

Learning 3D Equivariant Implicit Function with Patch-Level Pose-Invariant Representation

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Xin Hu, Xiaole Tang, Ruixuan Yu, Jian Sun

Definition of Neural Vector Fields (NVF)

Given a sparse point cloud $X \in \mathbb{R}^{N_x \times 3}$ sampled on a shape \mathcal{X} , and a query set $Q \in \mathbb{R}^{N_q \times 3}$ sampled near the surface of \mathcal{X} , where N_x and N_q represent the number of the input points and query points respectively.

A shape \mathcal{X} is defined as the zero displacement of the implicit function \mathcal{F}

$$\mathcal{X} = \{x \in \mathbb{R}^3 \mid \mathcal{F}(x) = \vec{0}\},$$

where x is a point in point cloud X , containing its spatial coordinate. $\vec{0}$ represents the zero displacement of point x .

Problem Statement for Equivariant Neural Vector Fields (NVF)

For a query point $q \in \mathbb{R}^3$, the implicit function \mathcal{F} is formulated by

$$\mathcal{F}(q) = \Delta q = \hat{x} - q, \quad \text{where } \hat{x} = \operatorname{argmin}_{x \in \mathcal{X}} \|x - q\|,$$

and \hat{x} is the nearest point of query q on the \mathcal{X} .

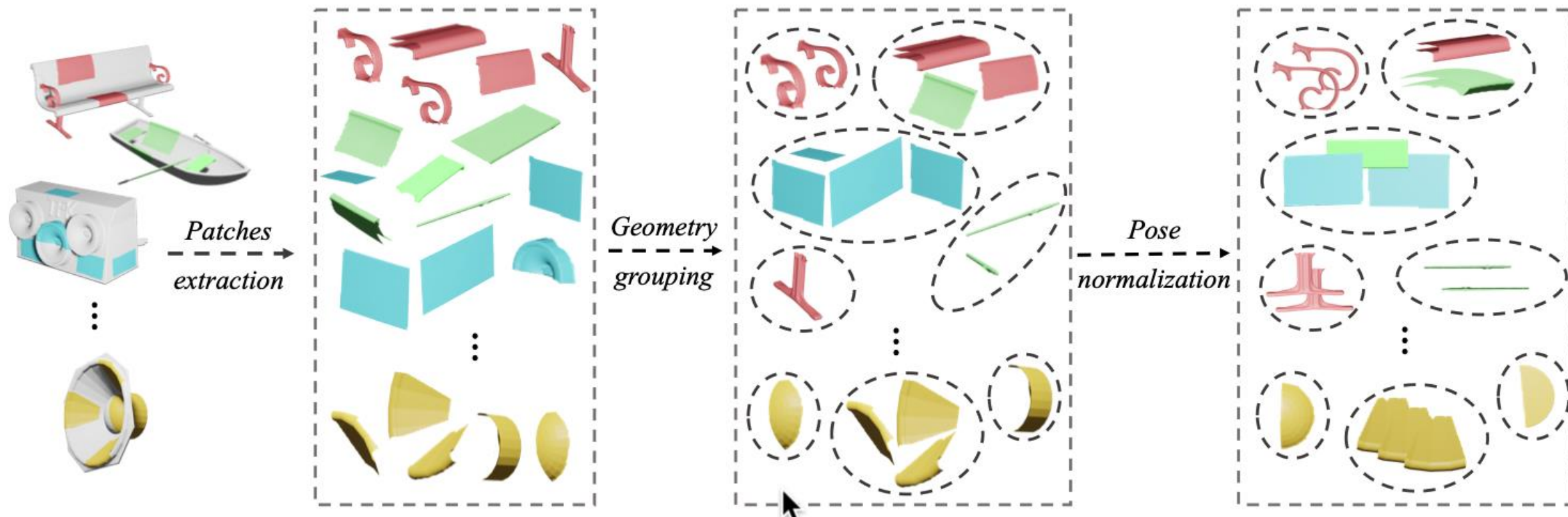
Definition 1 (Equivariant Implicit Function). Given an abstract group G , the implicit function \mathcal{F} based on NVF is equivariant with regard to G , if

$$\mathcal{F}(\zeta \circ q) = \zeta \circ \mathcal{F}(q) = \Delta q, \quad \forall \zeta \in G,$$

where q is a query point near or on the surface of \mathcal{X} . In this work, the group G is $SE(3)$.

Motivation

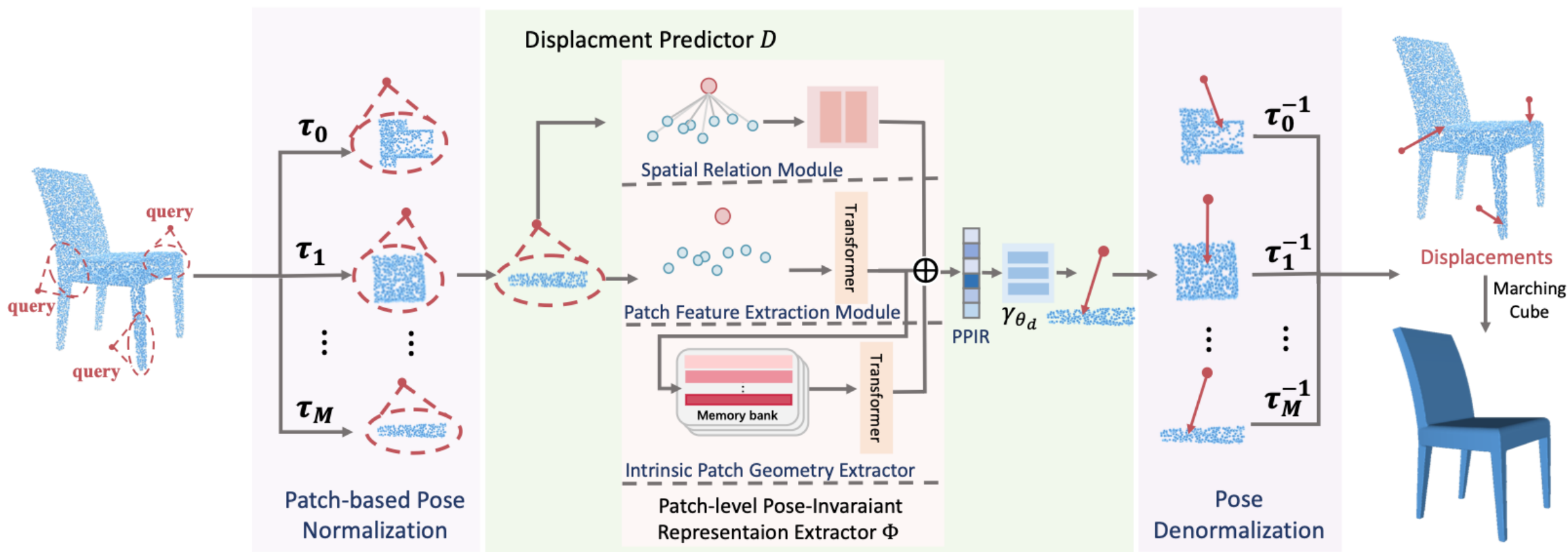
Local 3D patches may exhibit geometric similarity, but with different poses. When the pose is removed, these local regions appear repeatedly.



Patch-level Equivariant Implicit Function (PEIF)

- Given a query point q , the corresponding patch for q on point cloud X is $P = \{p_i\}_{i=0}^K$, i.e., the KNN of q based on Euclidean distance.
- The patch P and query point q are normalized by patch-based pose normalization τ , obtaining $SE(3)$ -invariant ones $\{\tau(P), \tau(q)\}$.
- Taking $\{\tau(P), \tau(q)\}$ as input, the displacement predictor D learns $SE(3)$ -invariant representation and predicts the displacement $\Delta\bar{q}$.
- This predicted displacement is transformed back to the pose of P with τ^{-1} .

Patch-level Equivariant Implicit Function \mathcal{F}



➤ Pose Normalization

The patch P is first decentralized by subtracting the center μ of the points, then the rotation matrix U is obtained by computing the Singular Value Decomposition (SVD) over the covariance matrix $(P - \mu)^T (P - \mu)$. The pose-normalized patch \bar{P} and query point \bar{q} are obtained as follows:

$$\bar{P} \triangleq \tau(P) = (P - \mu)U, \quad \bar{q} \triangleq \tau(q) = (q - \mu)U.$$

➤ Displacement Predictor Design

Taking the pose-normalized patch \bar{P} and query \bar{q} as input, the displacement predictor D is designed to predict the displacement $\Delta\bar{q}$.

Spatial Relation Module:

$$h_{\bar{q}} = \text{SRM}(\bar{P}, \bar{q})$$

Patch Feature Extraction Module:

$$f_{\bar{q}}, \{f_{p_i}\}, f_{\bar{P}} = \text{PFEM}(\bar{P}, \bar{q})$$

Intrinsic Patch Geometry Extractor:

$$g_{\bar{P}} = \text{IPGE}(f_{\bar{P}})$$

The displacement $\Delta\bar{q}$ for query point \bar{q} can then be derived by

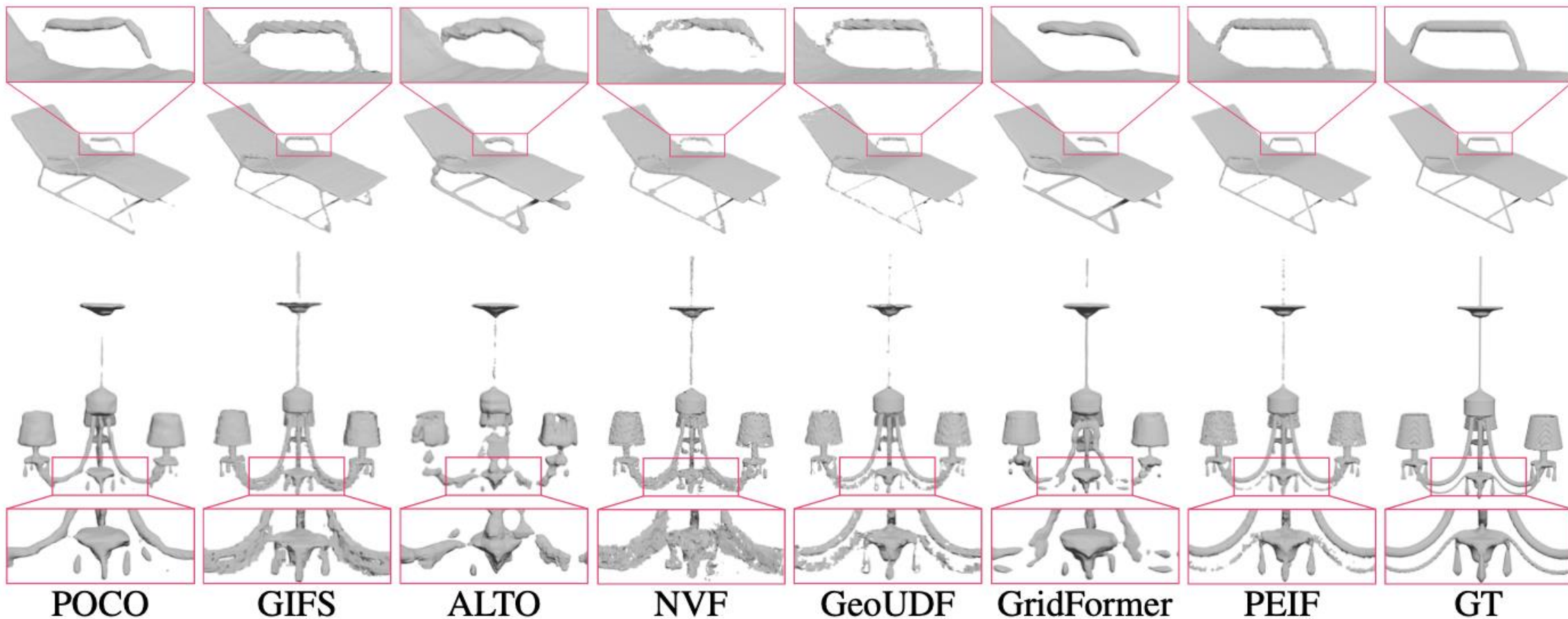
$$\Delta\bar{q} = \gamma_{\theta_d}(\gamma_{\theta_a}(h_{\bar{q}} \oplus f_{\bar{q}} \oplus \{f_{p_i}\}) \oplus g_{\bar{P}}).$$

➤ Pose Denormalization

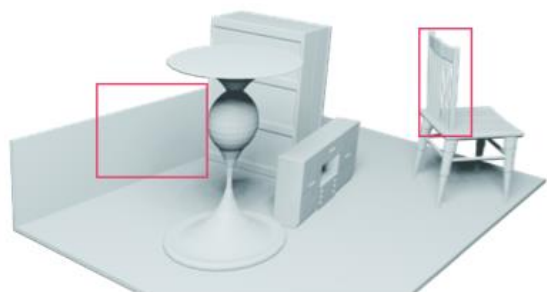
The final $SE(3)$ -equivariant displacement is obtained by transforming back $\Delta\bar{q}$ with pose denormalization

$$\Delta q = \tau^{-1}(\Delta\bar{q}).$$

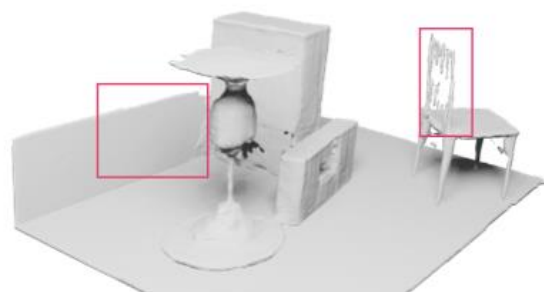
Experiments



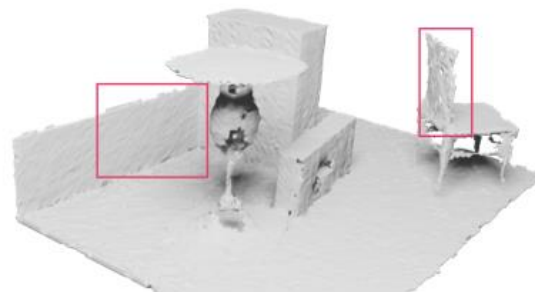
Experiments



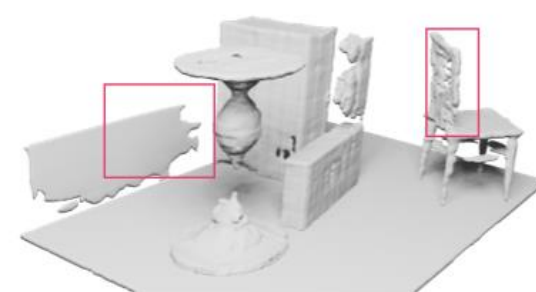
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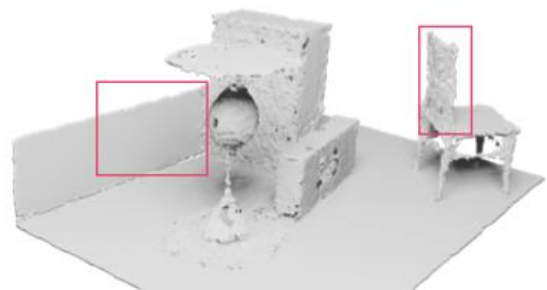
POCO



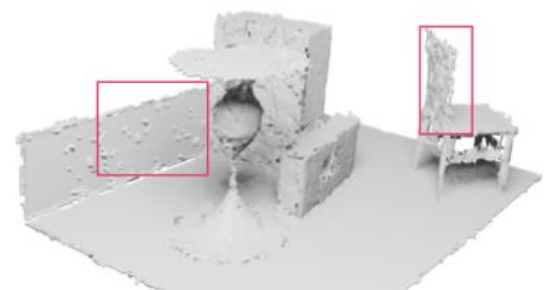
GIFS



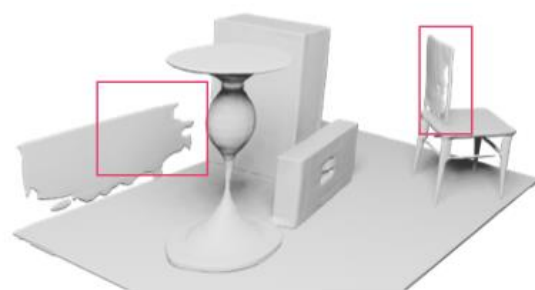
ALTO



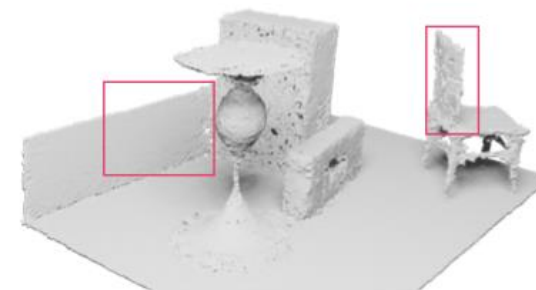
NVF



GeoUDF

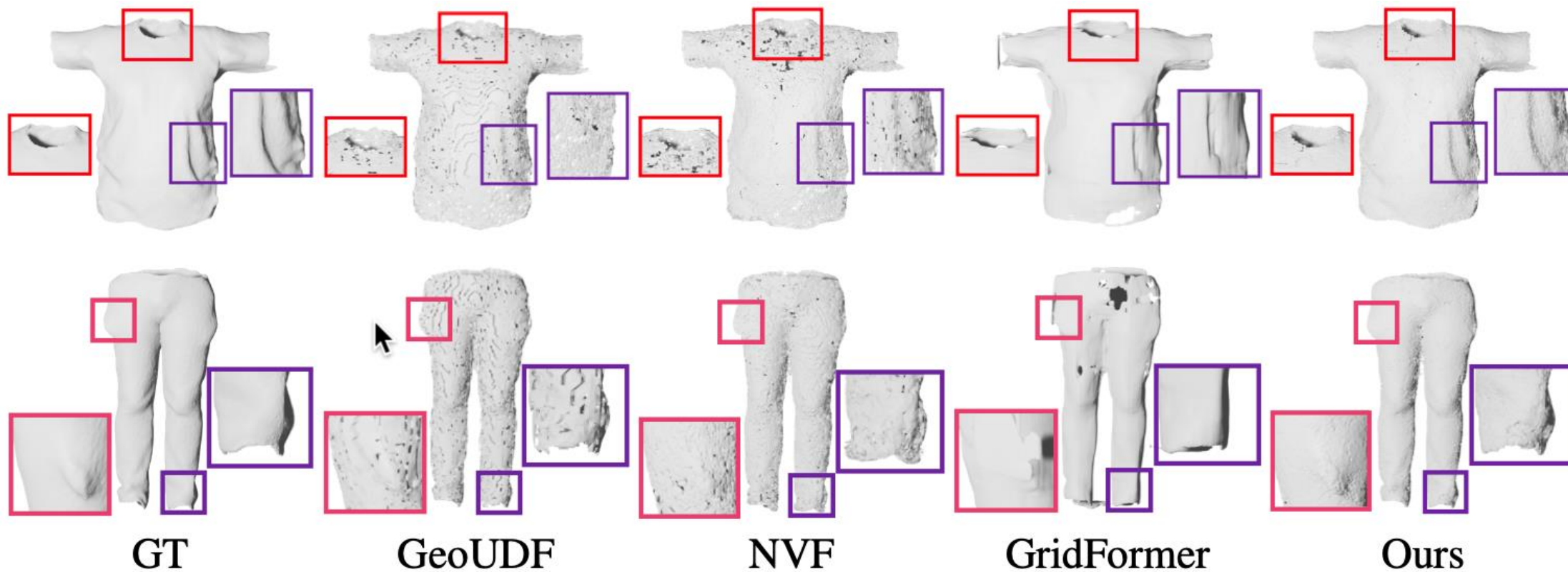


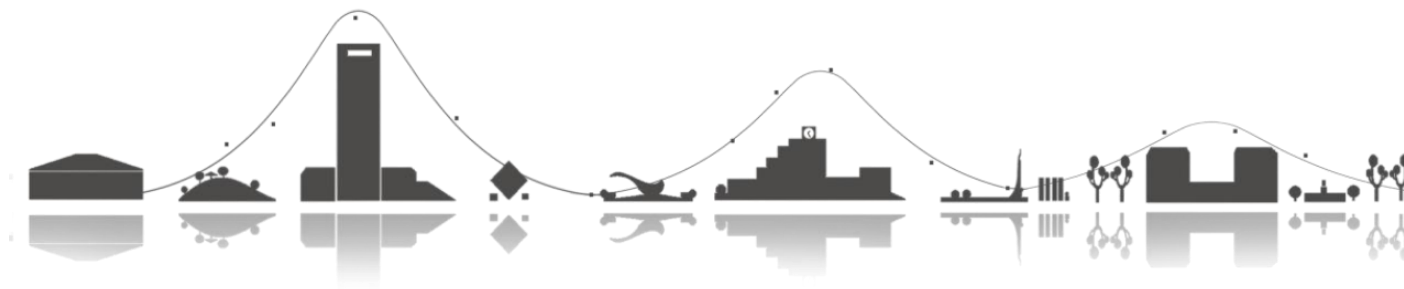
GridFormer



PEIF

Experiments





Thank You !