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

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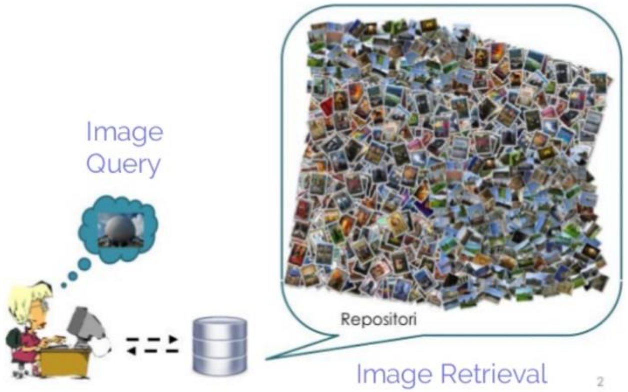
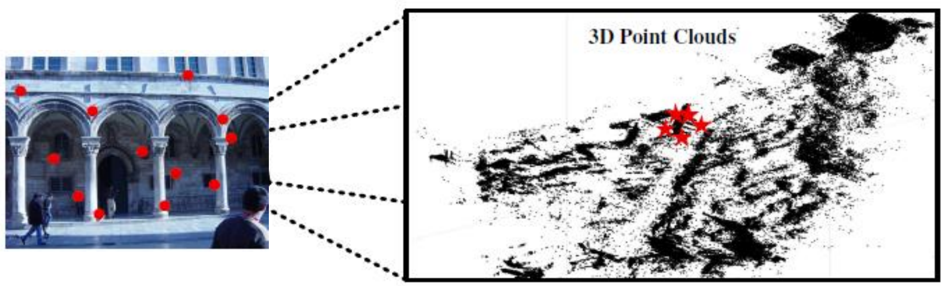
Outline

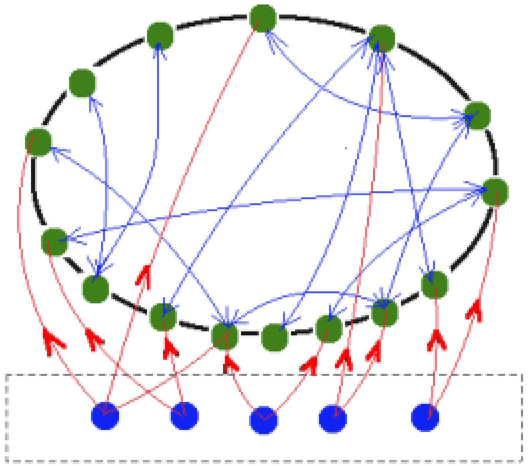
- Research field
- Motivation
- Proposed scheme
- Experiment and comparison
- Conclusion

What is IBL?

- **Image-based localization → feature similarity**
  - image retrieval: without building the global map in advance
  - direct 2D-3D matching: map is needed
  - covisibility: consider the relationship among multiple global sub-models





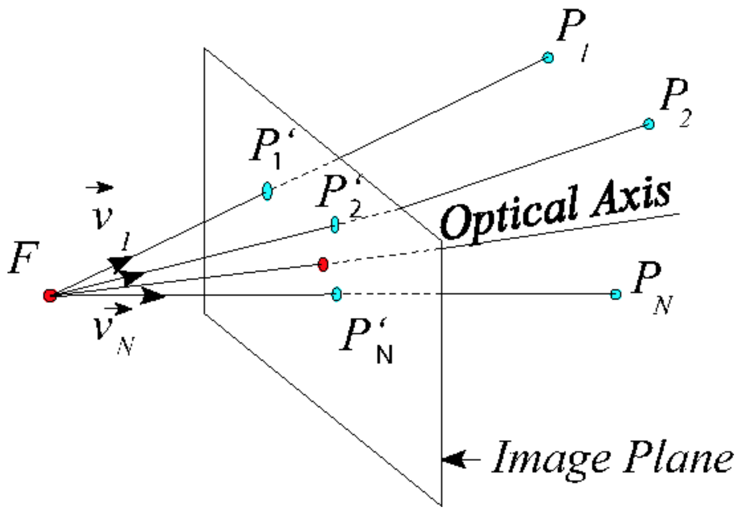


https://www.slideshare.net/xavigiro/deep-image-retrieval-learning-global-representations-for-image-search

General solution for 2D-3D matching localization

- **Selection of 2D-3D matches**
  - PnP + RANSAC

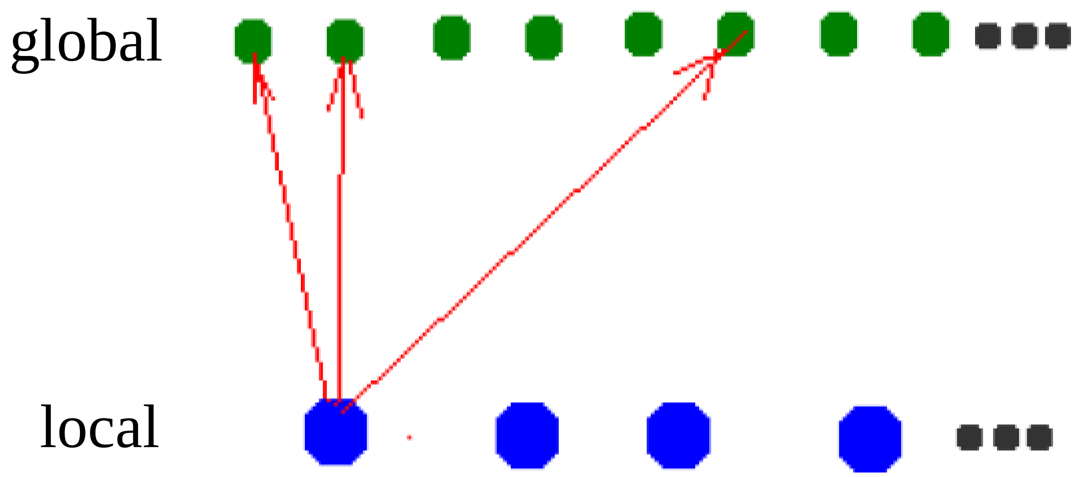
- **Remove ambiguous matches**
  - ratio test



https://www.semanticscholar.org/paper/An-Analytical-Solution-to-the-Perspective-n-Point-Fabrizio-Devars/95cacfebed0cde6b111559342e9b29fff69c06e6/figure/0

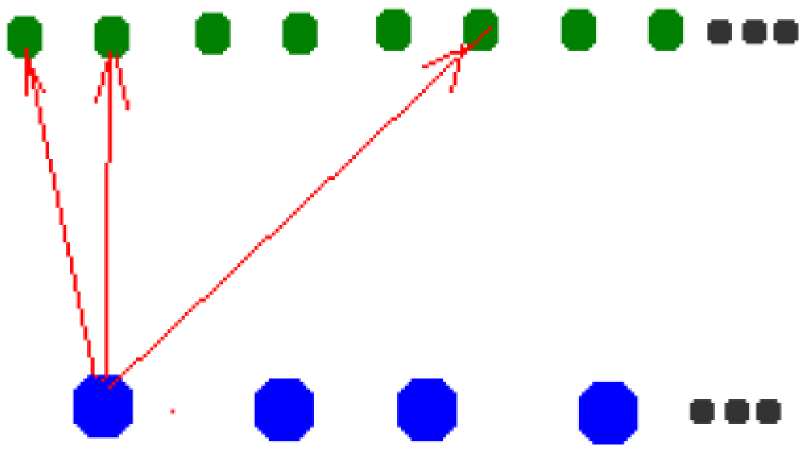
Why?

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

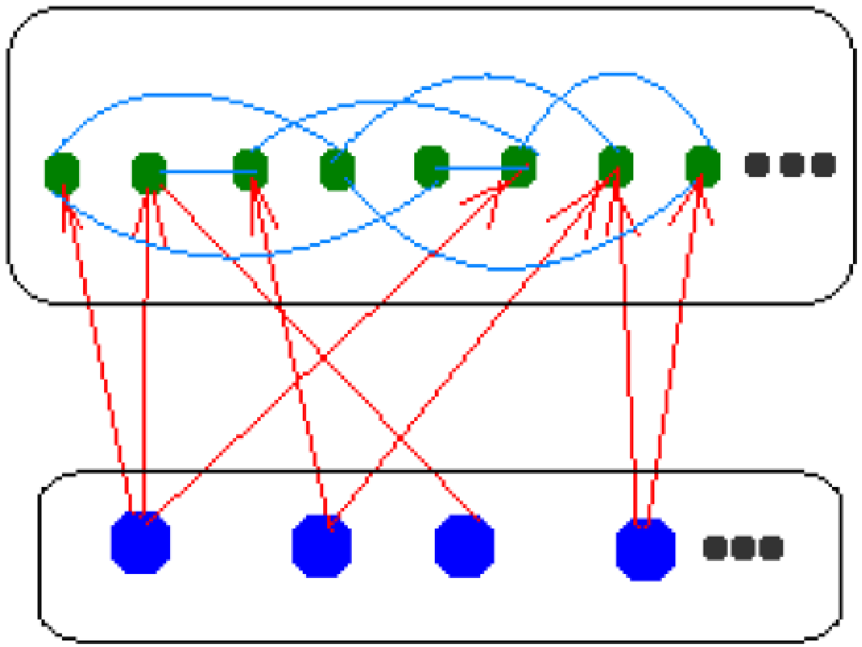


Why?

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



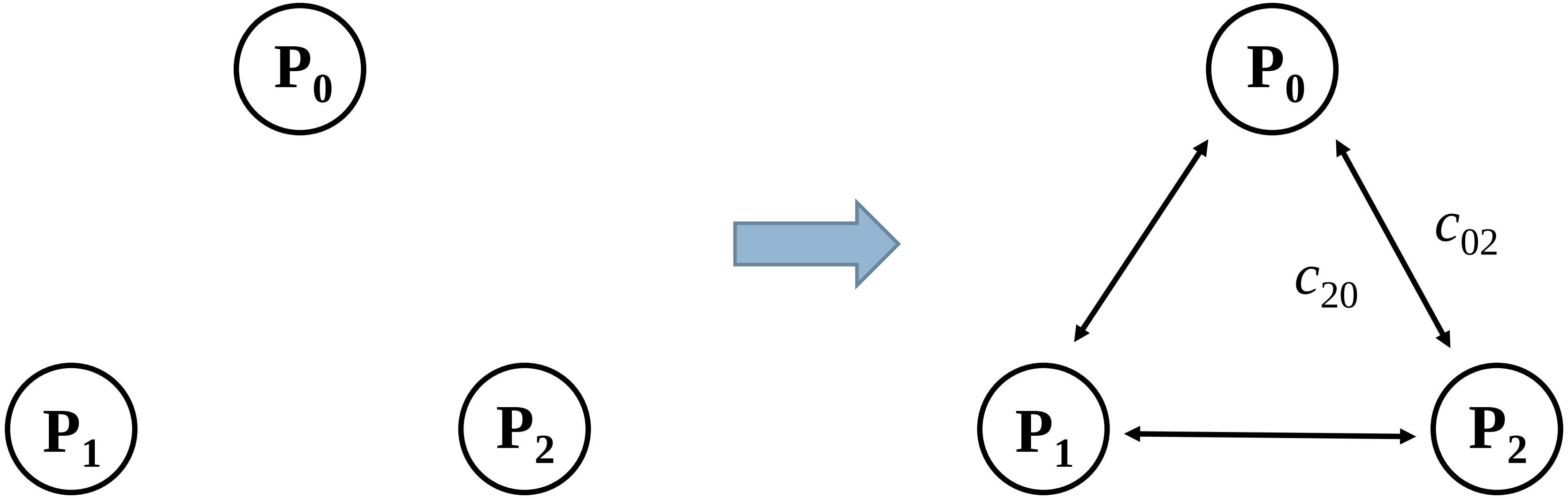
Local search



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



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

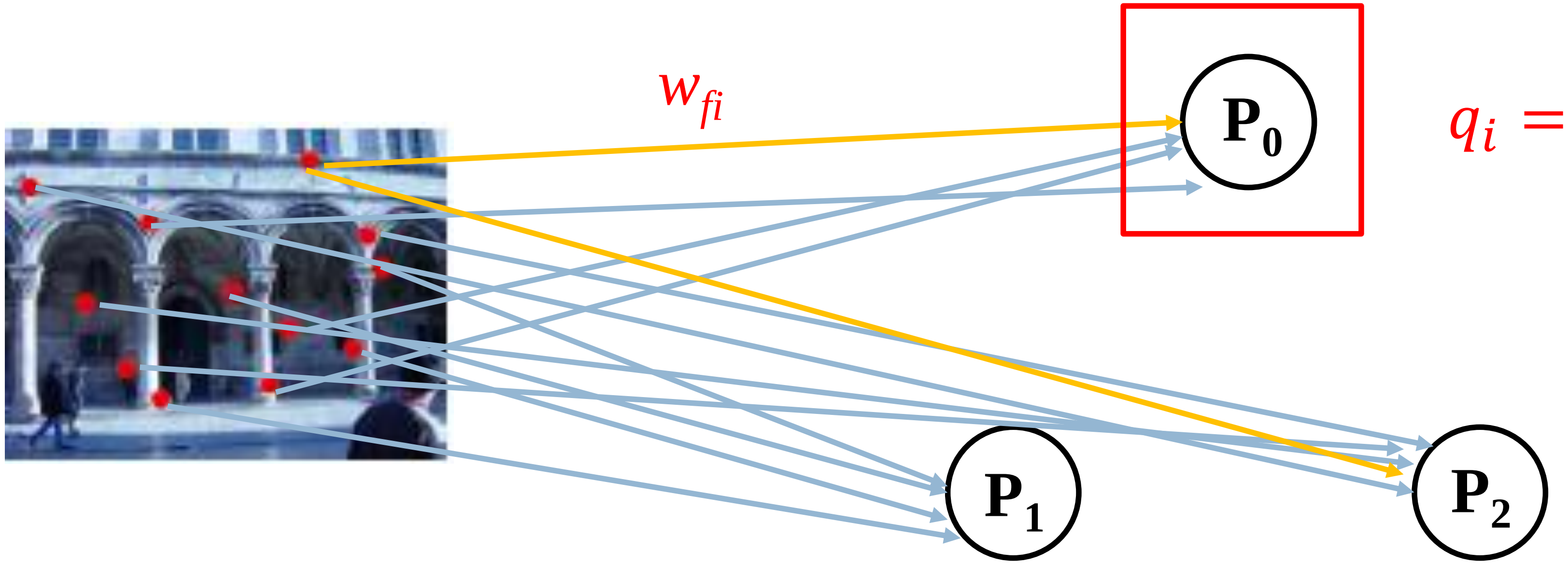
How? – Step 1 (build a map graph)

- 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

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

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



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

How? – Step 2 (query vector)

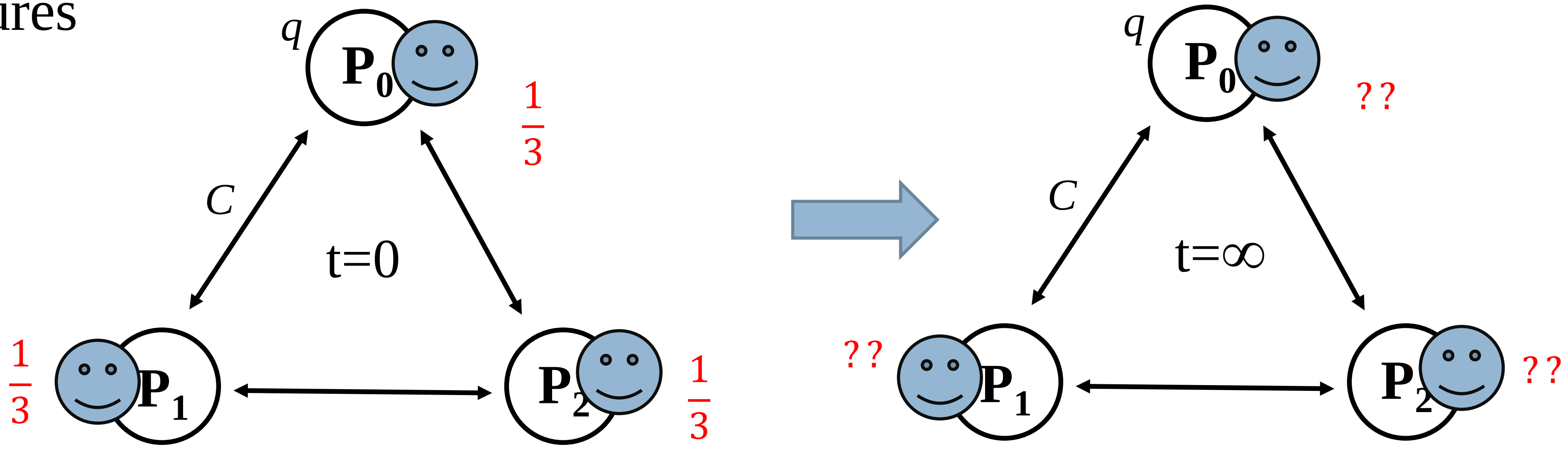
- collect all q_i into a column vector q
- normalize q to have unit norm $$q_i \leftarrow \frac{q_i}{\sum_{i=1}^{N} q_i}$$
- q can also be interpreted as a probability
  - measures the probability of point cloud i belongs to the optimal sub-set of 3D points that can be matched to the set of 2D query features

How? – Step 3 (random walk)

- **Map graph → Markov network (aka. Markov Random Field)**
  - for global match between 2D query image and 3D map
  - $p_v(t)$ 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
  - when random walkers converge, they reach steady state

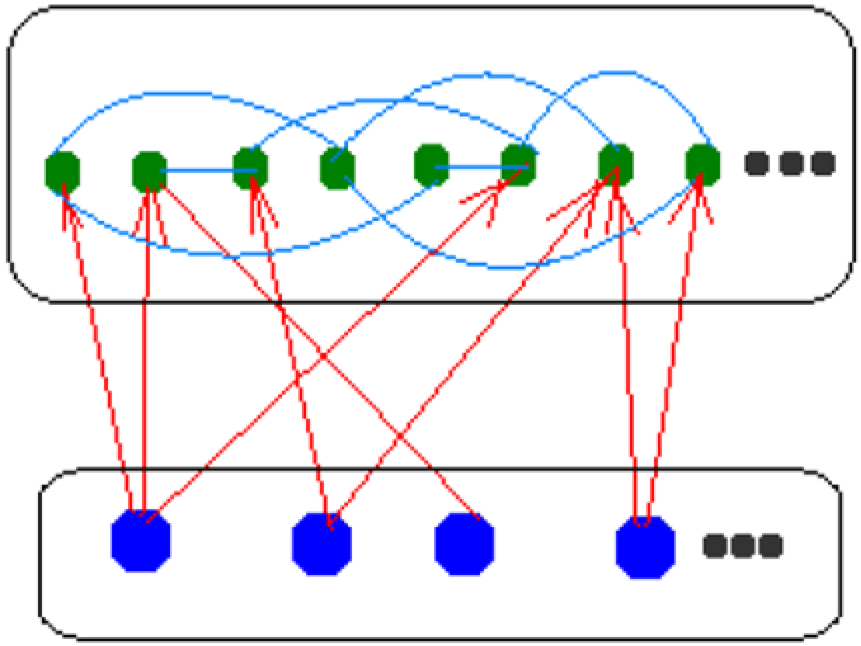
How? – Step 3 (random walk)

- **Random Walk with Restart (RWR)**
  - $p(t+1) = \alpha C p(t) + (1-\alpha) q$
  - α is chosen empirically between 0.8–0.9
  - $p(0)$ is initialized by $1/N$
  - $p(\infty)$ stands for the final matchability of every 3D point to the set of 2D query features

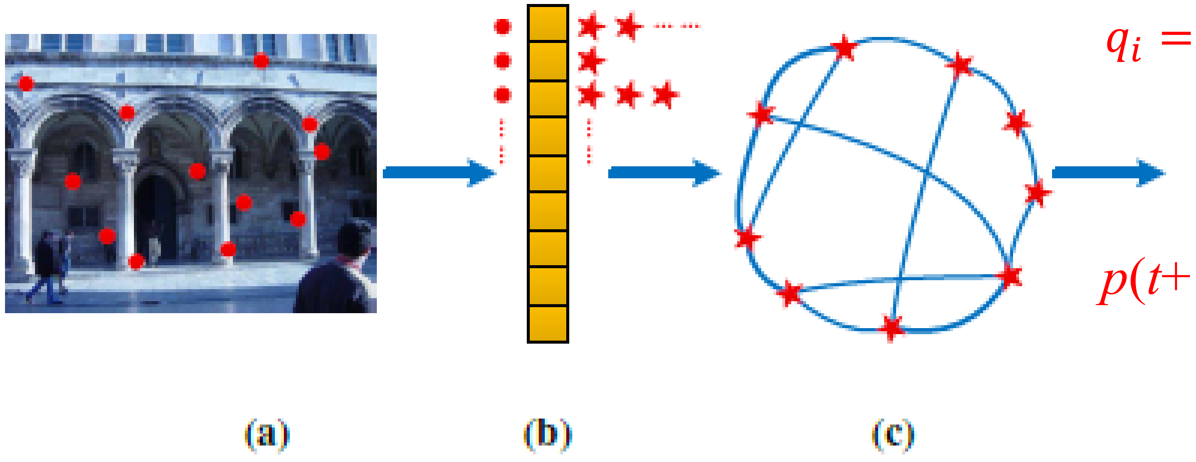


How? – Step 4 (camera pose computation)

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

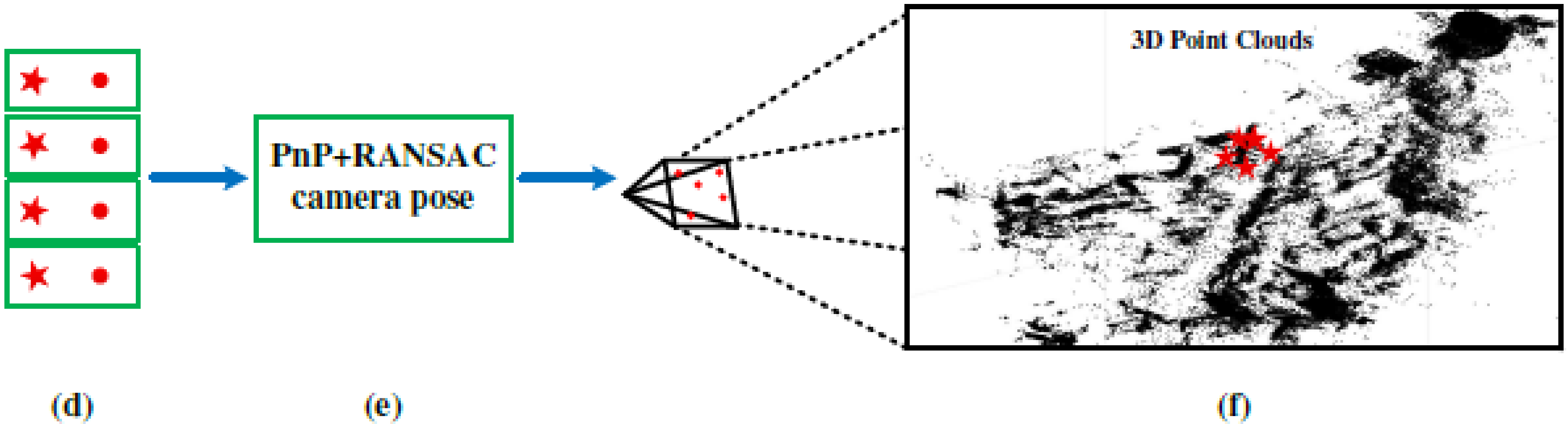


How? – Summary



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

$$p(t+1) = \alpha C p(t) + (1-\alpha) q$$



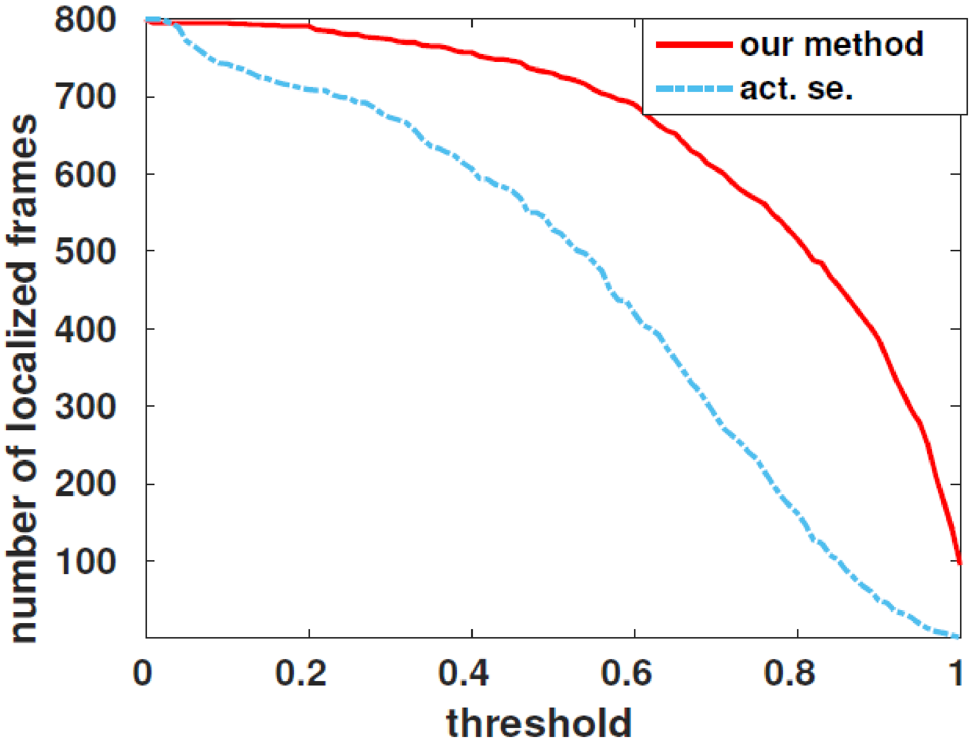
Experiment – dataset selection

- 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)

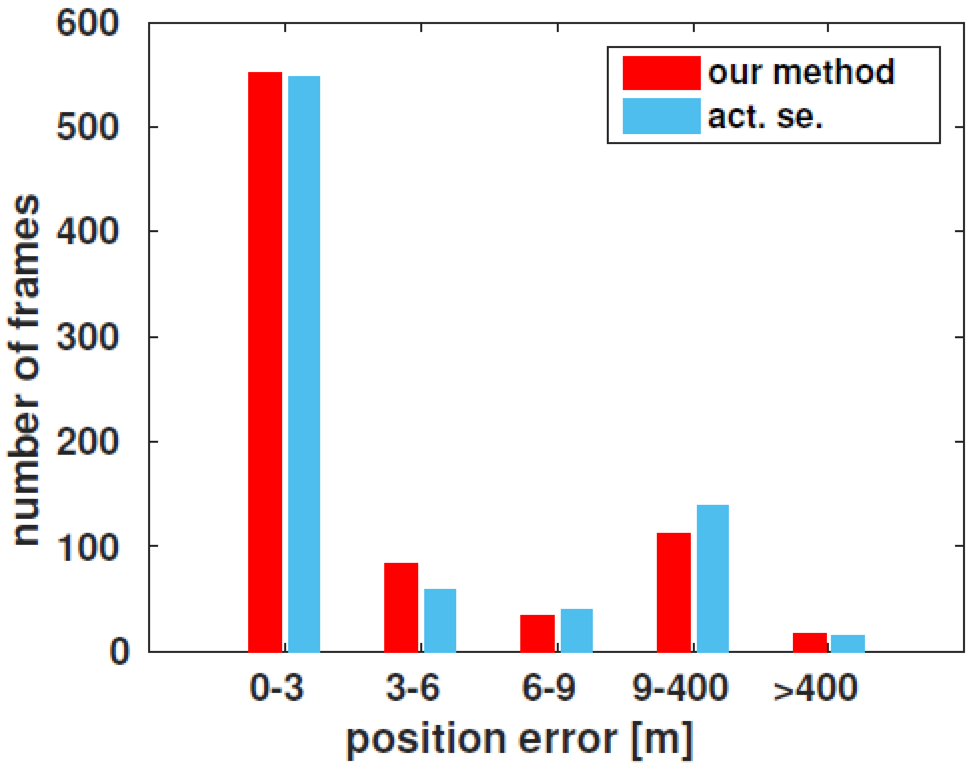


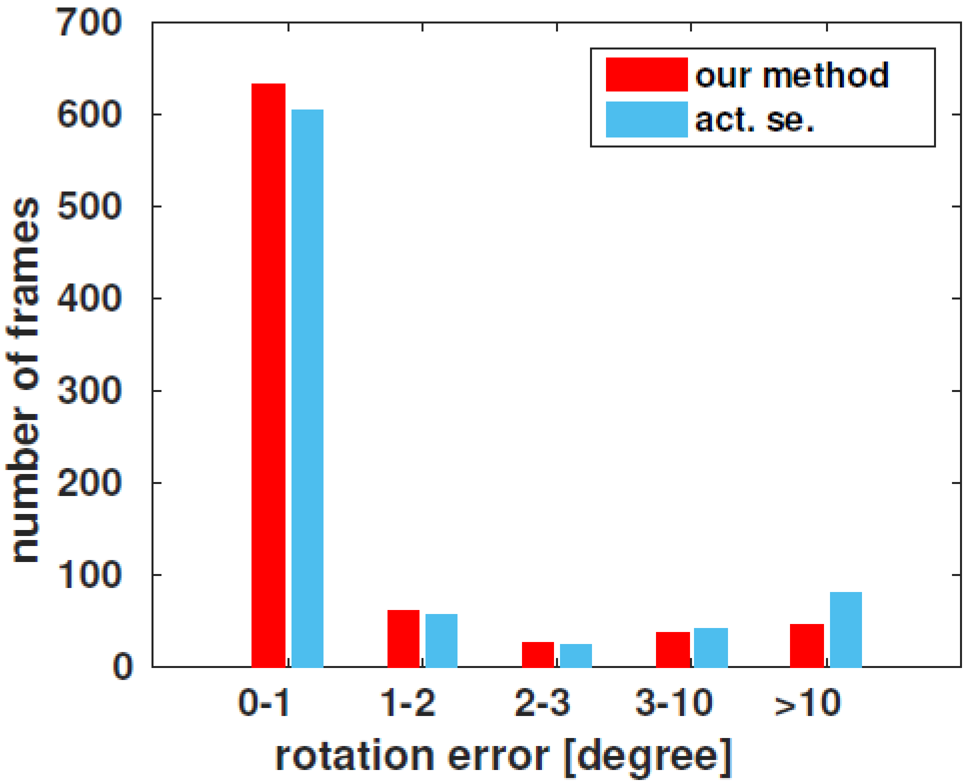
Method	Inlier thresholds						
	0.2	0.3	0.4	0.5	0.6	0.7	0.8
Active Search [43,44]	709	673	607	528	420	287	162
Our method	**791**	**774**	**757**	**730**	**690**	**607**	**516**

[43] T. Sattler, B. Leibe, and L. Kobbelt, "Improving image-based localization by active correspondence search," ECCV'12
[44] T. Sattler, B. Leibe, and L. Kobbelt, "Efficient effective prioritized matching for large-scale image-based localization," IEEE Transactions on Pattern Analysis and Machine Intelligence,2016.

Experiment

- In term of precision (camera localization error)



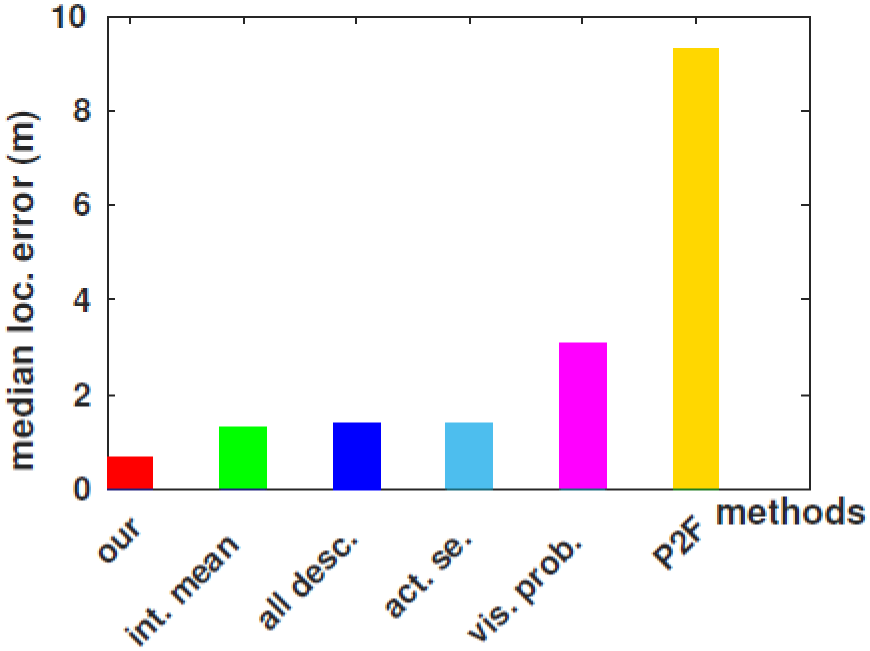


[43] T. Sattler, B. Leibe, and L. Kobbelt, "Improving image-based localization by active correspondence search," ECCV'12.
[44] T. Sattler, B. Leibe, and L. Kobbelt, "Efficient effective prioritized matching for large-scale image-based localization," IEEE Transactions on Pattern Analysis and Machine Intelligence,2016.

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

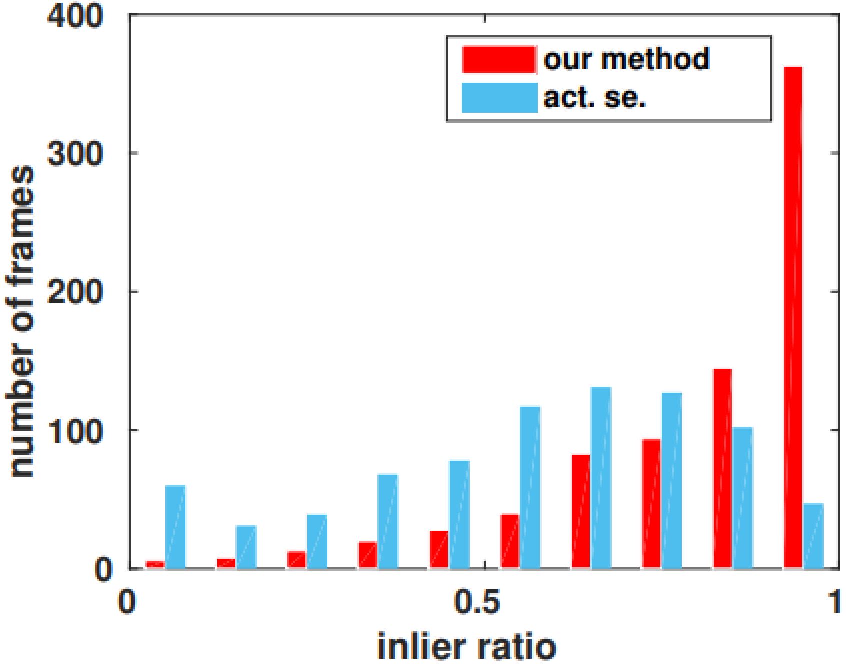


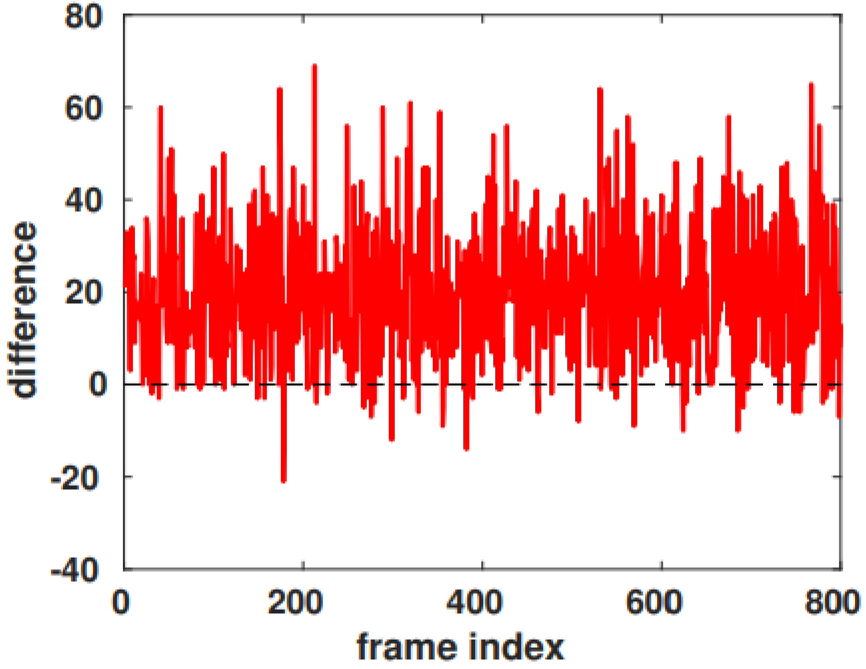
[42] T. Sattler, B. Leibe, and L. Kobbelt, “Fast image-based localization using direct 2d-to-3d matching,” ICCV’11.
[13] S. Choudhary and P. Narayanan, “Visibility probability structure from sfm datasets and applications,” ECCV’12.
[32] Y. Li, N. Snavely, and D. P. Huttenlocher, “Location recognition using prioritized feature matching,” ECCV’10.

Experiment

- In terms of accuracy (the inlier ratio in the final matched 2D-3D feature pairs after applying RANSAC)

average inlier ratio of our method: 81%
average inlier ratio of active search: 57%





[43] T. Sattler, B. Leibe, and L. Kobbelt, “Improving image-based localization by active correspondence search,” ECCV’12.
[44] T. Sattler, B. Leibe, and L. Kobbelt, “Efficient effective prioritized matching for large-scale image-based localization,” IEEE Transactions on Pattern Analysis and Machine Intelligence,2016.

Experiment

- In terms of scalability [use SF-0 dataset]

Dataset	#(images)	#(points)	#(query images)
SF-0 [12]	610,773	30,342,328	803

  - our method localizes 652 images (out of totally 803 query images), and the average time spent per image is 0.30s
  - active search [43,44] is only able to localize 31 images

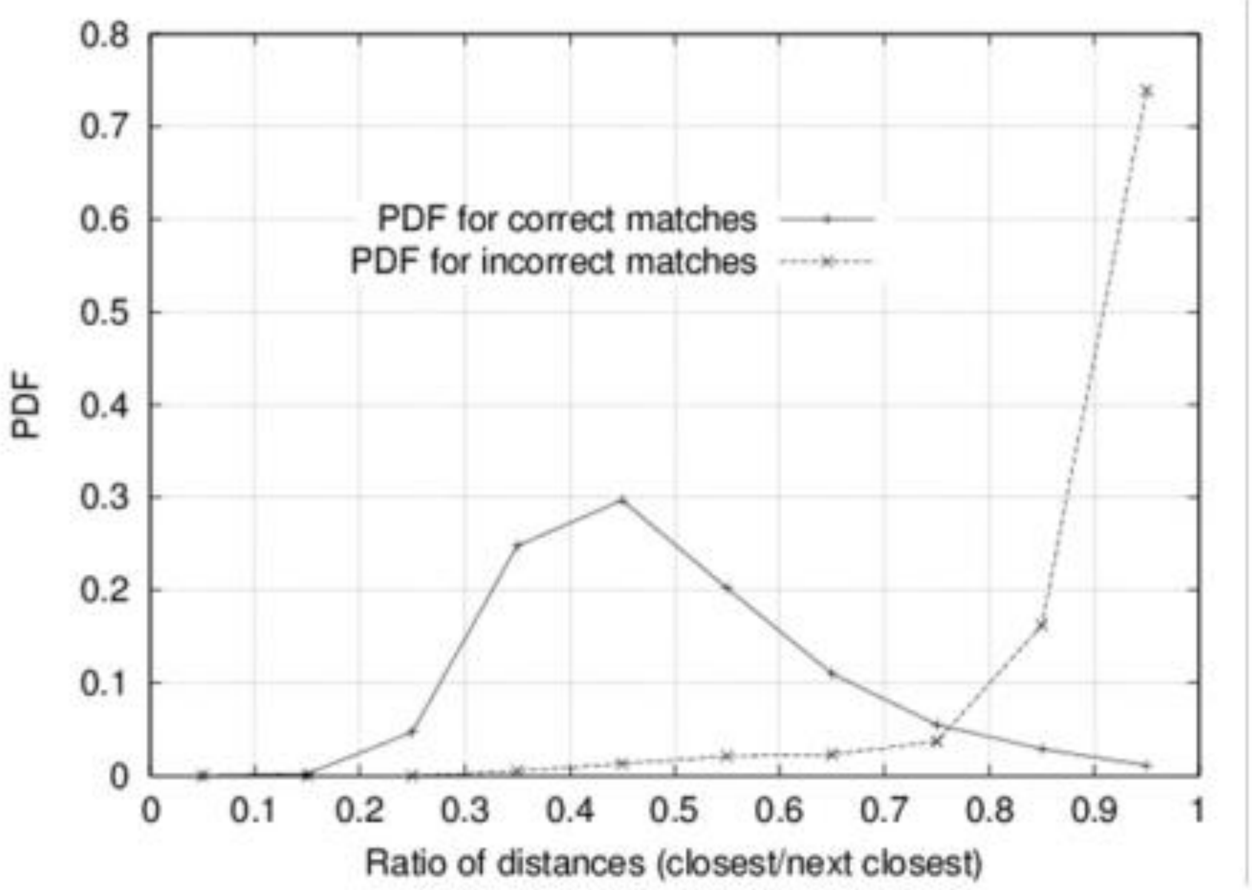
- For Rome and Vienna datasets
  - has about 4-millions and 1-millions 3D map points
  - localized 990 (out of 1000) and 213 (out of 266) query images
  - the average query time by our unoptimized code was 2.35s and 1.67s

[43] T. Sattler, B. Leibe, and L. Kobbelt, "Improving image-based localization by active correspondence search," ECCV'12.
[44] T. Sattler, B. Leibe, and L. Kobbelt, "Efficient effective prioritized matching for large-scale image-based localization," IEEE Transactions on Pattern Analysis and Machine Intelligence,2016.

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.

Ratio test



David G. Lowe. "Distinctive image features from scale-invariant keypoints." IJCV 60 (2), pp. 91-110, 2004