

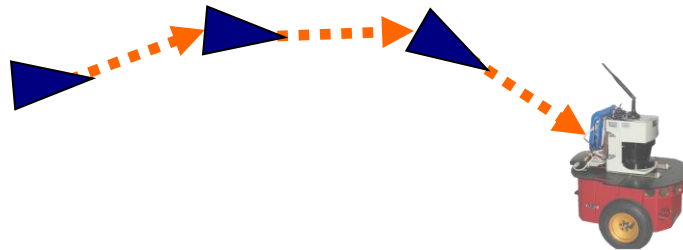
Robot Mapping

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

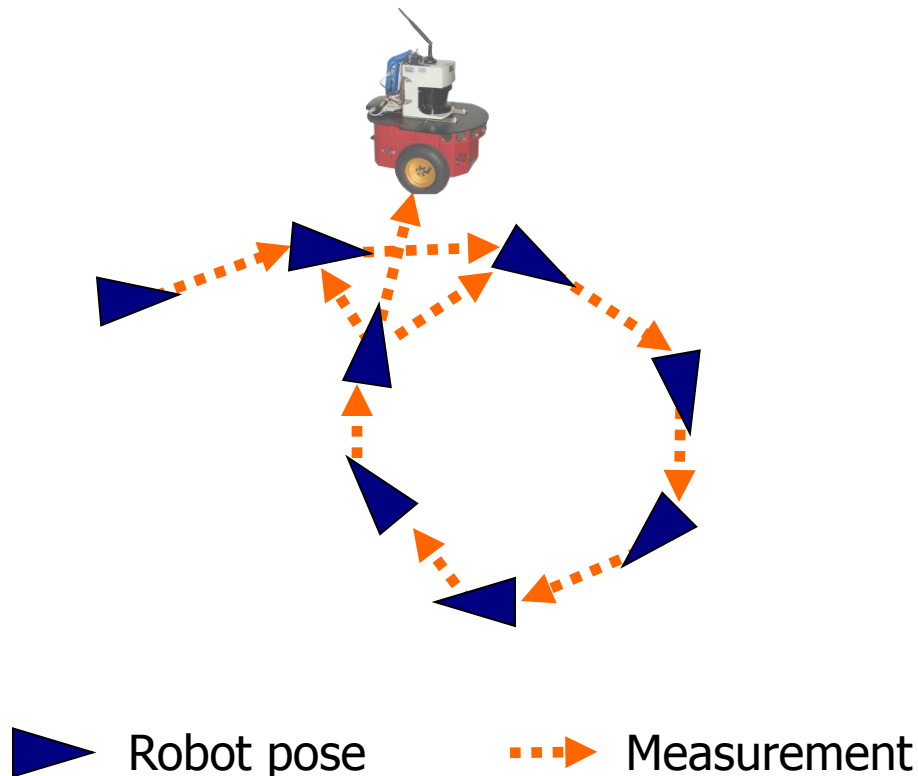


▶ Robot pose

⋯▶ Measurement

Graph-Based SLAM

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

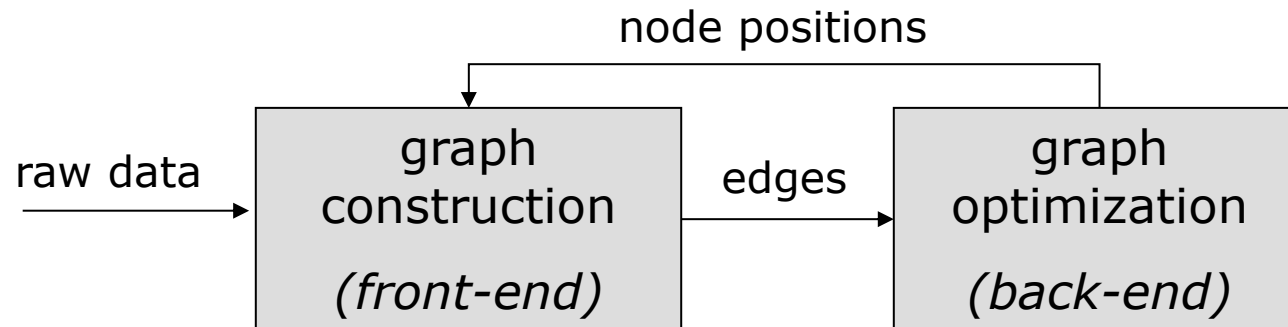


Graph-Based SLAM

- 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

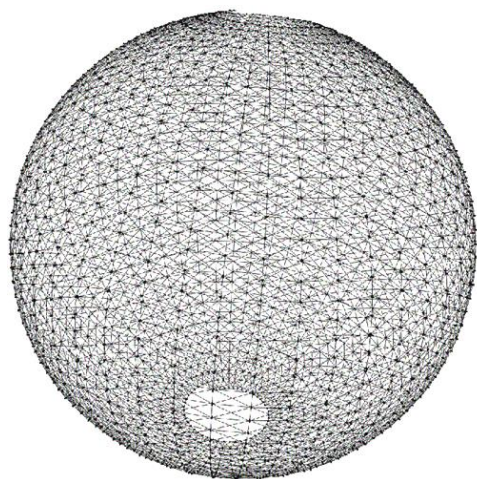
Front-End and Back-End

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

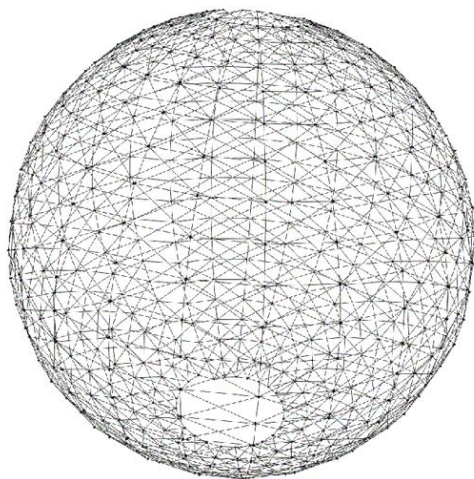


➔ Intermediate solutions are needed to make good data associations

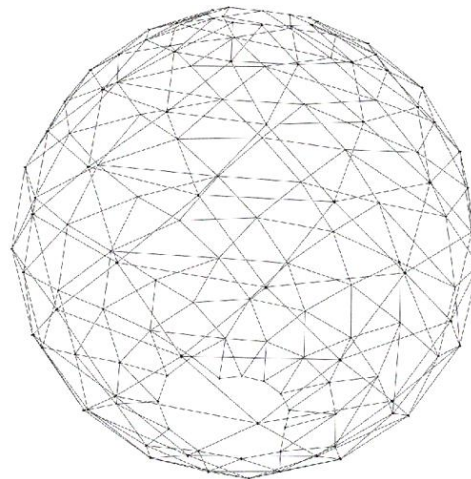
Hierarchical Pose-Graph



bottom layer
(input data)



first layer



second layer

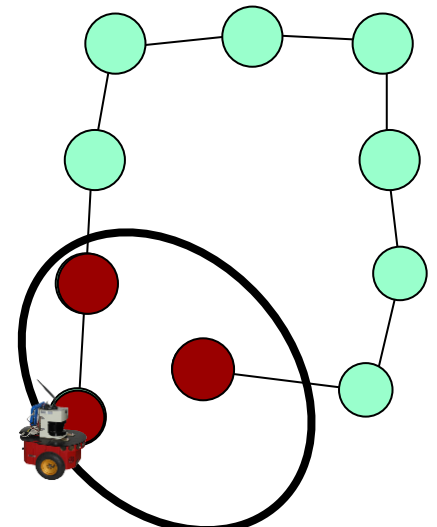
top layer



“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**

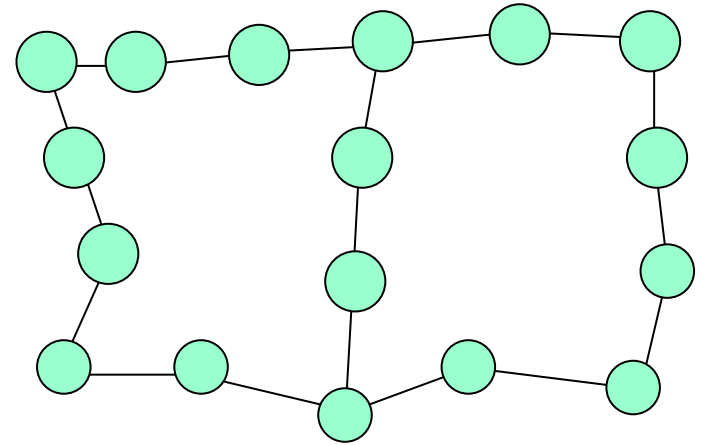


Hierarchical Approach

- **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

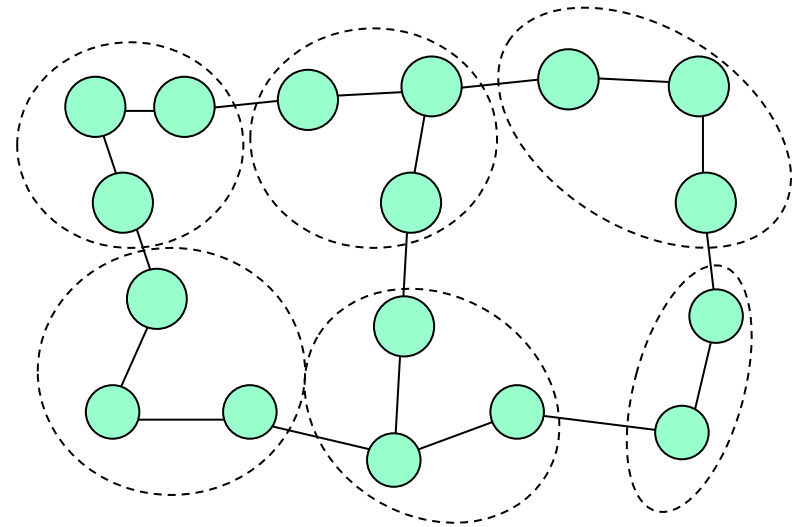
Key Idea of the Hierarchy

- Input is the dense graph



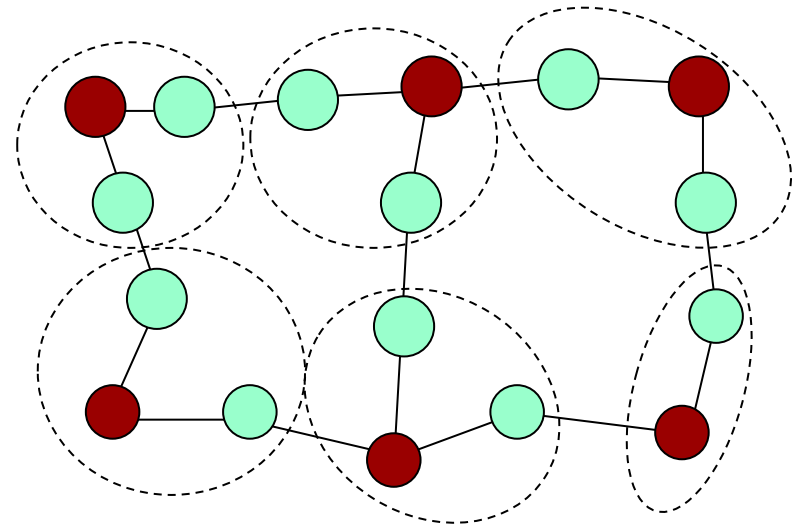
Key Idea of the Hierarchy

- Input is the dense graph
- Group the nodes of the graph based on their local connectivity



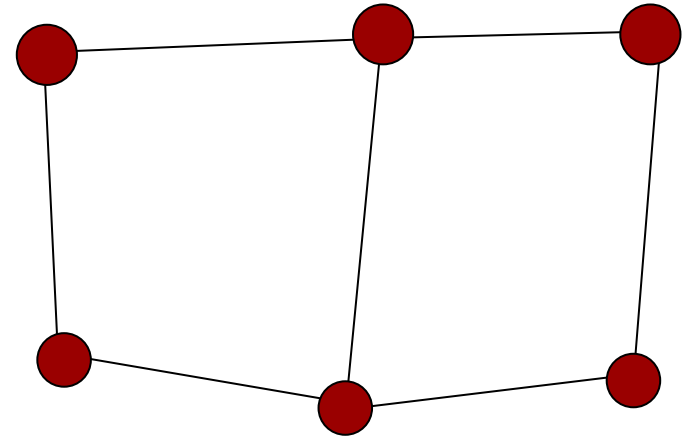
Key Idea of the Hierarchy

- 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”



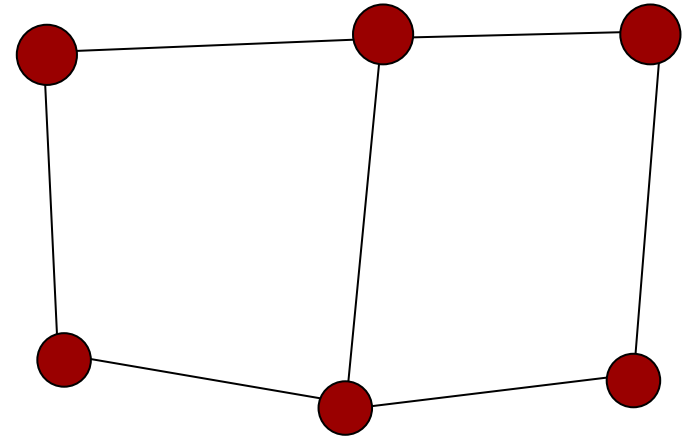
Key Idea of the Hierarchy

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



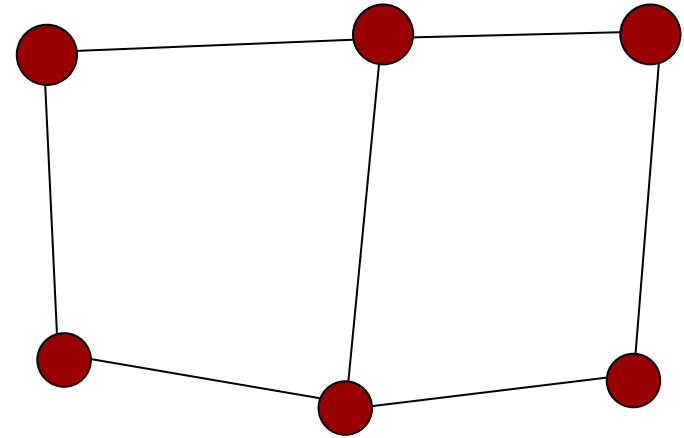
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- The representatives are the nodes in a new sparsified graph (upper level)
- Edges of the sparse graph are determined by the connectivity of the groups of nodes
- The parameters of the sparse edges are estimated via local optimization



Key Idea of the Hierarchy

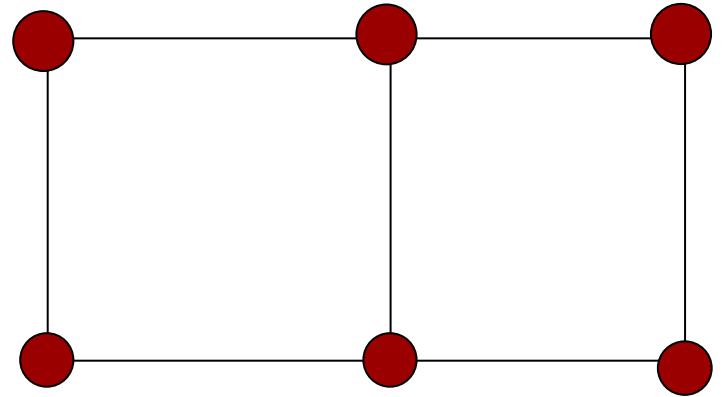
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Process is
repeated
recursively

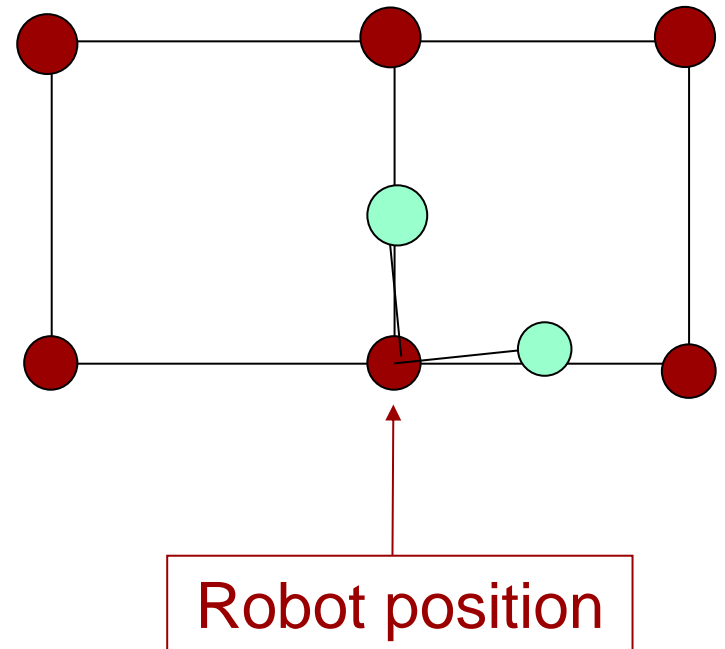
Key Idea of the Hierarchy

- Only the upper level of the hierarchy is optimized completely



Key Idea of the Hierarchy

- 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

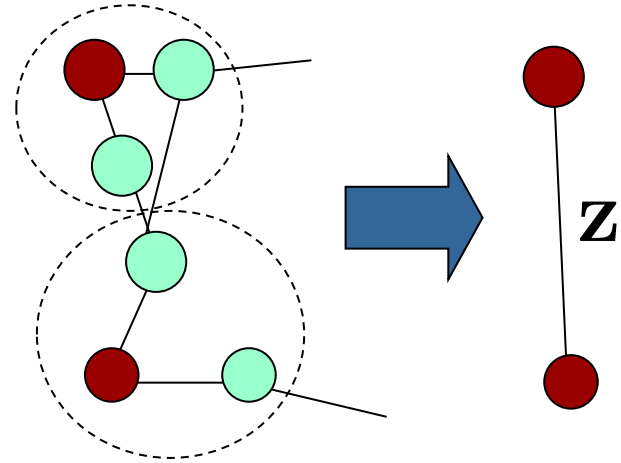


Construction of the Hierarchy

- 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

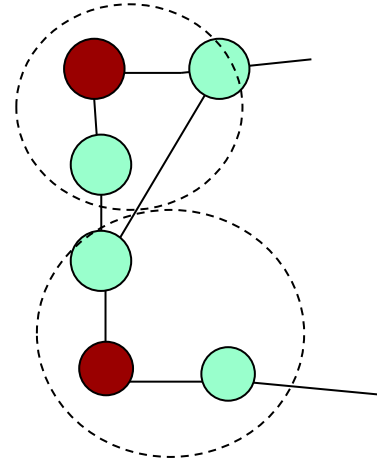
Determining Edge Parameters

- Given two connected groups
- How to compute a virtual observation \mathbf{z} and the information matrix $\mathbf{\Omega}$ for the new edge?



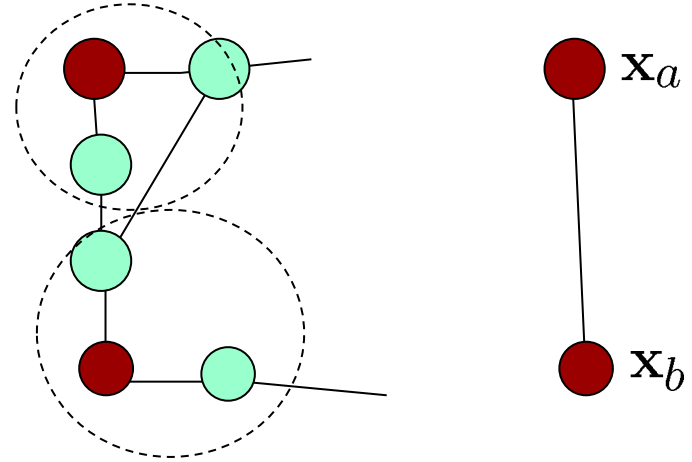
Determining Edge Parameters

- Optimize the two subgroups independently from the rest



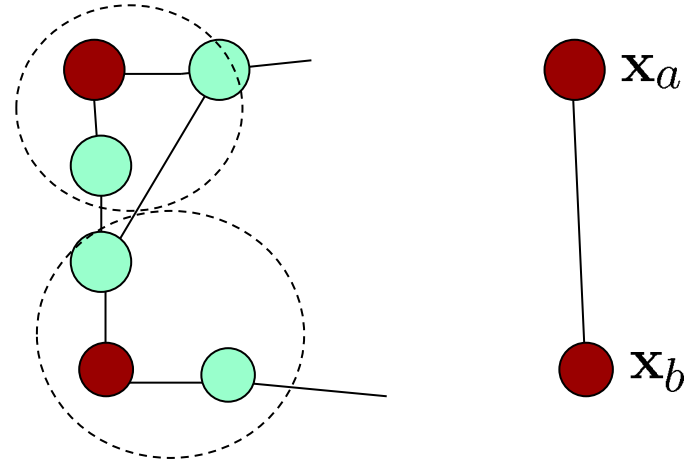
Determining Edge Parameters

- Optimize the two subgroups independently from the rest
- The observation is the relative transformation between the two representatives



Determining Edge Parameters

- Optimize the two subgroups 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 \mathbf{H}

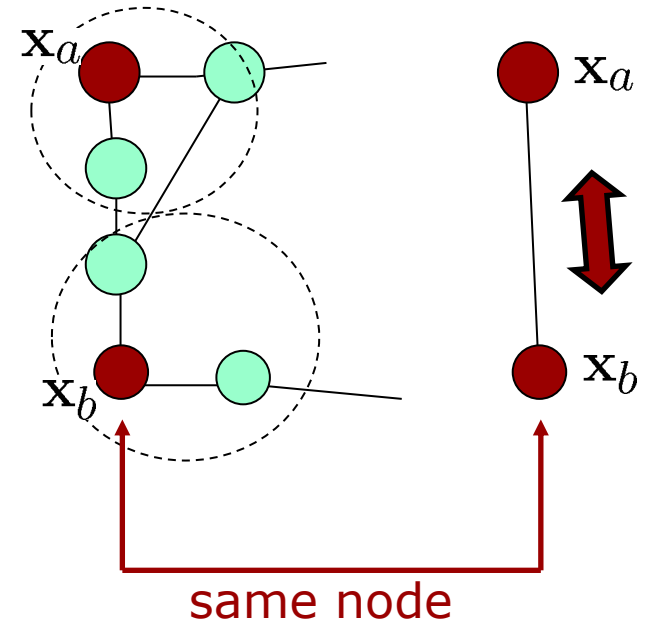


Inverse of the $[b,b]$
block of \mathbf{H}^{-1}

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

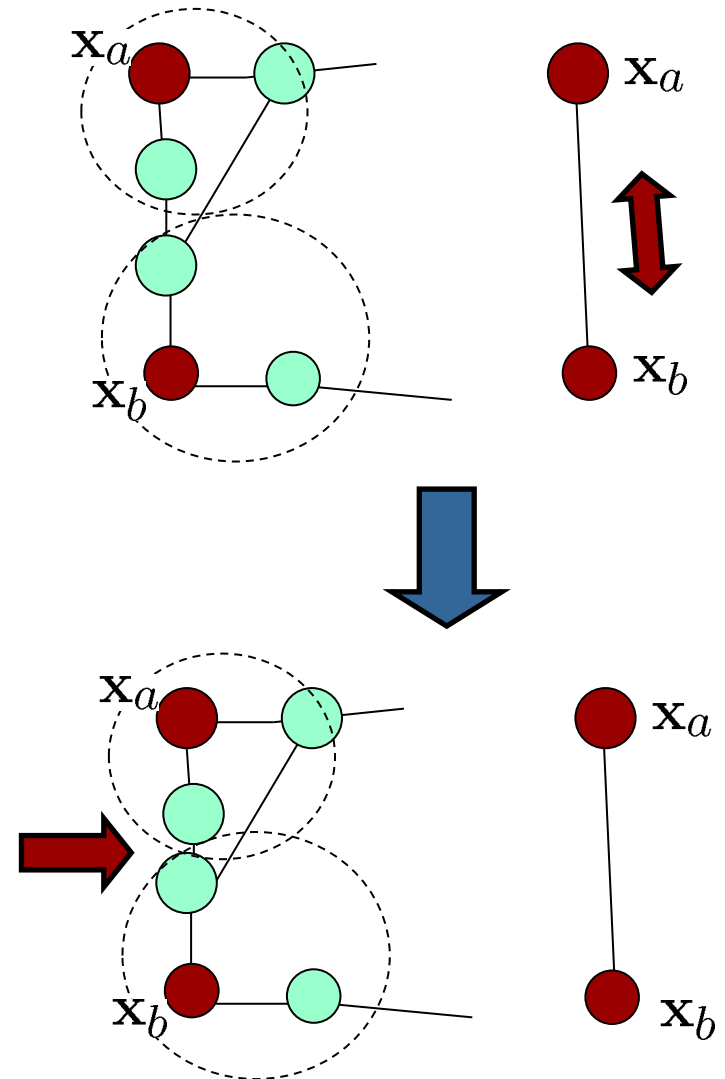
Propagating Information Downwards

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



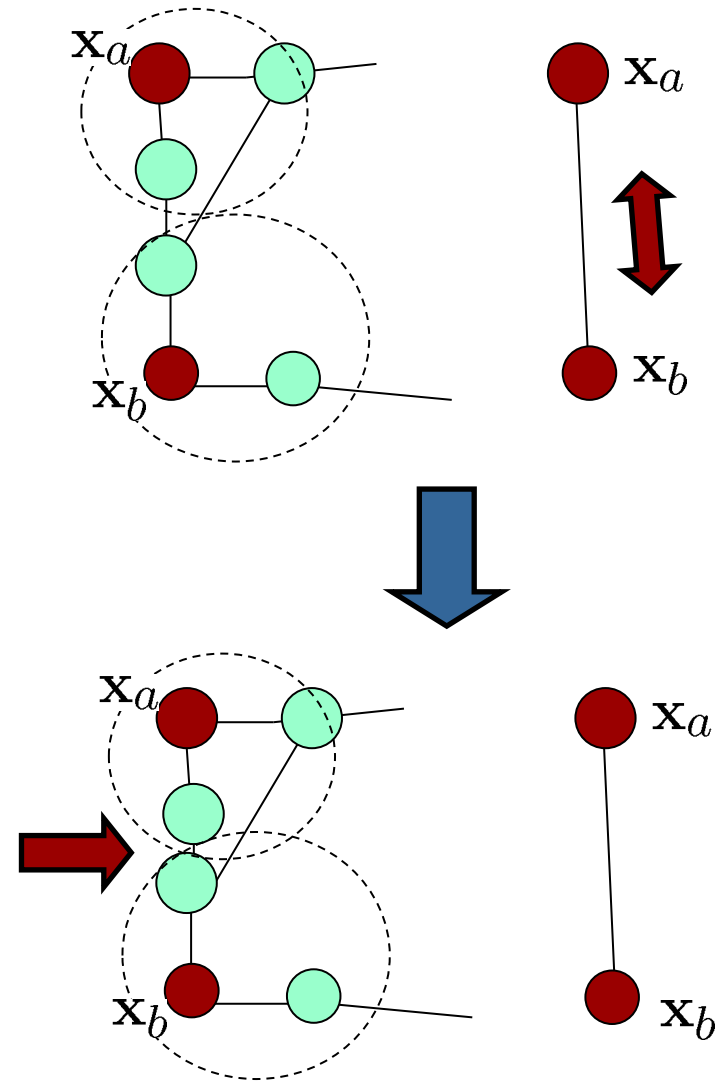
Propagating Information Downwards

- 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



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...

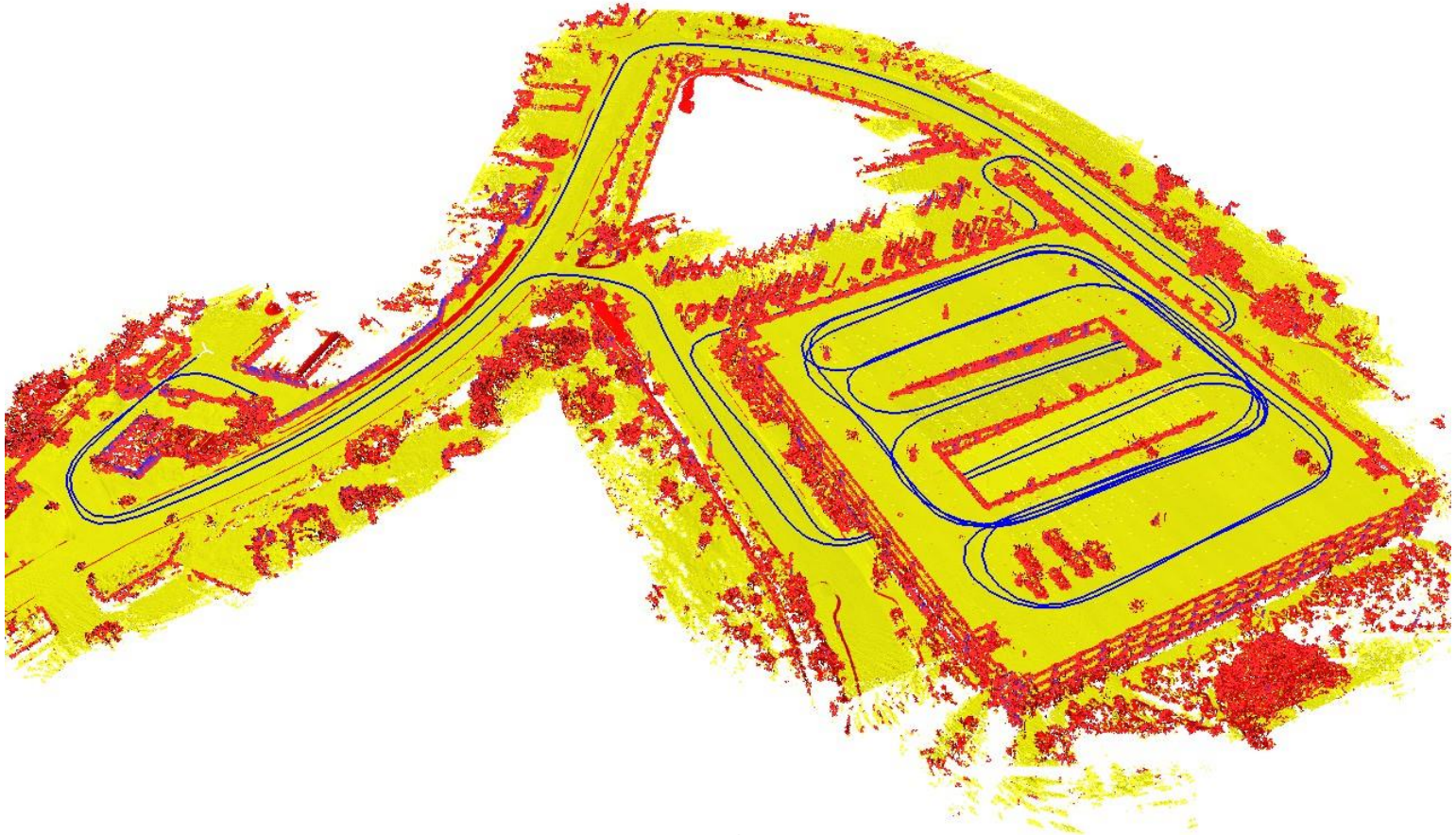
- Run the optimization on the lowest level (at the end)
- For offline processing with all measurements, the hierarchy helps convergence in case of large errors
- In this case, one pass up the tree (to construct the edges) followed by one pass down the tree is sufficient

Stanford Garage



- Parking garage at Stanford University
- Nested loops, trajectory of $\sim 7,000\text{m}$

Stanford Garage Result



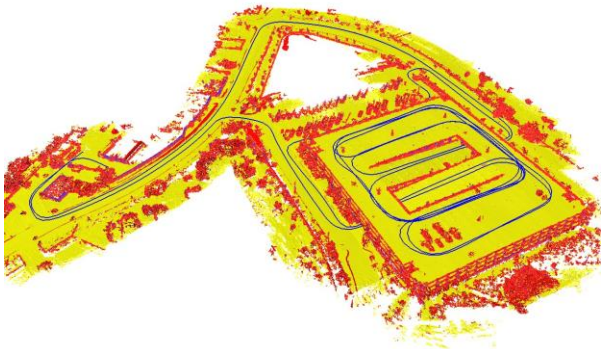
- Parking garage at Stanford University
- Nested loops, trajectory of $\sim 7,000\text{m}$

Stanford Garage Video

Level 0



Level 2



Consistency

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

Consistency

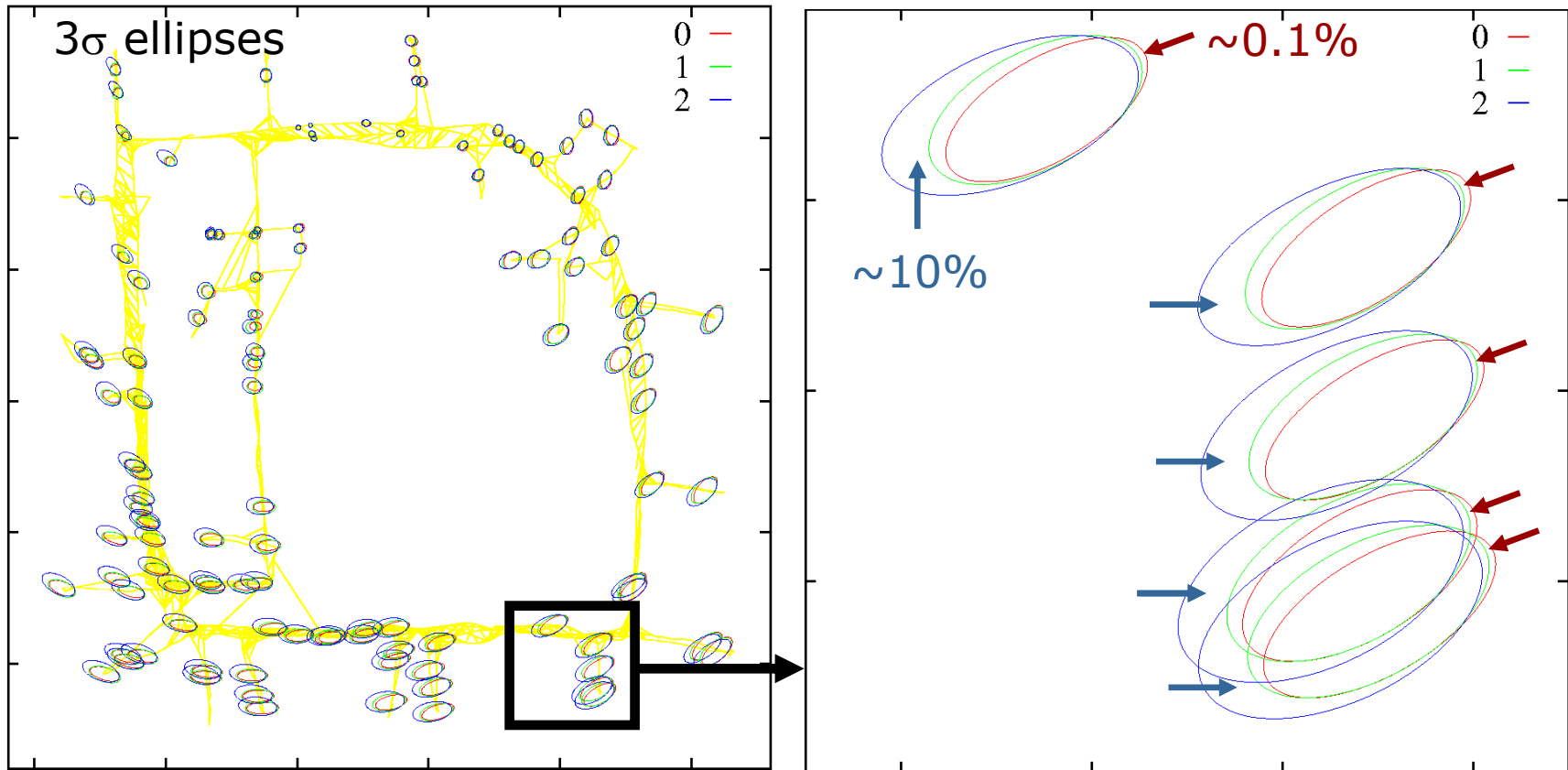
- How well does the top level in the hierarchy represent the original input?
- Probability mass of the marginal distribution in the highest level vs. the one of the true estimate (original problem, lowest level)

	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 ($\sim 0.1\%$ prob. mass)
- **Blue**: under confident ($\sim 10\%$ 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

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