上海交通大学 SHANGHAI JIAO TONG UNIVERSITY

NEURAL INFORMATION PROCESSING SYSTEMS

SJTU

H3D-DGS: Exploring Heterogeneous 3D Motion Representation for Deformable 3D Gaussian Splatting

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Methodology

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Requirements → **Potential Technologies**

What should a truly effective dynamic 3D scene reconstruction method focus on, and what potential technologies could address these requirements?

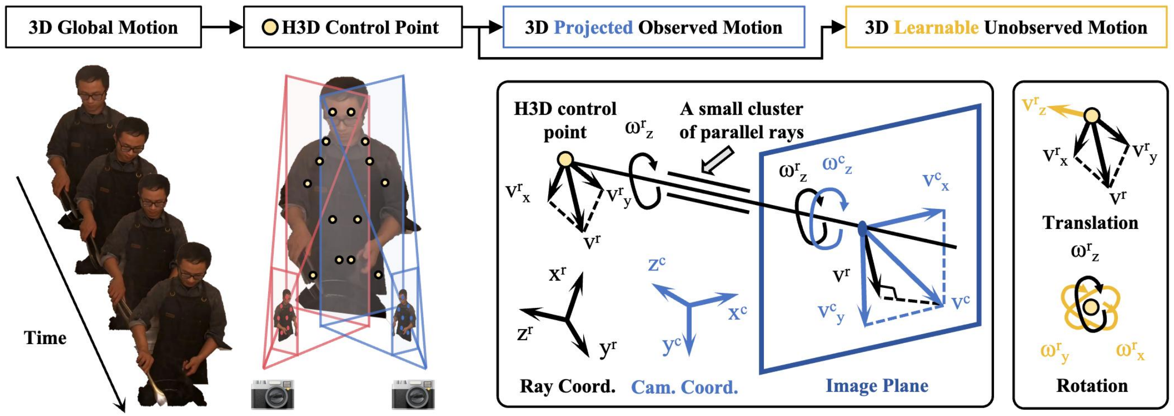
Requirements	Potential Technologies
rendering time	Gaussian Splatting
streamability	Streaming pipeline
encoding time	Utilize spatiotemporal continuity ; Prior usage
compression rate	Decoupling of scenes and actions ; Compact representation ; Post prune
visual quality	Representation with precision & robustness & scalability

Dynamic Scene Reconstruction

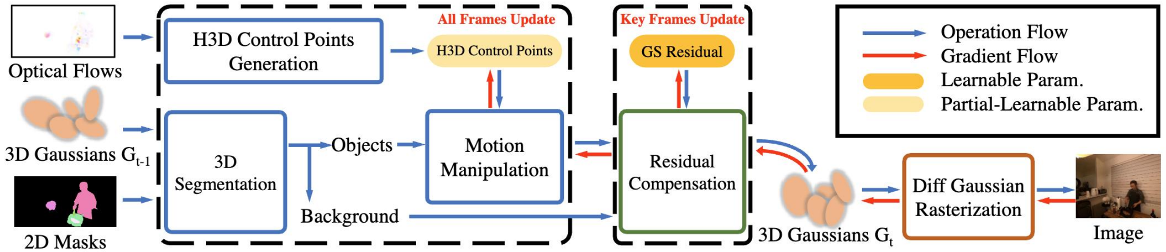
- **3D Gaussian Splatting** for static scene representation → **Fast rendering**, **Scalability**
- **Streaming Pipeline** for streamability → **Streamability**, **Robustness**
- **H3D Control Points** for motion representation → **Fast encoding**, **Precision**, **Scalability**, **Compactness**

Our framework and the contribution of each component to the final performance.

Methodology and performancce



H3D control points generation



Streaming pipeline

Subjective Quality Comparison

Table 3: Per-scene results for the Neu3DV dataset. Each cell is color-coded to denote performance ranking: best for the top performance, second for the second best, and third for the third best.

Scene	*sear_steak*			*cook_spinach*			*cut_roasted_beef*		
Metrics	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Dynamic-GS [27]	31.38	0.9469	0.1119	29.98	0.9388	0.1179	29.64	0.9360	0.1248
MA-GS [11]	30.36	0.9508	0.0854	31.15	0.9378	0.1053	31.17	0.9401	0.1157
4D-GS [48]	31.62	0.9569	0.0808	32.79	0.9522	0.0926	32.13	0.9467	0.0959
SP-GS [43]	30.75	0.9474	0.0931	31.32	0.9445	0.0914	30.44	0.9457	0.0942
SC-GS [14]	31.60	0.9510	0.1345	-	-	-	-	-	-
Ours-GoS1	33.23	0.9654	0.0719	33.20	0.9586	0.0796	33.00	0.9609	0.0795
Ours-GoS5	33.72	0.9661	0.0704	32.91	0.9579	0.0819	33.23	0.9592	0.0835
Ours-GoS10	33.64	0.9655	0.0716	32.65	0.9553	0.0861	32.47	0.9555	0.0890

Scene	*flame_steak*			*flame_salmon_1*			*coffee_martini*		
Metrics	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Dynamic-GS [27]	30.41	0.9429	0.1121	20.19	0.8875	0.1583	24.29	0.8870	0.1630
MA-GS [11]	29.14	0.9456	0.1008	25.05	0.9075	0.1274	25.72	0.8979	0.1533
4D-GS [48]	29.28	0.9545	0.0836	28.27	0.9106	0.1289	28.87	0.9198	0.1168
SP-GS [43]	25.59	0.8934	0.1248	25.13	0.9057	0.1320	19.26	0.8291	0.1996
SC-GS [14]	-	-	-	-	-	-	24.82	0.8972	0.2239
Ours-GoS1	32.84	0.9645	0.0723	28.00	0.9173	0.1083	26.90	0.9140	0.1170
Ours-GoS5	33.18	0.9649	0.0707	27.65	0.9155	0.1127	26.71	0.9119	0.1242
Ours-GoS10	32.94	0.9631	0.0733	27.17	0.9127	0.1165	26.51	0.9100	0.1283

Table 4: Per-scene results for the CMU-Panoptic dataset.

Scene	*softball*			*boxes*			*basketball*		
Metrics	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Dynamic-GS [27]	26.93	0.9076	0.1804	27.79	0.9069	0.1769	28.54	0.9032	0.1812
Ours-GoS2	27.48	0.9264	0.1374	27.88	0.9227	0.1413	27.72	0.9203	0.1423