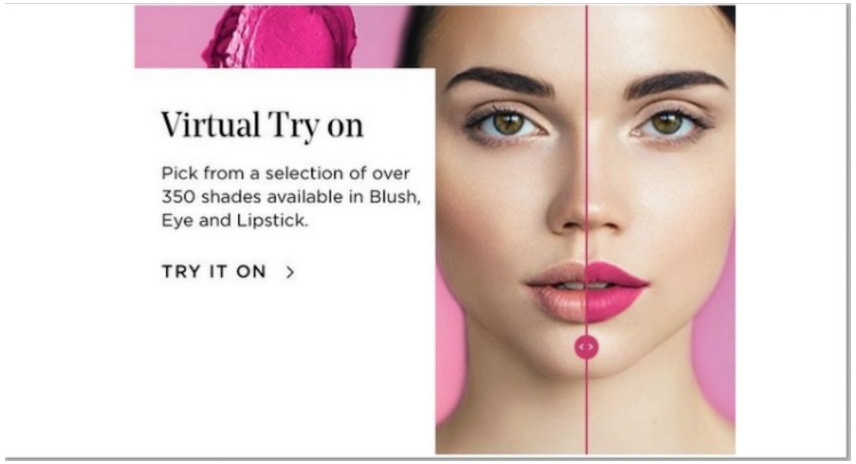
Dynamics-Inspired Garment Reconstruction and Synthesis for Simulation-Based Virtual Try-On

Junbang Liang

Ph.D. Thesis Defense
May 14, 2021

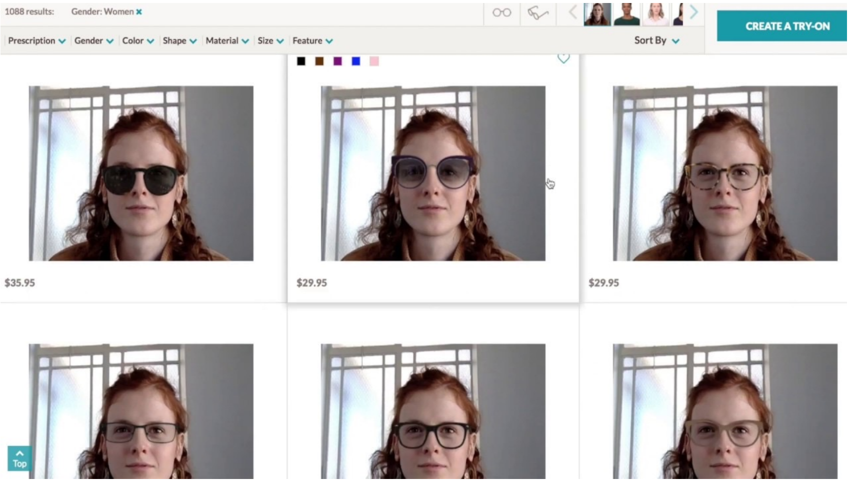
Committee members: Dinesh Manocha (chair), Min Wu, Ming Lin, Soheil Feizi, Tom Goldstein

Virtual Try-On



www.ulta.com

www.facecake.com



www.zennioptical.com/

www.timberland.com

Virtual Reality

Games (CyberPunk)

Meetings
(www.roomkey.co/workshops)

Movies (Ready Player One)

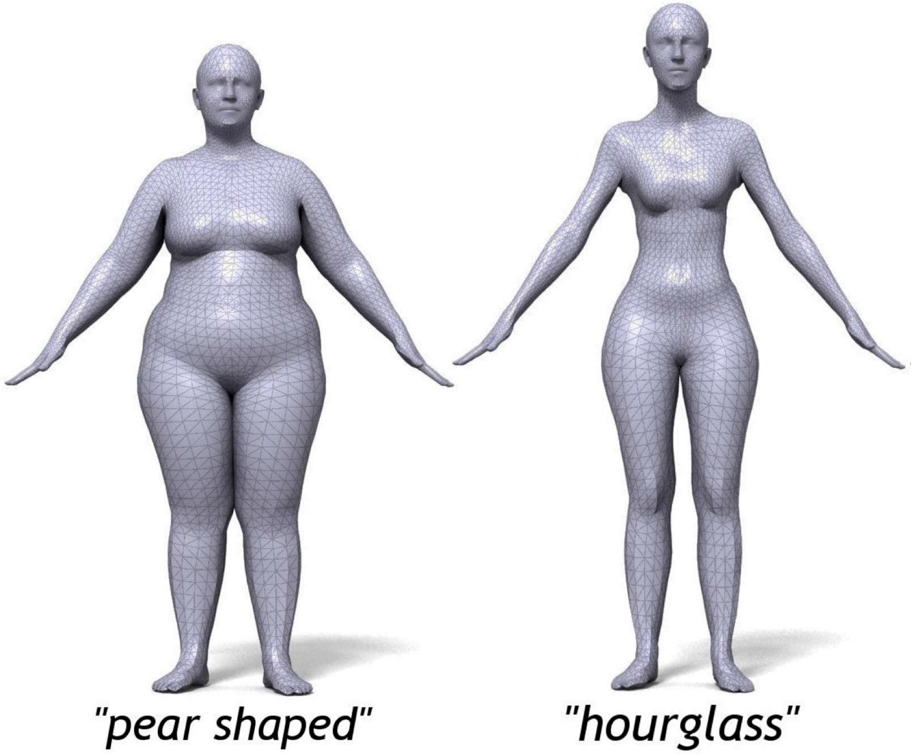
Physical Simulation

Let It Go (Frozen)

Simulation-Based Try-On?

Challenges for Virtual Try-On

- Accurate reconstruction of human.
- Faithful estimation of garment materials.
- User-friendly recovery of garment geometry.
- Real-time cloth simulation system.
- Fast and realistic visual rendering.



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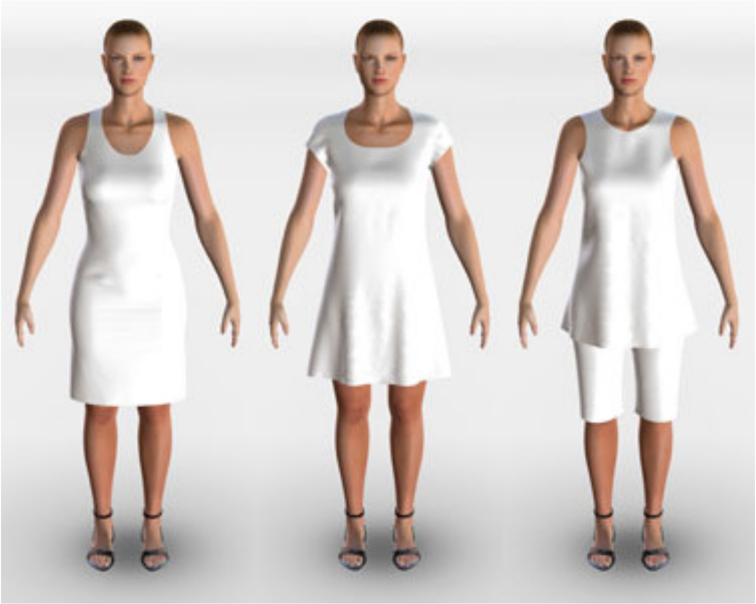

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Thesis Statement

- *Dynamic constraints can be effectively enforced in human body estimation, garment material and geometry reconstruction, simulation acceleration, and draping prediction for virtual try-on systems, by coupling machine learning and optimization methods with cloth simulation.*

Proposed Solutions

- Accurate reconstruction of human.
  - Shape-aware human body recovery using multi-view images
- Faithful estimation of garment materials.
  - Differentiable cloth simulation for material optimization
- User-friendly recovery of garment geometry.
  - Joint estimation of human and garment from video
- Real-time cloth simulation system.
  - Time-domain parallelization for accelerating cloth simulation
- Fast and realistic visual rendering.
  - Dynamics-Inspired garment draping prediction

Thesis Statement:

Dynamic constraints can be effectively enforced in ***human body estimation****, garment material and geometry reconstruction, simulation acceleration, and draping prediction for virtual try-on systems, by coupling* ***machine learning*** *and optimization methods with cloth simulation.*

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- Background
- Reconstruction
  - Shape-aware human body recovery using multi-view images
  - Differentiable cloth simulation for material optimization
  - Joint estimation of human and garment from video
- Synthesis
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Introduction to Simulation

- What is simulation?
    - Given the states of objects, compute their evolutions through time
- Why simulation?
    - Approximation to the real world
        - Design, control, etc.
    - Convenient: no extra equipment required
- How to do simulation?

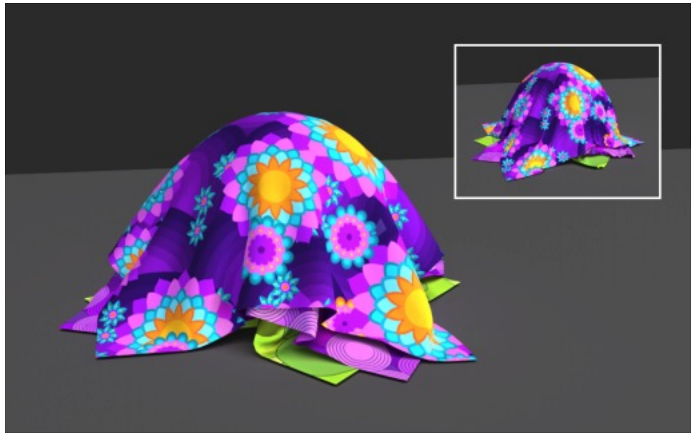
Introduction to Simulation

- Partial differential equation of Newton's law:
  - Solve $y(x,t)$ satisfying $\frac{\partial^2 y}{\partial t^2} = \frac{1}{\rho} f(y, \frac{\partial y}{\partial x})$ where $y(x,0) = y_0(x)$
- Discretization to ordinary differential equations:
  - Solve $\boldsymbol{y}(t) = [y(x_i,t)]_i$ satisfying $\frac{\partial^2 \boldsymbol{y}}{\partial t^2} = \frac{1}{m} \boldsymbol{f}(\boldsymbol{y}, \frac{\Delta \boldsymbol{y}}{\Delta \boldsymbol{x}})$ where $\boldsymbol{y}(0) = [y_0(x_i)]_i$

y: Position
x: Configuration space
t: Time
f: Force field
ρ: Density
m: Mass
$[*]_i$: Vector stacked by elements *

Collision Handling

- Challenge: 0-thickness deformable mesh
  - Self-collision
  - Non-penetration (continuous detection)
  - Dynamic/static friction



- State-of-the-art solutions
  - Quadratic optimization [Narain et al., SIGGRAPH Asia 2012]
  - Dry frictional contact [Ly et al., TOG 2020]

Inverse Problems

- Definition: given the simulation results (images, videos, meshes, etc.), estimate the initial/internal values of the system
- Traditional solution:
  - Gradient-free optimization [Yang et al., TOG 2018]
  - Data-driven methods [Bouman et al., ICCV 2013]
- Learning-based solution:
  - Simulation + supervised learning [Yang et al., ICCV 2017]

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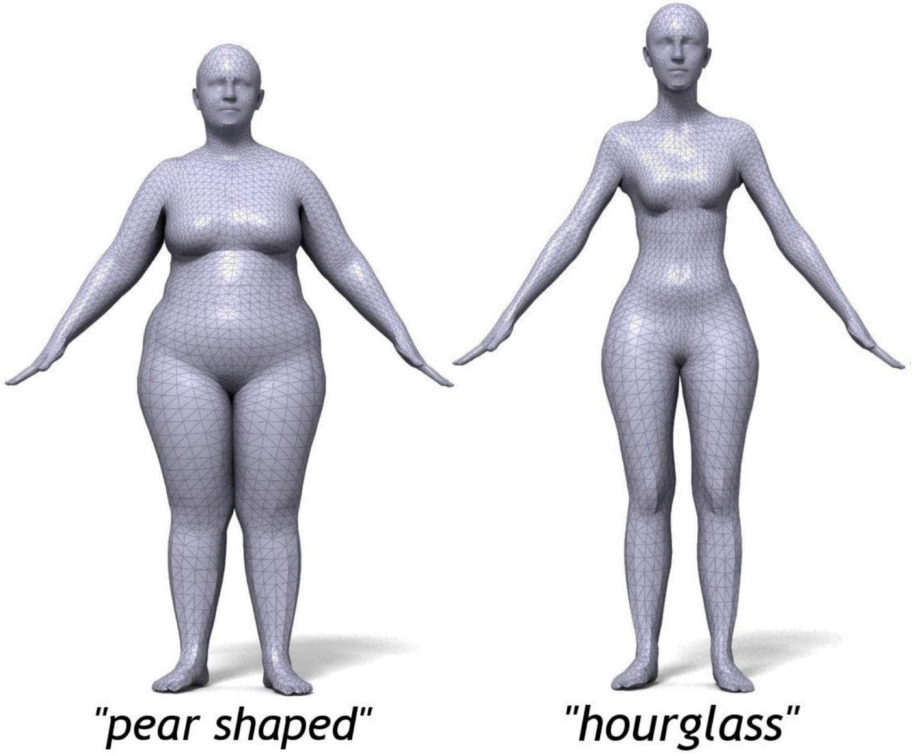
Junbang Liang, Ming C. Lin. Shape-Aware Human Pose and Shape Reconstruction Using Multi-View Images. ICCV 2019

Motivation

- Accurate reconstruction of human.
  - Accuracy: human shape
  - Convenience: predicting from RGB images



Limitations with State-of-the-Art

- 2D/3D pose from images [Mehta et al., 3DV 2017]
  - *Skeleton Only*
- Pose and shape from scanned meshes [Pons-Moll et al., TOG 2017]
  - *Expensive and less widely applicable*
- Optimization-based pose and shape from images [Dibra et al., 3DV 2016]
  - *Long computation time*
- Learning-based pose and shape from images [Kanazawa et al., CVPR 2017]
  - *No supervision on human shapes*

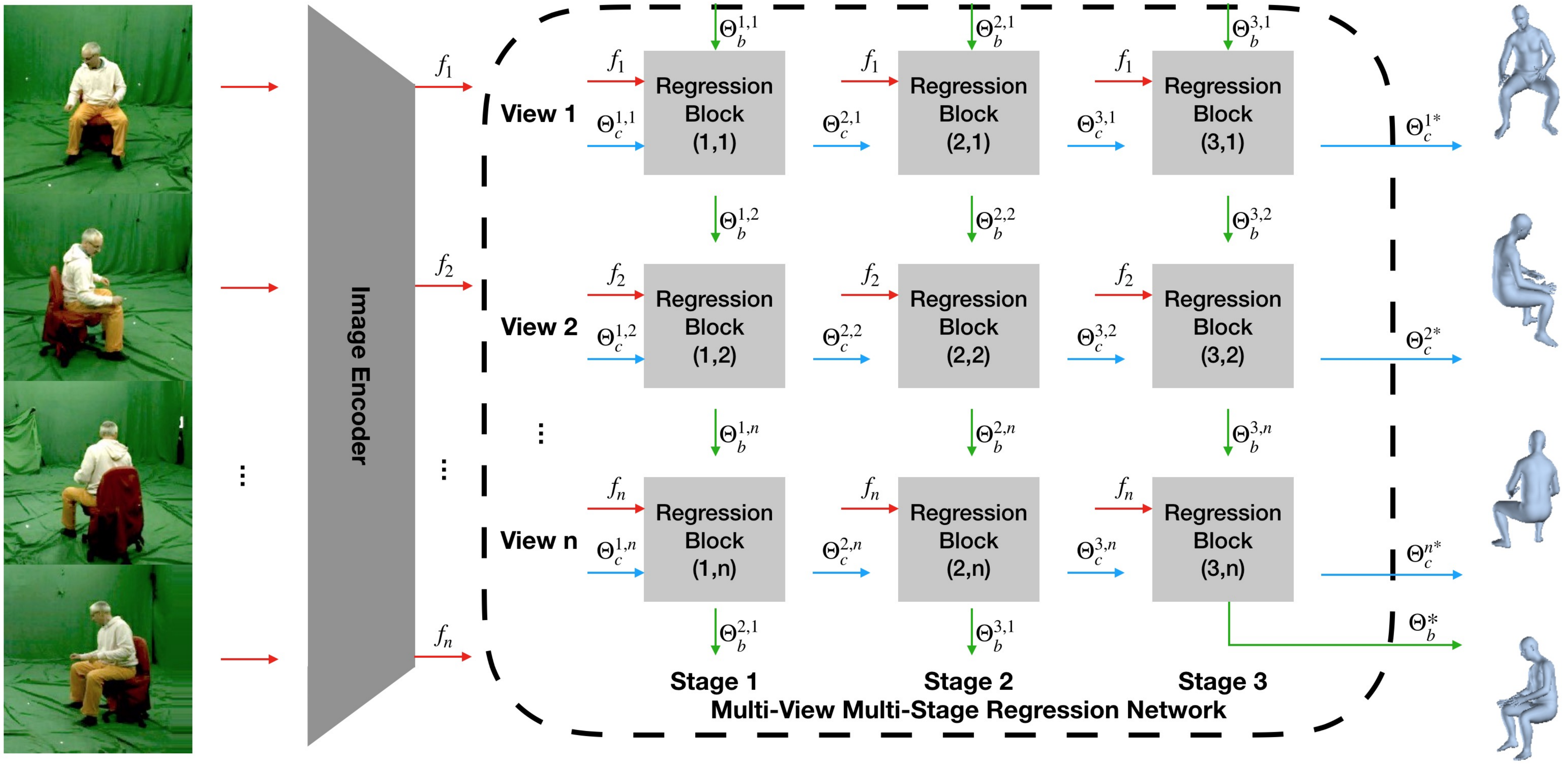
Our Contributions

- First shape-aware human body reconstruction model
  - Scalable multi-view learning framework
  - A large synthetic dataset with ground-truth parameters

Problem Definition

- Input: a person in multiple images
  - # views: 1-4
- Output: the body parameters of the person

Network Structure



Network Structure

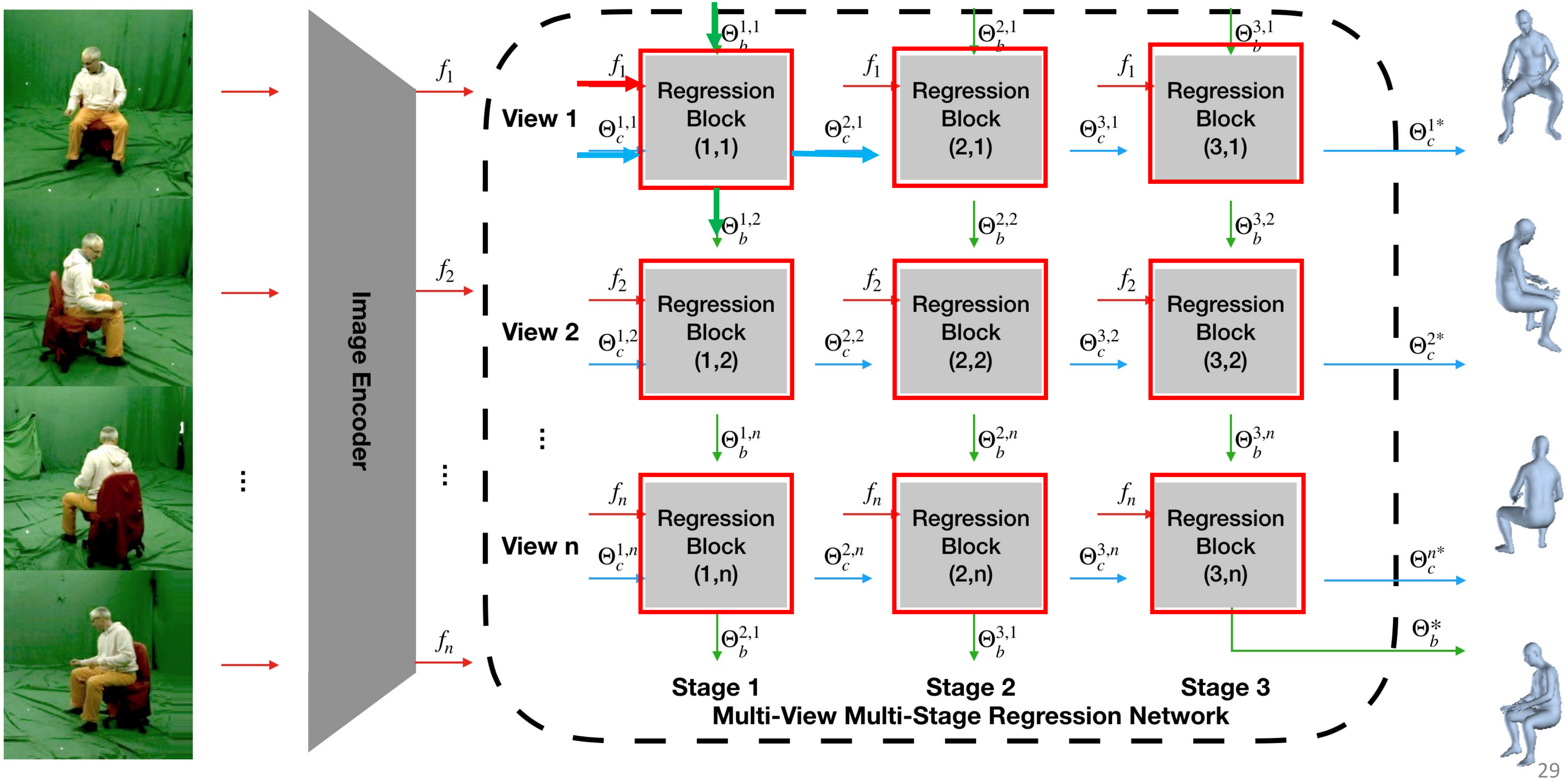
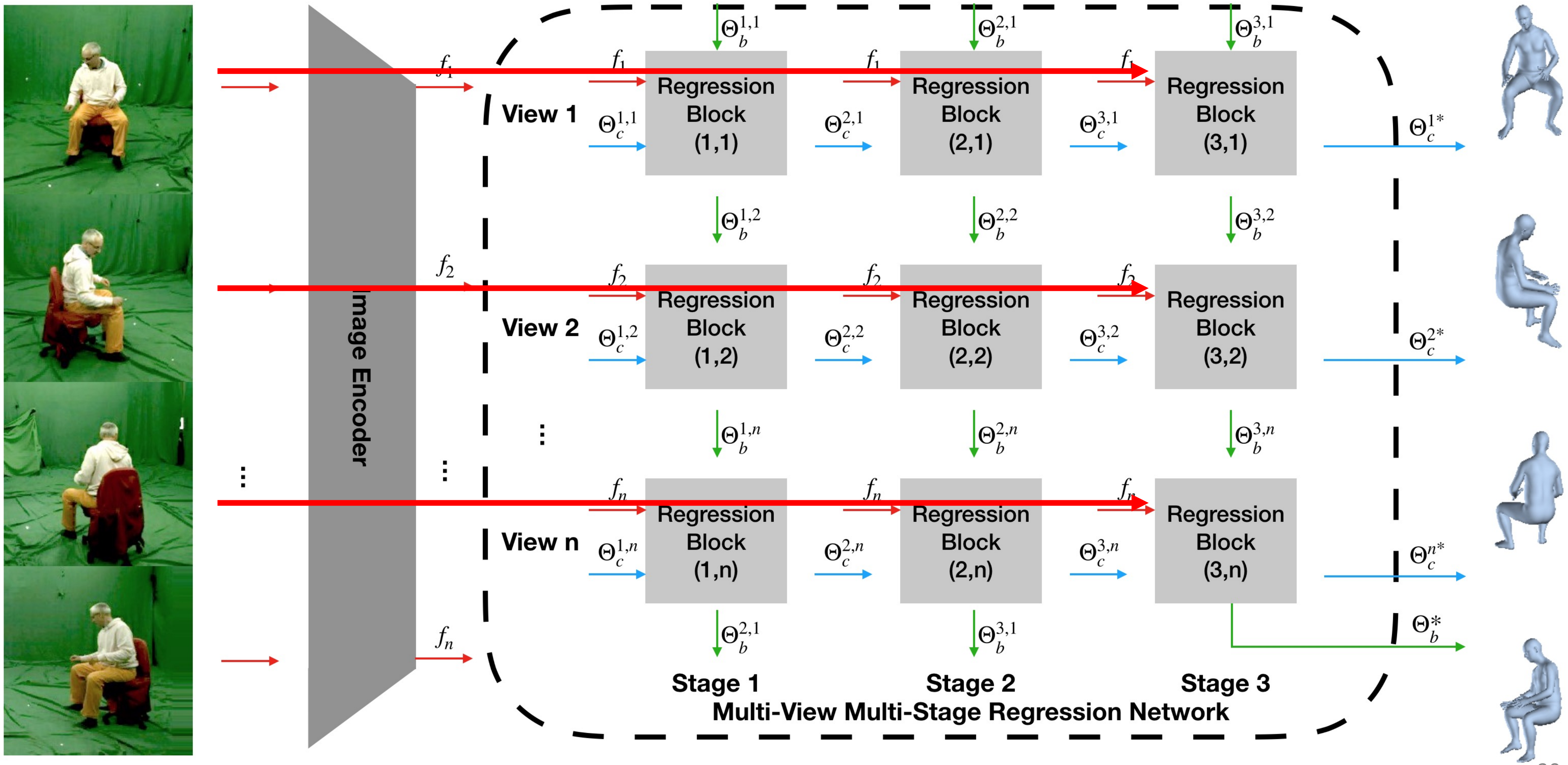
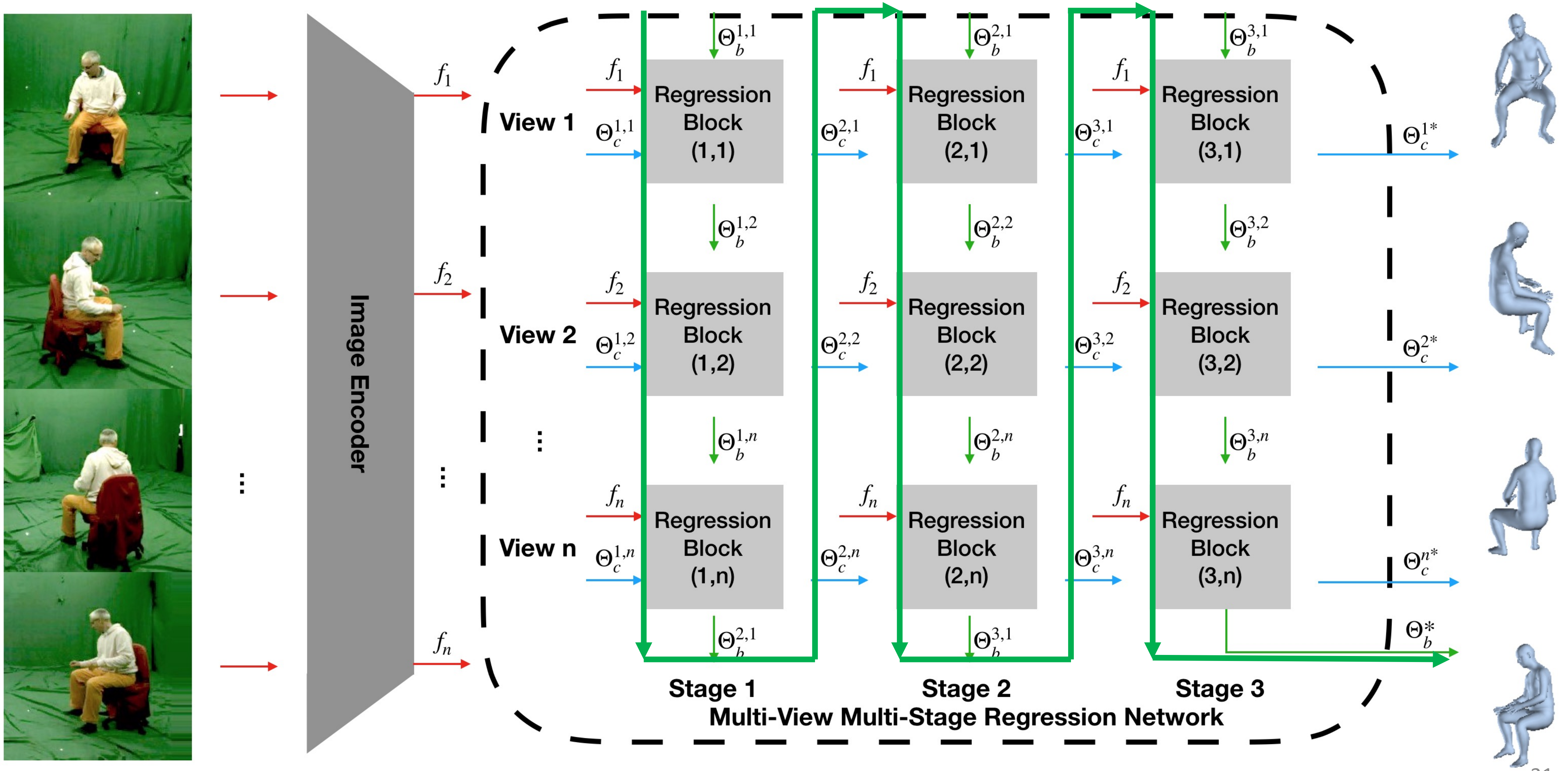


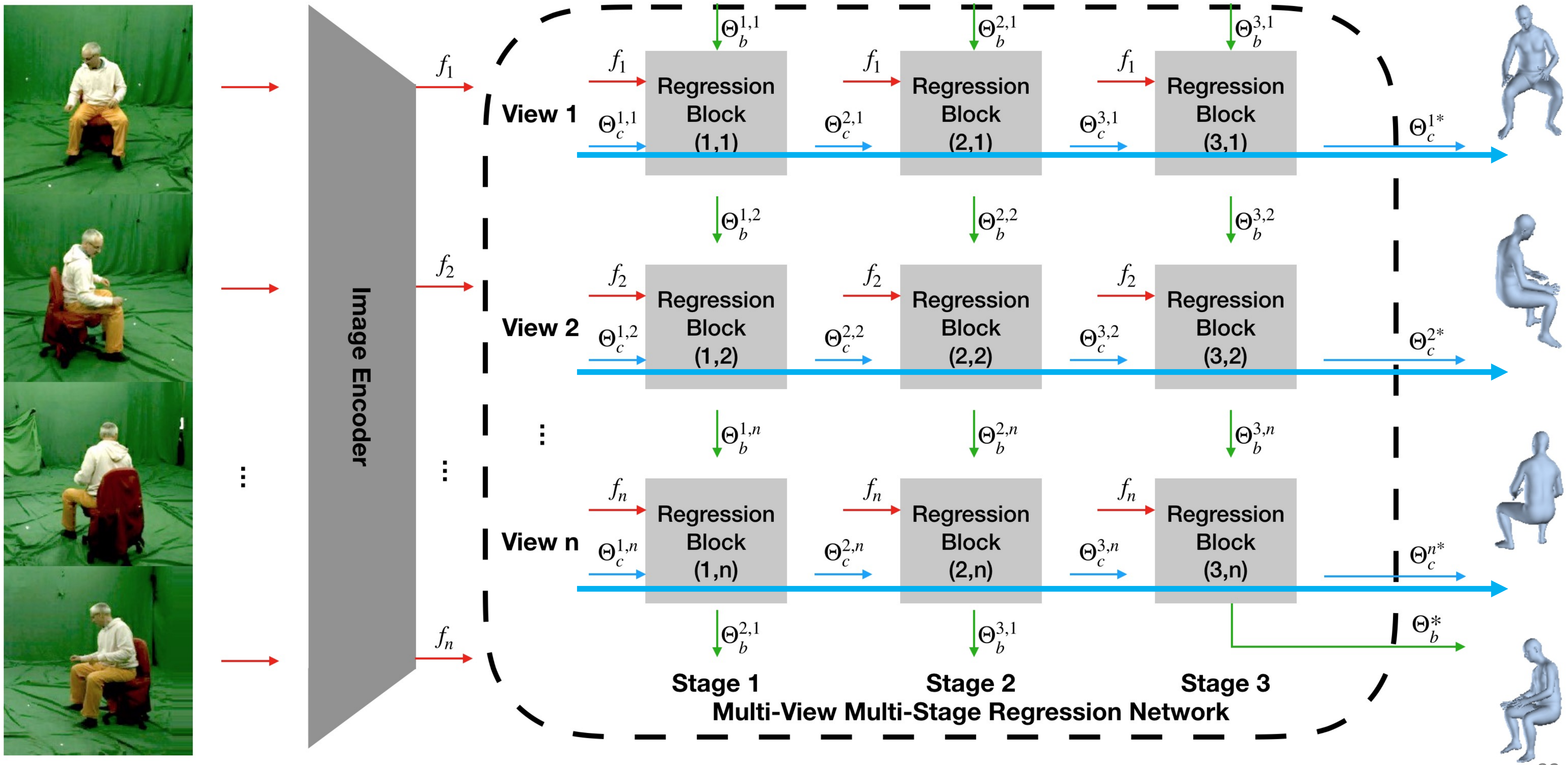
Image Feature Flow



Human Parameter Flow

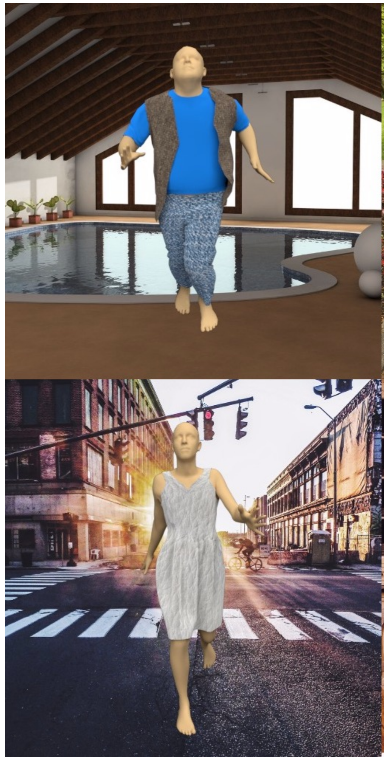


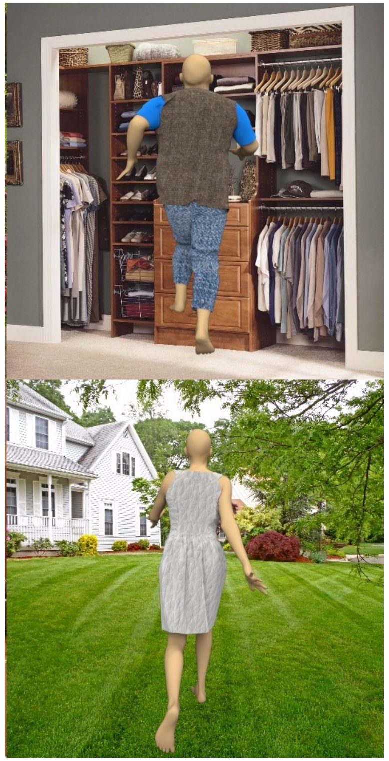
Camera Parameter Flow



Synthetic Data Generation

- CMU MoCap + Shape variation + cloth simulation + rendering





Results

- Metric:
  - Body pose: Mean Per Joint Position Error
  - Body shape: Hausdorff Distance

Method	MPJPE/HD w/ syn. training	MPJPE/HD w/o syn. training
HMR	42/83	89/208
Ours (single)	44/65	102/283
Ours (multi)	**27/53**	**84**/273

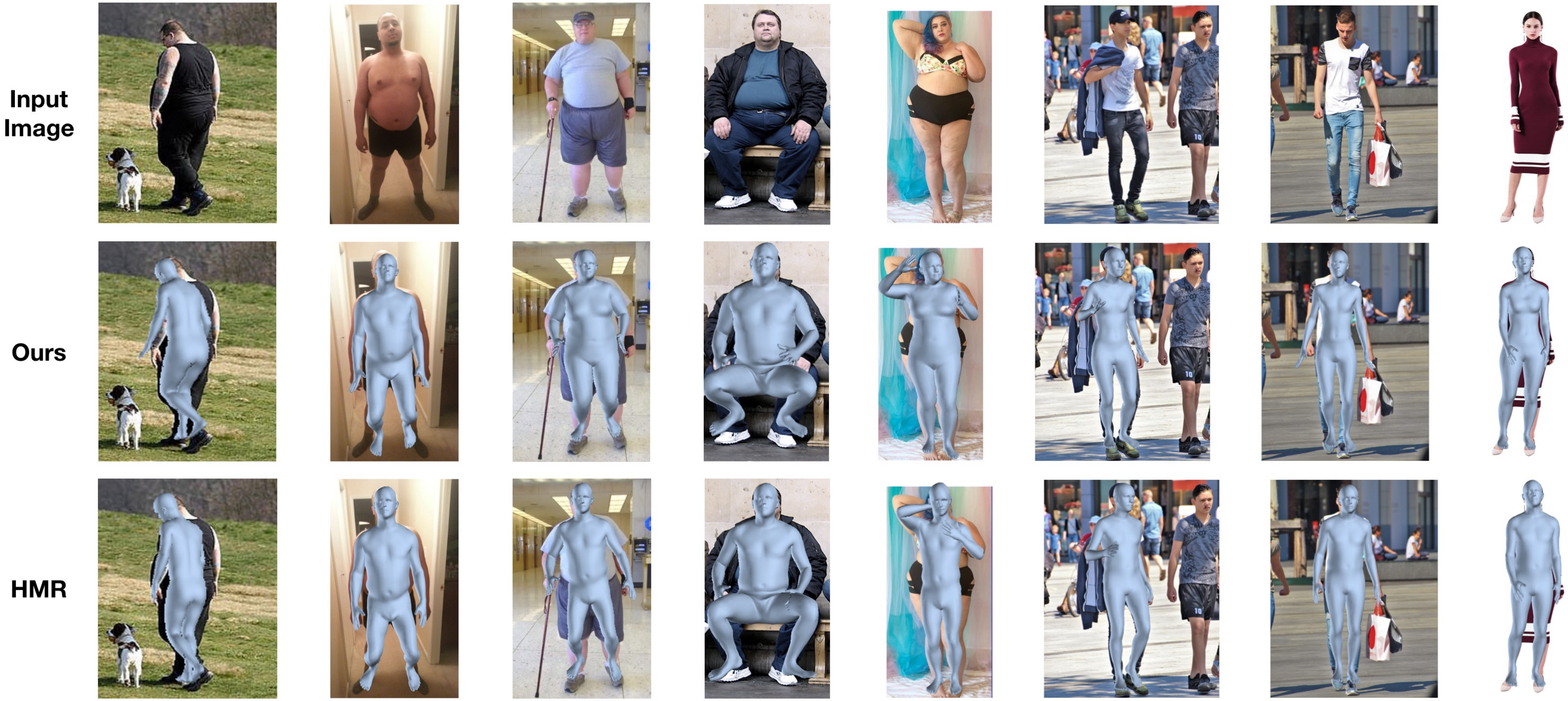
Our method has smaller errors even with single view input, and performs much better using multi view images.

Qualitative Comparison

(a) The input image. (b) Our result. (c) HMR.

Our method has better shape recovery in non-standard human shape input.

Qualitative Comparison



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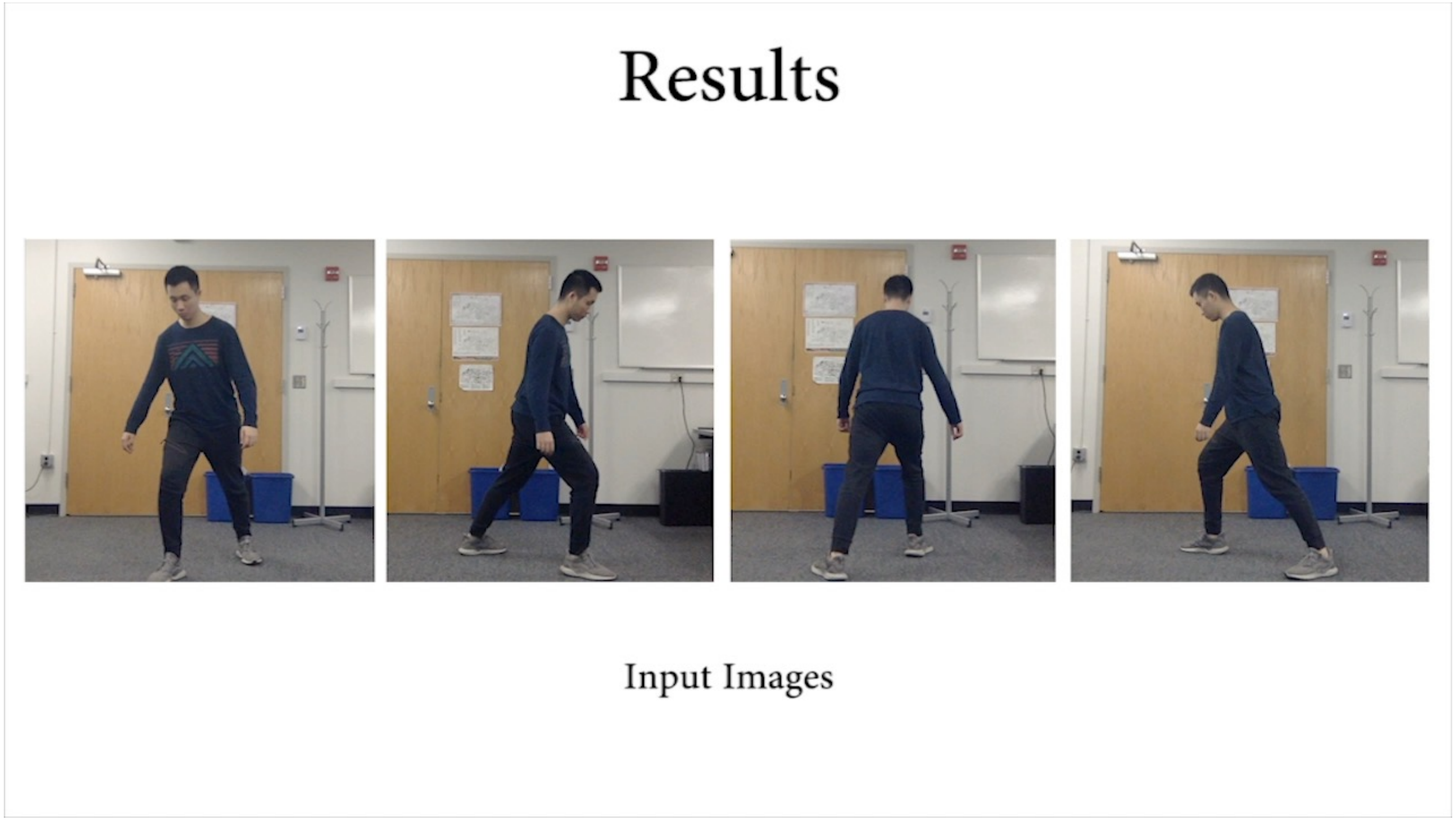
Qualitative Comparison



Our method has better pose recovery with multi-view images.

Summary

- First shape-aware human estimation model
  - Multi-view iterative network
    - Can accept any number of views as input
  - Synthetic data generation pipeline
    - Enable direct shape supervision
- Performance improvement on human reconstruction
  - Better pose estimation using multi-view input
  - Better shape estimation on non-standard human body

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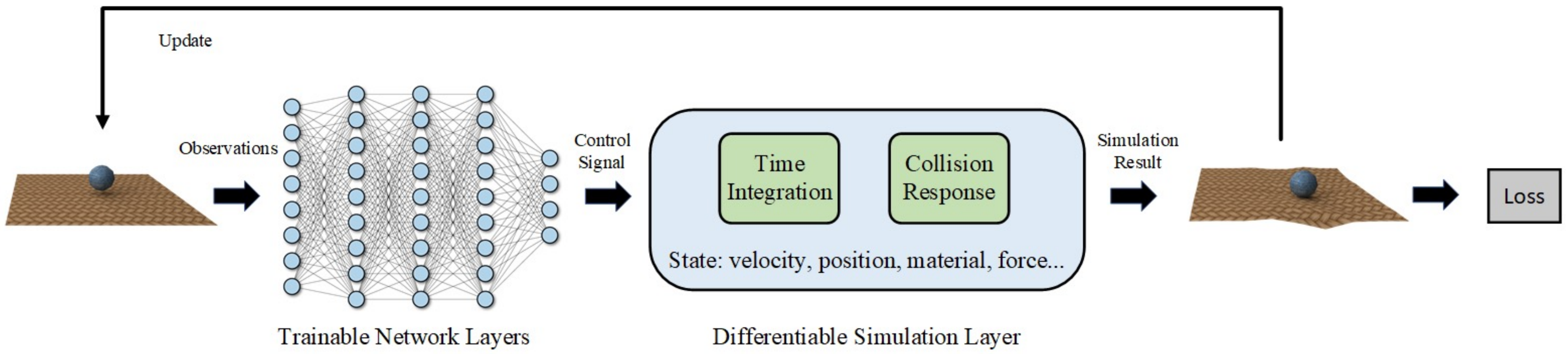
Junbang Liang, Ming C. Lin, Vladlen Koltun. Differentiable Cloth Simulation for Inverse Problems. NeurIPS 2019

Motivation

- Faithful estimation of garment materials.
  - Works as a layer in deep neural network
  - Enables gradient-based optimization, learning and control



Limitations with State-of-the-Art

- Differentiable rigid body simulation [Degrave et al., Frontiers in Neurorobotics 2019]
  - *Formulation not scalable to high dimensionality*

- Learning-based physics [Li et al., ICLR 2018]
  - *Unable to guarantee physical correctness*

Our Contributions

- The first differentiable cloth simulation
  - Dynamic collision detection to reduce collision dimensionality
  - Gradient computation of collision response using implicit differentiation
  - Optimized backpropagation using QR decomposition

Collision Response

- Objective formulation: Quadratic Programming:

$$\begin{aligned} \underset{\mathbf{z}}{\text{minimize}} \quad & \frac{1}{2}(\mathbf{z}-\mathbf{x})^\top \mathbf{W}(\mathbf{z}-\mathbf{x}) \\ \text{subject to} \quad & \mathbf{Gz}+\mathbf{h} \leq \mathbf{0} \end{aligned}$$

z: optimized vertex positions
W: weight matrix
G, **h**: constraint matrices

Gradients of Collision Response

- Karush–Kuhn–Tucker condition:

$$\begin{aligned} \mathbf{W}\mathbf{z}^* - \mathbf{W}\mathbf{x} + \mathbf{G}^\top \lambda^* &= 0 \\ D(\lambda^*)(\mathbf{G}\mathbf{z}^* + \mathbf{h}) &= 0 \end{aligned}$$

- Implicit differentiation:

$$\begin{bmatrix} \mathbf{W} & \mathbf{G}^\top \\ D(\lambda^*)\mathbf{G} & D(\mathbf{G}\mathbf{z}^* + \mathbf{h}) \end{bmatrix} \begin{bmatrix} \partial \mathbf{z} \\ \partial \lambda \end{bmatrix} = \begin{bmatrix} \mathbf{W}\partial \mathbf{x} - \partial \mathbf{G}^\top \lambda^* \\ -D(\lambda^*)(\partial \mathbf{G}\mathbf{z}^* + \partial \mathbf{h}) \end{bmatrix}$$

z: current vertex positions
W: weight matrix
G, **h**: constraint matrices
λ: Augmented Lagrangian multiplier
D(): diagonalize operator
*: optimization output

Gradients of Collision Response

- Solution:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = \mathbf{d}_{\mathbf{z}}^{T}\mathbf{W}$$
$$\frac{\partial \mathcal{L}}{\partial \mathbf{G}} = -D(\lambda^*)\mathbf{d}_{\lambda}\mathbf{z}^{*\top} - \lambda^*\mathbf{d}_{\mathbf{z}}^{\top}$$
$$\frac{\partial \mathcal{L}}{\partial \mathbf{h}} = -\mathbf{d}_{\lambda}^{T} D(\lambda^*).$$

where d_z and d_λ is provided by the linear system:

$$\begin{bmatrix} \mathbf{W} & \mathbf{G}^{\top}D(\lambda^*) \\ \mathbf{G} & D(\mathbf{G}\mathbf{z}^* + \mathbf{h}) \end{bmatrix} \begin{bmatrix} \mathbf{d}_{\mathbf{z}} \\ \mathbf{d}_{\lambda} \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial \mathbf{z}}^{\top} \\ \mathbf{0} \end{bmatrix}$$

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D(): diagonalize operator
*: optimization output
$\mathcal{L}$: loss function

Acceleration of Gradient Computation

- Explicit solution of the linear equation:

$$\mathbf{d}_{\mathbf{z}} = \sqrt{\mathbf{W}}^{-1}(\mathbf{I} - \mathbf{Q}\mathbf{Q}^\top)\sqrt{\mathbf{W}}^{-1}\frac{\partial \mathcal{L}}{\partial \mathbf{z}}^\top$$

$$\mathbf{d}_{\lambda} = D(\lambda^*)^{-1}\mathbf{R}^{-1}\mathbf{Q}^\top\sqrt{\mathbf{W}}^{-1}\frac{\partial \mathcal{L}}{\partial \mathbf{z}}^\top$$

where Q and R is obtained from:

$$\sqrt{\mathbf{W}}^{-1}\mathbf{G}^\top = \mathbf{Q}\mathbf{R}$$

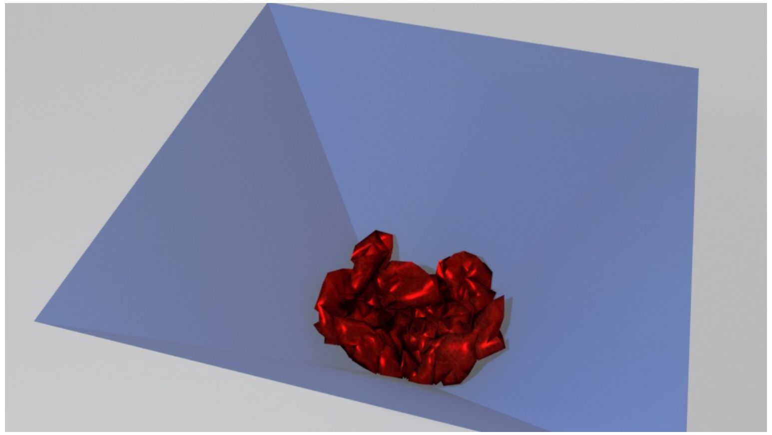
- Theoretical speedup: $O((n+m)^3)$ → $O(nm^2)$

z: current vertex positions
W: weight matrix
G, **h**: constraint matrices
λ: Augmented Lagrangian multiplier
D(): diagonalize operator
*: optimization output
$\mathcal{L}$: loss function
n: number of DOFs
m: number of constraints

Results: Performance Speedup

- Scene setting: A large piece of cloth crumpled inside a pyramid.

Mesh resolution	Baseline Matrix size	Baseline Runtime (s)	Ours Matrix size	Ours Runtime (s)	Speedup Matrix size	Speedup Runtime
16x16	599 ± 76	0.33 ± 0.13	$\mathbf{66 \pm 26}$	$\mathbf{0.013 \pm 0.0019}$	8.9	25
32x32	1326 ± 23	1.2 ± 0.10	$\mathbf{97 \pm 24}$	$\mathbf{0.011 \pm 0.0023}$	13	112
64x64	2024 ± 274	4.6 ± 0.33	$\mathbf{242 \pm 47}$	$\mathbf{0.072 \pm 0.011}$	8.3	64



The runtime performance of gradient computation is significantly improved by up to two orders of magnitude.

Application: Material Estimation

- Scene setting: A piece of cloth hanging under gravity and a constant wind force.

Initial guess

Optimized result

Target

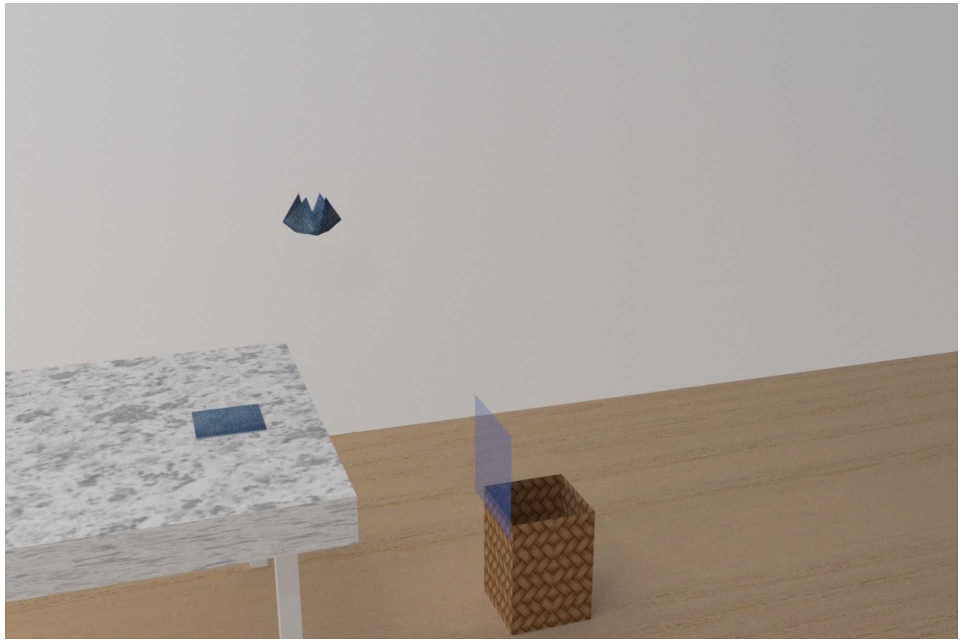
Method	Runtime (sec/step/iter)	Density Error (%)	Non-Ln Streching Stiffness Error (%)	Ln Streching Stiffness Error (%)	Bending Stiffness Error (%)	Simulation Error (%)
Baseline	-	68 ± 46	74 ± 23	160 ± 119	$\mathbf{70 \pm 42}$	12 ± 3.0
L-BFGS [30]	2.89 ± 0.02	4.2 ± 5.6	64 ± 34	72 ± 90	$\mathbf{70 \pm 43}$	4.9 ± 3.3
Ours	$\mathbf{2.03 \pm 0.06}$	$\mathbf{1.8 \pm 2.0}$	$\mathbf{57 \pm 29}$	$\mathbf{45 \pm 41}$	77 ± 36	$\mathbf{1.6 \pm 1.4}$

Our method achieves the best runtime performance and the smallest overall error.

Application: Motion Control

- Scene setting: A piece of cloth being lifted and dropped to a basket.

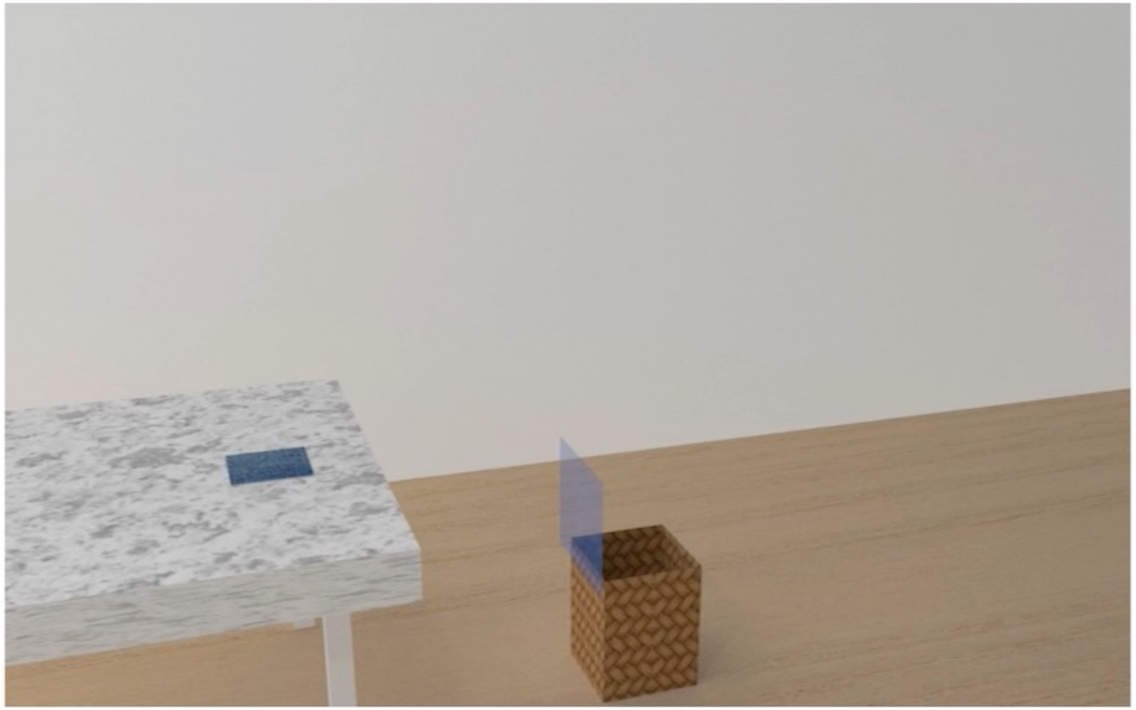
Method	Error (%)	Samples
Point Mass	111	–
PPO [18]	432	10,000
Ours	**17**	**53**
Ours+FC	39	108



Our method achieves the best performance with a much smaller number of simulation samples.

Visualization

Motion Control - Optimization



Baseline - Treating as point mass

Summary

- First differentiable cloth simulation
  - Applicable to optimization tasks (e.g. fabric material estimation)
  - Embedded in neural networks for learning and control
  - Fast backpropagation for collision response

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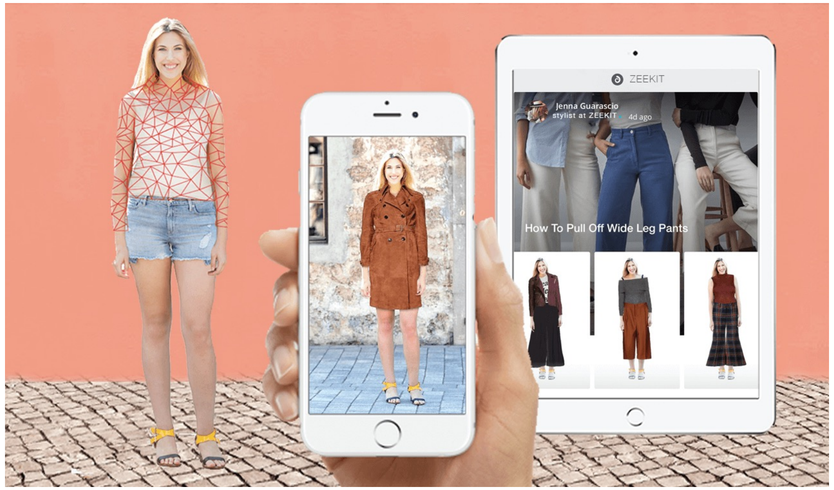
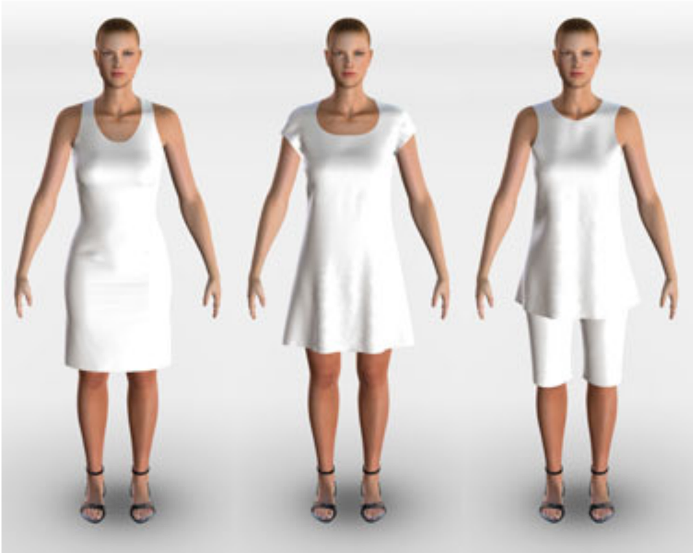
Junbang Liang, Ming C. Lin. Fabric Material Estimation from Video Using Multi-Scale Geometric Auto-Encoder. ICCV 2021 submission

Motivation

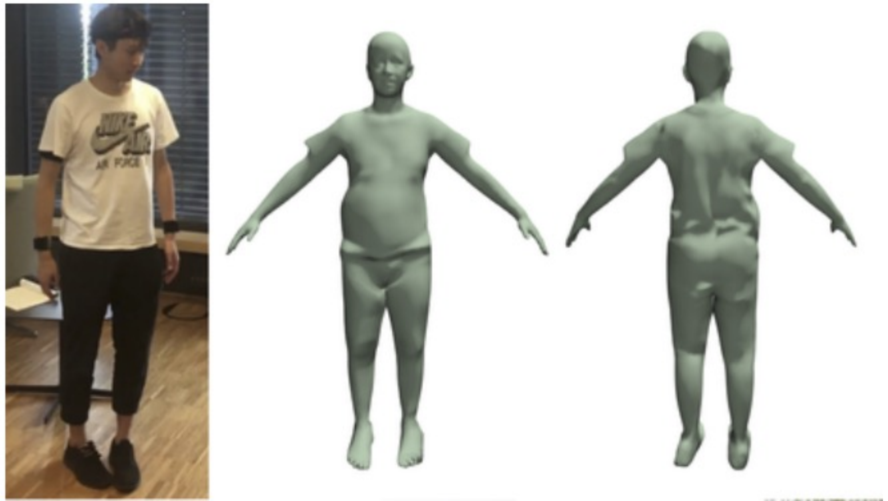
- User-friendly recovery of dressed garments.
  - Real-to-virtual garment cloning
    - Geometry + material
  - Ability to account for different topologies





Limitations with State-of-the-Art

- Garment reconstruction from images [Alldieck et al., ICCV 2019]
  - *Heavy human assistance*
  - *Simple topology*
- Cloth material recovery from videos [Yang et al., ICCV 2017]
  - *Simplified input with fixed scenarios*



Key Idea

- Use temporal garment geometry features to infer the fabric material
- Use an auto-encoder to model garment geometry

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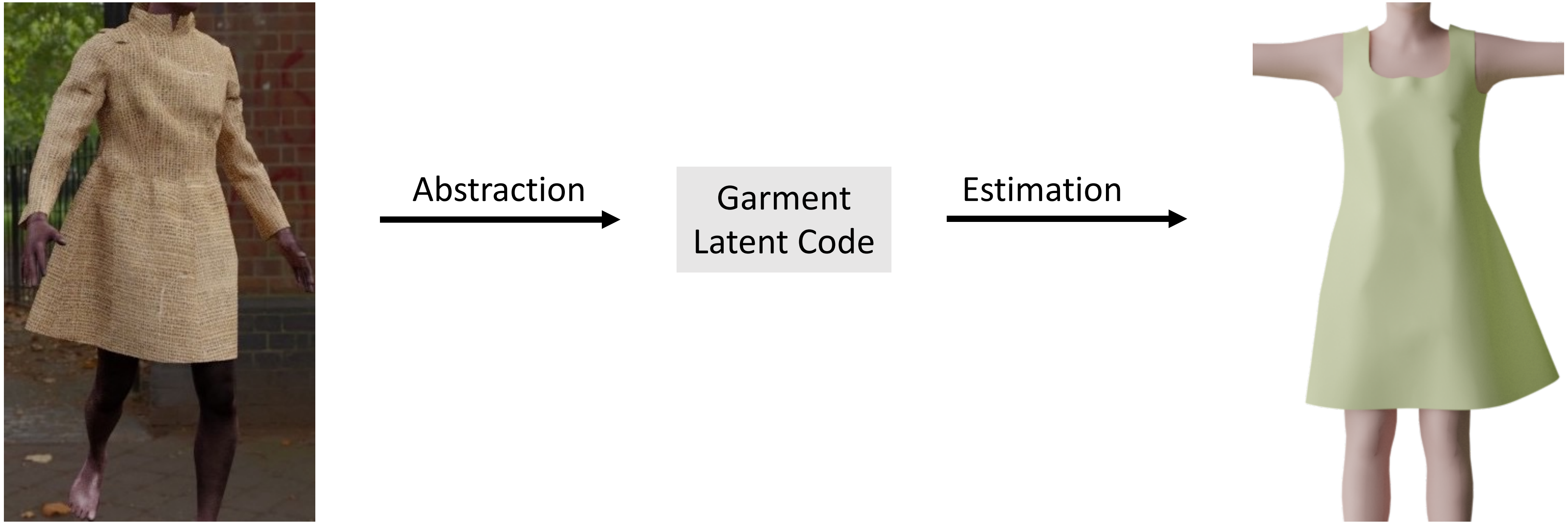
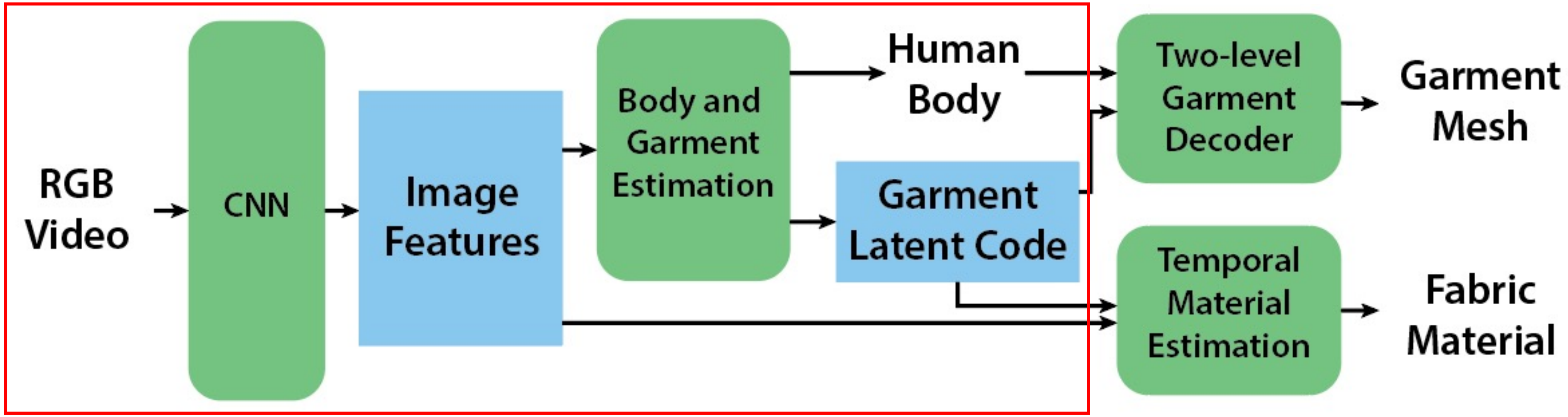


Our Contribution

- The first end-to-end neural network for fabric material recovery of dressed garments from one single RGB video.
  - A two-level auto-encoder for garments
    - The first parametric garment model that can account for arbitrary topologies
  - Joint estimation of human body and apparels
    - A closed-loop structure for multi-tasking
  - Garment features for material classification

System Outline

- Per-frame estimation of human and cloth
- Temporal information for material prediction



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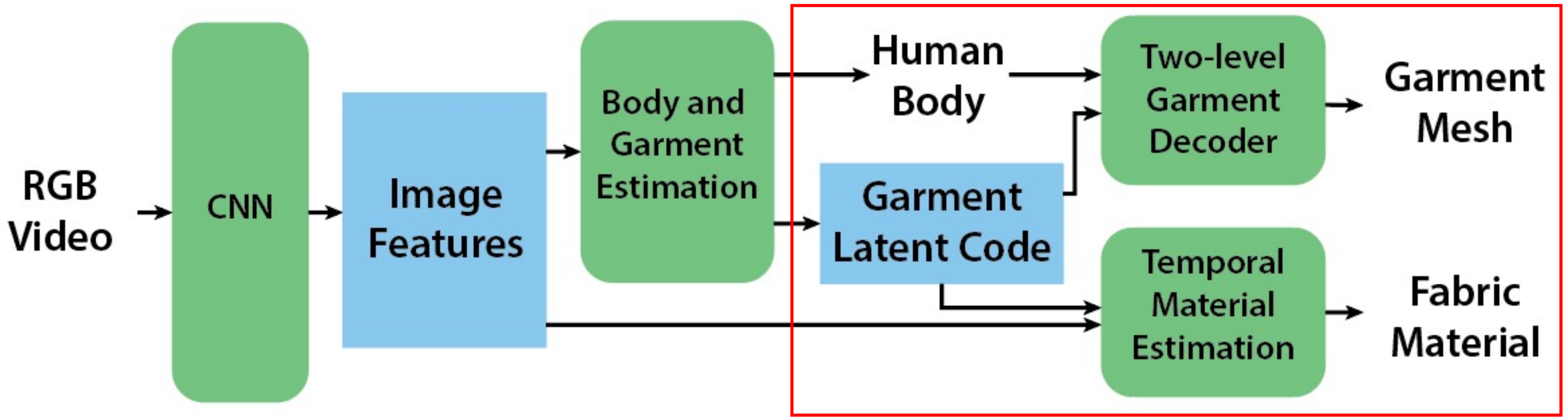
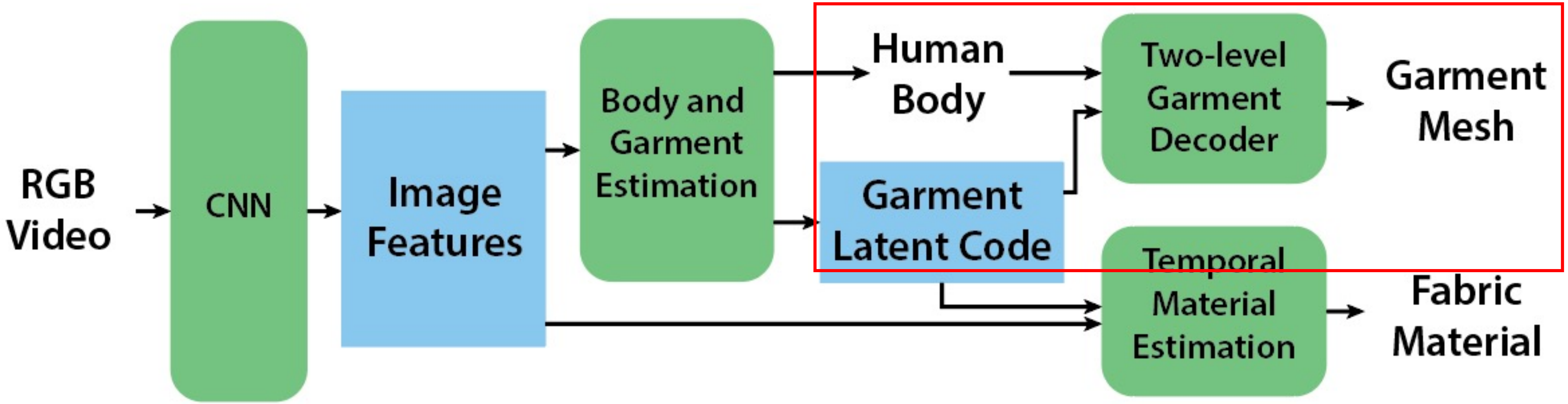
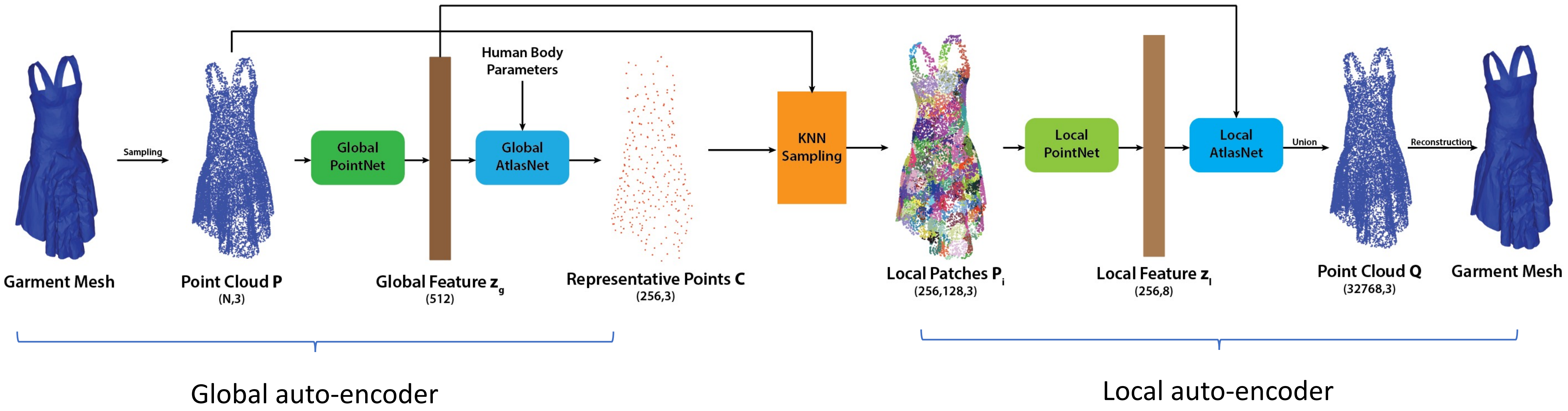


Garment Auto-Encoder



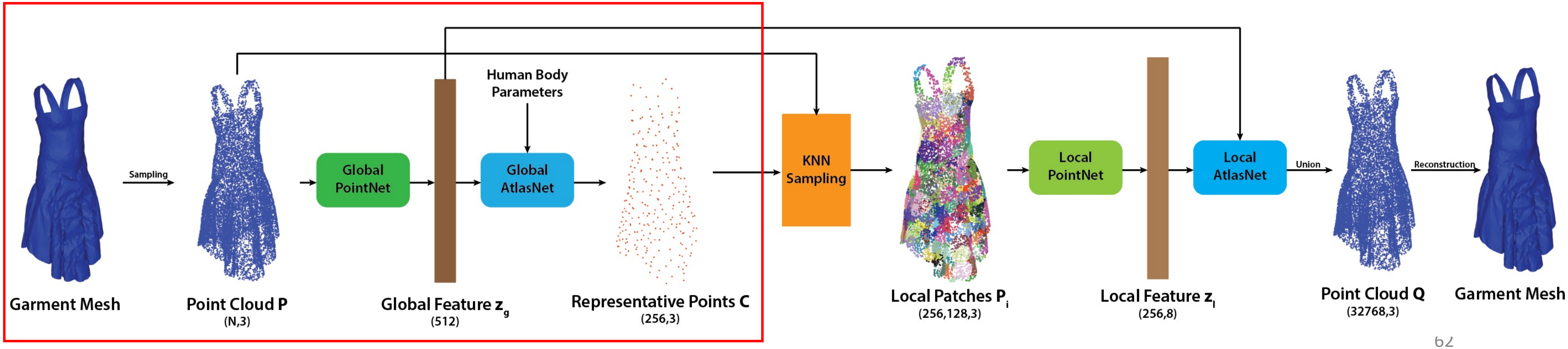
Garment Auto-Encoder

- Two-level auto-encoder for point clouds



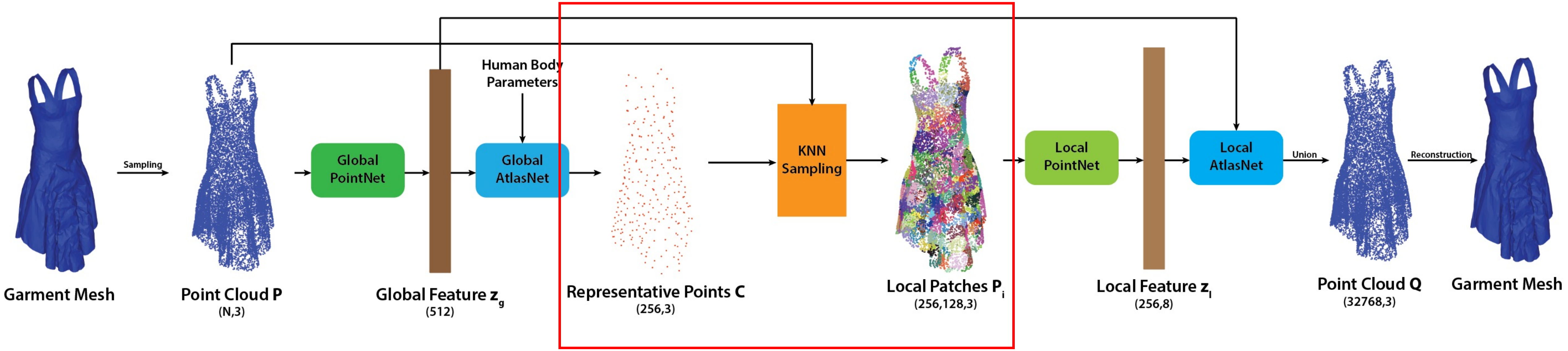
Global Auto-Encoder

- PointNet [Qi et al. 2016] + AtlasNet [Deprelle et al. 2019]
  - Low frequency shape
  - Conditioned on human body parameters
  - Representative points (patch centers) proposed by the network



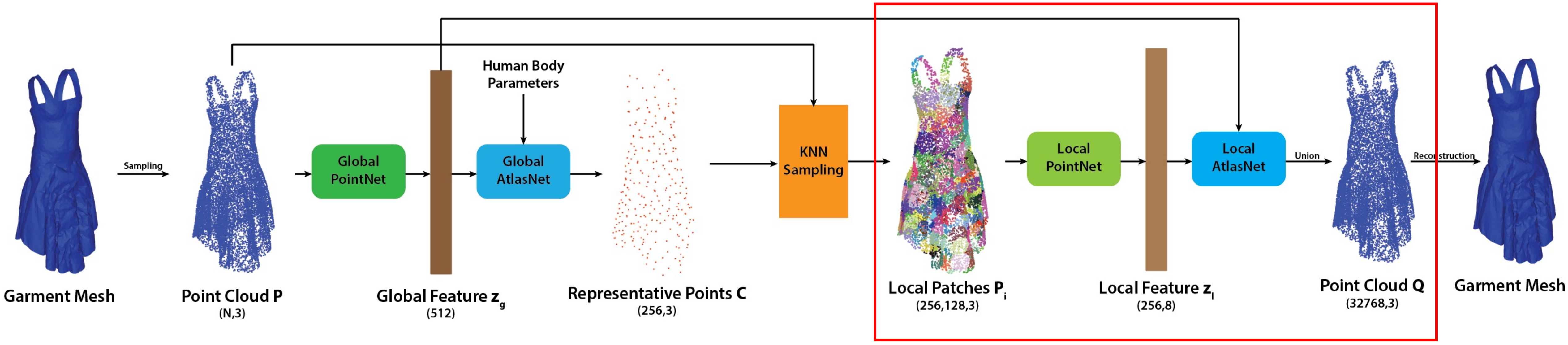
Local Patch Extraction

- K-Nearest-Neighbor
  - Simpler geometry: easy to auto-encode



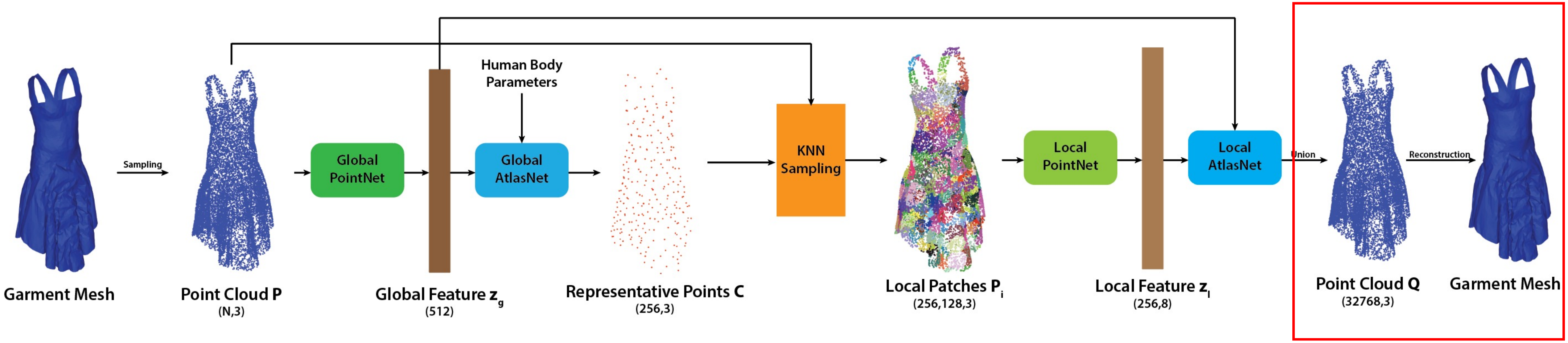
Local Auto-Encoder

- PointNet + AtlasNet
  - Local shape distribution
  - Conditioned on Patch Center and the global latent code



Mesh Reconstruction

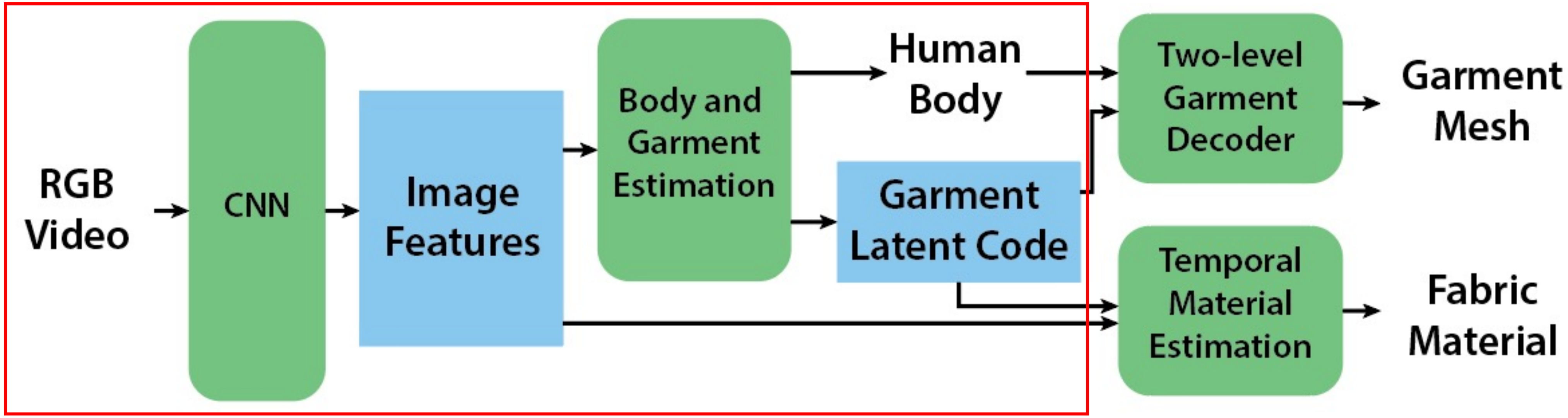
- Screen Poisson
- Vertex-filtering + wrinkle optimization



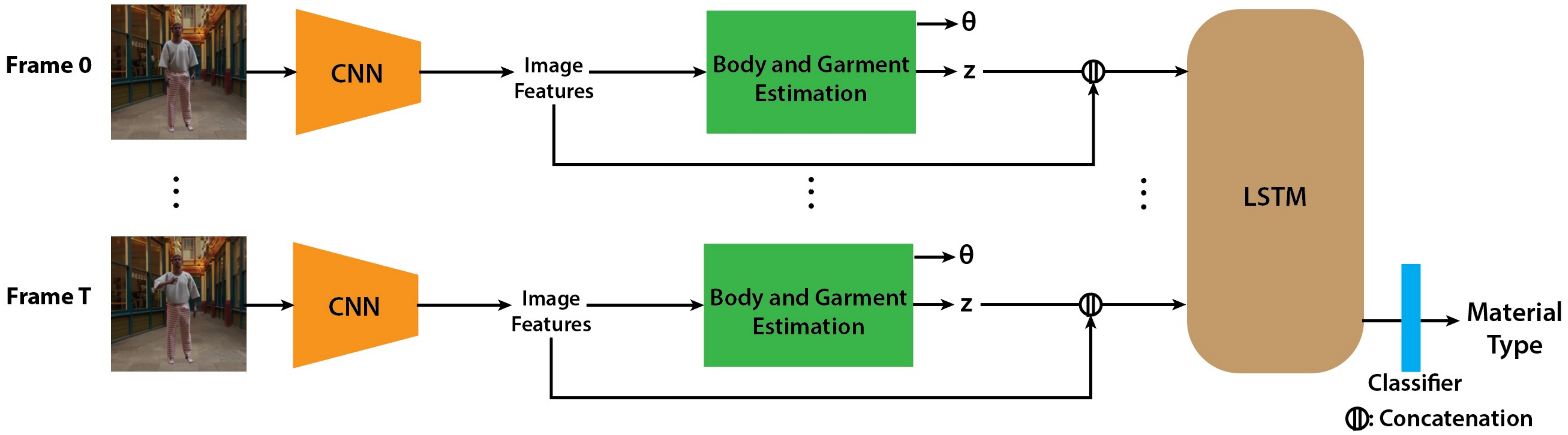
Key Improvements

- Two-level decoder
  - Disentangle global shape and local deformation
- Separate patches
  - Avoid interwound or vanished patches
- Human body parameters prior
  - Higher accuracy for global shape reconstruction

Appearance Estimation



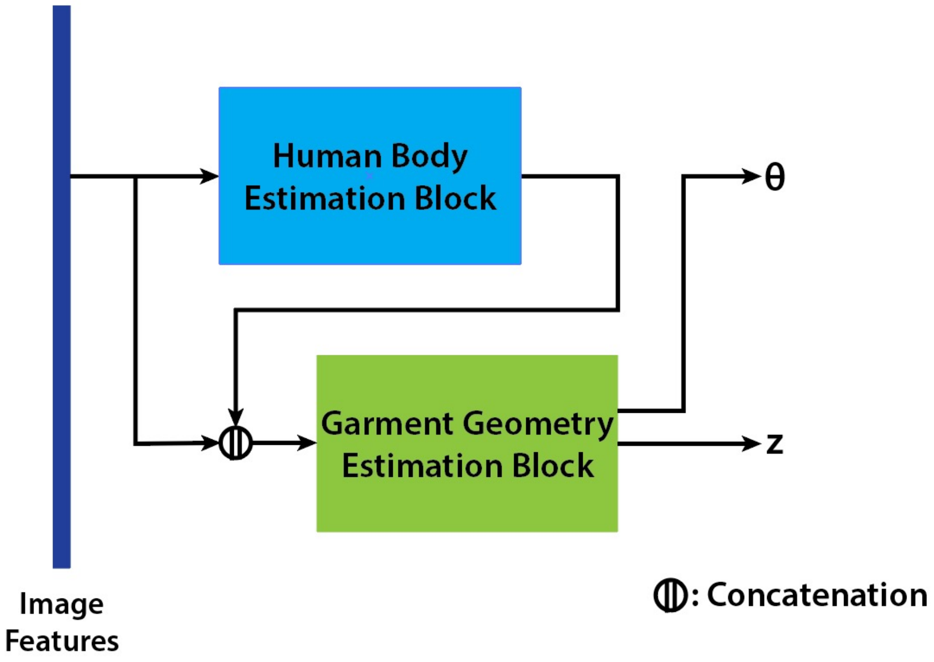
Network Structure: Overview

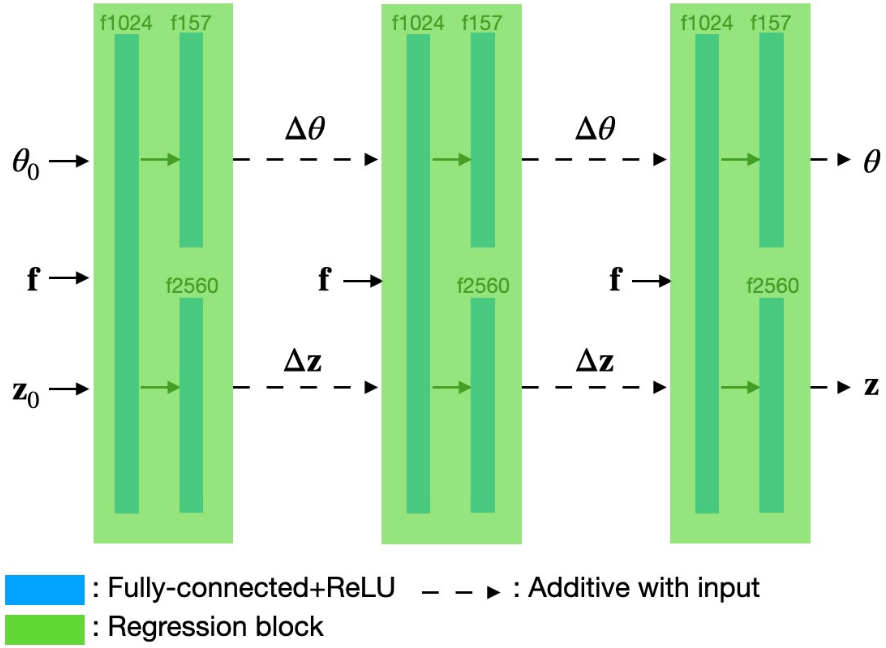


θ: Human body parameters
z: Garment latent code

Body and Garment Estimation

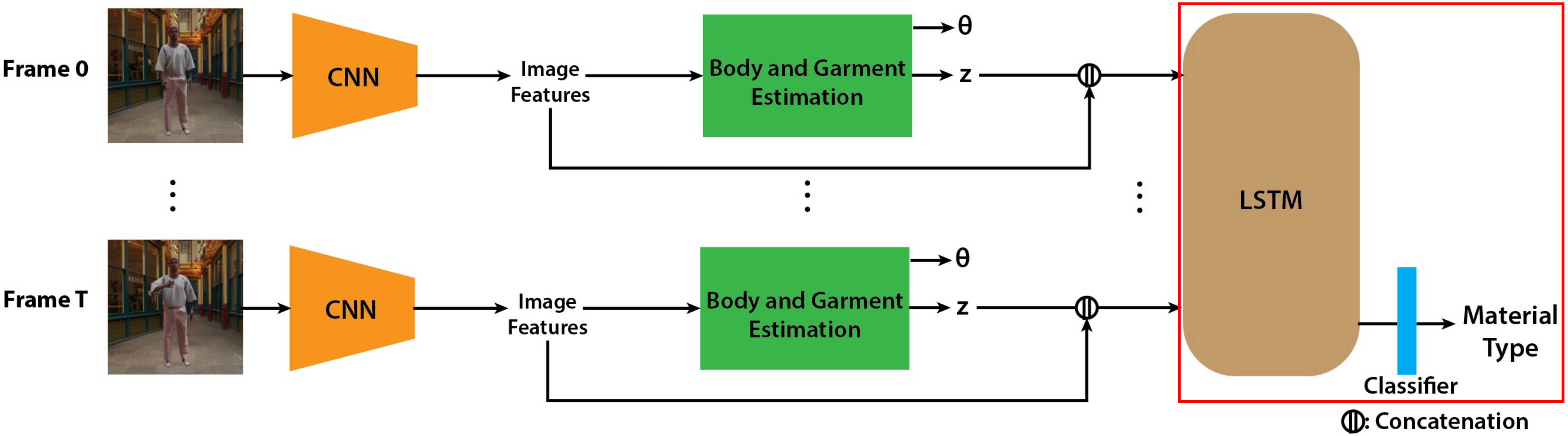
- Input: Single frame image feature
- Output: human parameter θ, garment latent z
- Garment Estimation: Prediction-correction blocks





Network Structure: Material Classification

- Input: feature sequence of image and garment latent code
- Output: material class



Simulated Data Samples

Results: Garment Material Estimation

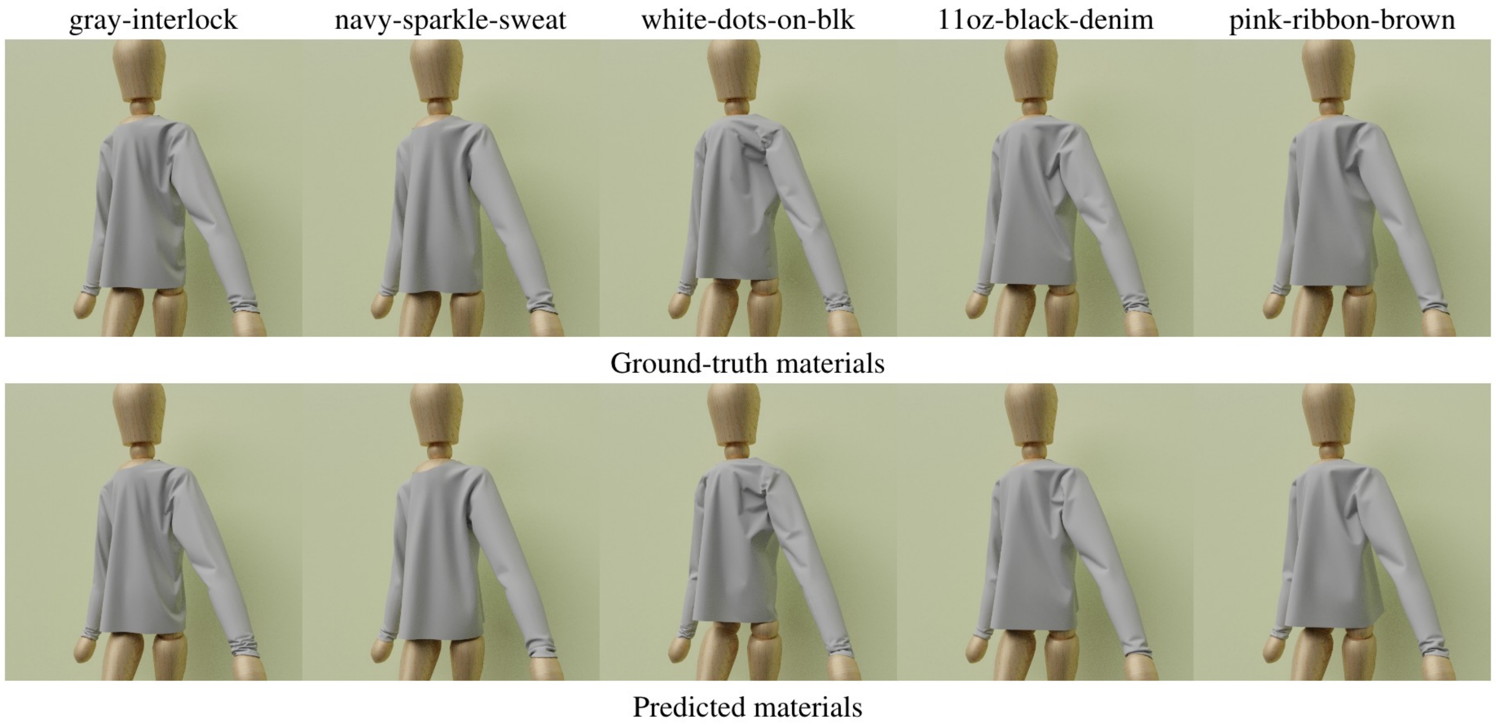
- Baseline: single frame input, image-only input
- Metrics: classification accuracy

Method	Mean Accuracy	Temporal Gain	Garment Features Gain
Random guess	1.85%	-	-
Image only, CNN	5.11%	40.16%	-
Image only, LSTM [65]	45.27%		-
Garment only, CNN	11.85%	53.31%	6.74%
Garment only, LSTM	65.16%		19.89%
Image + Garment, CNN	12.62%	**57.52%**	7.51%
Image + Garment, LSTM **(ours)**	**70.14%**		**24.87%**

Our method achieves the highest accuracy with the help of garment features and temporal information

Result: User Study

- Test scenario: synthetic scenes
  - Metric: similarity scores (0-distint, 5-similar, 10-identical)



Scores: 6.6±2.0 8.5±1.5 6.7±2.5 5.7±2.6 7.9±1.8

Our method recovers the real-world materials with only minor differences

Qualitative Results: Garment Reconstruction

Input image	MGN (Bhatnagar et al. 2019)	Ours (point cloud)	Ours (mesh)
Input image	DeepCap (Habermann et al. 2020)	Ours (point cloud)	Ours (mesh)
Input image	DeepCap (Habermann et al. 2020)	Ours (point cloud)	Ours (mesh)

Our method achieves similar visual appearance without any prior knowledge

Estimations on Unseen Real-World Videos

Input Video from DeepCap

Estimation Result

Our method can be applied to unseen real-world videos to infer garments of arbitrary topology without any prior.

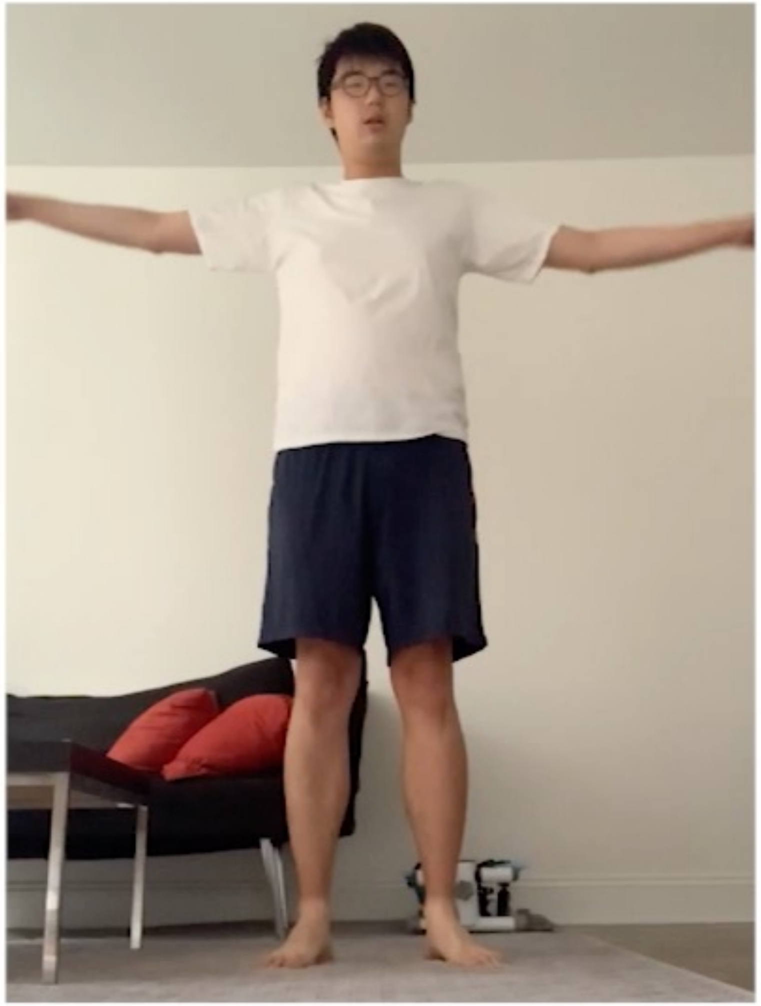
Application: Material Transfer

Video input

Cloned material

Soft silk

Application: Avatar Transfer



Video input

Cloned avatar

Application: Virtual Try-On

Input video

Summary

- First end-to-end model for joint estimation of body and garment
  - Two-level auto-encoder for garment geometry
    - Supports arbitrary topology
    - No prior knowledge on garment style
  - Closed-loop refinement connection for better prediction
- Usage of garment features boosts the accuracy of material estimation
- Applicable to material/garment/avatar transfer

Outline

- Background
- Reconstruction
  - Shape-aware human body recovery using multi-view images
  - Differentiable cloth simulation for material optimization
  - Joint estimation of human and garment from video
- Synthesis
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  - Dynamics-Inspired garment draping prediction
- Conclusion

Junbang Liang, Ming C. Lin. Time-Domain Parallelization for Accelerating Cloth Simulation. Symposium on Computer Animation, 2018

Motivation

- Real-time cloth simulation system
  - Low-latency, real-time try-on
  - Rapid apparel prototyping

Limitations with State-of-the-Art

- Spatial domain parallelization [Thomaszewski and Blochinger, EG 2006]
  - *High communication overhead (low scalability)*
  - *Fixed mesh structure*

- GPU acceleration [Tang et al., CGF 2016]
  - Unscalable
  - Fixed mesh structure

- Time parallel time integration for continuous energy space PDE [Emmett and Minion, CAMCS 2012]
  - Inapplicable to collision-involved discontinuous problem

Key Contributions

- First time-domain parallelization for cloth simulation
  - Two-level mesh representation
    - Enables time domain parallelization
  - Adaptive domain partitioning
    - Workload balancing
  - Iterative detail recovery at partition points
    - Smoothed results

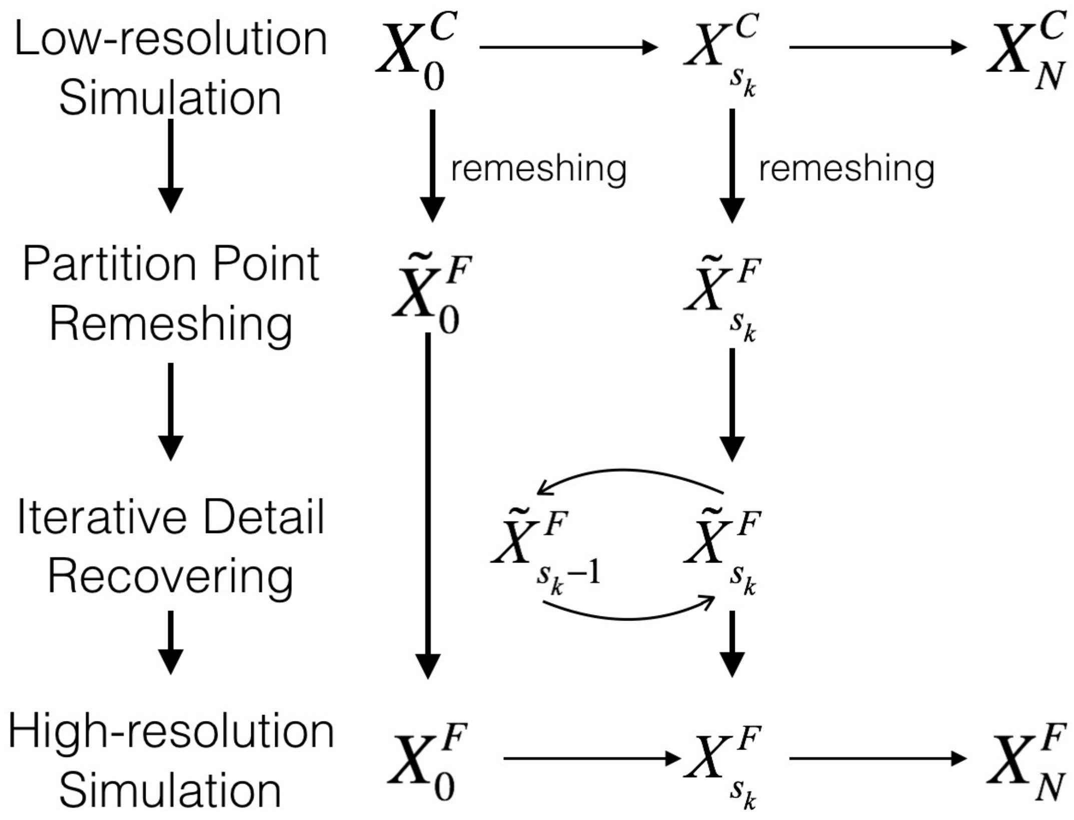
System Pipeline

- Input:
  - initial mesh X_0^C
  - up-sampling function $u(X^C)$
  - simulation function $f(X, \Delta t)$
- Output: high resolution mesh sequence $X_0^F \sim X_N^F$

Notations:

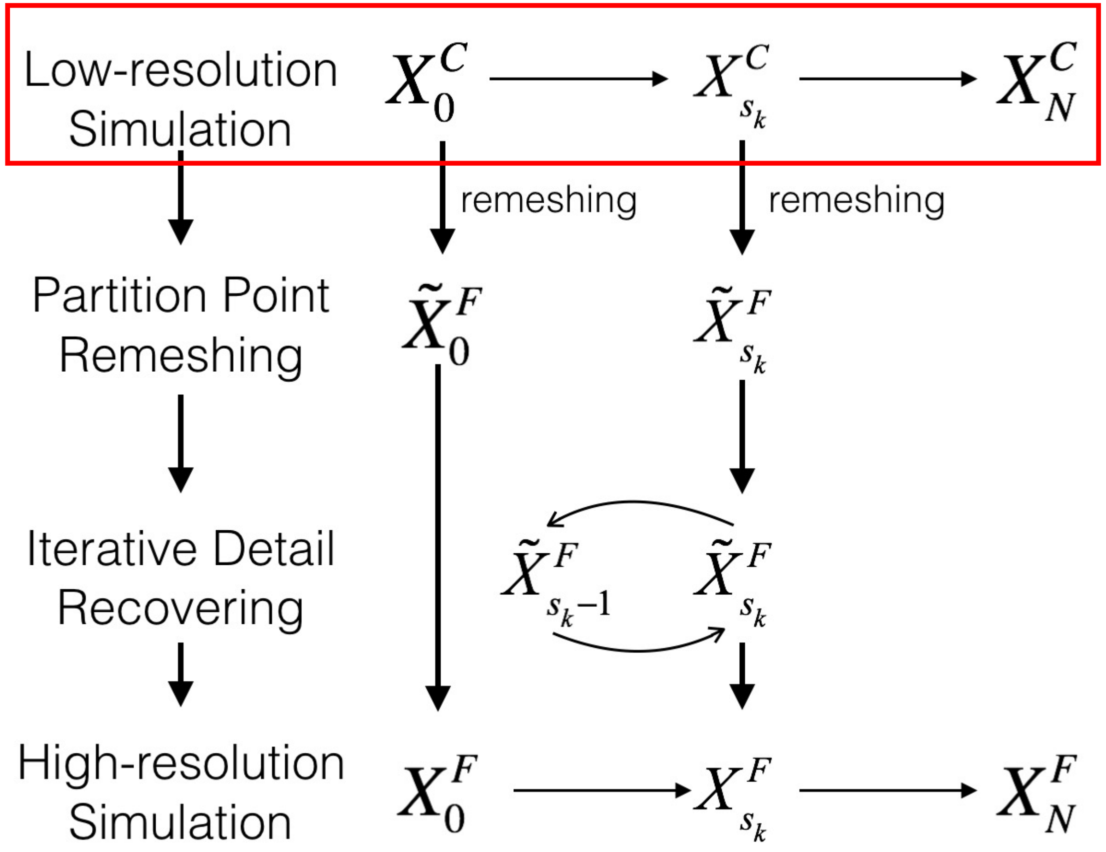
s_i: partition point of the i-th processor

N: number of simulation steps



System Pipeline

1. Run low-resolution simulation



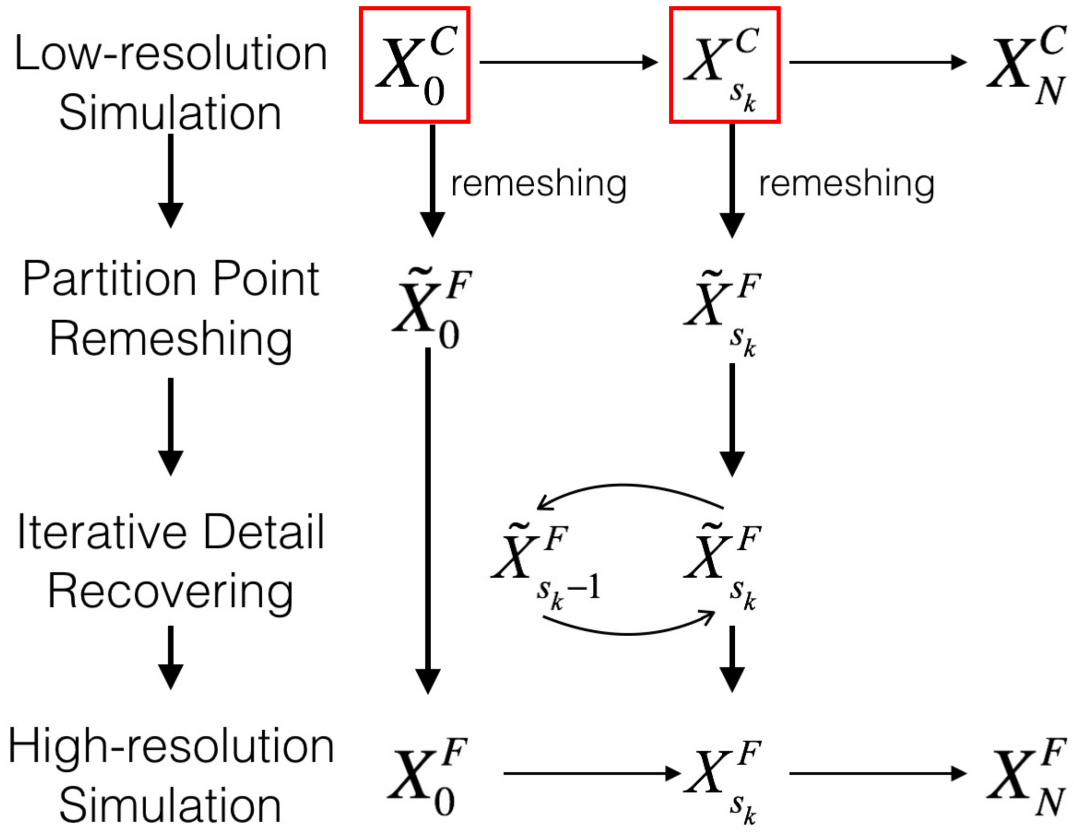
Notations:

s_i: partition point of the i-th processor

N: number of simulation steps

System Pipeline

1. Run low-resolution simulation
2. Determine the partition point



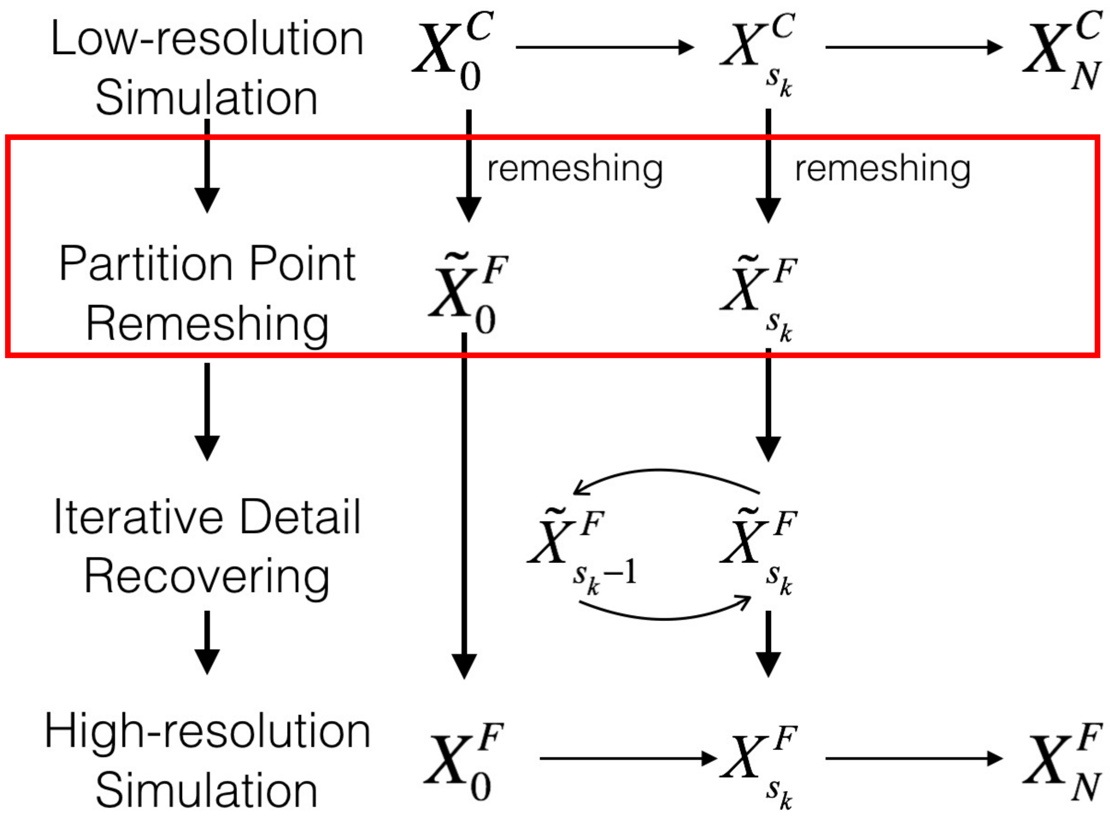
Notations:

s_i: partition point of the i-th processor

N: number of simulation steps

System Pipeline

1. Run low-resolution simulation
2. Determine the partition points
3. Up-sample the mesh to high-resolution



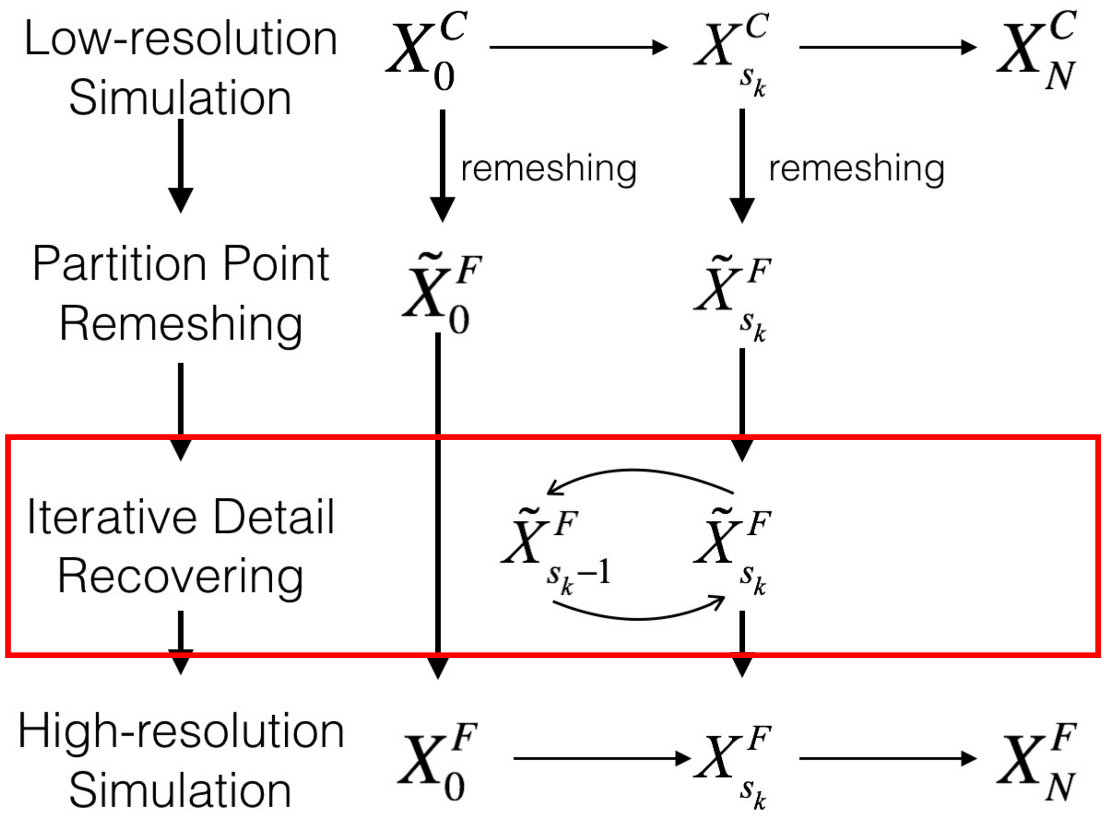
Notations:

s_i: partition point of the i-th processor

N: number of simulation steps

System Pipeline

1. Run low-resolution simulation
2. Determine the partition points
3. Up-sample the mesh to high-resolution
4. Iteratively recovers the detail



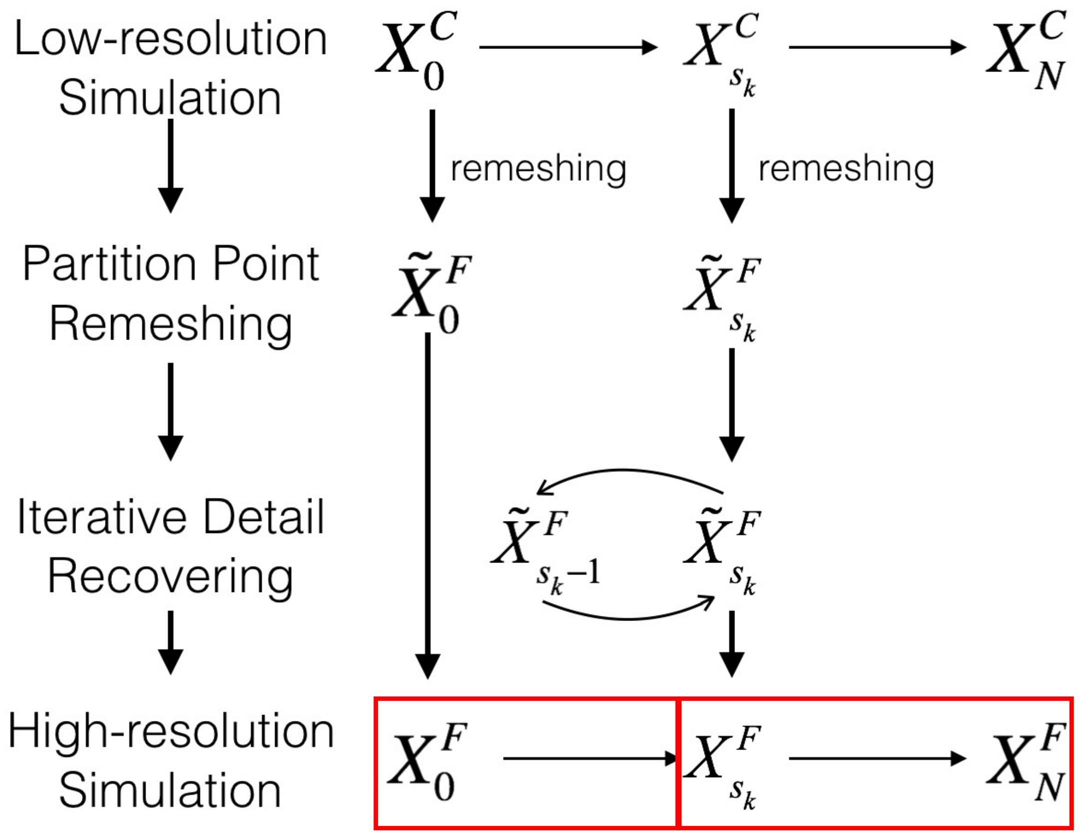
Notations:

s_i: partition point of the i-th processor

N: number of simulation steps

System Pipeline

1. Run low-resolution simulation
2. Determine the partition points
3. Up-sample the mesh to high-resolution
4. Iteratively recovers the detail
5. Run high-resolution in parallel



Notations:

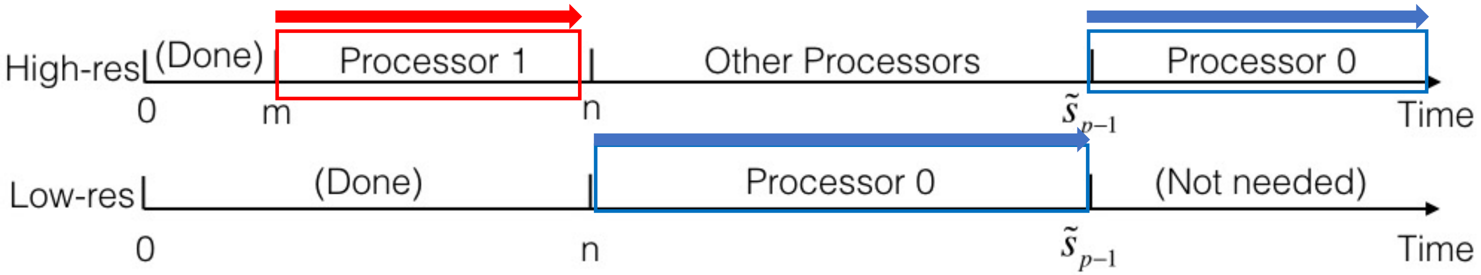
s_i: partition point of the i-th processor

N: number of simulation steps

Adaptive Temporal Partitioning

- Estimate the coarse-to-fine ratio K on the fly
- n is the partition point if:

  (est. time on Processor 0) = (est. time on Processor 1)
- $n = \frac{N}{\tilde{K}} + \frac{\tilde{K}-1}{\tilde{K}}(N - \tilde{s}_{p-1})$



Notations:

$\tilde{s}_{p-1}$: estimated partition point of the last processor

N : number of simulation steps

p : number of processors

$\tilde{K}$: estimated coarse-to-fine ratio (= High-res time / low-res time)

Iterative Detail Recovery

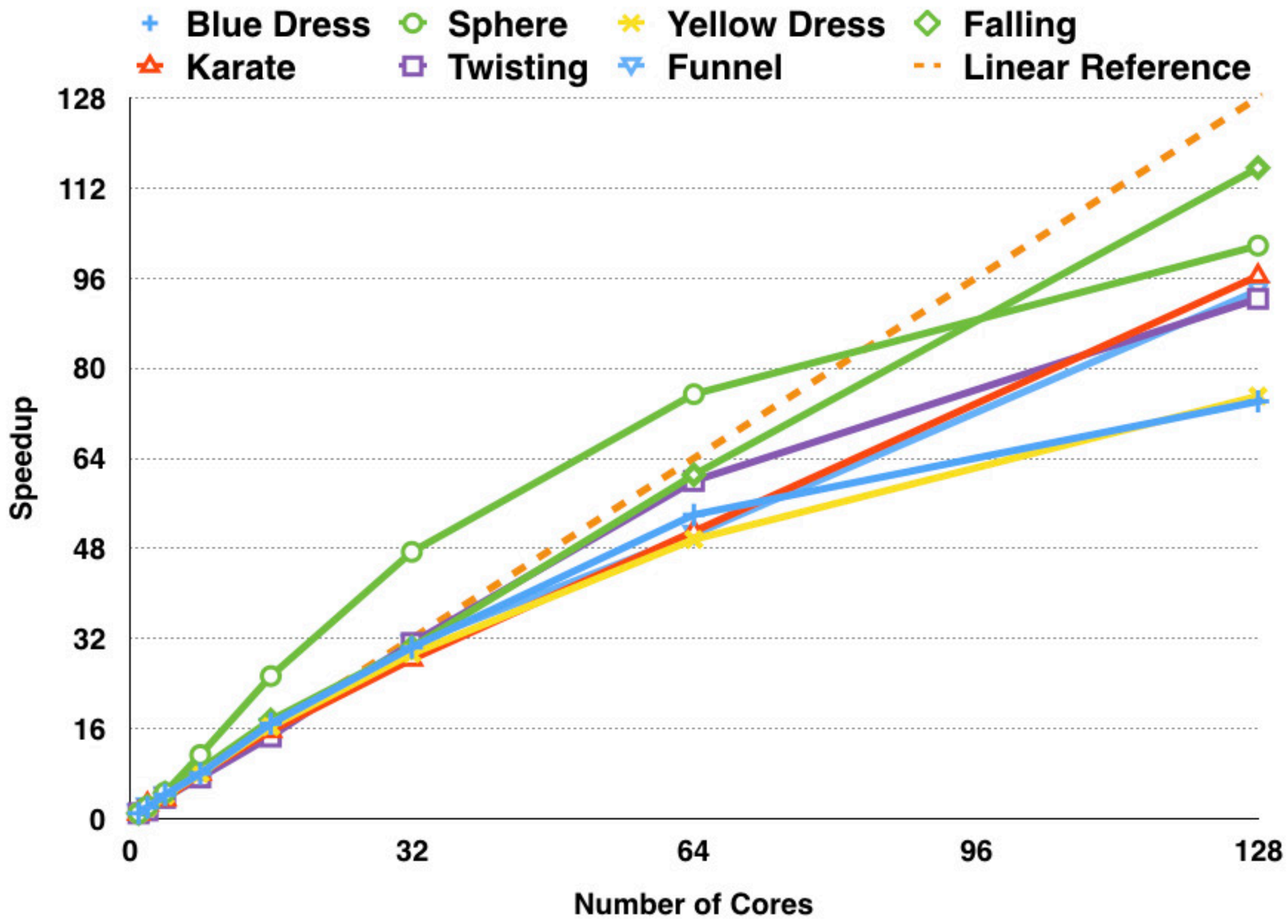
- Loss of high frequency information in low resolution meshes
- Use simulation itself to recover the missing details
- Record the ‘change of the state’ in each step of the low-resolution simulation

$$
\begin{tikzcd}
\tilde{X}^F_{s_i - 1} \arrow[rr, bend right, "f(X, \Delta t)"'] & & \tilde{X}^F_{s_i} \arrow[ll, bend right, "-\Delta u(X^C)"']
\end{tikzcd}
$$

Notations:

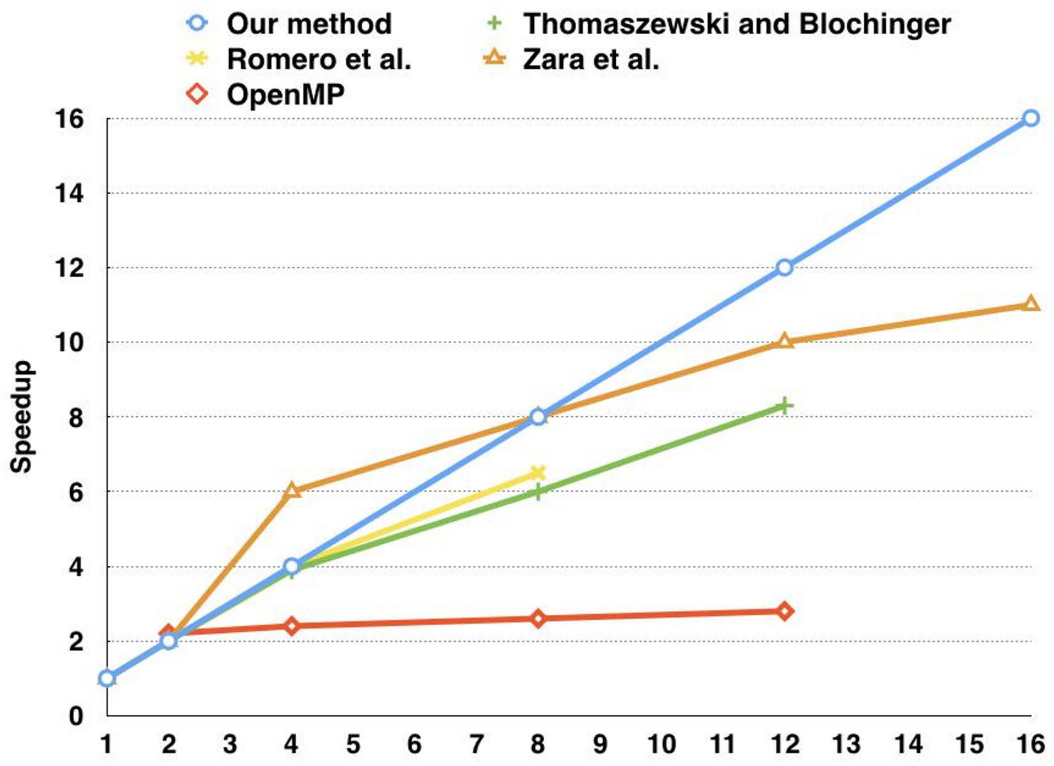
u(): user-specified up-sampling function
X^C: low resolution mesh
X^F: high resolution mesh
f(): simulation function
s_i: partition point of the i-th processor

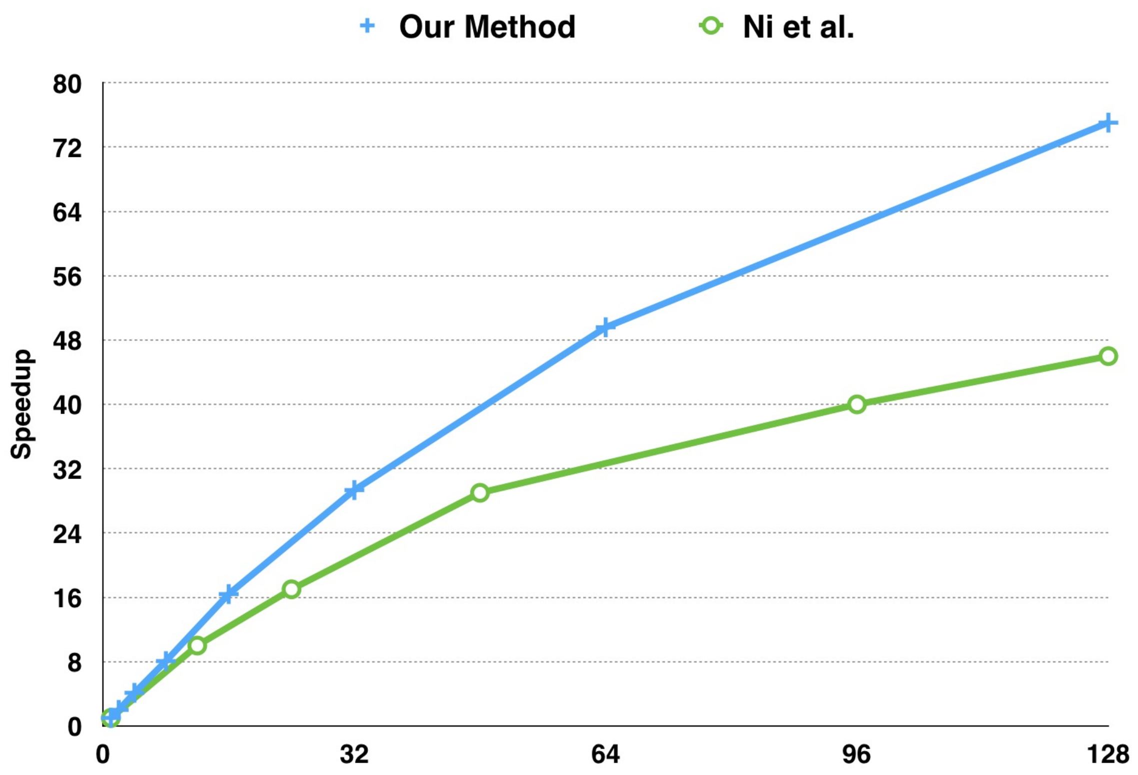
Results: Scalability Test



A nearly linear scalability is achieved

Comparison with Previous Work





Our method achieves linear scalability in small systems and is 50% more efficient than previous distributed methods

Result: Falling

Serial

70 seconds/frame

Parallel

1.5 seconds/frame

Summary

- First temporal-domain parallelization for cloth simulation
  - Adaptive domain partitioning for workload balance
    - Nearly linear scalability up to the theoretical bound
  - Iterative detail recovery algorithm for smooth transitioning
    - High-fidelity visual results comparable to sequential simulation

Outline

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  - Joint estimation of human and garment from video
- Synthesis
  - Time-domain parallelization for accelerating cloth simulation
  - Dynamics-Inspired garment draping prediction
- Conclusion

Junbang Liang, Ming C. Lin, Javier Romero. Semi-Supervised Learning of Physics-Enforced Garment Prediction. NeurIPS 2021 submission

Motivation

- Fast and realistic visual rendering.
  - Real-time feedback bypassing the simulation
  - Accuracy: predictions as realistic as simulated ones

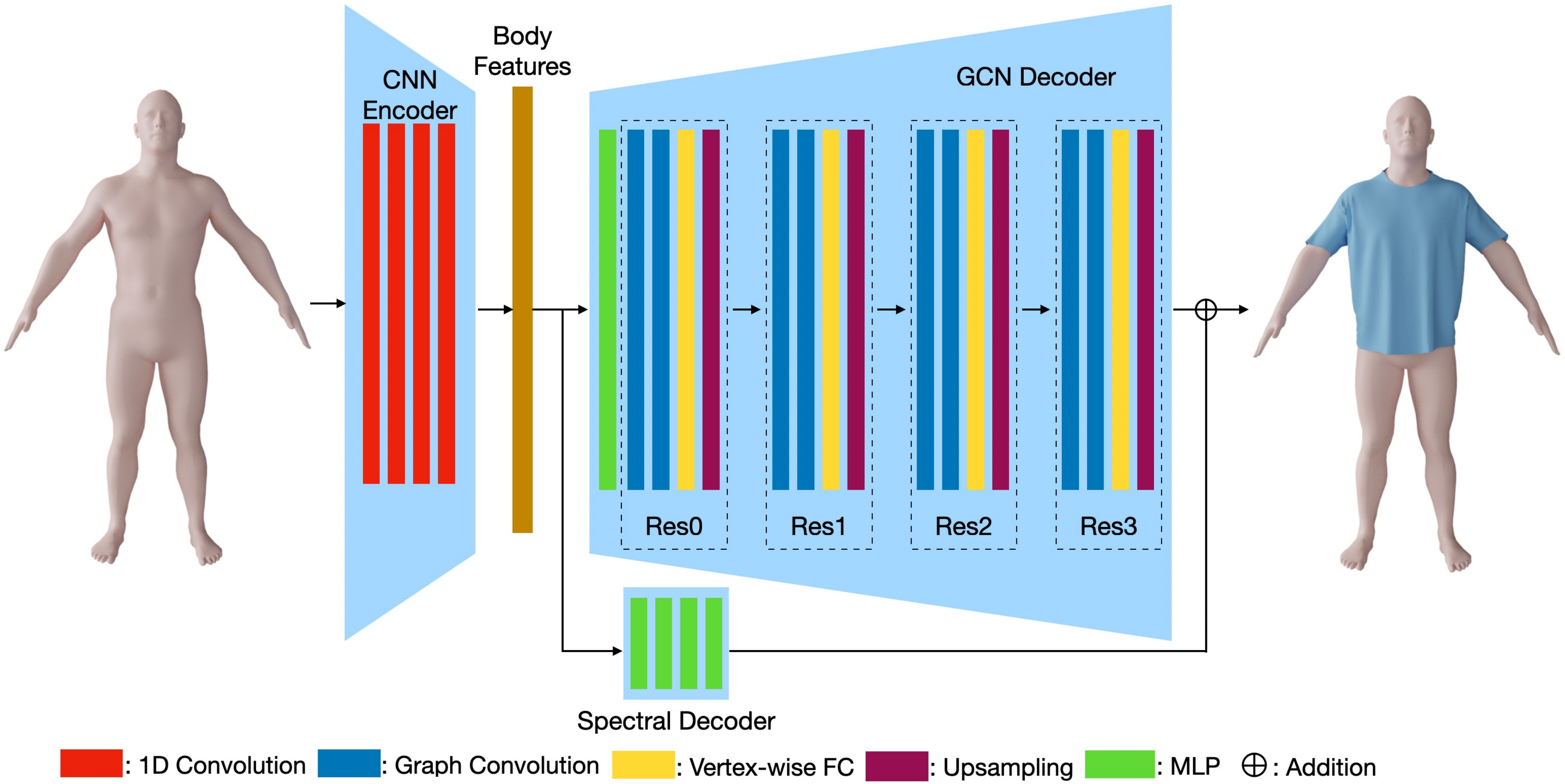
Limitations with State-of-the-Art

- Learning-based garment draping [Patel et al., CVPR 2020]
  - *Unable to cover all body shapes*
  - *Cannot deal with loose clothing*
  - *Overly smoothed results*

Our Contribution

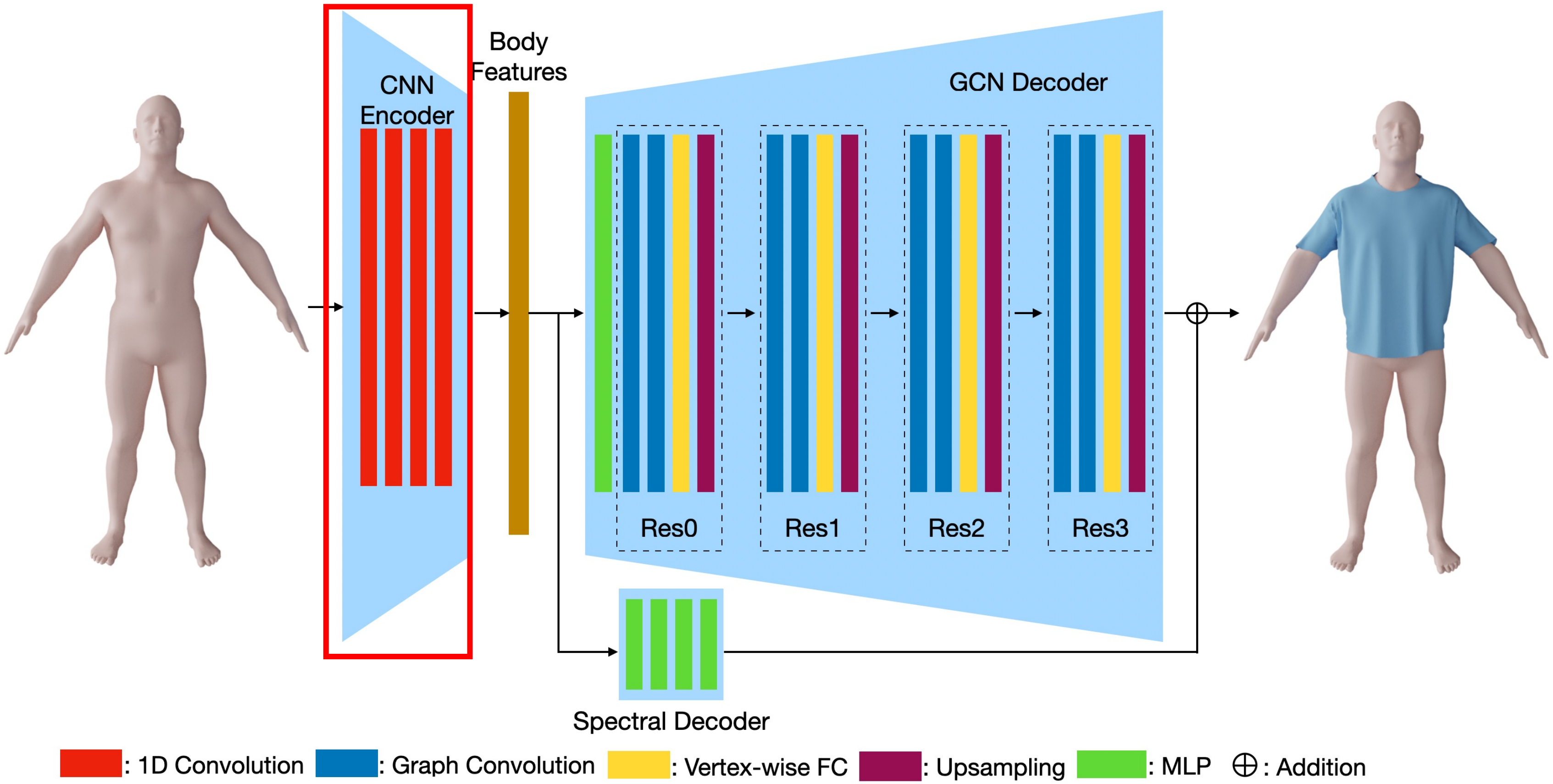
- A novel encoder/decoder network that effectively captures global and local features from the input body.
- Novel loss functions that encode geometric, physical, design, and tailoring constraints.
- A semi-supervised framework to integrate dynamical constraints into the deep learning model.

Network Structure



Encoder

- 1D CNN
  - 91.24% vertices have neighbors also adjacent in index space

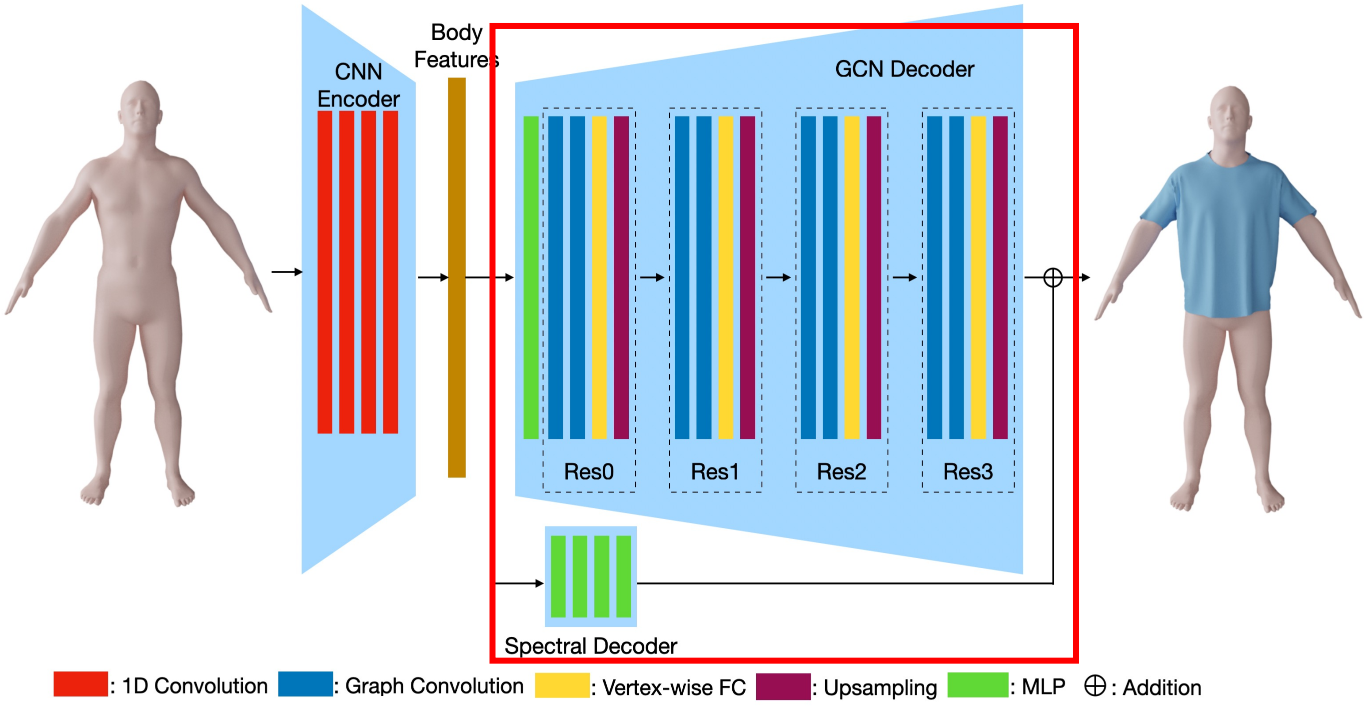


Decoder

- Multi-resolution Graph Convolution Network (GCN)
  - Learnable adjacency matrix values

$$\mathbf{y} = \mathbf{f}_{\theta_1}(\mathbf{A}_{\theta_2}\mathbf{x})$$
$$\mathbf{A}_{\theta_2}[i,j] = \theta_2[i,j]$$

- MLP: spectral decoder
  - Mid-frequency signal refinement



Loss Functions

- Direction: penetration prevention

$$\mathcal{L}_{dir} = R(-\frac{\mathbf{n}^\top(\mathbf{c}_x - \mathbf{c}_y)}{\|\mathbf{c}_x - \mathbf{c}_y\|}) + (1 - \frac{(\mathbf{x} - \mathbf{c}_y)^\top \mathbf{d}_y}{\|\mathbf{x} - \mathbf{c}_y\|\|\mathbf{d}_y\|})$$

- Edge: garment stretchable length

$$\mathcal{L}_e = \frac{1}{|E|} \sum_{(\mathbf{u},\mathbf{v}) \in E} \frac{|\|\mathbf{u}_x - \mathbf{v}_x\| - \|\mathbf{u}_y - \mathbf{v}_y\||}{\|\mathbf{u}_y - \mathbf{v}_y\|}$$

- Face deformation: garment potential energy

$$\mathcal{L}_d = \sum_{\mathbf{f} \in \mathcal{M}} \|\mathbf{F}_x(\mathbf{f}) - \mathbf{F}_y(\mathbf{f})\|_1$$

- Laplacian difference: first-order smoothness/shape

$$\mathcal{L}_l = \sum_{k=0}^{3} \|\mathbf{L}_k(\mathbf{x} - \mathbf{y})\|_1$$

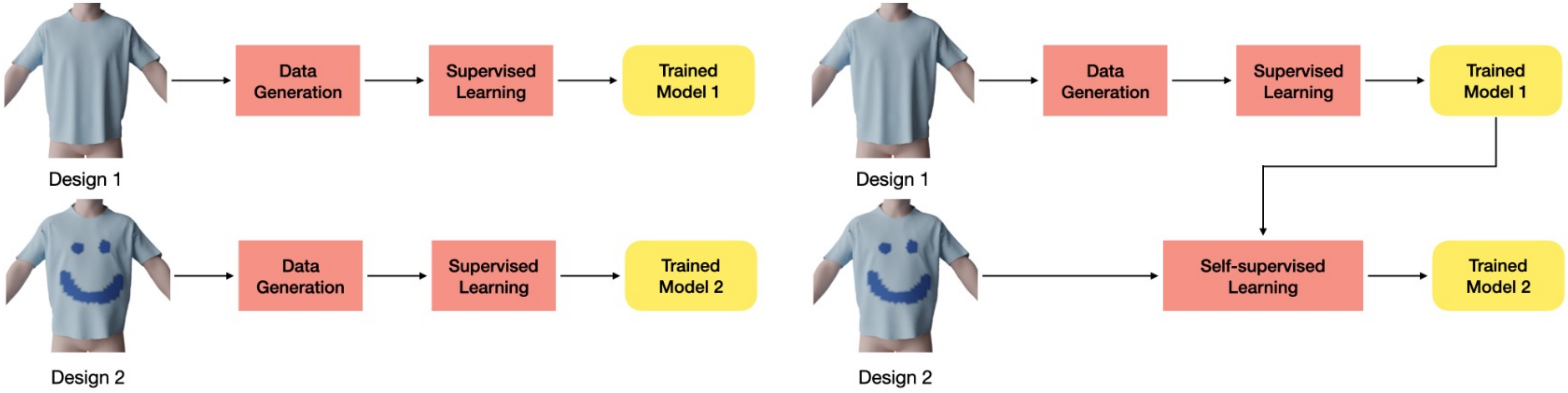
- Spectral difference: spectral component density

$$\mathcal{L}_s = \|\mathbf{V}^\top(\mathbf{x} - \mathbf{y})\|_1$$

R: ReLU
n: vertex normal
c: body correspondence
d: garment displacement
x: network prediction
u, **v**: edge vertices
E: edge set
f: face of the mesh
M: garment mesh
F: deformation gradient
$\mathbf{L}_\mathbf{k}$: Mesh Laplacian on the k-th level resolution
V: spectral domain decomposition matrix

Semi-Supervision

- Motivation
  - Adaptation to new materials, body poses without simulation data
  - Online refinement for better results
    - Intersection removal and drape smoothing



(a) Supervised Models (b) Our Semi-Supervised Method

Physics-Enforced Optimization

- Apply losses based on garment potential energy and penetration:
  - Potential energy:
    - Gravity

$$\mathcal{L}_g = \sum_{\mathbf{v} \in \mathcal{M}} m(\mathbf{v}) \mathbf{g}^\top \mathbf{x}(\mathbf{v})$$

    - Stretching energy

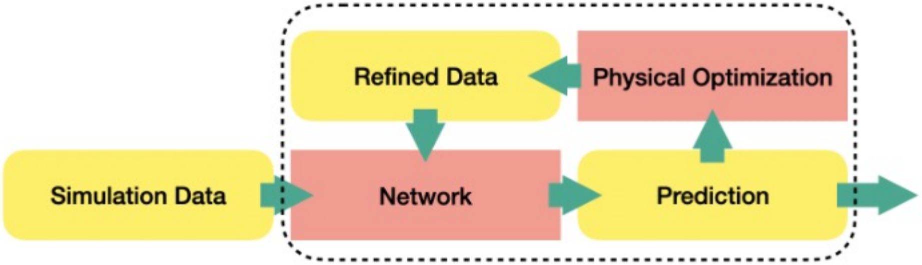
$$\mathcal{L}_{st} = \sum_{\mathbf{f} \in \mathcal{M}} \mathbf{S}(\mathbf{f})$$

    - Bending energy

$$\mathcal{L}_b = \sum_{\mathbf{e} \in \mathcal{M}} \mathbf{B}(\mathbf{e})$$

  - Penetration:

$$\mathcal{L}_c = \sum_{\mathbf{v}} R(-d(\mathbf{v}, \mathcal{M}_{body}) - \delta)$$



v: mesh vertex
M: garment mesh
g: gravity
x: network prediction
S: stretching energy
f: mesh face
B: bending energy
e: mesh edge
R: ReLU
d: signed distance
M_{body}: body mesh
δ: garment thickness

Results: Direct Prediction

- Test metrics:
  - Mean Euclidean (ME)
  - Different loss components
    - Laplacian (l), edge (e), spectral (s), deformation (d)
  - Penetration ratio p

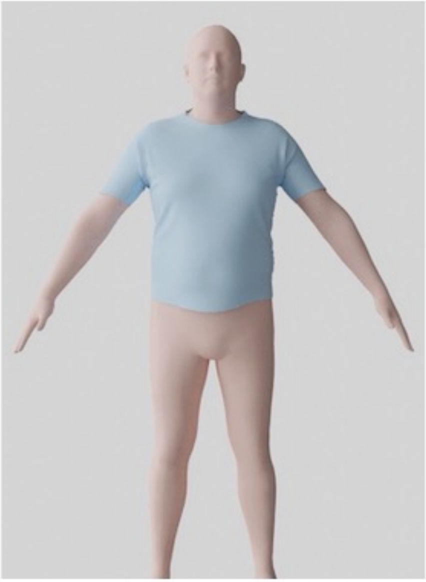
Methods	ME (cm)	$\mathcal{L}_l$ (cm)	$\mathcal{L}_e$ (%)	$\mathcal{L}_s$	$\mathcal{L}_d$	p (%)
TailorNet [31]	1.36	0.29	17.65	2.1e-3	8.8e-3	3.1
Ours	**0.33**	**0.16**	**9.21**	**1.0e-3**	**4.5e-3**	**0.05**
Improvement	75%	44%	47%	52%	48%	98%

Our method has 44%-98% error reduction compared to state-of-the-art.

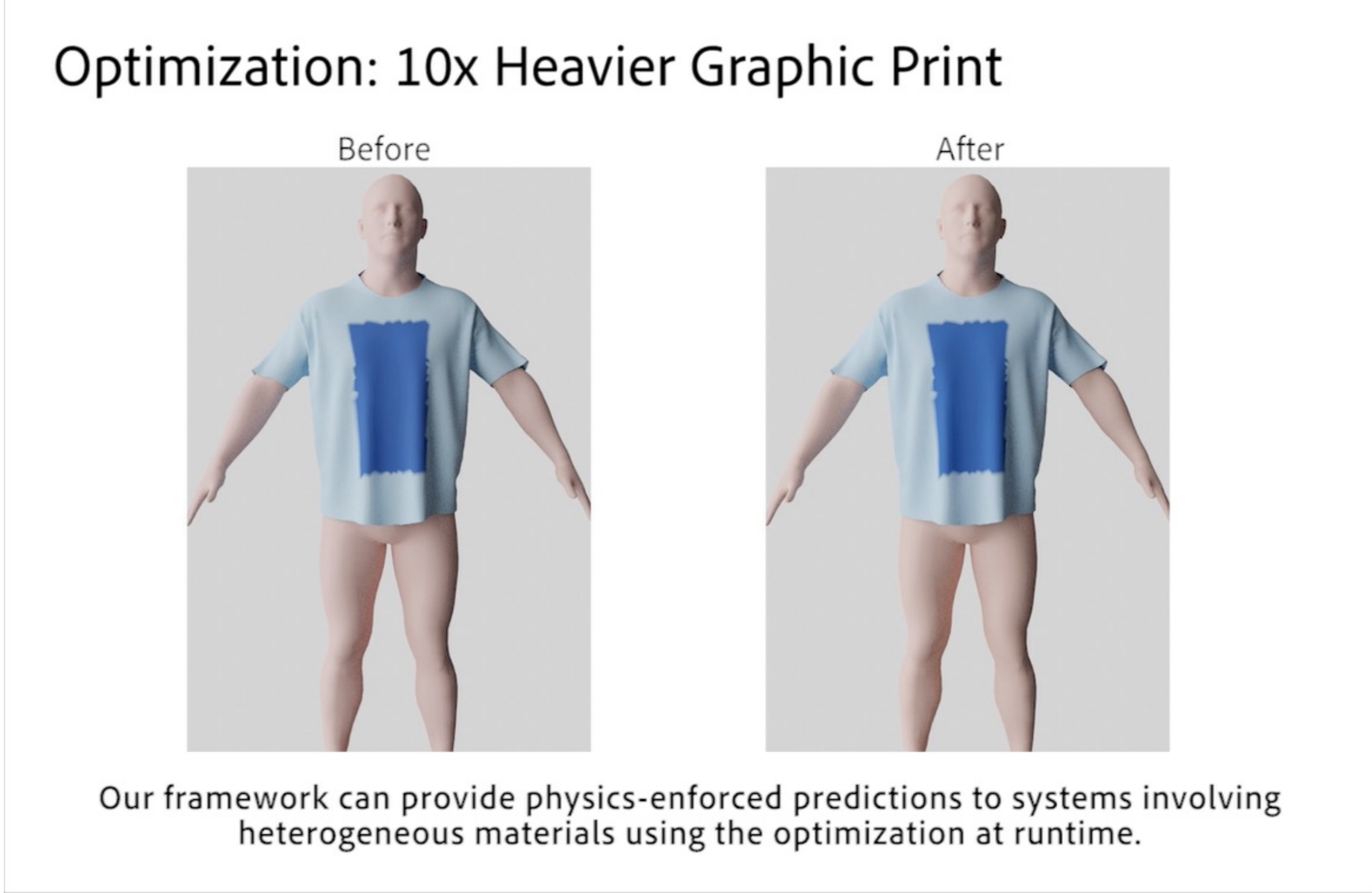
Results Visualization: Normal Body

Garment Prediction: Male T-shirts

Simulation



Results: Semi-Supervision



Summary

- Novel network and loss functions for addressing physical constraints
  - Better detailed wrinkle formations
  - Much fewer penetrations
  - Larger coverage on body shapes
- Semi-supervision method for adaptation to new distribution
  - Applicable to fit different fabric materials and frontal prints

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  - Dynamics-Inspired garment draping prediction
- Conclusion

Thesis Statement

- *Dynamic constraints can be effectively enforced in human body estimation, garment material and geometry reconstruction, simulation acceleration, and draping prediction for virtual try-on systems, by coupling machine learning and optimization methods with cloth simulation.*

Conclusion

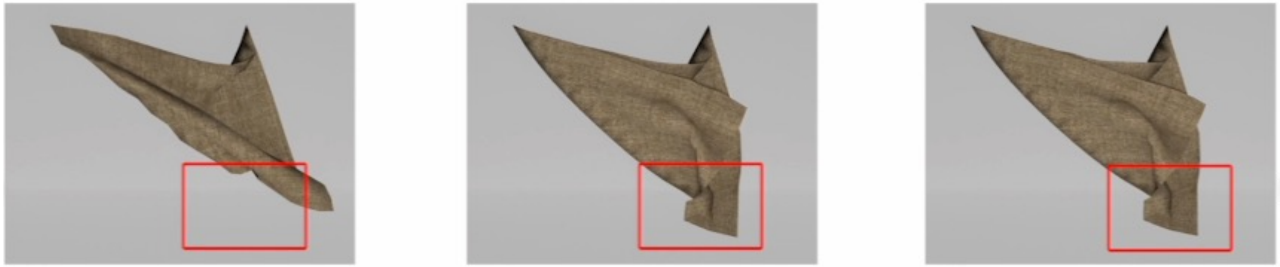
- Shape-aware human body recovery using multi-view images
  - Multi-view multi-stage structure for higher accuracy
  - Synthetic dataset for large scale supervision

Thesis Statement:

*Dynamic constraints can be effectively enforced in **human body estimation**, garment material and geometry reconstruction, simulation acceleration, and draping prediction for virtual try-on systems, by coupling **machine learning** and optimization methods with cloth simulation.*

Conclusion

- Differentiable cloth simulation for material optimization
  - Implicit differentiation and QR decomposition for faster backpropagation



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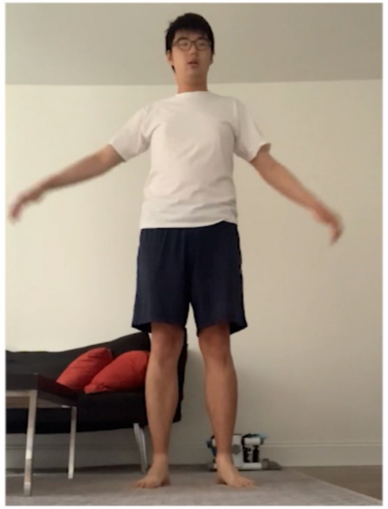
*Dynamic constraints can be effectively enforced in human body estimation, **garment material** and geometry **reconstruction**, simulation acceleration, and draping prediction for virtual try-on systems, by coupling **machine learning and optimization** methods with cloth simulation.*

Conclusion

- Joint estimation of human and garment from video
    - Two-level auto-encoder for representing arbitrary garments
    - Closed-loop structure and garment features for higher accuracies



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Conclusion

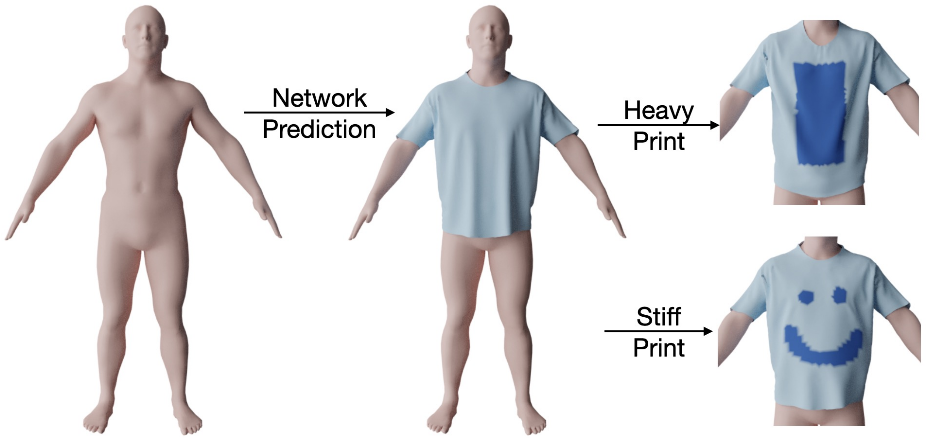
- Time-domain parallelization for accelerating cloth simulation
  - Adaptive workload distribution for best scalability possible
  - Iterative refinement to ensure temporal consistency

Thesis Statement:

Dynamic constraints can be effectively enforced in human body estimation, garment material and geometry reconstruction, ***simulation acceleration****, and draping prediction for virtual try-on systems, by coupling machine learning and* ***optimization*** *methods with cloth simulation.*

Conclusion

- Dynamics-Inspired garment draping prediction
  - Physics-inspired network structure and loss functions
  - Semi-supervision pipeline for quick adaptation to new distributions



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Dynamic constraints can be effectively enforced in human body estimation, garment material and geometry reconstruction, simulation acceleration, and ***draping prediction*** *for virtual try-on systems, by coupling* ***machine learning and optimization*** *methods with cloth simulation.*

Limitations and Future Work

- Training data
  - Better details in hair, skin, and lighting
  - Self (semi-) supervision?
- Networks and learning algorithms
  - A network dedicated to fit tasks related to garments?
- Parametric garment models
  - Multi-layer cloth, accessories, multi-fold shapes
  - UV coordinates for sewing patterns
- Human body representation
  - Parameterization for deformable bodies
- Visual rendering and synthesis
  - Spatial + temporal parallelization on GPU systems
- Generalization and robustness of draping networks
  - Support of multiple poses, shapes, and temporal motions

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  - Multi-layer cloth, accessories, multi-fold shapes
  - UV coordinates for sewing patterns
- Human body representation
  - Parameterization for deformable bodies
- Visual rendering and synthesis
  - Spatial + temporal parallelization on GPU systems
- Generalization and robustness of draping networks
  - Support of multiple poses, shapes, and temporal motions

Publications

- Shan Yang, **Junbang Liang**, Ming C. Lin. Learning-based Cloth Material Recovery from Video. ICCV 2017
- **Junbang Liang**, Ming C. Lin. Time-Domain Parallelization for Accelerating Cloth Simulation. Symposium on Computer Animation, 2018
- **Junbang Liang**, Ming C. Lin. Shape-Aware Human Pose and Shape Reconstruction Using Multi-View Images. ICCV 2019
- **Junbang Liang**, Ming C. Lin, Vladlen Koltun. Differentiable Cloth Simulation for Inverse Problems. NeurIPS 2019
- Yi-Ling Qiao, **Junbang Liang**, Vladlen Koltun, Ming C. Lin. Scalable Differentiable Physics for Learning and Control. ICML 2020
- Yu Shen, **Junbang Liang**, Ming C. Lin. GAN-based Garment Generation Using Sewing Pattern Images. ECCV 2020
- Yi-Ling Qiao*, **Junbang Liang***, Vladlen Koltun, Ming C. Lin. Efficient Differentiable Simulation of Articulated Bodies. ICML 2021

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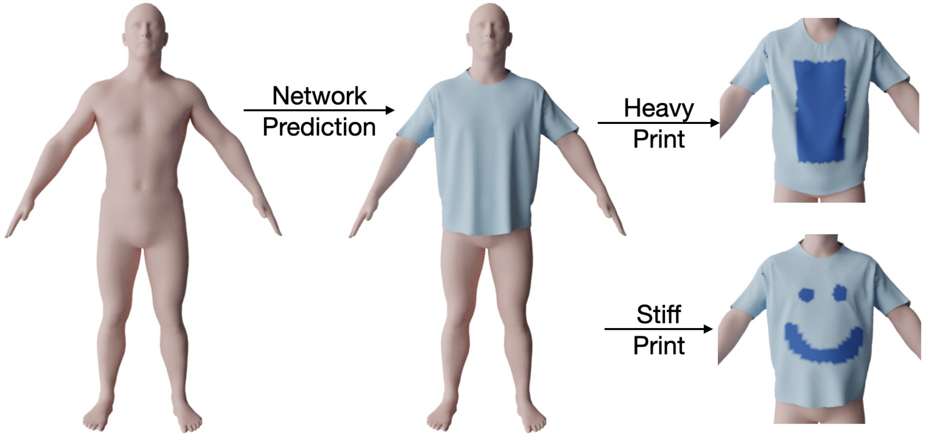

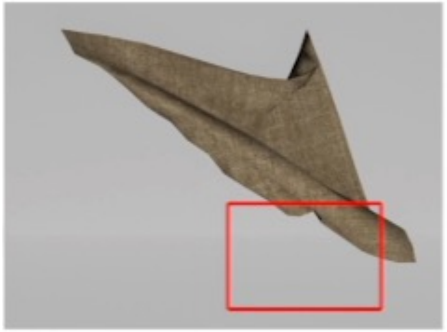

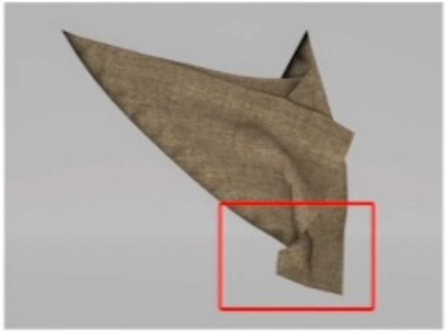

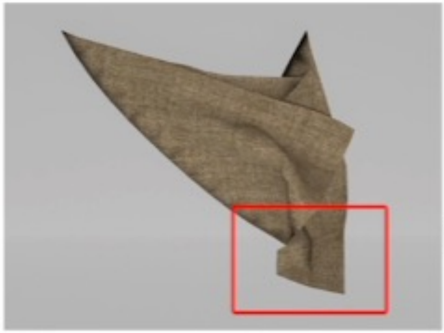

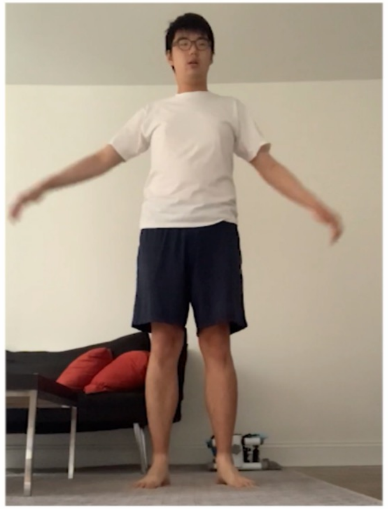

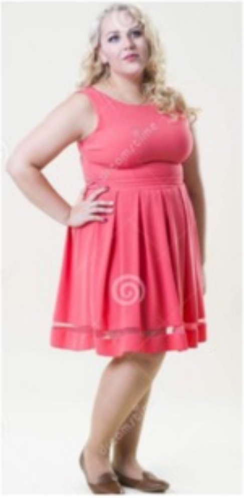

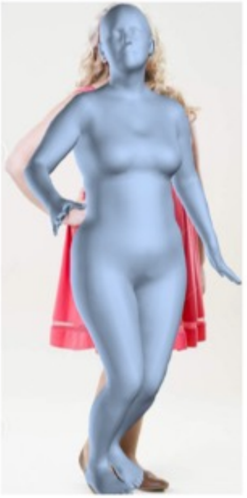

Thank you!