Image Restoration Using Progressive Image Denoising and Blind Image Deblurring

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Abstract— The purpose of image restoration is to remove the defects which degraded an image. Degradation can be caused by many factors such as blur, noise. In this paper we propose a combined approach of denoising and deblurring to restore a sharp image from the degraded one. Denoising is done by Progressive image denoising followed by image sharpening and deblurring.Spectral properties of convolution operators are used for image deblurring.

Keywords— Image Restoration,Robust noise estimation,Deterministic annealing, Image deblurring,Blind deconvolution, Blur kernel estimation,Spectral methods.

INTRODUCTION

Blur and noise are the two problems that exist in digital image processing. Image restoration deals with the reconstruction of the uncorrupted image from a blurred and noisy one. Blurring of an image can be caused by many factors. Movement during the capture process and using long exposure times are the main causes. A blurry image, denoted as B , is generated by the convolution of a sharp image I_0, and a generic blur kernel, denoted as K_0

$$B \approx I_0 * K_0$$

Blind deconvolution is to recover the sharp image I_0 when the blur kernel K_0 is unknown. In this work Image deblurring is done by using spectral properties of convolution operators. In this work, we derive an effective regularizer for the blur kernel. This regularizer is based on a well-known observation. Blurry images are usually low-pass and sharp images are often high-pass.That is blurring can decrease the image frequencies in Fourier domain. For a given image consider its convolution with any other matrix. The spectrum (Fourier frequencies) of the linear operator for a blurry image should be significantly smaller than that for its sharp part.

Based on this observation, we can derive convex regularizer which tends to be minimal at the blur kernel of desired, K_0. Given an image B represented by a certain image feature L. A convex function denoted as $h^{L(B)(}K)$ can be derived from the image. Desired kernel K_0 can be approximately retrieved by minimizing $h^{L(B)(}K)$ This convex kernel significantly benefit the solution of the blind deconvolution problem.

In addition to these blurring effects, noise always affect the image. Noise may be introduced at the time of capturing or transmission of the image. Progressive method of image denoising[2] is used in this work. Progressive image denoising (PID) is based on deterministic annealing and robust noise estimation. Deterministic annealing (DA) is a method that solves the complex optimization problems where many local extrema exist. Progressive image denoising combine deterministic annealing with redescending M-estimators.

In this paper we propose an efficient method for image denoising and image deblurring.Denoising is done by progressive image denoising. Then we use spectral properties of convolution opeartors for blind image deblurring.[1].

Image Restoration Using Progressive Image Denoising and Blind Image Deblurring

We describe the method in three parts.In the first section we present progressive image denoising.Then in the second section we present the image deblurring method. Processing blocks of this image restoration method is given below.

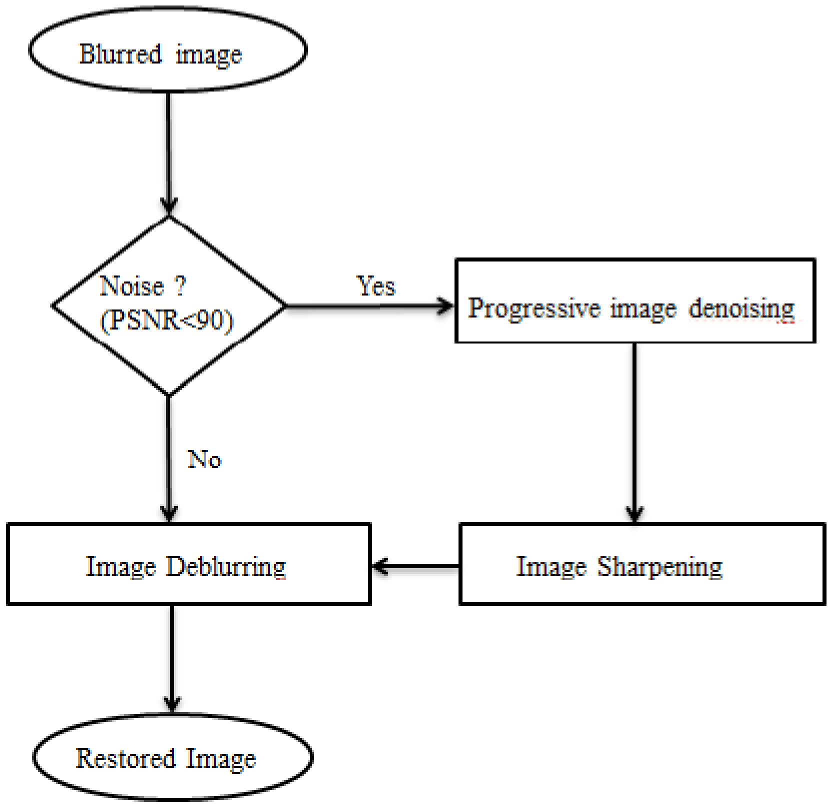

Figure 1: Processing blocks of the image restoration

Progressive Noise Removal

A signal x has been contaminated with additive white Gaussian noise n and variance σ^2. The task is to decompose the degraded signal y into original signal x and noise n.

$$y=x+n \quad (1)$$

In practice, we can only estimate decomposition. Thus, we formulate denoising as a gradient descent with

$$x_{i+1} = x_i - \lambda\nabla E(x_i) \quad (2)$$

The scale factor λ controls the step size in the direction of the gradient descent .Gradient of this energy, $\nabla E(xi)$, can be estimated as a noise estimate n_i . Substituting $\nabla E(x_i) \rightarrow n_i$, we get

$$x_{i+1} = x_i - \lambda\, n_i \qquad (3)$$

Robust Noise Estimation

To compute the noise estimate n_i for iteration *i* ,distinguish signal from noise. Noisy signal can be classified into three types. Large amplitude signals and medium amplitude signals and small amplitude noise. Large amplitude signals can be detected in the spatial domain. When the amplitude of the signal is smaller it is more similar to the noise. Signal is auto-correlated and noise is uncorrelated. Robust estimators reject large amplitude gradients in the spatial domain .Medium amplitude signals are rejected in the frequency domain, Then we can estimate the small amplitude noise.

In the spatial domain, where we remove large amplitude signals. We consider pixel p and pixels q in a neighbourhood window Np with window radius r. Then subtract the center pixel value $x_{i,p}$ from all the neighboring pixels $x_{i,q}$ yielding a "gradient" $d_{i,p,q}$ as

$$\boldsymbol{Di,p,f = \sum d_{i,p,q} k_r\left(\frac{|d_{i,p,q}|^2}{T_i}\right) * k_s(\frac{|q-p|^2}{Si}) e^{-j\,\frac{2\Pi}{2r+1} f.(q-p)}} \qquad (4)$$

Similar procedure is performed in the frequency domain. Remove medium amplitude signals in the frequency domain to obtain the remaining small amplitude noise. Thus, we use another range kernel *K* to mask out large Fourier coefficients $D_{i,p,f}$ .Then estimate the noise by taking the center pixel after inverse Fourier transforming the signal.

$$\boldsymbol{n_{i,p} = \frac{1}{(2r+1)^2} \sum_{f \varepsilon F_p} D_{i,p,f} K(\frac{|D_{i,p,f}|^2}{V_i})} \qquad (5)$$

Image Deblurring

Blind deconvolution is to recover the sharp image I_0 when the blur kernel K_0 is unknown. Image gradient based regularizers generally favor a blurry solution over a sharp one. Hence regularize the kernel variable K. we can derive a novel convex regularizer, denoted as $h^{L(B)(}$K). This regularizer tends to be minimal at the desired blur kernel, K_0. This regularizer is based on a well-known observation.Blurry images are usually low-pass and sharp images are often high-pass.That is blurring of an image can largely decrease the image frequencies in Fourier domain.

For a given image ,that is matrix consider its convolution with any other matrix. Then the classical observation suggests that the spectrum (the set of eigenvalues, that is , the Fourier frequencies of the blurry image should be significantly smaller than sharp image.

Given an observed image B,which is represented by an image feature *L*, we derive a convex function, denoted as $h^{L(B)(}$K).

$$h^{L(B)(}K): R^{m1\times m2} \rightarrow R \qquad (6)$$

The desired kernel K_0 can be approximately retrieved by minimizing $h^{L(B)(}$K) directly. Experimental performance of deblurring algorithm is surprising. This algorithm can restore a sharp version,even when the observed image is blurred to the extent where human eyes cannot recognize its details. Convex kernel regularizer is effective for various blurs such as motion blur and de-focus.

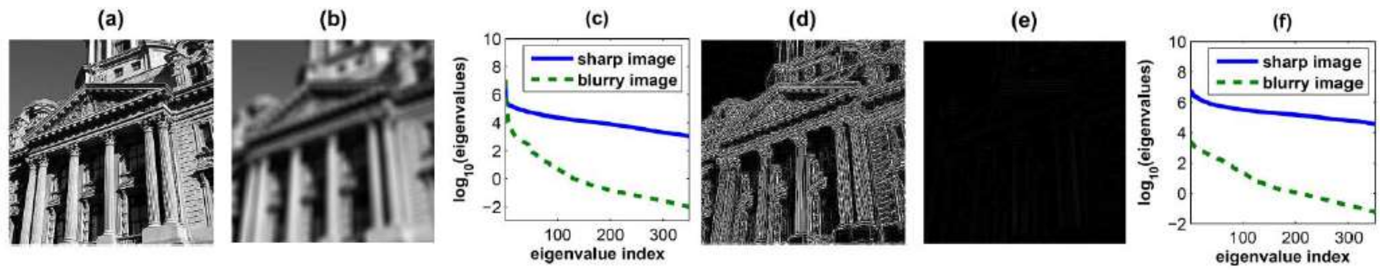

Figure 2: (a) Sharp image (b)The blurry image created by the convolution of sharp image with a Gaussian kernel. (c) Plots of all convolution eigenvalues of the sharp and blurry images, using L = δ. (d) Edges of sharp image, using L = LoG. (e) The edges of the blurry image (f) Plots of convolution eigenvalues of the sharp and blurry images, choosing L = LoG.

Figure 2 shows that blurring could significantly reduce the image frequencies or convolution eigenvalues. obtain an approximate estimate of the desired blur kernel K_0 by

$$K_0 = \operatorname{argmin}_k h^{L(B)(}K) \qquad (7)$$

Where S denotes the $(m_1m_2 - 1)$-dimensional simplex, and $\{m_1,m_2\}$ are the sizes of the blur kernel. Where $h^{L(B)(}K) = (\nu(K))^T H\nu(K)$ with the Hessian matrix H given by

$$H = \sum_{i=1}^{s1s2} \frac{(A_{m1,m2}\left(k_i^L(B)\right))^T A_{m1,m2}\left(k_i^L(B)\right)}{(\sigma_i^L(B))^2} \qquad (8)$$

Algorithm for Computing the Hessian Matrix H is given below.Then fixing the blur kernel K, the estimate of the image is updated by $\min\|B-I*k\|^2_F + \lambda\| \nabla I\|$ which can be solved by any of the many non-blind deconvolution algorithms. We use Fast image deconvolution using hyper-Laplacian priors[3].

Algorithm

Input:Blurry image

Parameters:Kernel sizes$\{k_1,k_2\}$ and Sampling sizes$\{s_1,s_2\}$

1.Compute the edge map of B by L(B)=B*LoG.

2.Compute the convolution matrix $A_{s1,s2}(L(B))$.

3.Let $M=(A_{s1,s2}(L(B)))^T A_{s1,s2}(L(B))$. Then obtain the convolution eigenvalues $\sigma_i^L(B)$ and eigenvectors $k_i^L(B)$.

4. For each $k_i^L(B)$., compute its convolution matrix $A_{k1,k2}(k_i^L(B))$.

5. Compute the Hessian matrix H using equation 8.

Output:H

Experimental Results

We present the results of our algorithm. We analyze the denoising and deblurring process for the given text image. Figure 3 shows the results.

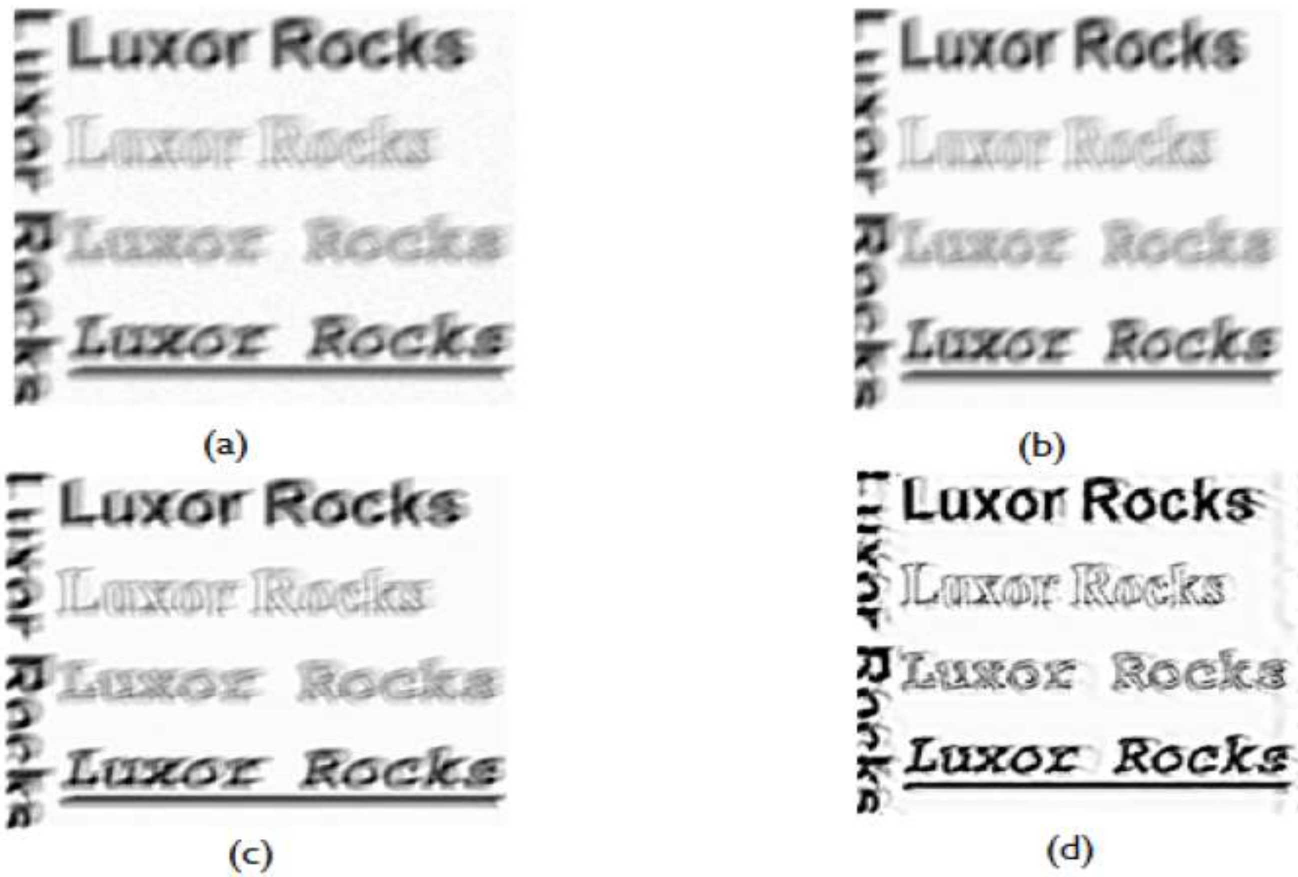

Figure 3: (a) Image degraded by blur and noise (b) Denoised image (c) Sharpened image (d) deblurred image

CONCLUSION

An efficient method for image restoration is presented in our paper. Restoration is done by denoising followed by deblurring.In progressive denoising first, we perform a gradient descent by progressively estimating noise differentials and subtracting them iteratively from the noisy image. Second, the noise differentials are estimated using robust kernels in two spatial domains. Third, the kernel scale parameters are modified according to an annealing schedule.In deblurring process,by studying spectral properties of convolution operator, we have derived a convex regularizer on the blur kernel. For the blind deconvolution problem, this convex regularizer can deal with various types of blurs.

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