A Study on Blind Image Restoration of Blurred Images using R-map

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***Abstract*—Image restoration which restores a clear image from a single blur image is a difficult problem of estimating two unknowns: a point spread function (PSF) and its ideal image. In this paper, we propose a novel blind deconvolution method to alternately estimate PSF and the latent image. And we incorporate the gradient reliability map (R-map) that enables edge selection appropriate for PSF estimation processing. This method improves restoration performance by excluding noise that adversely affects the estimation, and the experimental results show that robustness is improved in our proposed method.**

***Keywords*—blur; blind deconvolution; image restoration**

I. Introduction

Recently, smart phones and SNS have become widely used, and it is now easy to take photos. Many pictures suffer from image blurring due to various factors such as camera shake and poor focus. Furthermore, image blurring cannot be visually discriminated on these small displays. However, image blurring can be recognized on large displays such as HDTVs and laptop displays. Because this degradation is visually undesirable, restoration of the degraded image is required.

Blur is one of representative image deterioration, and many researches on its restoration has been proposed [1] - [5]. In case of restoring a degraded image, if the blurring function is unknown, it is necessary to estimate a point spread function (PSF) and its ideal image by using an input image. A method of alternately repeating the PSF and ideal image estimations produces good results. However, there are some problems such as occurrence of ringing due to an estimation error of the PSF and emphasis of noise. Therefore, further improvements in restoration performance are required.

In this paper, a novel algorithm based on two-step blind deconvolution is proposed. In our proposed method, during the latent image restoration step, total variation regularization [6], [7] is applied to reduce texture components and noise; and a shock filter [8], [9] is applied to emphasize the edges, this results in an improvement of the PSF estimation performance. The method of Krishnan et al., which offers fast processing, is implemented in the deconvolution and high-speed processing is achieved. The gradient reliability map is then applied to decrease edges, which are badly affected in the PSF estimation, to improve the performance of the PSF estimation, this is a main proposal in this paper compared with our conventional work [5]. In our experiments, first the parameters for the threshold process of the gradient distributions are optimized to improve restoration performance, and then Sun's test sets [3] are used to validate our proposed method in the objective evaluations. Finally, actual blurred pictures are used to evaluate our proposed method objectively and subjectively.

II. Image Restoration Algorithm

When image blurring in an image as a whole is uniform, blurred image b is modeled as the convolution of latent image x and its PSF k as follows, where n is noise.

$$b = x \otimes k + n \tag{1}$$

In this paper, we restore images using this blur degradation model. Image restoration can be classified as non-blind deconvolution and blind deconvolution. Non-blind deconvolution is image restoration when the PSF is known, and blind deconvolution is image restoration when the PSF is unknown. Blind deconvolution is the problem of estimating both an ideal image and its PSF from a single degraded image. In general, we estimate the final PSF by alternately repeating the latent image estimation (x-step) and its PSF estimation (k-step). We restore the degraded image by performing a final non-blind deconvolution using the estimated PSF.

III. Blind Image Restoration

Blind deconvolution is a method of estimating an ideal image and its PSF from a blurred image. We refer to the blind deconvolution method [5] which is using Total Variation Regularization and Shock Filter at x-step, and PSF estimation using calculate a slope distribution and thresholding process at k-step.

A. Latent Image Estimation (x-step)

In the x-step, restored image x is first obtained by deconvolution. The texture component of restored image x is removed to process the total variation regularization for noise removal. Then, a shock filter is applied to the obtained structure component to restore the edge component of the latent image x estimation.

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During the deconvolution process, latent image x is restored by using the PSF k obtained by the PSF estimation process. Fast deconvolution utilizing the hyper-Laplacian priors [10] is adopted. Latent image x is determined by solving the following minimization problem.

$$\mathrm{x} = min_x \sum_{i=1}^{N} \left(\frac{\lambda}{2} (x \otimes k - b)_i^2 + \sum_{j=1}^{J} \left| (x \otimes d_j)_i \right|^2 \right) \quad (2)$$

where d is a differential filter and $|.|^2$ is a penalty function.

Total variation regularization is often used to decompose an image into a structure component, which consists of edges and low-frequency components; and a texture component, which consists of small oscillating signals and noise. In the ROF model [6], the evaluation function *F(u)* is minimized to solve an image decomposition as shown in Eq. (3):

$$\inf_u F(u) = \sum_{i,j} |\nabla_{i,j}| + \lambda \sum_{i,j} |u_{i,j} - f_{i,j}|^2 \quad (3)$$

where $f_{i,j}$ is an input pixel value, $u_{i,j}$ is a computed output pixel value, i and j are pixel coordinates, and λ is a positive constant. To minimize evaluation function *F(u)*, we adopt the projection method proposed by Chambolle [7], which is known to be a fast solution. The values u and $v = f - u$ are the structure component and texture component, respectively.

The shock filter [8] is a filter for the restoration or the enhancement of signal edges by repeated calculation as shown in Eq. (4):

$$x_{t+1} = x_t - \mathrm{sign}(\Delta x_t)\|\nabla x_t\|\mathrm{dt} \quad (4)$$

where *dt* is the step-size parameter for the shock filter.

B. PSF Estimation (k-step)

In the k-step, we perform a thresholding process to obtain latent image x estimated in the x-step and estimate PSF k by solving a minimization problem by using degraded image b and ideal image x.

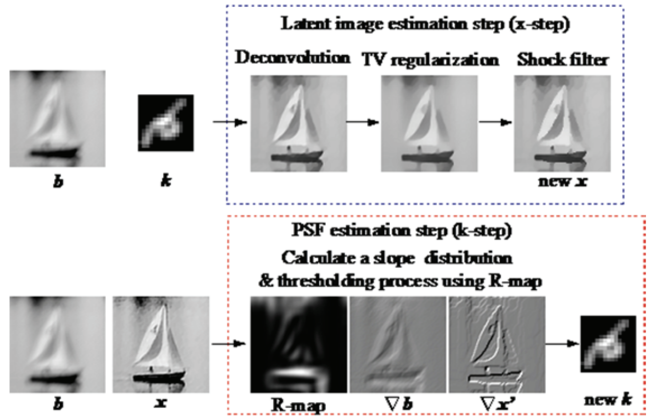


Fig. 1. Processing flow of our proposed blind deconvolution

One specific method for a thresholding process is to divide the directions of the gradient into four groups: 0º, 45º, 90º, and 135º. We then set the threshold α_g which is a coefficient of a number of pixels to select for each group.

In the PSF estimation, by using observed image gradient distribution ∇b and predicted latent image gradient distribution ∇x, PSF k is estimated. By minimizing the conjugate gradient method of an energy function as shown in Eq. (5), the PSF k is estimated thusly:

$$E_k(k) = \|\nabla x' \otimes k - \nabla b\|^2 + \lambda_k \|k\|^2 \quad (5)$$

IV. Proposed Method

The blind deconvolution occasionally causes an estimation error of PSF due to the fine texture components and may result in failure to restore images. To further improve the restoration performance of the blind deconvolution, we add a new process called the gradient reliability map (R-map) in the k-step. The R-map enables edge selection appropriate for PSF estimation processing. Therefore, this method has become a robust method which is hardly affected by noise. Figure 1 shows the processing flow of the proposed method.

A. Gradient Reliability Map (R-map)

In the minimization problem for the PSF estimation of our proposed method, strong edges are used. However, those may have a negative influence due to noise or narrow signals such as impulse signals. A narrow signal, which is narrower than the blur size, causes a smaller amplitude value when the shock filter emphasizes its edge. This results in an incorrect estimation. Therefore, we apply the gradient reliability map, which is called the R-map, as shown in Eq. (6): where $N_h(x)$ is a h × h window at a center position x. Figure 2 shows an example of R-map.

$$r(x) = \frac{\left\| \sum_{y \in N_{h(x)}} \nabla b(y) \right\|}{\sum_{y \in N_{h(x)}} \|\nabla b(y)\| + 0.5} \quad (6)$$

(a) Burred image (b) R-map

Fig. 2. Example of gradient reliability map

V. Experimental Results

We use a benchmark dataset proposed by Sun *et al.* [3] for quantitative evaluation. In this dataset, we restored 640 degraded images generated by using 80 ideal images and 8 PSFs, with 1% white Gaussian noise being added to these 640 images. We then calculate the PSNR between an ideal image and its restored image. In addition, we calculate error ratio r as follows:

$$r(x) = \frac{\|x - \tilde{x}_{\tilde{k}}\|^2}{\|x - \tilde{x}_k\|^2} \tag{7}$$

where x is an ideal image and $\tilde{x}_{\tilde{k}}$ is the image restored by blind deconvolution. $\tilde{x}_k$ is an image restored by non-blind deconvolution using an ideal PSF, and we refer to this non-blind deconvolution method as the "known PSF". The restoration results are better when the error ratio r approaches one. Table I shows the experimental parameters for our proposed method.

A. Objective Evaluation

Table II and Fig. 3 show the experimental results when Zoran's method [11] is used in the final non-blind deconvolution of each method, so that we evaluate only the performance of the PSF estimation. In Table II, the success rate is defined as being when $r \leqq 5$, which was proposed in [4], and the restored image quality is still good. The average PSNR, the average error ratio and the success rates of our proposed method offer the best performance of currently available methods. However, the maximum error rate in Michaeli et al. method is the lowest, which implies that the method of Michaeli et al. method is a robust method. Therefore, there is some room for improvement with respect to the error ratio in our proposed method. In Fig. 3, the upper left line shows the best performance in the success rate, so our proposed method is highest compared with the other methods.

B. Subhective Evaluation for Sun's Test Set

Figure 4 shows blurred images and the restored images using the house image. Figure 5 shows the PSFs. In these figures, (a), (b), (c) and (d) are the original blurred image, those obtained by the Michaeli et al. method, those for our conventional method [5], and those for our proposed method, respectively. In Figs. 4 and 5, the house images are clear enough in the Michaeli method and our proposed method, although ringing occurred in our conventional method.

TABLE I. Experimental Parameters For Proposed Method

PSF size			31 × 31
Iterative number at each scale			5
Latent image estimation process	Deconvolution	λ_d	1500
	TV Regularization	Iterative number	10
		λ_d	20
	Shock Filter	Iterative number	1
		Dt	1.0
PSF estimation process	Iterative number		30
	Threshold value		0.05
	α_g		45

C. Subjective Evaluation for Actual Pictures

Figure 6 shows the blurred image and the reconstructed images using the Lyndsey image, and Fig. 7 shows the estimated PSFs for each method in which Krishnan et al. method is used in the final non-blind deconvolution. In Figs. 6 and 7, blurred noise remains in the image obtained using the Michaeli et al. method and our conventional method, however, a clear image is obtained for our proposed method. Also, the same results are obtained for the other actual pictures.

D. Processing Time

Table III shows the processing time, which is calculated for MATLAB running on an Intel Core i5-4210M (2.60 GHz) and 8GB RAM on Windows7 for the Michaeli et al. method, our conventional method and our proposed method. In Table III, the processing time for our conventional method and our proposed method is almost the same, and both are more than 123 times faster than that for the Michaeli et al. method.

TABLE II. Experimental Results of Objective Evaluation

Methods	Average PSNR [dB]	Average Error Ratio	Max Error Ratio	Success Rates[%] ($r \leqq 5$)
Blur input	24.62	6.86	25.92	35.63
Known PSF	32.33	1.00	1.00	100.00
Cho&Lee[1]	26.65	9.00	118.28	68.26
Xu & Jia[2]	29.19	3.08	65.36	88.63
Sun et al.[3]	30.20	2.14	24.98	93.71
Michaeli & Irani [4]	29.06	2.38	**9.23**	95.47
Conventional method[5]	30.21	2.23	48.39	93.44
Proposed method	**30.87**	**1.64**	24.13	**96.72**

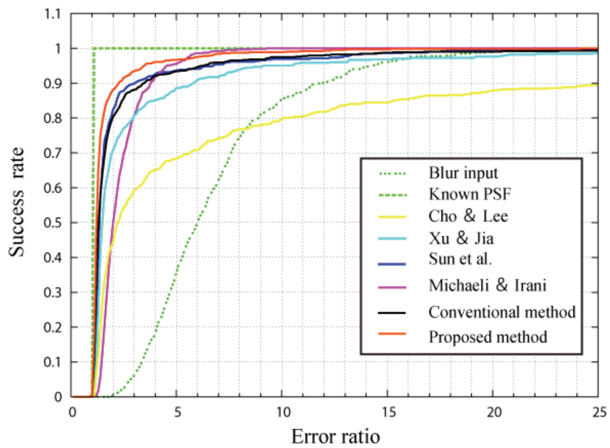
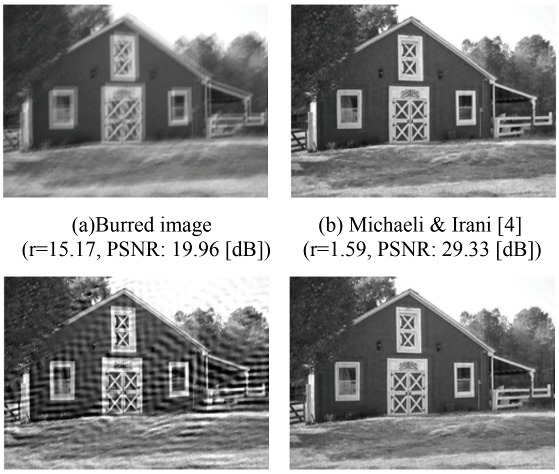
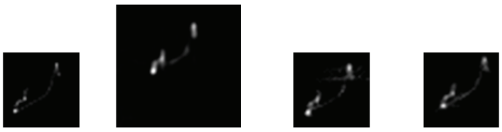


Fig. 3. Experimental results of cumulative error rate



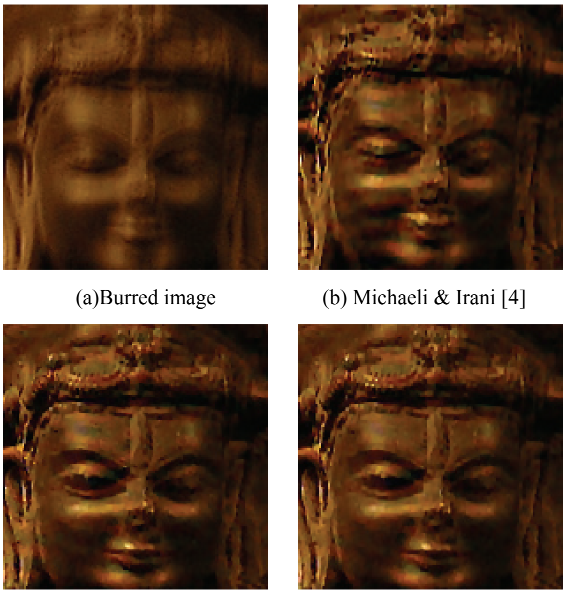
(a)Burred image (r=15.17, PSNR: 19.96 [dB]) (b) Michaeli & Irani [4] (r=1.59, PSNR: 29.33 [dB]) (c) Conventional method [5] (r=15.24, PSNR: 19.49 [dB]) (d) Proposed method (r=1.56, PSNR: 29.44 [dB])

Fig. 4. Blurred image and Restored images (House image)



(a)Ideal PSF (b) Michaeli & Irani [4] (c) Conventional method[5] (d) Proposed method

Fig. 5. Ideal PSF and estimated PSFs (House image)



(a)Burred image (b) Michaeli & Irani [4] (c) Conventional method [5] (d) Proposed method

Fig. 6. Blurred image and Restored images (Lyndsey image)

(a) Michaeli & Irani [4] (b) Conventional method[5] (c) Proposed method

Fig. 7. Estimated PSFs (Lyndsey image)

TABLE III. PROCESSING TIME [SEC]

Image size	Michaeli & Irani	Conventional Method	Proposed method
716×451	2596.0	20.9	21.1
724×905	4498.1	34.4	35.0
1920×1024	15671.1	112.6	113.3

VI. CONCLUSION

In this paper, we have proposed a novel PSF estimation method utilizing total variation regularization, a shock filter and the gradient reliability map. The results of the experiment clearly show that we have achieved the best performance for average PSNR, average error ratio, and success rate in the objective evaluation. The clearest images were obtained in the Sun's test set and for an actual image in the subjective evaluation. Also, the processing time of our proposed method was 123 times faster than that of the Michaeli et al. method. Thus, our proposed method clearly offers state-of-the-art performance. For further research, we intend to improve the maximum error ratio, which was decreased because there were a few restored failure images using our proposed method, and it will be achieved to select optimized parameters of total variation regularization.

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