A Compact Dynamic 3D Gaussian Representation for Real-Time Dynamic View Synthesis

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Highlight

PSNR: 33.56	PSNR: 36.27	PSNR: 33.61	PSNR: 21.52	PSNR: **37.45**	
FPS: 0.54	FPS: 1.23	FPS: 0.25	FPS: 169	FPS: **146**	
Mem: 471MB	Mem: 1.2GB	Mem: **48MB**	Mem: 21MB	Mem: 89MB	
K-Planes	V4D	TiNeuVox-B	3DGS	**Our method**	Ground Truth

Our method achieves high quality, high speed, and compact dynamic view synthesis

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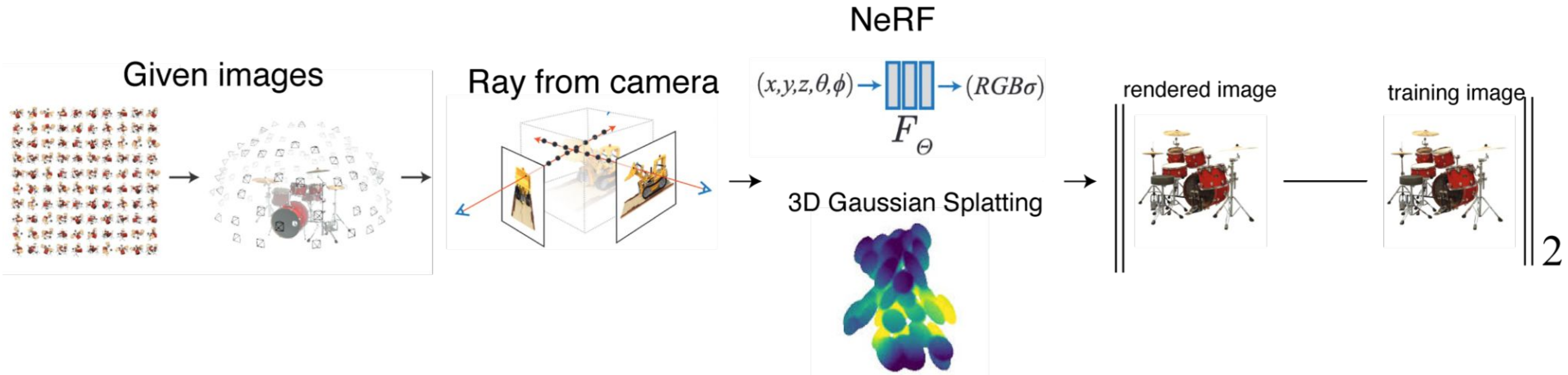
Novel View Synthesis

Given multiple images from different viewpoints, novel view synthesis aims to generate images from new viewpoints. Two popular approach: neural radiance fields (NeRF) and 3D Gaussian Splatting.

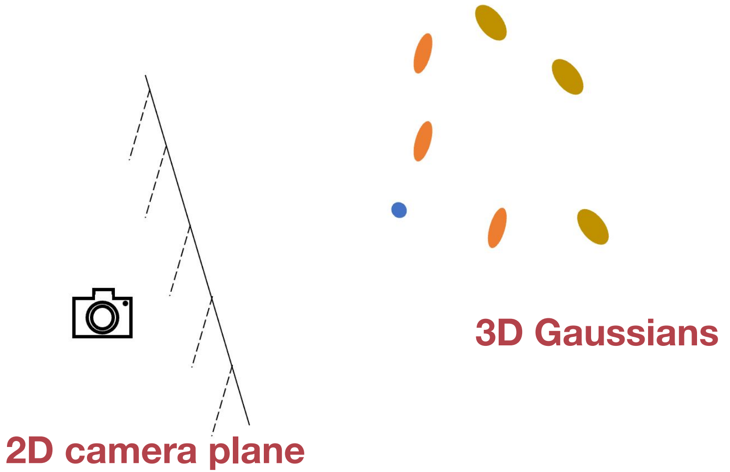


Fast, data-efficient, compact representation is essential for synthesis

3D Gaussian Splatting

1) a 3D position: $[x, y, z]^\top \in \mathbb{R}^3$,
2) a 3D rotation represented by a quaternion: $[q_x, q_y, q_z, q_w]^\top \in \mathbb{R}^4$
3) a scaling factor: $[s_x, s_y, s_z]^\top \in \mathbb{R}^3$
4) spherical harmonics coefficients representing color with the degrees of freedom k: $h \in \mathbb{R}^{3\times(k+1)^2}$
5) an opacity: $o \in \mathbb{R}$

3D Gaussian parameters



project and blend 3D Gaussians

Kerbl et al., "3D Gaussian Splatting for Real-Time Radiance Field Rendering," SIGGRAPH 2023

Extending to dynamic scenes

Static 3D Gaussian parameters

1) a 3D position: $[x, y, z]^\top \in \mathbb{R}^3$,
2) a 3D rotation represented by a quaternion: $[q_x, q_y, q_z, q_w]^\top \in \mathbb{R}^4$
3) a scaling factor: $[s_x, s_y, s_z]^\top \in \mathbb{R}^3$
4) spherical harmonics coefficients representing color with the degrees of freedom k: $h \in \mathbb{R}^{3\times(k+1)^2}$
5) an opacity: $o \in \mathbb{R}$

Dynamic 3D Gaussian parameters

1) a 3D position at time t: $[x_t, y_t, z_t]^\top \in \mathbb{R}^3$,
2) a 3D rotation at time t represented by a quaternion: $[q_t^x, q_t^y, q_t^z, q_t^w]^\top \in \mathbb{R}^4$,
3) a scaling factor: $[s_x, s_y, s_z]^\top \in \mathbb{R}^3$,
4) spherical harmonics coefficients representing color with the degrees of freedom k: $h \in \mathbb{R}^{3\times(k+1)^2}$,
5) an opacity: $o \in \mathbb{R}$.

O(TN) parameters

Challenges: multi-view assumption and huge memory consumption.

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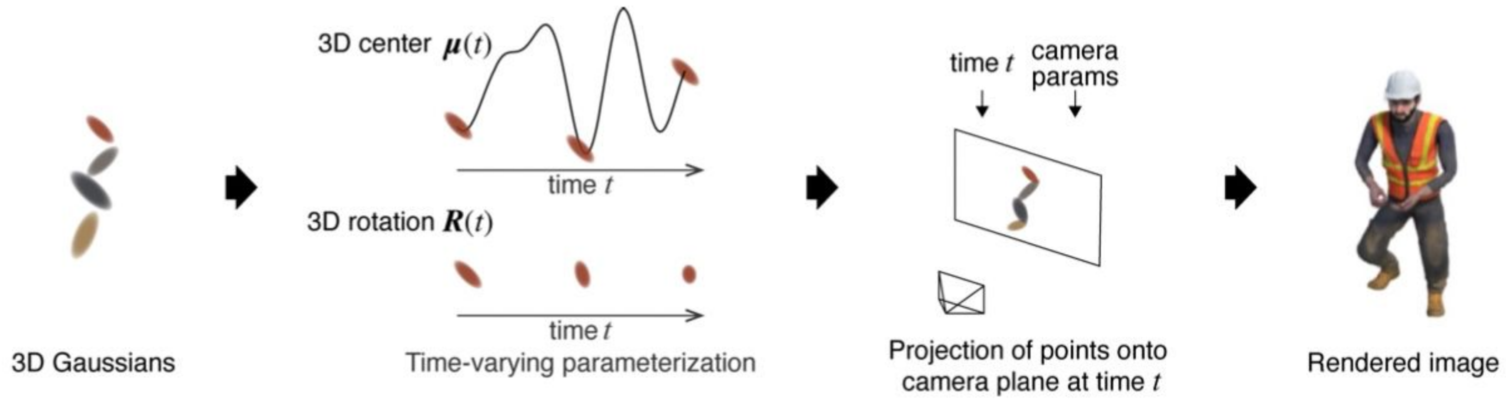
Our approach

Key idea

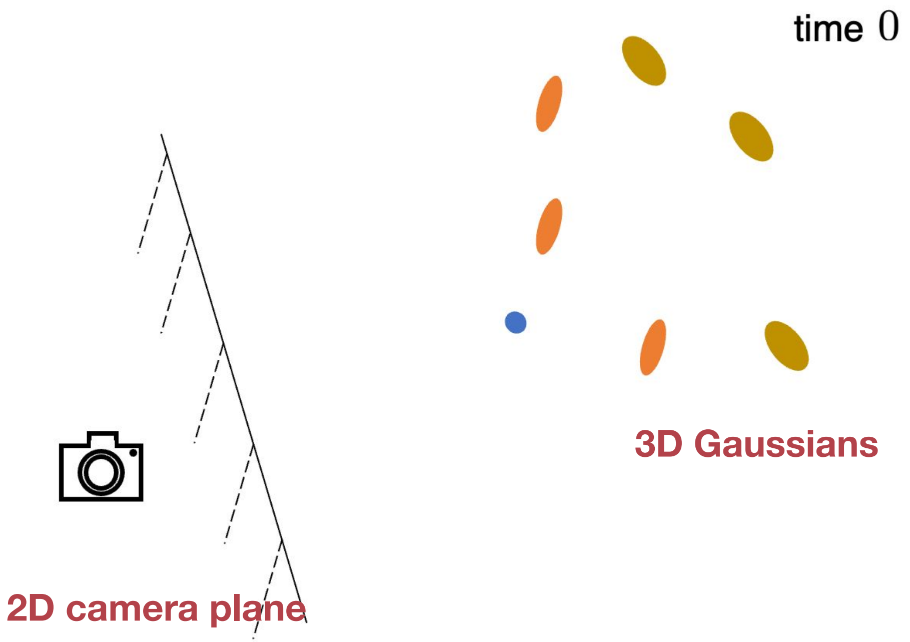
Representing time-varying parameters as functions of time with a few parameters

Our dynamic 3D Gaussian parameters

1) a 3D position at time t: $[x(t), y(t), z(t)]^\top \in \mathbb{R}^3$,
2) a 3D rotation at time t represented by a quaternion: $[q_x(t), q_y(t), q_z(t), q_w(t)]^\top \in \mathbb{R}^4$
3) a scaling factor: $[s_x, s_y, s_z]^\top \in \mathbb{R}^3$
4) spherical harmonics coefficients representing color with the degrees of freedom k: $h \in \mathbb{R}^{3\times(k+1)^2}$
5) an opacity: $o \in \mathbb{R}$



Intuition of our approach



Approximation of position and rotation

$$x(t) = w_{x,0} + \sum_{i=1}^{L} w_{x,2i-1} \sin(2i\pi t) + w_{x,2i} \cos(2i\pi t),$$

$$y(t) = w_{y,0} + \sum_{i=1}^{L} w_{y,2i-1} \sin(2i\pi t) + w_{y,2i} \cos(2i\pi t),$$

$$z(t) = w_{z,0} + \sum_{i=1}^{L} w_{z,2i-1} \sin(2i\pi t) + w_{z,2i} \cos(2i\pi t),$$

$$q_x(t) = w_{qx,0} + w_{qx,1} t,$$

$$q_y(t) = w_{qy,0} + w_{qy,1} t,$$

$$q_z(t) = w_{qz,0} + w_{qz,1} t,$$

$$q_w(t) = w_{qw,0} + w_{qw,1} t,$$

Fourier approximation for position, linear approximation for rotation

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Experiment

- Metrics:
  - PSNR
  - MS-SSIM

  Visual quality
  - FPS: rendering speed
  - Train time
  - Memory size: memory used to store optimized parameters

  Challenges in neural radiance field methods

DyNeRF dataset

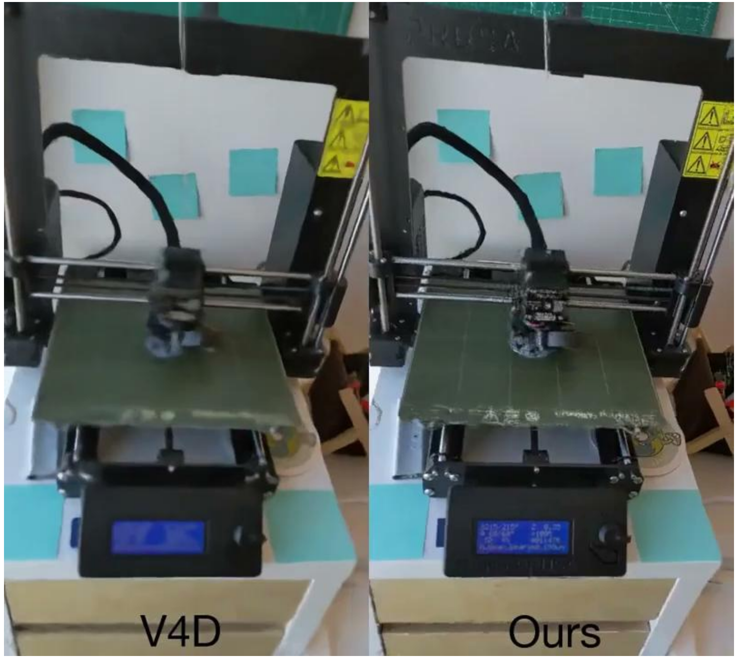
	PSNR↑	MS-SSIM↑	LPIPS↓	FPS↑	Train Time↓	Mem↓
K-Planes [Fridovich-Keil+, 2023]	**31.63**	**0.964**	-	0.31	1.8 hrs	~**309MB**
V4D [Gan+, 2024]	28.96	0.937	0.17	0.11	4 hrs	1.2GB
3DGS [Kerbl+, 2023]	20.94	0.800	0.29	109	20 mins	~198MB
D-3DGS	24.36	0.834	0.25	**119**	**51 mins**	~2.3GB
Dynamic3DGaussians [Luiten+, 2023]	27.79	0.869	0.23	51	2.1 hrs	~6.6GB
Ours	30.46	0.955	**0.15**	118	1 hrs	~338MB

Comparable **300x faster** **10x smaller**

HyperNeRF dataset

	FPS↑	Train Time↓	Mem↓	Broom		3D Printer		Chicken		Peel Banana		**Mean**	
				PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑
HyperNeRF [Park+, 2021]	0.36	48 hrs	**15MB**	19.3	0.591	20.0	0.821	26.9	**0.948**	23.3	0.896	22.2	0.811
TiNeuVox-B [Fang+, 2022]	0.14	**30 mins**	48MB	21.5	0.686	22.8	0.841	28.3	0.947	24.4	0.873	24.3	0.837
V4D [GAN+, 2024]	0.15	7 hrs	1.2GB	**22.1**	0.669	23.2	0.835	**28.4**	0.929	25.2	0.873	24.7	0.827
Ours	**188**	1 hrs	~720MB	**22.1**	**0.789**	**25.5**	**0.919**	28.3	0.934	**26.6**	**0.920**	**25.6**	**0.890**

Qualitative results



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Application of Adding 3D object into scene

Conclusion

Goal: Compact, fast, and high-quality dynamic novel view synthesis

Challenges: Multi-view assumption and huge memory consumption

Approach: Approximation of motion of 3D Gaussians by a function with a few parameters

Result: Cutting-edge visual quality, 3DGS-level inference speed, reasonable memory footprint

Thank you for your attention.

Join us at poster session 2 Tue Oct 1st, 16:30~18:30

Contact