**Rebuttal**

We appreciate all reviewers for their constructive comments. Please find what below our itemized responses.

R1

1. Same noise level for all channels

As suggested, we added AWGN noise with standard deviation (std) 25 to the R, G, B channels of the 24 color images from the Kodak PhotoCD dataset. The average PSNR results by the competing methods are: 29.26dB for CBM3D, 30.06 dB for MLP, 30.08 dB for TNRD, 25.82dB for NI, 27.15dB for NC, 29.91dB for WNNM-1, 30.02dB for WNNM-2, 30.32dB for WNNM-3 and MC-WNNM (WNNM-3 and MC-WNNM are identical when the noise levels of R, G, B channels are equal). One can see that MC-WNNM still achieves the best PSNR.

2. Complexity and speed

In the proposed ADMM algorithm for solving our MC-WNNM model, the cost for updating X is O (max(p^4\*M, M^3)), while the cost for updating Z is O(p^4\*M+M^3). So the overall complexity is O(p^4\*M+M^3). By our implementation, the proposed MC-WNNM takes about 200s (in Matlab) to process a color image of size 512\*512\*3, which is faster than the default WNNM algorithm (700s), comparable to DnCNN (180s), while slower than the other competing methods (e.g., CBM3D, MLP, TNRD, NI, NC). We will add the complexity analysis and comparison on speed to the revised paper.

3. Practical importance

In real-world noisy images, the noise statistics will vary across different channels. We for the first time incorporate the noise statistics across channels into the well-known WNNM model, making it practical to real-world color image denoising. Our results, especially on real-world noisy color images, demonstrated its superior performance to state-of-the-arts.

4. Comparison with DnCNN

We performed the DnCNN method to the 24 color images in Kodak PhotoCD dataset and the 15 real-world noisy images in [18].

On the Kodak PhotoCD dataset, we tested two cases. In the 1st case, we added AWGN noise with std 25 to all channels. The average PSNR results of MC-WNNM and DnCNN are 30.32dB and 30.18dB, respectively. In the 2nd case, we added AWGN noise with stds 40, 20, 30 to R, G, B, channels, respectively. The average PSNR results of MC-WNNM and DnCNN are 29.31dB and 20.58dB, respectively. DnCNN failed in the 2nd case because it is trained to process color images with uniform noise levels across color channels.

On the 15 real noisy images in [18], the average PSNR results of MC-WNNM and DnCNN are 37.71dB and 33.86dB, respectively. DnCNN performs not very well because it was trained by simulated noisy images, where the noise statistics can be very different from real-world noisy images.

We will add the comparison with DnCNN in the revision.

5. Parameter tuning

We tune the parameters of MC-WNNM such as the number of iterations, the size of image patches, the window size to balance the performance on PSNR and speed on the Kodak PhotoCD dataset. All the parameters are fixed on all the experiments in our paper, except for the parameters rho and the number of iteration K2, which are fixed on each dataset, as mentioned in our paper. Besides, we tune the parameters of WNNM-2 and WNNM-3 to achieve their highest PSNR results without considering their speed. For WNNM-1, we use the default parameters of WNNM.

6. Presentation of results on real noisy images

Thanks for the good suggestion. We will add the estimated noise level of each channel in the figures.

R2

1. The motivation of using nuclear norm

It is known that natural images share nonlocal self-similarity (NSS) prior. We can find many similar patches to a local patch in an image. By stretching each patch to a vector and stacking the similar patches to a matrix (please refer to Section 3.1 of the main paper), the matrix is inherently of low rank since the vectors are similar to each other. Such NSS induced low rank priors are widely used in image restoration problems such as denoising, super-resolution, deblurring, and inpainting, etc. Since the minimization of matrix rank is non-convex and NP hard, one popular approach is to minimize the nuclear norm of the matrix, which is a convex optimization problem. The latterly developed weighted nuclear norm minimization is a generalization of the nuclear norm minimization problem.

2. About Eq. 5

The maximum a-posteriori (MAP) estimation, i.e., Eq. 5, is a commonly used technique to find the solution of many inverse problems such as image restoration. The MAP framework holds true and works well in general image restoration tasks such as denoising, super-resolution, deblurring, and inpainting, etc.

3. About Eq. 6

As described in our paper, we assume that the noise is independent across RGB channels and independently and identically distributed (i.i.d.) in each channel with Gaussian distribution (this is a commonly adopted assumption in literature). Hence, we have P(Y|X)=\prod\_{c=r,g,b} P(Y\_{c}|X\_{c}) and Eq. 6 holds true.

R3

1. Abstract and code

Thank you very much for the comments. We will rephrase the 1st sentence of the abstract, and will surely release the code to the public.

**Confidential Comments to the ACs/PCs (not visible to Reviewers)**

We sincerely thank all reviewers for their comments. However, it can be seen that R2 is not familiar with the area of image restoration. The maximum a-posteriori (MAP) is a very fundamental technique in statistical image modeling, and nuclear norm minimization is a popular technique in low-rank approximation for low-level vision problems. It seemed that R2 knows very little about them.