GaussTac: Unified Neural Rendering and Tactile Simulation for Dexterous Hands

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Abstract

Simulating dexterous hands with both photorealism and tactile feedback remains an open challenge. Recent neural rendering approaches enable realistic visual simulation but lack tactile modeling, while existing tactile methods rely on traditional graphics pipelines with limited visual fidelity. We present GaussTac, the first framework unifying photorealistic neural rendering and deformable tactile simulation for dexterous robotic hands. GaussTac leverages 3D Gaussian Splatting (3DGS) for RGB rendering and a Partly Controlled Material Point Method (MPM) paradigm for fine-grained deformation. Rigid articulated parts are controlled via MuJoCo, while deformable fingertip regions are simulated with MPM, allowing simultaneous rigid control and non-rigid dynamics. Tactile signals are extracted from MPM particle states. Experiments show that GaussTac achieves state-of-the-art visual and tactile fidelity, and we release code, models, and data for future research.

1. Introduction

Simulation is indispensable in robotics, enabling expert data generation for imitation learning [8, 18], robust policy evaluation [29], and safe exploration [13]. Since robots often rely on multimodal sensing—particularly vision and touch—to perceive their environment [4, 26, 28], joint simulation of these modalities has become a powerful tool for developing and validating robotic algorithms [1, 25, 30].

For vision, neural-field methods such as 3D Gaussian Splatting (3DGS) achieve photorealistic, real-time rendering by representing scenes as continuous Gaussian kernels with spherical harmonics [11, 14, 20]. Unlike mesh-based methods, 3DGS updates kernels directly, avoiding costly remeshing. On the tactile side, physics-based techniques capture contact and deformation across scales: Position-Based Dynamics (PBD) propagates geometric constraints, the Finite Element Method (FEM) solves stress–strain equations, and the Material Point Method (MPM) combines particles and grids to handle large deformations, nonlinear elasticity, plasticity, and friction [3, 10, 12, 16, 21, 22]. MPM's hybrid formulation and constitutive models make it especially effective for simulating elastomers, soft bodies, and granular media, and recent work has shown its potential in coupling appearance and deformation [27].

Yet, existing frameworks such as Isaac Gym [15], PyBullet [7], and MuJoCo [24] focus primarily on fast rigid-body dynamics for closed-loop control. They rarely integrate high-fidelity neural rendering or particle-based tactile simulation, forcing researchers to combine separate engines and sacrifice synchronization, performance, or ease of use. This gap hinders seamless sim-to-real transfer for tasks requiring tightly coupled multimodal feedback.

We present **GaussTac**, a unified simulation–control–rendering pipeline that combines a 3DGS-based renderer for photorealistic visuals, an MPM engine for soft–rigid interaction and tactile feedback, and a MuJoCo controller for lightweight real-time control.

Our contributions are:

- **Integrated Visual–Tactile Simulator:** A system that merges high-fidelity rendering with physics-based tactile simulation.
- **Unified Pipeline:** A single environment coupling 3DGS rendering, MPM physics, and MuJoCo control.
- **Benchmarks:** Experiments on grasping gestures and force profiles demonstrating GaussTac's real-time performance and accuracy.

2. Related Works

Radiance field rendering. NeRF-based methods have advanced 3D scene generation [6, 17, 19], with 3D Gaussian Splatting (3DGS) achieving real-time, high-quality rendering [5, 11]. Extensions (e.g., SC-GS [9], HDR-GS [2], SplatSim [20]) improve dynamics and integration, but focus mainly on visuals without physics-based tactile modeling or closed-loop control.

Material Point Method simulation. MPM effectively handles large deformations and contacts [10, 12], and has

Table 1. Comparison of simulators for robotic tasks

Simulator	Object model		Robot body	Interactivity	Method	Renderer	Tactile
	Rigid	Soft					
Splatsim	✓	✗	✓	✓	Rigid-body Dynamics	3DGS	✗
Touch-GS	✓	✗	✗	✗	GPIS+MonoDepth	3DGS	✓
Taxim	✓	✓	✗	✗	Example-based Lookup	–	✓
VR-Doh	✓	✓	✗	✓	MPM	3DGS	✗
DiffTactile	✓	✓	✗	✓	MPM,PBD&FEM	-	✓
TACTO	✓	✗	✗	✓	Phong model	PyRender&OpenGL	✓
Tacchi2.0	✓	✓	✓	✗	MPM&FEM	-	✓
TacSL	✓	✗	✓	✓	Soft-contact Penalty Model	Internal	✓
FOTS	✓	✗	✓	✓	MLP	Internal	✓
Ours	✓	✓	✓	✓	MPM	3DGS	✓

been applied to haptics (DIFFTACTILE [22]) and visual simulation (PhysGaussian [27]). However, most works remain open-loop or single-object, lacking real-time closed-loop control.

Tactile simulation. FEM- and MPM-based simulators [3, 21, 23] capture deformation and contact, yet often lack efficient rendering or integrated control.

As summarized in Table 1, prior simulators trade off between rendering, tactile realism, and robot interactivity. GaussTac is the first to unify all three—photorealistic 3DGS rendering, MPM-based tactile simulation, and MuJoCo-driven real-time control.

3. Approach

GaussTac is a simulation pipeline that combines photorealistic 3DGS-based rendering with physically plausible tactile sensing. We reconstruct the hand geometry via 3DGS, simulate deformable regions with MPM while controlling rigid links through MuJoCo, and extract tactile feedback for downstream tasks. An overview is shown in Fig. 1, with details provided in the appendix.

3.1. 3DGS Dexterous Hand Reconstruction

We reconstruct the dexterous hand by combining high-fidelity 3D scans with its URDF mesh. The scanned point cloud is aligned to the URDF model via ICP and segmented by parts. Gaussian primitives are then assigned to links, with rigid structures, deformable regions (e.g., tendons and finger pads), and tactile sensor areas explicitly distinguished. This integration preserves accurate sensor placement and enables both photorealistic rendering and physically plausible dynamics.

3.2. Partly Controlled MPM Simulation

Following [27], we treat all Gaussians as MPM particles, but additionally integrate MuJoCo control signals to achieve kinematic actuation. This design decouples position-based rigid hand control from deformable hand–object interactions, significantly reducing simulation cost.

Hybrid update. In standard MPM, particles are transferred to the grid (P2G), grid velocities are updated under forces, and particle states are interpolated back (G2P). For rigid regions, however, we overwrite the G2P step with MuJoCo-provided transforms. Specifically, for particle p belonging to rigid link ℓ with transform $(\mathbf{R}_\ell^n, \mathbf{p}_\ell^n)$, its velocity is updated by finite differences:

$$\mathbf{v}_p^{n+1} = \frac{\mathbf{p}_\ell^n - \mathbf{p}_\ell^{n-1}}{\Delta t} + \frac{(\mathbf{R}_\ell^n - \mathbf{R}_\ell^{n-1})\mathbf{x}_p^0}{\Delta t},$$

where $\mathbf{x}_p^0$ is the rest-space coordinate. This ensures precise rigid motion control, while soft fingertip and tendon particles evolve through standard MPM. Importantly, rigid particles still contribute to P2G momentum transfer, keeping them physically coupled with surrounding soft regions and objects.

Gaussian updates. To maintain consistency, we update each rigid Gaussian's deformation gradient $\mathbf{F}_p$ and covariance Σ_p using the angular velocity $\boldsymbol{\omega}$:

$$\mathbf{F}_p^{n+1} = (\mathbf{I} + \Delta t[\boldsymbol{\omega}]_\times)\mathbf{F}_p^n$$

$$\Sigma_p^{n+1} = \Sigma_p^n + \Delta t\big([\boldsymbol{\omega}]_\times \Sigma_p^n + \Sigma_p^n [\boldsymbol{\omega}]_\times^T\big).$$

This partly controlled scheme enables simultaneous rigid actuation and soft deformation, crucial for dexterous tactile simulation.

3.3. Tactile Extraction and Rendering

We extract fingertip-level tactile signals by expressing particle positions in each fingertip's local frame and measuring displacements relative to rest shape. Interpolating these deformations over a grid yields dense tactile maps aligned with real sensor layouts, enabling sim-to-real transfer.

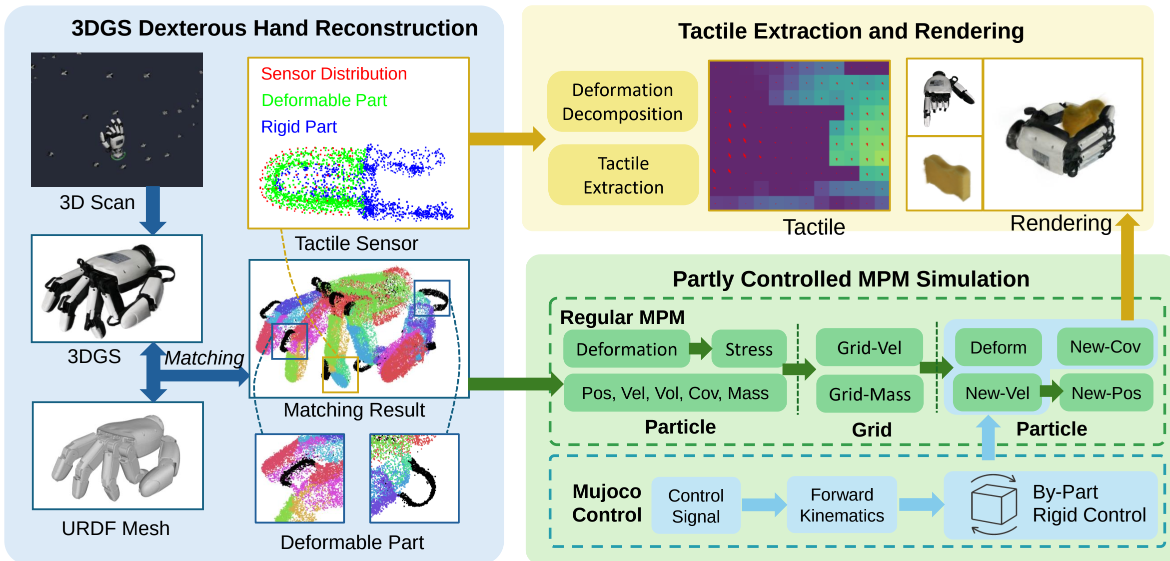

Figure 1. **Method Overview.** The GaussTac framework integrates 3DGS for photorealistic hand reconstruction, MPM for soft–rigid interaction simulation, and MuJoCo for real-time control. Starting from 3D scanning and mesh alignment, it builds a deformable–rigid hand with tactile regions, simulates interactions via MPM, controls joints with MuJoCo, and outputs synchronized tactile maps and RGB renderings, enabling high-fidelity real-time visual–tactile simulation.

For rendering, deformable Gaussian ellipsoids are updated by the MPM deformation gradient and rotated via polar decomposition to avoid artifacts. Their spherical-harmonic coefficients are accordingly adjusted, and the ellipsoids are composited in a real-time 3DGS pipeline to produce photorealistic views consistent with simulated deformations.

4. Experiments

We evaluate GaussTac through three tasks: (i) static gesture control and visual reconstruction, (ii) dynamic interaction with deformable objects, and (iii) tactile simulation under different contact modes.

Static Gesture Control and Visual Reconstruction. Setup. Six dexterous hand gestures (Fig. 2) were reproduced in simulation, with similarity to ground-truth images measured using DINOv2, MS-SSIM, and LPIPS-VGG across multiple views. GaussTac, PyBullet, and MuJoCo were all provided with equivalent hand models and joint poses. **Results.** GaussTac faithfully reproduced hand details, including cables and tags, which outperformed all baselines across metrics.

Dynamic Interaction with Deformable Objects. Setup. A dexterous hand grasped and squeezed a sponge block, with physical parameters (e.g., Young's modulus, Poisson's ratio) matched to real-world settings. **Results.** As shown in Fig. 3, GaussTac accurately captured block deformations during interaction.

Tactile Simulation. Setup. We tested fingertip pressing and sliding against a rigid cube, comparing simulated tactile maps with real sensor data. **Results.** GaussTac predicted the main contact regions and force magnitudes well (Fig. 4), with errors mainly at edges due to parameter mismatches between simulation and reality.

5. Conclusions

In this paper, we have presented **GaussTac**, the first unified pipeline for real-time, high-fidelity simulation of dexterous hand manipulation that tightly couples physics, control and rendering. GaussTac integrates (i) an enhanced MPM solver for soft–rigid contact, (ii) MuJoCo-driven kinematic control of non-sensor links, and (iii) real-time 3DGS for photorealistic rendering. Through static gesture control and visual reconstruction, dynamic multi-object interaction simulation in grasping tasks, and tactile simulation, we demonstrated that GaussTac outperforms state-of-the-art vision and tactile frameworks. Looking forward, we plan to further accelerate and generalize our approach by integrating Position-Based Dynamics into the MPM core to reduce computational overhead for soft-body updates.

Figure 2. Comparison of visual simulation results against ground-truth and across different simulation methods and hand gestures.

Figure 3. We perform dexterous grasping of a soft object (a sponge) in both the real world and in simulation. The physical parameters are empirically set and may not align with real-world conditions. The discrepancy between simulation and reality arises from both initial state biases and limitations in the physical model.

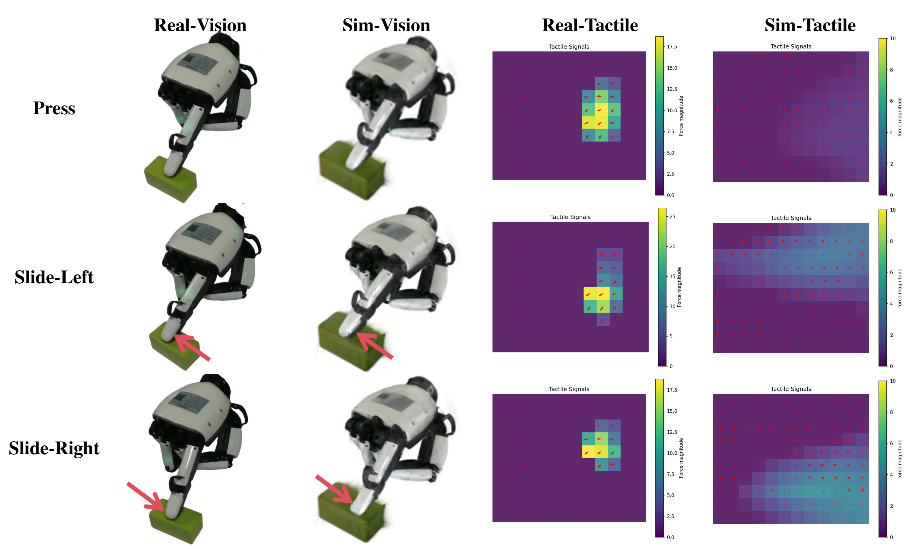

Figure 4. Comparison of real and simulated vision/tactile signals across different tactile actions.

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