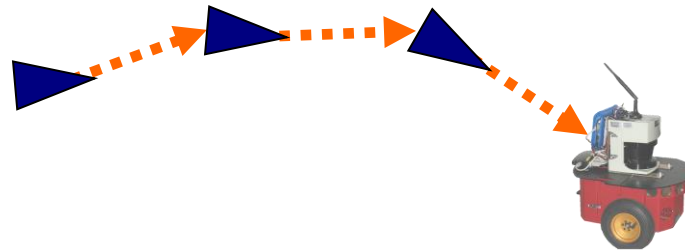# Robot Mapping

Hierarchical Pose-Graphs for Online Mapping

Gian Diego Tipaldi, Wolfram Burgard

Graph-Based SLAM

- Measurements connect the poses of the robot while it is moving
- Measurements are inherently uncertain

◀ Robot pose   ▶ Measurement

Graph-Based SLAM

- Observing previously seen areas generates measurements between non-successive poses
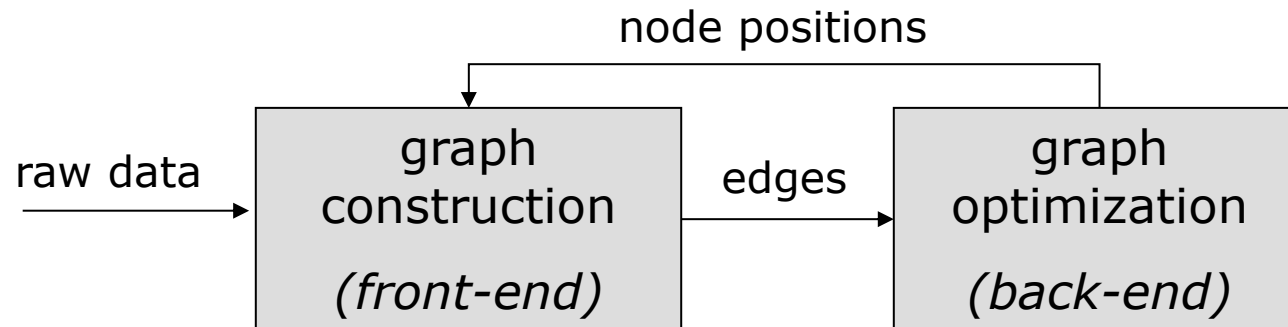

Robot pose   Measurement

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 measurement between them
- **Graph-Based SLAM:** Build the graph and find a node configuration that minimize the measurement error
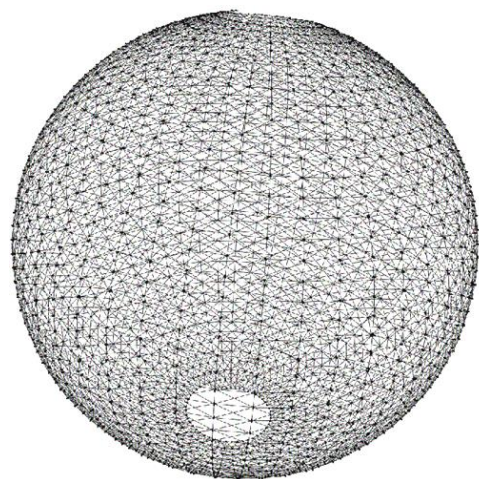
Front-End and Back-End

- Front-end extracts constraints from the sensor data (data association!)
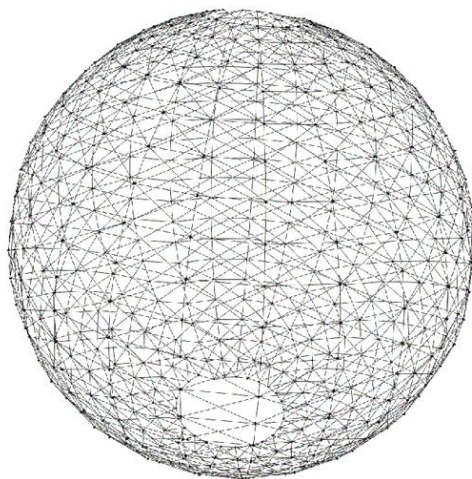- Back-end optimizes the pose-graph to reduce the measurement error

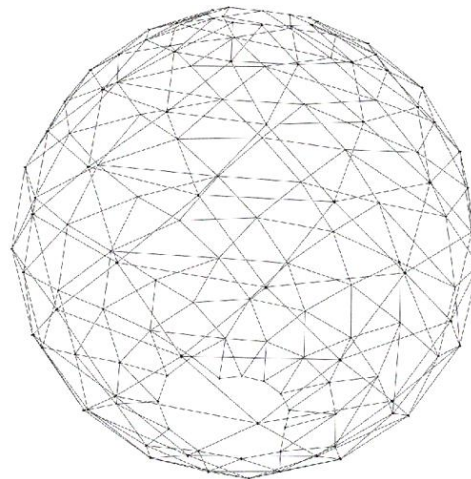➡ Intermediate solutions are needed to make good data associations

Hierarchical Pose-Graph

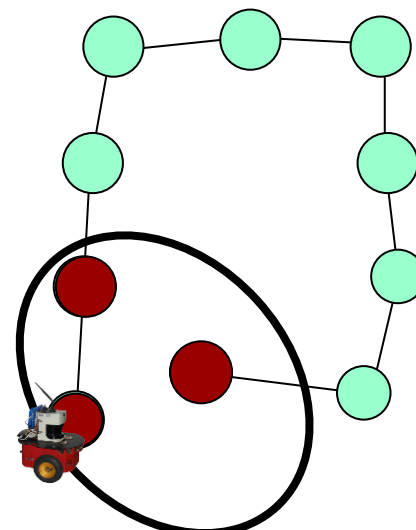bottom layer (input data)   first layer   second layer   top layer

"There is no need to optimize the whole graph when a new observation is obtained"

Motivation

- SLAM front-end seeks for loop-closures

- Requires to compare observations to all previously obtained ones

- In practice, limit search to areas in which the robot is likely to be

- This requires to know **in which parts of the graph to search for data associations**
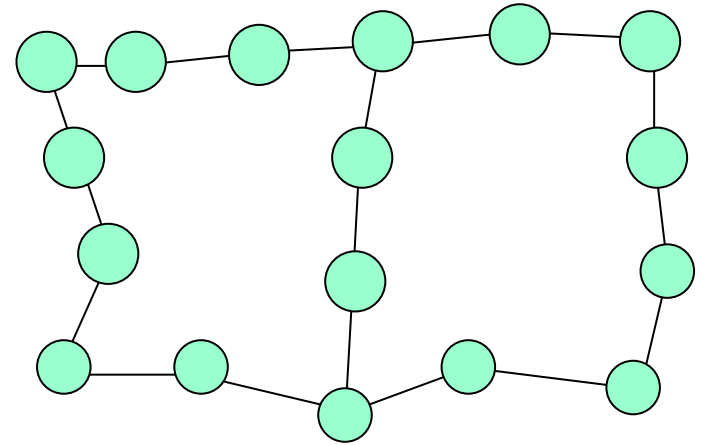
Hierarchical Approach

- **Insight:** to find loop closing points, one doesn't need a perfect global map
- **Idea:** correct only the core structure of the scene, not the overall graph
- The hierarchical pose-graph is a sparse approximation of the original
- It exploits the facts that in SLAM
  - Robot moved through the scene and it not "teleported" to locations
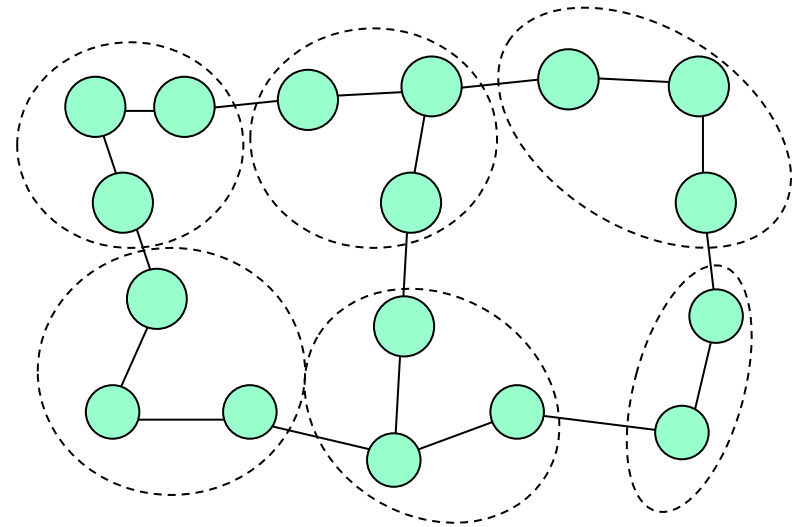 - Sensors have a limited range

Key Idea of the Hierarchy
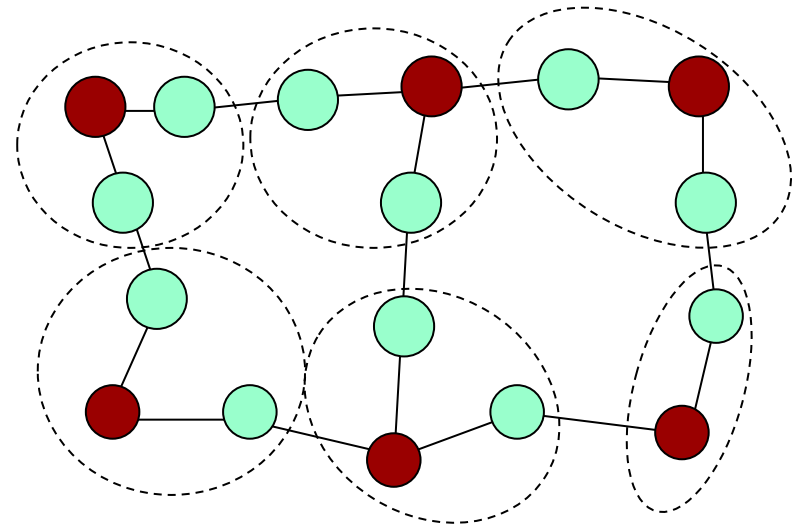
- Input is the dense graph

Key Idea of the Hierarchy

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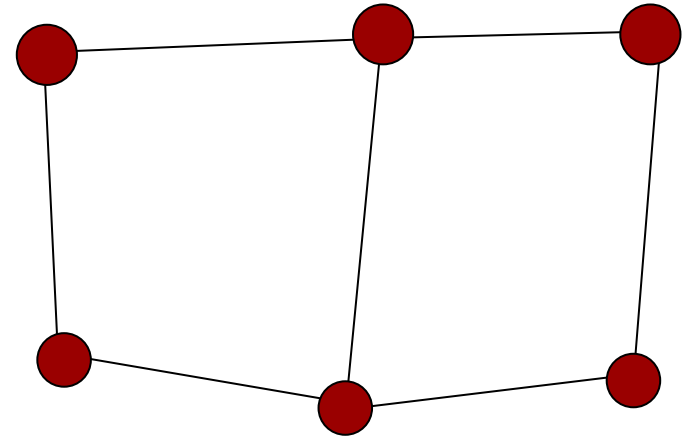- Group the nodes of the graph based on their local connectivity

Key Idea of the Hierarchy

- Input is the dense graph
- Group the nodes of the graph based on their local connectivity
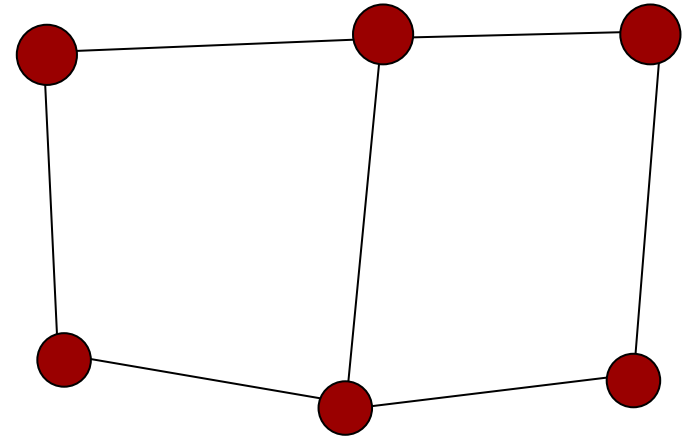- For each group, select one node as a "representative"

Key Idea of the Hierarchy

- The representatives are the nodes in a new sparsified graph (upper level)

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- Edges of the sparse graph are determined by the connectivity of the groups of nodes
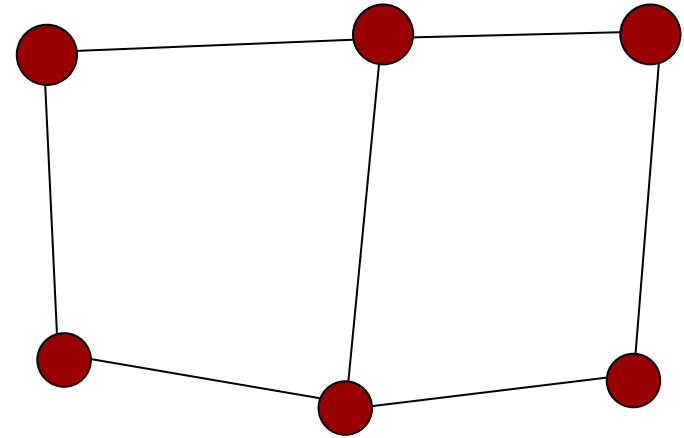- The parameters of the sparse edges are estimated via local optimization
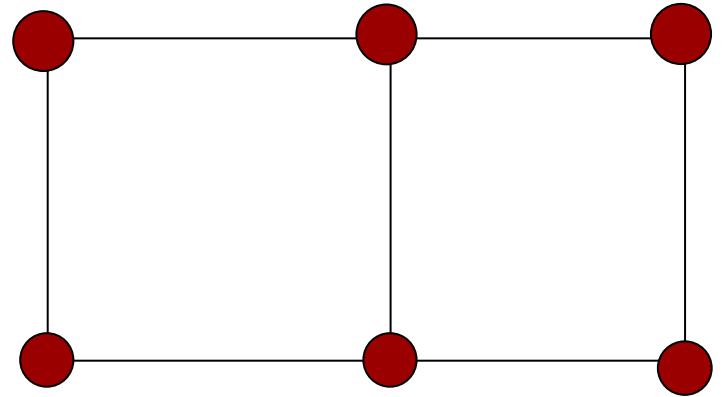
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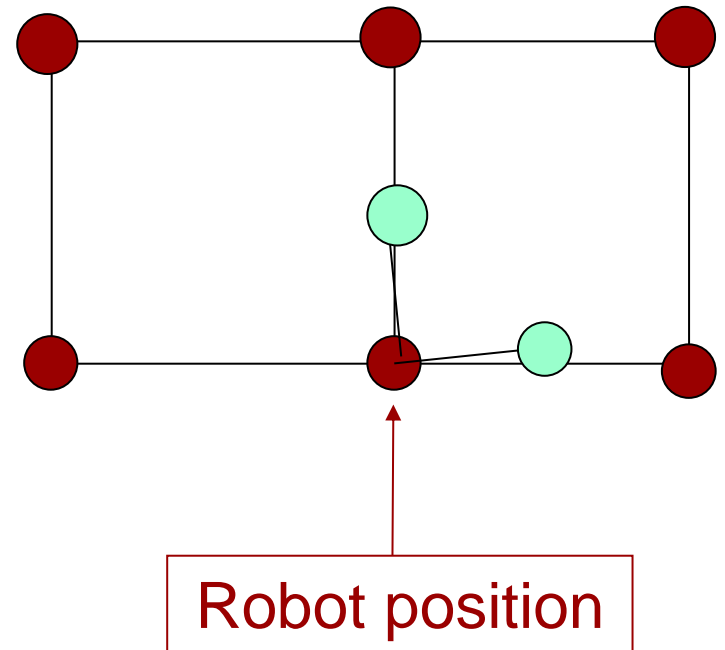
Process is repeated recursively

Key Idea of the Hierarchy

- Only the upper level of the hierarchy is optimized completely

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- Only the upper level of the hierarchy is optimized completely

- The changes are propagated to the bottom levels only close to the current robot position

- Only this part of the graph is relevant for data association
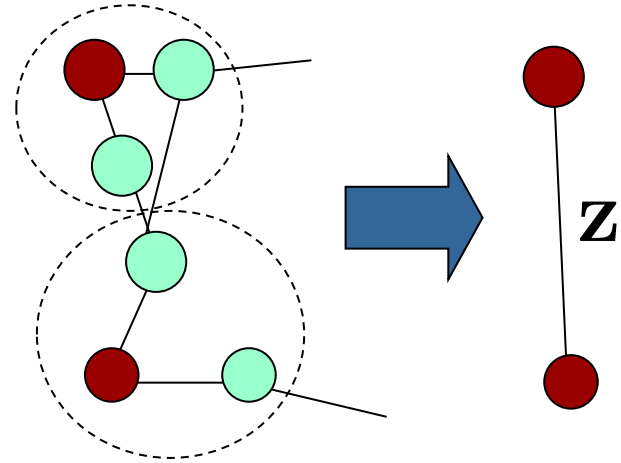
Robot position

Construction of the Hierarchy

- When and how to generate a new group?
  - A (simple) distance-based decision
  - The first node of a new group is the representative
- When to propagate information downwards?
  - Only when there are inconsistencies
- How to construct an edge in the sparsified graph?
  - Next slides
- How to propagate information downwards?
  - Next slides
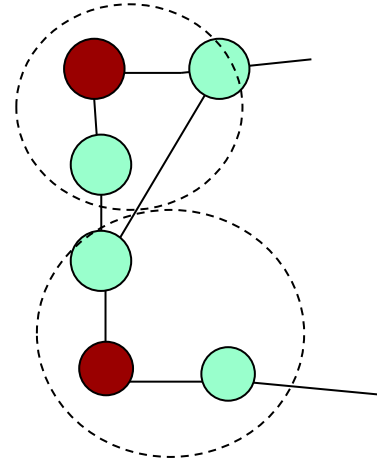
Determining Edge Parameters

- Given two connected groups
- How to compute a virtual observation z and the information matrix Ω for the new edge?
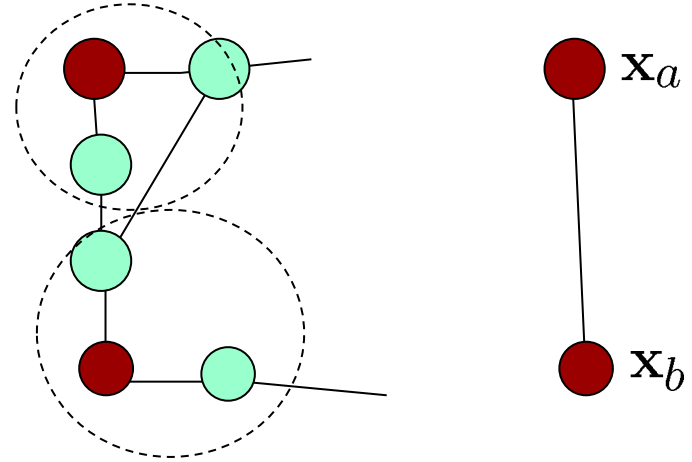
Determining Edge Parameters

- Optimize the two sub-groups independently from the rest

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- The observation is the relative transformation between the two representatives
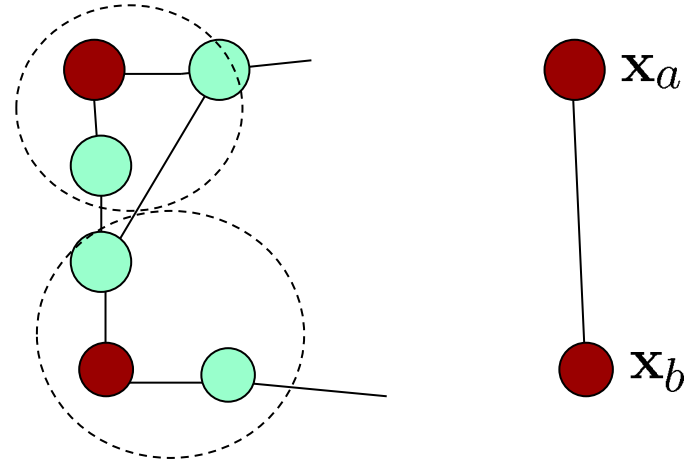
$$\mathbf{x}_a$$

$$\mathbf{x}_b$$

Determining Edge Parameters

- Optimize the two sub-groups independently from the rest

- The observation is the relative transformation between the two representatives

- The information matrix is computed from the diagonal block of the matrix **H**

Inverse of the *[b,b]* block of ***H⁻¹***

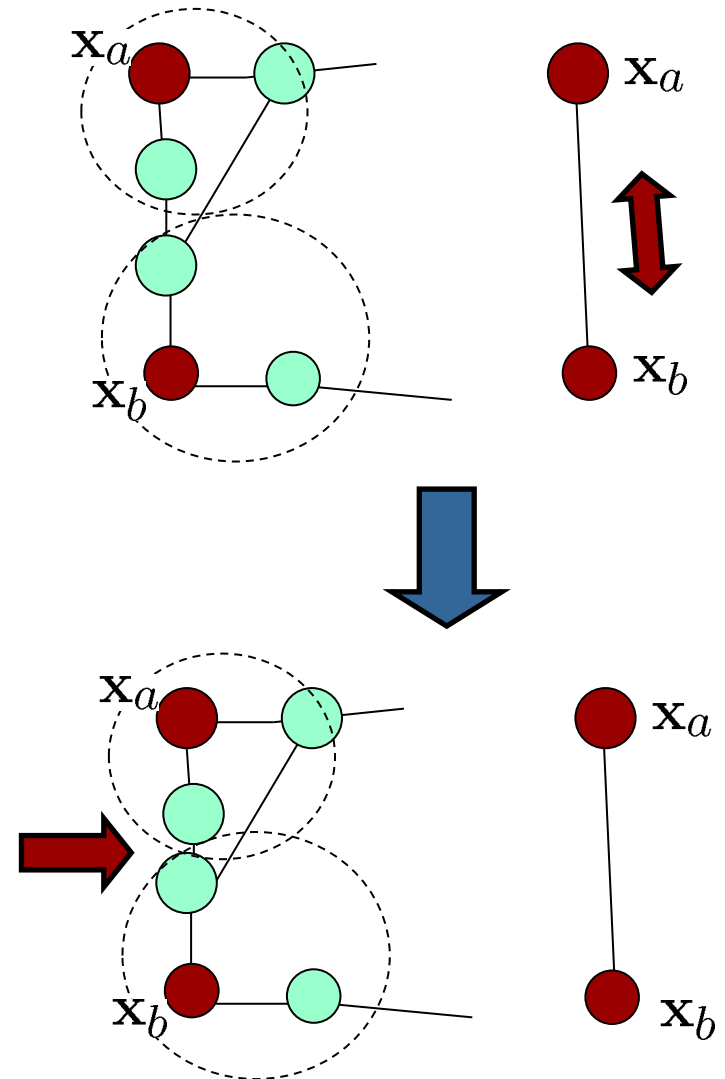$$\Omega_{ab} = (\mathbf{H}^{-1}_{[b,b]})^{-1}$$

Propagating Information Downwards

- All representatives are nodes from the lower (bottom) level

same node

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- Information is propagated downwards by transforming the group at the lower level using a rigid body transformation
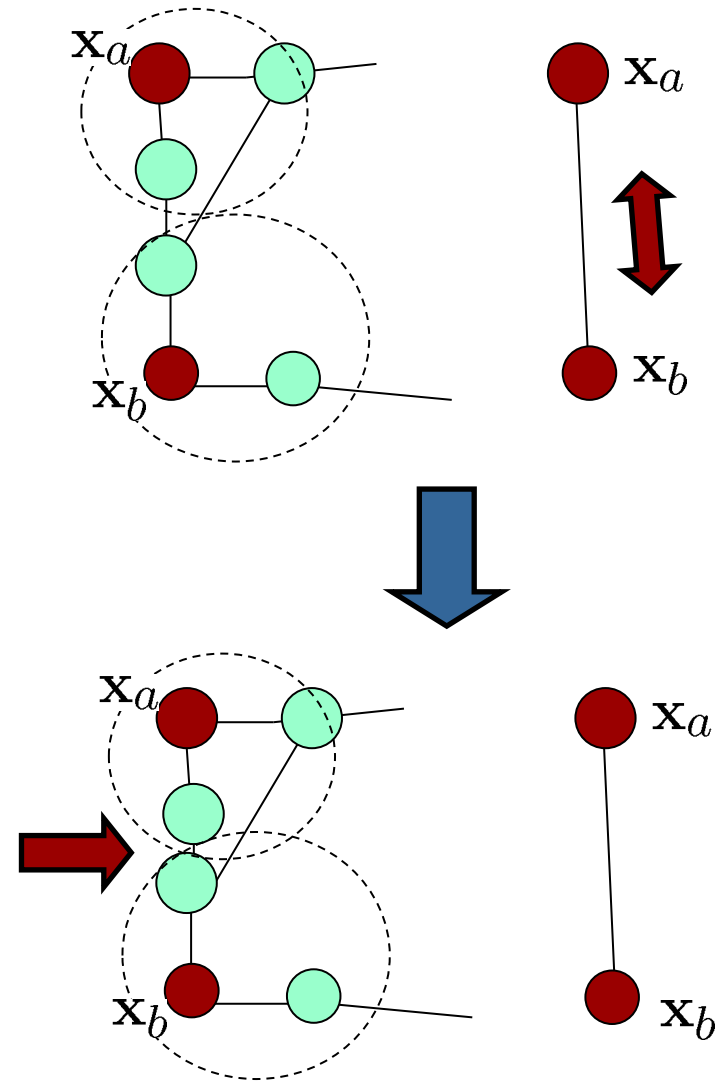
Propagating Information Downwards

- All representatives are nodes from the lower (bottom) level

- Information is propagated downwards by transforming the group at the lower level using a rigid body transformation

- Only if the lower level becomes inconsistent, optimize at the lower level

For the Best Possible Map...

- Run the optimization on the lowest level (at the end)

- For offline processing with all measurements, the hierarchy helps convergence in case of large errors

- In this case, one pass up the tree (to construct the edges) followed by one pass down the tree is sufficient

Stanford Garage

- Parking garage at Stanford University
- Nested loops, trajectory of ~7,000m

Stanford Garage Result

- Parking garage at Stanford University
- Nested loops, trajectory of ~7,000m

Stanford Garage Video

Level 0

Level 2

Intel Research Lab Video

Consistency

- How well does the top level in the hierarchy represent the original input?
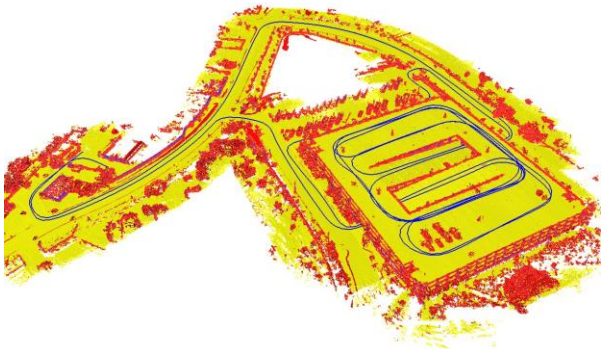
Consistency

- How well does the top level in the hierarchy represent the original input?
- Probability mass of the marginal distribution in the highest level vs. the one of the true estimate (original problem, lowest level)

	Prob. mass not covered	Prob. mass outside
Intel	0.10%	10.18%
W-10000	2.53%	24.05%
Stanford	0.01%	7.88%
Sphere	2.75%	10.21%

low risk of becoming overly confident

one does not ignore too much information

Consistency

- **Red**: overly confident (~0.1% prob. mass)
- **Blue**: under confident (~10% prob. mass)

Conclusions

- Hierarchical pose-graph to estimate the structure to support efficient data association

- Designed for online mapping (interplay between optimization and data association)

- Higher level represent simplified problem

Literature

Hierarchical Pose-Graph Optimization

- Grisetti, Kümmerle, Stachniss, Frese, and Hertzberg: "Hierarchical Optimization on Manifolds for Online 2D and 3D Mapping"

- Open-source implementation hosted at http://openslam.org/hog-man.html

Slide Information

- These slides have been created by Cyrill Stachniss as part of the robot mapping course taught in 2012/13 and 2013/14. I created this set of slides partially extending existing material of Giorgio Grisetti and myself.

- I tried to acknowledge all people that contributed image or video material. In case I missed something, please let me know. If you adapt this course material, please make sure you keep the acknowledgements.

- Feel free to use and change the slides. If you use them, I would appreciate an acknowledgement as well. To satisfy my own curiosity, I appreciate a short email notice in case you use the material in your course.

- My video recordings are available through YouTube:
  http://www.youtube.com/playlist?list=PLgnQpQtFTOGQrZ4O5QzbIHgl3b1JHimN_&feature=g-list

Cyrill Stachniss, 2014
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