An Efficient Natural Image Deblurring Algorithm

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Abstract. This paper has considered the problem of deblurring of an image which is an ill-posed and challenging problem due to not only the large number of unknowns but also non-availability of more number of images of the same scene or objects. It uses the Variational Bayesian approach to optimize the posterior probability and to derive the most probable Point Spread Function (PSF). Lucy Richardson algorithm [1] has been modified to get the deblurred image. The algorithm is found to be very effective for natural images.

Keywords: Deblurring, Point Spread Function, Variational Bayesian, Signal to Noise Ratio.

1 Introduction

Relative motion between camera and the subject is a primary reason for blurring in an image. It can take convoluted paths and thus making the restoration more complex. Restoring of blurred image involves two components, namely, identification of blur and restoration of image using the blurring parameters. To restore a blurred image successfully, blurring function, referred to as Point Spread Function (PSF), needs to be estimated accurately. PSF is the response of an imaging system to a point source or it can be said as the impulse response of a focused optical system. It is non-parametric and spatially varying.

Deblurring is an ill-posed problem because of the number of unknown parameters is more than the available parameters. Attempts have been made to address the problem of blind deconvolution for deblurring of a natural image. Recent algorithms have achieved dramatic progress. However, there exist many aspects of the problem which are still challenging and hard to solve. Lokhande et. al. [2] have worked on identification of motion blur parameters using frequency domain analysis and have tried to reconstruct the PSF using the length and angle information. It may fail to perform well for natural images because the algorithm assumes PSF to be perfectly box (linear) which is not the case in many natural images. The algorithm also does not cater for varying noise levels. Joshi et.al. [3] have tried to estimate the PSF using

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sharp edge prediction. They have tried to predict the ideal edge by finding the local maximum and minimum pixel intensities. It does not perform well for larger blurs. Levin et.al. [4] have proposed an algorithm to deblur a blurred image using image statistics. They have shown that the direction of motion blur is the direction with minimal derivative variation and the value which gives the maximum likelihood of the derivatives is the blur length. It gives good results only for box kernels which are the characteristics of perfect motion blurs. Blurs may not be always motion blurs and most of the motion blurs do not have perfect box PSF. Fergus et. al.[5] have approached the problem using a Variational Bayesian approach for PSF estimation. Shan et. al.[6] have used a semi maximum a-posteriori (MAP) algorithm which is used to get a point estimate of the unknown quantity based on empirical data. They have used a Gaussian prior for natural image and edge reweighting and iterative likelihood update for approximation of latent image. It does not perform well for all images which are sparse or a bit away from Gaussian. Yuan et.al. [7] have used two sets of images (one blurry and one noisy) to recover the original image. A comprehensive literature review to approach a deconvolution problem can be found in [8]. Miskin and Mackay [9] have used ensemble learning algorithm to extract hidden images from a given image. They have used Variational Bayesian approach to do ensemble learning.

2 General Blur Model

There are two types of deblurring approaches namely, non-blind deblurring and blind deblurring. In non-blind deblurring, knowledge of the Point Spread function (PSF) is available which is not the case with blurred deblurring. Let *F, H* and *N* be the true image, the point spread function (PSF) and the additive random noise respectively. Then the measured image *G* is given by

$$G = F * H + N \tag{1}$$

That means, for each pixel (x,y), the intensity value of the measured image *G* can be computed by

$$g(x, y) = f(x,y) * h(x,y) + n(x,y) \tag{2}$$

$$= \sum_{m=0}^{m-1} \sum_{n=0}^{n-1} f(x,y)h(x-m, y-n) + n(x,y) \tag{3}$$

where * is convolution operation.
If one considers frequency domain, then one gets

$$G(u,v) = F(u,v)H(u,v) + N(u,v) \tag{4}$$

where parameters on the right hand side of Equation (4) are unknown. For a perfect motion blur, parameters to be considered are the length and the direction of blur. In this case if it is assumed that there is no noise, it is easy to reconstruct the PSF using the length and the angle parameters and to do a non-blind deblur operation. Some of the typical PSFs are shown in Figure 1. There are four different types of Point Spread Functions, namely Motion Blur, out of Focus Blur, Gaussian Blur and Scatter Blur that are very basic and generic in nature. Out of those four, two functions belong to the category of sharp edged PSFs and remaining two belong to the category of smooth edged PSFs. These PSF models are in time domain.

3 Proposed Algorithm

Lokhande et. al [2] have used frequency domain to estimate the blurring parameters such as length and angle. It uses the spectrum of an image to analyze the blur and considers hough transform to determine the blurring angle. But spectrum of an image does not remove all noise and displays lines which do not represent the blur direction in the image. Further, hough transform does not perform well in such a case and is computationally intensive. If we use the cepstrum of the image instead of spectrum and consider radon transforms instead of hough transforms, computation becomes easy and we get better estimates of blurring angle. The binary cepstrum image is rotated by the estimated angle and average of each column is taken. The distance between the zero-crossings represents the inverse of the length parameter. The algorithm is as follows:

Algorithm Blurring-Parameters

Convert the image to grayscale
Calculate Log and square of the image
Calculate Inverse Fast Fourier Transform to get the cepstrum.
Convert to binary
Apply radon transform for various angles
Find the angle at which the radon transform value is maximum to get blurring angle
Calculate average along each column
Find the distance between the zero crossings to get the periodicity to get blurring length

Using parameters like blurring length and angle, the PSF can be constructed and the latent image can be reconstructed using any well known deconvolution algorithm such as Wiener Filter which is computationally less expensive. Approximating the correct value of Noise to Signal Ratio dictates the quality of the output of the Wiener Filter. We have approximated Noise to Signal Ratio (NSR) as follows:-

$$\text{NSR}= \frac{1}{20\log_{10}\frac{A-B}{\sigma}} \tag{5}$$

where A, B and σ are the maximum, the minimum and the standard deviation of the intensities of the image.

This algorithm works well for synthetically generated blurs but fails for natural blurs. The main reason for this is the fact that most of the natural blurs are not perfect motion blurs which have an angle and length. These blurs are either out of focus blurs or non-linear motion blurs due to camera shake, or random blurs. The biggest challenge is to know the type of blur and then decide the method of finding the PSF which has random shape.

This section proposes an efficient blind deconvolution algorithm which can be used to deblur any natural image without the knowledge of the PSF. It consists of 3 major steps and they are (i) selection of region of interest, (ii) PSF estimation, and (iii) generation of deblured image.

3.1 Region of Interest Selection

Any blurred image *I* can be either colour or grayscale. In order to reduce the computational cost, the image *I* is converted to grayscale. However, the colour information is retained so that the same can be regenerated to obtain the deblurred coloured image. An inverse gamma correction is done to the image during pre-processing. We use a gamma value of 2.2, which is decided empirically.

Since processing of the whole image is computationally intensive, only a specific patch of the image is considered for deblurring. Let the gray scale blurred patch of the image *I* be *G*. One should be careful while selecting the patch region so that it does not contain any saturated region because this type of area does not any gradient variation. Gradients of an image are considered to represent better change of patterns than image intensities. Gradients in horizontal and vertical directions are calculated and concatenated to get the gradient matrix inverted *triangle G*.

$$\nabla G = \left[\nabla G_x, \nabla G_y\right] \tag{6}$$

One can use simple gradient kernel [1 -1] and [-1 1] for horizontal and vertical gradients respectively.

3.2 PSF Estimation

The Point Spread Function (PSF) (*H*) is initialized to a 3X3 matrix which is selected according to the selection of vertical or horizontal directions. The value of *H* for horizontal direction is

$$\begin{pmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

and for vertical direction is

$$\begin{pmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

The extent of processing depends on the size of the PSF which is initialized to an approximate value Ø. The estimation of PSF is done on a coarse to fine manner by varying the image resolution (at the coarsest scale *H* is 3X3). The number of iterations is decided by the scale *S* which is given by

$$S = -2 \log_2 \left(\frac{3}{\phi} \right) \tag{7}$$

where Ø is the approximate size of the PSF. The initial estimate of the latent image is obtained by variational bayesian inference algorithm [9] having fixed *H.* The inference is done at each scale to find out converged values of *H* and *S.* These converged values act as the initial values of the next inference at next scale. At the finest scale, the full resolution Kernel is achieved. Minor inaccuracies or noise in the estimated PSF can affect the output. The algorithm uses a threshold for the PSF so that it is refined and noisy values are suppressed to zero.

$$Threshold = \frac{C}{15} \tag{8}$$

where *C* is the maximum intensity value of *H.*

3.3 Recovering Latent Image

A smoothing function is applied to the sharp edges of the image to reduce sharp the ringing artifacts. The non-blind accelerated damped Lucy-Richardson Algorithm is used to deblur the whole image using the estimated Point Spread Function (PSF). The number of iterations to be used in the Lucy Richardson algorithm [1] depends on the extent of blur. Higher the extent of blur, larger is the number of iterations. A default value of 10 has been used in this algorithm. Gamma correction is applied to the image to revert the inverse-gamma applied earlier. Histogram equalisation of the recovered image is done to match with the original image. The recovered image is a colour image in case the input image is coloured. The algorithm is given below.

Algorithm Deblurring

Convert image to grayscale

Perform inverse gamma correction to image, γ=2.2

Select ROI

Compute horizontal gradients⟦∇G⟧_x and vertical gradients⟦ ∇G⟧_y

Concatenate gradients[⟦∇G⟧_x⟦∇G⟧_y]

Compute number of scales S

Loop over scales starting with coarsest to fine

Rescale gradients

Compute initial estimate of latent image F using variational bayesian inference holding H fixed.

Rescale estimated F and H from previous scale

Modify latent image and PSF using variational bayesian inference

Threshold PSF

Edge smoothening of G to reduce ringing artifact

Apply accelerated damped Lucy Richardson Algorithm to deblur

Perform gamma correction to the recovered image, γ=2.2

Do histogram equalisation to get the original colour values.

4 Experimental Results

To test the performance of the proposed algorithm, we have considered 7 blurred images and they are Car1, Car 2, Bike, Gate, Peacock, Ground and Face. To verify the correctness of the proposed algorithm, we have synthetically blurred the images. Results are shown in Figure 1 - Figure 4. Although the quality of the image as whole has not improved much, it can be clearly seen that information like the number plate of the vehicle, name written on the gate, the title written on the erected board and the peacock's feathers are available of the recovered image.

Fig. 1. Blurred Images of Number Plates with their Respective Deblurred Images

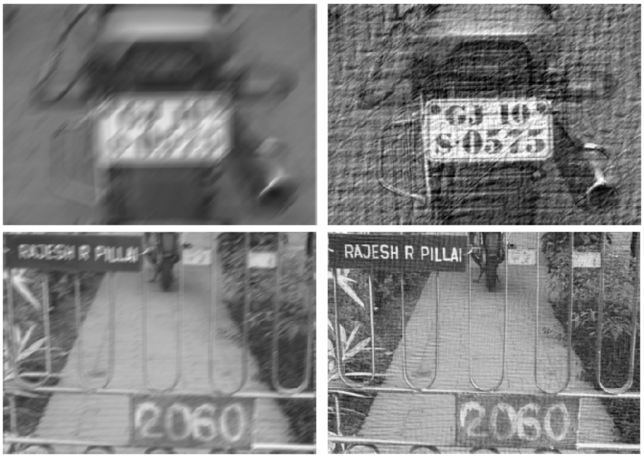

Fig. 2. Blurred Images of Number Plates and Gate with their Respective Deblurred Images

Fig. 3. Blurred Images of Ground, Face with their Respective Deblurred Images

Fig. 4. Blurred Image of Peacock with its Deblurred Image

5 Conclusion

This paper has proposed an efficient algorithm to deblur a natural image. However it has made the assumption of uniform blur throughout the image. It has used the Variational Bayesian approach to find the most probable Point Spread Function. A modified Lucy Richardson algorithm is used to perform the deconvolution to get the deblurred image. It has been tested on several sets of blurred natural images and found that the algorithm could deblur the images effectively.

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