Efficient Global 2D-3D Matching for Camera Localization in a Large-Scale 3D Map

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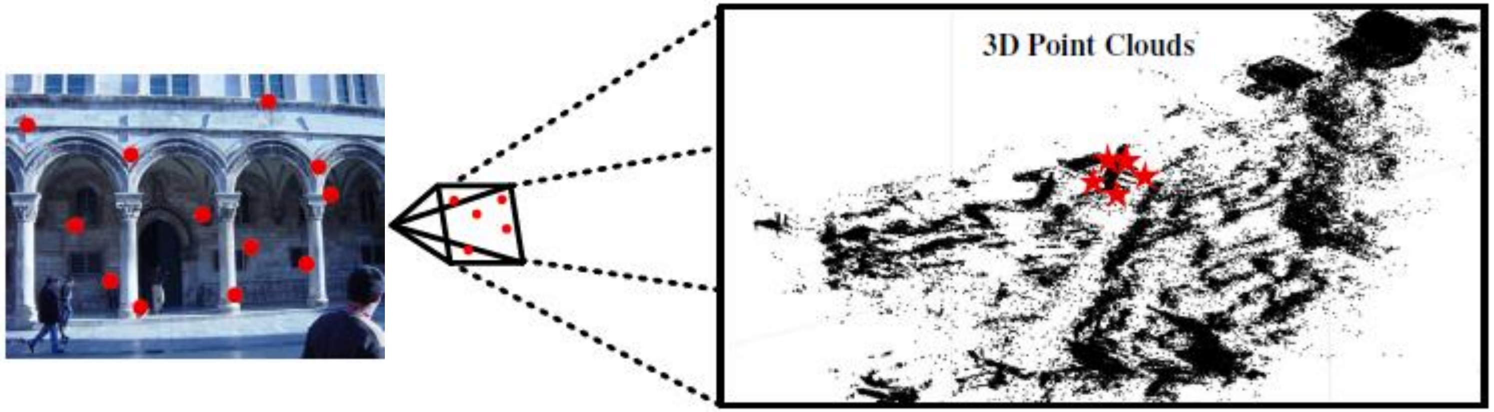
Outline

- Research field
- Motivation
- Proposed scheme
- Experiment and comparison
- Conclusion

What?

- Image-based localization

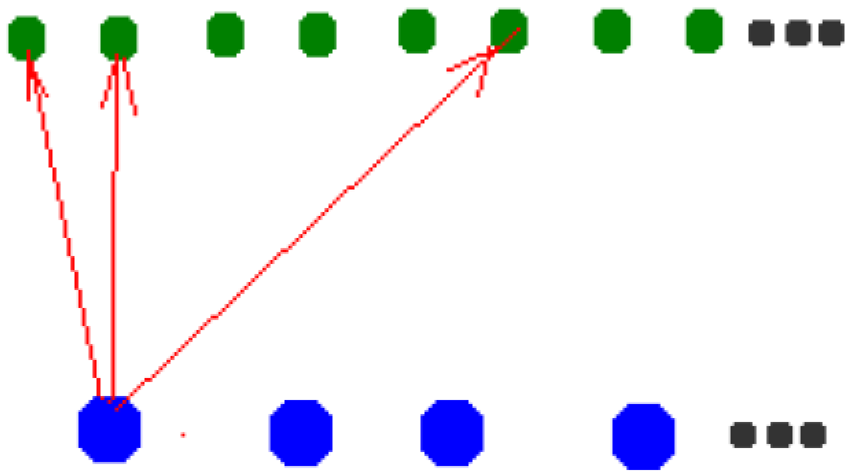


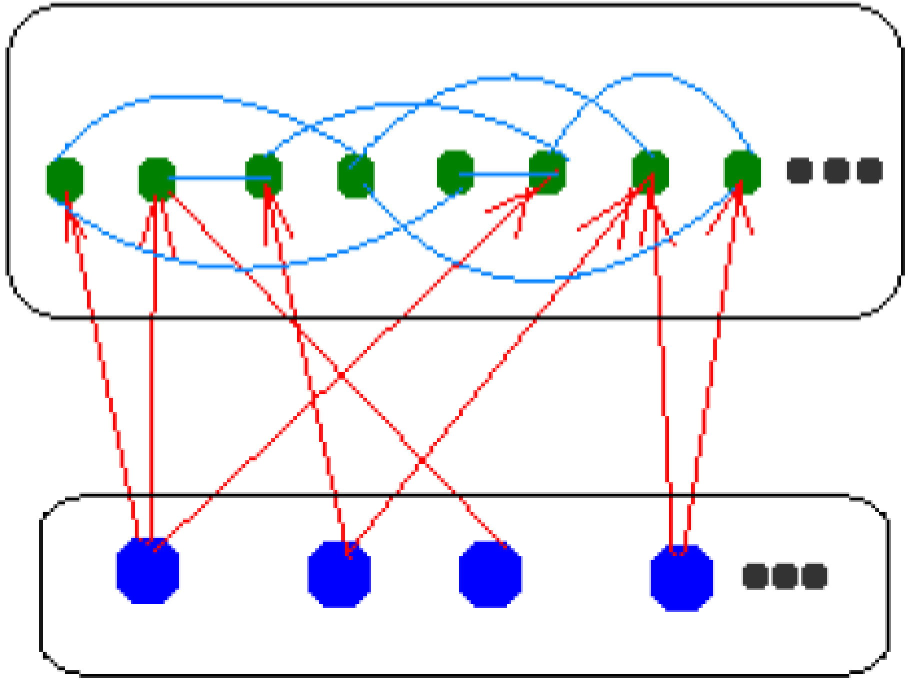
Why?

- **Large-scale problem → ambiguity**
  - 3D points can be visually similar or even identical (repeated structure)
  - ambiguous matches are almost inevitable

- **Local search → sub-optimal solution**
  - take account of similarities between 2D-3D matches
  - involves in global compatibility among all matching pairs? effective?

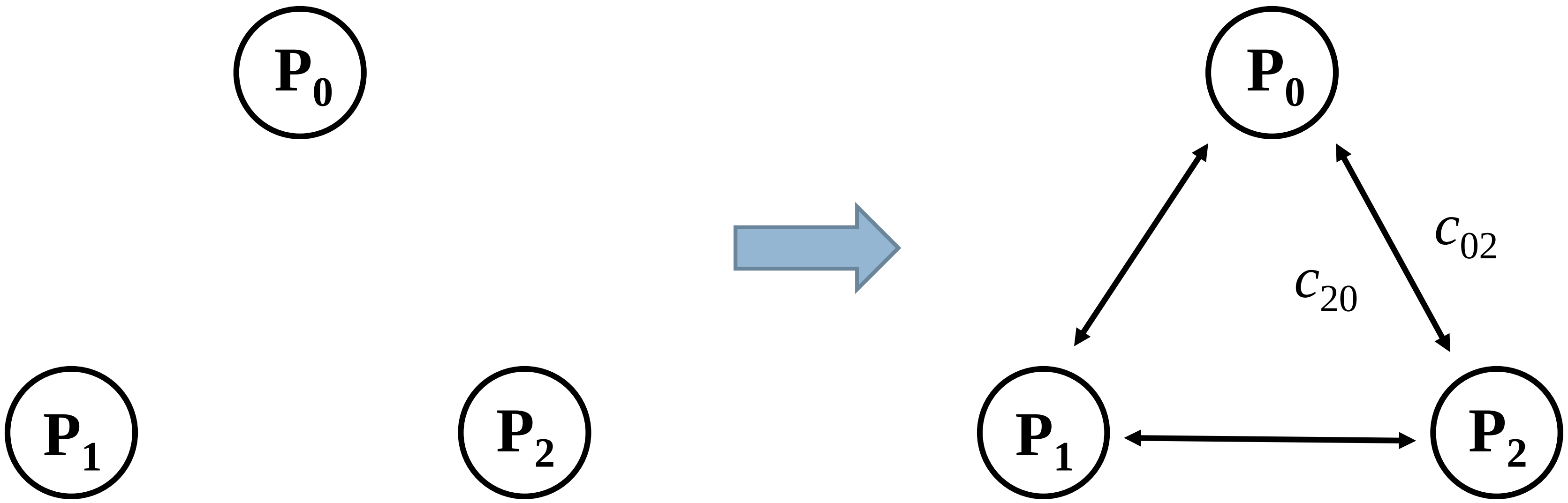
Local search V.S. Global search





How? – Step 1 (Build a map graph)

- Traditionally, 3D map is in the form of unordered point clouds
- Transform into weighted and bi-directed map graph
  - covisibility c_{ij} – if P_j is seen by an image set, how likely P_i can also be seen from the same image set



$$c_{ij} = \frac{|A_i \cap A_j|}{|A_j|}$$

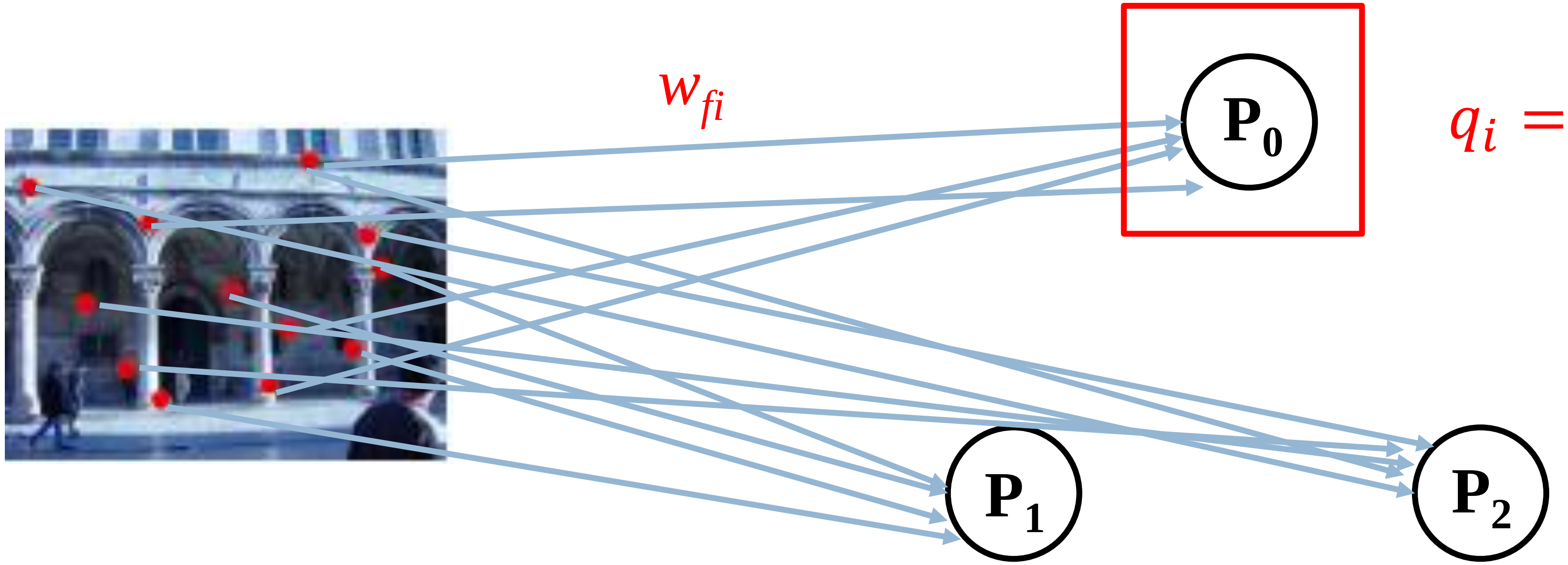
How? – Step 1 (Build a map graph)

- Collect all c_{ij} into a square matrix C = $[c_{ij}]$ of size $N \times N$
- Normalize each column unit norm to form a left stochastic matrix
  - with each column summing to 1
- Also call C as state transition matrix

$$c_{ij} = \frac{|A_i \cap A_j|}{|A_j|} \Rightarrow \begin{bmatrix} c_{00} & \cdots & c_{0N} \\ \vdots & \ddots & \vdots \\ c_{N0} & \cdots & c_{NN} \end{bmatrix}$$

How? – Step 2 (query vector)

- query image → a set of 2D feature points
- for every 2D feature points, find a set of tentative matches from 3D graph nodes, by comparing their descriptor similarity via Bag-of-words vocabulary tree search



$$q_i = \sum_{f \in O(i)} \frac{\sqrt{w_{fi}}}{N_i} \log\left(\frac{N}{N_f}\right)$$

How? – Step 2 (query vector)

- Collect all q_i into a vector q
- Normalize q to have unit norm $q_i \leftarrow \frac{q_i}{\sum_{i=1}^{N} q_i}$

- q can also be interpreted as a probability
  - measures the probability of point i belongs to the optimal sub-set of 3D points that can be matched to the set of 2D query features

How? – Step 3 (random walk)

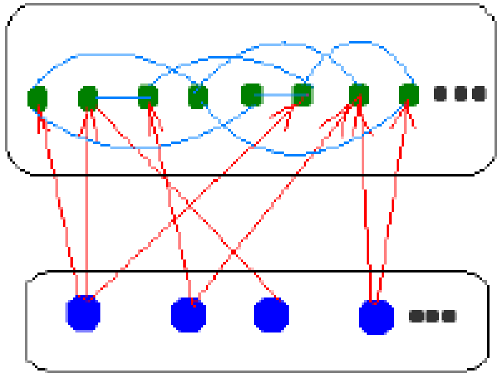
- **Map graph → Markov network (aka. Markov Random Field)**
  - for global match between 2D query image and 3D map
  - when random walks converge, reach steady state
  - $p_v(t)$ is the probability of finding random walker at node v at time t
  - $p_v(\infty)$ gives the probability that the random walker eventually ends at node v

How? – Step 3 (random walk)

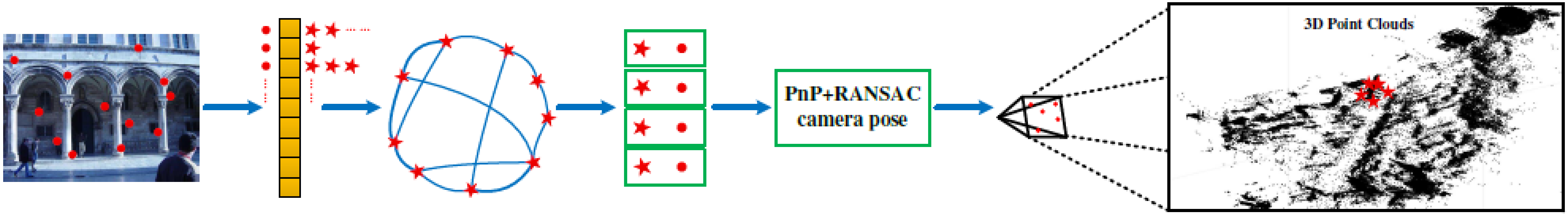
- **Random Walk with Restart (RWR)**
  - $p(t+1) = \alpha C p(t) + (1 - \alpha) q$
  - $p(0)$ is initialized by q
  - $p(\infty)$ stands for the final matchability of every 3D point to the set of 2D query features
  - sort $p(\infty)$ in descending order

How? – Step 4 (camera pose computation)

- **Recover one-to-one correspondences**
  - do ratio test to retrieve one-to-one matches
  - fed into PnP-RANSAC to find camera position and orientation



How? – Summary



(a) (b) (c) (d) (e) (f)

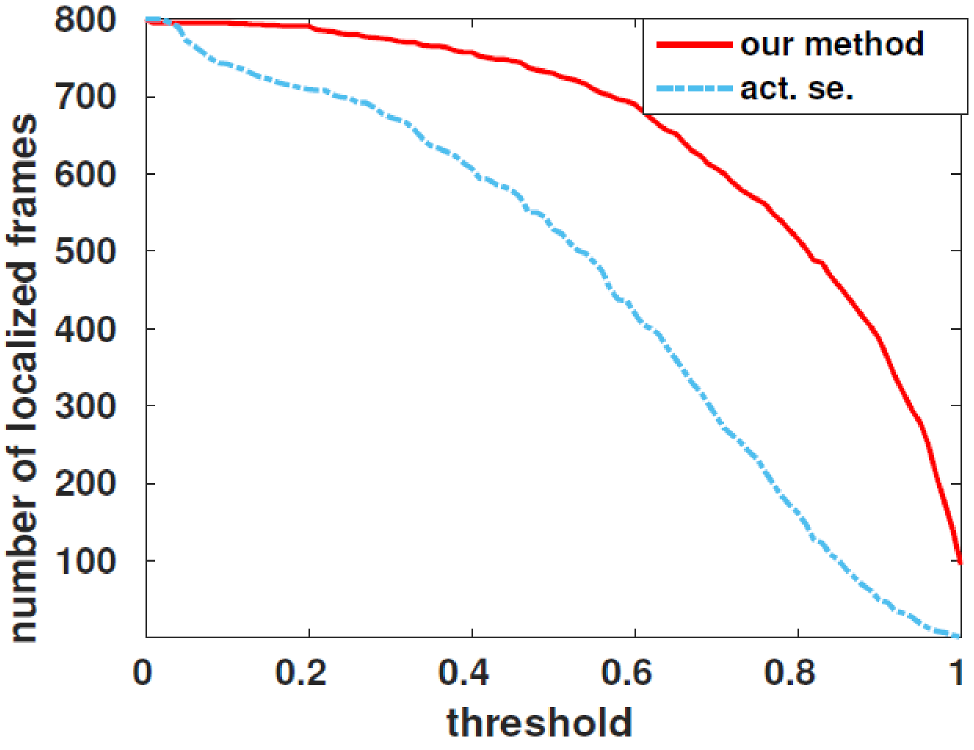
Experiment – dataset selection

- Four standard publicly available benchmark datasets for city-scale localization
  (1) Dubrovnik, (2) Rome, (3) Vienna, (4) San Francisco (SF-0)

Dataset	#(images)	#(points)	#(query images)
Dubrovnik [32]	6,044	1,975,263	800
Rome [32]	15,179	4,067,119	1,000
Vienna [23]	1,324	1,123,028	266
SF-0 [12]	610,773	30,342,328	803

Experiment

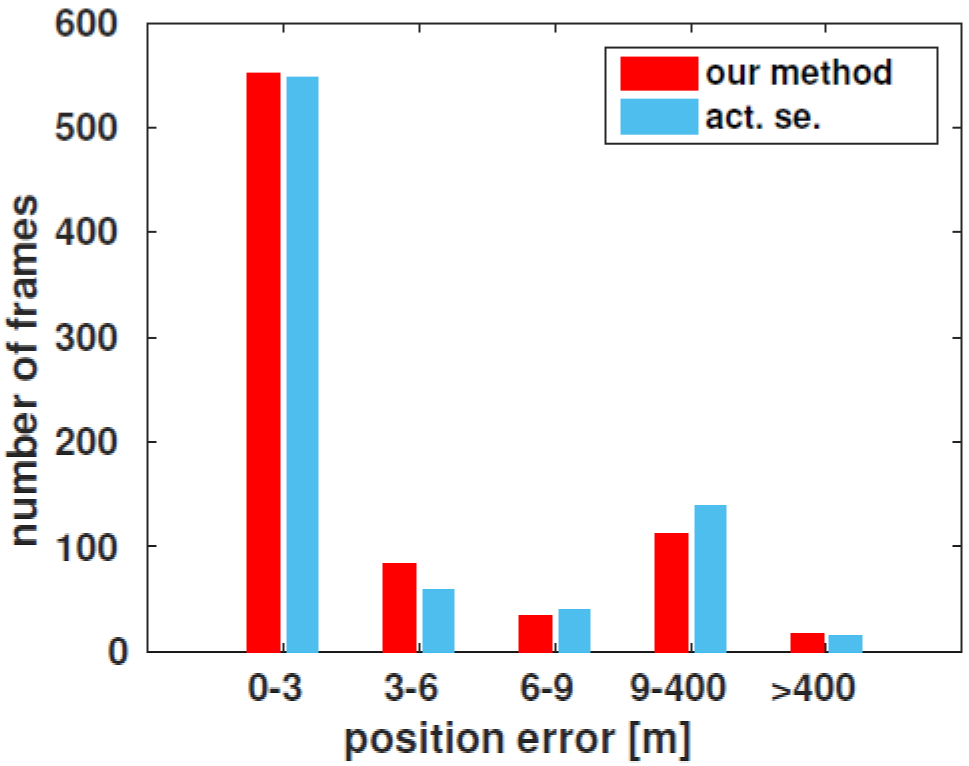
- In term of recall-rate (# images have been successfully localized)

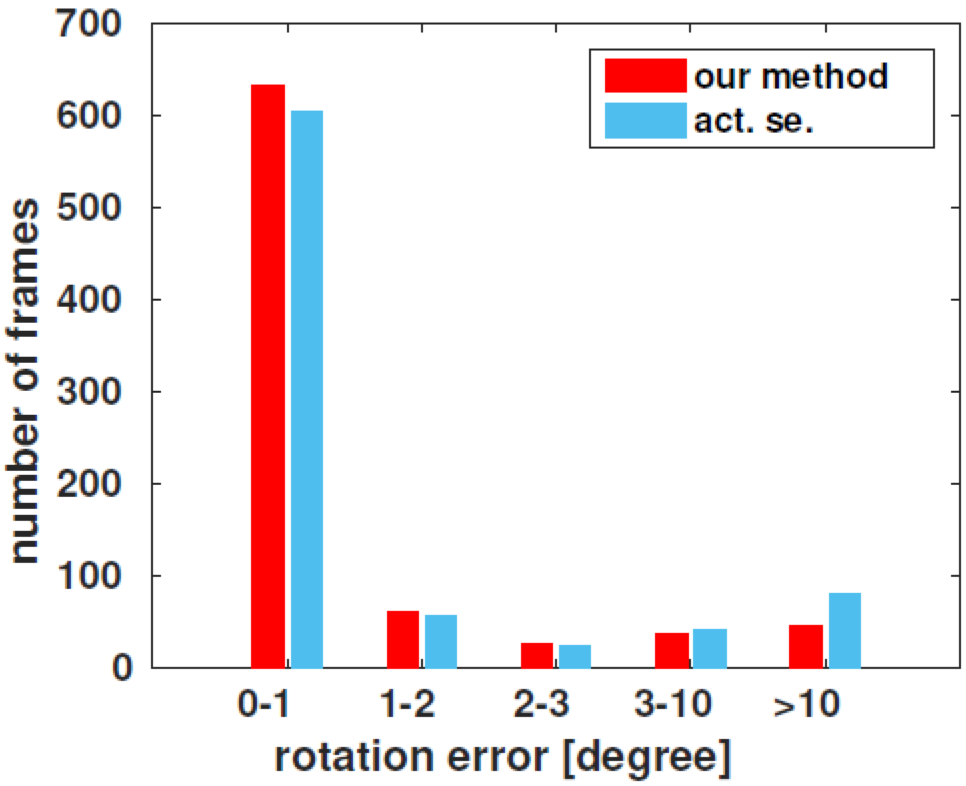


Method	Inlier thresholds						
	0.2	0.3	0.4	0.5	0.6	0.7	0.8
Active Search [43, 44]	709	673	607	528	420	287	162
Our method	**791**	**774**	**757**	**730**	**690**	**607**	**516**

Experiment

- In term of precision (camera localization error)

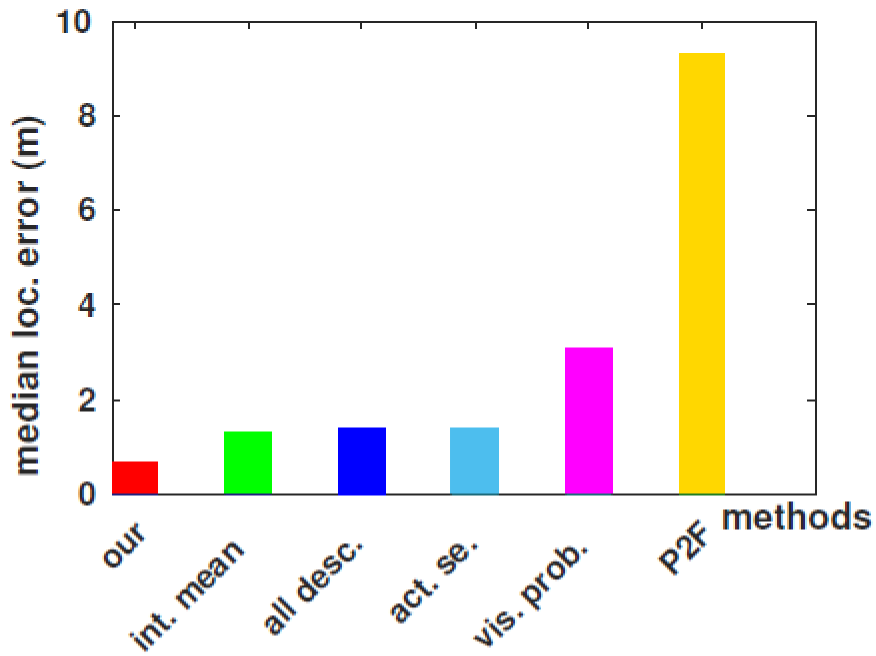




Experiment

- In term of precision (camera localization error)

Method	quartile errors (m)			num. of images		
	1st	median	3rd	<18.3m	>400m	#(reg.)
our method	**0.24**	**0.70**	**2.67**	**743**	**7**	794
act. se. [43,44]	0.40	1.40	5.30	704	9	**795**
all desc. [42]	0.40	1.40	5.90	685	16	783
int. mean [42]	0.50	1.30	5.10	675	13	782
P2F [32]	7.50	9.30	13.40	655	-	753
vis. prob. [13]	0.88	3.10	11.83	-	-	788



Experiment

- Demo

Conclusion

- a global method, taking account of not only individual feature match's visual similarity but also the global compatibilities as measured by the pair-wise covisibility, to deal with scalability and ambiguity for localization