D^2IM-Net: Learning Detail Disentangled Implicit Fields from Single Images

Manyi Li Hao Zhang

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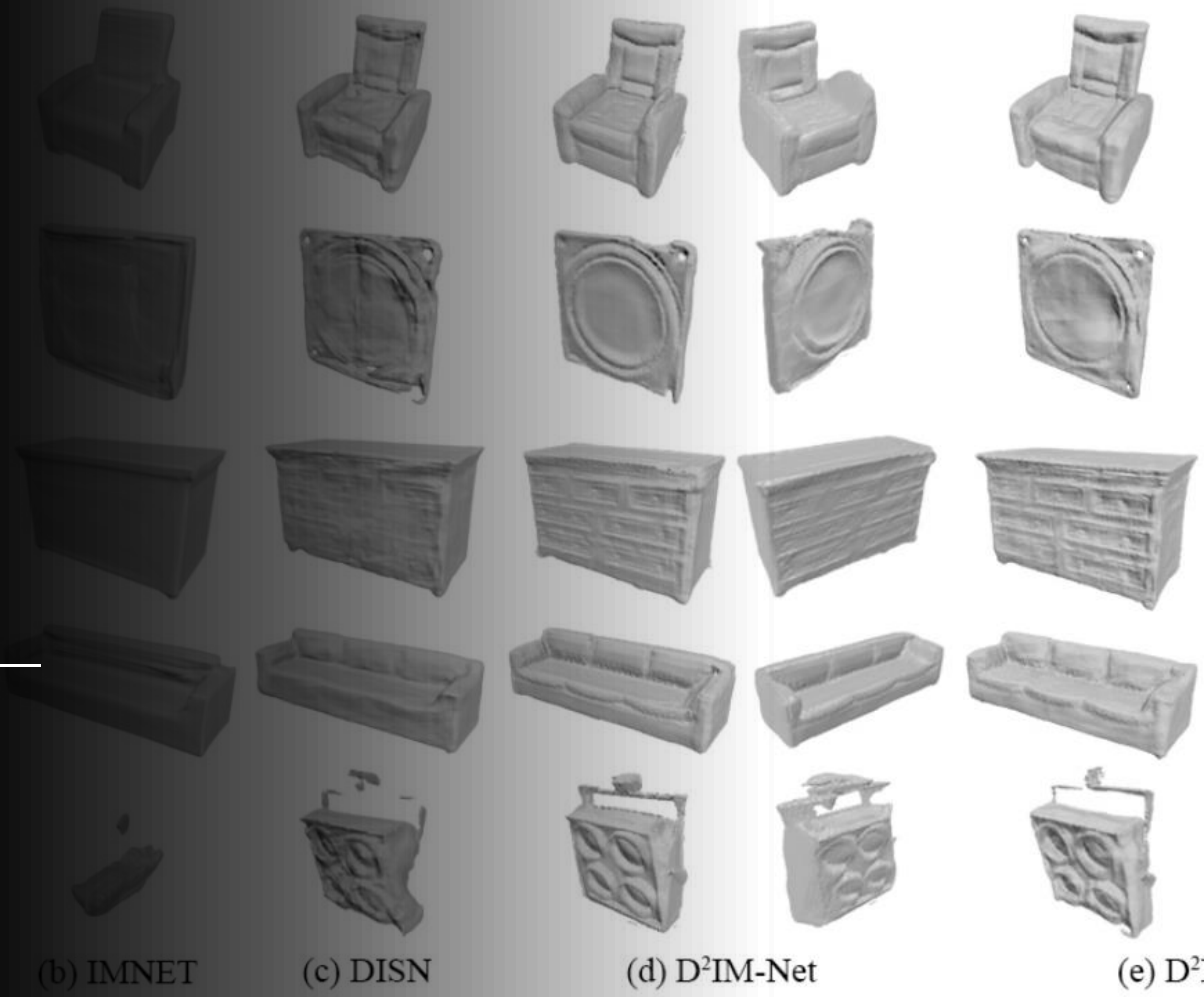
By Alberto Tono



Motivation

IM-NET Learning Implicit Fields for Generative Shape Modeling

Aimed at recovering a ***detail disentangled reconstruction*** from:

- **Coarse** 3d shapes as implicit field -> **topological shape structures**
- **Fine detail --> with surface features**

Paste-n-reconstruct

Learning Implicit Fields for Generative Shape Modeling
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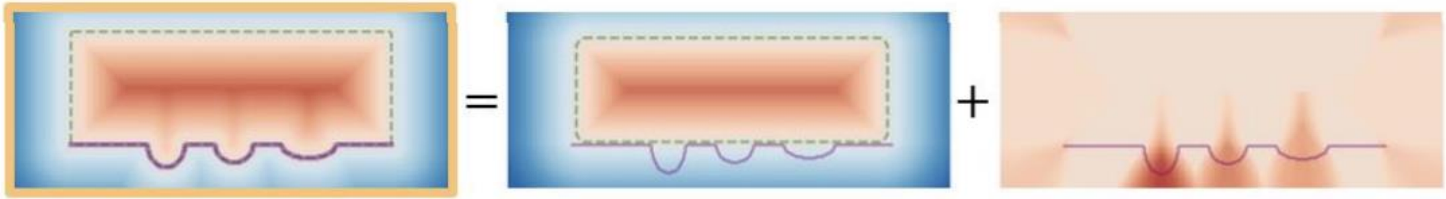
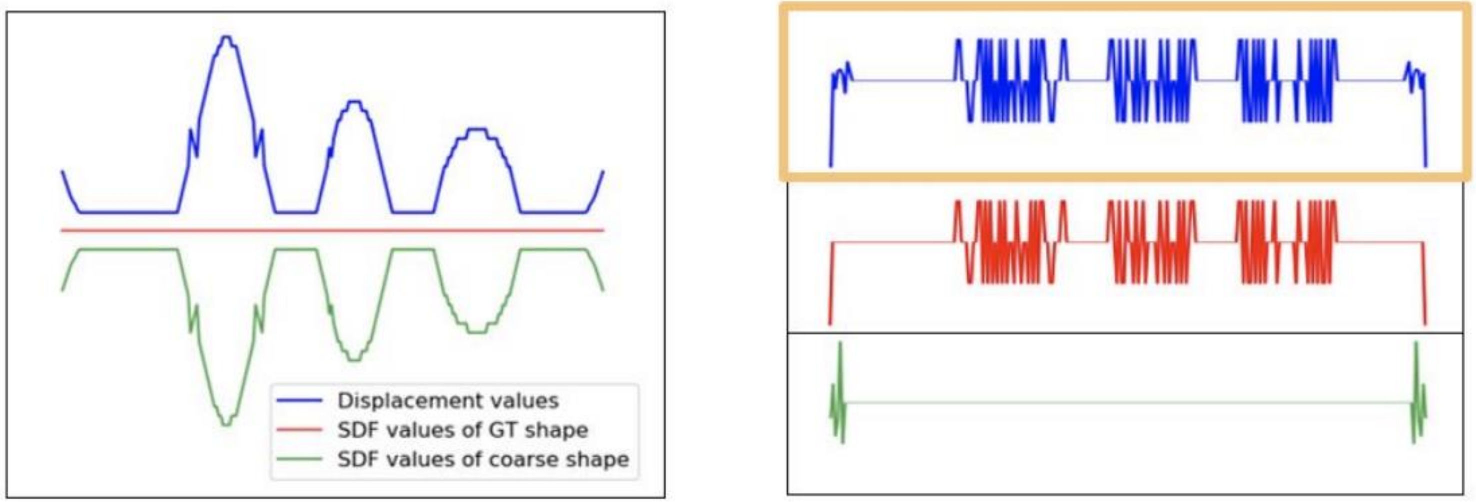


(a) SDF of GT shape in dashed lines; front surface in thick purple. (b) SDF of coarse shape in dashed lines; front surface in light purple. (c) Displacement field; front surface in light purple.



(d) Plot of SDF and displacement field values along the front surface. (e) Plot of Laplacian values of the fields shown on the left.

$$F_{SDF}(p) = f_B(p) + f_D(p),$$
$$f_B : \mathbb{R}^3 \rightarrow \mathbb{R},\ f_D : \mathbb{R}^3 \rightarrow \mathbb{R},$$

$$\triangle f_B \approx 0$$

$$\triangle f_D(p) = \triangle F_{SDF}(p), |dist(p, S)| < \delta.$$

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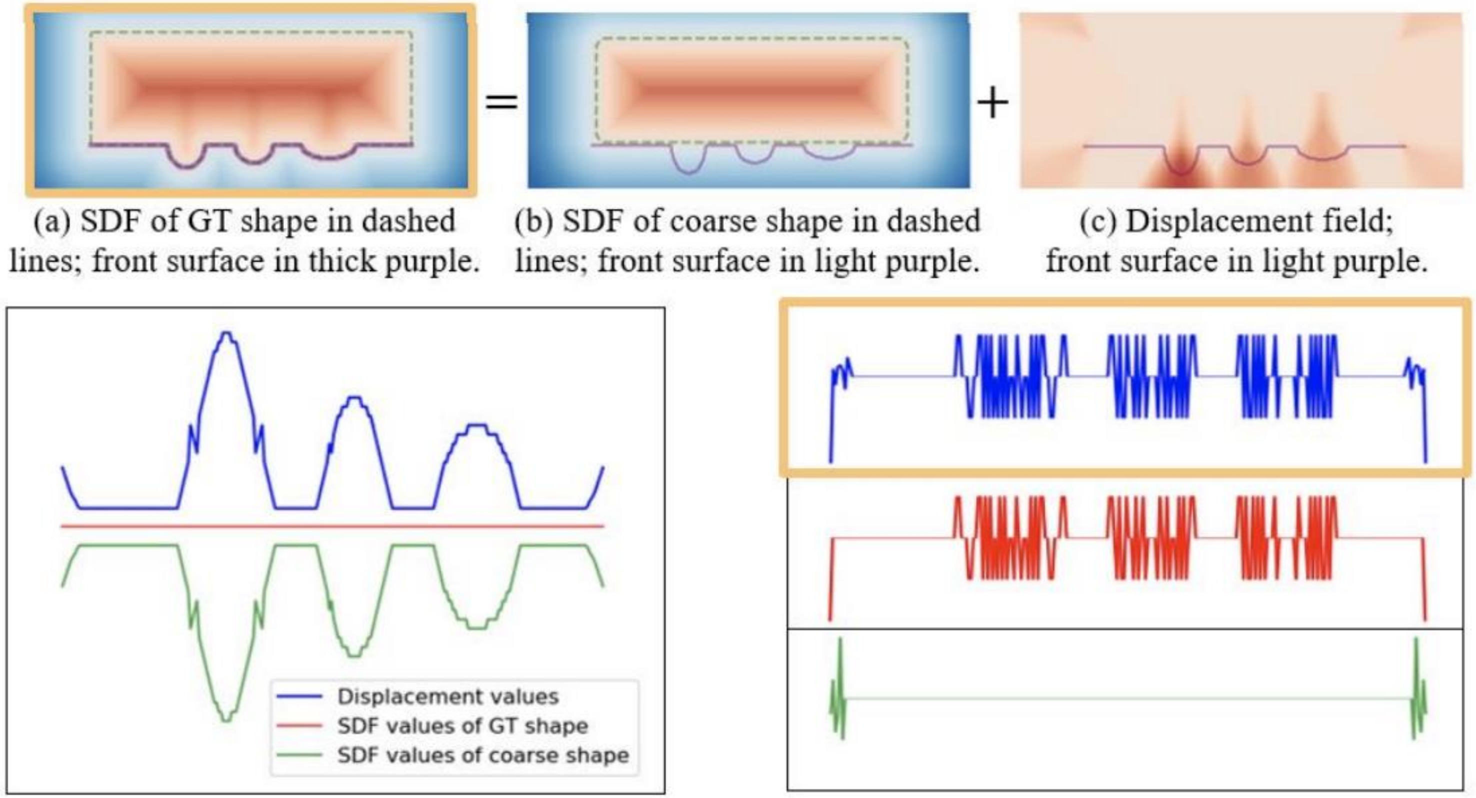

(a) SDF of GT shape in dashed lines; front surface in thick purple.

(b) SDF of coarse shape in dashed lines; front surface in light purple.

(c) Displacement field; front surface in light purple.

(d) Plot of SDF and displacement field values along the front surface.

(e) Plot of Laplacian values of the fields shown on the left.

Assumption: the coarse shape is smooth and lies close to the surface.

The smoothness herein implies that the (residual) displacement field contains information about surface details.

Weighted Sampling

Randomly sample
near object surfaces

Point densities as sampling weights

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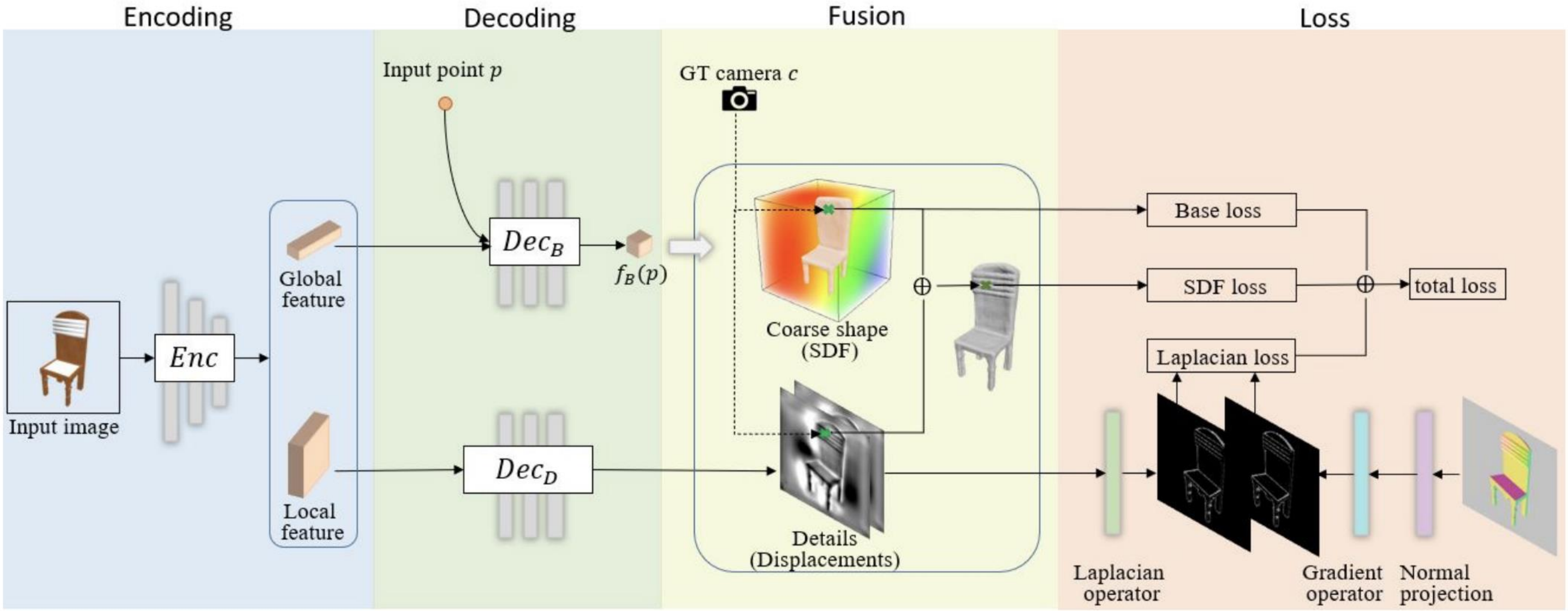
Disn: Deep implicit surface network for high-quality single-view 3d reconstruction
Qiangeng Xu, Weiyue Wang, Duygu Ceylan, Radomir Mech, and Ulrich Neumann.

Network Pipeline



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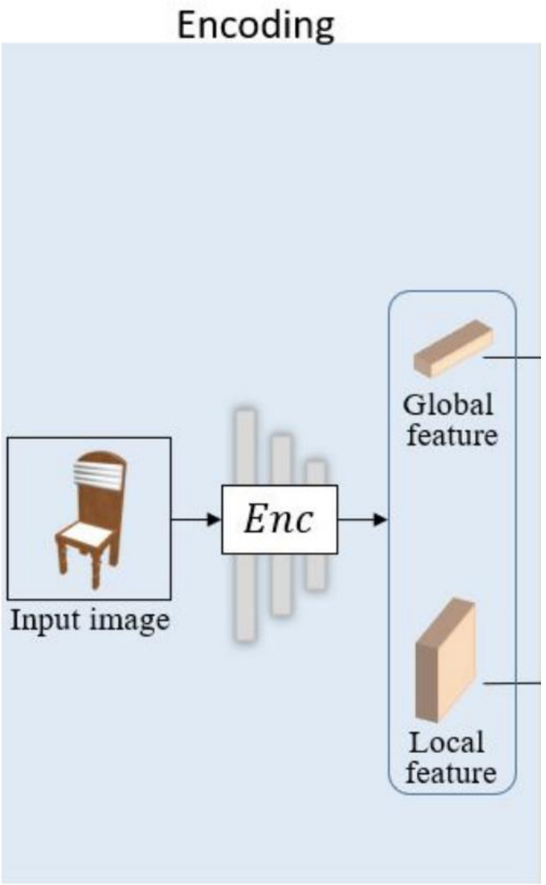
Network Pipeline



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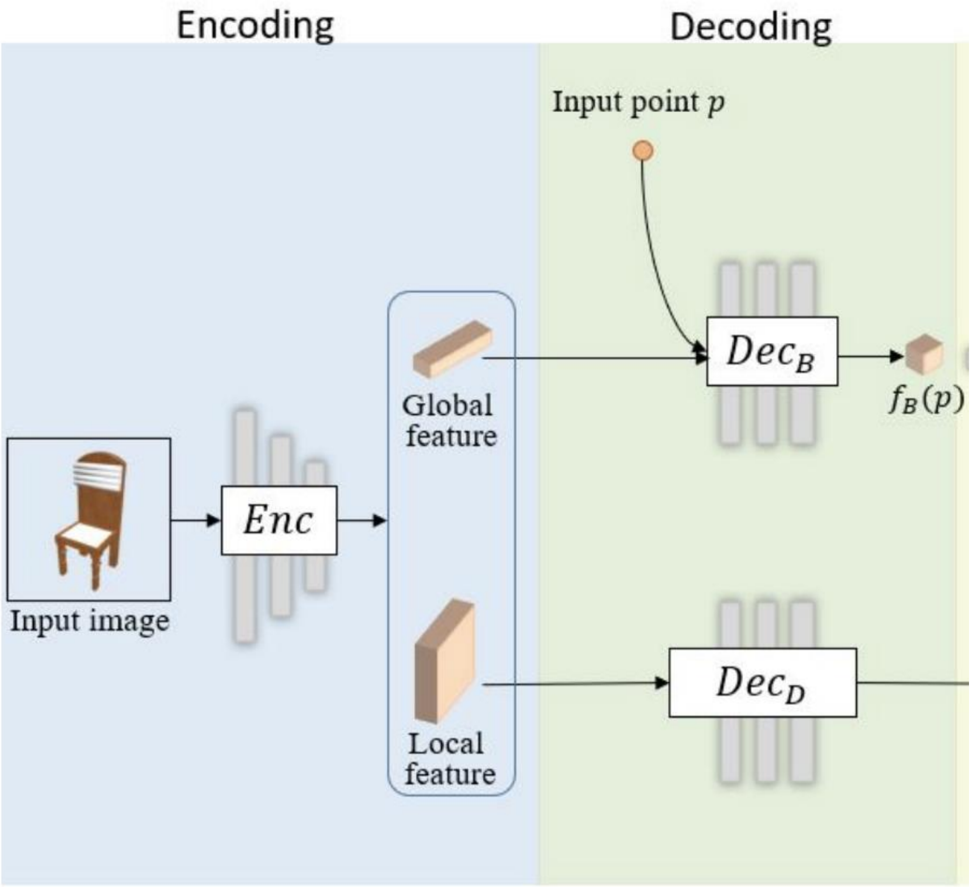
Network Pipeline



global feature vector + X,Y,Z

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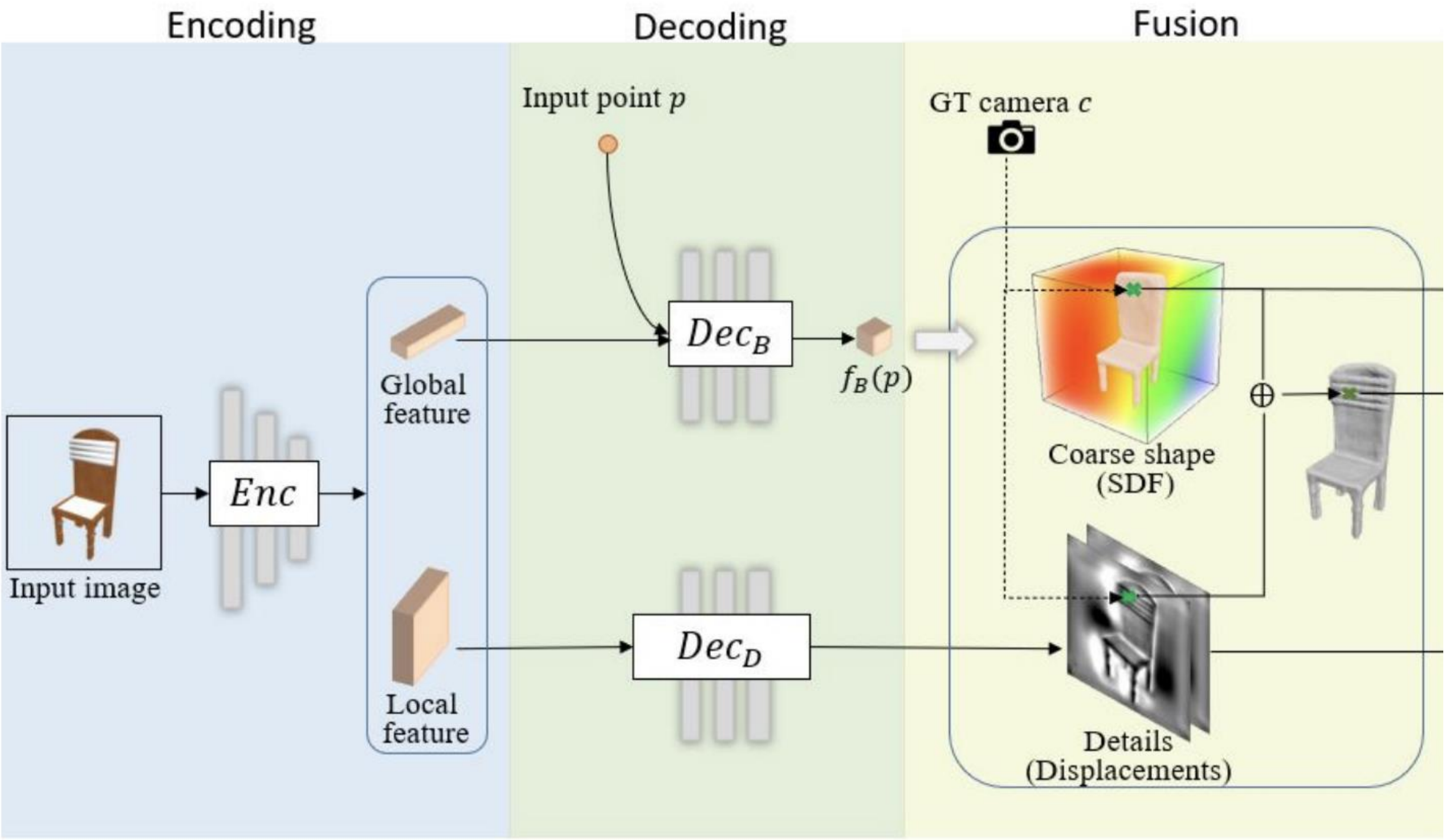
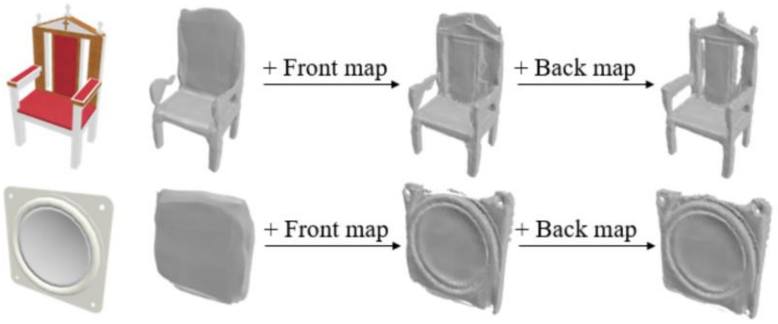
Network Pipeline





$$F_{SDF}(p) = \begin{cases} f_B(p) + f_{DF}(u(p)), p \in P_F, \\ f_B(p) + f_{DB}(u(p)), otherwise, \end{cases}$$

$$\Delta f_{DF}(u(p)) = \Delta F_{SDF}(p), p \in P_F,$$

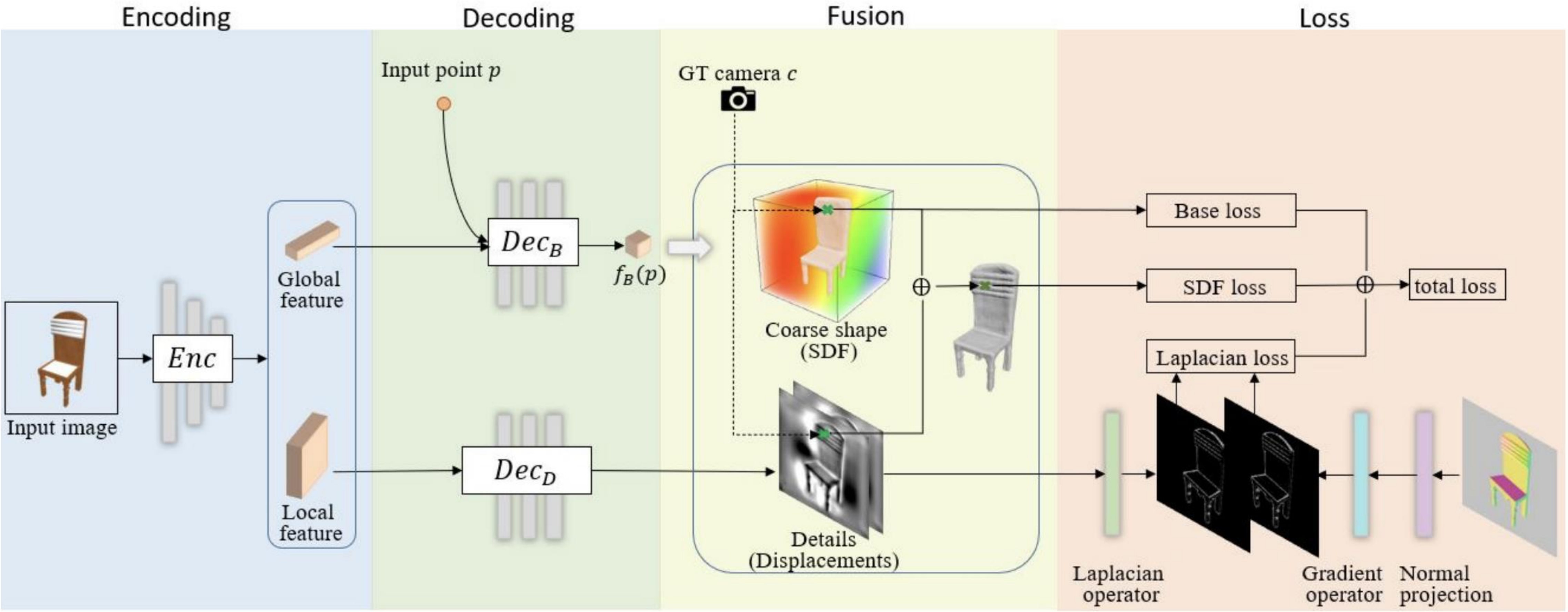
$$f_B : \mathbb{R}^3 \to \mathbb{R}, f_{DF} : \mathbb{R}^2 \to \mathbb{R}, f_{DB} : \mathbb{R}^2 \to \mathbb{R},$$

Why in 2D Dis Map and not 3D:

- learn the small-scale details with contemporary CNN networks.
- aligns the details with the input images to compute the Laplacian loss

Disn: Deep implicit surface network for high-quality single-view 3d reconstruction
Qiangeng Xu, Weiyue Wang, Duygu Ceylan, Radomir Mech, and Ulrich Neumann.

Network Pipeline



Learning Implicit Fields for Generative Shape Modeling
[Zhiqin Chen](), [Hao Zhang]()

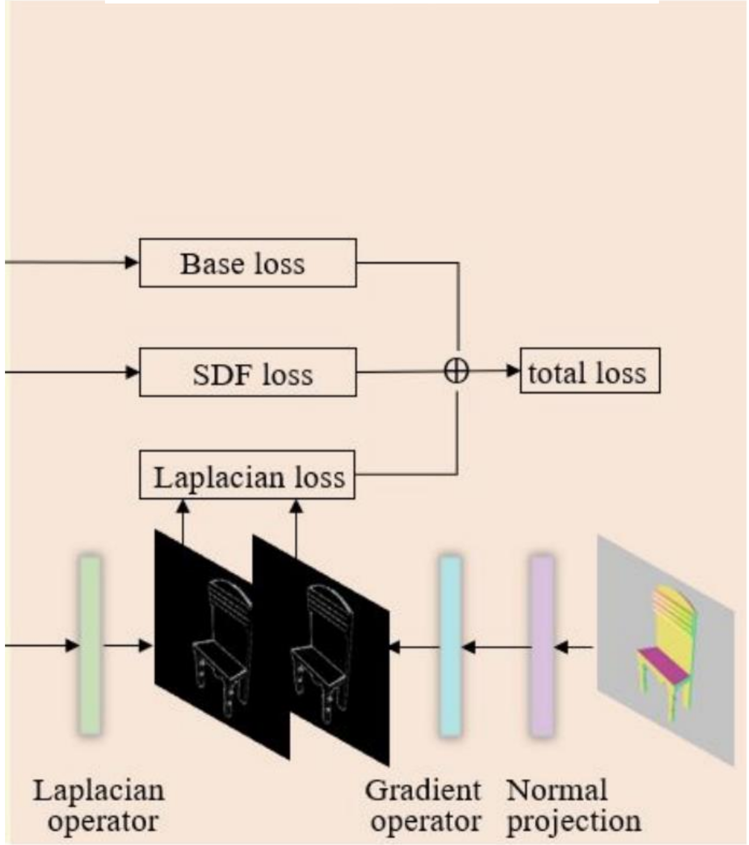
Losses

$$L_B = \frac{1}{M}\sum_{i=1}^{M} \| f_B(p_i) - F_{SDF}(p_i) \|_2^2$$

$$L_{sdf} = \frac{1}{M}\sum_{i=1}^{M} | f(p_i) - F_{SDF}(p_i) |$$

$$L_{lap} = \frac{1}{|P_F|}\sum_{p_i \in P_F} \| \triangle f_{DF}(u(p_i)) - l(u(p_i)) \|_2^2 \, .$$

$$L = L_B + L_{lap} + L_{sdf}$$



Laplacian-steered neural style transfer. 2017
Shaohua Li, Xinxing Xu, Liqiang Nie, and Tat-Seng Chua.

Laplacian Loss

$$L_{lap} = \frac{1}{|P_F|} \sum_{p_i \in P_F} \| \triangle f_{DF}(u(p_i)) - l(u(p_i)) \|_2^2 .$$

$$L_{lap} = \frac{1}{|P_F|} \sum_{p_i \in P_F} \| \triangle f'_{DF}(u(p_i)) - l'(u(p_i)) \|_2^2$$

$$l'(u(p)) = \frac{N(u(p))}{\partial u_x} + \frac{N(u(p))}{\partial u_y}$$

$$\triangle f'_{DF}(u(p)) = \frac{f_{DF}(u(p))}{\partial^2 u_x} \cdot \frac{\partial u_x}{\partial p'_x} + \frac{f_{DF}(u(p))}{\partial^2 u_y} \cdot \frac{\partial u_y}{\partial p'_y}.$$

Front displacement map

$$\triangle f_{DF}(u(p)) = \frac{\partial^2 f_{DF}(u(p))}{\partial (u_x)^2} + \frac{\partial^2 f_{DF}(u(p))}{\partial (u_y)^2}.$$

$$N'(u(p)) = (N(u(p)) \cdot \frac{\partial p'}{\partial u_x}, N(u(p)) \cdot \frac{\partial p'}{\partial u_y}),$$

$$N'(u(p)) = (N(u(p)) \cdot \frac{\partial p'}{\partial u_x}, N(u(p)) \cdot \frac{\partial p'}{\partial u_y}),$$

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Evaluation Metrics

Unit normal vectors for respective points

Edge Chamfer Distance (ECD) $$\sigma(p_i) = min_{p_j \in \mathcal{N}_i} \underbrace{|n_i \cdot n_j|}_{\text{Unit normal vectors for respective points}},$$

Bspnet: Generating compact meshes via binary space partitioning
Zhiqin Chen, Andrea Tagliasacchi, and Hao Zhang.

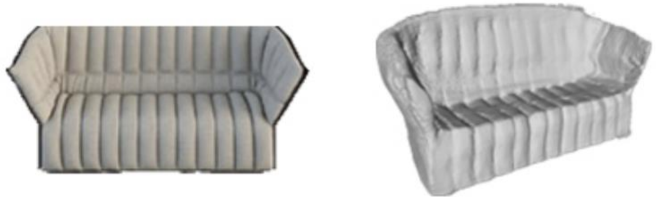
PROS	CONS

PROS

- Small-scale geometric details
- Not overfitting to specific inputs
- No symmetry priors or color/material cues

CONS

- Assumption: surface details defined by a **height field** over **flat surface**
- Unable to recover surface details over **sufficiently** curved surfaces



- **Laplacian loss** is defined only on the front surface of the recovered shape
- View dependent

Credit to