# Gaussian SPH Fluid: Physics-integrated 3D Gaussians for SPH Fluid Dynamics

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## Introduction

#### Why fluid + 3DGS a challenge?

Recent work integrates physics with 3D Gaussian Splatting (3DGS). PhysGaussian treats Gaussians as a continuum and advances them with an MPM solver: centers and covariances evolve from the deformation gradient F, and SH lobes rotate consistently, enabling a WS<sup>2</sup> ("what you see is what you simulate") pipeline. However, liquids are governed by incompressibility. MPM-based approaches need extra handling to enforce density and velocity constraints, and the surface-biased distribution of 3DGS becomes problematic beyond "hollow interiors." PhysGaussian itself suggests internal filling.

#### Our idea

We simulate Gaussians directly in an SPH solver. Using DFSPH (divergence-free + constant-density constraints), we obtain fluid-specialized behavior. We also update each Gaussian covariance  $\Sigma$  from the SPH velocity gradient  $\nabla \mathbf{v}$  via an implicit integration rule and render the updated Gaussians directly.

## Background

#### From Navier–Stokes to DFSPH

#### Governing equations

$$\rho \frac{D\mathbf{v}}{Dt} = -\nabla p + \mu \nabla^2 \mathbf{v} + \rho \mathbf{g}, \qquad \nabla \cdot \mathbf{v} = 0$$

These encode momentum conservation such as pressure, viscous, and gravity forces and mass conservation which represents incompressibility.

#### **SPH discretization**

- The continuum is represented by particles carrying mass, density, velocity.
- Local quantities are estimated by smoothing kernels,  $W(\|\mathbf{r}_i \mathbf{r}_j\|, h)$ .
- Discrete forces are pairwise-symmetric, preserving mass and momentum, and are stable for free surfaces.

#### Gaussian representation

Instead of an isotropic kernel, each particle is a 3D Gaussian field:

$$g_i(\mathbf{x}) = \alpha_i \exp\left[-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu}_i)^{\top} \boldsymbol{\Sigma}_i^{-1}(\mathbf{x} - \boldsymbol{\mu}_i)\right],$$

with center  $\mu_i$  covariance  $\Sigma_i$  (anisotropic shape), and density weight  $\alpha_i$ 

This keeps the same physical operators while improving smoothness and anisotropy for rendering.

#### Why DFSPH for fluid?

DFSPH enforces incompressibility at two levels in each time step:

- constant-density correction  $ho pprox 
  ho_0$ ,
- divergence-free velocity  $\frac{D\rho}{Dt} \approx 0$ .

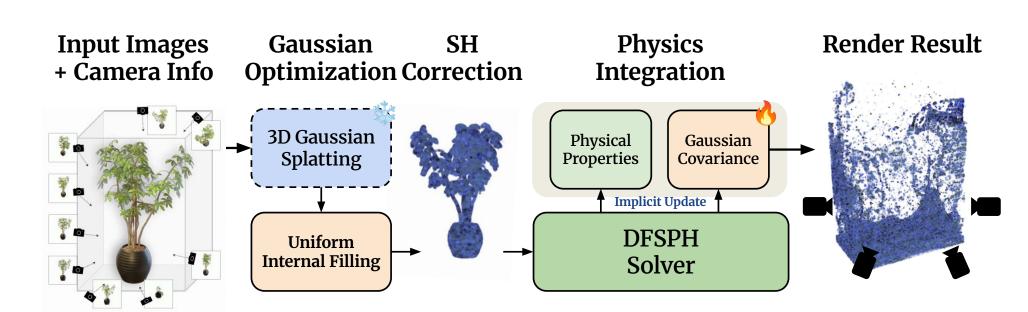
It converges quickly and remains stable with practical time steps—ideal for fluid-like behavior.

#### Related Work

- **PhysGaussian (MPM)**: evolve Gaussians by F; rotate SH; optional internal filling to avoid hollow interiors. Strong for solids/granulars, less direct for liquids.
- Gaussian Splashing (PBD/PBF): adds SPH density constraints but decouples simulation particles from render Gaussians and later interpolates; the initial Gaussians themselves are not simulated.

**Gap**: a unified pipeline that simulates the original Gaussians while strictly enforcing incompressibility.

## Method



**Figure 1. Method Overview** 3DGS optimization  $\rightarrow$  uniform internal filling (+isotropic Σ, surface subsampling)  $\rightarrow$  SH color correction  $\rightarrow$  DFSPH (density & divergence constraints) with implicit Σ update from SPH  $\nabla v \rightarrow$  Gaussian rendering.

#### **Uniform Internal Filling**

- Build a **smoothed opacity field** from surface Gaussians to counter hollow interiors.
- Evaluate a **uniform 3D grid** in the scene AABB (spacing 4r, r=SPH particle radius).
- At grid point x, select the k-nearest surface Gaussians:

$$\hat{d}(\mathbf{x}) = rac{\sum_{i \in N_k(\mathbf{x})} \expig(-\|\mathbf{x} - \mathbf{p}_i\|^2/(2\sigma^2)ig)\,\sigma_i}{\sum_{i \in N_k(\mathbf{x})} \expig(-\|\mathbf{x} - \mathbf{p}_i\|^2/(2\sigma^2)ig)}$$

- Compute a smoothed opacity from them, and seed a particle if it exceeds a threshold  $\hat{d}(\mathbf{x}) > \sigma_{\mathrm{th}}$ .
- Initialize Gaussian attributes: copy SH color/opacity from the nearest surface Gaussian o set covariance  $\Sigma_0 = {
  m diag}(r_{
  m iso}^2)$

#### DFSPH Coupling

- Apply DFSPH's two constraints each step:
- $\circ$  Constant density: correct predicted density to  $ho_0$ .
- o Divergence-free: drive  $D\rho/Dt \rightarrow 0$  to remove velocity divergence.
- Warm-start iterations; feed updated positions/velocities straight to rendering.

#### Covariance update from SPH $abla \mathbf{v}$

• SPH discretization of  $\nabla \mathbf{v}$ :

$$abla \mathbf{v}_i = \sum_j rac{m_j}{
ho_j} \left( \left. \mathbf{v}_j - \mathbf{v}_i \, 
ight) \otimes 
abla_i W(\|\mathbf{x}_i - \mathbf{x}_j\|, h)$$

Where j is the neighbor index, m is particle mass,  $\varrho$  is particle density, W is SPH kernel, and h is support radius.

• Update the covariance matrix  $\Sigma$  at the next time step by implicit Euler integration:

$$oldsymbol{\Sigma}_i^{t+\Delta t} pprox (\mathbf{I} - \Delta t \, 
abla \mathbf{v}_i)^{-1} \, oldsymbol{\Sigma}_i^t \, (\mathbf{I} - \Delta t \, 
abla \mathbf{v}_i^ op)^{-1}$$

#### Color handling

SH colors for static scenes are not ideal for water. We apply hue/gamma adjustment to obtain legible fluid appearance while keeping WS<sup>2</sup> rendering.

## Results

## Internal Filling Ablation Study

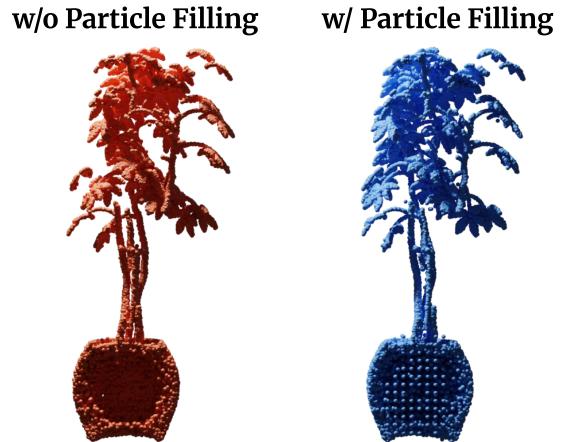


Figure 2. Internal Filling (ablation)
Left: initialization without filling shows
a hollow, surface-biased interior. Right:
with filling, uniformly seeded interior
particles stabilize the initial density for

## without internal filling. The right panel uses uniform interior

Figure 2 contrasts our

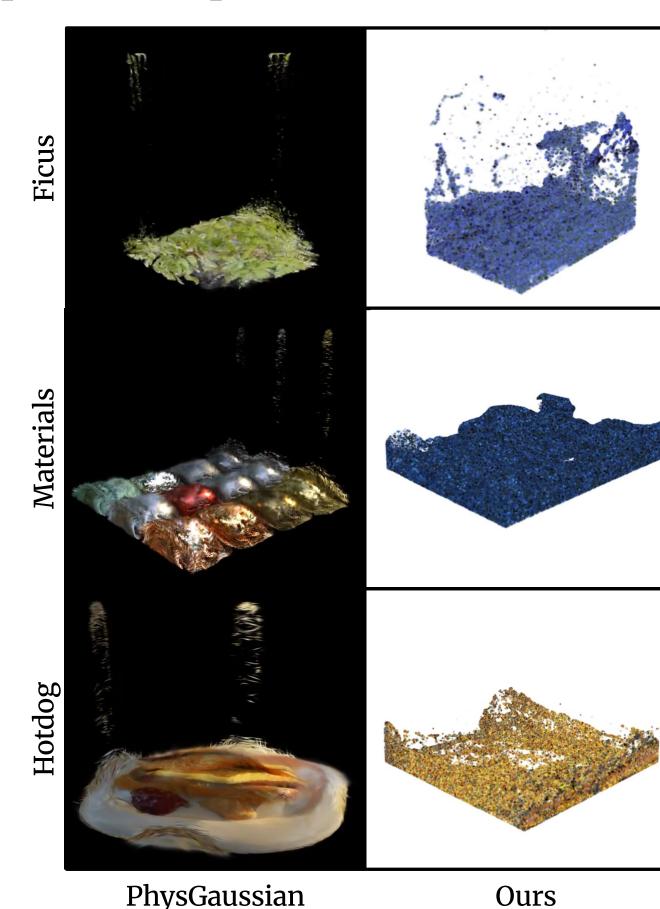
initialization with and

uniform interior seeding obtained by thresholding a Gaussian-smoothed opacity field.

Parameters: opacity

threshold 0.40, k=8 neighbors, neighbor-radius scale 3.0, and  $\sigma$  scale 1.0.

## **Comparison Experiments**



**Figure 3. Comparison** Three scenes from the dataset Synthetic NeRF: Materials, Hotdog, and Ficus.

Dataset: Synthetic-NeRF (Ficus, Materials, Hotdog).

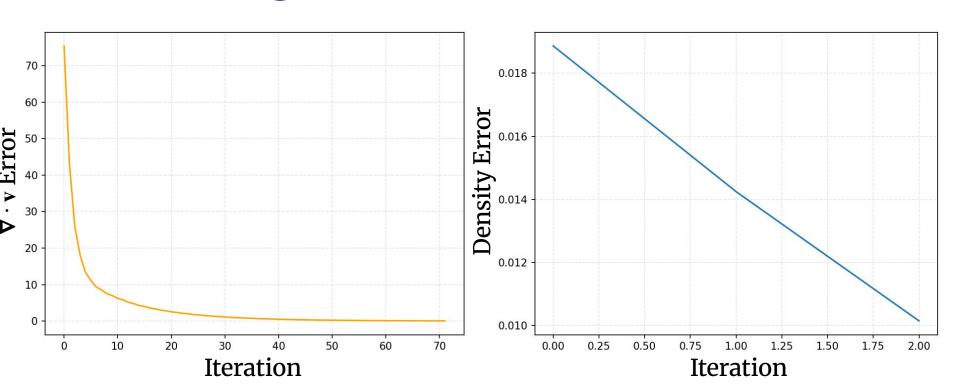
Baseline (PhysGaussian): no fluid model available; evaluated with the authors' granular "sand" material.

**Ours:**  $\Delta t = 10^{-3}$ ; particle radius  $5 \times 10^{-3}$ ; termination  $< 10^{-2}$  for both density error and velocity divergence.

Collisions: axis-aligned bounding box for both methods.

**Rendering:** SH hue/gamma correction for all scenes except Hotdog (raw SH).

#### Solver Convergence



**Figure 4. Error rate on frame 120** Velocity divergence on the left, and density error on the right. Both errors smoothly converges, reaching 0.01% of compression rate.

## Conclusion

#### Summary

We present Gaussian SPH Fluid, a unified simulation–rendering pipeline that advances 3D Gaussians with an SPH (DFSPH) solver and renders them directly. A uniform internal filling converts surface-biased 3DGS into SPH-ready volumes, and an SPH  $\nabla$ v-based implicit covariance update aligns anisotropic shapes with the local flow. The method enforces incompressibility via DFSPH, exhibiting stable evolution and clear convergence; the ablation confirms that internal filling is critical for robust initialization. Compared with MPM-based baselines, our coupling preserves liquid-like coherence and density while maintaining a single, point-based representation for simulation and rendering.

#### Limitations and Future Work

Sensitivity to surface-biased initialization can produce mild free-fall jitter in early frames, and appearance currently relies on SH hue/gamma adjustments rather than a fluid-specific optical model. Future work will address multi-phase flows, coupling with rigid/soft bodies, and improved optics/BSDF toward a fully end-to-end, VFX-ready pipeline.

### References

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