

PhysConvex: Physics-Informed Dynamic Convex Fields for Reconstruction and Simulation

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Challenges

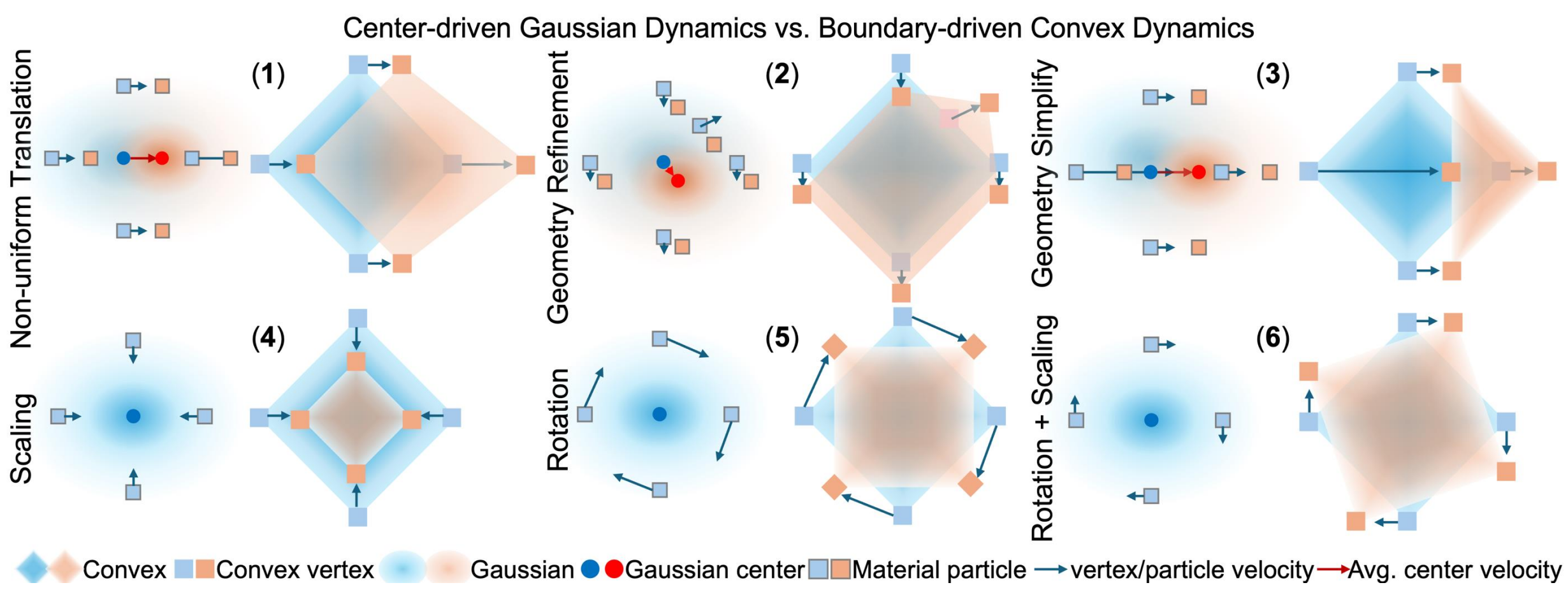
Video-based deformable reconstruction requires a 4D representation that **preserves geometry, captures physics, and generalizes to unseen conditions**. Existing dynamic NeRF and Gaussian methods render well, yet their voxel or ellipsoidal primitives are primarily designed for appearance rendering and typically driven by centers or predefined particle bindings, limiting **physically meaningful non-uniform deformation and sharp boundary evolution**.

Approach

Key insight: **the rendering primitive should also be the material support for physical deformation and simulation**.

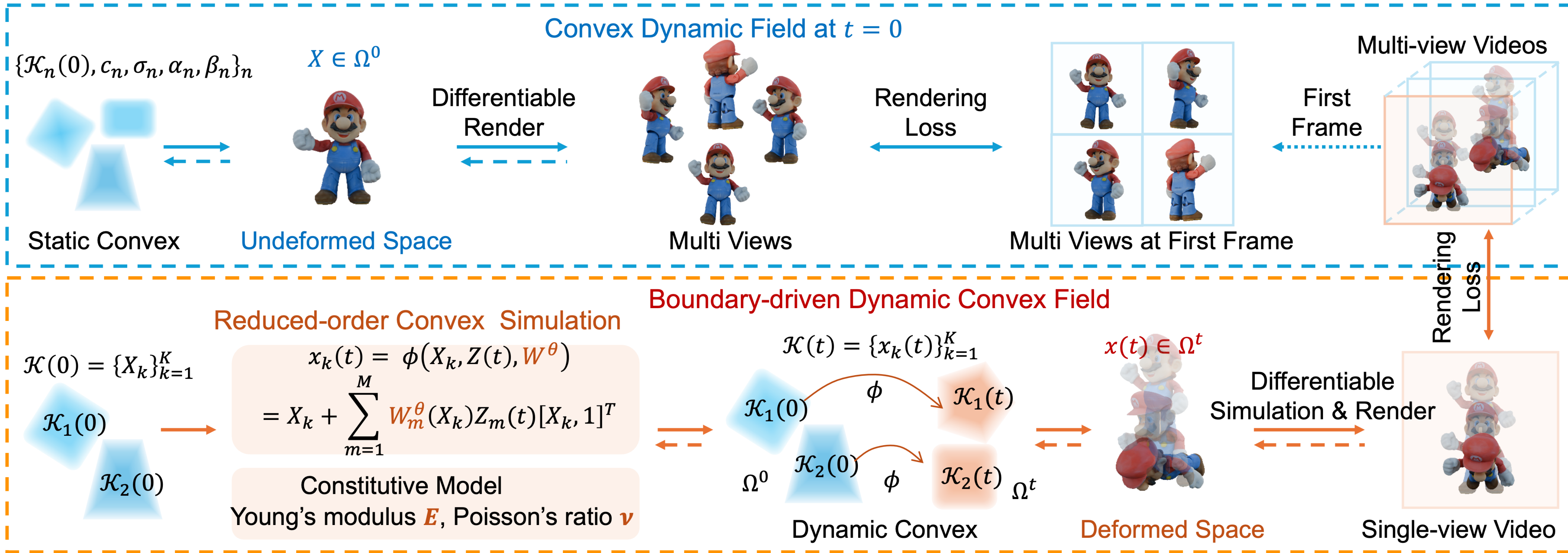
As such, we propose **PhysConvex**, a dynamic 4D representation that preserves appearance, geometry, and physical behavior. Specifically, we introduce:

- Boundary-driven dynamic convex representation** that gives each vertex spatially adaptive deformation capacity, rather than forcing primitives to move as a center-driven kernel.
- Mesh-free reduced-order convex simulation** where dynamic convexes are advected under continuum mechanics via a continuous implicit neural skinning field that encodes physics-informed, shape- & material-aware deformation modes.



Pipeline

Our dynamic 4D convex is simultaneously a rendering element, a deformation carrier, and a physical support. (1) **For rendering**, the deformed boundary induces a smooth convex occupancy that can be splatted differentiably. (2) **For physical deformation & dynamics**, the same material-space support allows each primitive to translate, rotate, shear, stretch, and change its active supporting faces over time, and defines where mass, elastic response, forces, and contacts are evaluated.



PhysConvex introduces boundary-driven dynamic convex fields integrated with mesh-free reduced-order convex simulation for dynamic reconstruction, system identification, physical generalization. It recovers appearance, geometry, and physics from videos, improving dynamic and physical reconstruction, and training efficiency. In **stage 1**, an undeformed convex field is reconstructed over the first multi-view frame. In **stage 2**, the reduced-order convex simulation advects our boundary-driven dynamic convex field under continuum mechanics, and physical properties can be optimized through joint differential simulation and rendering using video supervision.

Quantitative results

Dynamic reconstruction over 12 GSO sequences												
		backpack	bell	blocks	bus	cream	elephant	grandpa	leather	lion	mario	sofa
FoVDP ↑	PAC-NeRF	6.043	7.473	7.001	6.540	5.991	6.791	6.626	6.485	7.006	6.876	6.543
	Spring-Gaus	5.455	6.862	6.890	6.377	5.899	6.524	6.998	5.988	6.902	6.153	6.300
	Vid2Sim w/o LGM	7.778	6.884	8.792	7.622	9.117	7.468	6.246	8.949	7.681	6.325	8.034
	GIC	6.130	6.230	6.062	6.552	5.889	6.907	6.855	6.737	6.331	6.985	7.069
	Ours	8.403	7.843	8.783	8.005	8.708	8.178	7.752	9.153	7.617	7.792	7.925
PSNR ↑	PAC-NeRF	19.37	25.00	23.36	20.72	23.24	22.27	21.63	20.85	22.66	21.01	22.49
	Spring-Gaus	17.42	20.49	22.78	20.06	23.58	21.30	21.64	18.29	21.95	20.23	21.89
	Vid2Sim w/o LGM	26.87	26.59	32.57	26.53	34.82	26.99	24.45	31.21	27.62	24.83	30.01
	GIC	18.94	19.55	18.78	20.84	23.81	21.86	20.50	21.00	19.33	21.28	24.16
	Ours	28.09	29.67	32.65	27.97	34.62	29.17	27.67	33.50	27.58	27.46	30.15
SSIM ↑	PAC-NeRF	0.887	0.956	0.940	0.908	0.893	0.922	0.939	0.932	0.936	0.921	0.926
	Spring-Gaus	0.867	0.941	0.941	0.903	0.912	0.919	0.948	0.917	0.937	0.920	0.921
	Vid2Sim w/o LGM	0.931	0.959	0.973	0.937	0.955	0.942	0.944	0.973	0.954	0.936	0.952
	GIC	0.903	0.945	0.930	0.925	0.922	0.936	0.948	0.949	0.934	0.938	0.942
	Ours	0.950	0.972	0.975	0.948	0.960	0.957	0.964	0.980	0.958	0.954	0.955

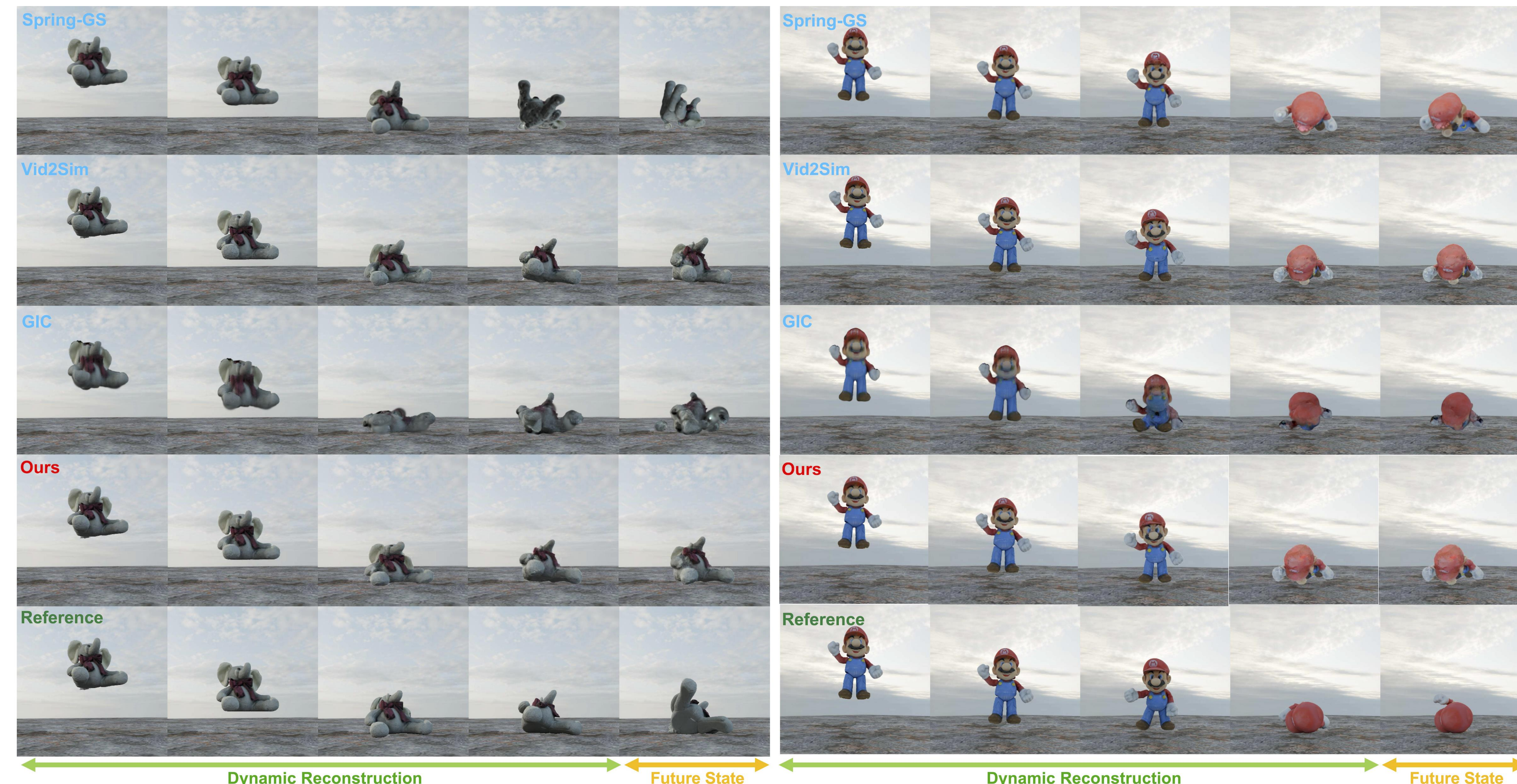
Physical System Identification												
	methods	backpack	bell	blocks	bus	cream	elephant	grandpa	leather	lion	mario	sofa
log(E)	PAC-NeRF	3.28	1.08	4.02	3.30	3.22	3.05	2.99	1.20	2.34	3.37	0.20
	Spring-Gaus	0.69	0.15	0.54	0.26	0.95	0.18	1.07	0.73	0.48	0.50	0.18
	Vid2Sim	1.16	2.87	2.12	1.93	2.13	1.53	0.42	3.45	2.85	1.82	0.65
	GIC	0.32	0.34	0.10	0.28	0.34	0.60	0.97	0.18	0.23	0.54	0.01
	Ours	0.21	0.23	0.33	0.16	0.12	0.06	0.36	0.26	0.14	0.33	0.30
nu	PAC-NeRF	0.10	0.10	0.07	0.06	0.11	0.05	0.02	0.06	0.05	0.06	0.08
	Spring-Gaus	0.11	0.24	0.29	0.18	0.08	0.24	0.26	0.02	0.14	0.22	0.01
	Vid2Sim	0.06	0.09	0.02	0.02	0.05	0.08	0.03	0.02	0.03	0.12	0.02
	GIC	0.06	0.09	0.02	0.02	0.05	0.08	0.03	0.02	0.03	0.12	0.02
	Ours	0.06	0.09	0.02	0.02	0.05	0.08	0.03	0.02	0.03	0.12	0.02

Training & Primitive Efficiency					
	PAC-NeRF	GIC	Spring-GS	Vid2Sim	Ours
Avg. Training Time (min)	51	69	32	8	6
Primitive Num.	-	-	22882	31363	23681

Ablation of Our Dynamic Convex Field with Boundary-driven Kinematics via Model Order Reduction Simulation (MOR)					
Model	3D Primitive	Kinematics	Simulation	Dynamic Reconstruction	Physics Identification
	Gaussian	Convex	Center	Boundary	MOR
A	✓	✓	✓	✓	28.65
B	✓	✓	✓	✓	29.16
C	✓	✓	✓	✓	30.00

Dynamic reconstruction + future prediction

PhysConvex preserves object identity, surface detail, and deformation dynamics while extrapolating beyond the observed sequence.



Physical generalization

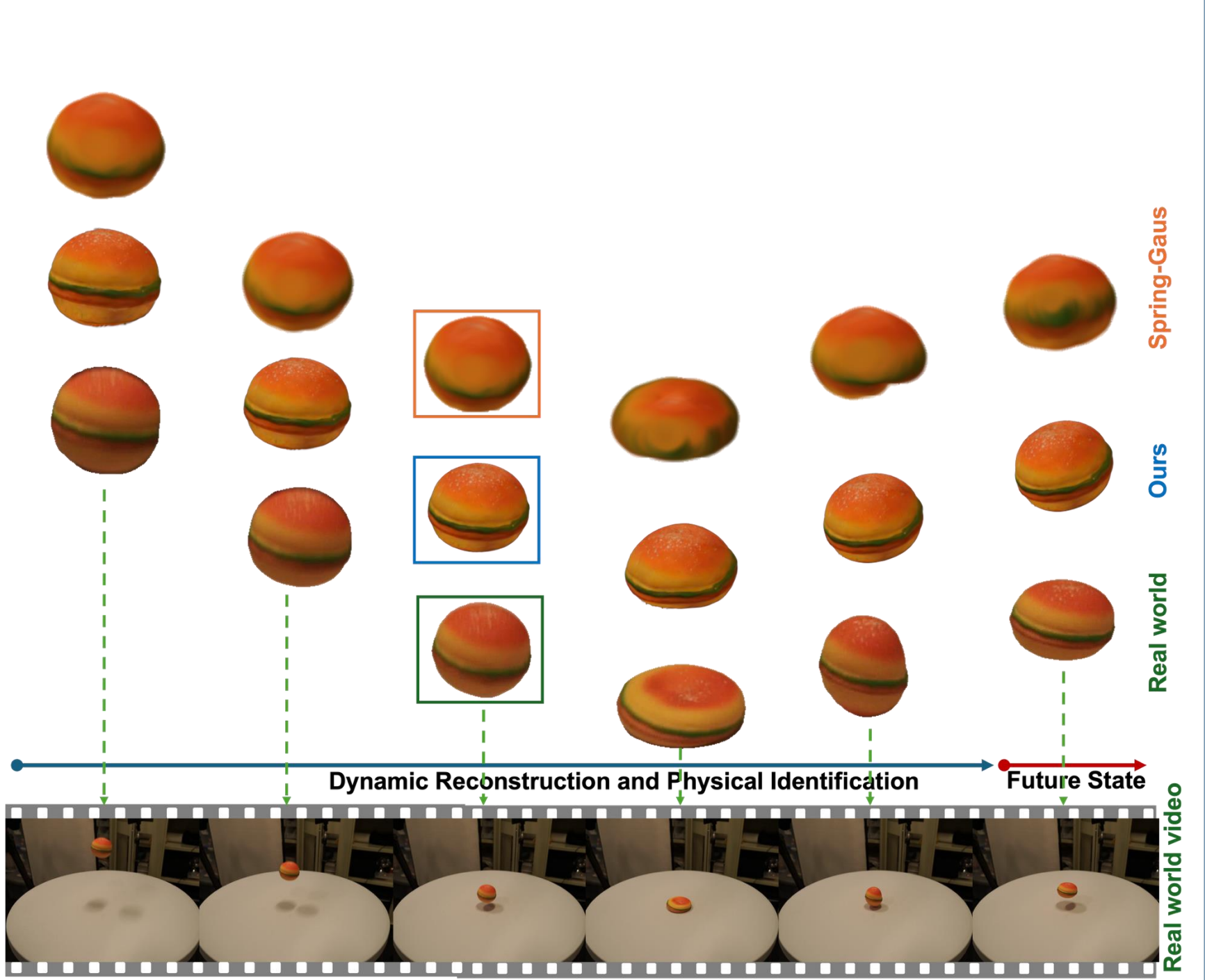
Generalization to novel materials.



Generalization to novel force and complex boundary conditions.



Real-world dynamics



Compared with blurred real video observations and Spring-Gaus reconstructions, our method recovers geometry and appearance with clearer deformable details. Moreover, the reconstructed dynamics closely match the real video, exhibiting physically consistent motion and deformation.

ONE REPRESENTATION
RECONSTRUCT appearance + geometry
IDENTIFY Young's modulus + Poisson ratio
SIMULATE held-out future dynamics
GENERALIZE novel material, force, and boundary

PAPER

