A NEW COLOR IMAGE REGULARIZATION SCHEME FOR BLIND IMAGE DECONVOLUTION

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ABSTRACT

This paper proposes a new regularization scheme to address blind color image deconvolution. Conventional blind monochromatic image deconvolution algorithms handle each color channel independently, thereby ignoring the inter-channel correlation present in the color images. Further, most existing blind color deconvolution algorithms do not take the parametric information of the blurs into consideration. In view of these, a regularization scheme is proposed to perform blind color image deconvolution. A new regularization operator is developed in the blur domain. A reinforcement blur modeling scheme is adopted to evaluate the relevance of manifold parametric blur structures, and the information is integrated into the deconvolution scheme. In addition, a regularization scheme for image is developed to recover edges of color images and reduce color artifacts. Experimental results show that the method is able to achieve satisfactory restored color images under noisy environment.

Index Terms— Color image deconvolution, conjugate gradient methods, image regularization.

1. INTRODUCTION

In many imaging applications, the captured images may experience blurring due to factors such as out-of-focusing, diffraction degradation, and relative motion between the camera and imaging scenes, among others. Blind color image deconvolution is a process to estimate the original color image from the observed blurred color image, given limited or no prior knowledge of the blurring function.

Although there is a number of work in the literature on blind monochromatic image deconvolution [1], the direct extension of these methods to blind color image restoration may be suboptimal, because the correlation across the color channels is not fully utilized. From a probabilistic point of view, the techniques for blind color image deconvolution can be divided into two categories: stochastic and deterministic. Stochastic methods model images as random fields and estimate the original color image as the most probable realization of a certain random process. The maximum likelihood (ML) technique, in conjunction with expectation maximization (EM) algorithm, has been used to perform image restoration [2]. This approach [2] requires the assumption that both the image and noise are Gaussian-distributed. Recently, a Bayesian approach [3] is proposed for deconvolving and demosaicing of blurred color image from the super-resolution point of view. Deterministic methods find an estimate of the original color image by minimizing the norm of a certain residuum. Chow et al. extend the framework of single-channel (SC) grayscale image restoration to blind color image restoration [4]. A three-dimensional (3D) Laplacian operator is employed to regularize the color channels of the images. Blomgren and Chan extend the total variation (TV) norm to vector color image in order to achieve edge preservation and noise suppression [5]. In the Beltrami framework, a color image is considered as a two-dimensional surface embedded in a five-dimensional 'spatial-feature' space, and an operator is proposed for the recovery of the blurred color image in [6] and [7]. Nevertheless, most of these methods employ only spatial correlation of the images. They do not take the characteristics of the blurring function into consideration, thereby leading to underutilization of the information available.

This paper proposes a new color image regularization scheme for blind image deconvolution. A new regularization operator is developed in the blur domain. A reinforcement-learning blur modeling scheme is adopted to evaluate the relevance of manifold parametric blur structures, and the information is integrated into the deconvolution scheme. In addition, a regularization scheme for image is developed to recover edges of color images and reduce color artifacts. An optimization procedure called alternating minimization (AM) is then employed to minimize the image- and blur-domain cost functions iteratively.

2. PROBLEM FORMULATION

In many imaging applications, the observed blurred color image can be represented in the vector-matrix form as follows.

$$\boldsymbol{z} = \boldsymbol{Hf} + \boldsymbol{n} = \boldsymbol{Fh} + \boldsymbol{n} \qquad (1)$$

where $\boldsymbol{z} = [\boldsymbol{z}_r^T, \boldsymbol{z}_g^T, \boldsymbol{z}_b^T]^T$, $\boldsymbol{f} = [\boldsymbol{f}_r^T, \boldsymbol{f}_g^T, \boldsymbol{f}_b^T]^T$, $\boldsymbol{h} = [\boldsymbol{h}_{rr}^T, \boldsymbol{h}_{gg}^T, \boldsymbol{h}_{bb}^T]^T$ and $\boldsymbol{n} = [\boldsymbol{n}_r^T, \boldsymbol{n}_g^T, \boldsymbol{n}_b^T]^T$ are vectors representing the discrete, concatenated and lexicographically-ordered ith blur channel z_i, ith original color channel f_i, ith channel blur h_{ii} and ith channel noise n_i, respectively. $\boldsymbol{H}$ and $\boldsymbol{F}$ are given by

$$\boldsymbol{H} = \begin{pmatrix} \boldsymbol{H}_{rr} & \boldsymbol{O} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{H}_{gg} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{O} & \boldsymbol{H}_{bb} \end{pmatrix}, \boldsymbol{F} = \begin{pmatrix} \boldsymbol{F}_{r} & \boldsymbol{O} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{F}_{g} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{O} & \boldsymbol{F}_{b} \end{pmatrix}$$

where $\boldsymbol{H}_{ii}$ and $\boldsymbol{F}_i$ are the corresponding matrices constructed from h_{ii} and f_i.

As the blind deconvolution problem is ill-posed with respect to unknown variables $\boldsymbol{f}$ and $\boldsymbol{h}$, a deterministic regularization technique is required to find the solution of (1). To address this, the following cost function is proposed:

$$\begin{aligned} J(\hat{\boldsymbol{f}},\hat{\boldsymbol{h}}) &= \frac{1}{2}\| z - \hat{\boldsymbol{H}}\hat{\boldsymbol{f}} \|_2^2 + Q(\hat{\boldsymbol{f}}) + S(\hat{\boldsymbol{h}}) \\ &= \frac{1}{2}\| z - \hat{\boldsymbol{F}}\hat{\boldsymbol{h}} \|_2^2 + Q(\hat{\boldsymbol{f}}) + S(\hat{\boldsymbol{h}}) \end{aligned} \tag{2}$$

where the first term in (2) represents the least-square data fidelity of the estimated image $\hat{\boldsymbol{f}}$ and blurs $\hat{\boldsymbol{h}}$, $Q(\hat{\boldsymbol{f}})$ and $S(\hat{\boldsymbol{h}})$ denote the regularization functionals in the image- and blur-domains, respectively. In the next section, we will discuss the selection procedure for the regularization functionals $Q(\hat{\boldsymbol{f}})$ and $S(\hat{\boldsymbol{h}})$.

3. REGULARIZATION ISSUES

Generally, the color image restoration problem is ill-conditioned. Procedures adopted to stabilize the inversion of the ill-posed problem are called regularization. In this section, we present a new deterministic regularization approach for blind color image deconvolution. The regularization functionals $Q(\hat{\boldsymbol{f}})$ and $S(\hat{\boldsymbol{h}})$ in (2) are introduced.

3.1. Image-Domain Regularization Functional $Q(\hat{\boldsymbol{f}})$

We develop a regularization scheme by introducing the functional below:

$$Q(\hat{\boldsymbol{f}}) = \alpha Q_{ep}(\hat{\boldsymbol{f}}) + \beta Q_{cr}(\hat{\boldsymbol{f}}) \tag{3}$$

where $Q_{ep}(\hat{\boldsymbol{f}})$ imposes the smoothness on each color channel while preserving the edge information and $Q_{cr}(\hat{\boldsymbol{f}})$ plays the role of reducing the color artifacts. α and β are regularization parameters that control the relative contribution of the constraint terms in the cost function. $Q_{ep}(\hat{\boldsymbol{f}})$ uses TV technique and is given as:

$$Q_{ep}(\hat{\boldsymbol{f}}) = \frac{1}{2}\sum_{i=r,g,b}\int |\nabla \hat{f}_i| \, d\boldsymbol{x} \tag{4}$$

where $\boldsymbol{x} = (x, y)$ and ∇f_i denotes gradient of each channel image. On the other hand, a vector-based regularization term $Q_{cr}(\hat{\boldsymbol{f}})$ is developed to suppress the color artifacts. The idea behind this scheme is that pixels within a small neighborhood are very similar in color. This implies that the color vectors of pixels within a small neighborhood should have small angle amongst them, as discussed in [8] and [9]. In our scheme, we can minimize the cross product of the color vectors within the neighborhood to reduce the color difference between neighboring pixels. We denote the adjacent pixels for each pixel in the channel $\hat{f}_i$ as $\boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_i$, where $\boldsymbol{S}_{pq}$ represents the translational integer-shift operator of an image by translational vector (p,q). The size of neighborhood region is set to 3×3 (i.e., $-1 \le p,q \le 1$). Then, the vector-based regularization term $Q_{cr}(\hat{\boldsymbol{f}})$ can be developed as:

$$\begin{aligned} &\frac{1}{2}\sum_{p=-1}^{1}\sum_{q=-1}^{1}[\| \hat{\boldsymbol{f}}_g .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_b - \hat{\boldsymbol{f}}_b .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_g \|_2^2 \\ &+ \| \hat{\boldsymbol{f}}_b .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_r - \hat{\boldsymbol{f}}_r .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_b \|_2^2 + \| \hat{\boldsymbol{f}}_r .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_g - \hat{\boldsymbol{f}}_g .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_r \|_2^2] \\ &= \frac{1}{2}\sum_{i=r,g,b}\sum_{p=-1}^{1}\sum_{q=-1}^{1}[\| \hat{\boldsymbol{f}}_i .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_{i+1} - \hat{\boldsymbol{f}}_{i+1} .* \boldsymbol{S}_{pq}\hat{\boldsymbol{f}}_i \|_2^2] \end{aligned} \tag{5}$$

where $(.*)$ is element-by-element product operator. Here we define that $r+1=g,\ g+1=b,\ b+1=r$. By using this $Q_{cr}(\hat{\boldsymbol{f}})$, we can minimize the angle among the color vectors of the adjacent pixels and effectively alleviate the unexpected color artifacts.

3.2. Blur-Domain Regularization Functional $S(\hat{\boldsymbol{h}})$

The proposed regularization functional in the blur domain consists of a regularization term $U(\hat{\boldsymbol{h}})$ and a reinforcement soft parametric blur learning term $R(\hat{\boldsymbol{h}})$. It can be expressed as

$$S(\hat{\boldsymbol{h}}) = \mu U(\hat{\boldsymbol{h}}) + \lambda R(\hat{\boldsymbol{h}}) \tag{6}$$

μ and λ are regularization parameters that control the relative contribution of the constraint terms in the cost function. $U(\hat{\boldsymbol{h}})$ imposes constraint to ensure that the spectral correlation of the high-frequency information among different color channels are similar. $R(\hat{\boldsymbol{h}})$, on the other hand, functions as a reinforcement blur estimation term to integrate the parametric information of blurring function into the algorithm.

We first discuss the formulation of the regularization term $U(\hat{\boldsymbol{h}})$. The development of the regularization term is centered on the idea that color images usually contain strong high-frequency correlation between three color (RGB) channels. Let a denotes the high-pass filter. Ignoring the additive noise and using the commutativity property of convolution, each high-passed blurred color channel is given as follows:

$$z_{iH} = a \otimes z_i = h_{ii} \otimes f_{iH} \quad (7)$$

where z_{iH} and f_{iH} are the high-frequency information of the i-th blurred channel and the i-th original channel, respectively. Equation (7) shows that the high-frequency component of the observed blurred image z_j can be considered as the high-frequency component of the original image f_i convoluted by the channel blur. Following the idea of spectral similarity in [10] and [11], this paper considers the high frequency components in each channel are highly correlated and approximately equal. Based on the subspace theory for single-input multi-output (SIMO) system [12], we will develop a new regularization operator by observing that the following condition will be satisfied, in the absence of noise:

$$z_{iH}(x,y) \otimes \hat{h}_{jj}(x,y) - z_{jH}(x,y) \otimes \hat{h}_{ii}(x,y) = O \quad i,j = r,g,b \quad (8)$$

Therefore the condition in (8) can be transformed into minimization of a constraint term:

Minimize:

$$\sum_{(x,y)\in\Omega} \sum_{\substack{i \neq j \\ i,j=r,g,b}} \left[z_{iH}(x,y) \otimes \hat{h}_{jj}(x,y) - z_{jH}(x,y) \otimes \hat{h}_{ii}(x,y) \right]^2 \quad (9)$$

The constraint can then be expressed as a regularization term in the vector-matrix form, $U(\hat{\boldsymbol{h}})$ as follows:

$$U(\hat{\boldsymbol{h}}) = \frac{1}{2} \| \boldsymbol{E}\hat{\boldsymbol{h}} \|_2^2, \text{ where } \boldsymbol{E} = \begin{pmatrix} \boldsymbol{z}_{gH} & -\boldsymbol{z}_{rH} & \boldsymbol{O} \\ \boldsymbol{z}_{bH} & \boldsymbol{O} & -\boldsymbol{z}_{rH} \\ \boldsymbol{O} & \boldsymbol{z}_{bH} & -\boldsymbol{z}_{gH} \end{pmatrix} \quad (10)$$

The matrix z_{iH} $i \in \{r,g,b\}$ is the convolution matrix formed by z_{iH}.

Next we will introduce the soft parametric blur-learning term $R(\hat{\boldsymbol{h}})$. The idea behind the framework is that it is well known that most real-life blurs satisfy, up to a degree of, parametric structure in most practical applications [13]. Therefore, we will try to find the best-fit parametric blur model for each color channel and induce reinforcement learning towards it. The learning term $R(\hat{\boldsymbol{h}})$ for the blurs is given as:

$$R(\hat{\boldsymbol{h}}) = \frac{1}{2} \| \hat{\boldsymbol{h}} - \hat{\boldsymbol{h}}_P \|_2^2, \text{ where } \hat{\boldsymbol{h}}_P = \begin{bmatrix} \hat{\boldsymbol{h}}_{rP} \\ \hat{\boldsymbol{h}}_{gP} \\ \hat{\boldsymbol{h}}_{bP} \end{bmatrix} \quad (11)$$

$\hat{\boldsymbol{h}}_{iP}$ are the vectors formed by the reinforcement-learning blur models for each channel. The detail for determining $\hat{\boldsymbol{h}}_{iP}$ can be found in [13].

4. SCHEMETIC OVERVIEW

The schematic overview of the proposed algorithm is given in Fig. 1. After the initialization of the color image and blurs, we apply AM strategy with conjugate gradient (CG) optimization to minimize the cost function given in (2). The cost function is projected with respect to the blur and image domain, and minimized alternatingly. We adopt the CG optimization method to solve the minimization problem as it utilizes conjugate direction instead local gradient to search for the minima. Therefore, it can achieve faster convergence when compared with other methods, such as steepest descent method. The iteration will be terminated when the algorithm is converged or a maximum number of iterations is reached.

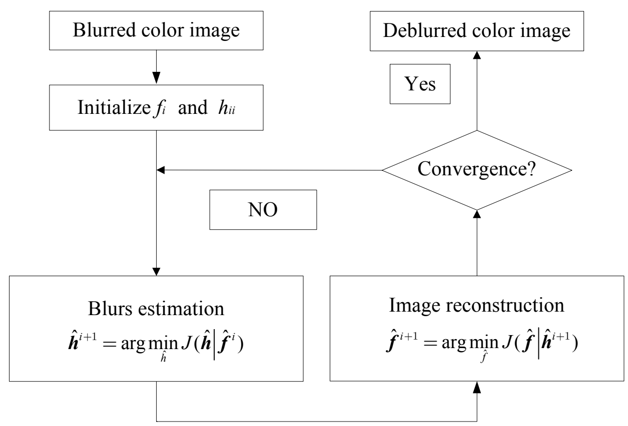

Fig. 1 Schematic diagram of the proposed algorithm

5. EXPERIMENT

In this section, we illustrate the effectiveness of the proposed method to handle blind restoration of degraded color image blurred by different channel blurs. This corresponds to the scenarios in remote sensing. The "Woman" image was selected as the test image in Fig. 2(a). In this experiment, the RGB channels of the color image were blurred by different Gaussian blurs with standard deviation of $\sigma = 2.0, 2.5, 3.0$ and with support of 3×3, 5×5, 7×7 respectively. An additive noise of 30dB was added to each channel to simulate the noisy blurred image shown in the Fig.2 (b). The proposed algorithm was run to perform blind color image deconvolution. The AM algorithm was terminated when the maximum number of 5 iterations was reached. We also compared the results with that obtained using the double regularization (DR) method in [4]. We used peak signal-to-noise ratio (PSNR) for reconstructed color image and normalized mean squared errors (NMSE) for estimated blurs to compare the performance. The results are given in Figs. 2 (c) and (d). From the figures, it can be observed that the proposed method offers superior color image quality, such as near the face region. Further, there are less color artifacts especially near the textured region of the scarf. Table I shows that the proposed method has better NMSE and PSNR values. It is noted that the subjective observation is confirmed by the objective performance measure where the proposed method renders a PSNR of 27.9 as compared to 25.87 offered by the DR method shown in Fig. 2(c).

6. CONCLUSION

The objective of blind color image deconvolution is to estimate the original color image from the observed blurred color image, given limited or no prior knowledge of the blurring function. In this paper, a regularization scheme is proposed to perform blind color image deconvolution. A reinforcement blur modeling scheme is adopted to evaluate the relevance of manifold parametric blur structures, and the information is integrated into the deconvolution scheme. In addition, a regularization scheme for image is developed to recover edges of color images and reduce color artifacts. Experimental results show that the proposed method is able to provide good restored color images under noisy environment.

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TABLE I PERFORMANCE OF BLIND COLOR IMAGE DECONVOLUTION

	DR [4]	Proposed method
NMSE	2.43	0.54
PSNR	25.87	27.9

(a) (b) (c) (d)

Fig. 2 Blind color deconvolution of "Woman" image. (a) Original image, (b) noisy blurred image, (c) restored image using the DR method, (d) restored image using the proposed method