Gaussian Splatting Lucas-Kanade

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Introduction

Background

•Dynamic 3D scene reconstruction from monocular video is limited by sparse viewpoints.

•Dynamic Gaussian splatting requires accurate geometry for high-quality rendering.

Challenges

•Limited parallax leads to incorrect warp fields and unstable motions.

•Depth and optical flow priors are noisy and fail to regularize dynamics.

Related Works

•Learned warp fields via MLPs or offsets.

•Structural cues (depth, flow) applied, but insufficient for reliable motion modeling.

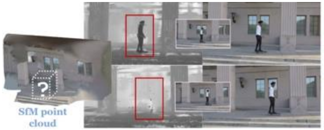
Contributions

•Derive analytical velocity fields from the warp field via Lucas-Kanade adaptation.

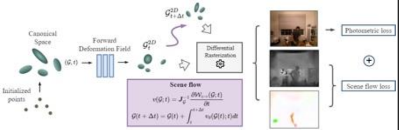
•Enable continuous time integration without extra networks.

•Improve motion accuracy and tractability over data-driven methods.

Failure Modes

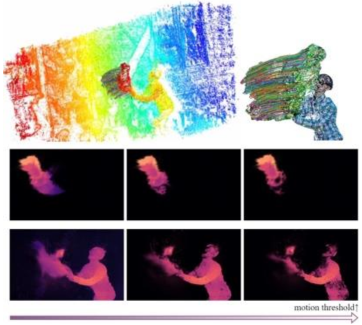


Regularizing Warp Field



The warp field can be regularized by suppressing the irregularities in the motion Jacobians for smoother predictions.

Underlying motion fields



Without regularization, the Gaussians could over-compensate for photometric quality with inaccurate motions.

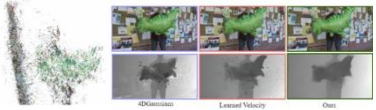
Experiment Results

Experiment Setup

•Evaluated on five dynamic scene datasets with varying camera motion (DyCheck, Dynamic Scene, Plenoptic Video, HyperNeRF, DAVIS 2017).

•Achieves state-of-the-art results under static and dynamic cameras, validated quantitatively and qualitatively.

Reconstructed glass geometries



The underlying geometry is more complete with the warp field regularization

Comparisons with baseline methods

Quantitative Comparisons

Experiments on Dynamic Scenes dataset

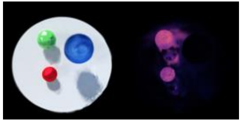
method	Playground			Balloon1			Balloon2			Umbrella		
	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓
NSFF	24.69	0.889	0.065	24.36	0.891	0.061	30.59	0.953	0.030	24.40	0.847	0.088
NR-NeRF	14.16	0.337	0.363	15.98	0.444	0.277	20.49	0.731	0.348	20.20	0.526	0.315
Nerfies	22.18	0.802	0.133	23.36	0.852	0.102	24.91	0.864	0.089	24.29	0.803	0.169
(w flow)	22.39	0.812	0.109	24.36	0.865	0.107	25.82	0.899	0.081	24.25	0.813	0.123
Flow-sup. NeRF	16.70	0.597	0.168	19.53	0.654	0.175	20.13	0.719	0.113	18.00	0.597	0.148
Deformable GS	24.82	0.646	0.343	22.40	0.833	0.137	24.19	0.818	0.153	22.35	0.711	0.186
4DGaussians	21.39	**0.776**	0.204	24.48	**0.849**	0.144	24.72	0.801	0.219	21.29	0.560	0.332
Ours	**26.34**	0.756	**0.184**	**26.35**	0.848	**0.133**	**25.89**	**0.911**	**0.151**	**23.02**	**0.746**	**0.176**

DyCheck dataset and ablated results

Method	Apple	Spin	Block	Teddy	Paper Windm
NSFF	17.54	18.38	16.61	13.65	17.34
Marbles	17.57	15.49	16.88	13.57	18.67
4D Gaussians	15.41	14.41	11.28	12.36	15.60
Ours	16.03	16.71	15.46	13.60	17.41
Ours - pose refined	22.61	24.09	23.27	17.78	19.91

Method	PSNR	SSIM	LPIPS
Deformable GS w/ flow	20.97	0.690	0.31
Deformable GS w/ depth	21.17	0.673	0.29
Deformable GS w/ both	23.94	0.702	0.28
Deformable GS	24.82	0.646	0.34
Ours	26.34	0.756	0.18

Warp Field Uncertainty



The covariance of warp Jacobians can be used to estimate motion uncertainties over time.

Conclusion

We derive analytical velocity fields to regularize dynamic Gaussian splatting, improving motion accuracy and reconstruction quality from limited views. Future work explores 3D tracking from casual captures and dynamic scene rendering in the wild.

Acknowledgement

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