A Hybrid direct feature matching based on-line loop-closure detection algorithm for topological mapping

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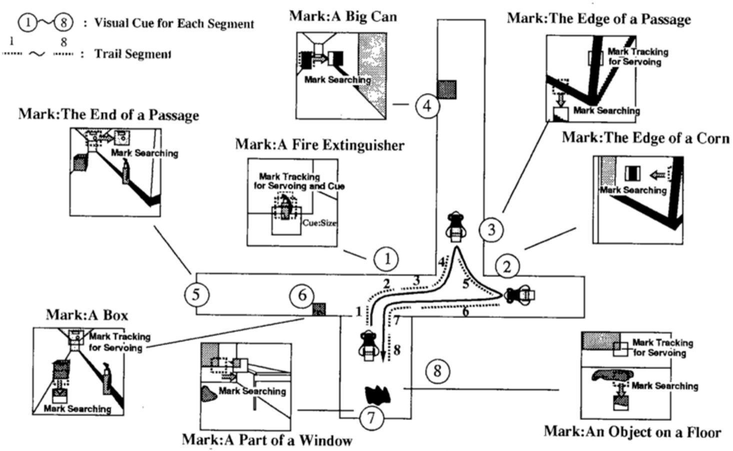
Overview

- Motivation
- Existing Solutions for Appearance-based Schemes
- The Proposed Method: HDFM
  - Loop Closure Detection
  - Node Update
  - Map Generation through Bayesian Learning
- Experimental Results
  - Performance Analysis
- Future Work
- Conclusion

Motivation

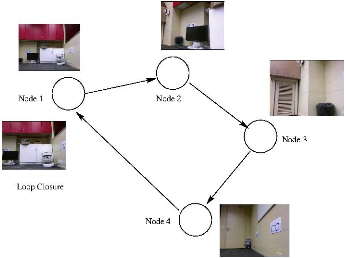
- Topological mapping is suitable for human-robot interaction



Shibata, Matsumoto, et al., IEEE Trans Mechatronics, 1996

Motivation

- Topological mapping aims at building a graphical model of the environment comprising of *key locations* and their connectivity.
  - Images are used to identify places.
  - Geometrical information is not used.



- Challenges
  - Loop-closure detection: Robot has to recognize previously visited places.
  - Perceptual Aliasing: Physically distinct locations may appear similar to robot sensors.
  - Growing computational complexity with increasing map size.

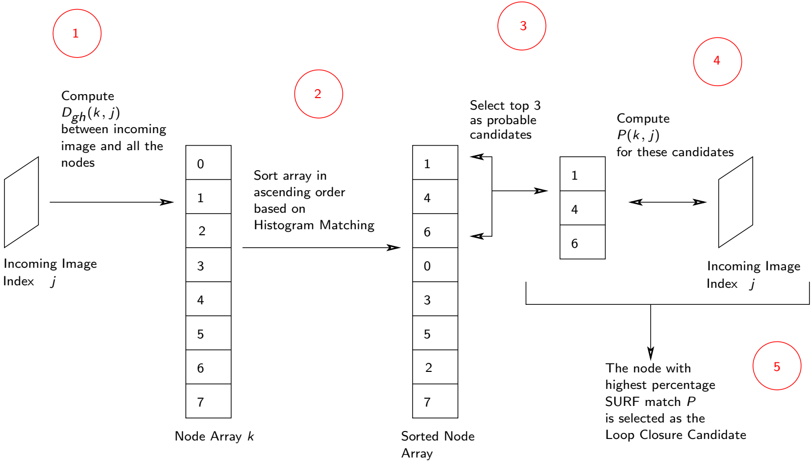
Existing Solutions: Appearance based schemes

- Pixel-wise matching, local/global histogram matching and Bag-of-words.
  - Histogram matching is simpler and faster - Perceptual aliasing due to quantization error.
- Bag-of-Words method is most commonly used method for topological mapping: Filiat (2007), Angeli (2008), Cummins & Newmann (2008), Lopez & Tardos (2012), Nicosevici & Garcia (2012).
- Direct feature matching is superior to other methods for finding similarity between images: Zhang (2010)
  - Bag of Raw features (BoRF): Zhang (2007)
  - Use of KD-tree for loop closure detection: Liu (2012)
  - Use of LSH to deal with computational complexity: Shahbazi (2013)
  - Growing computational complexity with map size.

The proposed Approach

- Combining simplicity of histogram matching and accuracy of direct feature matching: Hybrid Direct Feature Matching (HDFM)
- New locations identified as images are stored in a binary search tree.
- For every incoming image, three loop closure candidates are selected using histogram matching (Hellinger distance): $\sim \log n$, n is the map size.
- The best loop closing candidate is selected using direct feature matching: fixed time independent of map size.
- The node in the graph is updated on loop closure detection.
- The effect of wrong decisions are reduced over time through a naive Bayesian filter.
  - The map of an environment is comprises of most frequently travelled locations.

Proposed method for loop closure detection

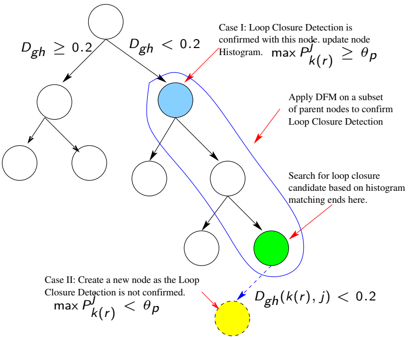


Loop Closure Detection

Two Step method:

- Select a set of possible loop closure candidates (nodes) using global histogram matching.
- Best loop closure candidate is selected using direct feature matching.
- Percentage match for an incoming image I_j with a given node k is defined as

$$P_k^j = \frac{|\mathscr{V}_k \cap V(I_j)|}{|V(I_j)|} \times 100 \tag{1}$$



Hellinger Distance: $D_{gh} = \sqrt{1 - \sum_x \sqrt{p(x)q(x)}}$

where $p(x)$ and $q(x)$ are the source and target histograms

Node Update

- A node k is represented by a histogram H_k and a pool $\mathscr{V}_k$ of SURF descriptors.
- Whenever a loop closure is detected, the node update include two steps
  - Adding descriptors of incoming image into the pool

$$\mathscr{V}_k = \mathscr{V}_k \cup V(I_j) \tag{2}$$

    A fixed size descriptor pool could be maintain to limit the growing memory requirement.
  - Histogram of the node is updated by re-distributing the descriptors of the new image among the histogram bins.

Experimental Results

Detecting Loop Closures:

Case I:	Query Image $j = 436$	Node (k)	Images belonging to the node
		1	
		5	
		12	
Case II:	**Query Image $j = 942$**	**Node (k)**	**Images belonging to the node**
		18	
		24	
		27	

Figure : Loop Closure Detection under two cases.

Loop Closure Detection

Table : Confirming Loop Closure Detection using Direct feature matching

Case I: $j = 436$				Case II: $j = 941$		
r	Node (k)	D_{gh}	$P^j_{k(r)}$	Node (k)	D_{gh}	$P^j_{k(r)}$
1	1	0.1615	06%	18	0.1349	01%
2	5	0.1586	30%	24	0.2028	04%
3	12	0.1848	05%	27	0.1862	16%

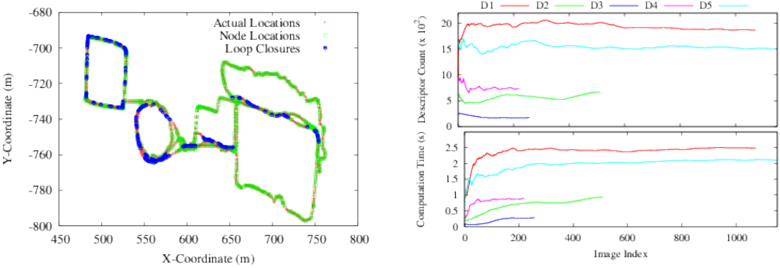
- Two-step process involving histogram matching and direct-feature matching is crucial in correctly identifying loop closures.
- Case I: For query image $j = 436$, loop closing node is $k = 5$ for which D_{gh} is minimum and $P^j_{k(r)}$ is maximum.
- Case II: For query image $j = 942$, loop closing node is 27 for which D_{gh} is NOT minimum but $P^j_{k(r)}$ is maximum.

Performance on different datasets

S. No	Data Set	No. of Images, Resolution, Avg. no. of descriptors/image	No. of nodes	No. of loop closures	Recall (%)	Avg. comp. time per image (sec)	Total time (hours)
D1	New College dataset (Cummins)	2146, 640×480, 1800	1573	220	24	2.4	1.48
D2	Hallway dataset #6 (Zhang)	512, 640×480, 500	128	0		0.7	0.13
D3	Hallway dataset #2 (Zhang)	259, 320×240, 200	32	76	70	0.23	0.017
D4	Our own Indoor Lab data	222, 640×480, 800	40	150	87	0.8	0.054
D5	City Centre dataset (Cummins)	2474, 640×480, 1500	1866	244	22	2.1	1.44

- If the dictionary is created off-line the computation time per image is comparable to existing methods.
- Recall rate is comparatively lower.

Computation time for different algorithms



- Computation time has a sub-linear growth w.r.t map size.
- Computation time per image is directly proportional to the number of SURF descriptors available in the image.
- If the dictionary is created off-line, the computation time per image is comparable to existing methods.
- Recall is comparatively lower.

Computational Complexity of the Algorithm

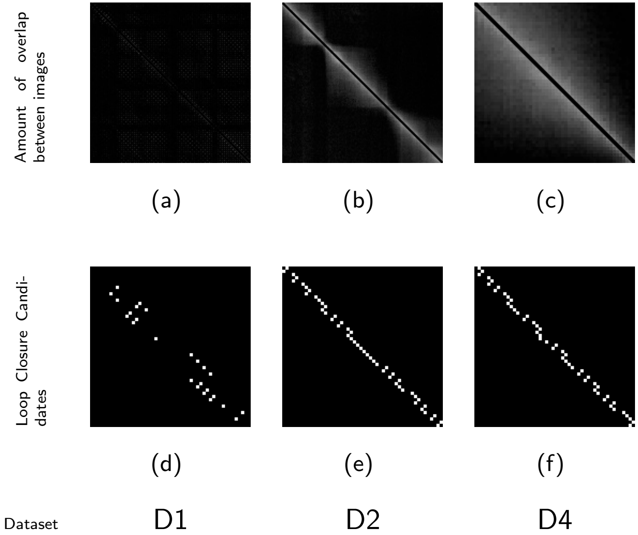
Total computation time for each image: $T = T_e + T_1 + T_2$

- T_e: Time needed for extracting SURF descriptors from each image.

$$
\begin{aligned}
T_e &\propto N_d \quad \left(\text{\scriptsize Number of descriptors in an image}\right) \\
T_e &= C \quad \left(\text{\scriptsize constant w.r.t map size}\right)
\end{aligned}
$$

- T_1: Time needed for finding loop closure candidates through histogram matching. $T_1 \sim O(\log M)$, M being the map size
- T_2: Time needed for confirming loop closure using direct feature matching. $T_2 = C$ and does not increase with map size.
- Overall, the computation time increases logarithmically with map size.

Dealing with Similarity between consecutive images



Conclusion

- A new method for loop closure detection is proposed by combining histogram matching with direct feature matching.
- It does not require any off-line dictionary.
- The computation time per image is comparable to other direct feature matching methods.
- However, our recall rates are lower.
- Future work: focus on increasing recall rates and reducing computation time.

Thank You

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