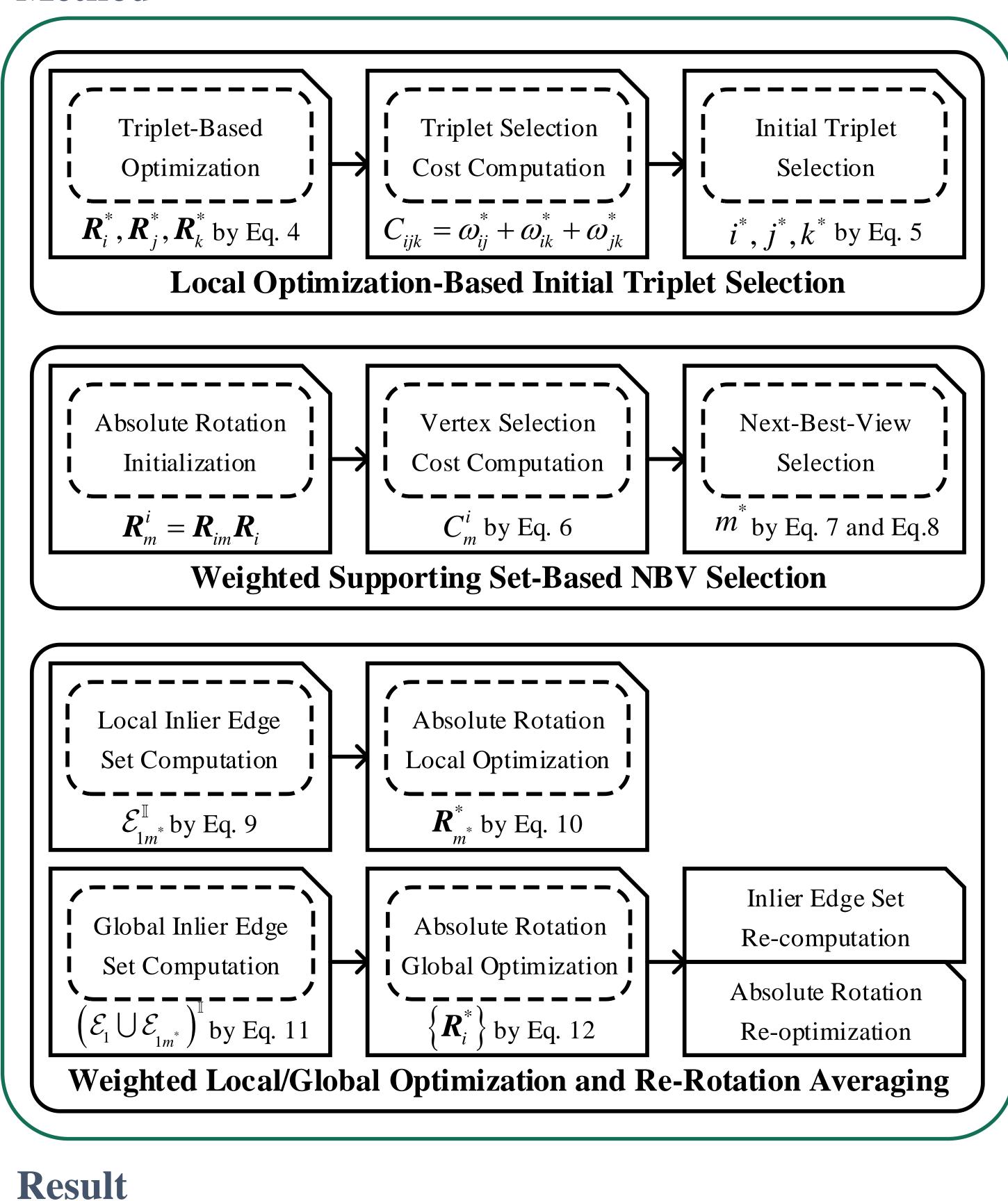




Xiang Gao¹, Lingjie Zhu^{2,3}, Zexiao Xie¹, Hongmin Liu^{4,*}, and Shuhan Shen^{2,3,*} ¹College of Engineering, Ocean University of China ²NLPR, Institute of Automation, Chinese Academy of Sciences ³School of Artificial Intelligence, University of Chinese Academy of Sciences ⁴School of Automation and Electrical Engineering, University of Science and Technology Beijing Method Introduction

- **Rotation averaging**^[1] estimates the absolute camera orientations given the relative rotation measurements.
- It is non-trivial because some of the relative rotations in the Epipolar-geometry Graph (EG) are **outliers**.
- Existing methods either seek to design **robust loss** functions to make the optimization process more robust^[2-3] or try to develop effective filtering strategies to clean the outlier-contaminated EG^[4-5].



- In order to achieve a more accurate and robust absolute rotation estimation, we present a novel rotation averaging pipeline, which is inspired by the well-developed incremental SfM techniques.
- Instead of estimating all the absolute rotations simultaneously like traditional rotation averaging methods, they are estimated in an **incremental** way.

Preliminary

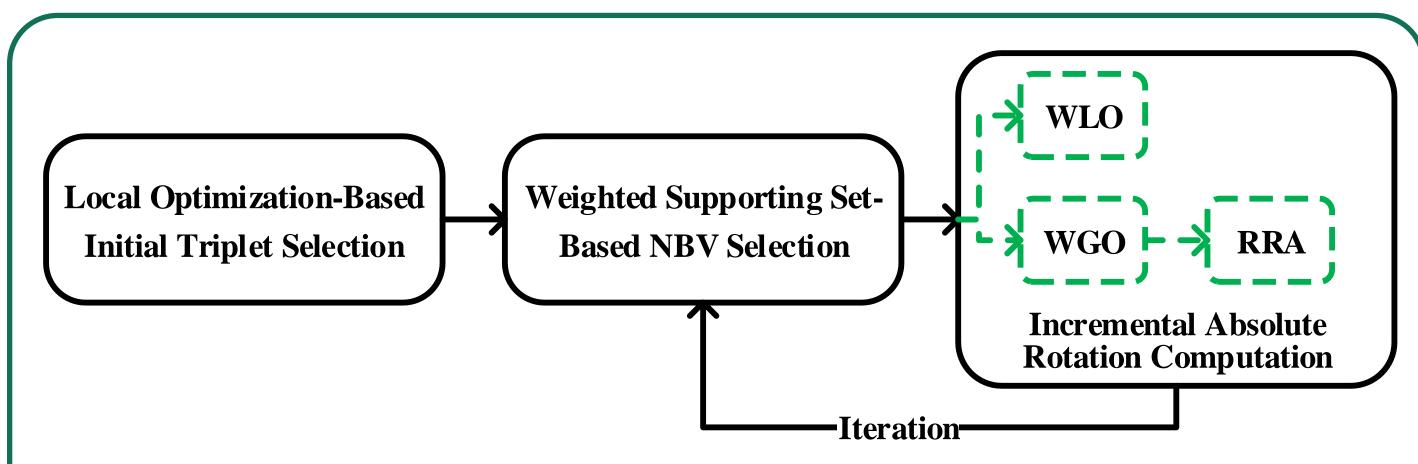
• Given an EG, $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where each vertex $v_i \in \mathcal{V}$ corresponds to a camera with an absolute rotation R_i to estimate, and each edge $e_{ij} \in \mathcal{E}$ links a matched image pair with a relative rotation measurement R_{ii} . The rotation averaging problem here is defined as:

$$\{\boldsymbol{R}_{i}^{*}\} = \arg\min \sum_{\substack{\boldsymbol{v}_{i}, \boldsymbol{v}_{j} \in \mathcal{V} \\ e_{ij} \in \mathcal{E}}} d_{\theta}^{2} (\boldsymbol{R}_{ij}, \boldsymbol{R}_{j} \boldsymbol{R}_{i}^{\mathrm{T}}).$$

• The
$$\mathbf{R}_{ij}$$
 inlier/outlier criterion is defined as:

$$\mathbf{R}_{ij} = \begin{cases} \mathbf{R}_{ij}^{\mathbb{I}} & \text{if } d_{\theta}(\mathbf{R}_{ij}, \mathbf{R}_{j}^{*}\mathbf{R}_{i}^{*\mathrm{T}}) \leq \theta_{th} \\ \mathbf{R}_{ij}^{\mathbb{O}} & \text{if } d_{\theta}(\mathbf{R}_{ij}, \mathbf{R}_{j}^{*}\mathbf{R}_{i}^{*\mathrm{T}}) > \theta_{th} \end{cases}$$

Overview



Input: relative rotation measurements and the feature

| Data | ℓ_1 -IRLS ^[2] | $\boldsymbol{\ell}_1 \text{-} \text{IRLS}(\boldsymbol{\ell}_{0.5})^{[3]}$ | WRST-RA ^[4] | OMSTs-RA ^[5] | IRA | ℓ_1 -IRLS($\ell_{0.5}$) w/ IR. |
|------|-------------------------------|---|------------------------|-------------------------|------|---------------------------------------|
| ALM | 2.12 | 2.14 | 2.11 | 1.26 | 0.83 | 1.23 |
| ELS | 1.02 | 1.15 | 1.32 | 0.75 | 0.51 | 0.52 |
| MDR | 2.75 | 3.08 | 35.38 | 1.12 | 0.85 | 1.02 |
| MND | 0.77 | 0.71 | 1.03 | 0.68 | 0.51 | 0.55 |
| NYC | 1.43 | 1.40 | 4.51 | 1.30 | 1.00 | 1.11 |
| PDP | 2.19 | 2.62 | 1.48 | 1.73 | 0.90 | 1.30 |
| PIC | 2.38 | 3.12 | 14.40 | 1.41 | 1.67 | 1.63 |
| ROF | 1.59 | 1.70 | 10.55 | 1.85 | 1.51 | 1.48 |
| TOL | 2.55 | 2.45 | 4.08 | 2.10 | 2.45 | 2.45 |
| TFG | 1.85 | 2.03 | 13.25 | 2.63 | 3.30 | 3.22 |
| USQ | 4.34 | 4.97 | 15.39 | 3.83 | 4.40 | 4.22 |
| VNC | 4.47 | 4.64 | 3.63 | 3.30 | 1.02 | 1.06 |
| YKM | 1.71 | 1.62 | 2.90 | 1.55 | 1.57 | 1.44 |
| CPS | 2.06 | 2.05 | 1.24 | 2.35 | 1.24 | 1.75 |
| SNF | 3.05 | 3.56 | 15.07 | 3.26 | 2.06 | 2.36 |

Conclusion

A simple yet effective rotation averaging pipeline, IRA, is presented, which shares similar workflow with the incremental SfM, thus it is accurate in parameter estimation and **robust** to measurement outliers as well.

match number on each EG edge, $\{\mathbf{R}_{ij}, n_{ij} | e_{ij} \in \mathcal{E}\}$.

- Output: optimized absolute rotations, $\{\mathbf{R}_i^* | v_i \in \mathcal{V}\}$.
- Several key techniques are proposed to push the results further for the particular rotation averaging assignment.

Reference

[1] R. Hartley, J. Trumpf, Y. Dai, and H. Li. Rotation Averaging[J]. International Journal of Computer Vision, 2013, 103: 267–305.

[2] A. Chatterjee and V. M. Govindu. Efficient and Robust Large-Scale Rotation Averaging[C]. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2013: 521–528.

[3] A. Chatterjee and V. M. Govindu. Robust Relative Rotation Averaging[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2018 40(4): 958–972.

[4] V. M. Govindu. Robustness in Motion Averaging[C]. In Asian Conference on Computer Vision (ACCV), 2006: 457–466.

[5] H. Cui, S. Shen, W. Gao, H. Liu, and Z. Wang. Efficient and Robust Large-Scale Structure-from-Motion via Track Selection and Camera Prioritization[J]. ISPRS Journal of Photogrammetry Remote Sensing, 2019, 156: 202–214.