ParticleGS: Learning Neural Gaussian Particle Dynamics from Videos for Prior-free Physical Motion Extrapolation

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CVPR 2026 Highlight

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1. Motivation, Insight & Contributions

Motivation & Insight

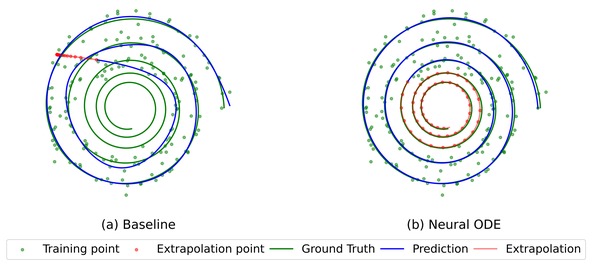
The ability to extrapolate dynamic 3D scenes beyond the observed timeframe is fundamental to advancing physical world understanding and world model.

- Existing dynamic 3D reconstruction methods achieve high-fidelity temporal interpolation, but typically lack physical consistency in predicting the future.
- Our key insight is to treat each Gaussian as a particle whose temporal evolution is driven by a physical state vector governed by the underlying physical laws.

Contributions

- From a physical perspective, we reformulate time-conditioned deformation using neural ordinary differential equations, enabling a physics-grounded representation of the driving dynamics.
- We propose ParticleGS, an Encoder-Evolver-Decoder framework that represents the scene as a physical particle system with static properties and initial dynamic fields, where a Neural ODE-based evolver learns and extrapolates the latent physical laws directly from observations.
- Numerical experiments show that our method achieves the best performance in future Gaussian extrapolation on multiple datasets.

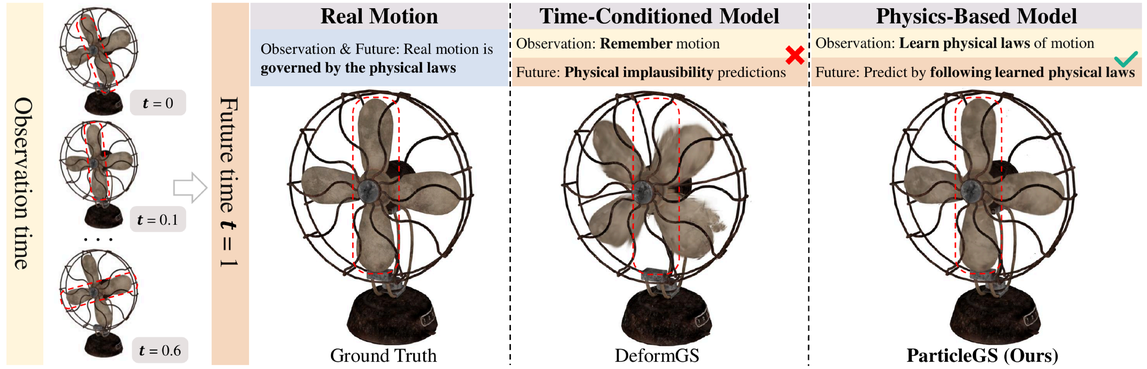
2. Why Neural ODEs



Toy experiment. Time-conditioned fitting fails during extrapolation, while Neural ODEs integrate the same law to generate physically plausible future states.

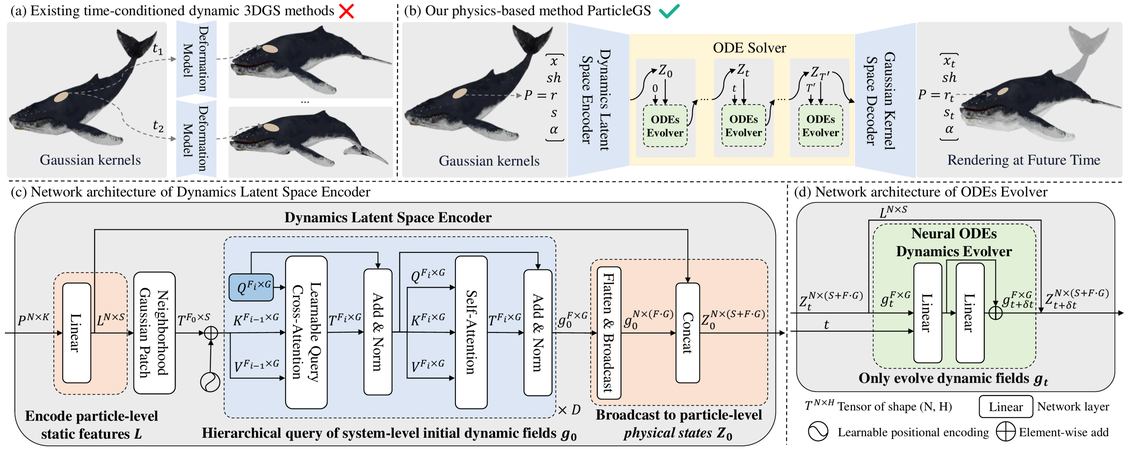
Neural ODEs integrate continuous-time dynamical systems with neural networks by learning the derivative of the system state. This enables ParticleGS to follow learned neural physical laws over time instead of memorizing timestamp-to-position mappings.

3. Learn Physical Dynamics for Future Motion



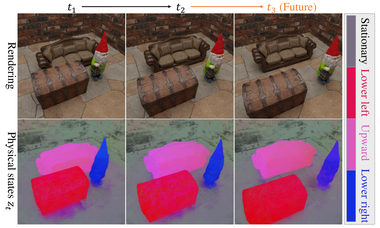
Teaser. Given multi-view RGB video observations, ParticleGS learns latent physical dynamics and extrapolates future Gaussians with physically consistent motion and appearance; existing time-conditioned deformation methods fail to predict plausible future motion.

4. ParticleGS Framework and Analysis



Framework. (a) Existing time-conditioned methods learn a deformation model for each independent discrete time. (b) Our physics-based framework, ParticleGS, uses latent physical states to drive 3D Gaussian deformation, enabling motion extrapolation. (c) The Dynamics Latent Space Encoder maps Gaussians to an initial physical state, factorized into static properties and dynamic fields. (d) The Neural ODEs Evolver learns the underlying physical laws by modeling the continuous-time evolution of the dynamic fields.

5. Physical State Visualization



Physical states. Motion-similar Gaussians exhibit comparable features, and their physical states change stably over time.

6. Experimental Conclusions

Table 1. Quantitative results on the Dynamic Objects and Dynamic Indoor Scene dataset, rendered at the source resolution. **Bold** and underline indicate the best and second best performance.

Method	Dynamic Object Dataset (Synthetic)						Dynamic Indoor Scene Dataset (Synthetic)					
	Reconstruction			Extrapolation			Reconstruction			Extrapolation		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
HexPlane [3]	21.585	0.910	0.125	22.418	0.934	0.078	17.978	0.482	0.626	23.192	0.671	0.474
TiNeuVox [12]	20.278	0.927	0.104	19.513	0.935	0.080	23.706	0.681	0.373	21.111	0.714	0.333
DeformGS [59]	37.376	0.964	0.034	26.163	0.946	0.038	20.020	0.595	0.445	21.982	0.769	0.233
Grid4D [58]	37.583	0.961	0.034	27.674	0.949	0.080	20.548	0.590	0.442	20.633	0.736	0.284
NVFi [25]	29.390	0.969	0.047	26.821	0.968	0.047	17.117	0.494	0.669	23.716	0.672	0.502
GSPrediction [61]	36.408	0.978	0.033	23.154	0.932	0.081	16.154	0.585	0.600	20.017	0.689	0.343
TRACE [26]	38.006	0.991	0.011	33.356	0.983	0.013	22.846	0.642	0.377	29.476	0.849	0.205
FreeGave [27]	38.637	**0.992**	0.011	33.632	0.983	**0.012**	19.681	0.589	0.453	28.983	0.854	0.212
ParticleGS	**39.782**	**0.992**	**0.009**	**36.471**	**0.984**	**0.012**	**25.504**	**0.748**	**0.291**	**31.103**	**0.892**	**0.133**

Table 2. Quantitative results on the Dynamic Multipart dataset and FreeGave-GoPro dataset, rendered at the source resolution. **Bold** and underline indicate the best and second best performance.

Method	Dynamic Multipart Dataset (Synthetic)						FreeGave-GoPro Dataset (Real World)					
	Reconstruction			Extrapolation			Reconstruction			Extrapolation		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
DeformGS [59]	38.430	0.988	**0.019**	27.989	0.942	0.045	20.106	0.832	0.212	21.665	0.858	0.195
TRACE [26]	36.269	**0.990**	0.021	33.458	0.984	0.015	20.103	0.838	**0.205**	25.915	0.892	0.163
FreeGave [27]	36.142	**0.990**	0.020	33.526	0.981	0.019	19.953	0.838	0.206	26.510	0.896	0.160
ParticleGS	**38.608**	**0.990**	**0.019**	**36.136**	**0.985**	**0.014**	**20.116**	**0.839**	**0.205**	**26.789**	**0.903**	**0.150**

Tables 1-2. ParticleGS reaches SOTA extrapolation performance across synthetic and real-world benchmarks while preserving strong reconstruction quality.

- **SOTA:** best future Gaussian extrapolation on all reported datasets.
- **Quality:** clearer and more physically plausible future frames than time-conditioned and velocity-field baselines.

7. Limitation & Future Outlook

- **Limitation:** ParticleGS currently cannot predict motions that deviate from the physical dynamics observed during training, such as sudden object breakage.
- **Future outlook:** Prior-free neural physical dynamics can serve as a predictive 3D representation for world models, helping them reason about how scenes may evolve beyond observations.