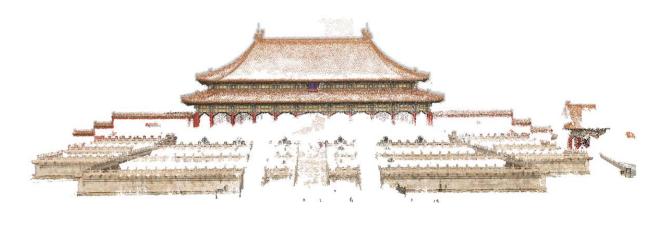
12. Simultaneous Localization And Mapping (SLAM)







Outline

- LiDAR SLAM
- Visual SLAM
- Robustness Techniques





SLAM

- Simultaneous Localization and Mapping
 - Localization: estimating the sensor's pose (location and orientation)
 - Mapping: building a map
 - SLAM: building a map and locating the sensor at the same time
- A chicken-and-egg problem
 - A map is needed for localization
 - A pose estimate is needed for mapping





Visual SLAM Demos







ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras

Raúl Mur-Artal and Juan D. Tardós

raulmur@unizar.es

tardos@unizar.es





Visual SLAM Applications







Augmented Reality

Microsoft Hololens



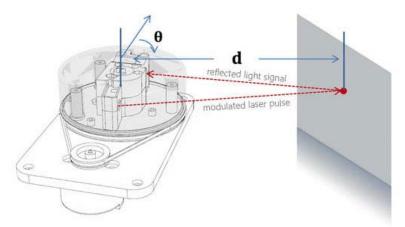




2D LiDAR SLAM

- Widely used for ground robots
- Use a 2D LiDAR sensor to track planar motion
- 2D LiDAR sensor
 - With a rotating laser beam
 - Return distances to obstacles in a plane
 - E.g. 10×360 measurements per second



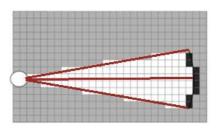


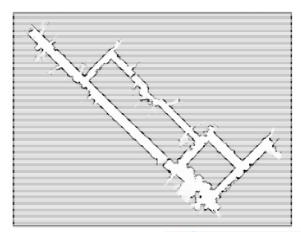




Map Representation (Occupancy Grid Map)

- Discretize the environment by a grid
 - E.g. 10 m \times 20 m space, 5 cm resolution \rightarrow 200 \times 400 map
 - Large maps require substantial memory resources
- Each grid cell can be empty, occupied, or unknown
 - E.g. white is empty, black is occupied, and grey is unknown
- Each laser beam tells the occupancy of some cells
 - Mark empty for cells on its path
 - Mark occupied for the cell at its end





occupied



free

space



Mapping with Known Poses

- Suppose the robot pose is known at all time
 - E.g. by some SLAM algorithms
- Accumulate empty/occupied votes from the LiDAR sensor over time
 - A cell is occupied, if the number of occupied votes is larger (by a threshold)
 - A cell is empty, if the number of empty votes is larger (by a threshold)
 - Otherwise, a cell is unknown

A sample map built from known poses along the red trajectory

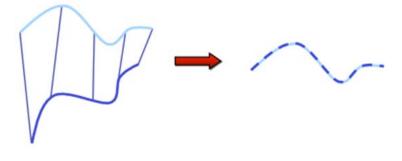






Pose Estimation

- Find the sensor pose according to its scan and a map
- It might be solved by the ICP (iterative closest point) algorithm
 - A widely used algorithm to register two sets of points
- ICP iterates the following two steps till converge
 - Find correspondence as nearest neighbors
 - Solve sensor motion from the found correspondences







Registration with Known Correspondence

Given two sets of corresponding points

$$X = \{x_1, x_2, ..., x_n\}$$
 and $P = \{p_1, p_2, ..., p_n\}$

- ullet Want: translation t and rotation R that register these two sets
- Mathematically, that means to minimize the following error

$$E(R,t) = \sum_{i=1}^{n} |x_i - Rp_i - t|^2$$

A closed-form solution can be derived easily (try it yourself)





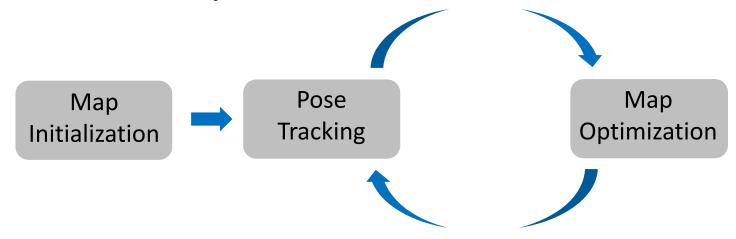
2D LiDAR SLAM Summary

- Initialize at t=0
 - The raw LiDAR scan is the initial map
- Start from t=1, iterate the following to steps:
 - Solve sensor pose at time t by the ICP algorithm
 - Update map according to the new scan at time t





Typical SLAM Systems Architecture



- LiDAR SLAM
 - Initialization: the first scan
 - Pose Tracking: ICP
 - Map Optimization: occupancy grid map

- Visual SLAM
 - Initialization: (essential matrix, triangulation, etc)
 - Pose Tracking:
 - 1. Feature tracking (next-next week)
 - 2. Pose-only BA (today)
 - Map Optimization:
 - 1. Triangulation, BA
 - 2. Loop closure, pose-graph (today)





Questions?





Outline

- LiDAR SLAM
- Visual SLAM
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Visual SLAM by SfM

• Solve an incremental SfM at every new frame VSLAM可以视作在连续的vi deo sequence上应用SfM,而且是采用增量式的SfM。

- Realtime constraint (many trade-offs for better efficiency)
 - Keyframe based mapping (only a subset of frames are used for mapping)
 - Local BA (bundle adjustment with only nearby video frames)

不会将所有的frame用来重建,而是挑出key frame进行重建, local BA:只对相邻的frame做BA,而不是对当前时刻以前的所有frame都做BA。

- Sequential video input
 - Sorted input images (match each image to its previous frame)
 - Regular time interval between frames (motion model to facilitate matching)

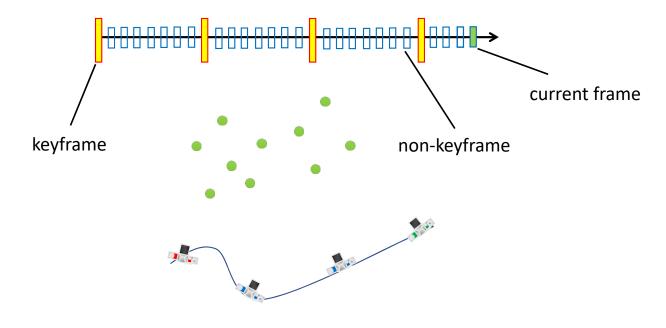
当前帧只需要和前一帧做特征匹配





Key-frame based Visual SLAM

- Solving camera pose for every input frame
- Only use some "keyframes" to triangulate/optimize map points

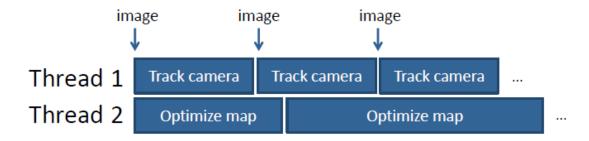






Parallel Tracking and Mapping (PTAM)

- Parallel tracking and mapping
 - A real time tracking thread runs in real-time (30Hz)
 - An offline mapping thread for map maintenance



需要同时维护两个线程

Parallel Tracking and Mapping for Small AR Workspaces

Georg Klein*

6一个要实时的计算相机姿态.

9二个可以延后性的维护地图构建(因为只对关键帧进行重建)

Active Vision Laboratory
Department of Engineering Science
University of Oxford

David Murray†

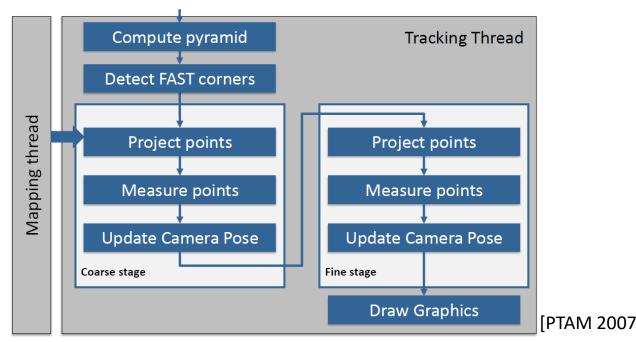
[ISMAR 2007]





Tracking

- Step 1: feature correspondence
 - Option 1: KLT feature tracking (next week)
 - Option 2: feature detection & matching (within a nearby neighborhood)





feature correspondence

- Generate 8x8 matching template (warped from keyframe)
- Search for correspondence in a fixed radius around projected position
 - Using SSD
 - Only search at pre-detected corner points (e.g. FAST points)







Tracking

- Step 2: solve camera motion
 - With camera pose initialized by extrapolation, e.g. constant velocity motion
 - With 3D map points fixed
 - Perform local camera only BA (BA with map points fixed)
 - Typically, use a robust cost function ρ on the re-projection error
 - Camera might also be initialized by PnP





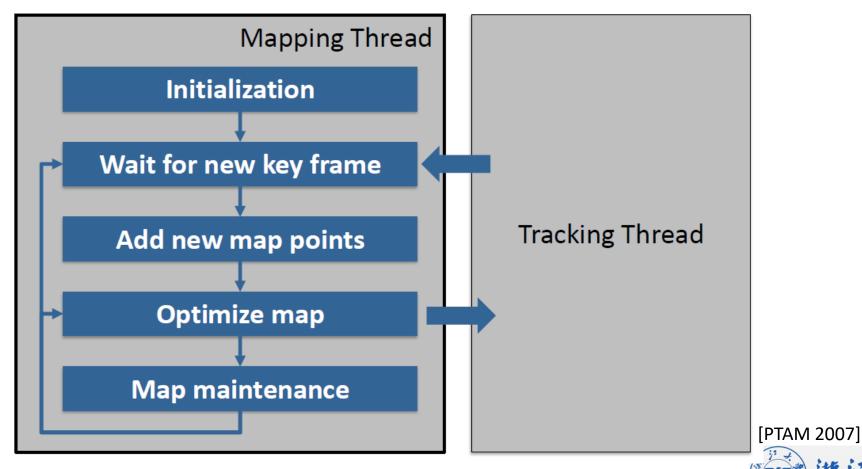
Mapping

- Triggered by the insertion of a new keyframe
- Triangulate any tracked image corners that are not reconstructed
- Run corner detection (e.g. Harris) to generate more points for tracking
- Call local BA to optimize both points and poses
 - BA is slow, may be called after several keyframe insertions





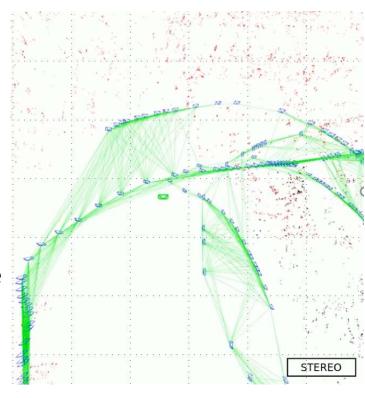
Mapping





Keyframes

- Defined heuristically, various from system to system
- A keyframe is typically inserted when:
 - Camera tracking is robust
 - There are insufficient corner points to track
 - There is a large camera motion (rotation or translation
 - There is no keyframe inserted for a while (e.g. more than 30 frames)
 - Etc.. 相机自带要稳定 跟踪角点丢失较多 相机运动(R和T)较大 隔多久取一个key frame







PTAM – Example Timings

Tracking thread

Total	19.2 ms	
Key frame preparation	2.2 ms	
Feature Projection	3.5 ms	
Patch search	9.8 ms	
Iterative pose update	3.7 ms	

Mapping thread

Key frames	2-49	50-99	100-149
Local Bundle Adjustment	170 ms	270 ms	440 ms
Global Bundle Adjustment	380 ms	1.7 s	6.9 s





Questions?





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Re-localization

- Tracking can lose due to various reasons
 - Motion blurs
 - Moving objects
 - Large occlusion
 - Sudden fast motion
 - Sudden illumination change
- Re-localization is to recover from such a sudden tracking failure





Re-localization

- Re-localization typically includes the following steps
 - Image search: search the current frame among the pre-indexed keyframes
 - E.g. by bag-of-words models (next next week)
 - It returns a keyframe with sufficient view overlap with the current frame
 - Feature matching between these two frames
 - PnP and local BA to register the current frame to the map
 - Continue the original SLAM





Localization

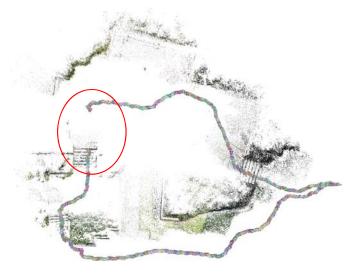
- The re-localization technique can be used in a different scenario:
 - Solve the mapping beforehand (offline)
 - Solve only the tracking online
 - E.g. solve every frame by re-localization
 - Frame-to-frame constraint might also be included
- The advantages of separate mapping and tracking
 - A high quality map is guaranteed
 - The most time consuming step (i.e. global BA) is moved to offline



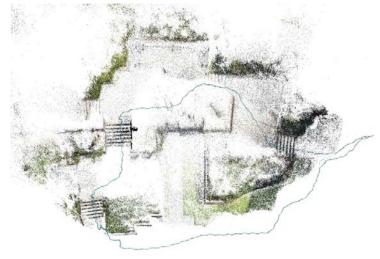


Drifting

- Small error accumulates to large map distortions
- The technical to reduce drifting is called loop closure



result with drifting error



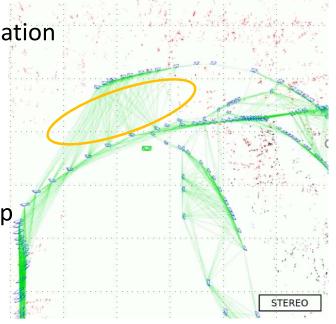
result after loop closure





Loop Closure

- Loop detection
 - Identify if a loop exist
 - Again, by the same image search technical in re-localization
 - Typically, applied to every newly inserted keyframe
- Construct a pose-graph for the next step
 - Where a keyframe is a vertex
 - Two keyframes are connected if they have view overlap



connection due to loop detection





Loop Closure

- Loop optimization
 - In the simplest case, a direct BA can generate good result
 - In many cases, the drifting error is too large to be corrected by BA
- Most of the time, a global SfM is desirable
 - Solving all keyframe poses from input pairwise relative motion constraints
 - Update map points afterwards
 - Referred as 'pose-graph optimization' in robotics
 - the keyframe graph is a graph with camera poses (no 3D points)
 - The most challenging problem is to deal with wrong loops (due to repetitive structures)
 - Studied in both computer vision and robotics community





Repetitive Structures

- Repetitive structures cause wrong essential matrices
- This is a problem for both global & incremental SfM
- Essentially, some pose-graph edges should be removed











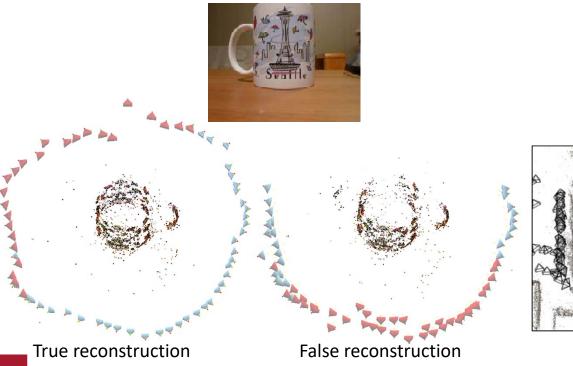




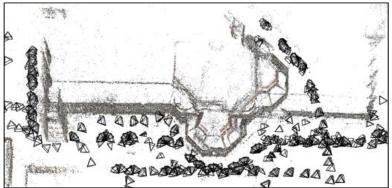


Repetitive Structures

• Repetitive structures could generate catastrophic fails to SfM (or pose-graph optimization)







False reconstruction



Questions?





A Brief History of Visual SLAM

- MonoSLAM, Andrew Davison [ICCV 2003] [PAMI 2007]
 - The first work of visual SLAM with a single camera
- Visual Odometry, David Nister [CVPR 2004]
 - Visual slam by SfM
- PTAM, Klein & Murray [ISMAR 2007] (open source)
 - Separating tracking and mapping
- LSD-SLAM, Engel et al. [ECCV 2014] (open source)
 - Direct method
- ORB-SLAM, Mur-Artal et al. [PAMI 2015] (open source)
 - A stronger version than PTAM, with re-localization, pose-graph, etc
- DSO, Engel et al. [PAMI 2017] (open source)
 - A stronger version of LSD-SLAM, with photometric auto-calibration, etc.



