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A Comparative Analysis of Motion-Blur Magnitude Parameter Estimation Techniques

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***Abstract*-Motion blur in a digital image is caused due to motion of an object while capturing it. This motion blur may cause significant problems for image processing algorithms. So, it may be required to remove it from the image or identify inconsistency of it in an image for tempering detection.**

The magnitude and direction are two parameters of motion blur used to distinguish it from rest of the image. Here, three algorithms are discussed for estimation of this magnitude parameter. They are viz. a. Radon transform based b. Cepstral Method c.PBM (Perceptual Blur Metric) Based. The results are compared for accuracy and execution time required. PBM based method gives optimum results considering both parameters.

1. INTRODUCTION

Motion blur is caused by the relative motion between the camera and the pictured object during the time the shutter is open. As blurring can significantly degrade the visual quality of images, many researchers have been working either on preventing motion blurring during image capturing or on post-processing of the image to remove motion blur.

The slow speed of the camera shutter relative to the object being imaged is one of the possible causes of motion blur. Camera shake is found to be the culprit for the presence of motion blur in many images. Reducing the exposure interval of the camera is a possible solution, but this often affects the parameters like amount of noise or depth of field adversely. Some hardware like tripods and flashes also offer solutions to the problem of motion blur by allowing for more stable exposures or greater illumination in a short interval of time, respectively, but these are often impractical. Hence, many images containing motion blur do exist and so, it is useful to utilize the inconsistencies in motion blur in order to detect image tampering.

2. PROBLEM FORMULATION

Motion blur can be modelled by averaging the instantaneous intensity falling on a pixel over the shutter interval. Such an averaging process can be weighted by a “soft” Gaussian window instead of using the idealized shutter interval, in order to allow for non-ideal mechanical shutter effects. Alternatively, blurs arising from motion, like other types of blur, can also be considered as convolving an in-focus image with a blur kernel in the spatial domain. The motion blur kernel is determined by the relative velocities of the camera and the objects in the image.

Blur Model:

For uniform motion blur, the process of blurring is usually modelled as the following convolution:

$$I=(H*P)+N \qquad (1)$$

where I is the blurred image, H is the sharp image, P is the blurring kernel, and N is the noise present.

For a horizontal uniform velocity motion blur, the blurring kernel P can be modelled as P = 1/L[1 1….1]1xL, where L is the length of the kernel. Note that a directional blurring kernel P_θ can be formulated by rotating P by θ degrees about the x-axis.

To identify the amount of blurring from its blurred version I, parametric knowledge of the blurring kernel P is required. Methods for calculating the magnitude parameter of motion blur are discussed next [1][4].

2.1 Radon Transform method based on image gradient

A periodic pattern that is easier to detect also exists in the gradient of blurred image in the spectral domain. Differentiating (1),

$$I' = H'P' + N' \qquad (2)$$

Taking the Fourier transform and omitting the noise term

$$\hat{I}'(\omega) = \hat{H}'(\omega)\hat{P}'(\omega) \qquad (3)$$

The Radon transform, which is widely used for detecting straight lines in noisy images, is used[5][6]. For a motion-blurred image, there are periodic large negative lines in $\log|\hat{I}'|$ with slope θ and periodicity proportional to L value. Denoting the Radon transform by R, $R(\log|\hat{I}'|)$, will have periodic peaks located at (±1/L,90-θ˚), (±2/L,90-θ˚), (±3/L,90-θ˚)……..Therefore, this should correspond to a peak in the Fourier transform of $R(\log|\hat{I}'|)$. Calculating Fourier transform of this Radon transform, the peak occurs at (ω,φ)

Then $\omega = \frac{1}{L}$ and $\varphi = 90-\theta^0 \qquad (4)$

This estimated motion blur is represented as a two-element vector $\mathbf{\Phi} = [\mathbf{\Phi}_{mag}, \mathbf{\Phi}_{dir}]$, where $\mathbf{\Phi}_{mag}$ = L and $\mathbf{\Phi}_{dir}$ = θ. Here L and θ are motion blur parameter [1].

2.2 Cepstral Method

As the degraded image is the result of convolution with the blur model, it is impossible to separate the blur in spatial domain. However, the blur information can be easily extracted in cepstrum domain. The cepstrum of an image I is defined as [3],

$$C = F^{-1}\{\log(|\hat{I}|)\} \qquad (5)$$

where $\hat{I}$ is the Fourier transform of motion blurred image I, and F^{-1} is the inverse Fourier transform. As Eq. (5) shows, the image in cepstrum-domain is the inverse Fourier transform of the logarithm power spectrum of the original image.

2.3 PBM variation method

The L value is calculated using Perceptual Blur Metric [2]. Let S_α be the set of edge pixels in the binary edge map of image obtained by applying the Sobel operator in the vertical, horizontal and diagonal directions. A modified metric, named as *oriented blur metric* PBM_α, is defined as [1]

$$PBM_\alpha(I) = \frac{\sum_{p \in S_\alpha} E(p)}{|S_\alpha|} \qquad (6)$$

where $E(p)$ is the width of the edge along the direction perpendicular to α at the edge pixel p and |.| denotes cardinality. The oriented PBMs are computed for orientations α_i, i=1 to t, where t is the number of orientations evaluated and then define the overall PBM as,

$$PBM(I)=\max(PBM_{\alpha i})\ \forall \alpha_i \qquad (7)$$

3. Results and Comparison

3.1 Test data for parameters estimation

The images with the range 1-50 of motion blur magnitude and a fixed theta are generated and checked against all three methods for magnitude estimation. The fig.1 shows different images for testing.

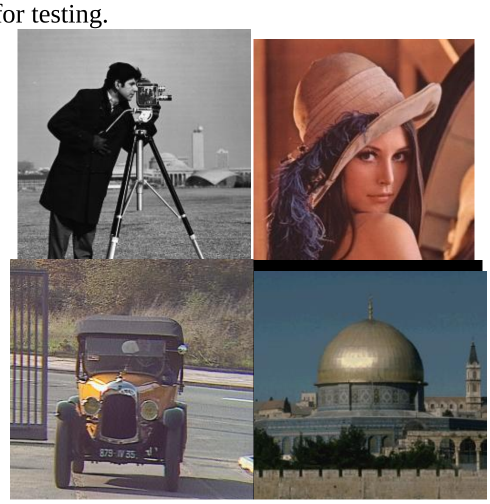

Fig. 1 test images a. Cameraman b. Lena c. Car d. Jerusalem

3.2 Cepstral Method

The graph of fig. 2 shows the linearity of blur parameter magnitude values in the range of middle values from 5-25 only.

3.3 Radon Transform Method

The graph of fig. 3 shows the linearity of blur parameter magnitude values for a range of nearly 10 to 50 are accurate.

3.4 PBM variation Method

The graph of fig.4 shows the linearity of blur parameter magnitude values for a wide range of 1-50 and nearly accurate.

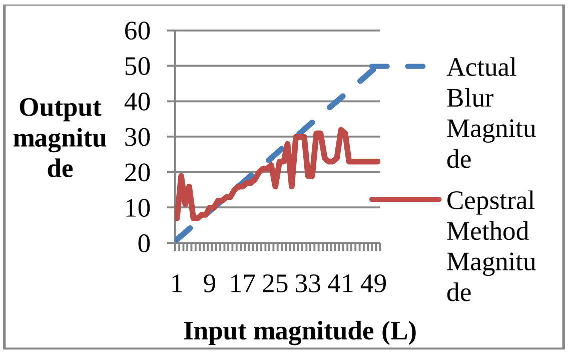

Fig. 2 Actual Vs. Cepstral method magnitude

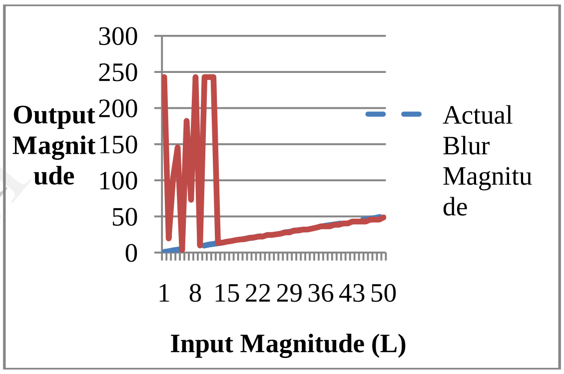

Fig. 3 Actual Vs. Radon Transform method magnitude

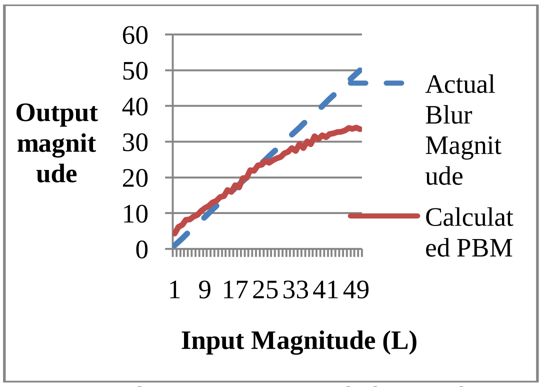

Fig. 4 Actual Vs. PBM variation method magnitude

3.5 Performance bounds

The time required for PBM based method used for estimation of motion blur magnitude parameters is minimum among all. The accuracy for PBM based method is good for a wide range of input values (1-50).

As shown in fig. 5, time computation is done for a set of images of magnitude values in range of 1-50 and direction angle 45. It shows Radon transform method requires maximum time for magnitude estimation. Cepstral method requires minimum time but accuracy is less in this method as shown in fig. 2. Hence PBM variation is best to use for further processing.

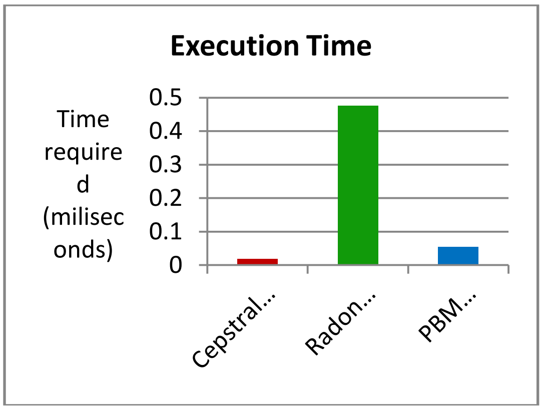

Fig. 5 Execution Time of Cepstral, Radon transform and PBM variation methods for magnitude estimation

4. CONCLUSIONS

As motion blur in an image can be characterised by two parameters viz. Magnitude and direction. For magnitude parameter estimation, a comparative analysis of the three techniques, viz. PBM based, Cepstral based, Radon Transform based, is done.

The techniques are compared for 4 test images with variation of magnitude values from 1-50. The experimental results show that the PBM based method gives fast results for an image with a good accuracy over a wide range of magnitude parameter values.

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