Point Cloud Sampling Preserving Local Geometry for Surface Reconstruction

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Introduction

Motivation

- Surface reconstruction from point clouds with neural fields can faithfully reconstruct high-resolution geometry.
- State-of-the-art methods have **limited scalability** for training due to memory requirements that increase with the size of the point cloud.

Our Goal

- Improving the scalability for training surface reconstruction networks with **point cloud sampling**.

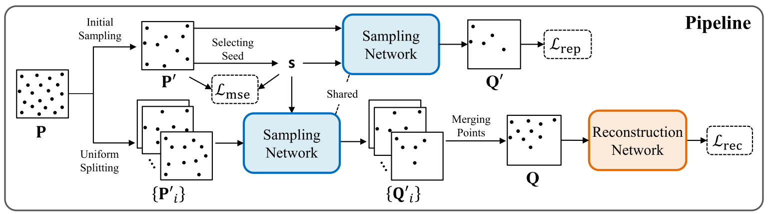
Contributions

- Propose a novel method to learn neural fields as a 3D surface representation using point clouds sampled with a **learnable sampling network**.
- Propose a sampling network considering a **seed point** to sample points that represent both global structure and local geometry on a part of the scene.
- Introduce a split-and-merge approach that suppresses the input size fed into the sampling network in order to avoid increasing the **memory footprint**.

Proposed Method

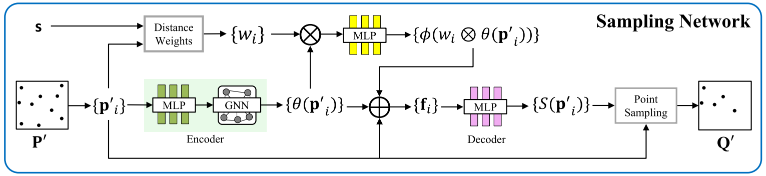
Pipeline

- Our method feeds a point cloud $\mathbf{Q}$ **sampled** from the input point cloud $\mathbf{P}$ to the reconstruction network.
- Split-and-merge approach suppresses the input size to the sampling network by **splitting** the input point cloud, and then **merging** all sampling results.



Sampling Network

- The sampling network samples a point cloud $\mathbf{Q}'$ from **a size-suppressed** point cloud $\mathbf{P}'$ with a seed point $\mathbf{s}$.
- The **seed point** is introduced to sample a point cloud from a partial region.



Training

- The sampling network is trained to minimize the weighted sum of a **MSE** loss $\mathcal{L}_{\text{mse}}$ and a **repulsion** loss $\mathcal{L}_{\text{rep}}$ modified in a probabilistic manner.

$$\mathcal{L}_{\text{mse}} = \frac{1}{N'} \sum_{i=1}^{N'} g(S(\mathbf{p}'_i)) \|\mathbf{s} - \mathbf{p}'_i\|^2 \qquad \mathcal{L}_{\text{rep}} = \frac{1}{M' \cdot K} \sum_{i=1}^{M'} \sum_{j \in \mathcal{N}(\mathbf{q}'_i)} g(S(\mathbf{q}'_j)) \eta(\|\mathbf{q}'_i - \mathbf{q}'_j\|) \omega(\|\mathbf{q}'_i - \mathbf{q}'_j\|)$$

Acknowledgement

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Experiments

Reconstruction Performance

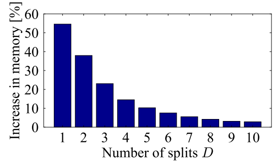
- We compare with state-of-the-art sampling/simplification methods.
- The proposed method achieves the **best performance** in all metrics.

Method	IoU↑	CD↓	NC↑
Baseline	0.810	0.310	0.923
SampleNet	0.811	0.308	0.925
RPCS	0.840	0.306	0.936
Ours	**0.924**	**0.291**	**0.948**

CD is scaled by 10^2. ↑ (↓) denotes higher (lower) is better.

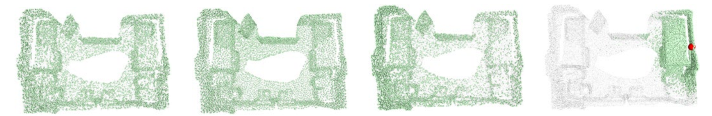
Memory Efficiency

- The additional memory requirement for the proposed method is only **2.8%** (D=10).



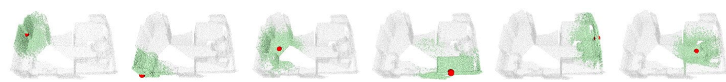
Sampled Point Clouds

- The proposed method samples points intensively **around the seed point** (shown as a red point), while also sampling points far from it.



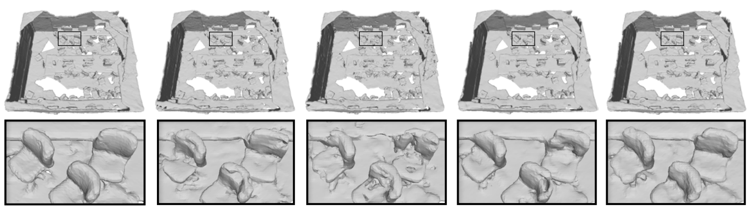
Baseline SampleNet RPCS Ours

- In the proposed method, various seed points are selected from the input points **during training**.



Reconstructed Surfaces

- Compared with the other methods that have low accuracy for **local geometry**, the proposed method reconstructs surfaces more **faithfully**.



Ground truth Baseline SampleNet RPCS Ours