Supplementary materials: Woven Fabric Capture with a Reflection-Transmission Photo Pair

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Table 1: Notation used for our BSDF model.

$\omega_\mathrm{i}/\omega_\mathrm{o}$	incident / outgoing direction
ω'_o	rotated outgoing direction
ω_m	macroscopic surface normal
ω_n	yarn normal
ω_t	yarn orientation
ω_h	half vector between ω_i and ω_o
ω'_h	half vector between ω_i and ω'_o
$D(\omega)$	directional distribution of SGGX microflakes
$G(\omega_\mathrm{i}, \omega_\mathrm{o})$	shadowing-masking term for single scattering
$D_m(\omega)$	directional distribution of ASGGX microflakes
$G_m(\omega_\mathrm{i}, \omega_\mathrm{o})$	shadowing-masking term for multiple scattering
$\sigma(\omega)$	projected area of microflakes
ρ	microflake density
$T^{s,m}$	layer thickness for single/multiple scattering
$k_s^{s,m}$	specular albedo for single/multiple scattering
$\alpha^{s,m}$	microflake roughness for SGGX/ASGGX
$f_\mathrm{s}(\omega_\mathrm{i}, \omega_\mathrm{o})$	SpongeCake single scattering BSDF
$f_\mathrm{m}(\omega_\mathrm{i}, \omega_\mathrm{o})$	Our multiple scattering BSDF
$f_d^{r,t}(\omega_\mathrm{i}, \omega_\mathrm{o})$	Our diffuse term for reflection and transmission
$f^\delta(\omega_\mathrm{i}, \omega_\mathrm{o})$	Delta transmission

Table 2: Distributions used to sample the parameter space of our model. The third column notes whether the parameter has separate versions for weft and warp. $\mathcal{U}(x, y)$ represents a continuous uniform distribution in the interval (x, y). $\mathcal{V}(X)$ is a discrete uniform random variable on a finite set X. Yarn density is defined in yarns per inch, and converted internally to actual yarn size. Note that we didn't keep the multiple scattering albedo k_s^m as a parameter directly, but use a weight term w_m to control it, where $k_s^m = (k_s^s)^{\frac{1.0}{w_m}}$.

Parameter	Sampling Function	weft / warp
yarn pattern	$\mathrm{W} = \mathcal{V}(\{0, 1, 2, 3, 4\})$	No
yarn density	$y = \mathcal{U}(45, 335)$	Yes
roughness	$\alpha^{s,m} = \mathcal{U}(0.1, 1)^2$	Yes
thickness	$T^{s,m} = \mathcal{U}(0.1, 5)$	Yes
diffuse albedo	$k_\mathrm{d}^{r,t} = \mathcal{U}(0, 1)$	No
specular albedo	$k_\mathrm{s}^s = \mathcal{U}(0, 1)$	Yes
multiple weight	$w_\mathrm{m} = \mathcal{U}(0.1, 2)$	No
blending weight	$w = \mathcal{U}(0, 1)$	No
height field scaling	$\beta = \mathcal{U}(0.1, 2)$	Yes
gap scaling	$\xi = \mathcal{U}(0.1, 1)$	Yes

1 OUR FORWARD MODEL

Multiple scattering. Our multiple scattering term is defined as:

$$f_\mathrm{m}(\omega_\mathrm{i}, \omega_\mathrm{o}) = \frac{k_s^m \, D_m(\omega'_h) \, G_m(\omega_\mathrm{i}, \omega_\mathrm{o})}{2\cos\omega_\mathrm{i} \cdot \cos\omega_\mathrm{o}}, \tag{1}$$

$$G_m(\omega_\mathrm{i}, \omega_\mathrm{o}) = \frac{1 - e^{-T^m \rho(\Lambda(\omega_\mathrm{i}) + \Lambda(\omega_\mathrm{o}))}}{\Lambda(\omega_\mathrm{i}) + \Lambda(\omega_\mathrm{o})}, \tag{2}$$

$$D_m(\omega) = \frac{1}{\pi \alpha^m q^2}, \text{ where } q = \omega^\top S^{-1} \omega, \tag{3}$$

where ω_i and ω_o represent the incident and outgoing directions respectively, ω'_h is the half-vector in our ASGGX by rotating ω_i and ω_o to the same plane. S is a symmetric, positive definite 3×3 matrix defined in SGGX, T^m and α^m is the thickness and roughness for the multiple scattering. The G and D terms are identical as the SpongeCake model [Wang et al. 2022], except using the modified parameters.

Gap scaling. We scale the yarn width by a gap scaling factor to express the gaps between the weft and warp yarns, as shown in Fig. 1. We use the same delta transmission as Zhu et al. [2023] when light paths traverse the gaps:

$$f^\delta(\omega_\mathrm{i}, \omega_\mathrm{o}) = \frac{\delta(\omega_\mathrm{i} + \omega_\mathrm{o})}{\langle \omega_\mathrm{i} \cdot \omega_m \rangle}. \tag{4}$$

2 DISCRETE PARAMETERS OPTIMIZATION

During optimization, we treat six parameters as discrete: the yarn density of the weft and warp, the gap scaling of the weft and warp, and the twist angle for weft and warp. This is because we do not currently implement their gradients. With some effort, these gradients could be added, but our discrete solution gives good results. We randomly perturb these parameters every five iterations and

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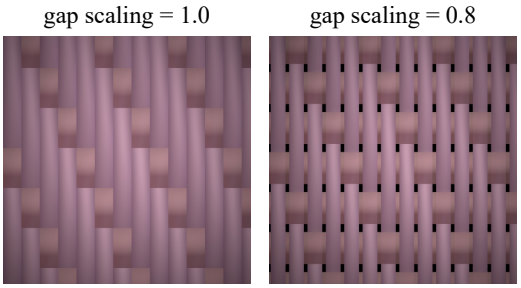

Figure 1: The renderings with different gap scaling factors.

Table 3: Comparison between the estimated and the ground-truth parameters (roughness and thickness for both warp and weft) on the synthetic data. The materials are shown in Fig. 16 (main paper).

Sample		Roughness		Thickness	
		warp	weft	warp	weft
yellow plain	GT	0.26	0.26	1.23	1.23
	predicted	0.22	0.20	0.99	0.83
bule satin	GT	0.22	0.90	1.12	3.75
	predicted	0.28	0.80	1.27	3.30
brown satin	GT	0.34	0.80	1.20	2.81
	predicted	0.43	0.48	1.28	3.12
pink twill	GT	0.87	0.93	3.98	1.08
	predicted	0.81	0.91	2.46	1.82
green twill	GT	0.50	0.71	2.46	2.16
	predicted	0.47	0.79	2.75	1.87

accept the perturbation if it results in a lower loss than before. The yarn densities are perturbed as follows: +/- 10 yarns per inch before 100 iterations; +/- 5 yarns per inch from 100 to 150 iterations, and +/- 2 yarns per inch from 150 to 300 iterations. For the twist angles, it is perturbed as follows: +/- 0.5 degrees before 100 iterations; +/- 0.25 degrees from 100 to 150 iterations, and +/- 0.1 degree from 150 to 300 iterations. For the gap scalings, it is perturbed as follows: +/- 0.05 before 100 iterations; +/- 0.025 from 100 to 150 iterations, and +/- 0.01 from 150 to 300 iterations.

3 MORE RESULTS

Real data. In Fig. 2, we provide more results on the real data, and report the ƎLIP error between the captured and the recovered images. The renderings of our reconstructed parameters can match the captured images. In Fig. 3, we further validate our method by capturing the fabric samples from a novel view (by rotating them) and rendering them under the same configuration. By comparison, the rendering results of our estimated fabrics can match the captured fabrics at the novel view. Note that, in the transmission rendering, we include the out-of-focus effect by projecting the point light to the rendered image and generating a Gaussian around the projected center.

Synthetic data. We validate our method on synthetic data by comparing the estimated parameters (roughness and thickness for both warp and weft) to the ground-truth parameters. As shown in Table 3, our recovered parameters are close to the ground truth.

Impact of the loss function. In Fig. 4, we provide an ablation study for each loss term in the optimization step. We find that the pixel loss and the Gram matrix loss reduce the color bias, while the prior loss improves the robustness, especially for the gap scaling factor estimation.

REFERENCES

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Junqiu Zhu, Adrian Jarabo, Carlos Aliaga, Ling-Qi Yan, and Matt Jen-Yuan Chiang. 2023. A Realistic Surface-Based Cloth Rendering Model. In *ACM SIGGRAPH 2023 Conference Proceedings (SIGGRAPH '23).* Association for Computing Machinery, New York, NY, USA, Article 5, 9 pages. https://doi.org/10.1145/3588432.3591554

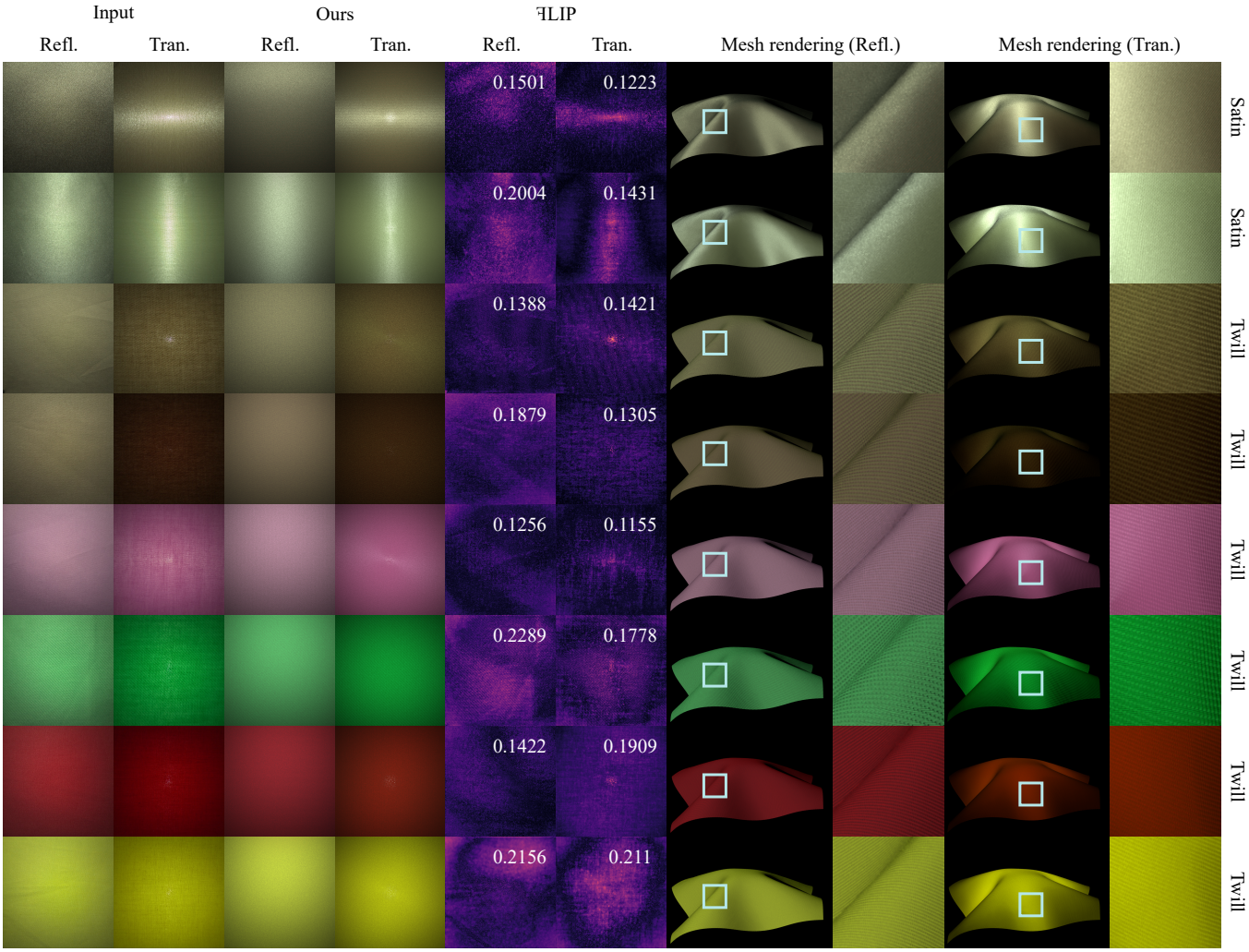

Figure 2: More results on the real captured data. The differences between the rendered and captured images are shown in the middle.

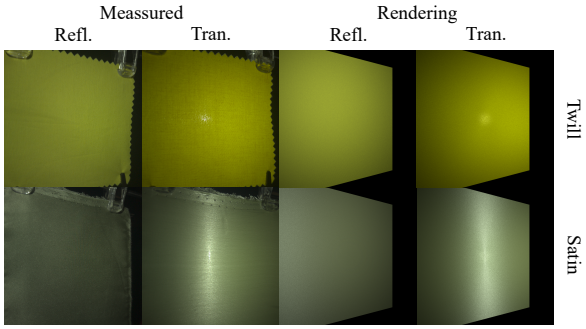

Figure 3: Novel view validation. We capture the fabrics from a novel view and compare it with our rendered result in the same configuration. Our results can match with real fabrics at novel view.

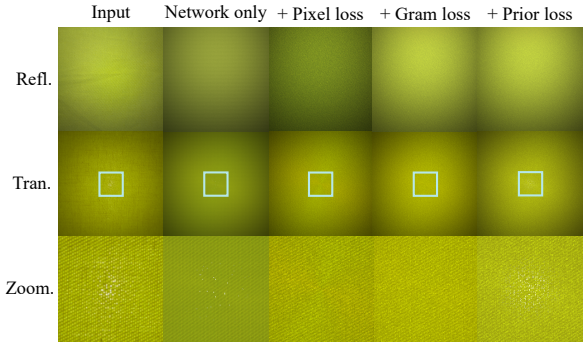

Figure 4: The impact of the loss terms. The pixel loss and the Gram matrix loss reduce color bias, and the prior loss helps find a suitable gap scaling factor, which contributes to the delta transmission in the center.