EDM: Equirectangular Projection-Oriented Dense Kernelized Feature Matching

Dongki Jung, Jaehoon Choi, Yonghan Lee, Somi Jeong, TaeJae Lee, Dinesh Manocha, Suyong Yeon

CVPR 2025

Fri 13 Jun 5PM -7PM, ExHall D Poster #92

Problem Definition

Goal: Dense Feature Matching in indoor environments using omnidirectional images

Challenges of Indoor Scenes

- Textureless regions
- Repetitive Patterns
- Prevalent Occlusions

Problem Definition

Goal: Dense Feature Matching in indoor environments using omnidirectional images

Challenges of Indoor Scenes

- **Textureless regions**
- Repetitive Patterns
- Prevalent Occlusions

Problem Definition

Goal: Dense Feature Matching in indoor environments using omnidirectional images

Challenges of Indoor Scenes

- Textureless regions
- **Repetitive Patterns**
- Prevalent Occlusions

Problem Definition

Goal: Dense Feature Matching in indoor environments using omnidirectional images

Challenges of Indoor Scenes

- Textureless regions
- Repetitive Patterns
- **Prevalent Occlusions**

Problem Definition

Goal: Dense Feature Matching in indoor environments using omnidirectional images

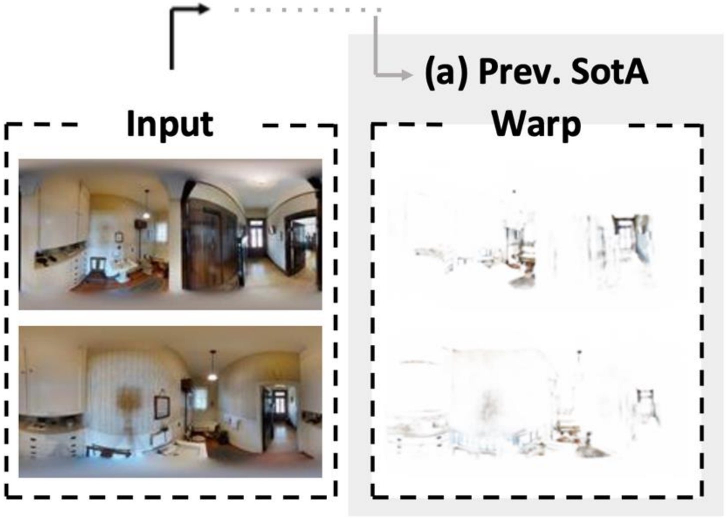
Challenges of Indoor Scenes

- Textureless regions
- Repetitive Patterns
- Prevalent Occlusions

360 cameras can capture global information from a single image.

Background and Motivation

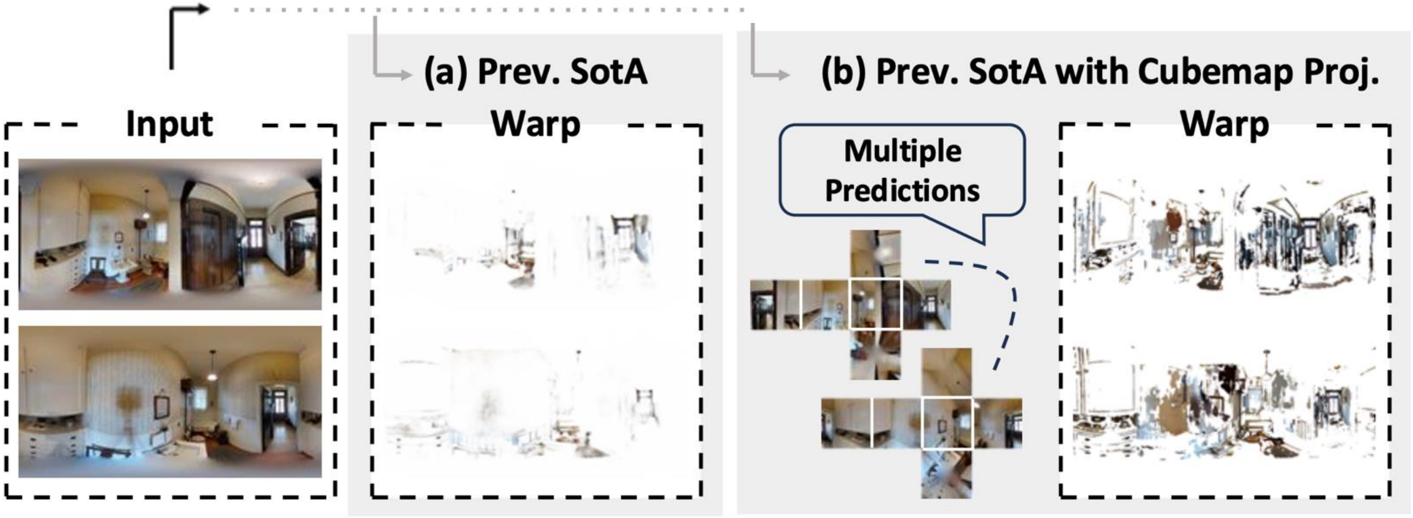
- Equirectangular Projection Images have inherent distortion.
- Previous SOTA [1] struggle to achieve accurate matching due to distortion.



[1] Edstedt, Johan, et al. "DKM: Dense kernelized feature matching for geometry estimation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023.

Background and Motivation

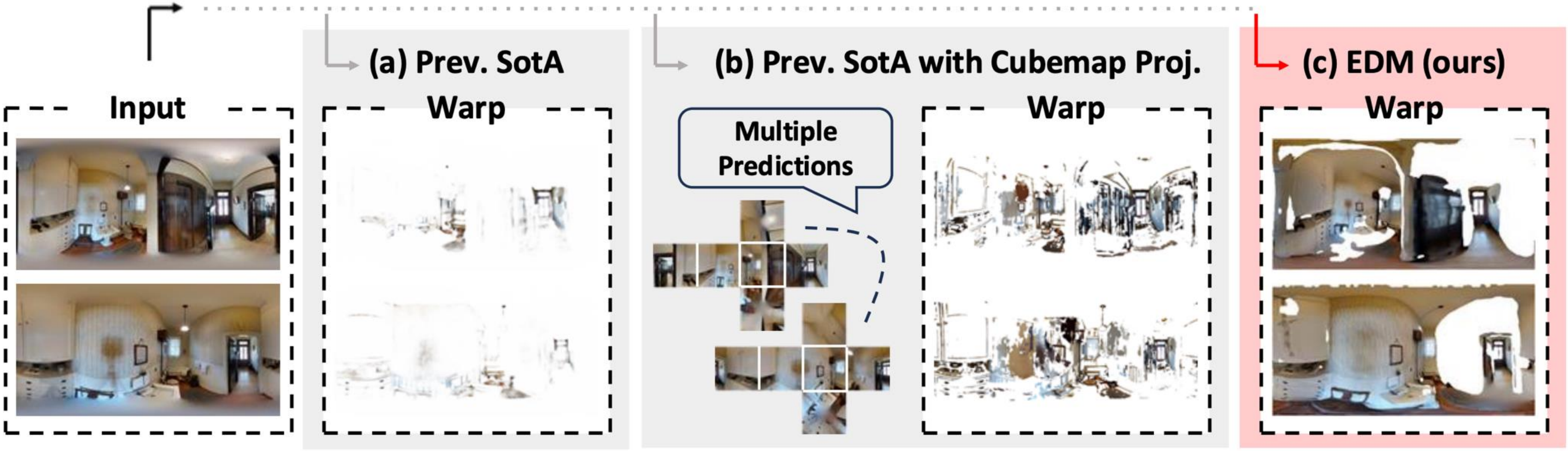
- Equirectangular Projection Images have inherent distortion.
- Previous SOTA [1] struggle to achieve accurate matching due to distortion.



[1] Edstedt, Johan, et al. "DKM: Dense kernelized feature matching for geometry estimation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023.

Background and Motivation

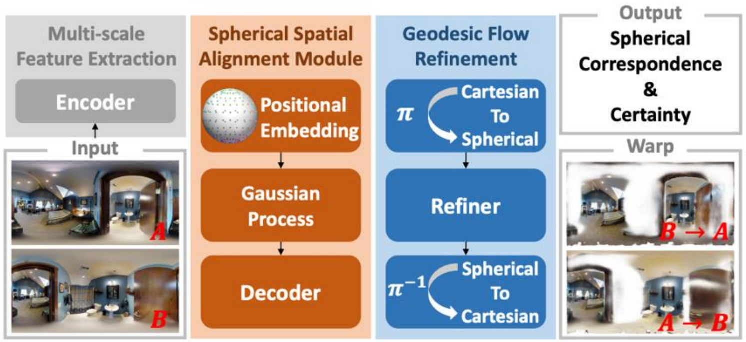
- Equirectangular Projection Images have inherent distortion.
- Previous SOTA [1] struggle to achieve accurate matching due to distortion.



[1] Edstedt, Johan, et al. "DKM: Dense kernelized feature matching for geometry estimation." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023.

Method

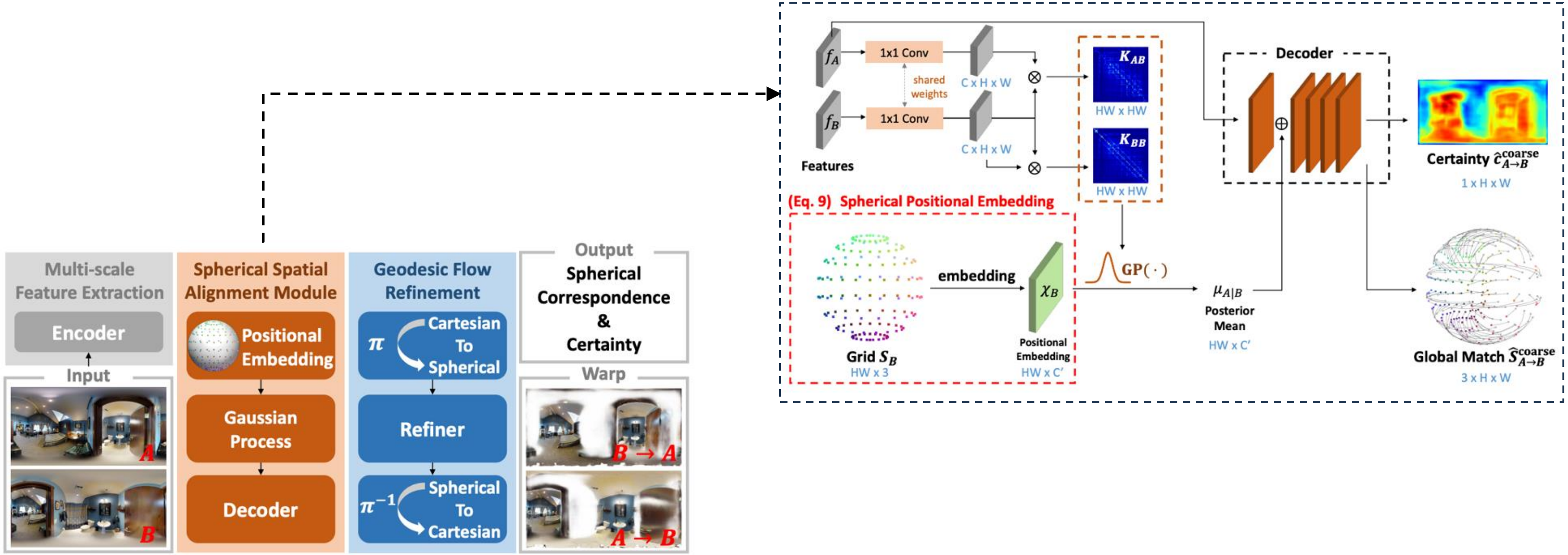
- First learning-based dense matching algorithm for 360 images
- Network Architecture



$$\begin{cases} S^x = \sin(\theta)\cos(\phi) \\ S^y = \sin(\phi) \\ S^z = \cos(\theta)\cos(\phi) \end{cases} \qquad \begin{cases} \theta = \arctan(\frac{S^x}{S^z}) \\ \phi = \arcsin(\frac{S^y}{|\mathbf{S}|}) \end{cases}$$

Method

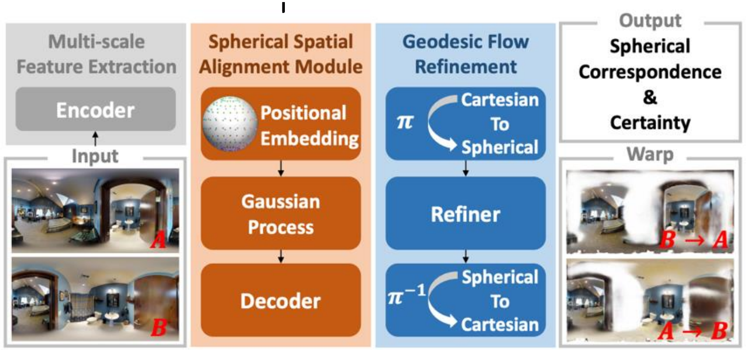
- First learning-based dense matching algorithm for 360 images
- Network Architecture

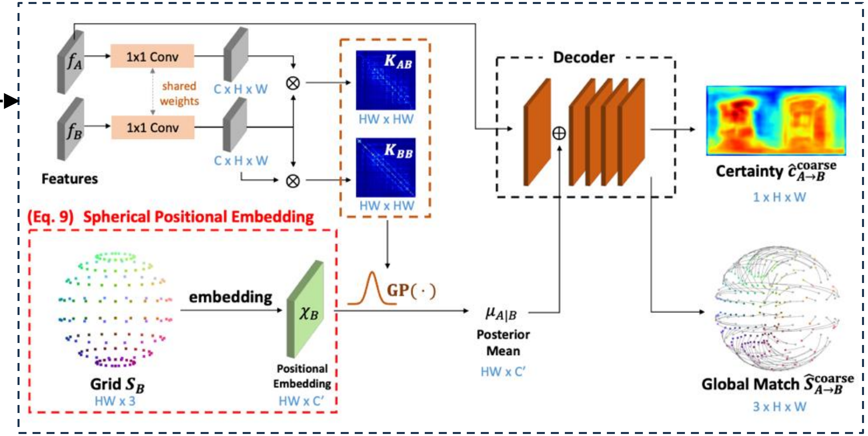


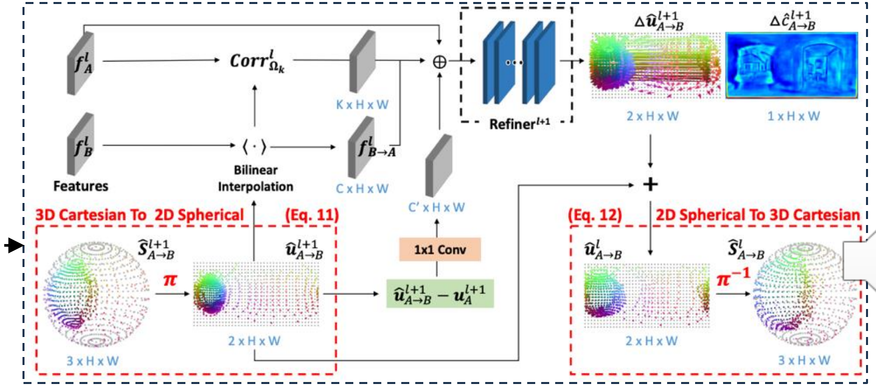
$$
\begin{cases}
S^x = \sin(\theta)\cos(\phi) \\
S^y = \sin(\phi) \\
S^z = \cos(\theta)\cos(\phi)
\end{cases}
\qquad
\begin{cases}
\theta = \arctan(\dfrac{S^x}{S^z}) \\
\phi = \arcsin(\dfrac{S^y}{|\mathbf{S}|})
\end{cases}
$$

Method

- First learning-based dense matching algorithm for 360 images
- Network Architecture



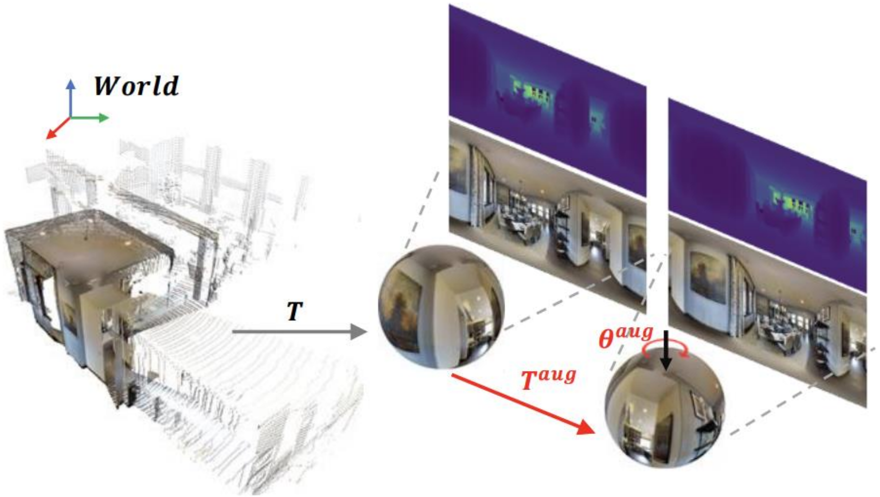




$$\begin{cases} S^x = \sin(\theta)\cos(\phi) \\ S^y = \sin(\phi) \\ S^z = \cos(\theta)\cos(\phi) \end{cases} \qquad \begin{cases} \theta = \arctan(\frac{S^x}{S^z}) \\ \phi = \arcsin(\frac{S^y}{|\mathbf{S}|}) \end{cases}$$

Quantitative Results

- Rotational Augmentation



$$
\begin{cases}
I_A \leftarrow I_A\langle \pi\left(T_A^{aug}\pi^{-1}\left(I_A^{grid}\right)\right)\rangle \\
D_A \leftarrow D_A\langle \pi\left(T_A^{aug}\pi^{-1}\left(D_A^{grid}\right)\right)\rangle \\
T_A \leftarrow T_A T_A^{aug}
\end{cases}
$$

Quantitative Results

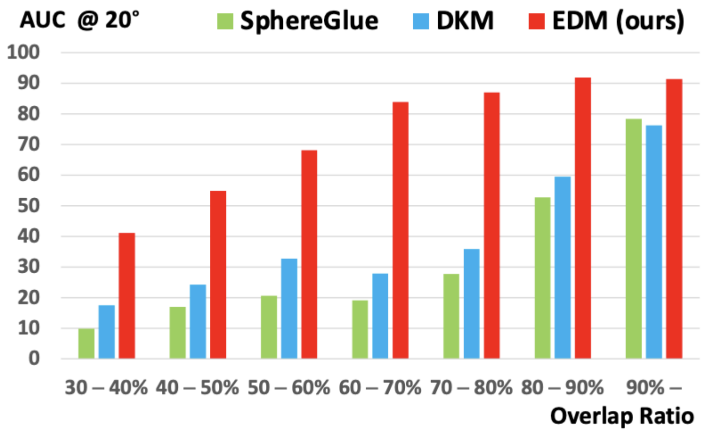
- Rotational Augmentation

Method	Image	Feature	AUC @5°	AUC @10°	AUC @20°
SPHORB [69]	ERP	sparse	0.38	1.41	3.99
SphereGlue [19]	ERP	sparse	11.29	19.95	31.10
DKM [15]	persepctive	dense	18.43	28.50	38.44
RoMa [16]	perspective	dense	12.45	22.37	34.24
EDM (ours)	ERP	dense	**45.15**	**60.99**	**73.60**

Table 1. Quantitative comparison on Matterport3D with recent algorithms. EDM improves AUC@5° by 26.72.

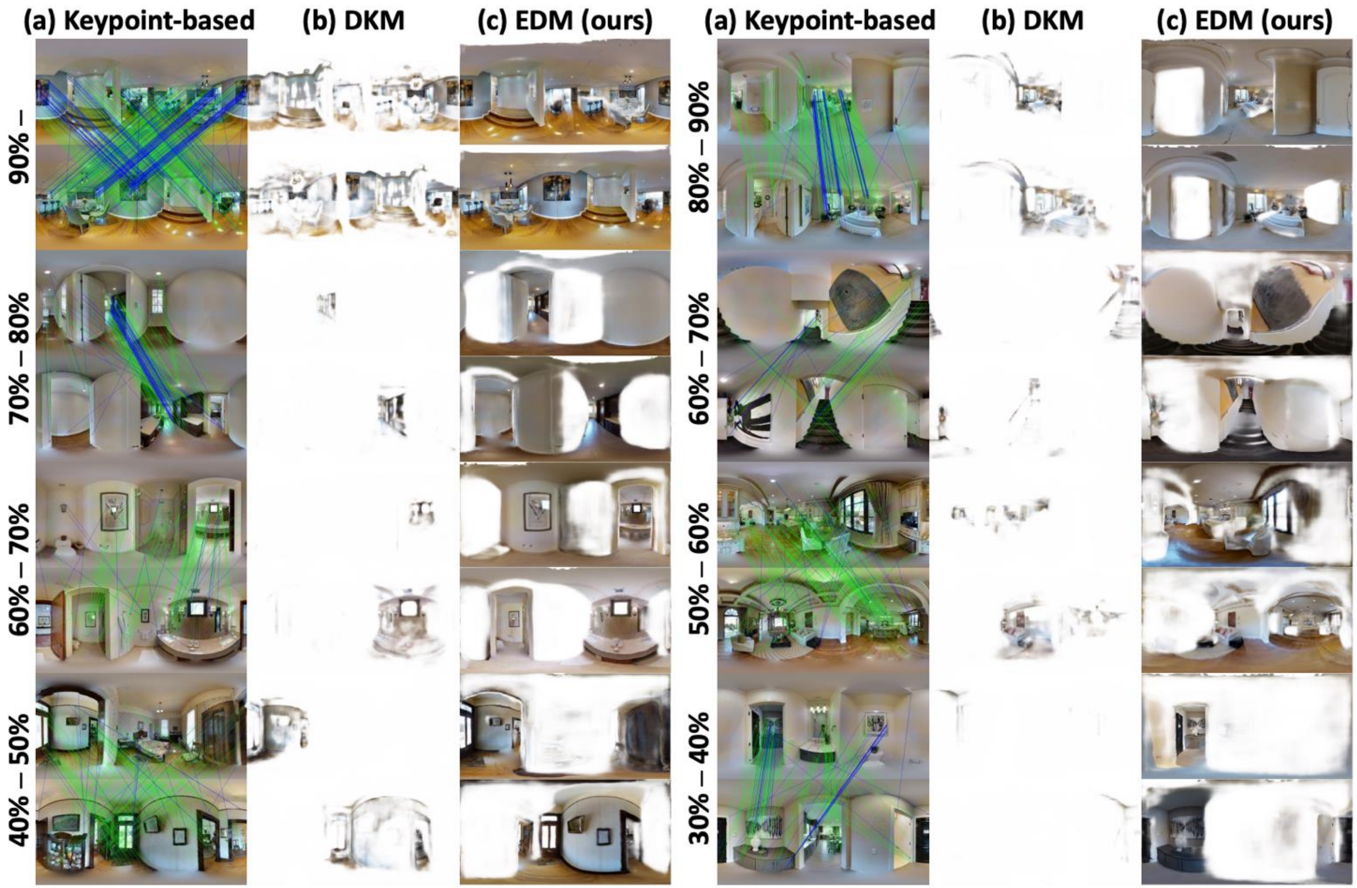
Method	Image	Feature	AUC @5°	AUC @10°	AUC @20°
SPHORB [69]	ERP	sparse	0.14	1.01	4.08
SphereGlue [19]	ERP	sparse	11.25	22.41	36.57
DKM [15]	perspective	dense	12.46	22.18	34.13
RoMa [16]	perspective	dense	11.48	22.52	37.07
EDM (ours)	ERP	dense	**55.08**	**71.65**	**82.72**

Table 2. Quantitative comparison on Stanford2D3D with recent algorithms. EDM improve AUC@5° by 42.62.



Qualitative Results

- Matching



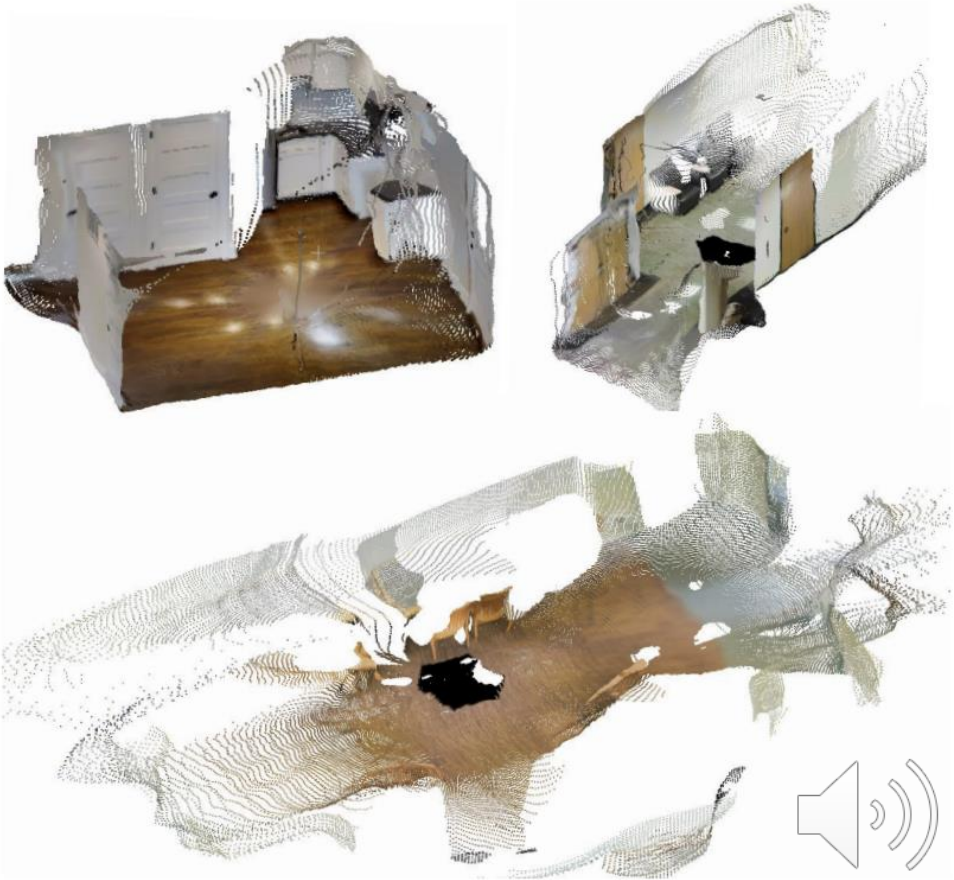
Downstream Task

- Triangulation $AX = b$.

$$\mathbf{S} \times (R(\mathbf{X} - \mathbf{C})) = \mathbf{0},$$

$$S^x \mathbf{r}^{3\mathrm{T}}(\mathbf{X} - \mathbf{C}) - S^z \mathbf{r}^{1\mathrm{T}}(\mathbf{X} - \mathbf{C}) = 0,$$
$$S^y \mathbf{r}^{3\mathrm{T}}(\mathbf{X} - \mathbf{C}) - S^z \mathbf{r}^{2\mathrm{T}}(\mathbf{X} - \mathbf{C}) = 0,$$
$$S^x \mathbf{r}^{2\mathrm{T}}(\mathbf{X} - \mathbf{C}) - S^y \mathbf{r}^{1\mathrm{T}}(\mathbf{X} - \mathbf{C}) = 0,$$

$$A = \begin{pmatrix} S^x_{\mathcal{M}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{M}} - S^z_{\mathcal{M}} \mathbf{r}^{1\mathrm{T}}_{\mathcal{M}} \\ S^y_{\mathcal{M}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{M}} - S^z_{\mathcal{M}} \mathbf{r}^{2\mathrm{T}}_{\mathcal{M}} \\ S^x_{\mathcal{N}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{N}} - S^z_{\mathcal{N}} \mathbf{r}^{1\mathrm{T}}_{\mathcal{N}} \\ S^y_{\mathcal{N}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{N}} - S^z_{\mathcal{N}} \mathbf{r}^{2\mathrm{T}}_{\mathcal{N}} \end{pmatrix} \quad \mathbf{b} = \begin{pmatrix} (S^x_{\mathcal{M}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{M}} - S^z_{\mathcal{M}} \mathbf{r}^{1\mathrm{T}}_{\mathcal{M}})\mathbf{C}_{\mathcal{M}} \\ (S^y_{\mathcal{M}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{M}} - S^z_{\mathcal{M}} \mathbf{r}^{2\mathrm{T}}_{\mathcal{M}})\mathbf{C}_{\mathcal{M}} \\ (S^x_{\mathcal{N}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{N}} - S^z_{\mathcal{N}} \mathbf{r}^{1\mathrm{T}}_{\mathcal{N}})\mathbf{C}_{\mathcal{N}} \\ (S^y_{\mathcal{N}} \mathbf{r}^{3\mathrm{T}}_{\mathcal{N}} - S^z_{\mathcal{N}} \mathbf{r}^{2\mathrm{T}}_{\mathcal{N}})\mathbf{C}_{\mathcal{N}} \end{pmatrix}$$



Thank you

Fri 13 Jun 5PM -7PM, ExHall D Poster #92