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Research Article

Blind Image Restoration Based on Signal-to-Noise Ratio and Gaussian Point Spread Function Estimation

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Abstract: In order to improve the quality of restored image, a blind image restoration algorithm is proposed, in which both the Signal-to-Noise Ratio (SNR) and the Gaussian Point Spread Function (PSF) of the degraded image are estimated. Firstly, the SNR of the degraded image is estimated through local deviation method. Secondly, the PSF of the degraded image is estimated through error-parameter method. Thirdly, Utilizing the estimated SNR and PSF, high resolution image is restored through Wiener filtering restoration algorithm. Experimental results show that the quality and peak signal-to-noise of the restored image are better around the real value and justify the fact that the SNR an-d PSF estimation plays great important part in blind image restoration.

Keywords: Blind image restoration, point spread function, signal-to-noise ration, wiener filtering

INTRODUCTION

High resolution images are often required in many areas such as medical imaging, military, remote sensing, etc. Image restoration algorithms are researched to reconstruct high resolution image from a degraded low resolution image.

In most of the current image restoration algorithms, the Point Spread Function (PSF) of the imaging system is often assumed to be a PSF with given parameters. It doesn't meet the real imaging process and the quality of the restored image is restricted. Blind image restoration problem arises naturally and is expressed as estimate the high resolution image and the PSF of the imaging system simultaneously (Yan, 2001). In image processing area, blind image restoration has always been a challenge and hot discussed problem (Lopez-Martinez and Kober, 2011; Marrugo, 2011; Luo and Fu, 2011; Seghouane, 2011; Giannoula, 2011).

Wiener filtering is broadly applied in signal and image processing. Practical experience shows that it is a deconvolution technique with good restoration effect and small amount of calculation. If the image and the noise are assumed to be generalized stationary process, image may be restored through Wiener filter.

When the Discrete Fourier Transform (DFT) method is used to estimate the restored image, the Wiener filter the Wiener filter is usually approximated by the following formula:

$$X = \frac{H^* Y}{|H|^2 + \Gamma} \tag{1}$$

where,

X : The DFT of the real image (x)
Y : The blurred image (y)
H : The point spread function (h)
* : The conjugate operation
Γ : A positive constant

The best value of Γ is the reciprocal of the Signal-to-Noise Ratio (SNR) of the observed image.

In most Wiener Filtering algorithms, the PSF (H) is commonly assumed to be known previously and the parameter Γ is often taken as an experience value. In this study, the PSF and SNR are estimated and their importance in the quality of restored image is justified through experimental results.

In this study, a blind image restoration method is proposed. The SNR and the PSF are estimated simultaneously with high accuracy. By experiments, the effects of SNR estimation and the Gaussian PSF estimation in image restoration are tested. The experimental results show that the quality of the restored images is better around the real SNR and PSF.

SNR ESTIMATION METHOD

The estimated Signal-to-Noise Ratio (SNR) may be a reference to select the regularized parameters in the Wiener filtering restoration algorithm. The SNR of a blurred image is usually defined as follows:

$$SNR = 10\log_{10}(\delta_x^2 / \delta_n^2) \tag{2}$$

where,
δ^2_x = The variance of the blurred image
δ^2_n = The variance of the noise

The local variances between the flat region and the edge are different from each other in an image. Places with large local variance shows that there are many detail information and places with small local variance means that it is relatively flat in this region. If the quality of the observed image is good (for example, the SNR is above 30 dB), it is reasonable to take the region with the maximum local variance as the edge and to take the area with the minimum local variance as the flat region (Yan, 2001). Thus, the variance of the image (δ^2_x) is taken as the maximum local variance and the variance of the noise (δ^2_n) is approximated as the minimum local variance. The local variance of the observed image (*y*) at position (*i*, *j*) is defined as follows:

$$\delta^2_{yL}(i,j) = \frac{1}{(2p+1)(2q+1)} \sum_{k=-p}^{p} \sum_{l=-q}^{q} [y(i+k, j+l) - \mu_y(i,j)]^2 \quad (3)$$

where,

p & *q* : The sizes of the local area

μ_y : The local mean value which is defined as follows:

$$\mu_y = \frac{1}{(2p+1)(2q+1)} \sum_{k=-p}^{p} \sum_{l=-q}^{q} y(i+k, j+l) \quad (4)$$

Generally, the local variance is taken as $p = q = 2$ and the template may be expressed as:

$$c = \frac{1}{(2p+1)(2q+1)} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (5)$$

So, the local mean value may be denoted as:

$$\begin{aligned} \mu_y &= \frac{1}{(2p+1)(2q+1)} \sum_{k=-p}^{p} \sum_{l=-q}^{q} y(i+k, j+l) \\ &= \sum_{k=-p}^{p} \sum_{l=-q}^{q} y(i+k, j+l) \cdot c(k,l) = y * c \end{aligned} \quad (6)$$

where, $*$ denotes the convolution operation. The local variance may be written as:

$$\begin{aligned} \delta^2_{yL}(i,j) &= \frac{1}{(2p+1)(2q+1)} \sum_{k=-p}^{p} \sum_{l=-q}^{q} [y(i+k, j+l) - \mu_y(i,j)]^2 \\ &= \sum_{k=-p}^{p} \sum_{l=-q}^{q} \{[y(i+k, j+l) - \mu_y(i,j)]^2 c[k,l]\} \\ &= (y - \mu_y)^2 * c \end{aligned} \quad (7)$$

Thus, the SNR of image *y* may be estimated as the ratio of the maximum local variance and the minimum local variance, namely:

$$SNR = 10\log_{10}(\max(\delta^2_{yL}) / \min(\delta^2_{yL})) \quad (8)$$

GAUSSIAN PSF ESTIMATION

Gaussian PSF is the most common blur function in many optical measurements and imaging systems. Generally, the Gaussian PSF may be expressed as follows:

$$h(m,n) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma} \exp\{-\frac{1}{2\sigma^2}(m^2+n^2)\} & (m,n) \in R \\ 0 & \text{ot her s} \end{cases} \quad (9)$$

where,

σ = The standard deviation

R = A supporting region

Commonly, R = denoted by a matrix with size of *K*×*K* and K = often an odd number.

From the mathematical description of Gaussian PSF, 2 parameters need to be identified for the Gaussian PSF, namely, the size (*K*) and the standard deviation (σ).

Given a size K of the Gaussian PSF, one error-parameter curve is generated at different standard deviation (σ). In the case of different sizes of the Gaussian PSF, multiple curves will be generated. By analyzing the relationship between these curves, the real size and standard deviation can be estimated approximately (Yan, 2001).

According to these curves, the criteria to estimate the parameters of the Gaussian PSF is as below: the size where the distance between the curves decreases evidently is assumed to be the estimated size and the standard deviation where the corresponding curve increases obviously is assumed to be the estimated standard deviation.

In order to estimate the parameters of Gaussian PSF automatically, 2 thresholds T_1 and T_2 are set. Firstly, given an estimation error e, the curve where once the distance between curves is smaller than T_1 gives out the estimated size ($\hat{K}$) of the Gaussian PSF. The distance is defined as the absolute difference of the cycle number (*j*) of standard deviation at e. Then, by calculating the slop of the estimation error at different standard deviations on the estimated curve, the deviation value can be estimated. The deviation once the slop is greater than the threshold T_2 is the estimated deviation ($\hat{\sigma}$).

EXPERIMENTAL RESULTS

Simulated images: In order to test the effectiveness of our algorithm objectively and subjectively, experiments are performed on simulated low resolution image.

The original high resolution image is taken as a standard image 'lena.bmp' of size 256×256, which is shown in Fig. 1. The original image is passed through a imaging model to simulate a low resolution image. Firstly, the original image is convolved with a Gaussian PSF to simulate the blurring process.

Fig. 1: The original high resolution image

Fig. 2: The simulated low resolution image

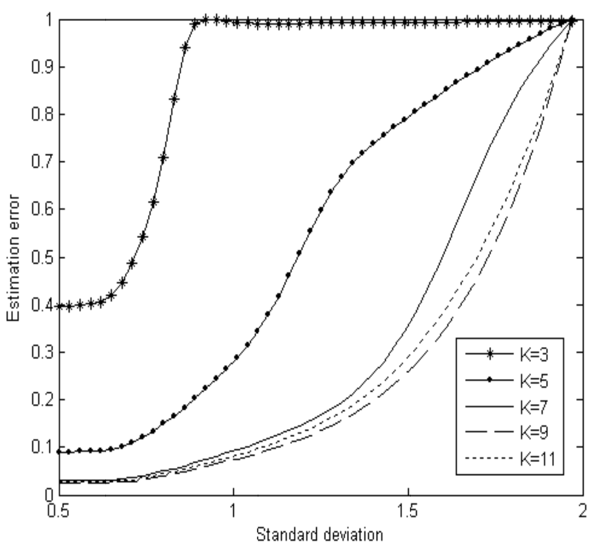

Fig. 3: The error-parameter curves

Here, the original size (K_0) and the original standard deviation (σ_0) of the Gaussian PSF are 7 and 1.2, respectively. Then, the blurred image is added by noise with a given SNR. Here, the original SNR of the noised image relative to the blurred image is taken as 45 *dB*. The simulated low resolution is shown in Fig. 2.

The SNR and PSF estimation: Utilizing the SNR estimation method based on local deviation, the estimated SNR of the low resolution is 46.4793 and the relative estimation error is:

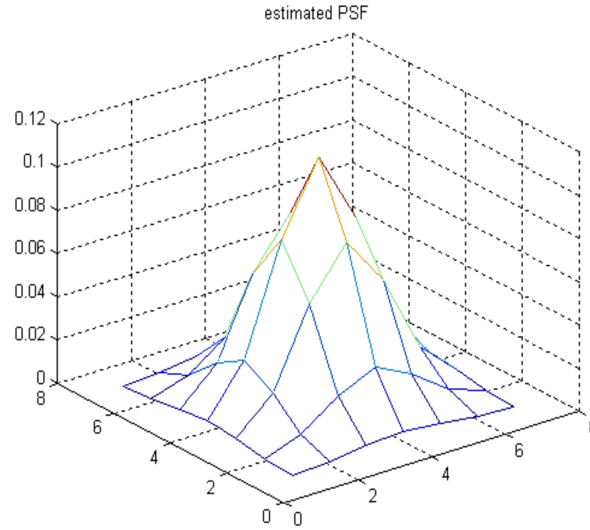

Fig. 4: The estimated Gaussian PSF

Fig. 5: The restored image

$$Relative\_SNR = |46.4793\text{-}45| / 45 = 0.0329 \quad (10)$$

In the Gaussian PSF estimation method based on error-parameter estimation method, the sizes (K) of the Gaussian PSF are taken as 3, 5, 7, 9 and 11 respectively. The estimation error e is taken as 0.1. The range of the standard deviation (σ) is taken as [0.5, 2]. The searching time is taken as 50. The threshold T_1 is taken as 3. The threshold T_2 is taken as 0.5. The generated error-parameter (E-σ) curves of the LR image at different sizes are shown in Fig. 3.

According to the error-parameter curves, the estimated size ($\hat{k}$) of Gaussian PSF is 7, which is equal to the original size. The estimated standard deviation ($\hat{\sigma}$) of Gaussian PSF is 1.28 and the relative estimation error is:

$$Relative\_\sigma = |\sigma - \sigma_0| / \sigma_0 = |1.28 - 1.2| / 1.2 = 0.0667 \quad (11)$$

The parameters of Gaussian PSF are estimated with high accuracy. The estimated Gaussian PSF is shown in Fig. 4.

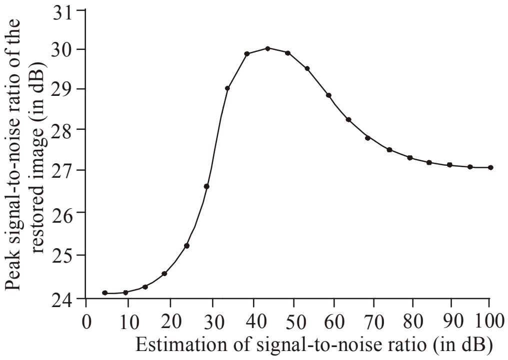

Fig. 6: The PSNR of restored image at different estimated SNR

Fig.7: The restored image at different estimated SNR (a) when the estimated SNR is 20 dB (PSNR = 24.5809 dB), (b) when the estimated SNR is 45 dB (PSNR = 30.0017 dB), (c) when the estimated SNR is 60 dB (PSNR = 28.8848 dB), (d) when the estimated SNR is 80 dB (PSNR = 27.3557 dB)

Image restoration: When the estimated SNR is 46.4793 *dB* and the estimated size and standard deviation are 2 and 1.28 respectively, using Wiener filtering restoration method, the restored image is shown in Fig. 5 and the Peak Signal to Noise Ratio (PSNR) relative to the high resolution image is 29.9965 *dB*.

The effect of SNR estimation in image restoration: In order to justify the importance of SNR estimation in image restoration, when the estimated size and standard deviation of the Gaussian PSF are 7 and 1.28, respectively, images are restored at different estimated SNR and the corresponding PSNR of the restored image is shown in Fig. 6.

When the estimated SNR are 20, 45, 60 and 80 *dB*, respectively, the corresponding restored images are shown in Fig. 7a-d. From Fig. 5 to 7, around the real SNR, the restored image has higher PSNR and better visual effect.

Fig. 8: The restored images at PSF with different estimated standard deviations (a) when the estimated standard deviation is 0.1 (PSNR = 30.3850), (b) when the estimated standard deviation is 0.5 (PSNR = 30.3408), (c) when the estimated standard deviation is 1.2 (PSNR = 30.0511), (d) when the estimated standard deviation is 2 (PSNR = 28.8116)

The effect of PSF estimation in image restoration: In addition, in order to show the effect of SNR estimation in image restoration, when the estimated SNR is 46.4793, image restoration is performed at different estimated Gaussian PSFs. Though the PSF estimation based on error-parameter, the size of the Gaussian is estimated accurately. When the estimated size is 7, images are restored at different standard deviations. When the estimated standard deviation is 0.1, 0.5, 1.2 and 2 respectively, the restored images are shown in Fig. 8a-d.

From the experimental results, the restored image as shown in Fig. 8c has better visual effect around the real standard deviation. Namely, the quality around the real Gaussian PSF is better. If the estimated standard deviations are smaller than the real value, the restored images as shown in Fig. 8a and b are illegible, though the PSNRs are a bit higher. If the estimated standard deviation is smaller than the real value, the restored image as shown in Fig. 8d appears heavy ringing effect and the corresponding PSNR decreases.

CONCLUSION

Blind image restoration has always been the challenge and difficult problem in image processing. In this study, a blind image restoration method is proposed. The SNR and the PSF are estimated simultaneously with high accuracy. By experiments, the effects of SNR estimation and the Gaussian PSF estimation in image restoration are tested. The experimental results show that the quality of the restored images is better around the real SNR and PSF.

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