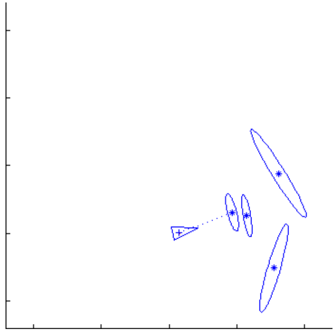
Data Association and Loop Closing

Brian Williams

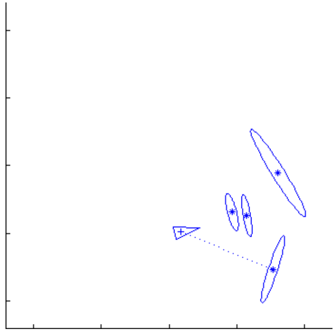
Introduction



Localization and Mapping

Observations of map features help improve our estimates of both the map and the robot position.

Introduction



Localization and Mapping

Observations of map features help improve our estimates of both the map and the robot position.

Introduction

In order to use a sensor measurement the robot must know what that measurement corresponds to:

- an observation of a feature already in the map
- the first observation of a new part of the world
- a spurious observation due to noise

Data Association

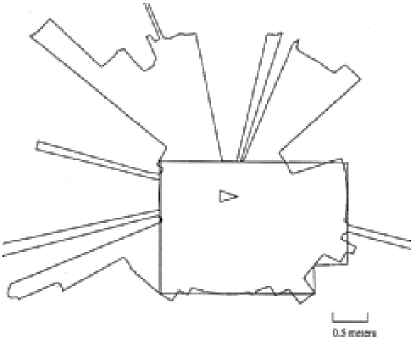
Data association is the process of making this decision for each sensor observation.

Why Data Association is Difficult

Difficulties in Data Association

- Some parts of the world appear the same to the sensor.

Why Data Association is Difficult



Noisy Ultrasound Scan

Difficulties in Data Association

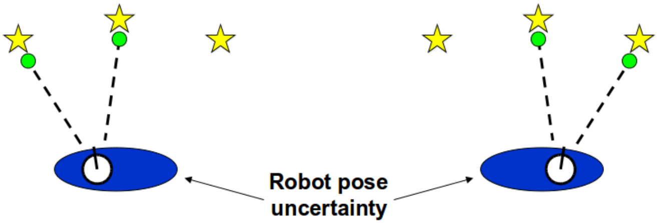
- Sensor measurements are noisy

Why Data Association is Difficult

Difficulties in Data Association

- Unmodeled objects in the environment.

Why Data Association is Difficult



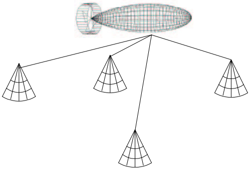
Difficulties in Data Association

- The relative position of the robot and the map features is uncertain.

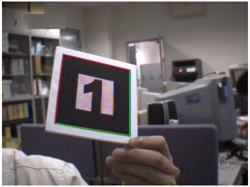
Artificial Landmarks

Data association can be made much easier if the environment can be altered to suit the robot.

- Give each artificial landmark a unique ID visible to the sensor.



Sonar Beacons



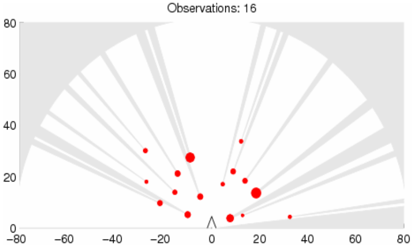
ARToolkit

Infrared Beacons

Natural Landmarks

In an unaltered environment, a natural difference between landmarks can be used.

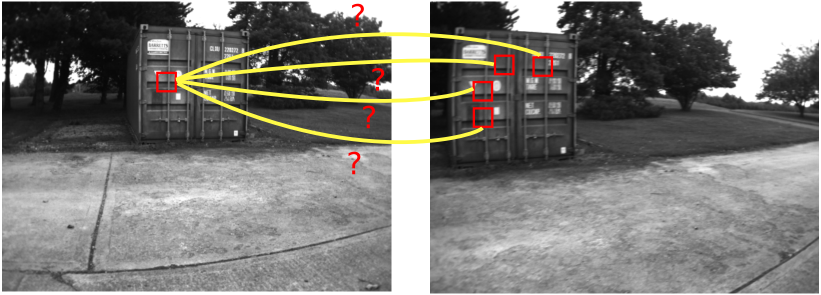
- Some variable aspect of the landmarks must be visible to the sensor.



Data association in laser scans using tree trunk width.

Visual Observations

Cameras provide rich sensor data which makes data association easier – but there are still ambiguities.



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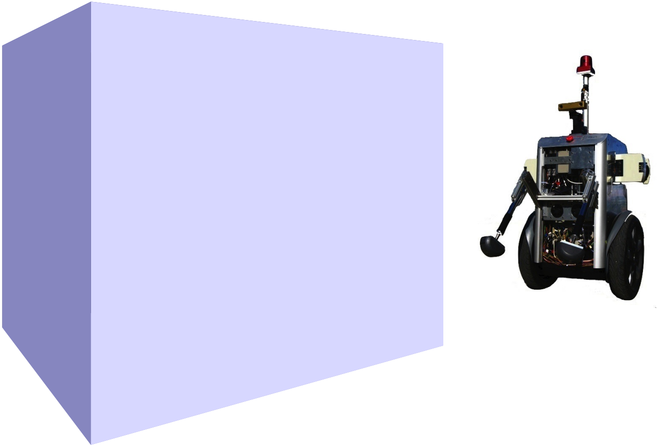
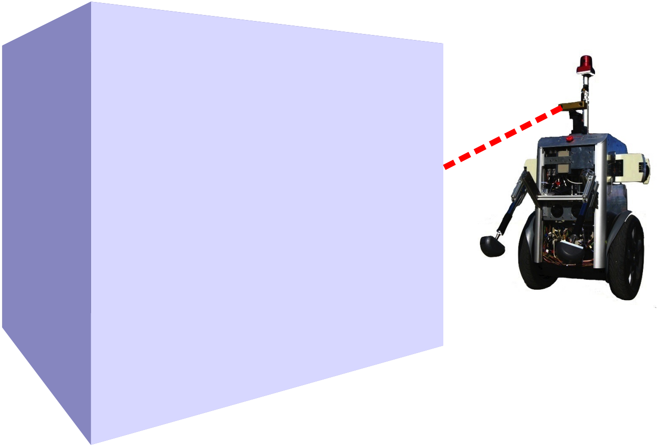


Use the Prediction

The current SLAM estimate for the robot pose and the map feature position in 3D can provide a predicted observation (image coordinates) for each map feature.



Use the Prediction

The current SLAM estimate for the robot pose and the map feature position in 3D can provide a predicted observation (image coordinates) for each map feature.

Predicted Observation Position

Predicted Observation Uncertainty

Two Possible Measurements Within 3σ

Measurement Closest to Prediction

Algorithm 1: Nearest Neighbor

Nearest Neighbor

Select the observation which is closest to the predicted measurement using the Mahalanobis Distance, $D_M(x)$, and the Innovation Covariance, $\mathtt{S}$.

Mahalanobis Distance

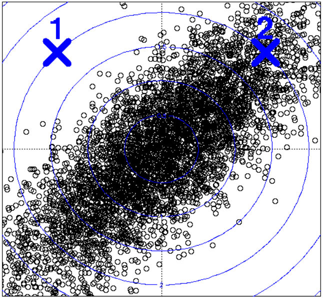
$$D_M(x) = \sqrt{(\mathbf{x} - \boldsymbol{\mu})^\top \mathtt{S}^{-1} (\mathbf{x} - \boldsymbol{\mu})}$$

Innovation Covariance

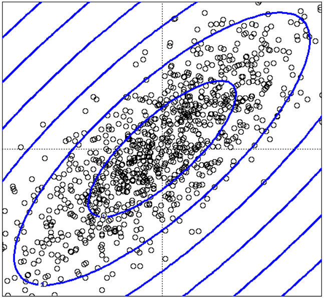
$$\mathtt{S} = \mathtt{H}_x \underbrace{\mathtt{P}(k|k-1)}_{\text{State Covariance}} \mathtt{H}_x^\top + \underbrace{\mathtt{R}}_{\text{Measuremant Uncertainty}}$$

Mahalanobis Distance

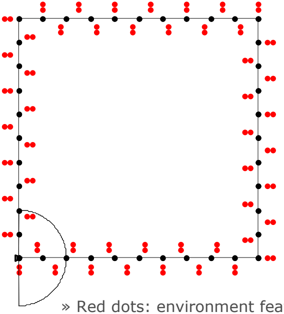
Contour plot of the Euclidian distance to the origin

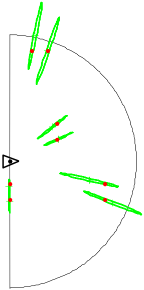


Contour plot of the Mahalanobis distance to the origin



Simulated Example



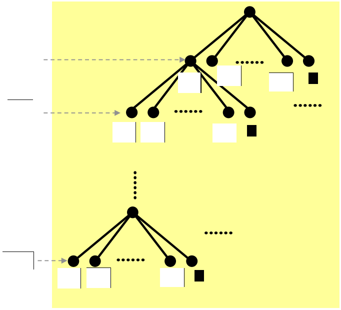


» Red dots: environment features (columns)
» Black line: robot trajectory
» Black semicircle: sensor range

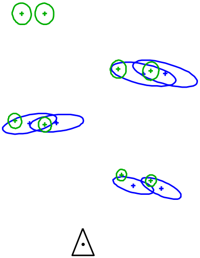
Simulated Example

- Robot moves around a 2D cloister
- Measure range and bearing to columns

Interpretation tree



$(n+1)^m$ possible hypotheses



Green points: measurements
Blue Points: predicted features

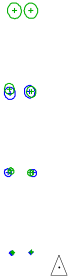
Data Association

The data association algorithm must interpret each sensor scan. For each observation corresponds to:

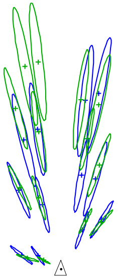
- one of the features in the map
- or a previously unmapped feature

Sensor Noise

- Low sensor error



- High sensor error

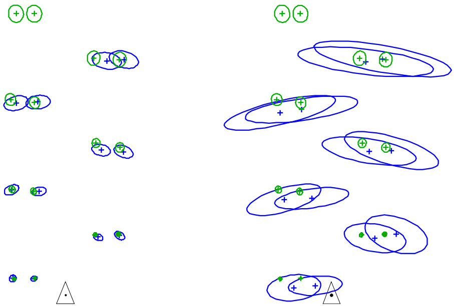


Sensor Noise

- Noisy sensors make data association more difficult.

Odometry Noise

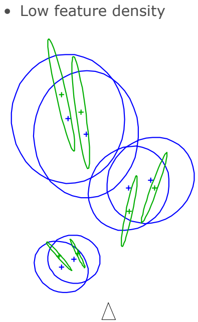
- Low odometry error
- High odometry error



Odometry Noise

- A larger uncertainty in the robot pose makes data association more difficult.

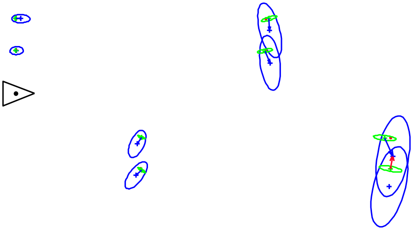
Feature Density



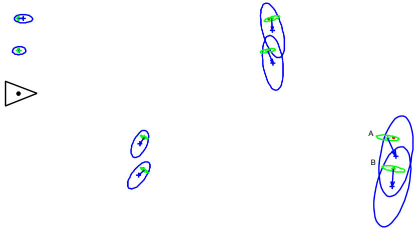
Feature Density

- High feature density makes data association more difficult.

Nearest Neighbor Failure



Nearest Neighbor Failure



Algorithm 2: JCBB

Joint Compatibility Branch and Bound

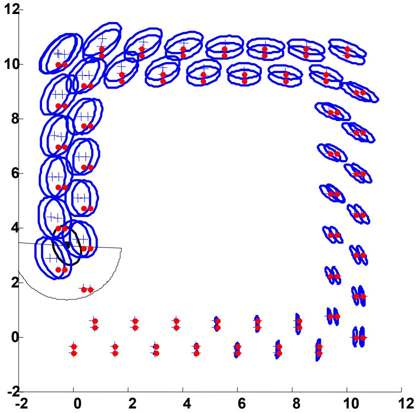
- Consider all observations in a scan jointly.
- Uses branch and bound algorithm to efficiently search for a good joint interpretation.

Comparison of Data Association Algorithms

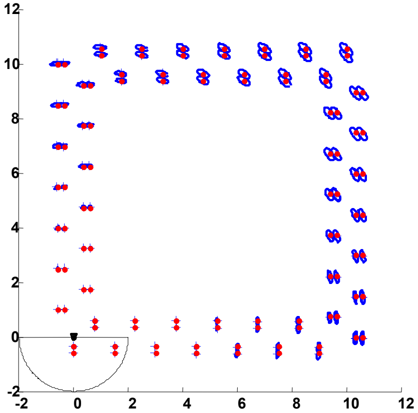
Comparison Video

Loop Closure

Loop Closure



Loop Closure

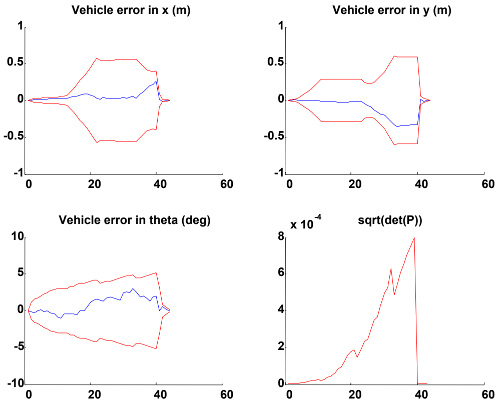


Loop Closure

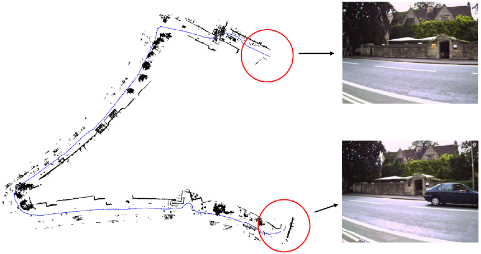
Loop Closure

- Loop closure is
  - the recognition of when the robot has returned to a previously mapped region
  - and the use of this information to reduce the uncertainty in the map estimate.
- Without loop closure, the uncertainty grows without bounds.

Loop Closure



Loop Closure



Appearance information can recover position where metric approaches may fail.

Loop Closure Detection

- After traversing a large loop the map is
  - locally good throughout the loop
  - globally very bad.
- The local data association techniques cannot be trusted to match observations during the loop closure.

Loop Closure

University Courtyard Video

Map Before Loop Closure Video

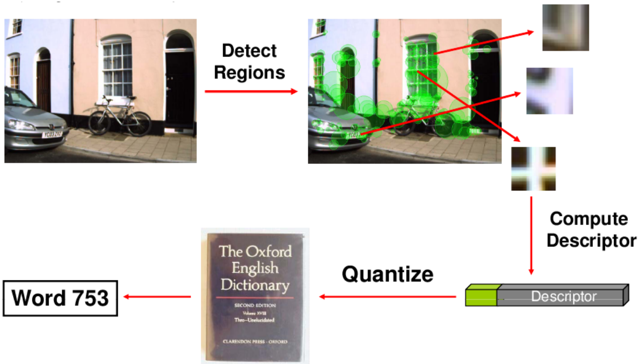
Map After Loop Closure Video

Loop Closure

Loop Closure Detection Techniques

- Map-to-Map
  - Match geometric features within the map
- Map-to-Sensor
  - Match the latest sensor data to other regions of the map
- Sensor-to-Sensor
  - Match the latest sensor data to some previously acquired sensor data

Appearance Based Loop Closure Detection



Salient visual features in the image are identified and matched to a visual vocabulary.

Appearance Based Loop Closure Detection

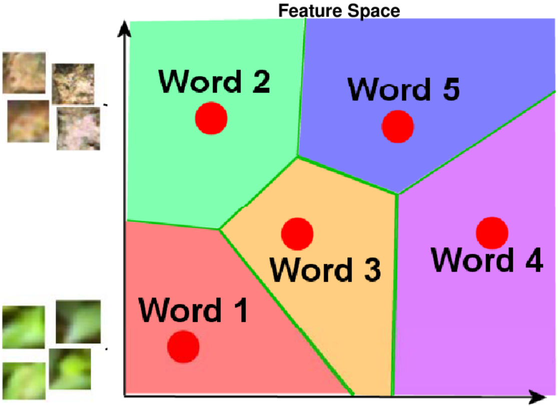


Image features are quantized to words in a previously learned visual vocabulary.

Appearance Based Loop Closure Detection

Z = [1 1 1 0 0 ...]

Observation likelihood

All observations up to k

Prior

$$p(L_i|\mathcal{Z}^k) = \frac{p(Z_k|L_i)p(L_i|\mathcal{Z}^{k-1})}{p(Z_k|\mathcal{Z}^{k-1})}$$

Location i

Partition Function

Observations for each frame is a binary vector indicating which words in the vocabulary were present in the image.

Appearance Based Loop Closure Detection


(a) p=0.53 (b) p=0.30 (c) p=0.31

Prior training allows the algorithm to account for visual words that tend to occur together in the world to reduce false positive loop closures.

Appearance Based Loop Closure Detection

Appearance Based Loop Closure Video

Global Localization

Global Localization

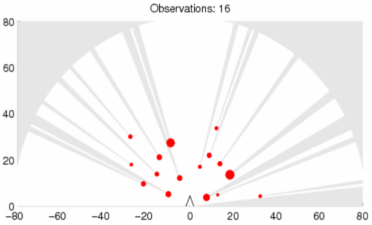
Kidnapped Robot Problem

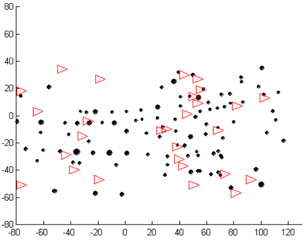
- The robot is provided with a map of the environment but has no idea where in the map it is.
- The goal is to determine the robot's pose using the sensor measurements.

Global Localization

Kidnapped Robot Problem Video

Global Localization





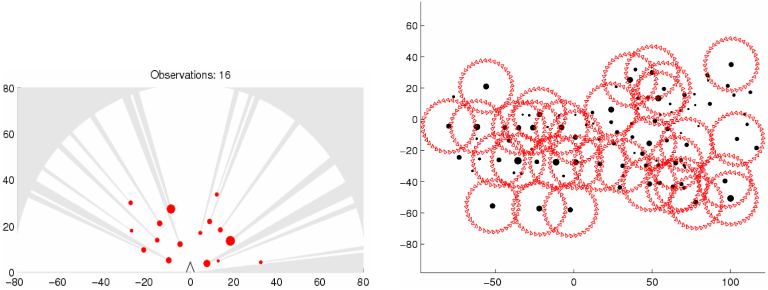
Monte Carlo Localization

- Randomly sample robot locations in Configuration Space.

Global Localization

Monte Carlo Localization Video

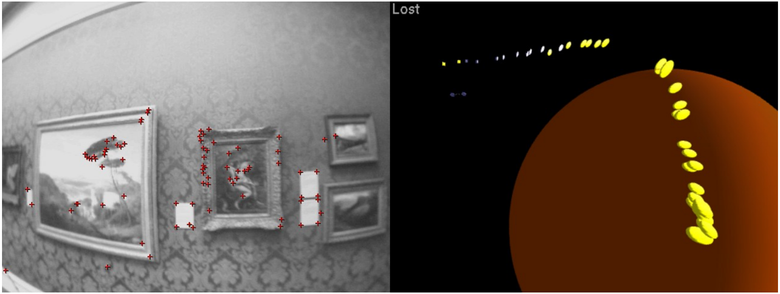
Global Localization



Correspondence Space Localization

- Consider consistent combinations of measurement-feature pairings.

Correspondence Space Localization



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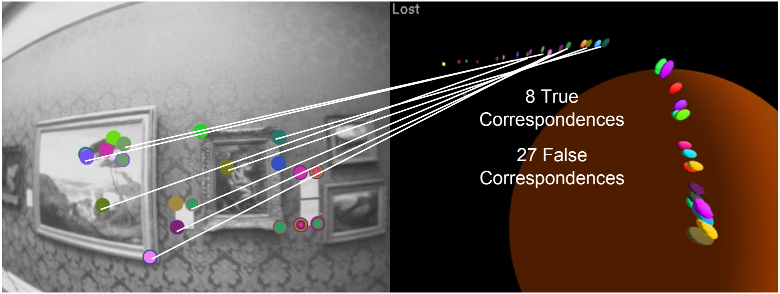

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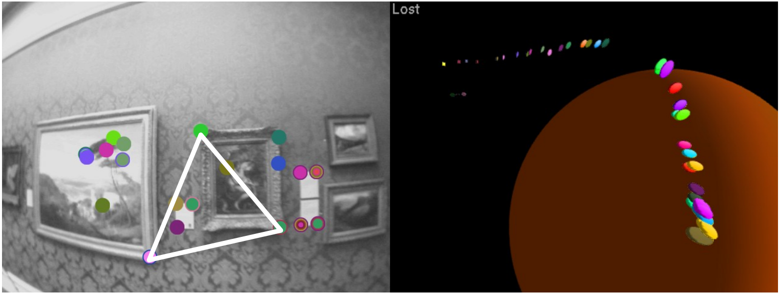

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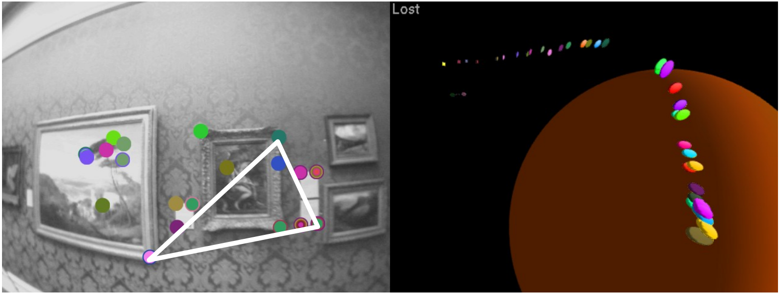

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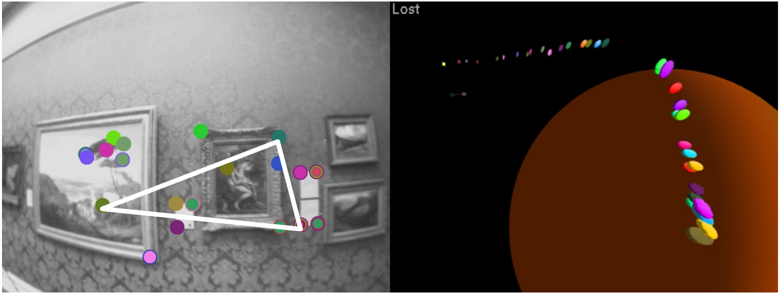

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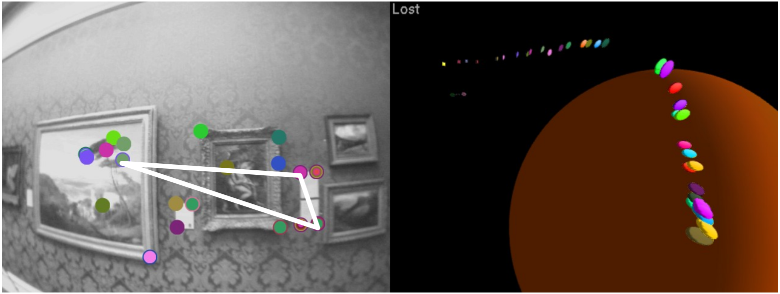

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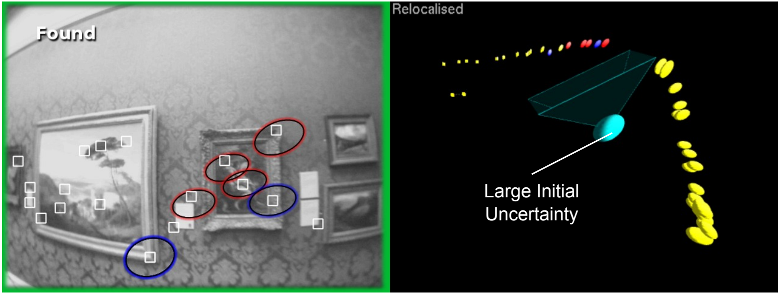

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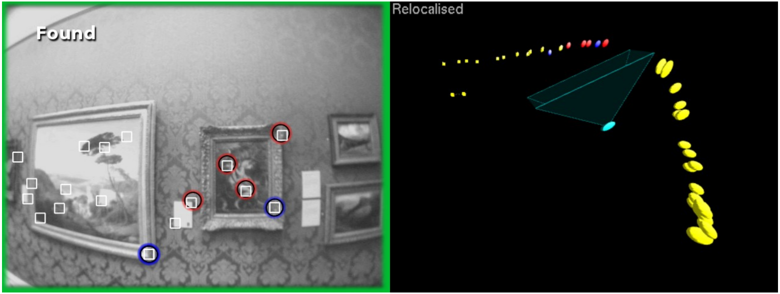

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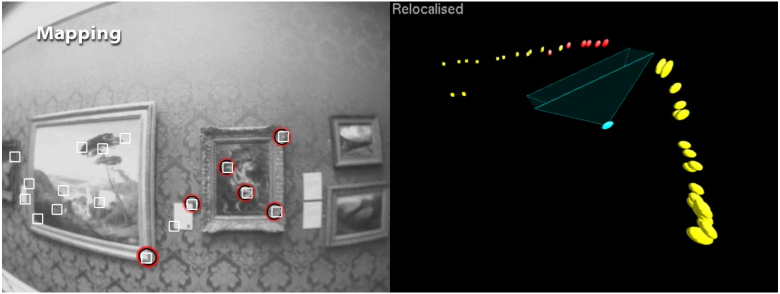

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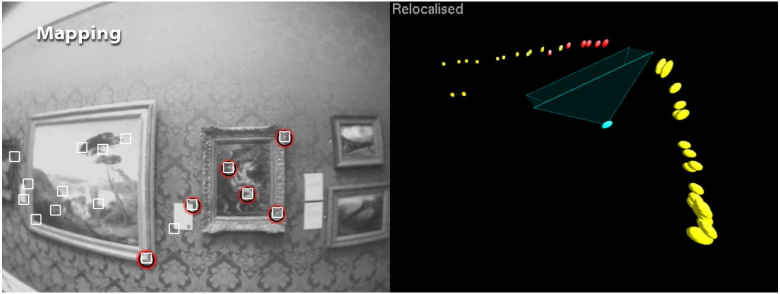
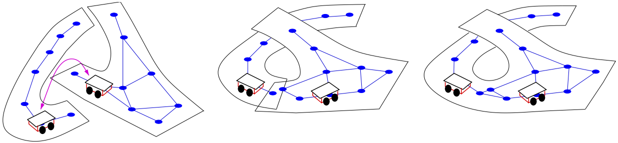


Global Localization

Ransac Localization Video

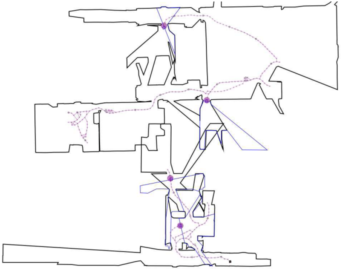
Multi-Robot Mapping

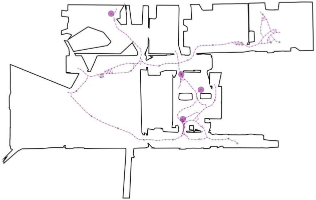


Multi-Robot Mapping

- Each robot begins building an independent map of the environment.
- When these maps overlap, the relative transformation is determined and the maps are joined.
- The overlab is recognised:
  - When the other robot is observed, or
  - Using loop closing / global localization techniques.

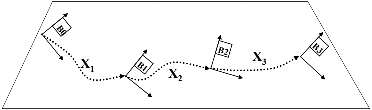
Multi-Robot Mapping

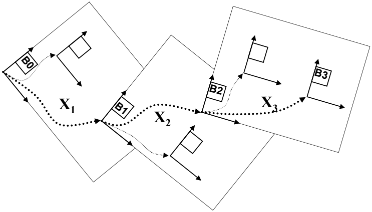




Submapping

Submapping





Submapping

Creates a series of small submaps rather than one large global map.

- Improved consistency
- Reduced computation time
- Loop closure is handled topologically on the global level

Conclusion

Conclusion

Data Association

- Determining which sensor measurement corresponds to which part of the map.

Loop Closure

- Detecting when the robot has returned to a previously visited region of the world.
- Essential for limiting the growth in uncertainty.

Global Localisation

- Solving the kidnapped robot problem.

Multi-robot Mapping

- Join independent maps when overlaps are found.