Adobe

Fully Convolutional Mesh Autoencoder using Spatially Varying Kernels

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A Collaboration with Facebook Reality Labs and USC:

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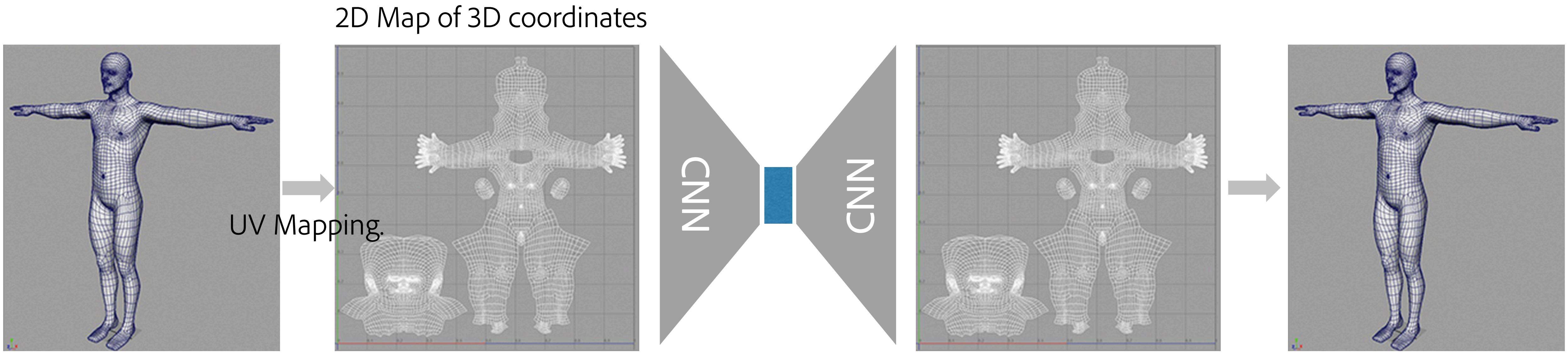
"Fully Convolutional Mesh Autoencoder using Efficient Spatially Varying Kernels."
Accepted by Neurips 2020

How to apply CNN on registered 3D meshes?

Registered Mesh: Mesh with the same number and order of vertices and edges.

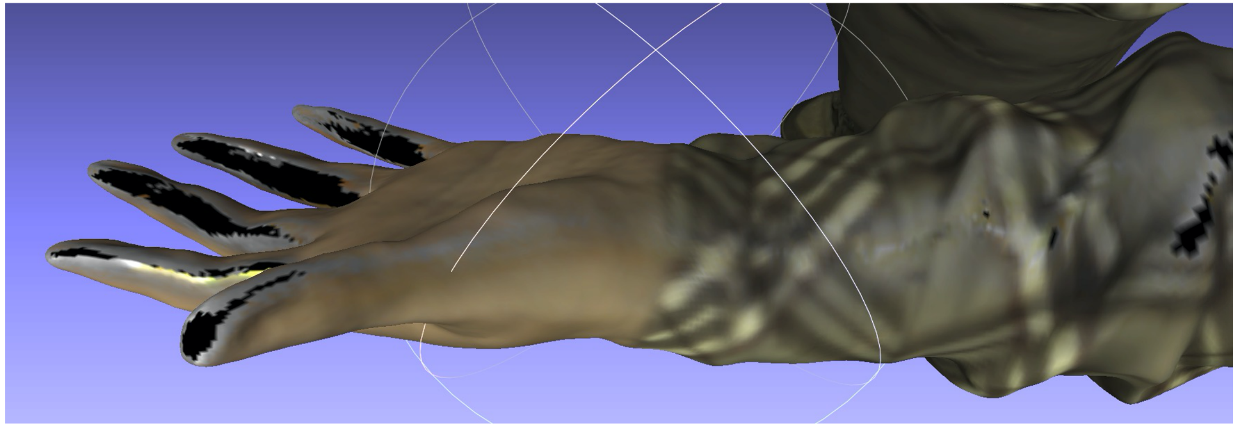
http://dfaust.is.tue.mpg.de/

Common Practice: 2D CNN in UV space



Problems:

1. Artifacts along seam lines and from distortion
2. Poor performance when reconstructing global deformation

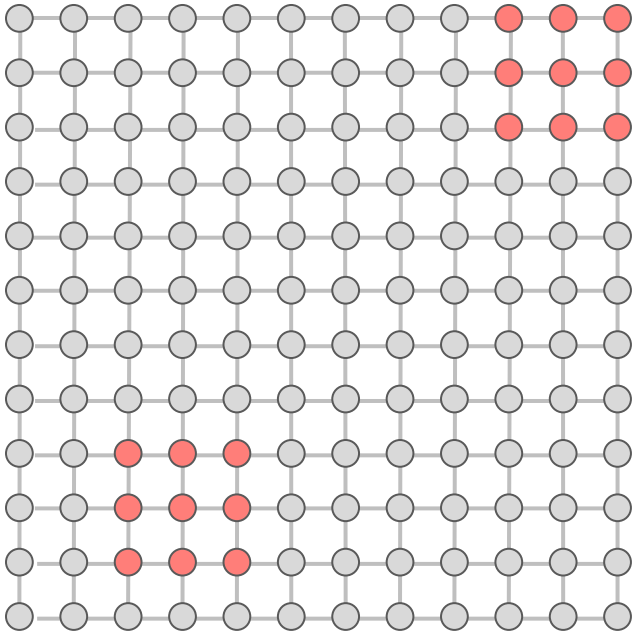


CNN on 3D Meshes

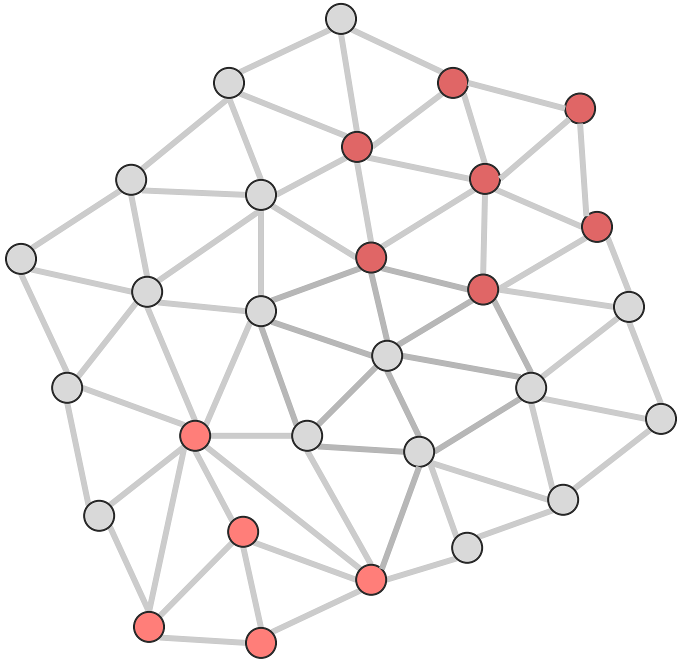
Difficulties

A Mesh is usually a non-uniform discretization.

Cannot sample uniform kernels on a non-uniform mesh



Shift-invariance Grid



Shift-variance Mesh

Existing Methods

Spectral Method:

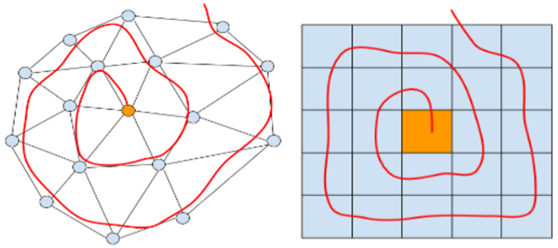
(Chebyshev ...)

Lose Fidelity, unstable

Special Method:

(Spiral CNN [Neural3DMM 2020])

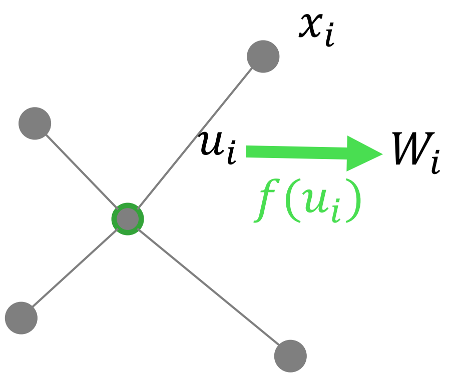
Ad-hoc, limited to 2-D manifold



Feature-Conditioned Method:

(GAT, MoNet, FeaStNet ...)

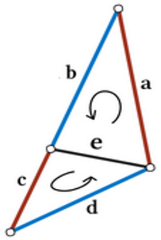
Sensitive to big variations.



$$y = \sum W_i A x_i$$

(EdgeCNN [MeshCNN 2019])

Slow, limited to 2-D manifold, Lose geometry information.



Mesh Convolution

Mesh CNN with Up and Down-Scaling

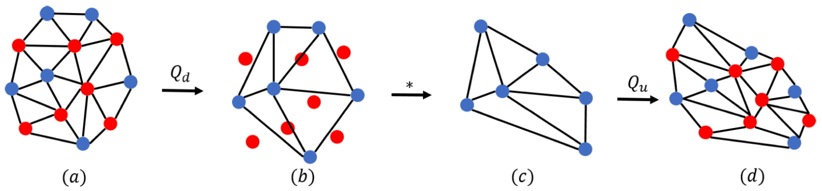
Existing Methods

Quadric Mesh Simplification:

[CoMA 2018, Neural3DMM 2019]

Fixed parameters

Overfit to one template mesh



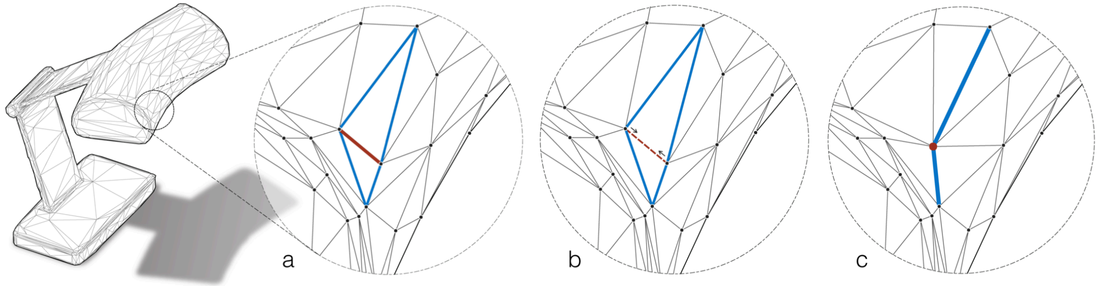
Dynamic Edge Collapsing:

[MeshCNN 2019]

Very slow

limited to 2-D manifold

minimal downscaling size requirements.



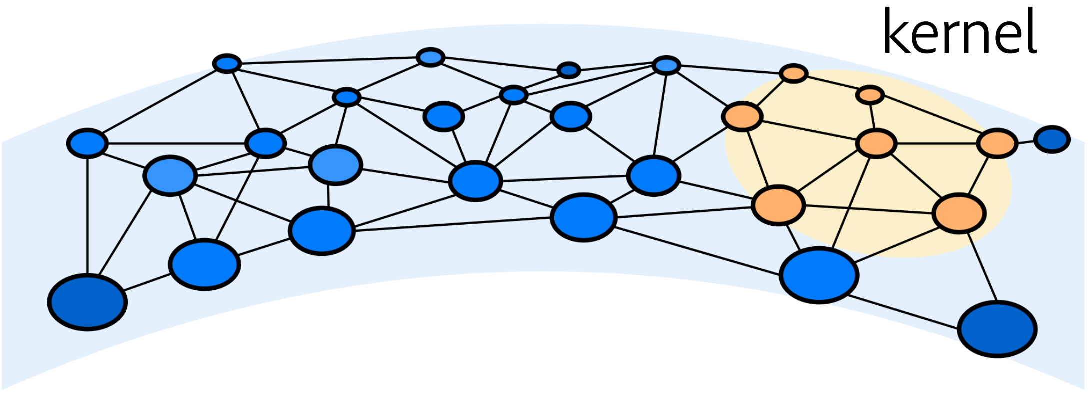
Our Method

Insights

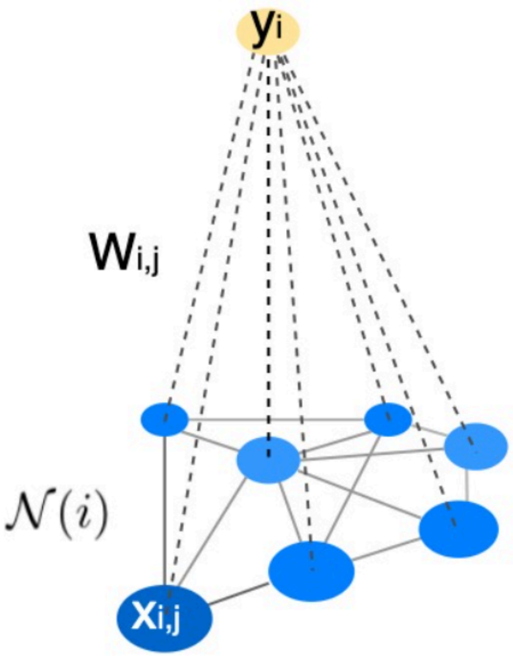
A continuous kernel can be shared in a continuous space.

A discretized kernel can be sampled from a continuous kernel.

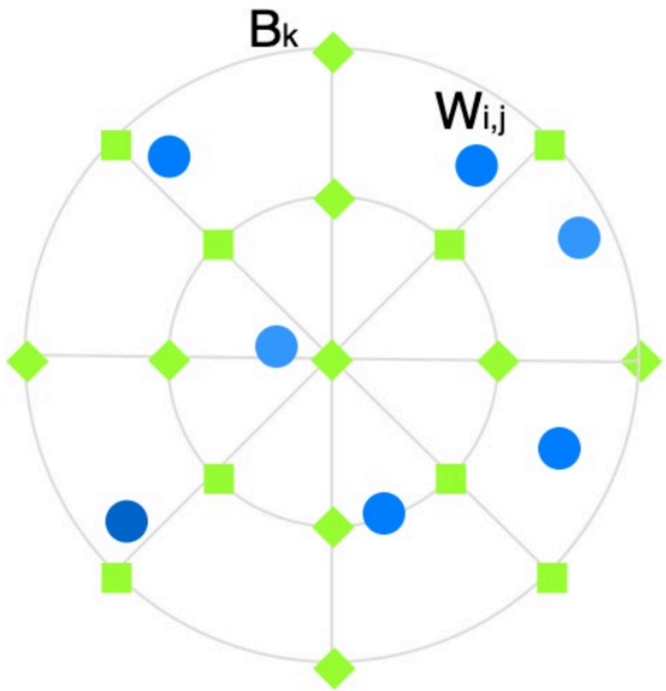
The sampling function needs to be defined per vertex locally.



Insights



Discrete Conv Filter at A Local Patch



◆ : Weight Basis on an imaginary grid

● : final weights

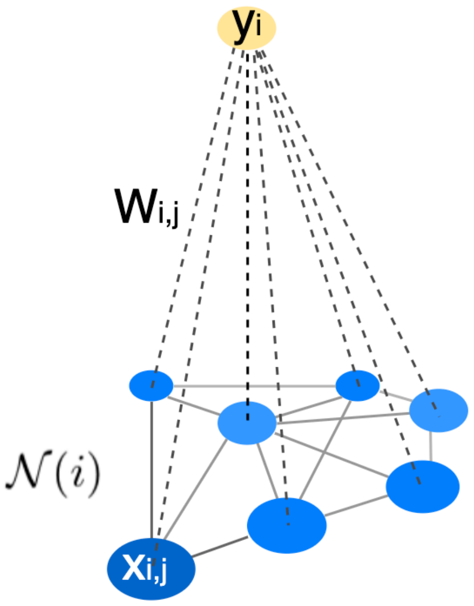
Our Convolution Operation

Each Convolution Layer has one kernel basis $B = \{\mathbf{B}_k\}_{k=1}^{M},\ \mathbf{B}_k \in \mathbb{R}^{I \times O}$

Each edge j for a local vertex i has coefficients $A_{i,j} = \{\alpha_{i,j,k}\}_{k=1}^{M},\ \alpha \in \mathbb{R}$:

The weight $\mathbf{W}_{i,j}$ on each edge is computed as $\mathbf{W}_{i,j} = \sum_{k=1}^{M} \alpha_{i,j,k} \mathbf{B}_k$

The output feature is computed as $\mathbf{y}_i = \sum_{x_{i,j} \in \mathcal{N}(i)} \mathbf{W}_{i,j} \mathbf{x}_{i,j} + \mathbf{b}$



B and $A_{i,j}$ are training parameters, shared across the dataset.

Our Pooling Operation

Observation: local density is non-uniform

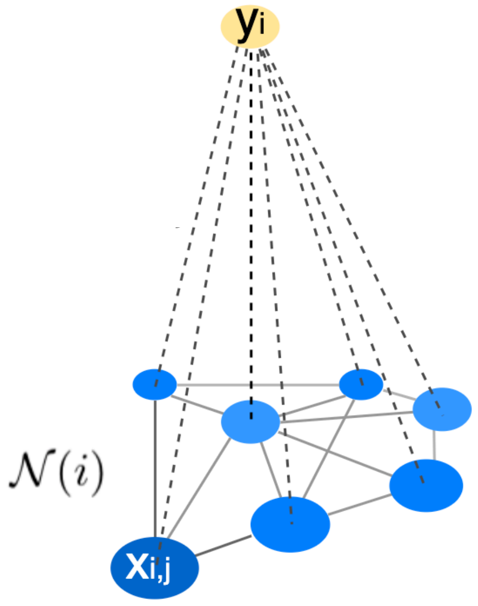
Solution: Monte Carlo Integration with learned density coefficients

Formulation:

Each local vertex j has a density coefficient $$\rho'_{i,j} = \frac{|\rho_{i,j}|}{\sum_{j=1}^{E_i} |\rho_{i,j}|}$$

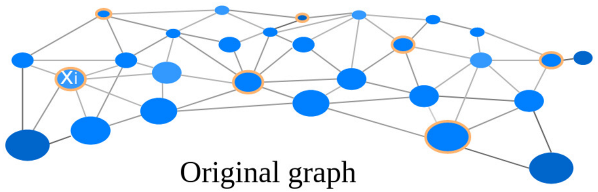
The output feature is computed as $$\mathbf{y}_i = \sum_{j \in \mathcal{N}(i)} \rho'_{i,j} \mathbf{x}_{i,j}$$

$\rho_{i,j}$ are training parameters, shared across the dataset.

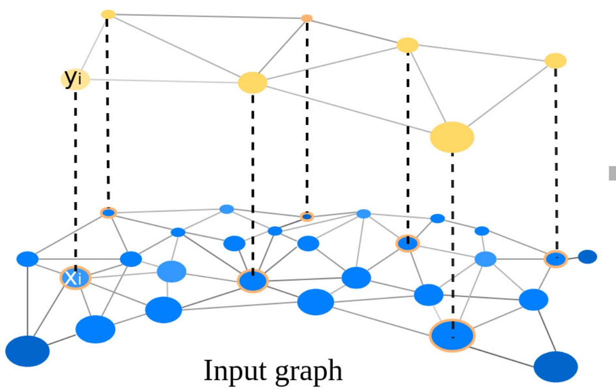


Down and Up Scaling Based Only on Graph Connectivity

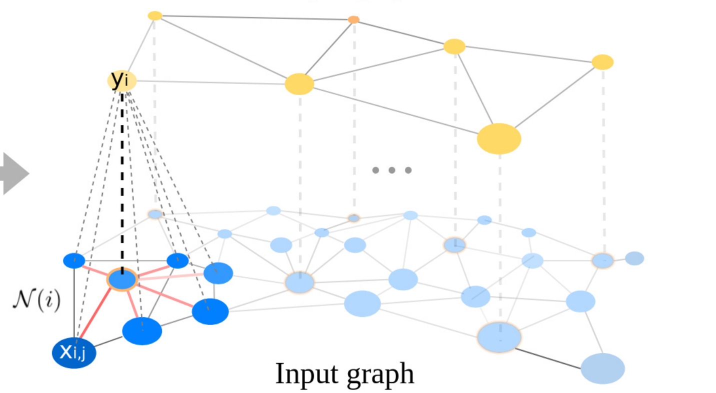
Down-sampling



Select sampled vertices with stride=1.



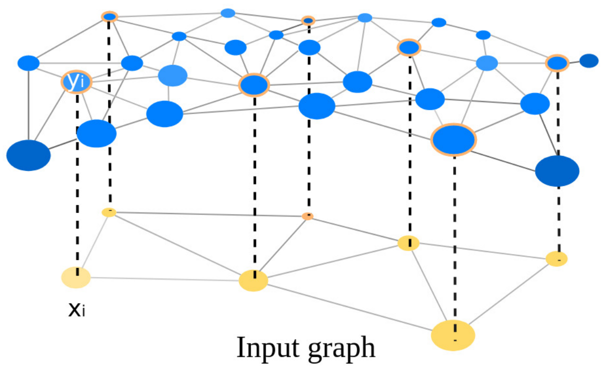
Create input/output graphs for Conv/Pool.

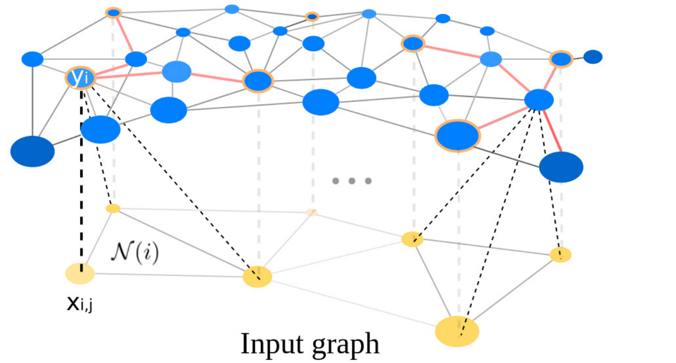


Create edges between input and output graphs.

Reverse

Up-sampling

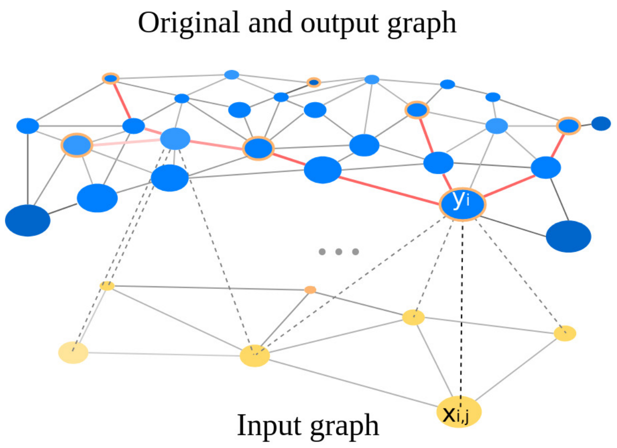


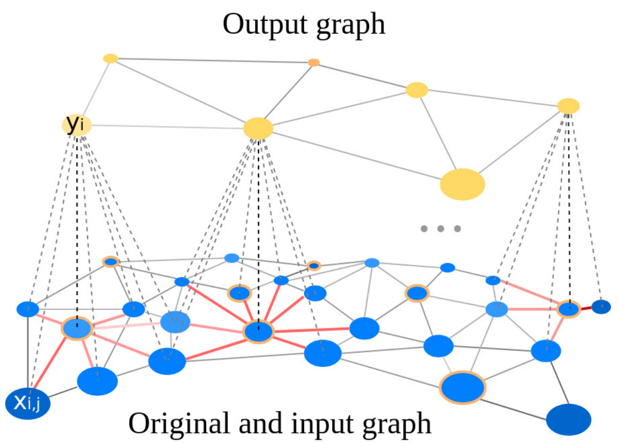


Create edges between input and output graphs.

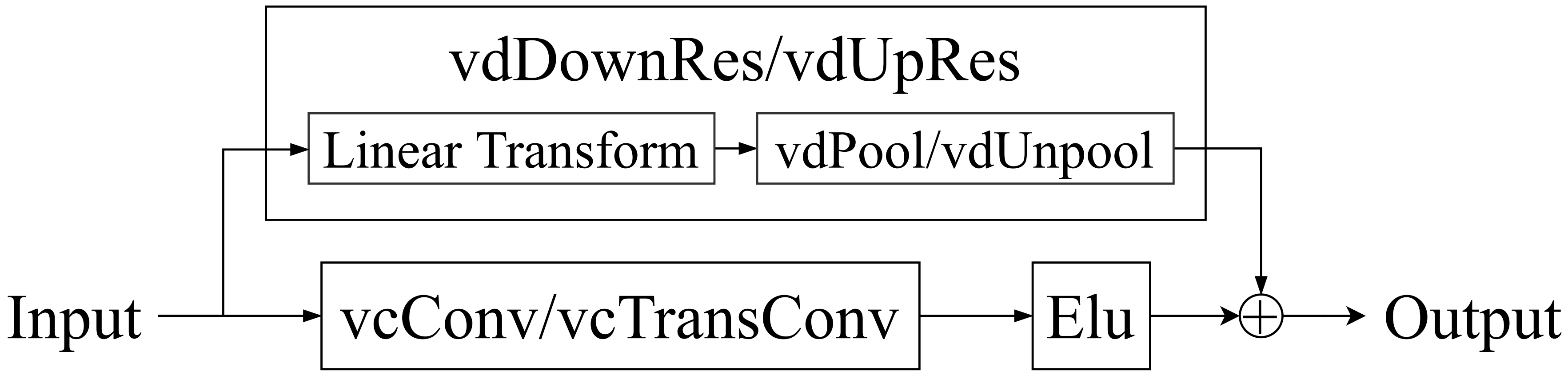
Operations Analog to Regular CNN

Down-sampling	Up-sampling	Attributes
vcConv	vcTransposeConv	(Stride, kernel radius, basis size, in_channel, out_channel, dilation)
vdPool	vdUnpool	(Stride)
vdDownResidual	vdUpResidual	(In_channel, out_channel)

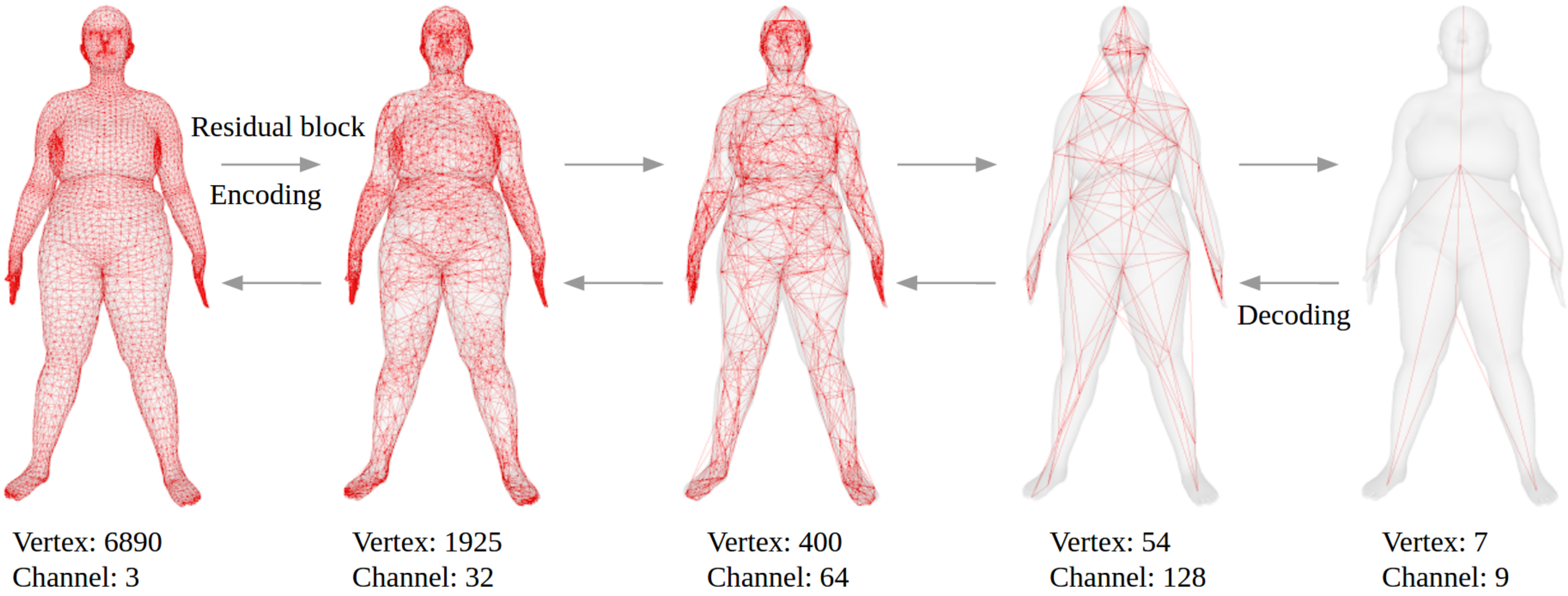




Residual Block

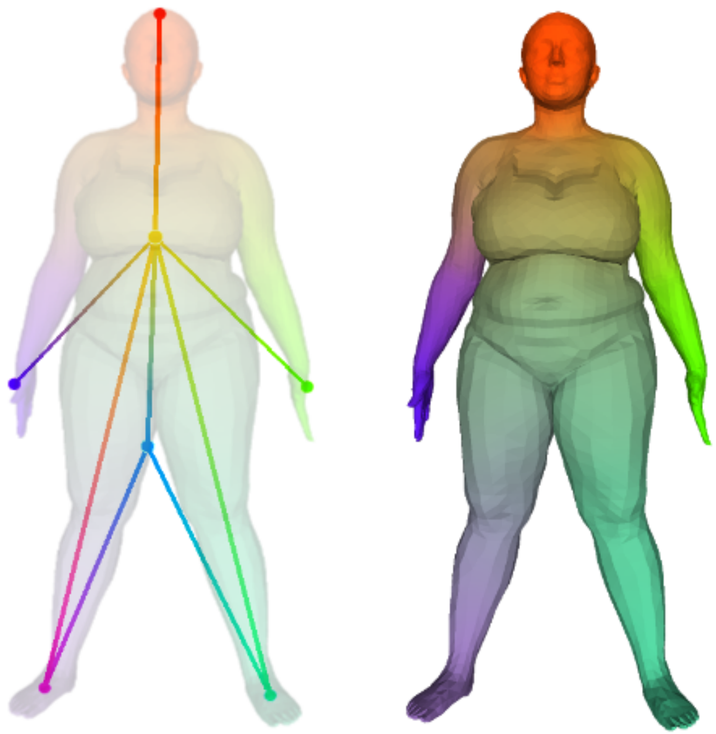


Auto-Encoder for DFAUST Dataset



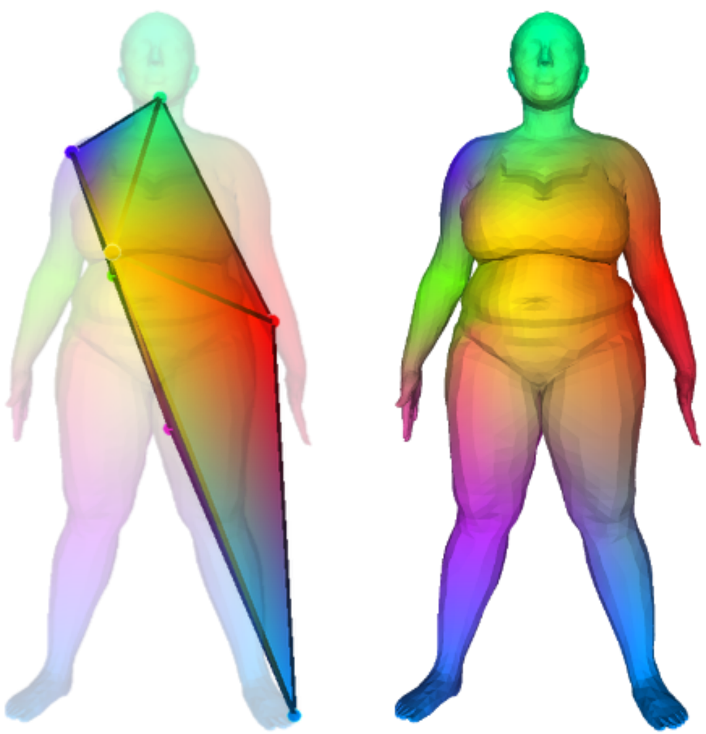
Stride=2, Kernel radius =2

Localized Latent Features



Middle layer graph Receptive field

Ours

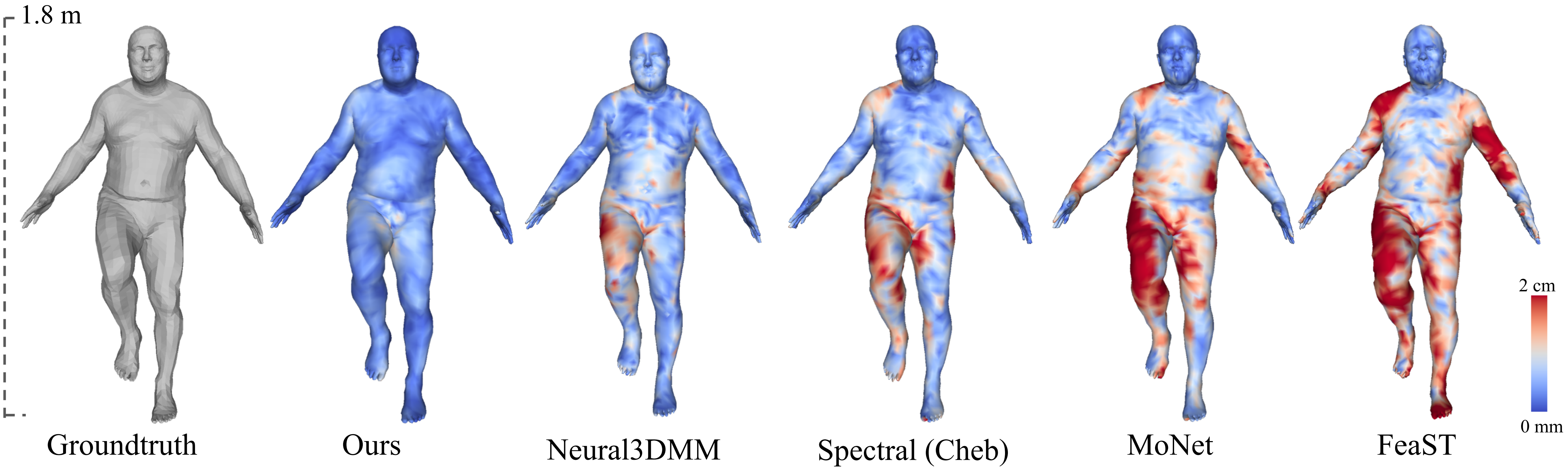


Middle layer graph Receptive field

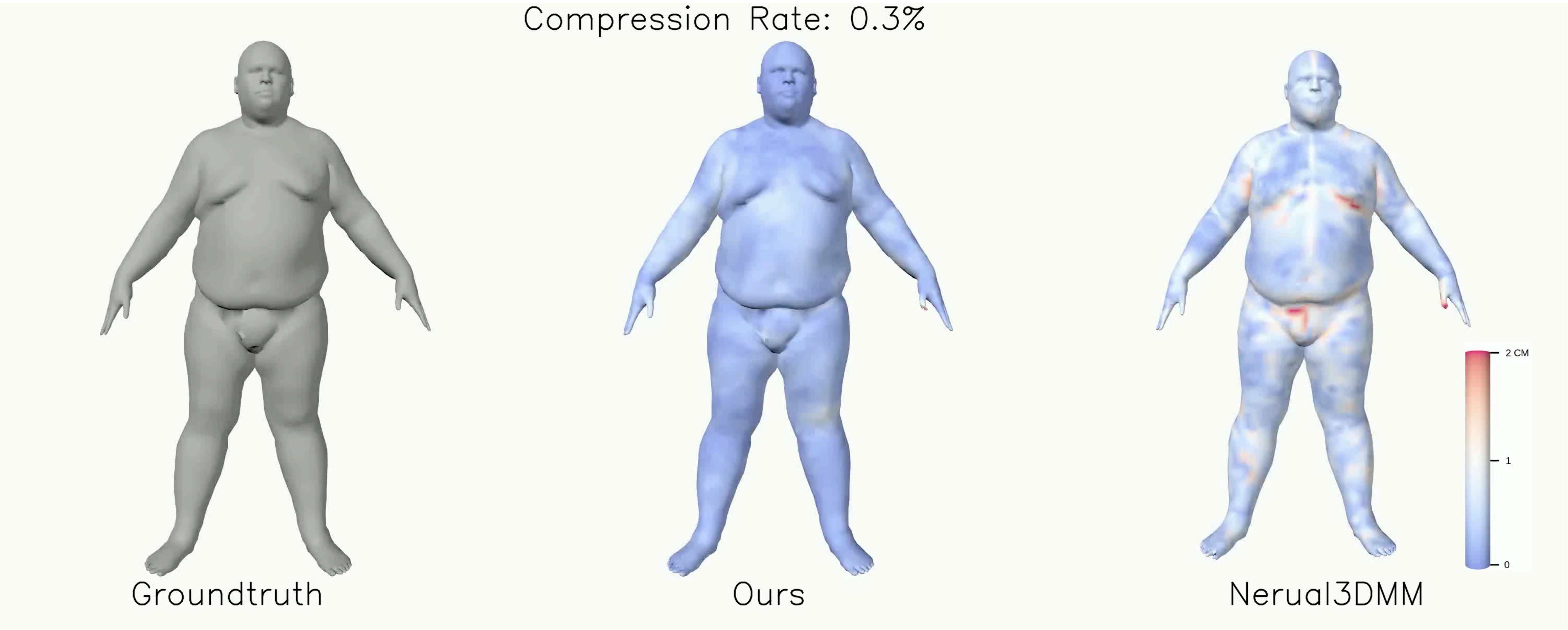
Quadric Mesh Simplification

Results

Ours: Lowest Reconstruction Error

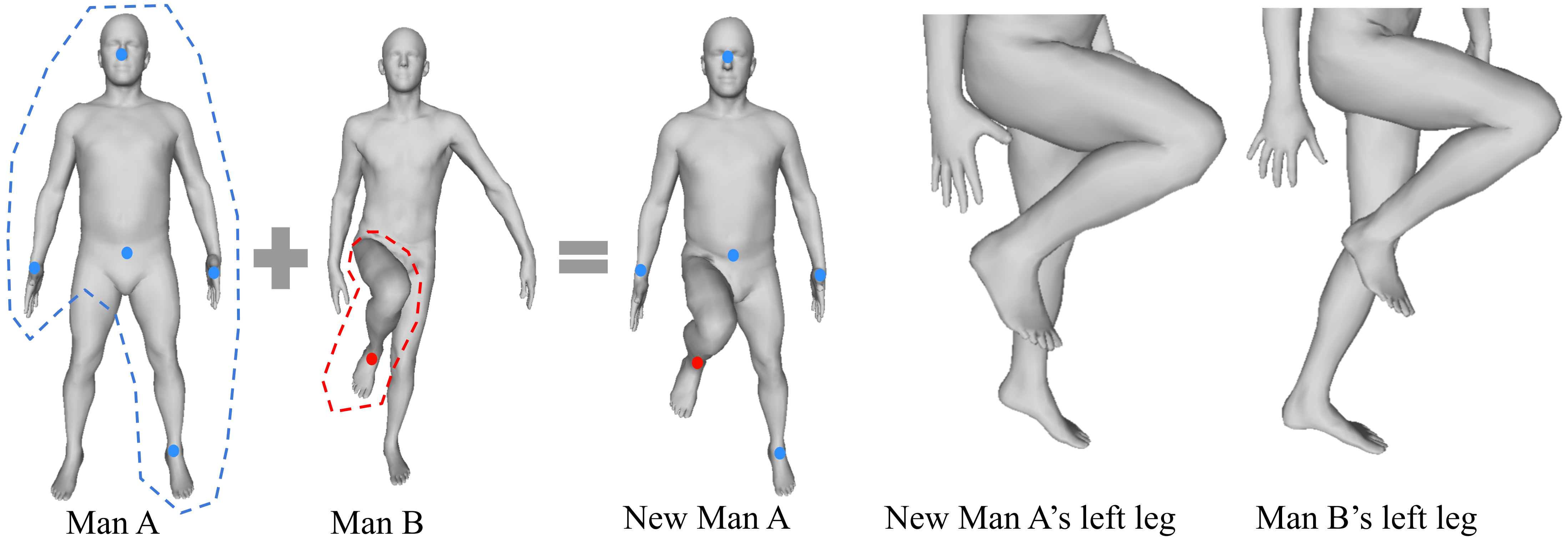


Ours: Lowest Reconstruction Error

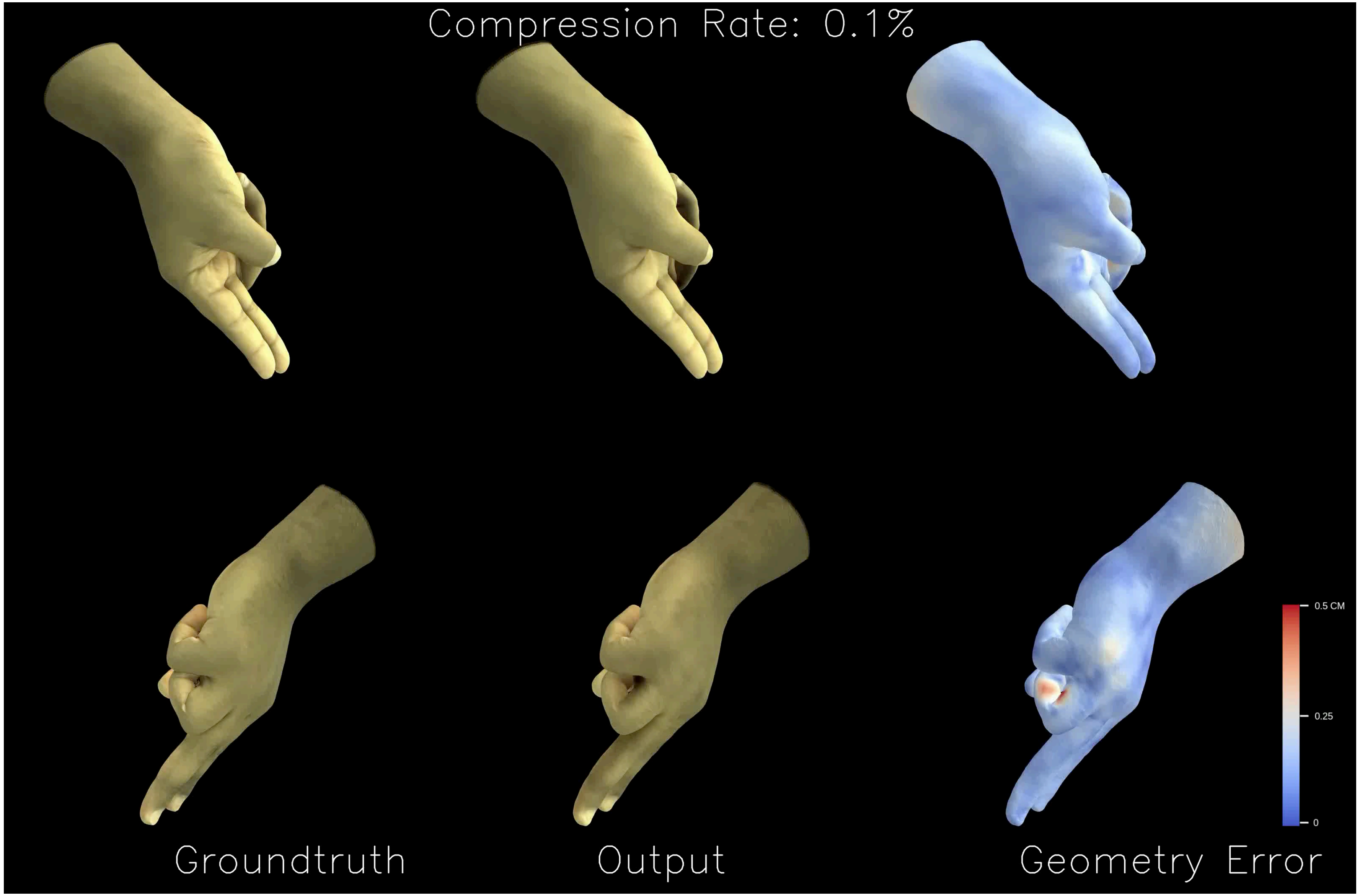


Videos can be watched at https://zhouyisjtu.github.io/project_vcmeshcnn/vcmeshcnn.html

Localized Latent Space Interpolation



Reconstruct both Geometry and Color



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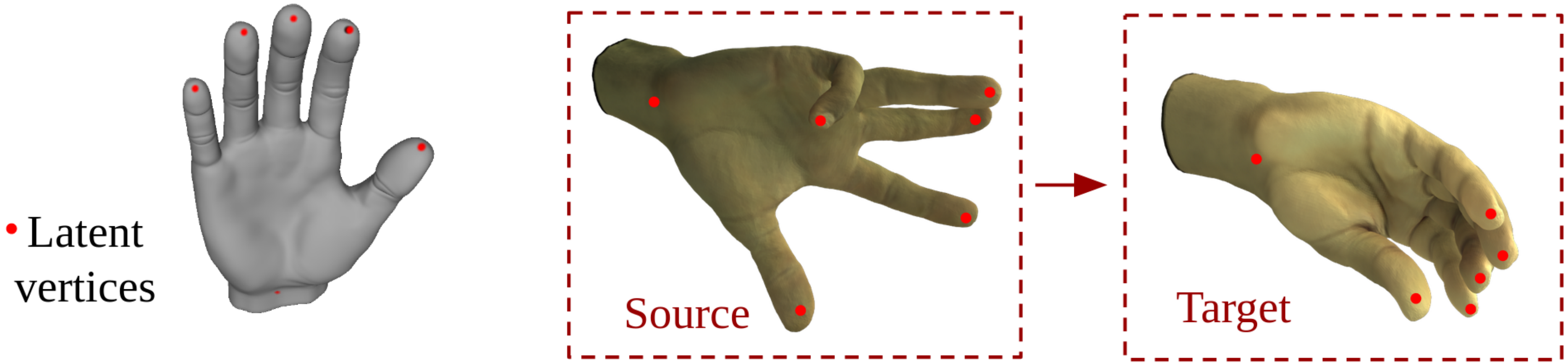
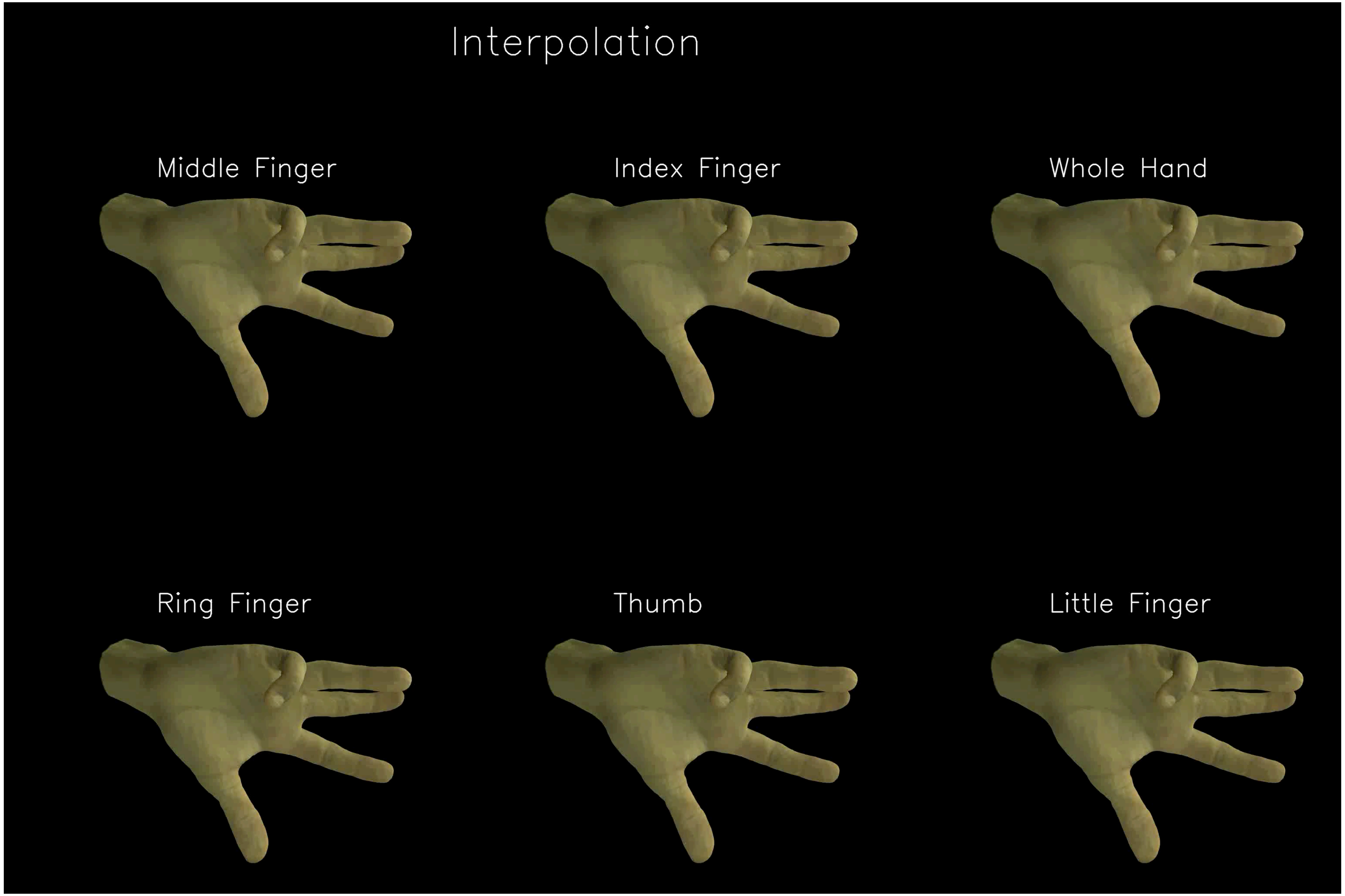
Localized Latent Space Interpolation



Localized Latent Space Interpolation



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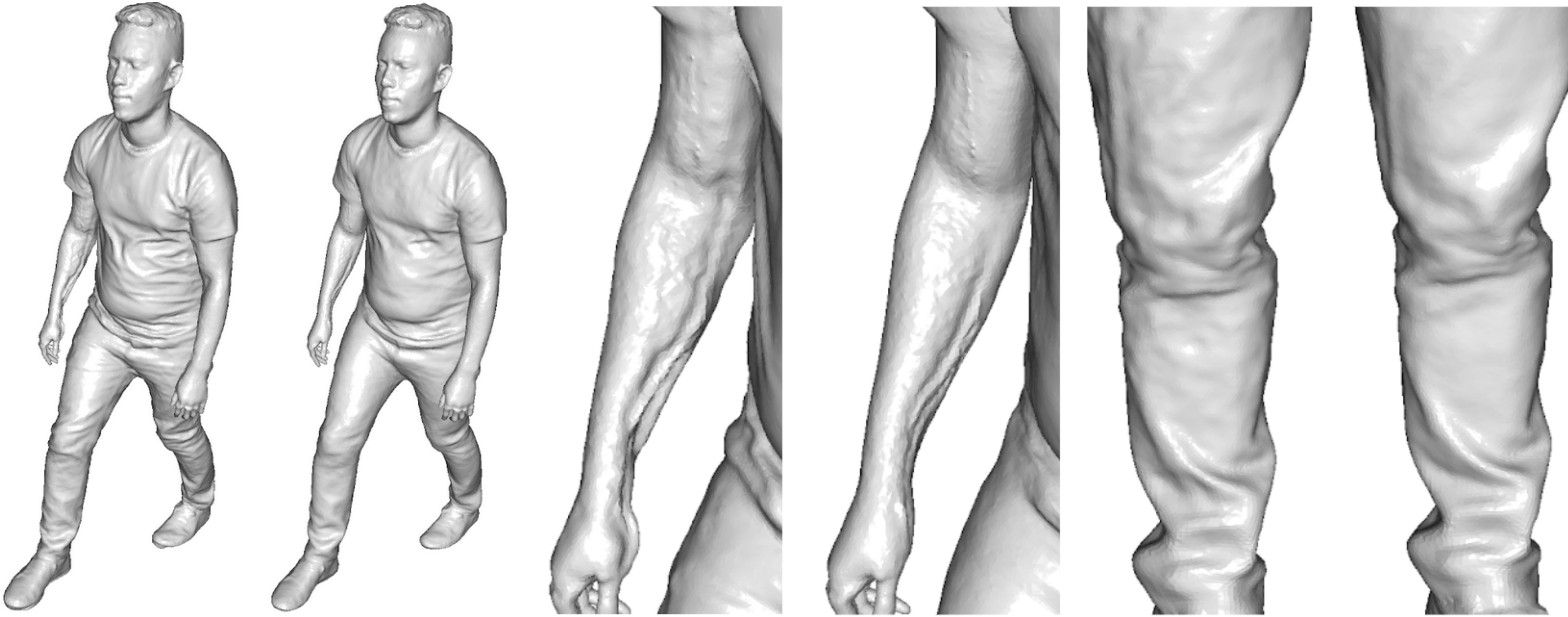
Efficient for High Resolution Meshes

153,000 Vertices, 24k training meshes, 2k test meshes, compression rate 0.75%.

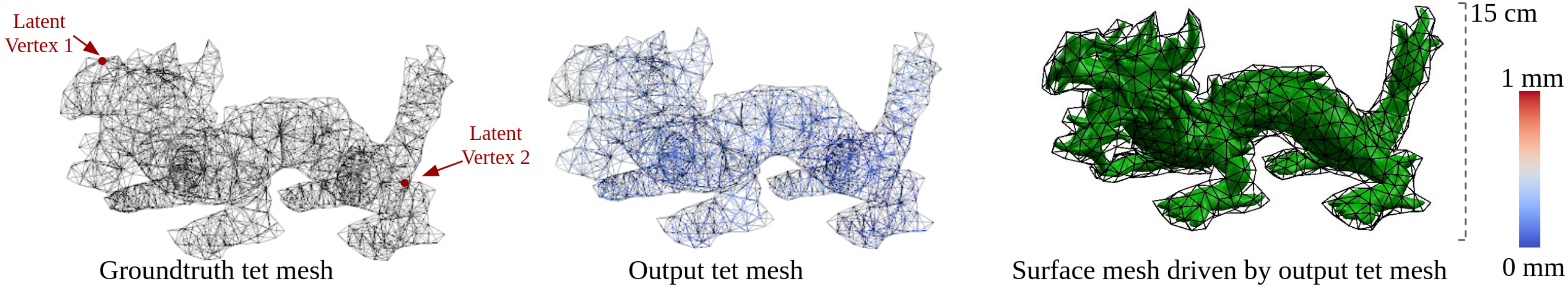


Groundtruth Output groundtruth output groundtruth output

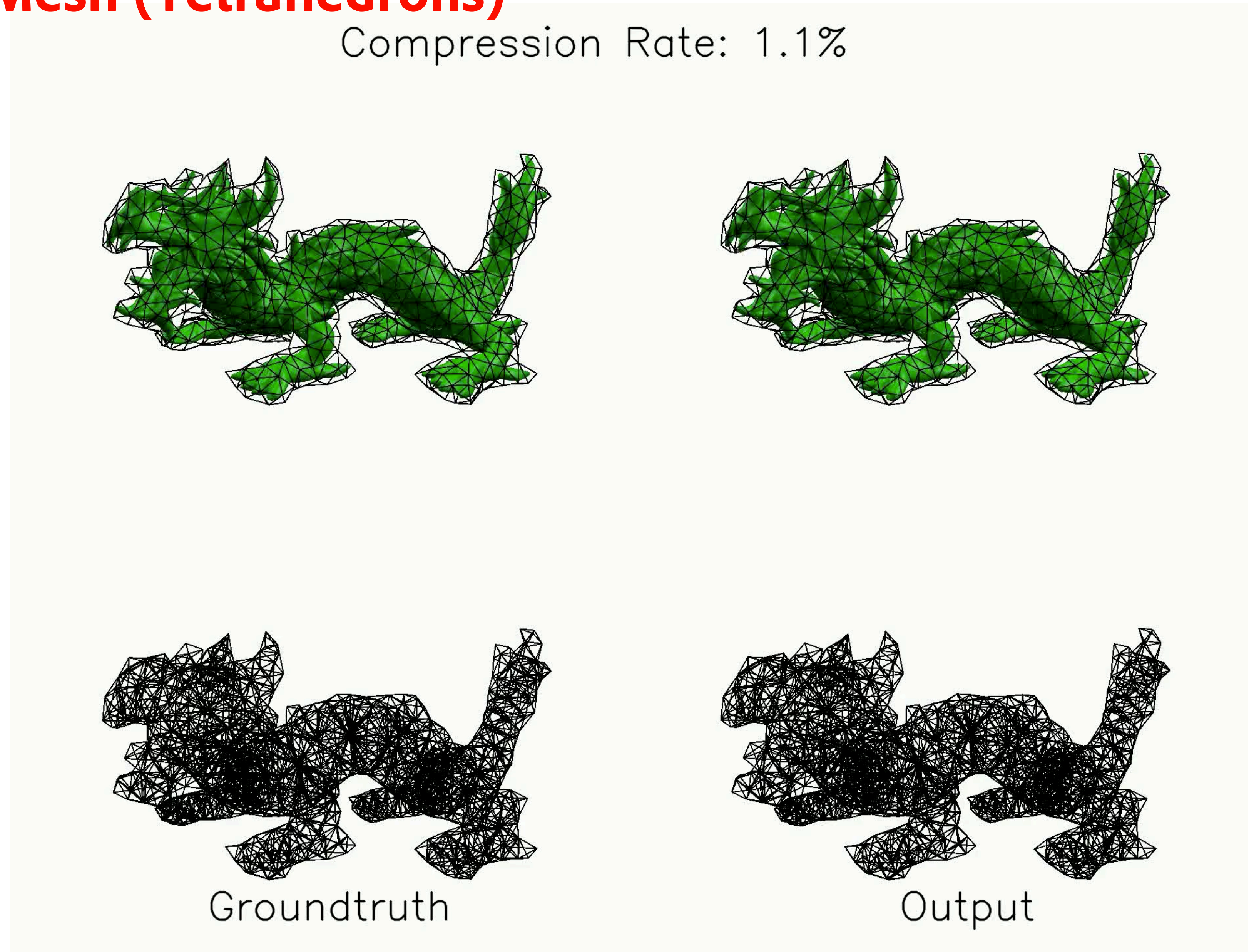
Videos can be watched at https://zhouyisjtu.github.io/project_vcmeshcnn/vcmeshcnn.html

Volumetric Mesh (Tetrahedrons)

960 Vertices, 7k training meshes, 562 test meshes, compression rate 1.1%, test error 0.2 mm.



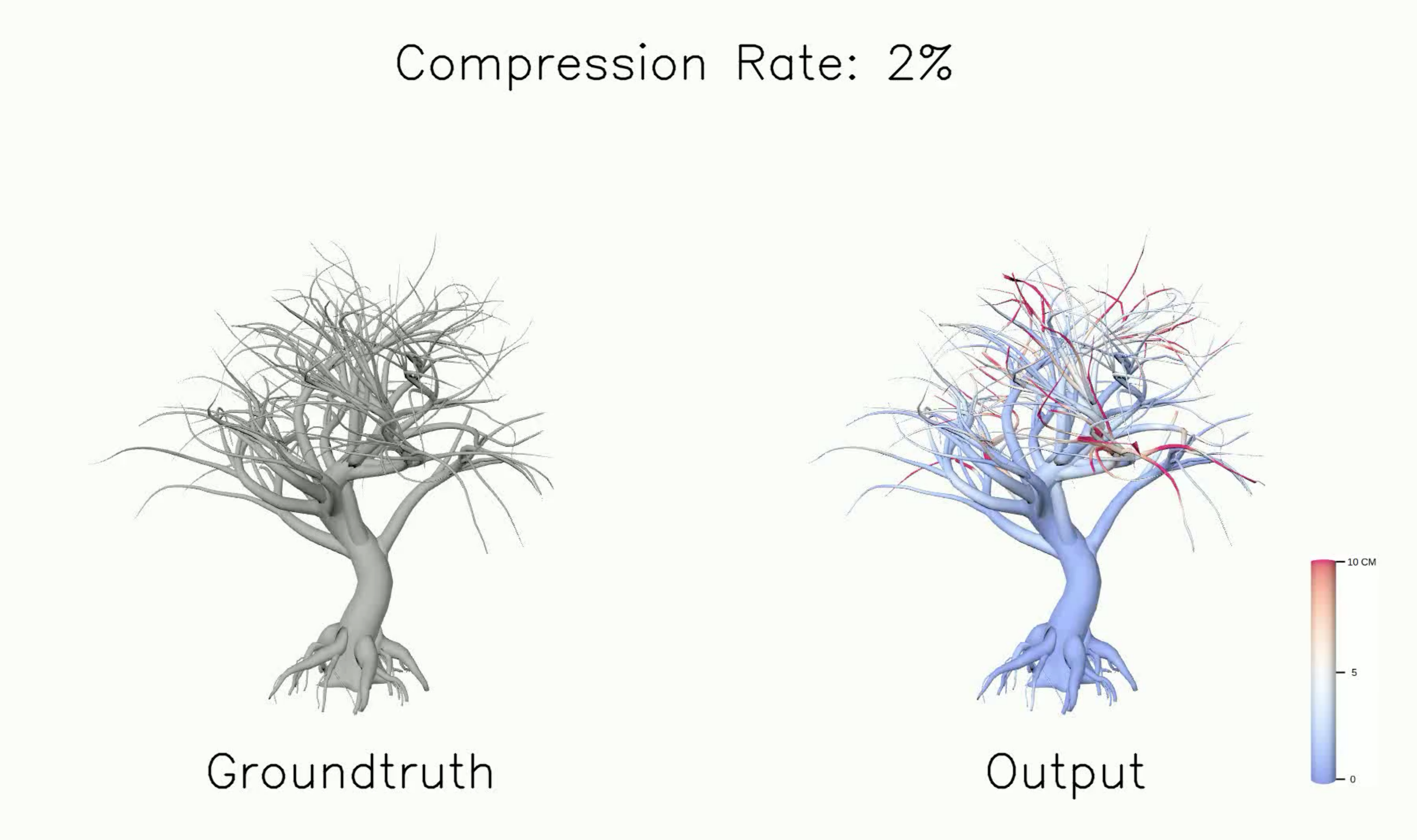
Volumetric Mesh (Tetrahedrons)



Videos can be watched at https://zhouyisjtu.github.io/project_vcmeshcnn/vcmeshcnn.html

Non-Manifold Mesh

20,000 Vertices, 10k training meshes, 2k test meshes, compression rate 2%, test error 4.1 cm.



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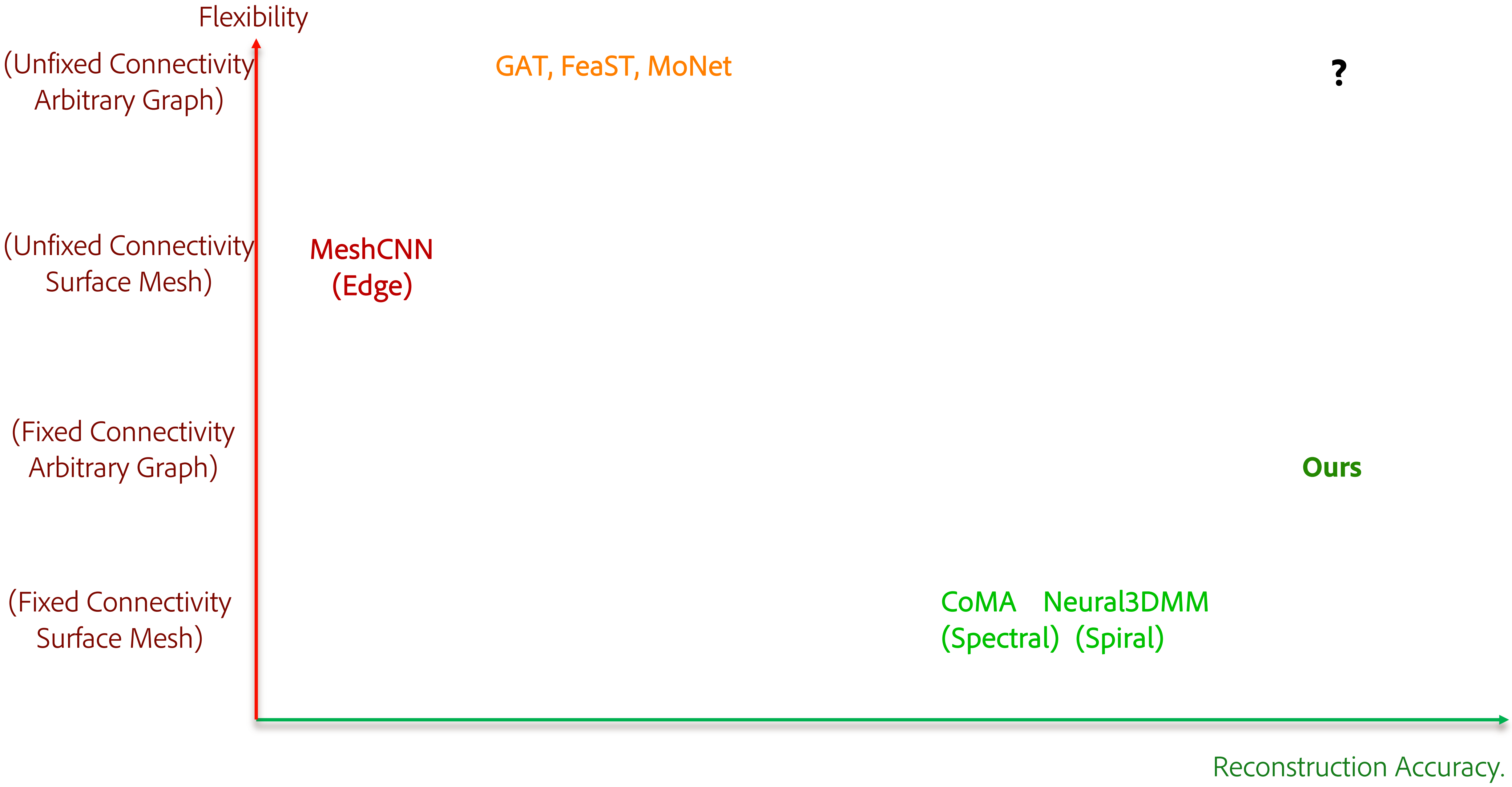
Future Work


Flexibility
(Unfixed Connectivity
Arbitrary Graph)
(Unfixed Connectivity
Surface Mesh)
(Fixed Connectivity
Arbitrary Graph)
(Fixed Connectivity
Surface Mesh)
GAT, FeaST, MoNet
?
MeshCNN
(Edge)
Ours
CoMA
(Spectral)
Neural3DMM
(Spiral)
Reconstruction Accuracy.

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