This paper proposes a novel approach to estimate the parameters of motion blur (orientation and extension) simultaneously from the observed image. The motion blur estimation would be used in a standard non blind deconvolution algorithm, thus yielding a blind motion deblurring scheme. Our algorithm is based on the correlation between the modified logarithm power spectrum from natural image model and the blur kernel. The local minima of the modified spectrum are closer to the horizontal line, and thus more similar to the sinc function. Compared to previous estimation algorithm, the results are more accurate in noisy images.

Index Terms— Motion blur, Blur identification, Correlation.

1. INTRODUCTION

Motion blur is caused by the relative motion between the camera and the scene during exposure time of each images or frame in a video frames. This image degradation arises when the time integration is long and the camera moves during this time. It occurs in low light conditions to get better images, with large zoom, or with recent sensor, in which pixels are numerous but smaller and smaller with a lost of sensitivity. One solution to reduce the degree of blur is to capture images using shorter exposure intervals but it is not always possible, and in this case noise becomes visible in the image. The classical approach is to try to remove the blur off-line. Blur is usually modeled as a linear convolution of an image with a blurring kernel, the point spread function (PSF). For deblurring an image, it should estimate the PSF at first, and then uses a classical restoration algorithm such as Lucy-Richardson filter [1,2] and Wiener filter [3] with these two PSF parameters to enhance the image. Therefore the accurate estimation of these parameters is of great importance, even if a high quality restoration algorithm is applied.

Several algorithms have been proposed to estimate these parameters, based on power spectrum, cepstrum, correlation, etc.
bad estimation of the first parameter leads to a bad estimation of the second parameter. We propose a model of natural image spectrum, which allows us to estimate the two parameters of constant linear motion simultaneously.

Most of the methods in the literature use the power spectrum or cepstrum of blurred image to estimate the parameters. Our works present an estimation of the motion blur PSF parameters, using power spectrum and correlation, with a model of modified logarithm power spectrum from natural image model.

2. MOTION BLUR AND FREQUENCY SPACE

Generally, an image can be corrupted by motion blur and additive noise. The relation between the observed image \( g(x, y) \) and its original image \( f(x, y) \), with the size of \( N_1 \times N_2 \), is shown by Eq. (1):

\[
g(x, y) = f(x, y) * h(x, y) + n(x, y) \tag{1}
\]

where \( h(x, y) \) is the blurring function, that is the PSF, and \( n(x, y) \) is the additive Gaussian noise function. The PSF for motion blur is linear. It can be formulated using the blur extension \( L \) and blur orientation \( \theta \), as it is shown by Eq. (2):

\[
h(x, y) = \frac{1}{L} \prod_L (x \cos \theta + y \sin \theta) \tag{2}
\]

Fig. 1: Images and logarithm power spectrum of images
(a) Original image, (b) Logarithm power spectrum of original image, (c) Motion blur image with \( L=10, \ \theta = 45^\circ \), (d) Logarithm power spectrum of motion blur image.

In the absence of noise, Eq. (1) can be transformed to frequency domain as:

\[
G(\xi, \eta) = H(\xi, \eta) F(\xi, \eta) \tag{4}
\]

where \( (\xi, \eta) \) are spatial frequencies, \( G(\xi, \eta) \), \( F(\xi, \eta) \) and \( H(\xi, \eta) \) are frequency responses of observed image, original image and degradation function, respectively.

\( H(\xi, \eta) \) is a \text{sinc} function (Fig. 2) and it has regular patterns of zeros depending on the blur length \( L \) and the blur direction \( \theta \). As shown in Fig. 1(d), the \text{sinc}-like ripple of \( H(\xi, \eta) \) is preserved in the observed power spectrum \( G(\xi, \eta) \).

In the case that \( N_1 = N_2 = N \), as the image is a discrete function, in the motion direction, \( H(\xi, \eta) \) is given by:

\[
H(\xi, \eta; L, \theta) = \frac{\sin((L \xi \cos \theta + \eta \sin \theta) \pi / N)}{L \sin((\xi \cos \theta + \eta \sin \theta) \pi / N)} \tag{5}
\]

In one dimension case, solving \( H(u)=0 \), we can find the relation between blur extension and periodicity of the powers spectrum:

\[
L = N / d \tag{6}
\]

where \( L \) is the blur length and \( d \) is the distance between two zeros of the power spectrum \( H(u) \), such in Fig. 2.

3. ESTIMATION OF THE BLUR PARAMETERS

Classical methods use this property to find motion parameters: motion direction is first estimated, and then \( H(u) \) is computed and zero patterns are detected.

Unfortunately, in natural images, the power spectrum \( H(u) \) is often corrupted by noise in this iterative scheme. Fig. 3 shows a classical example, which is different from the ideal one (Fig. 2). Because of the discrete space and noise, the detection of the zero values is quite difficult.
To overcome this drawback, we propose to find orientation and extension simultaneously. If the power spectrum \( F(\xi, \eta) \) is known, it is easy to work out the \( H(\xi, \eta) \) as:

\[
H(\xi, \eta) = |G(\xi, \eta)|/|F(\xi, \eta)|
\]

which is determined by extension and orientation using Eq. (5).

However, the power spectrum of the unblurred image \( F(\xi, \eta) \) is unknown; this is an ill-posed problem. As pointed out in [15], the behavior of \( \log|F(\xi, \eta)| \) along lines \( \eta = \xi \tan \theta \) in the spatial frequencies is roughly the same for most natural images. While local behavior may be irregular, the global behavior is essentially monotonically decreasing with polynomial function of \( \log|F(\xi, \eta)| \).

To respect the quasi-isotropy, the approximate model of natural image log power spectrum will be as follows:

\[
\log|F(\xi, \eta)| \sim (|\xi| + |\eta|)^{-p}
\]

where \( p \) is an unknown constant to be estimated.

Since Eq. (4), the decreasing speed of \( \log|F(\xi, \eta)| \) should be found on \( \log|G(\xi, \eta)| \). To identify \( p \), several methods can be used. In this paper, we use the “Calculus of Variations” to estimate the real exponent \( \hat{p} \) from \( \log|G(\xi, \eta)| \):

\[
\hat{p} = \arg\min_{p \in (0,1)} \left\{ \var(\log|G(\xi, \eta)| - (|\xi| + |\eta|)^{-p}) \right\}
\]

Now, we can calculate the modified logarithm power spectrum of motion blur by:

\[
\tilde{H}(\xi, \eta) \overset{\text{def}}{=} \log|G(\xi, \eta)| - (|\xi| + |\eta|)^{-\hat{p}}
\]

where the local minima are closer to the horizontal line, and thus more similar to the \( \text{sinc} \) function. To identify the two parameters at the same time, we can use the correlation method between the modified logarithm power spectrum of motion blur (Eq. (10)) and a detect \( \text{sinc} \) function since logarithm does not change the occurrence period of local minima. Let

\( (a) \) (b) (c)

Fig. 3: Profile line of a natural blurred power spectrum

Fig. 4: The profile lines of (a) \( \log|G(\xi, \eta)| \), (b) estimated \( \log|F(\xi, \eta)| \) and (c) calculated \( |H(\xi, \eta)| \).

Fig. 5: The SRAE graphs of extension and orientation estimation errors in noisy blur images.

(a) Blur image

Fig. 6: Real blur image and its restoration result.
$\text{Corr}(L, \theta) = \sum_{\xi} \sum_{\eta} w(\xi, \eta) \left| H(\xi, \eta; L, \theta) \right| H(\xi, \eta)$ \hspace{1cm} (11)

where $w(\xi, \eta)$ is a truncate function, which used to get rid of the central part as well as the remote part of the spectrum since it becomes extremely singular around central point and behaves irregularly near the edges.

The maximum of the correlation gives the extension and the orientation of the blur motion.

4. EXPERIMENTAL RESULTS

Several experiments have been done on simulated motion different blur gray images with noise, that were degraded by different orientations and extensions of motion blur and added additive Gaussian noise with zero mean and different standard deviations to these images.

The essential steps of our algorithm are illustrated in Fig. 4. Obviously, it is easier to identify the parameters on the modified logarithm power spectrum of motion blur.

The linear motion blur parameters of synthesized blurred images are estimated by the proposed algorithm and one of the most popular algorithms, cepstrum algorithm. We have compared the results of the two algorithms. Since we can not evaluate all possible scenes, we considered five different extensions and five different orientations ($L \in \{5, 10, 15, 18, 20\}$, $\theta \in \{0, 10, 20, 45, 60\}$). For each simulated scene, we set 31 different blurred SNRs (BSNR, shown as Eq. (12)), from 10dB to 30 dB. For each BSNR, we estimate 20 times. Fig. 5 shows the result of square root average errors (SRAE) of extension and orientation. The proposed algorithm has obviously higher success rate than 2D cepstrum algorithm through the all noise levels. For our algorithm, the estimation becomes more accurate as the extension goes larger; while it becomes worse as the orientation approaches to the 45 degree.

$\text{BSNR} = 10 \times \log_{10} \left( \frac{\sigma^2_g}{\sigma^2_n} \right)$ \hspace{1cm} (12)

For the blurred real image in Fig. 6, it was taken with a camera without tripod and stabilization. In Fig. 6(a), the fish is blurred. The estimated result is $L = 31$ pixel and $\theta = 0$ with our proposed algorithm. Restored by Lucy-Richardson filter using the estimated blur parameters, the fish in the restoration result can be recognized much easier.

5. CONCLUSIONS

The novel algorithm presented in this paper is a robust algorithm to estimate the motion blur parameters simultaneously. By modeling the logarithm power spectrum of natural image, the effect of noise has been reduced. When the blur extension is slight or the BSNR of the image is low, our algorithm is obviously more robust than previous ones.

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7. REFERENCES