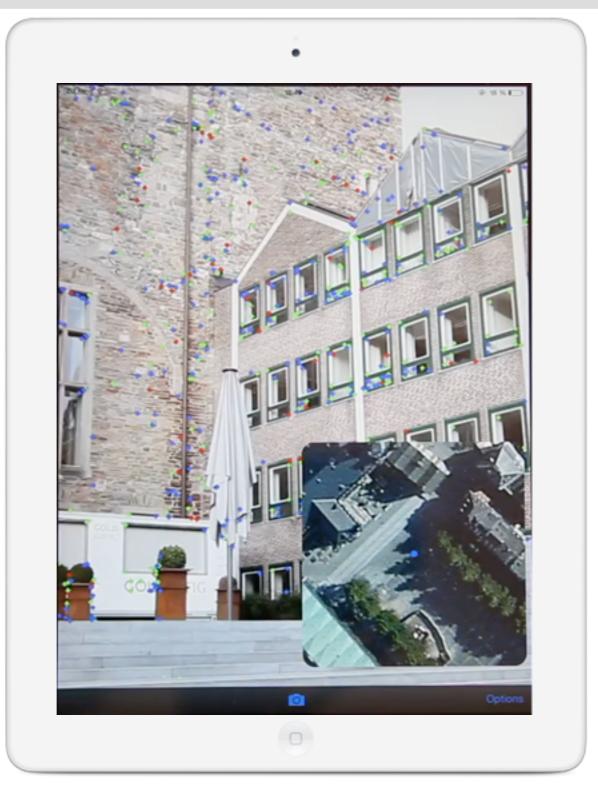


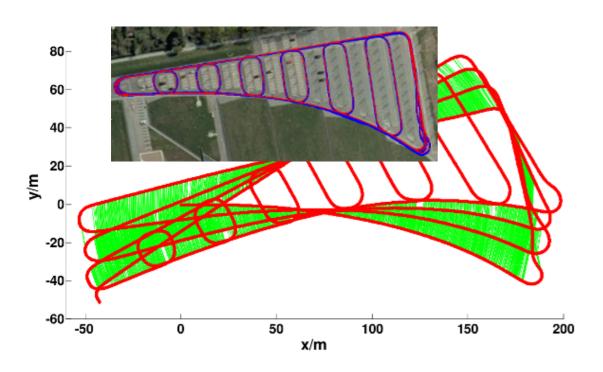
### Mobile Localisation



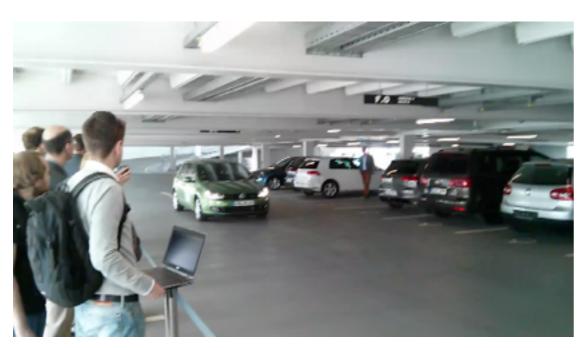
S. Middelberg, T. Sattler, O. Untzelmann, L. Kobbelt. Scalable 6-DOF Localization on Mobile Devices. ECCV 2014.

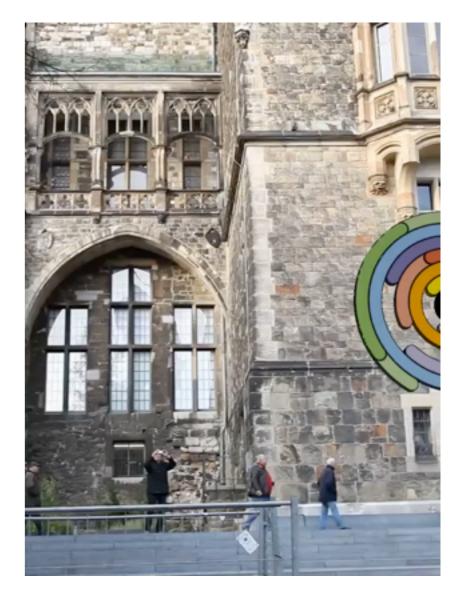


#### Mobile Localisation



loop closures





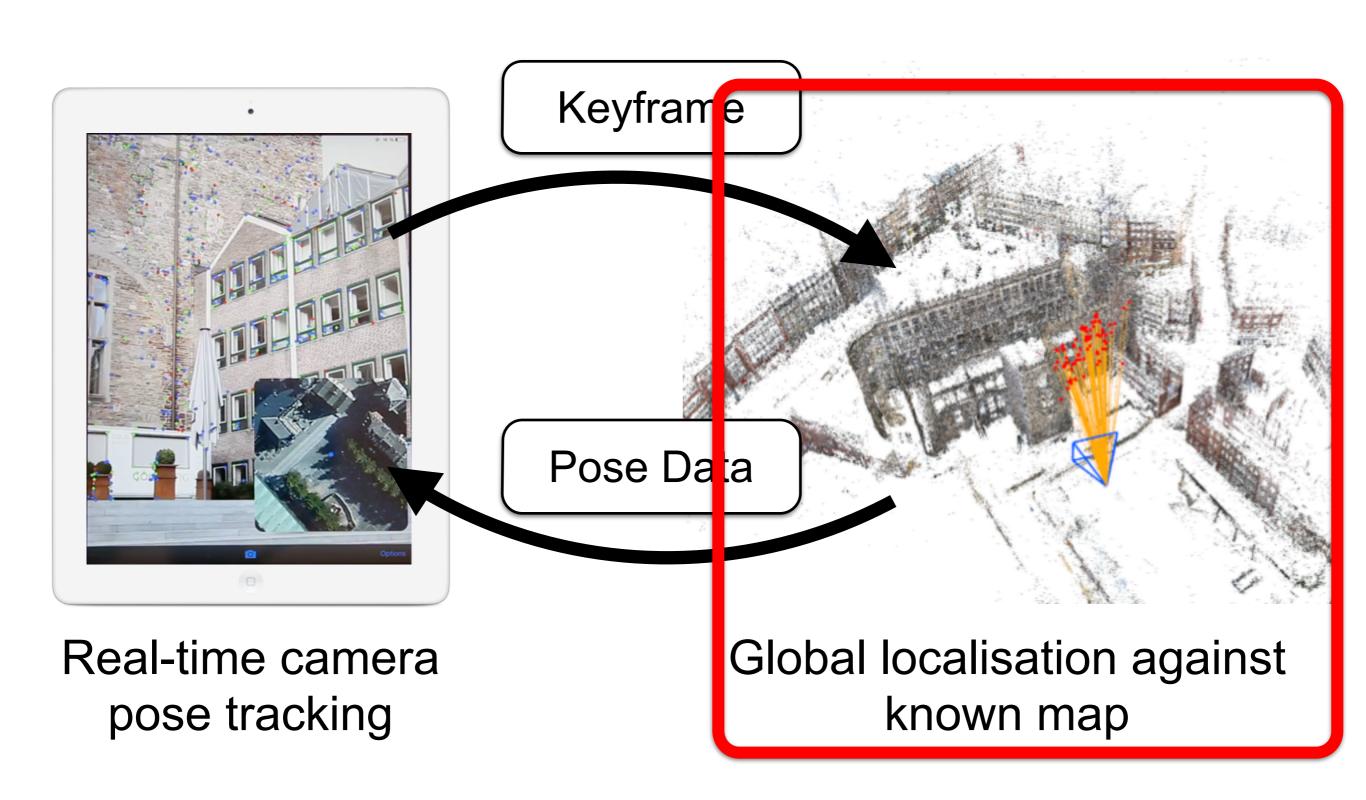
AR / VR

robotics / autonomous vehicles





### Mobile Localisation





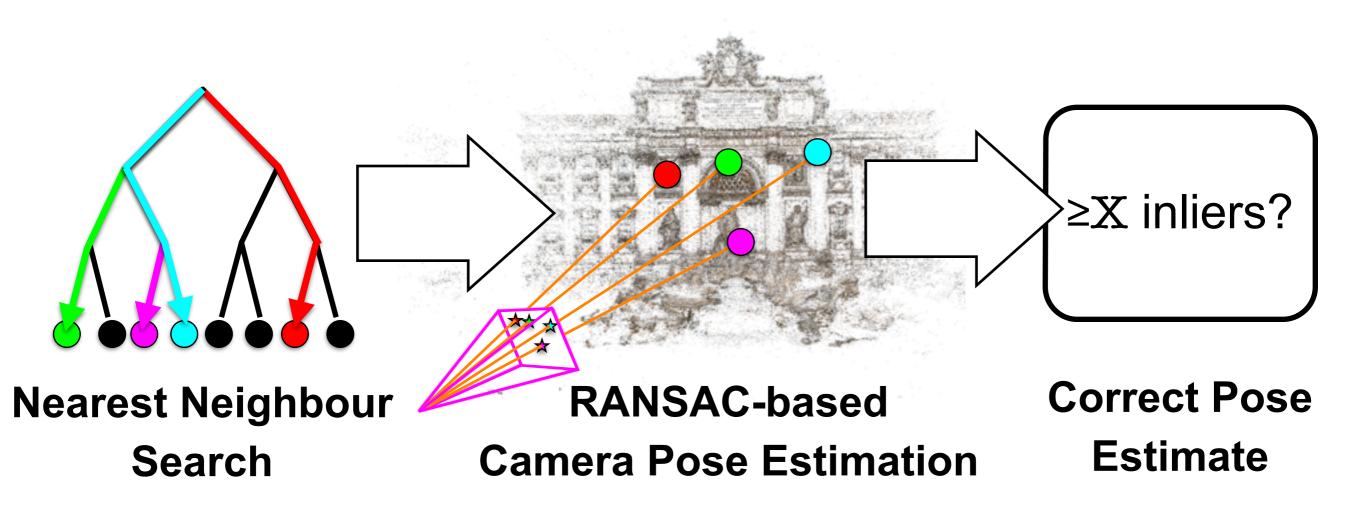


## Global Localisation

Structure-from-Motion / SLAM model 3D Point: 3D point + descriptors 2D Feature: 2D position + descriptor Database **Images Query Image** 



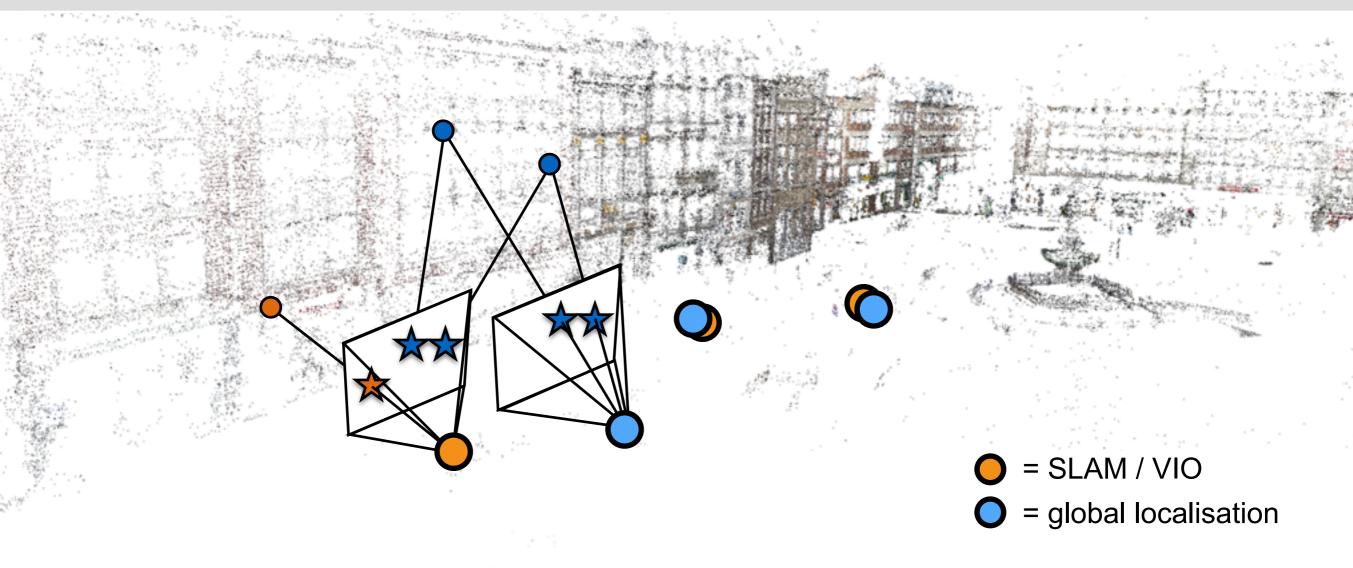
## Global Localisation







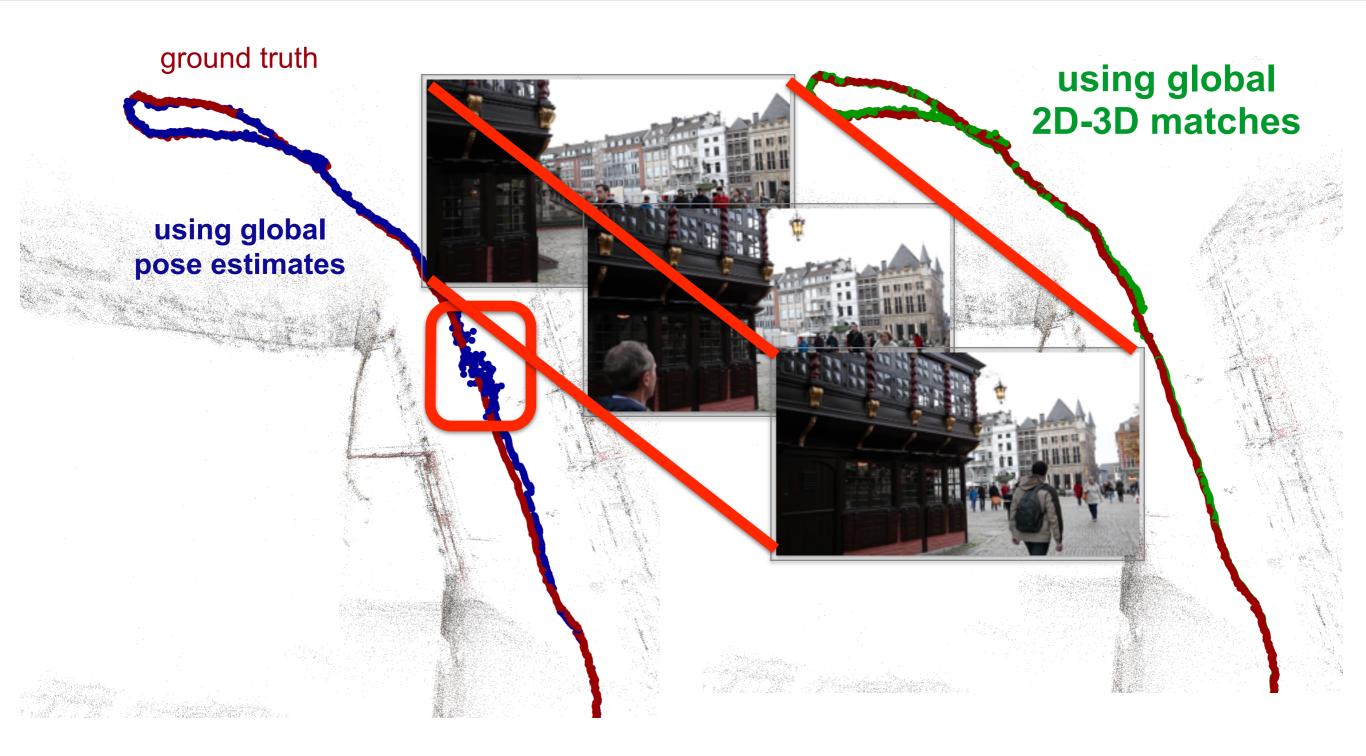
# Global Pose Integration



- Use inlier 2D-3D matches rather than estimate poses
  - "Control points" in Bundle Adjustment / Kalman Filter
  - Additional measurements for filter-based methods



## Matches vs. Poses



S. Middelberg, T. Sattler, O. Untzelmann, L. Kobbelt. Scalable 6-DOF Localization on Mobile Devices. ECCV 2014.



## Asynchronous Localisation



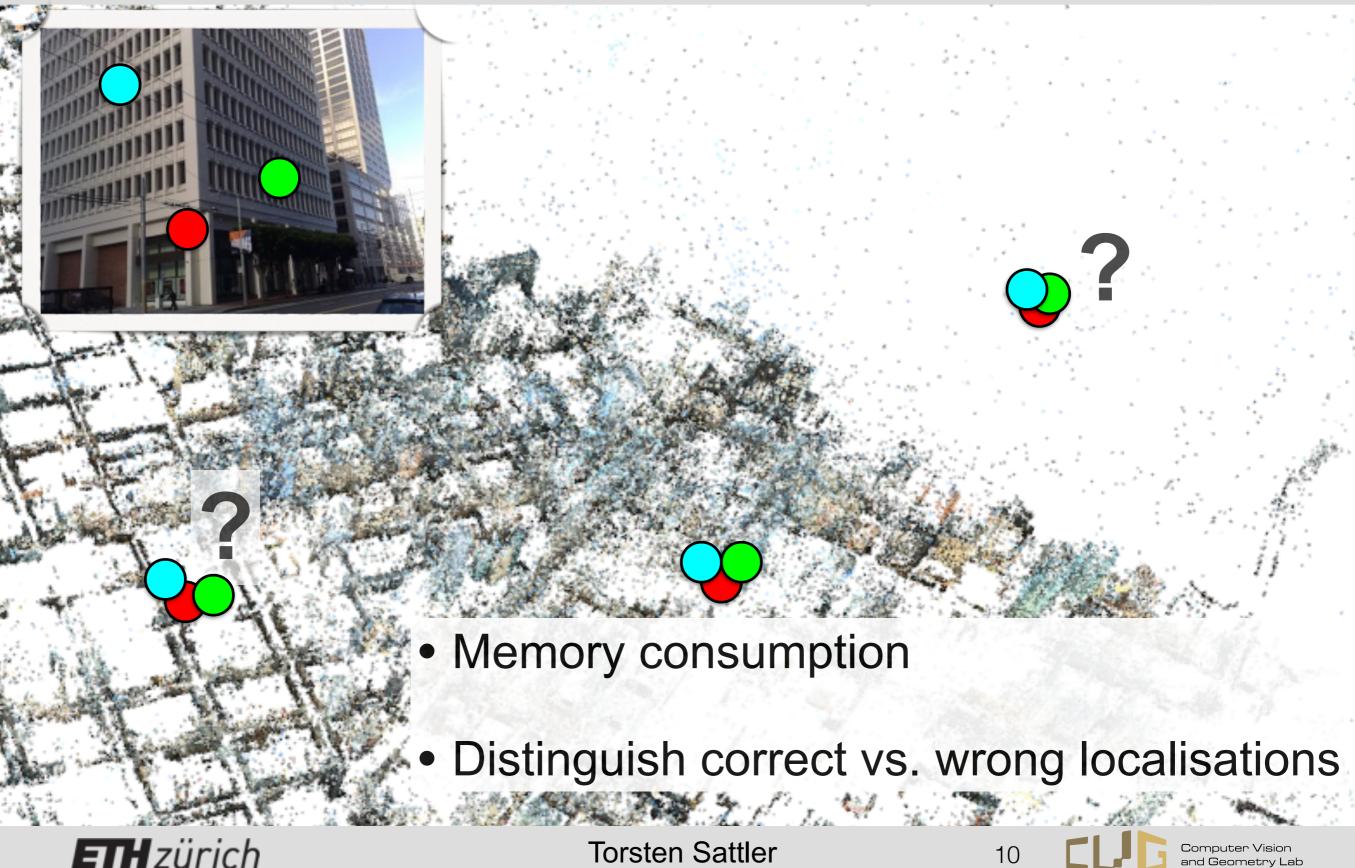


S. Lynen, T. Sattler, M. Bosse, J. Hesch, M. Pollefeys, R. Siegwart, Get Out of My Lab: Large-scale, Real-Time Visual-Inertial Localization. RSS 2015

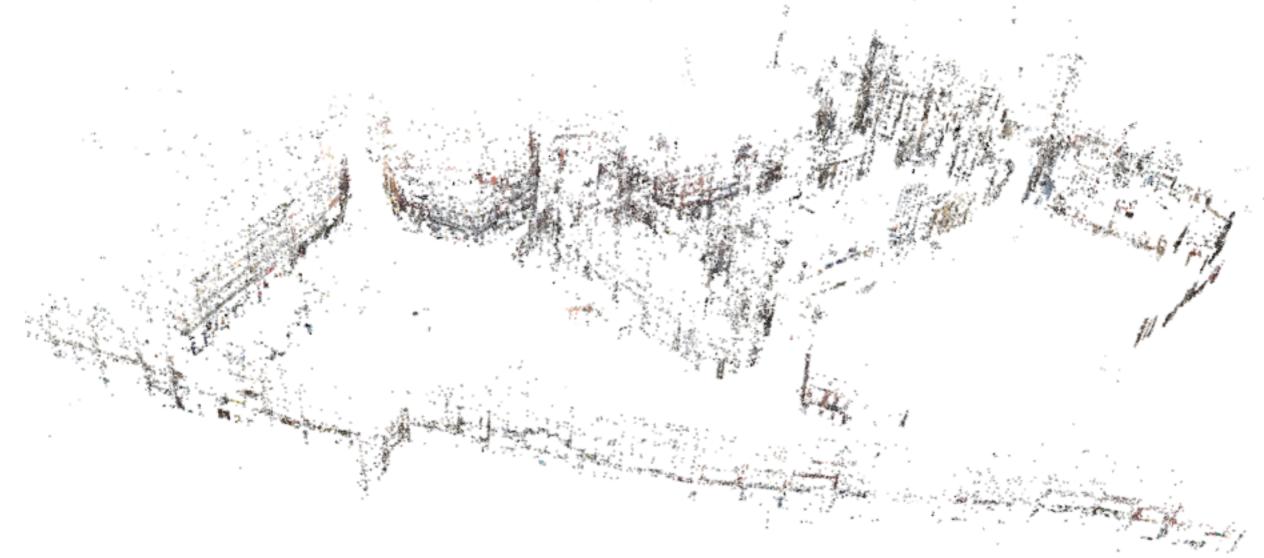




# Challenges at Large-Scale



# Compact Maps



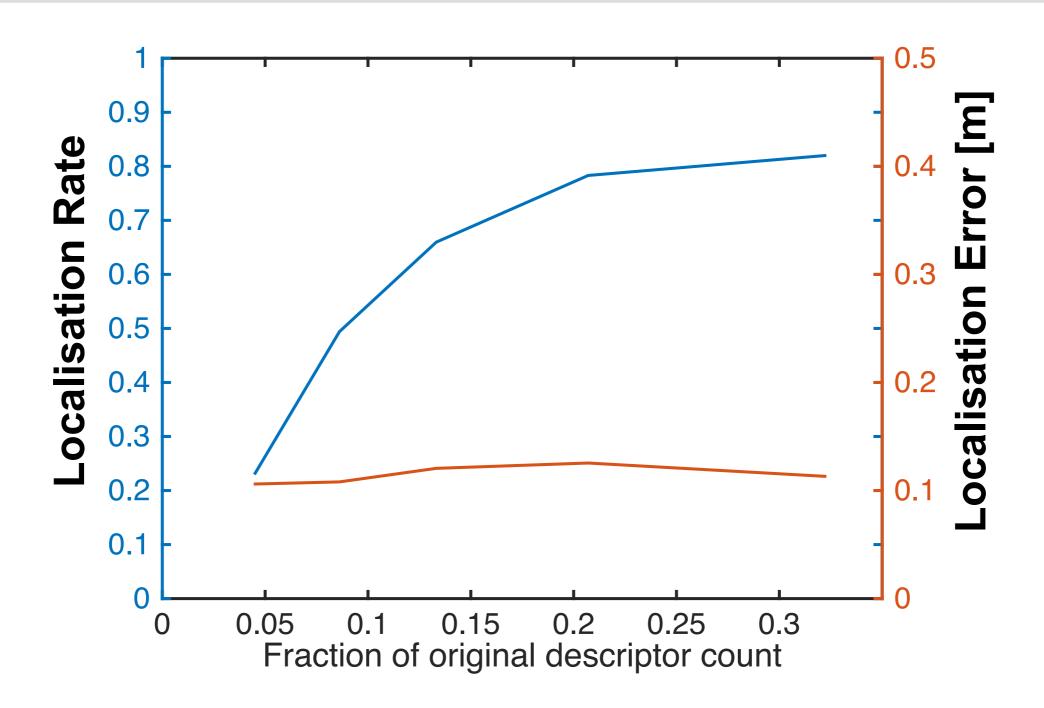
- Redundancy: Not every point required for localisation
- Select subset of points s.t. every database image observes ≥N points

[Li et al., ECCV'10] [Cao & Snavely, CVPR'14]





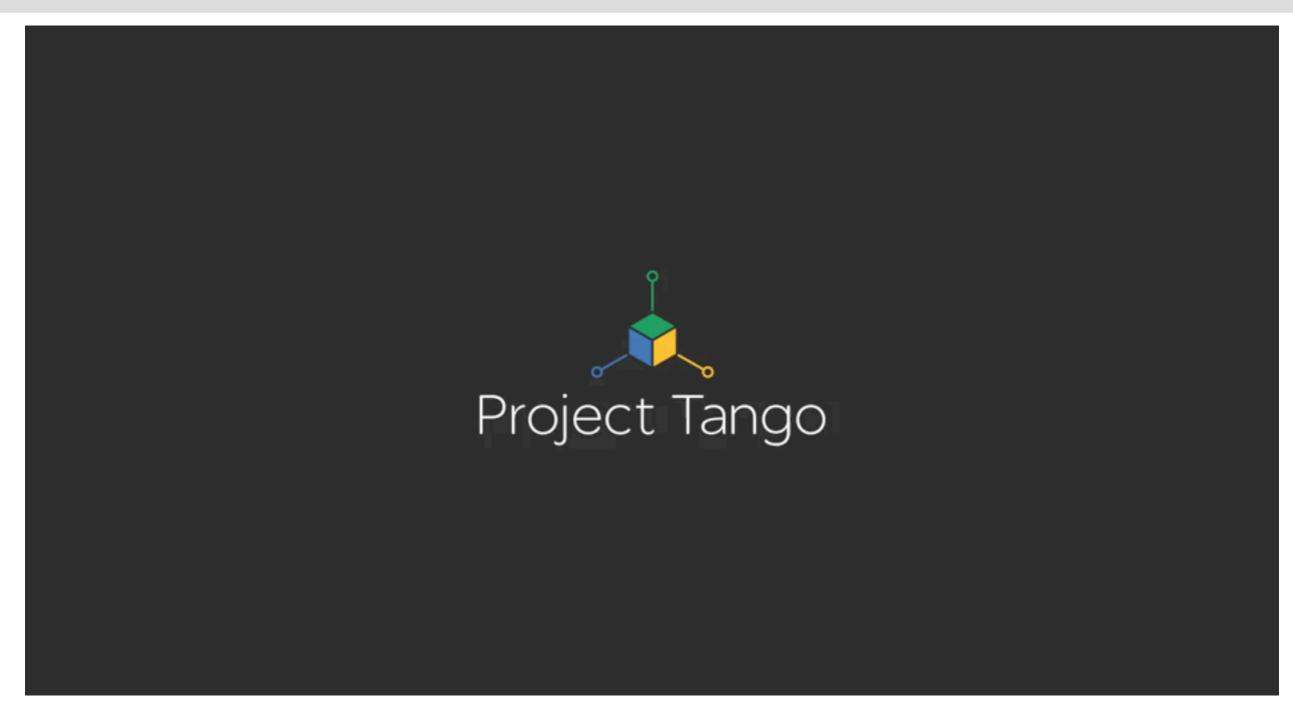
# Compact Maps



S. Lynen, T. Sattler, M. Bosse, J. Hesch, M. Pollefeys, R. Siegwart, Get Out of My Lab: Large-scale, Real-Time Visual-Inertial Localization. RSS 2015



# Compact Maps



Video credit: Simon Lynen

S. Lynen, T. Sattler, M. Bosse, J. Hesch, M. Pollefeys, R. Siegwart, Get Out of My Lab: Large-scale, Real-Time Visual-Inertial Localization. RSS 2015



## Compression by Quantisation

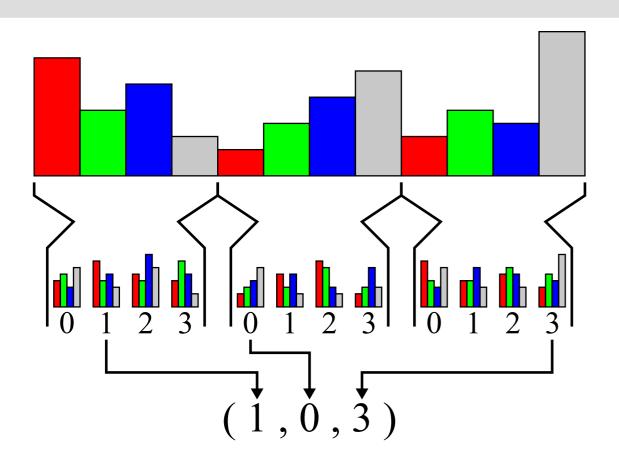
3D position	N descriptors	N image IDs	Add data
12 bytes	40 · N bytes	4 · N bytes	Auu. uala

3D point reconstructed from N database images

- Need certain number of points to enable localisation
- Further compression by descriptor quantisation



## Product Quantisation



**Original descriptor** 

Vocabulary per component

**Quantised descriptor** 

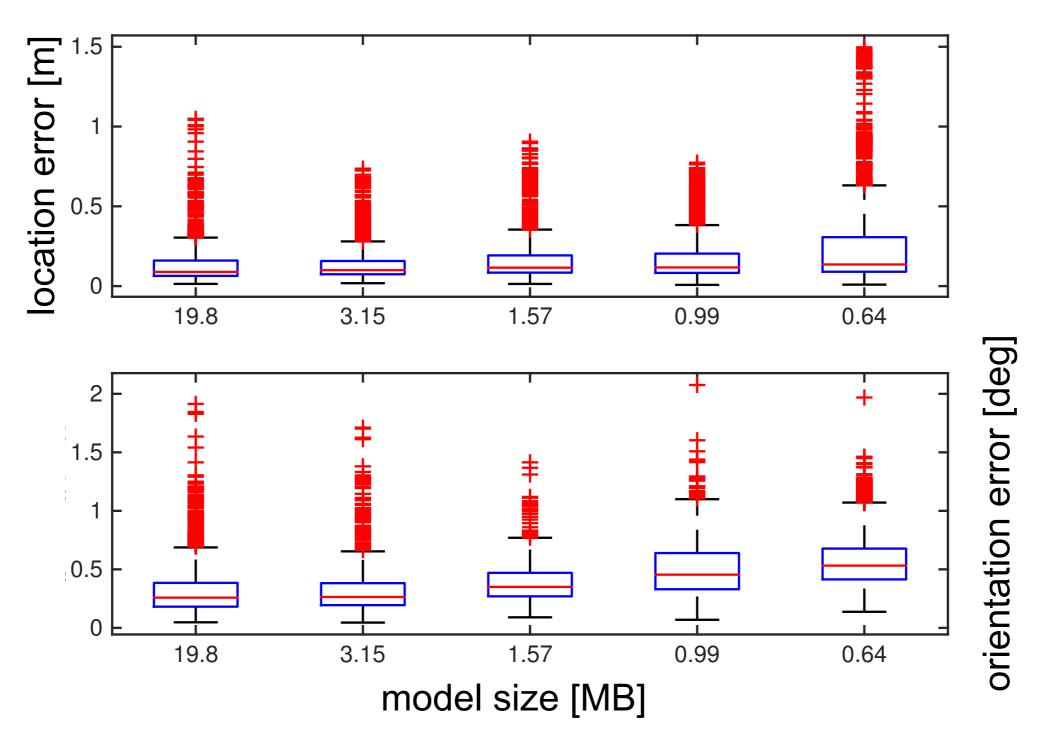
Example: 8 components with 256 words each

- Quantised descriptor requires 8 bytes
- $256^8 = 2^{64}$  product words
- Note: Many words not "meaningful"

[Jégou et al., PAMI'11]



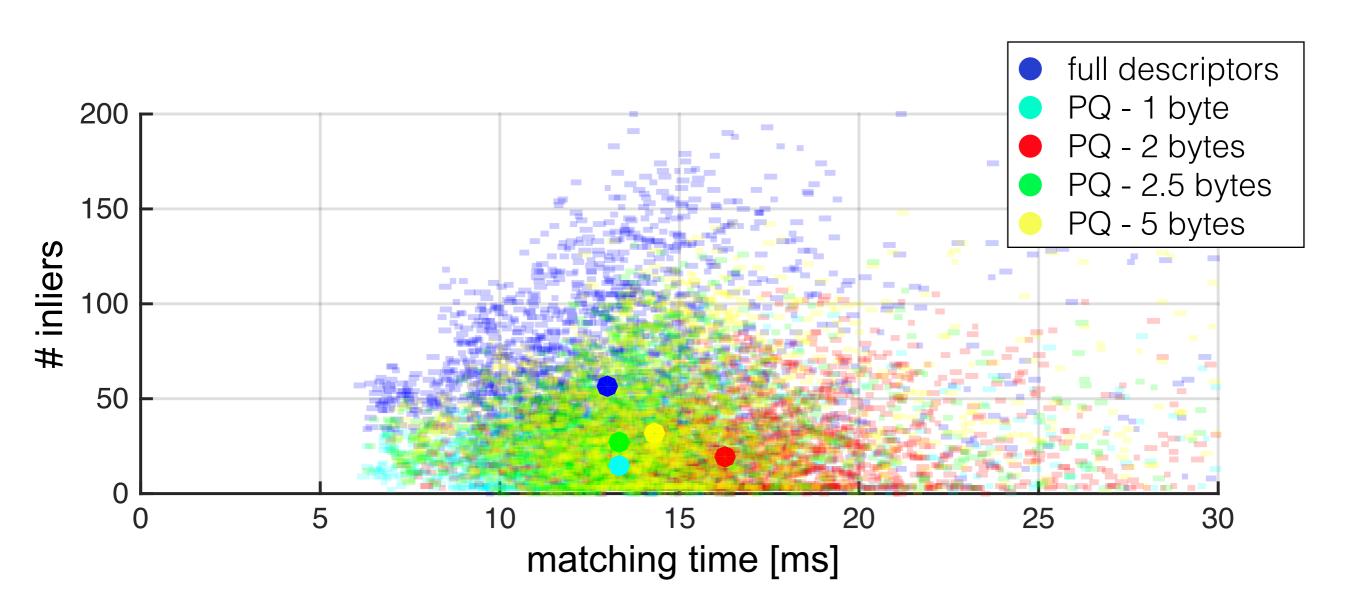
## Product Quantisation



S. Lynen, T. Sattler, M. Bosse, J. Hesch, M. Pollefeys, R. Siegwart, Get Out of My Lab: Large-scale, Real-Time Visual-Inertial Localization. RSS 2015



## The Price of Quantisation



S. Lynen, T. Sattler, M. Bosse, J. Hesch, M. Pollefeys, R. Siegwart, Get Out of My Lab: Large-scale, Real-Time Visual-Inertial Localization. RSS 2015



#### Lessons Learned

- Significant compression by descriptor quantisation
  - Storing descriptors not a bottleneck anymore
- Price of compression:
  - Fewer inliers
  - Reduced localisation rate
- Trade-off feasible for robust SLAM / VIO
  - Also applicable for large-scale, one-shot localisation?





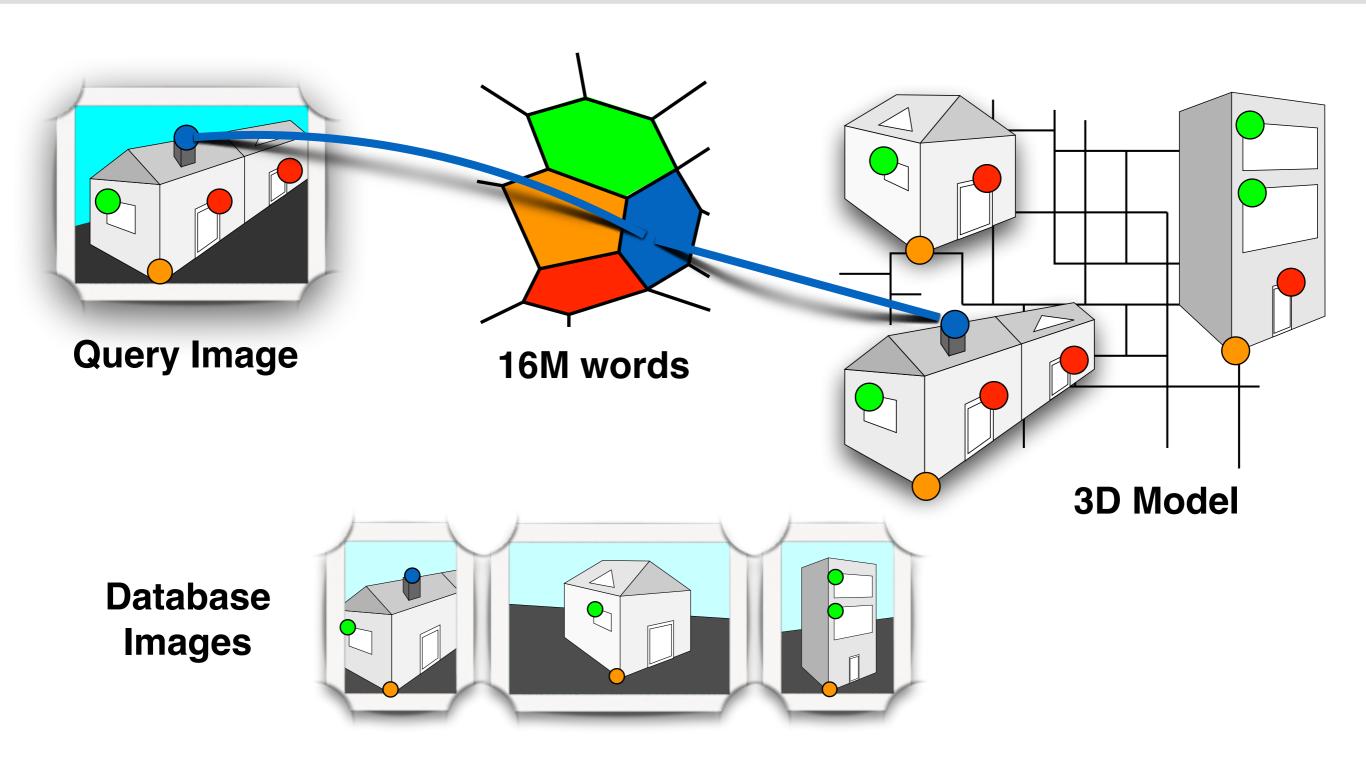
# Working on a Large Scale



Y. Li, N. Snavely, D. Huttenlocher, P. Fua, Worldwide Pose Estimation using 3D Point Clouds. ECCV 2012



# Matching with Hyperpoints



T. Sattler, M. Havlena, F. Radenovic, K. Schindler, M. Pollefeys, Hyperpoints and Fine Vocabularies for Large-Scale Location Recognition. ICCV 2015

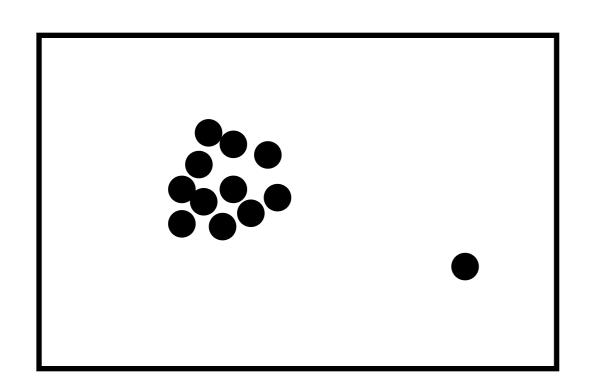




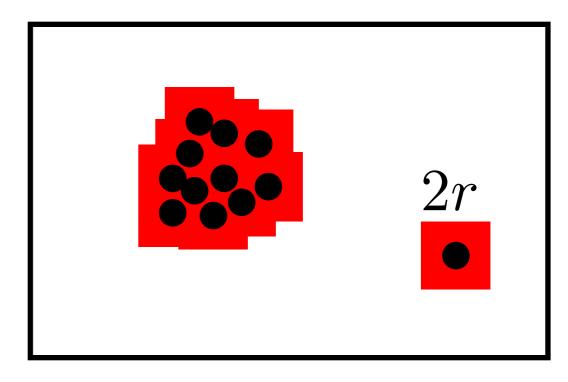
30 inliers







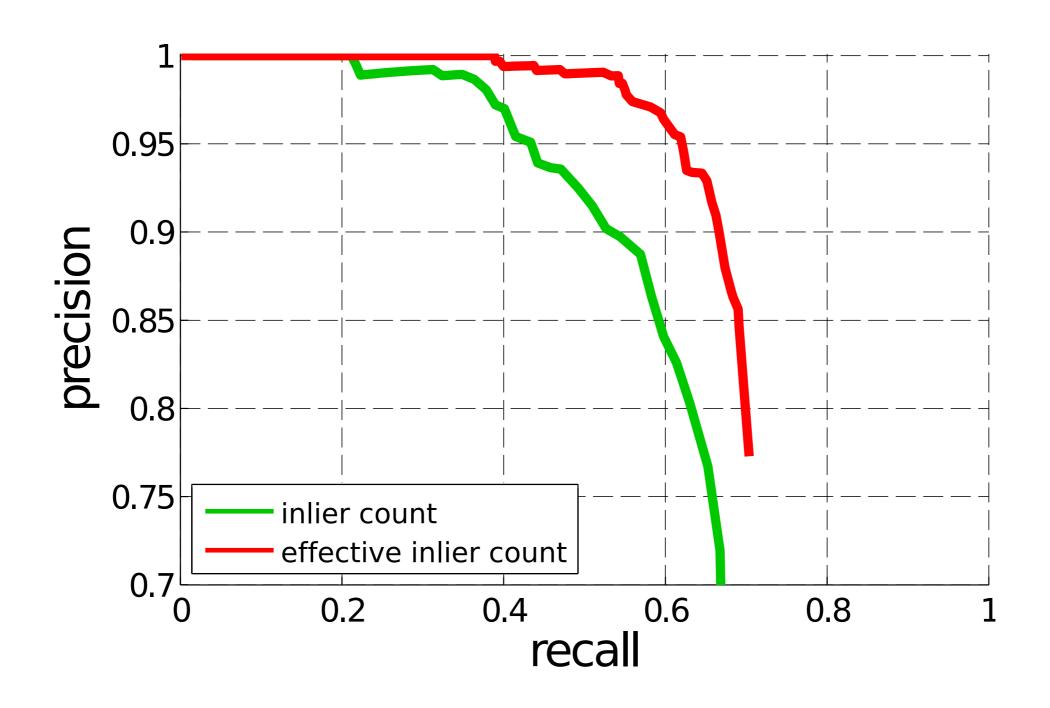
N inliers



 $area(\square)/(4r^2 \cdot N) \cdot N$  inliers

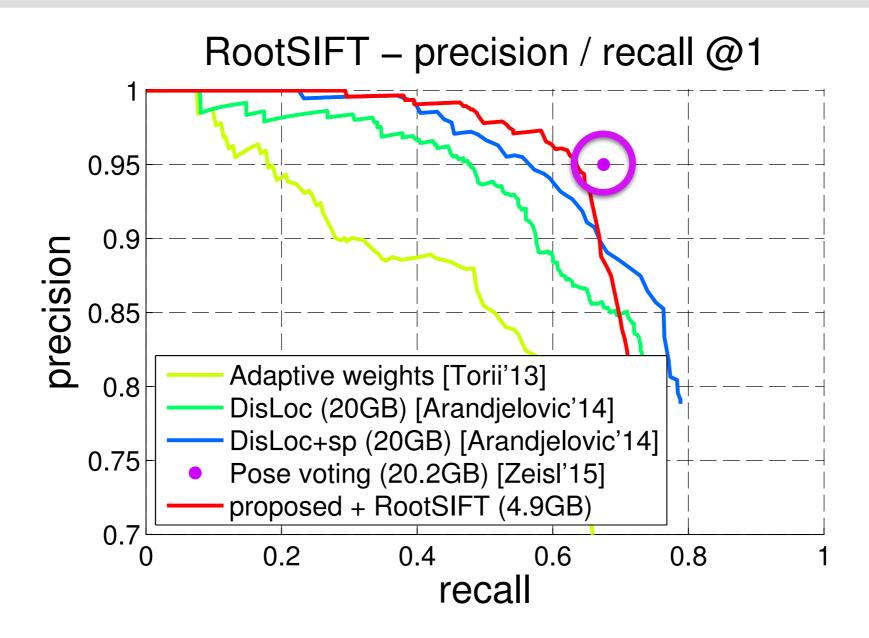
A. Irschara, C. Zach, J.-M. Frahm, H. Bischof, From Structure-from-Motion Point Clouds to Fast Location Recognition. CVPR 2009





T. Sattler, M. Havlena, F. Radenovic, K. Schindler, M. Pollefeys, Hyperpoints and Fine Vocabularies for Large-Scale Location Recognition. ICCV 2015





k-means vocabulary, specifically learned for dataset

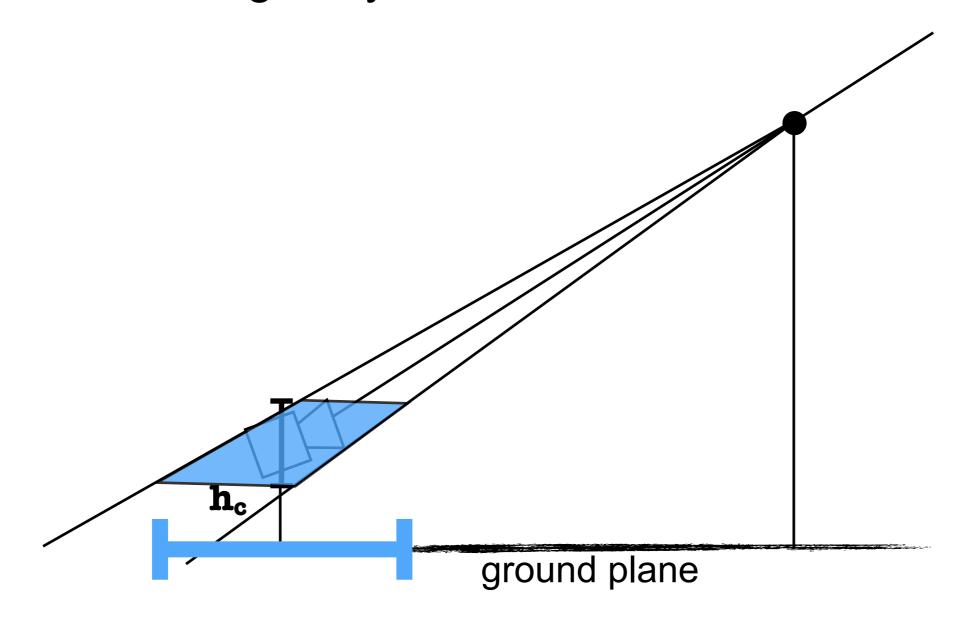
T. Sattler, M. Havlena, F. Radenovic, K. Schindler, M. Pollefeys, Hyperpoints and Fine Vocabularies for Large-Scale Location Recognition. ICCV 2015





## Local Registration Problem

Known: Intrinsics, gravity direction

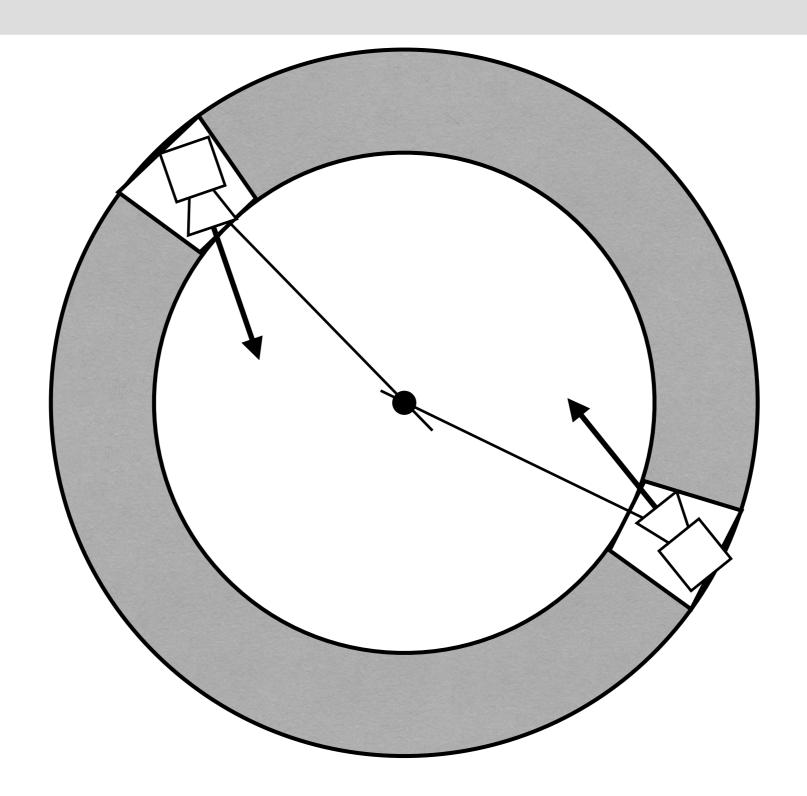


L. Svärm, O. Enqvist, M. Oskarsson, F. Kahl, Accurate Localization and Pose Estimation for Large 3D Models, CVPR'14





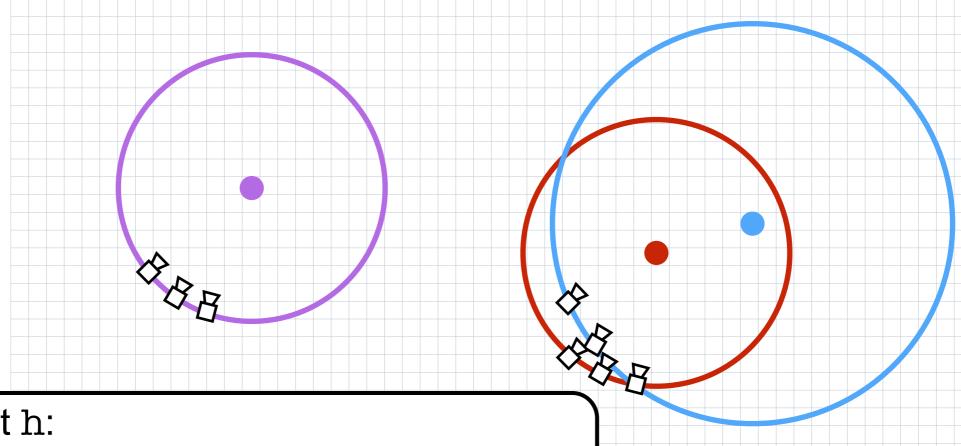
## Global Pose Estimation



B. Zeisl, T. Sattler, M. Pollefeys, Camera Pose Voting for Large-Scale Image-Based Localization, ICCV 2015



# Camera Pose Voting



for each height h:

for each viewing direction  $\theta$ :

for each 2D-3D match:

vote for position

find best position, update best pose

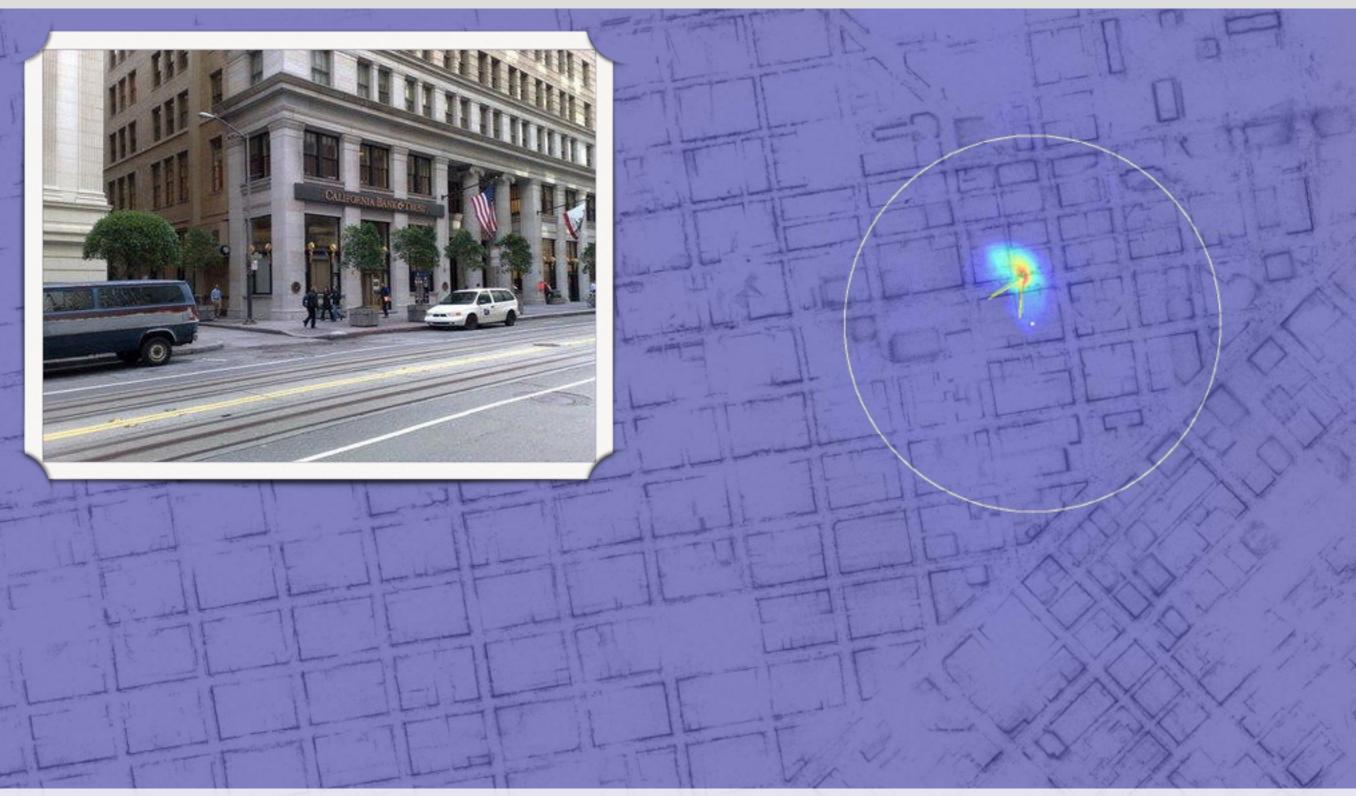
Refine pose using RANSAC

B. Zeisl, T. Sattler, M. Pollefeys, Camera Pose Voting for Large-Scale Image-Based Localization, ICCV 2015





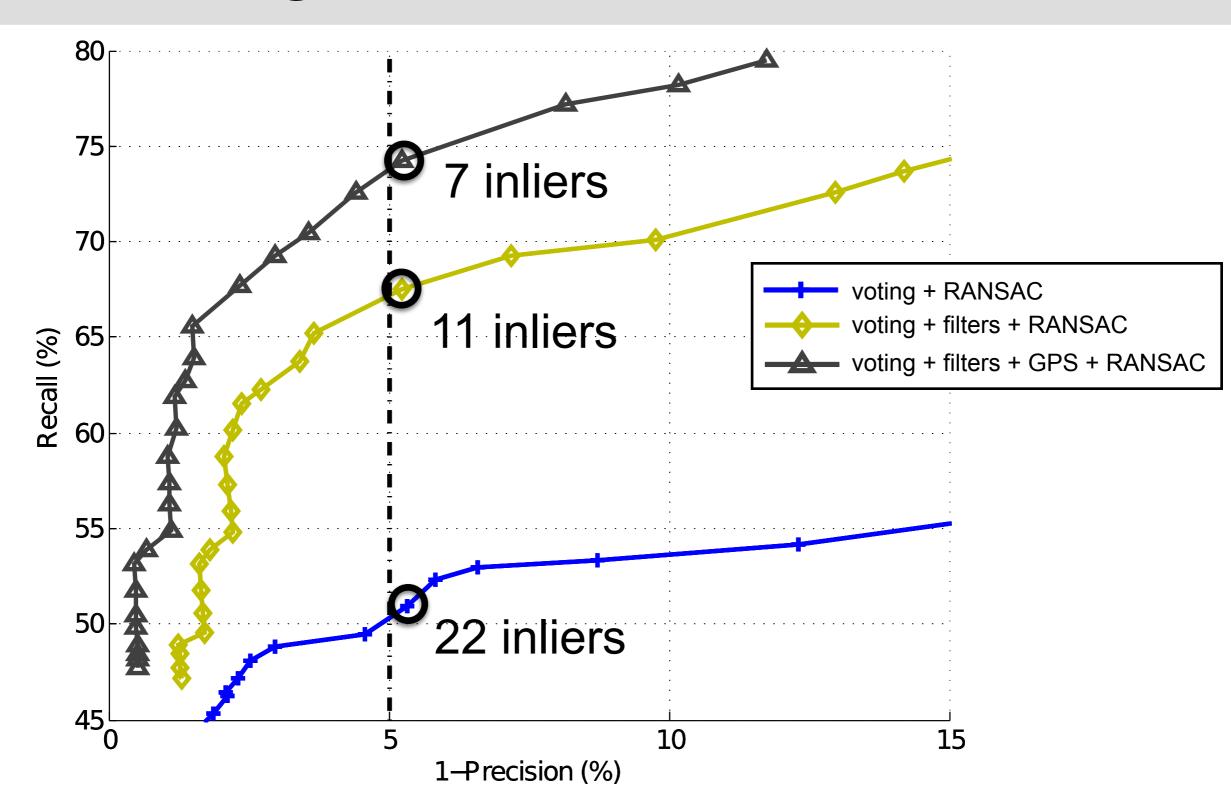
## Matching with Full Descriptors



B. Zeisl, T. Sattler, M. Pollefeys, Camera Pose Voting for Large-Scale Image-Based Localization, ICCV 2015



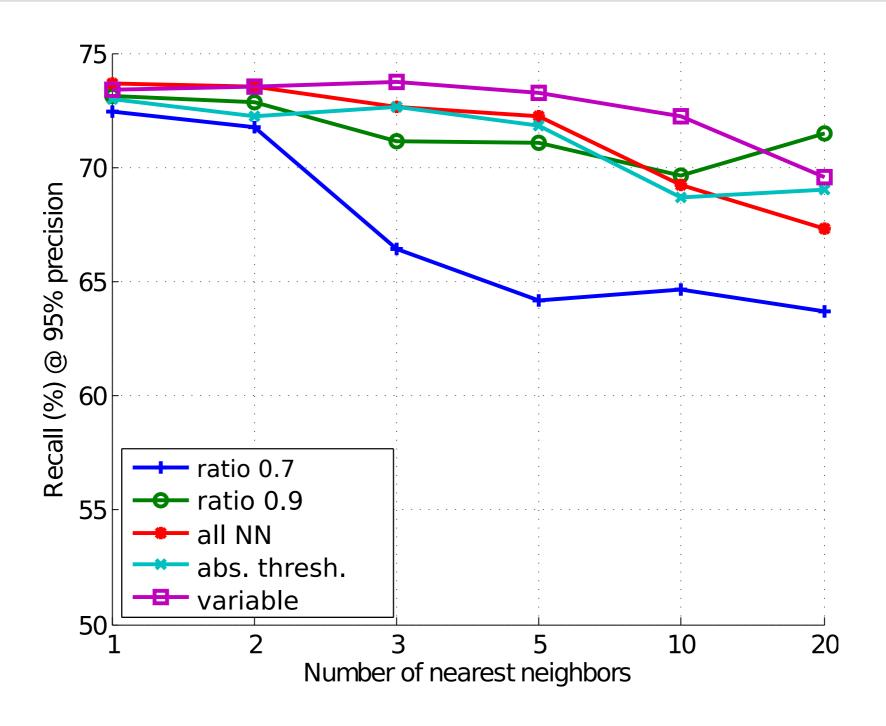
### Matching with Full Descriptors



B. Zeisl, T. Sattler, M. Pollefeys, Camera Pose Voting for Large-Scale Image-Based Localization, ICCV 2015



## Matching with Full Descriptors



B. Zeisl, T. Sattler, M. Pollefeys, Camera Pose Voting for Large-Scale Image-Based Localization, ICCV 2015



#### Lessons Learned

- Individual feature descriptors become less discriminative at large scale
  - Exploiting feature geometry helps...
  - but does not resolve the problem
- Matching with quantised descriptors works surprisingly well
  - ... but better understanding required
- #inliers not good for distinguishing between correct and wrong camera poses



#### The Future of (Real-Time) SLAM?

- Compact map representations?
- Better understanding on when to trust camera pose estimates
  - Semantic understanding of scenes?
- Handling more challenging scenes
  - Natural scenes (forests, ...)
  - Long-term localisation and mapping
  - Nighttime localisation against daytime maps?

