Improved Iterative Blind Image Deconvolution

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Abstract: The simple technique of iterative blind deconvolution of two convolved functions has been improved in this work. The proposed improvement imposes some new constraints to the iterative algorithm making the result more accurate and more visually appealing. The proposed scheme has also been equipped with a stopping criterion ensuring the convergence of the algorithm which was missing in the original work. As a result one need not look into the image produced after every iteration to decide the termination of the algorithm. Simulations indicate that the restored images of the proposed version of the scheme are more close to the true image.

Key–Words: Image restoration, blind image deconvolution, point spread function, motion blur

1 Introduction

Degradation of original image due to convolution is one of the frequently encountered problems in image processing. The convolution $g(x, y)$ of two functions, $f(x, y)$ and $h(x, y)$, can be written as

$$\begin{aligned} g(x,y) &= f(x,y) * h(x,y) \\ &= \sum_{m,n} f(m,n)h(x-m,y-n) \end{aligned} \quad (1)$$

where $f(x, y)$ is the true image and $h(x, y)$ is the linear-shift invariant blur known as point spread function (PSF) [1, 2, 3].

If $F(u, v)$, $H(u, v)$ and $G(u, v)$ are the Fourier Transform of $f(x, y)$, $h(x, y)$ and $g(x, y)$ respectively then the equation 1 can otherwise be expressed as

$$G(u,v) = F(u,v)H(u,v) \quad (2)$$

Deconvolution is performed for image restoration in many applications such as astronomical imaging, medical imaging and remote sensing. When one of the function $f(x, y)$ or $h(x, y)$ is known, the other function can be determined by inverse filtering or Winer filtering. In classical linear image restoration problem the PSF $h(x, y)$ is assumed to be known prior to the deconvolution process. To write in other words, when the blur function is known, the degradation process is inverted to get back the true image. However, in many practical situations the blur is often unknown, and little information is available about the original image [3, 4, 5].

Therefore, the image $f(x, y)$ must be identified directly from the convolved signal $g(x, y)$ using partial or no information about the blurring process and true image. Such an estimation problem, assuming the linear degradation model, is called blind deconvolution. Blind image restoration is the process of estimating both the true image and the blur from the degraded image characteristics using partial information about the imaging system. In this work one such image restoration technique has been improved for better and definite result.

Rest of the paper is organized as follows. The blur model is described in Section 2. The reported scheme for deconvolution is reviewed in Section 3. The proposed scheme is detailed in Section 4 followed by simulation results in Section 5. Finally, Section 6 provides the concluding remark.

2 Blur Model

Suppose that a scene to be recorded undergoes a planner motion relative to the sensor. Assume that the relative motion to be of uniform velocity v at an angle θ with the horizontal axis. If T is the duration of exposure, then the blur length is $L = vT$ and the motion blur PSF may be expressed as,

$$h(x,y) = \begin{cases} 1/L & \text{if } 0 \le |x| \le L\cos\theta; y = L\sin\theta \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

If the motion is along horizontal direction i.e. $\theta = 0$, the above equation may then be expressed as,

$$h(x,y) = \begin{cases} 1/L & \text{if } 0 \le |x| \le L; y = 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

3 Review of IBD

The iterative blind deconvolution (IBD) algorithm [5] iteratively estimates the original image as well as the PSF. IBD makes use of spatial domain as well as frequency domain constraints. In spatial domain, non negativity constraint is used on both image as well as PSF. Non negativity is used in spatial domain because image pixel intensity values are always positive. Similarly PSF values are observed to be always positive. The Fourier-domain constraint may be described as constraining the product of the Fourier spectra of $f(x, y)$ and $h(x, y)$ to be equal to the Fourier spectra of $g(x, y)$, in agreement with equation 2.

The basic deconvolution method consists of the following steps. First, a non-negative valued initial estimate of the PSF $h(x, y)$ is input into the iterative scheme. The size of the PSF must be known before starting the algorithm. However, the PSF values can be random numbers. Now $h(x, y)$ is Fourier transformed to yield $H(u, v)$, which is then inverted to form an inverse filter and multiplied by $G(u, v)$ to form the first estimate of the original image spectrum $F(u, v)$. This estimated Fourier spectrum is inverse transformed to obtained $f(x, y)$. The image domain constraint of non-negativity is now imposed by putting zero to all pixels of the image $f(x, y)$ that have a negative value. A positive constrained estimate $\hat{f}(x, y)$ is formed that is Fourier transformed to obtain the spectrum $\hat{F}(u, v)$. Now $G(u, v)$ is divided by $\hat{F}(u, v)$ to get the next spectrum estimate $H(u, v)$. A single iterative loop is completed by inverse Fourier transforming $H(u, v)$ to obtain $h(x, y)$ and by constraining this to be non-negative, yielding the next PSF estimate $\hat{h}(x, y)$. The iterative loop is repeated until a satisfactory restored image is obtained.

The calculations involved here are quite straight forward and simple. However, the output is not definite, the algorithm may run into infinite loop without converging. In order to get the approximation of the true image the initial estimate of the PSF should not vary much with the original PSF, which in itself is a difficult task to realize in practical situation. The proposed scheme, described in the next section, is an improvement upon the IBD.

4 Proposed Improvement

The drawbacks of the IBD are alleviated in the proposed scheme by imposing some more constraints. A convergence criterion has also been incorporated into the algorithm. The constraints used in the iterative deconvolution scheme are having substantial influence on the number of iterations required for the satisfactory restoration of the blurred image.

Support Support is the smallest rectangle which encompasses the image area in the original image. So the pixel values outside the support are considered as the background color. After every iteration, the pixel values outside the support are made equal to the background color.

Non-negativity Non-negativity constraint is applied on the image estimate and the PSF estimate. The negative values appearing in these estimates are replaced with zero. Also the sum of the PSF values is made equal to one after every iteration.

h_{min} The spatial domain value of the PSF is always made more than the threshold value.

$$h(x,y) = \begin{cases} h_{min} & \text{if } h(x,y) < h_{min} \\ h(x,y) & \text{otherwise} \end{cases} \tag{5}$$

F_{max} The upper limit of the frequency domain values of the image are always set to F_{max}.

$$F(u,v) = \begin{cases} F_{max} & \text{if } F(u,v) > F_{max} \\ F(u,v) & \text{otherwise} \end{cases} \tag{6}$$

f_{max} The upper limit of the spatial domain values of the image are fixed at f_{max}.

$$f(x,y) = \begin{cases} f_{max} & \text{if } f(x,y) > f_{max} \\ f(x,y) & \text{otherwise} \end{cases} \tag{7}$$

These constraints are found to be indispensable for approximating the true image from the degraded observations.

4.1 Algorithm

1. Get the initial PSF $h_0(x, y)$ with random values.

2. Find $\hat{H}_k(u, v)$ by taking Fourier transform of $h_k(x, y)$.

3. Compute $F_k(u, v)$ from $G(u, v)$ and $\hat{H}_k(u, v)$ as $F_k(u, v) = G(u, v)/\hat{H}_k(u, v)$.

4. Compute the inverse Fourier transform of $F_k(u, v)$ to obtain $f_k(x, y)$.

5. Impose the image constraint of non-negativity, support and f_{max} on $f_k(x, y)$ to obtain $\hat{f}_k(x, y)$.

6. Obtain $F_k(x, y)$ after Fourier transforming $\hat{f}_k(x, y)$.

7. Compute $H_k(u, v)$ from $G(u, v)$ and $\hat{F}_k(u, v)$ as $H_k(u, v) = G(u, v)/\hat{F}_k(u, v)$.

8. Compute the inverse Fourier transform of $H_k(u, v)$ to obtain $h_k(x, y)$.

9. Impose the h_{min} and PSF constraints on $h_k(x, y)$.

10. Compute power of the image for the k^{th} iteration as

$$\mathrm{P}_k = \sum_{x=1}^{M}\sum_{y=1}^{N} \hat{f}_k(x, y)^2 \tag{8}$$

11. Determine the standard deviation of power (σ) for the last s iterations. If the computed σ is less than a predetermined threshold value then stop the iteration otherwise repeat from step 2.

5 Simulation Results

The proposed improved version of the iterative blind image deconvolution (IIBID) is simulated along with the reported iterative blind deconvolution (IBD) scheme. Number of iterations required for convergence and the Peak Signal to Noise Ratio (9) are the two performance metrics considered for the comparison. Simulations are carried out in MATLAB 7 in Intel Core 2 duo, 2.13GHz machine.

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) dB \tag{9}$$

$$\mathrm{MSE} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(f(x, y) - \hat{f}(x, y)\right)^2 \tag{10}$$

where, MN is the size of the image, and $f(x, y)$ and $\hat{f}(x, y)$ represent the pixel values at $(x, y)^{th}$ location of original and restored image respectively. Two different binary images are blurred and restored with both the IBD and the IIBID. The results are shown in figures 1 and 2.

6 Conclusions

The improved iterative blind image deconvolution is an improvement of the classic iterative blind deconvolution scheme. The proposed scheme is incorporated with some more constraints to get a good restored image in reasonable amount of time. The scheme works very well for binary images, more suitable for astronomical imaging where images are obtained from a dark background. The improvement in the restored image quality is also substantial when compared with the earlier version.

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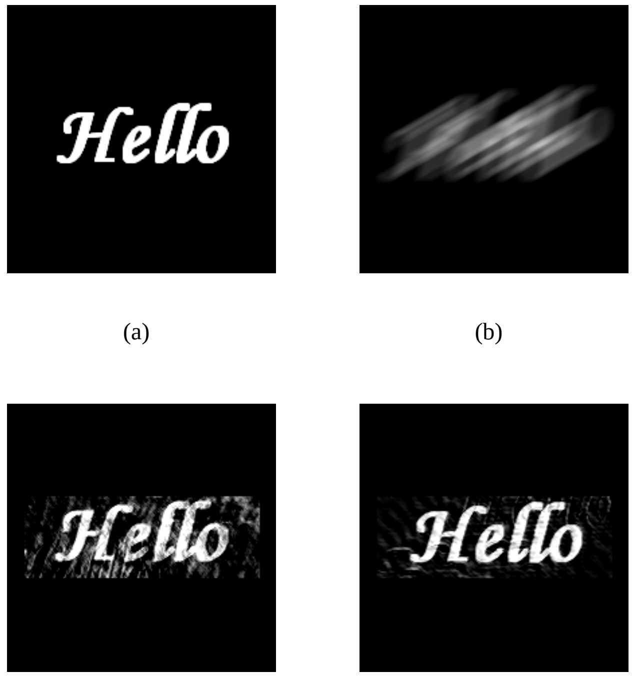
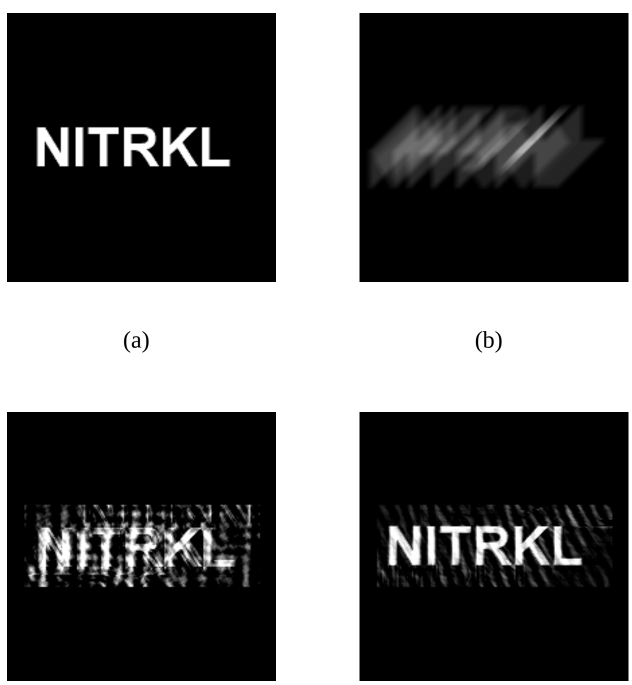


(a) (b)

(c) (d)

Figure 1: Restoration of *Hello* image. (a) True image, (b) Motion Blurred with $L = 60$, $\theta = 30$, (c) Restored with IBD in 126 iterations (PSNR=17.13dB), (d) Restored with IIBID in 50 iterations (PSNR=20.57dB)



(a) (b)

(c) (d)

Figure 2: Restoration of *NIT RKL* image. (a) True image, (b) Motion Blurred with $L = 50$, $\theta = 45$, (c) Restored with IBD in 638 iterations (PSNR=13.23dB), (d) Restored with IIBID in 206 iterations (PSNR=22.88dB)