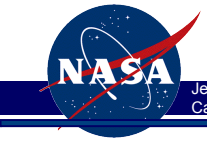
Hybrids
Mixed Approaches



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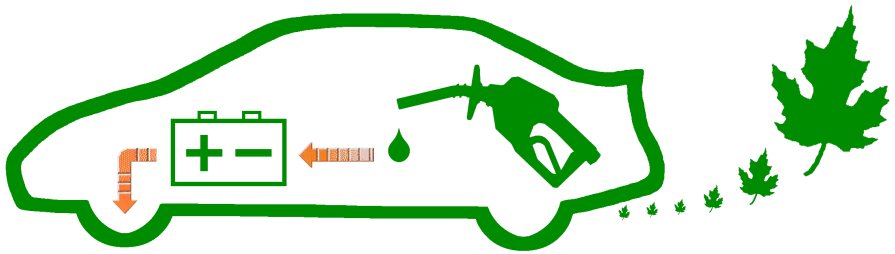


Outline

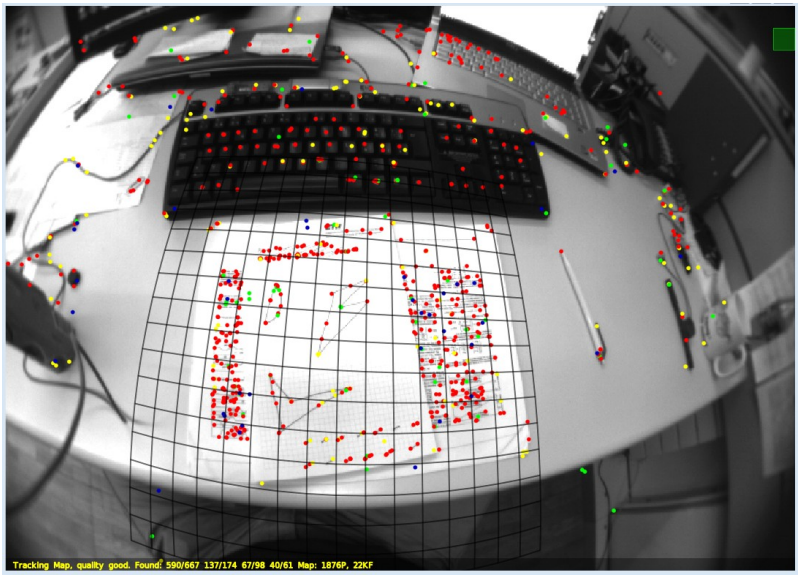
- Why mixing?
- Parallel Tracking and Mapping
  - Benefits and Issues
- Including Optical Flow
- Semi-Direct Visual Odometry
  - A dense'ish approach

PTAM, Klein & Murray ISMAR 2007

Why Mixing?

- Different approaches have different benefits
  - Mix to get “best” properties for specific application

- Visual odometry
  - Fast, easy to implement
  - Frame-to-frame VO drifts temporally
  - No notion of the past (i.e. visited places)



- SLAM
  - Full SLAM is globally consistent
  - Closes loops
  - Slow and more complex to implement

- Sparse and dense realizations

- For robotic applications:
  - Fast local pose information mostly is sufficient
  - Slow scale drift still is important

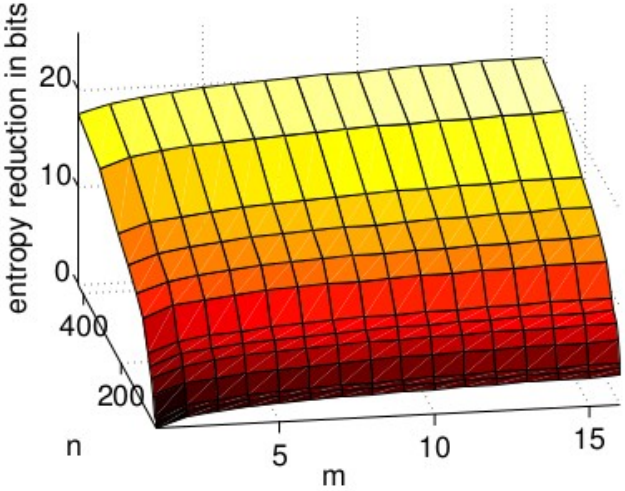
Newcombe & Davison CVPR 2010

PTAM: A FAST SLAM approach

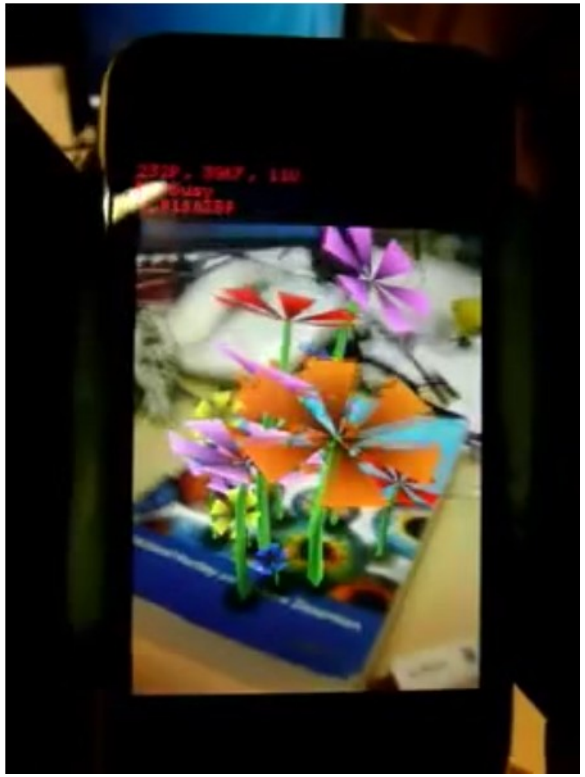
Parallel Tracking And Mapping (PTAM)

- Hybrid between BA, localization with known landmarks, and sparse VO
- Ran on a cell phone processor back in 2009
- Designed for small workspaces [Klein & Murray ISMAR 2007]
  - Reduced to windowed VO for large environments [Weiss et al. JFR 2013]

- Allows to track many features
  - Favorable over many camera poses



n=features, m=camera poses
[Strasdat et al. ICRA 2010]

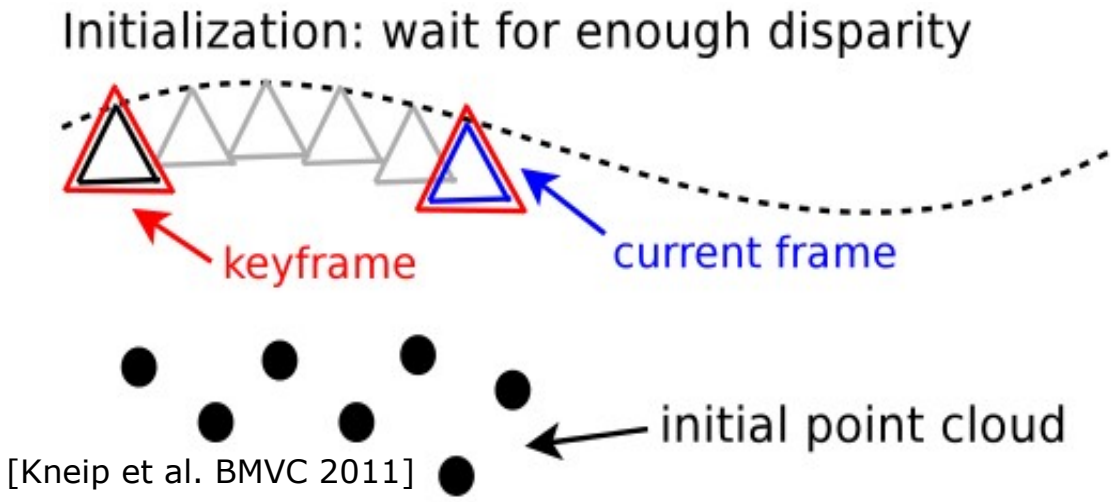


[Klein & Murray ISMAR 2009]

PTAM: A FAST SLAM approach

Parallel **T**racking **A**nd **M**apping (PTAM) [Klein & Murray ISMAR07]

- BA part:
  - Optimizes specific camera frames: keyframes
  - Optimizes 3D features in map
  - Runs in a separate thread in the background
  - Continuously optimizes the "world" if resources are available
  - Initialization and feature map required: can fail!

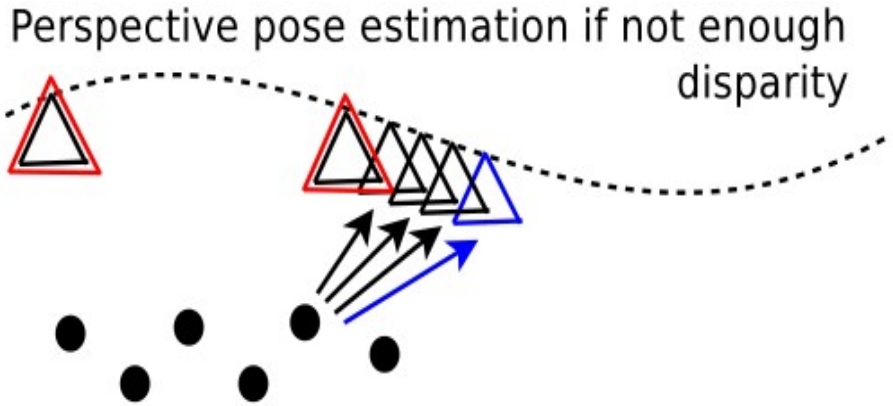


[Kneip et al. BMVC 2011]

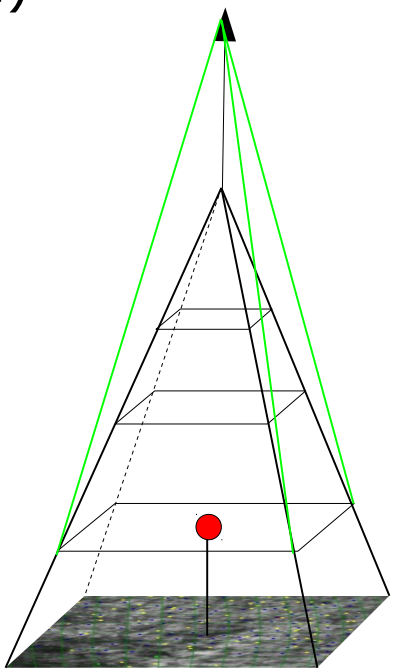
PTAM: A FAST SLAM approach

Parallel **T**racking **A**nd **M**apping (PTAM) [Klein & Murray ISMAR07]

- Localization with known landmarks
  - Only use "known" map features for pose estimation
  - Very fast: p3p algorithm, separate thread in foreground
  - Does not drift over time
  - Tracking: robust against view point and scale change
    - Warp feature descriptors (still fast though)
    - Use different pyramidal levels



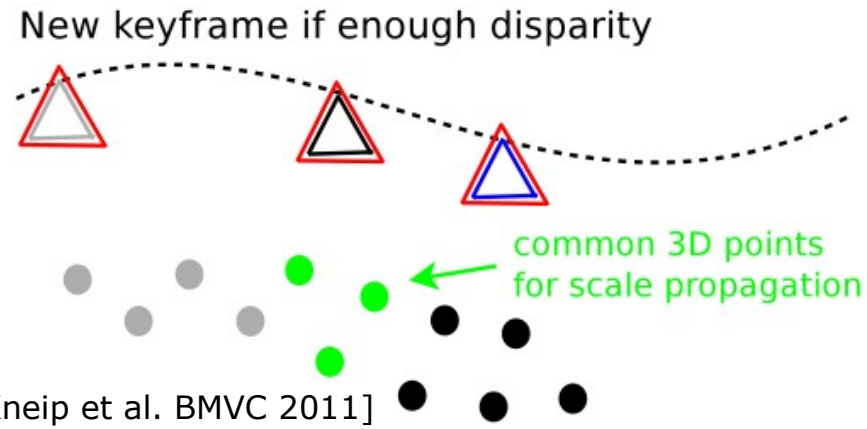
[Kneip et al. BMVC 2011]



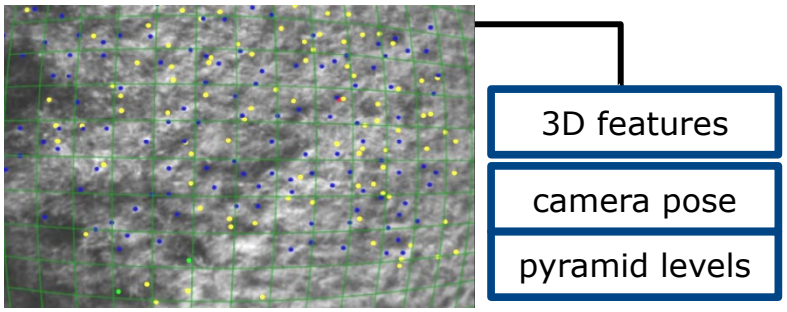
PTAM: A FAST SLAM approach

Parallel **T**racking **A**nd **M**apping (PTAM) [Klein & Murray ISMAR07]

- Visual odometry
  - Estimate R, T for first 2 keyframes: initialization
  - Add keyframe when entering unmapped area
    - Use epipolar constraint and motion model
  - Use known 3D points for scale propagation
  - Interleaves with tracking and mapping thread!



[Kneip et al. BMVC 2011]



Keyframe: typical outdoor scene

PTAM: From Small to Large Workspaces

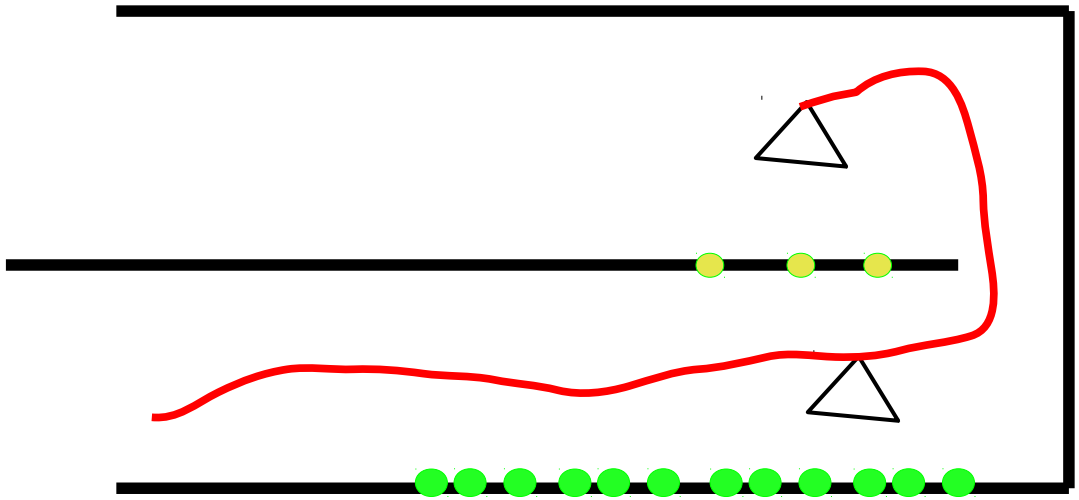
- Global BA is not tractable for large areas
  - Use local optimization/windowed techniques or iSAM2
  - Optimize local map with N closest key-frames
    reduce algorithm to constant complexity
    - Introduces drifts: scale, position, attitude

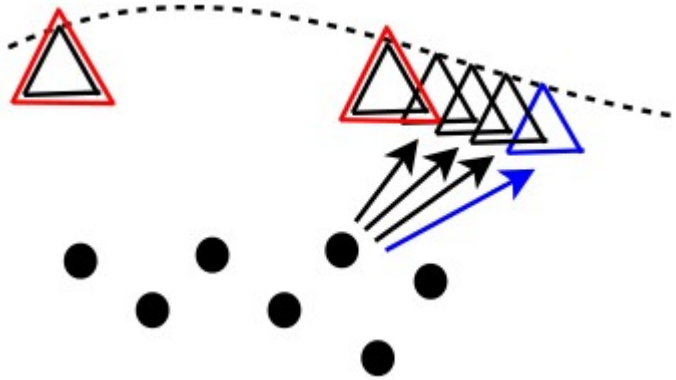
[Weiss et al. JFR 2013]

PTAM & IOF
Map Based Navigation with Map Free Fallback

- **Robot applications:** need pose information at any time
- BA part of PTAM generates known feature map
  - Needs 2-frame initialization
  - Can get corrupted/fail over time
  - How to determine if map is good? Re-initialization?
  - When to create a new keyframe?

- Non-Hybrid approaches:
  - Find global optimum or
  - Do not care about the past



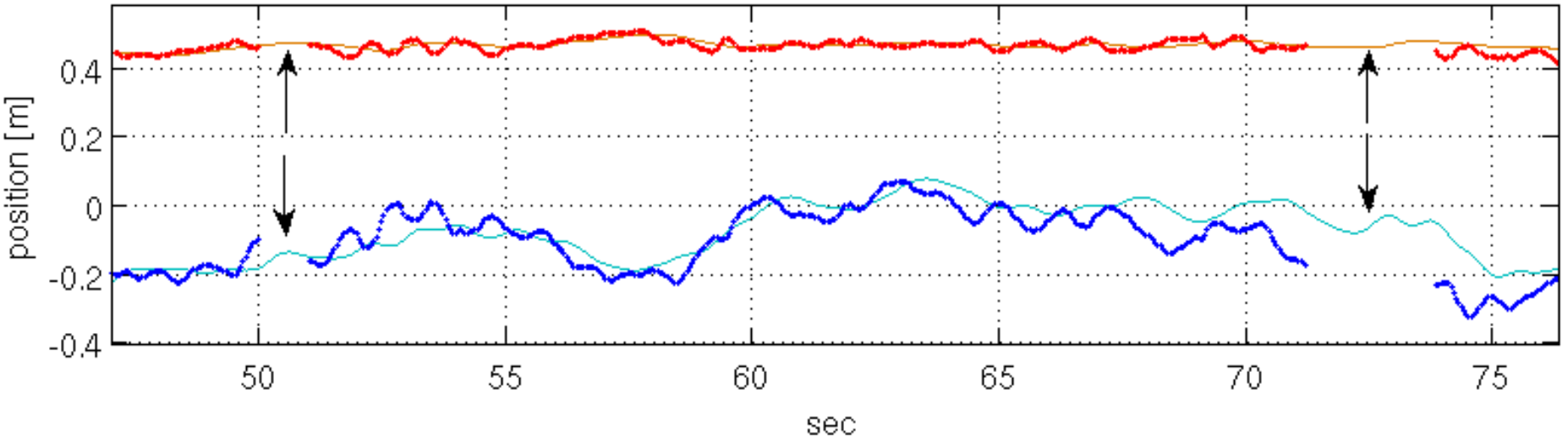


PTAM & IOF
Map Based Navigation with Map Free Fallback

- Mitigate map failures by using a map free approach
  - Optical flow only needs 2 images, provides velocity
  - Combined with inertial cues (IOF) yields metric velocity (see morning lecture)

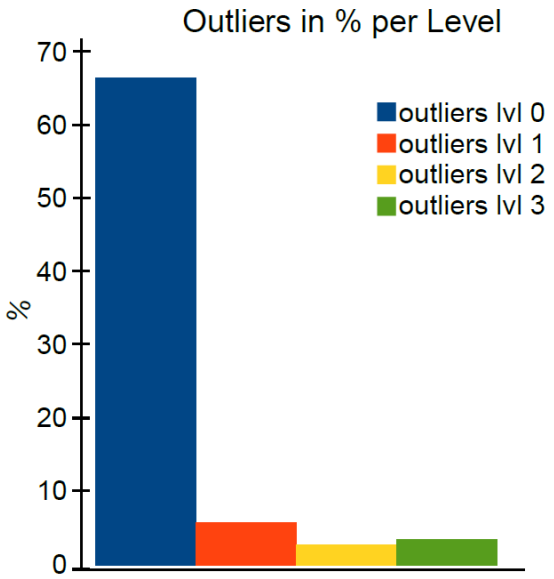
- Combination by separate algorithms, graph based or EKF based implementation (see morning lectures)

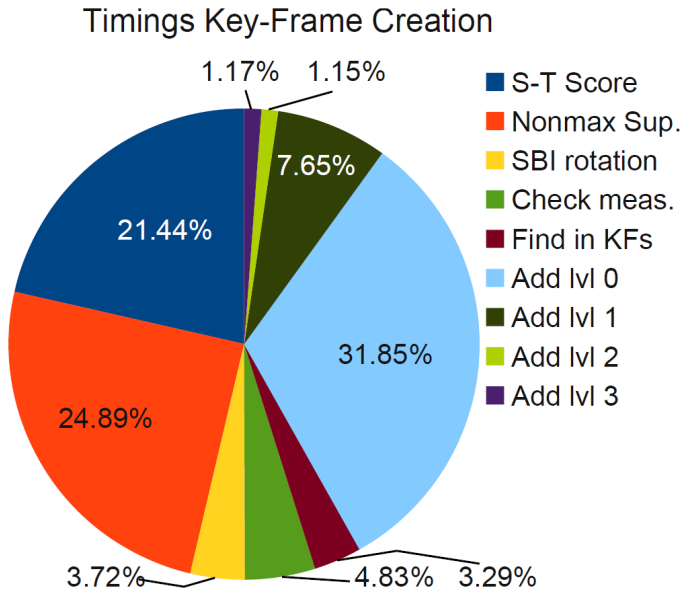
[Weiss et al. ICRA 2012]

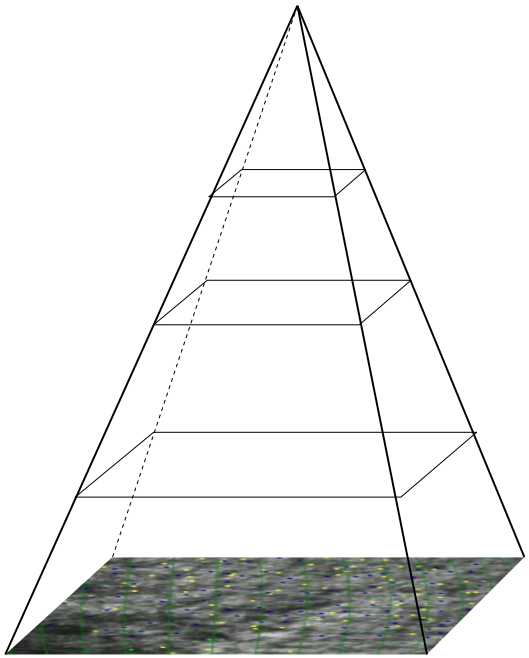


PTAM
Removing the Features

- Repetitive structures are difficult to disambiguate
- Motion blur can cause feature loss
- Example: PTAM outlier statistics
  - Critical at keyrfame creation
  - Lot of computation power for outliers



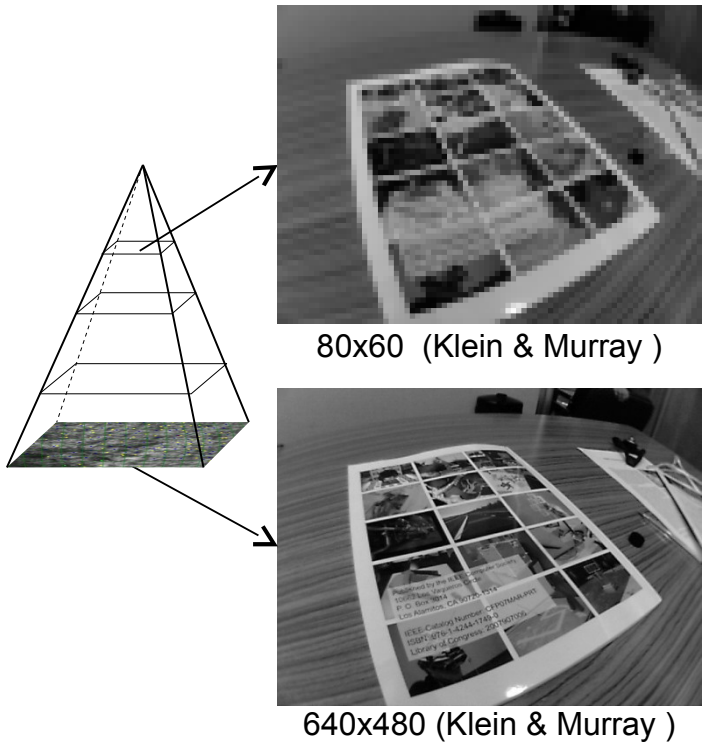


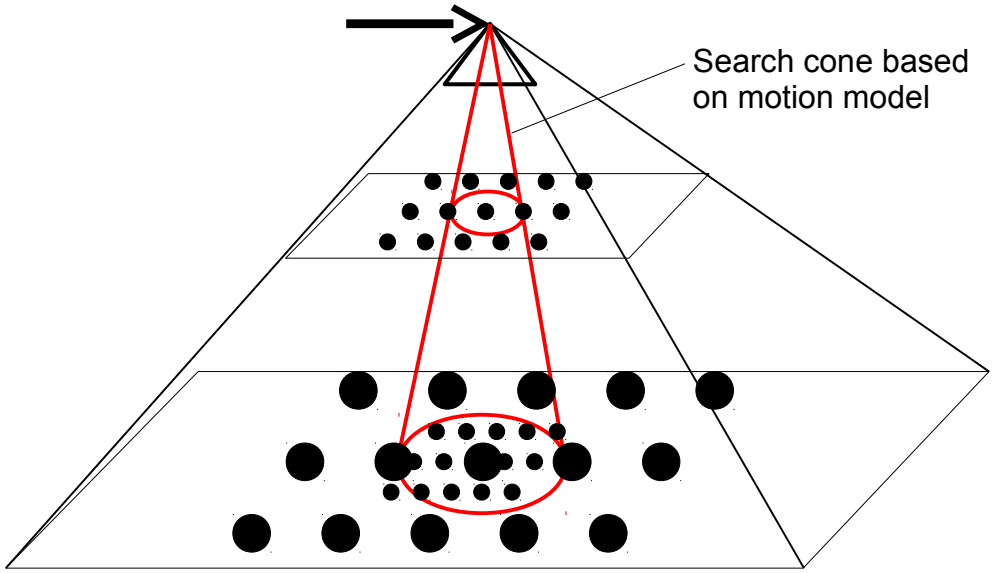


[Weiss et al. JFR 2013]

PTAM
Removing the Features

- Remove outlier-heavy pyramidal levels in map [Weiss et al. JFR 2013]
  - More accurate map, less drift
  - Beneficial for motion model: limit search region

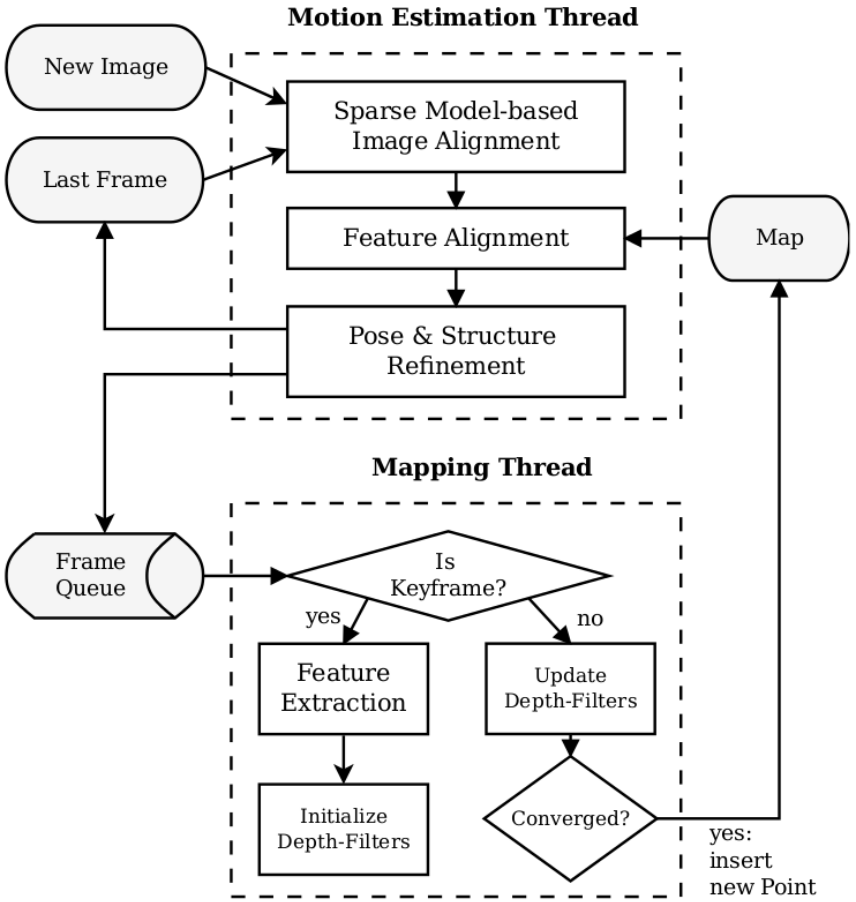




PTAM
Removing the Features

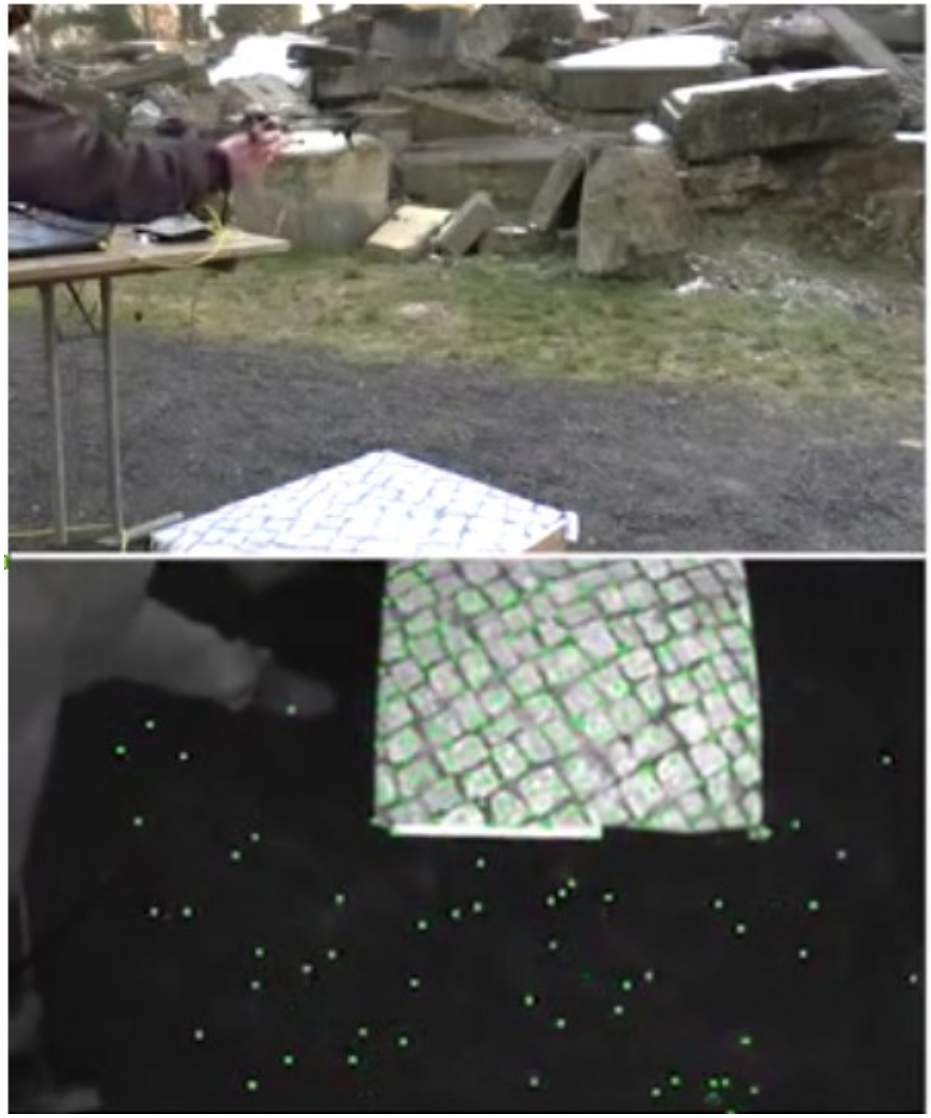
- Use dense approach for initial alignment in tracking part
  - Use dense VO to replace motion model
  - Refine: sparse feature matching with map
  - Good initial motion estimate disambiguates similar features and reduces wrong matches
  - Speed-up of feature matching due to small search region
  - Example: SVO

- Hybrid between sparse, dense, VO, and SLAM



[Forster et al. ICRA 2014]

PTAM
Removing the Features



Outdoor Example

3x

Q & A