

Multi-channel weighted nuclear norm minimization for color image denoising

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Abstract

Most of existing image denoising methods focus on grayscale images which contain a single channel, while little attention has been paid to color images containing multiple channels. In order to apply the existing denoising methods to color images, commonly used strategies are: 1) to process separately the patches in R, G, B channels; or 2) to process jointly the patch vectors concatenated by corresponding patches in the R, G, B channels. However, both processing strategies would generate fake colors or artifacts of the color images, which will definitely lose a certain of information in the color images. In this paper, we propose a new multi-channel model for color image denoising. We also concatenate the patches in the same positions of R, G, B channels to form joint patch vectors. In the data term, we employ the weighted Frobinous norm, in which we add a weighting matrix to adaptively deal with different channels with different weights. For each concatenated patch, we search its non-local similar patches to it and form the patch matrix. To fully exploit the low rank property of the non-local similar patches, we employ the well-defined weighted nuclear norm as the regularization term. The resulting multi-channel weighted nuclear norm minimization model is much more complex than the original weighted nuclear norm minimization (WNNM) model. We transform the proposed model into a linear constrained non-convex optimization problem, which can be solved by the alternating direction method of multipliers (ADMM) algorithm. For each alternative updating step, the problem has closed-form solution. We also proof that the proposed algorithm has convergence results. The proposed model has been evaluated on color image denosing problem. Experiments on benchmark datasets demonstrate that the proposed model outperforms state-of-the-art denoising methods on synthetic as well as real-world noisy images.

1. Introduction

Image denoising is an important problem in enhancing the image quality in computer vision systems. It aims

to recover the clean image \mathbf{x} from the noisy observation $\mathbf{y} = \mathbf{x} + \mathbf{n}$, where \mathbf{n} is often assumed to be additive white Gaussian noise (AWGN). Most image denoising methods [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12] are designed for grayscale (i.e., single channel) images. Though these methods have achieved excellant denoising performance on grayscale images, directly extending these methods to process each channel of color images seperately would generate false colors or artifacts [13].

When compared to the grayscale image denoising problems, little attention has been paid to their color counterparts. There are several work [13, 14, 15, 16, 17, 18] proposed specifically for color images. These methods either treat equally the R, G, B channels in color images [13, 14, 15] or fail to explore the properties of natural images [16, 17, 18]. On one hand, treating each channel equally in color images is not that reasonable, since the noise structures and levels among the R, G, B channels are different in natural images due to the on board processing in in-camera imaging pipelines [19]. Hence, the methods treating each channel equally would generate fake colors or artifacts [13]. On the other hand, the performance of denoising methods would be largely depressed if the non-local self similarity property of natural images has not been fully exploited [9]. Due to the two reasons, some important information in color images would be highly degraded when applying these denoising methods directly on color images.

Based on the above observations, we argue that new denoising algorithms are still desiable which can treat well the R, G, B channels in color images and exploit the non-local self similarity property of natural images. In order to deal with the R, G, B channels in color images more effectively, different noise properties of these channels should be considered in the new methods designed for color image denoising. Besides, the non-local self similarity (NSS) property of images has been extensively employed in image restoration tasks such as denoising [1, 2, 4, 6, 7, 8, 9]. Among these methods, the weighted nuclear norm minimization (WNNM) model has achieved the state-of-the-art performance on denoising the additive white Gaussian noise (AWGN) in grayscale images. Though among the

most effective methods, how to extend the single channel WNNM model to handle multi-channel images such as the real-world color images is still an open problem. Of course the WNNM method can be applied to denoising color images by processing each channel separately, its performance would be largely inferior than jointly processing the RGB channels by concatenating the RGB values into a single vector [13]. Besides, the searching of non-local similar patches would be unstable due to the separate processing of the RGB images and hence the power of the NSS would be largely reduced. This would also limit the performance of not only WNNM but also other NSS based methods [1, 2, 6, 7, 8]. This fact is also evaluated by our experiments on color image denoising task.

In this paper, we proposed a new multi-channel weighted nuclear norm minimization model for color image denoising. The original WNNM model has closed-form solutions under the weighted nuclear norm proximal operator (WNNP). However, if we add a weighting matrix \mathbf{W} to the left of the data term, the resulting multi-channel WNNM model no longer has the nice property of closed-form solutions. This makes the problem more challenging. To solve this problem, we formulate the proposed multi-channel WNNM problem into a linearly constrained non-convex program with an augmented variable. It is also not directly solvable due to the non-convexity of the existence of the weighted nuclear norm. Note that the reformulated model contains two variables with linear constraint. This can be solved by employing the alternating direction method of multipliers (ADMM) [20]. For the variable \mathbf{Z} , it is the original weighted nuclear norm minimization problem and can be solved with closed-form solution [9, 21]. For the variable \mathbf{X} , it is a standard least squares problem and we can also obtain its closed-form solution. The convergence of the proposed method is also given to guarantee a rational termination of the our model.

2. Related Work

2.1. Nuclear Norm Minimization

As the tightest convex surrogate function of the matrix rank minimization [22, 23], the nuclear norm minimization (NNM) problem has been extensively studied in low rank matrix approximation (LRMA) [24, 25, 26, 27]. A standard nuclear norm minimization problem is as follows:

$$\hat{\mathbf{X}} = \arg \min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{X}\|_F^2 + \lambda \|\mathbf{X}\|_* \quad (1)$$

This NNM problem has closed-form solution by soft-thresholding the singular values of the matrix \mathbf{Y} as

$$\hat{\mathbf{X}} = \mathbf{U} \mathcal{S}_{\frac{\lambda}{2}}(\Sigma) \mathbf{V}^T \quad (2)$$

where $\mathbf{Y} = \mathbf{U} \Sigma \mathbf{V}^T$ is the singular value decomposition (a.k.a. Eckart-Young Decomposition [28]) of \mathbf{Y} and $\mathcal{S}_{\tau}(\bullet)$

is the soft-thresholding function with parameter $\tau > 0$:

$$\mathcal{S}_{\tau}(\Sigma_{ii}) = \max(\Sigma_{ii} - \tau, 0) \quad (3)$$

One limitation of the original NNM model is that it treats all the singular values equally but ignore the different importance of them. To make the NNM model more flexible at processing singular values, it has been extended to the truncated nuclear norm minimization model [29], the partial sum minimization of singular values [30], and the weighted nuclear norm minimization (WNNM) model [9], etc. Among these models, the WNNM model has been applied on grayscale image denoising problem with highly effective performance. This model adds weights to each singular values and the problem is:

$$\min_{\mathbf{X}} \|\mathbf{Y} - \mathbf{X}\|_F^2 + \|\mathbf{X}\|_{\mathbf{w},*} \quad (4)$$

is firstly proposed for grayscale image denoising problem, where $\|\mathbf{X}\|_{\mathbf{w},*} = \sum_i w_i \sigma_i(\mathbf{X})$ is the weighted nuclear norm of matrix \mathbf{X} and $\mathbf{w} = [w_1, \dots, w_n]^T$, $w_i \geq 0$ is the weight vector. According to the Remark 1 of [31], the problem (4) has closed-form solution if the weights are in a non-decreasing order

Though having achieved excellent performance on grayscale image denoising task, the WNNM method could not be applied on color image denoising in a direct manner. Of course we can apply the WNNM on each channel separately, but it has been studied that this manner would get inferior performance when compared to the power of this model on grayscale images. In this paper, we would add a weighting matrix to the WNNM model and naturally extend it to deal with color images and maintain its powerful ability on exploring the non-local self similarity property of the natural images. The proposed multi-channel WNNM model can be solved via the famous ADMM [20] algorithm. For each variable, we can derive a closed-form solution and hence the overall model can be solved in an efficient way. Besides, we analysis the convergence results of the proposed model.

2.2. Color Image Denoising

Numerous methods [1, 2, 4, 5, 6, 8, 9, 10, 11, 12] has been proposed for grayscale image denoising task. These methods could be trivially employed to denoise each channel in color images separately. For example, the CBM3D [14] first transform the RGB image into luminance-chrominance color space (e.g., YCbCr) and perform BM3D [2] for each channels separately with the patches only being grouped in luminance channel. However, as pointed out in [13], the performance would be largely reduced when compared to the performance of these methods on grayscale images. This method [13] performs color image denoising by concatenating the patches in R,

G, B channels into a single vector. However, the concatenation would generate false colors and artifacts [13]. The major reason is that the concatenation methods treat multiple channels equally and ignore the different properties among these channels. To better explore the difference and correlation among the three channels in color images, several methods [15, 16, 17, 18, 32, 33, 34] have been proposed to deal with real noisy image denoising task. These methods often firstly estimate the parameters of the assumed noise model (usually Gaussian), and then perform denoising with the estimated noise model. In this paper, we propose a weighting matrix (diagonal) which add different noise levels on different channels for color image denoising. The proposed multi-channel method are able to deal with the distinct noise property among these channels. Experiments will demonstrate that the proposed model achieves better results than other competing methods for color image denoising.

3. Multi-channel Weighted Nuclear Norm Minimization

3.1. The Problem

Given In order to treat differently each channel in color images, we propose to add a weighting matrix to the original WNNM model and the resulting problem becomes

$$\min_{\mathbf{X}} \|\mathbf{W}(\mathbf{Y} - \mathbf{X})\|_F^2 + \|\mathbf{X}\|_{w,*} \quad (5)$$

where \mathbf{W} is the weighting matrix. For simplicity, we assume \mathbf{W} to be a diagonal matrix.

Unfortunately, the proposed multi-channel WNNM problem cannot be solved in an analytical form. In [31], when the weights on singular values are non-descending, the weighted nuclear norm proximal operator can have global optimum with closed-form solution. However, such property is not valid for the multi-channel WNNM model. The reason is that the weighting matrix \mathbf{W} is added to the matrix \mathbf{X} instead of its singular values. Besides, the elements in \mathbf{W} is not in a non-descending order with respect to the singular value of \mathbf{X} . This makes the proposed model more difficult to optimize than the original WNNM model.

This can be solved by introducing an augmented variable \mathbf{Z} , and the above multi-channel WNNM problem is equivalent to a linearly constrained non-convex problem with two variables.

$$\min_{\mathbf{X}, \mathbf{Z}} \|\mathbf{W}(\mathbf{Y} - \mathbf{X})\|_F^2 + \|\mathbf{Z}\|_{w,*} \quad \text{s.t.} \quad \mathbf{X} = \mathbf{Z}. \quad (6)$$

This is an optimization problem with functions of two variables \mathbf{X} and \mathbf{Z} with linearly constrained condition of $\mathbf{X} = \mathbf{Z}$. In fact, this problem can be solved by the alternating direction method of multipliers (ADMM) algorithm, which will be introduced in the next subsection.

3.2. Optimization

To solve the above optimization problem, we first derive its augmented Lagrangian function as

$$\mathcal{L}(\mathbf{X}, \mathbf{Z}, \mathbf{A}, \rho) = \|\mathbf{W}(\mathbf{Y} - \mathbf{X})\|_F^2 + \|\mathbf{Z}\|_{w,*} + \langle \mathbf{A}, \mathbf{X} - \mathbf{Z} \rangle + \frac{\rho}{2} \|\mathbf{X} - \mathbf{Z}\|_F^2 \quad (7)$$

where \mathbf{A} is the augmented Lagrangian multiplier and $\rho > 0$ is the penalty parameter. After some simple calculations, we can obtain the following equivalent form of the Lagrangian function

$$\mathcal{L}(\mathbf{X}, \mathbf{Z}, \mathbf{A}, \rho) = \|\mathbf{W}(\mathbf{Y} - \mathbf{X})\|_F^2 + \|\mathbf{Z}\|_{w,*} + \frac{\rho}{2} \|\mathbf{X} - \mathbf{Z} + \rho^{-1} \mathbf{A}\|_F^2 \quad (8)$$

We initialize the matrix variables \mathbf{X}_0 , \mathbf{Z}_0 , and \mathbf{A}_0 to be zero matrix of suitable size. Taking derivative of the Lagrangian function \mathcal{L} with respect to the variables \mathbf{X} and \mathbf{Z} and setting the derivative function to be zero, we can alternatively update the iterations of the ADMM algorithm as follows:

(1) Update \mathbf{X} while fixing \mathbf{Z} and \mathbf{A} :

$$\mathbf{X}_{k+1} = \arg \min_{\mathbf{X}} \|\mathbf{W}\mathbf{Y} - \mathbf{W}\mathbf{X}\|_F^2 + \frac{\rho_k}{2} \|\mathbf{X} - \mathbf{Z}_k + \rho_k^{-1} \mathbf{A}_k\|_F^2 \quad (9)$$

This is a mixed weighted least square and standard least square problem and we could derive its closed-form solution:

$$\mathbf{X}_{k+1} = (\mathbf{W}^\top \mathbf{W} + \frac{\rho_k}{2} \mathbf{I})^{-1} (\mathbf{W}^\top \mathbf{W}\mathbf{Y} + \frac{\rho_k}{2} \mathbf{Z}_k - \frac{1}{2} \mathbf{A}_k) \quad (10)$$

(2) Update \mathbf{Z} while fixing \mathbf{X} and \mathbf{A} :

$$\mathbf{Z}_{k+1} = \arg \min_{\mathbf{Z}} \frac{\rho_k}{2} \|\mathbf{Z} - (\mathbf{X}_{k+1} + \rho_k^{-1} \mathbf{A}_k)\|_F^2 + \|\mathbf{Z}\|_{w,*} \quad (11)$$

According to the Theorem 1 in [31], given the $\mathbf{X}_{k+1} + \rho_k^{-1} \mathbf{A}_k = \mathbf{U}_k \Sigma_k \mathbf{V}_k^\top$ be the SVD of $\mathbf{X}_{k+1} + \rho_k^{-1} \mathbf{A}_k$, where $\Sigma_k = \begin{pmatrix} \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_n) \\ \mathbf{0} \end{pmatrix} \in \mathbb{R}^{m \times n}$, then the global optimum of the above problem is $\hat{\mathbf{Z}} = \mathbf{U}_k \hat{\Sigma}_k \mathbf{V}_k^\top$, where $\hat{\Sigma}_k = \begin{pmatrix} \text{diag}(\hat{\sigma}_1, \hat{\sigma}_2, \dots, \hat{\sigma}_n) \\ \mathbf{0} \end{pmatrix} \in \mathbb{R}^{m \times n}$ and $(\hat{\sigma}_1, \hat{\sigma}_2, \dots, \hat{\sigma}_n)$ is the solution to the following convex optimization problem:

$$\min_{\hat{\sigma}_1, \hat{\sigma}_2, \dots, \hat{\sigma}_n} \sum_{i=1}^n (\sigma_i - \hat{\sigma}_i)^2 + \frac{2w_i}{\rho_k} \hat{\sigma}_i \quad (12)$$

$$\text{s.t.} \quad \hat{\sigma}_1 \geq \hat{\sigma}_2 \geq \dots \geq \hat{\sigma}_n \geq 0.$$

According to the Remark 1 in [31], the problem above has closed-form solution

$$\hat{\sigma}_i = \begin{cases} 0 & \text{if } c_2 < 0 \\ \frac{c_1 + \sqrt{c_2}}{2} & \text{if } c_2 \geq 0 \end{cases} \quad (13)$$

lar patches, it should be a low rank matrix. And hence the multi-channel WNNM model proposed in this paper can be used here. Compared to the original single channel WNNM model [9] proposed for grayscale image denoising

$$\min_{\mathbf{X}_j} \|\mathbf{W}_j(\mathbf{Y}_j - \mathbf{X}_j)\|_F^2 + \|\mathbf{X}_j\|_{w,*}. \quad (18)$$

When the weighting matrix $\mathbf{W}_j = \frac{1}{\sigma_n^2} \mathbf{I}$, where $\mathbf{I} \in \mathbb{R}^{3p^2 \times 3p^2}$ is the identity matrix, the multi-channel WNNM model will reduce to the WNNM model as a special case. The design of WNNM model also motivate us to consider a similar design of the weighting matrix. In order to deal with color image denoising task, the weighting matrix \mathbf{W}_j should be modified to be suitable for multi-channel cases. In fact, for the color image denoising task, a holistic try of the weighting matrix \mathbf{W}_j could be

$$\mathbf{W}_j = \begin{pmatrix} \sigma_{rj}^{-2} \mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \sigma_{gj}^{-2} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \sigma_{bj}^{-2} \mathbf{I} \end{pmatrix}. \quad (19)$$

Here, for simplicity, we assume that the noise in different channels are independent to each other. The experimental results have already demonstrated that this simple assumption could already generate the best denoising performance on benchmark real noisy image dataset. In this paper, we did not consider the correlations of noise among different channels, which is the future work of our research line. The determination of the weight vector in weighted nuclear norm is the same as in the WNNM model [31]. We set the weight vector as $w_i^{k+1} = \frac{C}{[\sigma_i(\mathbf{X}_k)] + \epsilon}$.

The multi-channel WNNM is applied to the non-local similar patches of each local patch in the noisy image \mathbf{y} . And then all the patches are aggregated together to form the final recovered image $\hat{\mathbf{y}}$. We also perform the denoising procedure for several (K_2) iterations to obtain better denoising results. In Algorithm 2 (A2), we summarizes the denoising steps of multi-channel WNNM model on color image denoising.

5. Experiments

We evaluate the proposed method on synthetic noisy images as well as real noisy images. The synthetic noisy images are generated by adding additive white Gaussian noise with known noise standard derivations $\sigma_r, \sigma_g, \sigma_b$ for the R, G, B channels, respectively. We compare the proposed method with other state-of-the-art denoising algorithms including CBM3D [2, 14], MLP [10], CSF [11], WNNM [9], TNRD [12], “Noise Clinic” [16, 33], and the commercial software Neat Image [34].

In order to take fully comparison with the original WNNM method, we extended the WNNM method [31] in three directions. The first one is to apply the WNNM

A2: Color Image Denoising by Multi-channel WNNM

Input: Noisy image \mathbf{y} , noise levels $\{\sigma_r, \sigma_g, \sigma_b\}$;

Initialization: $\hat{\mathbf{x}}^{(0)} = \mathbf{y}$, $\mathbf{y}^{(0)} = \mathbf{y}$;

for $k = 1 : K_2$ **do**

1. Set $\mathbf{y}^{(k)} = \hat{\mathbf{x}}^{(k-1)}$;

2. Extracte local patches $\{\mathbf{y}_j\}_{j=1}^N$ from $\mathbf{y}^{(k)}$;

for each patch \mathbf{y}_j **do**

3. Search non-local similar patches \mathbf{Y}_j ;

4. Estimate \mathbf{X}_j by applying the Algorithm 1 to \mathbf{Y}_j ;

end for

5. Aggregate $\{\mathbf{X}_j\}_{j=1}^N$ to form the image $\hat{\mathbf{x}}^{(k)}$;

end for

Output: Denoised image $\hat{\mathbf{x}}^{K_2}$.

method on each channel separately, this method is channel-wise and we call it the “WNNMCW” method. The second one is to concatenate the corresponding patches in the R, G, B channels into a joint patch. We call this method “WNNMJ”. These two methods are directly extended from the original WNNM and hence have closed form solutions for the denoising model. To validate the effectiveness of the weighting matrix \mathbf{W} in multi-channel WNNM model, we set $\mathbf{W} = \sigma_n^2 \mathbf{I}$ and reduce the multi-channel WNNM model to its special case: the WNNM model solved by ADMM algorithm. We call this third method “WNNM-Jadmm” method. We set the same parameters settings for the “WNNMJadmm” method and the proposed multi-channel WNNM method (called “Proposed”). For fair comparison, for the “WNNMCW” method, the corresponding noise level σ_c of the c ($c = r, g, b$) channel is input as known parameter; for the method “WNNMJ”, we input the noise level as $\sigma = \sqrt{(\sigma_r^2 + \sigma_g^2 + \sigma_b^2)/3}$ and tune the other parameters to achieve its best denoising performance (i.e., highest average PSNR results). We employ the same parameter settings for the “WNNMJadmm” method and the proposed multi-channel WNNM method, which will be introduced in details in corresponding sections.

5.1. Experiments on Synthetic Noisy Images

In this section, we compare the proposed method with other competing method [9, 10, 11, 12, 14, 16, 34] on 24 high quality color images from the Kodak PhotoCD Dataset (<http://r0k.us/graphics/kodak/>), which are shown in Fig. 1. Then we add additive white Gaussian noise with different standard deviations to different channels of the color images. The standard deviations of noise we add to the R, G, B channels of the 24 clean images are 40, 20, 30, respectively. We set the patch size as $p = 6$, the number of non-local similar patches as $n = 70$, the window size for searching similar patches as $W = 20$. For the proposed multi-channel WNNM model, we set the regularization parameter as $\lambda = 4$, the penalty parameter as

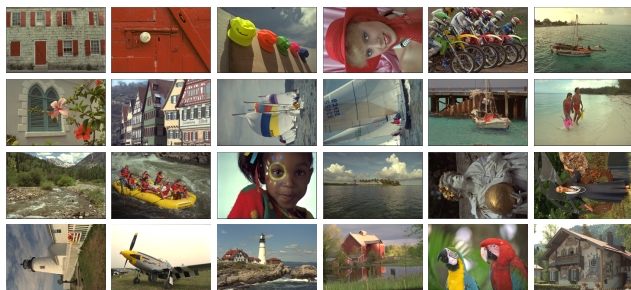


Figure 1. The 24 high quality color images from the Kodak PhotoCD Dataset.

$\rho = 6$, the $\mu = 1.1$, the number of iterations in Algorithm 1 as $K_1 = 10$, the number of iterations in Algorithm 2 as $K_2 = 8$.

We perform quantitative comparison on the 24 high quality images from the Kodak PhotoCD Dataset, which are widely used for color image denoising task. The PSNR results of CBM3D [2], MLP [10], TNRD [12], NC [16, 33], NI [34], “WNNMCW” [31], “WNNMJ”, “WNNMJadmm” and the proposed multi-channel WNNM methods are listed in Table 1. The best PSNR results of each image are highlighted in bold. One can see that on all the 24 images, our method achieves the best PSNR values. On average, our proposed method has 0.45dB PSNR improvements over the second best method, i.e., “WNNMJ” and much higher PSNR gains over other competing methods. Fig. 4 shows the denoised images of a scene in the Kodak PhotoCD Dataset. We can see that CBM3D, NC, and NI would either remain noise or generate artifacts, while MLP, TNRD “WNNMCW”, “WNNMJ”, “WNNMJadmm” over-smooth much the image. By using the proposed multi-channel WNNM model, our method preserves the structures (e.g., edges and textures) better across the R, G, B channels and generate less artifacts than other denoising methods, leading to visually pleasant outputs. More visual comparisons can be found in the supplementary file.

5.2. Experiments on Real Noisy Images

In the second part, we compare the proposed method with other competing methods on the 15 real noisy images, which are shown in Fig. 2, with “ground truth” clean images [17]. The noisy images were collected under controlled indoor environment. Each scene was shot 500 times under the same camera and camera setting. The mean image of the 500 shots is roughly taken as the “ground truth”, with which the PSNR can be computed. Since the image size is very large (about 7000×5000) and the scenes of this dataset share repetitive contents, the authors of [17] cropped 15 smaller images (of size 512×512) to perform experiments. In this section, we do not compare with the “WNNMCW” method due to its inferior performance.

We firstly perform quantitative comparison on the 15

cropped images used in [17]. The PSNR results of CBM3D [2], “WNNMJ” [9], MLP [10], TNRD [12], NC [16, 33], NI [34] and CC [17] are listed in Table 2 (The results of CC are copied from the original paper [17]). The best and second best PSNR results of each image are highlighted in red and blue, respectively. One can see that on 9 out of the 15 images, our method achieves the best PSNR values. CC achieves the best PSNR on 3 of the 15 images. It should be noted that in the CC method, a specific model is trained for each camera and camera setting, while our method uses the same model for all images. On average, our proposed method has 0.28dB PSNR improvements over [17] and much higher PSNR gains over other competing methods. Fig. 4 shows the denoised images of a scene captured by Canon 5D Mark 3 at ISO = 3200. We can see that CBM3D, WNNM, NC, NI and CC would either remain noise or generate artifacts, while MLP, TNRD over-smooth much the image. By using the proposed multi-channel WNNM model, our method preserves the structures (e.g., edges and textures) better across the R, G, B channels and generate less artifacts than other denoising methods, leading to visually pleasant outputs. More visual comparisons can be found in the supplementary file.

6. Conclusion

The multiple channels in color images makes the color image denoising problem more interesting and challenging than grayscale image denoising. To explore the correlations among the R, G, B channels in color images, in this paper, we proposed a novel method for color image denoising. Specifically, we add a weighting matrix to the original weighted nuclear norm minimization model and break the property of having closed-form solution of the WNNM model. However, by adding a new variable and a linear constraint, we proposed to solve the new model via the ADMM algorithm. The problem can be solved in an alternative updating manner and both variables can be updated with closed-form solutions. The convergence results of the proposed algorithm, i.e., Algorithm 1, has also been proofed. The proposed multi-channel WNNM model has been applied in color image denoising including real noisy image denoising problem. Extensive experiments on benchmark datasets demonstrate the effectiveness of the proposed model. The introduce of the weighting matrix can indeed improve the performance of the WNNM method, which are designed for denoising grayscale images, for color image denoising. We believe this work can be extended in at least three directions. Firstly, the proposed weighting matrix can be introduced into other methods designed for denoising grayscale images. Secondly, the weighting matrix beyond the diagonal form, such as correlation form [35], may bring better performance on color image denoising. Thirdly, the proposed multi-channel WNNM model can be further ex-

Table 1. PSNR(dB) results of different denoising algorithms on 20 natural images.

$\sigma_r = 40, \sigma_g = 20, \sigma_b = 30$									
Image#	CBM3D	MLP	TNRD	Noise Clinic	Neat Image	WNNMCW	WNNMJ	WNNMJadmm	Proposed
1	25.24	25.70	25.74	24.90	23.85	26.01			
2	28.27	30.12	30.21	25.87	25.90	30.08			
3	28.81	31.19	31.49	28.58	26.00	31.58			
4	27.95	29.88	29.86	25.67	25.82	30.13			
5	25.03	26.00	26.18	25.15	24.38	26.44			
6	26.24	26.84	26.90	24.74	24.65	27.39			
7	27.88	30.28	30.40	27.69	25.63	30.47			
8	25.05	25.59	25.83	25.30	24.02	26.71			
9	28.44	30.75	30.81	27.44	25.94	30.86			
10	28.27	30.38	30.57	28.42	25.87	30.65			
11	26.95	28.00	28.14	24.67	25.32	28.19			
12	28.76	30.87	31.05	28.37	26.01	30.97			
13	23.76	23.95	23.99	22.76	23.53	24.27			
14	26.02	26.97	27.11	25.68	24.94	27.20			
15	28.38	30.15	30.44	28.21	26.06	30.52			
16	27.75	28.82	28.87	26.66	25.69	29.27			
17	27.90	29.57	29.80	28.32	25.85	29.78			
18	25.77	26.40	26.41	25.70	24.74	26.63			
19	27.30	28.67	28.81	26.52	25.40	29.19			
20	28.96	30.40	30.76	25.90	24.95	30.79			
21	26.54	27.53	27.60	26.48	25.06	27.80			
22	27.05	28.17	28.27	26.60	25.36	28.21			
23	29.14	32.31	32.51	23.24	26.13	31.89			
24	25.75	26.41	26.53	25.73	24.55	27.10			
Average	27.13	28.54	28.68	26.19	25.24	28.84	28.85		

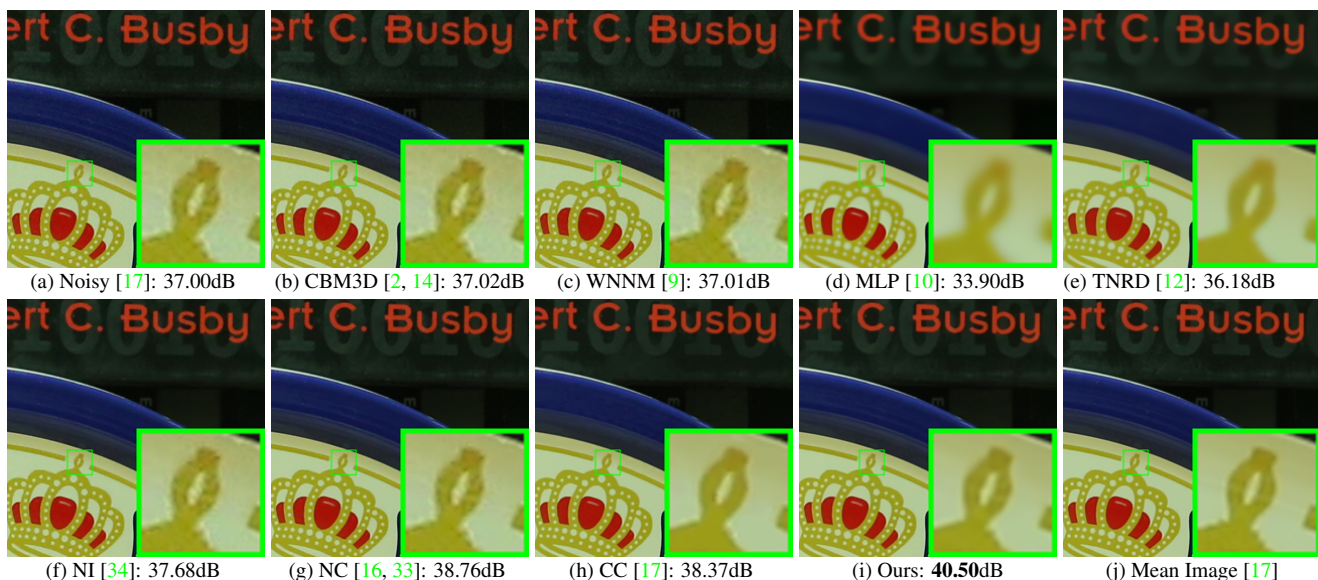


Figure 2. Denoised images of a region cropped from the real noisy image “Canon 5D Mark 3 ISO 3200 1” [17] by different methods. The images are better to be zoomed in on screen.

tended to deal with images with more channels, such as the hyperspectral images in remote sensing applications. We will focus our future work on these three directions.

7. A. Proof of Theorem 1.

Proof. 1. Firstly, we proof that the sequence $\{\mathbf{A}_k\}$ generated by Algorithm 1 is upper bounded. Let $\mathbf{X}_{k+1} + \rho_k^{-1} \mathbf{A}_k = \mathbf{U}_k \mathbf{\Sigma}_k \mathbf{V}_k^\top$ be its SVD in the $(k+1)$ -th iteration. According to Corollary 1 of [31], we can have the SVD of

$$\mathbf{Z}_{k+1} \text{ as } \mathbf{Z}_{k+1} = \mathbf{U}_k \hat{\mathbf{\Sigma}}_k \mathbf{V}_k^\top = \mathbf{U}_k \mathcal{S}_{\rho_k}(\mathbf{\Sigma}_k) \mathbf{V}_k^\top. \text{ Then we}$$

Table 2. PSNR(dB) results of different methods on 15 cropped real noisy images used in [17].

Camera Settings	CBM3D	MLP	TNRD	NI	NC	CC	WNNMJ	WNNMJadmm	Proposed
Canon 5D Mark III ISO = 3200	37.08	37.09	33.92	35.68	36.20	37.68	38.76	38.37	41.13
	33.94	33.93	33.24	34.03	34.35	34.87	35.69	35.37	37.28
	33.88	33.90	32.37	32.63	33.10	34.77	35.54	34.91	36.52
Nikon D600 ISO = 3200	33.33	33.34	31.93	31.78	32.28	34.12	35.57	34.98	35.53
	33.85	33.79	34.15	35.16	35.34	35.36	36.70	35.95	37.02
	35.02	34.95	37.89	39.98	40.51	38.68	39.28	41.15	39.56
Nikon D800 ISO = 1600	35.54	35.57	33.77	34.84	35.09	37.34	38.01	37.99	39.26
	35.79	35.77	35.89	38.42	38.65	38.57	39.05	40.36	41.43
	34.92	34.95	34.25	35.79	35.85	37.87	38.20	38.30	39.55
Nikon D800 ISO = 3200	33.34	33.31	37.42	38.36	38.56	36.95	38.07	39.01	38.91
	32.95	32.96	34.88	35.53	35.76	35.09	35.72	36.75	37.41
	32.98	32.96	38.54	40.05	40.59	36.91	36.76	39.06	39.39
Nikon D800 ISO = 6400	29.66	29.71	33.59	34.08	34.25	31.28	33.49	34.61	34.80
	30.01	29.98	31.55	32.13	32.38	31.38	32.79	33.21	33.95
	29.90	29.95	31.42	31.52	31.76	31.40	32.86	33.22	33.94
Average	33.48	37.27	34.32	35.33	35.65	35.49	36.43	36.88	37.712

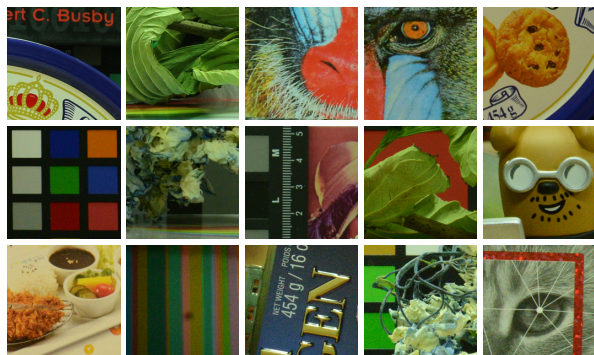


Figure 3. The 15 cropped real noisy images used in [17].

have

$$\|\mathbf{A}_{k+1}\|_F = \|\mathbf{A}_k + \rho_k(\mathbf{X}_{k+1} - \mathbf{Z}_{k+1})\|_F \quad (20)$$

$$= \rho_k \|\rho_k^{-1} \mathbf{A}_k + \mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F \quad (21)$$

$$= \rho_k \|\mathbf{U}_k \mathbf{\Sigma}_k \mathbf{V}_k^\top - \mathbf{U}_k \mathbf{S}_{\frac{\mathbf{w}}{\rho_k}}(\mathbf{\Sigma}_k) \mathbf{V}_k^\top\|_F \quad (22)$$

$$= \rho_k \|\mathbf{\Sigma}_k - \mathbf{S}_{\frac{\mathbf{w}}{\rho_k}}(\mathbf{\Sigma}_k)\|_F \quad (23)$$

$$= \rho_k \sqrt{\sum_i (\Sigma_k^{ii} - S_{\frac{w_i}{\rho_k}}(\Sigma_k^{ii}))^2} \quad (24)$$

$$\leq \rho_k \sqrt{\sum_i \left(\frac{w_i}{\rho_k}\right)^2} = \sqrt{\sum_i w_i^2}. \quad (25)$$

The inequality above can be proofed as follows: given the diagonal matrix $\mathbf{\Sigma}_k$, we define Σ_k^{ii} as the i -th element of $\mathbf{\Sigma}_k^{ii}$. If $\Sigma_k^{ii} \geq \frac{w_i}{\rho_k}$, we have $S_{\frac{w_i}{\rho_k}}(\Sigma_k^{ii}) = \Sigma_k^{ii} - \frac{w_i}{\rho_k} > 0$. If $\Sigma_k^{ii} < \frac{w_i}{\rho_k}$, we have $S_{\frac{w_i}{\rho_k}}(\Sigma_k^{ii}) = 0 < \Sigma_k^{ii} + \frac{w_i}{\rho_k}$. After all, we have $|\Sigma_k^{ii} - S_{\frac{w_i}{\rho_k}}(\Sigma_k^{ii})| \leq \frac{w_i}{\rho_k}$ and hence the inequality

holds true. Hence, the sequence $\{\mathbf{A}_k\}$ is upper bounded.

2. Secondly, we proof that the sequence of Lagrangian function $\{\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k)\}$ is also upper bounded. Since the global optimal solution of \mathbf{X} and \mathbf{Z} in corresponding subproblems, we always have $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k) \leq \mathcal{L}(\mathbf{X}_k, \mathbf{Z}_k, \mathbf{A}_k, \rho_k)$. Based on the updating rule that $\mathbf{A}_{k+1} = \mathbf{A}_k + \rho_k(\mathbf{X}_{k+1} - \mathbf{Z}_{k+1})$, we have $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_{k+1}, \rho_{k+1}) = \mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k) + \langle \mathbf{A}_{k+1} - \mathbf{A}_k, \mathbf{X}_{k+1} - \mathbf{Z}_{k+1} \rangle + \frac{\rho_{k+1} - \rho_k}{2} \|\mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F^2 = \mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_k, \rho_k) + \frac{\rho_{k+1} + \rho_k}{2\rho_k} \|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F^2$. Since the sequence $\{\|\mathbf{A}_k\|\}$ is upper bounded, the sequence $\{\|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F\}$ is also upper bounded. Denote by a the upper bound of $\{\|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F\}$, we have $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_{k+1}, \rho_{k+1}) \leq \mathcal{L}(\mathbf{X}_1, \mathbf{Z}_1, \mathbf{A}_0, \rho_0) + a \sum_{k=0}^{\infty} \frac{\rho_{k+1} + \rho_k}{2\rho_k} = \mathcal{L}(\mathbf{X}_1, \mathbf{Z}_1, \mathbf{A}_0, \rho_0) + a \sum_{k=0}^{\infty} \frac{\mu + 1}{2\mu^k \rho_0} \leq \mathcal{L}(\mathbf{X}_1, \mathbf{Z}_1, \mathbf{A}_0, \rho_0) + \frac{a}{\rho_0} \sum_{k=0}^{\infty} \frac{1}{\mu^{k-1}}$. The last inequality holds since $\mu + 1 < 2\mu$. Since $\sum_{k=0}^{\infty} \frac{1}{\mu^{k-1}} < \infty$, the sequence of Lagrangian function $\mathcal{L}(\mathbf{X}_{k+1}, \mathbf{Z}_{k+1}, \mathbf{A}_{k+1}, \rho_{k+1})$ is upper bound.

3. Thirdly, we proof that the sequences of $\{\mathbf{X}_k\}$ and $\{\mathbf{Z}_k\}$ are upper bounded. Since $\|\mathbf{W}(\mathbf{Y} - \mathbf{X})\|_F^2 + \|\mathbf{Z}\|_{w,*} = \mathcal{L}(\mathbf{X}_k, \mathbf{Z}_k, \mathbf{A}_{k-1}, \rho_{k-1}) - \langle \mathbf{A}_k, \mathbf{X}_k - \mathbf{Z}_k \rangle - \frac{\rho_k}{2} \|\mathbf{X}_k - \mathbf{Z}_k\|_F^2 = \mathcal{L}(\mathbf{X}_k, \mathbf{Z}_k, \mathbf{A}_{k-1}, \rho_{k-1}) + \frac{1}{2\rho_k} (\|\mathbf{A}_{k-1}\|_F^2 - \|\mathbf{A}_k\|_F^2)$. Thus $\{\mathbf{W}(\mathbf{Y} - \mathbf{X}_k)\}$ and $\{\mathbf{Z}_k\}$ are upper bounded, and hence the sequence $\{\mathbf{X}_k\}$ is bounded by Cauchy-Schwarz inequality and triangle inequality. We can obtain that $\lim_{k \rightarrow \infty} \|\mathbf{X}_{k+1} - \mathbf{Z}_{k+1}\|_F = \lim_{k \rightarrow \infty} \rho_k^{-1} \|\mathbf{A}_{k+1} - \mathbf{A}_k\|_F = 0$ and the equation (1) is proofed.

4. Then we can proof that $\lim_{k \rightarrow \infty} \|\mathbf{X}_{k+1} - \mathbf{X}_k\|_F =$

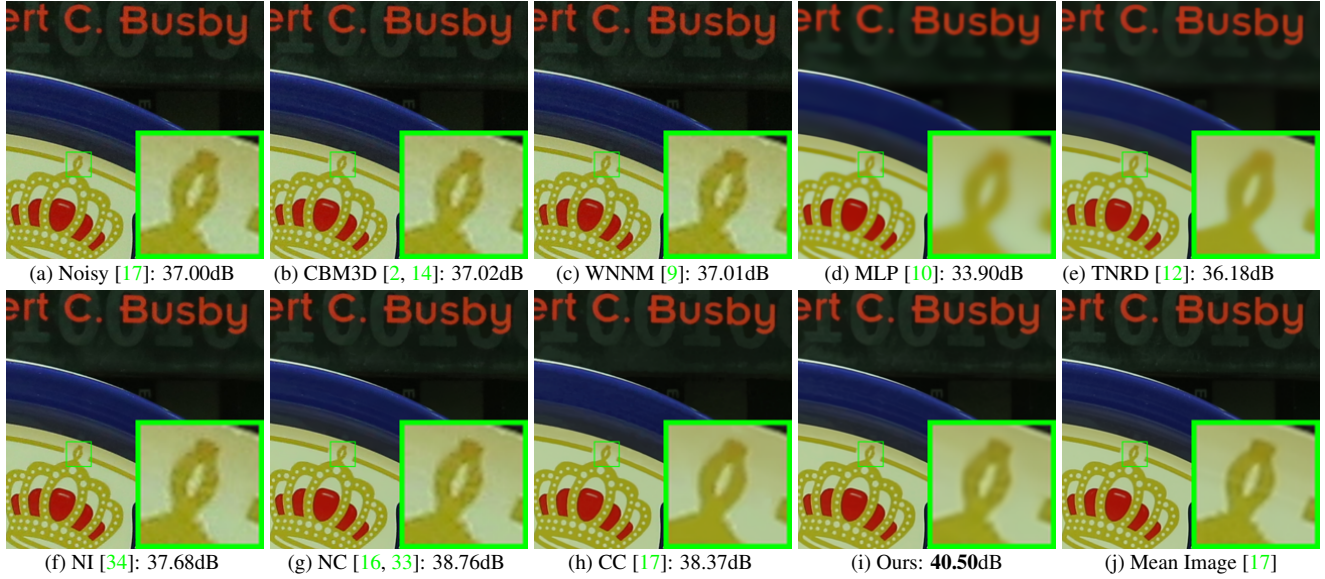


Figure 4. Denoised images of a region cropped from the real noisy image “Canon 5D Mark 3 ISO 3200 1” [17] by different methods. The images are better to be zoomed in on screen.

$\lim_{k \rightarrow \infty} \|(\mathbf{W}^\top \mathbf{W} + \frac{\rho_k}{2} \mathbf{I})^{-1}(\mathbf{W}^\top \mathbf{W} \mathbf{Y} - \mathbf{W}^\top \mathbf{W} \mathbf{Z}_k - \frac{1}{2} \mathbf{A}_k) - \rho_k^{-1}(\mathbf{A}_k - \mathbf{A}_{k-1})\|_F \leq \lim_{k \rightarrow \infty} \|(\mathbf{W}^\top \mathbf{W} + \frac{\rho_k}{2} \mathbf{I})^{-1}(\mathbf{W}^\top \mathbf{W} \mathbf{Y} - \mathbf{W}^\top \mathbf{W} \mathbf{Z}_k - \frac{1}{2} \mathbf{A}_k)\|_F + \rho_k^{-1} \|\mathbf{A}_k - \mathbf{A}_{k-1}\|_F = 0$ and hence (2) is proofed.

5. Then (3) can be proofed by checking that $\lim_{k \rightarrow \infty} \|\mathbf{Z}_{k+1} - \mathbf{Z}_k\|_F = \lim_{k \rightarrow \infty} \|\mathbf{X}_k + \rho_k^{-1} \mathbf{A}_{k-1} - \mathbf{Z}_k + \mathbf{X}_{k+1} - \mathbf{X}_k + \rho_k^{-1} \mathbf{A}_{k-1} + \rho_k^{-1} \mathbf{A}_k - \rho_k^{-1} \mathbf{A}_{k+1}\|_F \leq \lim_{k \rightarrow \infty} \|\mathbf{\Sigma}_{k-1} - \mathbf{S}_{w/\rho_{k-1}}(\mathbf{\Sigma}_{k-1})\|_F + \|\mathbf{X}_{k+1} - \mathbf{X}_k\|_F + \rho_k^{-1} \|\mathbf{A}_{k-1} + \mathbf{A}_{k+1} - \mathbf{A}_k\|_F = 0$, where $\mathbf{U}_{k-1} \mathbf{\Sigma}_{k-1} \mathbf{V}_{k-1}^\top$ is the SVD of the matrix $\mathbf{X}_k + \rho_{k-1} \mathbf{A}_{k-1}$. \square

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