Supplementary Material for "NeuDA: Neural Deformable Anchor for High-Fidelity Implicit Surface Reconstruction"

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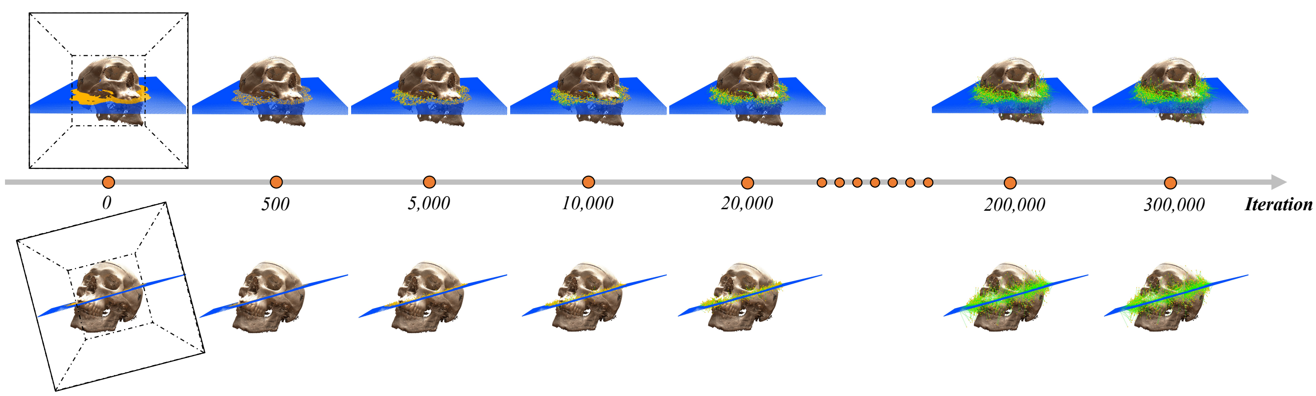


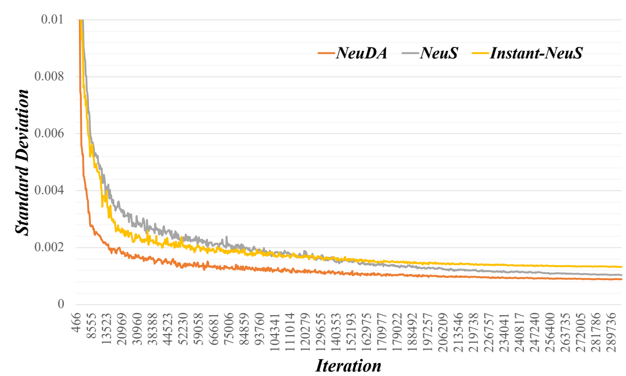
S.Figure 1. **Deformation Process of Anchor Points (Scan 65).** The anchor points (*e.g.* orange points) are uniformly distributed in the 3D box at beginning, and would move to object surfaces as training convergences. The observation could be a faithful support to our deformable anchor analyzes. Zoom in for a better view.

1. Qualitative Proof for Deformable Anchors

As discussed in Sec. 4.3 in the main paper, deformable anchors enable NeuDA to become a more flexible scene representation approach for surface reconstruction. Here, we provide qualitative proof by reporting the anchor points' deformation process in S.Figure 1. Taking a slice of grid voxels as an example, we can see the anchor points (*e.g.* orange points) are uniformly distributed in the 3D box at beginning, and would move to object surfaces as training convergences. This observation should be faithful support that deformable anchors optimized through backpropagation can adaptively represent surface geometries and achieve more flexibility in modeling fine-grained geometric structures.

2. Discussion: Standard Deviation

Following NeuS [4] (See Sec. E.4 and Figure 14 in their paper), we report the curves of standard deviation for different methods in S.Figure 2 to evaluate the sharpness of the reconstructed surface. NeuDA converges rapidly and yields the lowest value compared to NeuS and Instant-NeuS, which means NeuDA can produce more clear and sharper surfaces with less time cost. We find the "standard deviation curve" might not directly reflect to the global



S.Figure 2. **Discussion: Standard Deviation (Scan 65).** The standard deviation of NeuDA converges rapidly and achieves the lowest value compared to NeuS [4] and Instant-NeuS [3, 4]. NeuS [4] indicates that lower standard deviation means more clear and sharper surface.

reconstruction quality, as Instant-NeuS yields a slightly better mean CD score than NeuS.

Quoted Texts from NeuS: *As we can see, the optimization process will automatically reduce the standard deviation so that the surface becomes more clear and sharper with more* *training steps.*

3. Implementation Details

NeuDA consists of the hierarchical "deformable anchors" representation, an SDF network, and a color network. The hierarchical deformable anchors are arranged into L levels (L set to 8 as default), each contains T coordinate vectors, *e.g.*, (x, y, z). The number of coordinate vectors T is set to 16 at the coarsest level and is growing by $1.38\times$ than its coarser level. The deformable anchors and view directions are encoded by positional encoding with 8 frequencies and 4 frequencies, respectively. The signed distance function is approximated by the 4-layer MLPs with hidden-layer size of 256. We additionally predict a normal vector from the SDF network, and using it to construct a normal regularization loss defined in Eqn. 11 in the main paper. The color network follows a similar architecture as NeuS [4], including 4 layers with size of 256. We adopt the Adam optimizer [2] to opmize the model. We train NeuDA in 300k iterations and decay the learning rate from 5×10^{-4} to 2.5×10^{-5} via the cosine decay scheduler.

4. More Qualitative Results

S.Figure 3, S.Figure 4, and S.Figure 5 present the qualitative results of the remained cases on the DTU [1] and BlendedMVS [5] datasets for comprehensiveness. Though NeuDA outperforms NeuS and Instant-NeuS by large margins quantitatively, the qualitative improvements for some cases are not really obvious.

References

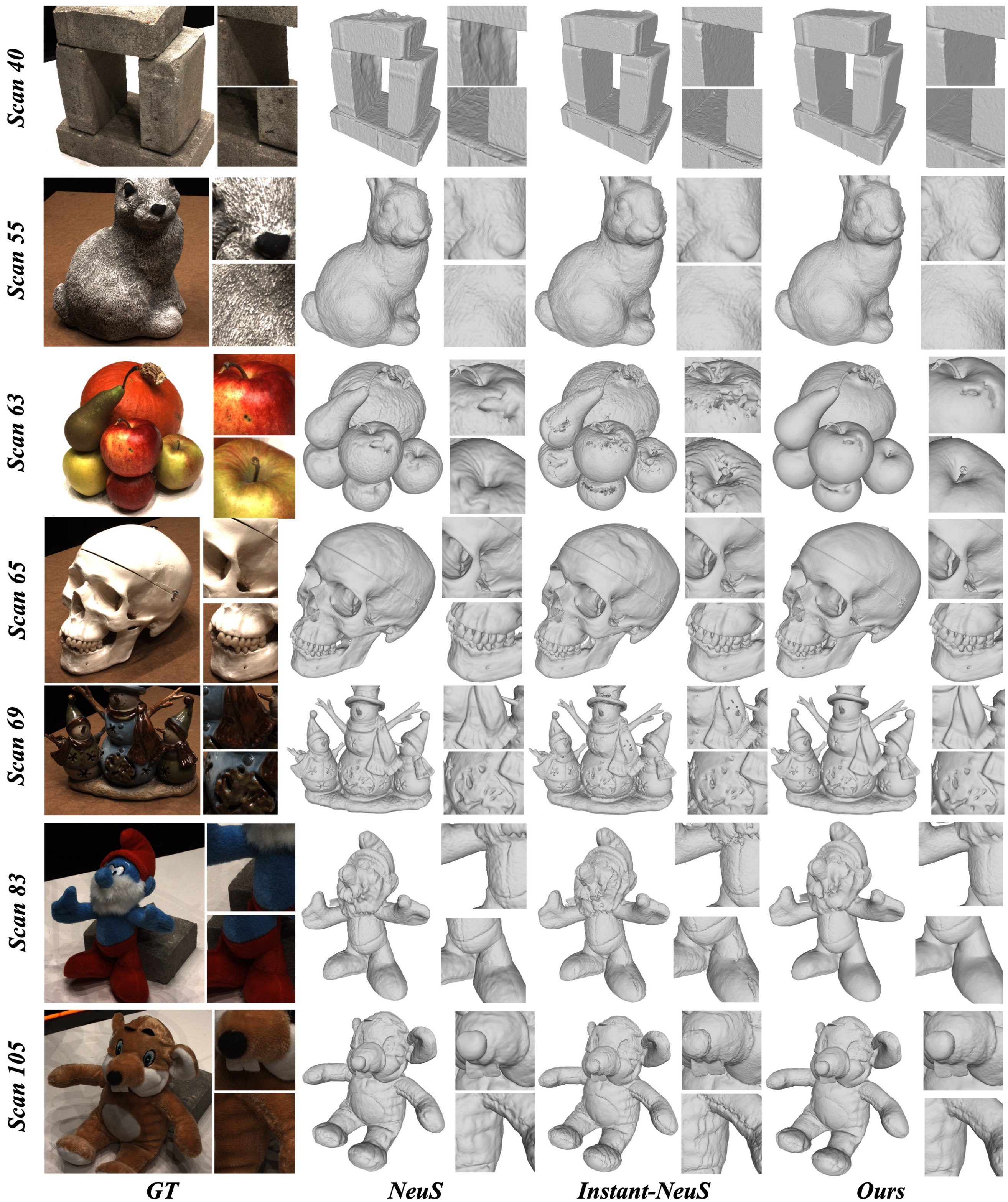
[1] Rasmus Jensen, Anders Dahl, George Vogiatzis, Engil Tola, and Henrik Aanæs. Large scale multi-view stereopsis evaluation. In *2014 IEEE Conference on Computer Vision and Pattern Recognition*, pages 406–413, 2014. 2

[2] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014. 2

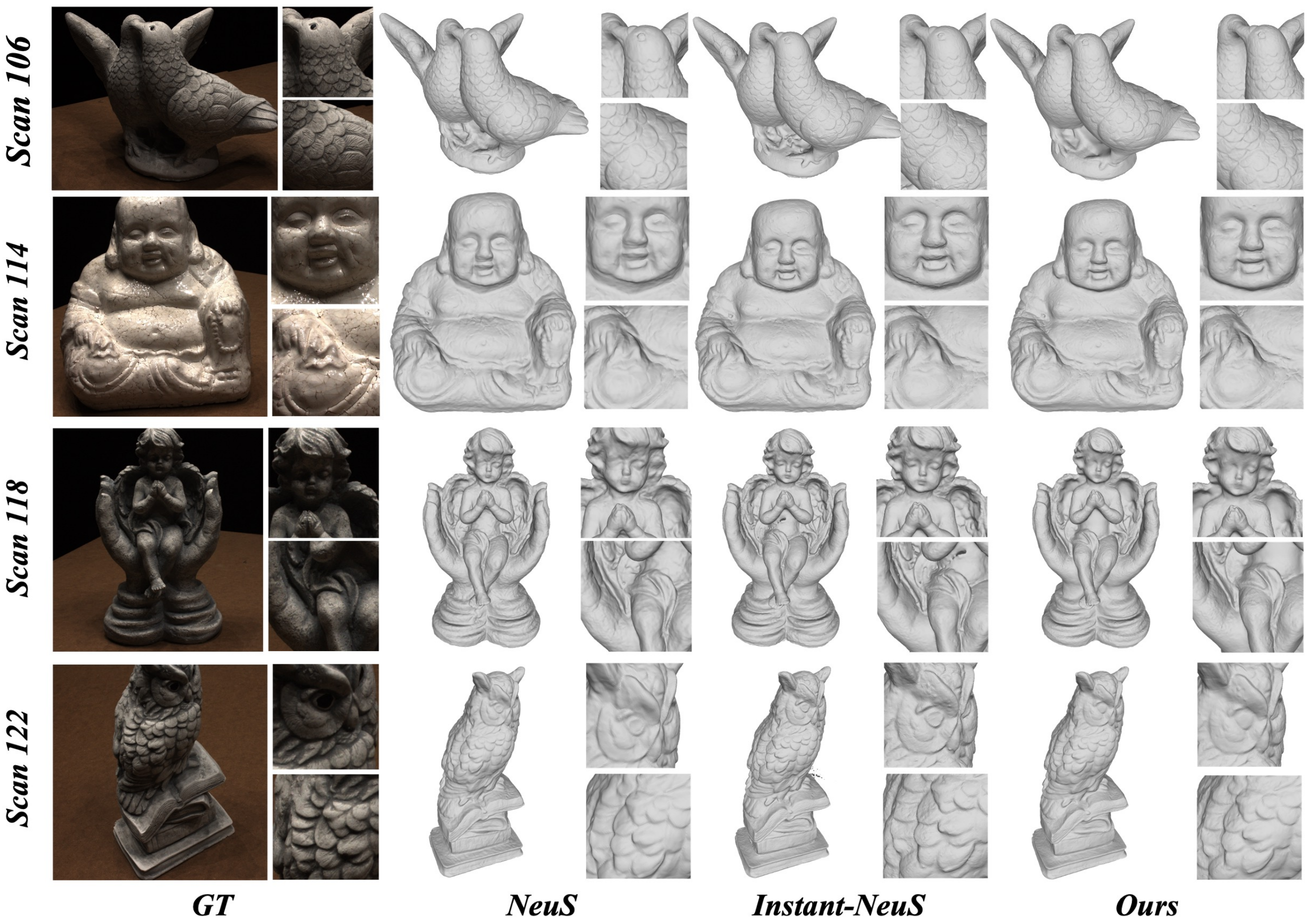
[3] Thomas Müller, Alex Evans, Christoph Schied, and Alexander Keller. Instant neural graphics primitives with a multiresolution hash encoding. *ACM Trans. Graph.*, 41(4):102:1–102:15, July 2022. 1

[4] 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. *NeurIPS*, 2021. 1, 2

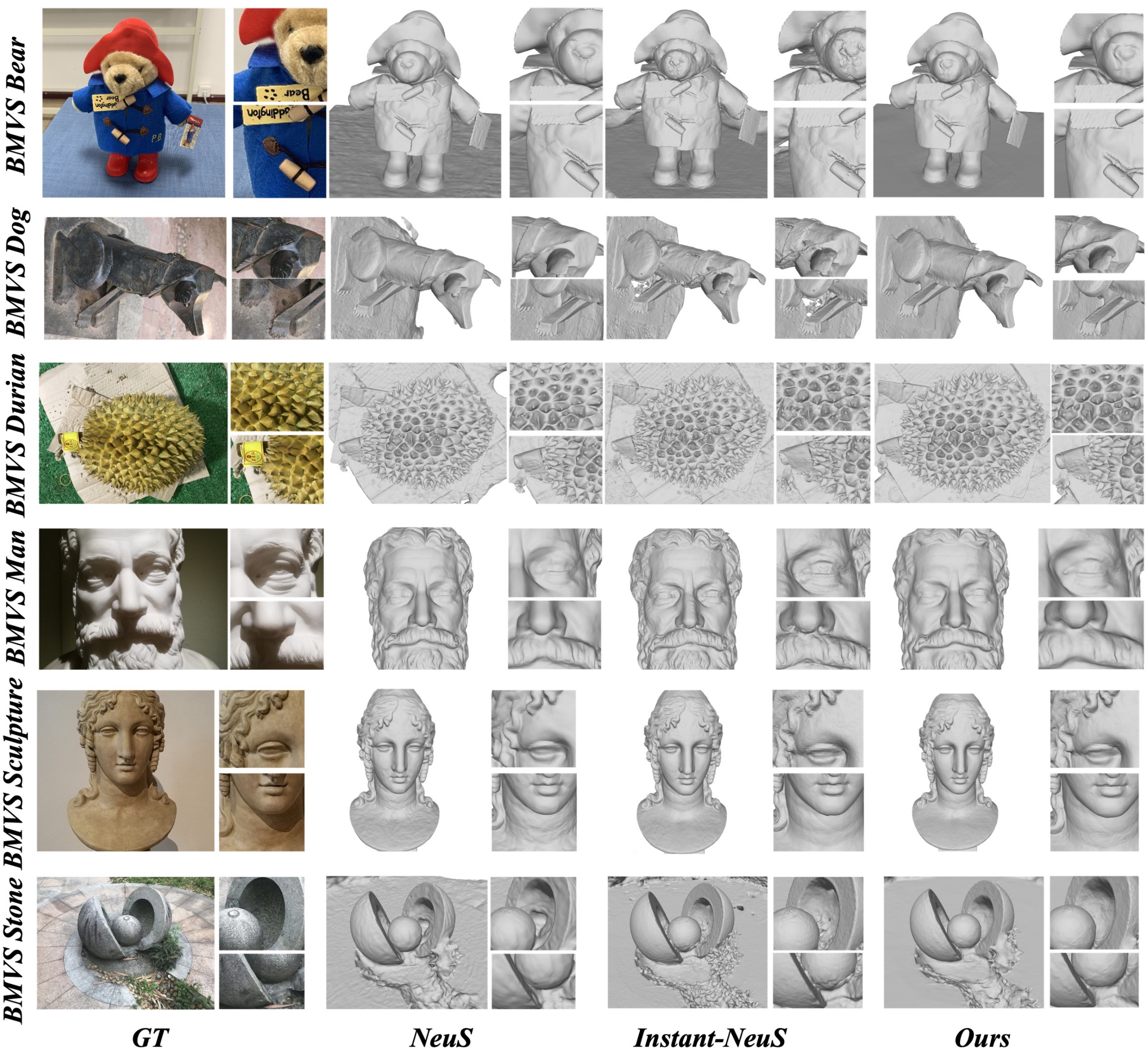
[5] Yao Yao, Zixin Luo, Shiwei Li, Jingyang Zhang, Yufen Ren, Lei Zhou, Tian Fang, and Long Quan. Blendedmvs: A large-scale dataset for generalized multi-view stereo networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1790–1799, 2020. 2



S.Figure 3. More surface reconstruction comparisons on DTU. (Part 1/2)



S.Figure 4. More surface reconstruction comparisons on DTU. (Part 2/2)



S.Figure 5. More surface reconstruction comparisons on BlendedMVS.