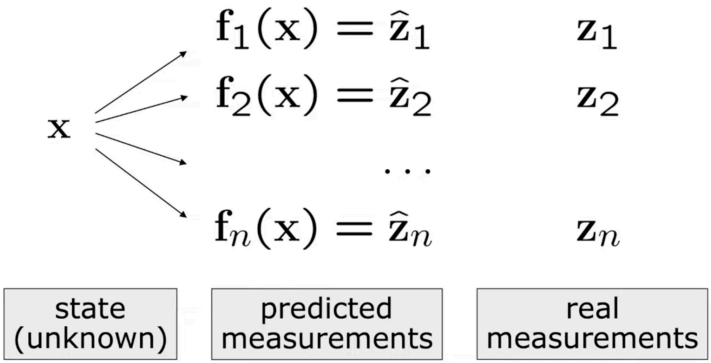
Idea of Pose Graph-based SLAM

- **Graph:** represents the problem
- **Node:** corresponds to an estimated pose in the robot at a given time
- **Edge:** an approximate spatial constraints between two nodes.
- **Graph-based SLAM:** Build the graph and find a node configuration that minimizes the error introduced by the constraints

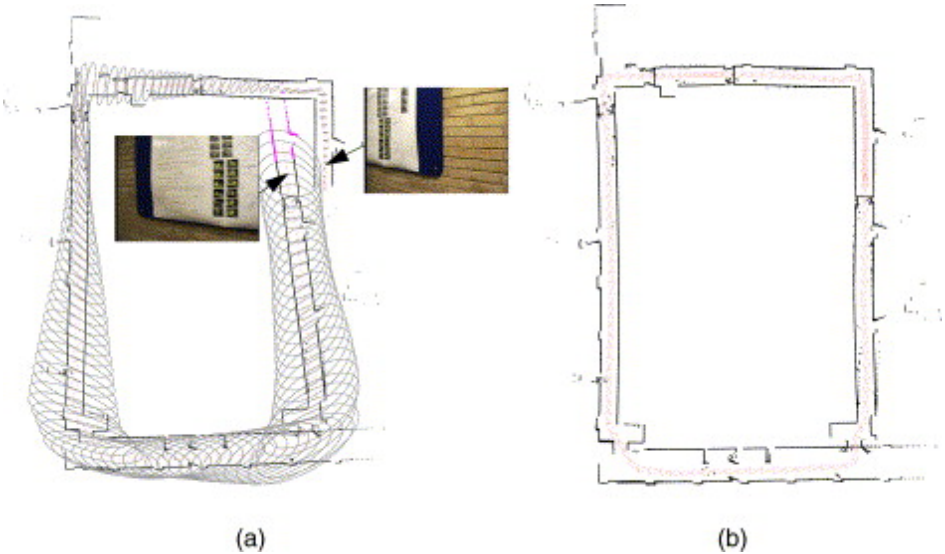
Idea of Pose Graph-based SLAM pt 2

- The nodes represent the state vector
- Given a state, we can compute what we expect to perceive.
- We have real observations that relate nodes to each other
- **Goal:** Find a configuration of the nodes so that the real and predicted observations are as similar as possible.

Graphical Explanation



Solving with least squares



Least Squares Approach

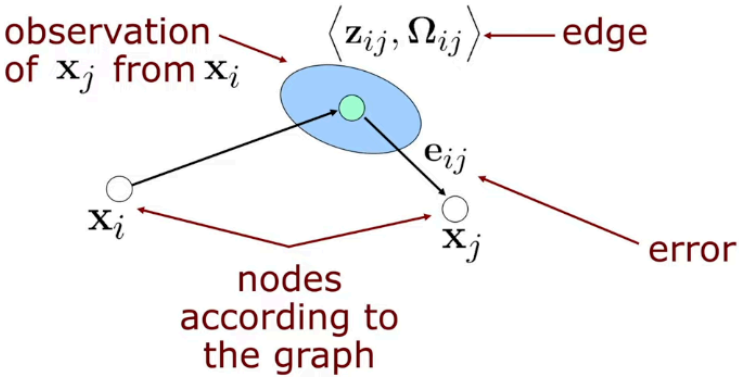
- Least squares error minimization

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

- Error function e_{ij} for an observation

$$e_{ij} = \left(x_j - x_i\right) - z_{ij}$$

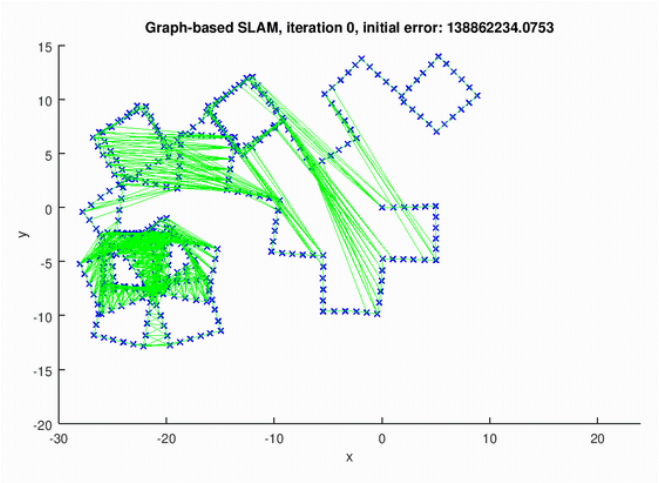
Pose Graph



Goal: $\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} \sum_{ij} \mathbf{e}_{ij}^\top \Omega_{ij} \mathbf{e}_{ij}$

Minimization

- Open problem. You can use Gauss-Newton if you were doing this from scratch, but ideally, use a minimization library (slam_toolbox uses Ceres).

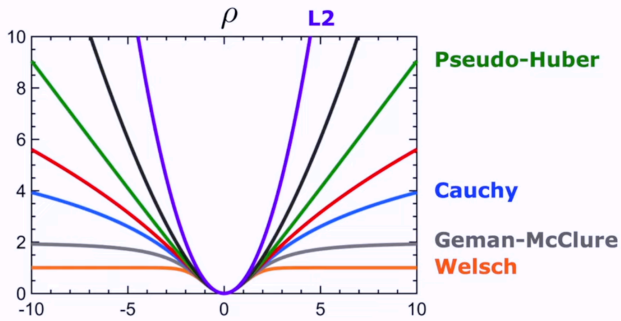


Removing outliers

M-Estimators

kernel function as weights for constraints

$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} \sum_{i=1}^{N} \rho(e_i(\mathbf{x}))$$



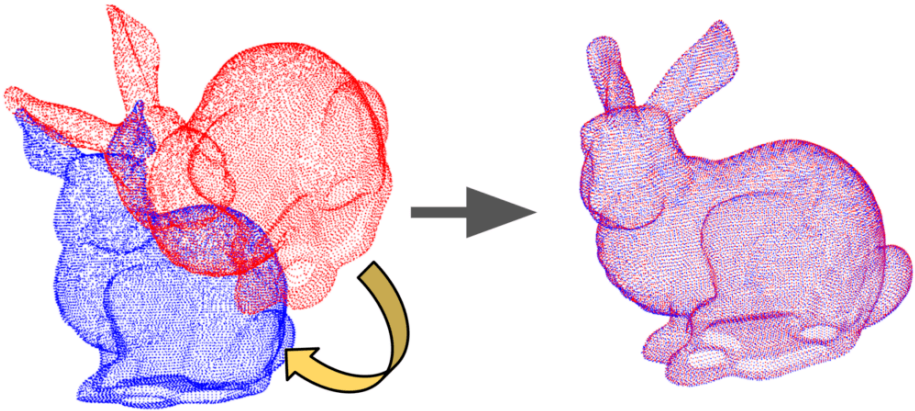
2 Scan matching

What is scan matching

- Scan matching creates the lidar edges between x_i and x_j by finding lidar observations of the same object.
- There are many different ways to do it:
  - Iterative closest point (ICP)
  - Scan-to-scan
  - Scan-to-map
  - Map-to-map
  - Feature-based
  - RANSAC for outlier rejection
  - Correlative matching

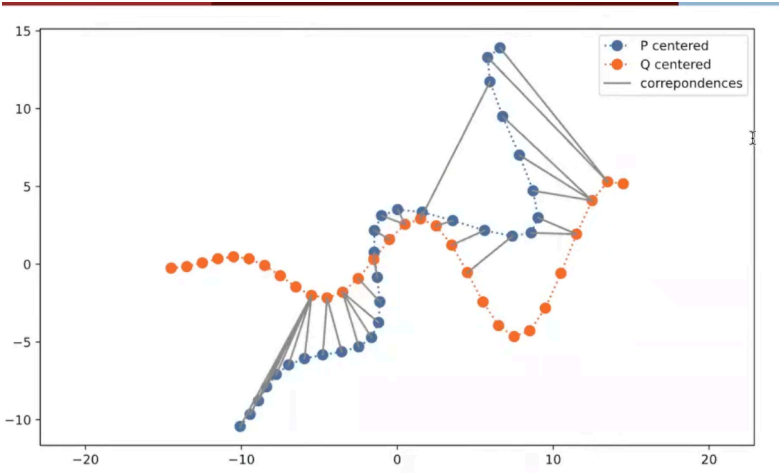
Iterative Closest Point

- ICP is a way to match two point clouds.



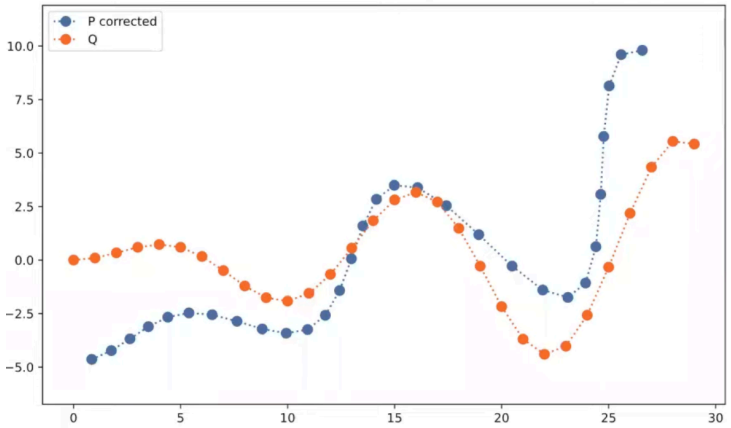
Data Association

- For each point a_i on point cloud a, find the closest point b_j.



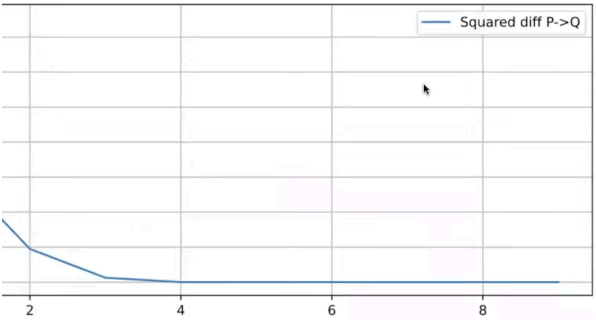
Transformation

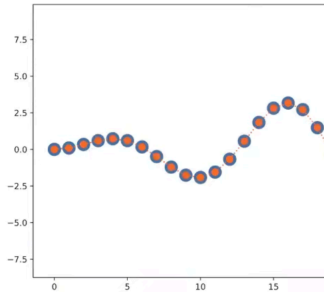
- Find a transformation to align the two point clouds
- First, align the center of mass of both point clouds, and then rotate them using SVD.



Iterate

- Keep going until they converge!

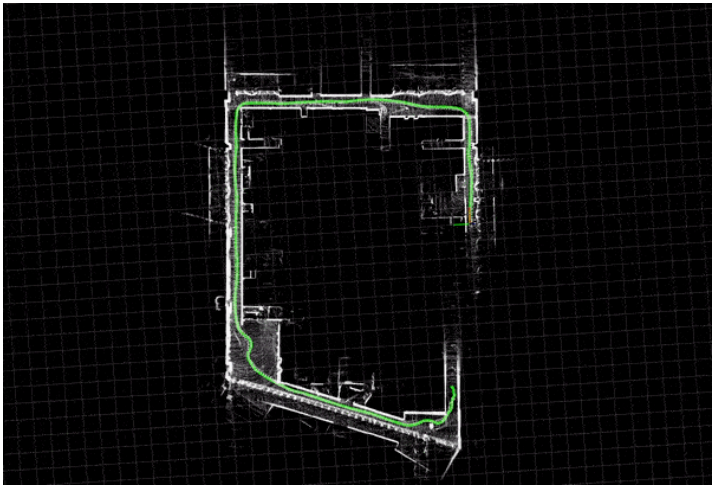




$$\boldsymbol{\xi}^* = \underset{\boldsymbol{\xi}}{\operatorname{argmin}} \sum_{i=1}^{n} \left[1 - M(\mathbf{S}_i(\boldsymbol{\xi}))\right]^2$$

3 All Together

Loop Closure



Slam Toolbox