Baking Gaussian Splatting into Diffusion Denoiser for Fast and Scalable Single-stage Image-to-3D Generation and Reconstruction

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Existing image-to-3D object-level generation methods are mainly two-stage. First generate blocked multi-view images and then lift to 3D, which easily leads to view-inconsistency.

Current single-view scene-level reconstruction algorithms usually rely on depth estimator and easily collapse when the viewpoint changes significantly.

To cope with these problems, we propose a 3D Gaussian Splatting-based diffusion model, DiffusionGS

prompt view

prompt view

LGM

VistaDream

12345++

Splatter-Image

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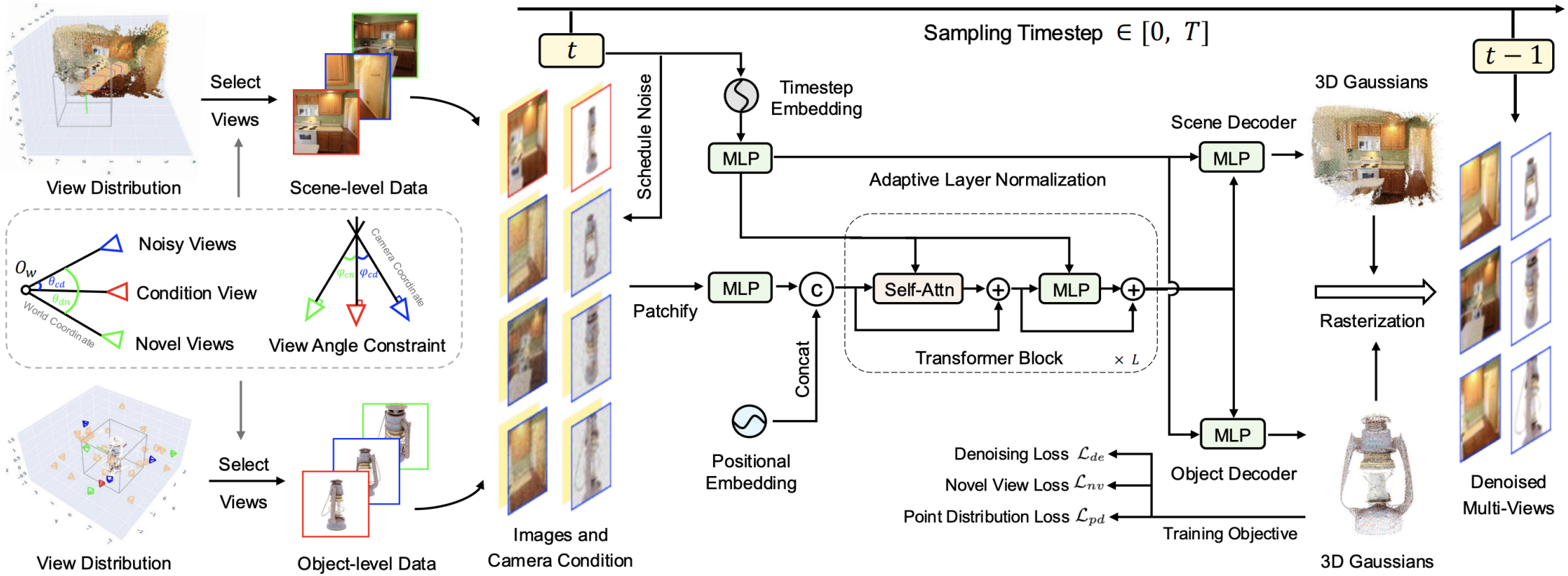


(a) Scene-Object Mixed Training

(b) Denoiser Architecture of Our DiffusionGS in a Single Timestep

- Our DiffusionGS predicts 3D Gaussian point clouds at each timestep and renders x0 at each view to proceed the multi-view denoising process.

$$\mathcal{G}_\theta(\mathcal{X}_t|\mathbf{x}_{con}, \mathbf{v}_{con}, t, \mathcal{V}) = \{G_t^{(k)}(\boldsymbol{\mu}_t^{(k)}, \boldsymbol{\Sigma}_t^{(k)}, \alpha_t^{(k)}, \boldsymbol{c}_t^{(k)})\}$$

$$\hat{\mathbf{x}}_{(0,t)}^{(i)} = F_r(\mathbf{M}_{ext}^{(i)}, \mathbf{M}_{int}^{(i)}, \mathcal{G}_\theta(\mathcal{X}_t|\mathbf{x}_{con}, \mathbf{v}_{con}, t, \mathcal{V}))$$

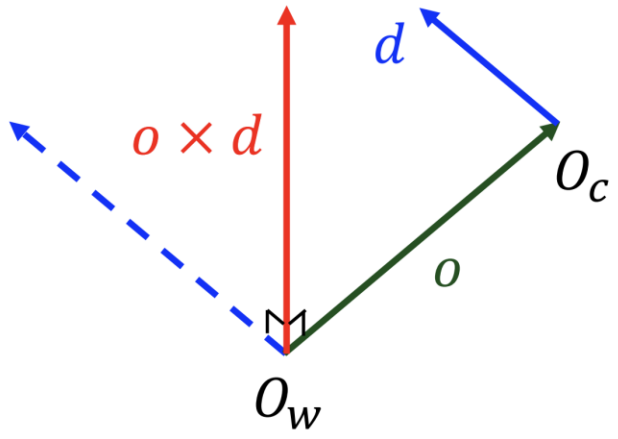
- We also design a scene-object mixed training strategy with two angle constraints

$$\theta_{cd}^{(i)} \leq \theta_1, \quad \theta_{dn}^{(i,j)} \leq \theta_2$$

$$\frac{\vec{z}_{con} \cdot \vec{z}_{noise}^{(i)}}{|\vec{z}_{con}| \cdot |\vec{z}_{noise}^{(i)}|} \geq \cos(\varphi_1) \qquad \frac{\vec{z}_{con} \cdot \vec{z}_{nv}^{(j)}}{|\vec{z}_{con}| \cdot |\vec{z}_{nv}^{(j)}|} \geq \cos(\varphi_2)$$

- To better perceive the relative depth and geometry, we customize a Reference-Point Plucker Coordinate (RPPC)

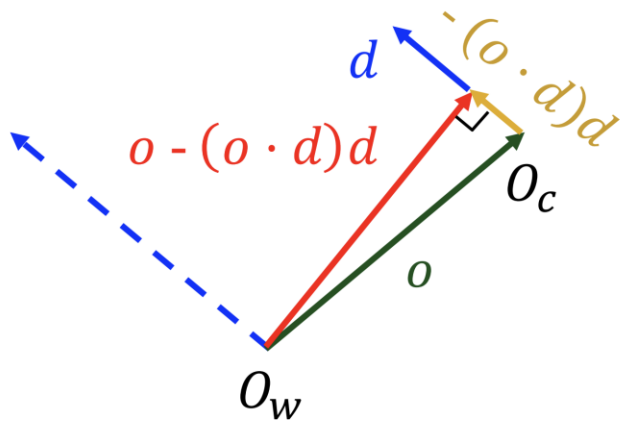
(a) $\boldsymbol{r} = (\boldsymbol{o} \times \boldsymbol{d}, \boldsymbol{d})$ (b) $\boldsymbol{r} = (\boldsymbol{o} - (\boldsymbol{o} \cdot \boldsymbol{d})\boldsymbol{d}, \boldsymbol{d})$



(a) Original Plücker Coordinate

- During the mixed training, we also impose a point distribution loss as the warm up for object-level generation:

$$\mathcal{L}_{pd} = \mathop{\mathbb{E}}_{k}[l_t^{(k)} - (\frac{l_t^{(k)} - \mathop{\mathbb{E}}_{k}[l_t^{(k)}]}{\sqrt{\mathrm{Var}(l_t^{(k)})}}\sigma_0 + \mathop{\mathbb{E}}_{k}[|\boldsymbol{o}^{(k)}|])]$$



(b) Reference-Point Plücker Coordinate

- Eventually, the overall training objective is

$$\mathcal{L} = (\mathcal{L}_{de} + \mathcal{L}_{nv}) \cdot \mathbf{1}_{\text{iter}>\text{iter}_0} + \mathcal{L}_{pd} \cdot \mathbf{1}_{\text{iter}\leq\text{iter}_0} \cdot \mathbf{1}_{\text{object}}$$

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Method	DreamGaussian [67]	LGM [68]	DMV3D [74]	CRM [71]	12345++ [36]	DiffusionGS (Ours)
User Study Score ↑	1.94	3.04	3.16	2.69	3.81	**4.88**
Runing Time (s) ↓	120	**4.1**	31.4	10	60.0	5.8

(a) User preference and running time comparison on object generation

Method	Infer Time	Post-hoc GS Time	PSNR ↑	SSIM ↑	LPIPS ↓	FID ↓
PhotoNVS [81]]	61s	2417s	15.31	0.5215	0.4589	28.30
Our DiffusionGS	**6s**	**0s**	**21.63**	**0.6787**	**0.2743**	**15.87**

(b) Comparison with the SOTA 2D method PhotoNVS on [90]

Method	PSNR ↑	SSIM ↑	LPIPS ↓	FID ↓
LGM [68]	16.01	0.7262	0.3255	86.32
GS-LRM [87]	18.78	0.7974	0.2720	123.55
DMV3D [74]	23.69	0.8634	0.1131	32.28
DiffusionGS	**25.89**	**0.8880**	**0.0965**	**9.03**

(c) Object generation results on ABO [11]

Method	PSNR ↑	SSIM ↑	LPIPS ↓	FID ↓
LGM [68]	14.27	0.7183	0.3003	75.55
GS-LRM [87]	17.70	0.7950	0.2411	112.96
DMV3D [74]	20.82	0.8347	0.1289	33.48
DiffusionGS	**22.07**	**0.8545**	**0.1115**	**11.52**

(d) Object generation results on GSO [13]

Method	PSNR ↑	SSIM ↑	LPIPS ↓	FID ↓
PixelNeRF [79]	17.46	0.5713	0.5525	159.52
Splatter-Image [65]	18.21	0.6115	0.4839	120.35
Flash3D [87]	20.29	0.6483	0.3610	35.03
DiffusionGS	**21.63**	**0.6787**	**0.2743**	**15.87**

(e) Scene reconstruction on Realestate10K [90]

Please visit our project page for more video and interactive results

Project Page

Code & Model

Code & Model : https://github.com/caiyuanhao1998/Open-DiffusionGS

Project page: https://caiyuanhao1998.github.io/project/DiffusionGS/