PSF Search Algorithm for Dual-Exposure Type Blurred Image

Moon Soo Chang, Sung Wook Yun, and PooGyeon Park

***Abstract*—** Many conventional blind image deconvolution algorithms have much processing time because the consideration of various cases and the optimization are required for general employment. Moreover, these algorithms are also complex to deal with various point spread functions (PSF). Therefore, this paper restricts the type of PSF to the dual-exposure type and proposes effective PSF search algorithm, using the point that the gain of PSF has a relatively small influence over the quality of the restored image though the size and direction of PSF are dominant in image restoration.

***Keywords*—** Blind image deconvolution, image restoration, the dual-exposure type blur, the hand shake blur.

I. Introduction

IMAGE restoration is an important issue in high-level image processing. It is widely used in various fields of applications, such as medical imaging, astronomical imaging, remote sensing, microscopy imaging and photography deblurring [1]. Deconvolution algorithms of image restorations can be largely divided into three branches, which are known or unknown PSF method, linear or non-linear method and one pass or iterative method [2].

Recently, blind image restorations are widely studied in the fields of deconvolution algorithms. Blind image restorations are to estimate original images without any information about the blur of degraded images. The image degradation model for linear shift-invariant system is commonly given by

$$= \quad + \qquad (1)$$

where is the blurred image, is the matrix form of PSF, is the original image and is the noise.

To solve image restoration problems, many methods are presented using answers about next two questions. First, how close estimated images are with original images. Second, how to find PSF about blurred images. Early efforts focus on the frequency domain to find directly original images using cepstrum [3] or bispectrum [4]. However, because these methods have many restrictions, parametric approaches which are to parametrically estimate PSF using ML (Maximum Likelihood) and EM (Expectation Maximization) are presented [5][6]. There are also blind deconvolution methods to estimate original images iteratively, such as Iterative Blind Deconvolution (IDB) and Nonnegative and Support constraints Recursive Inverse Filtering (NAS-RIF) [7][8][9]. Moreover, projection-based approaches and regularized adaptive iterative algorithms have been proposed in [10][11][1]. Recently, new studies of good performance, based on the other approaches about original images, are presented [12][13].

The objective of above methods is to estimate the original images with minimum errors from the degraded images. Because the consideration of various cases and the optimization are required for general employment, many deconvolution algorithms have much processing time. Moreover, these algorithms are also complex to deal with various PSF. Therefore, this paper presents a new deblurring algorithm which is fast and outperforms in the restricted case using conventional researches. Section II provides an image approximation model. In Section III, an algorithm for approximated model is presented. In Section IV, examples show the performance of the algorithm. Section V gives the concluding remarks.

II. Image Approximation Model

Considering the digital camera widely used in the image acquisition, the case that images are blurred can be largely divided into two branches, the motion blur and the hand shake blur. The motion blur occurs when an object moves faster than the shutter of the digital camera. The hand shake blur occurs when the digital camera is shaken. The above two cases have similar PSF in terms of the relative movement. In the motion blur, the background of images is stopped except for the moving object. However, in the hand shake blur, the entire image has the same spatially invariant blur ([13]-Figure 4). Therefore, not the entire image but the characteristic image patch of the entire image can be used to estimate PSF [13].

In the case of digital cameras, because the speed of the shutter is fast, the hand shake blur is almost not occurred. However, blurred images are easily generated because the speed or the shutter is slowed down in doors or in the night (Fig. 2.). In this case, while the human hands shake complicatedly ([13]-Figure 10), most of blurs are similar to the dual-exposure type blur. These blurs can be modeled as Fig. 1. or have the PSF, including spatially two dominant spots. When blurs are restricted to the dual-exposure type blur, the type of PSF can be simplified and the number of computation also decreases. Therefore, PSF can be easily estimated.

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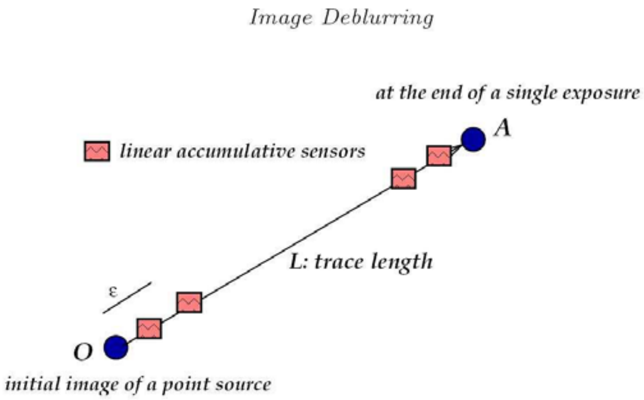

Fig. 1. Motion blur of the image of a point source

Fig. 2. The blurred image in the night

III. Algorithm for Approximated Model

As mentioned above, when deblurring problems are restricted to the dual-exposure blur problems, the complexity of the problems can be reduced. Therefore, Section III presents the algorithms and frameworks which can be applied to the various estimation methods.

To estimate the simple two spots PSF, the three steps are required as shown in Fig. 3.. In the case of the dual-exposure blur type, the PSF is sensitive not to the gain but to the direction and the size. Using MATLAB, the experiment results of the PSF and an original image are as shown in Fig. 4., Fig. 5. and Fig. 6.. (For convenient image restoration, not *imfilter()* function but *fft2()* function is used to multiply image and PSF in MATLAB.)

1) The gain of PSF is not sensitive. (Fig. 4.)
2) The direction of PSF is sensitive. (Fig. 5)
3) The size of PSF is sensitive. (Fig. 6)

(The top of PSF figures is the entire shape of PSF. The bottom of PSF figures represents only the position of the gain.)

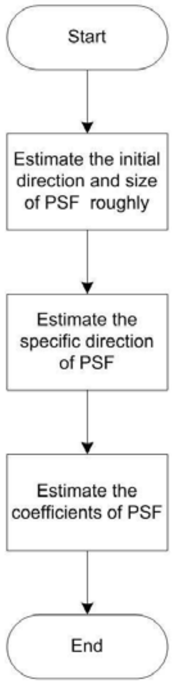

Fig. 3. The flowchart for estimating PSF

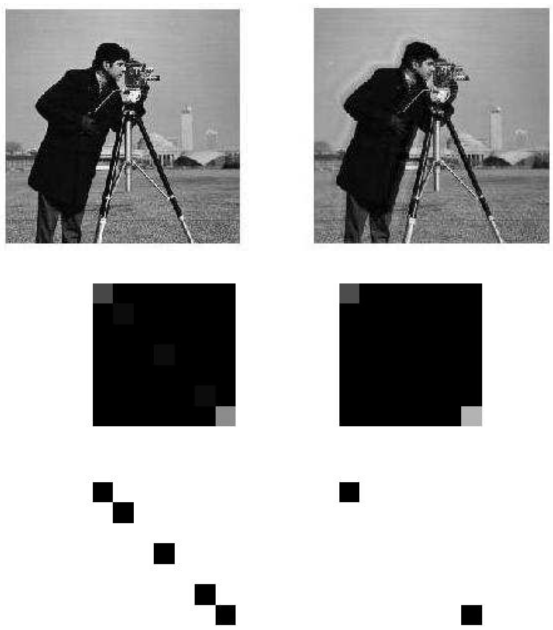

Fig. 4. The case of the different gain of PSF, Top: images of different gain PSF, Bottom: PSF figures

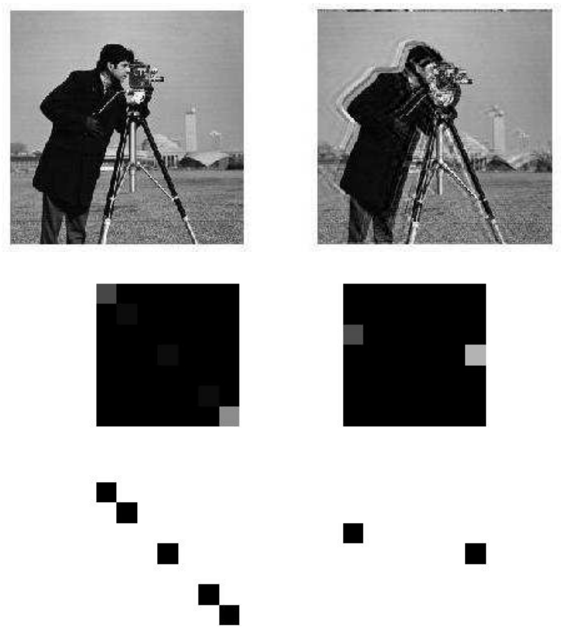

Fig. 5. The case of the different direction of PSF, Top: images of different direction PSF, Bottom: PSF figures

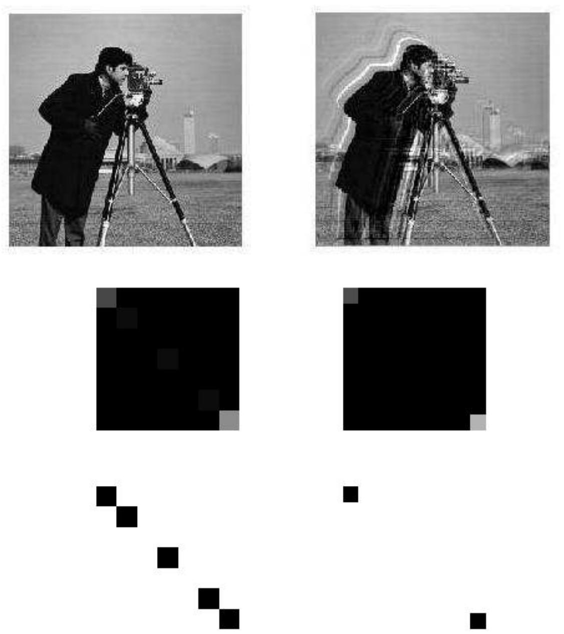

Fig. 6. The case of the different size of PSF, Top: images of different size PSF, Bottom: PSF figures

Though various sophisticated algorithms can make good results, these algorithms are also likely to make computation errors. When the size and direction of PSFs are inadequate, rough images can be acquired. Therefore, the following simple cost function is used.

$$
\begin{aligned}
&= \quad || \quad \hat{} \, || = ||(\quad) + (\quad \hat{} \,)|| \\
&= \quad || \quad + (\quad \hat{} \,)|| \\
&\cong \quad || \quad \hat{} \, ||, \quad (|| \quad || \ll ||(\quad \hat{} \,)||)
\end{aligned}
$$

where is the blurred image, is the original image, ˆ is the estimated original image using estimated PSF and || || means 2-norm. In the case of the dual-exposure blur type, || || is relatively much smaller than || ˆ||. Therefore, the cost function can be expressed as above.

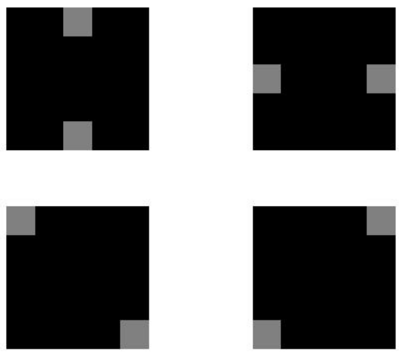

Fig. 7. The four directional PSFs

In the first step for estimating the PSF containing simple two spots, four directional PSFs, such as Fig. 7., are used to estimate the size and the direction of PSF roughly. In the second step, using the size and the direction estimated roughly in the first step, all possible PSFs are considered. Because the direction of PSF is determined roughly in the first step, the number of computations is reduced to one-fourth. Moreover, because the shape of PSF is symmetric, the total number of computations is

$$ {}_{4*[(\text{the size of PSF})-1]}\mathrm{C}_2 * \frac{1}{4} $$

where ${}_n\mathrm{C}_r$ means the combination. In the third step, because the number of computation is small as above, additional estimation methods and fine tuning methods can be used to estimate images which are more similar to the original image. The coefficients of PSF can be chosen as proper values because there are almost no errors of the estimated images in human eyes unless the first and second dominant gain of PSF are shifted.

IV. Results

Because the blind deconvolution algorithm of MATLAB, an iterative process similar to the accelerated, damped Lucy-

Richardson algorithm, has bad performance in the linear dual-exposure type blur, it can not be compared with the our algorithm. Therefore, two examples show the performance of the our algorithm.

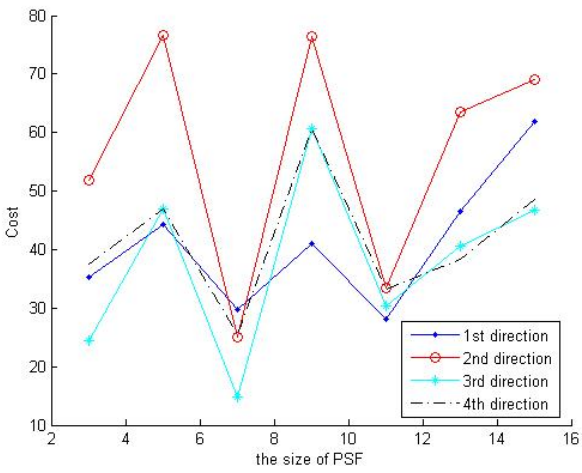

Fig. 8. The cost graph according to the size and initial directions of PSFs in the first step for estimating PSF

As shown in Fig.3., the estimation procedure for estimating the simple PSF is three steps. First, the size of PSF and the initial direction of PSF must be estimated among the 4 kinds of PSF in Fig.7.. In Fig.8., the x-axis value of the minimum extremum, which is 7, is determined to the size of the PSF. The 2nd and 3rd directions, having the minimum costs in the extremum 7, are determined to the initial directions among the 4 direction PSFs. Second, the direction of PSF must be decided specifically. Using the size and initial directions of PSF in the first step, the second step generates all possible directions. In Fig.9., the some directions corresponding to the relatively small errors of the cost function are determined to the directions of PSF candidates(the direction indices are 5, 11, 16 and 18.). Third, in Fig.10., by changing gains of the estimated PSFs in the 1st and 2nd steps , when the sum of pixel errors between the blurred image and the restored image is the minimum extremum (the gain index is 5 or 6), the corresponding PSF is finally determined to the estimated PSF (the direction index is 5).

As shown in Fig.11. and Fig.12., the two examples show the good performance of the our algorithm in the linear dual-exposure type blur. Especially in Fig.11., because the direction of PSF is dominant in image restoration and the directions of estimated PSF candidates are same, restored images have almost same qualities. In Fig.13., the magnified original and estimated images is almost alike.

V. Conclusion

There is no perfect solution of the blind deconvolution. Various methods for the blind deconvolution problem are presented and their performance is pretty good. However, probability-based and iteration-based methods consume much time in processing and one pass methods often produce bad results. Therefore, when the general blind deconvolution problem is restricted to the hand shake type blur problem, this paper presents the simplified PSF estimation method basing on the direction and the size of the PSF by approximating to dual-exposure type blur. For more accurate restoration, the various sophisticated algorithms can make better results in less time.

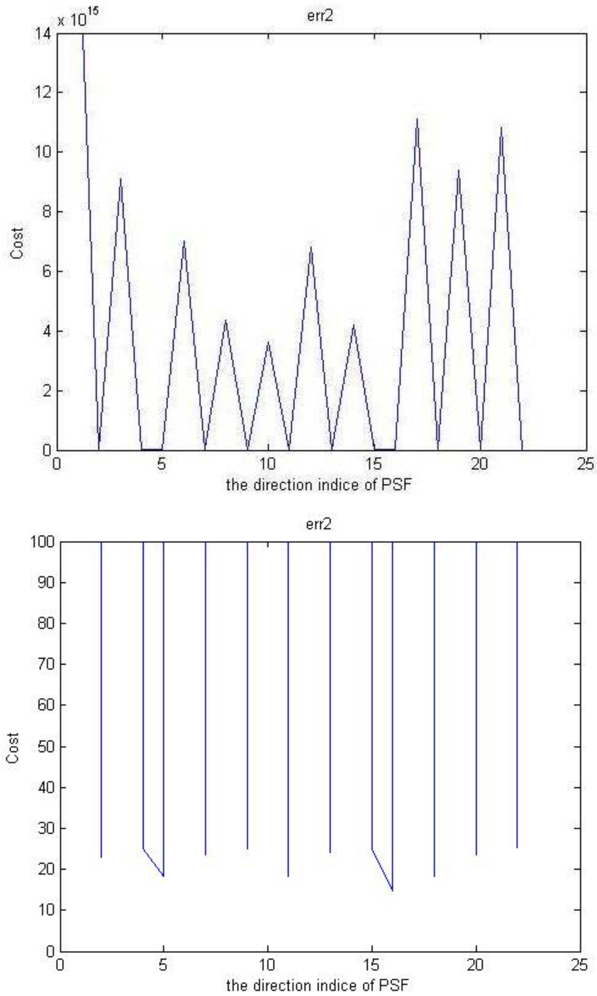

Fig. 9. The cost graph according to the directions of PSFs in the second step for estimating PSF.

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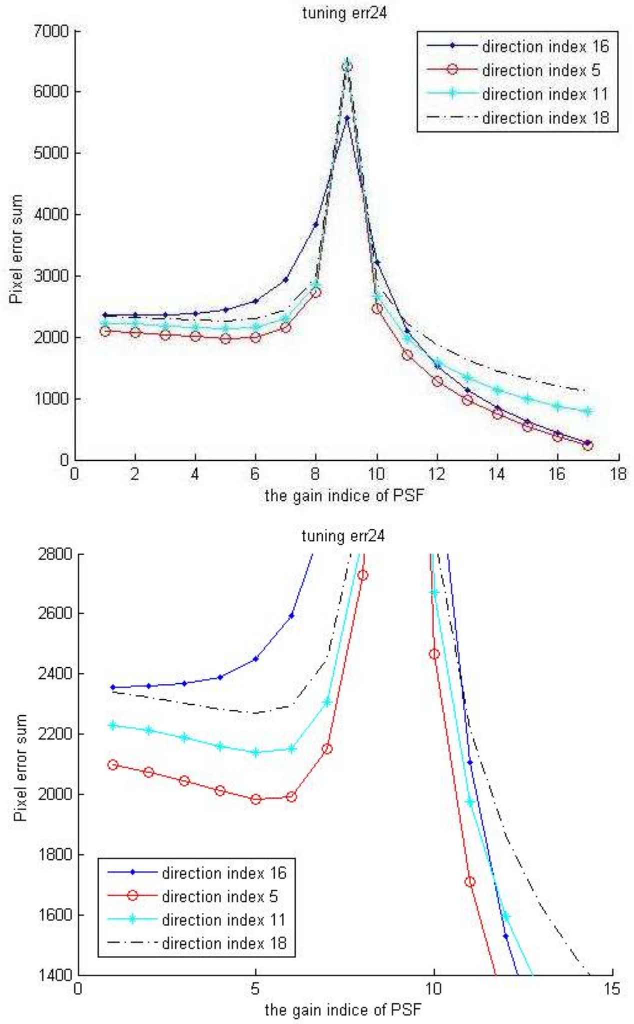

Fig. 10. The pixel error sum graph according to the gain of PSFs in the third step for estimating PSF.

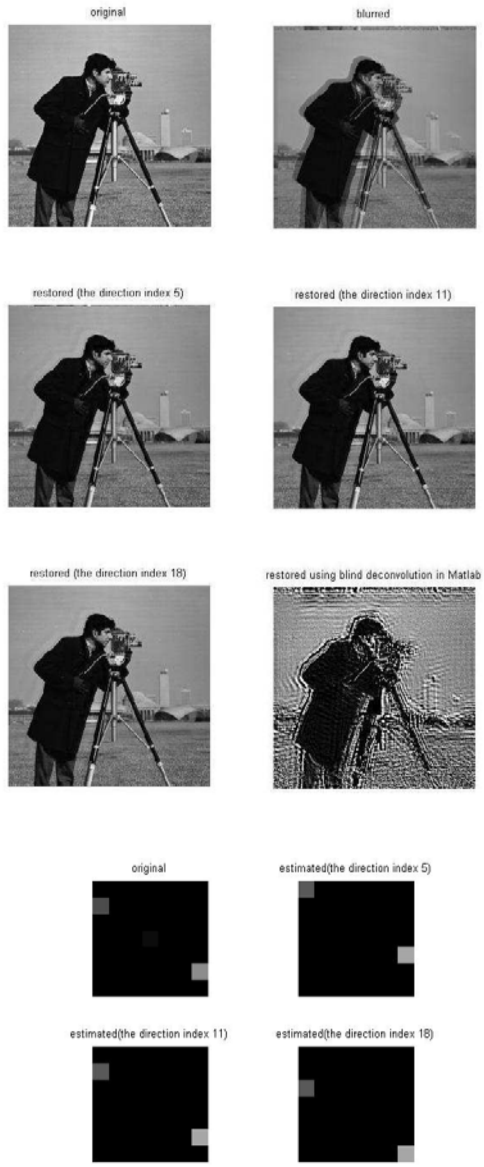

Fig. 11. The image restoration. 1st row (Left): original image, 1st row (Right): blurred image, 2nd row(Left): restored image (direction index 5), 2nd row(Right): restored image (direction index 11), 3rd row(Left): restored image (direction index 18), 3rd row(Right): restored image using Matlab blind deconvolotion Functions.
4th row (Left): original PSF, 4th row (Right): estimated PSF corresponding to the direction index 5. 5th row (Left): estimated PSF corresponding to the direction index 11. 5th row (Right): estimated PSF corresponding to the direction index 18.

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Fig. 12. The image restoration. 1st row (Left): original image, 1st row (Right): blurred image. 2nd row: restored image

Fig. 13. The image restoration. Left: magnified original image, Right: magnified restored image.

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