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Gaussian Blur Removal in Digital Images

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Abstract— **In many imaging systems, the observed images would unfortunately suffer blurring due to many degradations such as defocusing, diffraction, relative motion between the camera and the scene, and in some cases, atmospheric turbulence. The three forms of PSF models commonly used in image restoration are the defocus blur, the motion blur, and the Gaussian blur. A Gaussian blur is the result of blurring an image by a Gaussian function. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen. Blur removal is an important problem in image processing. The modified Wiener filter with Neumann Boundary Condition performs better than the existing methods. It assumes that the values outside the domain are a reflection of the data inside. As a result the computational load is reduced. The results show that it is more effective than the blind deconvolution function.**

Index Terms— **Boundary conditions, Gaussian blur, image deblurring, point spread function (PSF).**

I. Introduction

IMAGE processing is the field of signal processing where both the input and output signals are images. Images can be thought of as two-dimensional signals via a matrix representation. Image processing is a very important subject, and finds applications in such fields as photography, satellite imaging, medical imaging, and image compression, just to name a few.

A digital image is composed of picture elements called pixels. Each pixel is assigned an intensity meant to characterize the color of a small rectangular segment of the scene. Some blurring always arises in the recording of a digital image because it is unavoidable that scene information "spills over" to neighboring pixels. In many imaging systems, the observed images would unfortunately suffer blurring due to many degradations such as defocusing, diffraction, relative motion between the camera and the scene, and in some cases, atmospheric turbulence. The goal of image restoration is to recover the scene closely from the degraded image.

. In image deblurring, we seek to recover the original, sharp image by using a mathematical model of the blurring process. The key issue is that some information on the lost details is indeed present in the blurred image but this information is "hidden" and can only be recovered if we know the details of the blurring process. One of the challenges of image deblurring is to devise efficient and reliable algorithms for recovering as much information as possible from the given data.

Classical restoration method requires complete knowledge of the blur PSF prior to restoration [5]. However, in many applications, the PSF is often unknown *a priori* or is known only within a parameter due to various practical constraints. As the knowledge is rarely available, identification of the PSF from only the observed degraded images has been of great interest. A number of techniques have been proposed to address this problem.

Bispectrum [1] is proposed as an alternate method to reduce the effects of noise. But, these methods are not suited for Gaussian blur parameter identification, because there are no regular zeros in its frequency content as there are in defocus blur and motion blur. In other method [7], the original image has been modelled as an autoregressive (AR) process, and the blur as a moving average (MA) process. With the image and blur modelled in this way, the blur identification problem becomes a matter of determining the parameters of an ARMA model. The parameters can be estimated by the generalized cross validation (GCV) [7] method. However, their performance suffers from the possible poor convergence to local minima during the maximization process. Another limitation of them is that the computational load is heavy. Li [6], [9] proposed identifying the blurring parameter with kurtosis minimization. The deblurred image with the smallest kurtosis is chosen as the final restored image, and the corresponding parameter is regarded as the identified blurring parameter. However, the estimation error of this method is sometimes large.

The rest of the paper is organized as follows. Section II describes the implementation of our identification method. Section III presents experimental results that illustrate the effectiveness of this approach. Section IV compares the results with existing method and the Section V includes the concluding remarks.

II. Implementation Of Blur Identification

A. Mathematical Model

In many applications, the degradation procedure of imaging system could be modeled as the result of a convolution with a linear shift-invariant low-pass filter. This low-pass filter is often called point spread function (PSF).

Here, ξ(x,y) is the noise introduced in the procedure of image acquisition, and it is generally assumed to be zero-mean additive white Gaussian noise with variance σ.

The above equation can be expressed in matrix-vector formulation as,

$$g = Hf + n$$

where **g** is he blurred image, **H** is the distortion operator, also called the point spread function (PSF), **f** is the original true image and **n** is additive noise introduced during image acquisition, that corrupts the image.

In many applications the PSF of atmospheric turbulence is often modelled as Gaussian blur.

where x and y are the horizontal and vertical space variables, σ is the standard deviation, which parameterizes the severity of the blur, C is the region of support and K is normalization constant.

Thus the Gaussian PSF is characterized by single parameter σ. From a mathematical view point, given the model and the degraded picture g(x,y), the aim of picture restoration is to make as good an estimate as possible of the original picture or scene f(x,y). Evidently any such estimation would require some form of knowledge concerning the degradation function h(x,y).

B. Noise

In addition to blurring, observed images are usually contaminated with noise. Noise can arise from several sources and can be linear, nonlinear, multiplicative, and additive. Here the additive noise alone is taken into account. Further a Gaussian white noise at BSNR=30 dB is added to the blurred image. BSNR is defined as

where is the variance of the blurred image, is the variance of the noise.

C. Performance Measures

The Peak Signal-to-Noise Ratio (PSNR) is used as a quantitative measure for comparison. If f is the original image of dimension M x N and is the restored image, the PSNR of restored image is given by

where is the restored image, f is the original image.

D. Boundary Conditions

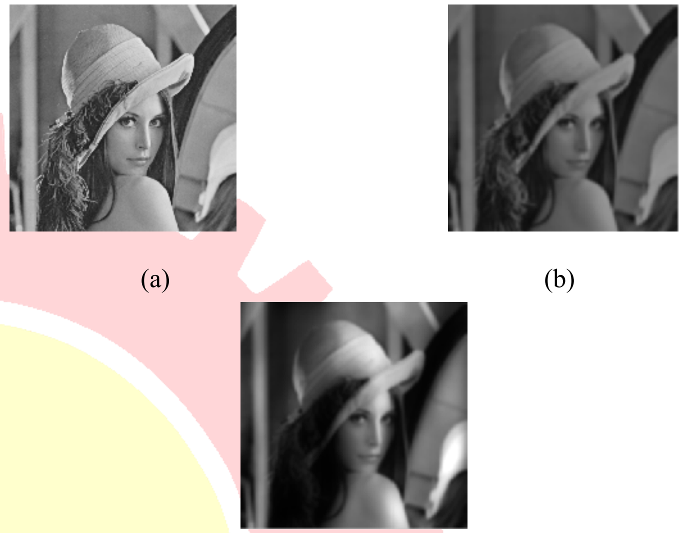
Boundary conditions specify our assumptions on the behavior of the scene outside the boundaries of the given image. In order to obtain a high-quality deblurred image we must choose the boundary conditions appropriately. Ignoring boundary conditions is equivalent to assuming zero boundary conditions. A good model for image deblurring must take account of boundary effects otherwise the reconstruction will likely contain some unwanted artifacts near the boundary. When these assumptions are used in the blurring model, we say that we impose boundary conditions on the reconstruction.

The simplest boundary condition is to assume that the exact image is black (i.e., consists of zeros) outside the boundary. This zero boundary condition can be pictured as embedding the image f in a larger image. Unfortunately, the zero boundary condition has a bad effect on reconstructions of images that are nonzero outside the border. Sometimes we merely get an artificial black border; at other times we compute a reconstructed image with severe "ringing" near the boundary, caused by a large difference in pixel values inside and outside of the border.

III. Gaussian Blur Identification

A. Blind Deconvolution

The Blind Deconvolution Algorithm can be used effectively when no information about the distortion (blurring and noise) is known.



(a) (b)

(c)

Fig.1. (a) Original "Lena" Image, (b) Gaussian Blurred Image (σ=3), (c) Restored image using Blind Deconvolution.

In image processing and applied mathematics, blind deconvolution is a deconvolution technique that permits recovery of the target scene from a single or set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF). Regular linear and non-linear deconvolution techniques utilize a known PSF. For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed.

The field of blind image deconvolution has several applications in different areas such as image restoration, microscopy, medical imaging, biological imaging, remote sensing, astronomy, non-destructive testing, geophysical prospecting, and many others.

The Blind Deconvolution problem refers to finding estimates and for f and h based on g and prior knowledge about f, h, and . It should be noted that although the degradation model is LSI, the deconvolution algorithm may be nonlinear or spatially varying or both.

Consider the Lena image be degraded by σ=3. The degraded image is shown in Figure 1(b). The deblurred image is shown in Figure 1(c).

B. Wiener Filtering with Neumann Boundary

Condition

Wiener filter is a discrete time linear FIR filter. This has been widely used in reconstruction of one-dimensional signals and two-dimensional images. The Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. Although Wiener filter is sensitive to noise, yet it can be used for good restoration of the original image. The elegance of Wiener filter lies in the fact that it incorporates the prior knowledge about the noise embedded in the signal and also the spectral density of the object being imaged. As a result, Wiener filter provides a better and improved restoration of original signal since it takes care of the noise process involved in the filtering. The discrete version of the Wiener filter is a straightforward extension to the continuous Wiener filter.

Let be the Wiener estimate of the original image in the frequency domain. Then

where is the PSF h in the frequency domain,) is the blurred image in the frequency domain, is the power spectra of the original image, is the power spectra of the noise. Because the power spectra of the original image and noise are sometimes hard to know, above equation is often simplified as

where τ is the regularization parameter. This is known as the Wiener filter or the minimum mean square error filter or the least square error filter. If the noise is zero, the second term in the denominator vanishes and the Wiener filter reduces to the inverse filter. So, the value of τ should carefully be selected in order to get the satisfactory result.

The estimate of restored image is, thus, the inverse Discrete Fourier Transforms (DFT).

By definition,

where is the restored image in frequency domain, M and N are horizontal and vertical dimension respectively.

In order to solve the above equation DFT should be computed. Although the Fast Fourier Transform could be implemented in very efficient way, the calculation of FFT takes it for granted that the boundary condition is periodic. As a result ringing effect occurs. The discrete Fourier transform (DFT), used by the deblurring functions, assumes that the frequency pattern of an image is periodic. This assumption creates a high-frequency drop-off at the edges of images. This high-frequency drop-off can create an effect called boundary related ringing in deblurred images.

In order to avoid the ringing effect, Neumann Boundary Condition(NBC) is used and a fast algorithm is designed to restore images. It assumes that the values of f outside the domain is a reflection of the data inside. By using Neumann BC, the blurring matrix is a Toeplitz-plus-Hankel matrix in the 1–D case and a block Toeplitz-plus-Hankel matrix with Toeplitz-plus-Hankel blocks (BTHTHB) in the 2-D case. They showed that if the PSF is symmetric

$$h(x,y) = h(-x,y) = h(x,-y) = h(-x,-y) \text{ for all } x, y$$

the BTHTHB matrix could be diagonalized by the Discrete Cosine Transform (DCT) matrices. Then their inverses can be obtained by using Fast Cosine Transforms (FCT). This approach is computationally interesting since the FCT requires only real operations and is about twice as fast as the FFT, and this is also true in two dimensions.

Because the Gaussian PSF satisfies the above symmetric condition, our modified Wiener deconvolution with Neumann boundary condition is where the H_{dct} denotes the convolution matrix. H's first column DCT result with Neumann BC and $G_{dct}(u,v)$ is the DCT of the degraded image.

Thus, the estimate of the restored image is the inverse DCT

(a)

(b)

(c)

Fig.2. (a) Original "Lena" Image, (b) Gaussian Blurred Image (σ=3), (c) Restored image using Wiener Filter with Neumann Boundary Condition.

C. *Regularization Parameter*

From our experiment results, we suggest choosing the regularization parameter τ with Gaussian interpolation. The value depends on the value of estimated BSNR. Thus estimating the BSNR value is the important task that affects the result of restoration method.

y =

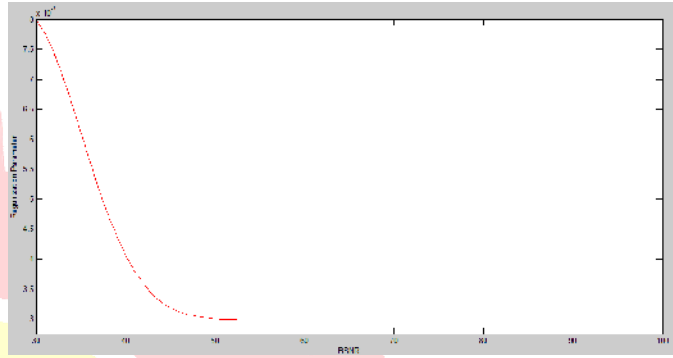


Fig.3. Regularization parameter Gaussian interpolation curve

Though other interpolation methods could be used, the differences between them may be very small. The interpolation curve is plotted in Figure 3.

IV. Results And Discussion

The PSNR of different restoration methodologies are tabulated below. The results of Wiener filter with Periodic boundary condition(PBC) are also taken for comparison. Here the image is assumed to be repetitive beyond the boundary.

TABLE I
PSNR VALUES FOR DIFFERENT RESTORATION METHODS (in db)

Restoration Method	σ = 1	σ = 2	σ = 3	σ = 4
Blind Deconvolution	28.89	28.84	20.80	28.75
Wiener Filter with PBC	36.18	32.32	30.68	30
Wiener Filter with NBC	36.48	32.70	31.84	30.26

Based on the results above it is obvious that the modified Wiener Filter with Neumann Boundary Condition(NBC) really outperforms the other methods.

V. Conclusion

A modified Wiener filter with Neumann Boundary Condition is presented for medium

Gaussian blur. This method consider the boundary of the image be a mirror reflection of original image. By applying Neumann Boundary Condition, the Wiener filter is reduced to calculation of Discrete Cosine Transform of the input image. This reduces the computational time and the visual of the image is improved. The modified method avoids the ringing effect in the restored image.

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