Learning Implicit Functions for Topology-Varying Dense 3D Shape Correspondence
Feng Liu  Xiaoming Liu
Department of Computer Science and Engineering, Michigan State University

Dense 3D Correspondence for Man-made Objects

Definition:
Given two shapes \( S_A \) and \( S_B \) belonging in the same category, for an arbitrary point \( p \in S_A \), we are seeking its semantically equivalent point \( q \) on \( S_B \).

\[ p \rightarrow q \]

Challenge:
- Man-made objects often differ not only by geometric deformations, but also by part constitutions;
- Prior methods have proven to be effective on organic shapes, e.g., Human bodies and mammals, they become less suitable for generic object;
- Existing method for man-made object either performance fuzzy correspondence or predict a constant number of semantic points;
- The lack of annotations on dense correspondence often leaves unsupervised learning the only option.

Contributions:
- We propose a novel paradigm leveraging implicit functions for category-specific unsupervised dense 3D correspondence, which is suitable for topology-varying objects;
- We estimate a confidence score measuring if the predicted correspondence is valid or not;
- We demonstrate the superiority of our method in shape segmentation and 3D semantic correspondence.

Proposed Method

Formulation:
- We assume a semantic embedding function (SEF) \( f : \mathbb{R}^3 \times \mathbb{R}^d \rightarrow \mathbb{R}^k \), the correspondence should satisfy:
  \[ \min_{z \in \mathbb{R}^d} \| f(p, z) - f(q, z_B) \| < \tau, \quad \forall p \in S_A \]
- If the distance is too large (\( \geq \tau \)), there is no corresponding point in \( S_B \) for \( p \);
- If SEF could be learned, then \( q = f^{-1}(f(p, z_A), z_B) \) inverse function

Solution:
- A branched implicit function \( f \) serves as the semantic embedding function (SEF).
- Design an inverse function \( g \) mapping from the embedding space to 3D space:
  \( g : \mathbb{R}^k \times \mathbb{R}^d \rightarrow \mathbb{R}^3 \), so that the learning objectives can be defined in 3D space.
- Loss functions:
  \[ L^{\text{overall}} = L^{\text{occupancy}} + L^{\text{SR}} + L^{\text{CR}} \]

Inference:
- Nearest neighbor search
- the same index refers to the correspondence

Experimental Results:

Unsupervised Shape Segmentation on ShapeNet

Part embedding visualization (t-SNE)

References