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

Jihyun Lee*, Minhyuk Sung*, Hyunjin Kim, Tae-Kyun (T-K) Kim

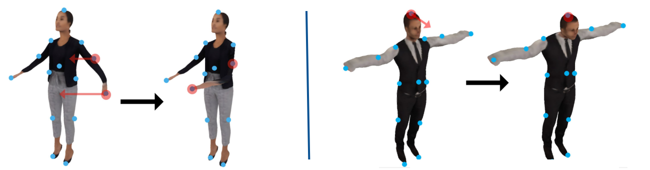
KAIST · Imperial College London

CVPR JUNE 19-24 2022 NEW ORLEANS LOUISIANA

Introduction

Objective

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



Motivation

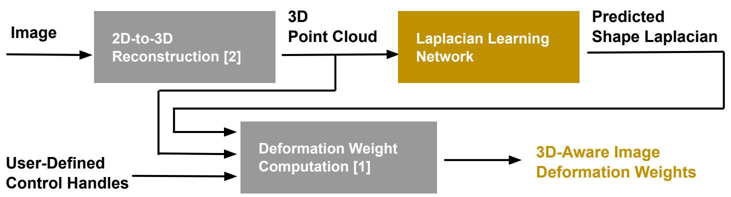
For **3D-aware deformation**, it is **necessary to reconstruct the object in a 2D image to 3D space**; however, it is **not sufficient in general**.

→ 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**.



References

[1] A. Jacobson, *et al*. Bounded biharmonic weights for real-time deformation. In SIGGRAPH, 2011.
[2] S. Saito, *et al.* PIFu: Pixel-aligned implicit function for high-resolution clothed human digitization. In ICCV, 2019.
[3] M. Kazhdan *et al*. Screened poisson surface reconstruction. TOG, 2013.
[4] G. Guennebaud and M. Gross. Algebraic point set surfaces. In SIGGRAPH, 2007.
[5] F. Bernardini *et al*. The ball-pivoting algorithm for surface reconstruction. TVCG, 1999.
[6] J. Park *et al.* DeepSDF: Learning continuous signed distance functions for shape representation. In CVPR, 2019.
[7] F. Williams *et al.* Deep geometric prior for surface reconstruction. In CVPR, 2019.
[8] M. Liu *et al.* Meshing point clouds with predicted intrinsic-extrinsic ratio guidance. In ECCV, 2020.
[9] M. Belkin, *et al*. Constructing laplace operator from point clouds in Rd. In Proc. Annu. ACM-SIAM Symp. Discrete Algorithms, 2009
[10] N. Sharp and K. Crane. A laplacian for nonmanifold triangle meshes. In SGP, 2020.
[11] F. Bogo, *et al.* Dynamic FAUST: Registering human bodies in motion. In CVPR, 2017

Handle-Based Deformation Weights [1]

Bounded Biharmonic Weights [1]

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

subject to: $w_{k,i} = 1 \quad \forall i \quad \text{s.t.} \quad \mathbf{v}_i \in \mathcal{H}_k$

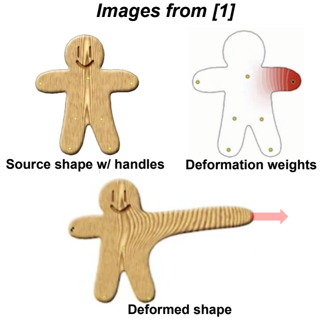
$w_{k,i} = 0 \quad \forall i \quad \text{s.t.} \quad \mathbf{v}_i \in \mathcal{H}_{l, l \neq k}$

$\sum_{k=1}^{m} w_{k,i} = 1$

$0 \leq w_{k,i} \leq 1.$

- $\mathcal{H}_k$: 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**

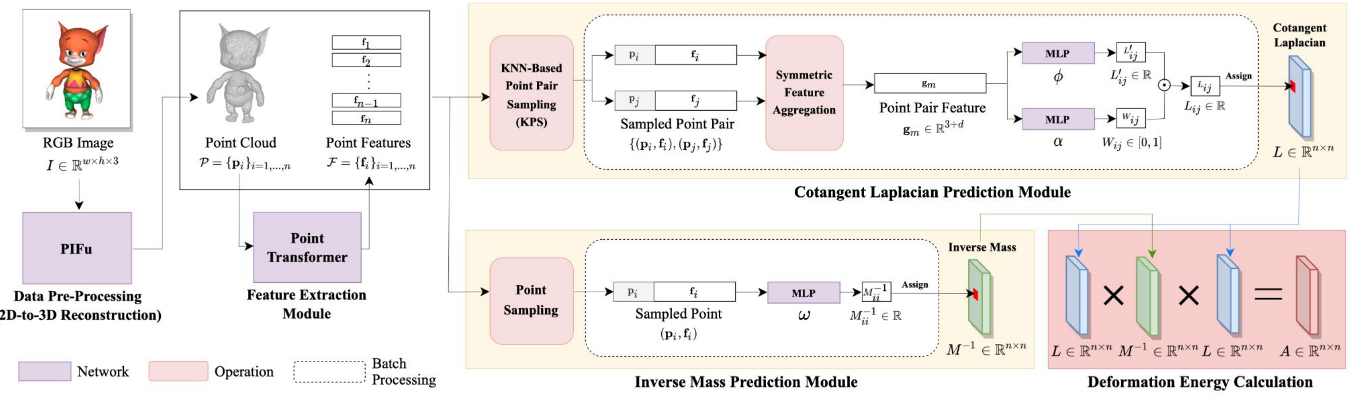
$L \in \mathbb{R}^{n \times n}$: **cotangent Laplacian**

$M^{-1} \in \mathbb{R}^{n \times n}$: **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.



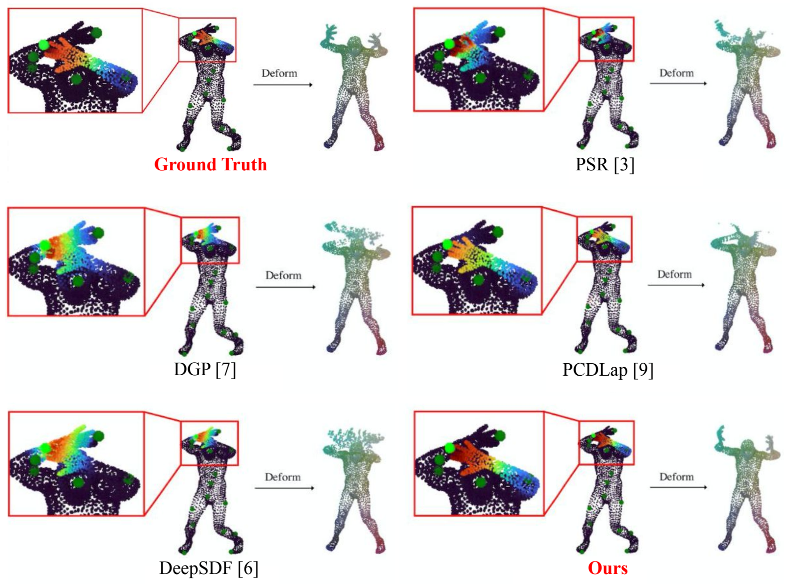
Quantitative Evaluation

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.