ABSTRACT

Motion blur detection and the relevant blurring parameter estimation are important for many computer vision tasks. The contribution of this paper is in two folds. First, we propose a closed-form solution for motion direction estimation on blurred image. Secondly, a novel method is proposed for motion blurred region detection. The proposed direction estimation is based on measurement of lowest directional high-frequency energy. Compared with traditional methods, it will improve accuracy with less computational cost. Moreover, the proposed motion blurred region detection can efficiently estimate blurred regions without Point Spread Function estimation. Encouraging results are shown by experiments.

Index Terms—Image motion analysis, image deblurring, image segmentation

1. INTRODUCTION

Camera motion normally will cause motion blur on the image captured. On partially blurred image, as shown on the top row of figure 1, the blur information can be used for fast moving object detection and tracking [1], speed estimation [2] and motion segmentation [3]. For these applications, blurred region detection and moving direction estimation are two crucial problems. This paper proposes novel methods to tackle these two problems.

Motion blurred images can be restored by advanced optimization methods [4][5] which perform PSF estimation and image deblurring simultaneously. However, these methods are computationally expensive and not suitable for blurred region detection. In the case of image blur caused by linear motion, the blurring process can be modeled by convolution. The relevant PSF is determined by motion direction and extent [6][2][7][8][9]. After PSF parameters are successfully estimated, the image can be restored by non-blind deconvolution.

To estimate motion direction, various methods have been investigated. In [11], the motion direction is estimated by detecting two negative spikes in Cepstrum image. In [7], Radon transform of the power spectrum image is employed to estimate the direction. These two methods, as well as Steerable filter based method [10], were compared in [8]. It showed that the Steerable filter based method is less reliable and the Radon transform based method is more accurate than others when motion extent is large.

Since it was observed that [6] high-frequency energy decreases significantly along motion direction on a blurred image, the motion direction can be estimated by detecting lowest directional high-frequency energy. In this paper, the main contribution is that a closed-form solution is derived. Therefore, we do not have to calculate energy in all directions as implemented in [6]. When compared with the traditional methods in the literatures, the proposed method can produce more accurate result but with less computation.

Moreover, based on the same rationale, we also propose a new approach for motion blurred region detection. Unlike learning-based methods [12][1] which identify blurred regions by statistical low-level image features, our approach detect motion blurred regions by directly estimating motion direction and analyzing high-frequency energy on image. Compared with learning-based method, our method is more robust and accurate. Moreover, our method has less computational cost than other method [9] which involves iterative image deconvolution operation.

The paper is organized as follows. In Section 2, a closed-form solution for motion direction estimation is derived. Then, we propose a new approach for motion blurred region detection in Section 3. In Section 4, comprehensive experimental results are presented to show the performance of the proposed methods. Conclusions are given in Section 5.

2. CLOSED-FORM SOLUTION FOR MOTION DIRECTION ESTIMATION

As stated in [13] [6], high-frequency energy decreases significantly along motion direction in blurred image. Therefore, the motion direction can be estimated by calculating directional high-frequency energy. In this paper, energy is regarded as the sum of the squared derivative of image. Based on this definition, a simple and effective solution is developed.
It is known that the derivative of image $f$ along direction $k$ degree is,
\[
\Delta f(x, y)_k = \begin{bmatrix} f_x & f_y \end{bmatrix} \begin{bmatrix} \cos(k) \\ \sin(k) \end{bmatrix},
\]  
(1)
where $f_x$ and $f_y$ are the horizontal and vertical derivatives respectively. The objective function for motion direction estimation is defined as a sum of the squared directional derivatives,
\[
J(k) = \sum_{i=x}^{M} \sum_{j=y}^{N} \left( f_{x,x} f_x + f_{x,y} f_y \right) \begin{bmatrix} \cos(k) \\ \sin(k) \end{bmatrix}^2,
\]  
(2)
where $M$ and $N$ are the width and height of image $f$. The above equation can be further developed as,
\[
J(k) = \begin{bmatrix} \cos(k) \\ \sin(k) \end{bmatrix}^T \left( \sum_{i=x}^{M} \sum_{j=y}^{N} \begin{bmatrix} f_{x,x} & f_{x,y} \\ f_{x,y} & f_{y,y} \end{bmatrix} \right) \begin{bmatrix} \cos(k) \\ \sin(k) \end{bmatrix},
\]
\[
= \begin{bmatrix} \cos(k) \\ \sin(k) \end{bmatrix} \cdot D \begin{bmatrix} \cos(k) \\ \sin(k) \end{bmatrix}^T,
\]  
(3)
where the matrix $D$ is defined as:
\[
D = \sum_{i=x}^{M} \sum_{j=y}^{N} \begin{bmatrix} f_{x,x} & f_{x,y} \\ f_{x,y} & f_{y,y} \end{bmatrix} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}.
\]  
(4)
Thus, we have
\[
J(k) = (d_{21} + d_{12}) \frac{1}{2} \sin(2k) + d_{11} + (d_{22} - d_{11}) \sin^2(k).
\]  
(5)
The minimum of $J(k)$ satisfies the condition $\frac{d}{dk} J(k) = 0$.
that is,
\[
(d_{21} + d_{12}) \cos(2\hat{k}) + (d_{22} - d_{11}) \sin(2\hat{k}) = 0.
\]  
(6)
Obviously, the solution of equation (6) is,
\[
\hat{k} = k_n + \frac{n\pi}{2}, \quad k_n = \frac{1}{2} \tan^{-1}\left(\frac{d_{21} + d_{12}}{d_{11} - d_{22}}\right).
\]  
(7)
n is any integer number. It is guaranteed that objective function along direction $\hat{k}$ will produce an extremum which may be a minimum or a maximum. Actually, the image details are smeared most significantly along the motion direction. In the direction perpendicular to motion direction, it has the strongest capability to conserve high-frequency energy [6] [2]. Thus, the motion direction can be uniquely determined by $J(k_n)$ and $J(k_n + \pi / 2)$. Let $k_{\min}$ denote the direction with smaller value of $J$ between $J(k_n)$ and $J(k_n + \pi / 2)$, $k_{\max}$ denote the perpendicular direction of $k_{\min}$. Then, motion direction is determined by $k_{\min}$.

Unlike the method proposed in [6] which computes the energy on all directions and chooses the one with minimum value as motion direction, our method is accurate and far more efficient. The accuracy of the direction estimated by method [6] may be improved by employing bilinear or higher order interpolation methods for image rotation. But it would cost more computation.

### 3. Motion Blur Detection

In this paper, motion blurred region detection on partially blurred image is also considered. A new method is proposed to solve this problem based on directional high-frequency energy analysis. In order to detect blurred regions, on each image patch of size $30 \times 30$, $k_{\min}$ and $J(k_{\min})$ are computed. $J(k_{\min})$ reflects lowest directional high-frequency energy of the patch. On the patch which is blurred by motion, $J(k_{\min})$ has smaller value. For other unblurred patches, $J(k_{\min})$ is much stronger. This method might recognize blank area as blurred regions since the $J(k_{\min})$ is also small. However, they can be distinguished from the real blurred regions by measuring $J(k_{\min})$. Since energy across all directions on blank areas are very small and $J(k_{\min})$ is small as well.

**Fig. 1.** The images on the first row are partially motion blurred. The second row images depicted the energy in each block. The third row images showed motion blurred region detected by our method.

Figure 1 shows two examples. The images on the first row are partially motion blurred. The pictures on second row depict $k_{\min}$ and $J(k_{\min})$ at each non-overlapping image block. The red line indicates the direction $k_{\min}$. The intensity of image block indicates energy $J(k_{\min})$. From these two images, it can be seen that most of the blurred regions have been detected successfully. Besides, red lines in most of the black regions are consistent with object moving direction. In order to segment blurred regions more accurately, we estimate object moving direction first. The energy in each block is then calculated on this direction. The whole algorithm is summarized as follows:
1) Estimate lowest directional high-frequency energy \( J(k_{\text{min}}) \) at all non-overlapping image blocks. The blocks with \( J(k_{\text{min}}) < \mu \) are merged to estimate motion direction. Let it be \( k_{\text{global}} \).

2) Define a neighborhood region \( 30 \times 30 \) centered at each pixel and compute matrix \( D \) relating to this patch. Then, calculate high frequency energy along direction \( k_{\text{global}} \), namely \( J(k_{\text{global}}) \), which reveals the likelihood that it is blurred.

The images on the third row in figure 1 are produced by the above method. The green clock at the top-left corner of the image manifests direction \( k_{\text{global}} \). The blurred regions are clearly revealed. More experimental results are presented in the next Section. In our experiments, \( \mu = 100 \). The patch size 30 is also empirically determined. It works well for most cases. For higher-resolution images, larger patch size may also produce good results.

4. EXPERIMENTS

To evaluate the accuracy of the proposed motion direction estimation method, we synthesized 36 motion blurred images from a latent image showed in Figure 2 (a). The motion direction ranges from 10 degree to 90 degree and motion extent ranges from 5 pixels to 20 pixels. Figure 2 (b) shows an example. The motion direction is 90 degree and the extent is 10 pixels.

![Fig. 2. (a) sharp image. (b) synthetic motion blurred image.](image)

To better evaluate the performance of the proposed method, comparison experiments are carried out across Cepstrum-based method [11], Yitzhaky’s method [6], Radon transform based method [7] and the proposed method using 36 synthesized images. Figure 3 shows the experimental results. The absolute error of the estimated direction on each image is presented. (a - d) are the results on images blurred with motion extent 5, 10, 15 and 20 pixels respectively. From these figures we observe that our method is reliable and accurate in all conditions with estimation error less than 3 degree. Particularly, in Figure 3 (a) the results estimated by Radon transform [7] are far from ground truth and thus are not been plotted, while our method produces the best results compared with the other methods.

We also evaluated the robustness of these methods by adding Gaussian noise with different variance into the blurred images. Experimental results reveal that, when motion extent is large the Radon transform based method is more robust than the Cepstrum based method [11]. Additionally, the proposed method and Yitzhaky [6] is more robust than Radon transform based method [7] in most cases.

For the computation, the proposed method is much faster than previous methods. Table 1 shows the time cost by these four methods on the images of typical size. They are tested using the same coding language and computer. For Yitzhaky [6], bilinear interpolation is employed for image rotation.

![Fig. 3. Comparison experiments on the four algorithms.](image)
Table 1. Computation time cost by the four algorithms.

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<tbody>
<tr>
<td>256×256</td>
<td>0.016s</td>
<td>0.09s</td>
<td>0.62s</td>
<td>17s</td>
</tr>
<tr>
<td>512×512</td>
<td>0.09s</td>
<td>0.35s</td>
<td>2.5s</td>
<td>70s</td>
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To show the performance of the proposed blurred region detection method, figure 4 and 5 provide more examples. Figure 4 shows a challenging image for blurred region segmentation. (a, b, c) are segmented by Levin et al. [9], Liu et al. [12] and the proposed method respectively. Compared with (b) which is segmented based on three blur features, our method produces more accurate result. Figure 5 shows additional four examples. The images on the first two columns are produced by the proposed method directly. The other two images are firstly separated to blurred and non-blurred regions. Then the detected blurry regions are restored by Lucy-Richardson deconvolution. Both motion direction and blurred regions are estimated by our method. Motion extent is estimated by autocorrelation [6].

5. CONCLUSIONS

This paper proposes a closed-form solution for motion direction estimation of motion blurred images. It produces reliable results with lower computational cost. Besides, a novel motion blurred region detection method is presented. It can efficiently detect blurred regions without PSF estimation and deblurring.

6. REFERENCES