Panelformer: Sewing Pattern Reconstruction from 2D Garment Images Supplemental Material

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In this supplemental material, we offer additional visual comparisons and quantitative evaluation to complement the main paper.

1. Groups defined in our data augmentation

In the main manuscript, we categorize each panel class into a specific group, denoted Q, based on their respective semantic information as described in Section 3.4. Here, we present a comprehensive list of all panel classes along with their corresponding assigned groups.

Table 1. **Defined groups and the assigned panel classes.** All panel classes are categorized into one of the groups.

class	group	class	group	class	group
top_front	top	sleeve_lf	sleeve	skirt_front	skirt
top_front_left	top	sleeve_lb	sleeve	skirt_back	skirt
top_back	top	sleeve_rf	sleeve	skirt_left	skirt
hood_left	hood	sleeve_rb	sleeve	skirt_right	skirt
hood_right	hood	pant_front_left	pant	skirt_front_left	skirt
wb_front	waistband	pant_front_right	pant	skirt_front_right	skirt
wb_back	waistband	pant_back_left	pant	skirt_back_left	skirt
		pant_back_right	pant	skirt_back_right	skirt

2. Additional ablation studies on data augmentation

Effect of our data augmentation techniques on NeuralTailor. We extend our proposed data augmentation techniques to accommodate 3D point cloud data. In our experiments, we compare the performance of the original NeuralTailor [1] method with a fine-tuned version that incorporates the extended *panel masking* and *garment mixing* techniques (referred to as NeuralTailor*). We show the improvements contributed by our *panel masking* and *garment mixing*in Table 2 and Table 3. Compared to the original NeuralTailor, the fine-tuned version significantly improves L2-P (by 2), #P (by 12.6%) and #E (by 5.2%) on the unseen garment types, while maintaining similar results on the seen garment types. The results highlight the contribution of our data augmentation tailored for garment modeling.

Table 2. **Quantitative comparisons on predicted panels.** We compare panels predicted by the original NeuralTailor and NeuralTailor fine-tuned with our *panel masking* and *garment mixing* (denoted as NeuralTailor*).

	Seen Types					Unseen Types				
	L2-P ↓	#P (%) ↑	#E (%) ↑	L2-R ↓	L2-T ↓	L2-P ↓	#P (%) ↑	#E (%) ↑	L2-R ↓	L2-T ↓
NeuralTailor	**1.5**	**99.7**	**99.7**	0.04	**1.46**	5.2	83.6	87.3	0.07	3.22
NeuralTailor*	1.6	99.0	99.5	**0.00**	1.61	**3.2**	**96.2**	**92.5**	**0.00**	**2.93**

Table 3. **Quantitative comparisons on predicted stitches.** We compare the stitches predicted from predicted panels of NeuralTailor and NeuralTailor fine-tuned with our *panel masking* and *garment mixing* (denoted as NeuralTailor*). Results for unseen types was evaluated only on sewing patterns with correct number of panels predicted to reduce error propagation.

	Seen Types		Unseen Types	
	Prec. (%) ↑	Rec. (%) ↑	Prec. (%) ↑	Rec. (%) ↑
NeuralTailor on GT	**96.6**	88.6	75.3	60.6
NeuralTailor on Preds.	96.3	**99.4**	74.7	83.9
NeuralTailor* on GT	94.2	84.3	76.9	67.9
NeuralTailor* on Preds.	91.3	99.2	**77.1**	**91.2**

Effect of different mask shapes. Our data augmentation techniques highly rely on the panel segmentation of each panel. It might seem intuitive to use panel segmentation masks instead of panel bounding boxes while performing our *panel masking* and *garment mixing*. Therefore, we trained another variant of our Panelformer (referred to as Ours*) using segmentation masks instead of bounding boxes for the *panel masking* and *garment mixing* process.The results of this variant are presented in Table 4. Interestingly, we observed that the bounding box variant outperforms the segmentation mask variant, albeit by a slight margin.

Table 4. **Quantitative comparisons on perdicted panels with different augmentation variant applied.** We compare the results without the fine-tuning with L_{trans}.

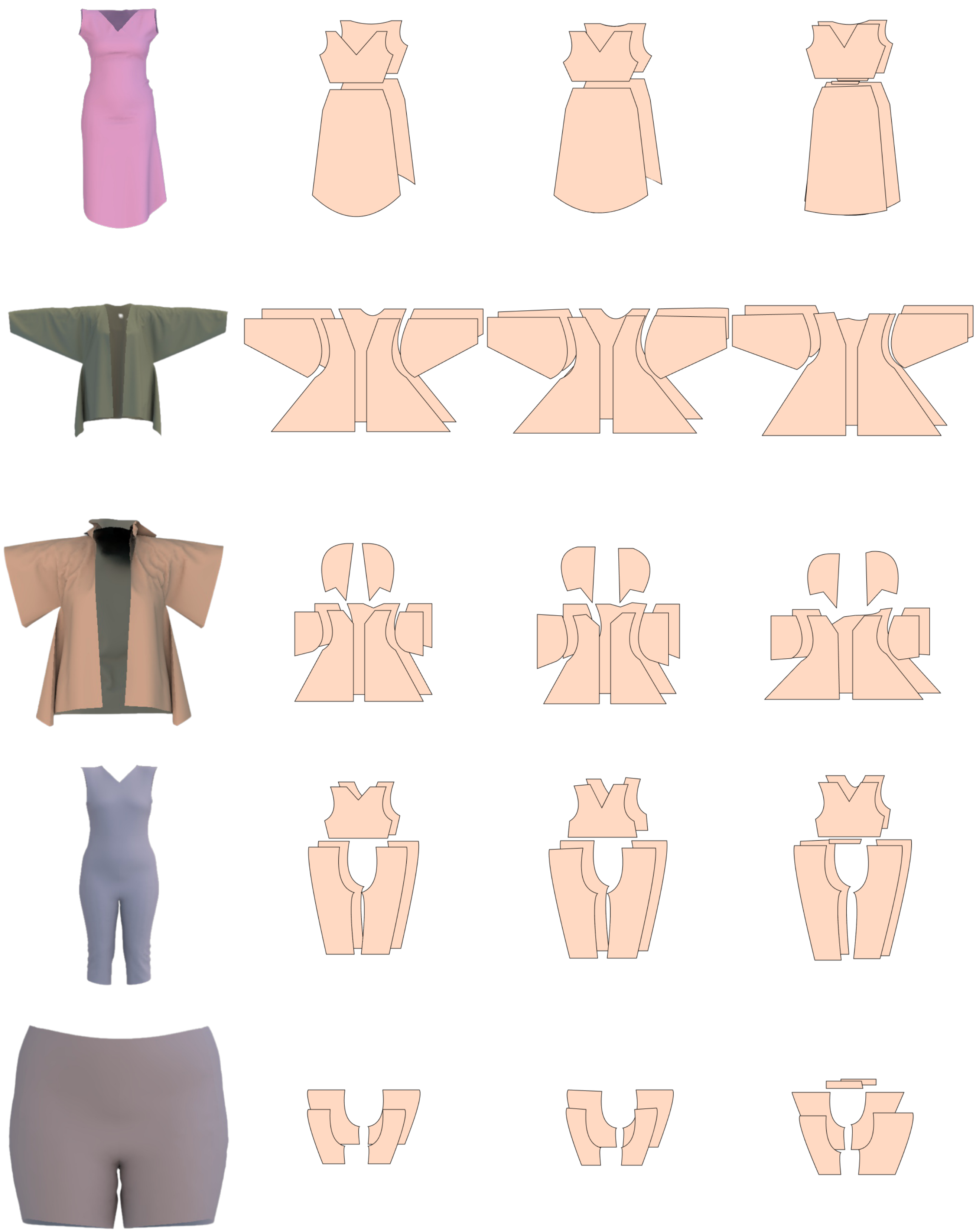
	Seen Types				Unseen Types			
	L2-P ↓	#P (%) ↑	#E (%) ↑	L2-R ↓	L2-P ↓	#P (%) ↑	#E (%) ↑	L2-R ↓
Ours*	2.9	99.5	**99.9**	0.01	5.8	93.2	**92.7**	**0.01**
Ours	**1.9**	**99.8**	99.7	**0.01**	**5.4**	**97.3**	**92.7**	**0.01**

3. Additional qualitative comparisons

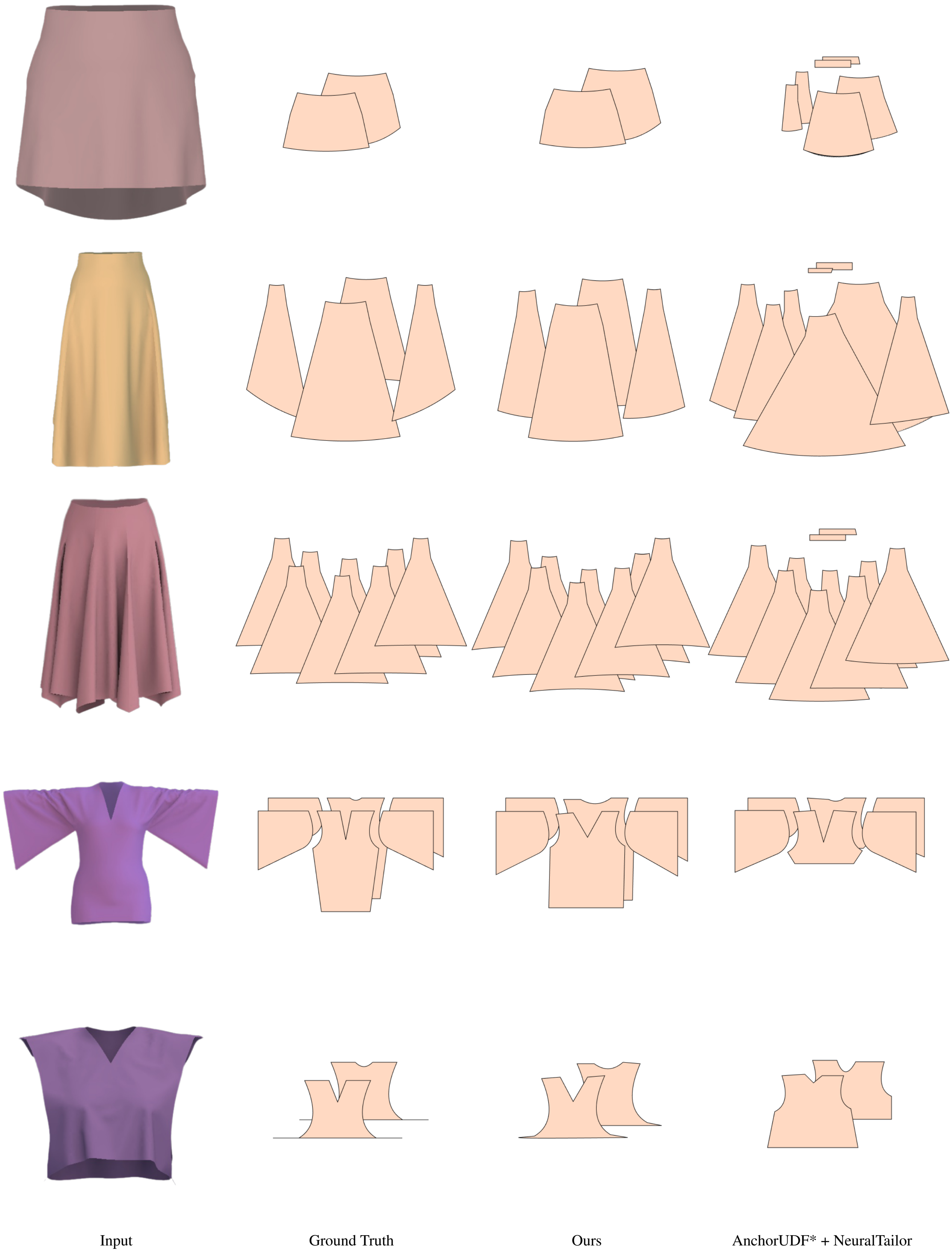
We provide additional qualitative comparisons in Figure 4, where we showcase one garment sample from each seen and unseen garment type for visualization purposes. Each row in the presented images represents a sample from the dataset. The top 12 rows show samples from the seen types testing set and the bottom 7 rows show samples from the unseen types testing set. From left to right, the figures in each row represent the input garment image, the ground truth sewing pattern, the results obtained using our proposed Panelformer, and the results obtained using AnchorUDF* + NeuralTailor.

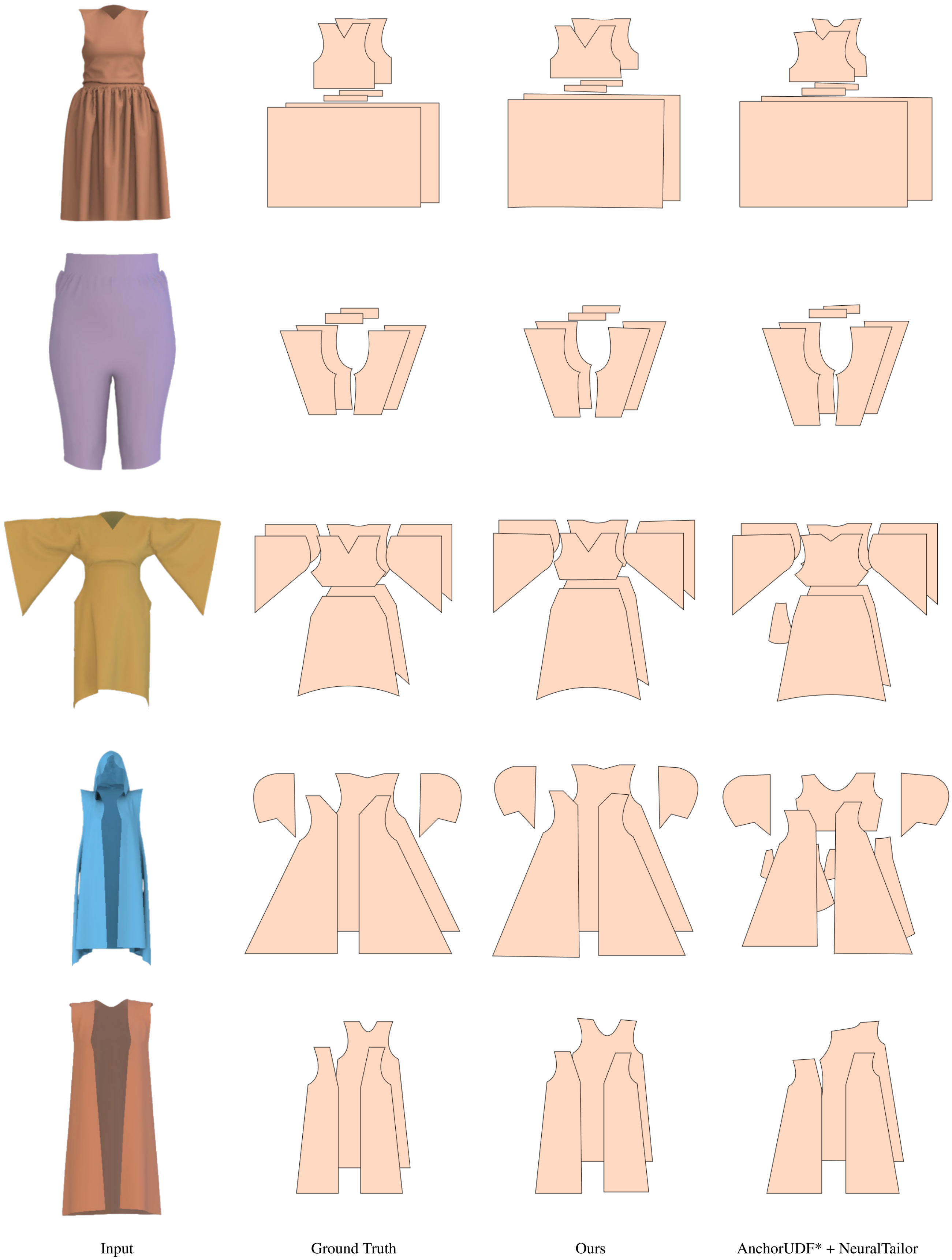
References

[1] Maria Korosteleva and Sung-Hee Lee. Neuraltailor: Reconstructing sewing pattern structures from 3d point clouds of garments. *ACM Trans. Graph.*, 41(4), 2022. 1



Input Ground Truth Ours AnchorUDF* + NeuralTailor


Input
Ground Truth
Ours
AnchorUDF* + NeuralTailor


Input
Ground Truth
Ours
AnchorUDF* + NeuralTailor

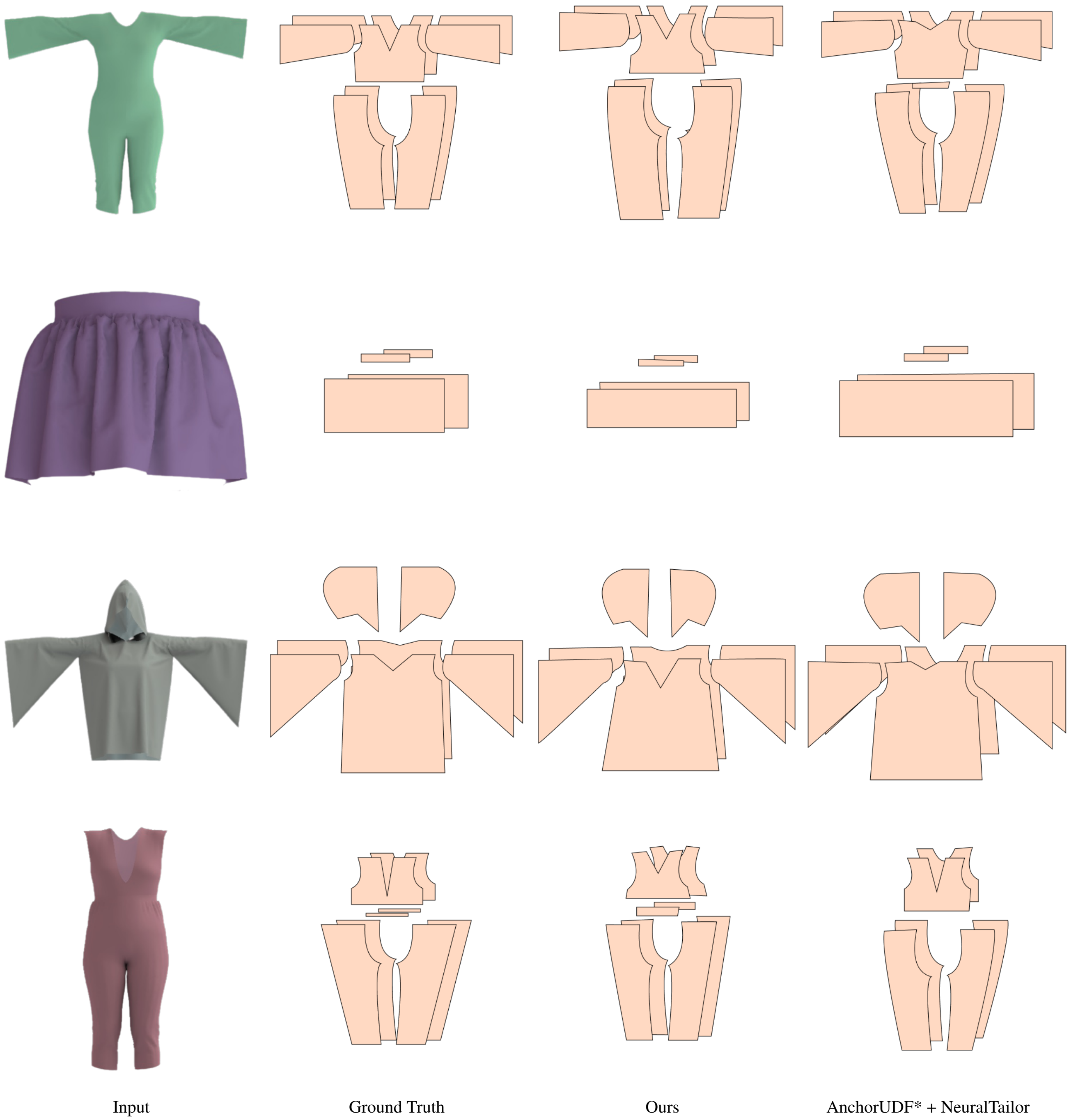


Figure 4. **Additional qualitative comparison on panel reconstruction.** The top 12 rows show samples from the seen types testing set and the bottom 7 rows show samples from the unseen types testing set.