

Fine-grained Differentiable Physics: A Yarn-level Model for Fabrics

Deshan Gong¹, Zhanxing Zhu^{2,3}, Andrew J. Bulpitt¹, and He Wang¹



Fine-grained differentiable physics model (DPM) in fabrics

Motivation: Existing differentiable cloth models usually treat cloths as continuum elastic sheets. They ignore cloths' complex structures and force interactions which, however, play an important role in cloths' dynamics. As a result, their granularity is insufficient to fully capture real-world cloths' dynamics. Our yarn-level DPM has a finer granularity such that it is more meaningful to the real-world applications of differentiable physics.

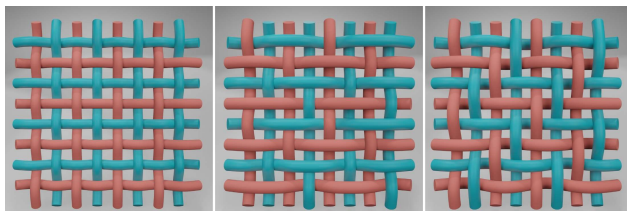
Contributions:

- The first fully differentiable yarn-level fabrics model
- It can model blend woven and various woven patterns
- A differentiable friction model with a smooth stick-slip transition
- A differentiable shear force model can captures "shear lock" effect
- Our model can accurately estimate intra- and inter-yarn cloth parameters
- Our model can find the needed forces for controlling cloths
- More explainable physical parameters
- High learning data efficiency

Cloth modeling

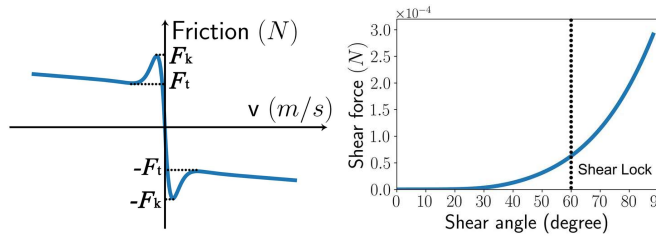
Cloth representation, blend woven, and woven pattern

Cloths are modeled as perpendicular yarns, i.e. warp and weft, that intersect at crossing nodes. Cloth dynamics are denoted by crossing nodes' position and velocity in the Eulerian-on-Lagrangian coordinate (Cirio et al., 2014). Crossing nodes are also the end-points of segments which are the minimal units for computing internal and external forces. By defining contacting yarns' relative position at crossing nodes, our DPM can model various woven patterns. Moreover, each individual yarn can be given independent physical parameters to simulate blend woven cloths.



The colors distinguish the yarns with different physical parameters. From left to right, the woven patterns are plain, satin, and twill.

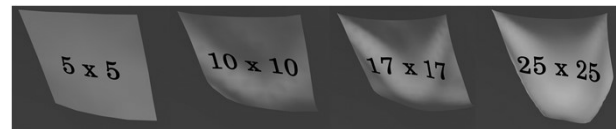
Differentiable friction and shear model



We propose a differentiable friction model with smooth stick-slip friction transition and can also capture Stribeck effect (Stribeck, 1902) to handle yarn-to-yarn contact friction. We also proposed a differentiable yarn shear force model that can capture the "shear lock" effect.

Cloth parameter estimation

We use our DMP to learn the physical parameters (density, stretch, bend, shear, and yarn contact friction coefficient) of blend woven cloth, which consist of two kinds of yarns, from 25 frames of wind blown cloth dynamics in various sizes: 5x5, 10x10, 17x17, and 25x25.

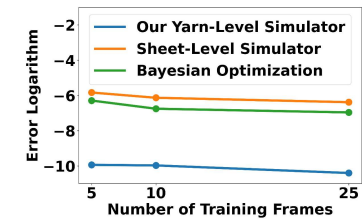


The wind blown cloths in different sizes shows observable differences in their dynamics.

Size	Shear	Friction	Yarn	Density	Stretch	Bend
5 x 5	5.10%	12.60%	1	1.40%	4.10%	0.93%
			2	2.00%	1.72%	1.09%
10 x 10	6.80%	9.00%	1	0.45%	3.06%	5.36%
			2	2.08%	2.26%	6.73%
17 x 17	5.30%	19.60%	1	1.55%	1.08%	5.50%
			2	2.40%	0.77%	6.00%
25 x 25	8.70%	24.00%	1	3.45%	2.04%	6.29%
			2	2.28%	2.31%	9.18%

The error percentage of the learned parameters when learning with various cloth sizes.

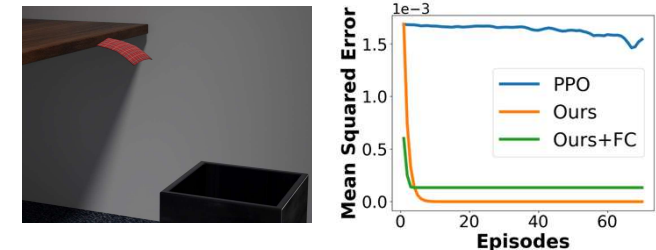
We also use initial 5, 10, 25 frames of 50 frames wind blown cloth dynamics to train our yarn-level DPM, a sheet-level DPM (Liang et al., 2019), and Bayesian optimization. Then, we evaluate them by the Mean Squared Error of all the 50 frames. Our DPM is better than the other two.



The logarithm of the evaluation Mean Squared Errors.

Cloth controlling

Compared with Proximal Policy Optimization (Schulman et al., 2017), our DPM can find the needed forces in fewer episodes. Additionally, our DPM can also be embedded as a layer in neural networks.



Estimating the needed forces to throw a piece of cloth from the table into the black bin.

References

Cirio, Gabriel et al. (2014). "Yarn-level simulation of woven cloth." . ACM Transactions on Graphics (TOG), 33(6), pp.1-11.
 Stribeck, R (1902). "Die Wesentlichen Eigenschaften der Gleit-und Rollenlager." . Z. Vereines Seutscher Ing., 46, pp.1432-1437.
 Liang, Junbang et al. (2019). "Differentiable cloth simulation for inverse problems." . Advances in Neural Information Processing Systems 32.
 Schulman, J et al. (2017). "Proximal policy optimization algorithms." . arXiv preprint arXiv:1707.06347.

