# Robot Mapping

## SLAM Front-Ends

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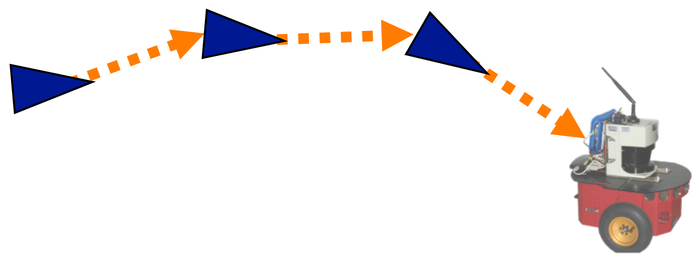
UNI FREIBURG

Autonomous Intelligent Systems

Partial image courtesy: Edwin Olson

# Graph-Based SLAM

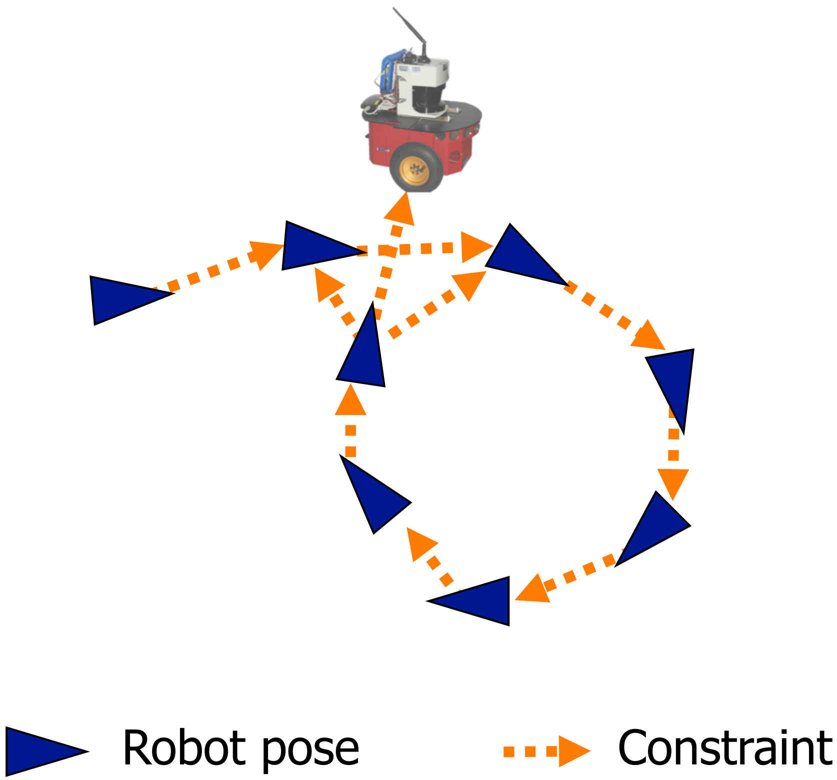
- Constraints connect the nodes through odometry and observations



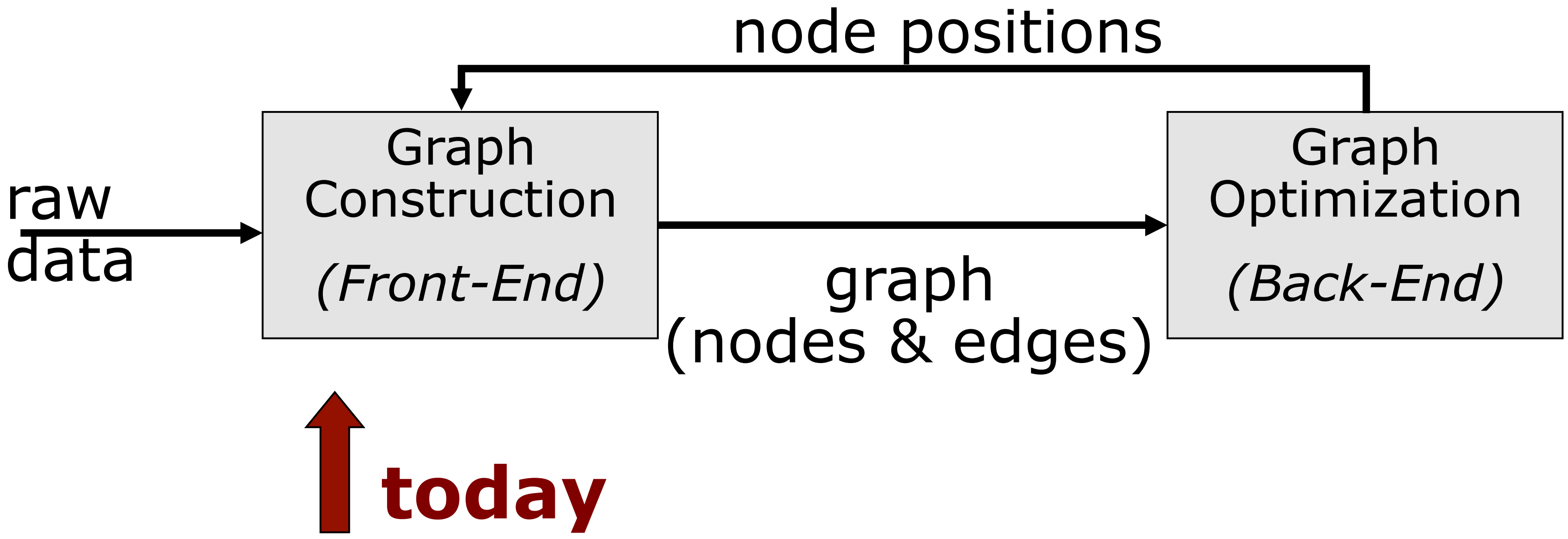
Robot pose Constraint

# Graph-Based SLAM

- Constraints connect the nodes through odometry and observations
- How to obtain the constraints?



# Interplay between Front-End and Back-End



# Constraints From Matching

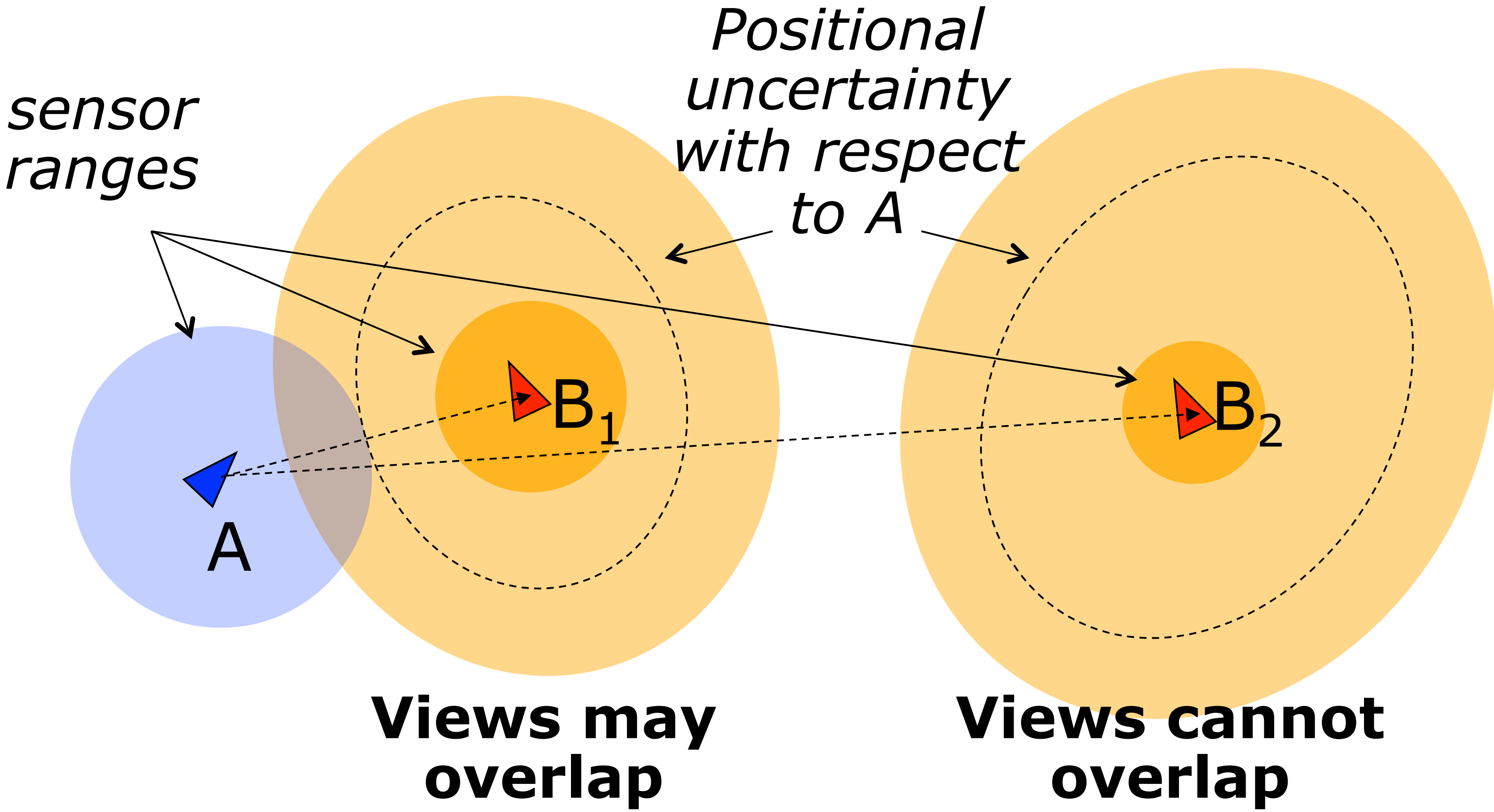
- Constraints can be obtained from matching observations

## Popular approaches

- Dense scan-matching
- Feature-based matching
- Descriptor-based matching

# Where to Search for Matches?

- Consider uncertainty of the nodes with respect to the current one



# Note on the Uncertainty

- In graph-based SLAM, computing the uncertainty relative to A requires inverting the Hessian **H**
- Fast approximation by Dijkstra expansion ("propagate uncertainty along the shortest path in the graph")
- Conservative estimate

# Simple ICP-Based Approach

- Assuming a laser range sensor
- Estimate uncertainty of nodes relative to the current pose
- Sample poses in relevant area
- Apply Iterative Closest Point algorithm
- Evaluate match
- Accept match based on a threshold

**Problems?**

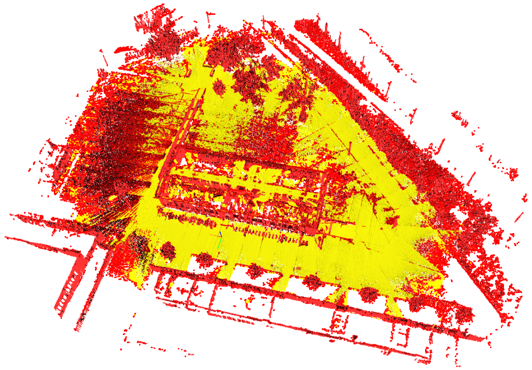
# Problems

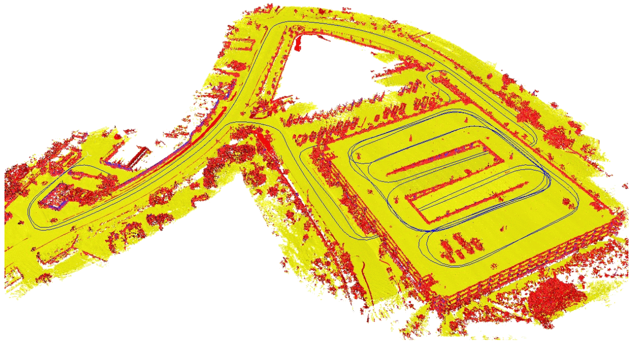
- ICP is sensitive to the initial guess
- Inefficient sampling
- Ambiguities in the environment

## Problems

- **ICP is sensitive to the initial guess**
- **Inefficient sampling**
- Ambiguities in the environment

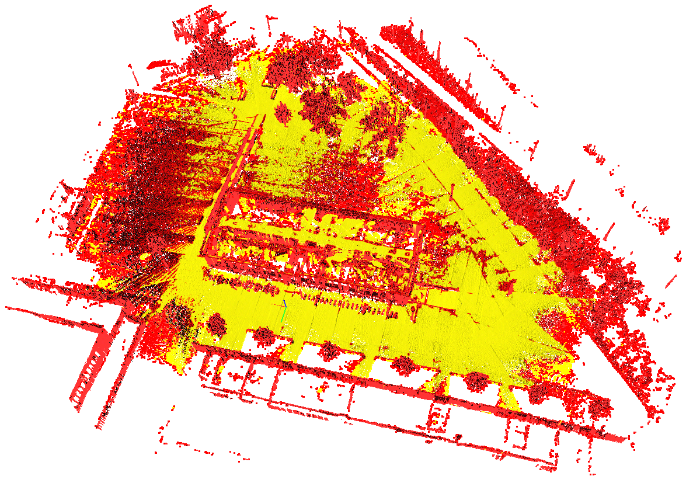
# Examples



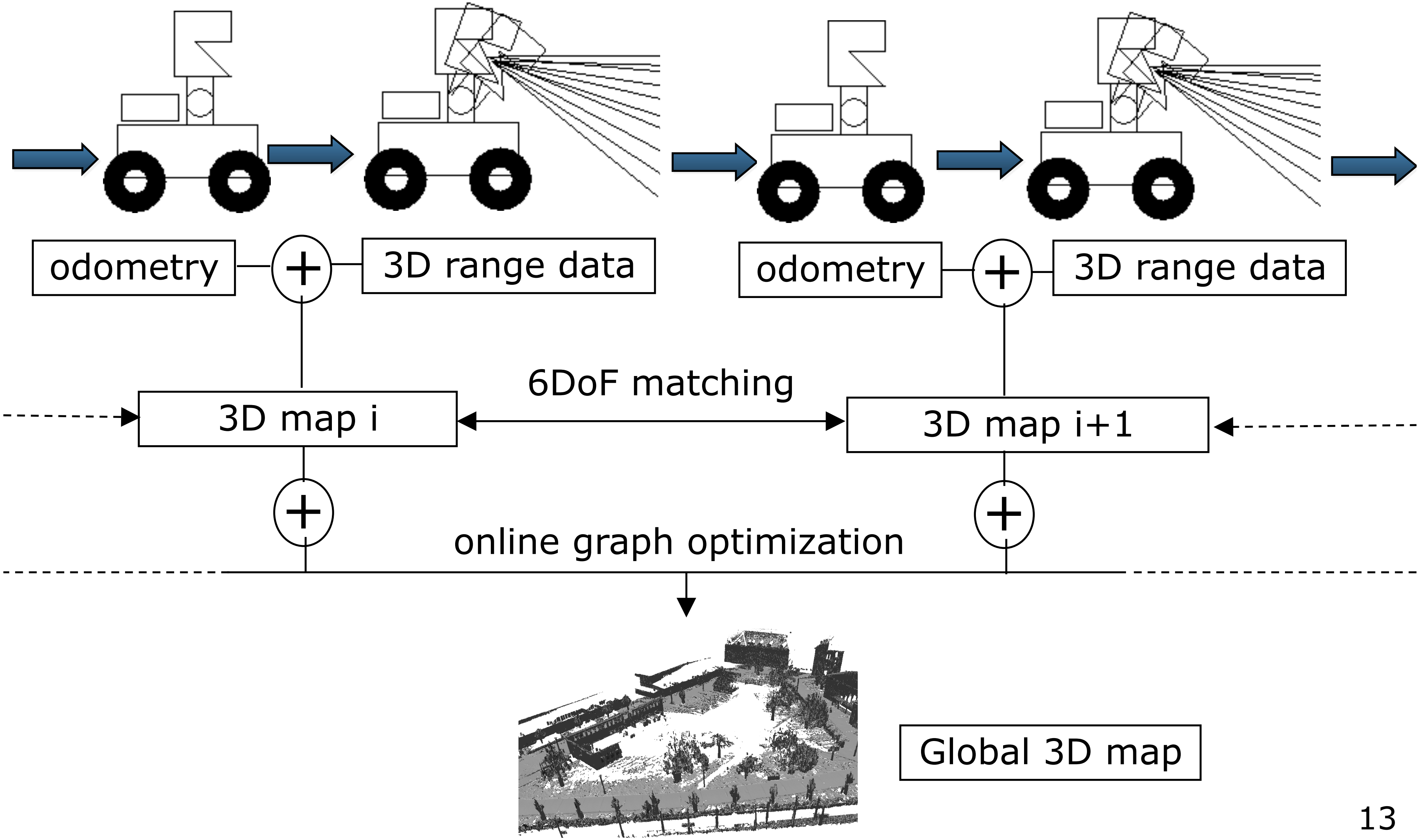



# Learning 3D Maps with Laser Data

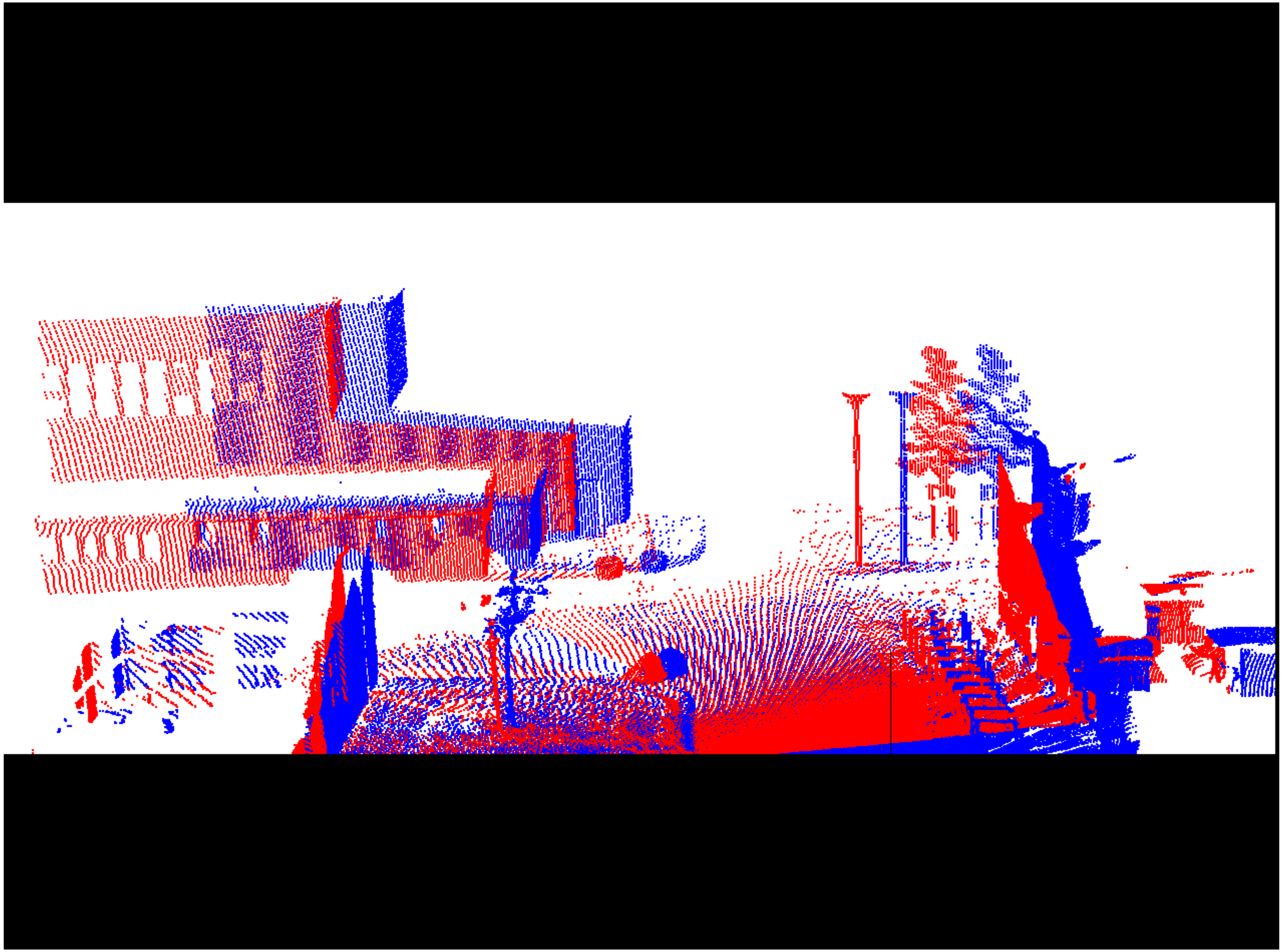
- Robot that provides odometry
- Laser range scanner on a pan-tilt-unit



# Incremental 6D SLAM



# Aligning Consecutive Maps



# Aligning Consecutive Maps

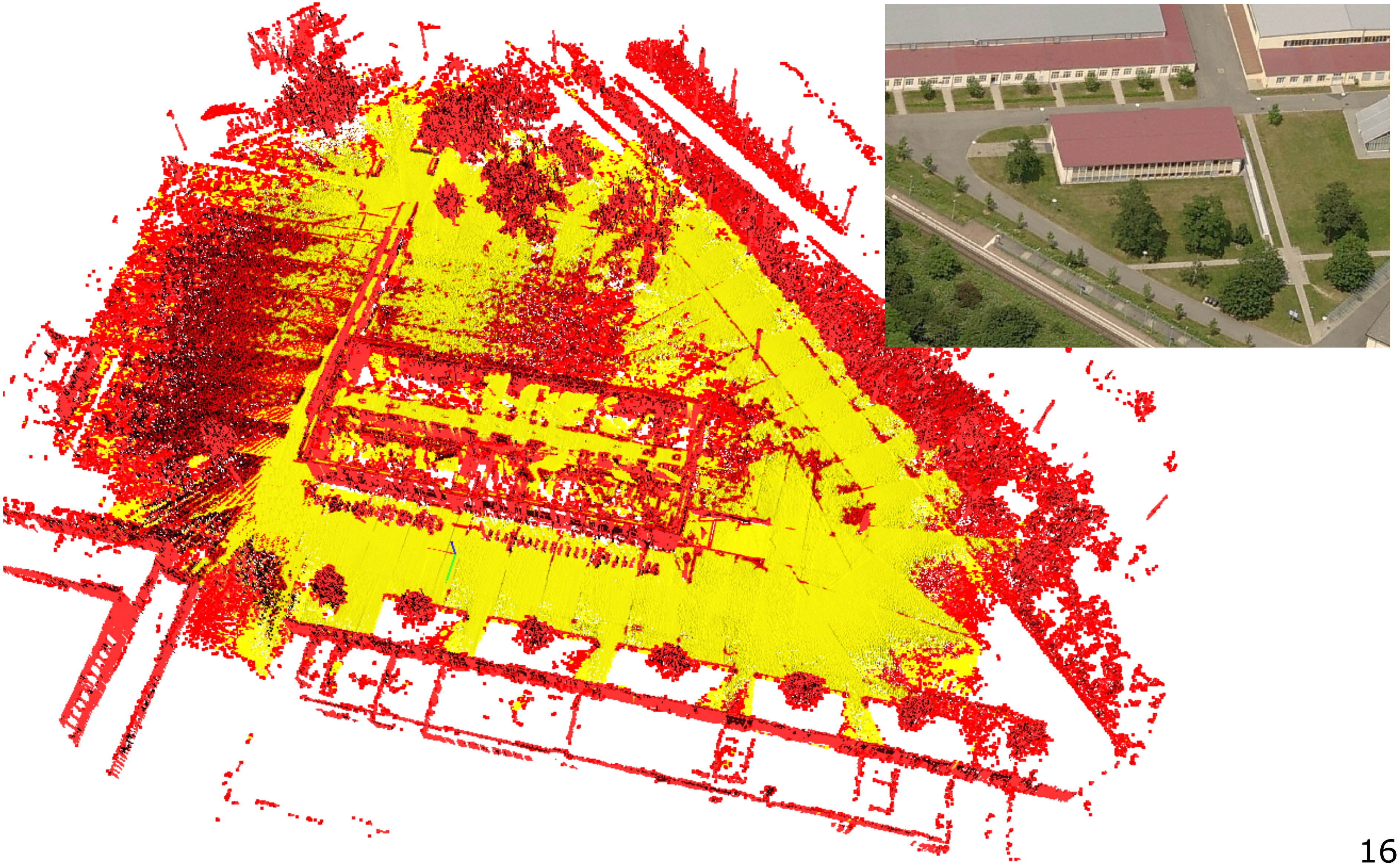
- Let $\mathbf{u}_{i_c}$ and $\mathbf{u}'_{j_c}$ be corresponding points
- Find the parameters R and t which minimize the sum of the squared error
- ICP

$$e(R, \mathbf{t}) = \sum_{c=1}^{C} d(\mathbf{u}_{i_c}, \mathbf{u}'_{j_c})$$

- ICP with additional knowledge

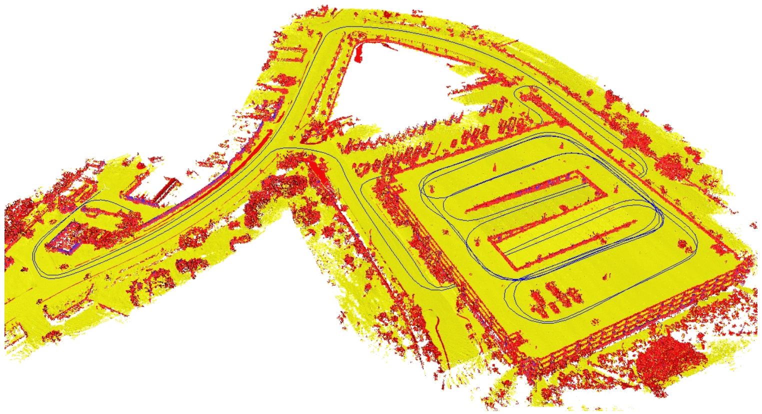
$$e(R, \mathbf{t}) = \underbrace{\sum_{c=1}^{C_1} d_v(\mathbf{u}_{i_c}, \mathbf{u}'_{j_c})}_{\text{vertical objects}} + \underbrace{\sum_{c=1}^{C_2} d(\mathbf{v}_{i_c}, \mathbf{v}'_{j_c})}_{\text{traversable}} + \underbrace{\sum_{c=1}^{C_3} d(\mathbf{w}_{i_c}, \mathbf{w}'_{j_c})}_{\text{non-traversable}}$$

# Online Estimated 3D Map



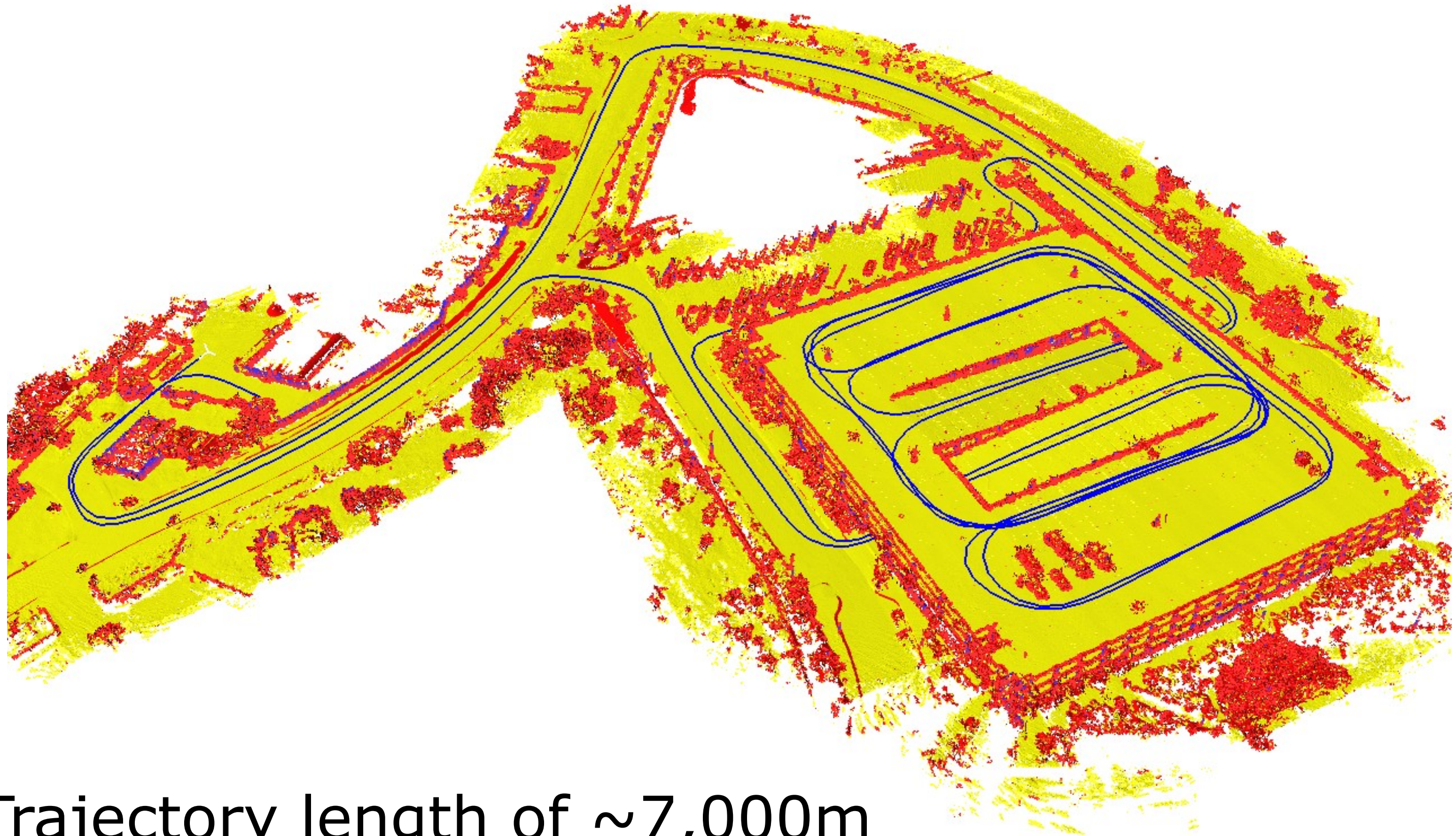
# Mapping with a Robotic Car

- 3D laser range scanner (Velodyne)
- Use map for autonomous driving



# Parking Garage

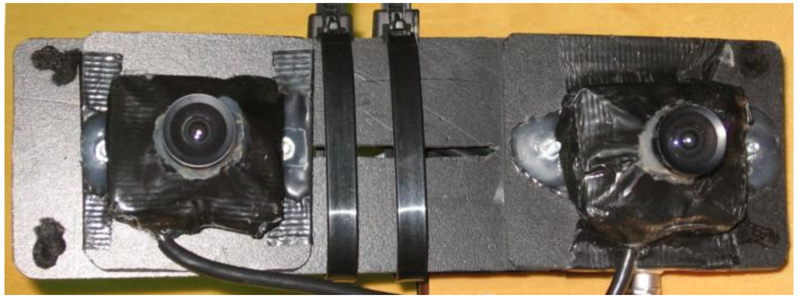
# Resulting Map



- Trajectory length of ~7,000m
- 1661 local 3D maps, cell size of 20cm x 20cm

# Mapping with Arial Vehicles

- Flying vehicles equipped with cameras and an IMU

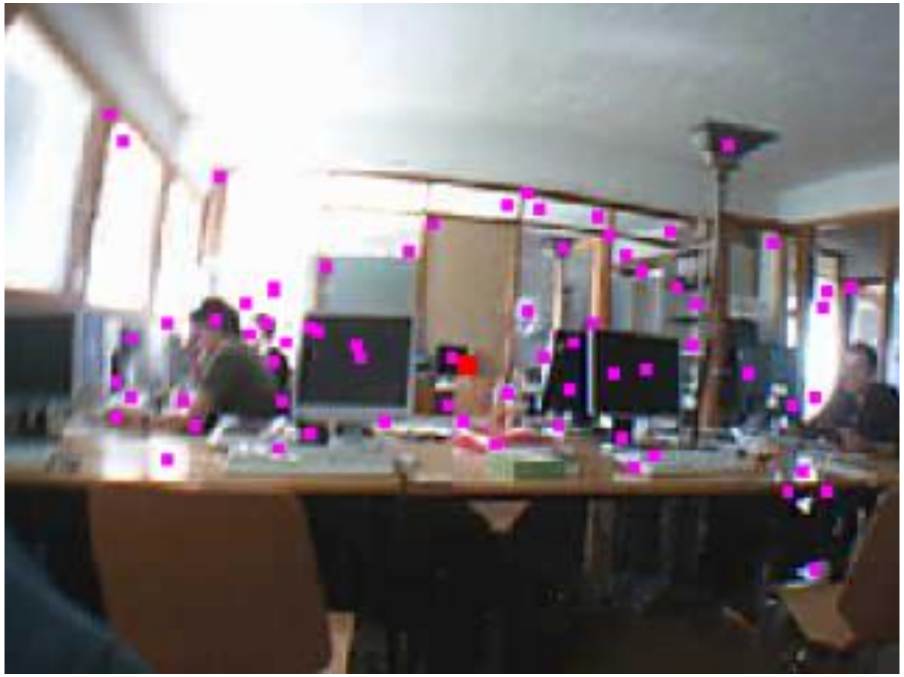


# Examples of Camera Images




# SURF Features

- Provide a description vector and an orientation
- Descriptor is invariant to rotation and scale



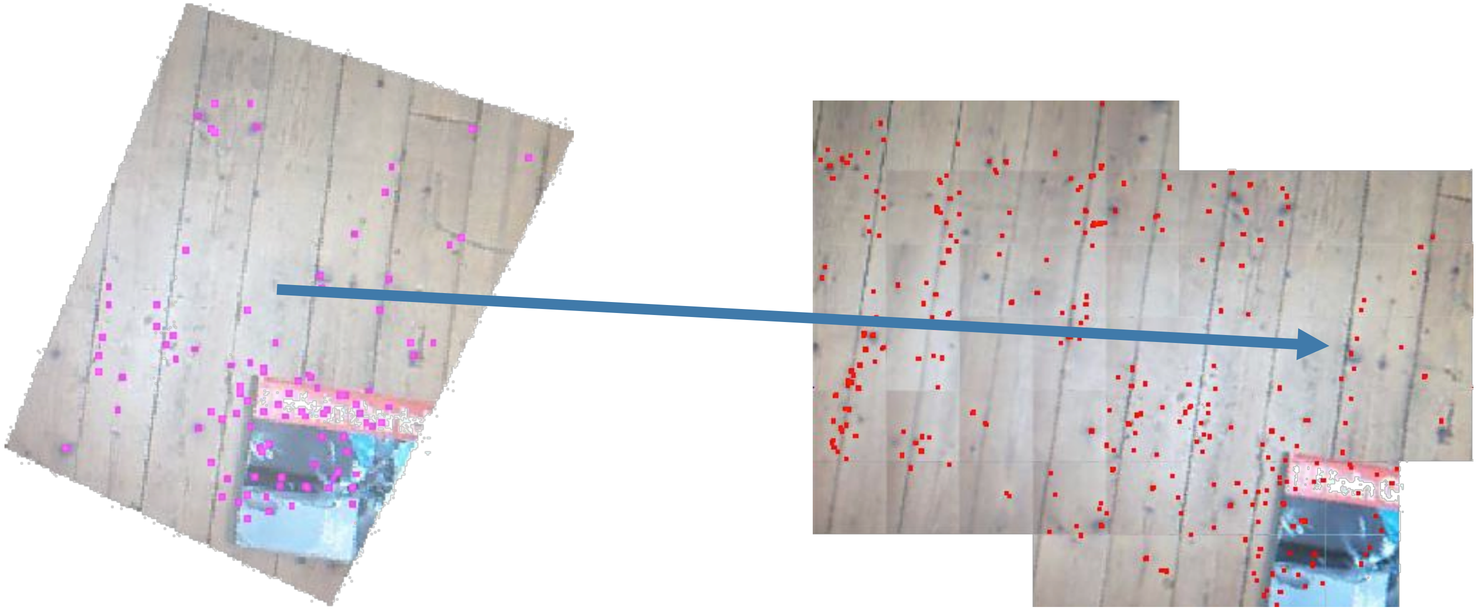
# Determining the Camera Pose

**Wanted**: x, y, z, φ, θ, Ψ (roll, pitch, yaw)

- IMU determines roll and pitch accurately
- x, y, z and the heading (yaw) have to be calculated based on the camera images

➡ 3D positions of **two** image features is sufficient to determine the camera pose

# Feature Matching for Pose Estimation



features in image features in map

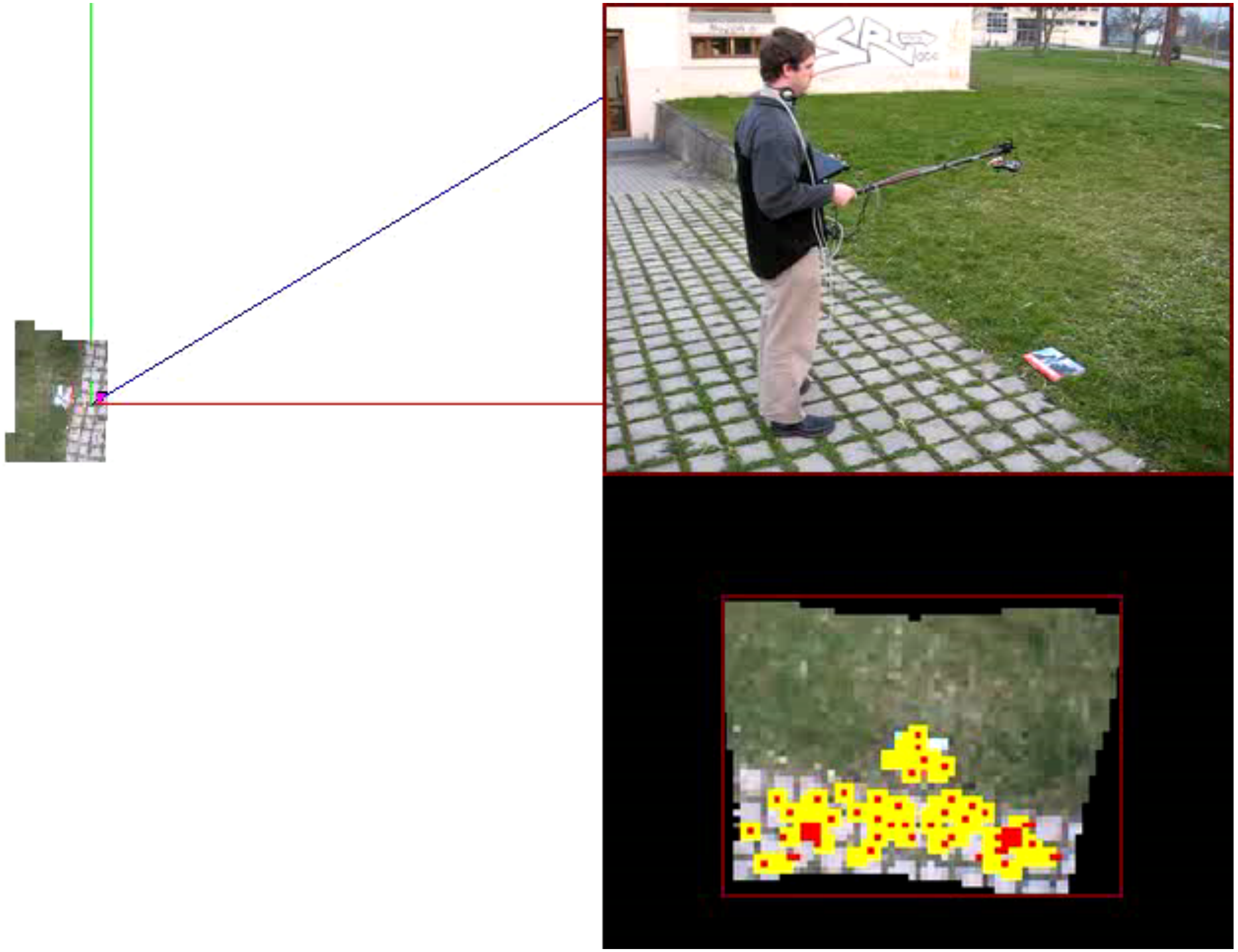
# Camera Pose Estimation

1. Find possible matches (kd-tree)
2. Order matches by descriptor distance
   - Use two matches to calculate the camera position, start with the best one
   - Re-project all features accordingly to get a quality value about this pose
   - Repeat until satisfactory pose is found
3. Update map

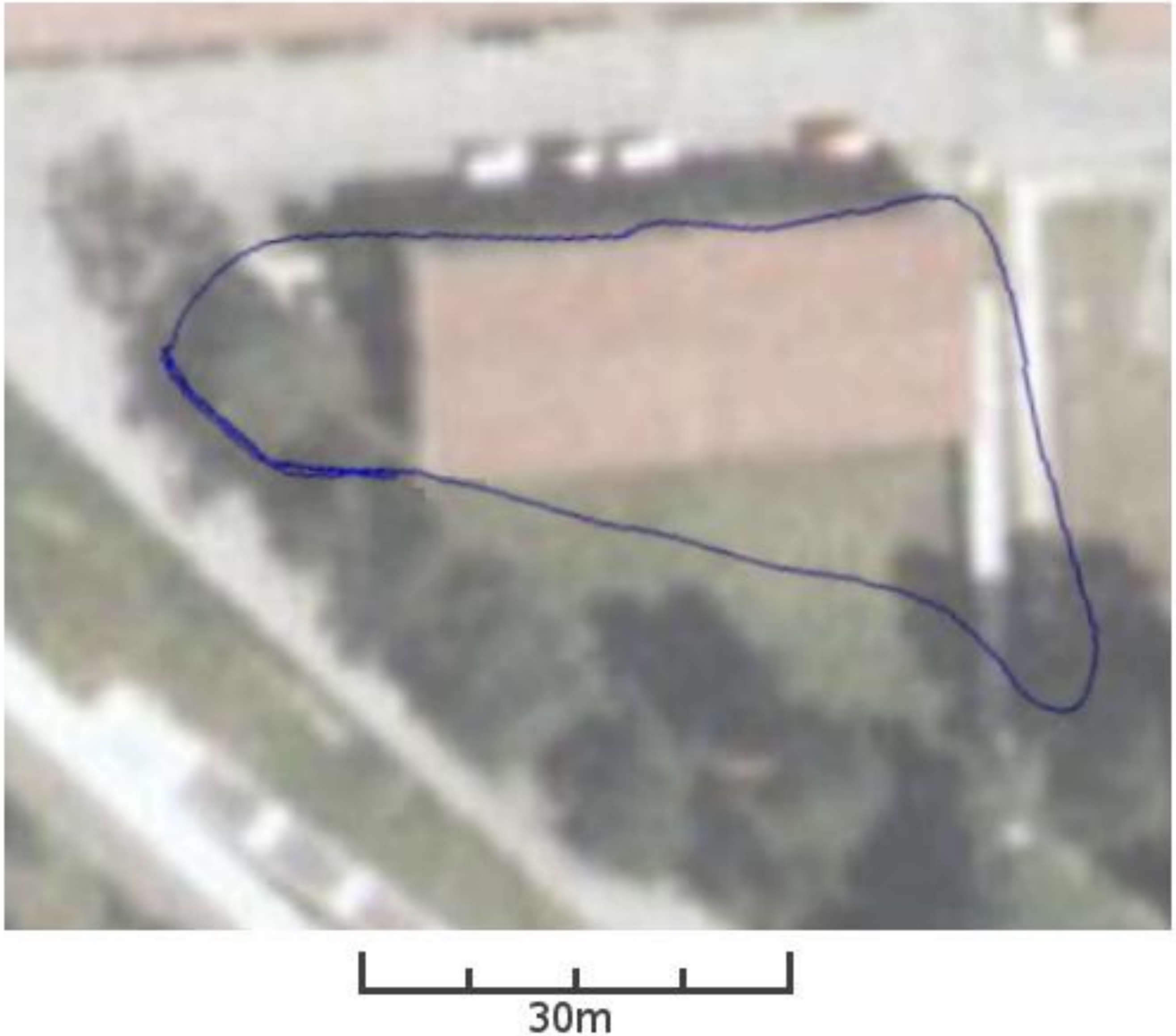
# Finding Edges

- **Visual odometry:** Match features against the N previously observed ones
- **Localization:** Match against features in the map in a given region around the odometry estimate (local search)
- **Loop closing:** Match a subset of the features against all map features. Match leads to a localization step

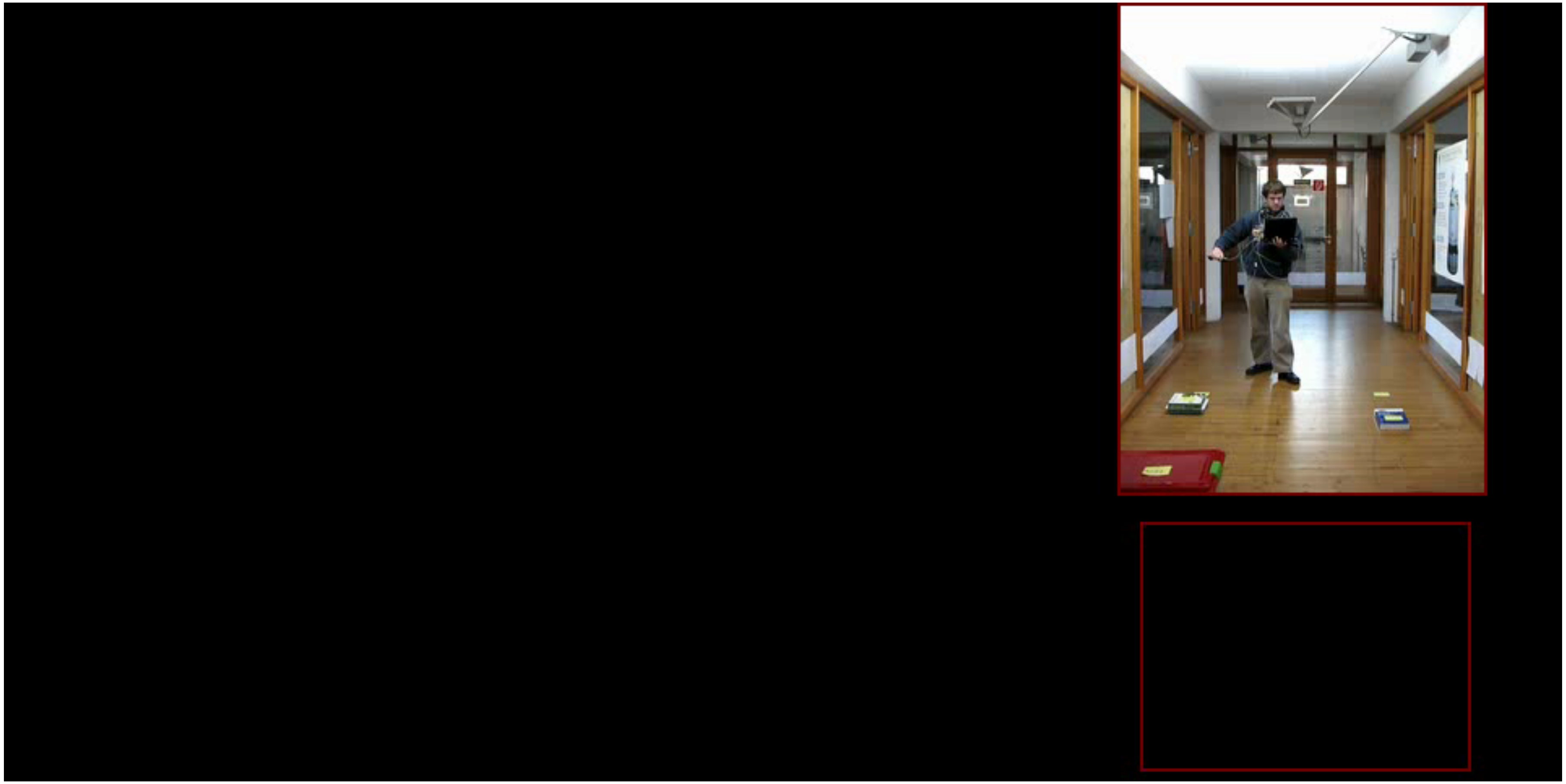
# Outdoor Example



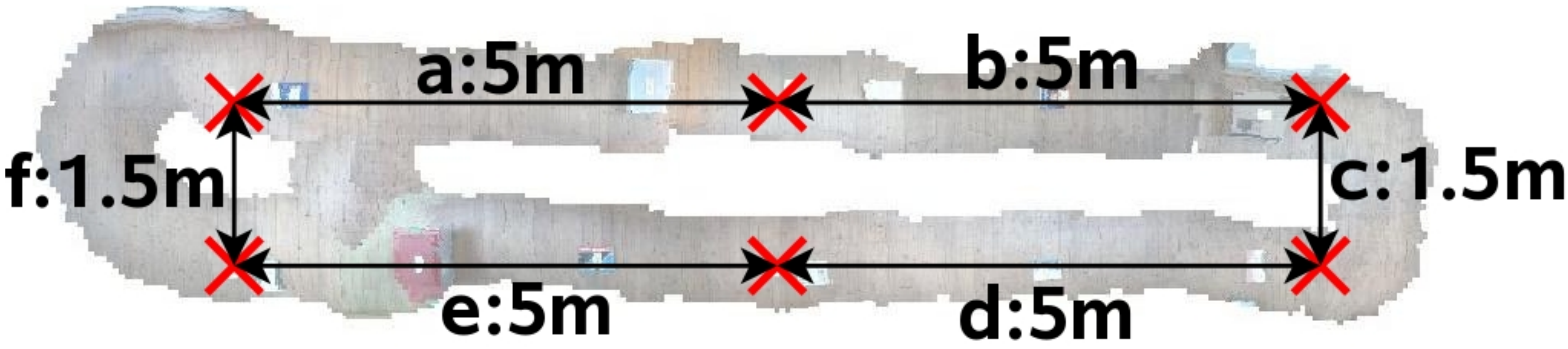
# Resulting Trajectory

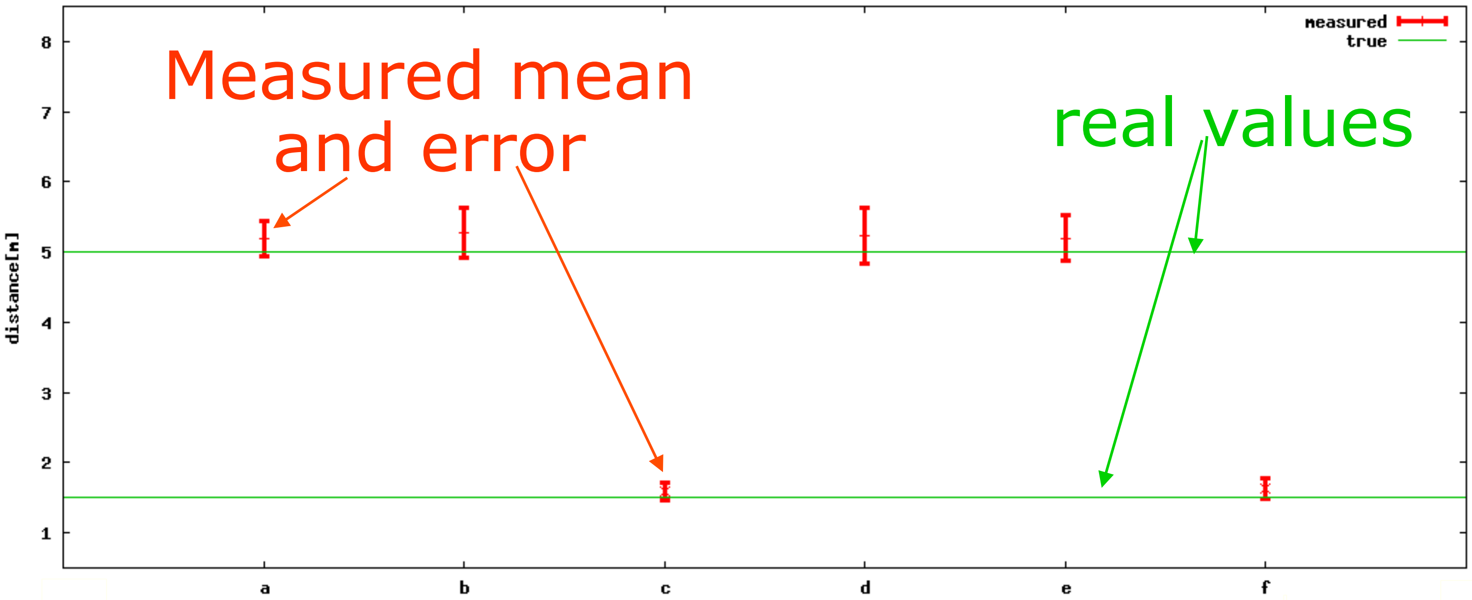


# Indoor Example

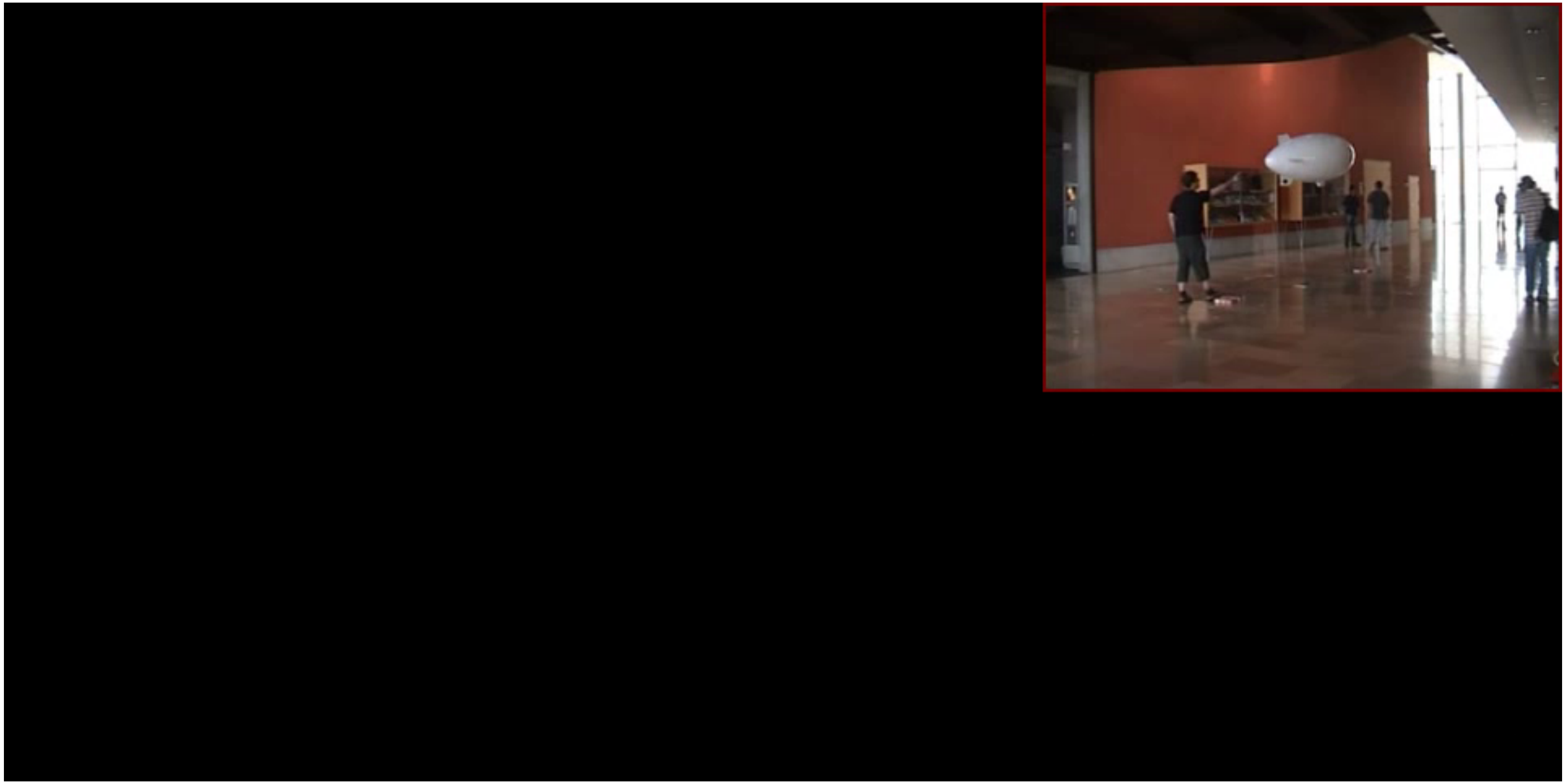


# Ground Truth



# System on a Blimp



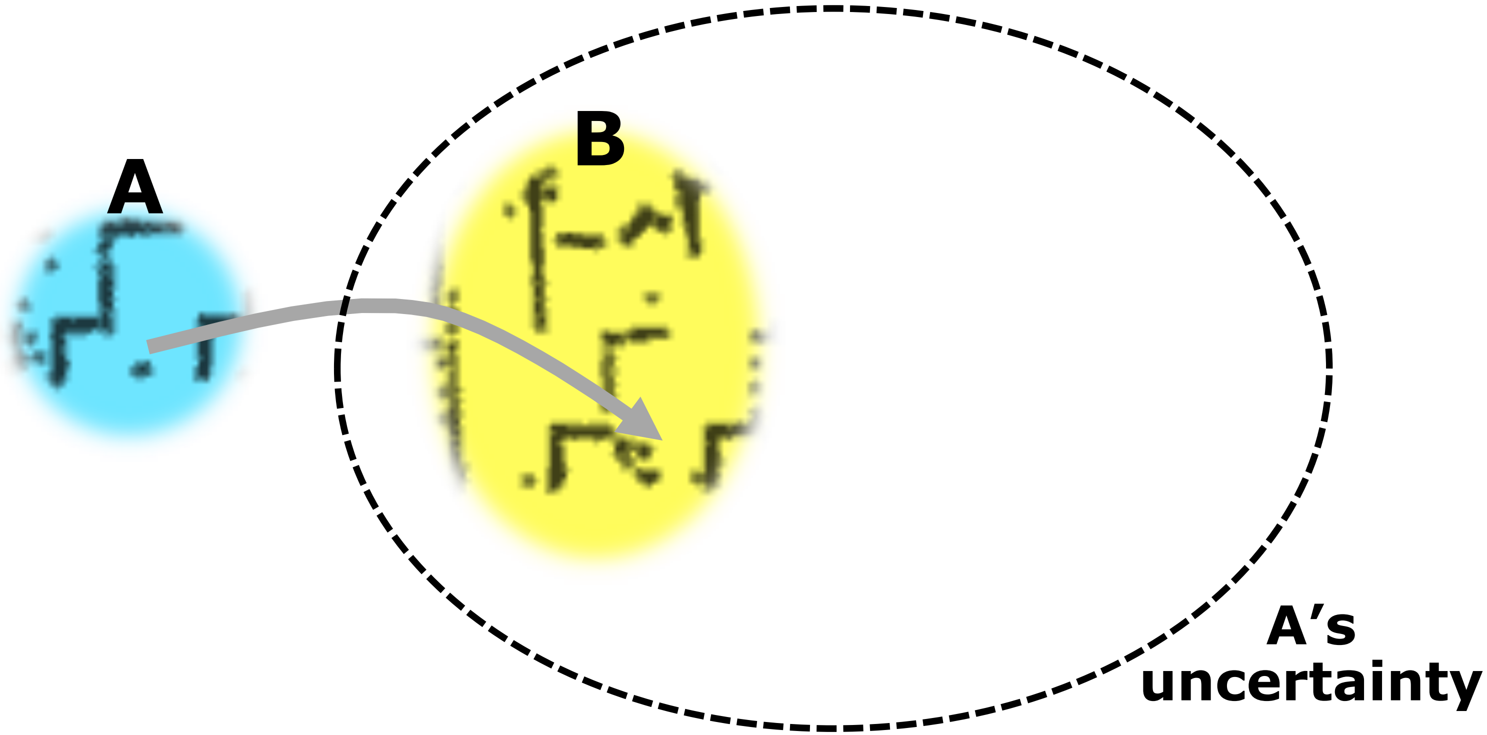
# Problems

- ICP is sensitive to the initial guess
- Inefficient sampling
- **Ambiguities in the environment**

- Dealing with ambiguous areas in an environment is essential for robustly operating robots

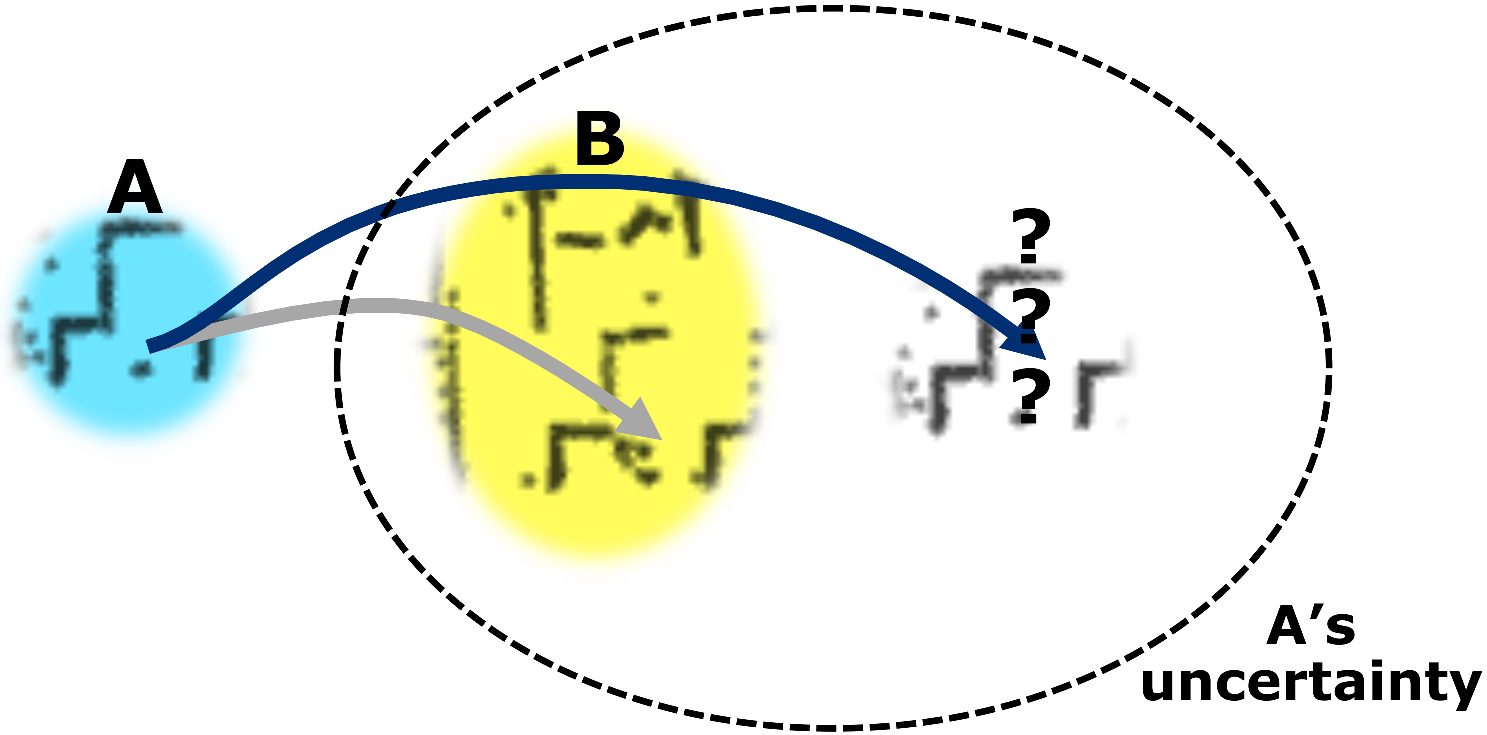
# Ambiguities - Global Ambiguity

- B is inside the uncertainty ellipse of A
- Are A and B the same place?



# Ambiguities - Global Ambiguity

- B is inside the uncertainty ellipse of A
- A and B might not be the same place



# Ambiguities - Global Ambiguity

- B is inside the uncertainty ellipse of A
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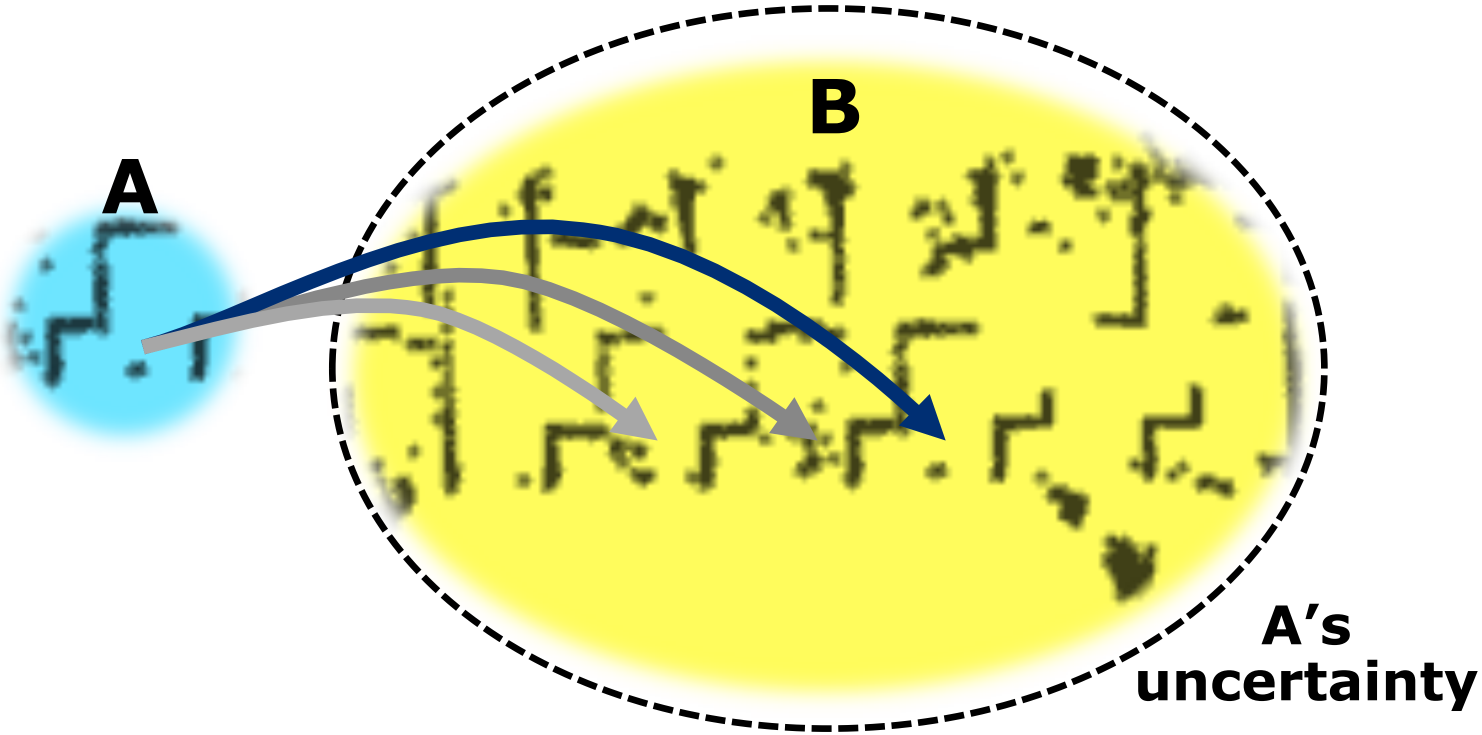
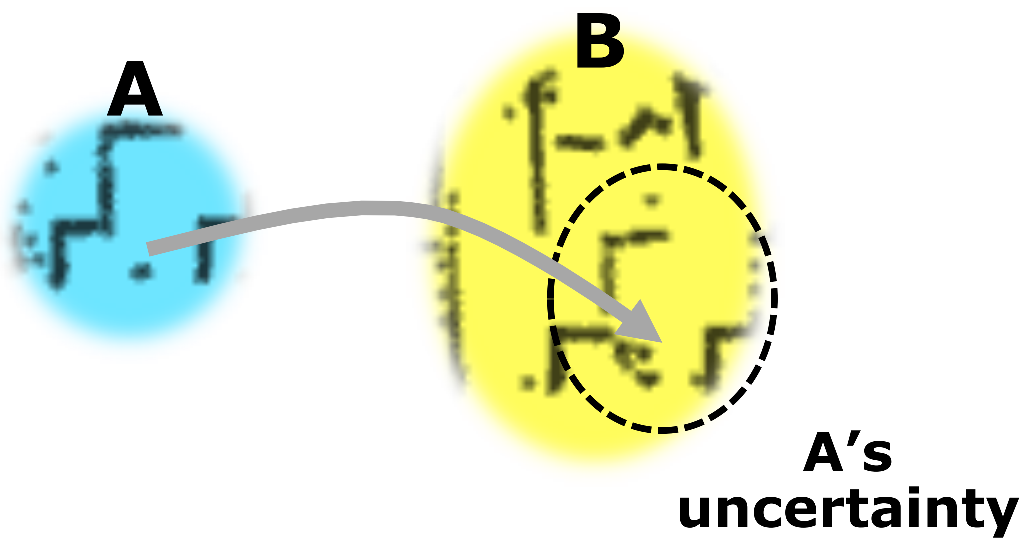


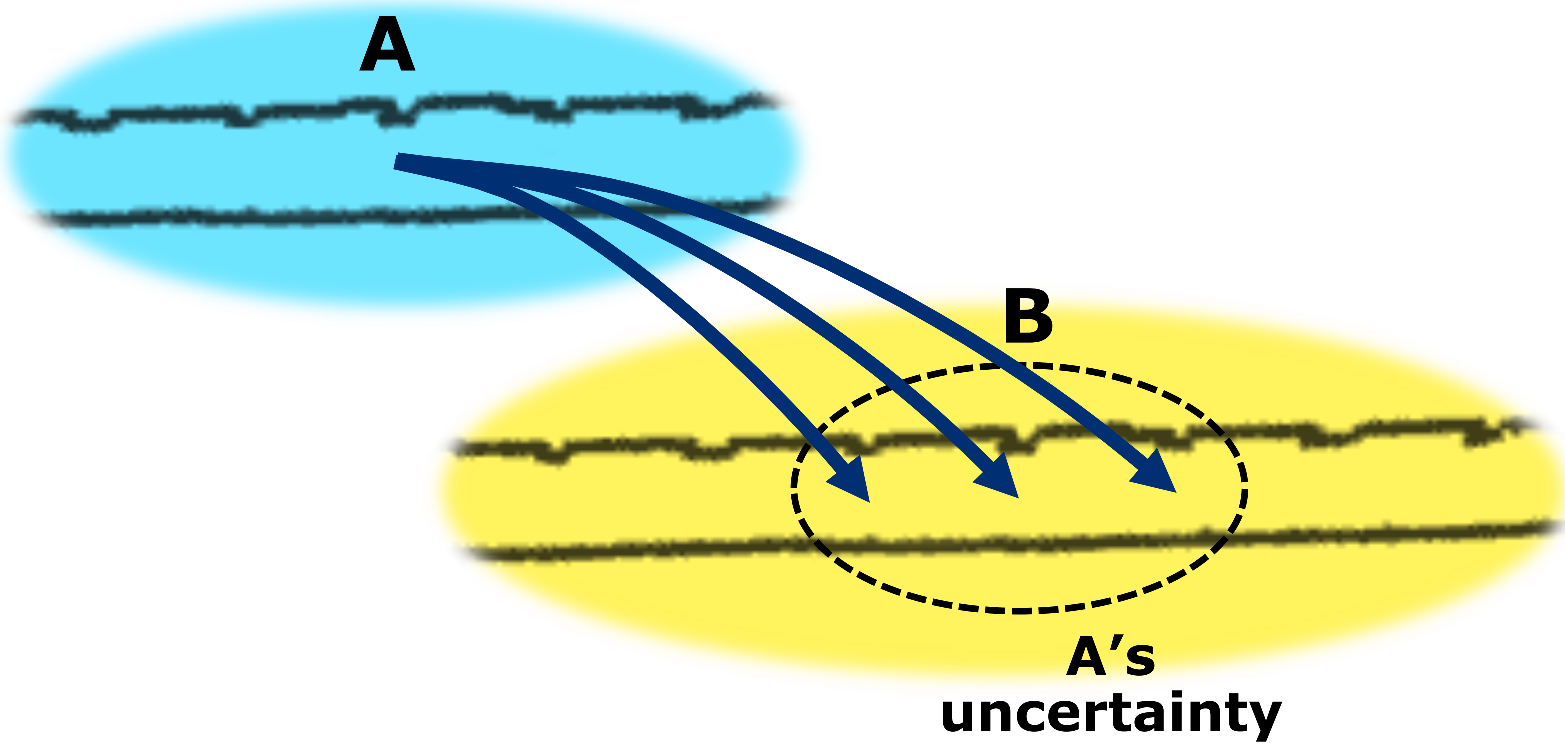
# Ambiguities - Global Sufficiency

- B is inside the uncertainty ellipse of A
- The is no other possibility for a match



# Ambiguities - Local Ambiguity

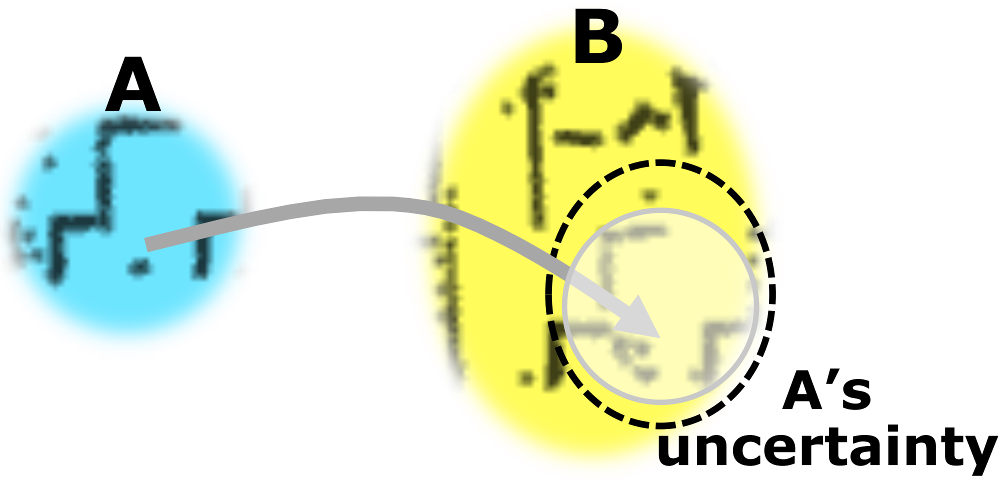
- "Picket Fence Problem": largely overlapping local matches



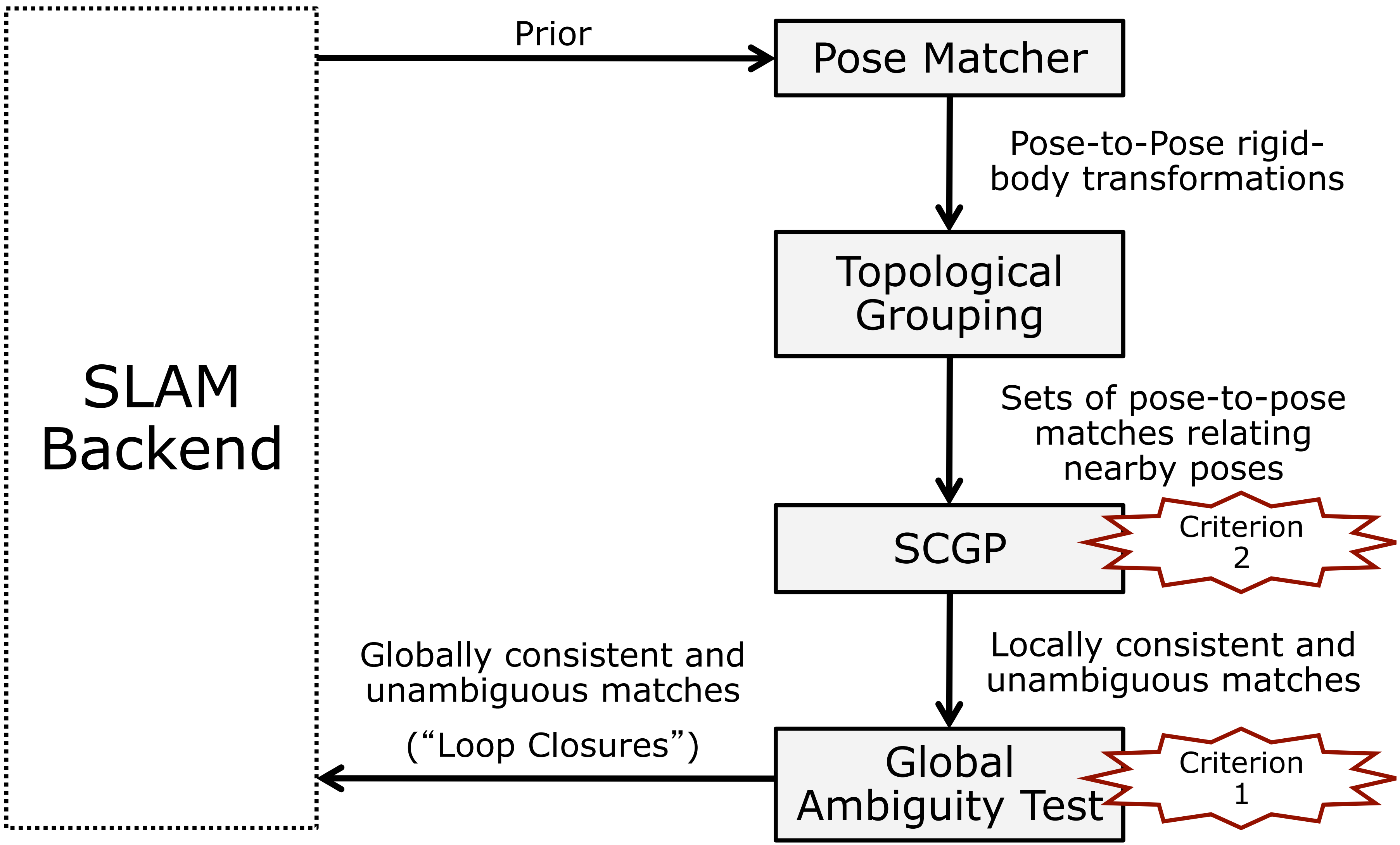
# Global Match Criteria

1. Global Sufficiency: There is no possible disjoint match ("A is not somewhere else entirely")
2. Local unambiguity: There are no overlapping matches ("A is either here or somewhere else entirely")

**Both need to be satisfied for a match**

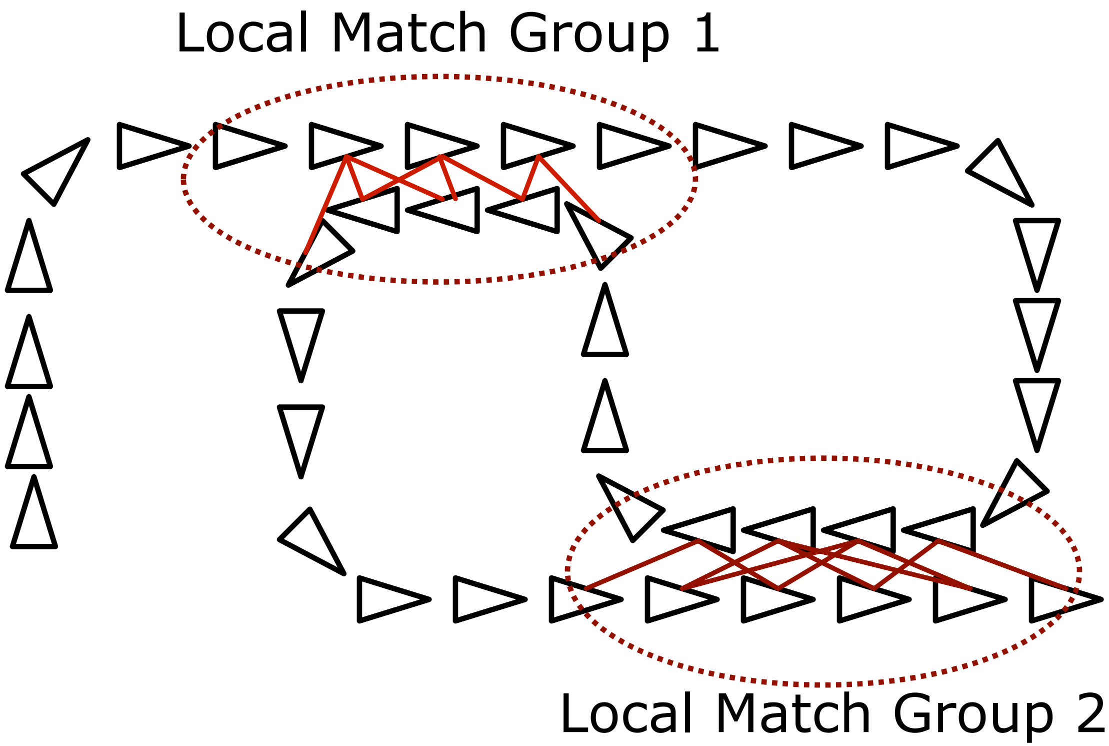


# Olson's Proposal



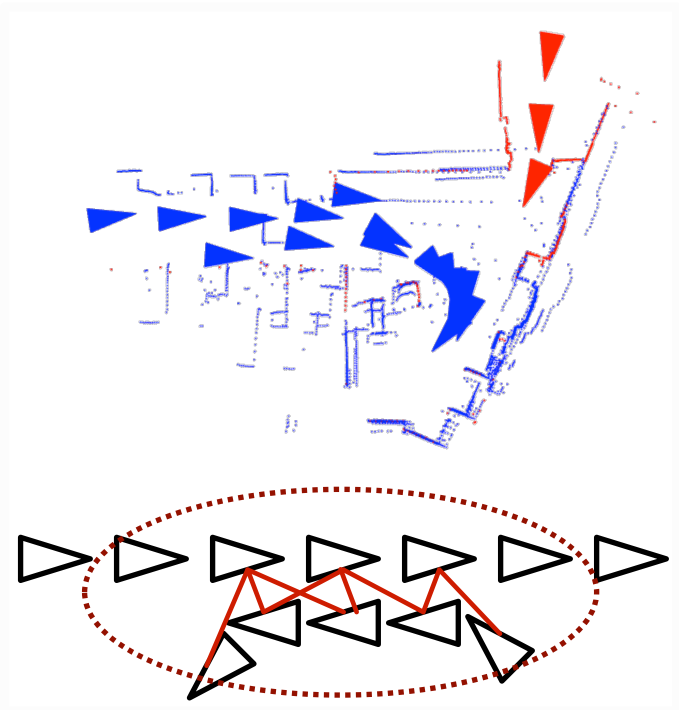
# Topological Grouping

- Group together topologically-related pose-to-pose matches to form local matches
- Each group asks a "topological" question: Do two local maps match?

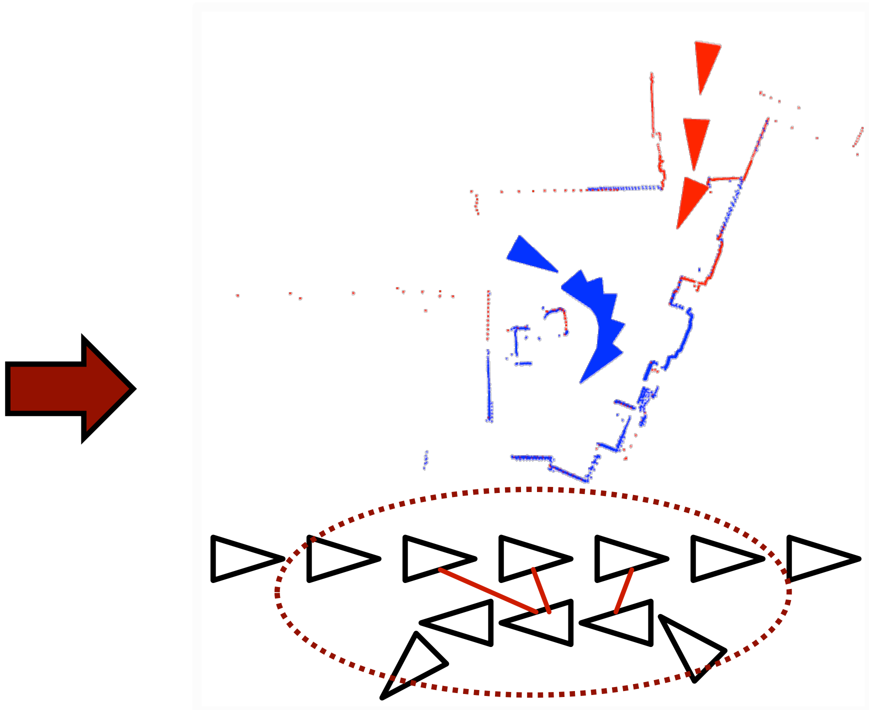


# Locally Unambiguous Matches

## Goal:



Unfiltered Local Match
(set of pose-to-pose matches)



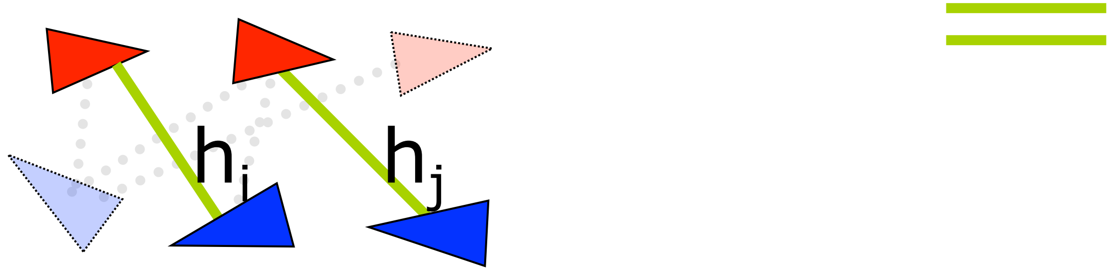
Locally consistent and
unambiguous local match
(set of pose-to-pose matches)

# Locally Consistent Matches

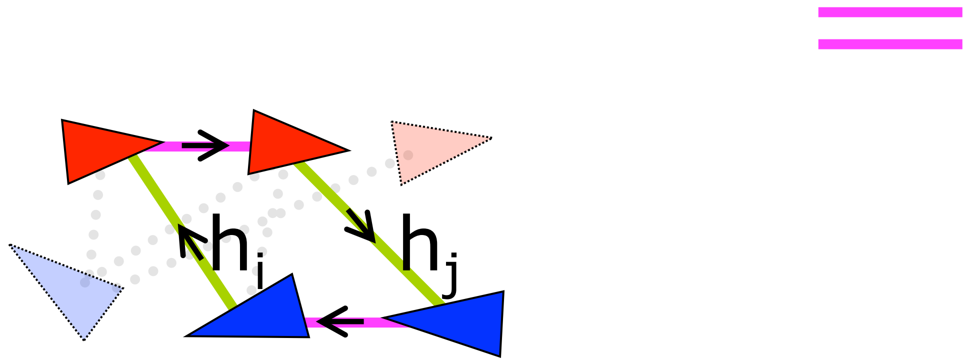
- Correct pose-to-pose hypotheses must agree with each other
- Incorrect pose-to-pose hypotheses tend to disagree with each other
- Find subset of self-consistent of hypotheses
- Multiple self-consistent subsets, are an indicator for a “picket fence”!

# Do Two Hypotheses Agree?

- Consider two hypotheses **i** and **j** in the set:



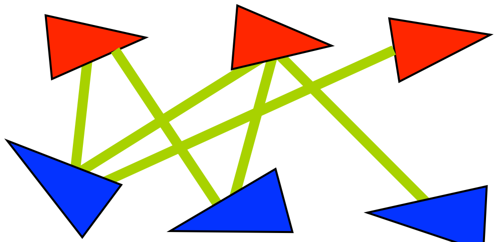

- Form a loop using edges from the prior graph



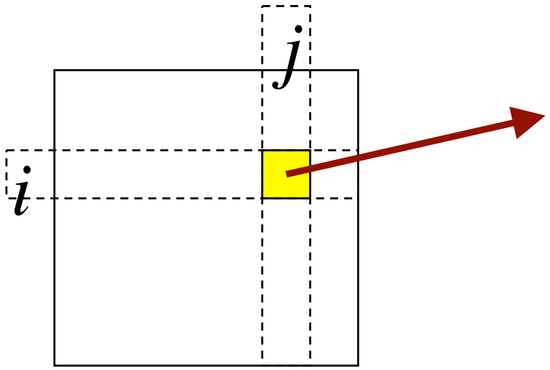

**Rigid-body transformation around the loop should be the identity matrix**

# Idea of Olson's Method

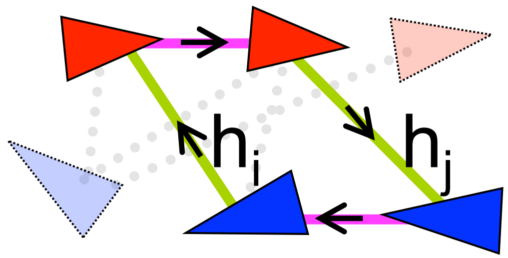
- Form pair-wise consistency matrix **A**



Hypothesis Set

A = 

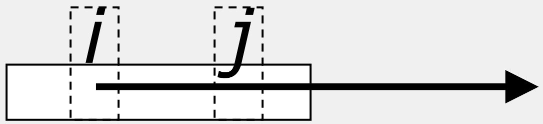

$$A_{ij} = P(\text{loop}(i, j) = I \mid h_i, h_j)$$



# Single Cluster Graph Partitioning

- Idea: Identify the subset of consistent hypotheses
- Find the best **indicator vector** (represents a subset of the hypotheses)

Indicator vector v




$v_i$ = 1 if $h_i$ is correct,
0 if $h_i$ is incorrect

# Single Cluster Graph Partitioning

- Identify the subset of hypotheses that is maximally self-consistent
- Which subset **v** has the **greatest average pair-wise consistency** λ?

$$\lambda = \frac{\mathbf{v}^{\mathbf{T}}\mathbf{A}\mathbf{v}}{\mathbf{v}^{\mathbf{T}}\mathbf{v}}$$

Sum of all pair-wise consistencies between hypotheses in v

Number of hypotheses in v

*Gallo et al 1989*

- Densest subgraph problem

# Consistent Local Matches

- We want find **v** that maximizes λ(**v**)

$$\lambda(\mathbf{v}) = \frac{\mathbf{v}^{\mathbf{T}}\mathbf{A}\mathbf{v}}{\mathbf{v}^{\mathbf{T}}\mathbf{v}}$$

- Treat as continuous problem
- Derive and set to zero

$$\frac{\partial \lambda(\mathbf{v})}{\partial \mathbf{v}} = 0$$

- Which leads to (for symmetric A)

$$\frac{\partial \lambda(\mathbf{v})}{\partial \mathbf{v}} = 0 \iff A\mathbf{v} = \lambda \mathbf{v}$$

# Consistent Local Matches

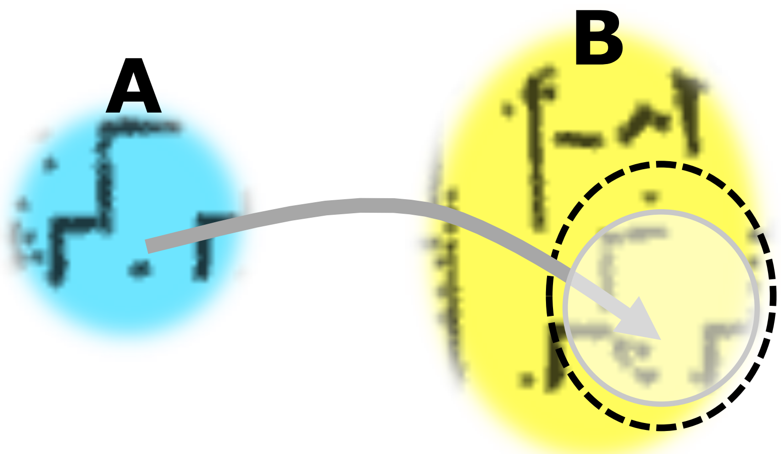
- $A\mathbf{v} = \lambda \mathbf{v}$ : Eigenvalue/vector problem
- The dominant eigenvector $\mathbf{v_1}$ maximizes

$$\lambda(\mathbf{v}) = \frac{\mathbf{v^T A v}}{\mathbf{v^T v}}$$

- The hypothesis represented by $\mathbf{v_1}$ is maximally self-consistent subset
- If $\lambda_1/\lambda_2$ is large (e.g., $\lambda_1/\lambda_2>2$) then $\mathbf{v_1}$ is regarded as locally unambiguous
- Discretize $\mathbf{v_1}$ after maximization

# Global Consistency

- **Correct method:** Can two copies of A be arranged so that they both fit inside the covariance ellipse?
- **Approximation:** Is the dimension of A at least half the length of the dominant axis of the covariance ellipse?
- Potential failures for narrow local matches



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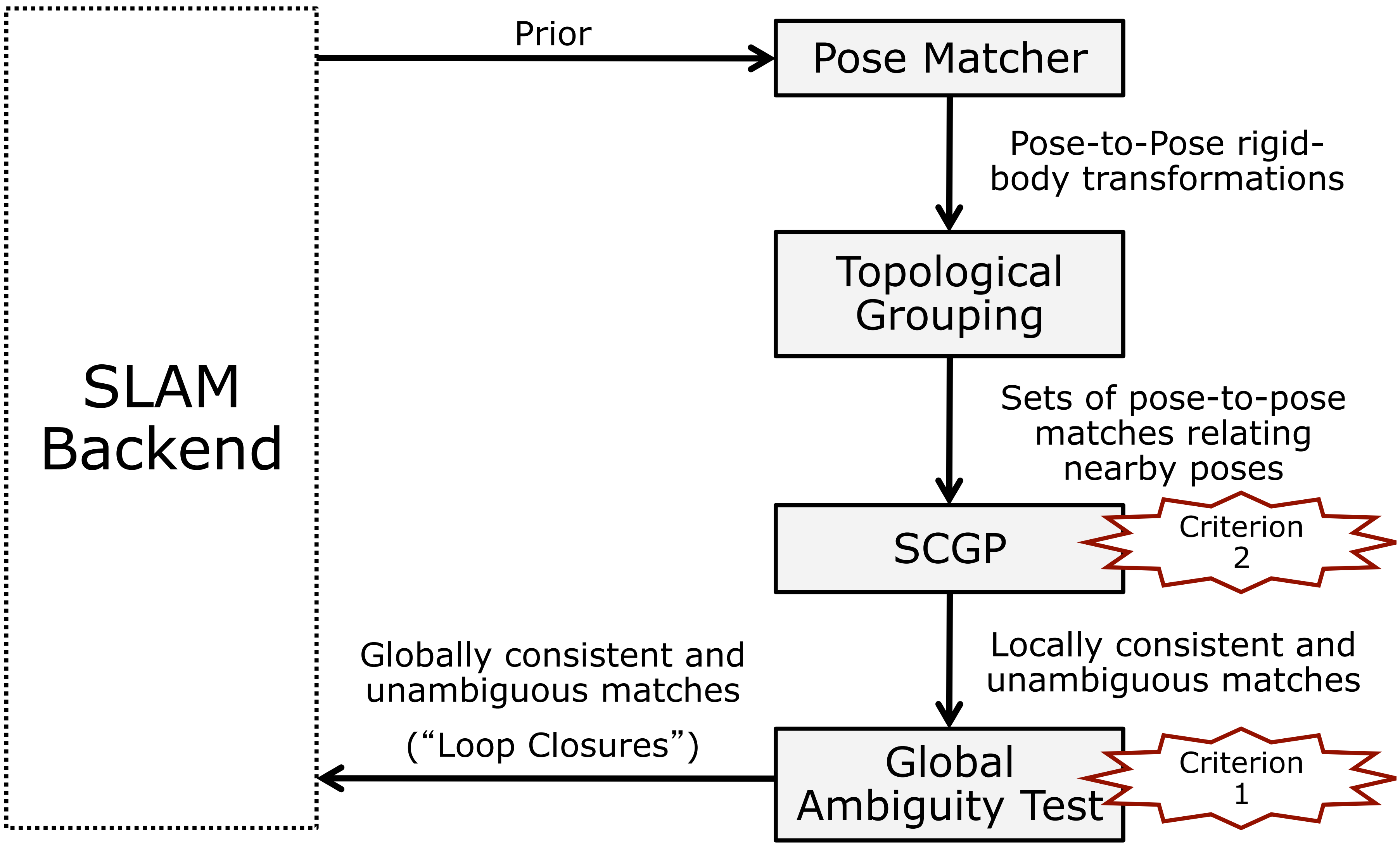
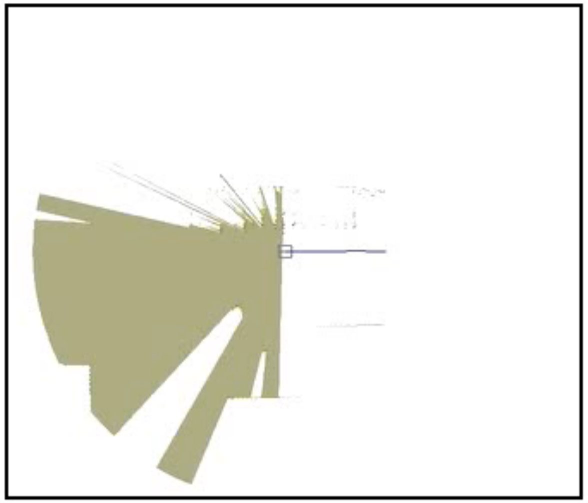


# Example



# Conclusions

- Matching local observations is used to generate pose-to-pose hypotheses
- Local matches assembled from pose-to-pose hypotheses
- Local ambiguity ("picket fence") can be resolved via SCGP's confidence metric
- Positional uncertainty: more uncertainty requires more evidence

# Literature

## Spectral Clustering

- Olson: “Recognizing Places using Spectrally Clustered Local Matches”