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# Visual-Inertial Simultaneous Localization and Mapping with Multiple Cameras

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# Outline

1. Motivation
2. Introduction to VIO and VI-Mapping
3. Flow of proposed VI-SLAM
4. Extend to multi cameras

# Advantages of using IMU

	Accurate when
IMU measurements	Small time interval
Triangulation (visual)	Large time interval (Large baseline)

The advantages of combining visual and IMU measurement are,

1. combine the strengths of both sensors
2. keep the map gravity aligned

# VI-Odometry and VI-Mapping

	Feature type	Loop detection
VI-Odometry (online)	Optical Flow	No, tend to drift over time
VI-Mapping (offline)	Orb-feature	yes

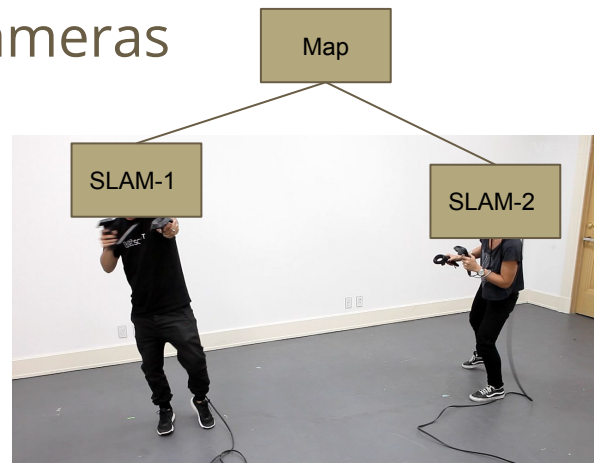
VI-SLAM ~ VI-Odometry + VI-Mapping

# Objectives

- try to build a VI-SLAM
- capable of working with multiple cameras

Use case:

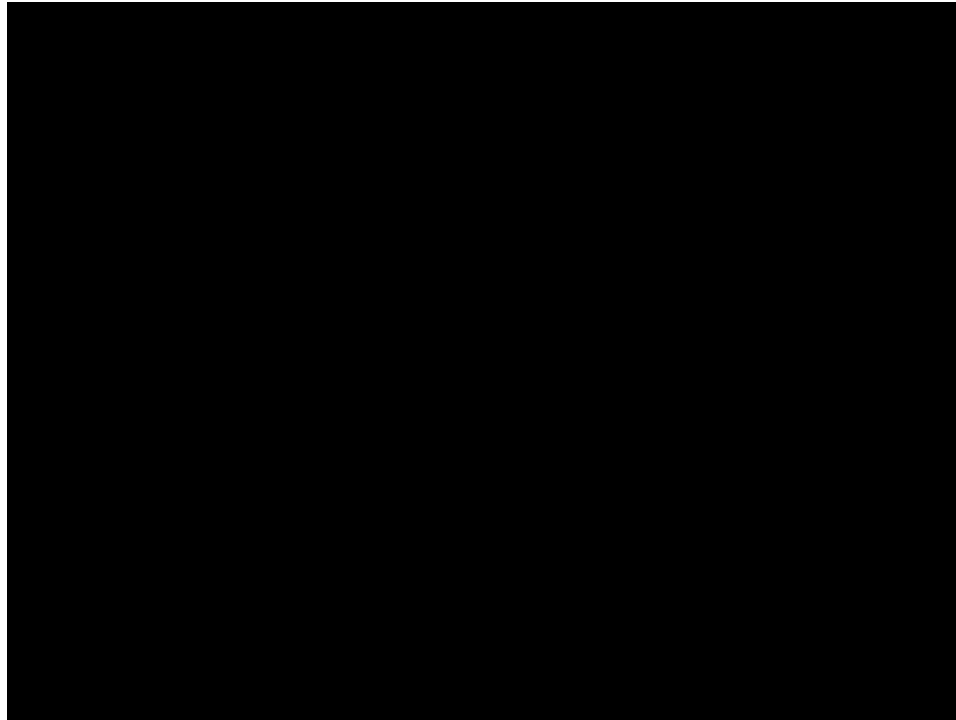
for example, multi-player VR gaming etc...



source:

<https://vrscout.com/news/cant-stop-playing-pool-nation-vr/>

# Demo of proposed method

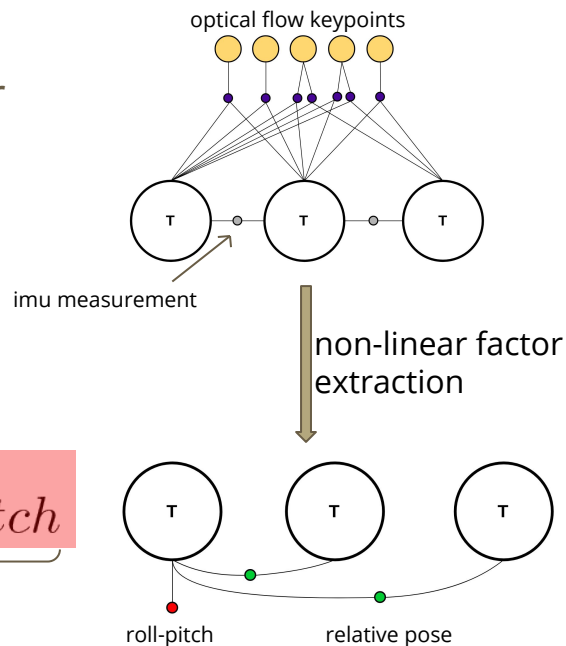


# How the mapper reuse information from VIO?

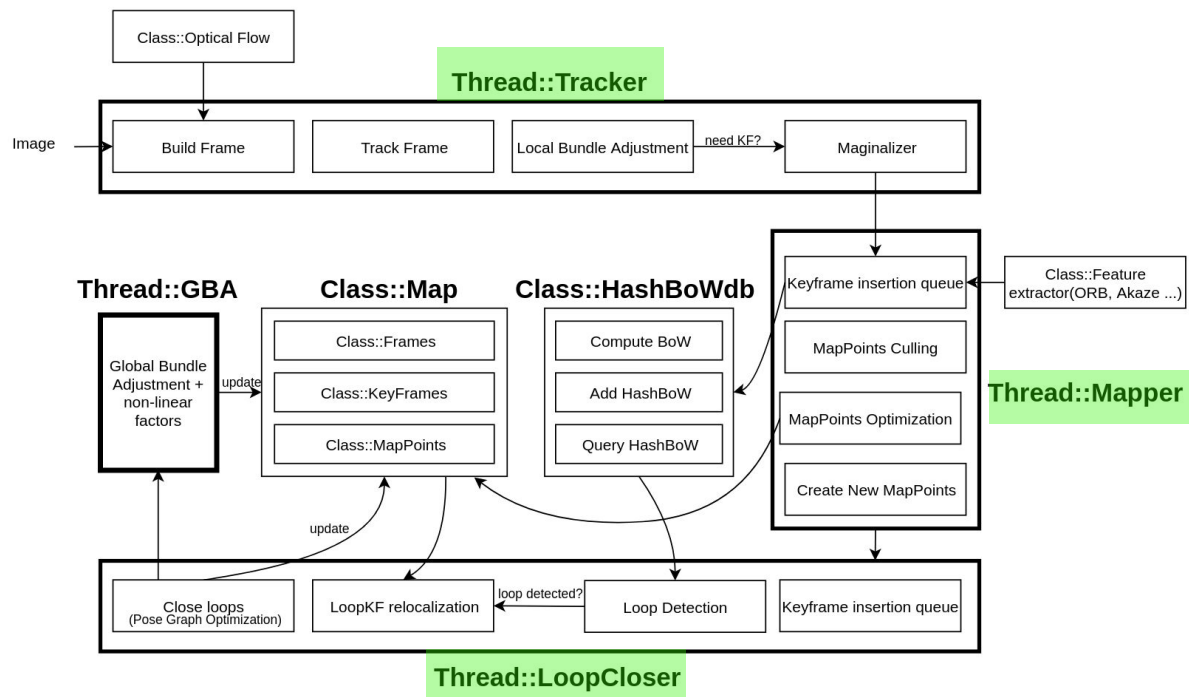
Turn optical flow kp and imu measurement to non-linear factors

- just need to store a few data for each frame in VIO
- smaller optimization problem in mapping

$$E = E_{reproj}^{orb} + \underbrace{E_{rel\ pose} + E_{roll\ pitch}}_{\text{from non-linear factors}}$$



# Structure of proposed VI-SLAM

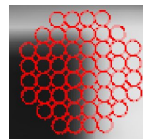




# Structure of proposed VI-SLAM (simplified)

Tracker

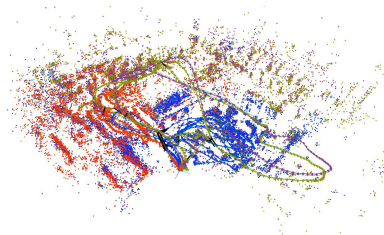
- track frame by **Basalt-VIO**



Credit: V. Usenko, N. Demmel, D. Schubert, J. Stickler, and D. Cremers, 2020

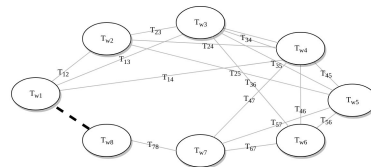
Mapper

- build and update map **bases on non-linear factor (faster)**



Loop closer

- detect and close loop by **using hash-bow**

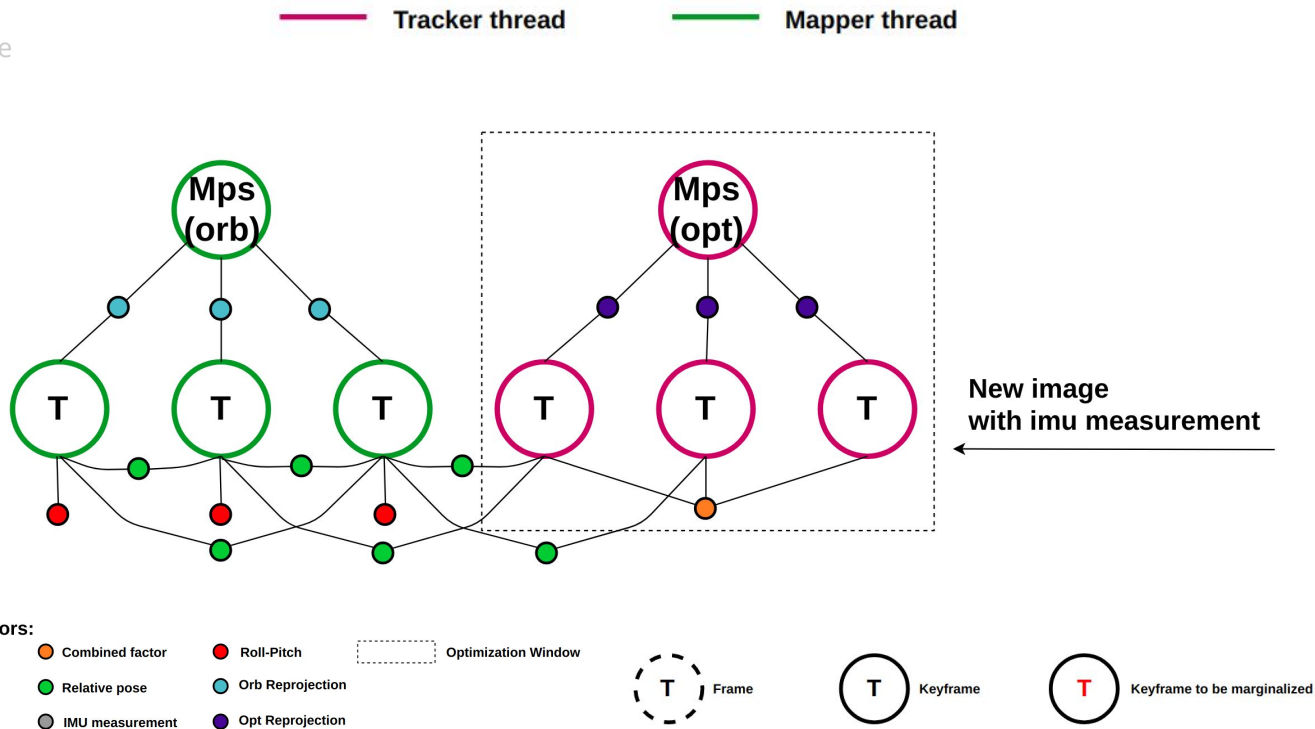


# Flow of proposed VI-SLAM

- T1. input data
- T2. set ini pose
- T3. search opt kps correspondence
- T4. local BA within window
- T5a. frame to kf
- T5b. select a kf to marginalize
- T6. extract non-linear factor
- T7. insert marginalized kf to map
- T8. repeat step T1-T7

- M1. receive a kf from tracker
- M2. search orb kps corresponder
- M3. detect loop
- M4. repeat step M1-M3

- L1. receive a kf from mapper
- L2. detect and merge loops
- L3. repeat step L1-L2

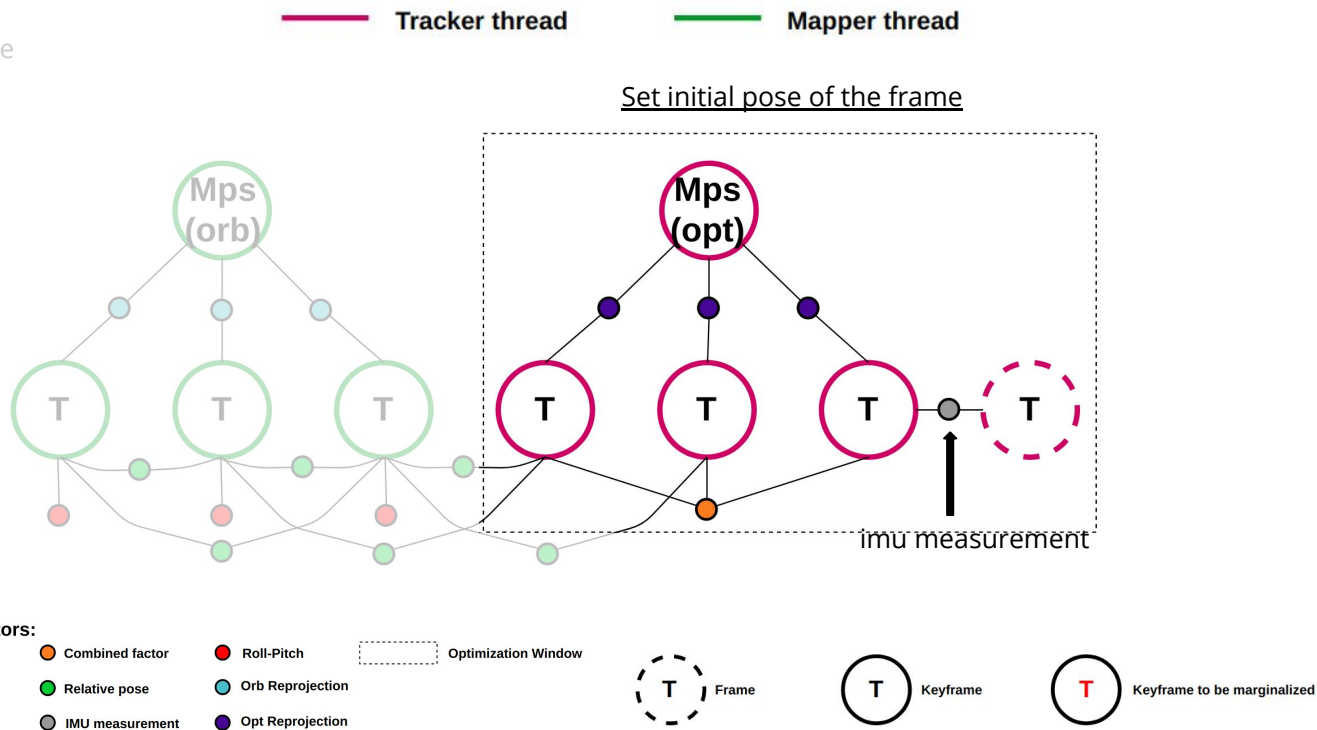


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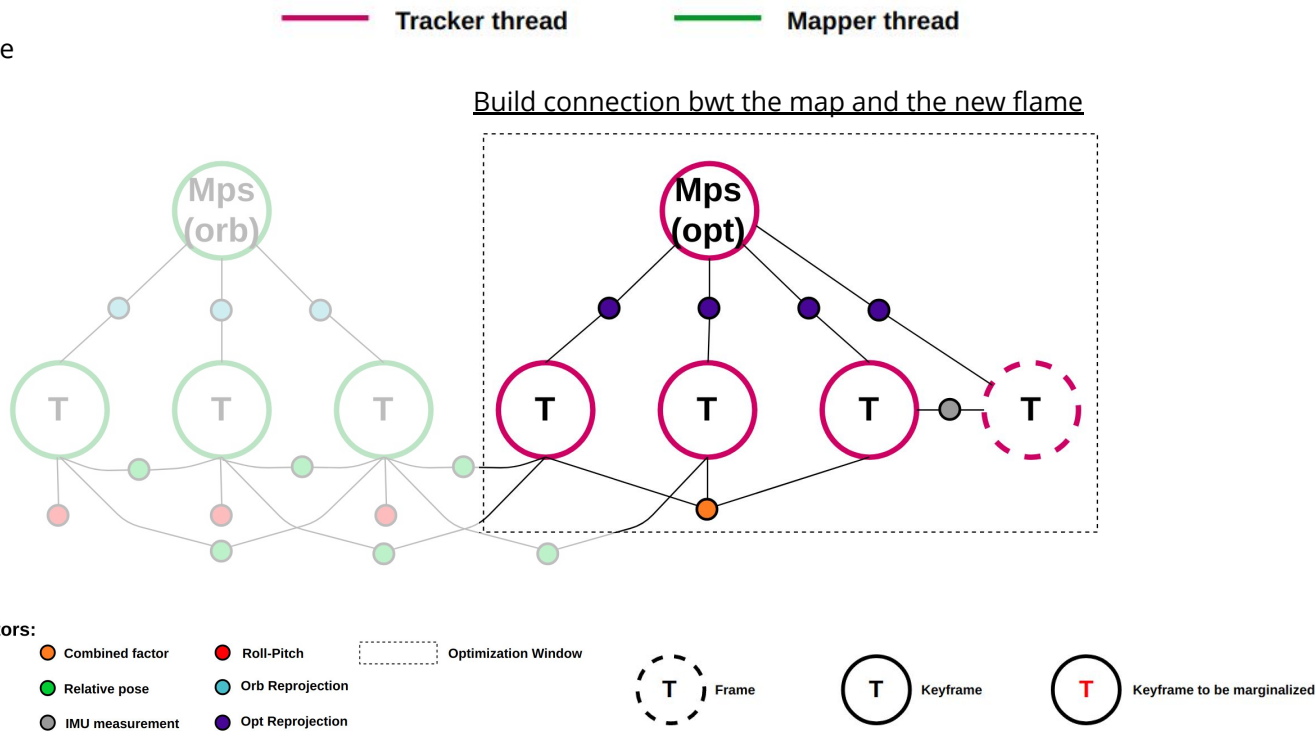


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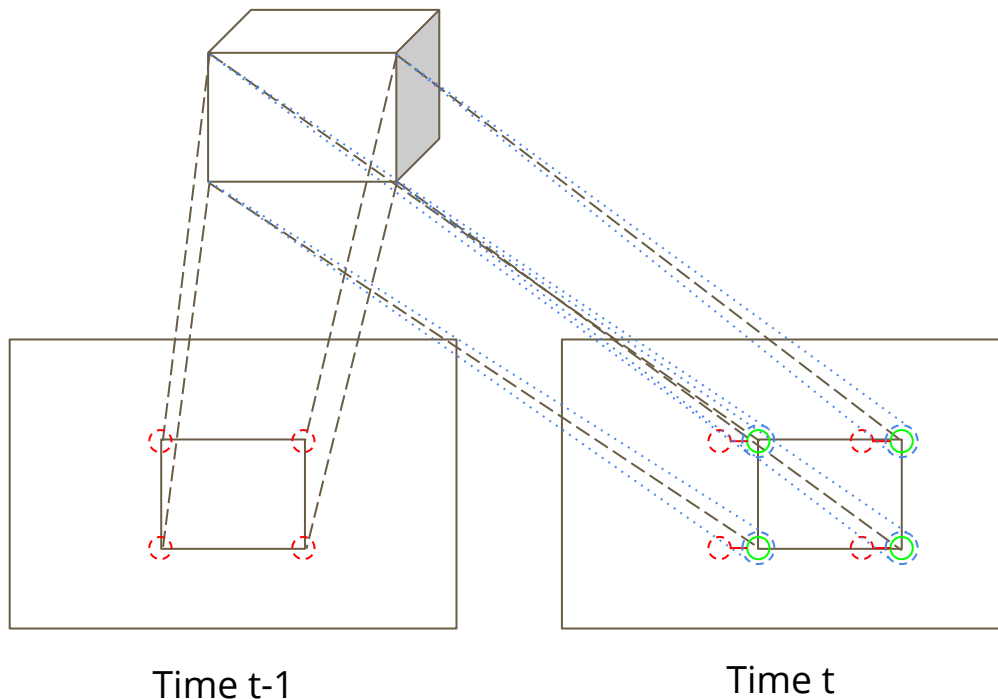


# Track optical flow keypoints by re-projection

- T1. input data
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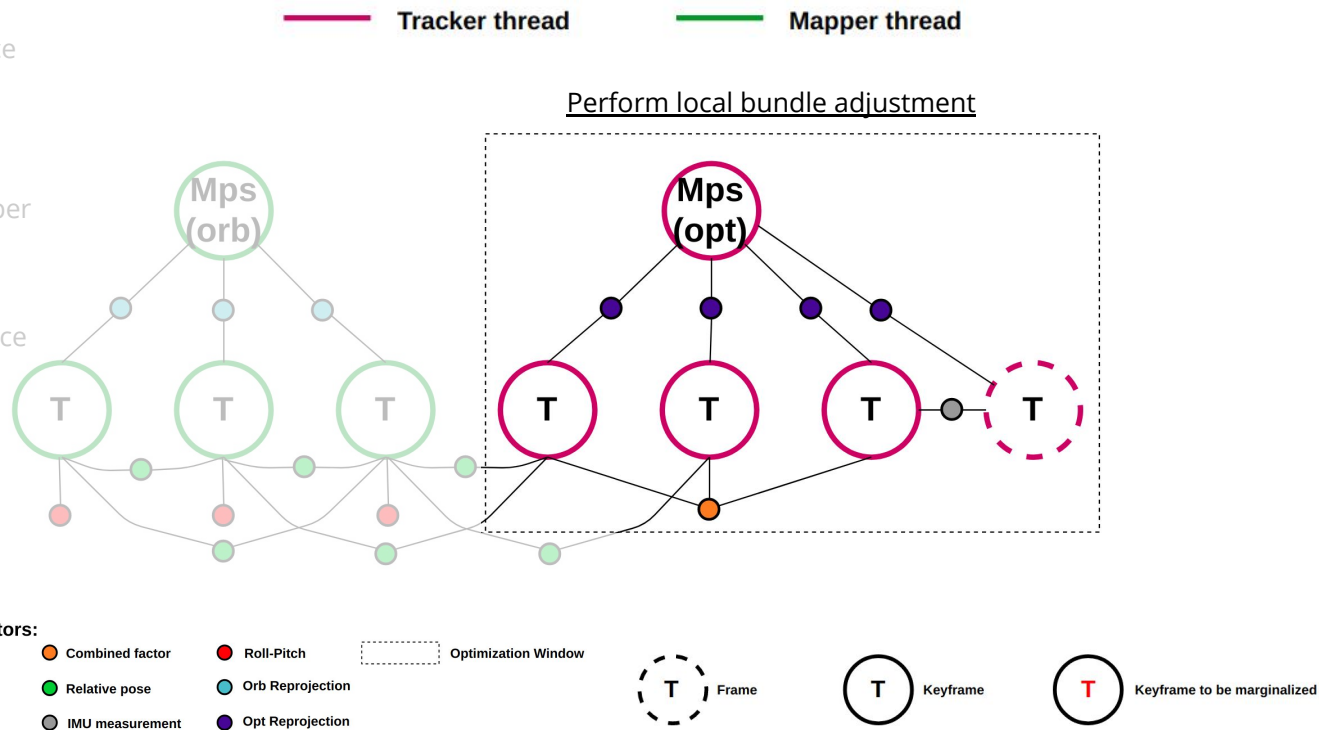
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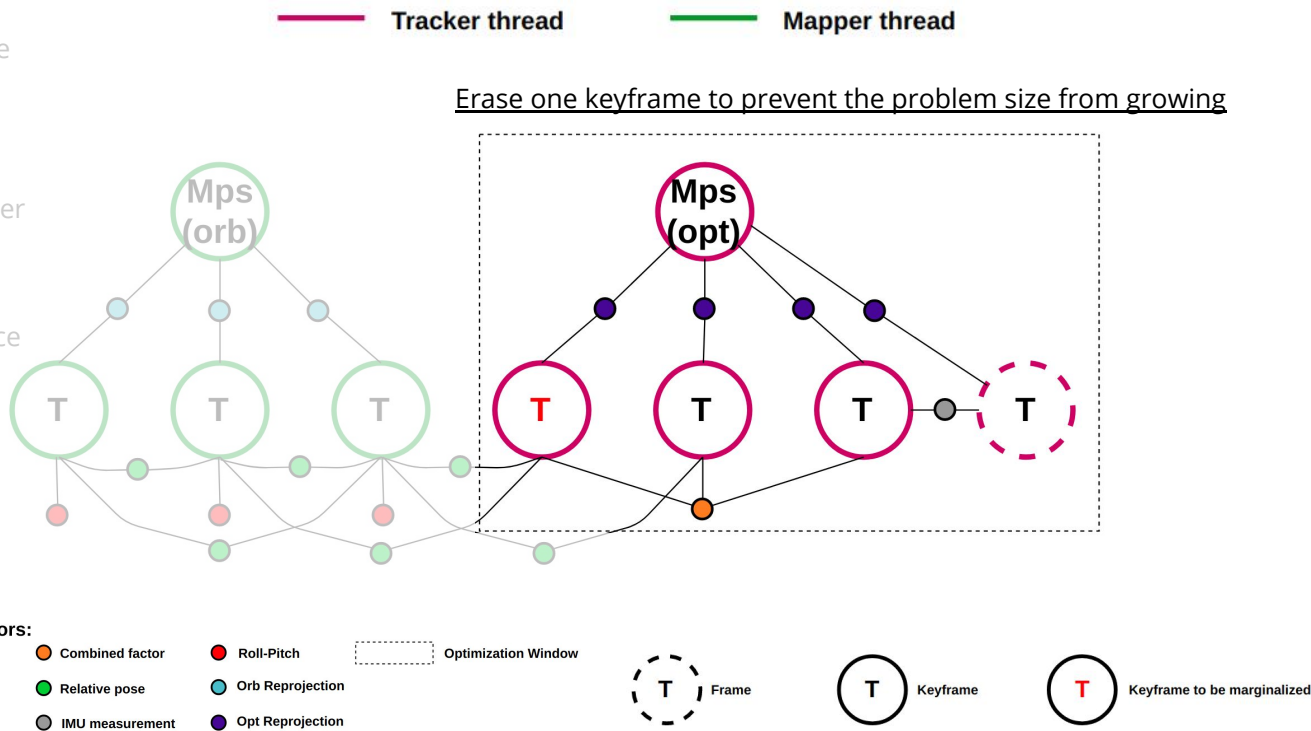


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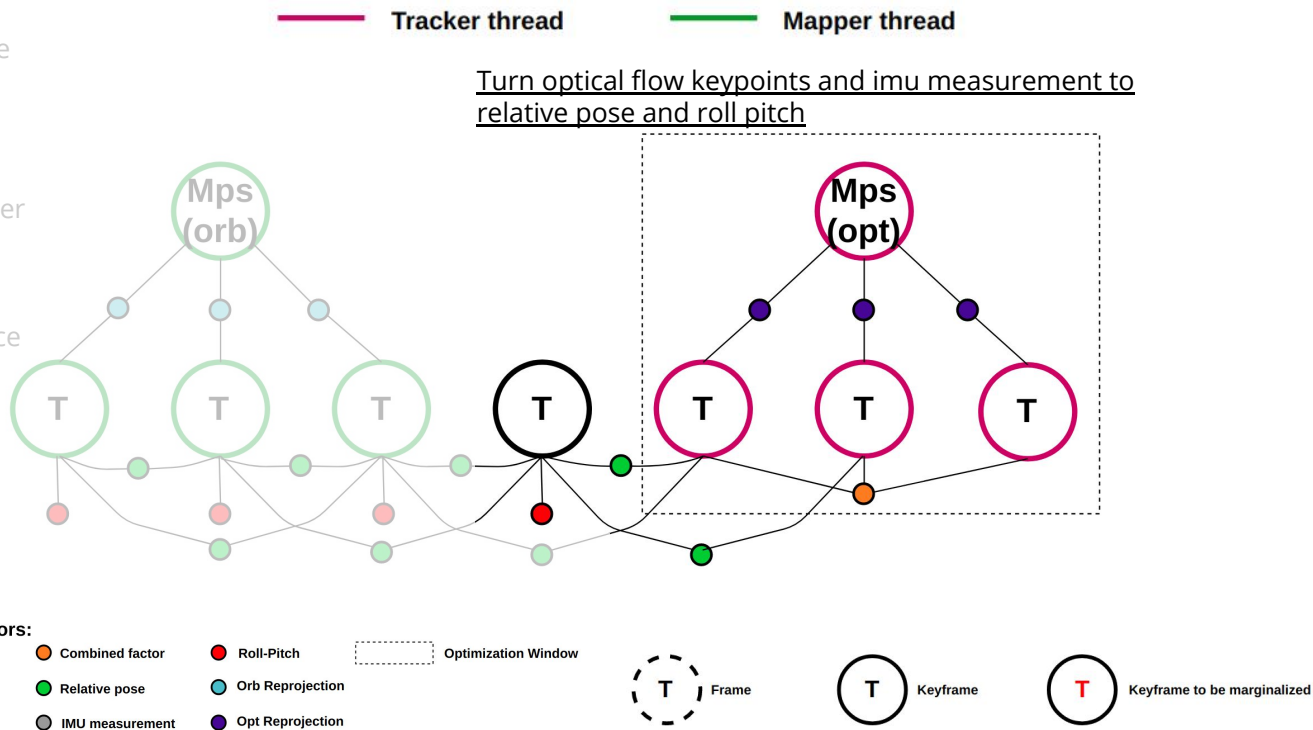


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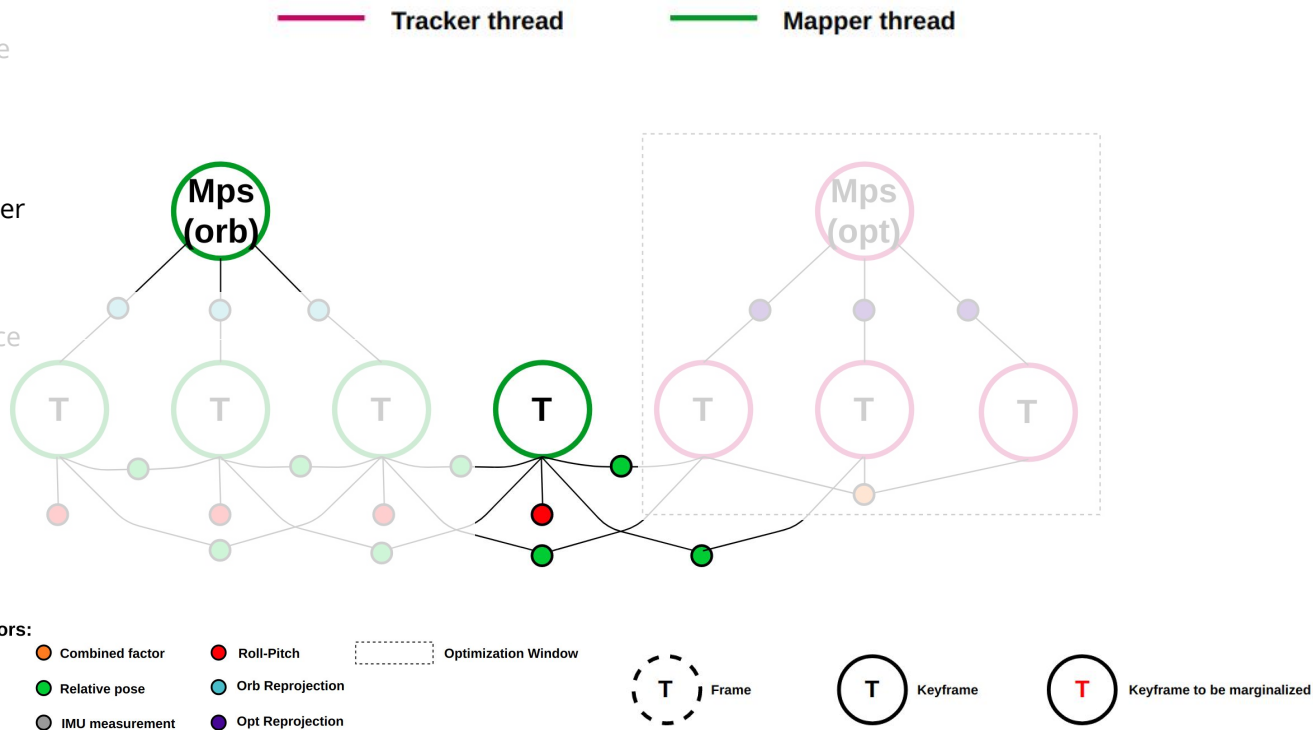


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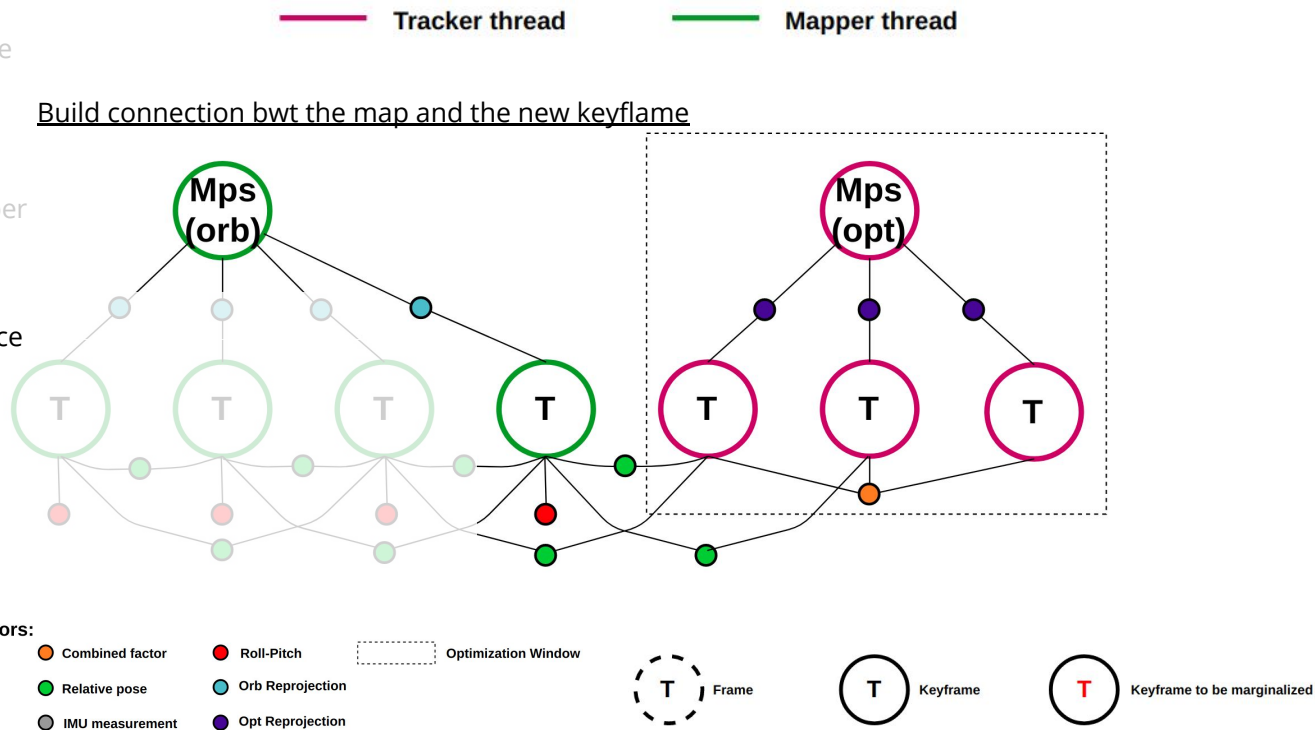


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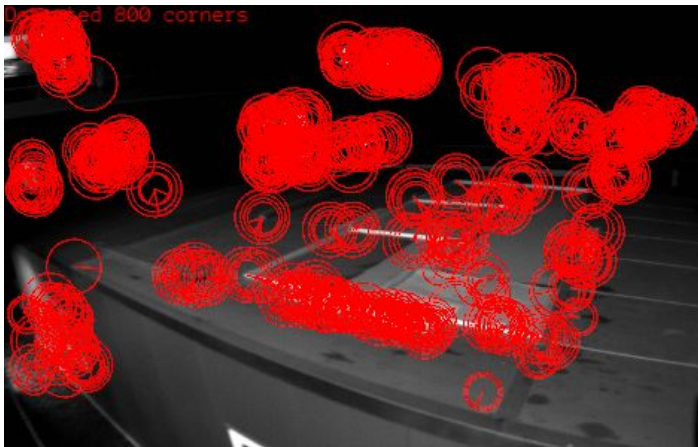


# Scaled features and Non-maximal suppression

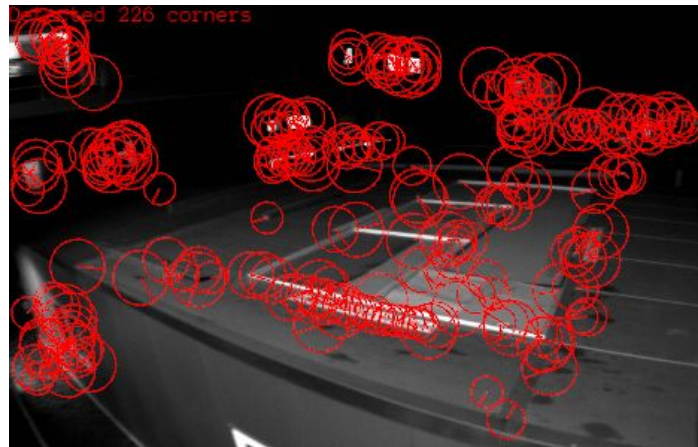
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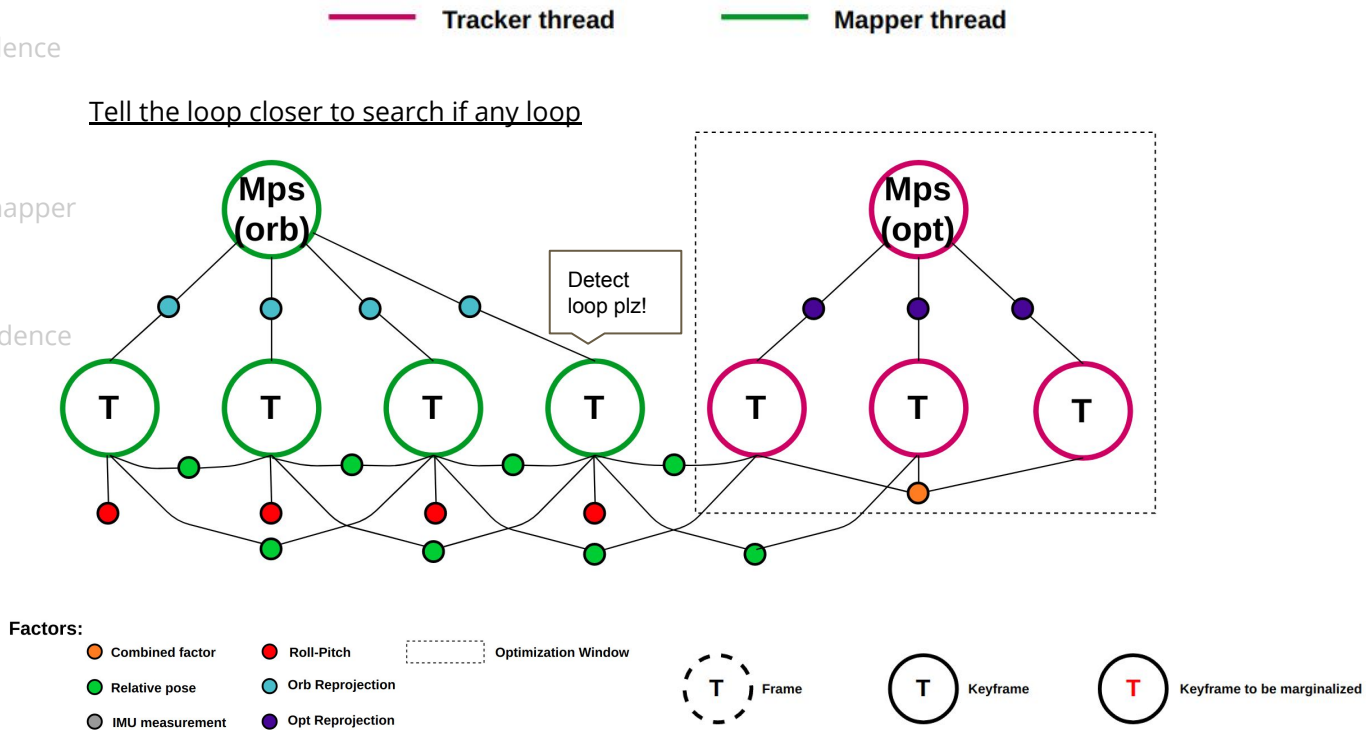
without non-maximal suppression



with non-maximal suppression

# Flow of proposed VI-SLAM

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  - M2. search orb kps correspondence
  - M3. detect loop**
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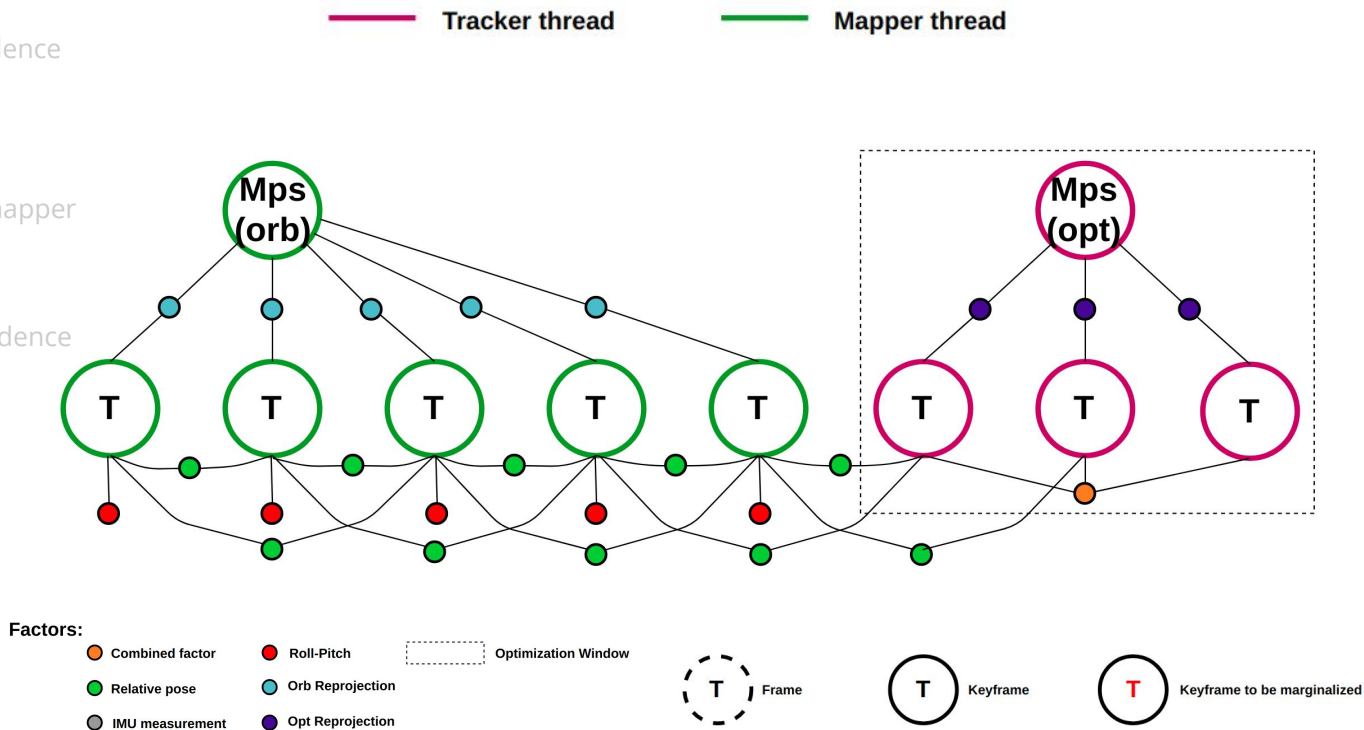


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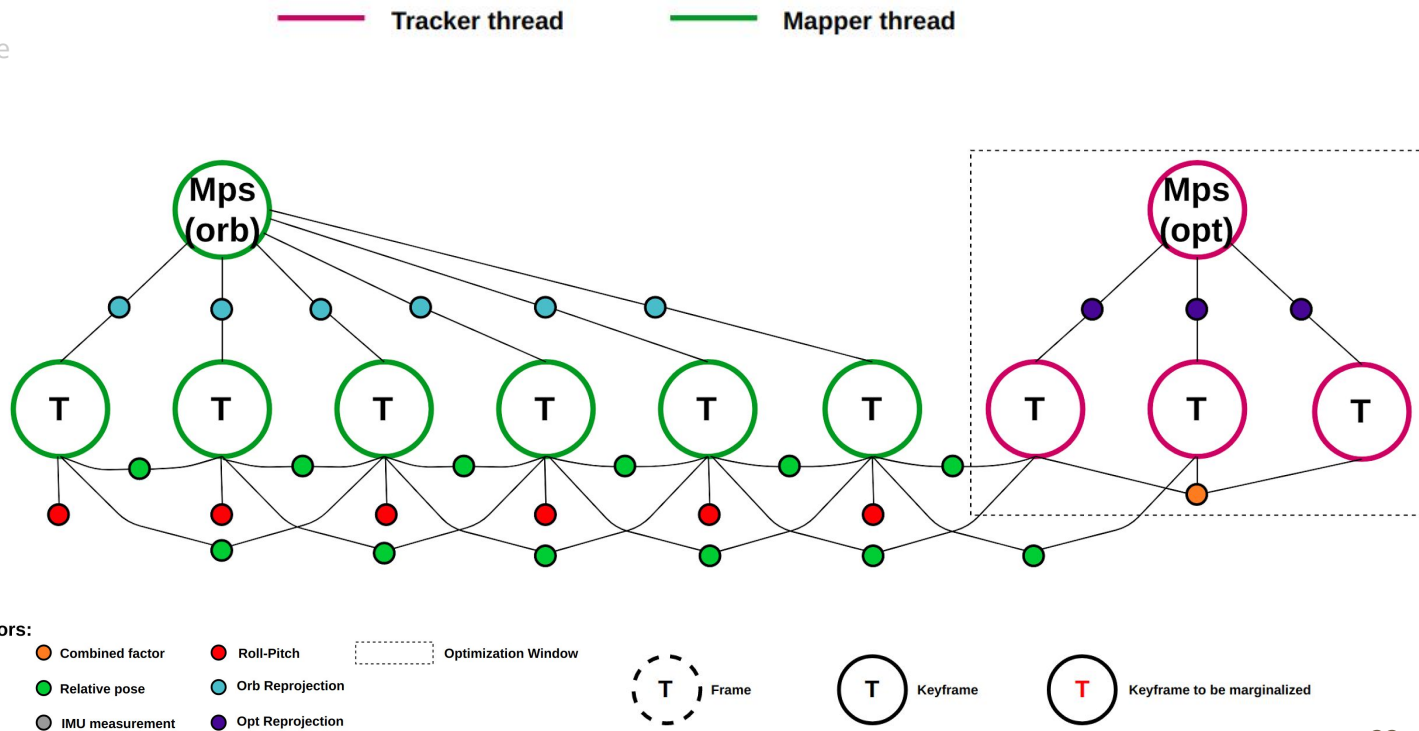


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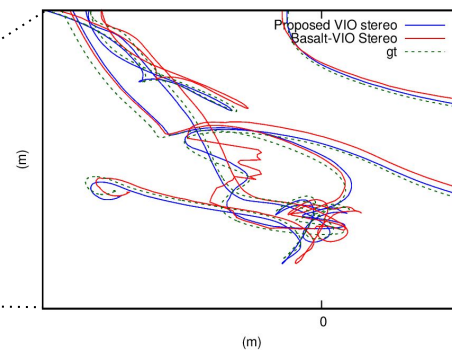
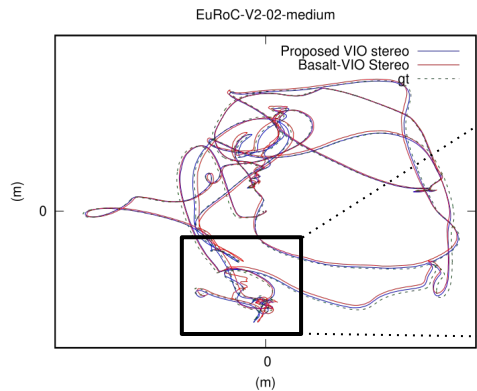
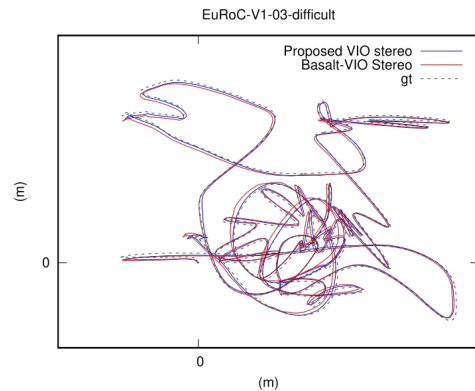
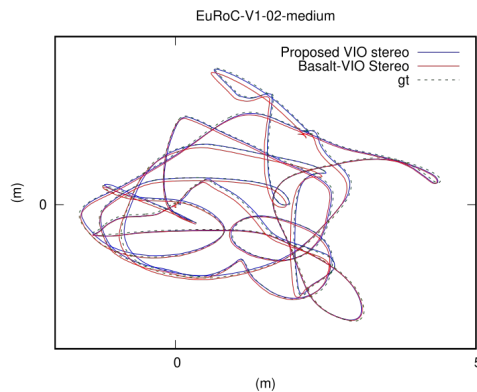
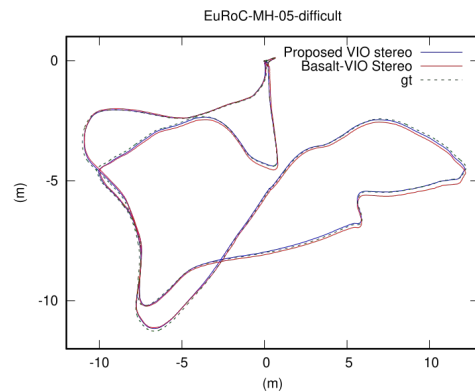
- L1. receive a kf from mapper
- L2. detect and merge loops
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# Quantitative results

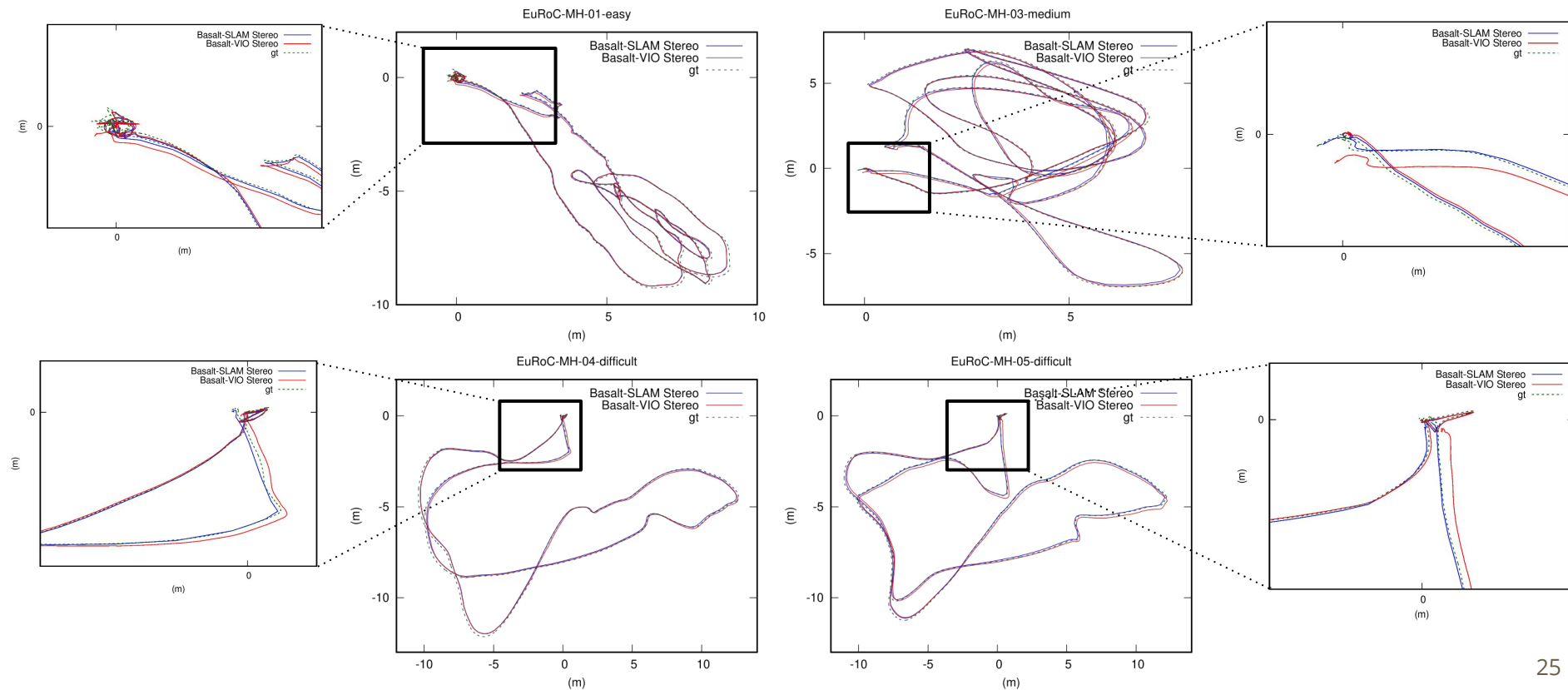
Sequence	MH_01	MH_02	MH_03	MH_04	MH_05	V1_01	V1_02	V1_03	V2_01	V2_02
Basalt VIO, stereo <a href="#">[33]</a>	<b>0.09</b>	<b>0.05</b>	0.09	<b>0.11</b>	0.11	<b>0.04</b>	0.06	0.07	<b>0.04</b>	0.06
Proposed VIO, stereo	<b>0.09</b>	0.06	<b>0.08</b>	<b>0.11</b>	<b>0.08</b>	<b>0.04</b>	<b>0.04</b>	<b>0.05</b>	0.05	<b>0.04</b>
Basalt VI Mapping, stereo, KF <a href="#">[33]</a>	0.08	0.06	<b>0.05</b>	0.11	<b>0.09</b>	<b>0.04</b>	<b>0.03</b>	<b>0.03</b>	<b>0.03</b>	<b>0.02</b>
Proposed SLAM (PGO), stereo, KF	0.08	<b>0.05</b>	<b>0.05</b>	<b>0.09</b>	<b>0.09</b>	0.05	0.04	0.05	0.05	0.05
Proposed SLAM (GBA), stereo, KF	<b>0.07</b>	<b>0.05</b>	<b>0.05</b>	<b>0.09</b>	<b>0.09</b>	<b>0.04</b>	<b>0.03</b>	0.05	0.04	0.04

# Improve lost tracking

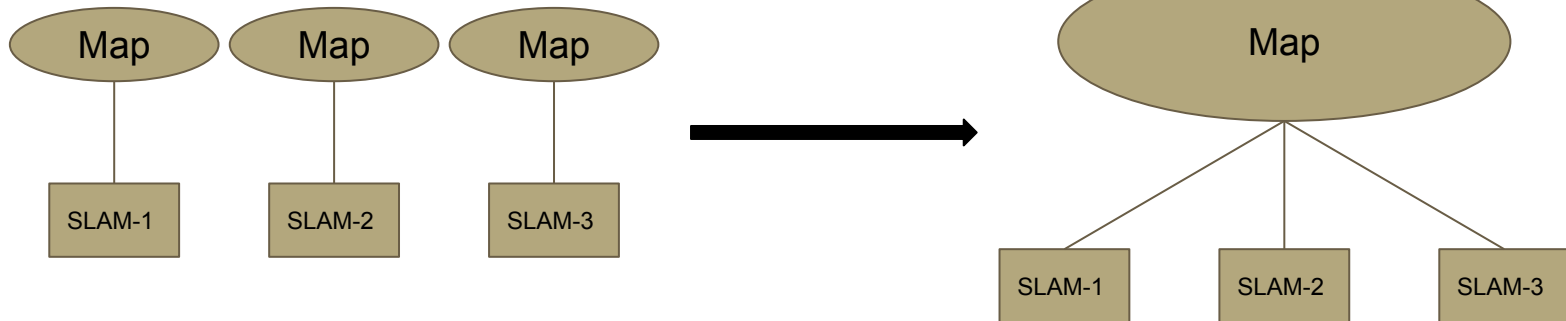




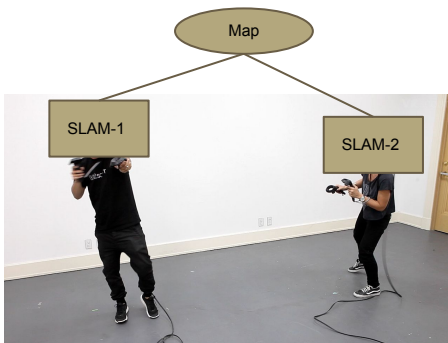
# Drift correction



# Structure of multi camera slam

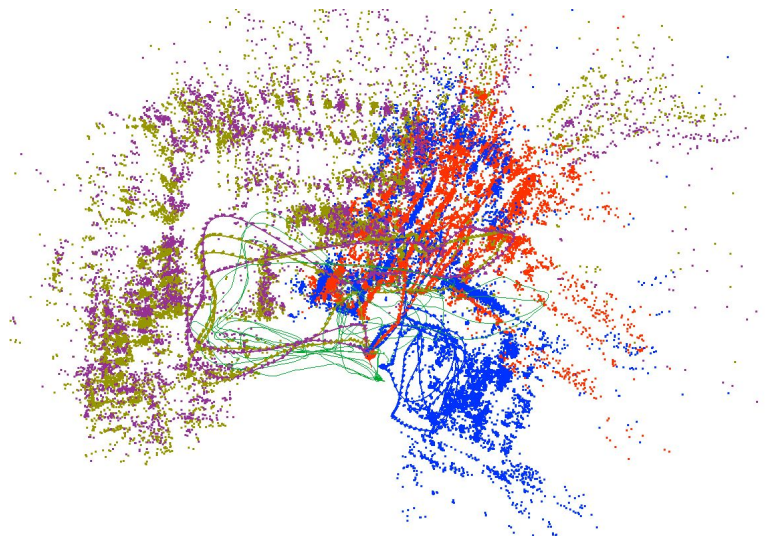
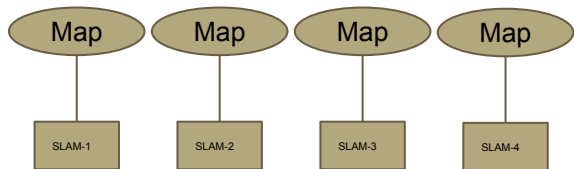


example:

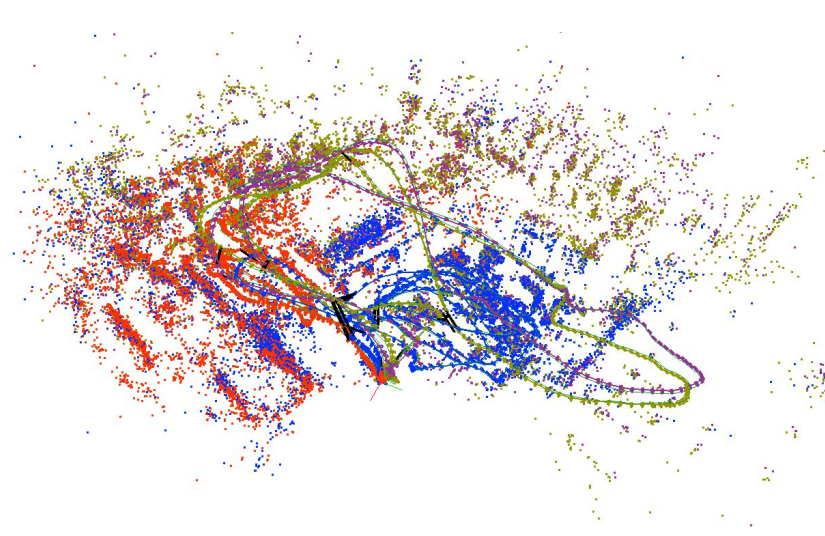
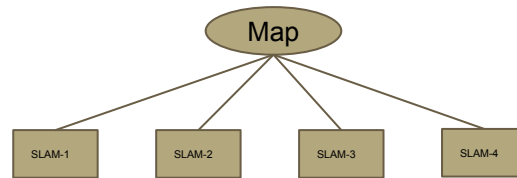


source: <https://vrscout.com/news/cant-stop-playing-pool-nation-vr/>

# Qualitative results

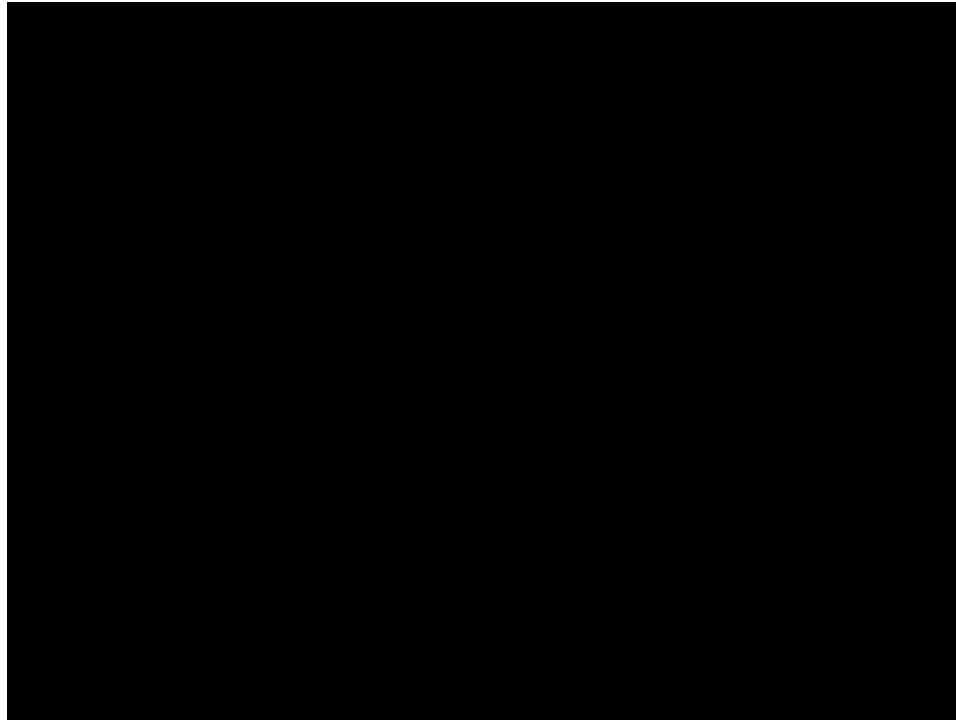


4 SLAM systems with 4 maps



4 SLAM systems with 1 map

# Demo of proposed method



End

Thank you !!!

# Demo

1 camera [Basalt-SLAM \(1 camera\)](#)

2 cameras [Basalt-SLAM \(2 cameras\)](#)

3 cameras [Basalt-SLAM \(3 cameras\) 4x](#)

4 cameras [Basalt-SLAM \(4 cameras\) 4x](#)

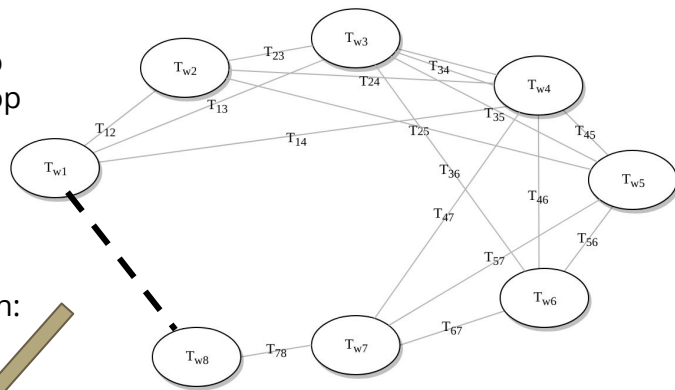
# Appendix: Merge loop

- T1. input data
- T2. set ini pose
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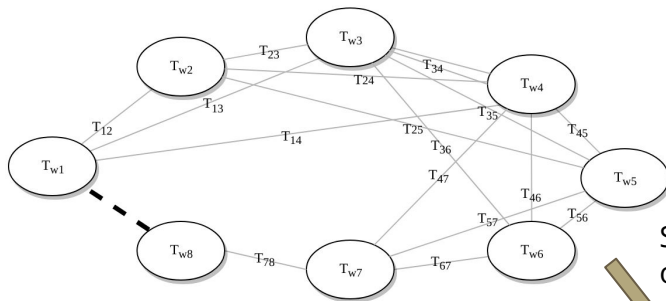
- L1. receive a kf from mapper
- L2. detect and merge loops
- L3. repeat step L1-L2

Use Hash-bow to find potential loop

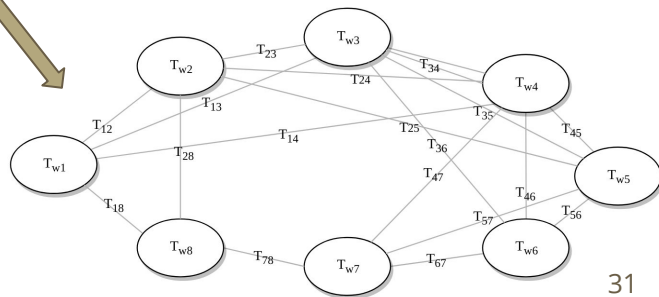


Pose graph optimization with error function:

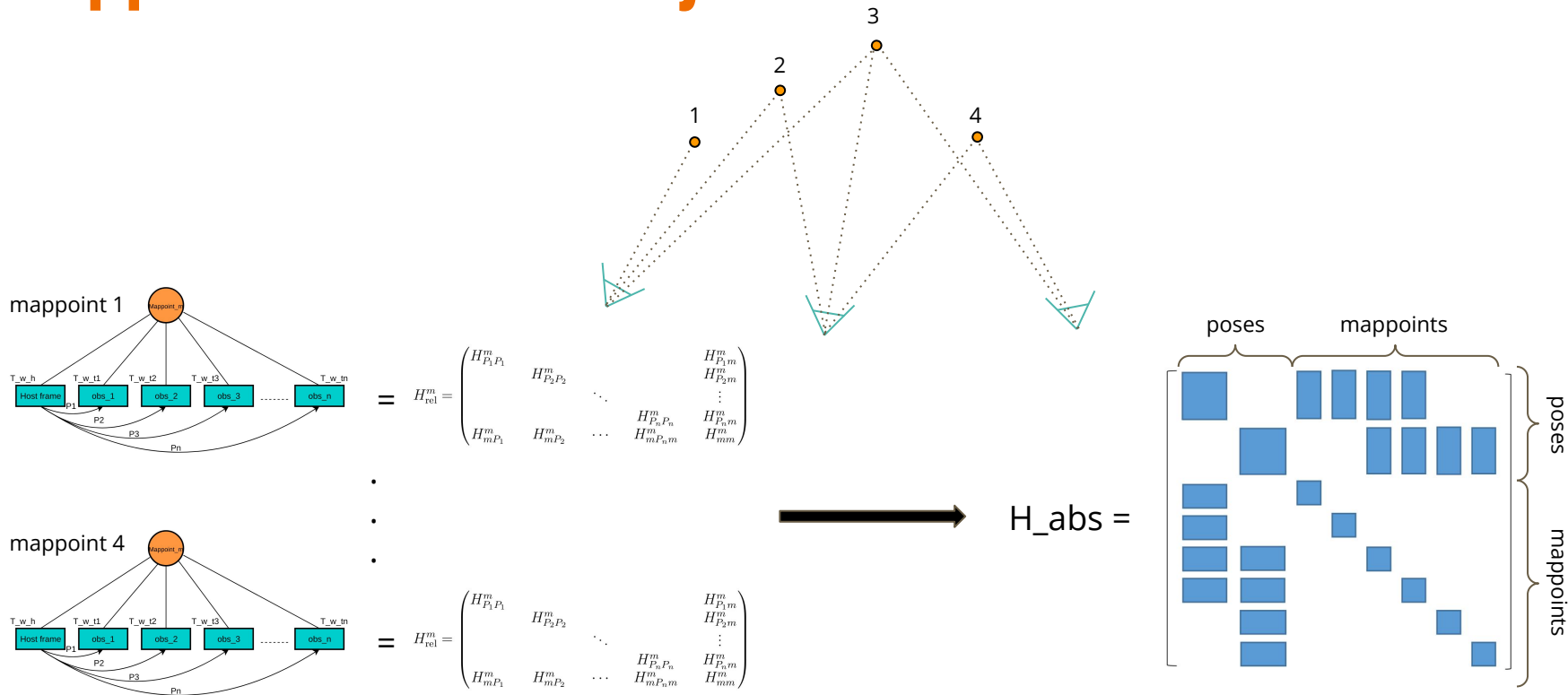
$$E = E_{rel\ pose}^{nfr} + E_{roll\ pitch}^{nfr} + E_{rel\ pose}^{loop\ edge}$$



Search observations

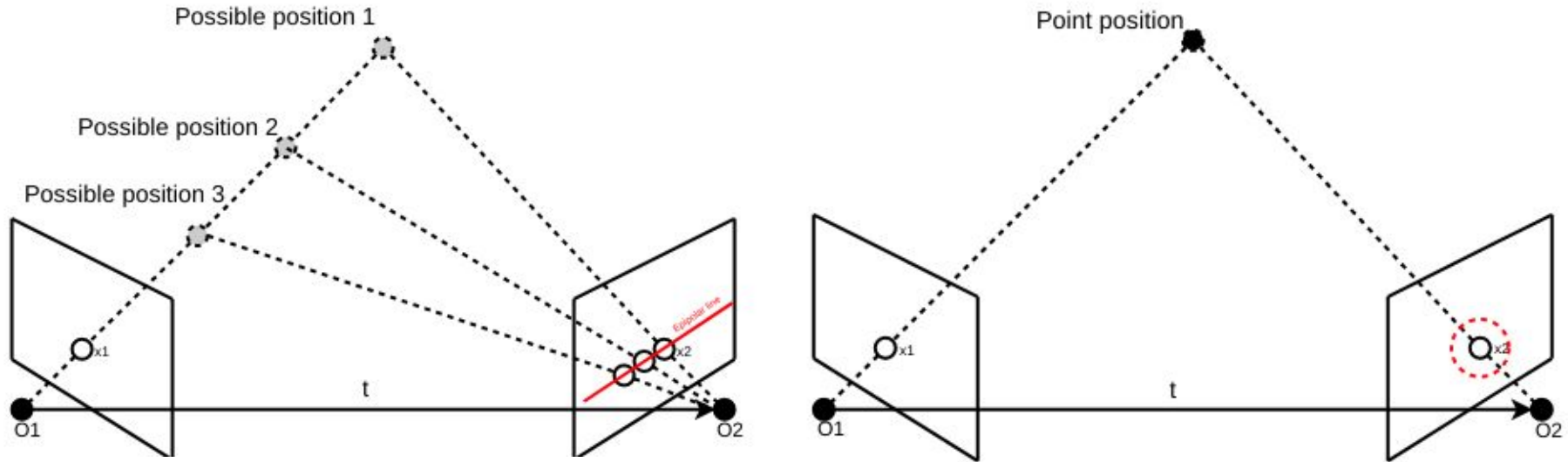


# Appendix: Bundle adjustment





# Appendix: Track optical flow keypoints by re-projection



# Appendix: Optical flow

$$E(\xi) = \sum_{p_i \in \Omega} \|\text{res}_{i,\Omega}(\xi)\|^2 = \sum_{p_i \in \Omega} \left\| \frac{I_{t+1}(e^{\xi^\wedge} p_i)}{\overline{I_{t+1,\Omega}}(\xi)} - \frac{I_t(p_i)}{\overline{I_{t,\Omega}}(\mathbf{0})} \right\|^2 \quad (3.1)$$

where  $\overline{I_{t,\Omega}}(\mathbf{0}) \equiv \frac{1}{|\Omega|} \sum_{p_i \in \Omega} I_t(p_i)$  and  $\overline{I_{t+1,\Omega}}(\xi) \equiv \frac{1}{|\Omega|} \sum_{p_i \in \Omega} I_{t+1}(e^{\xi^\wedge} p_i)$

To calculate  $\delta\xi$  for each iteration, we will use Gauss-Newton method to do so. First, we calculate the jacobian

$$J_i(\xi) = \frac{\partial \text{res}_{i,\Omega}(\xi)}{\partial \xi} = \frac{\partial}{\partial \xi} \left( \frac{I_{t+1}(e^{\xi^\wedge} p_i)}{\overline{I_{t+1,\Omega}}(\xi)} \right) = \frac{\partial}{\partial p'} \left( \frac{I_{t+1}(p')}{\overline{I_{t+1,i}}(\xi)} \right) \frac{\partial p'}{\partial \xi} \Big|_{p'=e^{\xi^\wedge} p_i} \quad (3.2)$$

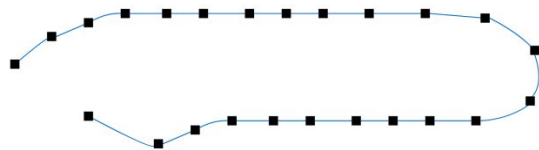
By using chain rule, we have

$$J_i(\xi) = \frac{\partial}{\partial p'} \left( \frac{I_{t+1}(p')}{\overline{I_{t+1,i}}(\xi)} \right) \frac{\partial p'}{\partial \xi} \Big|_{p'=e^{\xi^\wedge} (p_i+x)} \quad (3.3)$$

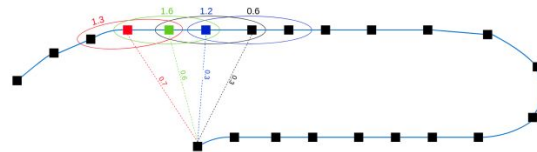
$\frac{\partial p'}{\partial \xi} \Big|_{p'=e^{\xi^\wedge} p_i}$  can be calculated by eq. 2.26 and the updated  $\xi_{new}$  is as follows,

$$\xi_{new} = \xi_{old} - \left( \sum_i J_i(\xi_{old}) (J_i(\xi_{old}))^T \right)^{-1} \left( \sum_i J_i(\xi_{old})^T \text{res}_{i,\Omega}(\xi_{old}) \right) \quad (3.4)$$

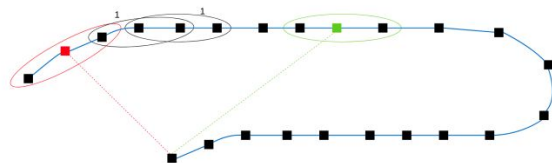
# Appendix: Steps of loop detection



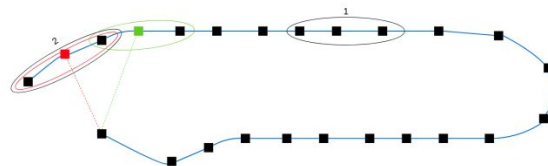
(a) Without loop detection.



(b) At time  $t$ , four query results with loop score 0.7 (red), 0.6 (green), 0.3 (blue) and 0.3 (black) respectively. The best accumulated score is 1.3, so the keyframes in red, green and blue are good loop kf candidates



(c) At time  $t+1$ , two consistent groups with consistent score 1, two new loop keyframe candidates (red, green).



(d) At time  $t+2$ , two consistent groups with consistent score 1 and consistent score 2 respectively, two new loop keyframe candidates (red and green).