

1 Motivation

- Structure-from-Motion point cloud: every point has ≥ 2 SIFT descriptors [4]
- 2D-to-3D correspondences needed for pose estimation for query image

- State-of-the-art registration performance obtained using a kd-tree for correspondence search, but kd-tree search is slow (>3 seconds) [6]
- Approaches with state-of-the-art registration efficiency (0.25-0.4 seconds) can register significantly less images [1,2,3,6]
- Our approach: State-of-the-art registration performance & efficiency using Active Correspondence Search and Visibility Filtering

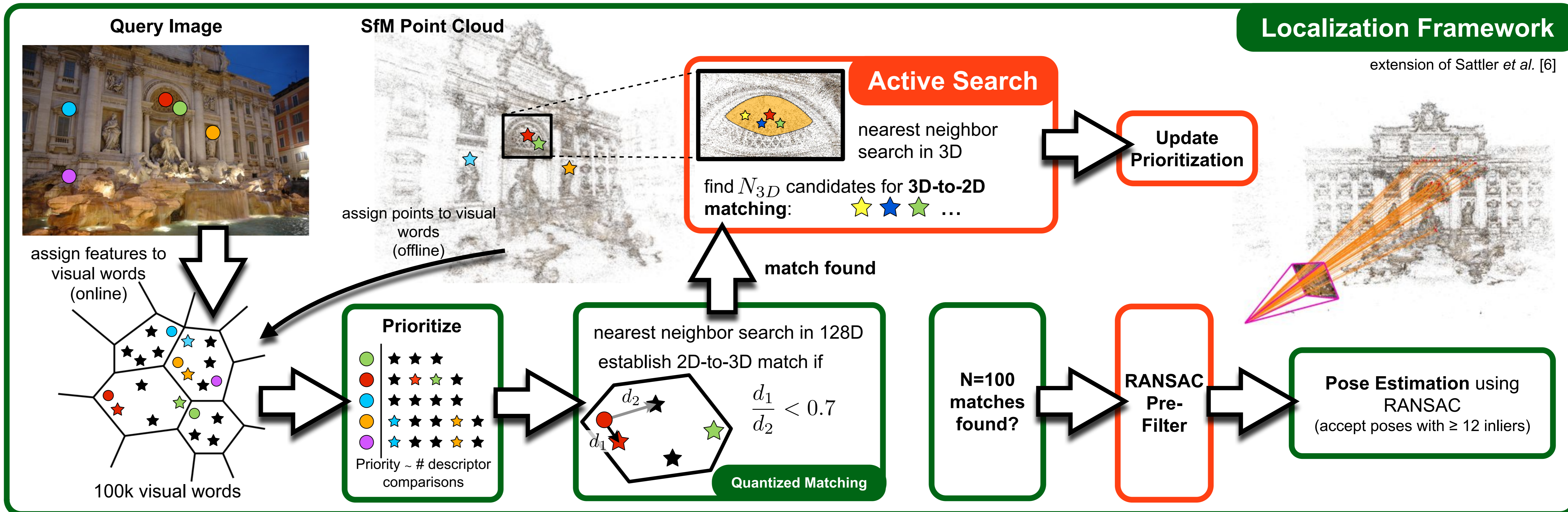
2 Datasets

- Same datasets used in [1,2,3,5]
- Query images have dimensions ≤ 1600 pixels

Dataset	# Cameras	# 3D Points	# Descriptors	# Query Images
Dubrovnik	6044	1.886.884	9.606.317	800
Rome	15.179	4.067.119	21.515.110	1000
Vienna	1324	1.123.028	4.854.056	266

3 2D-to-3D vs. 3D-to-2D matching

Complimentary Advantages	Method	Efficiency	Reject wrong matches	Accept correct matches
	3D-to-2D	✓	✗	✓
	2D-to-3D	✗	✓	✗



Source code available at <http://www.graphics.rwth-aachen.de/localization>

4 Active Correspondence Search

1. Find N_{3D} candidates for 3D-to-2D matching through nearest neighbor search in 3D

2. Insert into prioritization

Use 2D-to-3D matches to seed 3D-to-2D matching

Re-use structures for 3D-to-2D Matching: coarse vocabulary for 2D-to-3D matching, Vocabulary Tree, fine vocabulary for 2D-to-3D matching

Computational Complexity: Soft assignments [5] $\mathcal{O}(c \cdot F/W \cdot P)$, active search $\mathcal{O}(N \cdot F/W' \cdot N_{3D} \cdot \log_2(P))$ → Better scalability

constant: F = # image features, W = size fine voc., W' = size coarse voc., $c+1$ = # words a query feature is assigned to, P = # 3D points, N = # matches needed to terminate search, N_{3D} = # nearest neighbors in 3D

Active Search improves registration performance

Legend: all desc. [6] (cyan), int. mean [6] (blue), kd-tree [6] (magenta), direct (green), combined (red), afterwards (black), active search with different prioritization strategies (orange)

5 Prioritization

- Prioritize over estimated search cost ~ # descriptors inside a word [5]
- Independent of search direction!

2D-to-3D candidates: $\star \star \star \star$ → direct

3D-to-2D candidates: $\bullet \bullet \bullet \bullet$ → afterwards

combined afterwards

Prioritization Scheme	Preferred Direction	Registration performance	Localization accuracy
direct	3D-to-2D	best	worst
combined	cheaper direction	medium	good
afterwards	2D-to-3D	worst	good

Use the combined strategy, prioritize cheaper direction

6 Faster Localization using Visibility Filtering

bipartite point-camera graph models co-visibility

Filtering Points: Remove 3D-to-2D matching candidates not co-visible with 2D-to-3D match

RANSAC Pre-Filter: Keep only largest subgraph defined by matches

Cluster k nearest cameras to recover performance

combined strategy, $N_{3D} = 200$

7 Comparison with state-of-the-art

- active search: combined prioritization, both filters, $N_{3D} = 200, k = 10$ (CPU)
- all desc., int. mean: 3D-to-2D matching by Sattler et al. [6] without active search (CPU)
- P2F: Prioritized 3D-to-2D matching proposed by Li et al. [3] (CPU)
- P2F+F2P: Additional 2D-to-3D matching if P2F fails [3] (CPU)
- Vis. Prob.: 3D-to-2D matching based on visibility probabilities [1] (ECCV'12) (CPU)
- Image retrieval methods using a Vocabulary tree: Irschara et al. [2] (GPU), Li et al. [3] (CPU)

Method	Dubrovnik			Rome			Vienna		
	# reg. images	registr. time [s]	reject. time [s]	# reg. images	registr. time [s]	reject. time [s]	# reg. images	registr. time [s]	reject. time [s]
active search	795.5	0.25	0.56	991.5	0.28	2.14	220.1	0.27	0.52
all desc. [6]	783.9	0.31	2.22	976.9	0.29	1.90	207.7	0.50	2.40
int. mean [6]	782.0	0.28	1.70	974.6	0.25	1.66	206.9	0.46	2.43
Vis. Prob. [1]	788	0.25	0.51	977	0.27	0.61	219	0.4	0.49
P2F [3]	753	0.73	2.70	921	0.91	2.93	204	0.55	1.96
P2F+F2P [3]	753	0.70	3.96	924	0.87	4.67	205	0.54	3.62
Voc. tree (all) [3]	668	1.4	4.0	828	1.2	4.0	-	-	-
Voc. tree (points) [3]	677	1.3	4.0	815	1.2	4.0	-	-	-
Voc. tree GPU [2]	-	-	-	-	-	-	165	≤ 0.27 (worst case)	-
kd-tree [4]	795	3.4	14.45	983	3.97	6.27	220	3.44	2.72

Ground truth: Geo-registered version of Dubrovnik model

Pose estimation using 6-point DLT algorithm

Method	# reg. images	Median [m]	Quartiles [m]			#images with error	
			1st	3rd	< 18.3m	> 400 m	
active search	795.5	1.4	0.4	5.3	704 (88.5%)	9 (1.1%)	
all desc. [6]	783.9	1.4	0.4	5.9	685 (87.4%)	16 (2.0%)	
int. mean [6]	782.0	1.3	0.5	5.1	675 (86.3%)	13 (1.7%)	
Vis. Prob. [1]	788	3.1	0.88	11.83			
P2F [3]	753	9.3	7.5	13.4	655 (87%)	0	

Related Work

- S. Choudhary and P. J. Narayanan. Visibility Probability Structure from SfM Datasets and Applications. ECCV'12
- A. Irschara, C. Zach, J.-M. Frahm, and H. Bischof. From structure-from-motion point clouds to fast location recognition. CVPR'09.
- Y. Li, N. Snavely, and D.P. Huttenlocher. Location recognition using prioritized feature matching. ECCV'10.
- D. Lowe. Distinctive image features from scale-invariant keypoints. IJCV, 60(2):91-110, 2004.
- J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Lost in quantization: Improving particular object retrieval in large scale image databases. CVPR'08.
- T. Sattler, B. Leibe, and L. Kobbelt. Fast Image-Based Localization using Direct 2D-to-3D Matching. ICCV'11