An Improved Blind Deconvolution for Restoration of Blurred Images Using Ringing Removal Processing

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Abstract One of the most difficult challenges in image processing is restoring a defocused image by reducing blur and noise. Blurring characterizes image deterioration, and recovery is accomplished by point spread function estimation and ideal image estimation processing was repeated. Ringing, or wavelike artifacts that arise along strong edges, is a difficult challenge in latent image restoration. Therefore, this paper will introduce an improved blind deconvolution for restoring blurry images using ringing removal process. This paper provides an improved deconvolution technique that uses blur kernel prediction based on dark channels before achieving clear image recovery. To hold picture information and beautify the rims of the ringing impact created at some point of the authentic clean picture recuperation process, an easy bilateral clear out is used. The ringing removal method L_0 regularization is used with the restoration process, which can estimate a sharper image. By removing the difference map from the final deconvolution result, it is possible to get a clearer

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picture without ringing. Finally, the results are presented in terms of performance parameters such as signal-to-noise ratio (SNR), mean squared error (MSE), and peak signal-to-noise ratio (PSNR).The results show that the performance parameters of the improved blind deconvolution model are superior compared to existing image blur removal algorithms.

Keywords Blur image · Blind deconvolution · Ringing effect · Bilateral filter · Kernel estimation

1 Introduction

Digital photographs are utilized in a lot of fields, together with medical, military, transportation, microscopy imaging, and images deblurring, among others. The recorded picture is a noise and blurred model of the unique picture. Images are affected by blurring and noise in various areas of applied science.

Blurring is a problem created by an imaging system (caused, for example, by diffraction, aberrations, etc.), whereas noise is a part of the detecting process. As a result, picture deconvolution is essentially a post-processing of the recognized image with the target of decreasing blur and noise.

Convolution, which is frequently associated with the band-limited nature of acquisition technology, and contamination by additive Gaussian noise, which may be attributable to the electronics of the recording and transmission processes, is well-known sources of signal/image degradation in many practical situations. For example, the blur effect in remote sensing images is caused by the limited aperture of satellite cameras, optical system, and mechanical vibrations. A blurred image is created by convolution a sharp image with a blur kernel or point spread function (PSF). To get the crisp image, first extract the blur kernel from the sharp image. On the other hand, the problem is estimation of the blur kernel. Deconvolution is the estimation of an unknown blur kernel.

These concepts are used by the majority of deblurring techniques. A data restoration process is frequently required before any further processing to remove these artifacts. Many papers have been written on the deconvolution of noisy signals [1]. Inverse problems related to practical interest are often badly encountered so it is difficult to devise appropriate deconvolution methods. Deconvolution techniques are a computationally intensive image processing technique that is widely used to improve digital image contrast and resolution [2]. The basis of deconvolution is mainly designed using a set of methods to remove blurring of an image. Therefore, the deconvolution method is often recommended as a good choice to reduce the effects of visual blurring of captured images. In addition, image processing using a resolution technique offers an advantage in cases where images are captured using a pin hole aperture [3].

2 Literature Survey

Various works have been done on deblurring algorithms on different platforms and with different assumptions. Some related works are discussed below. Satoshi Motohashi [4] was responsible for the gradient reliability map (Rmap). This paper describes the implementation of a new algorithm based on a two-step blind deployment process. The latent image recovery phase employs an overall variation sort and a bump filter to reduce texture components and noise while improving edges. After that, the gradient reliability map is used to reduce the margins, which has a significant impact on the PSF rating. In this paper, the author [5] uses the frequency domain for image analysis because of the convenience of transforming the blur model between the spatial domain and the transmission domain. They first applied a Butterworth bandpass filter to the image to avoid signal noise. They use layer-specific data as an image before getting better results. To generate the latent image, this algorithm selects the true values of the frequency components from the training image. The latent image is built by combining the bandpass components of the training image. As a result, this technique provides high image accuracy while also dealing with blurred images lacking high-frequency detail. Although is algorithm has a limitation that it can only blur images containing only single objects, in practice that is assumed for a week.

In this paper, author [6] uses patch-based image priorities learned from a set of clean images in a particular class. Use a weak blur precursor to restore the various filters. Use a denoiser based on a Gaussian Mixed model (GMM). The proposed method is also incorporated into the alternating direction method of multipliers (ADMM) optimization algorithm for estimating both images and blur filters. This algorithm has several advantages which can process noisy text images and can be used for various blur filters. This algorithm also has limitations on the internal ADMM algorithm and the setting of regularization parameters and stop criteria for external iterations.

The author [7] proposes a new image based on elastic net regularization of singular values computed from similar image sections in this paper. They altered the algorithm to account for non-uniform blurring. The deblurring model is built on the missed approach point (MAP) framework. To choose the leading edge, the proposed method does not require a sophisticated filtering strategy. After finding the blur kernel, a set of non-blind deconvolution methods based on iteratively reweighted least squares (IRLS) can be used to estimate the latent picture. If the image has rich textures and are located in most regions of this rich texture, this method will fail. Yang et al. [8] proposed a novel blind deblurring algorithm for predicting the blur kernel. In a clear image, the color distribution of the edges is more distinct than in a blurred image. Filters are recommended to clear the edges of blurred image which is used as a reference image.

Marapareddy [9] worked on Wiener filtering to restore blurred images that were degraded due to complex environments. First, determine the pattern of atmospheric turbulence degradation. After applying the inverted filtering and the minimum average square error, i.e., the wiener filtering, the blurry images are restored. Some authors have considered ringing issues and sought to minimize deconvolution scheme artifacts. Liu et al. [10] invented the ring detection method design and build the pyramid at various scales of the restored image and compute the gradient difference between each level of the pyramid. Such artificial ringing detectors can only be used to assign the quality of blurry images. It is not directly involved in efforts to produce blurry images free of artifacts. The original ringing artifacts are eliminated by applying a residual multi-scale deconvolution approach to the edge-preserving bilateral filter and the traditional reinforcement learning (RL) algorithm.

3 Improved Blind Deconvolution Using Ringing Removal Processing

This paper gives a stepped forward blind blur elimination set of rules primarily based totally on darkish channels, in addition to a bilateral clear out shared with the unique set of rules, to eliminate ringing and generate a blur removal image. For example, ringing is effective in suppressing deterioration for the gradient's prior probability. As a result, only gradient information is used to estimate ideal images. This method compares the previously estimated ideal image with the image obtained using gradient information and a two-sided filter. The following Fig. 1 shows steps used for improved blind deconvolution using ringing removal process.

3.1 Image Blind Deblurring

The pixels of the remote sensing pictures are uniformly blurred due to the jitter and blur of the distant sensor. This is known as the mathematically clear picture and the blur kernel noise convolution. It can be expressed as:

$$b = k * x + n \tag{1}$$

where b denotes a blurred image, x denotes a sharpened image, k denotes a blur kernel, and n denotes noise. The blind image cloning algorithm works in two steps. The first step is to evaluate the blur kernel, followed by image decoding to produce a clearer image.

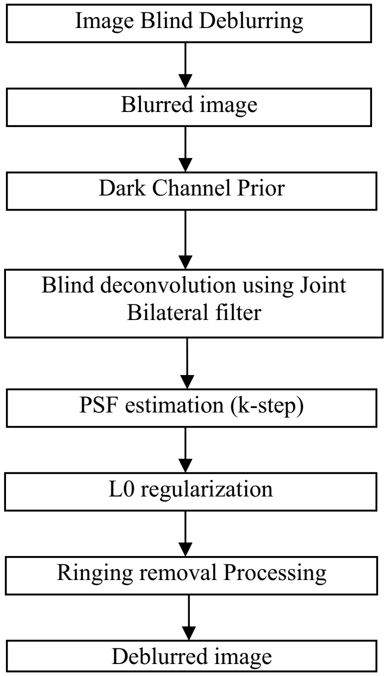

Fig. 1 Steps used for improved blind deconvolution using ringing removal process

3.2 Dark Channel Prior

The dark channels of a fog-free outdoor image have almost zero pixels, and the dark channels were previously applied to the image defog problem. Intuitively, the blurring process replaces the pixel values of very dark pixels with the weighted average of other bright pixels nearby, increasing the size of the very dark pixels. As a result, dark channel preferences can be used to enhance the dark channels potential for sharper images. The dark channel in image is defined as:

$$D(I)(X) = \min_{y \in N(x)} \left\{ \min_{c \in N(x)} I_C(y) \right. \tag{2}$$

If x and y are pixel positions, then $N(x)$ is the x-centered image point and I_C is the cth color channel. The dark channel solution will compute the smallest red, green, and blue (RGB) component per pixel, save it in the same grayscale image as the original image, and then scale it using Eq. (2).The size of the pop-up area determines the filter radius in the value filter.

3.3 Blind Deconvolution Using Joint Bilateral Filter

Blind deconvolution of a blurred image means deconvolution of the image without prior knowledge of the blur kernel and white Gaussian noise. The cost functions associated with sharp images and blur kernels must be determined by the deconvolution method. The bilateral filter is an advanced version of the Gaussian filter. Bilateral filters are edge-preserving filters with weights determined by the spatial region and range smoothing function. However, this method has its drawbacks due to the blurred edges. The weight of this bilateral clear out is unstable, and inversion happens close to the edges. General bilateral filtering, which is based on bilateral filters, was introduced to preserve image details while improving image edge functionality. In contrast to bilateral filtering, the values of a typical bilateral filter are calculated based on the input image rather than the improved image. The guide image refers to the image that serves as the filter's guide information.

$$\mathrm{JBF}[I, D]_m = \frac{1}{k_p} \sum_{n=\Omega(x)} I_n f(\|m - n\|) g(\|D_m - D_n\|) \tag{3}$$

F represents the spatial filter, g represents the distance filter, I represents the input image, D represents the guide image, Ω represents the spatial support of kernel f, and k_p represents the normalization coefficient.

3.4 PSF Estimation

The problem of blind image recovery can be divided into two parts: Calculating the PSF from the degraded **image** (k-step) and **the best image** from the PSF (x-step). A different method is used to repair the damaged image. This blind image reconstruction process employs a deconvolution based fast reconstruction method. By regularizing overall variation, X-step reduces the effects of noise and improves edges with shock filters and ideal images. Also, Rmap only the strong edge component remains in the k-step. The process is then repeated in a series of PSF calculations using the estimated ideal image's derivative thresholding and the conjugate gradient method. The PSF obtained from the iteration is used for the final deconvolution. For error detection and prevention, the power value is calculated (4). As this value increases, the estimated PSF threshold changes. When the objective function converges and the energy value decreases, the reconstruction is successful.

$$e = \frac{|b - x \times k|^2}{\omega \times h} \tag{4}$$

where $x \times k$ is the estimated blurred image and w and h are the horizontal and vertical pixel counts of an image.

3.5 Ringing Removal Processing

The regularized probability L_0 of the image is used in this method to remove blur. Based on the prior probabilities of the pixel values and the prior probability of the regular pixel value, L_0 calculates the image's pre-probability $P(x)$ (5).

$$P(x) = \sigma P_t(x) + P_t(\nabla x) \tag{5}$$

$P_t(x)$ represents the previous probability of the pixel value and $P_t(\nabla x)$ represents the gradient's previous probability. Prior probabilities for gradients can help you control deterioration like ringing. As a result, while reducing ringing, set to $\sigma = 0$ and estimate the ideal image represented by using only the gradient information (6).

$$x = \mathcal{F}^{-1}\left(\frac{\overline{\mathcal{F}(k)}\mathcal{F}(b) + \beta\mathcal{F}(u) + \mu\mathcal{F}_{\mathrm{G}}}{\overline{\mathcal{F}(k)} + \beta + \mu\overline{\mathcal{F}(\nabla)}\mathcal{F}(\nabla)}\right) \tag{6}$$

where u, β, and μ denote auxiliary variables, and $\mathcal{F}(\bullet)$ and $\mathcal{F}^{-1}(\bullet)$ are fast Fourier transform (FFT) and inverse FFT, respectively. $\overline{\mathcal{F}(\bullet)}$ denotes a complex conjugate operator which is expressed by FG (7).

$$\mathcal{F}_G = \overline{\mathcal{F}(\nabla_h)}\mathcal{F}(g_h) + \overline{\mathcal{F}(\nabla_u)}\mathcal{F}(g_u) \tag{7}$$

In (5), ∇_h and ∇_u are horizontal and vertical component operators, and g is a gradient auxiliary variable.

4 Results

The images were evaluated objectively for signal-to-noise ratio (SNR), mean squared error (MSE), and peak signal-to-noise ratio (PSNR). SNR is a simple metric used to assess the effectiveness of noise reduction techniques. Higher signal-to-noise ratios are regarded as a sign of effective noise reduction. The SNR is given as

$$\mathrm{SNR(dB)} = 20\log\frac{\text{RMS signal}}{\text{RMS Noise}} \tag{8}$$

MSE is a metric used to assess denoising accuracy. Lower MSE values indicate that the noise reduction signal is more similar to the original signal. This is thought to result in better noise reduction. The MSE is given as

$$\mathrm{MSE(dB)} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[1(i-j) - k(i-j)]^2 \tag{9}$$

PSNR is a metric similar to SNR, with higher values indicating more accurate noise reduction. The PSNR is given as,

$$\mathrm{PSNR(dB)} = 10\log_{10}\frac{\max j^2}{\mathrm{MSE}} \tag{10}$$

The results of objective evaluation are presented in Figs. 2 and 3. It shows the SNR and PSNR analysis of image at different steps of improved blind decovolution in Fig. 2. If it can be seen that the SNR has PSNR which has high values at after blind deconvolution compared to the stages at known PSF and in out blur image.

Figure 3 shows the MSE analysis of image at different steps of improved blind decovolution. It can be seen that the MSE has lower values at after blind deconvolution compared to the stages at known PSF and in out blur image.

Here, the performance of the image ringing removal scheme is evaluated. A series of blurry images was used for this purpose. Blurred images and their point spread function (PSF) pairs are used. An image containing motion blur (handshake) was captured by the camera. The PSF of the image was estimated using the blind deconvolution approach. Blurred images were deblurred by applying an improved blind deconvolution using a ringing removal process. The deblurring results are shown in

Fig. 2 Analysis of SNR and PSNR of image at different steps

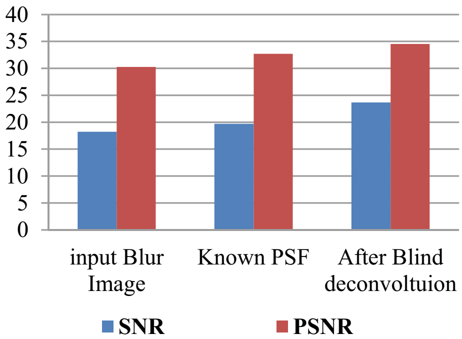

Fig. 3 MSE analysis of image at different steps

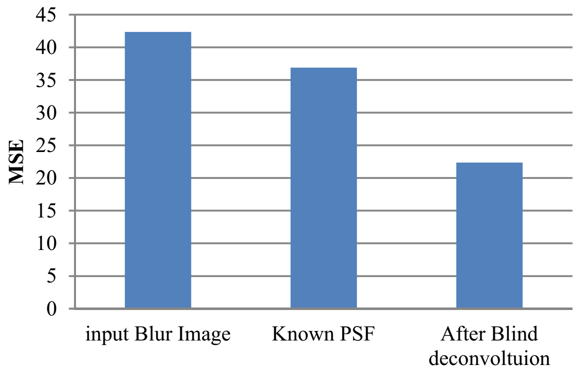

Fig. 4a–c. Input parameters for the deblurring algorithm such as rule weights and smoothing factors are chosen in such a way that they do not produce overly sensitive and cartoonish results. The deconvolution scheme, as seen in these figures, produces ringing artifacts, as shown in Fig. 4a.

To identify the artifacts generated during the deconvolution stage, the blurred image was subjected to a ringing removal process. It is used a filter to remove the ringing artifacts. The Gaussian parameters were determined during the ringing detection step. Because of the symmetry of the PSF Fourier transform, half of the detected minimum points are ignored. This cuts down on the number of filters needed during detection. Figure 4b illustrates the ringing artifact detection results. For example, the marked ring mask is superimposed on a yellow-colored blurred image. The algorithm identifies almost all ringing areas in the blurred image. Blind deconvolution was used to estimate the PSF used in the image deblurring process.

(a) DEBLURRING IMAGE AFTER DECONVOLUTION

(b) DETECTED RINGING REGIONS

(c) IMAGE AFTER RINGING REMOVAL

Fig. 4 Image deconvolution with ringing removal effect

5 Conclusion

This paper implemented an improved dark channel before image blur method with blind deconvolution and restored the image with a ringing removal process that targets the ringing effect of the image blur. Use common bilateral filtering during restoration to reduce ringing of the restored image, save edges more effectively, and enhance the image restoration effect. The signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), and mean squared error (MSE) of the performance parameters are calculated and graphically displayed. According to simulation results, when compared to non-blind deconvolution, the maximum signal-to-noise ratio and noise-to-signal ratio are higher, indicating that the signal information is higher, and the mean squared error is lower, indicating a lower amount of error. According to experimental results, this algorithm effectively eliminates motion blur in an image. The results obtained with this method show that the blind deconvolution method is superior. The simulation results show that the blind deconvolution technique performs better when reconstructing an image from an out-of-focus image.

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