Geometry-Driven 3D Reconstruction: *Structure-from-Motion, Rotation Averaging, and Registration*

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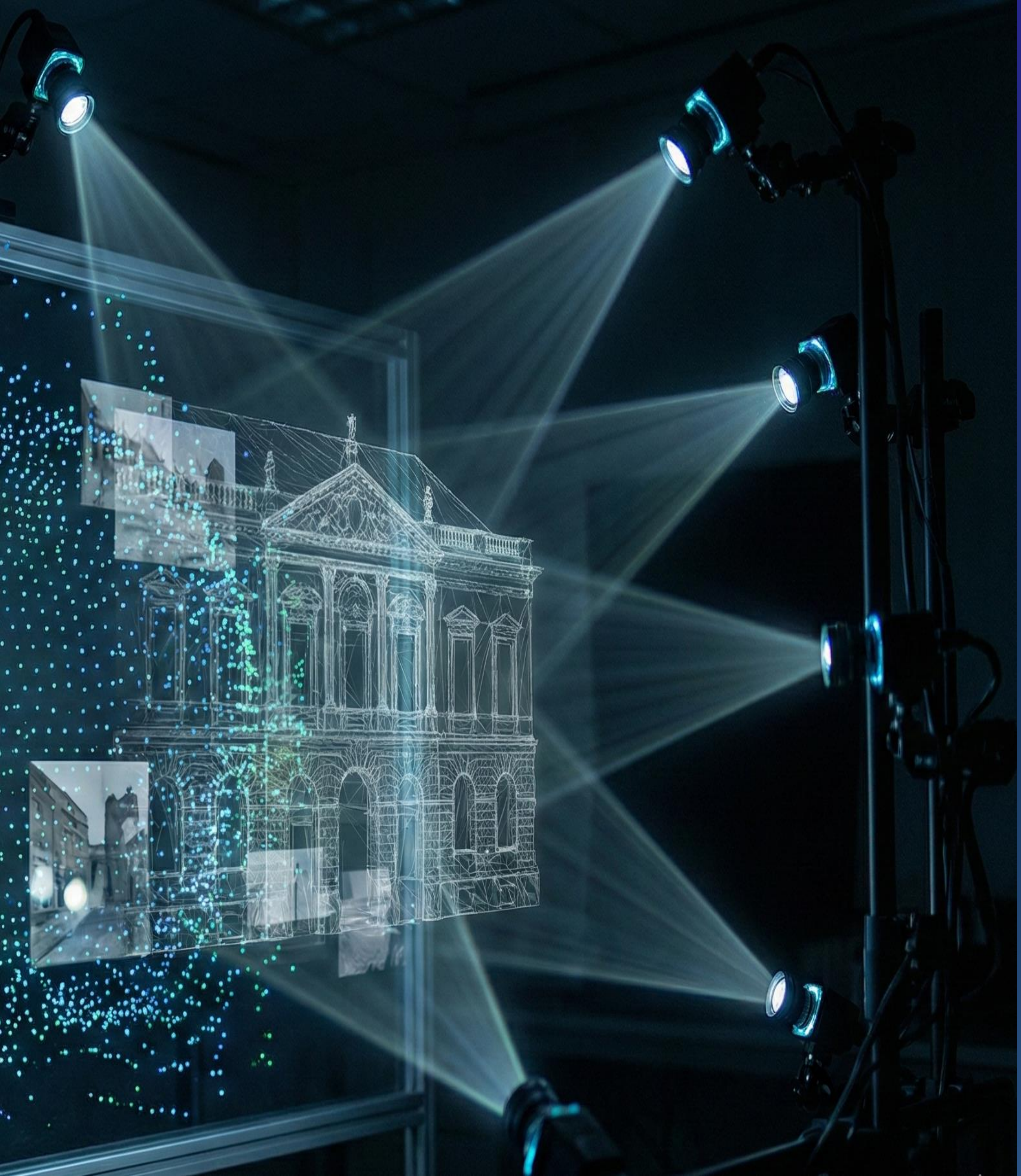


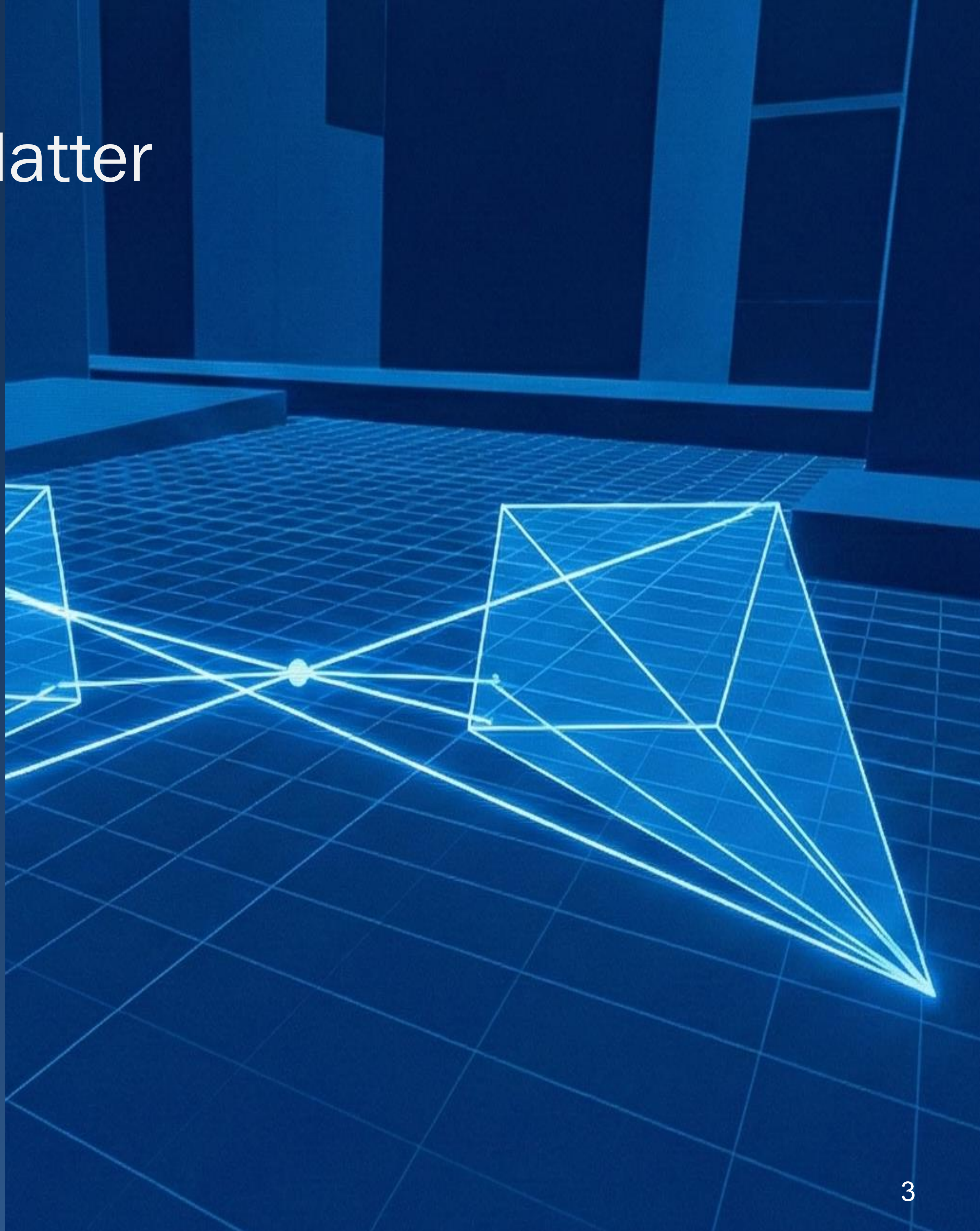
Motivation & Problem Statement

- 3D reconstruction from images is a core problem in computer vision
- Applications: AR, robotics, autonomous navigation, cultural heritage
- Despite learning advances, geometry remains indispensable
- Errors in reconstruction propagate across pipeline stages

[1] Snavely et al., *Photo Tourism*, ACM
[2] Agarwal et al., *Building Rome in a Day*, ICCV

Why Geometry-Driven Pipelines Still Matter

- Multi-view geometry imposes **hard physical constraints**
- Epipolar geometry, rigid motion, SO(3)/SE(3)
- Learning improves **front-end matching**
- Optimization and guarantees remain **geometric**

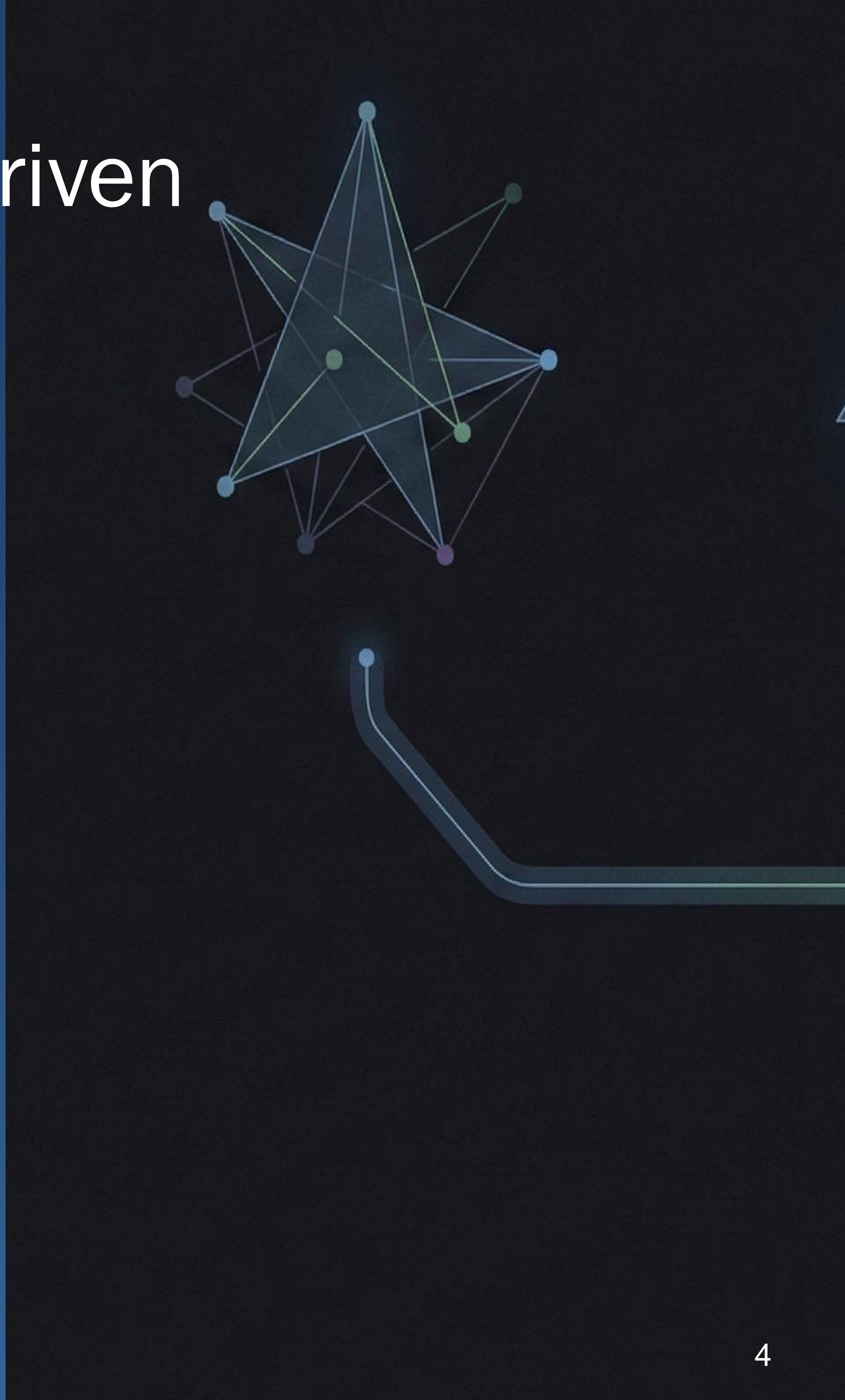


[3] Govindu, *Lie-algebraic averaging*, CVPR
[4] Hartley et al., *Rotation Averaging*, IJCV

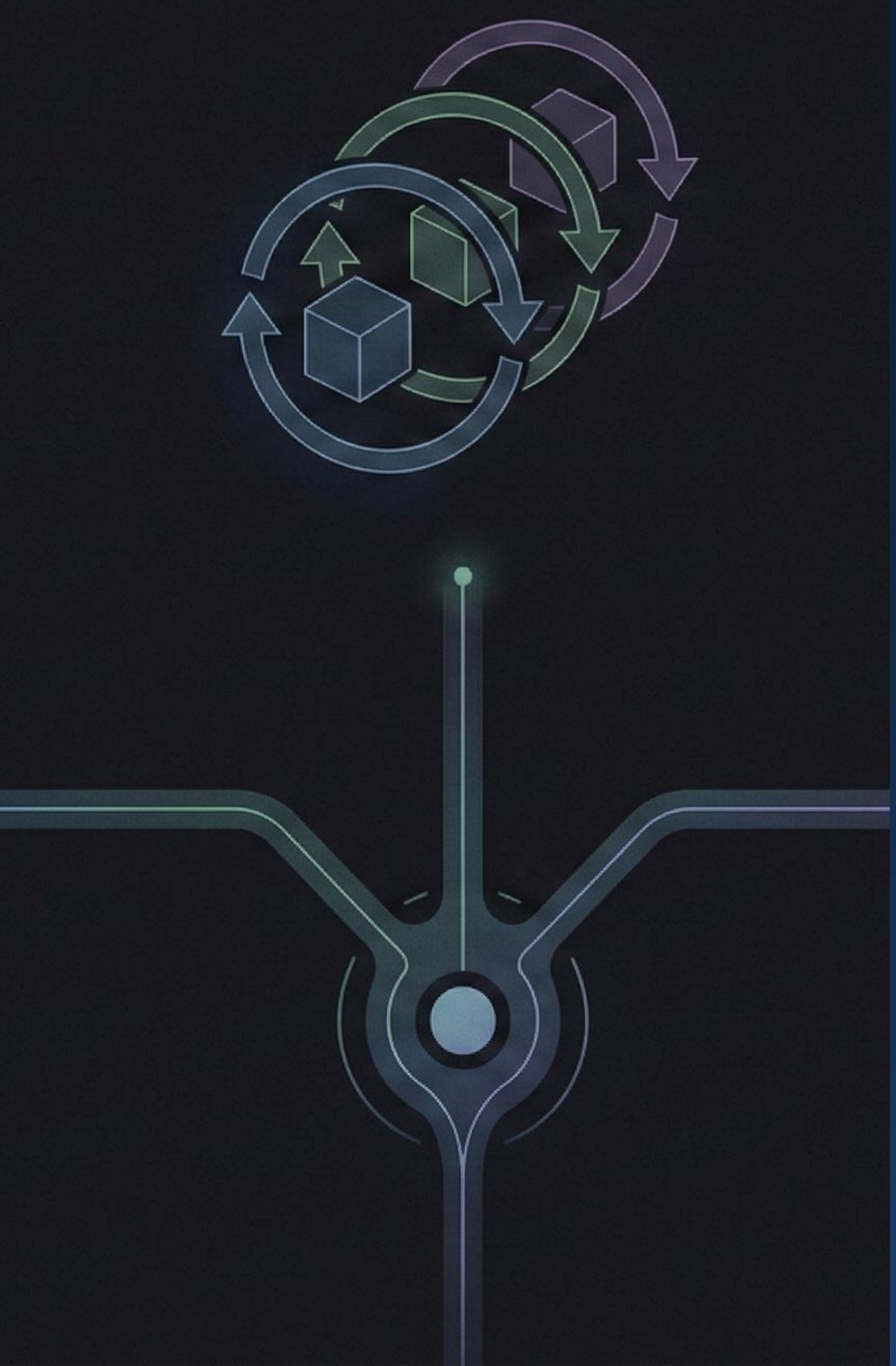
Taxonomy of Geometry-Driven Reconstruction

A. SfM Pipeline Families

- Incremental SfM
- Global SfM
- Hierarchical and Hybrid SfM



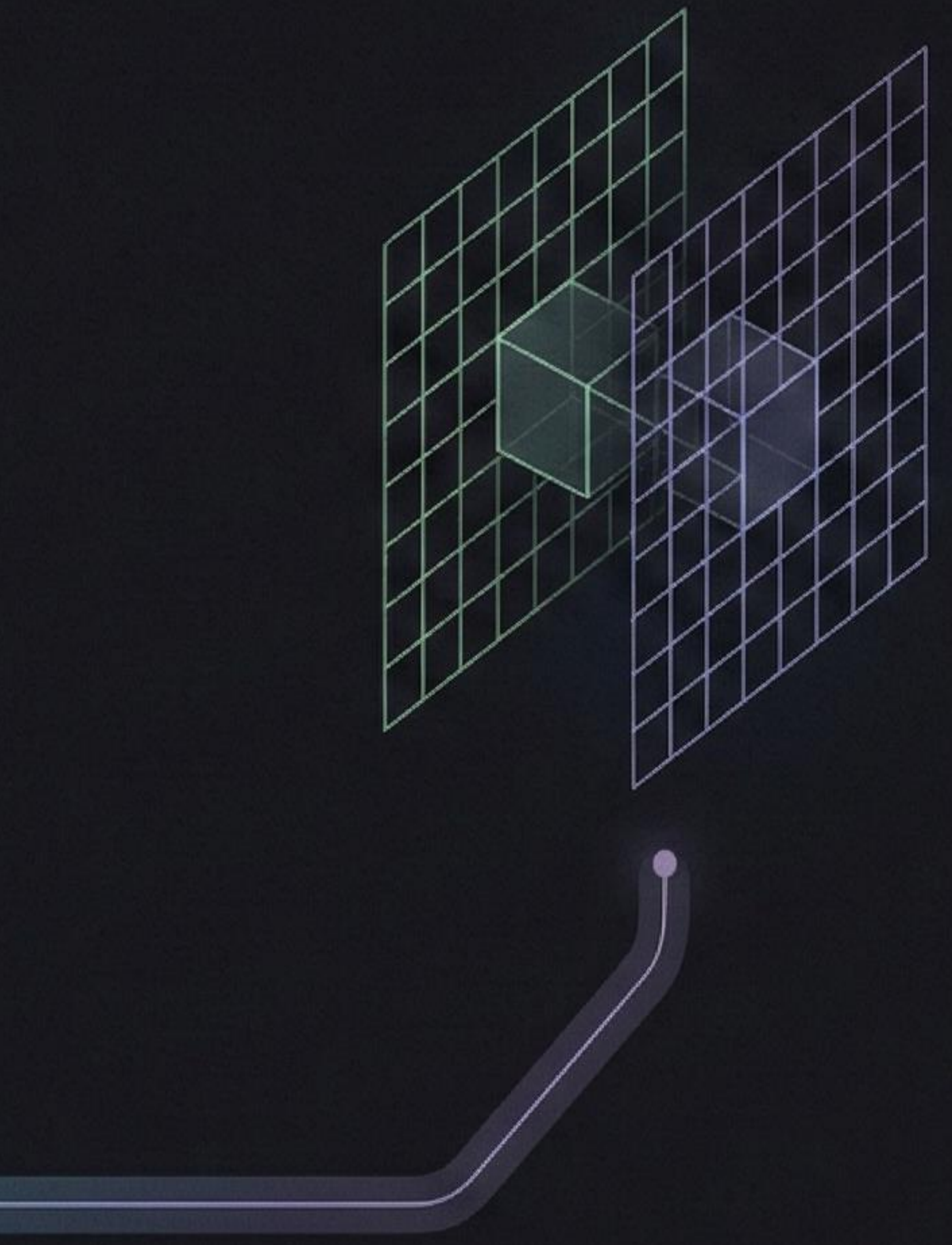
Taxonomy of Geometry-Driven Reconstruction



Rotation Averaging Categories

- Least-Squares Averaging
- Robust Averaging
- Certifiable Relaxations

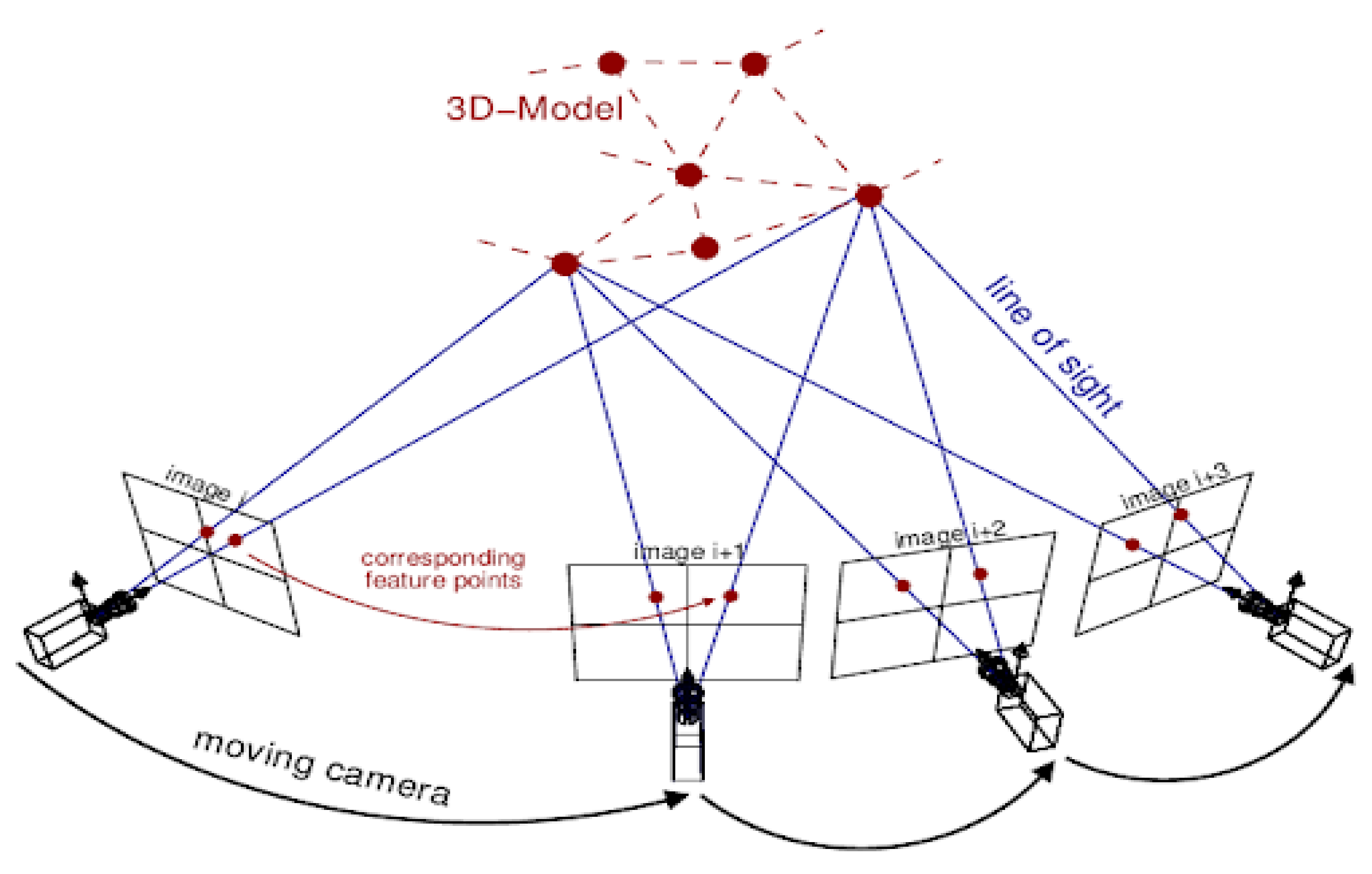
Taxonomy of Geometry-Driven Reconstruction



Registration Method Classes

- Local Registration
- Global Registration
- Learning-Augmented Registration

STRUCTURE-FROM-MOTION

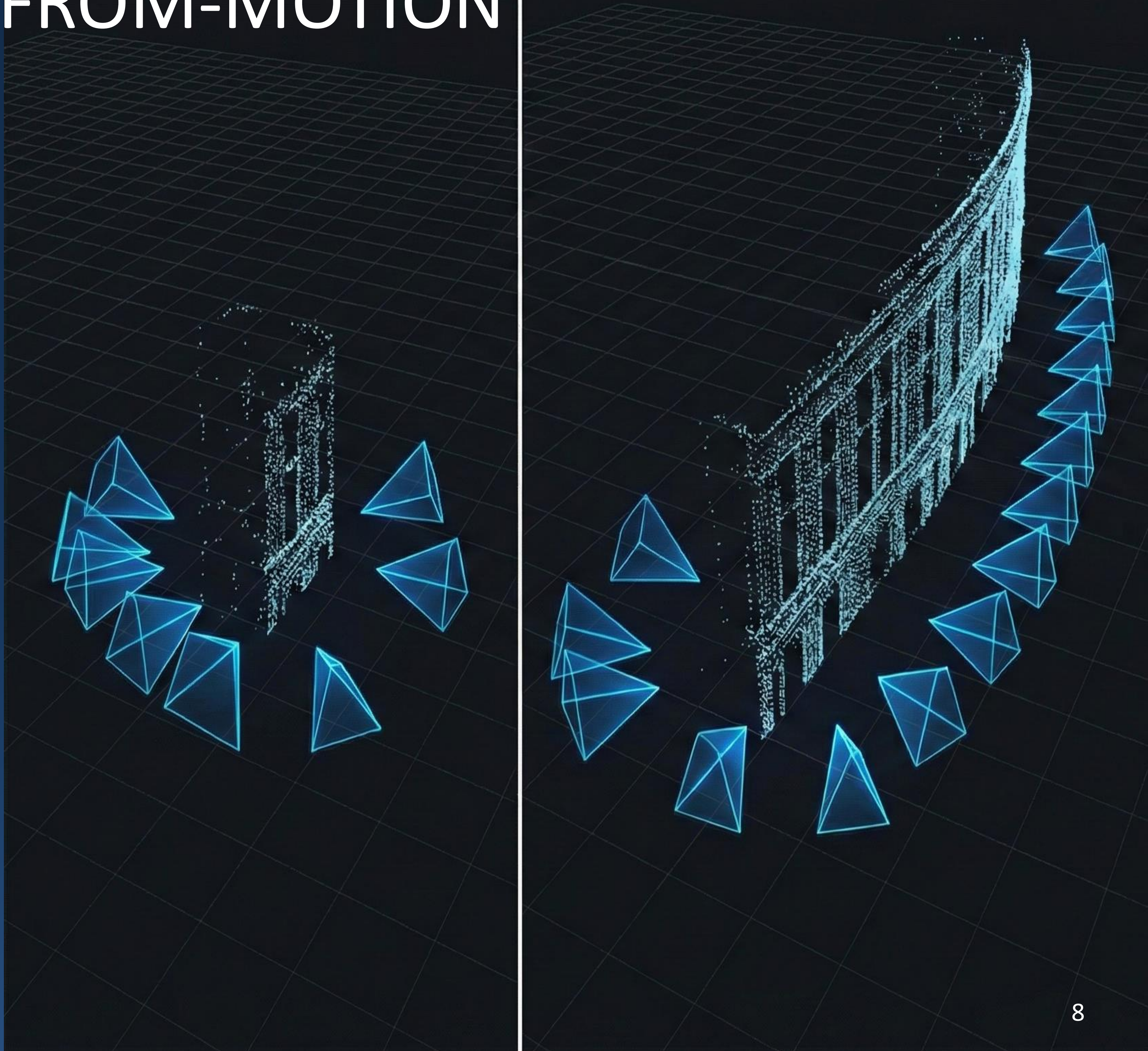


[1] Snavely et al., Photo Tourism

STRUCTURE-FROM-MOTION

Incremental SfM

- Strengths
  - Robust to outliers
  - Strong local bundle adjustment
- Weaknesses
  - Drift accumulation
  - High computationalCost
  - Initialization bias



[1] Snavely et al., Photo Tourism

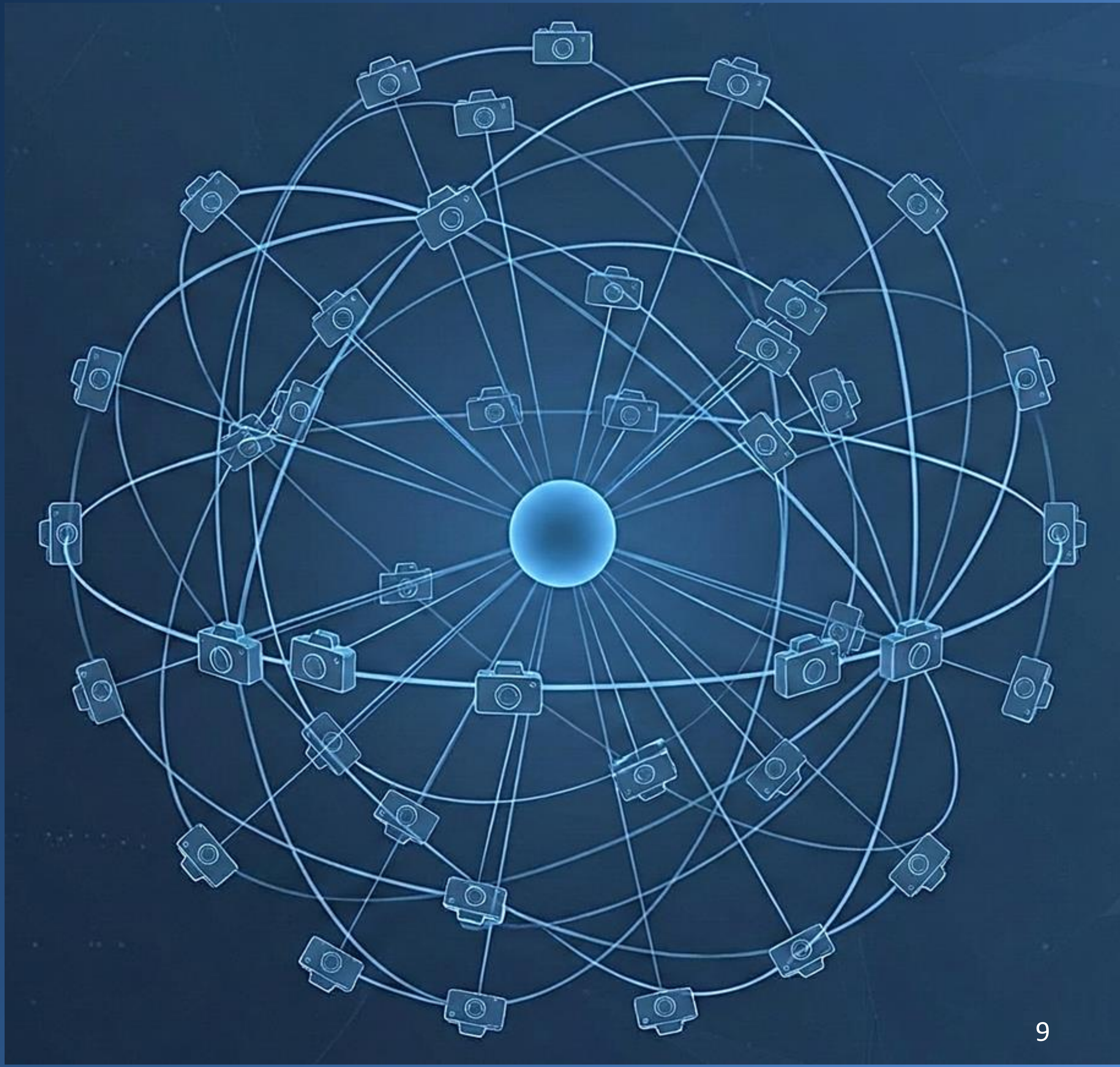
STRUCTURE-FROM-MOTION

Global SfM

- Drift-free
- Sensitive to outliers
- Depends on view-graph connectivity

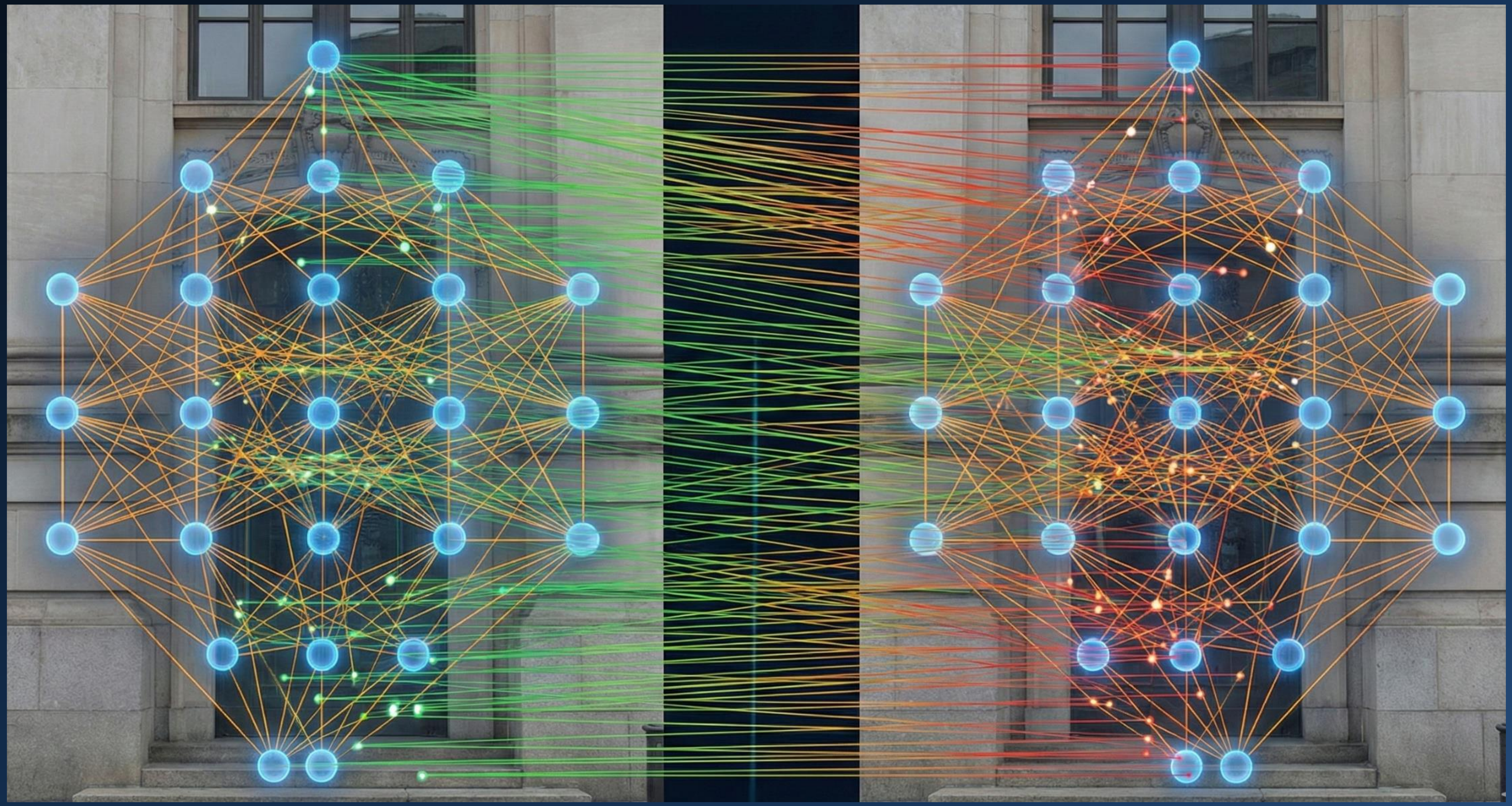
Hybrid / Hierarchical

- Combines robustness and scalability
- Still inherits weaknesses



[10] Wilson & Snavely, 1DSfM
[11] Schönberger & Frahm, COLMAP

STRUCTURE-FROM-MOTION



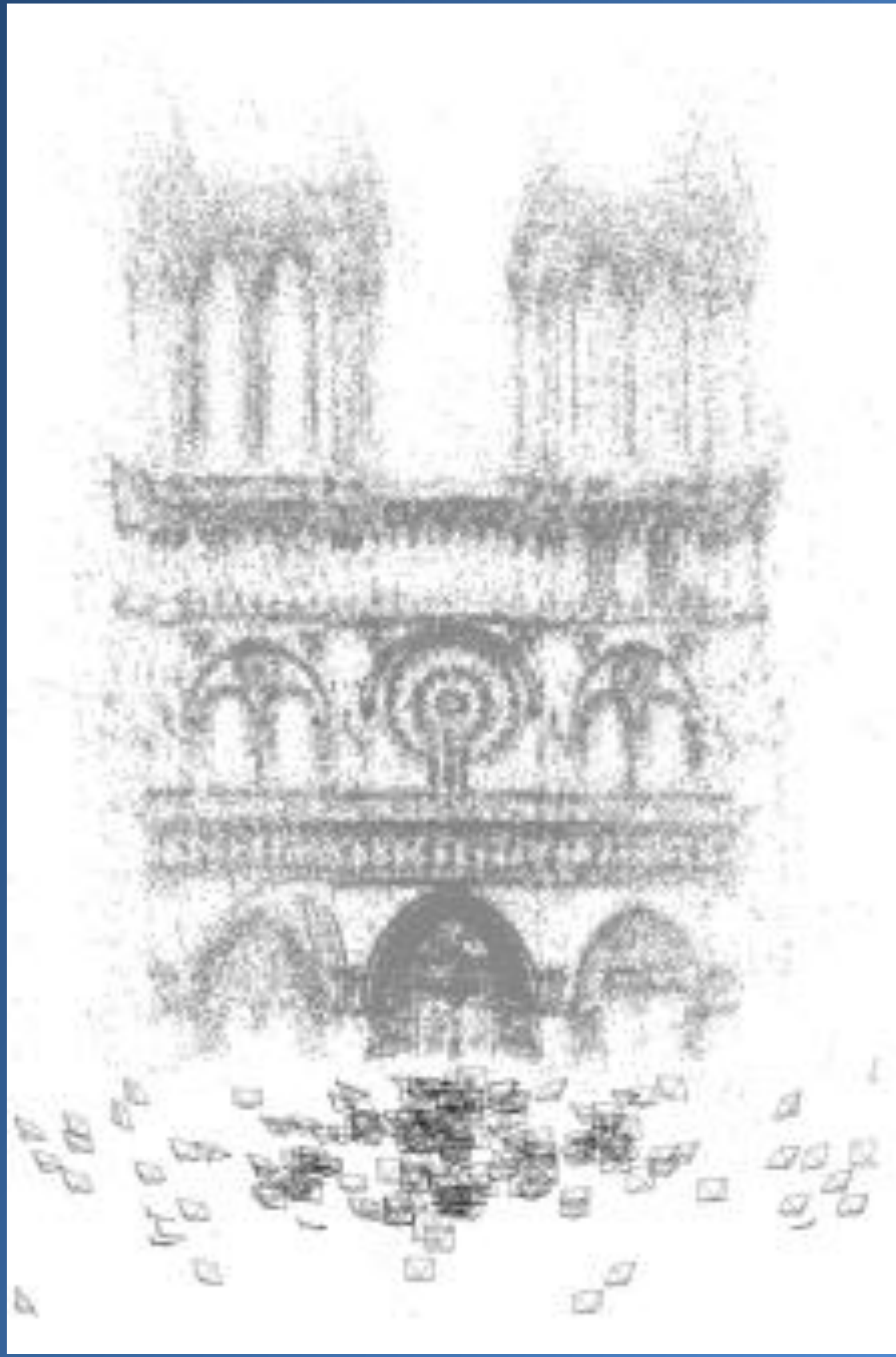
Learning-Augmented SfM

- Learned matchers: SuperPoint, SuperGlue
- Improve correspondence reliability
- Geometry remains the bottleneck
- Quadratic matching cost

[7] Sarlin et al., SuperGlue

Rotation Averaging

- Least-Squares Averaging: fast, fragile
- Robust Averaging (L1, IRLS): stable, slower
- Certifiable Methods (Shonan): guarantees, expensive



[3] Govindu
[4] Hartley et al.
[12] Chatterjee & Govindu
[13] Dellaert et al., Shonan Averaging

REGISTRATION

$\sigma = 0.01$ $\sigma = 0.02$ $\sigma = 0.03$

- Local Registration: ICP (fast, fragile)
- Global Registration: Go-ICP, 4PCS, FGR (robust, costly)
- Pose Graph Optimization
- Learning-Augmented Registration

[5] Besl & McKay, ICP
[6] Yang et al., Go-ICP
[14] Zhou et al., FGR
[15] Kümmerle et al., g2o
[8] Choy et al., DGR

Open Problems & Future Directions

- Robustness under extreme outliers
- Scalability to city-scale datasets
- Unstable translation averaging
- Learning generalization limits
- Need for unified optimization

Conclusion

- Geometry remains the backbone
- Learning strengthens but does not replace geometry
- Future lies in hybrid, certifiable, scalable frameworks

[1] N. Snavely, S. M. Seitz, and R. Szeliski, Photo tourism: exploring photo collections in 3D, 1st ed. New York, NY, USA: Association for Computing Machinery, 2023. [Online]. Available: https://doi.org/10.1145/3596711.3596766
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[11] J. L. Schonberger and J.-M. Frahm, "Structure-from-motion revisited," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 4104–4113.
[12] A. Chatterjee and V. M. Govindu, "Efficient and robust large-scale rotation averaging," in Proceedings of the IEEE international conference on computer vision, 2013, pp. 521–528.
[13] F. Dellaert, D. M. Rosen, J. Wu, R. Mahony, and L. Carlone, "Shonan rotation averaging: Global optimality by surfing so (p) n," in European Conference on Computer Vision. Springer, 2020, pp. 292–308.
[14] Q.-Y. Zhou, J. Park, and V. Koltun, "Fast global registration," in European conference on computer vision. Springer, 2016, pp. 766–782.
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