Supplemental Materials for "Learning a More Continuous Zero Level Set in Unsigned Distance Fields through Level Set Projection"

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1. Implementation Details

Network details. We employ a neural network containing 8 layers of MLP following OccNet [9] where each layer has 256 nodes. The neural network takes the 3-dimension coordinates of a 3D query q as input and learns to predict the unsigned distance from q to the represented shape. Similar to CAP-UDF [13], we adopt a non-linear projection $g(x) = |x|$ at the end to enforce the neural network to produce positive distances.

Sampling Strategy. We sample queries around the raw point cloud P for training our network and optimize the unsigned distance fields. We sample $t = M/N$ queries around each point p, where M is the total number of queries and N is the number of points in P. M is set to 1 million for shapes and will be increased appropriately for large-scale scenes. Following Neural-Pull [8] and CAP-UDF [13], a Gaussian function $\mathcal{N}(\mu, \sigma^2)$ is leveraged as the distribution to sample queries where $\mu = p$ and σ^2 is the distance from p to its 50-th nearest point in P.

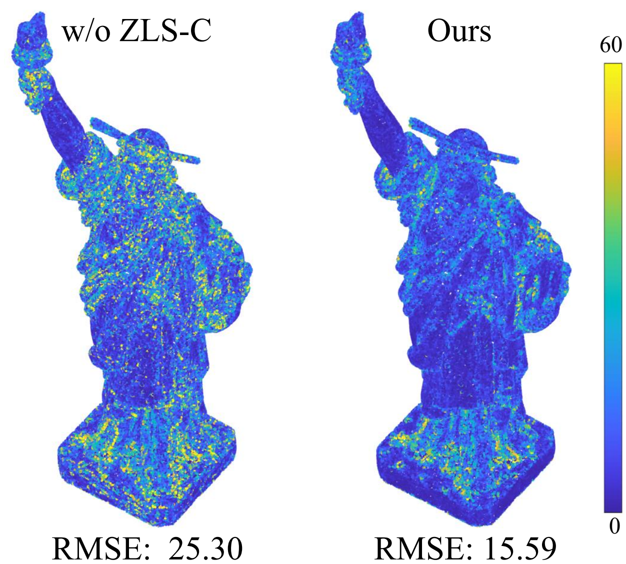

Figure 1. Visual comparison on error maps of estimated normals with or without our designed constraints on the zero level set (ZLS-C). Lower is better for RMSE.

2. More Visualizations

2.1. Scene Reconstruction from Depth Maps

Dataset. To further demonstrate the advantage of our method in surface reconstruction from depth maps, we follow NeuralRGB-D [2] to evaluate our method under the BlendSwap dataset [2]. We conduct experiments under the clean depth maps with ground truth camera poses for both our method and baselines. To achieve the input point clouds, we back-project the depth maps into world space with the known camera poses and fuse them together.

Comparison. We present a visual comparison with ConvOcc [11], Neural-Pull [8], NeuralRGB-D [2] and Go-Surf [12] in Fig. 2. Note that NeuralRGB-D [2] and Go-Surf [12] require both colored images and depth maps as input for surface reconstruction, while our method only takes depth maps as input. The visualization shows that our method significantly outperforms the other depth input methods and is also comparable with the state-of-the-art RGB-D input methods which require extra supervision from colored images. Furthermore, all the previous works fail to reconstruct the complex geometries with open surfaces (e.g. windows) while our method is able to represent scenes with arbitrary topology and reveal the geometry details.

*Equal contribution.
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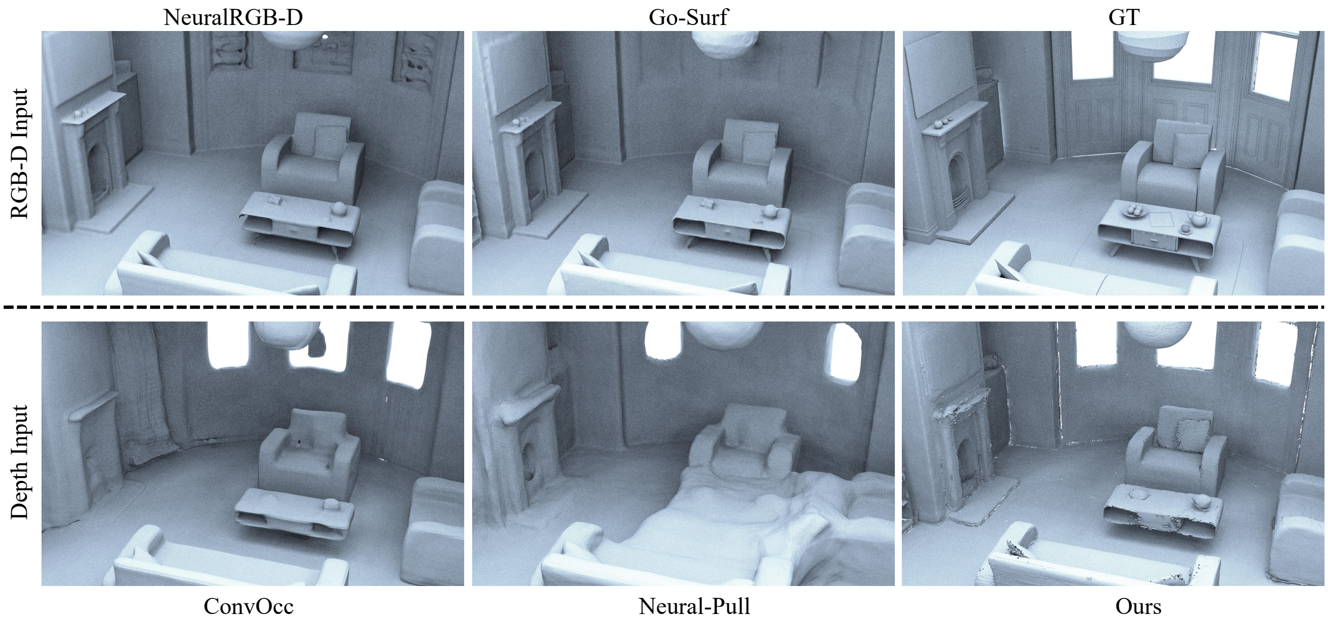

Figure 2. Visual comparison of surface reconstruction from depth maps on the BlendSwap dataset.

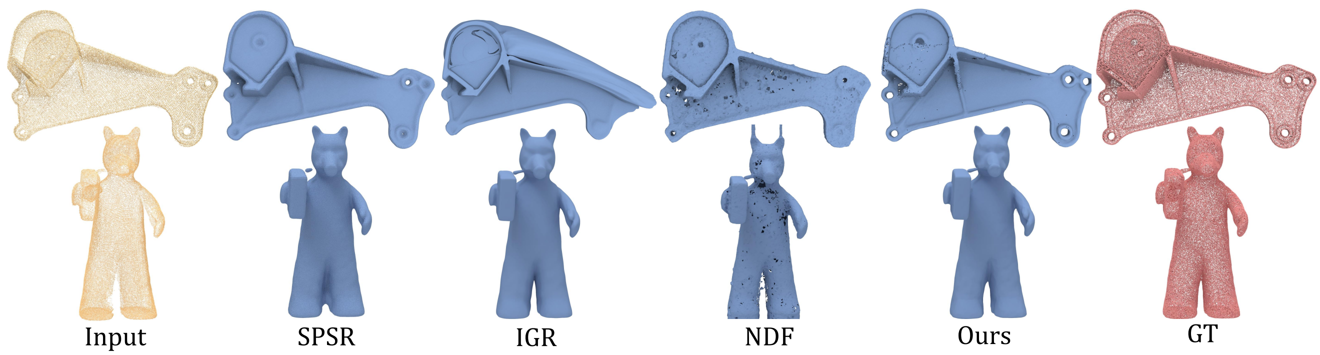

Figure 3. More visual comparisons of surface reconstruction on SRB dataset.

2.2. Ablations on Point Normal Estimation

Analysis. We further visually demonstrate the effectiveness of our designed constraints by providing the visualization on point normal estimation with or without our designed constraints in Fig. 1. Since we take the gradients at the zero level set as the estimated normals, the point normal estimation performance can greatly represent the accuracy and continuity of the zero level set.

As shown in Fig. 1, our proposed constraints greatly improve the normal estimation performance, especially on the complex geometries. The result demonstrates that our constraints lead to a more accurate and continuous zero level set of unsigned distance fields.

2.3. Surface Reconstruction from Real Scans

We further provide a visual comparison on the real scanned SRB dataset with more baselines, i.e. SPSR [6] (Screened Poisson Reconstruction), IGR [4] and NDF [3] in Fig. 3. Fig. 3 is a supplement for Fig. 6 of the submission where we compared our method with SAP [10] and CAP-UDF [13]. SPSR requires extra point normals as input where we leverage PCA [1] to first estimate the un-oriented point normals and re-orient the normals with the ground truth normal orientations of input point clouds. The superior performance compared with more baselines further justifies our effectiveness.

2.4. Unsupervised Scene Normal Estimation

To further demonstrate our performance on unsupervised point normal estimation for large-scale scenes, we follow HSurf-Net [7] to conduct experiments on the Semantic3D dataset [5] which contains large-scale outdoor scenes in real world. Note that the ground truth is not available for the dataset. We show the visualization of normal estimation re-

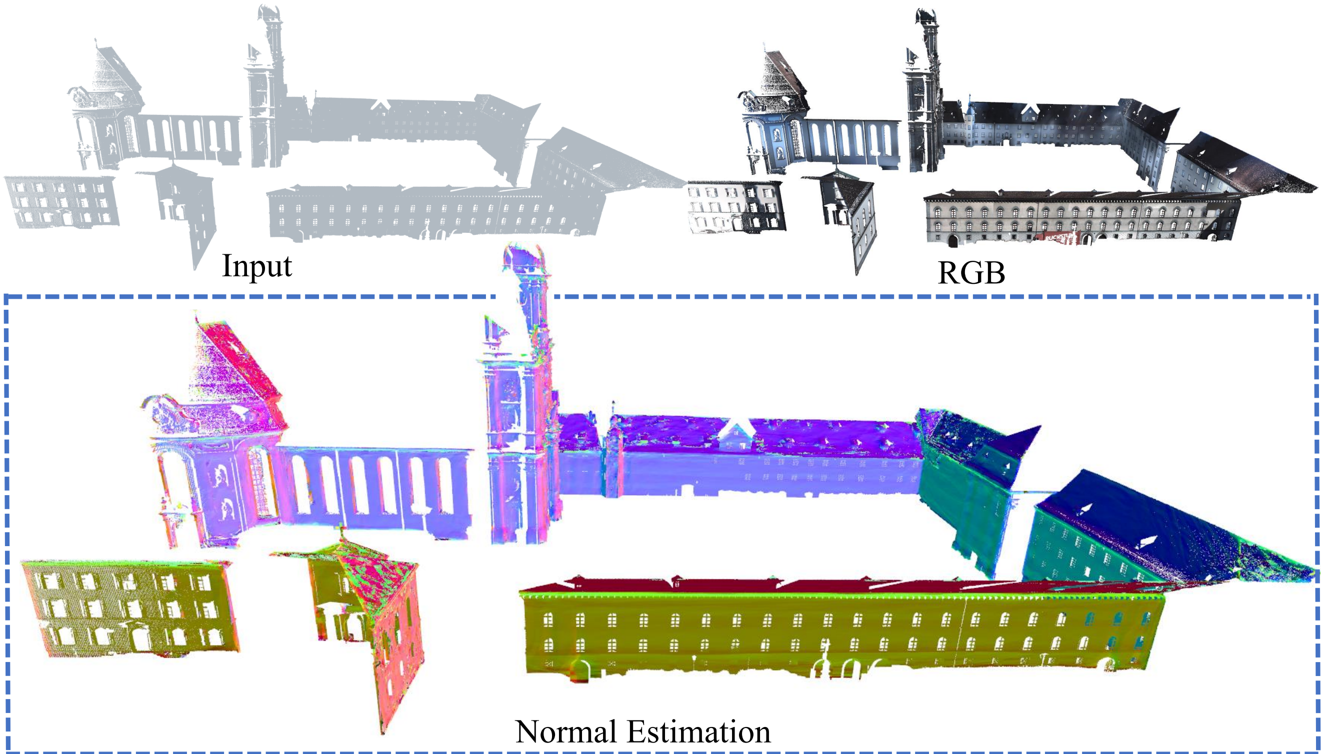

Figure 4. Visualization of the normal estimation results on a real-world outdoor scene on the Semantic3D dataset. "Input" indicates the raw point cloud and "RGB" is the visualization of the point cloud with RGB colors. "Normal Estimation" is visualized by mapping our estimated normals into RGB colors.

sults in Fig. 4, where our method can predict accurate normals for the large-scale outdoor scene in an unsupervised way.

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