We appreciate all the reviewers for their constructive comments.

R1

**Paper Weaknesses**

1 all the experimental results use different noise levels per color channels. It is interesting to see a direct comparison with the other method for the uniform case, when the same noise level affects all color channels

2 WNNM is very slow, a time complexity discussion and a runtime comparison with the other presented methods is a must;

3 how would the authors describe the practical importance of the proposed method in relation with the other compared methods?

4 I would appreciate comparison results with the recent DnCNN method from:

Zhang et al., "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising", 2016

5 line 535 : what means "tune for the best performance"? on which material the MC-WNNM performance was tuned?

6 for the real case visual results the authors could add the estimated noise level per each channel

1. Uniform noise levels for all channels

We added additive white Gaussian noise (AWGN) with standard deviation (std) of 25 to the R, G, B channels of the 24 color images from the Kodak PhotoCD dataset, and performed denoising with the methods listed in Table 1 of the main paper. The average results on PSNR of the compared 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 (the two methods are identical when the stds of R, G, B channel are equal).

1. Speed

We will add the complexity analysis and comparison on speed to the revised paper. In the proposed ADMM algorithm for solving our MCWNNM model, the computational cost for updating X is O (max(p^4\*M, M^3)), while the computational cost for updating Z is O(p^4\*M+M^3). So the overall complexity is O(p^4\*M+M^3). The proposed MC-WNNM need totally 20 (2\*10) iterations for denoising real color images, while WNNM, by its default setting, needs 24 (3\*8) iterations for denoising. We also optimize our code for faster speed. The proposed MCWNNM takes about 200 seconds to process a real color image of size 512\*512\*3, which is faster than WNNM (700 seconds), comparable to DnCNN (180 seconds), while slower than the other competing methods (e.g., CBM3D, MLP, TNRD, NI, NC).

1. Practical importance

In real-world noisy images, the noise statistics is different among different channels. We consider and incorporate the noise differences among different channels of real color images into the WNNM model. The resulting MCWNNM model achieves better performance on synthetic and real color image denoising than state-of-the-art denoising methods.

1. Compare with DnCNN

We performed the DnCNN method to the 24 color images in Kodak PhotoCD dataset and the 15 cropped images in [18]. Since DnCNN can automatically deal with color images without knowing the noise standard deviation (std), we did not modify its settings or tune the parameters. On the Kodak PhotoCD dataset, we compare with DnCNN on two cases. In the first case, we add AWGN noise with the same std of 25 on different channels of color images. The average PSNR results of the proposed MCWNNM and DnCNN are 30.32dB and 30.18dB, respectively. In the second case, we add AWGN noise with different stds of 40, 20, 30 on R, G, B, channels, respectively. The average PSNR results of the proposed MCWNNM and DnCNN are 20.58dB and 29.31dB, respectively. The failure of DnCNN is due to that it only consider uniform noise distribution in different channels while ignoring the different noise statistics among different channels. On the 15 real noisy images in [18], the average PSNR results of the proposed MCWNNM and DnCNN are 33.86dB and 37.71dB, respectively. On visual quality, DnCNN would either remain noise or generate artifacts while the proposed MC-WNNM remove the noise while maintaining the image details. Again, DnCNN ignores the differences in noise statistics among different channels of real color noisy images and therefore unable to deal with real noisy images.

1. Tune parameters

We tune the parameters (e.g., the number of iterations, the size of image patches, the window size, etc.) to balance the performance on PSNR and speed on the 24 images from the Kodak PhotoCD dataset. We roughly tune the parameters to achieve higher PSNR results than other methods while keeping the speed as fast as possible. All the parameters are fixed on all the experiments except 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 highest PSNR results, without considering the speed. For WNNM-1, we use the default parameters of WNNM.

1. Add noise level per channel

We will add the estimated noise level of each channel to the real color images in figures.

R2

**Paper Weaknesses**

1 I have a general concern about the concept of nuclear norm in the general scenario. Please example the motivation of the use of nuclear norm. It is general to different noise types.

2 I am not sure that Eq.5 holds. The hypothesis under which it will work should be discussed and clarified.

3 I am not convinced that Eq. 6 has a such assumption. I hope author(s) can explain this design more in rebuttal.

1. The motivation of using nuclear norm

The natural images share nonlocal self-similarity (NSS) prior, in which each local patch has many similar patches around it. If we stretch each image patch to a vector and stack the similar patches to form a matrix (refer to Section 3.1 of the paper), the matrix is inherently of low rank since the vectors are similar to each other. An extreme case is that the matrix consisting of the same patches is of rank 1. The NSS and low rank priors of natural images are widely used in many image processing problems such as denoising, super-resolution, deblurring, and compression, etc. Since the function of matrix rank is non-convex, a practice way in optimization is to employ the convex envelope of matrix rank, i.e., the function of nuclear norm, to replace the function of matrix rank.

1. About Eq. 5

The maximum a-posteriori (MAP) estimation, i.e., Eq. 5, is not proposed by us, but commonly used as the fundamental of solutions to many inverse problems such as image restoration. The MAP framework holds true and will work in general image restoration tasks such as denoising, super-resolution, deblurring, and inpainting, etc.

1. About Eq. 6

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

R3

**Paper Weaknesses**

1 well, perhaps the first sentence of the abstract could be rephrased - there exist many color denoising algo's - but they are difficult and not that well-known to the public.

2 and a statement that the code will be publicly available at xxx would be appreciated.

1. Abstract and code

Thank you very much for the encouraging comments. We will rephrase the abstract and add to the paper the publicly available address of the code in a revised version.