Pop-Out Motion: 3D-Aware Image Deformation via Learning the Shape Laplacian

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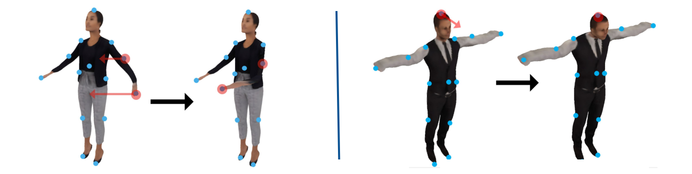
Introduction

Objective

We aim to enable **3D-aware image deformation** with **minimal restrictions on shape category and deformation type**.



Motivation

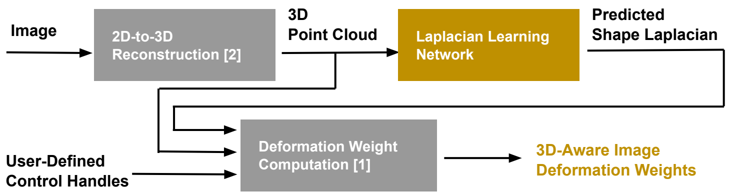
For **3D-aware deformation**, it is **necessary to reconstruct the object in a 2D image to 3D space**; however, it is **not sufficient in general**.

→ Modeling deformation often requires **the shape Laplacian** [1].

→ However, **most of existing methods of image-based 3D reconstruction** produce a surface **without proper consideration about intrinsic shape properties**.

Key Idea & Method Overview

We propose to take a **supervised learning-based approach** to **predict the shape Laplacian of the underlying volume of a 3D reconstruction**.



Handle-Based Deformation Weights [1]

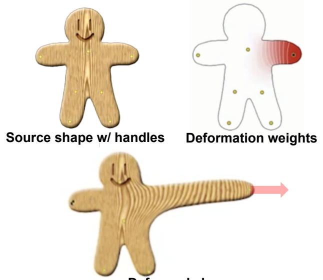
Bounded Biharmonic Weights [1]

$$\underset{\{\mathbf{w}_k\}_{k=1\cdots m}}{\operatorname{argmin}} \sum_{k=1}^{m} \frac{1}{2} \mathbf{w}_k^T A \mathbf{w}_k$$

$$\text{subject to: } w_{k,i} = 1 \quad \forall i \quad \text{s.t.} \quad \mathbf{v}_i \in \mathcal{H}_k$$
$$w_{k,i} = 0 \quad \forall i \quad \text{s.t.} \quad \mathbf{v}_i \in \mathcal{H}_{l, l \neq k}$$
$$\textstyle\sum_{k=1}^{m} w_{k,i} = 1$$
$$0 \le w_{k,i} \le 1.$$

- $\mathcal{H}_k$: k-th deformation handle
- $\mathbf{w}_k$: deformation weights associated with k-th handle

Images from [1]



Laplacian-Based Deformation Energy (A)

Desired properties:
positive semi-definiteness / symmetry / sparsity

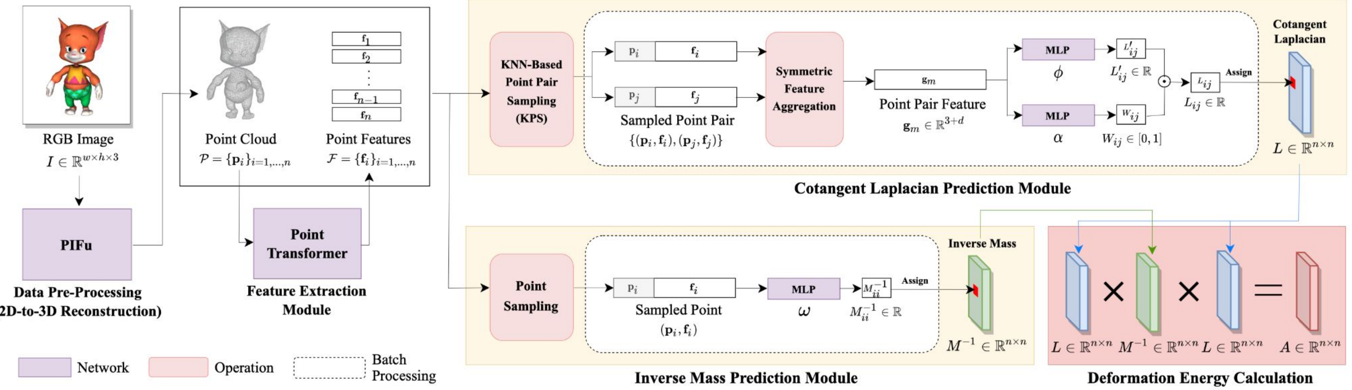
$$A = LM^{-1}L$$

$A \in \mathbb{R}^{n \times n}$: **deformation energy**
$L \in \mathbb{R}^{n \times n}$: **cotangent Laplacian**
$M^{-1} \in \mathbb{R}^{n \times n}$: **inverse mass**

- n : number of vertices in the source mesh

Laplacian Learning Network

We introduce **a novel network that can learn the shape Laplacian** with **several desired properties (i.e., positive semi-definiteness, symmetry and sparsity)** from a 3D reconstruction.



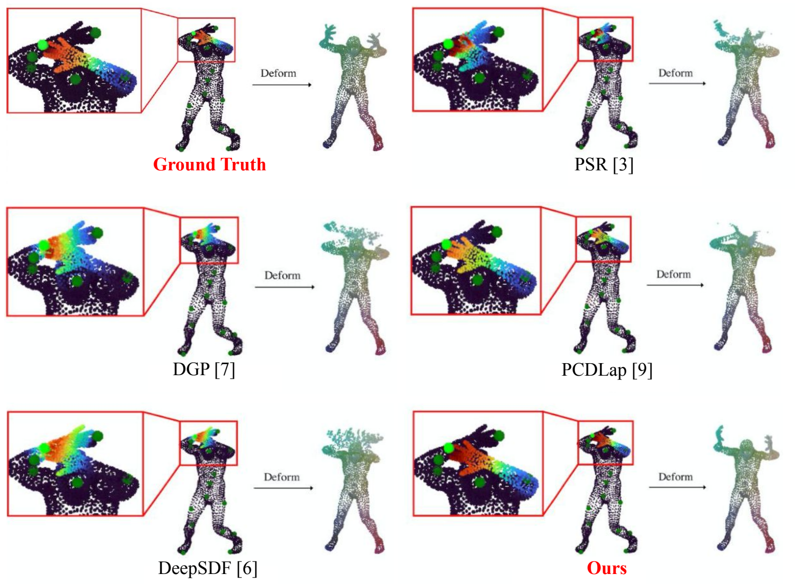
Quantitative Evaluation

Metric	PSR [3]	APSS [4]	BPA [5]	DeepSDF [6]	DGP [7]	MIER [8]	PCDLap [9]	NMLap [10]	Ours
Weight L1 (×100) ↓	3.86	3.46	4.32	2.66	4.15	3.26	3.53	3.34	**2.10**
Shape CD (×100) ↓	3.84	3.04	3.83	2.61	4.09	3.16	2.97	4.04	**1.81**
Shape HD (×0.1) ↓	1.81	1.31	1.73	0.48	2.85	1.13	**0.42**	0.43	**0.42**

- **Dataset**: DFAUST [11] • **Evaluation Metric**: Deformation Weight Error (L1 Distance) , Deformed Shape Error (Chamfer Distance, Hausdorff Distance)

3D-Aware Image Deformation

Deformation Weight Visualization



Please visit **our project page (QR code above)** for more results, including **motion videos** generated using our image deformation method.

References

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