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Research Article

Image Deblurring using Split Bregman Iterative Algorithm

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Abstract

This paper presents a new variational algorithm for image deblurring by characterizing the properties of image local smoothness and nonlocal self-similarity simultaneously. Specifically, the local smoothness is measured by a Total Variation method, enforcing the local smoothness of images, while the nonlocal self similarity is measured by transforming the 3D array generated by grouping similar image patches. A new Split Bregman-based algorithm is developed to efficiently solve the above optimization problem. Extensive experiments on image deblurring verify the effectiveness of the proposed algorithm.

Keywords: *Image deblurring, local smoothness, nonlocal self-similarity*

1. Introduction

The aim of image deblurring is to recover the original image x from a degraded observation y, is modeled as

$$y = Hx + n \tag{1}$$

Where x and y are lexicographically stacked representations of the original image and the blurred image, respectively; n is usually additive Gaussian white noise. In the case of image deblurring, H is the matrix representation of a convolution operator; if this convolution is periodic, is then a block circulant matrix. This type of observation model describes well several physical mechanisms, such as relative motion between the camera and the subject (motion blur), bad focusing (defocusing blur), or a number of other mechanisms which are well modeled by a convolution.

It is known that the problem of estimating x from y is ill-posed. To avoid such problem, some regularization terms should be used. The minimization problem can be generally formulated as

$$\arg\min_x \frac{1}{2}\|Hx - y\|_2^2 + \lambda\psi(x) \tag{2}$$

Where $\frac{1}{2}\|Hx - y\|_2^2$ is the l_2 data-fidelity term, ψ(x) is called the regularization term denoting image prior, and λ is the regularization parameter. In fact, the above regularization-based framework can be harshly derived from Bayesian inference with some image prior possibility model. It has been widely recognized that image prior knowledge plays an important role in the performance of image deblurring algorithms. Therefore, designing effective regularization terms to reflect the image priors is at the core of image restoration.

In this paper, a new variational algorithm for image deblurring is proposed within regularization framework. Our main contributions are twofold. First, a generalized variational scheme for image deblurring is formulated via exploiting image local consistency and nonlocal consistency simultaneously. Second, a new Split-Bregman based iterative algorithm is developed to solve the above optimization problem powerfully.

The rest of this paper is organized as follows: In Section 2, we introduce the image local smoothness and nonlocal self similarity. The details of our proposed algorithm are presented in Section 3. Experimental results are reported in Section 4 and we conclude this paper in Section 5.

2. Methodology and Design

2.1 Image Local Similarity

Local smoothness describes the closeness of neighboring pixels in 2D space domain of images, which means the intensities of the neighboring pixels are quite similar. We mathematically formulate a local statistical modeling for smoothness in 2D space domain. From the view of statistics, a natural image is preferred when its responses for a set of high pass filters are as small as possible, which intuitively implies that images are locally smooth and their derivatives are close to zero.

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In this paper, we measure the image local similarity by Total Variation model, defined by

$$TV(x) = \varphi_{LS}(x) = \sum_i \sum_j \sqrt{(\Delta^h_{i.j} x)^2 + (\Delta^v_{i,j} x)^2} \quad (3)$$

Where $\Delta^h_{i,j} x \equiv x_{i,j} - x_{i,j-1}$ and $\Delta^v_{i,j} x \equiv x_{i,j} - x_{i-1,j}$ denote linear operators corresponding to horizontal and vertical first order differences at pixel $x_{i,j}$ respectively. It is important to underline that local similarity is only used for characterizing the property of image smoothness.

3.2 Nonlocal Self Similarity

The Nonlocal self-similarity is another significant property of natural images. It can be used for retaining the sharpness and edges effectually to maintain image nonlocal consistency. In this paper, we mathematically illustrate the nonlocal self-similarity for natural images by means of the distributions of the transform coefficients, which are achieved by transforming the 3D array generated by stacking similar image patches. This can be formulated in the following four steps:

First, divide the image x with size N into n overlapped blocks x^i of size b_s, i=1, 2 ,...., n. The blurred image is processed by successively extracting reference block from it, find c blocks that are similar to the reference block within the searching window of size L*L i.e., $S_{x^i} = \{S_{x^i \otimes 1}, S_{x^i \otimes 2}, \ldots S_{x^i \otimes c}\}$. Third, stack then together to form a 3D array which is denoted by Z_{x^i}. Finally, denote T^{3D} as the operator of an orthogonal 3D transform and $T^{3D}(Z_{x^i})$ as the transform coefficients for Z_{x^i}. Let $\|\Phi_x\|_1$ be the column vector of all the transform coefficients of image x with size K= $b_s * c * n$ built from all the $T^{3D}(Z_{x^i})$ arranged in the lexicographic order.

$$\varphi_{NLS}(x) = \|\Phi_x\|_1 = \sum_{i=1}^{n} \|T^{3D}(Z_x)\|_1 \quad (4)$$

3. An Iterative Algorithm for Image Deblurring

By incorporating image local smoothness and nonlocal self similarity into the generic variational model (2), a new formulation for image deblurring can be expressed as follows:

$$\arg\min_x \|Hx - y\|_2^2 + \tau\varphi_{LS}(x) + \lambda_{NLS}(x) \quad (5)$$

Where τ and λ are control parameters.

We apply Split Bregman Iterative algorithm to solve the above equation. SBI is recently introduced by Goldstein and Osher for solving a class of l_1 related minimization problems. The basic idea of SBI is to convert the unconstrained minimization problem into a constrained one by introducing the variable splitting technique and then invoke the Bregman iteration to solve the constrained minimization problem. By utilizing variable splitting technique, the problem will change into an equivalent constrained optimization:

$$\hat{x}, \hat{w}, \hat{u} = \arg\min_x \|Hx - y\|_2^2 + \tau\varphi_{LS}(x) + \lambda\varphi_{NLS}(x)$$
$$\text{s.t. } x=w, x=u \quad (6)$$

Instead of solving (6) directly, here, an alternating direction technique is employed, which alternatively minimizes one variable while fixing the other variables, to split Problem (6) into the three sub-problems. Complete algorithm proposed for solving (5) is shown below:

Input: The observed image y and the linear matrix operator H

Initialization: k=0, $x^{(0)}$=y, $b^{(0)}$=$c^{(0)}$=$w^{(0)}$=$u^{(0)}$=0,μ, τ, λ

Repeat:

$$x^{(k+1)} = \arg\min_x \frac{1}{2}\|Hx - y\|_2^2 + \frac{\mu}{2}\|x - w^{(k)} - b^{(k)}\|_2^2 + \frac{\mu}{2}\|x - u^{(k)} - c^{(k)}\|_2^2 \quad (7)$$

$$p^k = x^{(k+1)} - b^{(k)}; \quad (8)$$

$$w^{(k+1)} = prox(\varphi_{LS})p^{(k)}; \quad (9)$$

$$r^{(k)} = x^{(k+1)} - c^{(k)}; \quad (10)$$

$$u^{(k+1)} = prox(\varphi_{NLS})(r^{(k)}); \quad (11)$$

$$b^{(k+1)} = b^{(k)} - (x^{(k+1)} - w^{(k+1)}; \quad (12)$$

$$c^{(k+1)} = c^{(k)} - (x^{(k+1)} - u^{(k+1)}); \quad (13)$$

Until: Stopping criterion is satisfied

Output: Final restored image x

The proximal maps related to most functions can only be solved in an approximation way. Proximal map of TV (φ_{LS}) is calculated by the well-known Chambolle's algorithm and proximal map of φ_{NLS} is solved by shrinkage in transform domain of all the 3D arrays centered at every pixel.

4. Results and Discussion

In this section, we present extensive experimental results to evaluate the performance of the proposed algorithm. Simulations are performed using MATLAB.

PSNR is used to evaluate the quality of image deblurring.

The true images are blurred by a blur kernel and then added by Gaussian noise with standard deviation σ. Three blur kernels, a 9*9 uniform kernel, a Gaussian blur kernel, and a motion blur kernel, are used for simulation. We compare the proposed deblurring method to three recently developed deblurring approaches, i.e., the SALSA deblurring method, the SA-DCT deblurring method, and the BM3D deblurring method. The PSNR results on a set of three images are presented in table. From Table, we can conclude that the proposed approach significantly better than other methods for all three types of blur kernels. The high performance of the proposed algorithm is achieved by the service of image local and nonlocal regularization at the same time. Simulation results shown in fig below:

- Deblurring using Motion Kernel

Fig.1 (a) Original Image, (b) blurred image with noise and (c) Deblurred Image

Table 1 PSNR (dB) Comparisons for Image Deblurring (Motion Kernel)

Image	SALSA	BM3D	Proposed
House	33.58	34.11	36.39
Leaves	30.12	31.66	32.52
Cameraman	29.24	30.12	31.64

- Deblurring using Gaussian Kernel

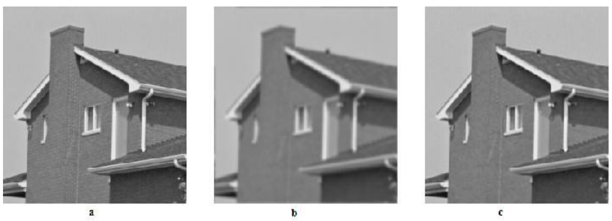

Fig.2 (a) Original Image, (b) blurred image with noise and (c) Deblurred Image

Table 2 PSNR (dB) Comparisons for Image Deblurring (Gaussian Kernel)

Image	SALSA	BM3D	Proposed
House	33.19	34.23	35.23
Leaves	28.13	29.56	30.59
Cameraman	26.23	27.46	28.51

- Deblurring using Uniform Kernel

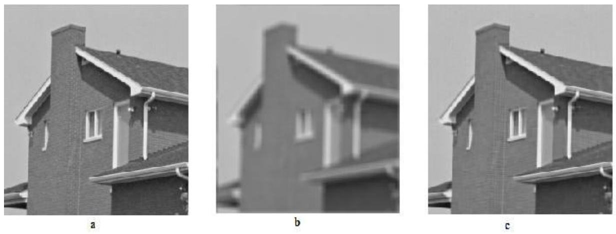

Fig.3 (a) Original Image, (b) blurred image with noise and (c) Deblurred Image

Table 3 PSNR (dB) Comparisons for Image Deblurring (Uniform Kernel)

Image	SALSA	BM3D	Proposed
House	33.95	35.53	36.23
Leaves	29.13	29.56	30.64
Cameraman	27.23	28.46	29.13

Conclusions

In this paper, a novel algorithm for image deblurring is proposed by characterizing both image local smoothness and nonlocal self-similarity of natural images. Extensive experiments demonstrate that the proposed algorithm is able to achieve significant performance improvements over the current state-of-the-art schemes, generating deblurring results with better quality. Future work will be centred at video restoration tasks.

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