Supplemental Materials for Towards Better Gradient Consistency for Neural Signed Distance Functions via Level Set Alignment

Baorui Ma[1]*, Junsheng Zhou[1]*, Yu-Shen Liu[1]†, Zhizhong Han[2]
[1]School of Software, BNRist, Tsinghua University, Beijing, China
[2]Department of Computer Science, Wayne State University, Detroit, USA
{mbr18,zhoujs21}@mails.tsinghua.edu.cn, liuyushen@tsinghua.edu.cn, h312h@wayne.edu

1. Network and Training

We evaluate our level set alignment loss with six baselines including NeuralPull [3], IGR [2], SIREN [4], NeuS [6] and MonoSDF [7]. For fair comparisons, we do not change the networks of baselines, and follow the same training procedure and parameter settings. We train each baseline method using our loss as an additional term in the objective function.

2. Query Sampling

In the experiments we learn implicit functions from point clouds, we leverage the same sampling method as the baseline method. For example, we follow the sampling introduced by NeuralPull [3] to sample queries around each point on the point cloud. We use Gaussian distribution with each point as its center and set the standard deviation as the distance to the 51th nearest neighbor in the point cloud. For IGR [2] and SIREN [4], we follow their sampling methods.

3. More Visualization

We visualize our loss on different level sets in Fig. 1. We show the level set alignment loss at vertices on each level set, and map the loss into color. We use the same set of level sets from our results, but calculate the loss in the fields learned with or without our loss respectively. We can see that NeuralPull [3] learns a signed distance field with consistent gradients especially in the area with high curvatures. While we can learn a field with more consistent gradients by conducting optimization with our loss. Please watch our video to visualize the change of our loss in the whole optimization process.

Moreover, we also visualize the learned level sets in the field in our video. We show the level sets on different cross sections in one iteration, the level sets on the same cross section but in different iterations, and the surfaces reconstructed with different level sets. Please watch our video for more information.

*Equal contribution.

†The corresponding author is Yu-Shen Liu. This work was supported by National Key R&D Program of China (2022YFC3800600), the National Natural Science Foundation of China (62272263, 62072268), and in part by Tsinghua-Kuaishou Institute of Future Media Data.

4. More Results

We report our numerical comparison in SIREN [4] dataset in Tab.1 in our main submission. Here, we show the visual comparison with SIREN in Fig. 2 and Fig. 4. The input is a point cloud with dense points without normals. We use SIREN and SIREN with our loss to learn SDFs from the point cloud, respectively, and then run the marching cubes algorithm to reconstruct surfaces. Due to the lack of normal supervision, SIREN reconstructs the surface of Thai statue with artifacts in Fig. 2, and totally fails to reconstruct surfaces in a more complex scene in Fig. 4. While our method produces smoother and more completed surfaces by eliminating signed distance ambiguity via aligning all level sets to the zero level set.

We also report visual comparison with SIREN with normal supervision in Fig. 3. We can see that our method also provide more geometry details than SIREN.

5. Comparisons with Supervised Methods

We report our advantage over methods using learned priors in Fig. 5. We compared with GenSDF [1] on shapes and ConOcc [5] on large scenes. We can see that our method reveals more geometries than the counterparts. Moreover, we do not produce artifacts inside of the shape like GenSDF.

6. Comparisons with NeuS

We report more comparisons with NeuS [6]. We first report the distance between ours and the GT, which is a single direction distance, under DTU dataset. Comparisons in Tab. 1 indicates that our method significantly outperforms NeuS. The comparisons we report in main text is the distance with both ours to the GT and the GT to ours.

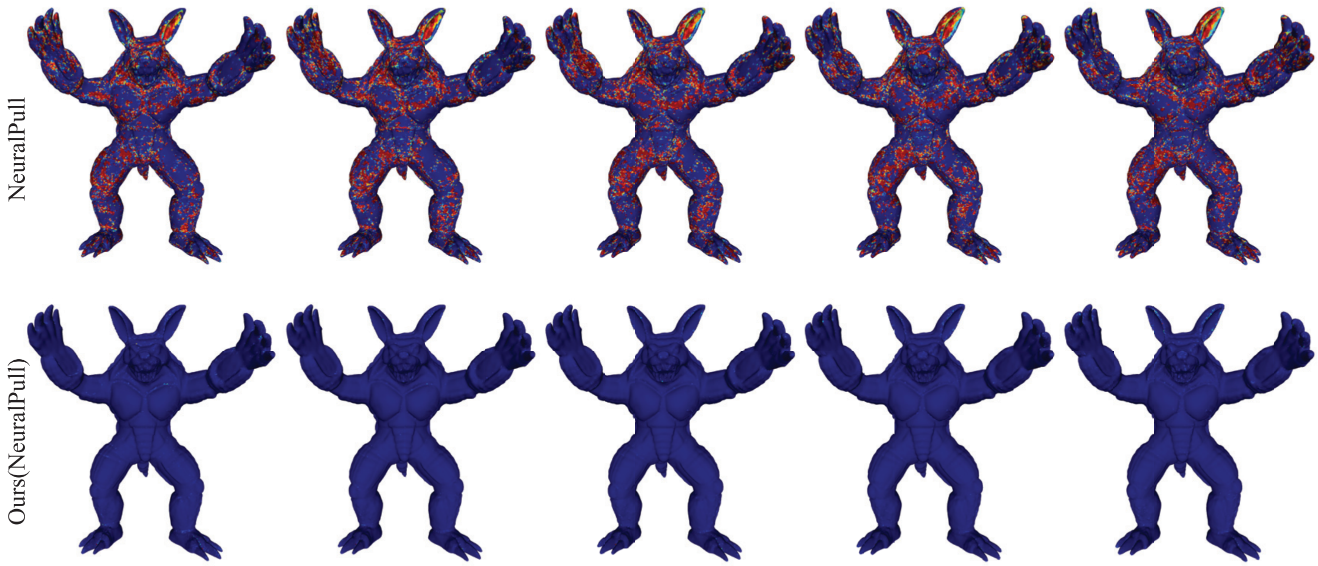

Figure 1. Visualization of level set alignment loss on different level sets.

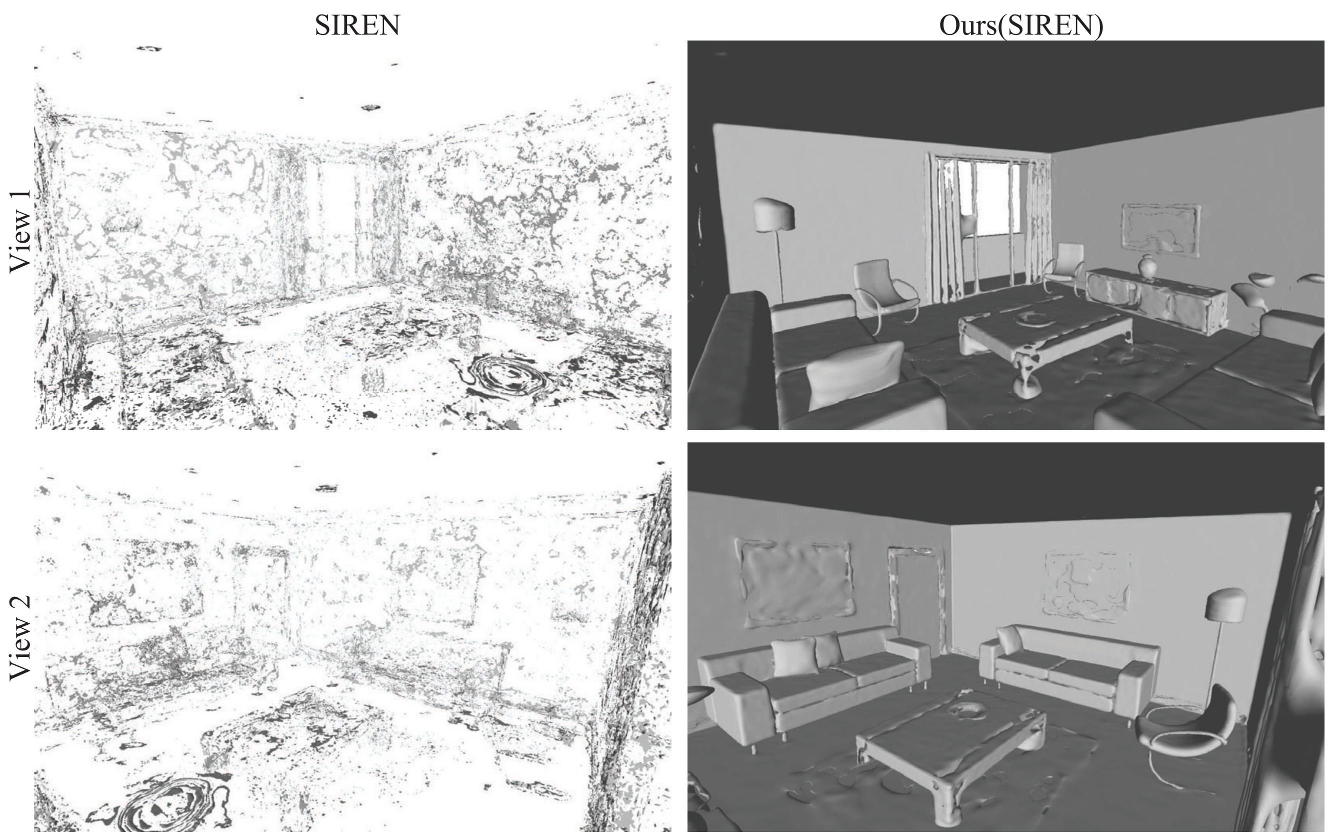

Figure 4. Visual comparisons with SIREN in learning SDFs from point clouds without normals.

The GT point clouds in DTU dataset contain large artifacts in some empty area in scenes like 40 and 83. Since we do not produce artifacts in empty space like NeuS, this makes the distance GT2Our increase even the distance in another direction Our2GT shown in Tab.1 is smaller than NeuS.

Method	24	37	40	55	63	65	69	83	97	105	106	110	114	118	122	Mean
NeuS	1.05	1.73	1.04	0.51	1.60	0.74	0.63	1.17	0.96	0.74	0.50	1.47	0.33	0.55	0.65	0.91
Ours(NeuS)	**0.98**	**1.04**	**0.81**	**0.49**	**1.59**	**0.73**	**0.61**	**1.00**	**0.95**	**0.72**	**0.49**	**1.37**	**0.30**	**0.54**	**0.64**	**0.82**

Table 1. The distance Our2GT in DTU dataset.

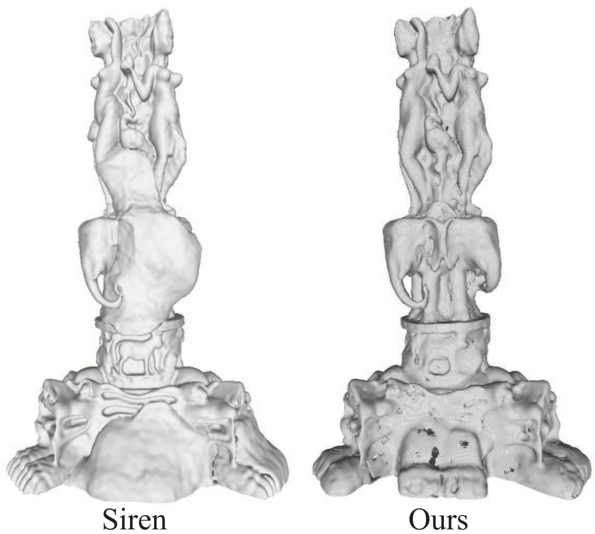

Figure 2. Visual comparisons with SIREN in learning SDFs from point clouds without normals.

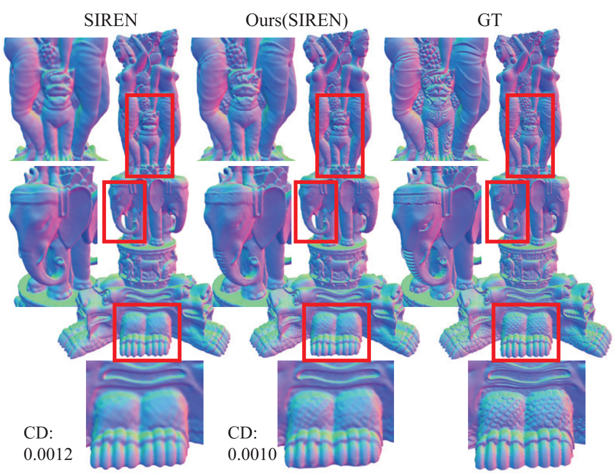

Figure 3. Reconstruction comparison with normal supervision.

Regarding the time complexity, we report results in Fig. 6. We did not observe significant computation increase. Although we involve two queries in each iteration, we converge faster. Fig.6 shows our accuracy is higher than NeuS at almost all time during training.

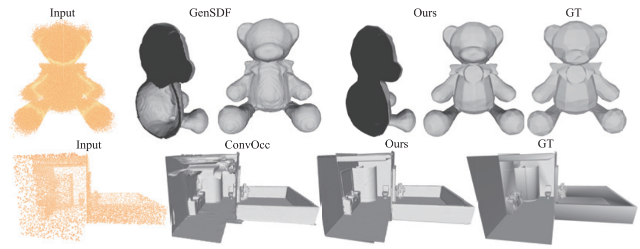

Figure 5. Visual comparison with methods using priors.

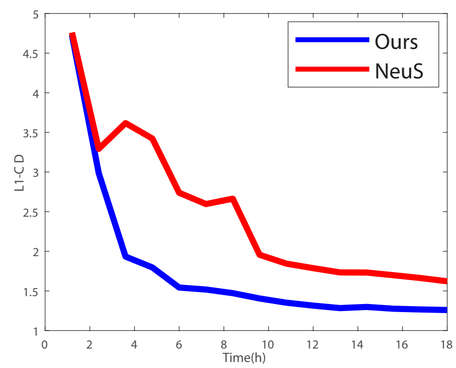

Figure 6. Time and accuracy.

7. Other Applications

Besides reconstructions from point clouds or multi-view images, we also evaluate our method in other applications including sphere tracing and collision detection. We show the results on a slice in the learned signed distance fields from NeuS and ours.

We do sphere tracing from a viewpoint inside of the shape, the SDF with better gradient consistency can guide sphere tracing to find more accurate intersections than the SDF learned by NeuS. The visual comparison is shown in Fig. 7 (a).

Similarly, we check the collision between a moving stick and a shape, the potential collision points determined by the SDF with better gradient consistency and the SDF learned by NeuS are shown. The comparisons show that better gradient consistency leads to more plausible collision points which further achieves more real simulation. The visual comparison is shown in Fig. 7 (b).

Please watch our video for more details.

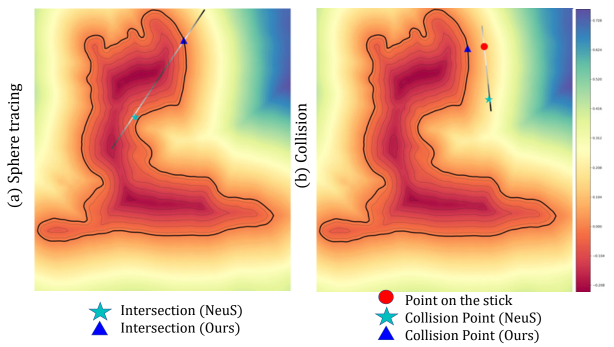

Figure 7. Comparisons in (a) sphere tracing and (b) collision detection.

8. Implementation

Code and data are available at `https://github.com/mabaorui/TowardsBetterGradient`.

References

[1] Gene Chou, Ilya Chugunov, and Felix Heide. GenSDF: Two-stage learning of generalizable signed distance functions. In *Proc. of Neural Information Processing Systems (NeurIPS)*, 2022. 1

[2] Amos Gropp, Lior Yariv, Niv Haim, Matan Atzmon, and Yaron Lipman. Implicit geometric regularization for learning shapes. In *International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pages 3789–3799, 2020. 1

[3] Baorui Ma, Zhizhong Han, Yu-Shen Liu, and Matthias Zwicker. Neural-pull: Learning signed distance functions from point clouds by learning to pull space onto surfaces. In *International Conference on Machine Learning*, 2021. 1

[4] Vincent Sitzmann, Julien N.P. Martel, Alexander W. Bergman, David B. Lindell, and Gordon Wetzstein. Implicit neural representations with periodic activation functions. In *Advances in Neural Information Processing Systems*, 2020. 1

[5] Lars Mescheder Marc Pollefeys Andreas Geiger Songyou Peng, Michael Niemeyer. Convolutional occupancy networks. In *European Conference on Computer Vision*, 2020. 1

[6] Peng Wang, Lingjie Liu, Yuan Liu, Christian Theobalt, Taku Komura, and Wenping Wang. NeuS: Learning neural implicit surfaces by volume rendering for multi-view reconstruction. In *Advances in Neural Information Processing Systems*, pages 27171–27183, 2021. 1

[7] Zehao Yu, Songyou Peng, Michael Niemeyer, Torsten Sattler, and Andreas Geiger. MonoSDF: Exploring monocular geometric cues for neural implicit surface reconstruction. *ArXiv*, abs/2022.00665, 2022. 1