Supplementary Material *for*
3DIAS: 3D Shape Reconstruction with Implicit Algebraic Surfaces

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Category	IoU		Chamfer		F-Score		#primitive	
	Multi	Single	Multi	Single	Multi	Single	Multi	Single
airplane	0.549	**0.621**	**0.087**	0.580	59.48	**69.51**	6.915	**23.42**
bench	**0.485**	0.462	**0.106**	0.677	**60.17**	59.60	16.97	**22.24**
cabinet	**0.730**	0.726	**0.123**	0.141	**61.81**	53.24	20.91	**22.98**
car	0.737	**0.747**	0.091	**0.082**	58.07	**61.08**	10.02	**37.96**
chair	**0.509**	0.493	**0.186**	0.304	**43.14**	38.85	17.17	**19.15**
display	**0.538**	0.511	**0.211**	1.137	**42.40**	37.85	13.88	**14.95**
lamp	**0.381**	0.352	**0.607**	1.494	**37.52**	35.96	9.946	**17.54**
speaker	**0.638**	0.632	0.351	**0.310**	**39.16**	34.19	19.24	**19.65**
rifle	0.423	**0.509**	**0.116**	0.760	47.44	**61.60**	4.719	**17.16**
sofa	**0.685**	0.667	**0.158**	0.186	**49.73**	45.20	21.35	**24.55**
table	**0.509**	0.478	**0.245**	0.369	**57.63**	50.96	15.97	**16.68**
phone	**0.751**	0.734	**0.080**	0.168	**71.35**	65.85	14.11	**18.23**
vessel	0.538	**0.550**	0.206	**0.200**	40.70	**43.89**	7.067	**19.41**
mean	**0.575**	**0.575**	**0.197**	0.493	**52.22**	50.60	13.71	**21.07**

Table S1: Comparison of multi-class and single-class single RGB image 3D shape reconstruction in terms of IoU, Chamfer, F-score, and the number of primitives.

S. 3DIAS analysis

In this section, we provide more experimental analyses of our proposed 3DIAS method. First, we prove that our scale constraint satisfies the criteria of the closedness constraint. Then we quantitatively and qualitatively show and compare our experiments of 3DIAS trained on single-class and multi-class. Finally, we show the effect of viewpoint in reconstructing 3D shapes with our proposed method.

S.1. Holding closedness constraint

In the section 3.1.2, we claim that the parametrized coefficient matrix A holds the criteria for the closedness constraint. To ensure the closedness constraint is satisfied, the coefficient matrix $A_{[5:10]}$ in Eq. 3 of the fourth-degree terms $p^4(x, y, z)$ must be positive definite. The matrix $A_{[5:10]}$, as the principal sub-matrix of the coefficient matrix A of $p(x, y, z)$, is the summation of the corresponding sub-matrices $H_{[5:10]}$ and $Q_{[5:10]}$. Since the matrix H is assumed positive definite, its principal sub-matrices (e.g., $H_{[5:10]}$) are also positive definite. Moreover, the corresponding sub-matrix $Q_{[5:10]}$ of the coefficient matrix Q is a diagonal matrix with the values $[1, 1, 1, 0, 0, 0]$; hence it is positive semi-definite. Accordingly, the sub-matrix $A_{[5:10]}$ as the summation of a positive definite matrix and a positive semi-definite matrix is also positive definite, which satisfies the closedness constraint.

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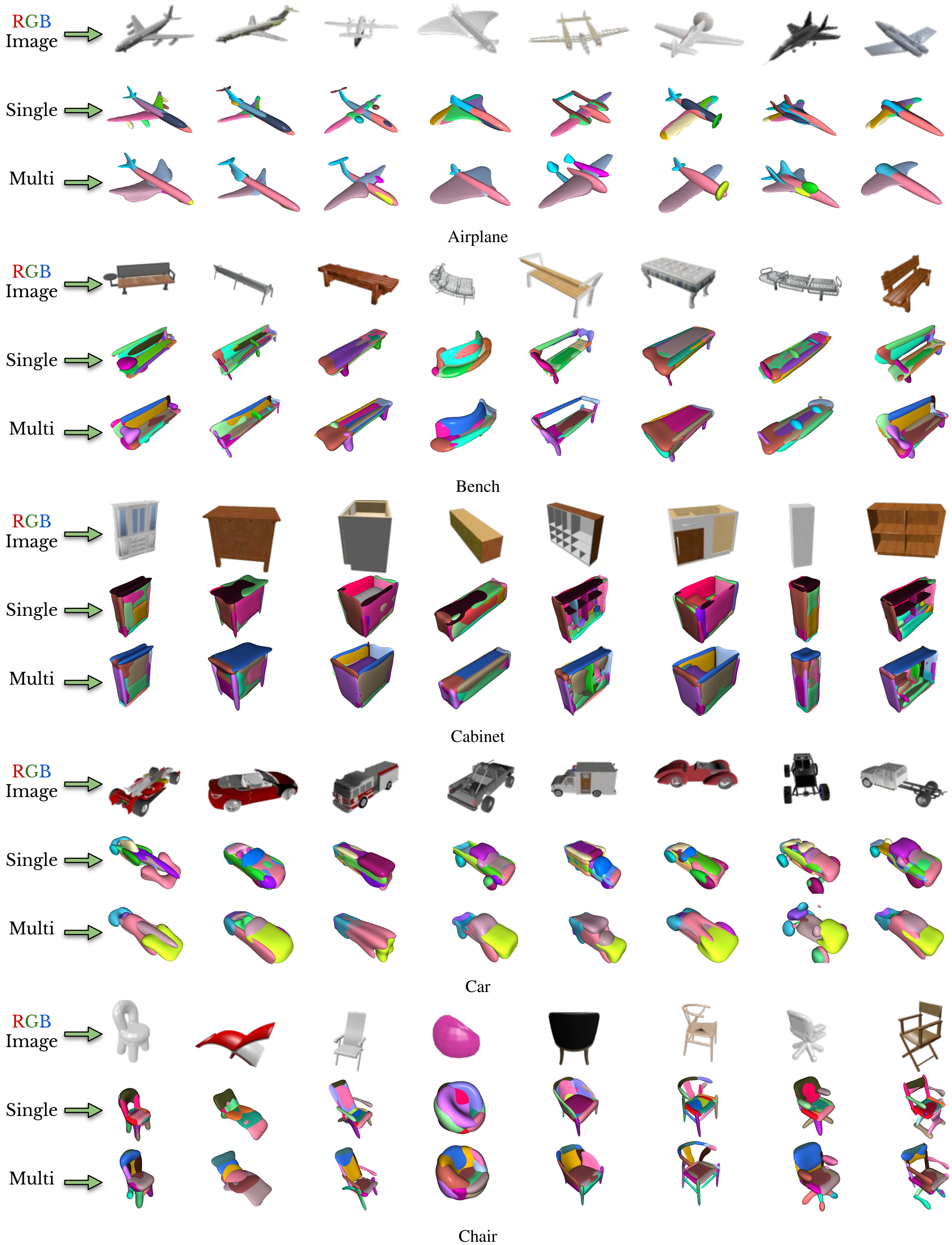
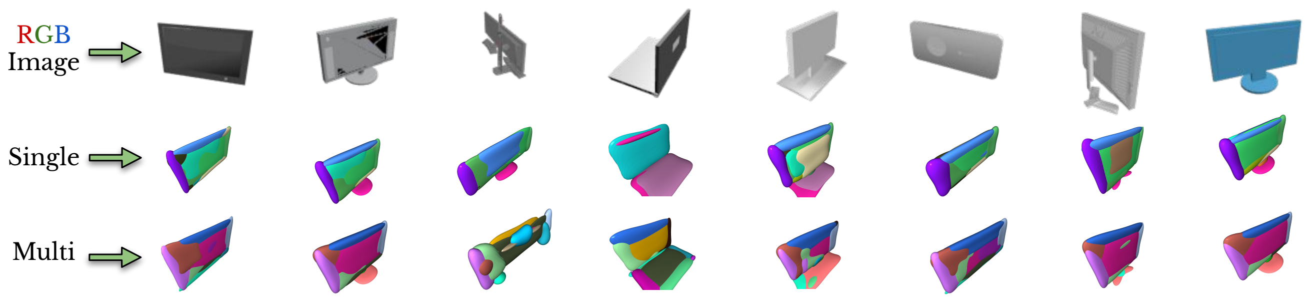
S.2. Multi-class vs single-class training

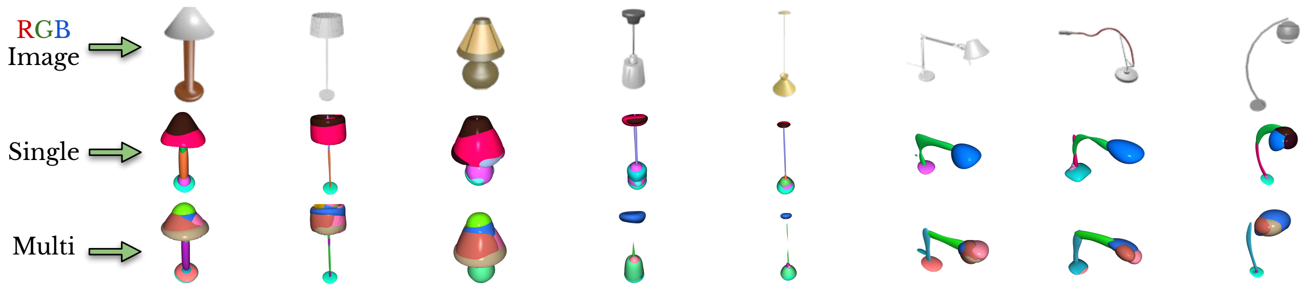
We also evaluate our method for the trained network individually on each class and compare the results in terms of IoU, Chamfer, and F-score with the multi-class case and summarize the results in Table S1. Surprisingly, the comparison demonstrates that our method trained on the multi-class can better reconstruct on average, presumably due to the overfitting to the training set. However, our method trained on the single-class selects more primitives on average to reconstruct 3D shapes as shown in Table S1. We believe it is because more available primitives are per class to represent 3D shapes in the single-class training, while the network must distribute the limited primitives among all categories in the multi-class training.

We also visualize the reconstructed 3D shapes by 3DIAS for both the single-class and the multi-class cases in Figure S2. The results show that the primitives share the same semantically meaning among the 3D shapes in the same category in both single-class and multi-class cases. Based on our qualitative and quantitative experiments, we believe that the Chamfer is not a suitable and reliable metric for the 3D shape reconstruction task. For instance, Chamfer shows better performance for multi-class training on airplane and rifle categories, while the qualitative results show better appearances for single-class training.

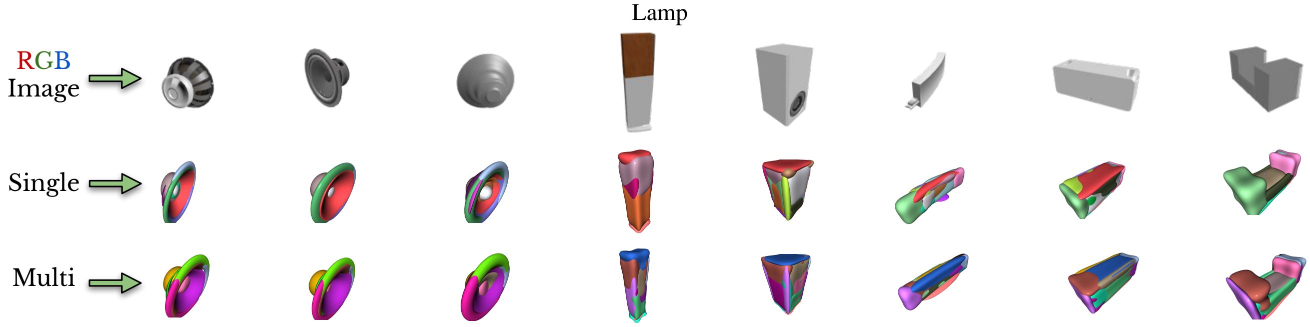

RGB Image
Single
Multi
Airplane
RGB Image
Single
Multi
Bench
RGB Image
Single
Multi
Cabinet
RGB Image
Single
Multi
Car
RGB Image
Single
Multi
Chair



Display

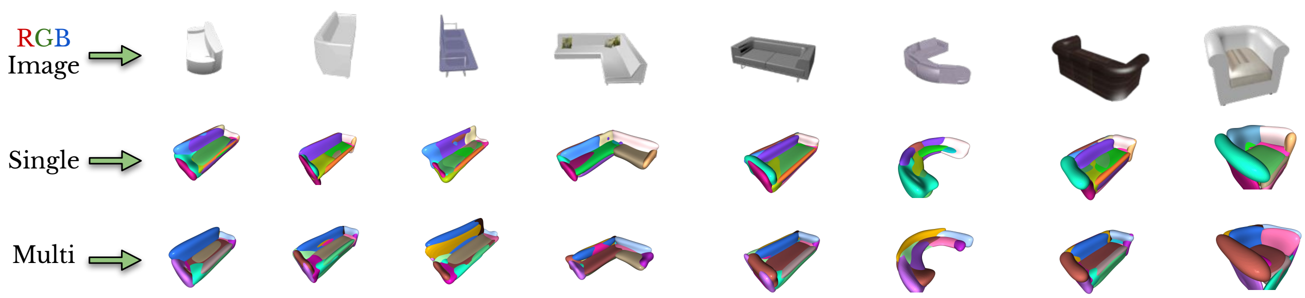


Lamp



Speaker

Rifle



Sofa

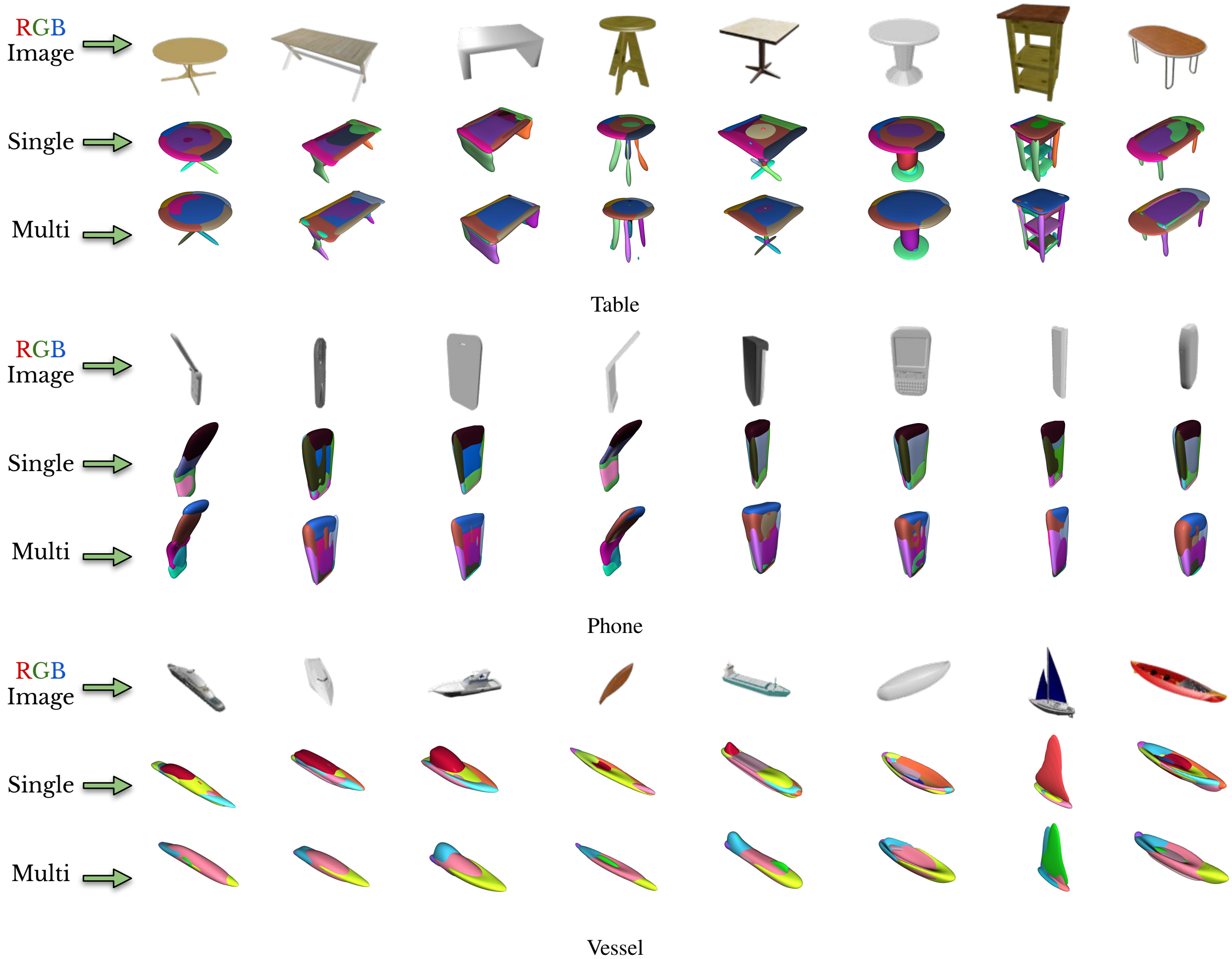


Figure S2: Qualitative comparison of single-class and multi-class cases. We visualize the results for some samples in each category. The first, second, and third lines for each category show the input RGB images, single-class training results, and multi-class training results, respectively.

S.3. Effect of viewpoint

We also show the effect of viewpoint in Figure S3. The results illustrate that the quality of the reconstructed 3D shapes is highly dependent on the point of view when similar shapes are rare in the training dataset (e.g., bottom airplane). However, we show that this effect decreases when there are enough similar shapes to the query shape (e.g., top airplane) in the training dataset.

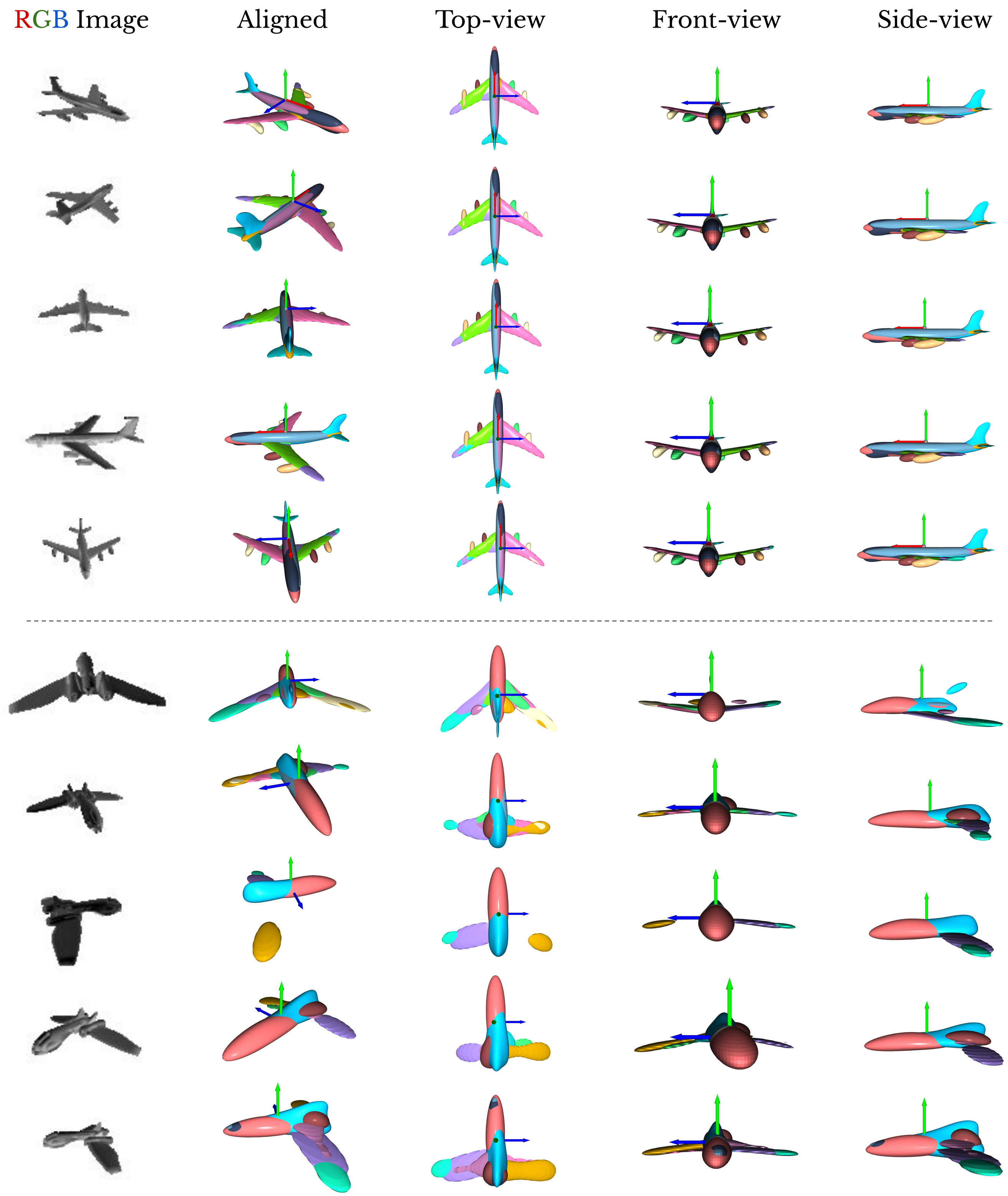


Figure S3: Effect of viewpoint in 3D shape reconstruction. We visualize the reconstructed 3D shape by 3DIAS for two samples. (top) and (bottom) show two airplanes with small and large viewpoint effects on their appearances, respectively.