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Motion Blur Parameters Estimation for Image Restoration

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ABSTRACT: The image restoration techniques are oriented towards constructing the original image from a degraded observation. Motion blur in images is one of the most common degradation phenomena. Restoration of such images requires correct estimation of motion blur parameters. In this paper we have proposed a novel technique for estimating the angle and the length of motion blur. Gabor filter has been used to find the angle of the blur and a simple neural network has been used to find the length of blur. The proposed method was tested on various standard images. The experimental results reveal that proposed method works better than the existing methods in terms of visual quality and PSNR

KEYWORDS: Image restoration, PSF, Gabor filtering.

I. INTRODUCTION

The objective of image restoration is to reconstruct an approximated version of the original image from a degraded observation. Image degradation occurs due to various reasonslike camera misfocus, atmospheric turbulence, camera or object motion etc. The blurring in images due to motion is commonly encountered when there is a relative motion between the camera and object. In many applications the observed image $g(x, y)$ can be expressed as a two dimensional convolution of the original image with the degradation function also known as point spread function (PSF) [1,2] as given below.

$$g(x, y) = f(x, y) * h(x, y) + \eta(x, y)$$

Where * denotes the two dimensional convolution and $\eta(x, y)$ is the additive noise. In classical restoration techniques, it is assumed that the PSF is known prior to restoration. Very often, in practical situations, this degradation function is not known. This makes the restoration process to recover the original image only from the observed image. Such restoration is commonly known as blind deconvolution. This paper attempts to solve such a problem, however, limited to motion degraded images. Several researchers have proposed methods[3,4,5,6] to determine the motion blur parameters. The blind restoration algorithms may broadly be classified into two categories. In the first category the PSF and the image are restored simultaneously. The other category of algorithms determines the point spread function and then uses it to restore the image. Our work falls in the second category of blind restoration techniques, where a parametric model of the PSF isassumed. In following section, there is Richardson Lucy Algorithm described which is used to restore the blurred image.

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II. RICHARDSON-LUCY ALGORITHM (RL)

This algorithm is derived by Richardson and Lucy in 1970’s.The Richardson–Lucy deconvolution algorithm has become popular in the fields of astronomy and medical imaging. The algorithm restores the image and the point-spread function (PSF) simultaneously. [7]

Algorithm
Step 1: Read image
Step 2: Simulate a blur
Step 3: Restore the blurred image using PSFs of various sizes
Step 4: Analyzing the restored PSF
Step 5: Improving the restoration
Step 6: Using additional constraints on the PSF restoration

Step 1: Read image
Read an image using imread command as shown below:

```
I = imread('cameraman.tif');
figure;
imshow(I);
title('Original Image');
```

Step 2: Simulate a blur
simulates the blur by convolving a Gaussian filter with the true image (using ***imfilter***). The Gaussian filter then represents a point-spread function (PSF).
PSF = fspecial('gaussian');

Fig 1. (a) Original image (b) blurred image

Step 3: Restore the blurred image using PSFs of various sizes
To illustrate the importance of knowing the size of the true PSF, this example performs three restorations. Each time the PSF reconstruction starts from a uniform array--an array of ones. The first restoration, J1 and P1, uses an undersized array, UNDERPSF, for an initial guess of the PSF. The size of the UNDERPSF array is 4 pixels shorter in each dimension than the true PSF. [7]

UNDERPSF = ones(size(PSF)-4);

The second restoration, J2 and P2, uses an array of ones, OVERPSF, for an initial PSF that is 4 pixels longer in each dimension than the true PSF.

OVERPSF=padarray(UNDERPSF,[44],'replicate','both');

The third restoration, J3 and P3, uses an array of ones, INITPSF, for an initial PSF that is exactly of the same size as the true PSF.

INITPSF=padarray(UNDERPSF,[22],'replicate','both');

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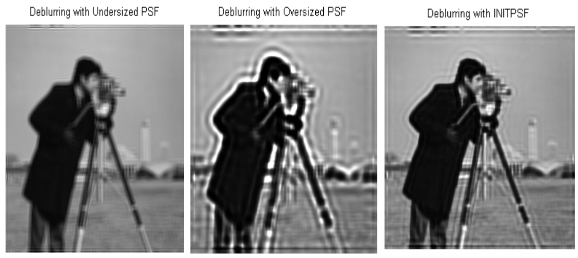

Fig 2. (a) deblurred image with undersized PSF (b) deblurred image with oversized PSF (c) deblurred image with INTPSF

Step 4: Analyzing the restored PSF

All three restorations also produce a PSF. The following pictures show how the analysis of the reconstructed PSF might help in guessing the right size for the initial PSF. In the trueThe third restoration, J3 and P3, uses an array of ones, INITPSF, for an initial PSF that is exactly of the same size as the true PSF.

INITPSF=padarray(UNDERPSF,[22],'replicate','both');

PSF, a Gaussian filter, the maximum values are at the center (white) and diminish at the borders (black). The PSF reconstructed in the first restoration, P1, obviously does not fit into the constrained size. It has a strong signal variation at the borders. The corresponding image, J1, does not show any improved clarity vs. the blurred image, Blurred. The PSF reconstructed in the second restoration, P2, becomes very smooth at the edges. This implies that the restoration can handle a PSF of a smaller size. The corresponding image, J2, shows some deblurring but it is strongly corrupted by the ringing. Finally, the PSF reconstructed in the third restoration, P3, is somewhat intermediate between P1 and P2. The array, P3, resembles the true PSF very well. The corresponding image, J3, shows significant improvement; however it is still corrupted by the ringing.[7]

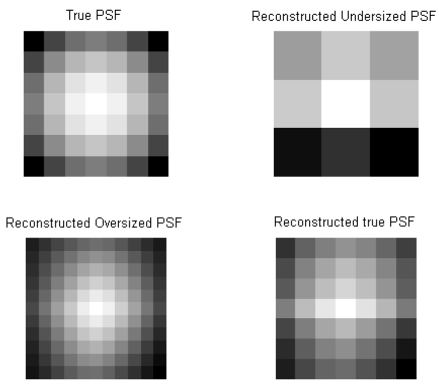

Fig 3. Various sized PSF

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Step 5: Improving the restoration

The ringing in the restored image, J3, occurs along the areas of sharp intensity contrast in the image and along the image borders. This example shows how to reduce the ringing effect by specifying a weighting function. The algorithm weights each pixel according to the WEIGHT array while restoring the image and the PSF.In this example, first start by finding the "sharp" pixels using the edge function. By trial and error, we determine that a desirable threshold level is 0.3.

WEIGHT = edge(I,'sobel',.3);

The image is restored by calling deconvblind with the WEIGHT array and an increased number of iterations (30). Almost all the ringing is suppressed.[7]

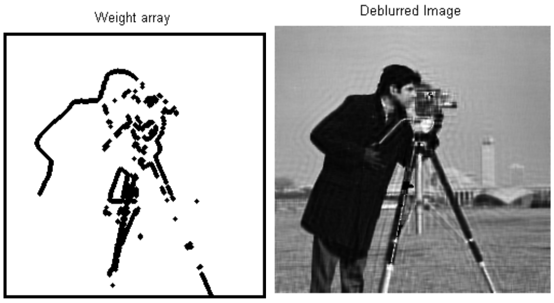

Fig 4. (a) weight array (b) deblurred image

III. MOTION BLUR MODEL

The Point spread function for motion blur can be described As,

$$h(x,y) = \quad \frac{1}{L} if \sqrt{x^2+y^2} \le \frac{L}{2},$$

`

tan θ=y/x

0 otherwise (2)

Where, L is the blur length and θ is the angle of motion blur. Two parameters govern the motion blur: length of blur Land angle of blur θ. So, the task is to determine these twoparameters from the blurred image. When an image is degraded due to motion, dominant parallel lines appear in thefrequency spectrum of the image. The parallel dark lines in the frequency spectrumof the degraded image are quite apparent (Fig. 5). Theorientation of these lines corresponds to the blur angle. So,any of the line detection algorithms can be used to determinethe orientation of the parallel lines.

Fig 5. Frequency spectrum of the blurred image

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IV. ALGORITHM FOR MOTION BLURRED IMAGE RESTORATION

Input: Motion Blurred Image
Output: Restored Image
Step 1: The blur angle (θ) is determined using **Gabor filter.**
Step 2: The blurred image is rotated in the direction opposite to the blur angle to obtain the equivalent horizontal blurred image.
Step 3: The blur length (L) is estimation
Step4: PSF is constructed using the estimated blur parameters.
Step 5: The image is restored using the Wiener filter.

V. GABOR FILTER

Gabor filters are Gaussian filters modulated by a sinusoidal wave. A good number of researchers have used Gabor filter bank to extract image features in applications like pattern recognition, image segmentation etc. The function for a typical two dimensional Gabor filter is shown below.

$$G(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left[-\frac{1}{2}\left(\frac{x^2}{{\sigma_x}^2} + \frac{y^2}{{\sigma_y}^2}\right)\right] \times exp(-j\omega(x\cos\varphi + y\sin\varphi)) \quad (3)$$

Where, σx and σy is the standard deviation in x and y direction respectively. Φ and ω represents the orientation and frequency of the Gabor filter.Modulated Gaussian filters can be used to find the orientationin the patterns. The two dimensional Gabor filters for different orientation and frequency. In this paper we have used a two dimensional Gabor filter to extract features of the blurred image. The two dimensional Gabor filter is convolved with the spectrum of the blurred image to get the response at specific frequency and orientation.

VI. ANGLE ESTIMATION ALGORITHM USING GABOR FILTER

One of the important observations in motion blurred images is that its frequency spectrum shows dominant parallel lines which corresponds to the angle of blur.This can be observed from ***Cameraman***image blurred with an angle $\boldsymbol{\theta}$ **= 50°and** $\boldsymbol{L}$ **= 30** as shown in Figure 3.1. So, any of the line detection algorithms can be used to determine the orientation of the parallel lines.

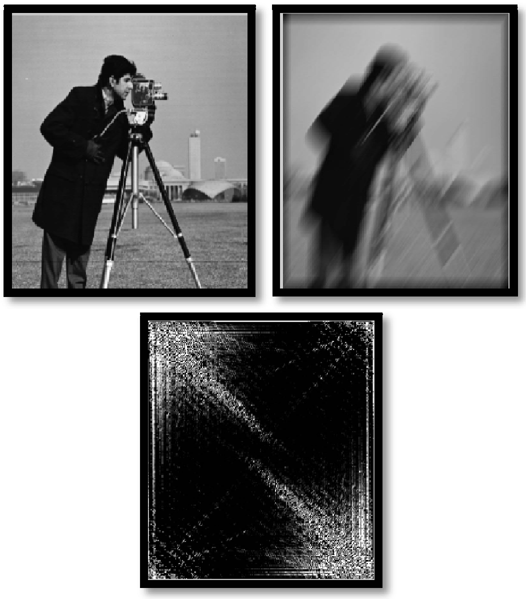

Fig 6. (a) original image (b) blurred image (c) Frequency spectrum of the blurred image

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Pattern of the frequency response of the blurred image has been used to find the motion direction. As it can be clearly seen from the Figure 3.1(c), for a blur angle θ the patterns are oriented at $\alpha = \theta + 90$. So, the orientation of the lines in the spectrum of the blurred image is directly related to the blur angle. Line detection algorithms such as Hough transform, Radon transform can be used to detect the orientation of the line. However, Hough transform requires a threshold to identify points on the line [6]. This threshold is different for different images. Any small error in threshold could result in a large variation in estimation of the blur angle. To alleviate this problem, Gabor filter has been used to determine the blur angle. The response of the Gabor filter depends upon the frequency and orientation of the input image. Gabor filter with different orientation are convolved with the spectrum of the blurred image and $L2$ norm of the result is computed. Detail of the motion direction estimation is described below.

Input: Motion Blurred Image

Output: Blur Angle (θ)

Step 1 The spectrum of the blurred image is computed.

Step 2 Logarithm of the spectrum of the blurred image.

i.e.; **I = log (G (u, v))** is used as input to the Gabor filter.

Step 3 Gabor filter with different orientation (θ) are convolved with I to get different responses R (θ).

Step 4 For every θ, the L2 norm of the result of the convolution is calculated. The blurring angle is then calculated as,

$$\hat{\boldsymbol{\theta}}_{\boldsymbol{blur}} = \boldsymbol{arg}\{^{\boldsymbol{max}}_{\boldsymbol{\theta}}\, \boldsymbol{R}(\boldsymbol{\theta})\} \qquad (4)$$

VII. SIMULATION RESULTS

Noise Free situation

Table 1.1 simulation results for Gabor filter algorithm in noise free situation

Image (256 x 256)	Original (θ degrees)	Expected Outcome of blur angle (θ)	Simulation Outcome
Cameraman	θ =50°	θ = 49°	θ = 52°
Lena	θ =30°	θ = 29°	θ = 28°
Tree	θ =45°	θ = 46°	θ = 44°

Noisy Situation

Table 1.2 simulation results for Gabor filter algorithm in noisy situation

Image (256 x 256)	Original (θ degrees)	Expected Outcome of blur angle (θ) SNR=25 dB	Simulation Outcome
Cameraman	θ =50°	θ = 49°	θ = 52°
Lena	θ =30°	θ = 31°	θ = 27°
Tree	θ =45°	θ = 46°	θ = 43°

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VIII. LENGTH ESTIMATION

The second parameter of motion blur is the length of the blur (L). This describes how much distance the object or camera has moved during the exposure time.The blur length is the number of pixels by which the image is blurred.

Length Estimation Algorithm

Input: Blurred Image, Blur angle

Output: Estimated Blur Length

Step 1: Perform Median filtering on blurred image before restoring the blurred image.
Step 2: Convert the image to Fourier domain.
Step 3: Apply log transform.
Step 4: Perform inverse Fourier transform to get the image in Cepstrum domain.
Step 5: Rotate the image.
Step 6: Calculating the blur length using first negative value. If Zero Crossing found then return it as the blur length.
Step 7: If Zero Crossing not found then find the lowest peak and Calculate the blur length using Lowest Peak.

Simulation Results

Noise free situation

Table 1.3 simulation results for blur length estimation in noise free situation

Image (256 x 256)	Original blur length(L)	Expected Outcome of blur Length (L)	Simulation Outcome
Cameraman	L=30	L=28.5	L=29
Lena	L= 15	L=13.3	L=14
Tree	L=20	L=18.42	L=19

Noisy Situation

Table 1.4 simulation results for blur length estimation in noisy situation

Image (256 x 256)	Original blur length(L)	Expected Outcome of blur Length (L) SNR =25dB	Simulation Outcome
Cameraman	L=30	L=28.5	L=29
Lena	L= 15	L=13.3	L=14
Tree	L=20	L=18.42	L=19

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IX. RESULTS

After the parameter estimation theta and blur length PSF is calculated and image is restored using wiener filter. Below figure shows the blurred image and restored image.

Fig7(a) Noisy blurred image (b) Restored image

Performance of the algorithm is measure in terms of PSNR (in dB) ratio. Here, the noisy blurred image has Signal to Noise ratio SNR= 25 dB. Restored image having PSNR= 23.18 dB.

X. CONCLUSION

In this paper, attempts have been made to restore images from their degrade observations. It deals with the motion blur parameter estimation for subsequent restoration using Wiener filter. In this regard, Gabor filter algorithm and an algorithm have been used to estimate blur angle and blur length respectively. Performance analysis have been made on only blurred images as well as noisy blurred images. The proposed scheme estimates the blur parameters close to the true value. Comparative analysis demonstrates the efficacy of the proposed scheme. However, the suggested scheme produces good restored images when the Gaussian noise of strength more than 25 dB SNR.

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BIOGRAPHY

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