Supplemental Material for "Latent Partition Implicit with Surface Codes for 3D Representation"

Chao Chen[1], Yu-Shen Liu[1]⋆, and Zhizhong Han[2]

[1] School of Software, BNRist, Tsinghua University, Beijing, China
[2] Department of Computer Science, Wayne State University, Detroit, USA
chenchao19@mails.tsinghua.edu.cn, liuyushen@tsinghua.edu.cn, h312h@wayne.edu

1 Network Architecture

We learn SDFs using a network that is modified based on NeuralPull [6] for fair comparison. We leverage tanh as the nonlinear function in the last layer, which produces signed distances with a range of [-1,1], where the sign indicates the inside or outside of the 3D shape. In addition, our network is formed by simple fully connected layers rather than Resblock [5].

We also leverage the method introduced by NeuralPull [6] to sample queries around the input point clouds.

2 Shape Abstraction

We leverage Quickhull algorithm [1] to produce the convex hull of each part that we reconstruct in shape abstraction. We visualize our results without any post processing. We show more visual comparison in Fig. 1.

We further visualize more shape abstraction results with semantic distances d_S in Fig. 2. We obtain the sparse point clouds with instance segmentation from ShapeNet [2]. The sparse point clouds are the centers of regions covered by surface codes.

3 Effect of Affinity with Semantic Distance

We report the effect of affinities with semantic distance d_S. Different from Euclidean distance d_E and Intrinsic distance d_G, we set the affinity without using distances. For each query, we set its affinity to its nearest segmentation label to 0.8, while setting its affinities to the rest segmentation labels uniformly to keep

⋆ The corresponding author is Yu-Shen Liu. This work was supported by National Key R&D Program of China (2020YFF0304100), the National Natural Science Foundation of China (62072268), and in part by Tsinghua-Kuaishou Institute of Future Media Data.

Affinity	CD2×100	CD×100	Normal
0.5	0.0049	0.570	**0.972**
0.6	0.0047	0.555	**0.972**
0.7	**0.0035**	**0.453**	0.957
0.8	0.0046	0.551	**0.972**
0.9	0.0036	0.456	0.959

Table 1. Effect of affinity with semantic distance.

the sum of affinity vector to be 1. To explore its effect, we set the affinity to its nearest segmentation label to $\{0.5, 0.6, 0.7, 0.8, 0.9\}$, respectively. We report the numerical comparison in Tab. 1 and the visual comparison in Fig. 3. We found that the affinity does not significantly affect the performance.

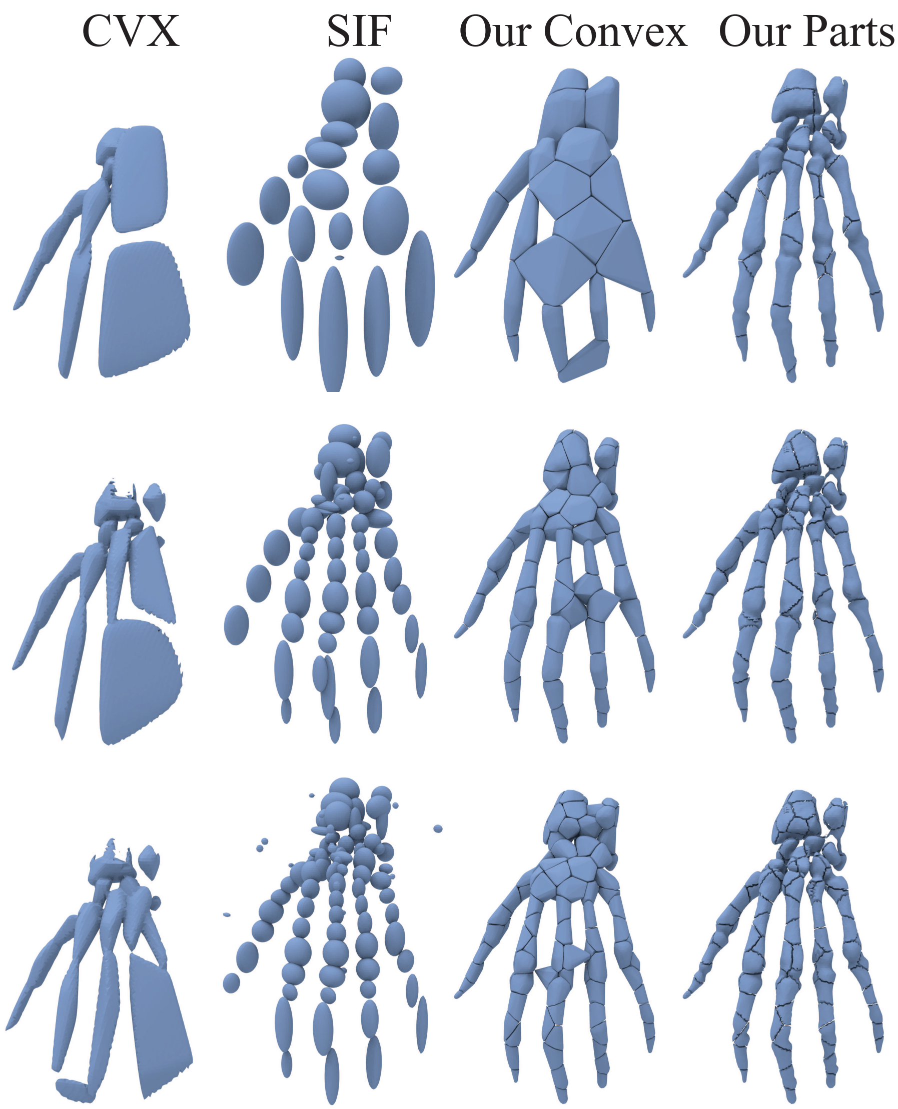

Fig. 1. Visual comparison with CVX [3] and SIF [4] in shape abstraction under FAMOUS.

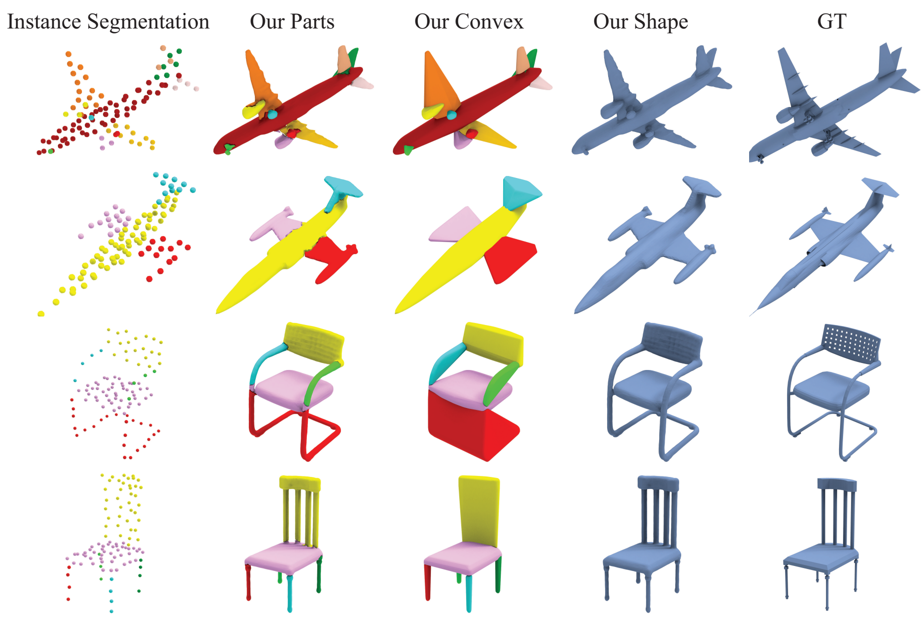

Fig. 2. Surface reconstruction with semantic distances.

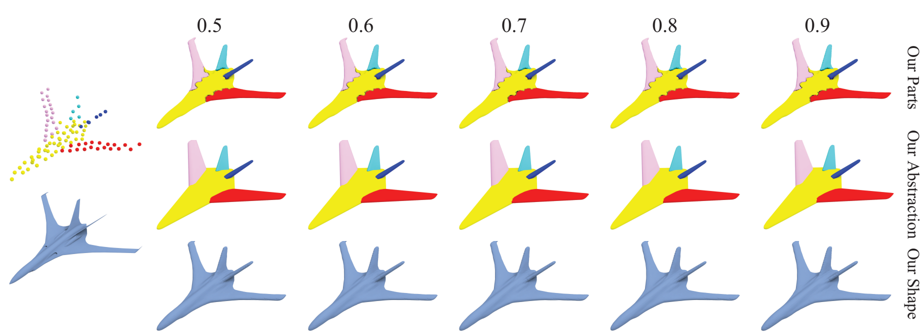

Fig. 3. Effect of affinities with semantic distances.

References

1. Barber, C.B., Dobkin, D.P., Huhdanpaa, H.: The quickhull algorithm for convex hulls. ACM Transactions on Mathematical Software **22**(4), 469–483 (1996)
2. Chang, A.X., Funkhouser, T., Guibas, L., Hanrahan, P., Huang, Q., Li, Z., Savarese, S., Savva, M., Song, S., Su, H., Xiao, J., Yi, L., Yu, F.: ShapeNet: An Information-Rich 3D Model Repository. Tech. Rep. arXiv:1512.03012 [cs.GR], Stanford University — Princeton University — Toyota Technological Institute at Chicago (2015)
3. Deng, B., Genova, K., Yazdani, S., Bouaziz, S., Hinton, G.E., Tagliasacchi, A.: Cvxnet: Learnable convex decomposition. In: IEEE Conference on Computer Vision and Pattern Recognition. pp. 31–41 (2020)
4. Genova, K., Cole, F., Vlasic, D., Sarna, A., Freeman, W.T., Funkhouser, T.: Learning shape templates with structured implicit functions. In: International Conference on Computer Vision (2019)
5. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: IEEE Conference on Computer Vision and Pattern Recognition. pp. 770–778 (2016)
6. Ma, B., Han, Z., Liu, Y.S., Zwicker, M.: Neural-pull: Learning signed distance functions from point clouds by learning to pull space onto surfaces. In: International Conference on Machine Learning (2021)