TailorNet: Predicting Clothing in 3D as a Function of Human Pose, Shape and Garment Style

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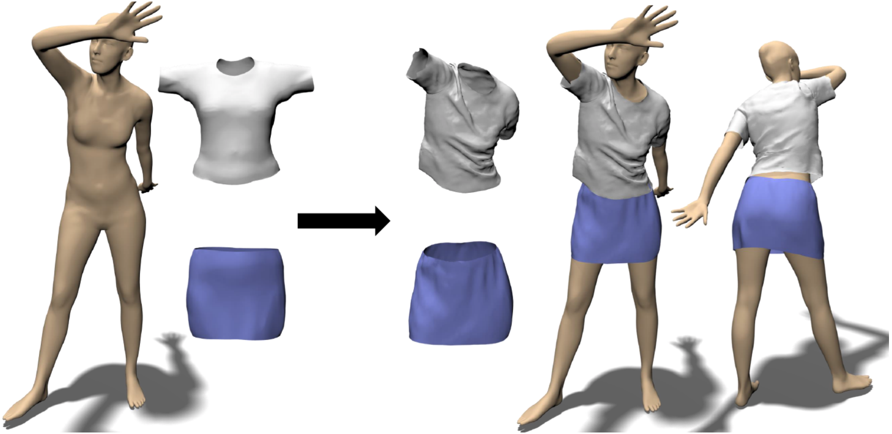
Right to Clothing, a Human Right



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Previously: Physics Based Simulation

- Realistic look
- Good generalization
- Computationally expensive
- Complex to implement and to control
- Time-consuming

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Previously: Earlier Data-Driven Methods

- A step forward to automate the process
- Do not jointly model style, pose and shape variation
- Over-smooth results
- Lack fine structure (wrinkles)

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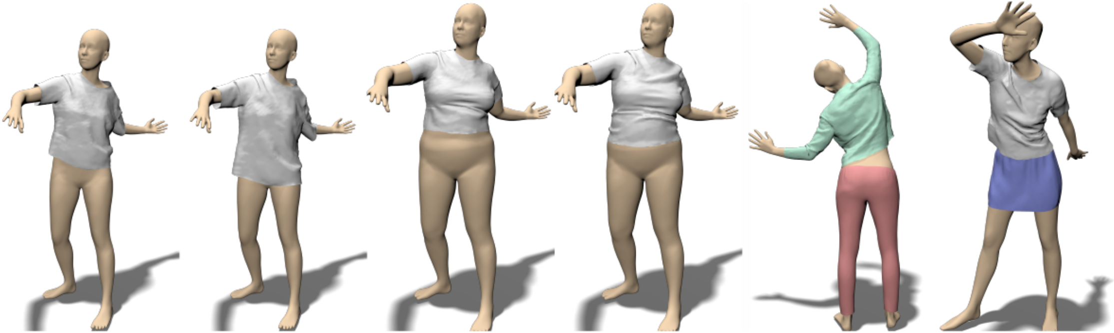
TailorNet



TailorNet: A model to estimate the clothing deformations with fine details from input body shape, body pose and garment style

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TailorNet

- Simple
- Easy to deploy
- Fully differentiable
- Fine structures are preserved by learning not only low-frequency components but also high-frequency components

Garment Model Aligned with SMPL

Human body skinning function skeleton pose blend weights

$$M(\boldsymbol{\beta}, \boldsymbol{\theta}) = W(T(\boldsymbol{\beta}, \boldsymbol{\theta}), J(\boldsymbol{\beta}), \boldsymbol{\theta}, \mathbf{W})$$

$$T(\boldsymbol{\beta}, \boldsymbol{\theta}) = \mathbf{T} + B_s(\boldsymbol{\beta}) + B_p(\boldsymbol{\theta})$$

mesh vertices in T-pose

shape-dependent deformations

pose-dependent deformations

$$G(\boldsymbol{\beta}, \boldsymbol{\theta}, \mathbf{D}) = W(T^G(\boldsymbol{\beta}, \boldsymbol{\theta}, \mathbf{D}), J(\boldsymbol{\beta}), \boldsymbol{\theta}, \mathbf{W})$$

$$T^G(\boldsymbol{\beta}, \boldsymbol{\theta}, \mathbf{D}) = \mathbf{I}\, T(\boldsymbol{\beta}, \boldsymbol{\theta}) + \mathbf{D}$$

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Un-posing Garment Deformation

$$\mathbf{D} = W^{-1}(\mathbf{G}, J(\boldsymbol{\beta}), \boldsymbol{\theta}, \mathbf{W}) - \mathbf{I}\, T(\boldsymbol{\beta}, \boldsymbol{\theta})$$

$$D(\boldsymbol{\beta}, \boldsymbol{\theta}, \boldsymbol{\gamma}) : \mathbb{R}^{|\boldsymbol{\theta}|} \times \mathbb{R}^{|\boldsymbol{\beta}|} \times \mathbb{R}^{|\boldsymbol{\gamma}|} \mapsto \mathbb{R}^{m \times 3}$$

- **Learn** deformation **D** as a function of shape β, pose θ and style γ.

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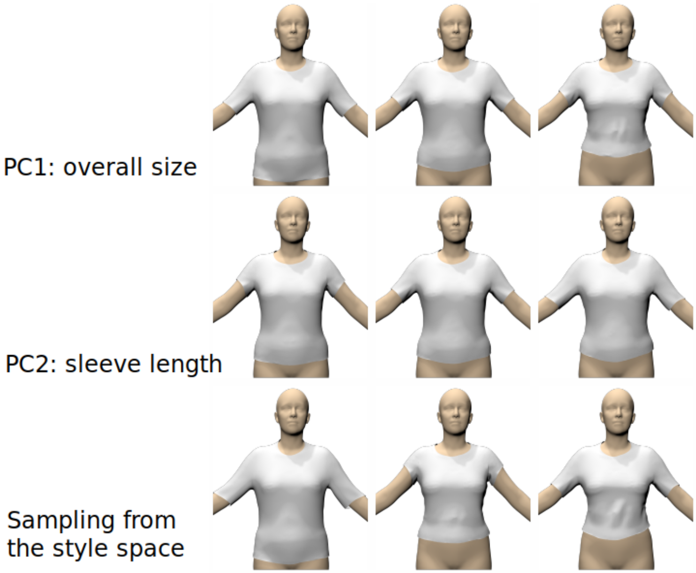
Generating Parametric Model of Style



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Tailoring

Low frequency component, single MLP, smooth but accurate

chosen shape-style pairs, K=20

$$D(\boldsymbol{\theta}, \phi) = D^{LF}(\boldsymbol{\theta}, \phi) + \sum_{k=1}^{K} \Psi(\phi, \phi_k) D^{HF}_{\phi,k}(\boldsymbol{\theta})$$

High frequency component, mixture of MLP, fine details

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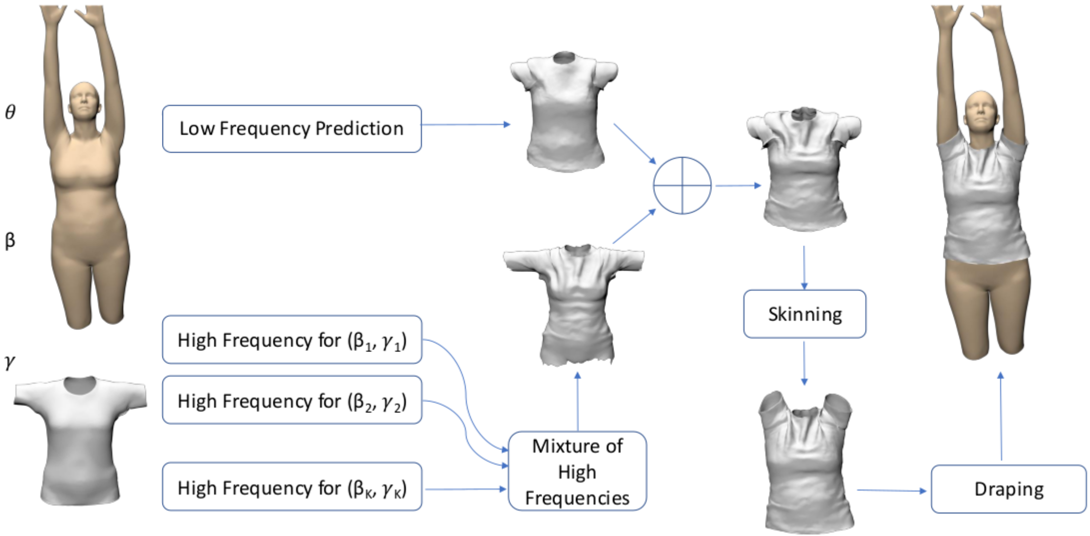
Tailoring



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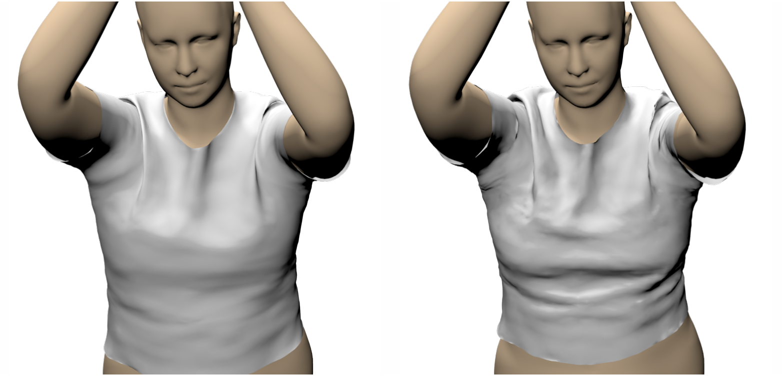
Model Evaluation



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1000 times faster than PBS

Results of Single Style-Shape Model

Style-shape	MLP	UV Decoder	Graph CNN
Loose-fit	14.5	15.9	16.1
Tight-fit	10.1	11.4	11.7

Results of TailorNet

Split No.	Style-shape set	Pose set	Our Baseline	Our Mixture Model
2	train	test	10.6	10.2
3	test	train	11.7	11.4
4	test	test	11.6	11.4

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Limitations

- the pose dependent deformations produce intersections sometimes, vertices are pushed out in real time
- only quasi-statics of clothing not dynamics

Questions?

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