Φ-SfT: Shape-from-Template with a Physics-Based Deformation Model

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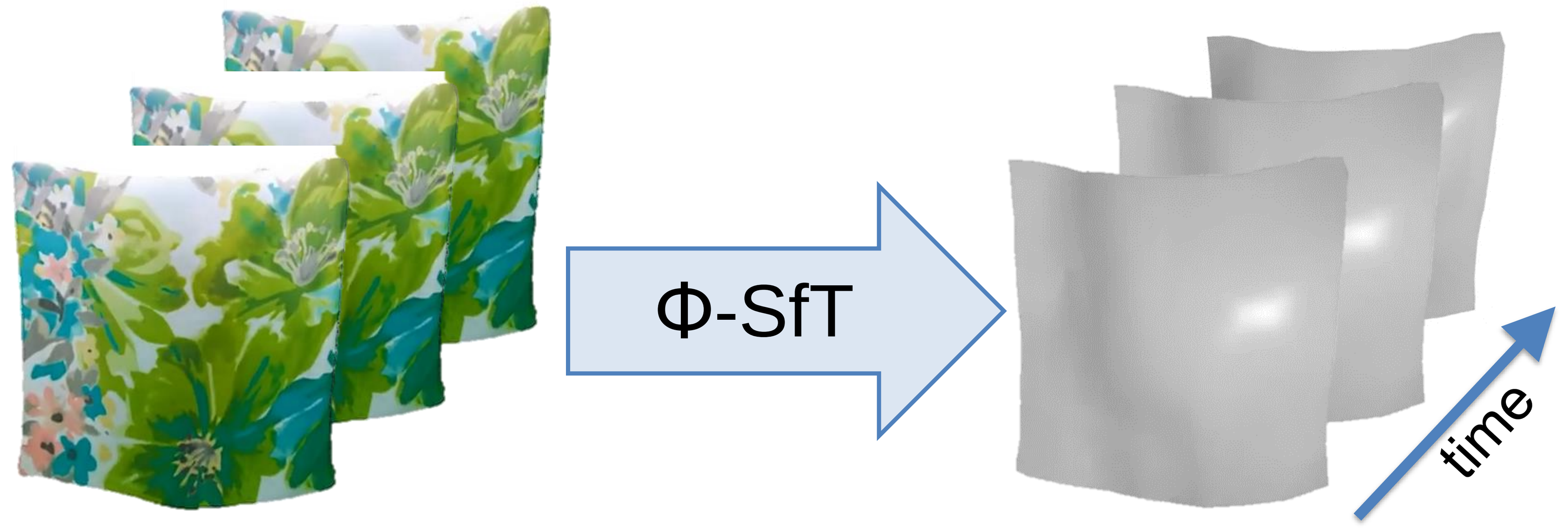
Overview

Goal: reconstruct the 3D shape of a deforming cloth from a monocular RGB input video



Contributions:

1. Differentiable physics-based deformation model [PS]
2. Differentiable mesh rendering for SfT
3. New dataset of real-world deforming surfaces with depth pseudo-ground truth

Dataset

- 9 real-world sequences
- Lengths: about 40 frames each
- Includes monocular RGB, depth, silhouettes, texture map, template
- Cloths of different material due to differences in weaving and fabric → different elasticity and densities
- Also different sizes and textures

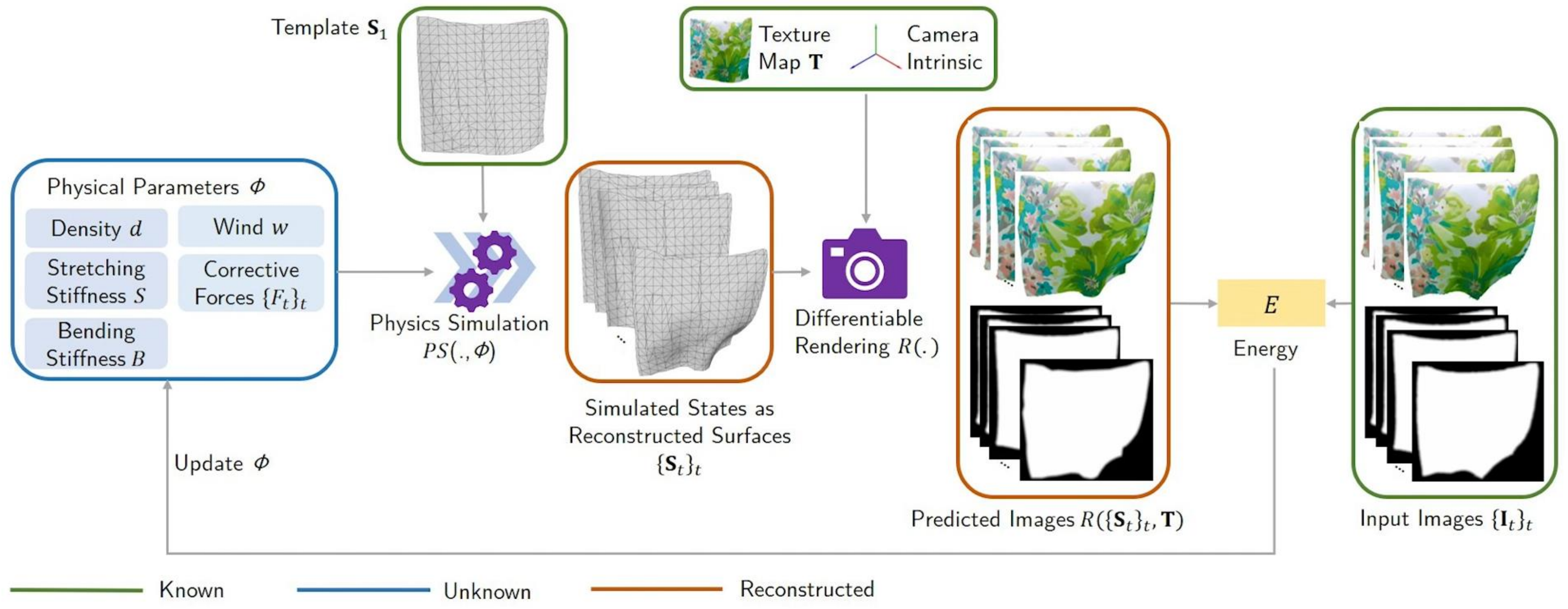
Further Resources

Project page (incl. source code & dataset): 4dqv.mpi-inf.mpg.de/phi-SfT/

Video: youtu.be/2jxDq8qyfg8

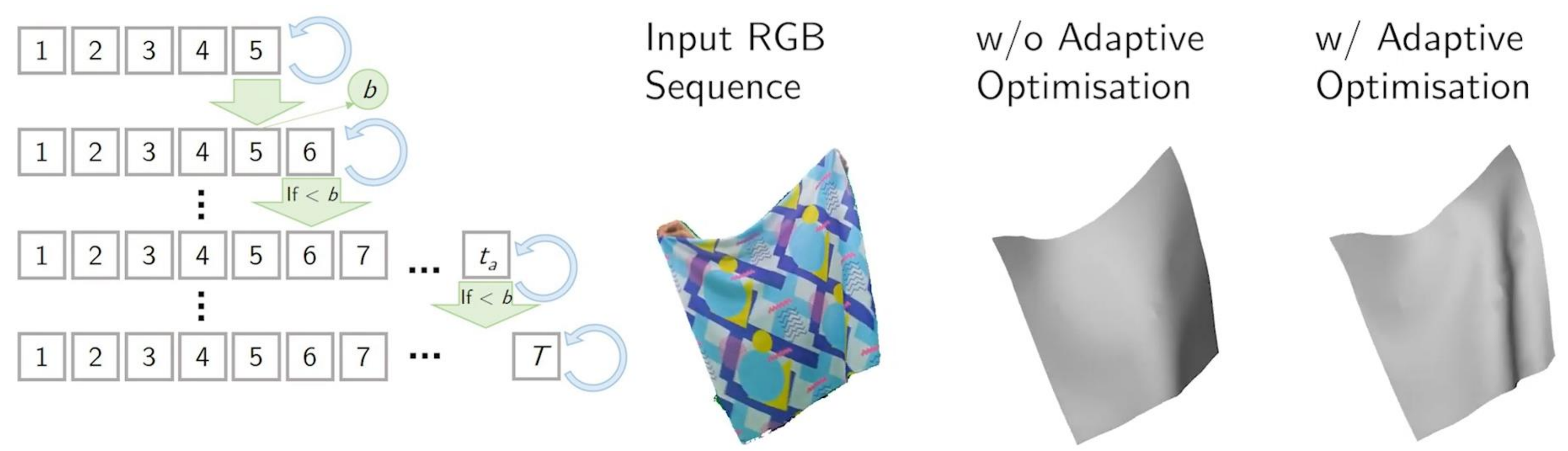
Project Page Video

Method

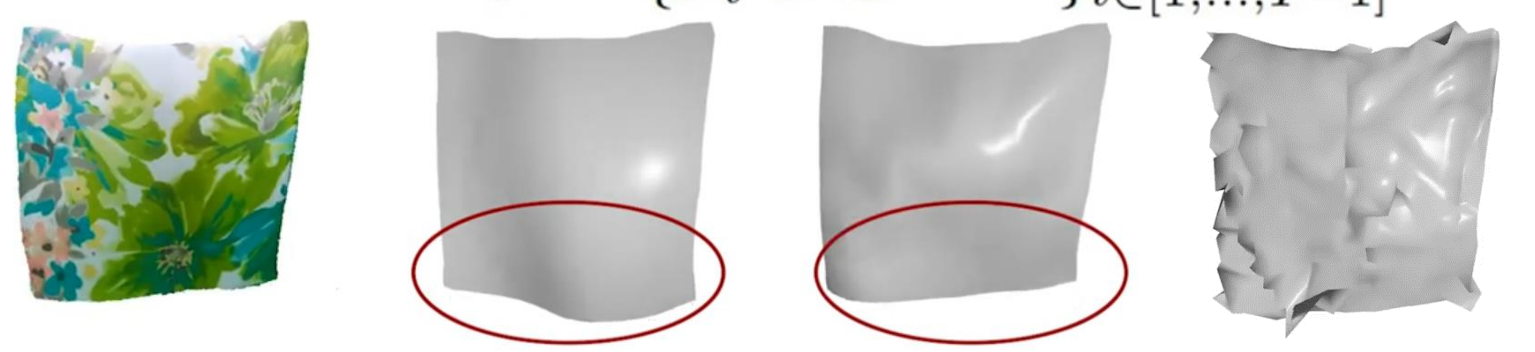


- Analysis by synthesis via dense image & silhouette energies
- Gradient-based optimisation of physical parameters Φ through differentiable physics simulation and differentiable rendering
- Auxiliary inputs: template, texture map, silhouettes, camera

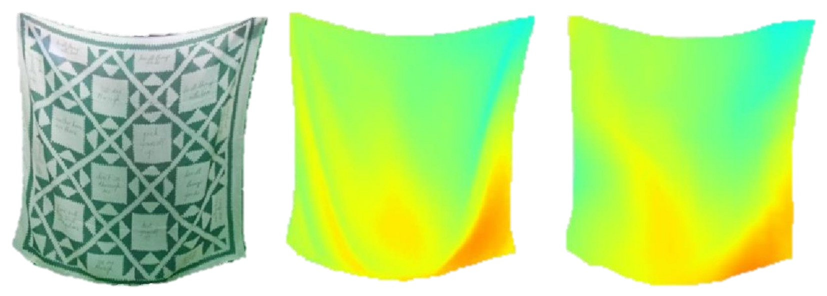
Ablations



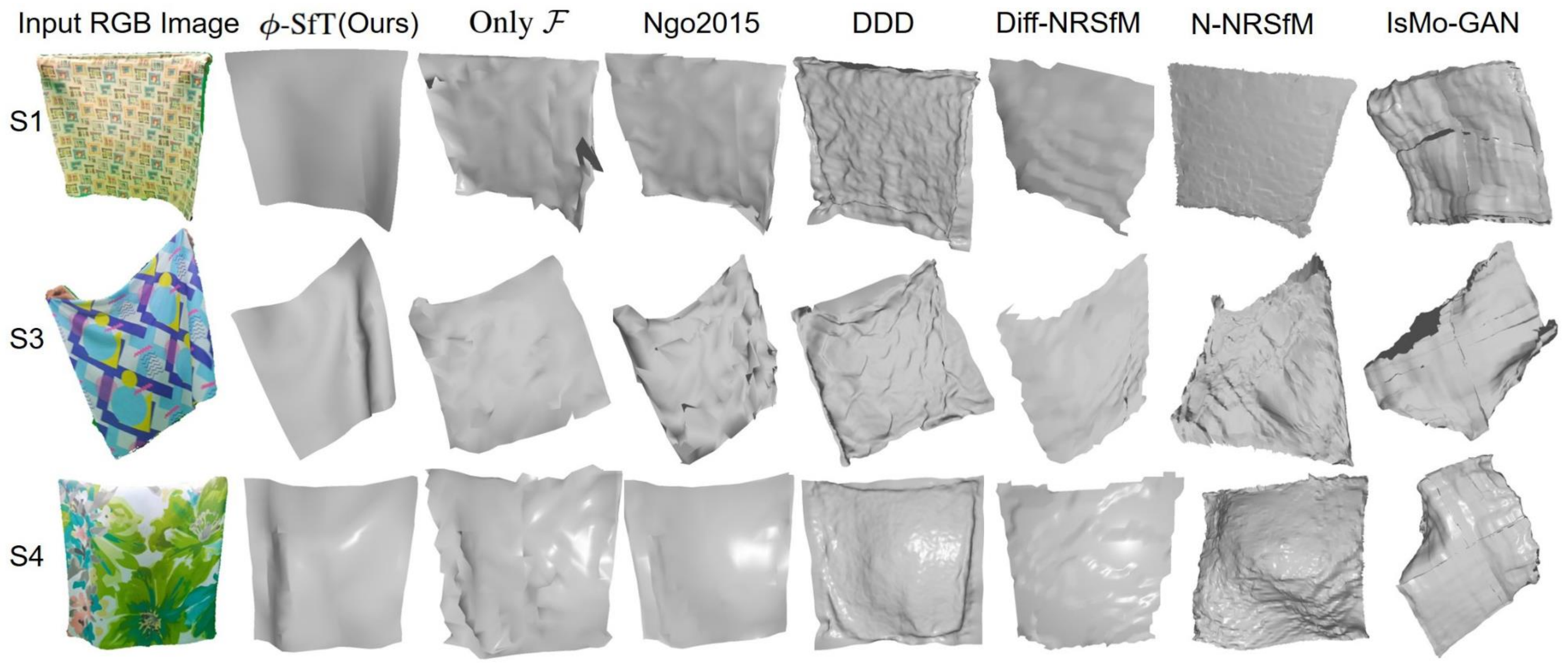
- Corrective forces: $\mathcal{F} = \{\mathcal{F}_t \in \mathbb{R}^{|\mathbf{V}_t| \times 3}\}_{t \in [1,\ldots,T-1]}$



Results



Comparisons



Average Chamfer distance to pseudo-GT depth:

Seq.	IsMo-GAN	N-NRSfM	DDD	Diff-NRSfM	Ngo2015	Only $\mathcal{F}$	ϕ-SfT
S1	19.69	8.25	2.95	17.14	2.19	2.59	**0.79**
S2	22.18	33.62	1.69	4.46	**1.51**	1.60	2.75
S3	33.54	104.60	3.80	4.40	**2.17**	3.23	3.54
S4	90.30	77.02	25.73	41.37	15.90	14.95	**7.60**
S5	92.78	72.66	10.46	26.92	10.72	21.32	**6.15**
S6	57.62	8.73	6.97	14.02	**3.01**	3.08	3.14
S7	49.27	129.44	15.64	12.49	7.95*	6.03	**4.73**
S8	24.45	38.06	7.61	9.91	fail	3.78	**2.52**
S9	53.12	19.81	11.77	5.29	fail	4.39	**2.36**
Avg.	49.22	54.69	10.87	15.11	5.92*	6.77	**3.93**

References:
[PS] Liang et al. Differentiable cloth simulation for inverse problems. NeurIPS 2019.
[IsMoGAN] Shimada et al. IsMo-GAN: Adversarial learning for monocular non-rigid 3D reconstruction. CVPRW 2019.
[N-NRSfM] Sidhu et al. Neural dense non-rigid structure from motion with latent space constraints. ECCV 2020.
[DDD] Yu et al. Direct, dense, and deformable: Template-based non-rigid 3D reconstruction from RGB video. ICCV 2015.
[Diff-NRSfM] Parashar et al. Local non-rigid structure-from-motion from diffeomorphic mappings. CVPR 2020.
[Ngo2015] Ngo et al. Dense image registration and deformable surface reconstruction in presence of occlusions and minimal texture. ICCV 2015.

Limitations

- Slow runtime of physics simulator
- Ambiguity between material and forces is not resolved