Unfolding Cloth: Neural Deformation Fields for Simulation and Monocular Tracking

Kairanda N., Habermann M., Naik S., Theobalt C., Golyanik V.

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SIC Saarland Informatics Campus

MAX PLANCK INSTITUTE FOR INFORMATICS

*Abstract: We represent clothes as **continuous neural fields** instead of discrete meshes to address core challenges in **cloth simulation** and **3D surface tracking**.*
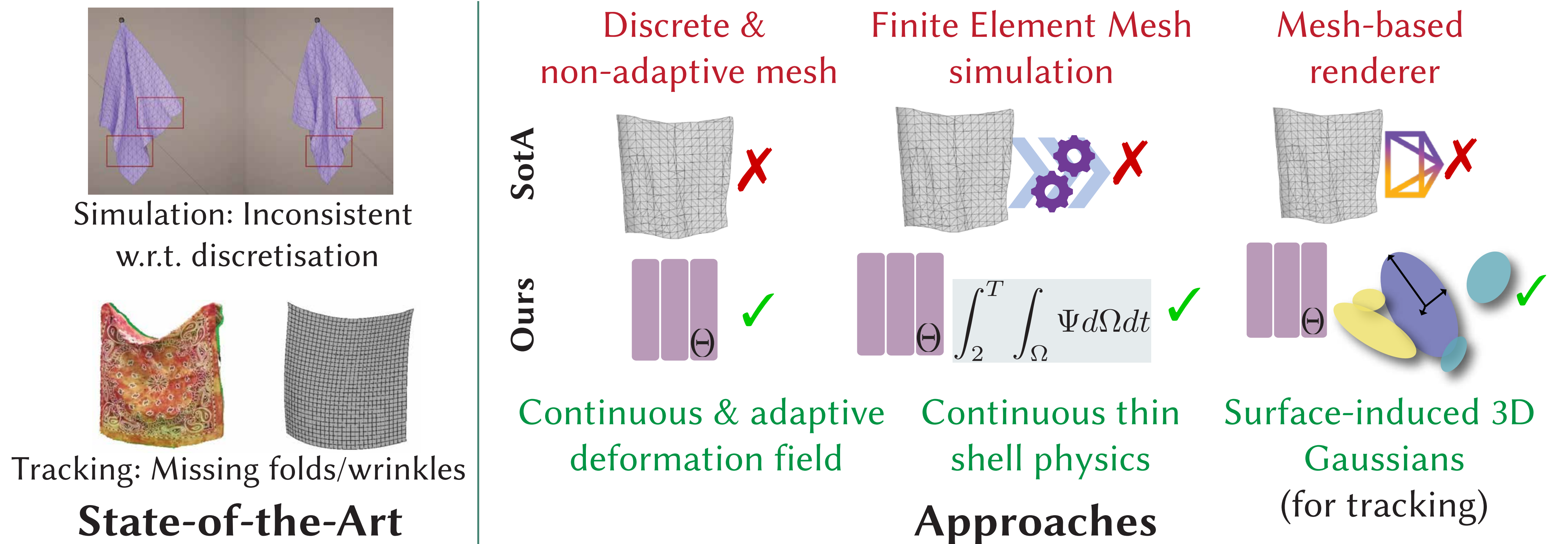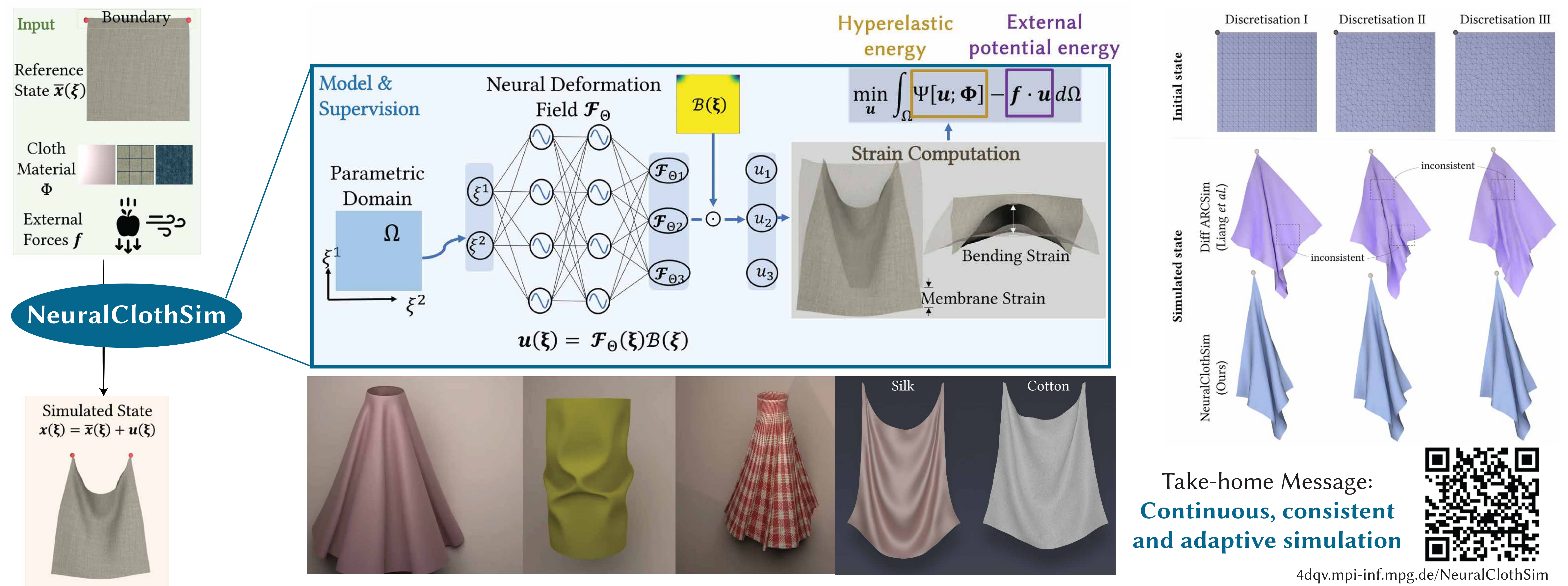
Motivation for Representing Cloths as Neural Fields

Cloth Simulation
Input: *Initial cloth state, material, forces*
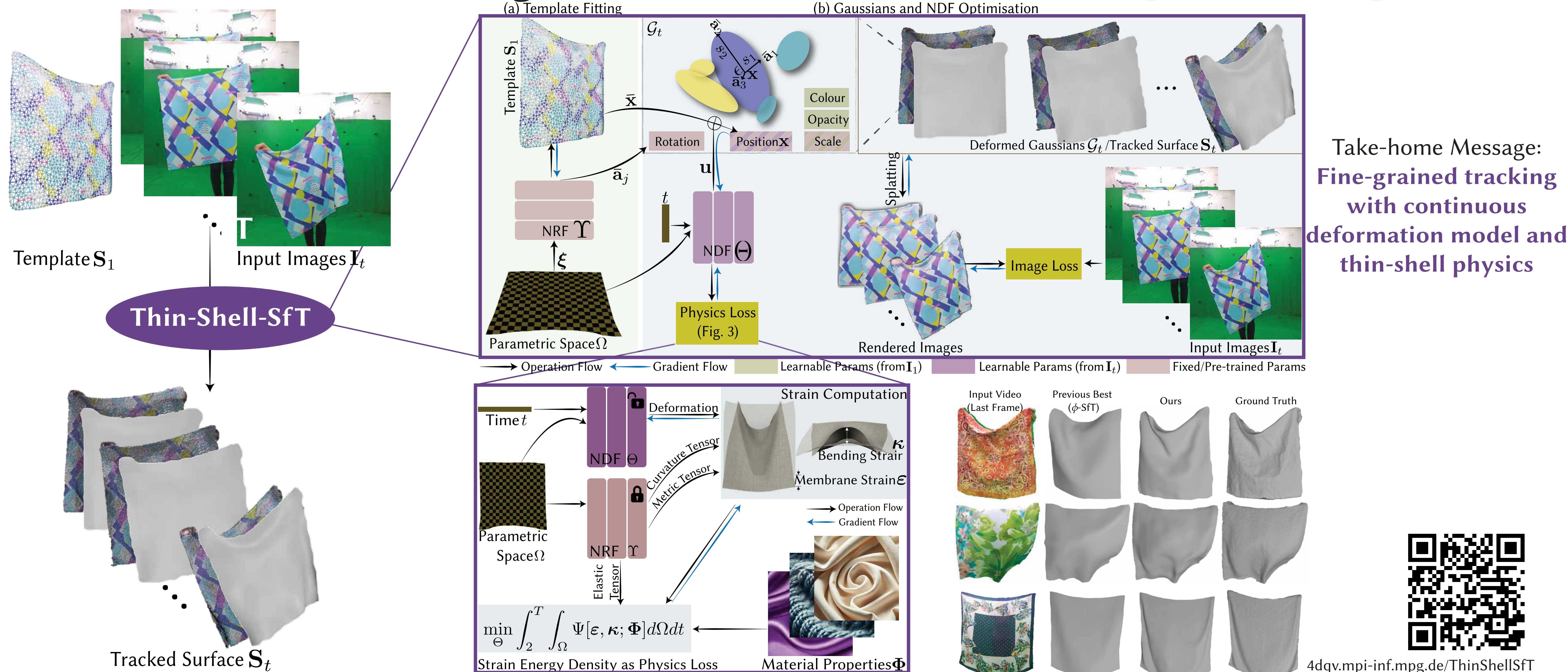**Output:** *Simulated cloth states*

3D Surface Tracking
Input: *Initial state, monocular video*
Output: *Reconstructed surface states*

Task

Simulation: Inconsistent w.r.t. discretisation

Tracking: Missing folds/wrinkles

State-of-the-Art

SotA:
- Discrete & non-adaptive mesh ✗
- Finite Element Mesh simulation ✗
- Mesh-based renderer ✗

Ours:
- Continuous & adaptive deformation field ✓ (Θ)
- Continuous thin shell physics ✓ ($\Theta \int_2^T \int_\Omega \Psi \, d\Omega \, dt$)
- Surface-induced 3D Gaussians (for tracking) ✓ (Θ)

Approaches

Cloth Simulation with Neural Deformation Fields [NeurIPS, 2024]

Input
Boundary
Reference State $\bar{x}(\xi)$
Cloth Material Φ
External Forces f

NeuralClothSim

Simulated State $x(\xi) = \bar{x}(\xi) + u(\xi)$

Model & Supervision

Neural Deformation Field $\mathcal{F}_\Theta$

Parametric Domain Ω, ξ^1, ξ^2

$\mathcal{B}(\xi)$

$\mathcal{F}_{\Theta 1}$, $\mathcal{F}_{\Theta 2}$, $\mathcal{F}_{\Theta 3}$ → u_1, u_2, u_3

$u(\xi) = \mathcal{F}_\Theta(\xi)\mathcal{B}(\xi)$

Hyperelastic energy / External potential energy

$$\min_u \int_\Omega \Psi[u; \Phi] - f \cdot u \, d\Omega$$

Strain Computation
Bending Strain
Membrane Strain

Silk / Cotton

Discretisation I / Discretisation II / Discretisation III

Initial state

Simulated state

Diff ARCSim (Liang et al.) — inconsistent

NeuralClothSim (Ours)

Take-home Message:
Continuous, consistent and adaptive simulation

4dqv.mpi-inf.mpg.de/NeuralClothSim

3D Surface Tracking with Neural Deformation Fields [CVPR, 2025]

Template S_1

Input Images I_t

Thin-Shell-SfT

Tracked Surface S_t

(a) Template Fitting

Template S_1
$\bar{x}$
$\bar{a}_j$
NRF Υ
Parametric Space Ω
ξ
t
Rotation / Position x
u
NDF Θ
Physics Loss (Fig. 3)

$\mathcal{G}_t$
a_3, a_2, a_1, x
Colour / Opacity / Scale

(b) Gaussians and NDF Optimisation

Deformed Gaussians $\mathcal{G}_t$ / Tracked Surface S_t

Splatting
Rendered Images
Image Loss
Input Images I_t

Operation Flow — Gradient Flow — Learnable Params (from I_1) — Learnable Params (from I_t) — Fixed/Pre-trained Params

Time t
NDF Θ
Deformation
Parametric Space Ω
NRF Υ
Curvature Tensor
Metric Tensor
Elastic Tensor
Strain Computation
Bending Strain κ
Membrane Strain ε
Operation Flow
Gradient Flow

$$\min_\Theta \int_2^T \int_\Omega \Psi[\varepsilon, \kappa; \Phi] \, d\Omega \, dt$$

Strain Energy Density as Physics Loss
Material Properties Φ

Input Video (Last Frame) / Previous Best (ϕ-SfT) / Ours / Ground Truth

Take-home Message:
Fine-grained tracking with continuous deformation model and thin-shell physics

4dqv.mpi-inf.mpg.de/ThinShellSfT

References

[1] Kairanda *et al.*, NeuralClothSim: Neural Deformation Fields Meet the Thin Shell Theory. *NeurIPS*, 2024.
[2] Kairanda *et al.*, Thin-Shell-SfT: Fine-Grained Monocular Non-rigid 3D Surface Tracking with Neural Deformation Fields. *CVPR*, 2025.
[3] Kairanda *et al.*, ϕ-SfT: Shape-from-Template with a Physics-based Deformation Model. *CVPR*, 2022.