

# Image2Garment: Simulation-ready Garment Generation from a Single Image

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## Motivation

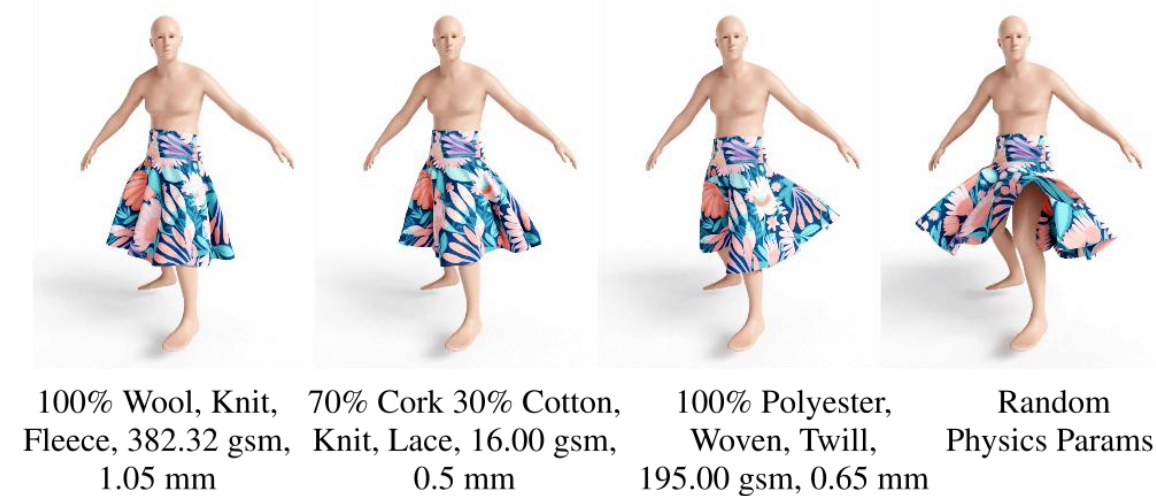


Figure 1: Impact of garment fabric parameters on simulation. We visualize the final frame of a jumping animation for four different fabrics each starting from the exact same initial condition. The choice of garment physics parameters changes the dynamics of the animation drastically. In turn, this makes it critical to estimate these parameters accurately.

- Creating realistic, simulation-ready digital garments from single images is crucial for virtual reality, gaming, and fashion design applications; accelerating garment prototyping, and benefiting platforms like cinema, and augmented/virtual reality.
- Estimating physics parameters from a single image is fundamentally ill-posed – we cannot directly see properties like stretch stiffness or bend resistance.

## Related Works

Existing methods either require:

- 1) expensive multi-view setups and hours of iterative optimization per garment [1]
- 2) only predict garment geometry without physical parameters needed for simulation [2,3]
- 3) or produce garments that collapse, over-stiffen, or exhibit unrealistic dynamics when simulated.

No method provides fast, single-image to simulation-ready garments.

## References

- [1] Li et al. Dress-1-to-3: Single image to simulation-ready 3d outfit with diffusion prior and differentiable physics. ACM Transactions on Graphics (TOG), 2025
- [2] Bian et al. Chatgarment: Garment estimation, generation and editing via large language models, CVPR, 2025
- [3] Nakayama et al. Aip apparel: A multimodal foundation model for digital garments. CVPR, 2025
- [4] Loper et al. SMPL: A skinned multi-person linear model. ACM TOG (SIGGRAPH Asia), 2015

## Method and Experimental Results

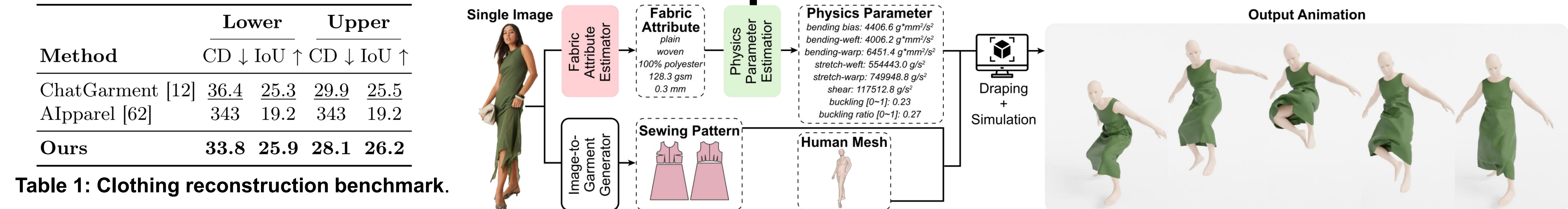


Table 1: Clothing reconstruction benchmark.

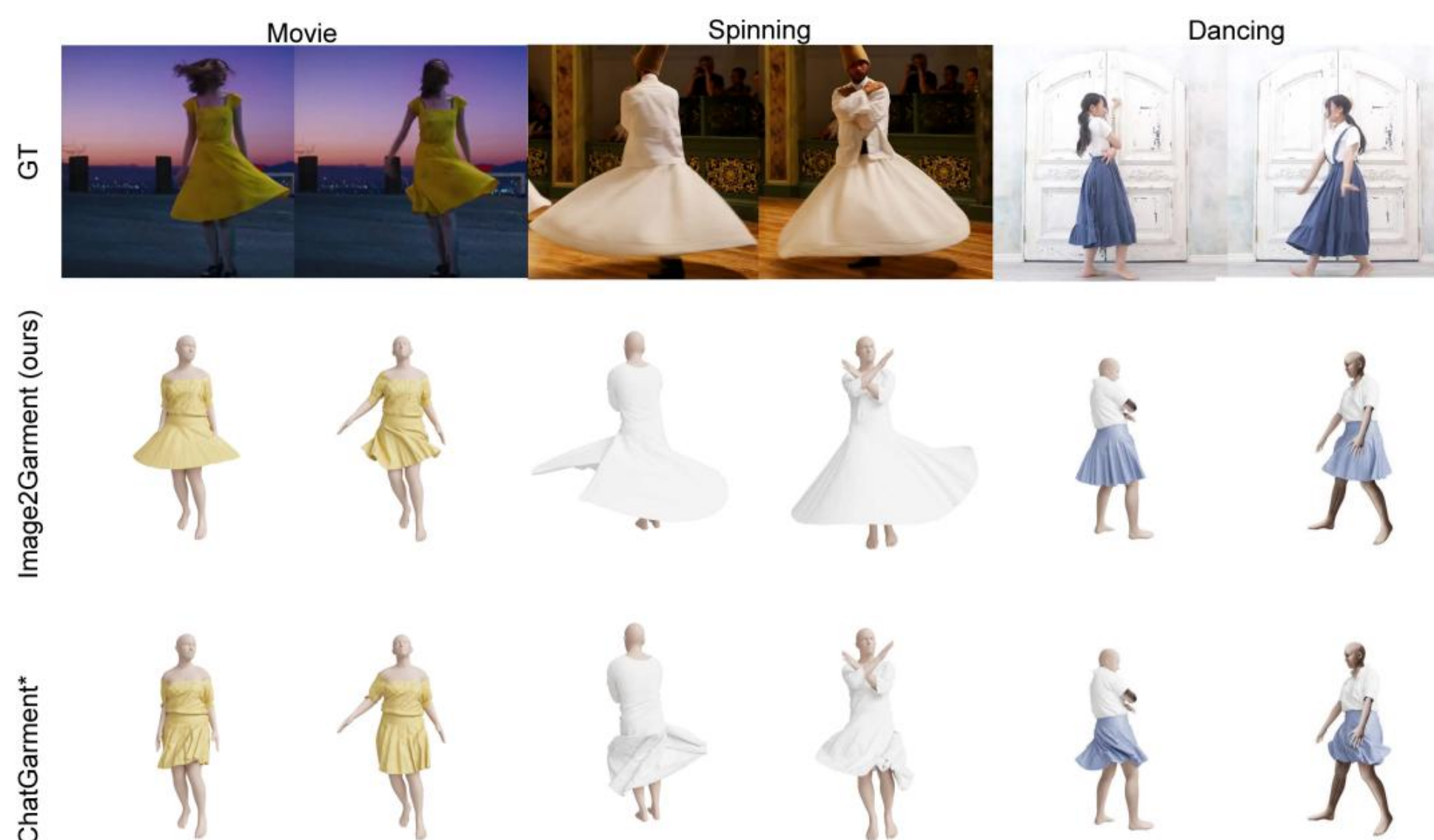
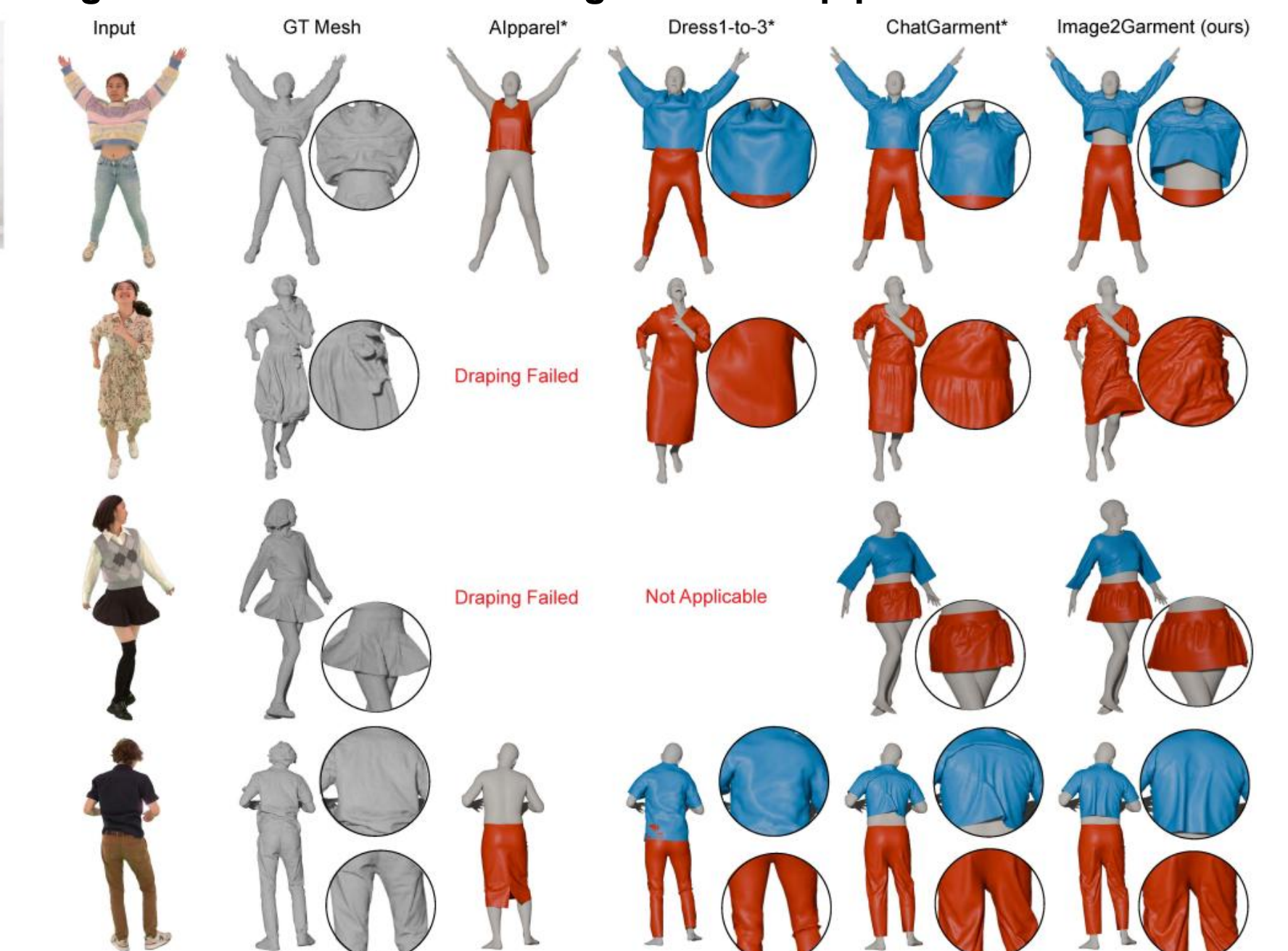


Figure 2: Overview of the Image2Garment pipeline.



Attribute Field	ChatGPT (zero-shot)	ChatGPT (few-shot)	Ours
Categorical Fields (Accuracy % / F1-score) ↑			
Fabric Family	0.58 / 0.42	0.61 / 0.43	0.75 / 0.72
Structure Type	0.74 / 0.68	0.75 / 0.69	0.86 / 0.85
Material Type	0.65 / 0.70	0.66 / 0.70	0.71 / 0.75
Continuous Fields (MAE % / NMAE) ↓			
Material Percentage	23.3 / 0.45	22.4 / 0.43	19.3 / 0.40

Table 2: Performance of fabric attribute estimation baselines

Sequence	Method	#Frames	CD↓	IoU↑	PSNR↑	SSIM↑	LPIPS↓
Jumping Jack	GarmentRecovery*	133	927.0	4.3	14.50	0.881	0.207
	AIpparel*		98.1	14.6	20.62	0.942	0.064
	ChatGarment*		88.9	20.0	21.66	0.951	0.056
	Image2Garment (ours)		64.4	21.6	22.10	0.954	0.053
Joyful Jump	GarmentRecovery*	91	58.7	11.7	18.46	0.934	0.102
	AIpparel*		46.8	17.4	24.64	0.965	0.034
	ChatGarment*		7.7	37.5	27.88	0.970	0.021
	Image2Garment (ours)		7.5	38.6	28.05	0.970	0.021
Northern Spin	GarmentRecovery*	125	275.0	5.3	14.00	0.828	0.262
	AIpparel*		257.0	14.0	17.86	0.881	0.156
	ChatGarment*		525.0	13.9	18.32	0.879	0.150
	Image2Garment (ours)		163.0	12.4	18.91	0.866	0.145
Hit Reaction	GarmentRecovery*	62	250.0	7.2	20.67	0.957	0.083
	AIpparel*		57.6	19.3	20.59	0.958	0.056
	ChatGarment*		109.0	20.6	21.62	0.957	0.056
	Image2Garment (ours)		101.0	23.0	22.10	0.961	0.049
Average	GarmentRecovery*	103	377.7	7.2	16.91	0.900	0.164
	AIpparel*		114.9	16.3	20.93	0.937	0.078
	ChatGarment*		182.7	23.0	22.37	0.939	0.071
	Image2Garment (ours)		84.0	23.9	22.79	0.938	0.067

Table 3: Quantitative comparison of image-to-garment prediction.

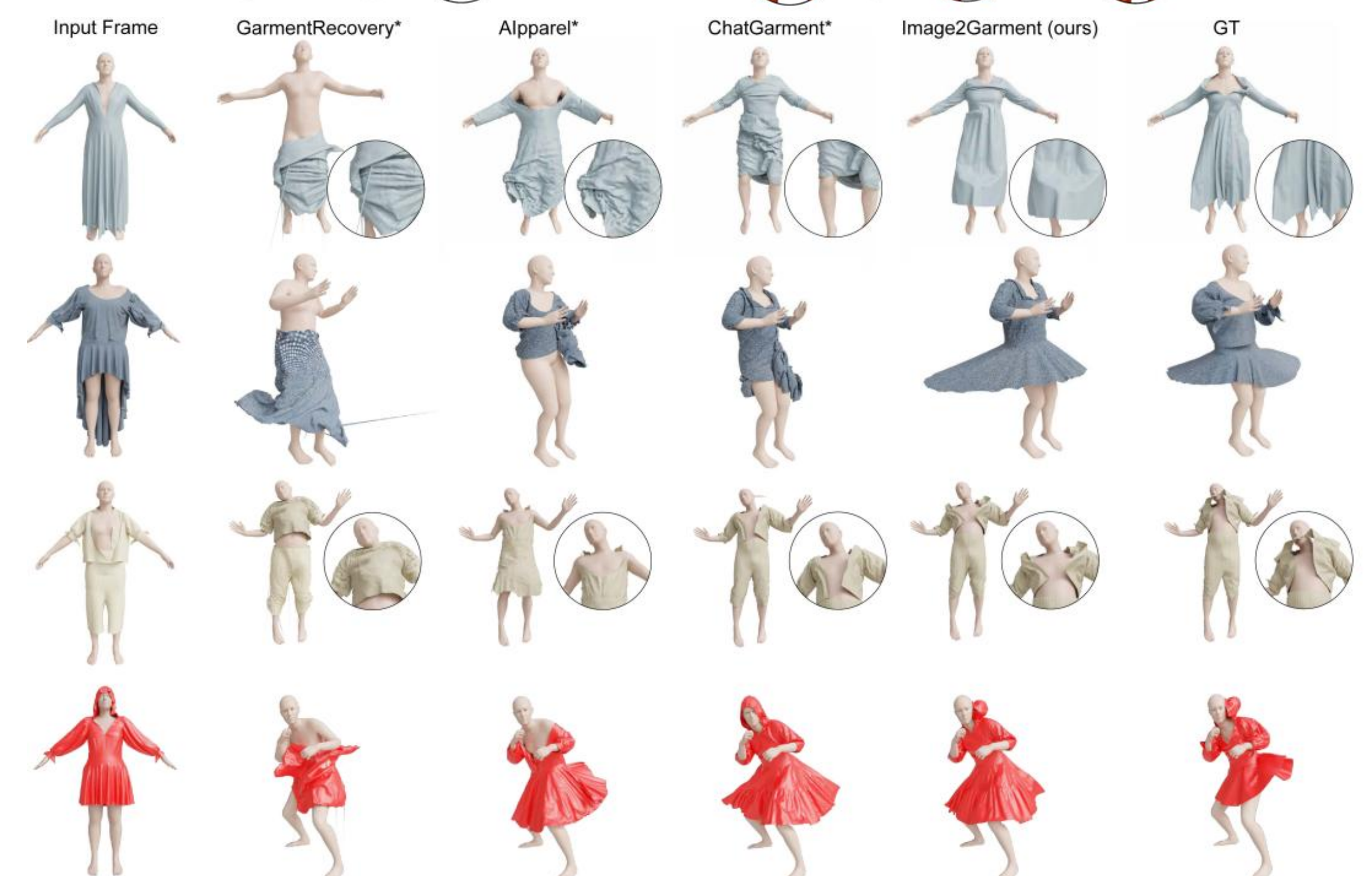


Figure 3: Qualitative Comparisons.