

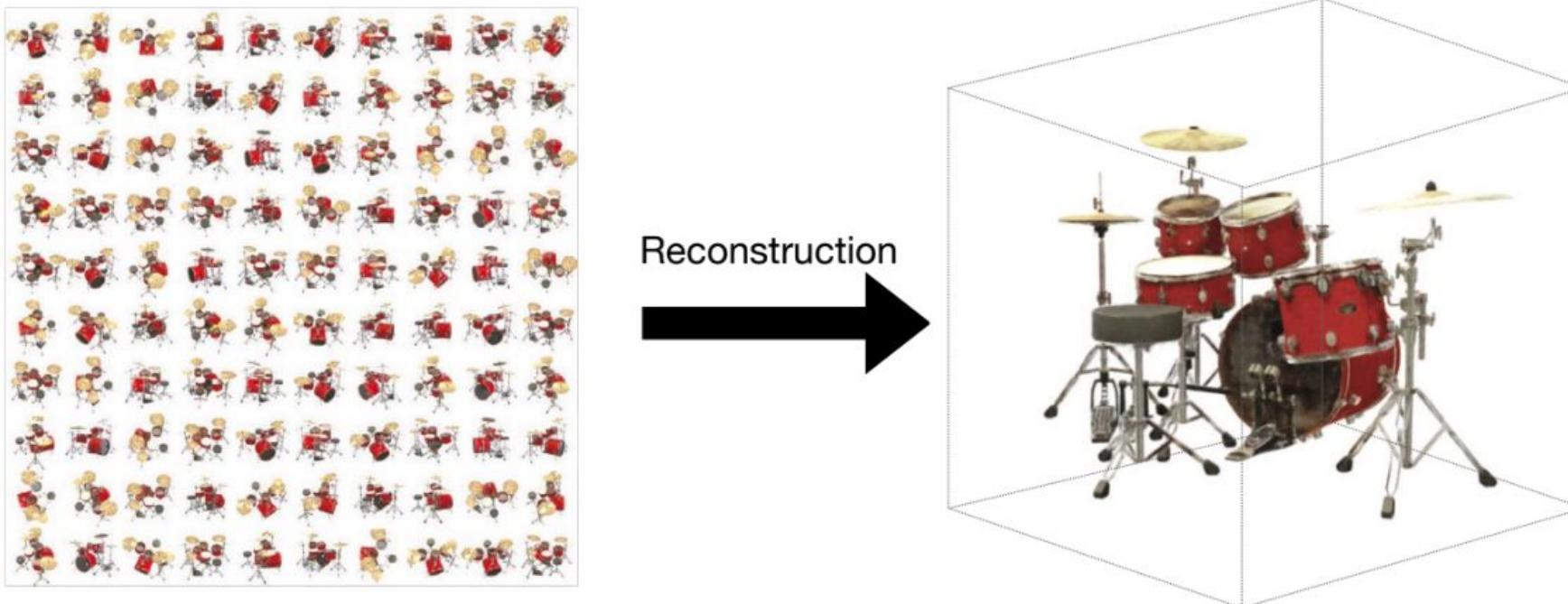
SPLATTER-360: GENERALIZABLE 360 GAUSSIAN SPLATTING FOR WIDE-BASELINE PANORAMIC IMAGES

DANIEL PERAZZO

1. INTRODUCTION

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- 3D Reconstruction aims to retrieve a 3D object
 - Collection of Views (with camera parameters)
 - Obtain a representation of the 3D object



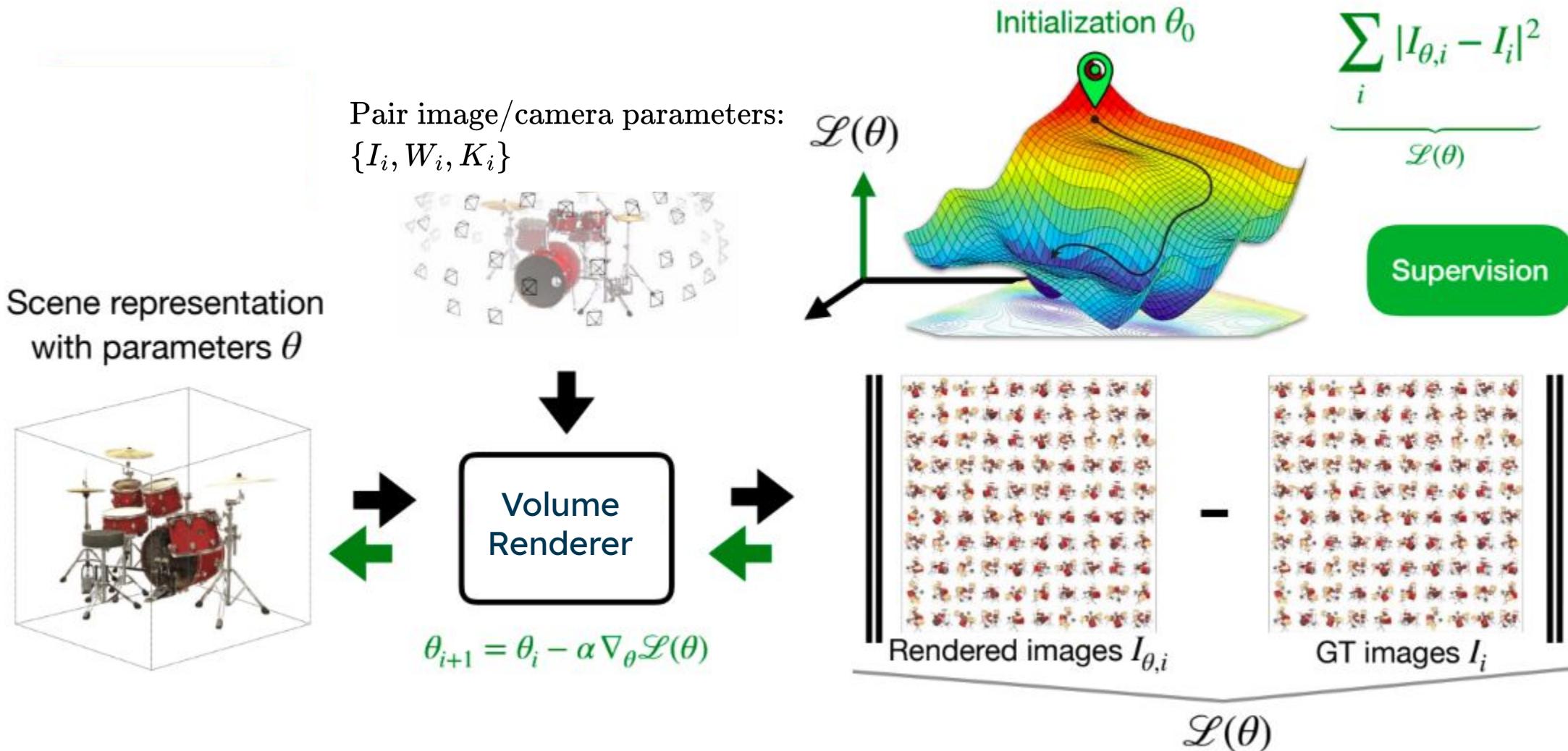
1. INTRODUCTION

- Revolutionized by 3D Gaussian Splatting
 - 3D Reconstruction technique
 - Represents the scene as 3D Gaussians
 - Fast and high-quality rendering



Kerbl, Bernhard, et al. "3D Gaussian Splatting for Real-Time Radiance Field Rendering." ACM Trans. Graph. 42.4 (2023): 139-1.

1. INTRODUCTION :: 3DGS



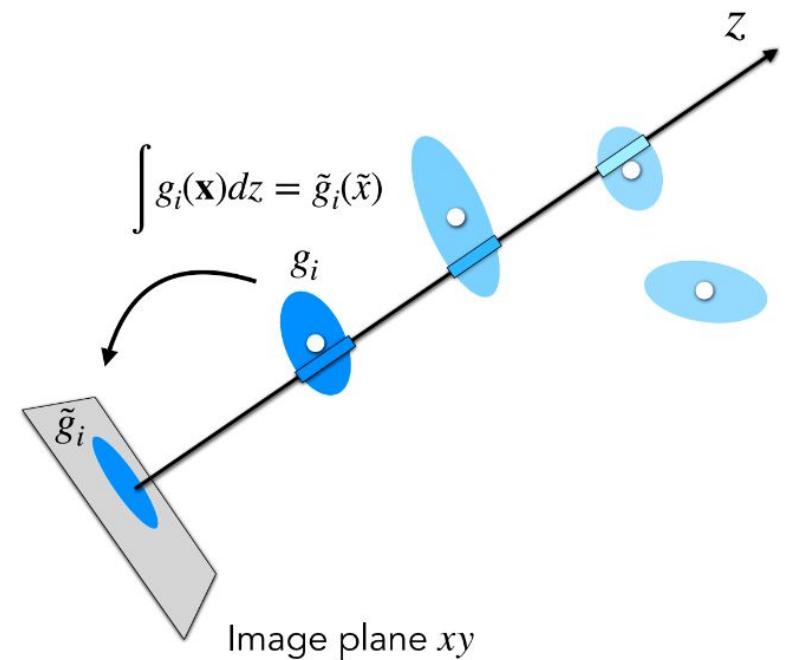
1. INTRODUCTION :: 3DGS RENDERING

Assume you have the N Gaussians ordered in the ray
And the Gaussians $g_i = (\Sigma_i, \mu_i, \sigma_i, c_i)$

Project the gaussians $\tilde{g}_i = (\tilde{\Sigma}_i, \tilde{\mu}_i, \tilde{\sigma}_i, c_i)$

$$I_f \approx \sum_i^N c_i \tilde{\sigma}_i \exp \left(-\frac{1}{2} (p - \tilde{\mu}_i)^T \tilde{\Sigma}_i^{-1} (p - \tilde{\mu}_i) \right) T_i(p)$$

$$\text{Where } T_i(p) = \prod_{j=0}^{i-1} (1 - \tilde{\sigma}_j \exp \left(-\frac{1}{2} (p - \tilde{\mu}_j)^T \tilde{\Sigma}_j^{-1} (p - \tilde{\mu}_j) \right))$$



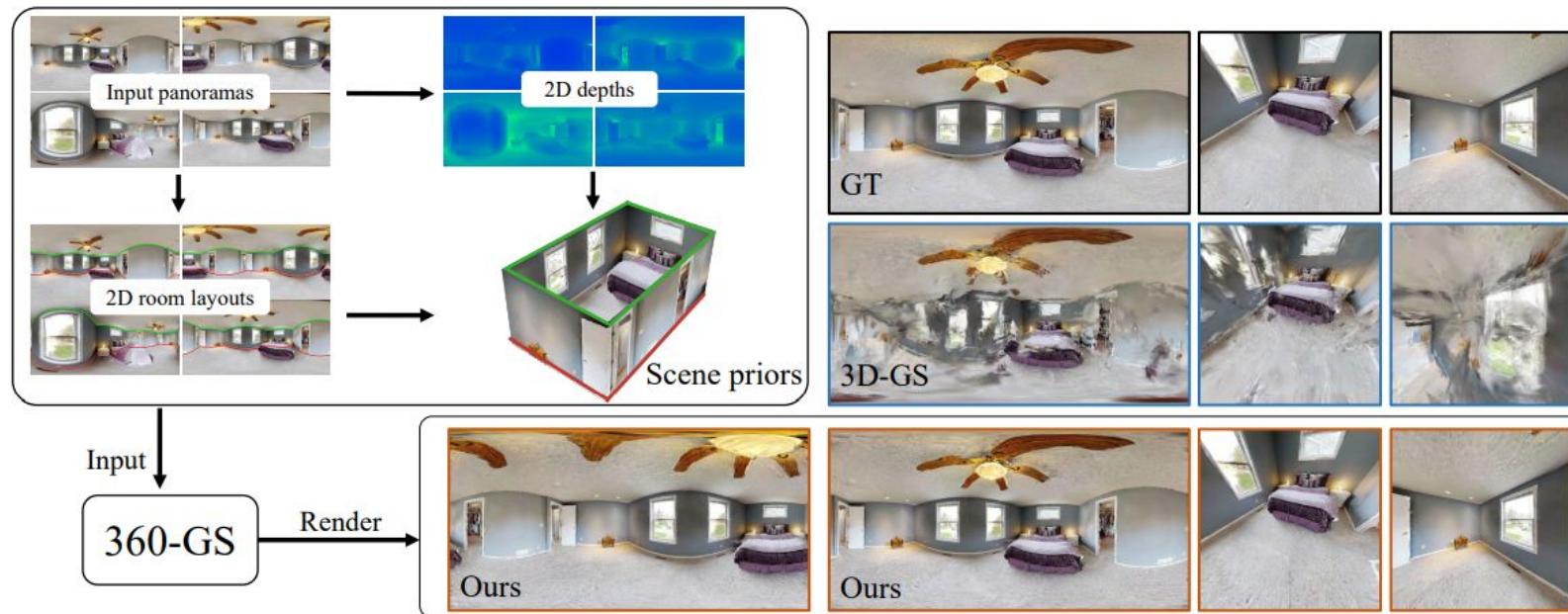
1. INTRODUCTION :: 360 IMAGES

- Created for “common” images
 - Not for “wide-angle” images
 - However, some techniques adapted to this setting



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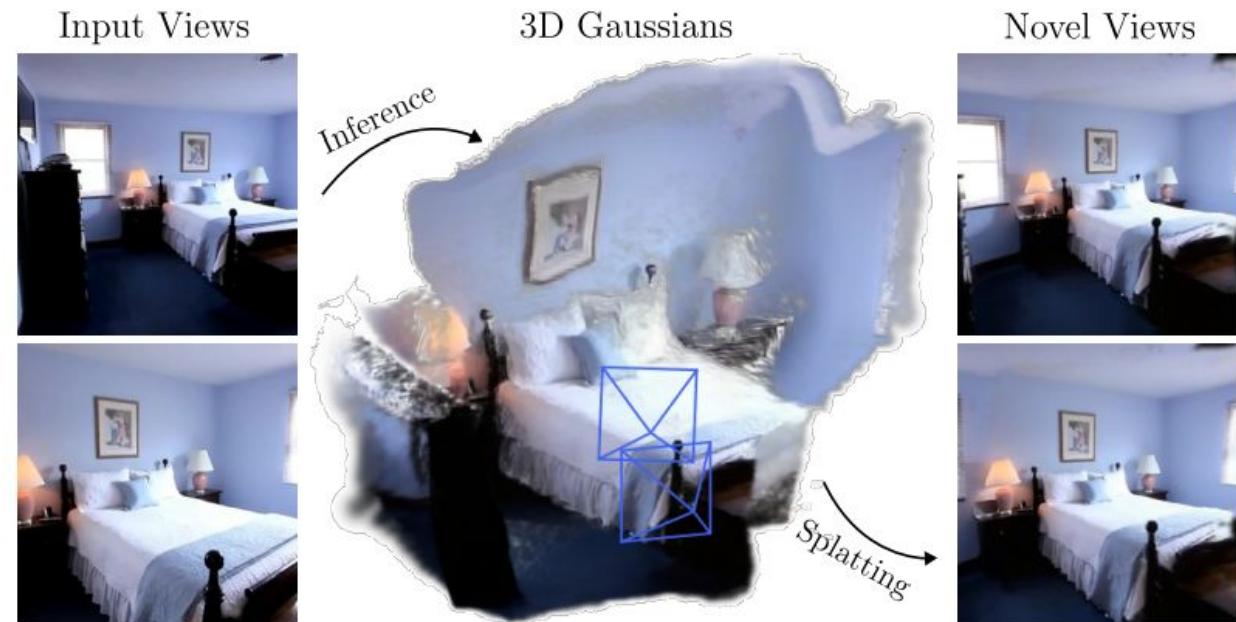


Bai, Jiayang, et al. "360-gs: Layout-guided panoramic gaussian splatting for indoor roaming." 2025 International Conference on 3D Vision (3DV). IEEE, 2025.



1. INTRODUCTION :: FEED-FORWARD SPLATTING

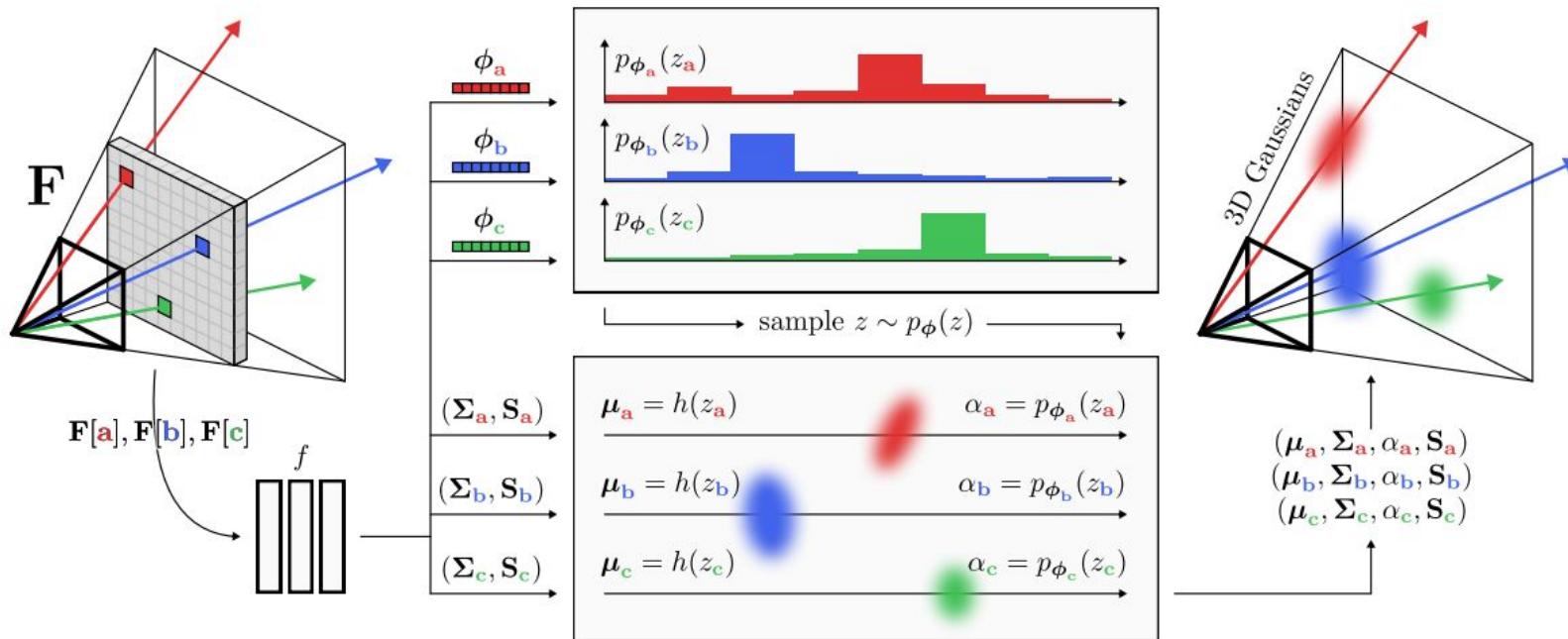
- 3DGS needs to optimize
 - Not ideal and can be slow
 - Only works for many views (no sparse)
 - Use neural networks!



Charatan, David, et al. "pixelsplat: 3d gaussian splats from image pairs for scalable generalizable 3d reconstruction." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2024.

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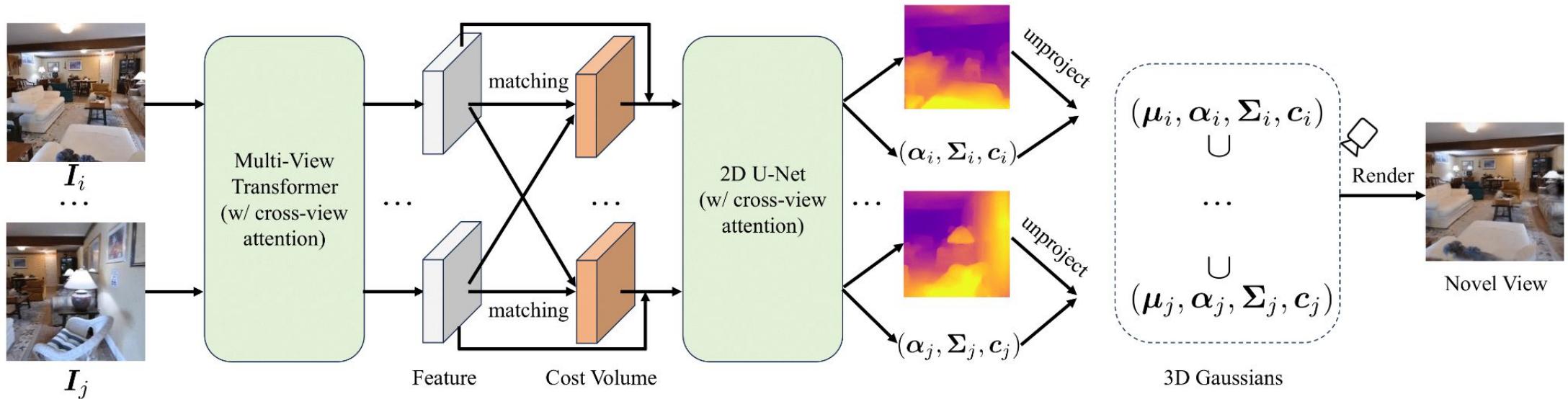
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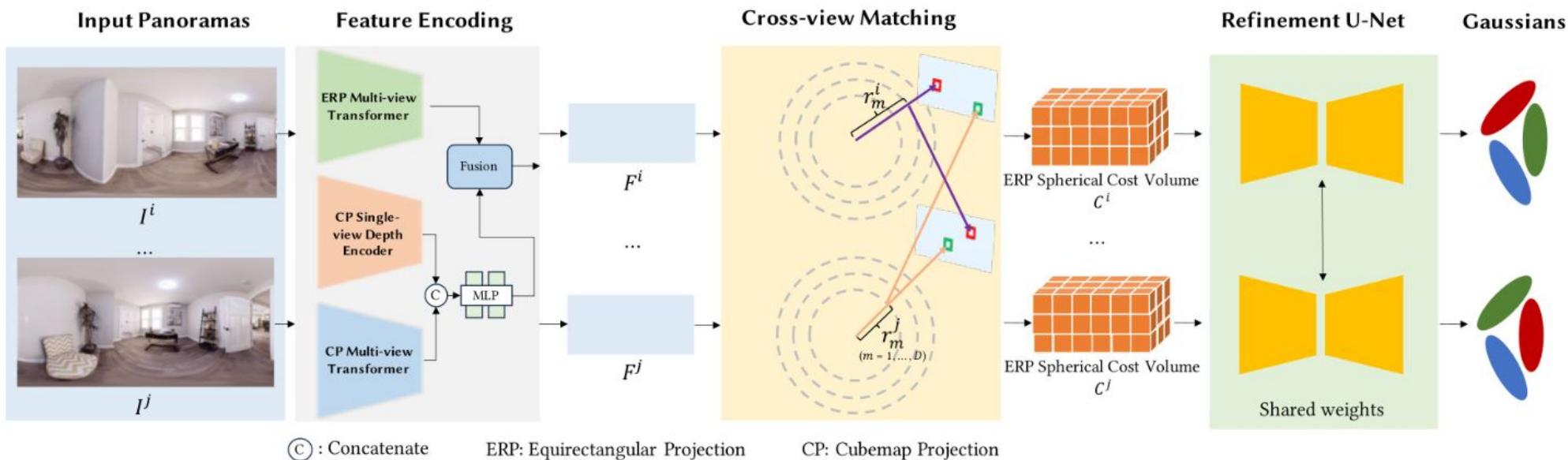


Chen, Yuedong, et al. "Mvsplat: Efficient 3d gaussian splatting from sparse multi-view images." European Conference on Computer Vision. Cham: Springer Nature Switzerland, 2024.



1. INTRODUCTION :: SPLATTER-360

- What if we mixed the problems?
 - Wide-angle
 - Feed-forward

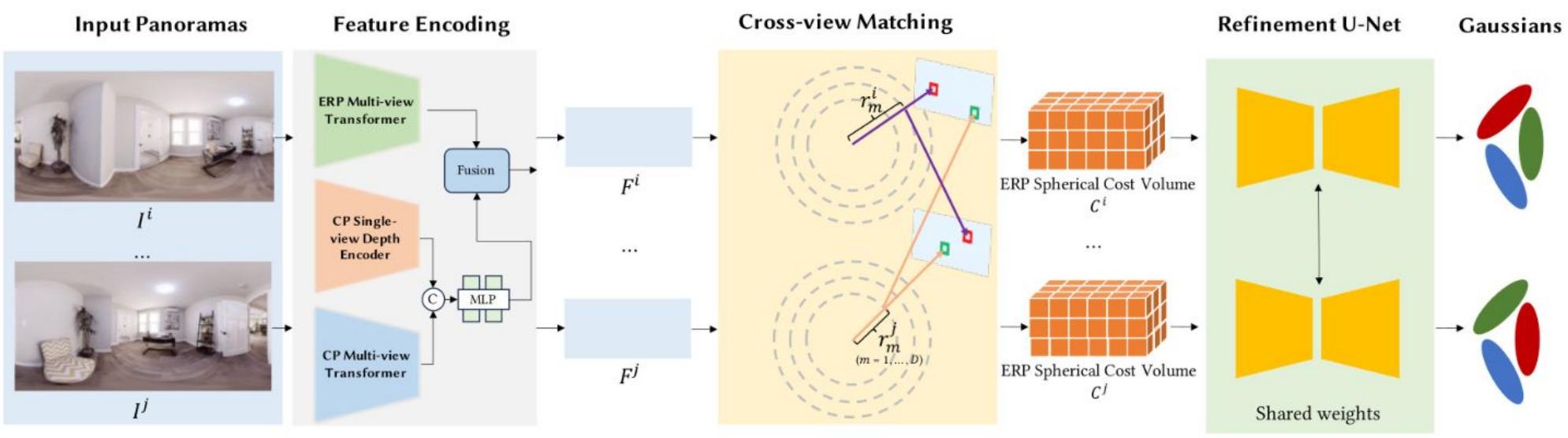


Chen, Zheng, et al. "Splatter-360: Generalizable 360 Gaussian Splatting for Wide-baseline Panoramic Images." Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.



1. INTRODUCTION :: SPLATTER-360

- Objective
 - Perform feed-forward splatting with few-views
 - Equirectangular projection images
 - Present technique



Chen, Zheng, et al. "SPLATTER-360: Generalizable 360° Gaussian Splatting for Wide-baseline Panoramic Images." Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.



2. SPLATTER -360

2. SPLATTER-360 :: INTRO

- Uses different representations
 - Strength of cube-map and equirectangular images
- Depth module

Chen, Zheng, et al. "Splatter-360: Generalizable 360 Gaussian Splatting for Wide-baseline Panoramic Images." Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.



2. SPLATTER-360 :: INPUT

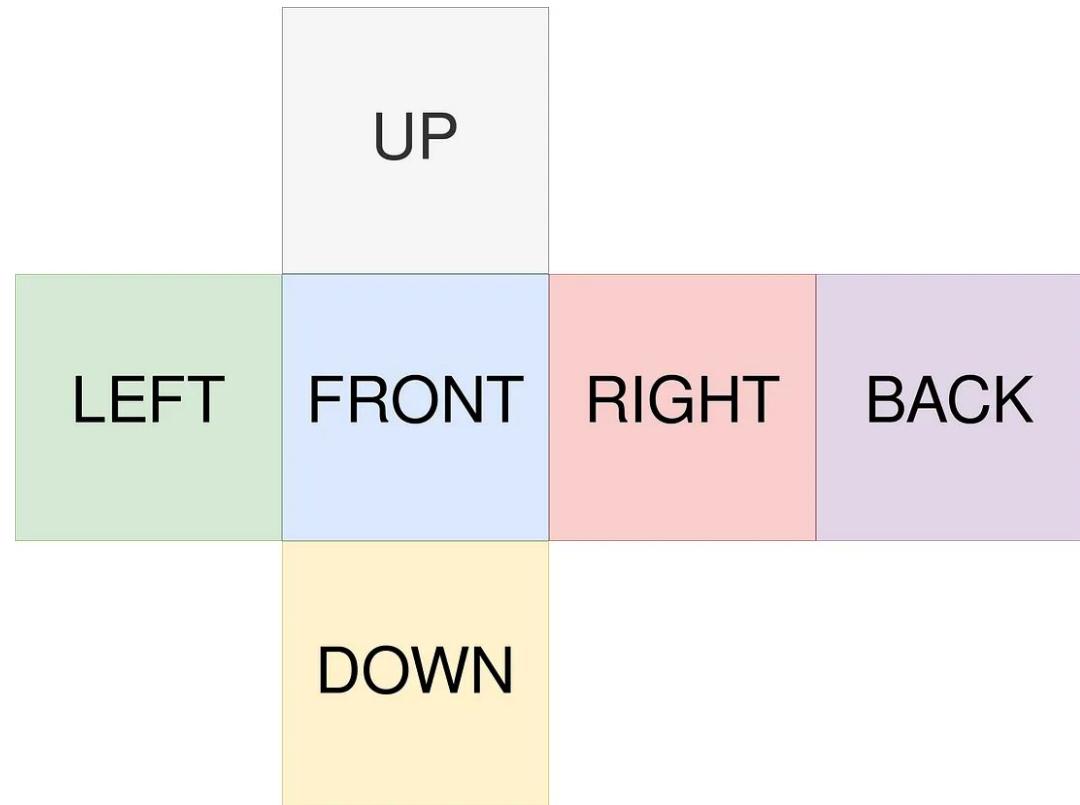
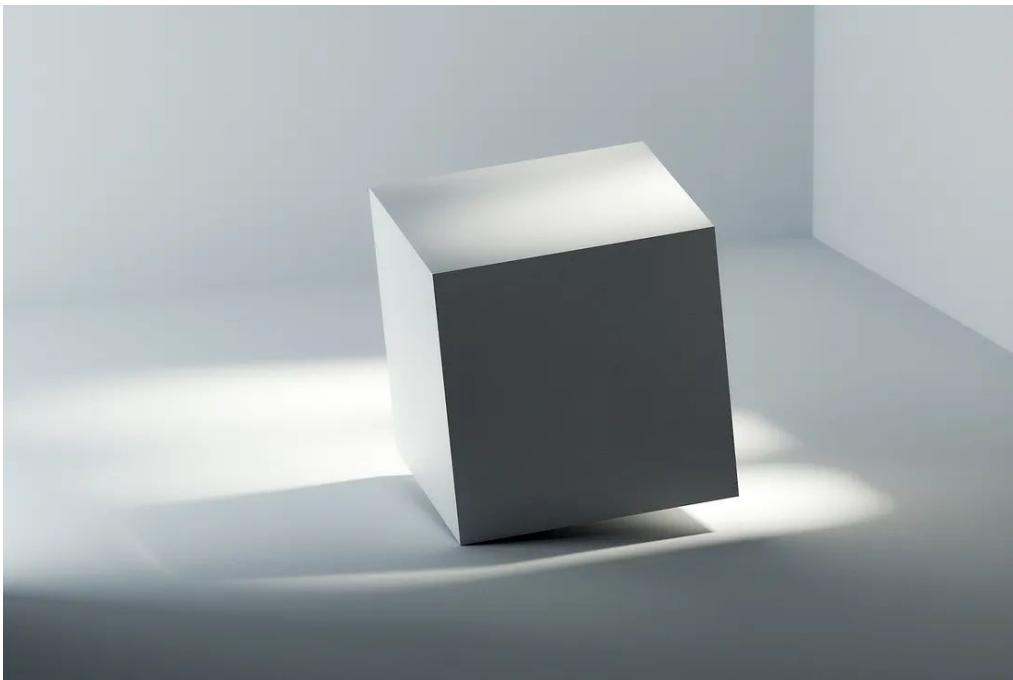
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Chen, Zheng, et al. "Splatter-360: Generalizable 360 Gaussian Splatting for Wide-baseline Panoramic Images." Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.

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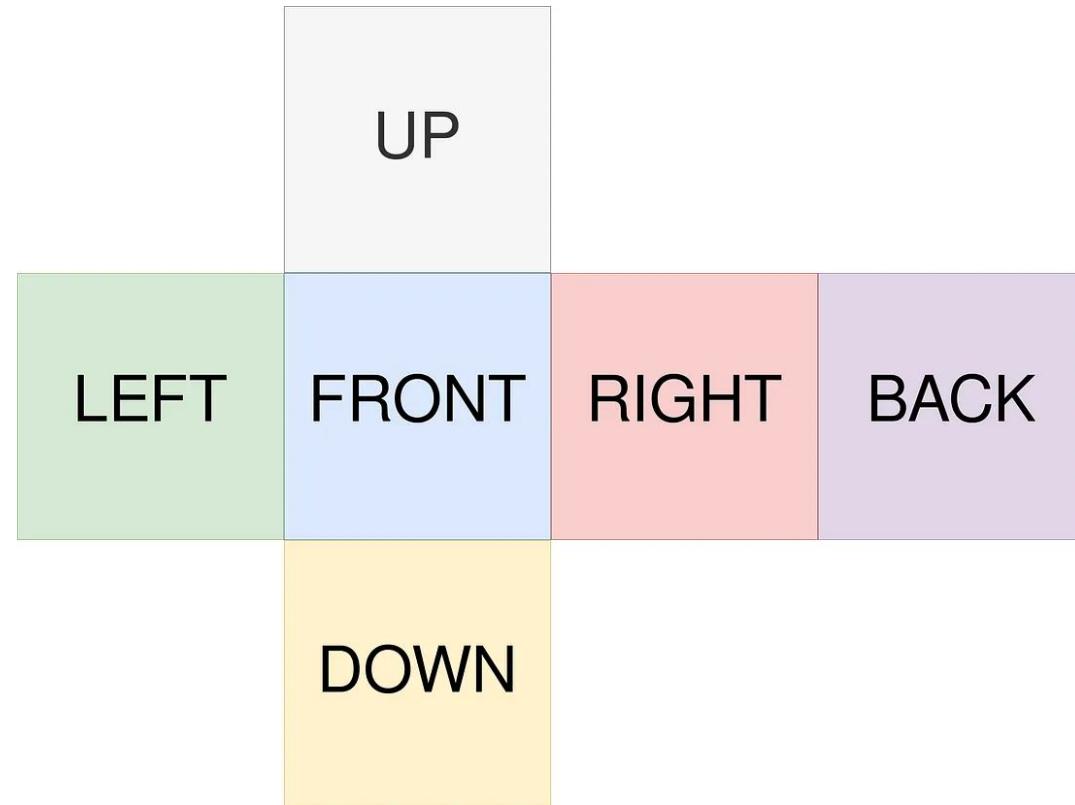
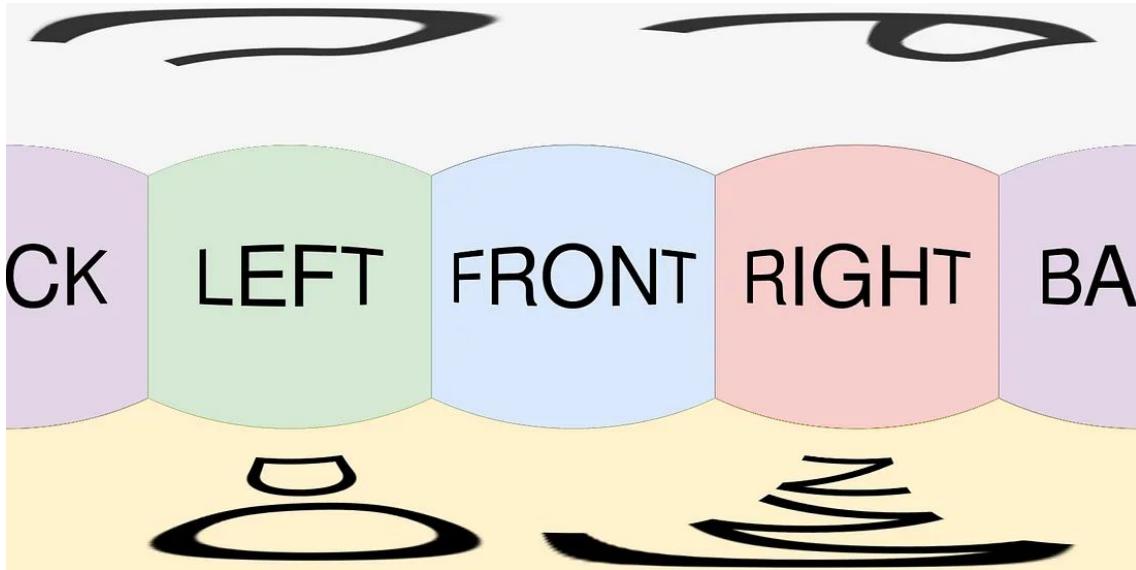
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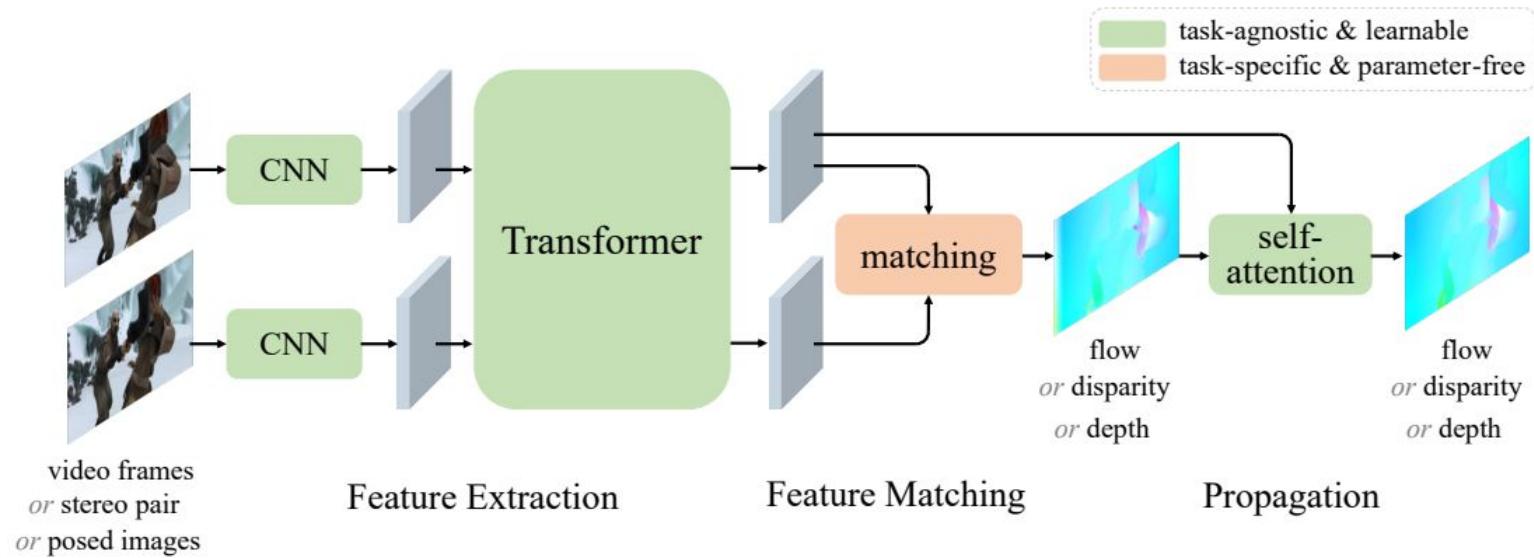
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Chen, Zheng, et al. "Splatter-360: Generalizable 360 Gaussian Splatting for Wide-baseline Panoramic Images." Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.

2. SPLATTER-360 :: INPUT

- Extract features F_{ERP} and F_{CP}
- Authors use Unimatch
 - Extract features from ERP and CP views

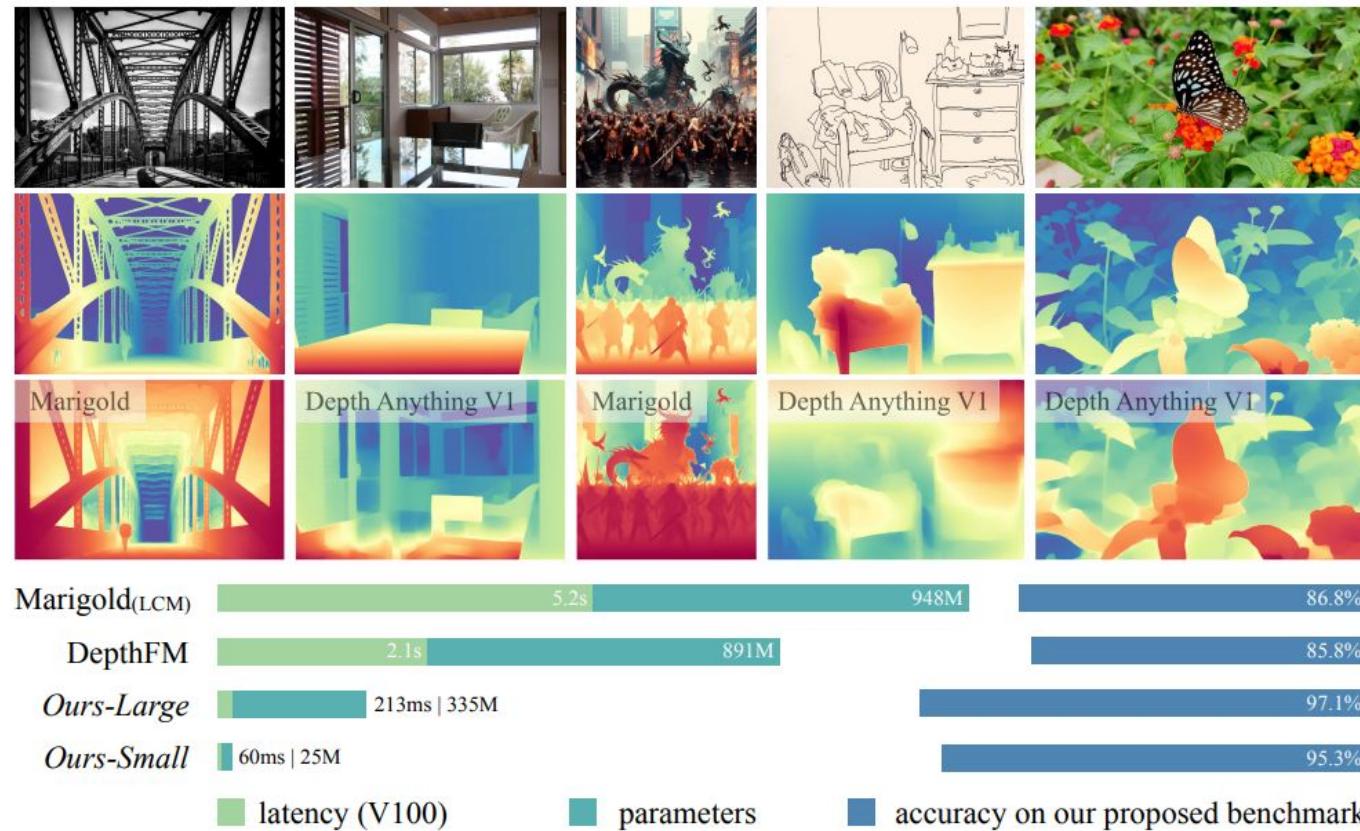


Chen, Zheng, et al. "Splatter-360: Generalizable 360 Gaussian Splatting for Wide-baseline Panoramic Images." Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.



2. SPLATTER-360 :: DEPTH

- For cube-map, extract depth features



Yang, Lihe, et al. "Depth anything v2." Advances in Neural Information Processing Systems 37 (2024): 21875-21911.

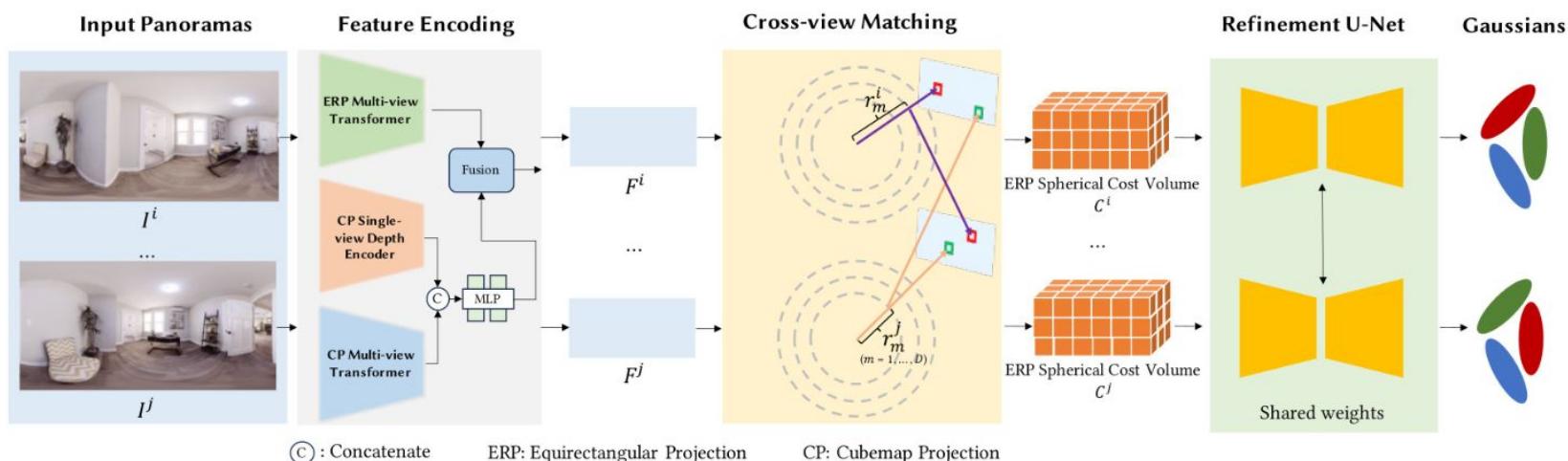


2. SPLATTER-360 :: FEATURES

- Use these features to perform feature encoding

$$\mathbf{F}'_{C2E} = \mathcal{F}_1([\mathbf{F}_{C2E}^{mono}, \mathbf{F}_{C2E}])$$

$$\mathbf{F} = \mathcal{F}_2(\mathbf{F}'_{C2E}, \mathbf{F}_{ERP})$$



2. SPLATTER-360 :: COST VOLUME

- Construct cost volume
 - Depth map computation
 - Use cube-map
 - Can get behind the camera
 - Use Diff-pano approach



$$\begin{cases} \theta = (0.5 - \frac{u}{W}) \cdot 2\pi \\ \phi = (0.5 - \frac{v}{H}) \cdot \pi, \end{cases}$$

$$\begin{cases} x_{cam} = r \cos(\phi) \cdot \sin(\theta) \\ y_{cam} = r \sin(\phi) \\ z_{cam} = r \cos(\phi) \cdot \cos(\theta), \end{cases}$$

Ye, Weicai, et al. "Diffpano: Scalable and consistent text to panorama generation with spherical epipolar-aware diffusion." Advances in Neural Information Processing Systems 37 (2024): 1304-1332.

2. SPLATTER-360 :: COST VOLUME

- Construct the cost volume
 - You have source points (i) and target (j)
 - Use these to get the corresponding points in the camera
- Given a feature image F_i , compute distance with target $F_{(j \rightarrow i)}$
 - Compute distance
 - Concatenate depths distance

$$p_{camera}^j = W^{i \rightarrow j} p_{camera}^i$$

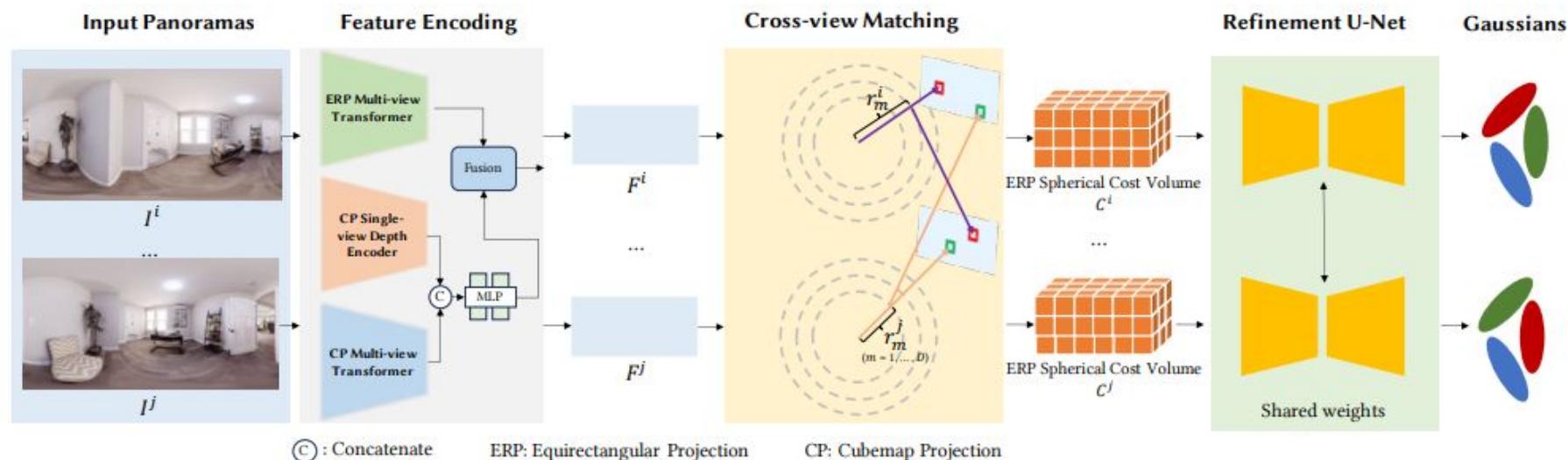
$$C_{r_m}^i = \frac{F^i \cdot F_{r_m}^{j \rightarrow i}}{\sqrt{C}} \in \mathbb{R}^{H \times W}, \quad m = 1, 2, \dots, D,$$

$$C^i = [C_{r_1}^i, C_{r_2}^i, \dots, C_{r_D}^i] \in \mathbb{R}^{H \times W \times D}$$



2. SPLATTER-360 :: COST VOLUME

- Use U-Net to refine cost volume
 - MVsplat
 - Finally, use softmax to compute final depth
 - Compute per-depth gaussians
 - Train as usual



Chen, Yuedong, et al. "Mvsplat: Efficient 3d gaussian splatting from sparse multi-view images." European Conference on Computer Vision. Cham: Springer Nature Switzerland, 2024.



3. RESULTS

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- Used HM3D and Replica
- Compared with some techniques
 - PanoGRF
 - HiSplat
 - DepthSplat
 - MVSplat
- For various settings



3. RESULTS

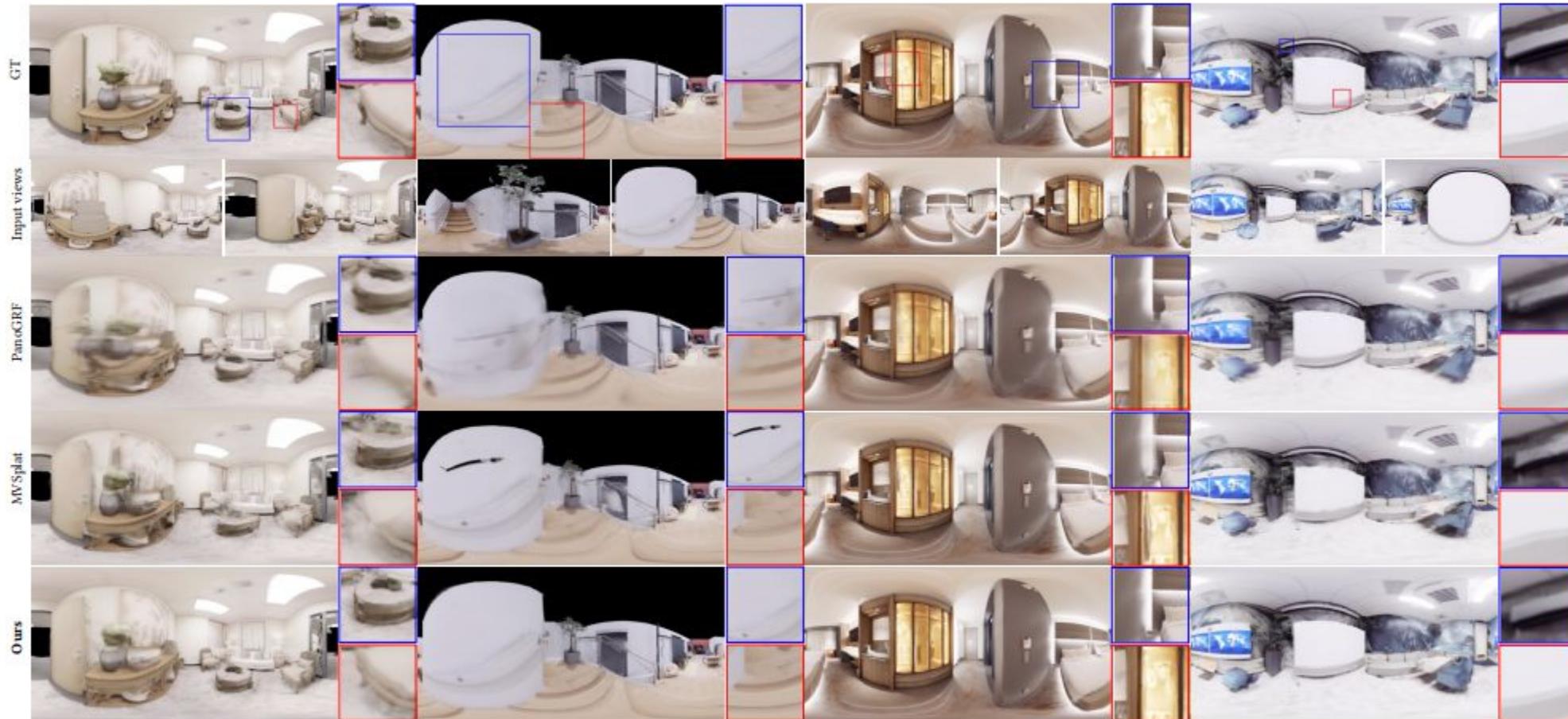


Figure 2. Qualitative comparison between our Splatter-360 and PanoGRF, MVSplat on the Replica dataset. Regions with notable differences are highlighted using red and blue rectangles. Please zoom in for a clearer view.

3. RESULTS



Figure 3. Qualitative comparison between our Splatter-360 and PanoGRF, MVSplat on the HM3D dataset. Regions with notable differences are highlighted using red and blue rectangles. Please zoom in for a clearer view.

3. RESULTS

Table 1. Quantitative comparison with baseline methods on the HM3D and Replica datasets. \dagger indicates models that were trained by us on the panoramic dataset, whereas for all other methods, we used the pre-trained models provided by the original authors.

Method	HM3D [27]			Replica [32]		
	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
HiSplat [35]	17.268	0.624	0.488	17.157	0.642	0.417
MVSplat [5]	17.574	0.636	0.441	18.005	0.631	0.512
DepthSplat [46]	20.224	0.695	0.383	19.369	0.732	0.334
PanoGRF [8]	25.631	0.813	0.268	27.920	0.892	0.171
MVSplat \dagger [5]	27.179	0.851	0.176	28.399	0.908	0.115
Splatter-360 \dagger	28.293	0.875	0.155	29.888	0.924	0.097

3. RESULTS

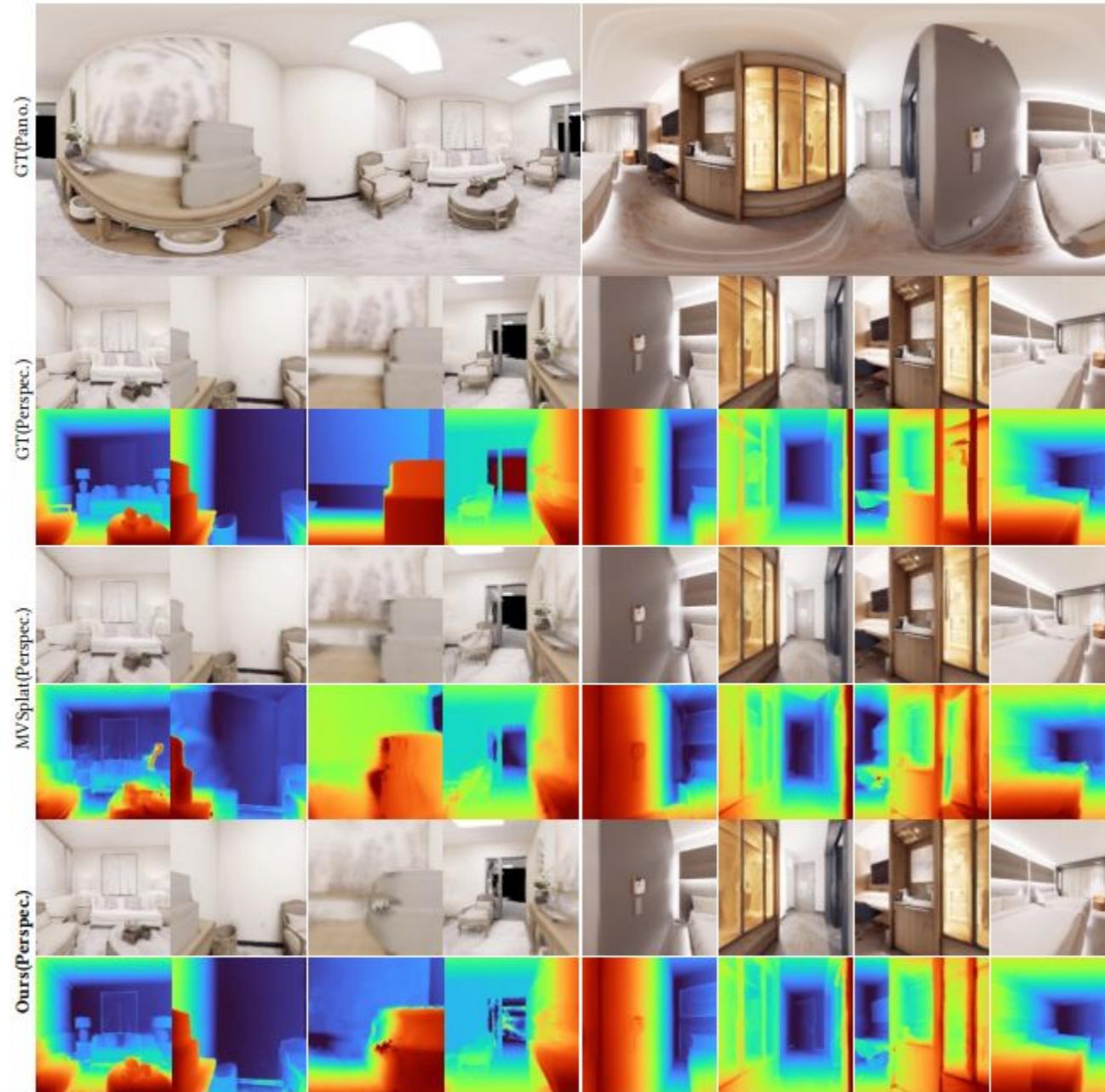


Figure 4. Novel view depth comparison between Splatter-360 and PanoGRF on the Replica dataset. “Pano.” denotes panoramic view and “Perspec.” denotes perspective view.



3. RESULTS

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Table 2. Estimated depth comparison between MVsplat and Splatter-360 on the Replica and HM3D datasets.

Dataset	Metric	MVsplat	Splatter-360
Replica [32]	Abs Diff \downarrow	0.132	0.102
	Abs Rel \downarrow	0.088	0.063
	RMSE \downarrow	0.247	0.197
	$\delta < 1.25 \uparrow$	89.913	94.572
HM3D [27]	Abs Diff \downarrow	0.130	0.106
	Abs Rel \downarrow	0.094	0.076
	RMSE \downarrow	0.271	0.223
	$\delta < 1.25 \uparrow$	90.469	93.851



3. RESULTS

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Table 3. Ablation studies were conducted on the HM3D and Replica datasets. For simplicity, we use the following abbreviations: ‘SCV’ for spherical cost volume and ‘CVA’ for cross-view attention.

Ablated module	Replica [32]			HM3D [27]		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
× SCV	23.850	0.818	0.210	25.224	0.802	0.223
× CVA	28.217	0.905	0.124	26.918	0.851	0.182
× ERP	26.985	0.887	0.142	25.905	0.827	0.202
× CP	28.673	0.909	0.117	27.277	0.857	0.174
× Mono Feat.	28.654	0.911	0.116	27.380	0.858	0.173
Full	29.121	0.914	0.111	27.487	0.860	0.171



3. RESULTS

Table 4. Quantitative comparison with three context views between MVSplat and Splatter-360 on the Replica and HM3D datasets.

Dataset	Metric	MVSplat	Splatter-360
Replica [32]	PSNR↑	29.121	29.109
	SSIM↑	0.908	0.913
	LPIPS↓	0.123	0.116
	Abs Diff↓	0.125	0.103
	Abs Rel↓	0.078	0.060
	RMSE↓	0.233	0.193
	$\delta < 1.25 \uparrow$	90.771	94.367
HM3D [27]	PSNR↑	27.858	27.905
	SSIM↑	0.861	0.868
	LPIPS↓	0.174	0.168
	Abs Diff↓	0.118	0.095
	Abs Rel↓	0.083	0.067
	RMSE↓	0.251	0.209
	$\delta < 1.25 \uparrow$	91.684	94.545



3. RESULTS

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Table 5. Quantitative comparison under a narrow baseline between MVSplat and Splatter-360 on the Replica and HM3D datasets.

Dataset	Metric	MVSplat	Splatter-360
Replica [32]	PSNR↑	32.521	33.282
	SSIM↑	0.951	0.957
	LPIPS↓	0.064	0.058
	Abs Diff↓	0.109	0.090
	Abs Rel↓	0.057	0.048
	RMSE↓	0.214	0.171
	$\delta < 1.25 \uparrow$	94.257	96.645
HM3D [27]	PSNR↑	30.851	31.493
	SSIM↑	0.915	0.925
	LPIPS↓	0.109	0.101
	Abs Diff↓	0.102	0.092
	Abs Rel↓	0.060	0.058
	RMSE↓	0.228	0.189
	$\delta < 1.25 \uparrow$	94.802	96.031



3. RESULTS

- Trained on a cluster of GPUs V100
 - Can't train
- Shared a model to test
 - However, need to download 11 Gb Replica dataset



4. CONCLUSION

4. CONCLUSION

- Review:
 - Great idea and technique!
 - But paper could be more clearly written (loss function not specified)
 - PSNR difference is small
- But great work!!



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