Mutual-Structure for Joint Filtering Supplementary File

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1. RGB/Depth Restoration

Our mutual-structure for joint filtering is extensively evaluated for noisy-RGB/depth image restoration. Experiments are conducted on the dataset of Lu et al. [3]. We compared our results with the joint bilateral filter [1], guided image filter [2] and the state-of-the-art RGB/depth restoration method of [3]. The PSNRs are reported in Figures 1 and 2. Our method outperforms others. Among all previous approaches, the method of [3] performs the best. However, it is not a very efficient method due to the intensive computation. Our running speed is 50+ times faster since we only need several fast iteration passes.

We show a few more examples in Figures 3, 4, 5, 6, 7 and 8. In these examples, the inputs are noisy depth and RGB image pairs shown in (a) and (b) respectively. (c) shows the ground truth. (d) and (e) are the results by joint bilateral filter and guided image filter respectively. (f) is the result of [3]. (g) is our restoration result and (h) shows the correspondent mutual-structure image. The PSNRs of each result are also reported. Another example for real depth/RGB restoration is shown in Figure 9 where (a) and (b) are the inputs captured by Microsoft Kinect and (c) is our restoration results.

2. Stereo Matching

Our mutual-structure for joint filtering also benefits stereo matching because of the structure inconsistency between the cost volume and color image. Here we provide more examples in Figures 10, 11 and 12. In these examples, (a) and (b) are the inputs. (c) shows the ground truth disparity. We show the results without post-processing by different joint filters in (d-g). The results with post-processing are shown in (h-k). The bad pixel errors are reported for all results. Our mutual-structure for joint filtering produces the best results.

3. Other Applications

The mutual structure exists in the target and reference images. We directly apply the mutual-structure for joint filtering to RGB/NIR image restoration as shown in Figure 13. Result of [4], shown in (c), has its shadow structure transferred because these edges are not consistent in the inputs. Our method restores the common structures between (a) and (b) as shown in (d). The result presents similar quality, while not suffering from the inconsistent edge problem.

Our extracted mutual structure can be also applied to joint shadow detection as shown in Figure 14 where (a) is the input with shadow and (b) is another input without shadow. The mutual structure shown in (c) contains common edges between (a) and (b). Thus, the shadow in (a) can be directly obtained by finding the difference between (a) and (c). Our shadow detection result is shown in (d).

References

- [1] T. Carlo and M. Roberto. Bilateral filtering for gray and color images. In ICCV, pages 839–846, 1998.
- [2] K. He, J. Sun, and X. Tang. Guided image filtering. In ECCV, pages 1–14. Springer, 2010.
- [3] S. Lu, X. Ren, and F. Liu. Depth enhancement via low-rank matrix completion. In CVPR, pages 3390–3397, 2014.
- [4] Q. Yan, X. Shen, L. Xu, S. Zhuo, X. Zhang, L. Shen, and J. Jia. Cross-field joint image restoration via scale map. In ICCV, 2013.

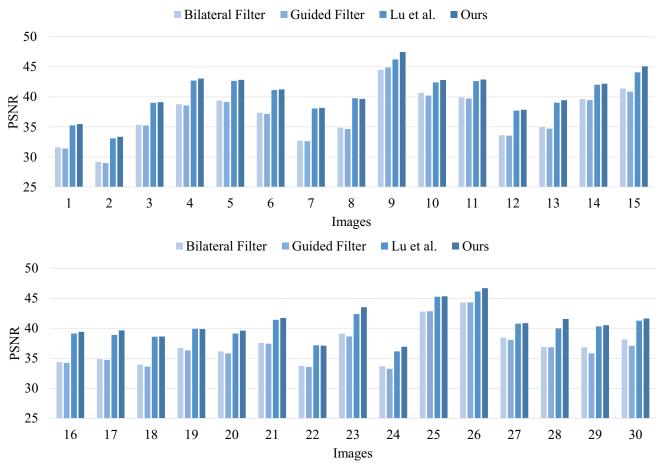


Figure 1. PSNR comparison with [3] on the Middleburry dataset.

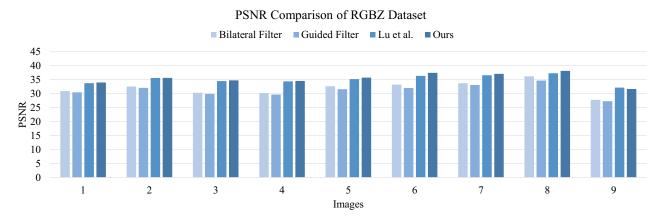


Figure 2. PSNR comparison with [3] on the RGBZ dataset.

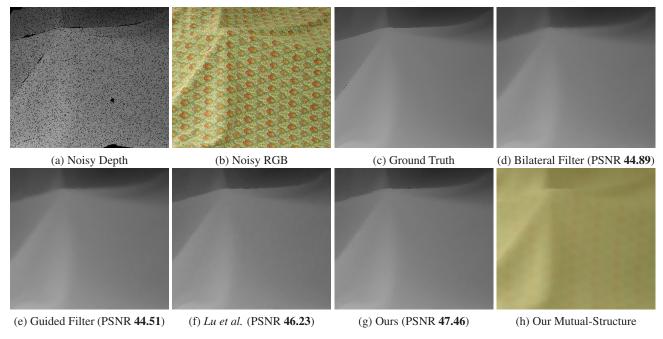


Figure 3. Example of noisy RGB/depth image restoration.

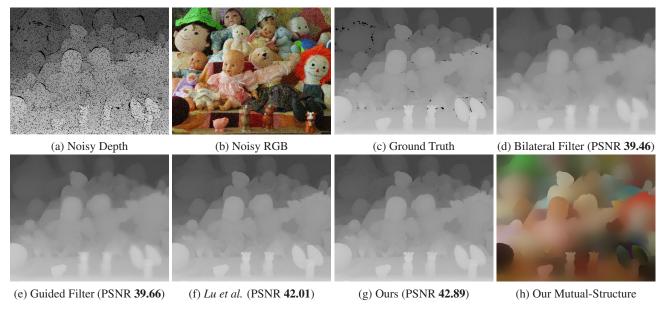


Figure 4. Example of noisy RGB/depth image restoration.

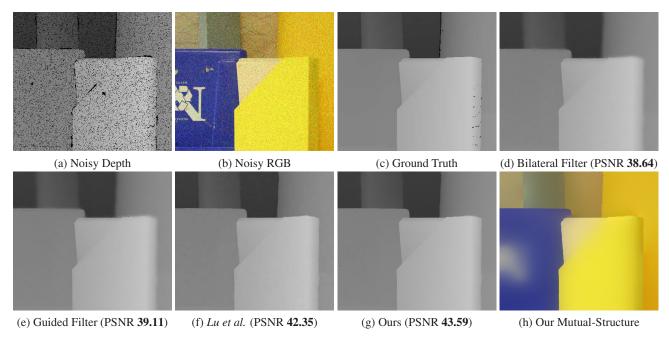


Figure 5. Example of noisy RGB/depth image restoration.

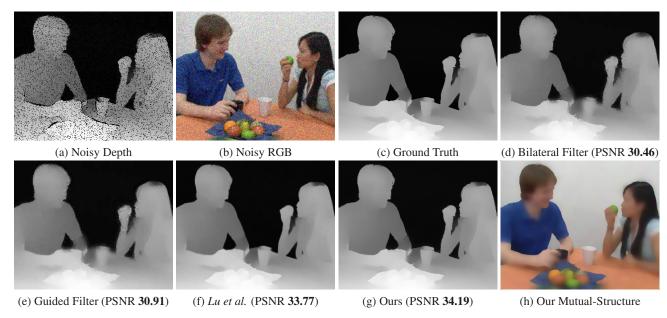


Figure 6. Example of noisy RGB/depth image restoration.

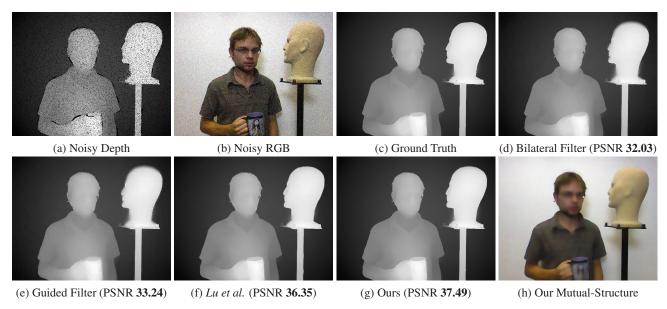


Figure 7. Example of noisy RGB/depth image restoration.

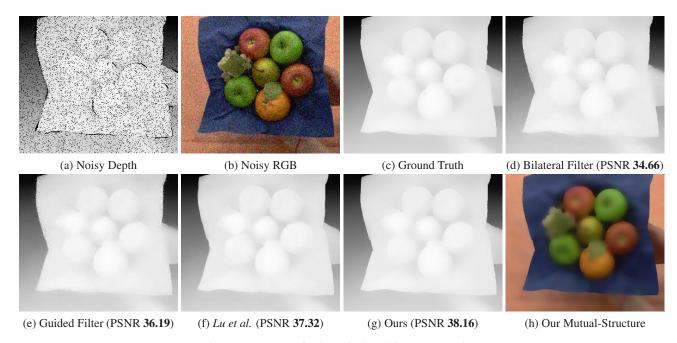


Figure 8. Example of noisy RGB/depth image restoration.



Figure 9. Example of noisy RGB/depth image restoration.

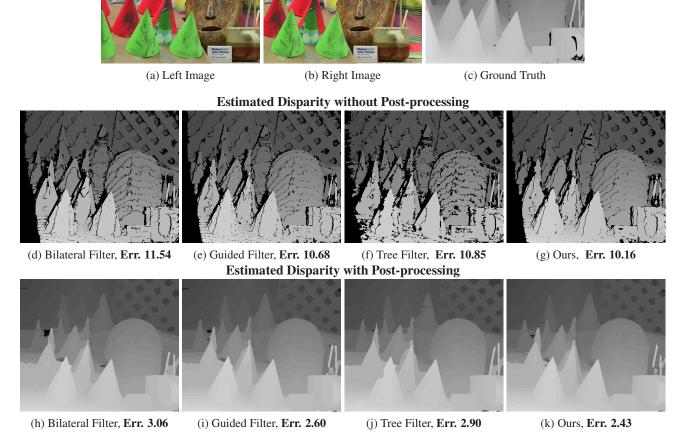


Figure 10. Comparisons of different joint filters on stereo matching. (a) and (b) are the left and right images respectively. (c) is the ground truth disparity. (d-g) are the stereo matching results of different joint filters without post-processing while (h-k) are the results with post-processing. We report the bad pixel error for each result.

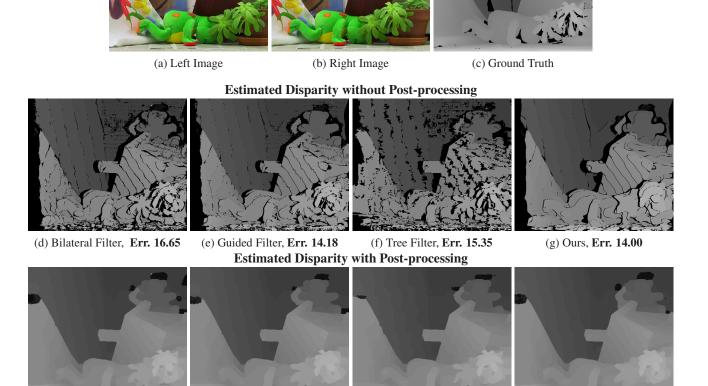


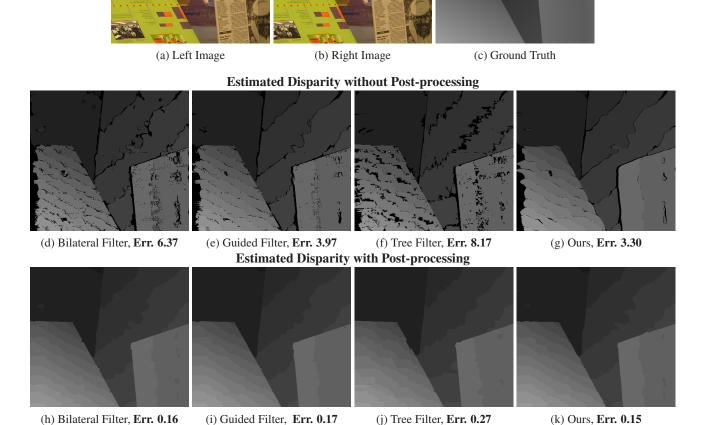
Figure 11. Comparisons of different joint filters on stereo matching. (a) and (b) are the left and right images respectively. (c) is the ground truth disparity. (d-g) are the stereo matching results of different joint filters without post-processing while (h-k) are the results with post-processing. We report the bad pixel error for each result.

(i) Guided Filter, Err. 6.96

(h) Bilateral Filter, Err. 7.16

(j) Tree Filter, Err. 6.33

(k) Ours, Err. 6.12



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Venus serve

Figure 12. Comparisons of different joint filters on stereo matching. (a) and (b) are the left and right images respectively. (c) is the ground truth disparity. (d-g) are the stereo matching results of different joint filters without post-processing while (h-k) are the results with post-processing. We report the bad pixel error for each result.

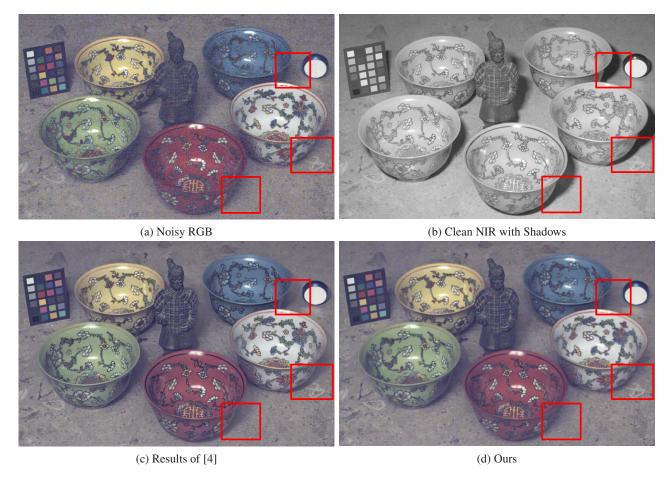


Figure 13. Example of RGB/NIR image restoration. (a) is the noisy RGB image and (b) is the clean NIR image with shadow. (c) is the result of [4], which transfers the shadow structure to the output. (d) is our result without this problem.

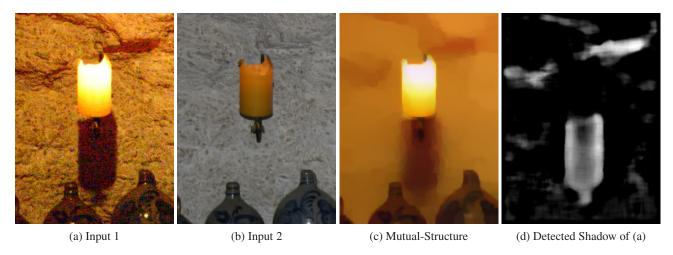


Figure 14. Example of joint shadow detection. (a) and (b) are the inputs. (c) is our estimated mutual structure of (a) and (b). (d) shows our shadow detection result.