Universal Beta Splatting

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Motivation

- **3D Gaussian Splatting**: While fast for static scenes, it struggles with view-dependent effects (needing complex Spherical Harmonics) and dynamic motion (requiring separate deformation networks).
- **6D/7D Gaussian Splatting**: Extends to time and view but uses a single symmetric profile, which prevents independent control over geometry sharpness, specular reflections, and temporal behavior; cannot generalize well on real-world datasets.
- **Goal**: Create a single unified primitive that maintains efficiency while providing both cross-dimension correlations and independent, per-dimension modeling for complex lighting and dynamics.

Method

- **ND Parameterization:**

$$\boldsymbol{\mu} = \begin{pmatrix} \boldsymbol{\mu}_x \\ \boldsymbol{\mu}_q \end{pmatrix}, \quad \boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_x & \boldsymbol{\Sigma}_{xq} \\ \boldsymbol{\Sigma}_{qx} & \boldsymbol{\Sigma}_q \end{pmatrix}$$

- **Spatial-orthogonal Cholesky:**

$$\Sigma = LL^\top \qquad L = \begin{pmatrix} \boldsymbol{R}_x\,\mathrm{diag}(\boldsymbol{s}_x) & 0 \\ \boldsymbol{L}_{qx} & \mathrm{diag}(\boldsymbol{s}_q) \end{pmatrix}$$

- **First-order Taylor Approximation for Rotation:**

$$\boldsymbol{R}_x \approx \boldsymbol{I} + \boldsymbol{A}_x \qquad A = \begin{pmatrix} 0 & -\omega_3 & \omega_2 \\ \omega_3 & 0 & -\omega_1 \\ -\omega_2 & \omega_1 & 0 \end{pmatrix}$$

- **Beta-Modulated Conditioning:**

$$\mathcal{B}(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}, b) = (1 - r(\boldsymbol{x}))^{\beta(b)}, \quad \beta(b) = 4\exp(b), \quad b \in \mathbb{R}, \quad r(\boldsymbol{x}) \in [0, 1)$$

$$\boldsymbol{\beta} = [\beta_x, \beta_x, \beta_x, \beta_{q_1}, \ldots, \beta_{q_C}] \quad \beta_x = 4\exp(b_x) \quad \beta_{q_i} = \exp(b_{q_i})$$

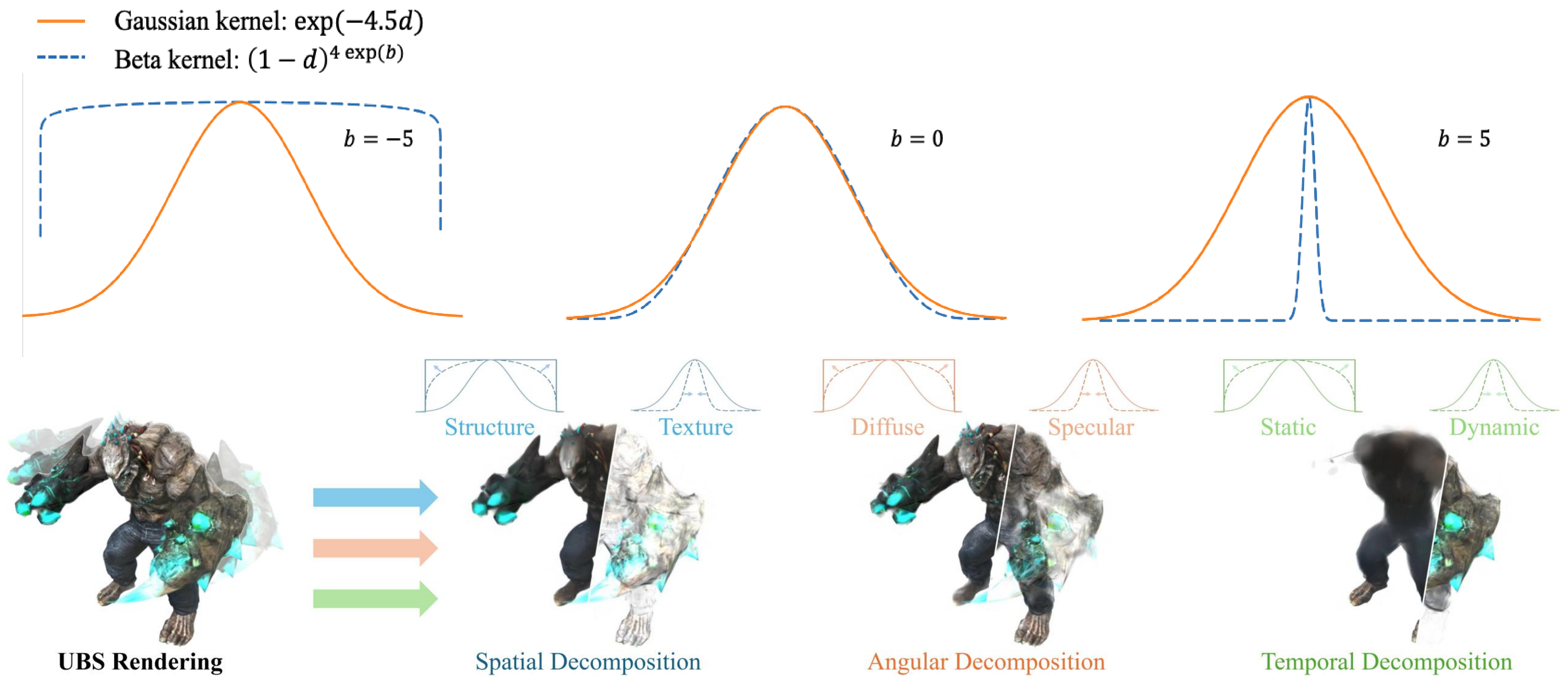
$$\boldsymbol{\mu}_{x|q} = \boldsymbol{\mu}_x + \boldsymbol{\Sigma}_{xq}\boldsymbol{\Sigma}_q^{-1}\,\mathrm{Diag}(\boldsymbol{\beta}_q)\,(\boldsymbol{q} - \boldsymbol{\mu}_q),$$

$$\boldsymbol{\Sigma}_{x|q} = \boldsymbol{\Sigma}_x - \boldsymbol{\Sigma}_{xq}\boldsymbol{\Sigma}_q^{-1}\,\mathrm{Diag}(\boldsymbol{\beta}_q)\,\boldsymbol{\Sigma}_{qx},$$

$$d_i^{\mathrm{raw}} = (\hat{\boldsymbol{L}}_q^{-1}(\boldsymbol{q} - \boldsymbol{\mu}_q))_i^2, \quad d_i = \tanh(d_i^{\mathrm{raw}}) \in [0, 1), \quad o(\boldsymbol{q}) = o\prod_{i=1}^{C}(1 - d_i)^{4\beta_{q_i}}$$

$$\sigma(\boldsymbol{x}, \boldsymbol{q}) = B(\boldsymbol{x};\, \boldsymbol{\mu}_{x|q},\, \boldsymbol{\Sigma}_{x|q},\, b_x) \cdot o(\boldsymbol{q})$$

Illustration



Qualitative Comparison

Ground Truth | 3DGS/4DGS | 6DGS/7DGS | UBS-6D/7D

Dynamic Decomposition

Full | Static | Dynamic

Quantitative Comparison

Dataset	3DGS/4DGS			6DGS/7DGS			UBS-6D/7D (**Ours**)		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
NeRF Synthetic	33.79	0.970	0.030	33.60	0.967	0.034	**34.92**	**0.975**	**0.026**
Mip-NeRF 360	27.43	0.814	0.218	26.35	0.738	0.298	**28.66**	**0.840**	**0.184**
6DGS-PBR	27.40	0.929	0.100	36.68	0.970	0.055	**40.10**	**0.979**	**0.039**
7DGS-PBR	27.74	0.933	0.077	31.75	0.955	0.055	**33.00**	**0.966**	**0.046**
D-NeRF	32.09	0.963	0.040	32.84	0.965	0.039	**33.35**	**0.965**	**0.038**

Table 1: Fidelity comparison on static and dynamic benchmarks

Dataset	3DGS/4DGS				6DGS/7DGS				UBS-6D/7D (**Ours**)			
	FPS↑	Num↓	Mem↓	Train↓	FPS↑	Num↓	Mem↓	Train↓	FPS↑	Num↓	Mem↓	Train↓
NeRF Synthetic	695.6	289.3K	68.5	3.6	648.0	240.7K	69.8	12.7	345.7	300.0K	40.1	8.7
Mip-NeRF 360	178.7	3.3M	775.9	21.7	157.4	2.0M	581.2	81.9	100.4	3.1M	409.0	25.2
6DGS-PBR	305.9	147.7K	34.9	16.8	339.8	84.3K	24.4	22.2	290.2	300.0K	40.1	27.7
7DGS-PBR	192.6	642.0K	613.1	127.2	376.0	88.4K	29.7	116.7	359.6	234.3K	39.4	59.9
D-NeRF	296.4	255.3K	380.3	52.6	377.8	43.8K	16.0	50.7	368.2	168.8K	28.4	42.1

Table 2: Efficiency comparison on static and dynamic benchmarks