Fast Fourier Intrinsic Network
– Supplementary Material –

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This supplementary material provides 1) the training&testing splits for MPI-Sintel and MIT Intrinsic; 2) more examples for visualization and comparison.

1. Training&Testing Splits

We use the same training&testing split files with [8] and [1] for MIP-Sintel and MIT Intrinsic, respectively. We think it would be good to publish these files such that any following-up works can use them and make a fair comparison with us or any previous relevant works. We report the scene-split for MPI-Sintel and object-split for MIT Intrinsic dataset below.

MPI-Sintel:
training: alley_1, bamboo_1, bandage_1,cave_2,market_2, market_6, shaman_2, sleeping_1, temple_2
testing: alley_2, bamboo_2, bandage_2, cave_4, market_5, mountain_1, shaman_3, sleeping_2, temple_3
MIT Intrinsic:
training: apple,box, cup1, dinosaur, frog1, panther, paper1, phone, squirrel, teabag2
testing: cup2, deer, frog2, paper2, pear, potato, raccoon, sun, teabag1, turtle

2. More Examples for Visualization

- Fig. 1 and Fig. 4: visual results on MPI-Sintel dataset with scene split and image split, respectively. We compare our method with [6, 8, 4, 5, 1]. We particularly point the readers to the flatten patches and fine textures (see red arrows) in the images to show the superiority of our method.
- Fig. 3: more visual results on MIT Intrinsic dataset. In Fig. 3 we compare our FFI-Net with different versions in [2]; ours are clearly visually better than [2].
- Fig. 2: visual results on IIW benchmark. We compare our FFI-Net with other representative approaches [3, 9, 7].

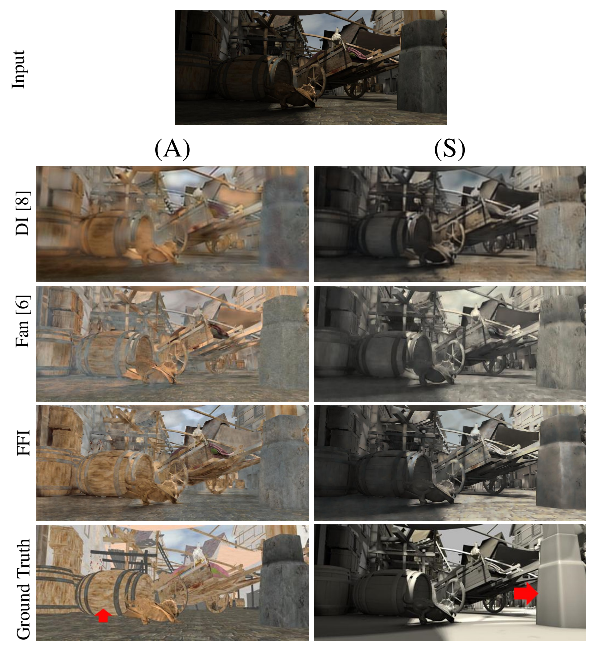

Figure 1: Examples on the MPI-Sintel dataset (scene split).

References

[1] Jonathan T Barron and Jitendra Malik. Shape, illumination, and reflectance from shading. *IEEE transactions on pattern analysis and machine intelligence*, 37(8):1670–1687, 2015.

[2] Anil S Baslamisli, Hoang-An Le, and Theo Gevers. Cnn based learning using reflection and retinex models for intrinsic image decomposition. In *CVPR*, 2018.

[3] Sean Bell, Kavita Bala, and Noah Snavely. Intrinsic images in the wild. *ACM Transactions on Graphics (TOG)*, 33(4):159, 2014.

[4] Qifeng Chen and Vladlen Koltun. A simple model for intrinsic image decomposition with depth cues. In *ICCV*, 2013.

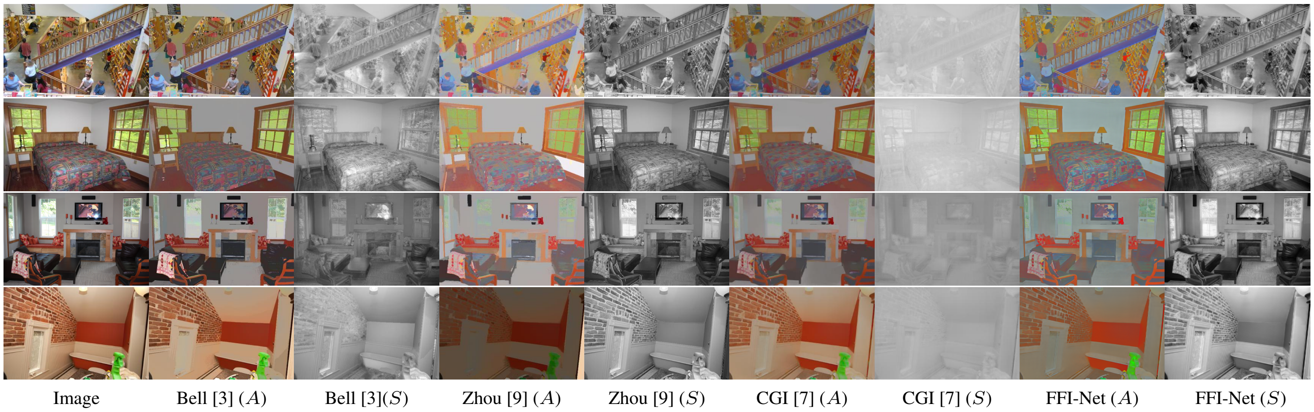

Figure 2: Qualitative comparisons of (A)lebdo and (S)hading on IIW.

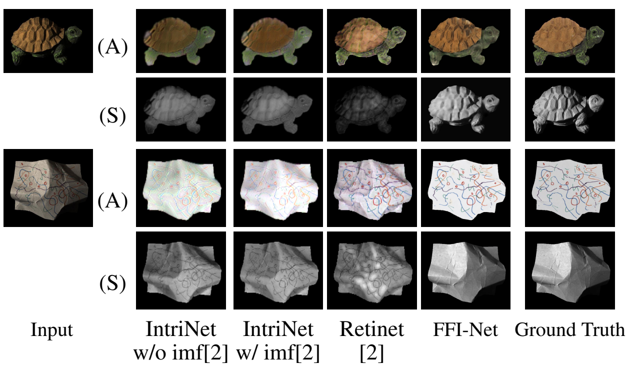

Figure 3: Sample (A)lbedo and (S)hading on MIT Intrinsic. Comparison with different versions in [2]. Results of [2] are downloaded from their project webpage.

[5] Lechao Cheng, Chengyi Zhang, and Zicheng Liao. Intrinsic image transformation via scale space decomposition. In *CVPR*, 2018.

[6] Qingnan Fan, Jiaolong Yang, Gang Hua, Baoquan Chen, and David Wipf. Revisiting deep intrinsic image decompositions. In *CVPR*, 2018.

[7] Zhengqi Li and Noah Snavely. Cgintrinsics: Better intrinsic image decomposition through physically-based rendering. In *ECCV*, 2018.

[8] Takuya Narihira, Michael Maire, and Stella X Yu. Direct intrinsics: Learning albedo-shading decomposition by convolutional regression. In *ICCV*, 2015.

[9] Tinghui Zhou, Philipp Krahenbuhl, and Alexei A Efros. Learning data-driven reflectance priors for intrinsic image decomposition. In *CVPR*, 2015.

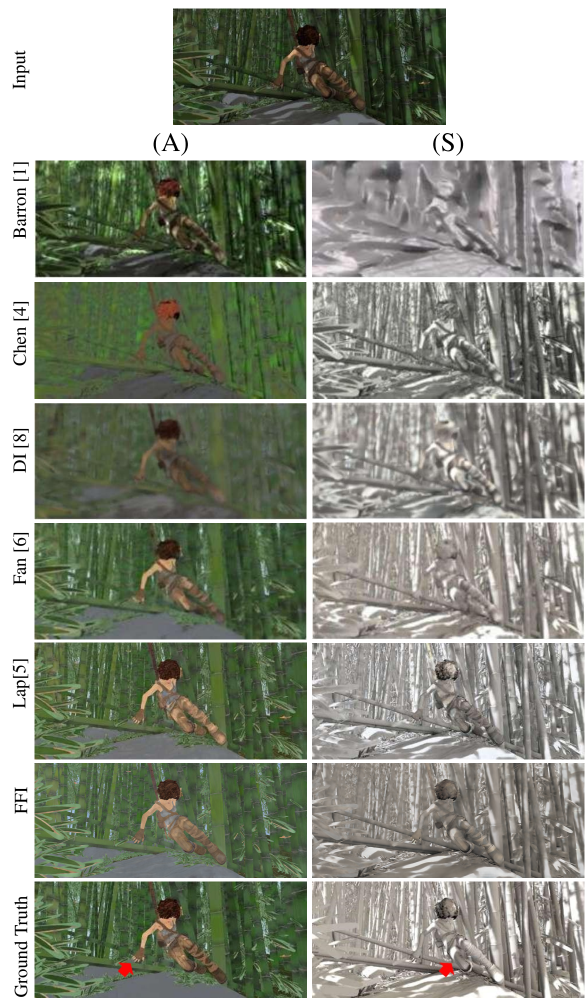

Figure 4: More Examples of (A)lbedo and (S)hading predictions on MPI-Sintel (image split).