Blind Motion Deblurring from a Single Image

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***Abstract*— Restoring a clear image from a single motion-blurred image due to camera shake has long been one challenging problem in digital imaging. Existing blind deblurring techniques either only can remove simple motion blurring, or need user interactions to work on more complex cases. In this paper, we present an approach to remove motion blurring from a single image by formulating the blind blurring as`a new joint optimization problem, which simultaneously maximizes the sparsity of the blur kernel and the sparsityof the clear image under certain suitable redundant tightframe systems (curvelet system for kernels and framelet system for images). Without requiring any prior information ofthe blur kernel as the input, our proposed approach is ableto recover high-quality images from given blurred images. Furthermore, the new sparsity constraints under tightframe systems enable the application of a fast algorithm called linearized Bregman iteration to efficiently solve the proposed minimization problem. The experiments on both simulated images and real images showed that our algorithm cans effectively removing complex motion blurring from nature images.

Keywords -- Blind image, psf, motion deblur, Bregman eterative method.

Introduction

Motion blur caused by camera shake has been one of the prime causes of poor image quality in digital imaging, especially when using telephoto lens or using long shuttle speed. In past, many researchers have been working on recovering clear images from motion-blurred images. The motion blur caused by camera shake usually is modeled by a spatial invariant blurring process:

$$f = g * p + n \ldots \qquad (1)$$

Where $*$ is the convolution operator, g is the clear image to recover, f is the observed blurred image, p is the blur kernel(or point spread function) and n is the noise. If the blur kernel is given as a prior, recovering clear image is called anon-blind deconvolution problem; otherwise called a blind deconvolution problem. It is known that the non-blind deconvolution problem is an ill-conditioned problem for its sensitivity to noise. Blind deconvolution is even more illposed .Because both the blur kernel and the clear image are unknown; the problem becomes under-constrained as there are more unknowns than available measurements. Motion deblurring is a typical blind deconvolution problem as the motion between the camera and the scene can be arbitrary.

1. Literature work

Early works on blind deblurring usually use a single image and assume a prior parametric form of the blur kernel p such that the blur kernel can be obtained by only estimating a few parameters (e.g., Pavlovic and Tekalp [1]).linear motion blur kernel model used in these works oftenis overly simplified for true motion blurring in practice. To solve more complex motion blurring, multi-image based approaches have been proposed to obtain more information of the blur kernel by either actively or passively capturing multiple images on the scene (e.g., Bascle et al. [2], Ben-Ezraand Nayar [3], Chen et al. [4], Lu et al. [5], Raskar [6],Tai et al. [7]).Recently, there have been steady progresses on removing complex motion blurring from a single image. There are two typical approaches. One is to use some probabilistic priors on images' edge distribution to derive the blur kernel(e.g., Fergus et al. [8], Levin [9], Joshi [10]) or manually selecting blurred edges to obtain the local blur kernel(Jia [11]). The main weakness of this type of methods is that the assumed probabilistic priors do not always hold true for general images. The other popular approach is to formulate the blind deconvolution as a joint minimization problem with some regularization on both the blur kernel p and the clear image g**:**

$E(p, q) = \min_{p,g\ \varphi} (g * p - f) + \lambda_1 1(p) + \lambda_2 2(g)$, …...(2)

Where $_\varphi$ (p∗g−f) is the fidelity term, 1(p) and 2(g) are the regularization terms on the kernel and the clear image 9respectively. In this paper, we focus on the regularization based approach. Among existing regularization-based methods, TV (Total Variation) norm and its variations have been the dominant choice of the regularization term to solve various blind deblurring problems (e.g., Bar et al. [17], Chan and Wong [18], Cho et al. [12]). In these approaches, the Fidelity term in (2) is usual ℓ2 norm on image intensity similarity; and the regularization terms 1 and 2 in (2) are both TV norms of the image g and the kernel p. Shan et al. [13] presented a more sophisticated minimization model where the fidelity term is a weighted ℓ2 norm on the similarity of both image intensity and image gradients. The regularization term on the latent image is a combination of a weighted TV norm of image and the global probabilistic constraint on the edge distribution as ([8]). The regularization term on the motion-blur kernel is the ℓ1 norm of the kernel intensity. These minimization methods showed good performance on removing many types of blurring. In particular, Shan et al.'smethod demonstrated impressive performance on removing modest motion blurring from images without rich textures. However, solving the resulting optimization problem (2) usually requires quite sophisticated iterative numerical algorithms, which often fail to converge to the true global minimum if the initial input of the kernel is not well set. One well-known degenerate case is that the kernel converges to a delta-type function and the recovered image remains blurred. Thus, these methods need some prior information on the blur kernel as the input, such as the size of the kernel (e.g., Fergus et al. [8], Shan et al. [13]). Also, the classic optimization techniques (e.g. interior point method)are highly inefficient for solving (2) as they usually requires the computation of the gradients in each iteration, which could be very expensive on both computation amount and memory consumption as the number of the unknowns could be up to millions (the number of image pixels).

Non Blind image deblurring technique:

1 Wiener Filter Deblurring Technique

The Wiener filter isolates lines in a noisy image by finding an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously so as to emphasize any lines which are hidden in the image. This filter operates in the Fourier domain making the elimination of noise easier as the high and low frequencies are removed from the noise to leave a sharp image. Using Fourier transforms means the noise is easier to completely eliminate and the actual line embedded in noise easier to isolate making it a slightly more effective method of filtering.Wiener filter is a method of restoring image in the presence of blur and noise. The frequency-domain expression for the Wiener filter is:

W(s) = H(s)/F+(s), H(s) = Fx,s (s) eas /Fx(s)
Where: F(s) is blurred image, F+(s) causal, Fx(s) anti-causal

Deconvolution using Wiener Filter

Weiner Filtering is also a non blind technique for reconstructing the degraded image in the presence of known PSF. It removes the additive noise and inverts the blurring simultaneously. It not only performs the deconvolution by inverse filtering (highpass filtering) but also removes the noise with a compression operation (lowpass filtering).It compares with an estimation of the desired noiseless image. The input to a wiener filter is a degraded image corrupted by additive noise. The output image is computed by means of afilter using the following expression:

f= g * (f + n) ……….(5)

In equation (5), f is the original image, n is the noise, f' is the estimated image and g is the Wiener filter's response.

2. Regularized filter deblurring method

Regulated filter is the deblurring method to deblured an Image by using deconvlution function which is effectively when the limited information is known about additive noise.

Deconvolution using Regularized Filtering

Regularized filtering is used effectively when constraints like smoothness are applied on the recovered image and limited information is known about the additive noise. The blurred and noisy image is restored by a constrained least square restoration algorithm that uses a regularized filter. Regularized restoration provides similar results as the wiener filtering but it has a very different viewpoint. In regularized filtering less prior information is required to apply restoration. The regularization filter is often chosen to be a discrete Laplacian. This filter can be understood as an approximation of a Wiener filter.

3. Lucy-Richardson algorithm method

The Richardson–Lucy algorithm, also known as Richardson–Lucy deconvolution, is an iterative procedure for recovering a latent image that has been the blurred by a known PSF.

$C_i = \sum_j P_{ij}\, u_j$

Where' Pij' is PSF at location i and j, uj is the pixel value at location j in blurred image .Ci is the observed value at pixel location i. Iteration process to calculate uj given the observed ci and known pij

$u_j^{(t+1)} = u_j^t \sum_i ci/ci\ p_{ij}$

where

$c_i = \sum_j u_j^{(t)}\, p_{ij}$

Lucy-Richardson Algorithm Technique Approach

In this paper, we propose a new optimization approach to remove motion blurring from a single image. The contribution of the proposed approach is twofold. First, we propose new sparsity-based regularization terms for both images and motion kernels using redundant tight frame theory. Secondly, the new sparsity regularization terms enable the application of a new numerical algorithm, namely linearized Bregman iteration, to efficiently solve the resulting ℓ1 normrelated minimization problem. Most of nature images have sparse approximation under some redundant tight frame systems, e.g. translation in variant wavelet, Gabor transform, Local cosine transform ([14]), framelets ([15]) and curvelets ([8]). The sparsity of nature images under these tight frames has been successfully used to solve many image restoration tasks including image denoising, non-blind image deblurring, image in painting, etc (e.g. [12, 6, 4]). Therefore, we believe that the high sparsity of images under certain suitable tight frame system is also a good regularization on the latent image in our blind deblurring problem. In this paper, we chose framelet system ([15, 13]) as the redundant tight frame system used in our approach for representing images. The motion-blur kernel is different from typical images. It can be viewed as a piece-wise smooth function in 2D image domain, but with some important geometrical property: the support of the kernel (the camera trajectory during exposure) is approximately a thin smooth curve. Thus, the best tight frame system for representing motion-blur kernel is Curvelet system, which is known for its optimal sparse representation for this type of functions ([8]).The sparsity-based regularization on images or kernels is not a completely new idea. Actually, the widely used TV-norm based regularization can also be viewed as a sparsity regularization on image gradients. However, redundant tight frame systems provide much higher sparsity when representing nature images, which will increase the robustness to the noise. More importantly, as Donoho pointed out in[14] that the minimal ℓ1 norm solution is the sparsest solution for most large under-determined systems of linear equations, using tight frame system for representing images/kernels is very attractive because the tight frame coefficients of images/kernels are indeed heavily redundant. Furthermore, TV-norm or its variations are not very accurate regularization terms to regularize motion-blur kernels, as they do not impose the support of the kernel being an approximately smooth curve. However, by representing the blur kernel in the curvelet system, the geometrical property of the support of motion kernels are appropriately imposed, because a sparse solution in curvelet domain tends to be smooth curves instead of isolated points.

Deconvolution using Lucy Richardson Algorithm

DLR is a non blind technique of image restoration, used to restore a degraded image that has been blurred by a known PSF. It is an iterative procedure in which the pixels of the observed image are represented using the PSF and the latent image as follows:

$d_i = \Sigma\, p_{ij}\, u_j$ … (2)

In equation (2), di is the observed value at pixel position,'i', pij is the PSF, the fraction of light coming from true locations' that is observed at position,'i', uj is the latent image pixel value at location ,'j' . The main objective is to compute the most likely 'uj' in the presence of observed di and known PSF pij as follows:

$u_j^{(t+1)} = u_j^{(t)}\, \Sigma_i d_i/c_i\, p_{ij}$ ….. (3) Where,

$c_i = \Sigma_j\, p_{ij}\, u_j^{(t)}$ ……. (4)

4. Blind deconvolution algorithm method

Definition of the blind deblurring method can be expressed by:

$g(x, y) = PSF * f(x,y) + \eta(x,y)$

Where: g (x, y) is the observed image, PSF is Point Spread Function, f (x,y) is the constructed image and η(x,y) is the additive noise term [16].

Blind Image Deconvolution

As the name suggests, BID is a Blind technique of image restoration which restores the degraded image that is blurred by an unknown PSF. It is a deconvolution technique that permits recovery of the target image from a single or set of blurred images in the presence of a poorly determined or unknown PSF.

In this technique firstly, we have to make an estimate of the blurring operator i.e. PSF and then using that estimate we have to deblur the image. This method can be performed Iteratively as well as non-iteratively. In iterative approach, each iteration improves the estimation of the PSF and by using that estimated PSF we can improve the resultant image repeatedly by bringing it closer to the original image. In non-iterative approach one application of the algorithm based on exterior information extracts the PSF and this extracted PSF is used to restore the original image from the degraded one.

Implementation platform
Technical Requirement:

Software Requirements:

Front End: Matlab.
Operating system: WINDOWS-XP.

Hardware Requirements:

Main processor : Pentium IV processor 1.13 GHz.
Internal memory capacity: 128 MB
Hard disk capacity : 40GB.
Cache memory : 512 MB.

Why MATLAB?

MATLAB provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. You can restore noisy or degraded images, enhance images for improved intelligibility, extract features, analyze shapes and textures, and register two images. Most toolbox functions are written in the open MATLAB language, giving you the ability to inspect the algorithms, modify the source code, and create your own custom functions. MATLAB provides a number of features for documenting and sharing your work. You can integrate your MATLAB code with other languages and applications, and distribute your MATLAB algorithms and applications.

Methodology / Algorithm

Blind deblurring is an under constrained problem with many possible solutions. Extra constraints on both the image and the kernel are needed to overcome the ambiguity and the noise sensitivity. In this paper, we present a new formulation to solve (1) with sparsity constraints on the image and the blur kernel under suitable tight frame systems. We propose to use framelet system (Ron and Shen et al.[15]) to find the sparse approximation to the image under framelet domain The blur kernel is a very special function with its support being an approximate smooth 2D curve. We use the curvelet system (Candes and Donoho [8]) to find the sparse approximation to the blur kernel under curvelet domain.

Algorithm 1 Outline of the alternative iterations

For k=0,1….

1) Given the blur kernel $p^{(k)}$,compute the clear image $g^{(k+1)}$,i.e.

$$g^{(k+1)} = \arg_g \min 1/2 \|p^{(k)} * g - f\|_2^{\,2} + \lambda_1 \theta_1(g) \ldots \quad (10)$$

Where $\theta_1(g)$ is the regularisation term on images and λ_1 the regularisation parameter.

2) Given the clear image ,compute the blur kernel i.e.

$$P^{(k+1)} = \arg_g \min 1/2 \|g^{(k+1)} * p - f\|_2^2 + \lambda_2 \theta_2(p) \ldots \quad (11)$$

Where $\theta_2(p)$ is the regularisation term on kernals and λ_2 the regularization parameter.

There are two steps in Algorithm 1, and both steps are about using regularization-based approach for nonblind deconvolution. Step 1 is a nonblind image deblurring problem, which has been extensively studied in the literature .However, there are subtle differences between step 1 and the classic nonblind deconvolution problems, i.e., the intermediate estimated blur kernel used for deblurring instep 1 is not perfect and it is far way from the truth during the initial iterations. Inspired by the strong noise robustness of the recent nonblind deblurring technique [1], we also use the analysis sparsity prior on the original image under the framelet system to regularize the nonblind image deblurring to alleviate the distortion caused by the erroneous intermediate estimate of the blur kernel.

Numerical Algorithms

This is devoted to the detailed numerical algorithm of our blind motion deblurring algorithm outlined in Algorithm1. Both steps in Algorithm 1 are solving the same type of large-scale minimization problems. The difficulties lie in then on separable L1-norm terms Wg1 and Wp1. One efficient solver for minimizations involving such terms is the split Bregman iteration which will be used in our solver. The split Bregman iteration is based on the Bregman iteration.The Bregman iteration was first introduced for nondifferentiable TV energy and was then successfully applied to wavelet-based denoising. The Bregman iteration was also used in TV-based blind deconvolution. To further improve the performance of the Bregman iteration, a linearized Bregman iteration was invented. More details and an improvement called "kicking" of the linearized Bregman iteration are described, and a for frame-based image deblurring was proposed. Recently, a new type of iteration based on the Bregman distance, called split Bregman iteration, was introduced in [2], which extended the utility of the Bregman iteration and the linearized Bregman iteration to more general -norm minimization problems. The split Bregman iteration for frame-based image deblurring wasfirst proposed. The basic idea of split Bregman iterationis to convert the unconstrained minimization problem (10) and (12) [(12) and (13), respectively] into a constrained one by introducing an auxiliary variable (respectively) and then invoke the Bregman iteration to solve the constrained minimization problem. Numerical simulations in show that it converges fast and only uses a small memory footprint, which make it very attractive for large-scale problems.

Algorithm 2:Numerical algorithm for blind motion deblurng

1) Set k = 0,p(0)= δ, d1=b1=0 and d2=b2=0 , where is a δ delta function.
2) Do

$$g^{(k+1/2)} = \arg_g \min 1/2 \| [p^{(k)}] * g - f \|_2^2 + \lambda_1 \quad \mu_1/2 \quad \|w_g - d_1^{(k)} + b_1^{(k)}\|_2^2$$

$$g^{(k+1)}(j) = \begin{cases} 1 & \text{If} g^{(k+1/2)}(j)>1; \\ 0 & \text{If} g^{(k+1/2)}(j)<0; \\ g^{(k+1/2)}(j) & \text{otherwise} \end{cases}$$

j=1,2,..N

$$d_1^{(k+1)} = T_1/\mu_1 \quad (wg^{(k+1)}+b_1^{(k)})$$

$$b_1^{(k+1)} = b_1^{(k)} + (wg^{(k+1)} - d_1^{(k+1)})$$

$$p^{(k+1/2)} = \arg_g \min 1/2 \| [g^{(k+1)}] * p - f \|_2^{\,2} + \lambda_2 T/2 \|p\|_2^{\,2} + \lambda_2 \mu_2/2 \|w_p - d_2^{(k)} + b_2^{(k)}\|_2^{\,2}$$

$$P^{(k+1)}(j)=\max(p(k+1/2)(j),0) , j=0,1,2,\ldots.N$$

$$P(k+1)=p(k+1)/ \|p(k+1)\| 1$$

$$d_2^{(k+1)} = T_1/ \mu_2 \quad (wp^{(k+1)}+b_2^{(k)})$$

$$b_2^{(k+1)} = b_2^{(k)} + (wp^{(k+1)} - d_2^{(k+1)})$$

$$K=k+1$$

$$\text{Until}(k>=k \text{ or } \|p^{(k)}-p^{(k-1)}\|^2_2 \quad <=\varepsilon)$$

Expected Outcomes

Image Restoration is a field of Image Processing which deals with recovering an original and sharp image from a degraded image using a mathematical degradation and restoration model. This study focuses on restoration of degraded images which have been blurred by known or unknown degradation function. On the basis of knowledge of degradation function image restoration techniques can be divided into two categories: blind and non-blind techniques. Three different image formats viz..jpg(Joint Photographic Experts Group), .png(Portable Network Graphics) and .tif(Tag Index Format) are considered for analyzing the various image restoration techniques like Deconvolution using Lucy Richardson Algorithm (DLR), Deconvolution using Weiner Filter (DWF), Deconvolution using Regularized Filter (DRF) and Blind Image Deconvolution Algorithm (BID).The analysis is done on the basis of various performance metrics like PSNR(Peak Signal to Noise Ratio), MSE(Mean Square Error) , RMSE(Root Mean Square Error).

Conclusion:

In this work, a new algorithm is presented to remove camera shake from a single image. Based on the high sparsity of the image in framelet system and the high sparsity of the motion-blur kernel in curvelet system, our new formulation on motion deblurring leads to a powerful algorithm which can recover a clear image from the image blurred by complex motion. Furthermore, the curvelet-based representation of the blur kernel also provides a good constraint on the curve-like geometrical support of the motion blur kernel, thus our method will not converge to the degenerate case as many other approaches might do. As a result, our method does not require any prior information on the kernel while existing techniques usually needs user interactions to have some accurate information of the blurring as the input. Moreover, a fast numerical scheme is presented to solve the resulted minimization problem with convergence analysis. The experiments on both synthesized and real images show that our proposed algorithm is very efficient and also effective on removing complicated blurring from nature images of complex structures. In future, we would like to extend this sparse approximation framework to remove local motion blurring from the image caused by fast moving objects.

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