Project Page

DySurface: Consistent 4D Surface Reconstruction via Bridging Explicit Gaussians and Implicit Functions

Minje Kim, Youngthyun Noh, Jaesoon Kim, Tae-Kyun Kim

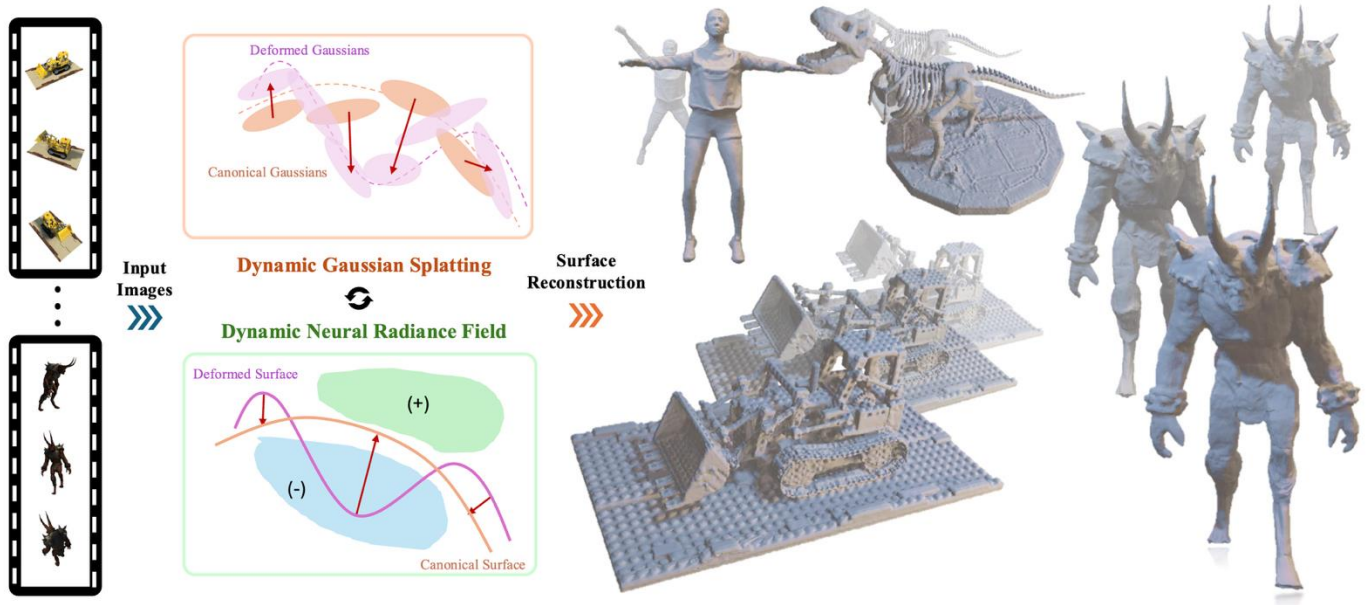
NIPS 2026

NEURAL INFORMATION PROCESSING SYSTEMS

KAIST kt KCVL

Motivation

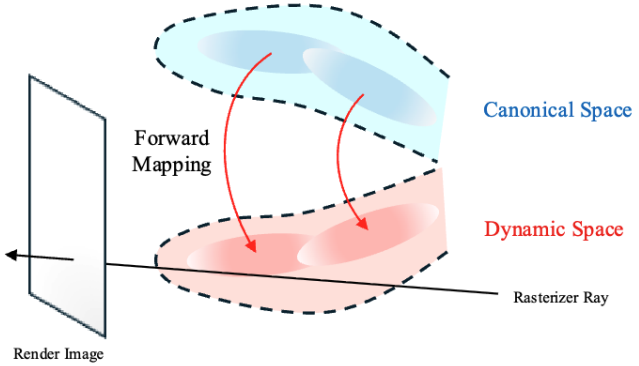
- Can we reconstruct a **geometrically accurate** and temporally consistent 4D surface by **combining the strengths of explicit 3D Gaussians and implicit SDFs, rather than relying on either representation alone?**



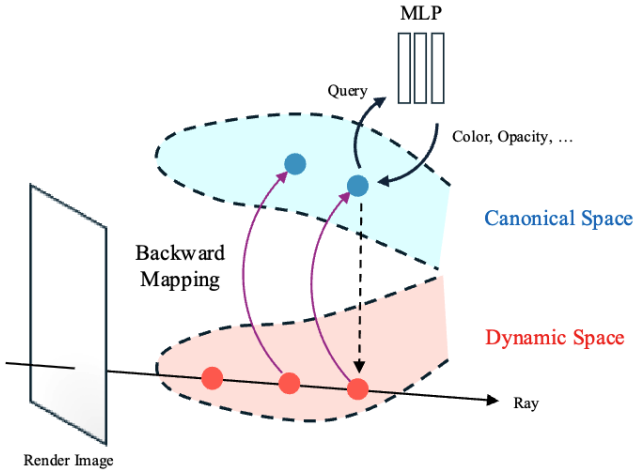
Background

- Forward Mapping
  - Canonical space → Dynamic space
  - Gaussian Splatting deformation

- Backward Mapping
  - Dynamic space → Canonical space
  - Neural Radiance Field (NeRF) deformation

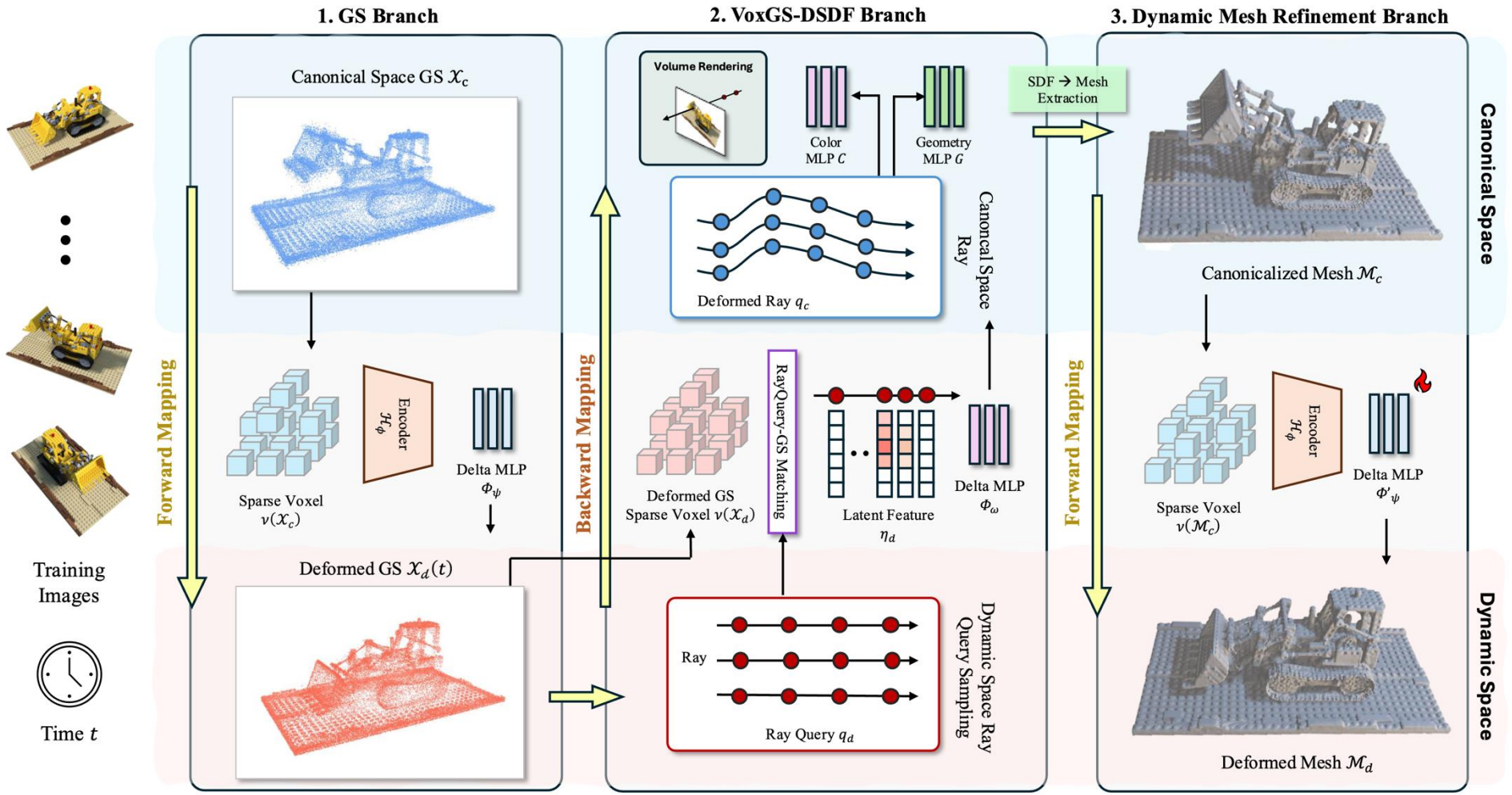


a) Gaussian Splatting Deformation

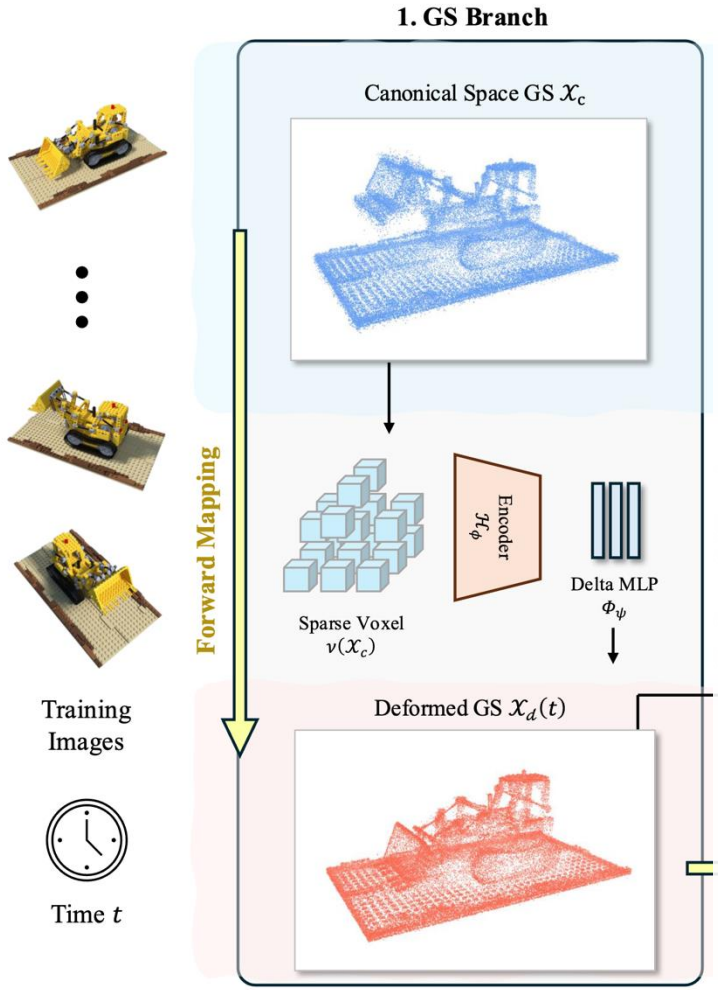


b) Neural Radiance Field Deformation

Methodology



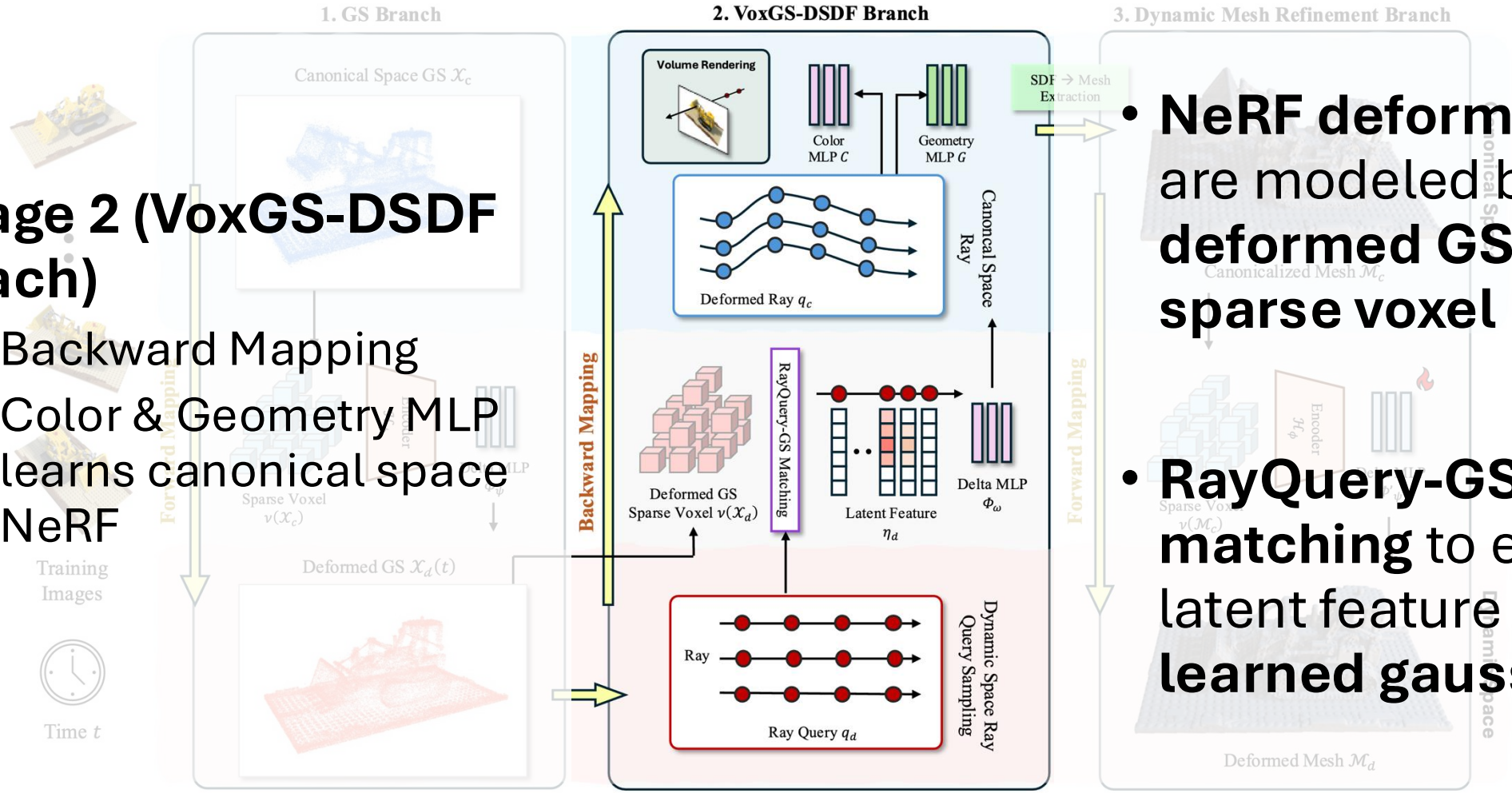
Methodology



- **Stage 1 (GS Branch)**
  - Forward Mapping
  - Pretrain gaussian splatting deformation
  - Deformation are modeled by sparse voxel decoding

Methodology

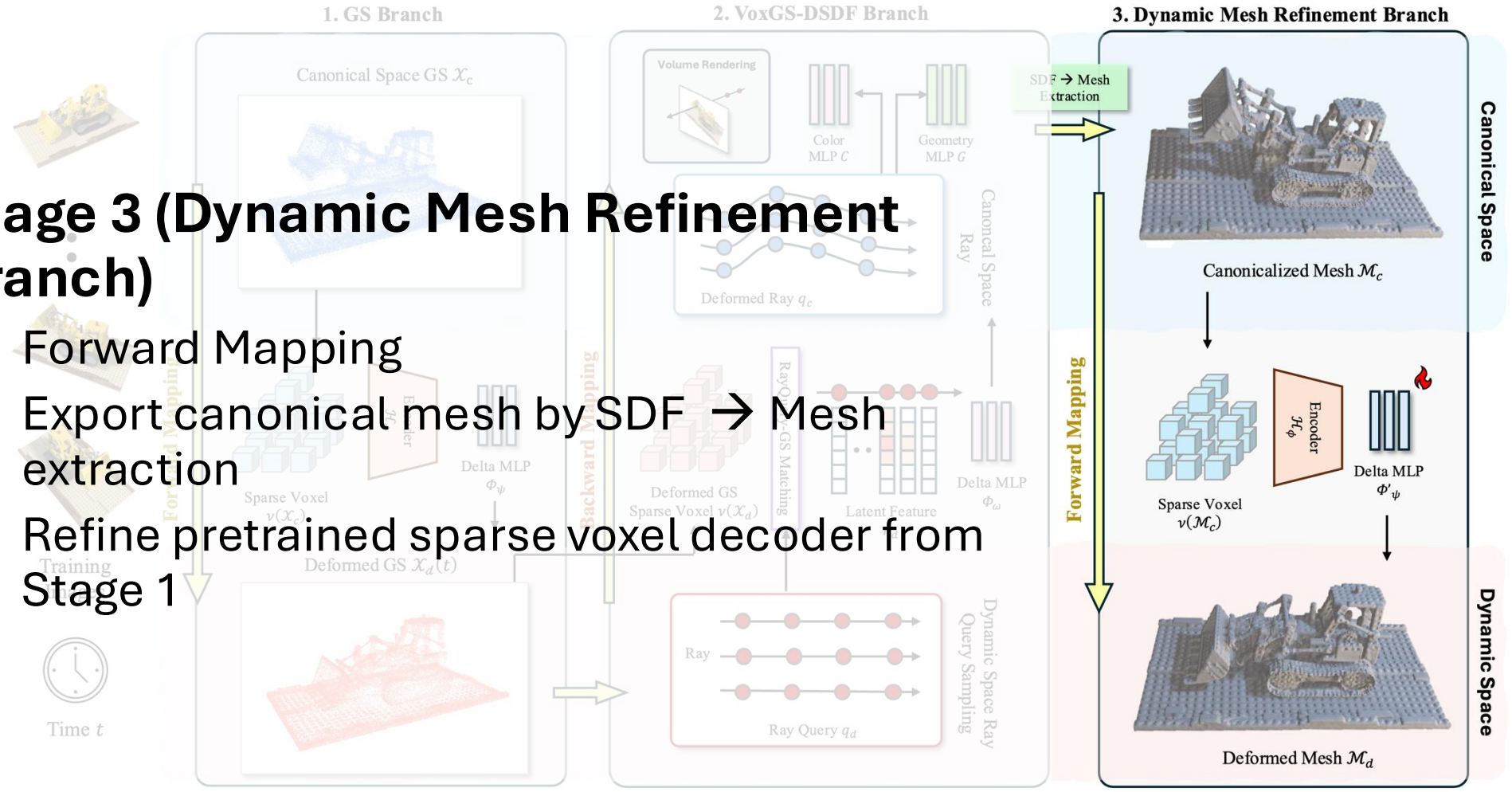
- **Stage 2 (VoxGS-DSDF Brach)**
  - Backward Mapping
  - Color & Geometry MLP learns canonical space NeRF



- **NeRF deformation** are modeled by **deformed GS sparse voxel**
- **RayQuery-GS matching** to export latent feature from **learned gaussians**

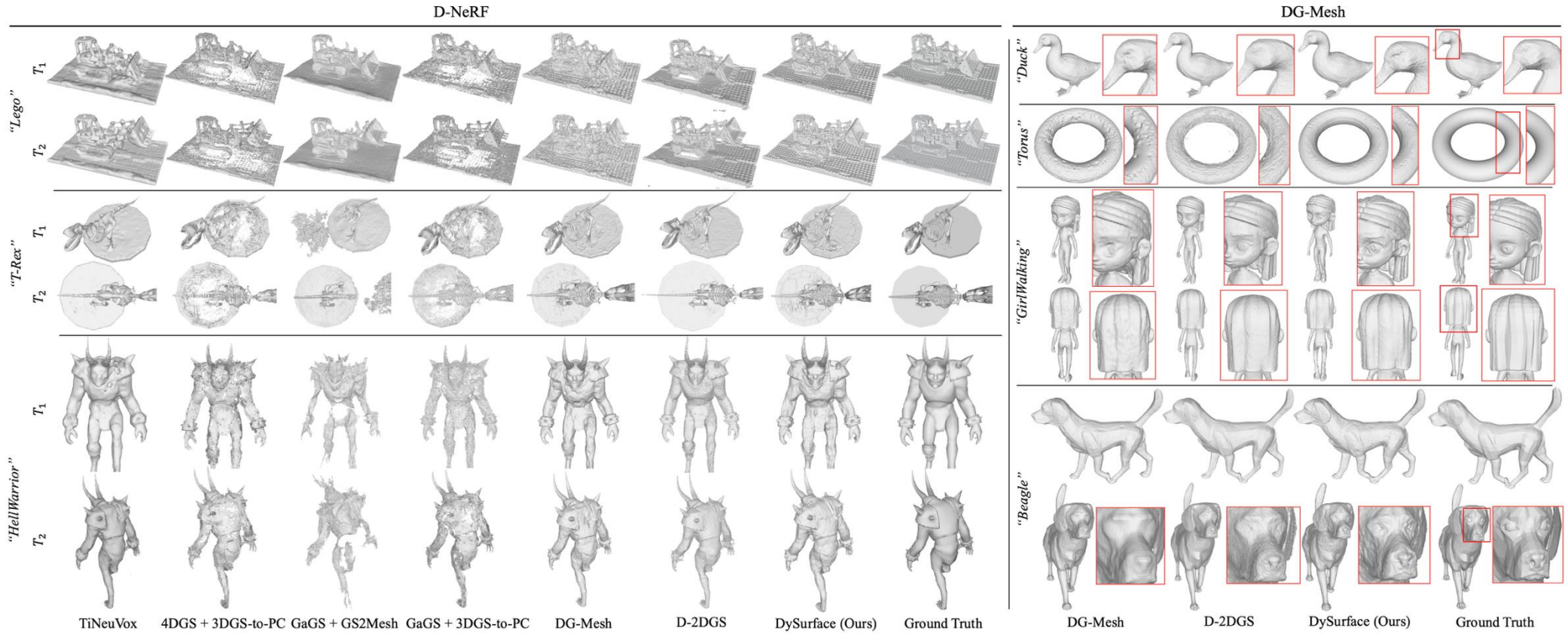
Methodology

- **Stage 3 (Dynamic Mesh Refinement Branch)**
  - Forward Mapping
  - Export canonical mesh by SDF → Mesh extraction
  - Refine pretrained sparse voxel decoder from Stage 1



Experiments

- Dataset: D-NeRF, DGMesh



Experiments

Scene	Methods	vIoU (↑)	CD (↓)	PSNR (↑)	SSIM (↑)	LPIPS (↓)
"Lego"	TiNeuVox [10]	0.1080	0.0174	25.17	0.9217	0.0689
	NeuS2 [42]	0.2578	0.0552	22.88	0.8945	0.0716
	4DGS [45]	0.2154	0.0180	25.40	0.9434	0.0377
	GaGS [29]	0.2309	0.0155	25.44	0.9474	0.0329
	DG-Mesh [26]	0.2655	0.0236	21.29	0.8382	0.1590
	D-2DGS [53]	0.2138	0.0135	23.29	0.8872	0.1121
	Ours	0.2988	0.0133	25.40	0.9439	0.0245
"T-Rex"	TiNeuVox	0.4232	0.0071	32.77	0.9783	0.0307
	NeuS2	-	-	-	-	-
	4DGS	0.2702	0.0710	33.39	0.9869	0.0130
	GaGS	0.2530	0.0069	39.02	0.9952	0.0052
	DG-Mesh	0.5736	0.0044	28.95	0.9590	0.0651
	D-2DGS	0.4997	0.0054	28.68	0.9668	0.0434
	Ours	0.5783	0.0050	36.75	0.9932	0.0069
"HellWarrior"	TiNeuVox	0.2468	0.0252	28.20	0.9661	0.0631
	NeuS2	0.2548	0.0326	18.02	0.8977	0.1064
	4DGS	0.2296	0.0221	28.12	0.9730	0.0276
	GaGS	0.2427	0.0215	32.27	0.9835	0.0164
	DG-Mesh	0.3068	0.0198	25.46	0.9590	0.0841
	D-2DGS	0.3079	0.0132	25.50	0.9583	0.0488
	Ours	0.3024	0.0124	31.14	0.9835	0.0169
Average	TiNeuVox	0.2593	0.0165	28.71	0.9382	0.0673
	NeuS2	-	-	-	-	-
	4DGS	0.2384	0.0370	28.97	0.9677	0.0261
	GaGS	0.2422	0.0146	32.24	0.9753	0.0181
	DG-Mesh	0.3814	0.0137	25.23	0.9186	0.1027
	D-2DGS	0.3426	0.0111	25.82	0.9374	0.0681
	Ours	0.3932	0.0102	31.09	0.9735	0.0161

1) D-NeRF Dataset

Methods	DG-Mesh [26]	Ours
PSNR(↑)	27.23	**27.91**
SSIM (↑)	0.9126	**0.9201**
LPIPS (↓)	0.0927	**0.0815**

2) DG-Mesh Dataset

Method	EPE3D ↓	Flow Angular ↓	TNAE ↓	Trajectory Position Error ↓
DGMesh	0.007823	20.42	15.08	0.00637
Ours	**0.007237**	**20.13**	**11.30**	**0.00508**

3) Temporal & Trajectory Flow Metrics

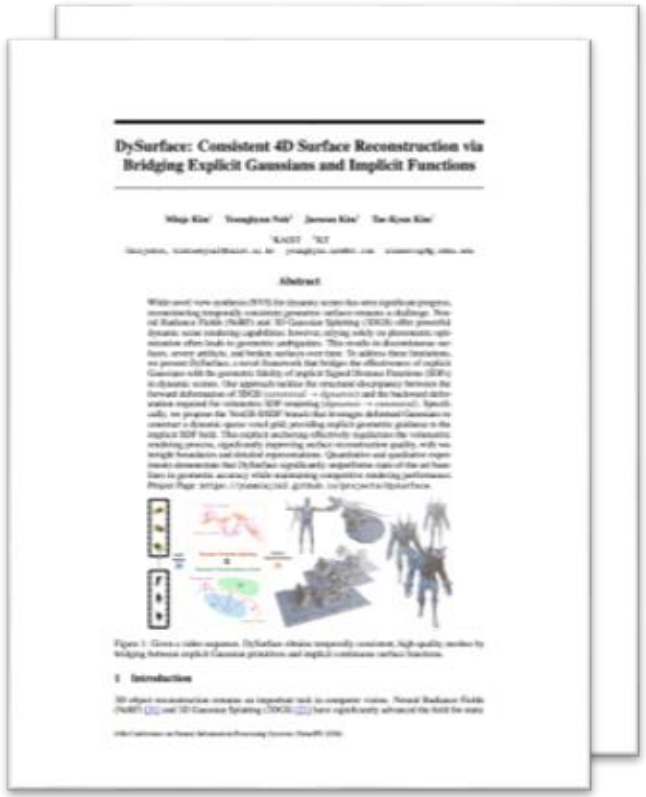
	vIoU (↑)	CD (↓)	PSNR (↑)	SSIM (↑)	LPIPS (↓)
w/o $\mathcal{L}_{SDF-GS}$	0.3388	0.0248	24.15	0.9308	0.0420
w/o $\mathcal{L}_{Cycle}$	0.3519	0.0197	27.50	0.9558	0.0298
w/o VoxGS-DSDF	0.3726	0.0120	27.22	0.9602	0.0297
Full (Ours)	**0.3932**	**0.0102**	**31.09**	**0.9735**	**0.0161**

4) Ablation Study

Conclusion

- We present **DySurface,** a novel **hybrid framework** designed to achieve high-fidelity and temporally consistent surface reconstruction in dynamic scenes.
- By bridging the structural gap between the **explicit 3D Gaussian Splatting** and the geometric fidelity of **implicit Signed Distance Functions (SDF)**
- It achieves significant performance in both geometric accuracy and photometric quality

Thank You!


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Papers

Project Page

GitHub

Github
Code