Sampling in image space for fast view based mapping

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Outline

Outline

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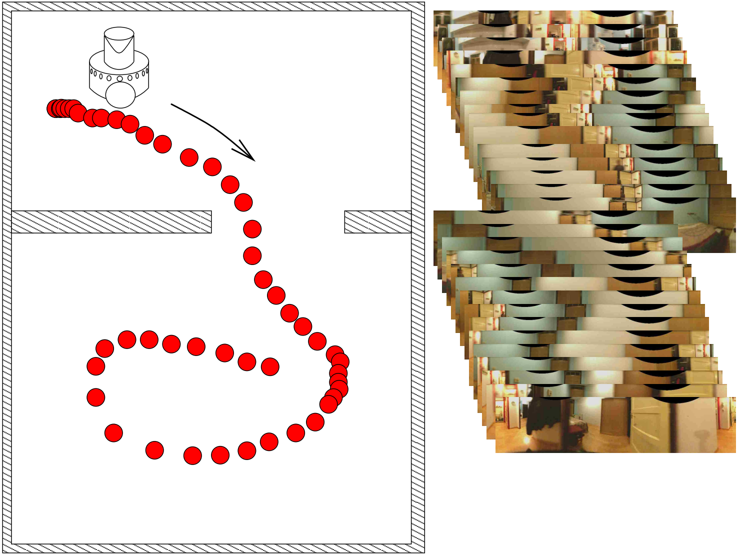
View Based Mapping



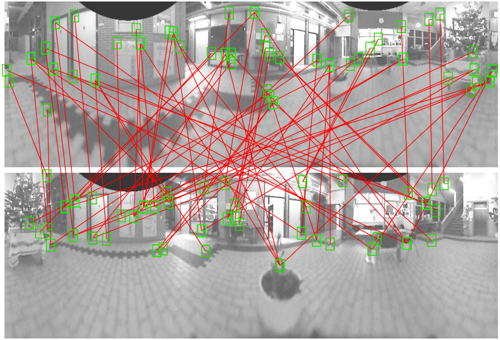
View Based Mapping

Comparing Images - computing a similarity

- Local image features are compared
- Use the epipolar constraint to find mismatches

$$\mathbf{a}^T E \mathbf{b} = 0$$

- Similarity $= \frac{\#matches}{\#features} > \theta$



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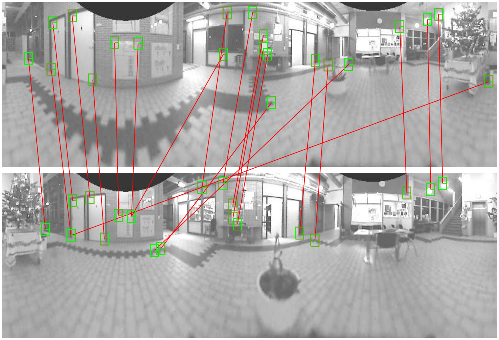

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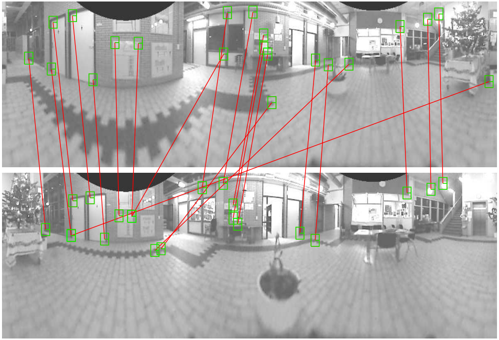

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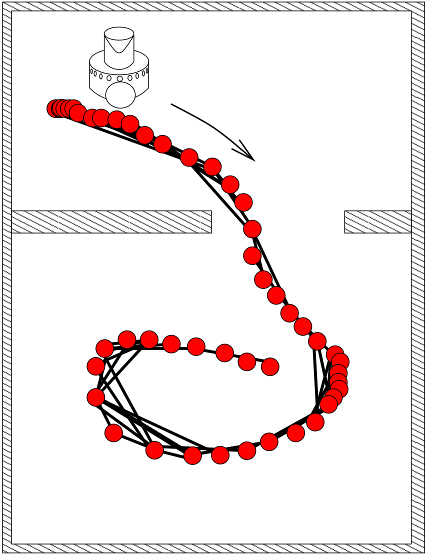

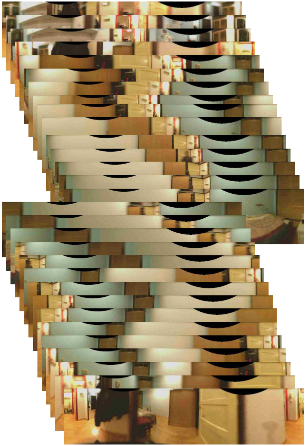

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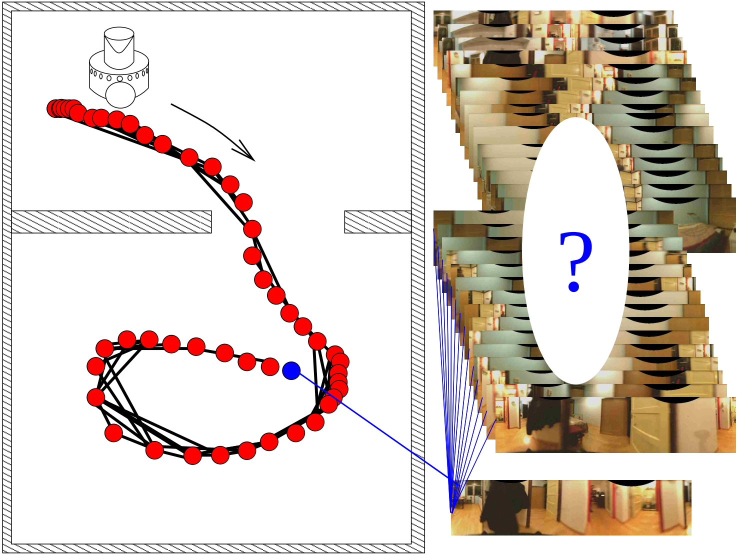

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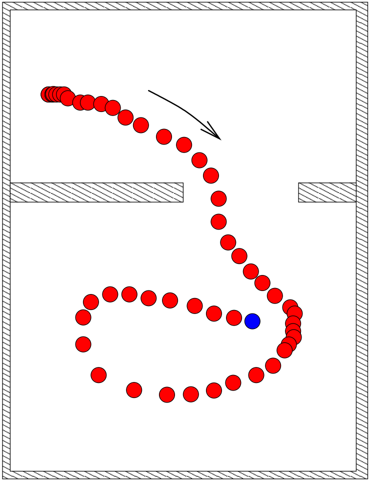
Sampling methods

- In the time domain
- In the 2D/3D space domain
- Using a navigation prior
- In image space



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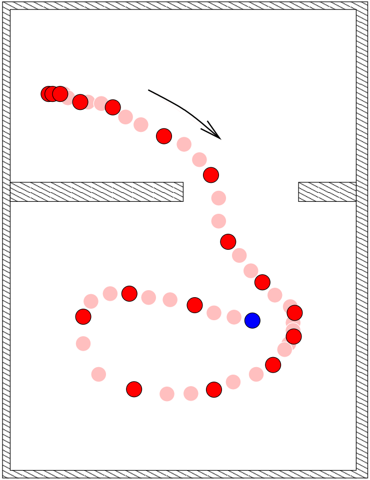

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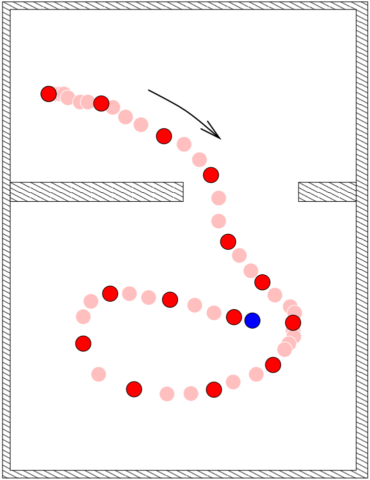

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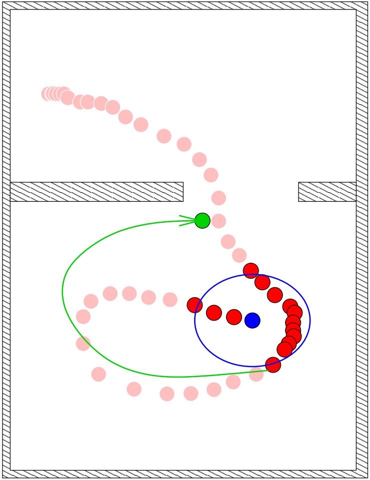

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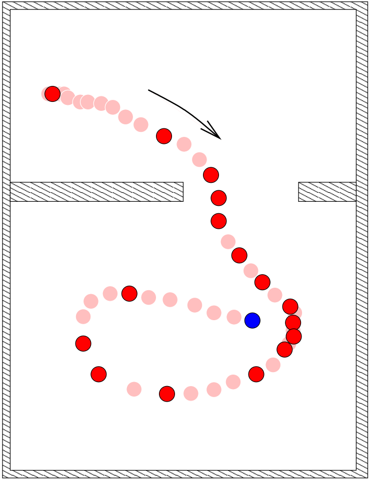

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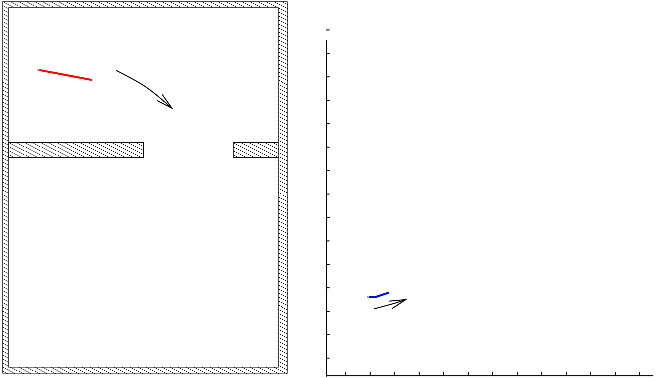

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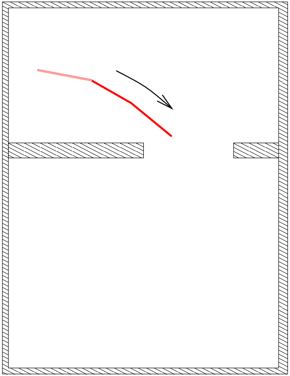

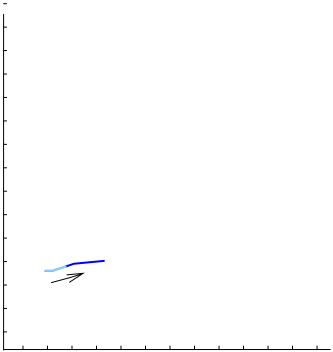

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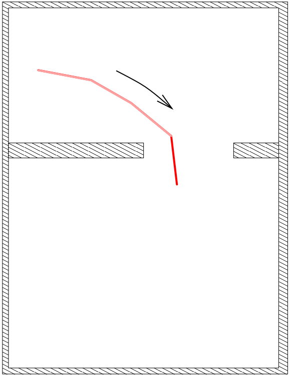

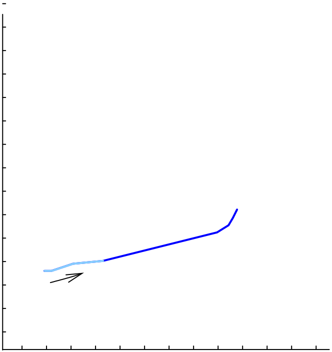

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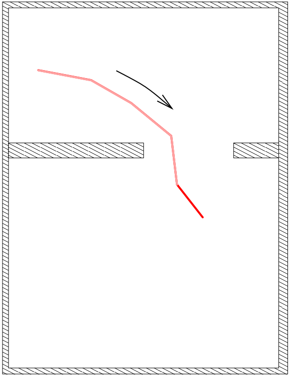

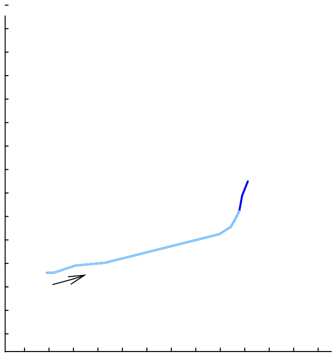

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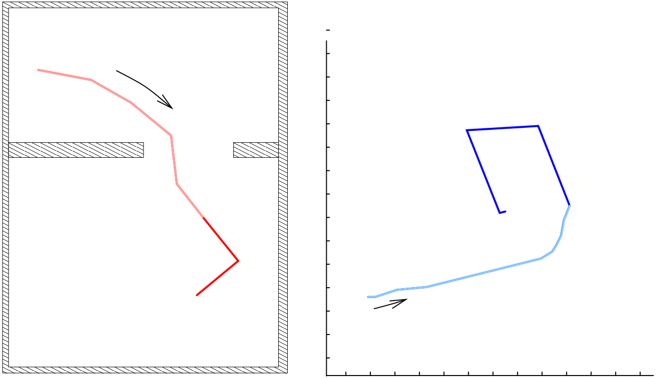

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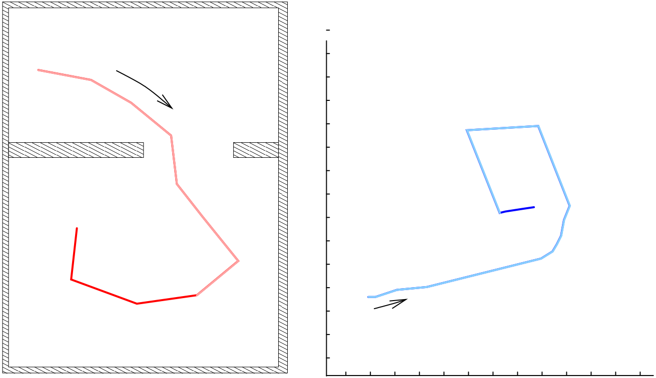

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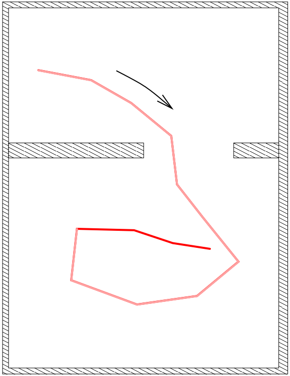

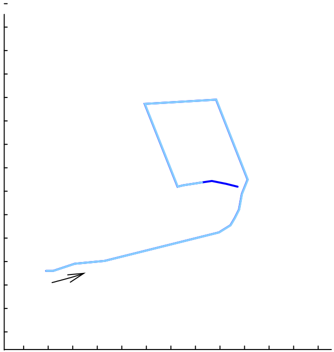

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Sampling

Sampling in image space

- Narrow passages, convexity of space
- Texture rich/poor areas
- Dark/brightly lit areas
- Dynamic lighting / moving objects
- Standing still
- ...

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Sampling

Image space

- What is this "image space"?
- We only have an image similarity measure $\neq$ proper metric.
- $\rightarrow$ use the topological structure.

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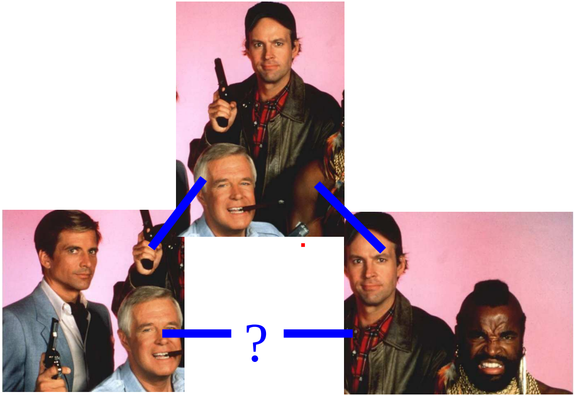

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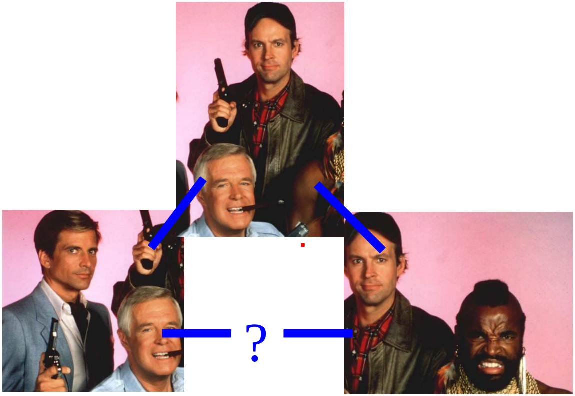

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Outline

Connected Dominating Set

Picking key images

- Cluster and choose one image/cluster
  - How many clusters?
  - Are we doing too much?
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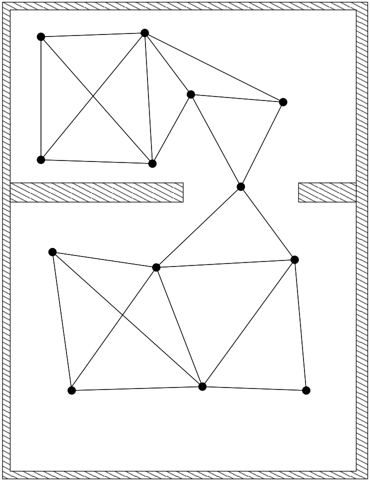
Idea behind CDS

- What if the robot is nearby a visited pose
- New image matches with all its neighbors in the graph
- Without the node the robot can still match
- Which other nodes can be left out?



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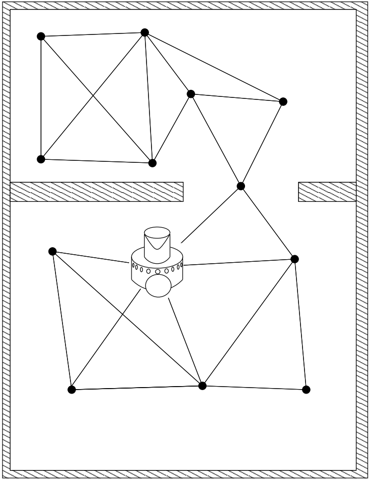

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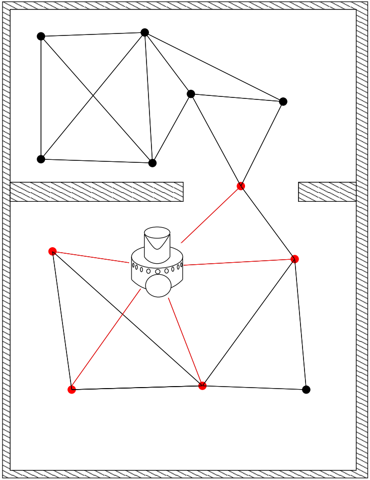

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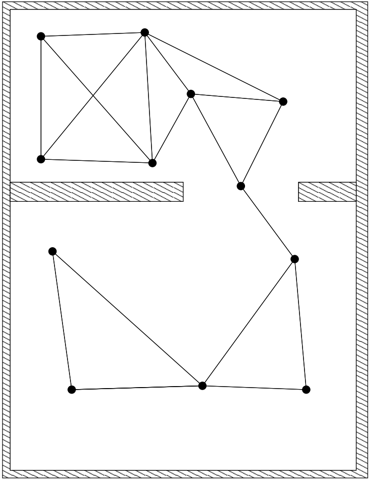

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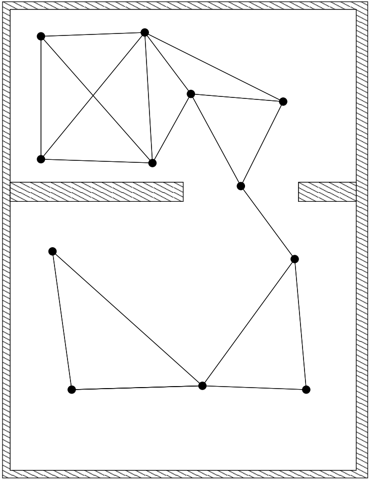

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- A CDS of a graph is a subset of nodes with the property:

Each node of the original graph is either in the CDS or is linked to some node in the CDS

$$\boxed{\forall n_1 \in \text{Graph} : n_1 \in \text{CDS} \vee \exists n_2 \in \text{CDS} : (n_1, n_2) \in \text{Graph}}$$

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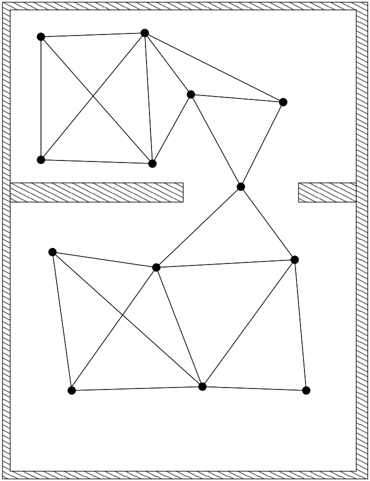
Computing a CDS

- Compute spanning tree with maximum nr of leaves
- Trim the leaves
- As always: NP-complete but approximations exist



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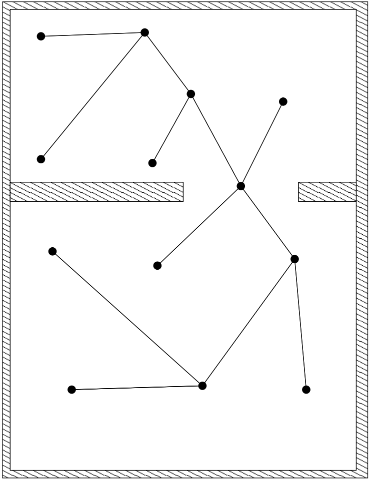

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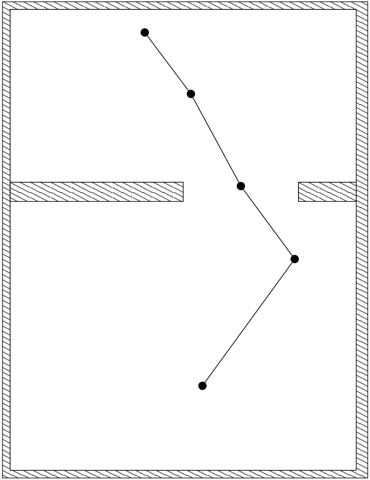

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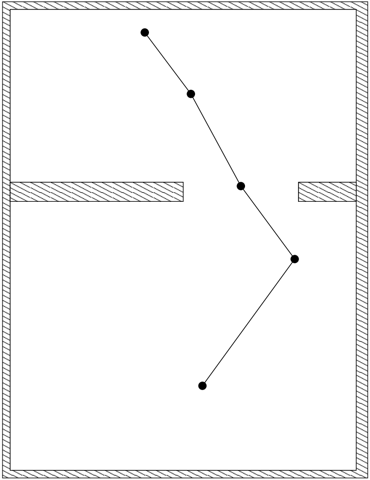

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CDS in practice

- Compute CDS key images
- Take a new image
- First match with key images
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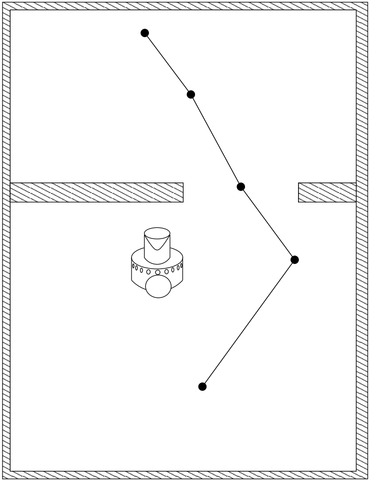

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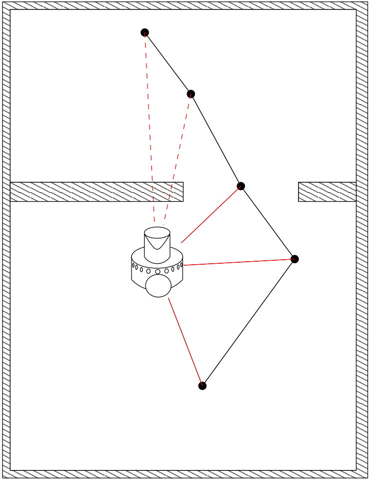

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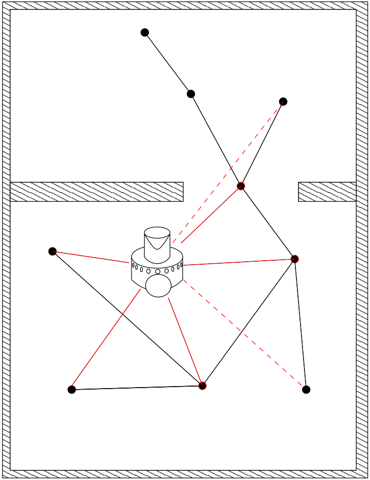

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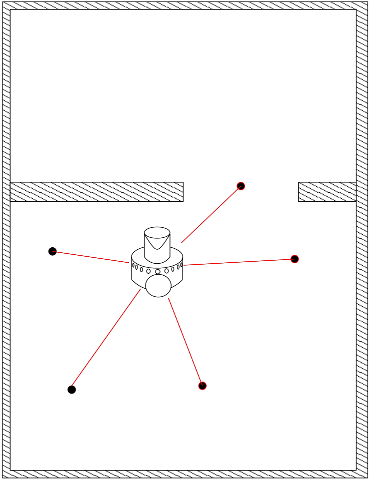

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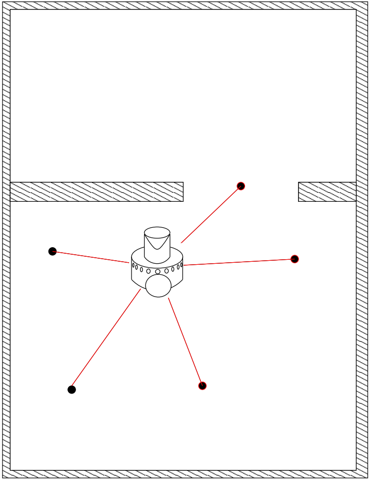

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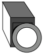
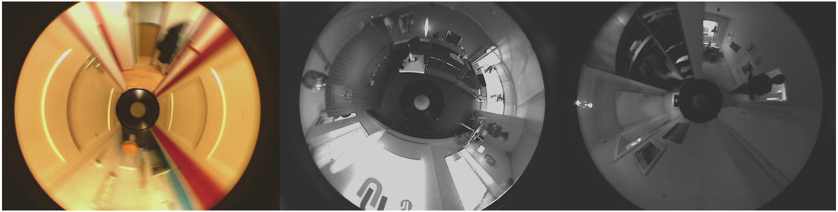
Results



Results

Dataset	#Images	#pairs	#links
Office	877	384,126	32,583
Home 1	1153	664,139	43,091
Home 2	1845	1,701,108	74,037
Home 3	1734	1,502,511	113,555



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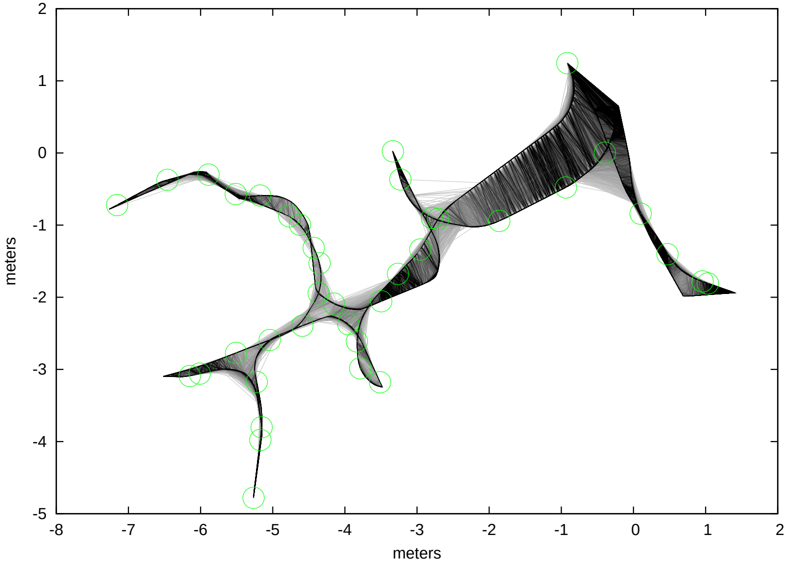

Results

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Results

Overview computational cost

Dataset	#comparisons	#matches	time	time/im
Office	74,585	31,199	303 s	.34 s
Home 1	93,789	42,529	850 s	.74 s
Home 2	192,876	72,240	1,359 s	.73 s
Home 3	267,465	105,843	934 s	.53 s

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Results

Comparison with other sampling methods

method	key images	#links	false neg	links/matched
Full	-	43,091	-	6%
Random	83	32,509	25%	33%
Position	64	37,382	13%	39%
Time	61	38,623	10%	39%
CDS	40	42,529	1%	45%

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Results

Online interactive topological mapping

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Wrap up

Conclusions

- Sampling in image space is most natural AND gives highest recall
- Given the view based graph, CDS gives the optimal set
- Orthogonal to other approaches (eg. bag of words)
- Makes real time mapping possible

Thanks

Questions....

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