Politecnico di Torino - M.Sc in Data Science and Engineering

AI-Driven Feature Detection, Matching, and Efficient Model Deployment for Space Applications

AIKO

INFINITE WAYS TO AUTONOMY

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Objectives

- ➔ Compare classical algorithms and state-of-art Deep Learning models in **Feature Detection and Matching (FDM)** for **Space** applications
- ➔ Apply **Knowledge Distillation** to replace Attention layers in Transformer-based models

AGENDA

- ➔ Feature Detection and Matching for space applications
- ➔ AI approaches for Feature Detection and Matching
- ➔ Comparison: Classical vs AI methods
- ➔ Knowledge Distillation

FDM for space applications

What is Feature Detection and Matching?

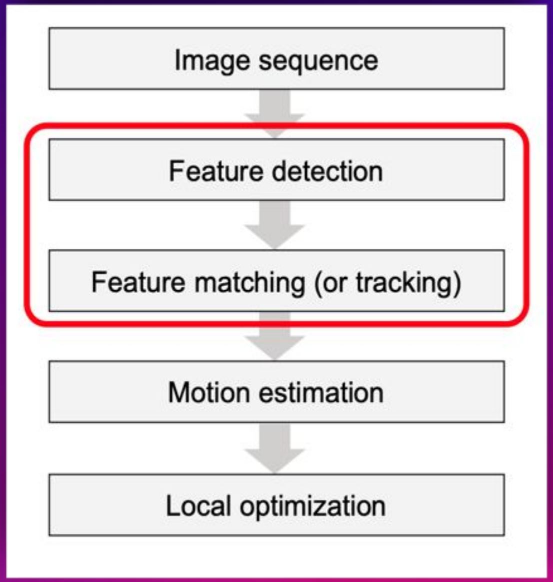
***FDM** is the process of identifying similar **interest points** between two images of the same scene captured under different conditions*

Why do we need keypoints?

Keypoints are fundamental for motion estimation

Many applications use local features tracking

- 3D object reconstruction
- Image registration
- Visual Simultaneous Localization and Mapping (V-SLAM)



Why FDM in space?

FDM can be used for **Optical Navigation (ON)** in space applications

Optical Navigation: *Use of on-board cameras to capture visual information of a target and perform relative navigation*

ON is relevant in space

➔ Enables autonomous navigation
➔ Substitutes traditional active navigation sensors
➔ Improves navigation precision

Space missions:

- Active Debris Removal
- On-Orbit Servicing
- Rendezvous and Proximity Operations
- Deep Space exploration

Space Datasets

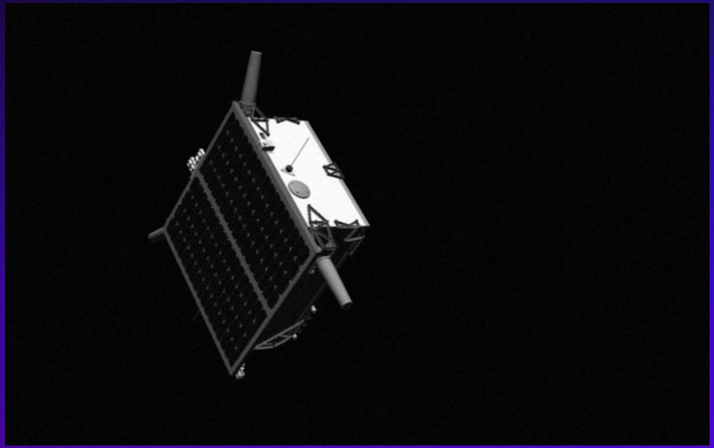
Space-related datasets for Satellite Pose Estimation

(Estimate position and orientation of a satellite target respect to the camera)

➔ **SPEED** [1]

➔ **SPEED+** [2]

➔ **SPEED-UE-Cube** [3]



TANGO spacecraft

3U CubeSat spacecraft

[1] Mark Kisantal et al. “Satellite Pose Estimation Challenge: Dataset, Competition Design and Results”.
[2] Tae Ha Park et al. “SPEED+: Next-Generation Dataset for Spacecraft Pose Estimation across Domain Gap”.
[3] Zahra Ahmed et al. “SPEED-UE-Cube: A Machine Learning Dataset for Autonomous, Vision-Based Spacecraft Navigation”.

Feature Detection and Matching through AI techniques

Classical FDM Algorithms

➔ Classical approaches in FDM: **SIFT** [4], **ORB** [5] and **AKAZE** [6]

➔ Traditional pipeline: Feature **Detection**, **Description** and **Matching**

➔ Algorithmic approach and mathematical operations:

- Gaussian and non-linear diffusion filtering, local image gradient
- Search of local extrema
- Fixed descriptor generation

➔ Matching:

- Descriptors similarity
- K-Nearest Neighbours with ratio test

[4] David G. Lowe. “Distinctive Image Features from Scale-Invariant Keypoints
[5] Ethan Rublee et al. “ORB: An efficient alternative to SIFT or SURF”
[6] Pablo F. Alcantarilla et al. “Fast Explicit Diffusion for Accelerated Features in Nonlinear Scale Spaces”

AI FDM Methods

- Deep Learning
- **SuperPoint** [7]
  - CNN-based
  - Simultaneous feature extraction and description
- **LightGlue** [8]
  - Attention-based Graph Neural Network (keypoints as “nodes”)
  - Feature matching only
- **LoFTR** [9]
  - Transformer-based
  - No feature detection
  - directly produces matches from dense grid of the images

Used together

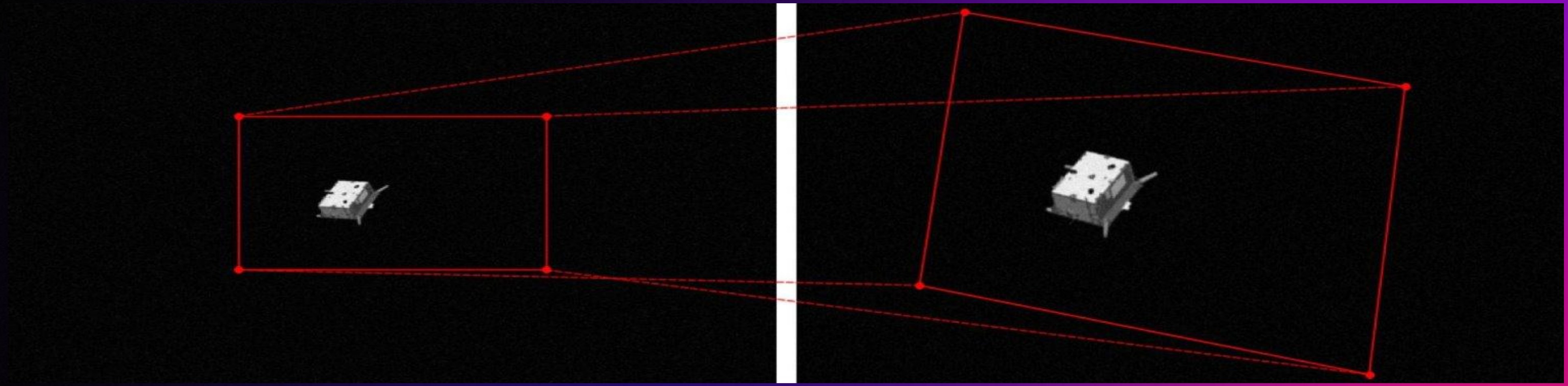
[7] Daniel DeTone et al. SuperPoint: Self-Supervised Interest Point Detection and Description. 2018
[8] Philipp Lindenberger et al. LightGlue: Local Feature Matching at Light Speed. 2023
[9] Jiaming Sun et al. LoFTR: Detector-Free Local Feature Matching with Transformers. 2021

Data Preparation and Evaluation metrics

Homography Estimation

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = H \cdot \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

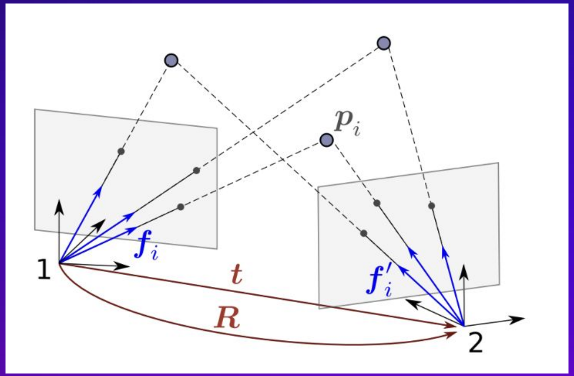
- ➔ Apply a random geometric transformation
  - ◆ Mix of rotation, translation, scaling, perspective distortion
- ➔ **Problem:** Estimate the ***homography matrix H*** between two images

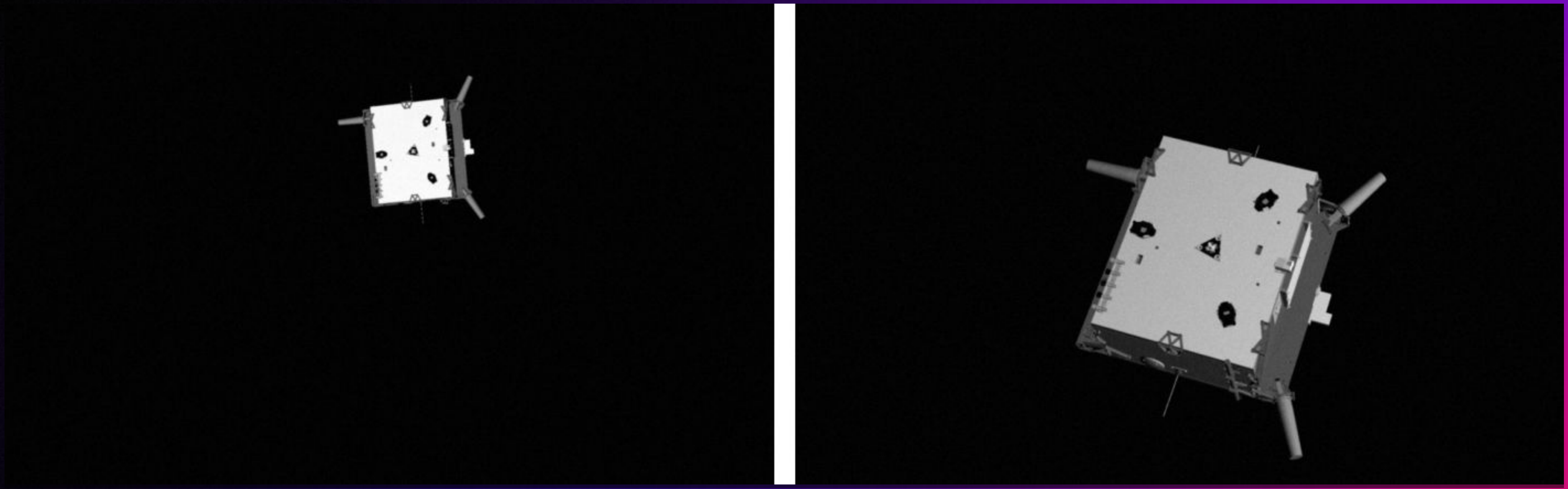


Relative camera pose estimation

➔ **Pose:** Position ***t*** and orientation ***R*** of 2° camera respect to 1° camera

➔ **Problem:** Estimate the camera pose between two frames

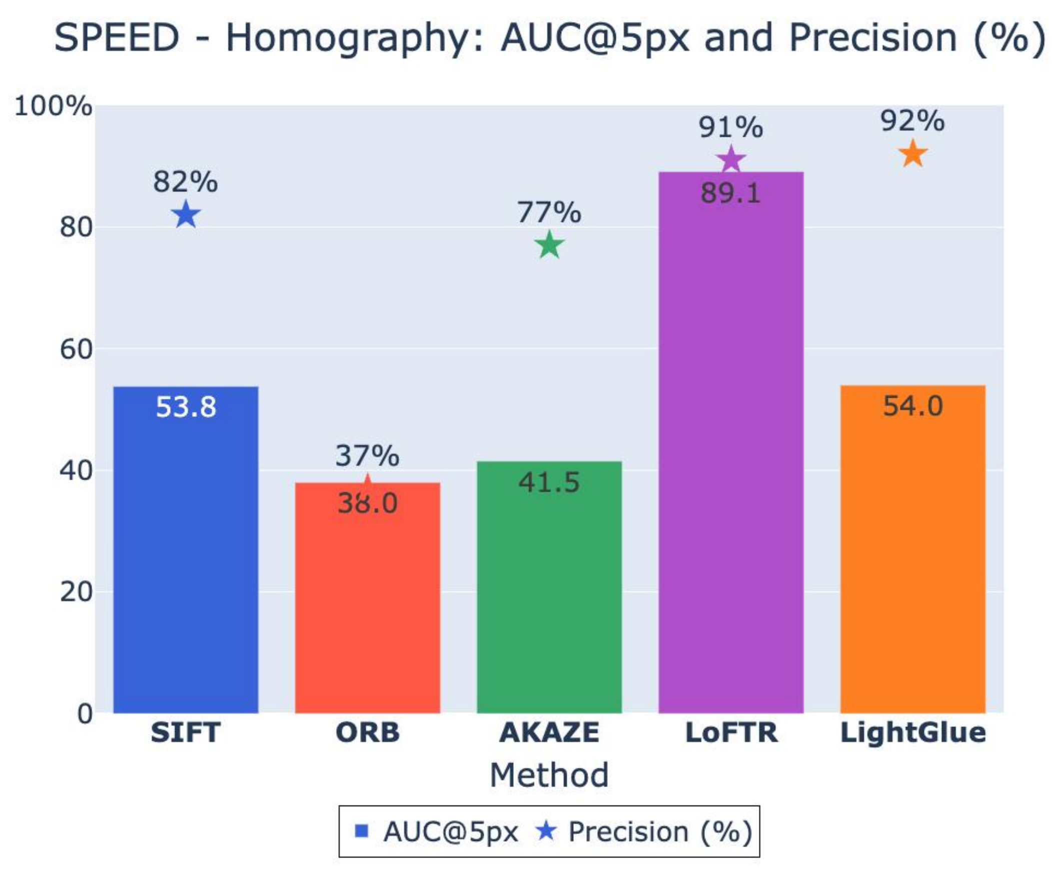




Comparison:
Classical vs AI methods

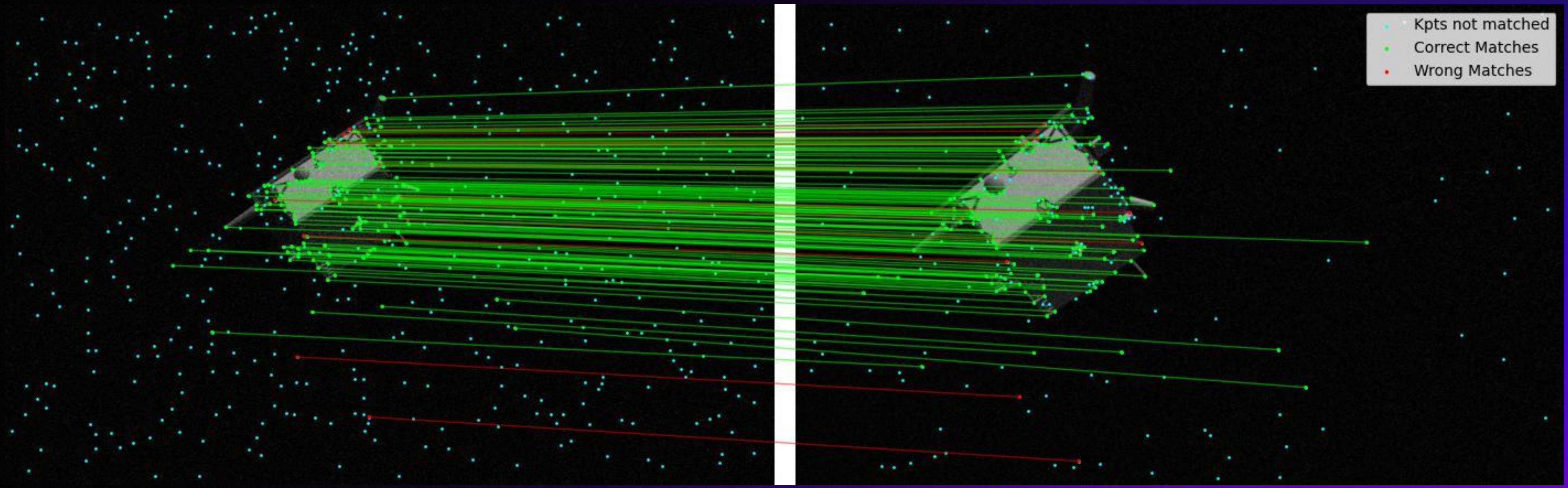
Homography estimation results

- **SPEED** Datasets
- **Mean reprojection error:** distance in pixels between corners image projected with the GT and estimated Homography
- **AUC** * at 5 pixel threshold
- **Precision:** Percentage of correctly predicted matches compared to GT correspondences

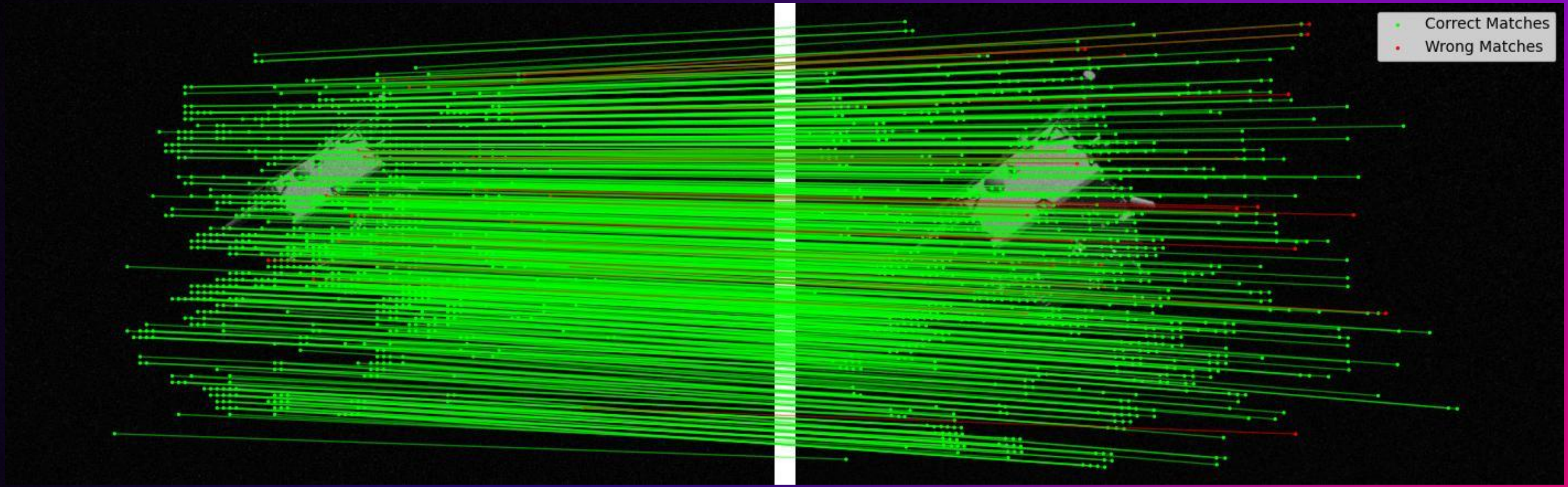


* **AUC:** Area under the cumulative curve of the error up to a specific threshold

LightGlue

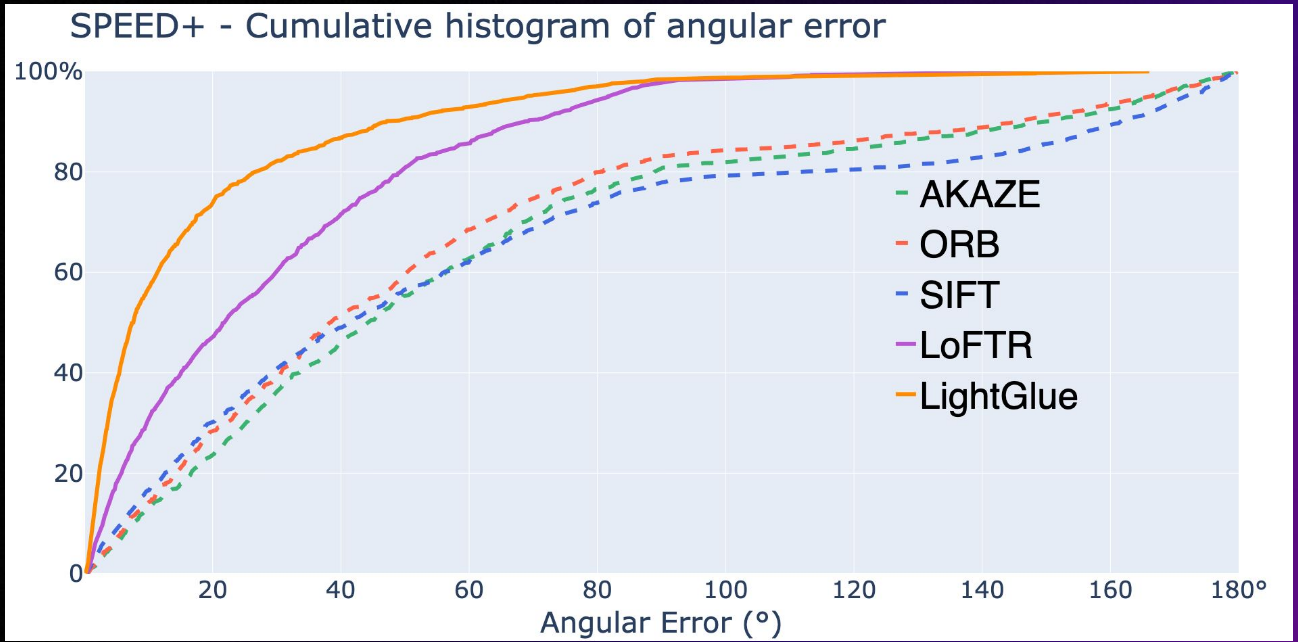


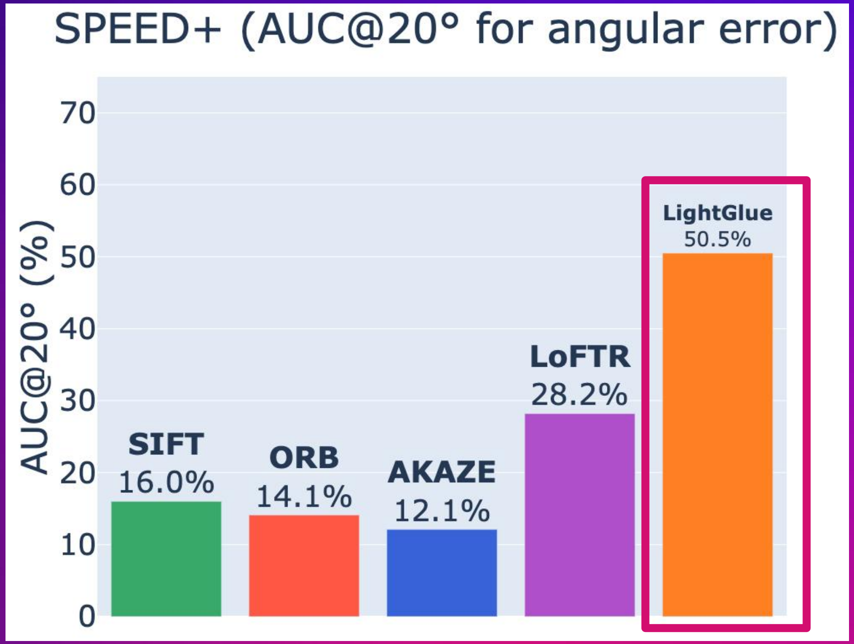
LoFTR



Relative pose estimation results

- ➔ **SPEED+** Datasets
- ➔ Metric: **Angular error** (maximum angular deviations [°] between rotation and translation error)





Knowledge Distillation

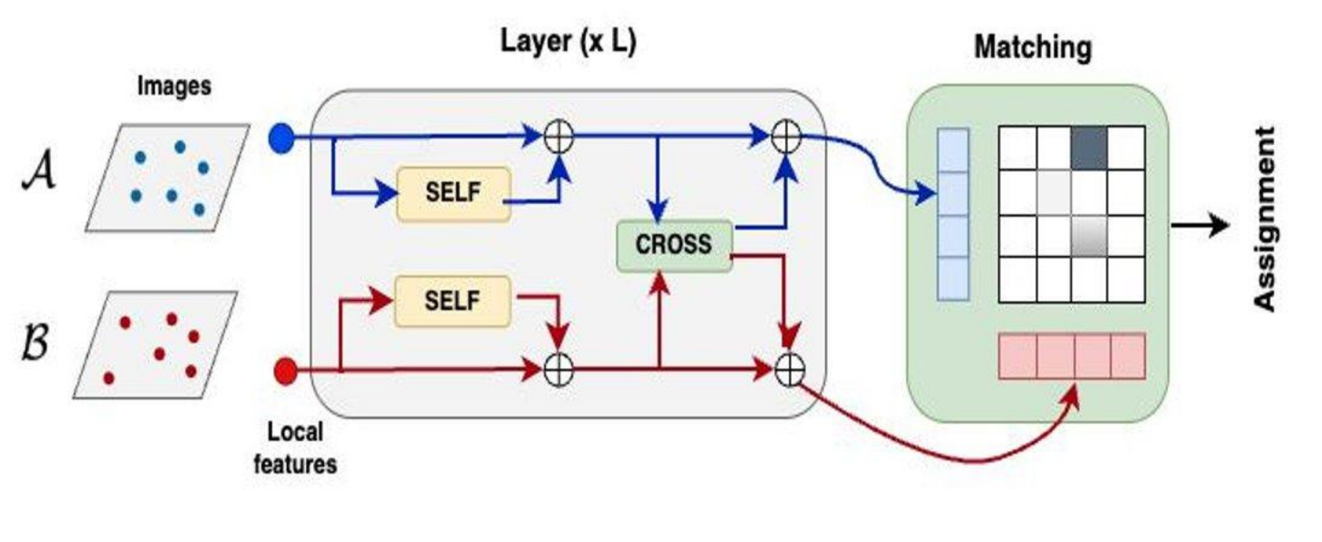
Knowledge Distillation *trains a Deep Learning model under the supervision of a different pre-trained model to effectively transfer knowledge*

Student Architecture

- ➔ Teacher model: **LightGlue**
- ➔ Student replaces the Attention layers
- ➔ Enable the deployment on space-grade hardware

Self-Attention
⬇
2D convolutional layers [10]

Cross-Attention
⬇
Cross-Graph learning module [11]

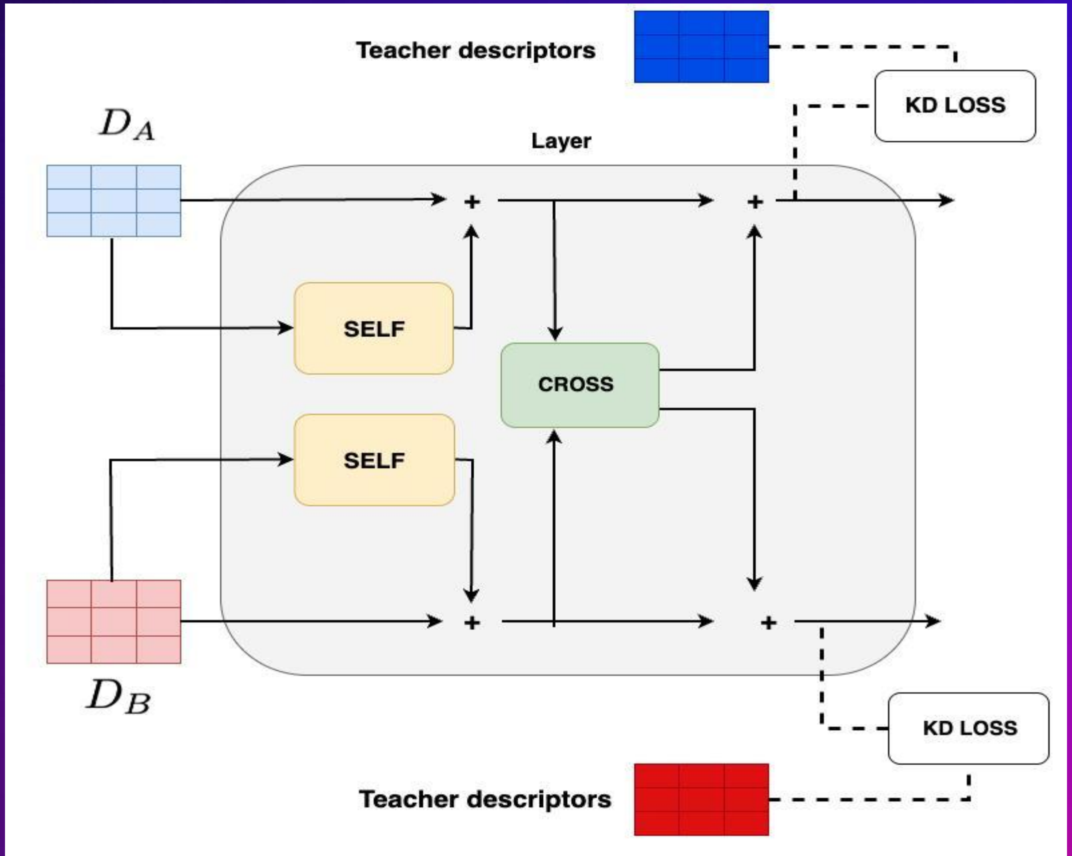


Overview student architecture

[10] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A ConvNet for the 2020s.
[11] Bo Jiang, Pengfei Sun, Jin Tang, and Bin Luo. GLMNet: Graph Learning-Matching Networks for Feature Matching

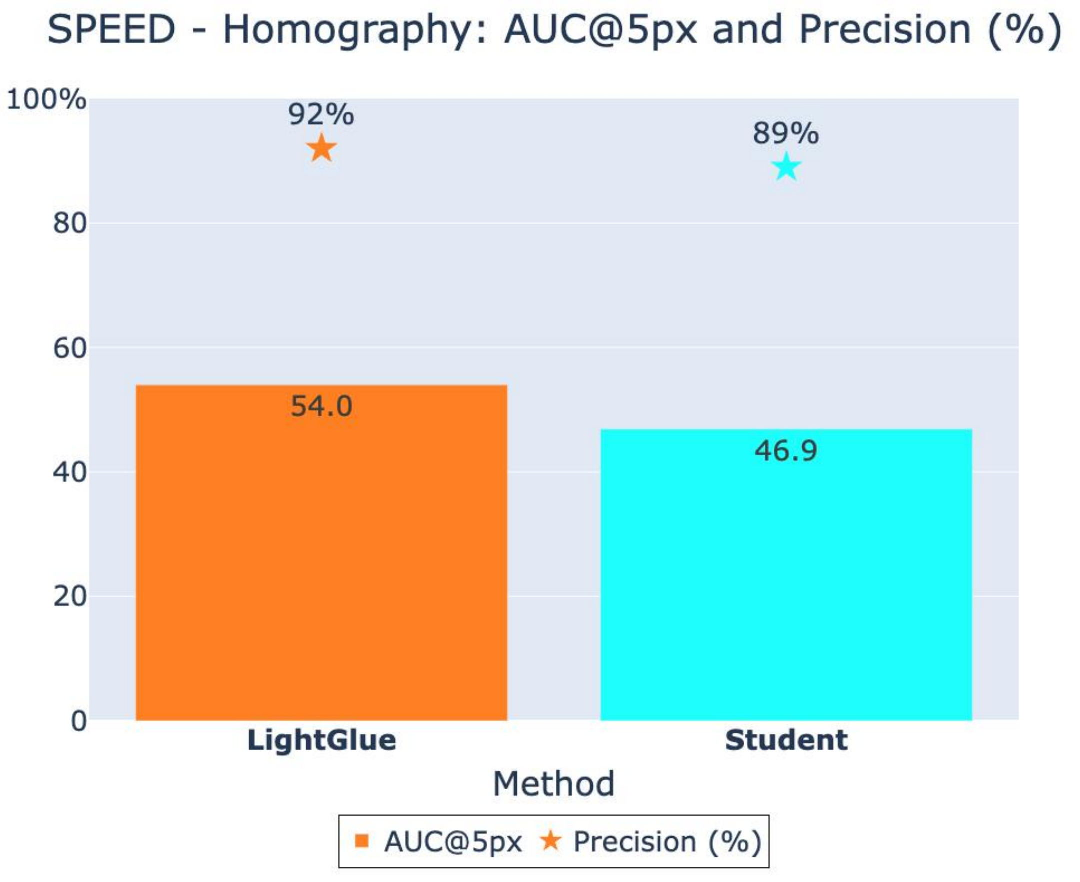
Training

- ➔ **Feature-based** Offline Distillation Strategy
- ➔ KD loss**: Mean Square Error**
- ➔ Training dataset: **SPEED**
- ➔ Pre-train:
  - ◆ Synthetic homographies ***H***
  - ◆ GT supervision from ***H*** + KD loss
- ➔ Fine-tuning:
  - ◆ Image pairs based on camera transformation
  - ◆ Pseudo GT (LightGlue predictions) + KD loss



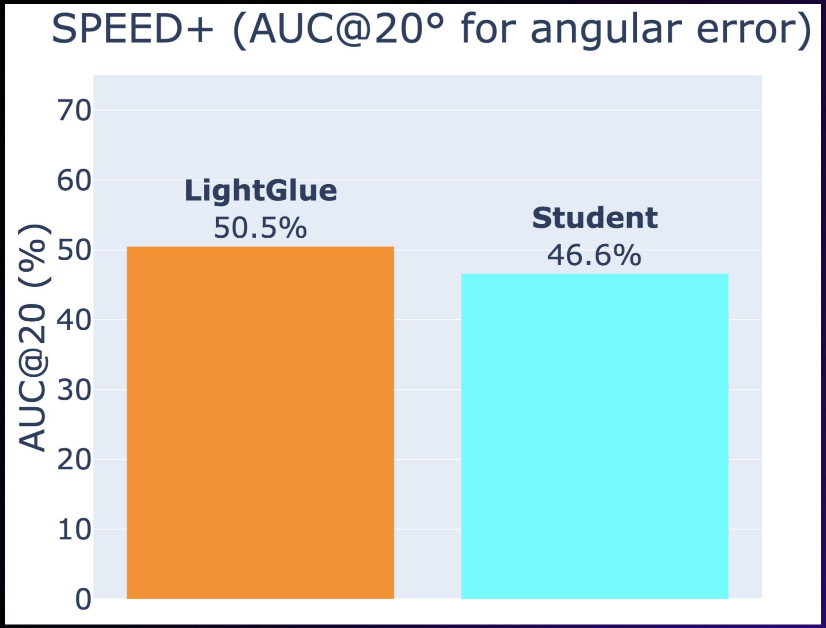
KD results

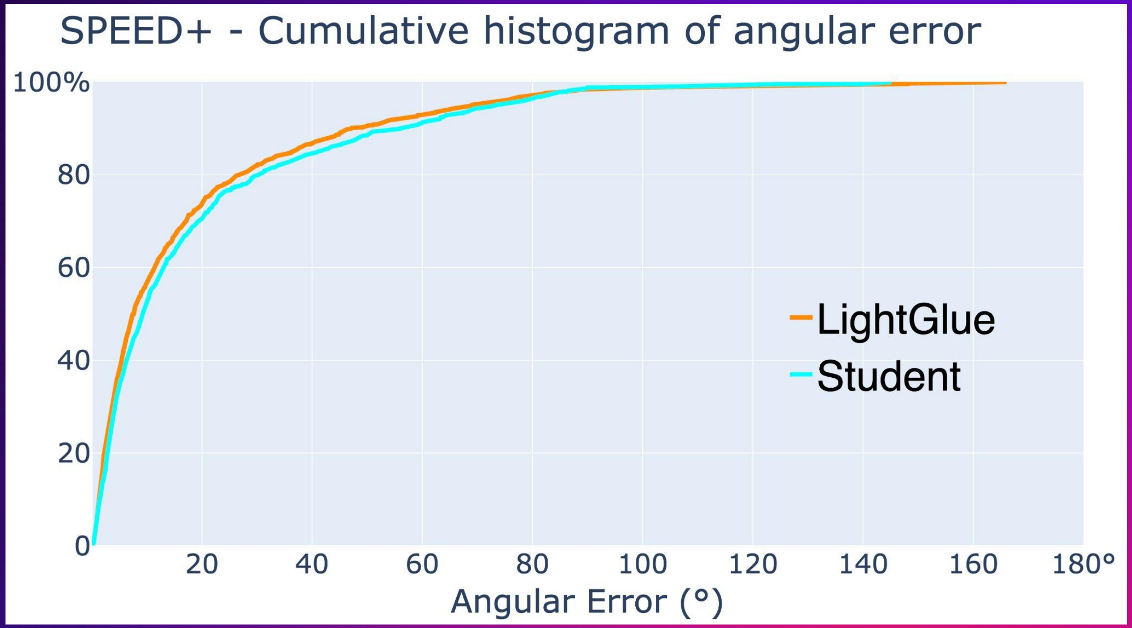
- **Homography** estimation
- SPEED dataset
- Gap teacher-student
  - Precision: **-3 %**
  - AUC@5px: **-7.1%**



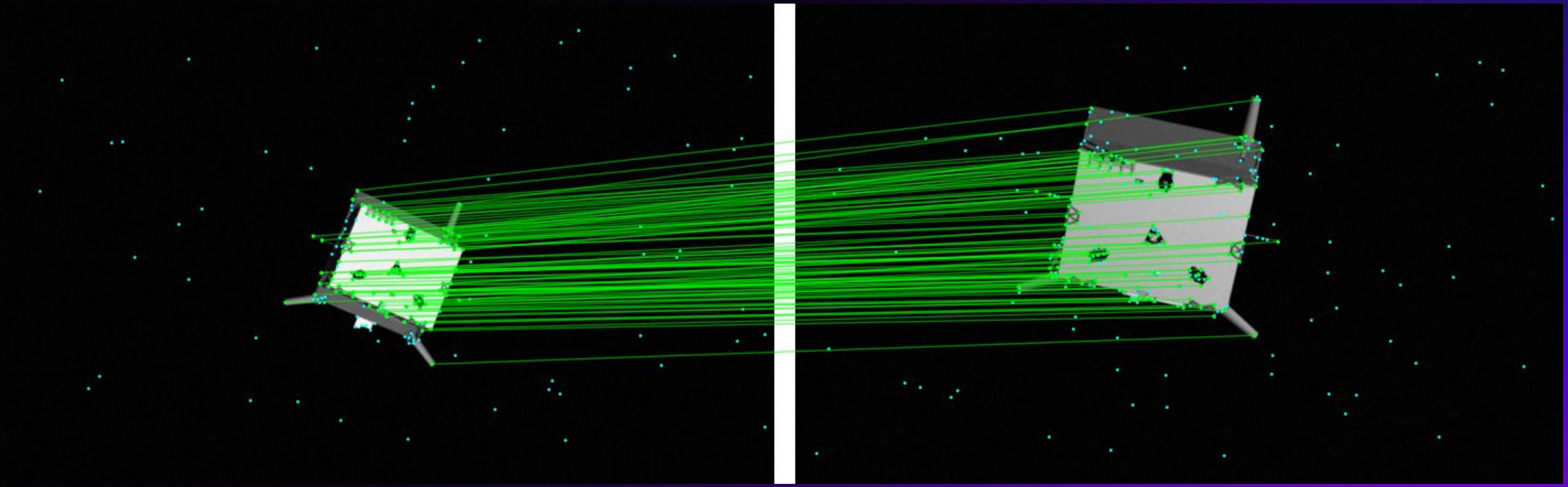
KD results

- ➔ **Relative camera pose** estimation
- ➔ SPEED+ dataset
- ➔ Gap teacher-student: **-3.9%** (AUC@20°)

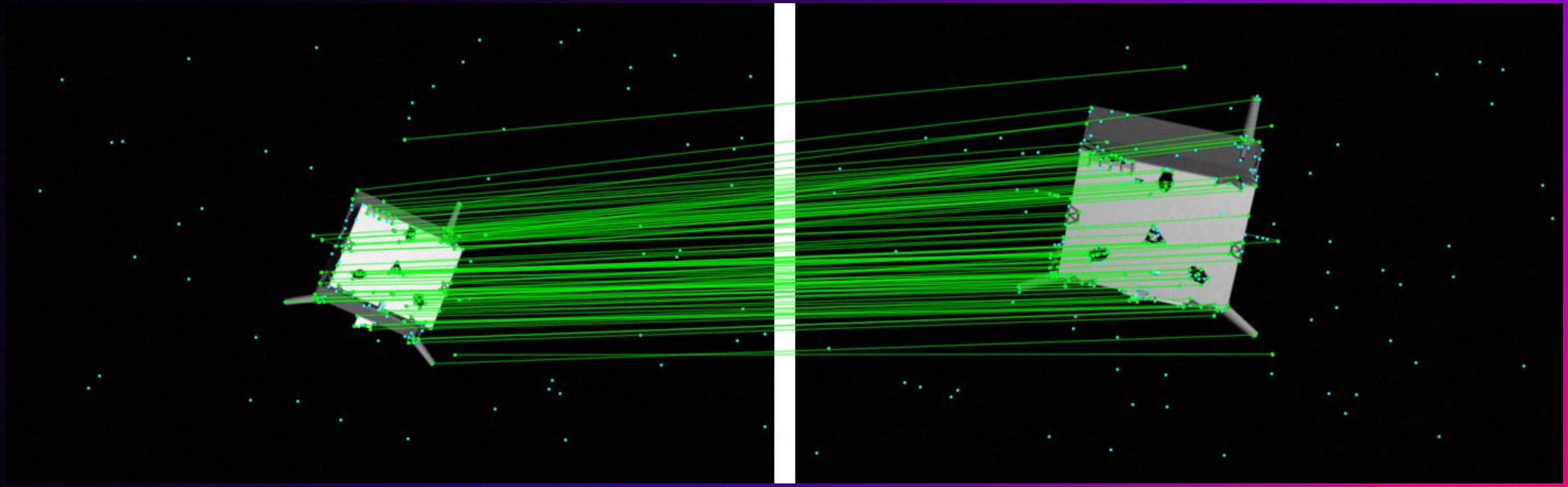




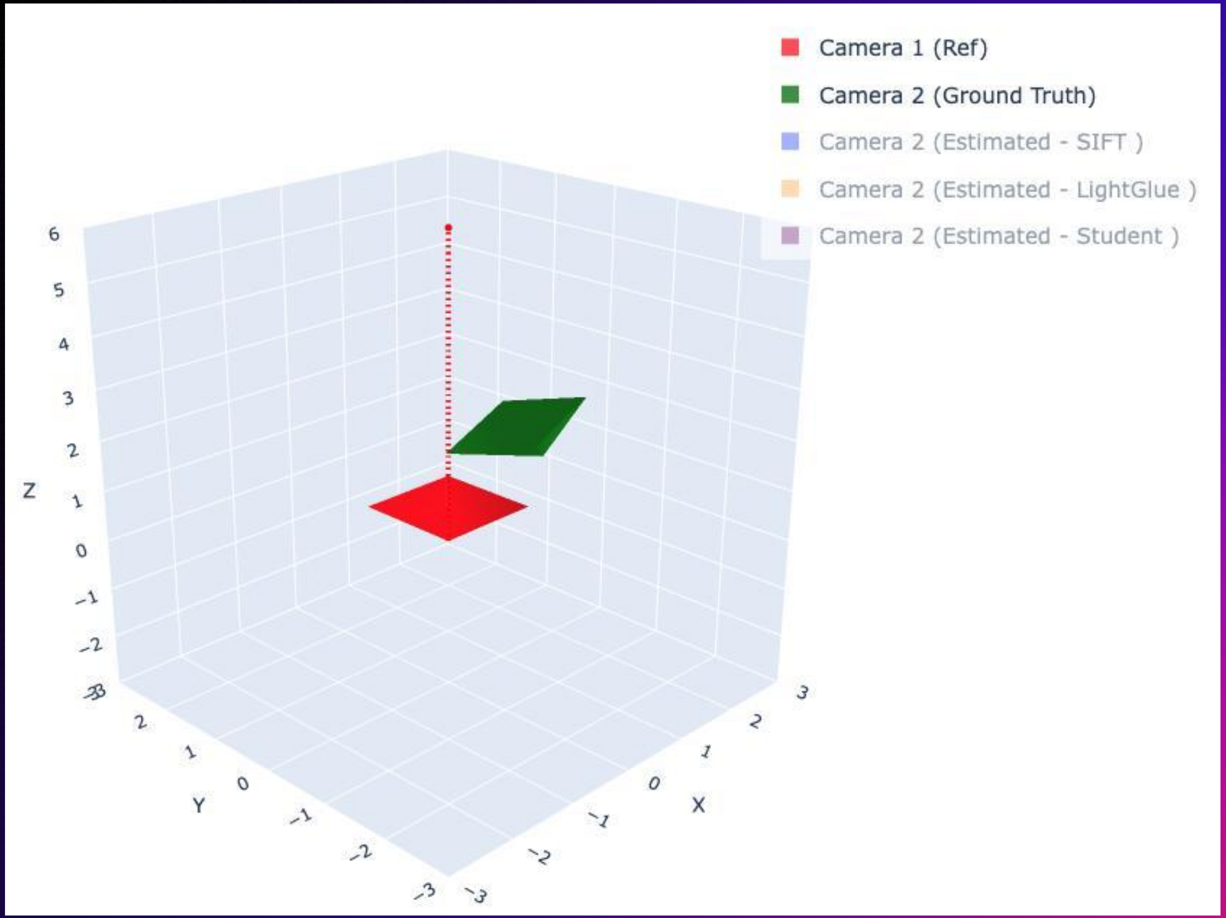
LightGlue



Student



Scene reconstruction from images

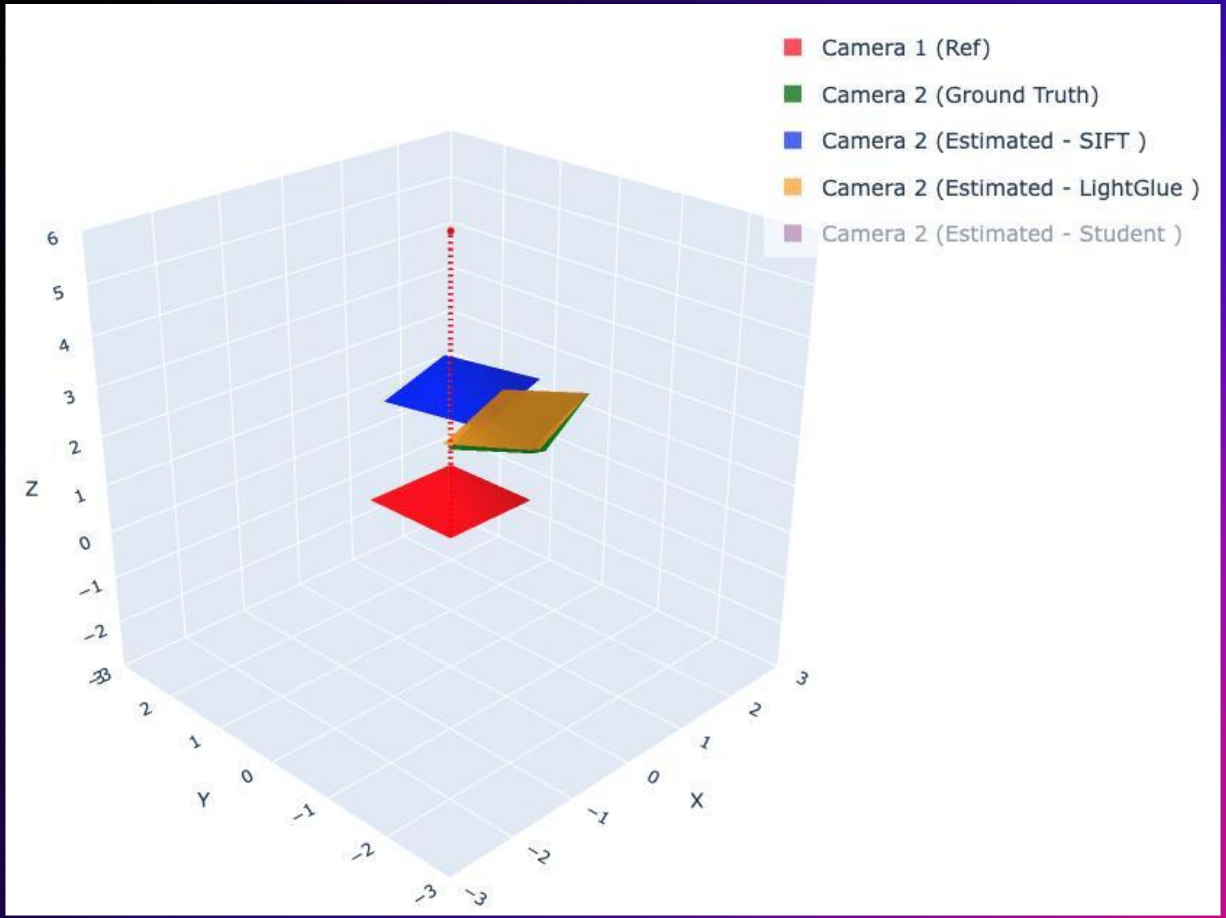


Scene reconstruction from images

Angular errors
(compared to GT pose):

SIFT: 54.6°

LightGlue: 5.9°



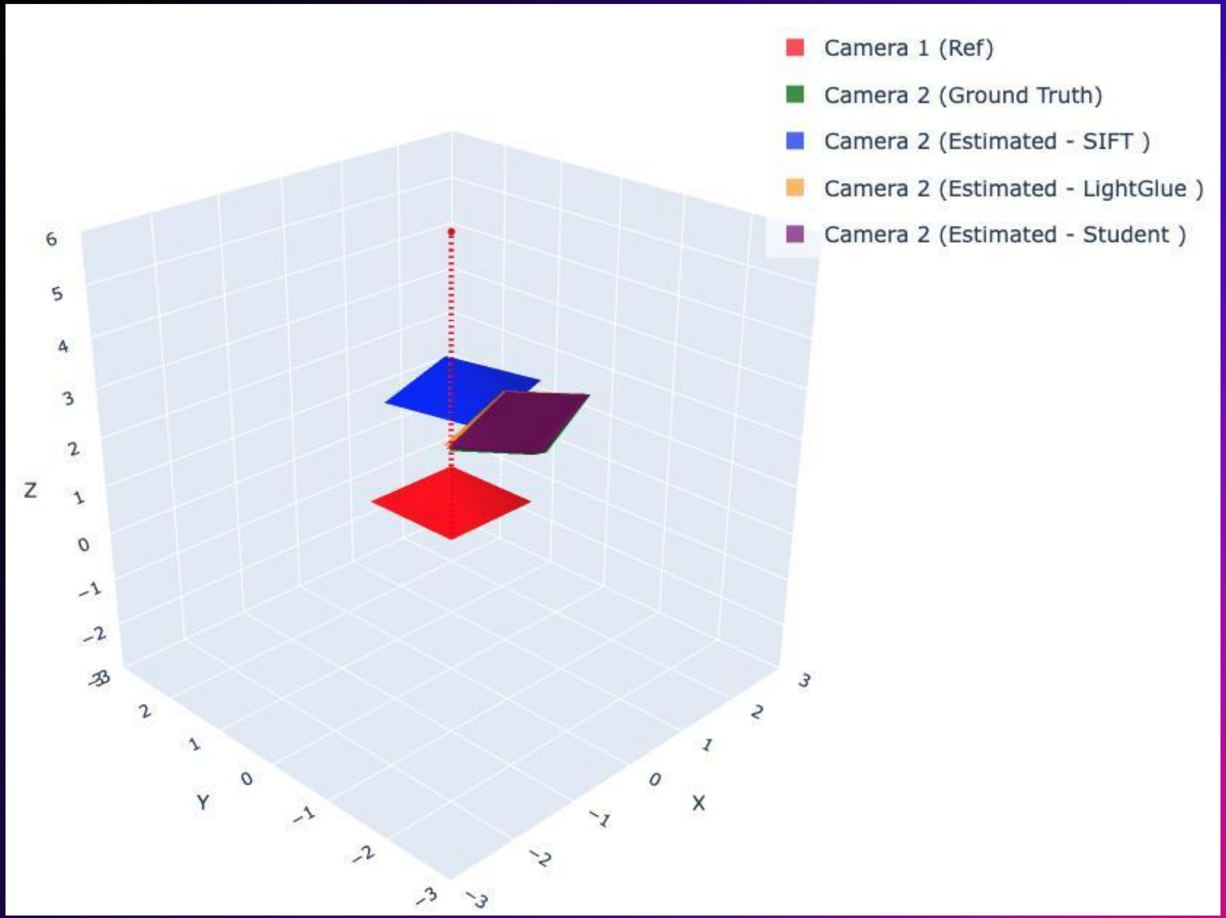
Scene reconstruction from images

Angular errors:

SIFT: 54.6° (vs GT)

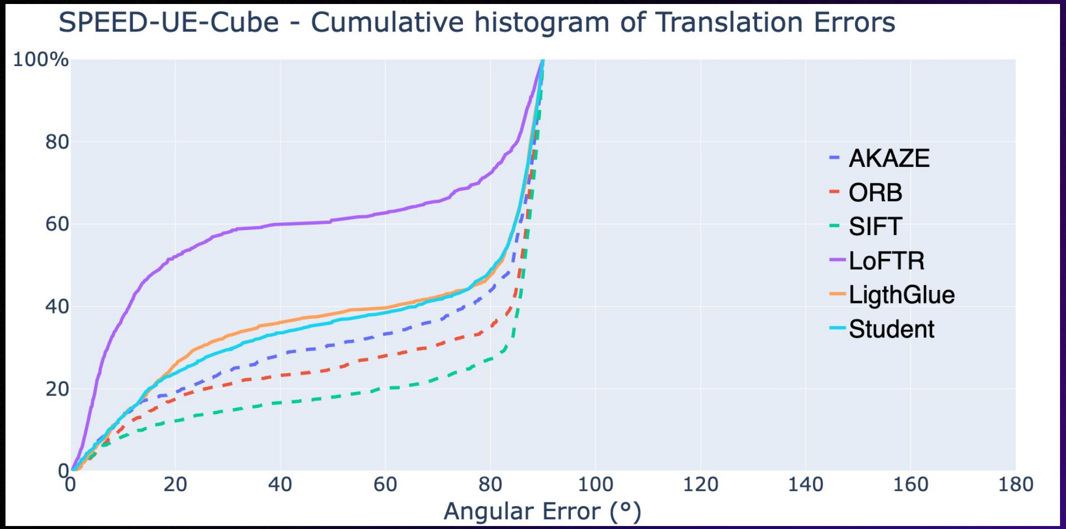
LightGlue: 5.9° (vs GT)

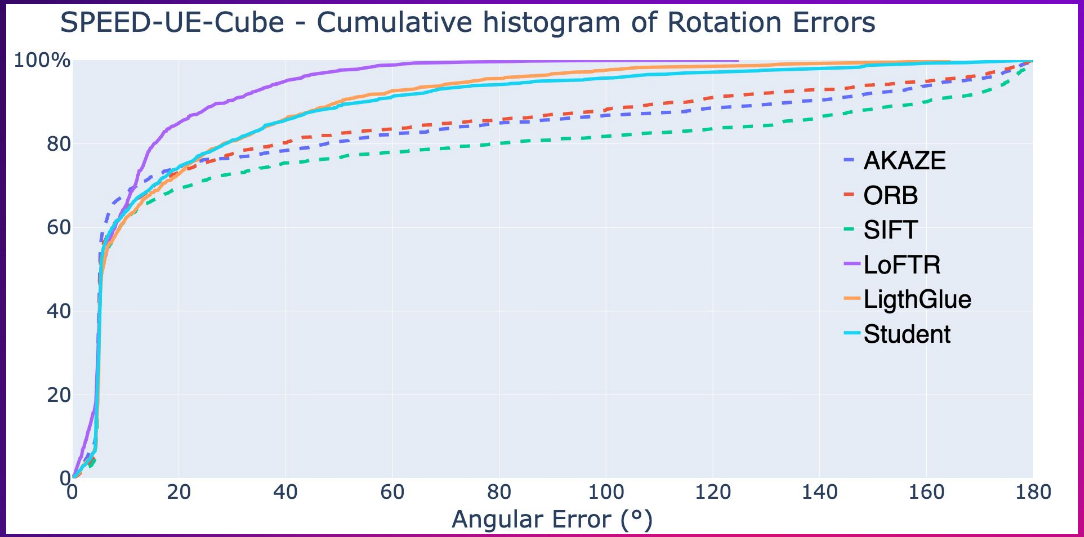
<u>Student:</u> 1.8° (vs GT)



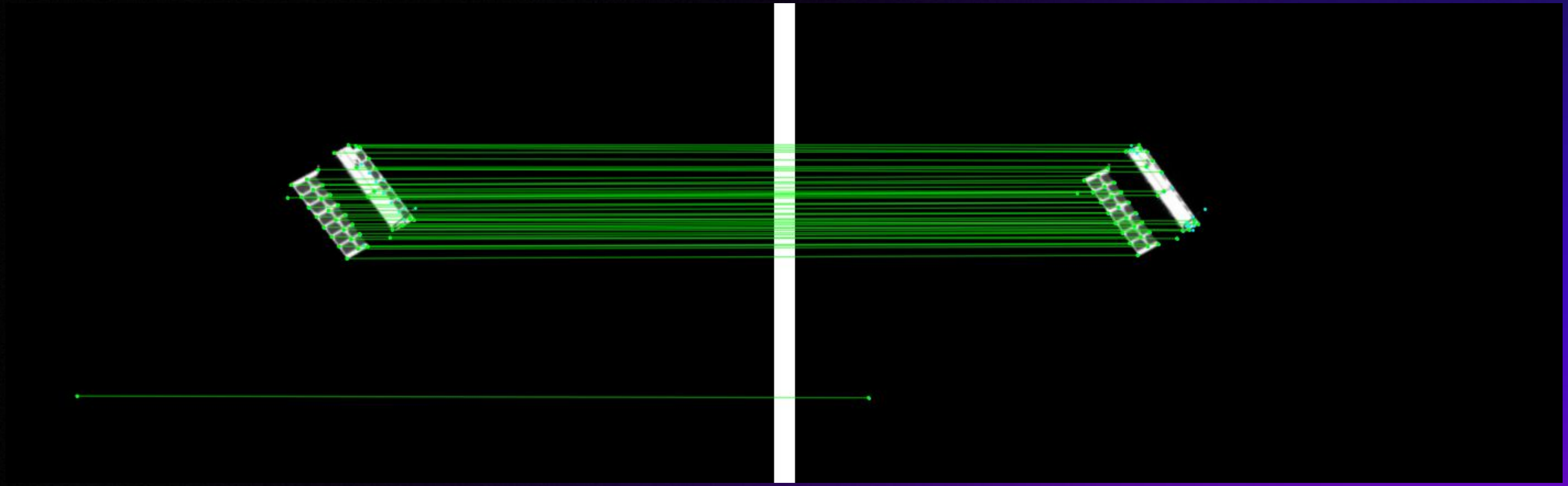
Relative pose estimation on trajectory

- ➔ **SPEED-UE-Cube** Datasets
- ➔ Trajectory set: sequential frames

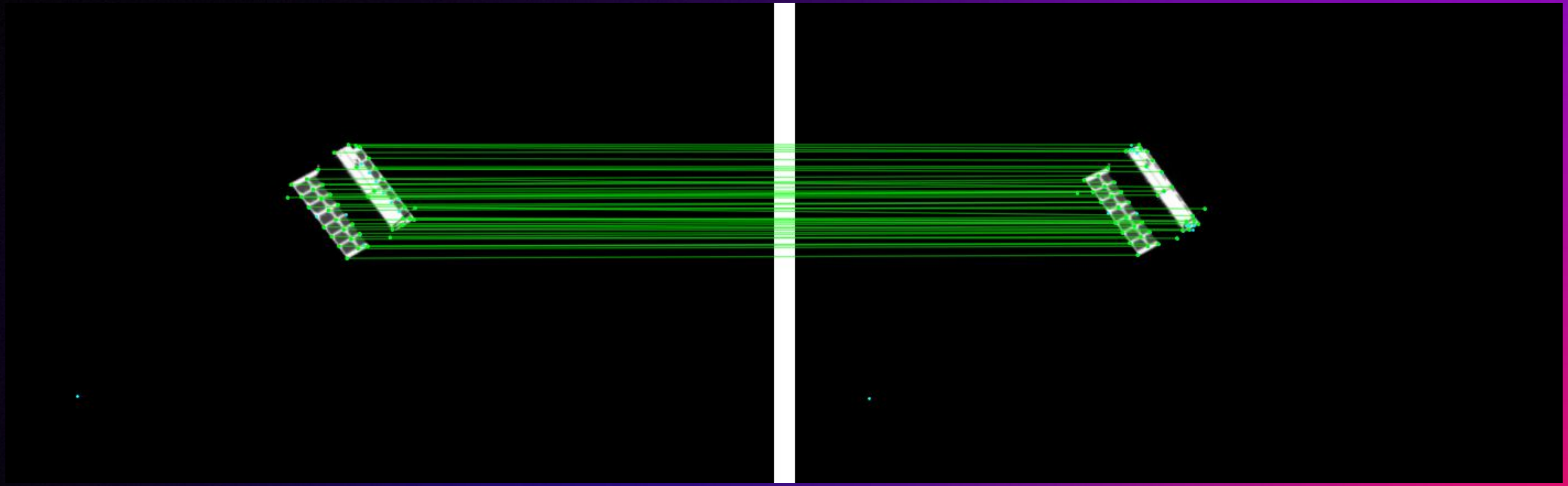




LightGlue

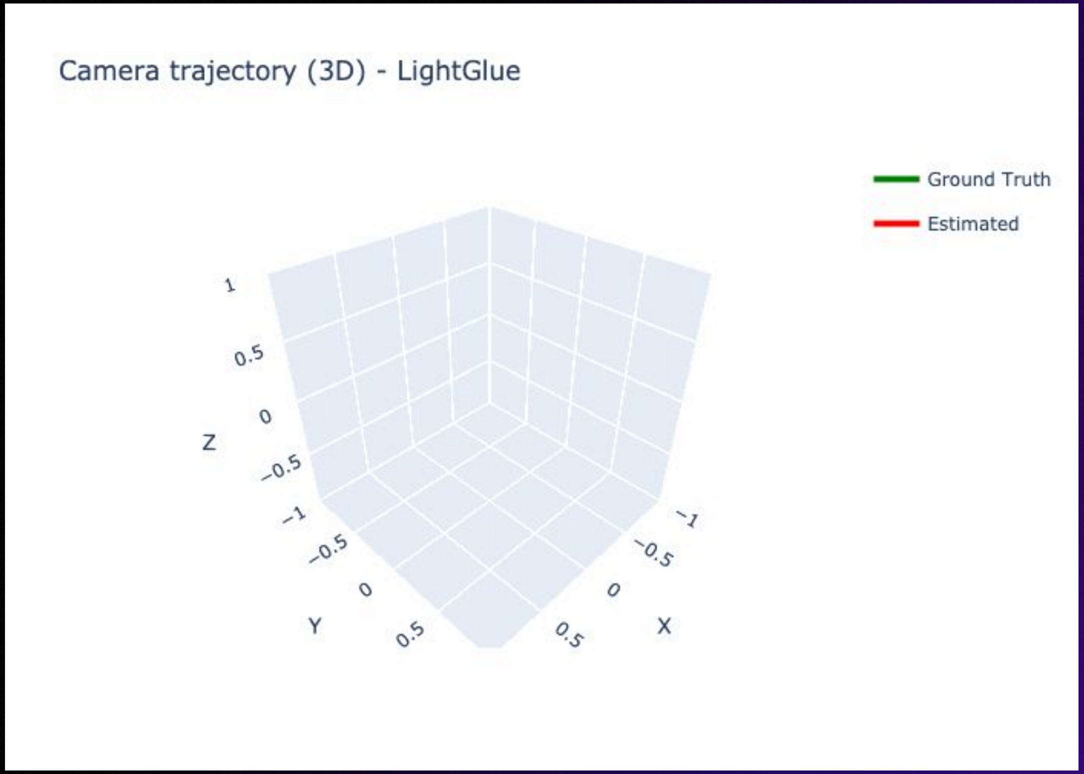


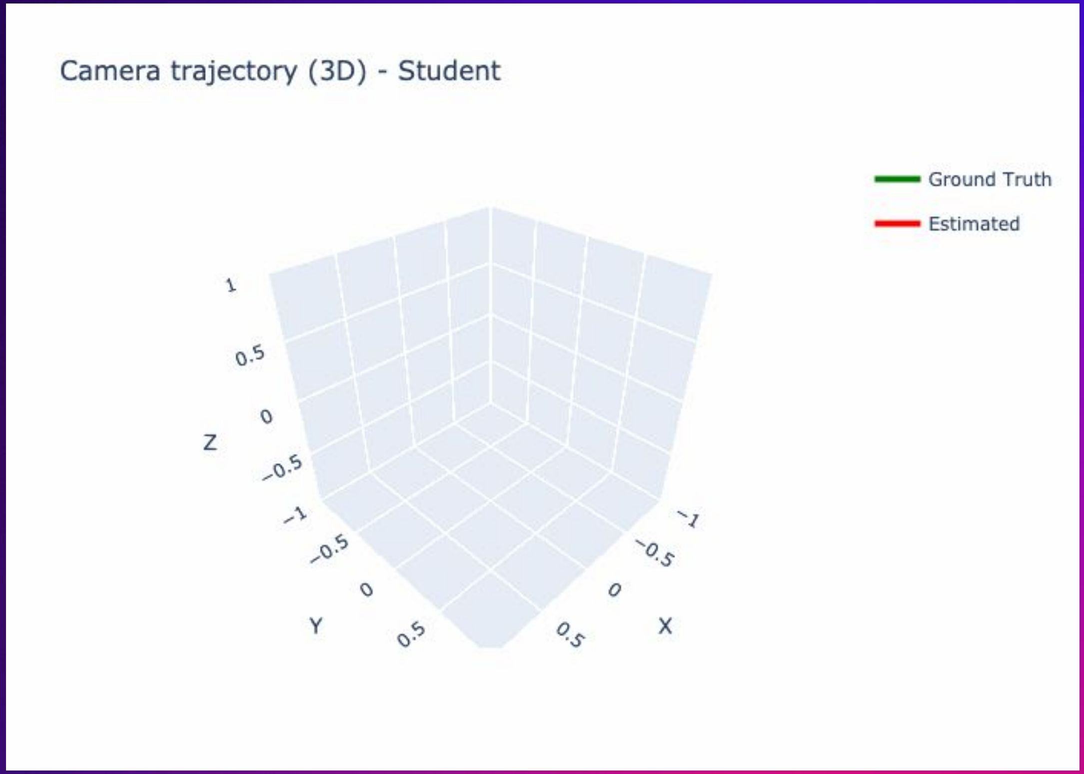
Student



Camera trajectory simulation

- Reconstruction of the trajectory from the images with **LightGlue** and **Student** model and GT trajectory.
- Position of camera at frame *i* is computed from GT position at frame *i-1* to avoid the accumulation of the error during the trajectory





Conclusions

- ➔ AI methods outperform classical algorithms in FDM
- ➔ AI models are able to specialize from generic visual context to more challenging space scenarios
- ➔ KD is effective to transfer knowledge in this task to a student model with different operations and fully-supervised by the teacher

Next Steps

- ➔ Apply optimization techniques to improve inference performance and dimensions of Student model
- ➔ Test deployment on space-grade hardware
- ➔ Integrate FDM in Optical Navigation systems

Thanks for your attention!

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Appendix

Metrics

➔ **Mean reprojection error:** distance in pixels between corners image projected with the GT and estimated Homography

$$\text{reprojection error} = \frac{1}{4}\sum_{j=1}^{4} \|\mathbf{c}'_j - \hat{\mathbf{c}}'_j\|$$

➔ **Angular deviations:** Deviations between the GT relative pose and the estimated relative pose

$$\theta_t = arccos(\frac{t \cdot \hat{t}}{||t|| \cdot ||\hat{t}||}) \qquad \theta_r = arccos(\frac{trace(R^T \cdot \hat{R}) - 1}{2})$$

Student architecture

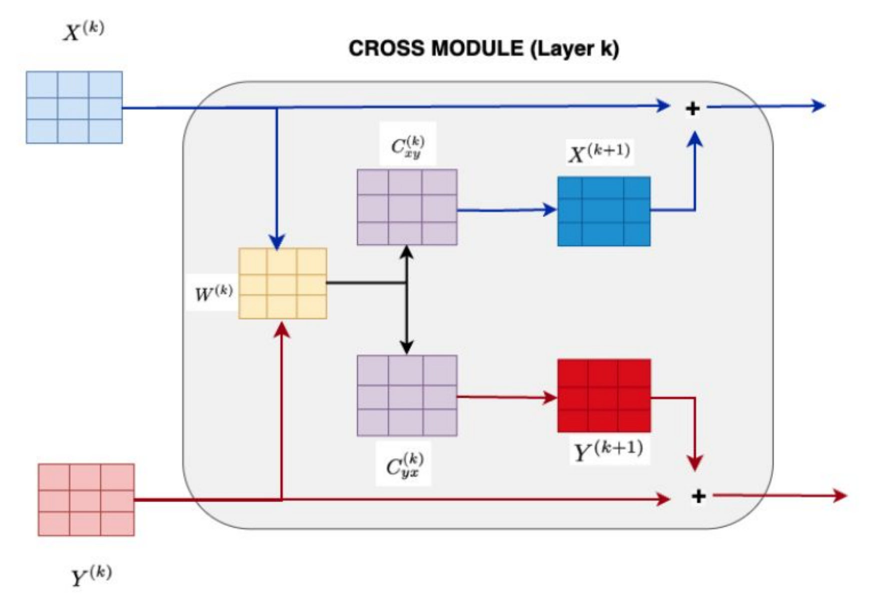
- ➔ Inputs: $X \in \mathcal{R}^{N \times d}, Y \in \mathcal{R}^{M \times d}$
- ➔ Self module: **2D convolutional layers**
- ➔ Cross module: **Cross-graph learning**

$$C_{xy}^{(k)}(i,j) = \exp\left(\frac{\left(X^{(k)^T} W^{(k)} Y^{(k)} \right)_{ij}}{\delta} \right) \in \mathbb{R}^{m \times n}$$

$$X^{(k+1)} = \left[C_{xy}^{(k)} Y^{(k)} \| X^{(k)} \right] \Theta_{xy}^{(k)}$$

$$Y^{(k+1)} = \left[C_{yx}^{(k)} X^{(k)} \| Y^{(k)} \right] \Theta_{yx}^{(k)}$$

Operation	Kernel Size	Input Channels	Output Channels
Pointwise Convolution	1×1	1	32
	Convolutional Blocks (3x)		
Depthwise Convolution	7×7	32	32
Layer Normalization	-	-	-
Pointwise Convolution	1×1	32	128
ReLU Activation	-	-	-
Pointwise Convolution	1×1	128	32



Computational performance

- ➔ Model parameters and size
- ➔ Average inference time (image pairs/sec)

Model	Parameters (M)	Model Size (MB)
SuperPoint	1.30	4.96
LightGlue	**11.85**	**45.21**
Student	**11.56**	**44.12**
LoFTR	28.35	108.13
SuperPoint + LightGlue	**13.15**	**50.17**
SuperPoint + Student	**12.86**	**49.08**

Model	Average Inference Speed (pairs/sec)
SuperPoint + LightGlue	**30.43**
SuperPoint + Student	**7.10**
LoFTR	10.23