3D Shape Segmentation with Projective Convolutional Networks
- Supplementary Material -

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1. Evaluation in PSB/COSEG

The labeling accuracy of our method (ShapePFCN), ShapeBoost [2] and Guo et al. [1] per category is presented in Table 1. Aggregate performance is shown in Table 2. The labeling accuracy for a shape is measured as the percentage of surface area labeled correctly according to the ground-truth face labeling provided in the L-PSB [2] and COSEG [3] datasets. Please see our paper for more discussion.

2. ShapeBoost results on RGB-D sensor data

We applied ShapeBoost on the same objects used in Figure 4 of our paper. The method failed to produce compelling results - see Figure 1 below, and compare with the results of our method shown in Figure 4 of our paper. We suspect that the underlying reason for these failure cases of ShapeBoost (and in general methods that rely on hand-engineered geometric descriptors) is that noise, holes, and mesh degeneracies easily distort geometric descriptors. Another potential reason is that shallow classifiers tend to underfit datasets of shapes with significant variability.

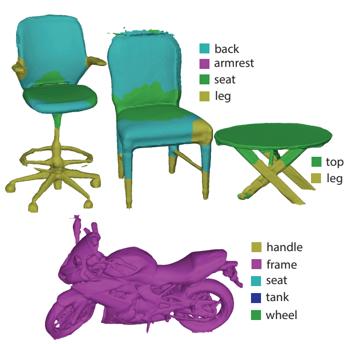

Figure 1. Labeled segmentations produced by ShapeBoost on noisy objects reconstructed from RGBD sensor data.

3. Additional data

In our supplementary material and project page (see: http://people.cs.umass.edu/kalo/papers/shapepfcn/), we provide visualizations of segmentations produced by our method, ShapeBoost [2] and Guo et al. [1] on our test shapes from ShapeNetCore, PSB and COSEG. We also provide a text file (*splits.txt*) that includes the training and test splits we used in our experiments.

	#train/test shapes	#part labels	ShapeBoost	Guo et al.	ShapePFCN
psbAirplane	12 / 8	5	96.1	91.6	93.0
psbAnt	12 / 8	5	98.7	97.6	98.6
psbArmadillo	12 / 8	11	92.6	85.0	92.8
psbBearing	12 / 8	5	92.2	77.4	92.3
psbBird	12 / 8	5	89.6	83.1	88.5
psbBust	12 / 8	8	63.4	34.8	68.4
psbChair	12 / 8	4	98.1	96.7	98.5
psbCup	12 / 8	2	94.0	92.1	93.8
psbFish	12 / 8	3	95.7	94.5	96.0
psbFourLeg	12 / 8	6	83.3	82.4	85.0
psbGlasses	12 / 8	3	96.9	95.3	96.6
psbHand	12 / 8	6	94.4	73.8	84.8
psbHuman	12 / 8	8	86.8	85.6	94.5
psbMech	12 / 8	5	99.5	98.5	98.7
psbOctopus	12 / 8	2	98.2	97.4	98.3
psbPlier	12 / 8	3	95.2	95.2	95.5
psbTable	12 / 8	2	99.4	98.5	99.5
psbTeddy	12 / 8	5	98.7	97.3	97.7
psbVase	12 / 8	5	81.7	77.8	86.8
cosegCandelabra	12 / 16	4	85.5	85.9	95.4
cosegChairs	12 / 8	3	94.8	93.8	96.1
cosegFourleg	12 / 8	5	92.3	88.2	90.4
cosegGoblets	6 / 6	3	97.0	86.1	97.2
cosegGuitars	12 / 32	3	97.7	97.7	98.0
cosegIrons	12 / 6	3	87.2	79.7	88.0
cosegLamps	12 / 8	3	76.3	78.0	93.0
cosegVases	12 / 16	4	86.4	84.4	84.8
cosegVasesLarge	12 / 288	4	89.7	80.1	90.6
cosegChairsLarge	12 / 388	3	76.5	80.8	91.1
cosegTeleAliens	12 / 188	4	81.7	80.0	95.7

Table 1. Dataset statistics and labeling accuracy per category for test shapes in PSB & COSEG.

	ShapeBoost	Guo et al.	ShapePFCN
Category Avg.	90.6	86.3	**92.6**
Category Avg. (>3 labels)	89.5	83.3	**90.9**
Dataset Avg.	84.2	82.1	**92.2**
Dataset Avg. (>3 labels)	87.2	81.0	**92.1**

Table 2. Aggregate labeling accuracy on PSB & COSEG.

References

[1] K. Guo, D. Zou, and X. Chen. 3D mesh labeling via deep convolutional neural networks. *Trans. Graph.*, 35(1):3:1–3:12, 2015. 1

[2] E. Kalogerakis, A. Hertzmann, and K. Singh. Learning 3D mesh segmentation and labeling. *Trans. Graph.*, 29(4):102:1–102:12, 2010. 1

[3] Y. Wang, S. Asafi, O. van Kaick, H. Zhang, D. Cohen-Or, and B. Chen. Active co-analysis of a set of shapes. *Trans. Graph.*, 31(6):165:1–165:10, 2012. 1