Patch Group Based Image Prior Learning for High Performance Denoising

Anonymous ICCV submission

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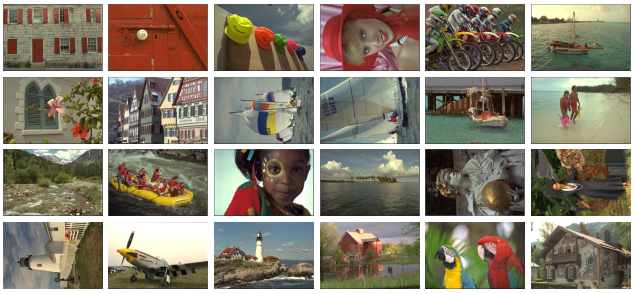
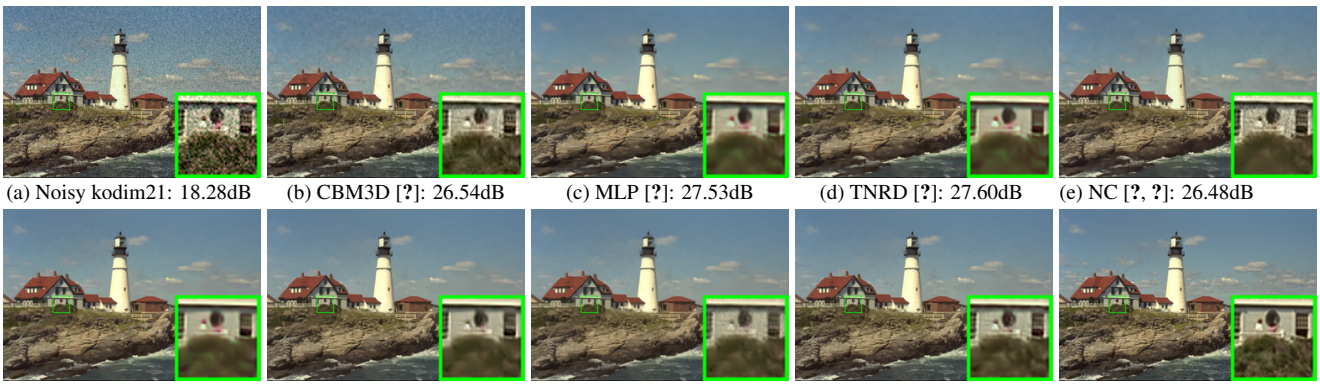


Figure 1. The 24 high quality color images from the Kodak PhotoCD Dataset.

Fig. 2 shows a scene denoised by the compared methods. We can see that the methods of CBM3D and NC would remain some noise on the recovered images. The methods of MLP, TNRD, and "WNNM0", which process separately the channels of color images, would over-smooth the images and generate false colors or artifacts. The method "WNNM1", which process jointly the channels of color images, would not generate false colors, but still over-smooth the image. The "WNNM2", which is the WNNM model solved by ADMM algorithm, would remain some noise on the image. By employing the proposed MC-WNNM model, our method preserves the structures (e.g., textures in windows and grass) better across the R, G, B channels and generate less artifacts than other denoising methods, leading to visually pleasant outputs.



(a) Noisy kodim21: 18.28dB (b) CBM3D [**?**]: 26.54dB (c) MLP [**?**]: 27.53dB (d) TNRD [**?**]: 27.60dB (e) NC [**?**, **?**]: 26.48dB

(f) WNNM0: 27.80dB (g) WNNM1: 27.75dB (h) WNNM2: 27.12dB (i) MC-WNNM: **28.34**dB (j) Clean kodim21

Figure 2. Denoised images of different methods on the image "kodim21" degraded by AWGN with different standard derivations of $\sigma_r = 40, \sigma_g = 20, \sigma_b = 30$ on R, G, B channels, respectively. The images are better to be zoomed in on screen.