Unsupervised Occupancy Learning from Sparse Point Cloud

Supplementary Material

A. Additional Implementation Details

Unless stated differently, We employ publicly accessible official implementations of established methods in our work. Specifically, for SPSR, in accordance with our peer-reviewed competition practices, we utilize publicly available implementations provided by Open3D and Pymeshlab. We select the superior result between the two and tune its hyperparameters including grid searches for parameters such as octree depth and the number of nearest neighbors utilized in constructing the Riemannian graph for normal orientation propagation. It is important to highlight that these libraries feature a normal estimation algorithm grounded in local point cloud co-variance estimation, coupled with normal orientation propagation employing minimum spanning trees.

B. Metrics

Following the definitions from [2] and [7], we present here the formal definitions for the metrics that we use for evaluation in the main submission. We denote by $\mathcal{S}$ and $\hat{\mathcal{S}}$ the ground truth and predicted mesh respectively. We follow [3] to approximate all metrics with 100k samples from $\mathcal{S}$ and $\hat{\mathcal{S}}$ for ShapeNet and Faust and with 1M samples for 3Dscene. For SRB, we use 1M samples following [1] and [4].

Chamfer Distance ($\mathbf{CD}_1$) The L_1 Chamfer distance is based on the two-ways nearest neighbor distance:

$$\mathrm{CD}_1 = \frac{1}{2|\mathcal{S}|}\sum_{v\in\mathcal{S}}\min_{\hat{v}\in\hat{\mathcal{S}}}\|v-\hat{v}\|_2 + \frac{1}{2|\hat{\mathcal{S}}|}\sum_{\hat{v}\in\hat{\mathcal{S}}}\min_{v\in\mathcal{S}}\|\hat{v}-v\|_2.$$

Chamfer Distance ($\mathbf{CD}_2$) The L_2 Chamfer distance is based on the two-ways nearest neighbor squared distance:

$$\mathrm{CD}_2 = \frac{1}{2|\mathcal{S}|}\sum_{v\in\mathcal{S}}\min_{\hat{v}\in\hat{\mathcal{S}}}\|v-\hat{v}\|_2^2 + \frac{1}{2|\hat{\mathcal{S}}|}\sum_{\hat{v}\in\hat{\mathcal{S}}}\min_{v\in\mathcal{S}}\|\hat{v}-v\|_2^2.$$

F-Score (FS) For a given threshold τ, the F-score between the meshes $\mathcal{S}$ and $\hat{\mathcal{S}}$ is defined as:

$$\mathrm{FS}\left(\tau,\mathcal{S},\hat{\mathcal{S}}\right) = \frac{2\ \text{Recall}\cdot\text{Precision}}{\text{Recall}\ +\ \text{Precision}},$$

where

$$\text{Recall}\left(\tau,\mathcal{S},\hat{\mathcal{S}}\right) = \left|\ \left\{v\in\mathcal{S},\ \text{s.t.}\ \min_{\hat{v}\in\hat{\mathcal{S}}}\|v-\hat{v}\|_2\langle\tau\right\}\ \right|,$$
$$\text{Precision}\left(\tau,\mathcal{S},\hat{\mathcal{S}}\right) = \left|\ \left\{\hat{v}\in\hat{\mathcal{S}},\ \text{s.t.}\ \min_{v\in\mathcal{S}}\|v-\hat{v}\|_2\langle\tau\right\}\ \right|.$$

Following [5] and [6], we set τ to 0.01.

Normal consistency (NC) We denote here by n_v the normal at a point v in $\mathcal{S}$. The normal consistency between two meshes $\mathcal{S}$ and $\hat{\mathcal{S}}$ is defined as:

$$\mathrm{NC} = \frac{1}{2|\mathcal{S}|}\sum_{v\in\mathcal{S}} n_v\cdot n_{\text{closest}(v,\hat{\mathcal{S}})} + \frac{1}{2|\hat{\mathcal{S}}|}\sum_{\hat{v}\in\hat{\mathcal{S}}} n_{\hat{v}}\cdot n_{\text{closest}(\hat{v},\mathcal{S})},$$

where

$$\text{closest}(v,\hat{\mathcal{S}}) = \text{argmin}_{\hat{v}\in\hat{\mathcal{S}}}\|v-\hat{v}\|_2.$$

Hausdorff distance (HD) This metric is defined as follows:

$$d_H = \max\left(\max_{v\in\mathcal{S}}\min_{\hat{v}\in\hat{\mathcal{S}}}\|v-\hat{v}\|_2, \max_{\hat{v}\in\hat{\mathcal{S}}}\min_{v\in\mathcal{S}}\|v-\hat{v}\|_2\right)$$

References

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