

Learning to Restore Low-Light Images via Decomposition-and-Enhancement (Supplementary Material)

Ke Xu^{1,2} Xin Yang^{1,†} Baocai Yin^{1,3} Rynson W.H. Lau^{2,†}

¹Dalian University of Technology ² City University of Hong Kong ³Pengcheng Lab

This material first visualizes the internal results of the proposed network in Figure 1 and Figure 2. It then provides visual comparisons between the proposed method and four state-of-the-art low-light image enhancement methods (SID [1], LIME [3], DSLR [4] and DeepUPE [7], which are the top four existing methods according to Table 1 in the paper) in Figure 3, Figure 4 and Figure 5. Finally, we provide visual comparison between our method and different combinations of deep learning based enhancement methods and denoising methods in Figure 6.

[†] Xin Yang and Rynson Lau are the corresponding authors. Rynson Lau led this project.

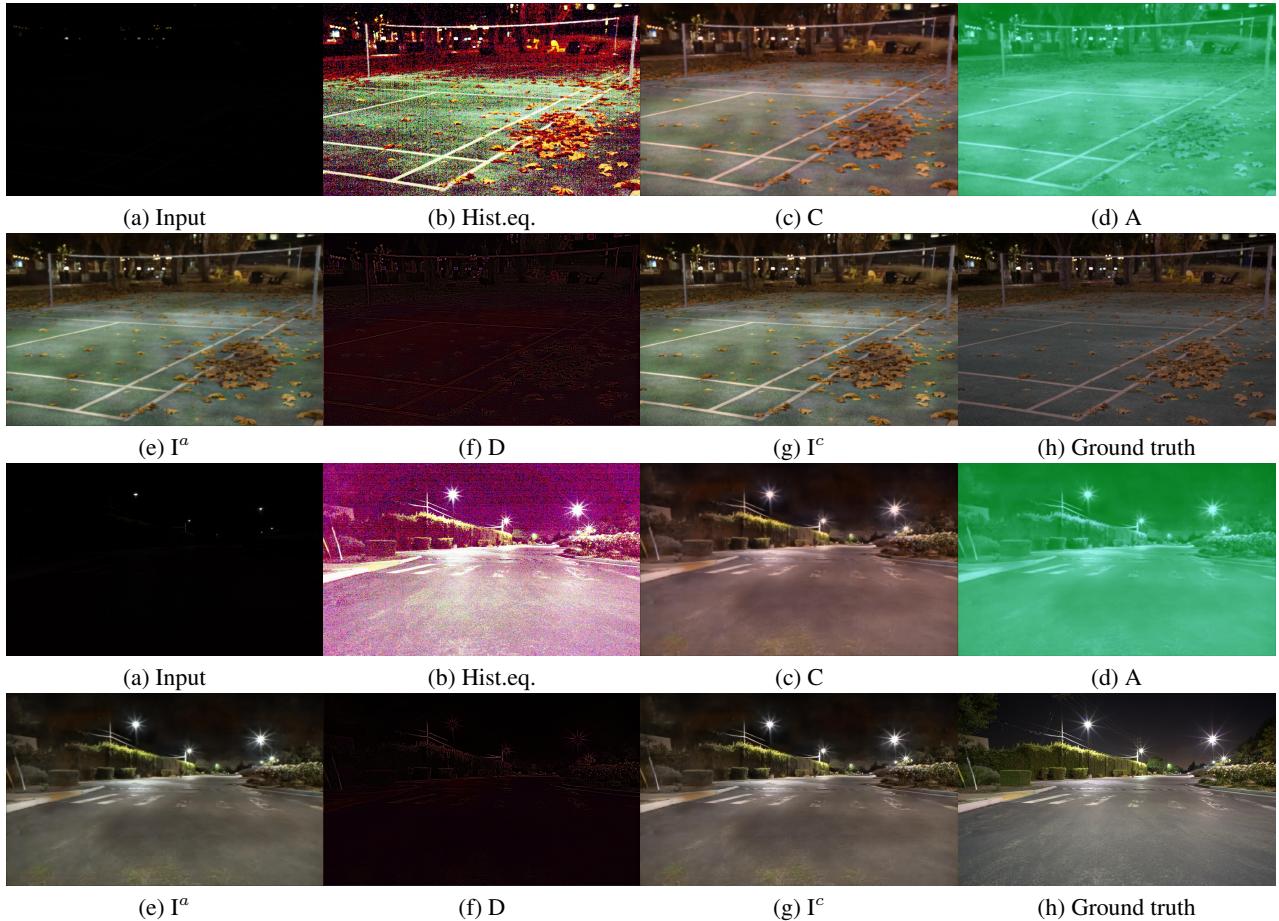


Figure 1: Visualization of internal results from the proposed network: (a) input image, (b) histogram equalization, (c) predicted content, (d) predicted amplification map, (e) predicted amplified image, (f) predicted detail map, (g) final output, and (h) ground truth.

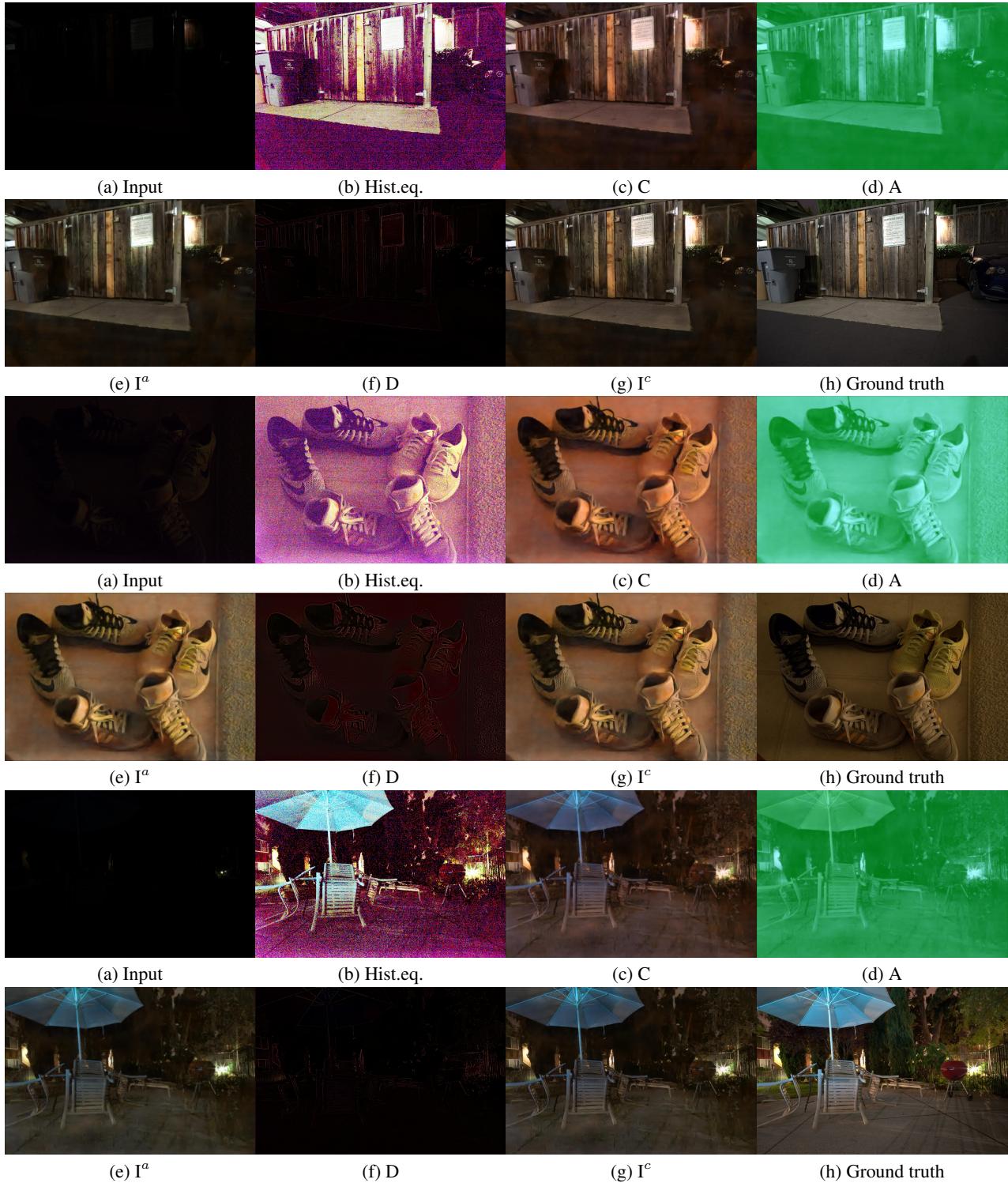


Figure 2: Visualization of internal results from the proposed network: (a) input image, (b) histogram equalization, (c) predicted content, (d) predicted amplification map, (e) predicted amplified image, (f) predicted detail map, (g) final output, and (h) ground truth.

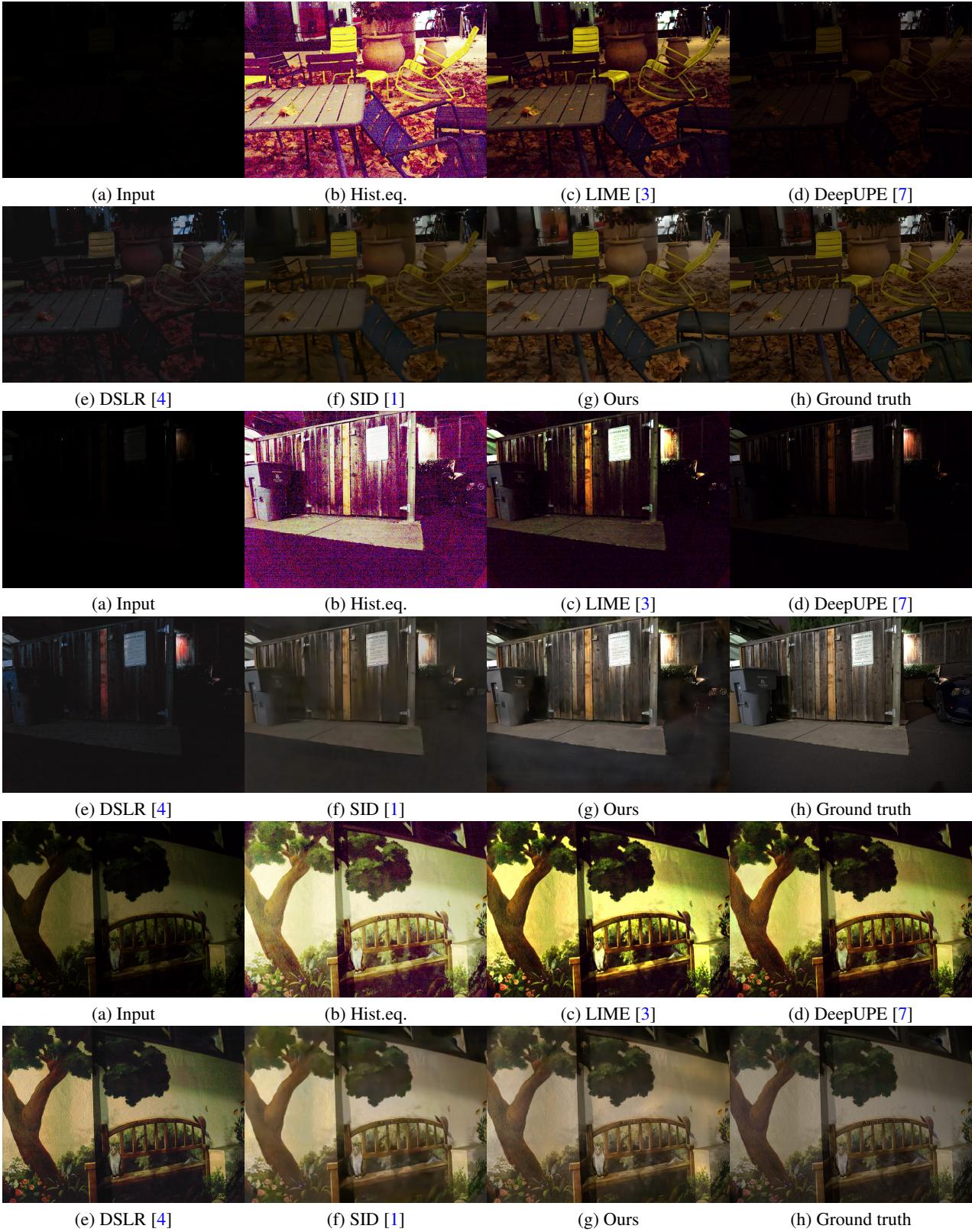


Figure 3: Visual results of state-of-the-art methods and ours on input low-light images from our test set.



(a) Input



(b) Hist.eq.

(c) LIME [3]

(d) DeepUPE [7]



(e) DSLR [4]

(f) SID [1]

(g) Ours

(h) Ground truth



(a) Input



(b) Hist.eq.

(c) LIME [3]

(d) DeepUPE [7]



(e) DSLR [4]

(f) SID [1]

(g) Ours

(h) Ground truth



(a) Input



(b) Hist.eq.

(c) LIME [3]

(d) DeepUPE [7]



(e) DSLR [4]

(f) SID [1]

(g) Ours

(h) Ground truth

Figure 4: Visual results of state-of-the-art methods and ours on input low-light images from our test set.

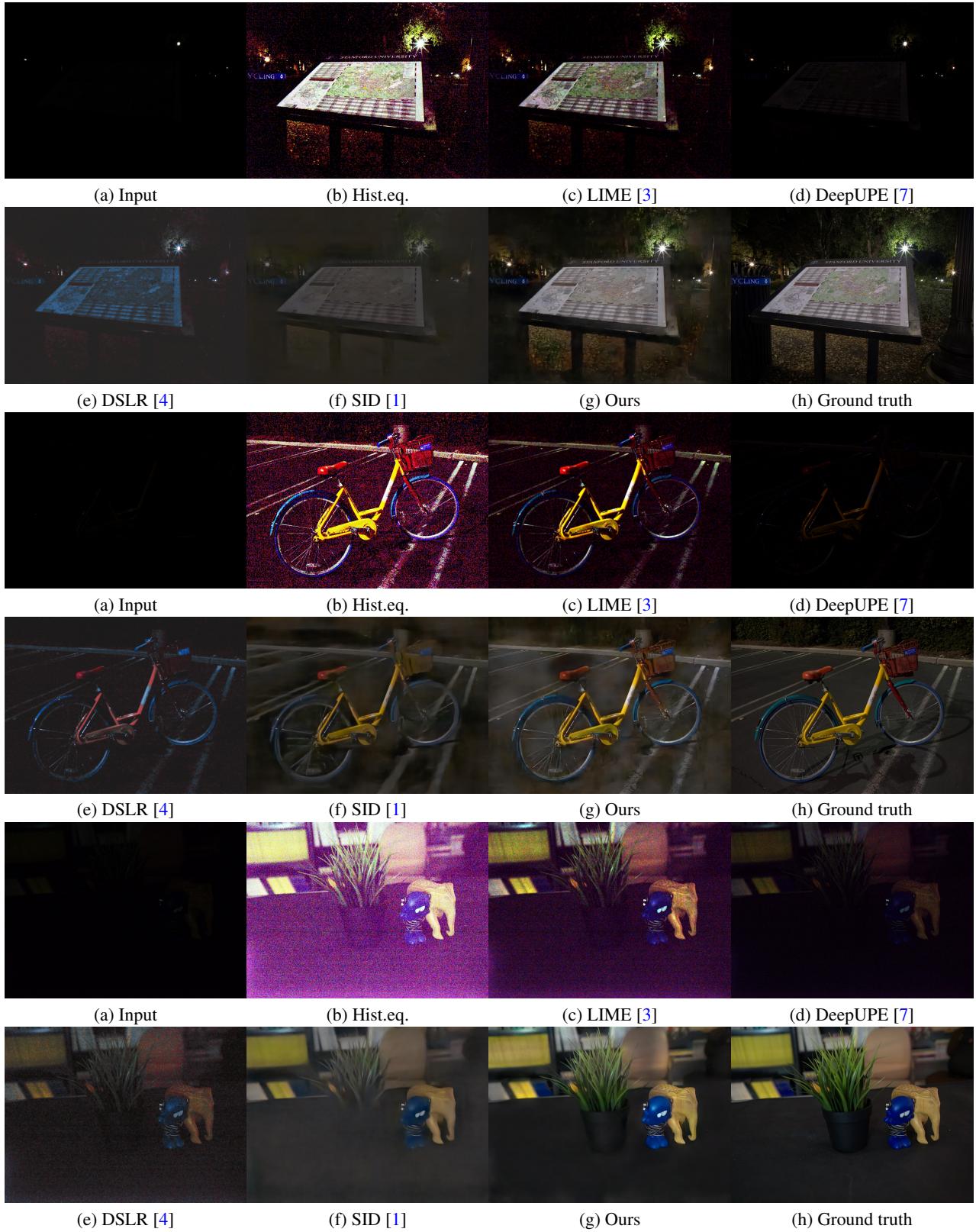


Figure 5: Visual results of state-of-the-art methods and ours on input low-light images from our test set.

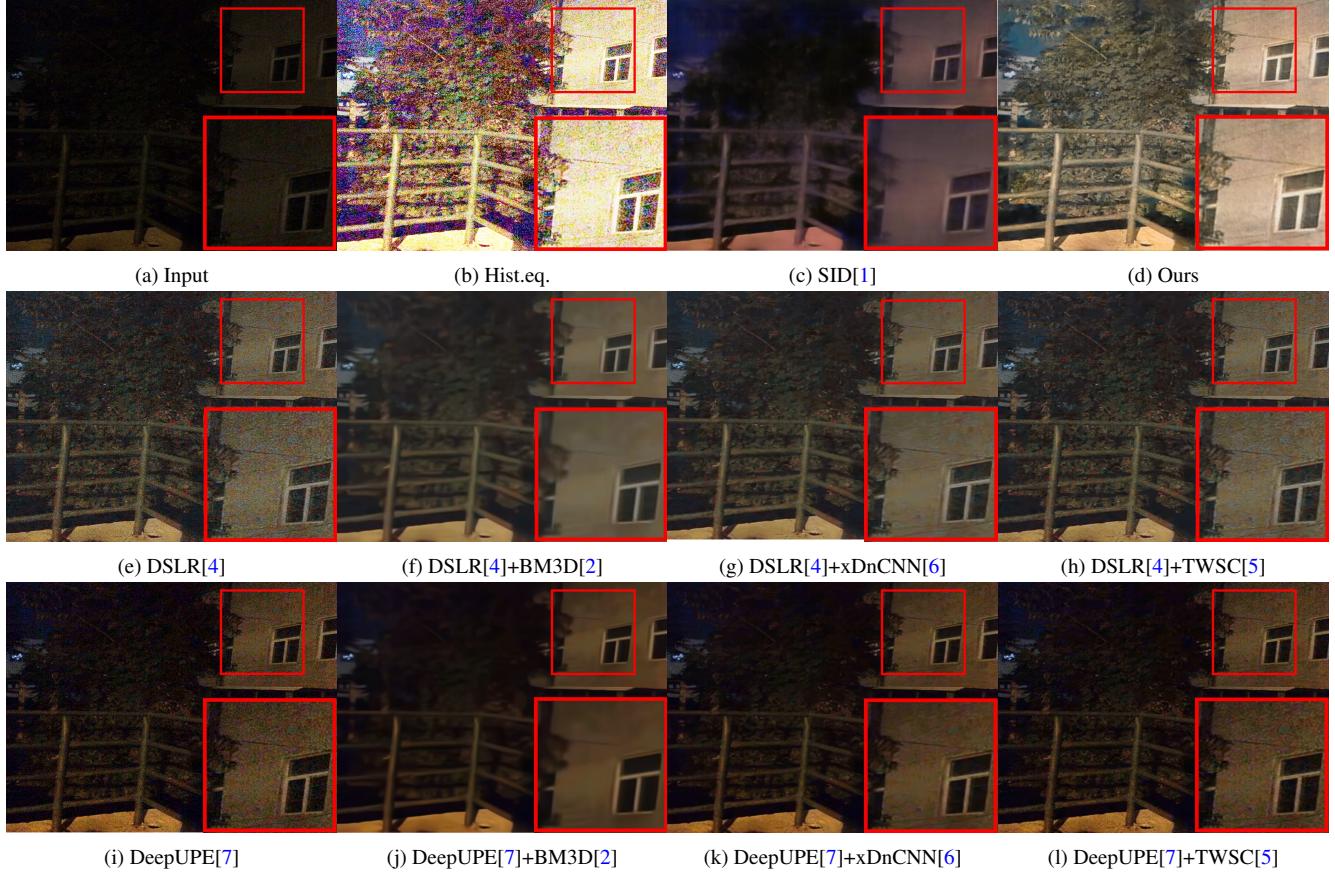


Figure 6: Comparison to different combinations of deep learning based enhancement methods (DeepUPE[7] and DSLR[4]) and denoising methods (BM3D[2], xDnCNN[6] and TWSC[5]).

References

- [1] Chen Chen, Qifeng Chen, Jia Xu, and Vladlen Koltun. Learning to see in the dark. In *CVPR*, 2018. [1](#), [3](#), [4](#), [5](#), [6](#)
- [2] Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian. Image denoising with block-matching and 3D filtering. In *Proc. SPIE*, volume 6064, 2006. [6](#)
- [3] Xiaojie Guo, Yu Li, and Haibin Ling. Lime: Low-light image enhancement via illumination map estimation. *IEEE TIP*, 2017. [1](#), [3](#), [4](#), [5](#)
- [4] Andrey Ignatov, Nikolay Kobyshev, Radu Timofte, Kenneth Vanhoey, and Luc Van Gool. DSLR-quality photos on mobile devices with deep convolutional networks. In *ICCV*, 2017. [1](#), [3](#), [4](#), [5](#), [6](#)
- [5] Xu Jun, Zhang Lei, and Zhang David. A trilateral weighted sparse coding scheme for real-world image denoising. In *ECCV*, 2018. [6](#)
- [6] Idan Kligvasser, Tamar Rott Shaham, and Tomer Michaeli. xunit: Learning a spatial activation function for efficient image restoration. In *CVPR*, 2018. [6](#)
- [7] Wang Ruixing, Zhang Qing, Fu Chiwing, Shen Xiaoyong, Zheng Weishi, and Jiaya Jia. Underexposed photo enhancement using deep illumination estimation. In *CVPR*, 2019. [1](#), [3](#), [4](#), [5](#), [6](#)