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Multiframe blind image deconvolution with split Bregman method

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ABSTRACT

In the paper, a multiframe blind image deconvolution method based on total variation and framelet regularizer is proposed. An adapted version of the split Bregman method is proposed to efficiently solve the resulting minimization problems. In each iteration, four sub-problems need to be solved, one of which can be very efficiently and easily solved via fast Fourier transform implementation or closed form solution. Both simulated noisy and blurred frames and real degraded frames are used to verify the effectiveness of the proposed method. Comparative experimental results show that the proposed method can efficiently remove the blur and noises and restore high quality sharp image.

1. Introduction

Deconvolution of images is a classical inverse problem in many areas of image processing and computer vision, such as astronomy [1,2], photography, surveillance, remote sensing. Image deconvolution in such fields can often formulated as linear ill-posed inverse problem, where the degraded image is obtained by convolving the original image with a spatially invariant point spread function (PSF) and then added with noise.

In some applications, such as video cameras, astronomical, and microscopy imaging, the system PSF is unknown or can not be obtained accurately because the exact knowledge about the mechanism of the image degradation process is not available. Therefore, the goal of deconvolution is to recover the latent image and PSF from the degraded observations where the complete knowledge about the degradation process and noise is unavailable, we often call it blind deconvolution (BD) problem. It is known that blind deconvolution is ill-posed, undetermined problem that has a multitude of solutions, not all of which are physically meaningful. To overcome this difficulty, regularization techniques have to be used in order to enforce stability, as well as incorporate prior knowledge about the solution. To date, numerous approachs have been developed to solve blind deconvolution problems [1,3–11]. These methods can be broadly classified into two categories in terms of the number of frames being used, i.e., single frame (channel) and multiframe (channel) blind deconvolution (MFBD).

Single frame blind deconvolution processes each frame independently, and this kind of blind deconvolution approaches can be divided into those that estimate the blurring kernel first and then some of the nonblind methods is used to restore the latent image [11,12] and those that estimate the latent image and the PSF simultaneously [3–5,9,10]. For the later methods, a typical approach is to formulate the blind deconvolution problem as a joint optimization problem based on regularization framework.

If several versions of the captured image of one scene are available and differ only in the blur kernel, they can be used for enhancing the quality of the blind deconvolution algorithm. This task is the above-mentioned MFBD task. The MFBD problem has recently attracted considerable attention [1,6–8,13]. Typical examples of such multiframe measuring processes are photography, remote sensing, and astronomy, in which the same scene is observed at different time instants through a time-varying inhomogeneous medium such as the atmosphere. In the MFBD case, the restoration algorithm can exploit the redundancy present in the observations, i.e., missing information about the latent image in one frame may be supplemented by information in the other frames, and, in principle, it can achieve performance not obtainable from a single measure. Sroubek et al. [6] proposed a method that imposes the total variation (TV) constraint on the image to handle noise and incorporates a coprimeness assumption for the PSF, and then simultaneously minimizes an energy function with respect to the image and the PSFs. This allows us to handle inexact PSF sizes and to compensate for small misalignment in input images, which made MFBD deconvolution more practical. Katkovnik et al. [13] proposed a projection gradient algorithm based on anisotropic LPA-ICI (Local Polynomial Approximation-Intersection of Confidence Intervals filters), which can efficiently restore images contaminated by white

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Gaussian noise by recursively iterate in frequency domain and LPA-ICI filters in spatial domain alternately. This algorithm, however, is too complicated to implement and time consuming because of LPA-ICI filters.

In summary, multiple frame images of the same scene provide much more information than a single frame image does, which leads to a better configuration for recovering a clear image of the scene. But, some new challenging computational problems also arise when taking a multi-frame approach.

The split Bregman method was first proposed by Goldstein and Osher in [14]. It can efficiently solve general ℓ_1-regularized optimization problems with multiple ℓ_1-regularized terms. If the considered optimization problem is uniquely solvable, then the convergence of the split Bregman iteration for ℓ_1-regularization term has been proved by Cai et al. [15] and the iteration method has a relatively small memory footprint and is easy to code by users. These properties are significant for large scale MFBD problems. In this paper, we propose two MFBD algorithms based on the split Bregman method. We formulate the MFBD problem as a joint optimization problem with respect to the image and the PSFs. First, the TV regularization is imposed on the image and the PSFs, respectively. Due to the nondifferentiation of the TV norm, some numerical problems are encountered. Considering the computational complexity of TV regularization, the split Bregman iteration is applied to solve the optimization problems based on TV regularization. Its basic idea is to introduce an auxiliary variable to decompose a complex optimization problem into two independent suboptimization problems, which are easy to implement. It can be considered as an extension of the single frame model by Li et al. in [16] to the multiframe case. In our method, the sizes of the true PSFs support are supposed to be unknown.

Recently, framelet regularization has been introduced in blind motion deblurring [9], which assumes that natural images have sparse approximation under the framelet transform. Since framelet transform has the ability of multiple-resolution analysis in nature, different framelet masks reflect different orders of difference operators, which can adaptively capture multi-scale edge structures in an image. Therefore, it can well preserve various types of edges simultaneously. It motivates us to apply framelet regularization in MFBD to regularize the image. The proposed method can preserve different scale structure information of the images and produce a sharper solution. Moreover, it can efficiently suppress noise.

The organization of this paper is as follows. Section 2 describes the multi-frame blind deconvolution algorithm based on the variation model. Detailed numerical algorithms are illustrated in Section 3. Some experimental results and comparative analysis are given in Section 4. Finally, Section 5 concludes this paper.

2. Proposed method

We formulate the problem in the discrete domain and use frequently vector-matrix notation throughout the paper. Images and PSFs are denoted by italic letters and their corresponding vectorial representations (lexicographically ordered pixels) are denoted by bold letters. The MFBD problem assumes that we have $K>1$ degraded frames $\{g_1, g_2, \ldots, g_K\}$ that are related to the latent image u according to model

$$g_k = h_k * u + n_k, \quad 1 \le k \le K, \tag{1}$$

where h_k represents an unknown PSF and n_k is the additive noise in the kth observation. Operator $*$ stands for convolution. In the matrix-vector notation, (1) becomes

$$\mathbf{g}_k = \mathbf{H}_k\mathbf{u} + \mathbf{n}_k = \mathbf{U}\mathbf{h}_k + \mathbf{n}_k, \tag{2}$$

where matrices $\mathbf{H}_k \in \mathbb{R}^{N\times N}$ denotes the matrix notation of the convolution of the point spread function (PSF) $\mathbf{h} \in \mathbb{R}^N$ and $\mathbf{U} \in \mathbb{R}^{N\times N}$ denotes the matrix formed from the latent image $\mathbf{u} \in \mathbb{R}^N$ (N is the number of pixels of the image.).

In the multiframe framework, the aim of MFBD is to restore the latent image and the PSFs in (1) simultaneously employing the available degraded observations. We propose to estimate u and h_k as a minimizer of the optimization problem

$$\min_{u,h_k} \frac{1}{2}\sum_{k=1}^{K} \|h_k * u - g_k\|_2^2 + \beta\sum_{k=1}^{K} R_1(h_k) + \alpha R_2(u), \tag{3}$$

where the first term is the data term and R_1 and R_2 are regularizers of the PSFs and the image, respectively. α and β are the regularization parameters. In practice, simultaneous estimation of the image u and h_k from (2) is a difficult task, the most commonly used approach to solve (2) is called alternative minimization (see [5] for example) and will be applied here as well. The optimization problem (2) can be divided into two separate subproblems using the alternative iteration scheme

$$h\text{-step:} \quad \min_{h_k} \frac{1}{2}\sum_{k=1}^{K} \left(\|h_k * u - g_k\|_2^2 + 2\beta R_1(h_k)\right), \tag{4}$$

$$u\text{-step:} \quad \min_{u} \frac{1}{2}\sum_{k=1}^{K} \|h_k * u - g_k\|_2^2 + \alpha R_2(u). \tag{5}$$

The solution can be reached by iteratively implementing h-step and u-step until convergence.

2.1. Formulation of the regularization terms

2.1.1. h-Step

h-Step in (4) is a nonblind deconvolution problem but the data to recover is the PSF h_k. Some common PSFs, such as the box-shaped motion blur and out-of-focus blur, can be regarded as piecewise constant functions, it is logical to regularize these PSFs by the TV norm. It is simply because piecewise constant functions can be sparsely approximated by the gradient transform. In the matrix-vector form, the isotropic TV model of the PSFs can be written as

$$R_1(\mathbf{h}_k) = \sum_i \sqrt{(\mathbf{D}_x\mathbf{h}_k)_i^2 + (\mathbf{D}_y\mathbf{h}_k)_i^2}, \tag{6}$$

where $\mathbf{D}_x$ and $\mathbf{D}_y$ are matrices performing derivatives with respect to x and y, respectively. For each given $\mathbf{g}_k$, each PSF can be computed separately by solving the following optimization problem

$$\min_{\mathbf{h}_k} \frac{1}{2}\|\mathbf{U}\mathbf{h}_k - \mathbf{g}_k\|_2^2 + \beta\sum_i \sqrt{(\mathbf{D}_x\mathbf{h}_k)_i^2 + (\mathbf{D}_y\mathbf{h}_k)_i^2}. \tag{7}$$

2.1.2. u-Step

u-Step in (5) is a nonblind image deconvolution problem. Inspired by the excellent edge preservation property of the TV regularization, we also use the TV regularizer to regularize the latent image. Thus, in the matrix-vector notation, u-step in (5) rewrites as

$$\min_{\mathbf{u}} \frac{1}{2}\sum_{k=1}^{K} \|\mathbf{H}_k\mathbf{u} - \mathbf{g}_k\|_2^2 + \alpha\sum_i \sqrt{(\mathbf{D}_x\mathbf{u})_i^2 + (\mathbf{D}_y\mathbf{u})_i^2}. \tag{8}$$

Although the TV model has the capable of preserving important attribute of an image, i.e., edges, meanwhile, the textures and detail information of the images on the regions of complex structures may be removed in the process of the image restoration. Motivated by