Supplementary Material for "Universal Denoising Networks : A Novel CNN Architecture for Image Denoising"

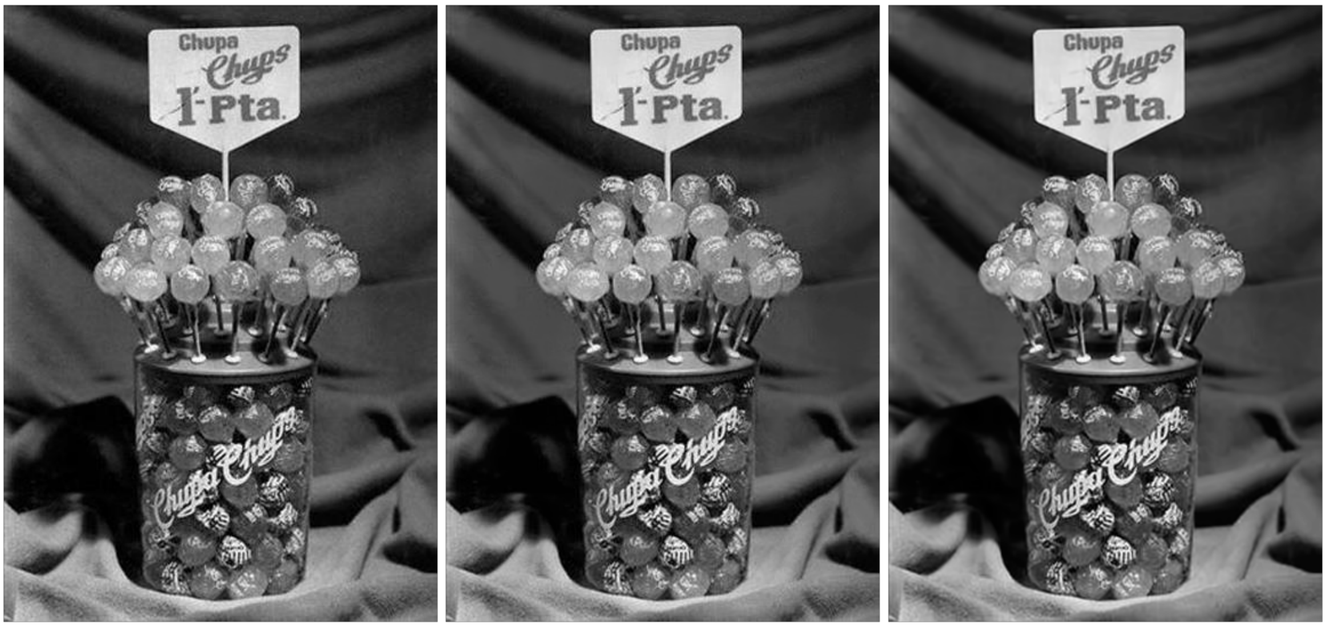
1. Image denoising results on real images

In Figs. 1-5 we provide additional grayscale and color image denoising results on images that have been distorted by real noise, whose level and distribution are unknown. Further, these images are quantized and their values are in the range [0, 255]. All the images are publicly available and were obtained from [2], except to Fig. 1 which is available from https://en.wikipedia.org/wiki/David_Hilbert. In our reported results we compare 5 different methods that are all applicable both to grayscale and color images. In particular, we consider the method proposed in [2], which the authors refer to as "noise clinic" and it was developed so that it can be adapted to any signal dependent colored noise, the BM3D algorithm [1], which has been the state-of-the-art Gaussian denoising method for almost a decade and still leads to very competitive results, DnCNN [3], which is a deep learning method that achieves the current state-of-the-art performance in Gaussian denoising, and the two variants (local and non-local) of our proposed denoising network. Since ground-truth images do not exist, we cannot provide any quantitative comparisons and the evaluation of the different methods is only possible by a visual comparison of their restoration results. It is also worth mentioning that all the methods under comparison but the "noise clinic" have been originally designed to deal with additive white Gaussian noise (AWGN). Therefore, the main goal of our comparisons is to assess how robust each method is when the noise deviates significantly from the assumed noise model. Finally, we note that the noise clinic method and the blind variant of the DnCNN network are equipped with an internal mechanism to estimate the noise level. On the other hand, the BM3D algorithm, the noise-specific variant of DnCNN (DnCNN-S) and our proposed networks apart from the noisy input, they accept a second input argument which corresponds to the standard deviation of the noise, σ. For these four methods, in our comparisons we have chosen empirically the value of σ (we indicate this value in the caption of each image) that led to the best restoration results.

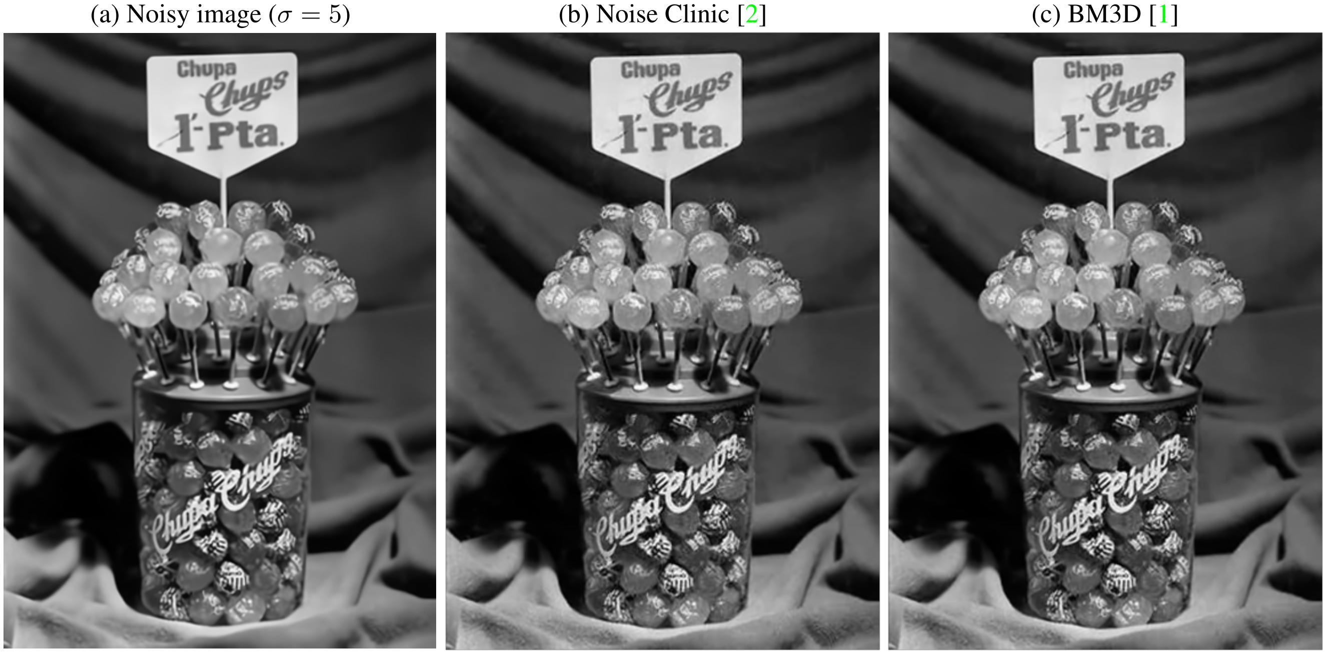
(a) Noisy image ($\sigma = 8$) (b) Noise Clinic [2] (c) BM3D [1]

(d) DnCNN [3] (e) UDNet_5 (f) $\mathrm{UNLDNet}_5$

Figure 1. Real grayscale image denoising. **Images are best viewed magnified on a computer screen.**



(a) Noisy image ($\sigma = 5$) (b) Noise Clinic [2] (c) BM3D [1]



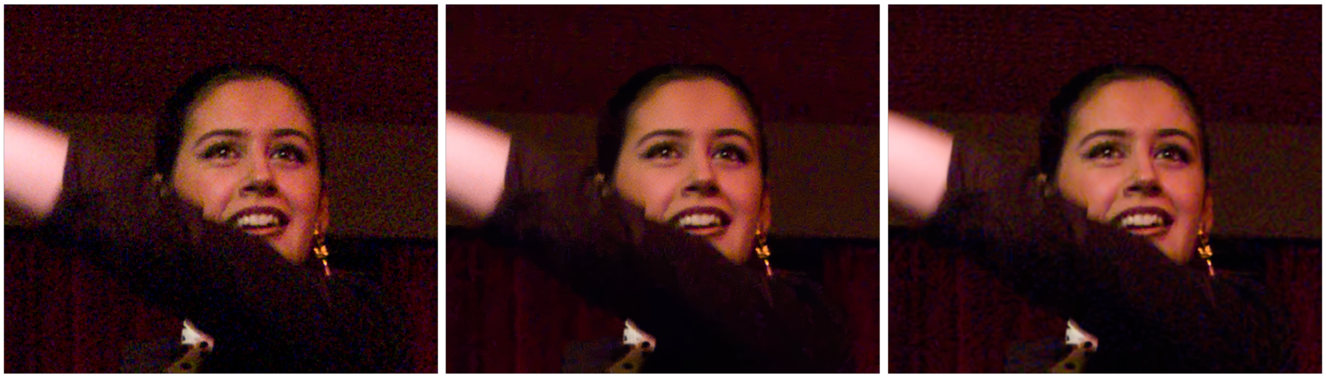
(d) DnCNN-S [3] (e) UDNet_5 (f) $\mathrm{UNLDNet}_5$

Figure 2. Real grayscale image denoising. **Images are best viewed magnified on a computer screen.**

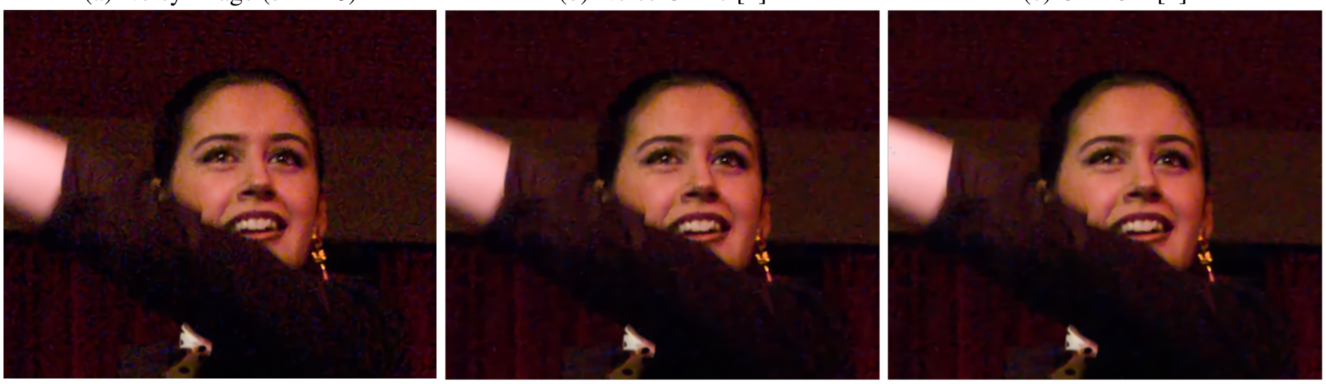
(a) Noisy image ($\sigma = 25$) (b) Noise Clinic [2] (c) CBM3D [1]

(d) CDnCNN [3] (e) CUDNet_5 (f) $\mathrm{CUNLDNet}_5$

Figure 3. Real color image denoising. **Images are best viewed magnified on a computer screen.**



(a) Noisy image ($\sigma = 15$) (b) Noise Clinic [2] (c) CBM3D [1]



(d) CDnCNN-S [3] (e) CUDNet_5 (f) $\mathrm{CUNLDNet}_5$

Figure 4. Real color image denoising. **Images are best viewed magnified on a computer screen.**

(a) Noisy image ($\sigma = 12$) (b) Noise Clinic [2] (c) CBM3D [1]

(d) CDnCNN-S [3] (e) CUDNet_5 (f) $\mathrm{CUNLDNet}_5$

Figure 5. Real color image denoising. Some important differences in the restoration quality between the methods under comparison can be spotted in the highlighted image region. **Images are best viewed magnified on a computer screen.**

References

[1] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian. Image denoising by sparse 3-d transform-domain collaborative filtering. *IEEE Trans. Image Process.*, 16(8):2080–2095, 2007. 1, 2, 3, 4, 5

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[3] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang. Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. *IEEE Trans. Image Process.*, 2017. 1, 2, 3, 4, 5