ORB-SLAM: A Versatile and Accurate Monocular SLAM System

16-833: Robot Localization and Mapping

Sudharshan Suresh

Spring 2021

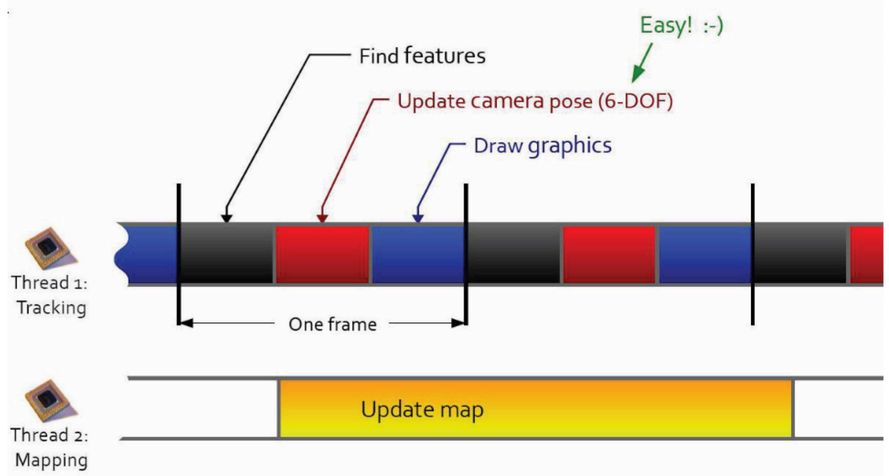
Slides courtesy: Paloma Sodhi

Mur-Artal, R., Montiel, J. M. M., & Tardos, J. D. **ORB-SLAM: a versatile and accurate monocular SLAM system**. IEEE Transactions on Robotics, 2015, 31(5), 1147-1163.

Parallel Tracking and Mapping

Key Ideas

- Keyframe-based monocular SLAM system
- Splits mapping and tracking in two parallel threads
- Bundle Adjustment possible in real-time



Limitations

- Restricted to small environments: no large-scale loop closing, keyframes grow unbounded
- Map initialization requires user interaction
- In tracking failure, re-localization not robust

Klein, Georg, and David Murray. "**Parallel tracking and mapping for small AR workspaces.**" Proceedings of IEEE and ACM International Symposium on Mixed and Augmented Reality (ISMAR), 2007.

ORB-SLAM

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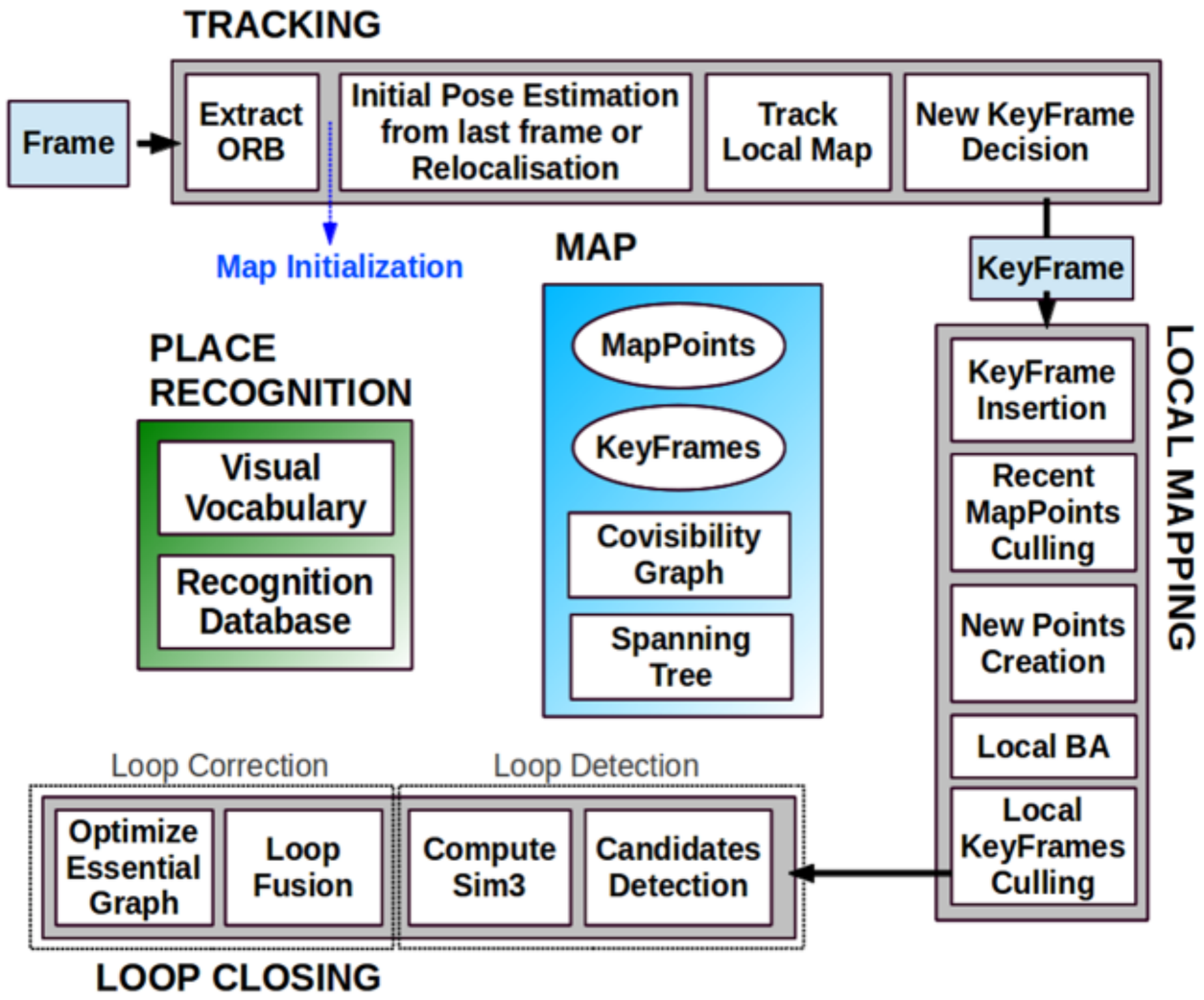
https://www.youtube.com/watch?v=8DISRmsO2YQ&t=61s

Threads: Tracking, Mapping, Loop Closing
Modules: Map, Place Recognition



Courtesy: Juan D. Tardos

Outline

1. Map Module

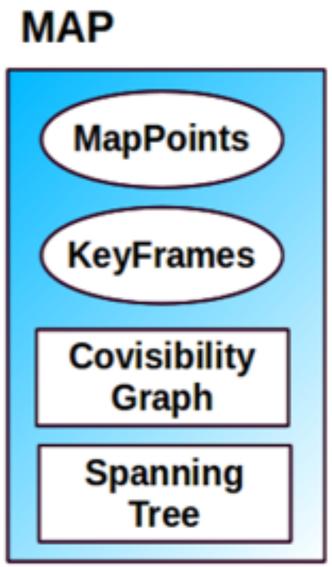
2. Place Recognition Module

3. Tracking Thread

4. Local Mapping Thread

5. Loop Closing Thread

Map Module: Key Concepts

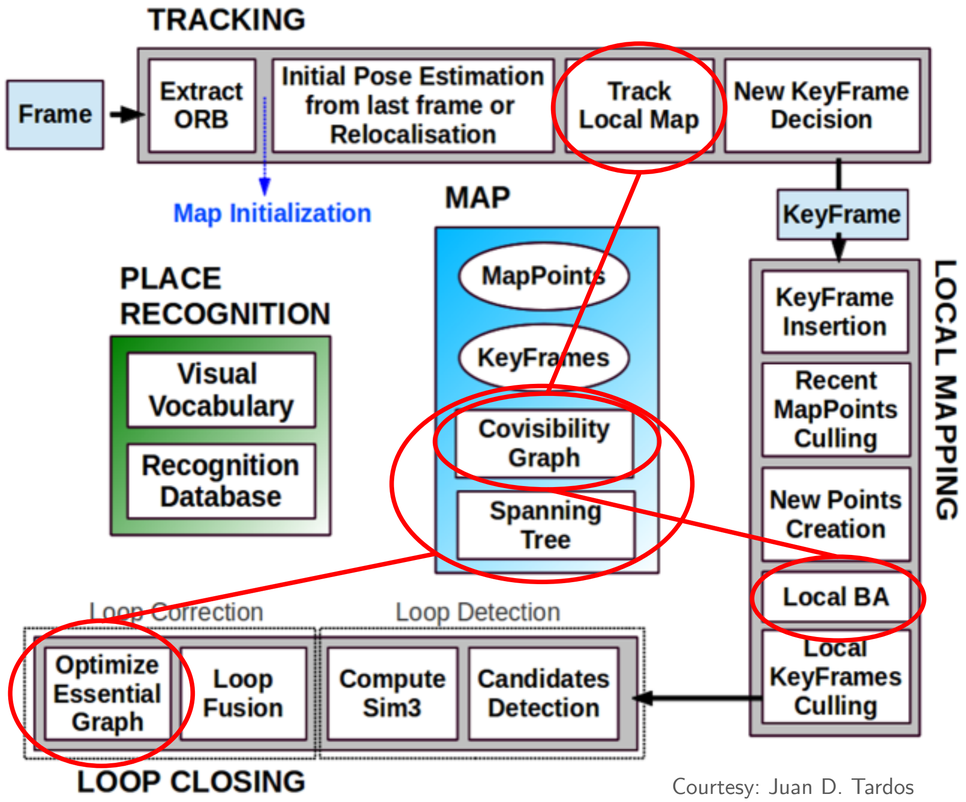


Map Module: Where is it used?

By tracking thread for tracking a local map

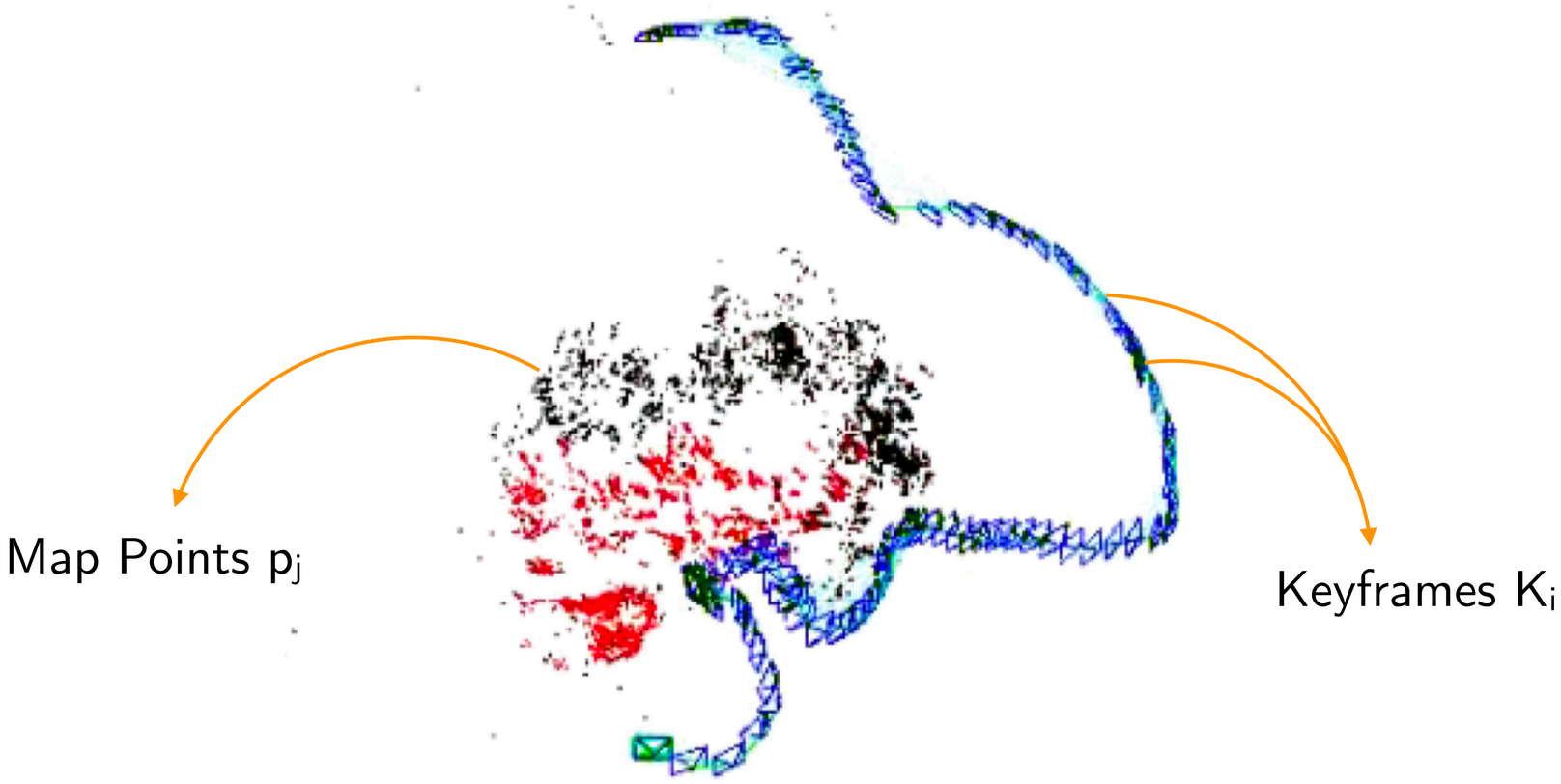
By mapping thread to do local bundle adjustment

By loop closing thread to optimize essential graph

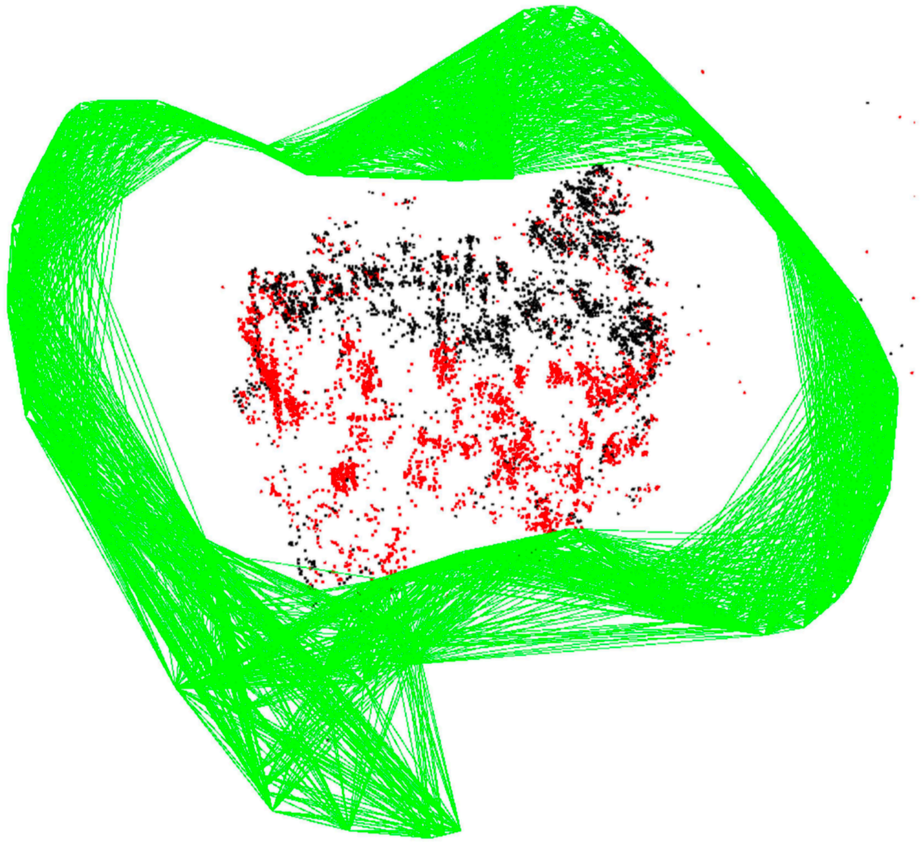


Courtesy: Juan D. Tardos

Map points, Keyframes



Covisibility Graph



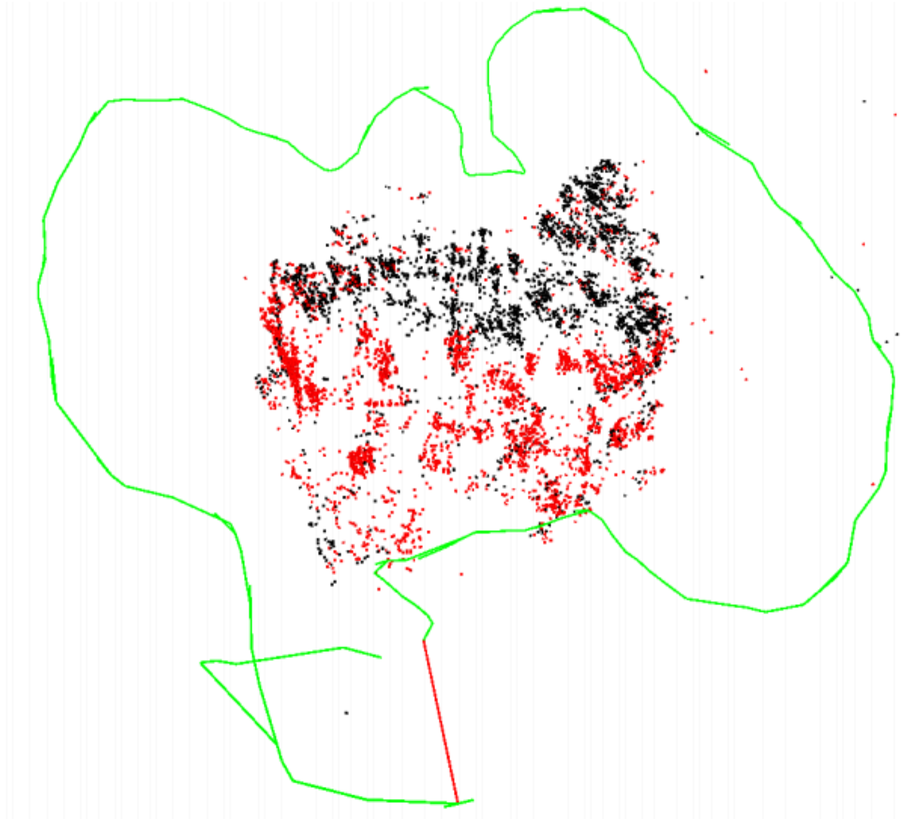
Undirected weighted graph

Each node a keyframe

Each edge weight the number of common map points

Edge exists if the two keyframes share >= 15 same map points

Spanning Tree

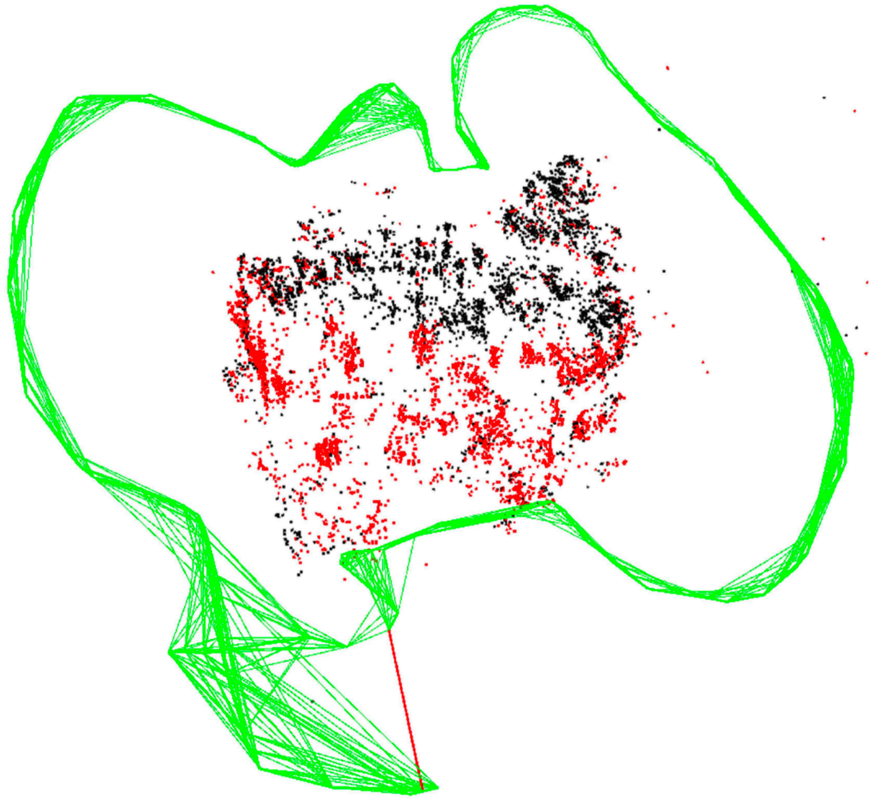


Minimal spanning tree with all vertices from covisbility graph but minimal number of edges

Connected subgraph of covisibility graph

Built incrementally

Essential Graph

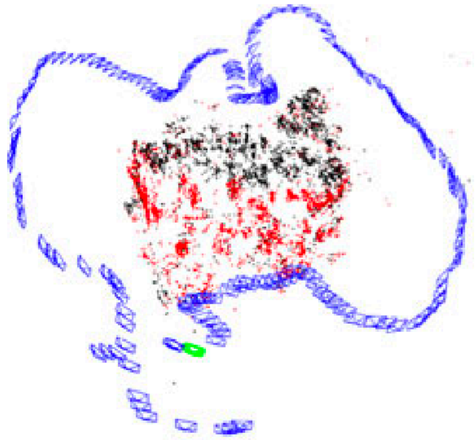


Spanning tree + subset of edges from covisibility graph

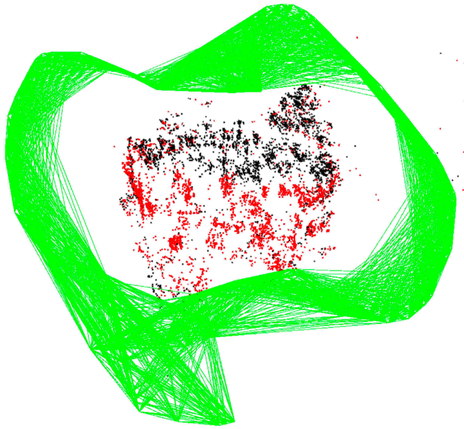
Subset of edges chosen: High covisibility edges (weights>=100) + loop closure edges

Stronger network of cameras over the spanning tree but not as dense as covisibility graph

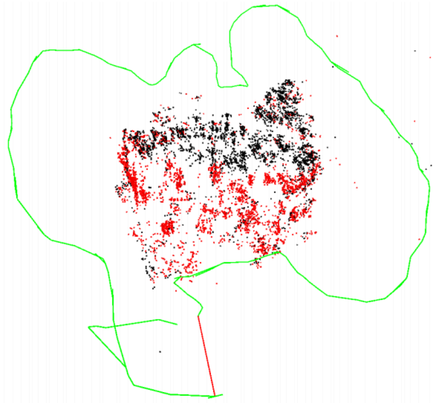
Map of Keyframes
and 3D points

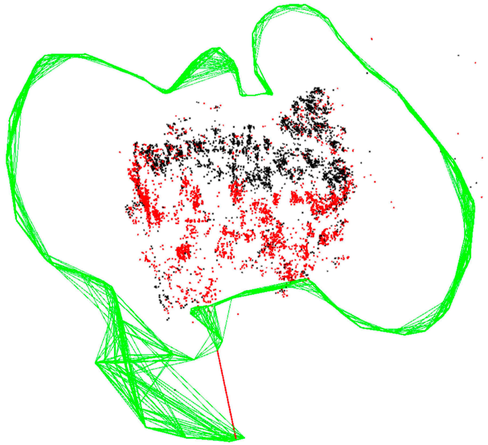


Covisibility Graph



Spanning Tree



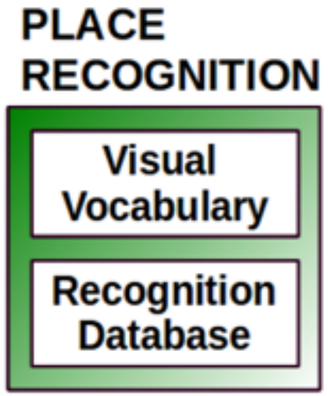


Essential Graph

Outline

1. Map Module
2. Place Recognition Module
3. Tracking Thread
4. Local Mapping Thread
5. Loop Closing Thread

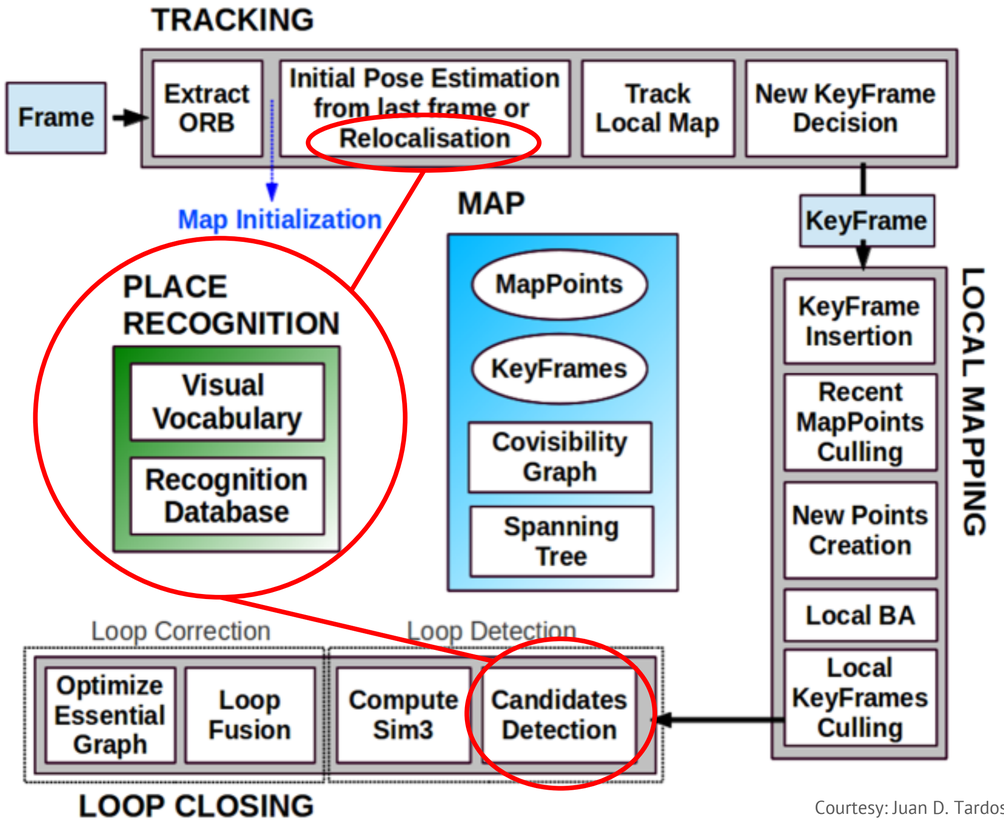
Place Recognition Module:
Key Concepts



Place Recognition Module: Where is it used?

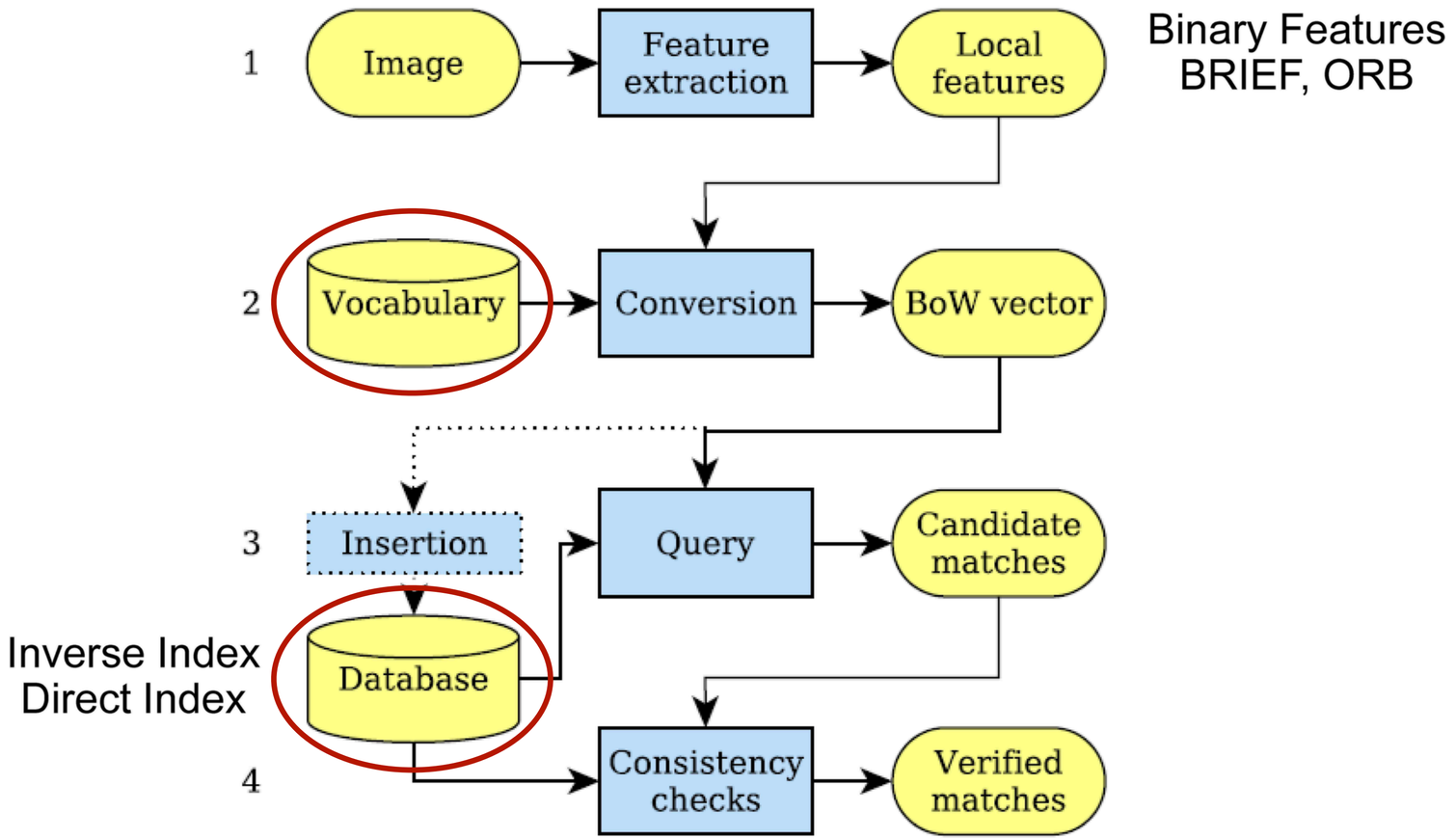
By tracking thread for global relocalization under tracking failure

By loop closing thread for loop candidates detection



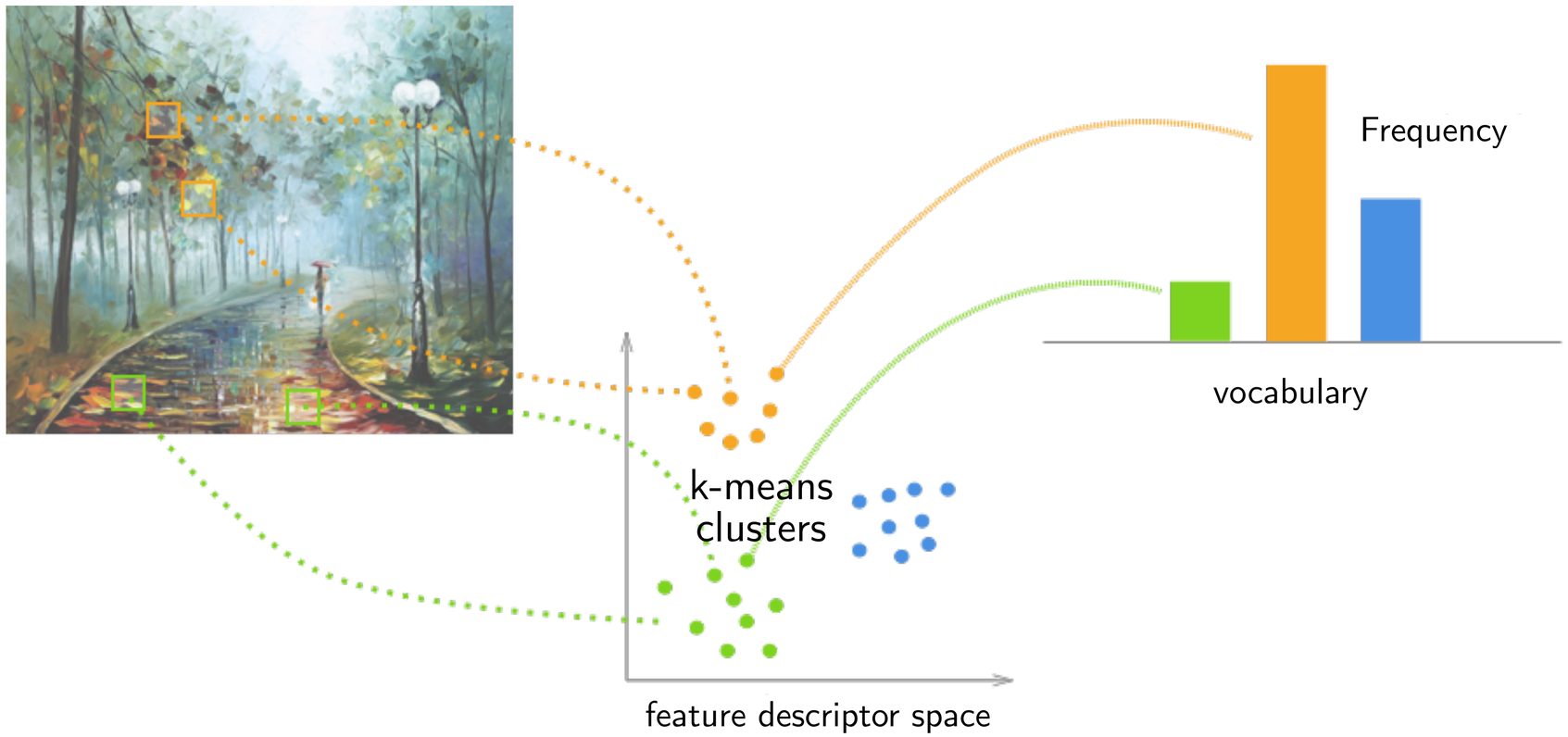
Courtesy: Juan D. Tardos

Recognition Database



Gálvez-López, Dorian, and Juan D. Tardos. "**Bags of binary words for fast place recognition in image sequences**." *IEEE Transactions on Robotics* 28.5, 2012: 1188-1197.

Vocabulary: Visual Vocabulary Histogram



Basic visual bag-of-words with fixed number of clusters k-means

https://blog.cometlabs.io/teaching-robots-presence-what-you-need-to-know-about-slam-9bf0ca037553

Vocabulary: Visual Vocabulary Tree

Hierarchical bag-of-words library (DBoW2) [1] used in ORB-SLAM

DBoW2 builds a vocabulary tree discretizing a binary FAST+BRIEF feature descriptor space

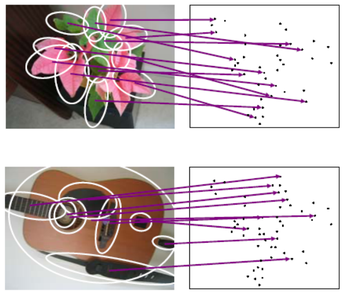
Vocabulary tree [2] constructed using hierarchical k-means clustering

Tree structure allows larger and more discriminatory vocabulary to be used efficiently

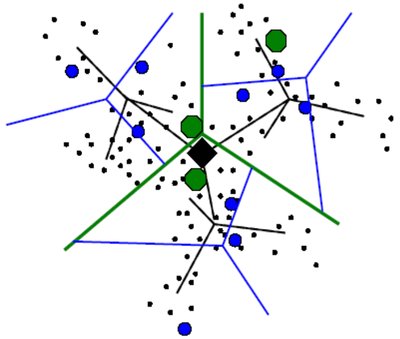
[1] Gálvez-López, Dorian, and Juan D. Tardos. "**Bags of binary words for fast place recognition in image sequences**." *IEEE Transactions on Robotics* 28.5, 2012: 1188-1197.
[2] Nister, David, and Henrik Stewenius. "**Scalable recognition with a vocabulary tree.**" *IEEE computer society conference on Computer vision and pattern recognition, 2006.*

Vocabulary: Visual Vocabulary Tree

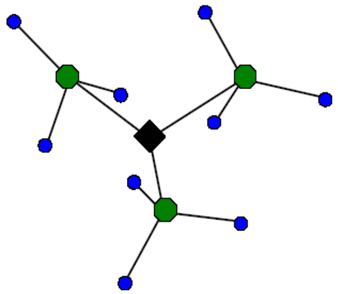
Train Vocabulary (Offline)



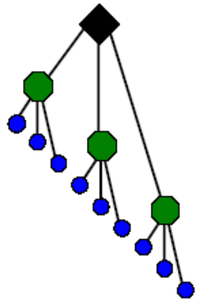
Extract Features



Hierarchical k-means



k-means centers

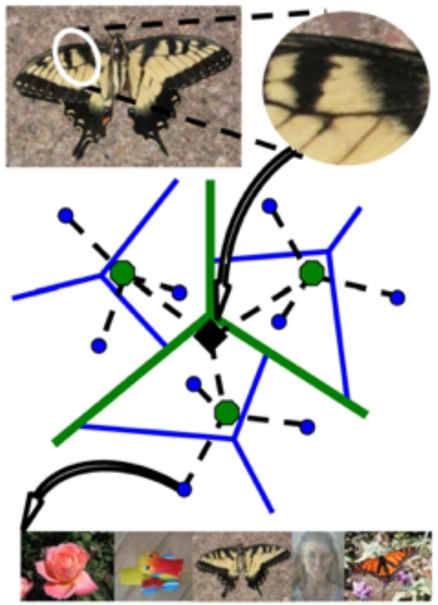


Vocabulary Tree

Nister, David, and Henrik Stewenius. "**Scalable recognition with a vocabulary tree.**" *Computer vision and pattern recognition, 2006 IEEE computer society conference on*. Vol. 2. IEEE, 2006.

Vocabulary: Visual Vocabulary Tree

Insertion/Query Database (Online)



vocabulary tree with branch factor three, quantization levels two

Hierarchical quantization levels

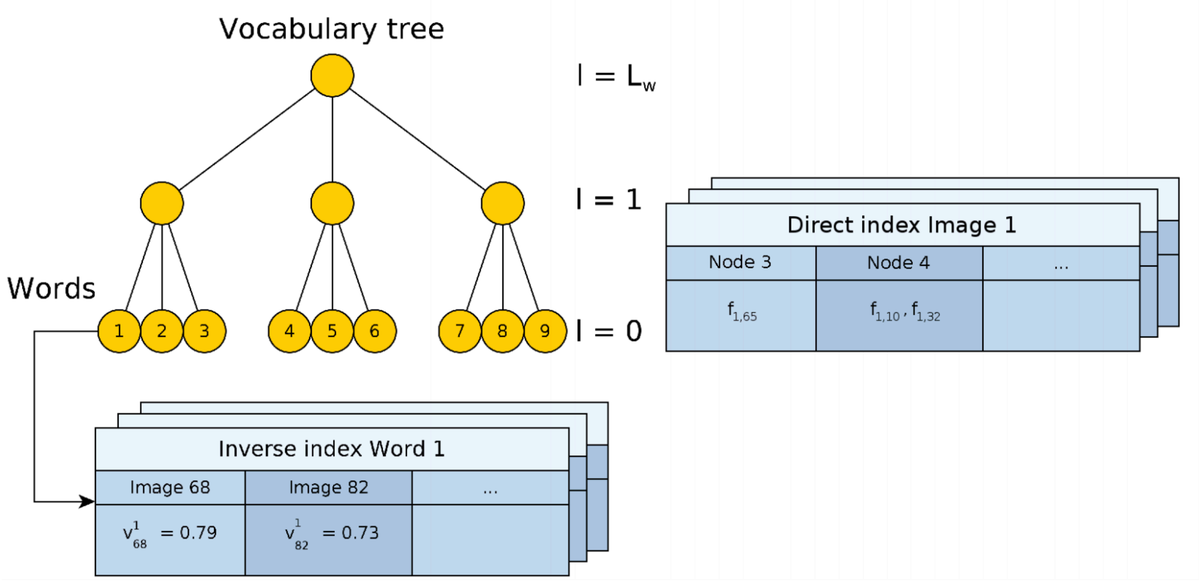
At first quantization level:
Descriptor assigned to closest of 3 green centers

At second quantization level:
Descriptor assigned to closest of 3 blue centers

Nister, David, and Henrik Stewenius. "**Scalable recognition with a vocabulary tree.**" *Computer vision and pattern recognition, 2006 IEEE computer society conference on*. Vol. 2. IEEE, 2006.

Database: Direct, Inverse Indexes

DBoW2 vocabulary tree consists of an inverse and direct index



Inverse Index: Used for fast retrieval of images potentially similar to a given one

Direct Index: Used to efficiently obtain point correspondences between images

Gálvez-López, Dorian, and Juan D. Tardos. "**Bags of binary words for fast place recognition in image sequences**." *IEEE Transactions on Robotics* 28.5 (2012): 1188-1197.

Outline

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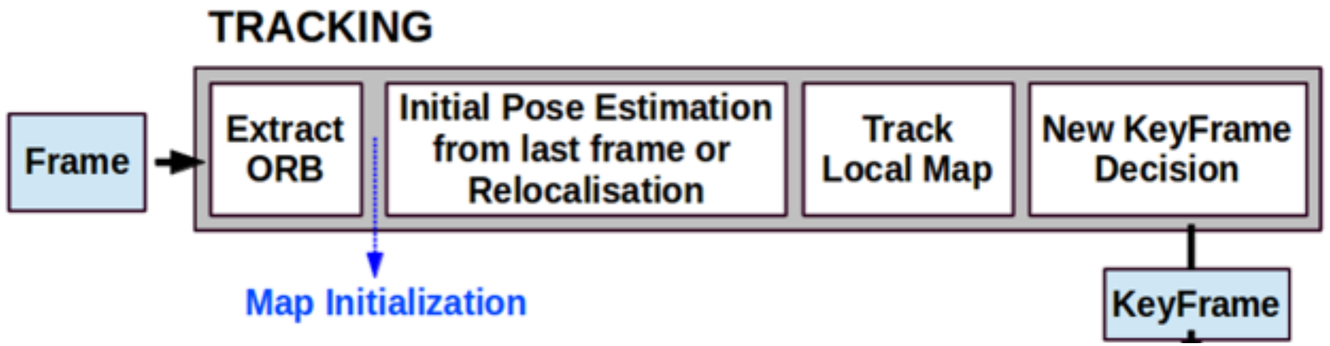
Tracking: Key Concepts



Automatic Map Initialization

Automatic Model Selection between,

Fundamental/Essential Matrix (General Scenes)

Homography (Planar or Low Parallax Scenes)

Problem	Inputs	Model to find	Basic Equation	d.o.f.	Min. # of matches	Minimal solution
Initialize 3D scene	$\mathbf{u}_{1j}, \mathbf{u}_{2j}$	Essential Matrix $\mathbf{E}_{12} = [\mathbf{t}]_\times \mathbf{R}$	$\mathbf{u}_{1j}^T \mathbf{E}_{12} \mathbf{u}_{2j} = 0$	5	5	5-point 8-point
Initialize 2D scene	$\mathbf{u}_{1j}, \mathbf{u}_{2j}$	Homography $\mathbf{H}_{12}$	$\mathbf{u}_{1j} = \mathbf{H}_{12} \mathbf{u}_{2j}$	8	4	

http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Key Ideas for Improved Tracking

ORB: FAST corner + Oriented Rotated Brief descriptor
- Binary descriptor
- Very fast to compute and compare

Use same features for Tracking, Mapping, Loop Closing, Relocalization

"Survival of fittest" strategy for points and keyframes: add to points and keyframes to map at a high rate and cull redundant points and keyframes

Only tracks a local map, computed using the covisibility graph

If tracking lost, global relocalization via place recognition module

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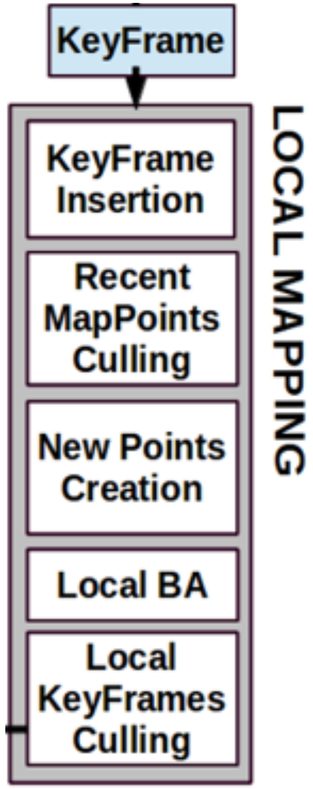
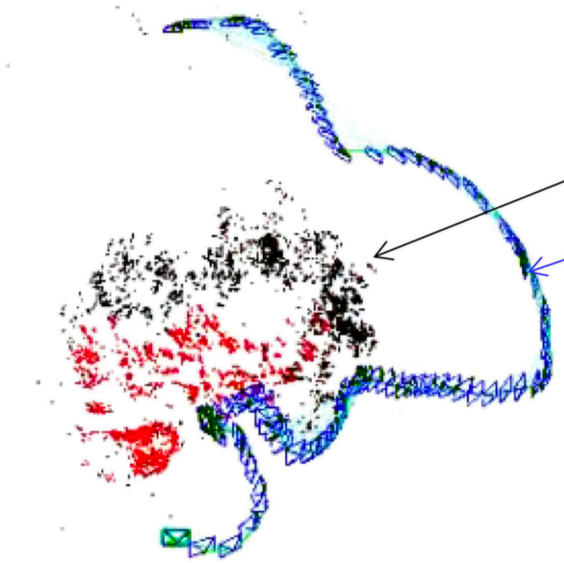
Local Mapping:
Key Concepts



Local Bundle Adjustment (BA)



States

$\mathbf{x}_{wj} \in \mathbb{R}^3$ Coordinates of point *j*

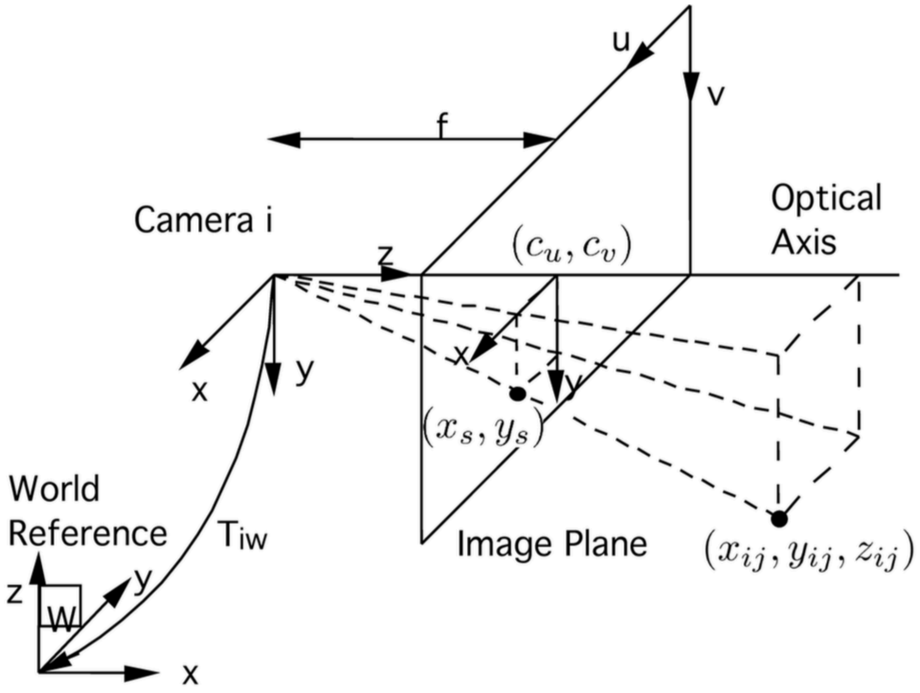
$\mathbf{T}_{iw} \in \mathrm{SE}(3)$ Pose of camera *i*

Measurements

$\mathbf{u}_{ij} = \begin{bmatrix} u_{ij} \\ v_{ij} \end{bmatrix}$ Observation of point *j* from camera *i*

http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Local BA: Camera Projection Model



focal length (mm)

$$x_s = f_i \frac{x_{ij}}{z_{ij}}$$

$$u = (s_u f_i) \frac{x_{ij}}{z_{ij}} + c_{i,u}$$

$$= f_{i,u} \frac{x_{ij}}{z_{ij}} + c_{i,u}$$

horizontal focal length (pixels)

principal point

- In summary:

$$\pi_i(\mathbf{T}_{iw}, \mathbf{x}_{wj}) = \begin{bmatrix} f_{i,u} \frac{x_{ij}}{z_{ij}} + c_{i,u} \\ f_{i,v} \frac{y_{ij}}{z_{ij}} + c_{i,v} \end{bmatrix}$$

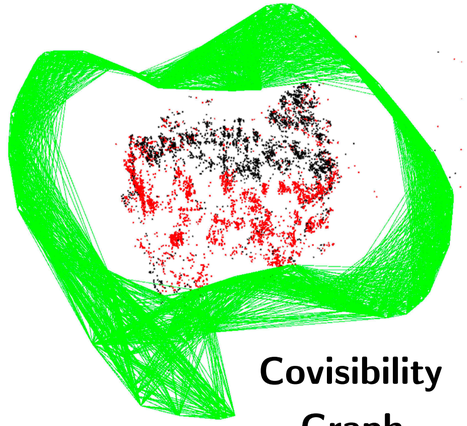
http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Local BA: Optimization

Optimizes a local map that is potentially visible,

Keyframes i include current keyframe and all keyframe connected to it in the covisibility graph

Map Points j seen by keyframes I

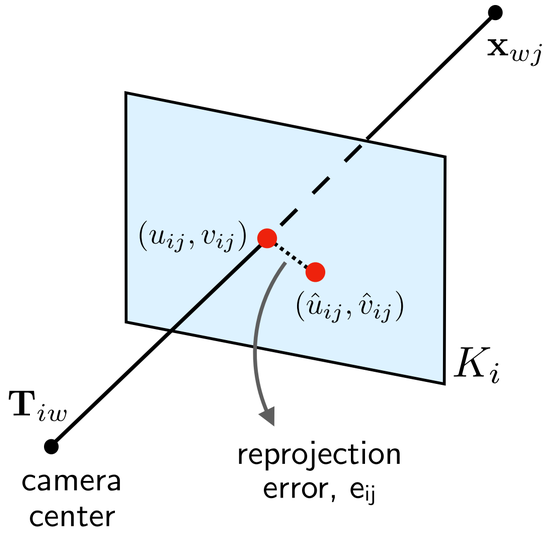


Covisibility Graph

$$\mathbf{e}_{ij} = \mathbf{u}_{ij} - \pi_i(\mathbf{T}_{iw}, \mathbf{x}_{wj})$$

Bundle Adjustment

$$\{\mathbf{T}_{1w}..\mathbf{T}_{nw}, \mathbf{x}_{w1}..\mathbf{x}_{wm}\}^\star = \arg\min_{\mathbf{T},\mathbf{x}} \sum_{i,j} \rho_h(\mathbf{e}_{ij}^T \boldsymbol{\Sigma}_{ij}^{-1} \mathbf{e}_{ij})$$



Reprojection Error

http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Local BA: Robust Estimators

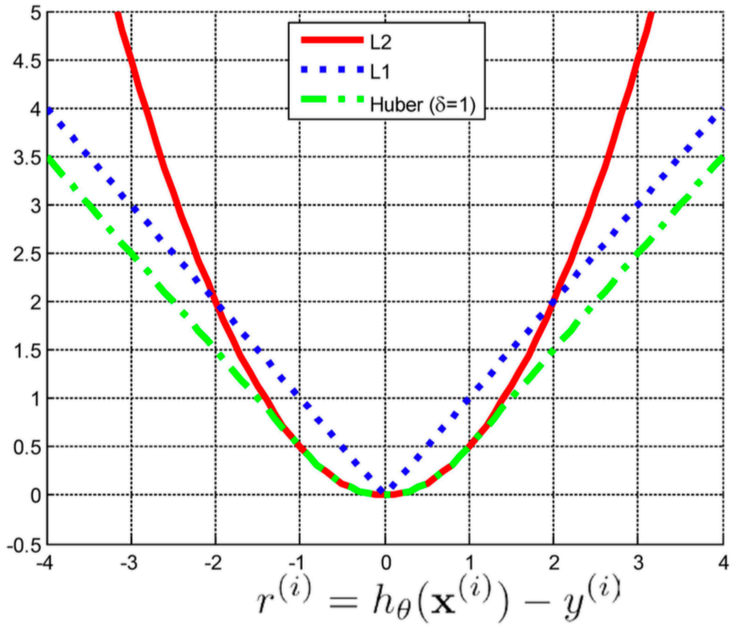
- L2 cost (quadratic)

$$J_{L2}(\theta) = \frac{1}{2}\sum_{i=1}^{N}\left(h_\theta(\mathbf{x}^{(i)}) - y^{(i)}\right)^2$$

- L1 cost (absolute value)

$$J_{L1}(\theta) = \sum_{i=1}^{N}\left|h_\theta(\mathbf{x}^{(i)}) - y^{(i)}\right|$$

- Huber cost:



$$L_H(r,\delta) = \begin{cases} r^2/2 & \text{if } |r| \le \delta \\ \delta|r| - \delta^2/2 & \text{if } |r| > \delta \end{cases}$$

$$J_H(\theta) = \sum_{i=1}^{N} L_H(r^{(i)},\delta) = \sum_{|r^{(i)}|\le\delta} {r^{(i)}}^2/2 + \sum_{|r^{(i)}|>\delta} \delta\left|r^{(i)}\right| - \delta^2/2$$

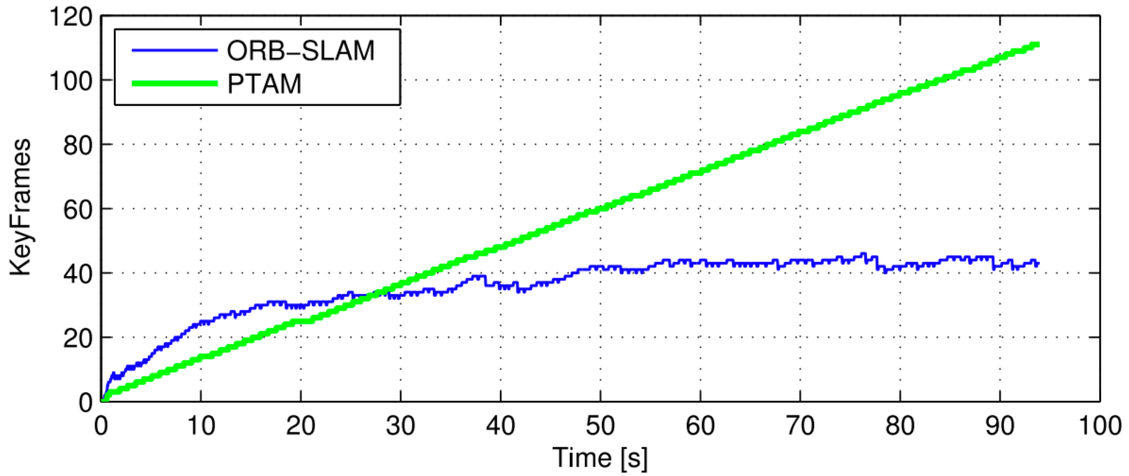
http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Local Keyframes Culling

Detect redundant keyframes and delete them

Discard all keyframes in essential graph whose 90% map points have been seen in at least three other keyframes in the same/finer scale

Enables lifelong operation in the same static environment (no visual changes) as number of keyframes will not grow unbounded



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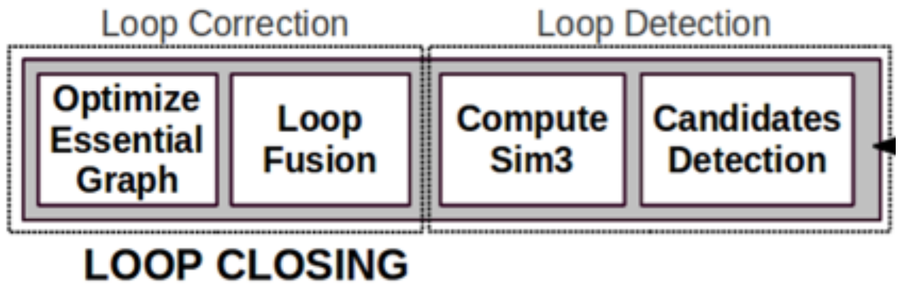
Loop Closing: Key Concepts



Loop Detection

For each frame, query a matching image in the Place Recognition Database

Is this a loop closure?

Image Frame Retrieved from Database

Current Image Frame

http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Loop Detection

For each frame, query a matching image in the Place Recognition Database

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Loop Detection

For each frame, query a matching image in the Place Recognition Database

Is this a loop closure?

No, but algorithm can return a false positive! Perceptual Aliasing.

http://www.dis.uniroma1.it/~labrococo/tutorial_icra_2016/icra16_slam_tutorial_tardos.pdf

Loop Detection

Some challenging loop detection examples with DBoW2 using ORB features

Gálvez-López, Dorian, and Juan D. Tardos. "**Bags of binary words for fast place recognition in image sequences**." *IEEE Transactions on Robotics* 28.5, 2012: 1188-1197.

Loop Correction

Essential Graph Optimization

Pose graph optimization over essential graph to distribute loop closing error along graph

To correct scale drift, optimization done over 7-DOF similarity transformations Sim(3) instead of 6-DOF rigid body transformations SE(3)

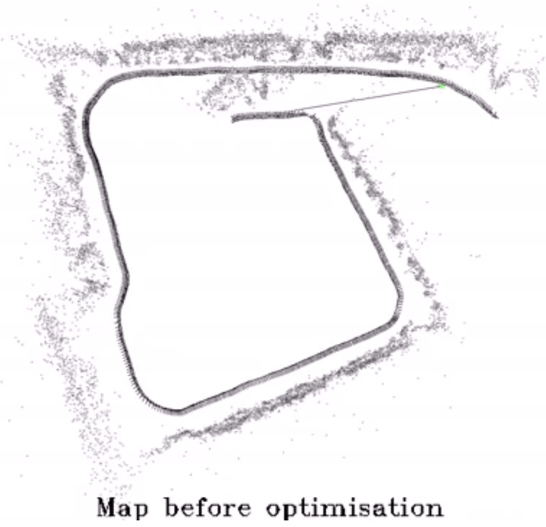
$$\mathbf{e_{i,j}} = \log_{Sim(3)}(\mathbf{S}_{ij}\mathbf{S}_{jw}\mathbf{S}_{iw}^{-1})$$

$$C = \sum_{i,j} \left(\mathbf{e}_{i,j}^{T}\Lambda_{i,j}\mathbf{e}_{i,j}\right)$$

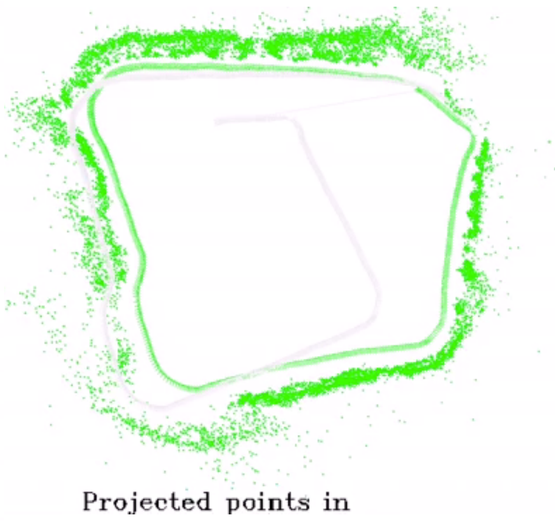
Map points not included as variables in the optimization (motion-only BA)

Loop Correction

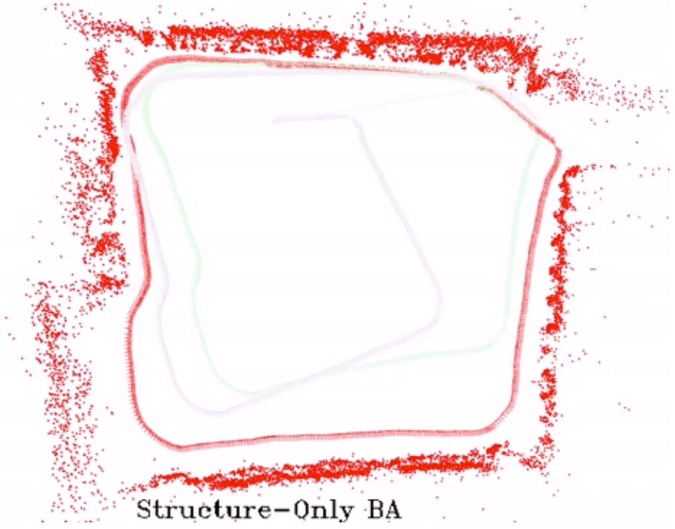
Map before optimization



6-DOF optimization

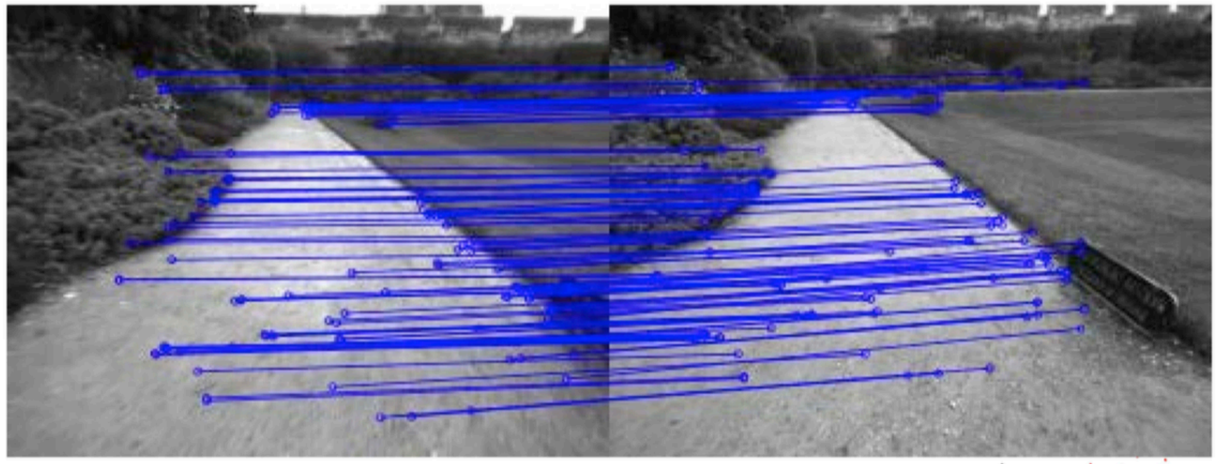


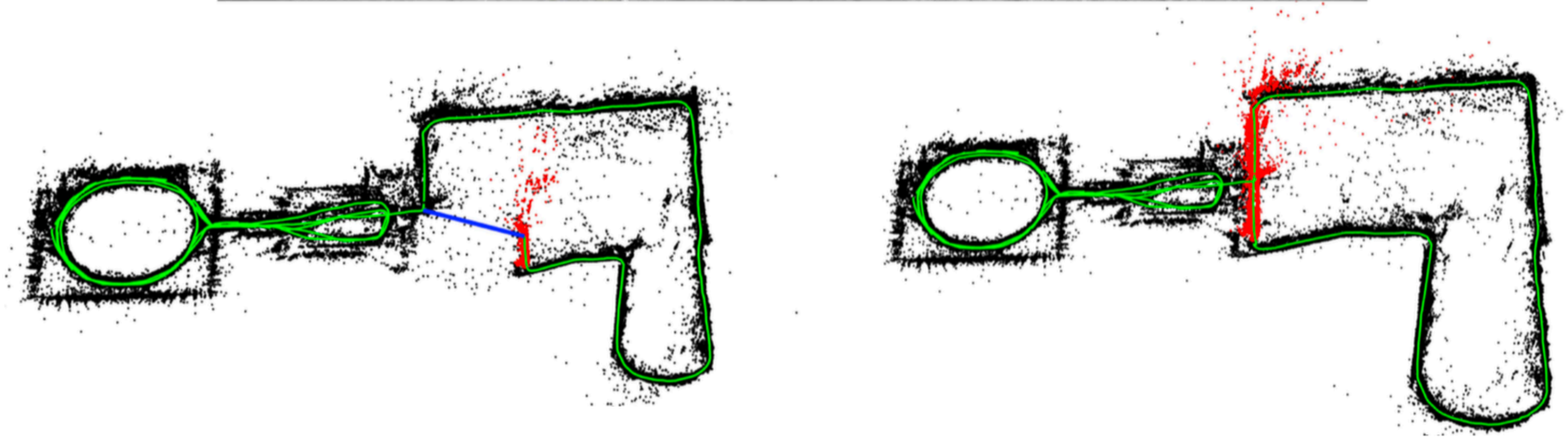
7-DOF optimization



Strasdat, Hauke, J. M. M. Montiel, and Andrew J. Davison. "**Scale drift-aware large scale monocular SLAM.**" Robotics: Science and Systems, 2010.
https://www.youtube.com/watch?v=Y6J6C_-mgRw

Loop Correction





Experiments

On Outdoor Sequence (KITTI)

https://www.youtube.com/watch?v=8DISRmsO2YQ&t=61s

On Indoor Sequence (TUM RGB-D Benchmark)

ORB-SLAM

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https://www.youtube.com/watch?v=_9VcvGybsDA&t=8s

Conclusions

A robust monocular SLAM system capable of operating for long durations in large-scale environments

Leverages parallel threads for tracking, local mapping and loop closing

Uses same ORB features for tracking, mapping, loop detection, relocalization

Introduces new key ideas in a monocular SLAM system,
- Covisibility and essential graphs
- DBoW2 based loop detection and relocalization
- Scale drift-aware loop correction

Limitations and Extensions

Limitations

- Monocular SLAM system, absolute scale unknown
- Needs texture, will fail with large plain walls
- Feature based maps too sparse a representation of environment

Extensions

- Use stereo cameras: real scale and robustness to quick motions [1]
- Use RGB-D cameras: track with features + dense map [1]
- Add Semi-dense or dense mapping [2]
- Improve agility using IMU [3]
- Incorporating semantic information

[1] Mur-Artal, Raul, and Juan D. Tardós. "ORB-SLAM2: An open-source slam system for monocular, stereo, and RGB-D cameras." IEEE Transactions on Robotics 33.5, 2017: 1255-1262.
[2] Mur-Artal, Raúl, and Juan D. Tardós. "Probabilistic Semi-Dense Mapping from Highly Accurate Feature-Based Monocular SLAM." Robotics: Science and Systems. 2015.
[3] Mur-Artal, Raúl, and Juan D. Tardós. "Visual-inertial monocular SLAM with map reuse." IEEE Robotics and Automation Letters 2.2, 2017: 796-803.

Questions?