Closing the Loop

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Outline

- Loop Closing Problem
- Fundamental Limitations
- Some Approaches
  - Laser Scan Matching (Gutman & Konolige)
  - E-M Mapping (Thrun, Burgard & Fox)
- Other limitations of SLAM
- Summary

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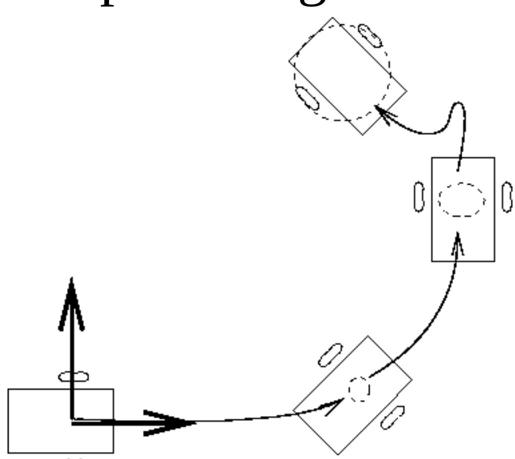
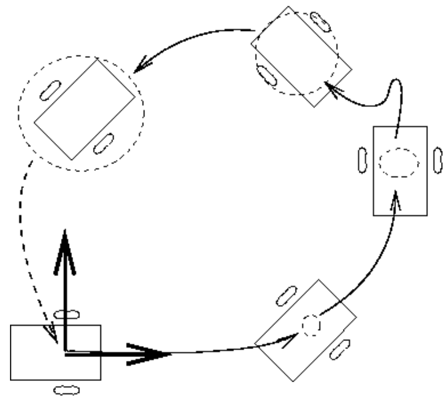
Loop Closing Problem



Loop Closing Problem



- During the SLAM mapping process, the robot may come to a place that it has been to before
- Most existing techniques need to have an explicit method to utilise this extra information

A Matter of Scale

- All techniques can close small loops
- All techniques can be made to fail
- Most techniques will become unreliable with some size of loop
- The loop size depends strongly on the system characteristics: odometric drift, sensing rate, sensor quality

Closing the Loop

1. Recognise a place that we have seen before
2. Add link to represent new knowledge
3. Update path taken to represent additional knowledge gained (propagate info backwards)

1) Place Recognition

- For loop closing, we must be able to recognise places that we have previously visited.
- Whole problem in itself

[Dudek '00]

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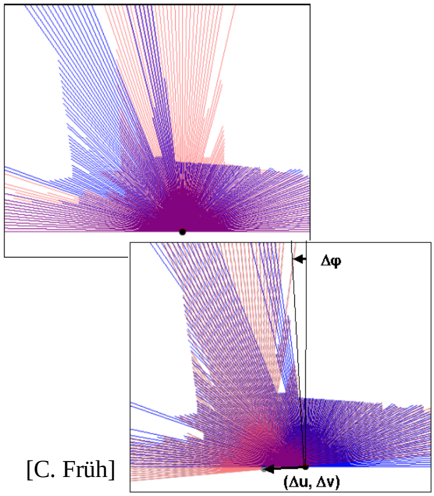
Raw Sensor Data Recognition



[C. Früh]

- E.g. Laser scan matching
- Not suitable for many sensors

PCA Based Recognition

- Principal Components Analysis (selection of most useful aspects of the images for storage)
- Compare PCA of new images to stored PCA values
- Need an attention operator to focus on “interesting” things

[Dudek ‘00]

Place Recognition Summary

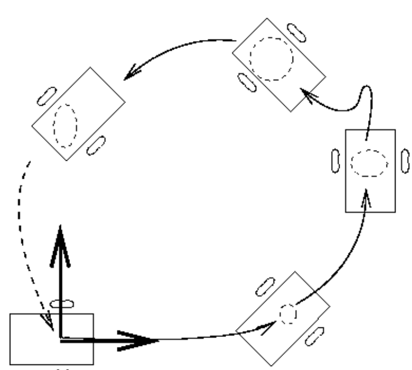
Cannot be done with absolute certainty

⇒ must maintain multiple map hypotheses OR

⇒ be able to correct mistakes

3) Update path taken

- Need to propagate backwards the new information gained by closing the loop
- For arbitrarily large loops, the computation can be arbitrarily large
- However, computation usually not a significant issue



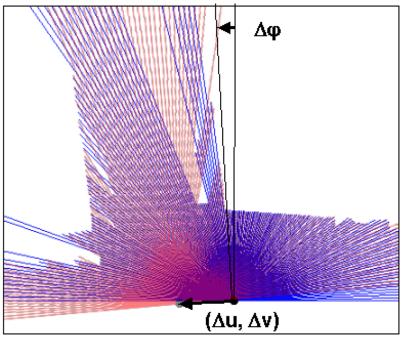
Fundamental Limitations

- As the size of the loop increases, so does the uncertainty, and so does the size of the search for matches
- Complexity blows up as we consider uncertainty in recognition
- Positional uncertainty will still grow with increasing radial distance from the origin

Approach 1 –Konolidge and Gutmann

- Three parts:
  1. Scan matching
  2. Consistent pose estimation
  3. Global registration
- Depends quite heavily on good estimates of position (must run frequently)
- Laser range scanner specific

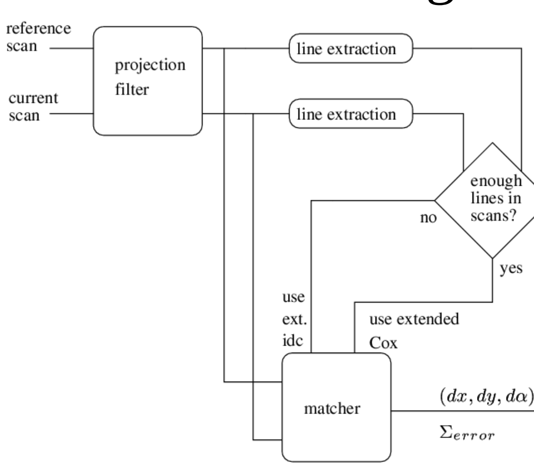
Scan Matching



[C. Früh]

- Estimate the translation and rotation between scans
- Nonlinear
- Different points of view, occlusion
- Requires some computation
- Many approaches
- Line-based vs point-based

Scan Matching II



[Konolige & Gutmann '99]

Consistent Pose Estimation

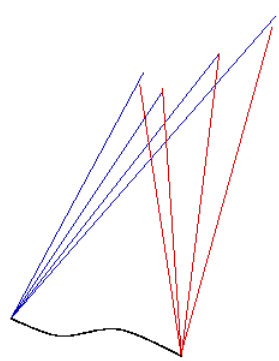
- Have two types of relationships
  1. Scan matches
  2. Odometric information

Both are uncertain and non-linear.

Complex optimisation problem to find best estimate

Assume good initial estimate and linearise

Pose Relations from Scan Matching



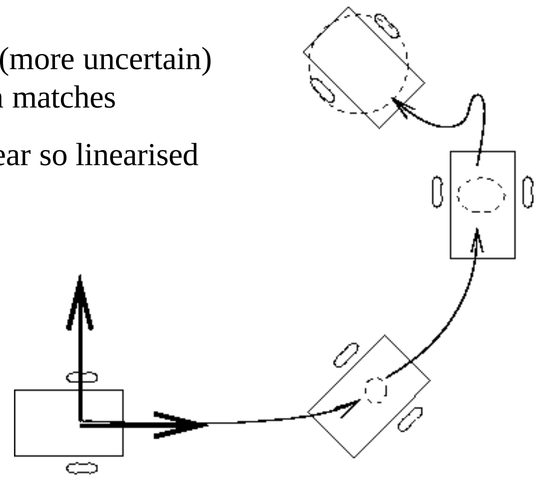
Matching points of the two scans leads to a (complex) relationship between the origins of the scans

The complex relationship is linearised to simplify the optimisation step

Pose Relations from Odometry

Much weaker (more uncertain) than laser scan matches

Again, nonlinear so linearised



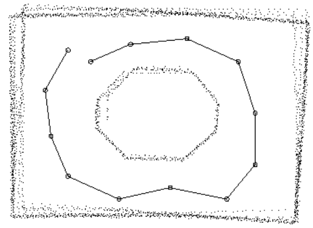
Consistent Pose Estimation II

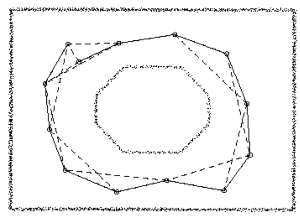
Solve linearised optimisation problem

$$W = \sum (D_{ij} - \overline{D}_{ij})^T C_{ij}^{-1} (D_{ij} - \overline{D}_{ij})$$

Iterate linear solution to converge

Consistent Pose Estimation III





[Konolige & Gutmann '99]

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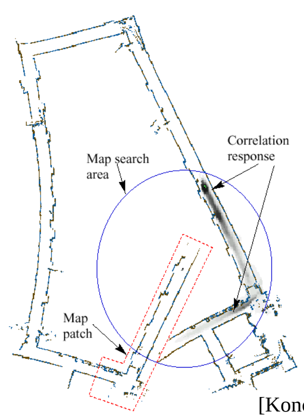
Global Registration

- Correlation of recent local map with relevant area of global map
- Search area grows as pose uncertainty grows
- False matches a real problem



[Konolige & Gutmann '99]

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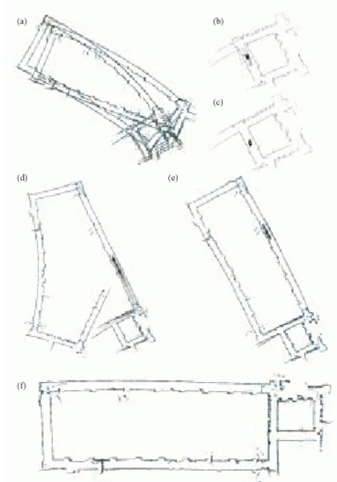
Results



(a) Raw data

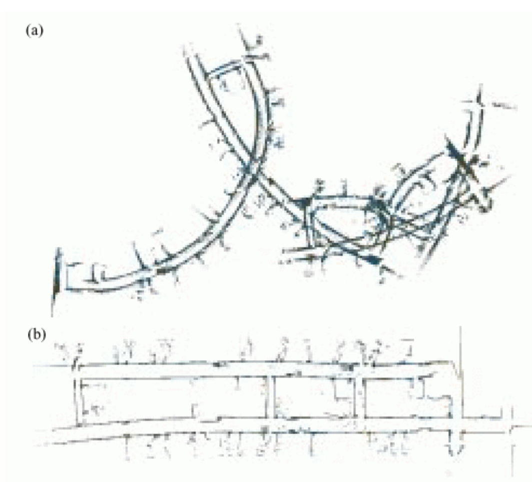
(b) & (c) Closing first small loop

(d) & (e) Closing second, larger loop

(f) Final map

[Konolige & Gutmann '99]

Results II



[Konolige & Gutmann '99]

Summary – Konolige & Gutmann

- Performs quite well
- Runs fast enough for on-line estimation
- However,
  - Laser range scanner specific
  - Needs good initial estimates of poses (frequent updates)

Approach 2 – Thrun, Burgard, Fox

- Use E-M to simultaneously estimate the map and the pose of the robot
- Requires considerable computation
- It is assumed that the robot observes a series of (indistinguishable) landmarks

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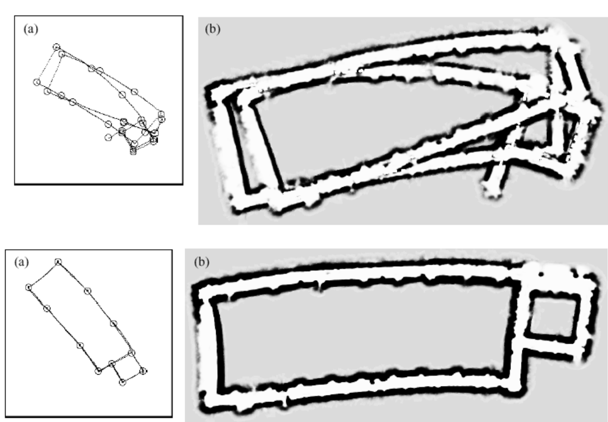
E-M Mapping

- Computing the maximum likelihood map, given the data
  1. Estimate the path of the robot, given current map
  2. Estimate the map, given current path
- Hill climbing approach
- Computationally expensive(!)
- No explicit loop-closing algorithm

Results



[Thrun, Burgard and Fox ’98]

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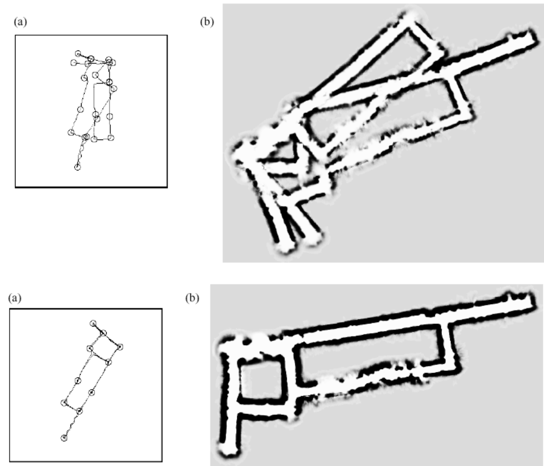
Results II



[Thrun, Burgard and Fox ’98]

Summary – Thrun, Burgard, Fox

- General method, few assumptions
- High computational costs
- Not (yet) suited to on-line execution

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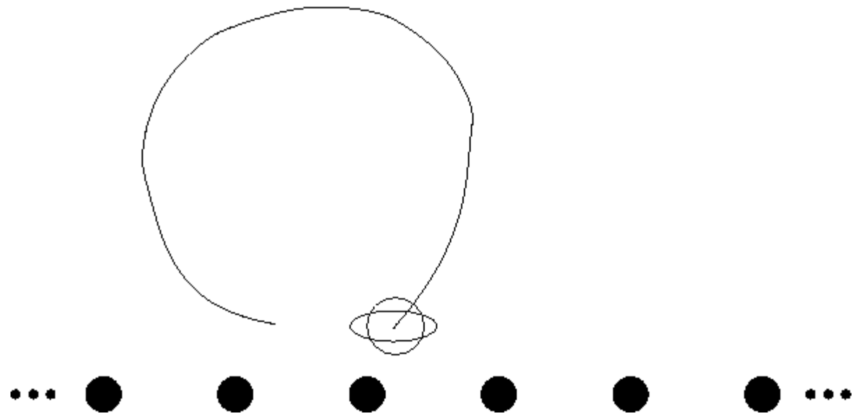
Loop Closing Can Be Hard



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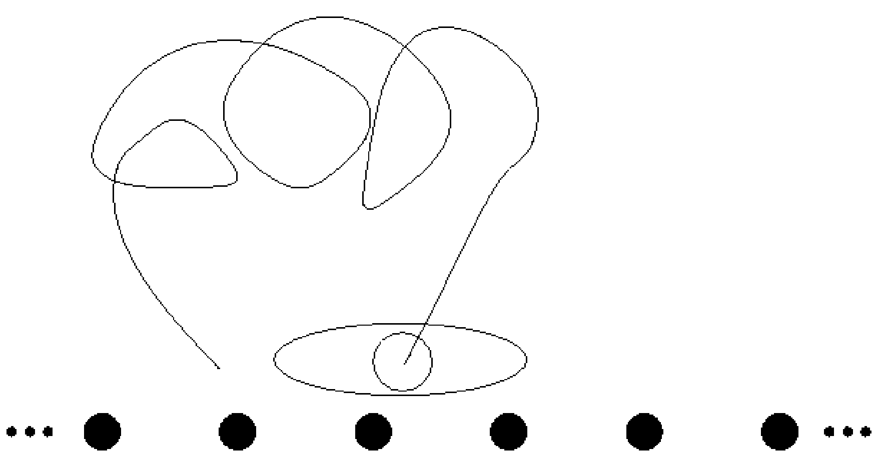
Loop Closing Can Be Hard



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Loop Closing Summary

- Practical loop closing is not so difficult
- Next (significant) advances will address problems of false loop closing/false correspondences
- Still issues with the amount of computation required to close large loops consistently

Other Limitations of SLAM

Need to keep in mind fundamental assumptions:

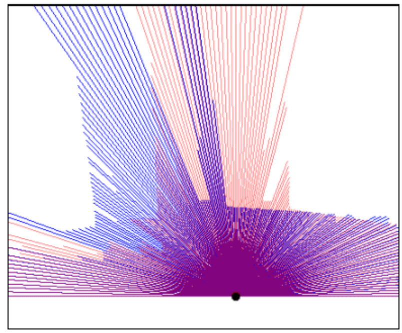
1. Independent observations
2. Stationary environment
3. Usefulness of position in an absolute map?

Also:

- Positional uncertainty will always grow with increasing radial distance from the origin

Independent Observations

- We assume that the observations are independent.
- This is plainly false
- Practical approach is to require a certain amount of movement for independence



Stationary Environment

- Assumption of stationary environment introduced through use of state
- Very few environments can be approximated this way.
- Motion (other than self-motion) is normally ignored or treated as noise.

Absolute Position

- Position in absolute map doesn’t always help solve the task

E.g. Door opening,
manipulation tasks in general

Summary

- Loop closing highly worthwhile – reduces uncertainty back along the path taken
- Closing the loop still an interesting problem
  - Trade-off between generality and computation
  - Correspondence problem rears its ugly head again
- The cost of closing loops will rise as the size of the environment grows, but seems to be manageable for indoor environments

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