An improved image blind deblurring based on dark channel prior*

WANG Man-wei (王曼威), ZHU Fu-zhen (朱福珍), and BAI Yu-yang (柏宇阳)**
College of Electronic Engineering, Heilongjiang University, Harbin 150000, China

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In order to solve the ringing effect caused by the incorrect estimation of the blur kernel, an improved blind image deblurring algorithm based on the dark channel prior is proposed. First, in the blur kernel estimation stage, high-pass filtering is introduced to enhance the image quality and enhance the edge information to make the blur kernel estimation more accurate. A combination of super Laplacian prior and dark channel prior is introduced to estimate the potential clear image. Then the accurate blur kernel is estimated through alternate iterations from coarse to fine. In the image restoration stage, a weighted least square filter is introduced to suppress the ringing effect of the original clear image to further improve the quality of image restoration. Finally, image deconvolution based on Laplace priors and L_0 regularized priors is used to restore clear images. Experimental results show that our approach improves the peak signal-to-noise ratio (*PSNR*) by about 0.4 dB and structural similarity (*SSIM*) by about 0.01, respectively. Compared with the existing image deblurring algorithms, this method can estimate the blur information more accurately, so that the restored image can achieve the effect of keeping the edges and removing ringing.

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The purpose of image blind deblurring is to restore the blur kernel of a blurred image and the clear potential image obtained from the blurred image. The problem of blind deblurring of images has become increasingly important because more and more photos are taken with handheld cameras. The problem of camera shake when taking pictures is inevitable, so that the blurred images produced cannot be used by humans. High quality images can be obtained by studying the problem of blind image defuzzing, and people are also exploring a high performance algorithm which is generally suitable for the general real image.

Blind image deblurring refers to the process of restoring the original clear image only by relying on the degraded image itself when the blurring method is unknown. In recent years, great progress has been made in image blind deblurring, so it is necessary to use the prior knowledge of clear image or fuzzy kernel to constrain the solution. The commonly used statistical priors include normalized sparse priori[1], L_0 regularized gradient priori[2,3], L_1 norm[4], L_p/L_2 norm[5], block priori[6], joint intensity and gradient priori[7], etc. Krishnan D et al[1] proposed to normalize the sparse prior, using the ratio of L_1 to L_2 norm as the prior. Zuo et al[8] used the generalized contraction threshold operator of L_p norm to estimate the fuzzy kernel of images of different degrees, and then constructed clear images. Pan et al[7] proposed intensity priori and gradient priori to remove the blur in the text image. Pan et al[9] also found that there are more or less dark channels in natural images, while the dark channels in fuzzy images are less sparse than the original clear images, so they proposed a dark channel priori to enhance the sparsity of dark channels in potential clear images. Zhang et al[10] proposed an effective blind image deblurring algorithm based on three-segment intensity, namely low, medium, and high parts, and achieved good results. In addition, the most popular deep learning methods have recently begun to be applied to image restoration algorithms, such as Jian Sun[11], S. Nah[12], Thekke M[13] method. Kupyn O[14] recently proposed Deblur GAN. Gong et al[15] proposed a self-reference deblurring generative confrontation network, namely SR-Deblur GAN. Compared with the most advanced Deblur GAN, it achieves better deblurring performance. But deep learning methods require a lot of training data. Due to the lack of real fuzzy training data, the application of this method is limited to a certain extent. Pan et al. achieved good restoration results, but the details of the images were suppressed during the restoration process of the clear images, and there was obvious ringing in the

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** E-mail: zhufuzhen@hlju.edu.cn

restored images. Research on the method to suppress the ringing effect will help improve the performance of the image restoration algorithm, so as to obtain high-quality recovered images[16]. By using super Laplacian priori, the main details of the image can be retained in the clear image and the ringing can be effectively suppressed. Aiming at the shortcomings of the method of Pan et al to restore the image, this paper proposes an improved method based on the dark channel prior blind deblurring algorithm[9]. In the stage of blur kernel estimation, high-pass filtering is introduced into the original algorithm to sharpen and enhance the blurred image and enhance the image edge information, so as to make the blur kernel estimation more accurate. By introducing the combination of hyper Laplacian prior and dark channel prior, the average image of both restored images is taken to obtain the potential clear image, and the blur kernel is better obtained. In the image restoration, the method of weighted least square filtering is introduced to suppress the ringing and obtain a clear image.

The motion blur process of the image can be modeled as the convolution of the clear image with the fuzzy kernel plus the noise, that is

$$g=k\cdot f+n, \tag{1}$$

where g is the observed blurred image, f is the sharp image, k is the blur kernel, and n is the noise. The image blind deblurring algorithm generally takes two steps, one is to estimate the fuzzy kernel, and the other is to deconvolute the image to obtain a clear image. The blur kernel of the blurred image is used to identify the blur path of the camera, and its value distribution is sparse. The estimation of blur kernel is produced by alternating iteration namely by estimating the potential clear image and the input blurred image. This newly estimated blur kernel and blurred image are used to estimate the potential sharp image. This process iterates repeatedly until a near-real blur kernel is obtained. For potentially clear image restoration, Pan et al showed that the dark channels of the blurred image were not as sharp as the image. Therefore, a prior dark channel is proposed to enhance the sparseness of dark channels of potentially sharp images.

The dark channel of the image reflects the distribution of dark points in the image. The definition of dark channel was first proposed by He K et al[17] and applied to the image defogging algorithm[18]. They observed that the dark channel pixel of the outdoor fogless image was almost zero, and the dark channel prior has been applied to image defogging[19]. He et al found that most pixels of a clear image are in its color channel, and at least one channel has extremely low brightness, which can be approximated to zero. Intuitively, the process of image blurring will make the pixel value of an extremely dark pixel be replaced by the weighted average value of other brighter pixels in the neighborhood, so that the extremely dark pixel will become larger, that is, the dark channel value of the fuzzy image is mostly non-zero. Therefore, Pan et al proposed that dark channel prior be used to constrain the dark channel sparsity of potential clear images. For image I, the dark channel is defined as

$$D(I)(x)=\min_{y\in N(x)}\left\{\min_{c\in\{r,g,b\}} I^c(y)\right\}, \tag{2}$$

where x and y represent the position of the pixel, $N(x)$ is the area centered on x, and I^c is the Cth channel of image I, for a grayscale image $\min_{c\in(r,g,b)} I^c(y)=I(y)$.

In view of the shortcomings of Pan et al's method for image restoration, this paper proposes an improved method. The algorithm steps of this paper are shown in Fig.1.

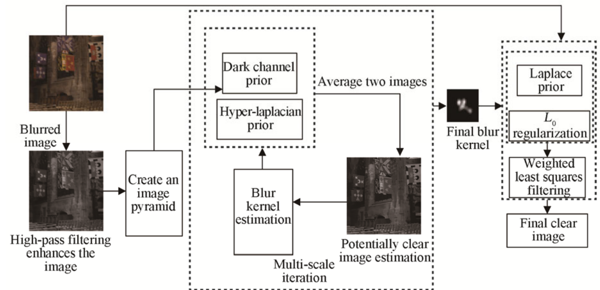
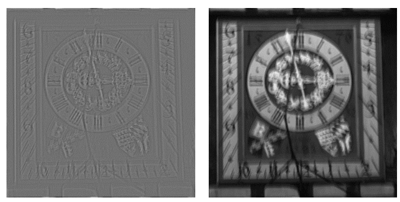


Fig.1 Block diagram of algorithm

The image edge of the blurred image is also blurred, which is not conducive to the estimation of the blur kernel. In this paper, preprocessing is added on the basis of the original algorithm, and high-pass filter is introduced to process the input image. After the image is Gaussian high-pass filtered, the edge of the blurred image is extracted and superimposed on the original blurred image, so that the edge of the input blurred image is strengthened and the edge contour is clearer. In this way, the edge of the image is enhanced, which is beneficial to the estimation of the blur kernel. The formula of Gaussian high pass filter is as follows:

$$H(u,v)=1-\mathrm{e}^{-D^2(u,v)/2D_0^2}, \tag{3}$$

where D_0 is the cut-off frequency, $D(u, v)$ is the distance from the origin of the Fourier. Fig.2 shows the image after high-pass filtering.



(a) (b)

Fig.2 (a) Image edges extracted by high-pass filtering; (b) Enhanced image after high-pass filtering

Pan J et al[9] found that dark channel priors are also applicable to blind deblurring of images. The dark channel blind deblurring algorithm can be transformed into the optimization problem of Eq.(4), that is

$$\min_{I,k}\|I\otimes k-B\|_2^2+\gamma\|k\|_2^2+\mu\|\nabla I\|_0+\lambda\|D(I)\|_0, \tag{4}$$

where I, k and B represent clear image, blur kernel and blurred image respectively; $D(I)$ is dark channel; $\|\cdot\|_0$ is L_0 norm; γ, μ and λ are weight coefficients; $\|I \otimes k - B\|_2^2$ is data fitting term; namely, the error between clear image and blurred image after convolving blur kernel. $\lambda\|D(I)\|_0$ is sparse prior of dark channel. A common way to solve such optimization problems is to convert them into two sub-problems for iterative alternation, that is, we iteratively solve the potential image I:

$$\min_I \|I \otimes k - B\|_2^2 + \mu\|\nabla I\|_0 + \lambda\|D(I)\|_0 , \tag{5}$$

and blur kernel k:

$$\min_k \|I \otimes k - B\|_2^2 + \gamma\|k\|_2^2 . \tag{6}$$

This paper introduces the combination of hyper Laplacian prior and the original dark channel prior to deblur the image. First, down-sampling is used to decompose the fuzzy image in a pyramid, and then the image obtained by dark channel priori and super Laplacian prior is averaged to estimate the potential clear image. By using the hyper Laplacian prior constraint on the clear image, the clear image obtained can better retain the details and effectively suppress the ringing. Therefore, this article combines the advantages of the dark channel prior and the super Laplacian prior method when estimating the potentially clear image.

In order to estimate an accurate blur kernel, it is necessary to alternately solve the potential clear image and the blur kernel. Similar to Refs.[7] and [20], the auxiliary variable u for $D(I)$ and g=(gh, gv) corresponding to the image gradient in the horizontal and vertical directions are introduced. Therefore, the objective function Eq.(5) can be rewritten as

$$\min_{I,u,g} \|I \otimes k - B\|_2^2 + \alpha\|\nabla I - g\|_2^2 + \beta\|D(I) - u\|_2^2 + \mu\|g\|_0 + \lambda\|u\|_0 , \tag{7}$$

where α and β are penalty parameters. Eq.(7) can be solved by minimizing I, u and g while fixing other variables. Using the iterative alternating method, the problem solving Eq.(7) is transformed into three sub-problems, namely

$$\min_I \|I \otimes k - B\|_2^2 + \alpha\|\nabla I - g\|_2^2 + \beta\|D(I) - u\|_2^2 , \tag{8}$$

$$\min_u + \lambda\|u\|_0 + \beta\|D(I) - u\|_2^2 , \tag{9}$$

$$\min_g \mu\|g\|_0 + \alpha\|\nabla I - g\|_2^2 . \tag{10}$$

The Laplace distribution is a continuous probability distribution named after Pierre-Simon Laplace. The gradient of the natural scene conforms to the long-tailing distribution. This prior knowledge has been confirmed and has been applied to the problems of denoising, deblurring and super-resolution reconstruction. This long tail distribution can be well approximated by the super Laplace distribution.

The formula for solving I_1 of potential clear image with hyper Laplacian prior is

$$\min_I \|I \otimes k - B\|_2^2 + \rho\|\nabla I\|^{\alpha} , \tag{11}$$

where ρ is the weight coefficient, $\alpha \in [0.5, 0.8]$, and the satisfactory effect can be obtained by adjusting the size of α. In this paper, α=2/3. Finally, the formula for calculating the latent clear image I is:

$$I = 1/2(I_1 + I_2). \tag{12}$$

Fig.3 shows a comparison rendering of the potentially clear image obtained by the algorithm in this paper with those obtained by other algorithms[7,9].

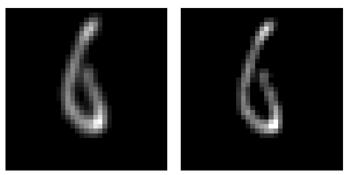
(a)   (b)   (c)

Fig.3 Comparison of potentially clear images obtained by algorithm in (a) Ref.[7], (b) Ref.[9] and (c) this paper

The blur kernel is calculated by estimating the potential clear image and the input blurred image, and the newly estimated blur kernel and blurerd image are used to estimate the potential clear image. In this process, one iteration at a time, to get close to the real blur kernel. When solving the blur kernel, given the potential clear image I, the blur kernel estimation problem in Eq.(6) is a least-squares problem. At present, the gradient-based blur kernel estimation[2] method has been proved to make the blur kernel estimation more accurate. Therefore, this paper estimates the blur kernel by gradient-based method:

$$\min_k \|\nabla I \otimes k - \nabla B\|_2^2 + \gamma\|k\|_2^2 . \tag{13}$$

The solution of Eq.(13) is obtained by the method of fast Fourier transform[21]. Fig.4 shows the comparison between the blur kernel estimated by the algorithm in this paper and the original algorithm.

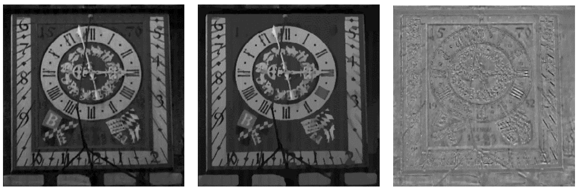


(a)   (b)

Fig.4 Estimated blur kernel comparison: (a) Blur kernel estimated by method in Ref.[9]; (b) Blur kernel estimated by the improved algorithm in this paper

When the image deconvolution process restores the image edges, ringing effects often occur, such as the classical Wiener filtering method, Richardson-Lucy method, and Laplace prior[22,23] method. It has been proved in the literature that the non-blind deblurring method with Laplace prior[23] can preserve the edge details of the image. However, this algorithm will introduce some artificial effects, which will result in a staircase effect in the smooth area of the restored image, that is, the original false edges that do not exist in the image.

The restored image obtained based on the L_0 regularization prior restoration method contains less details and artificial effects, which can well retain the significant edges of the image and suppress the details of the image. Therefore, in this paper, a deconvolution method combining L_0 regularization prior and Laplace prior is used. In order to obtain images with more details and less artificial effects, the difference images restored by the two priors are used to eliminate ringing. Effect, the difference image contains the artificial effects of image details and false edges. Therefore, this paper introduces the weighted least squares filter to smooth the details in the difference image, and extracts the inaccurately estimated structure, that is, the false edge. Finally, the inaccurate structure is subtracted from the image based on the Laplacian prior restoration, and a better restoration result is obtained. Fig.5 shows the intermediate results of image restoration. It can be seen that the poor image contains more details but also contains artificial effects.



(a) (b) (c)

Fig.5 Intermediate results of image restoration: (a) Laplace-based prior restoration results; (b) L_0 Regularization-based prior restoration results; (c) Two difference images

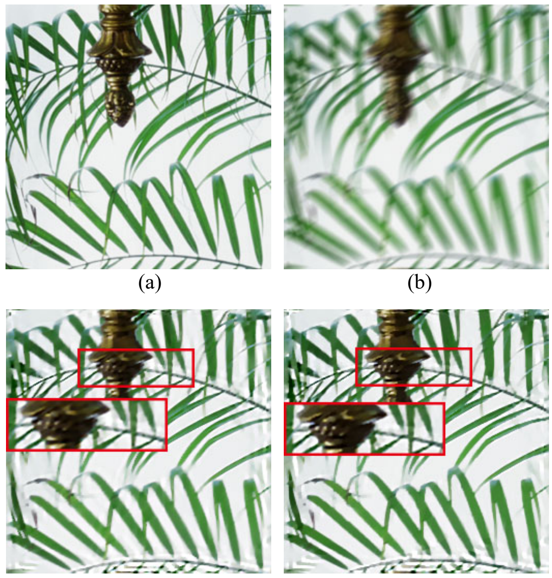
The weighted least squares filter can smooth the image while maintaining the edge, and is widely used in image processing. In order to extract the inaccurately estimated structure from the difference image and suppress the ringing effect of image restoration, this paper introduces a weighted least square filter to smooth the difference image details and preserve the difference image edges. Algorithms based on bilateral filtering cannot extract good detail information at multiple scales, and artifacts may appear. The purpose of weighted least squares filtering is to make the resulting image and the original image as smooth as possible, but keep the original shape at the edge as much as possible. The formula is as follows:

$$\sum_p \left((u_p - g_p)^2 + \lambda \left(\alpha_{x,p(g)} \left(\frac{\partial u}{\partial x}\right)_p^2 + \alpha_{y,p(g)} \left(\frac{\partial u}{\partial y}\right)_p^2 \right) \right), \qquad (14)$$

where p represents the spatial position of pixels, α_x and α_y are weight coefficients, the first term of the objective function represents the input image and the output image are as similar as possible; the second term is the regular term, by minimizing the partial derivative of u, the smoother the output image g is, the better. The increase of α will cause the reserved edge to be clearer. The default value of 1.2 is used in this paper; λ is the balance weight between data items and smoothness, and the increase of λ will produce a smoother image. The default value of 1.0 is used in this paper. When the input image contains noise, or the edge information is not rich enough, the weighted least squares filtering algorithm has better edge preservation effect.

In order to verify the effectiveness of the image deblurring algorithm proposed in this paper, ten sets of blurred images were tested in the Matlab environment. In the experiment, set the weight coefficient $\lambda=\mu=0.004$ for the latent image and the weight coefficient $\gamma=2$ for the blur kernel in Eq.(4). The effect of the image before and after deblurring is compared, and the evaluation index after image restoration is given. At the same time, peak signal-to-noise ratio (*PSNR*) and structural similarity (*SSIM*)[24] are used to objectively evaluate the restoration results of synthetic blurred images. For the restoration results of true blurred images, subjective evaluation is used.

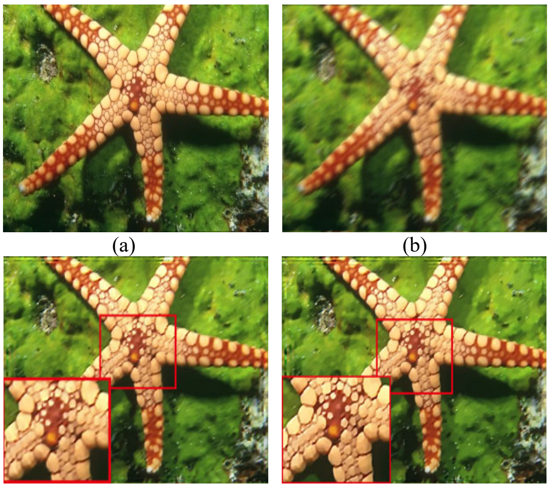
Figs.6 and 7 select the clear image as the standard image for testing. The clear image is affected by motion blur. For the clear image, add motion blur with a length of 10 and an angle of 30. It can be seen that the restored image of this algorithm has less ringing and the image is clearer.



(a) (b) (c) (d)

Fig.6 Composite image restoration results: (a) Original image; (b) Blurred image; (c) Ref.[9] method; (d) method in this paper

Fig.8 is an image deblurring image in the data set publicly provided by Kohler et al. The Kohler data set consists of 4 images and 12 different blur kernels to form 48 blurred images. This is a standard benchmark data set for evaluating deblurring algorithms. Comparing the algorithm of this paper with the algorithm of Pan et al, it can be seen that the algorithm of this paper restores the image more clearly, retains more details of the picture, has less artifacts, and the blur kernel estimation is more accurate.



(a) (b) (c) (d)

Fig.7 Composite image restoration results: (a) Original image; (b) Blurred image; (c) Ref.[9] method; (d) Method in this paper

$$PSNR = 10\log_{10}\frac{255^2 M \times N}{\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j)-I_w(i,j))^2}, \tag{15}$$

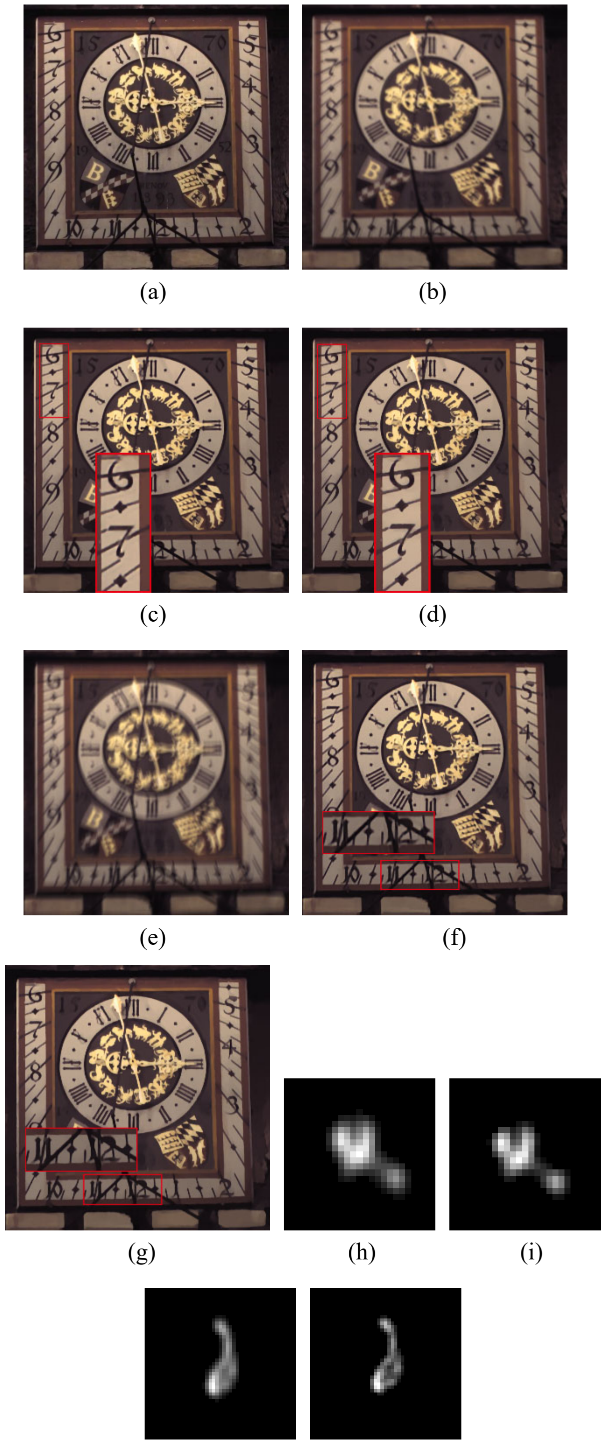
where M and N are the height and width of the image, respectively, and n is the number of bits per pixel, which is generally 8. The unit of $PSNR$ is dB. Generally, the larger the $PSNR$, the better the image quality.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_x\sigma_y + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}, \tag{16}$$

where μ_x and μ_y are means, σ_x^2 and σ_y^2 are variances, and σ_{xy} is the covariance of x and y. The value range of $SSIM$ is [0, 1], and the larger the value of $SSIM$, the better the image quality. Fig.9 and Tab.1 are the data comparison between the 6 synthetic images processed in this paper and the objective evaluation indexes of the methods in Ref.[9].

Tab.1 Comparison of *PSNR* (dB) and *SSIM* data of the test composite image

	Method in Ref.[9]	Ours
No.1	25.380 3/0.815 1	25.922 9/0.824 0
No.2	27.959 4/0.842 4	28.700 2/0.859 7
No.3	16.021 7/0.491 3	16.398 4/0.501 6
No.4	22.695 0/0.672 9	22.904 3/0.688 5
No.5	27.569 7/0.880 2	28.133 6/0.882 4
No.6	22.758 8/0.615 6	22.988 4/0.633 3



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k)

Fig.8 Composite image restoration results: (a) Original image; (b)(e) Blurred image; (c)(f) Ref.[9] method; (d)(g) Method in this paper; (h)(j) Ref.[9] estimated blur kernel; (i)(k) Estimated blur kernel in this paper

Fig.10 is a comparison of the algorithm's deblurring results for real blurred images with other algorithms. It can be seen that the algorithm in this paper restores the image more clearly, less ringing artifacts, and richer image detail retention.

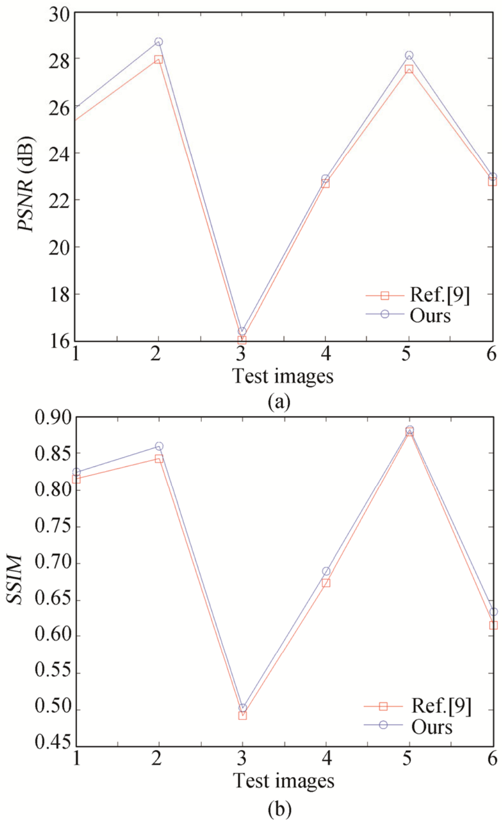


Fig.9 Intuitive comparison of (a) *PSNR* (dB) and (b) *SSIM* data of 6 groups of composite images

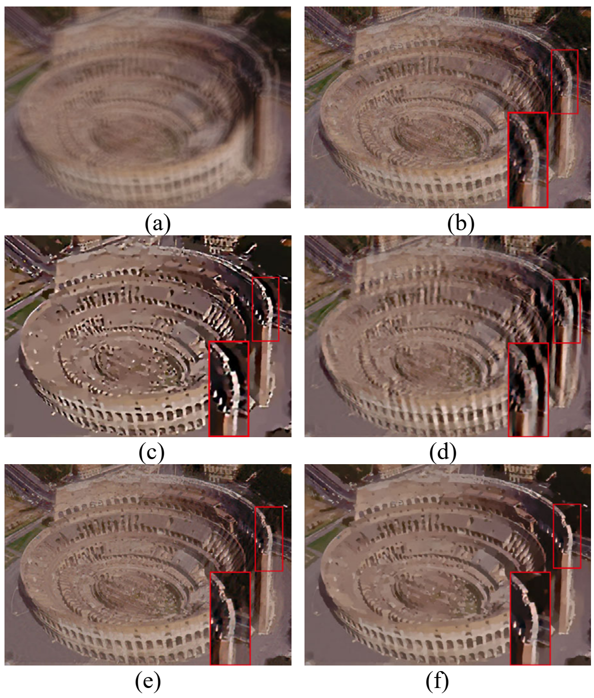


Fig.10 Real image restoration results: (a) Blurred image; (b) Ref.[25] method; (c) Ref.[7] method; (d) Ref.[9] method; (e) Ref.[10] method; (f) Method in this paper

Based on the analysis of the above experimental results, compared with other algorithms, the method in this paper has better image deblurring effect, clearer visual effect, more accurate fuzzy kernel estimation, less ringing artifacts, and richer image edge and texture information. At the same time, the *PSNR* and *SSIM* data of the synthetic image deblurring results in Tab.1 show that the *PSNR* of this algorithm is improved by about 0.4 dB and the *SSIM* value is increased by about 0.01. Therefore, the blind deblurring method in this paper has achieved better results, and both subjective visual effects and objective evaluation indicators have been improved.

To overcome the ringing effect of the existing image deblurring algorithm, this paper proposes an improved dark channel prior image deblurring algorithm. First, a high-pass filter is used to enhance the blurred image, and the dark channel prior and super Laplace prior are used to estimate the potential clear image; then an accurate blur kernel is estimated alternately and iteratively; finally, image deconvolution based on Laplace prior and L_0 regularized prior is used to achieve clear image restoration. The weighted least square filter is introduced to reduce the ringing effect in the restored image, and the edge is preserved better, which improves the image restoration effect. The experimental results show that the algorithm in this paper can effectively remove the image blur, while effectively ensuring the edge of the image, while suppressing the ringing effect. The *PSNR* of this algorithm is improved by about 0.4 dB and the *SSIM* value is increased by about 0.01. Compared with the blind deblurring algorithm based on the dark channel prior, the deblurred image quality obtained by the method in this paper is better.

Image noise will interact with blur kernel estimation, and a good algorithm should be fast and efficient. In the future, how to remove the influence of noise in blurred image on blur kernel estimation and how to develop faster defuzzification algorithm will be the issues to be considered in future work.

References

[1] Krishnan D, Tay T and Fergus R, Blind Deconvolution Using a Normalized Sparsity Measure, IEEE Conference on Computer Vision and Pattern Recognition, 233 (2011).

[2] Xu L, Zheng S and Jia J, Unnatural. L_0 Sparse Representation for Natural Image Deblurring, IEEE Conference on Computer Vision and Pattern Recognition, 1107 (2013).

[3] Yan J W, Xie T T, Peng H and Liu P H, Laser & Optoelectronics Progress **54**, 156(2017). (in Chinese)

[4] Feng X C, Liu X, Yang C Y and Wang W W, Journal of Beijing University of Posts and Telecommunications **41**, 8 (2018). (in Chinese)

[5] Yu Y B, Peng N and Gan J Y, Acta Electronica Sinica **44**, 1168 (2016). (in Chinese)

[6] Michaeli T and Irani M, Blind Deblurring Using Internal Patch Recurrence, European Conference on Computer Vision, 783 (2014).

[7] Pan J, Hu Z, Su Z and Yang M H, IEEE Transactions on

Pattern Analysis and Machine Intelligence **39**, 342 (2017).

[8] Zuo W, Ren D, Zhang D, Gu S and Zhang L, IEEE Transactions on Image Processing **25**, 1751(2016).

[9] Pan J, Sun D, Pfister H and Yang M H, IEEE Transactions on Pattern Analysis and Machine Intelligence **40**, 2315 (2018).

[10] Zhang H, Wu Y, Zhang L, Zhang Z and Li Y, Neurocomputing **398**, 265 (2020).

[11] J. Sun, W. Cao, Z. Xu and J. Ponce, Learning a Convolutional Neural Network for Non-Uniform Motion Blur Removal, IEEE Conference on Computer Vision and Pattern Recognition, 769 (2015).

[12] S. Nah, T. H. Kim and K. M. Lee, Deep Multi-scale Convolutional Neural Network for Dynamic Scene Deblurring, IEEE Conference on Computer Vision and Pattern Recognition, 257 (2017).

[13] T. M. Nimisha, A. K. Singh and A. N. Rajagopalan, Blur-Invariant Deep Learning for Blind-Deblurring, IEEE International Conference on Computer Vision, 4762 (2017).

[14] Kupyn O, Budzan V and Mykhailych M, DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks, IEEE Conference on Computer Vision and Pattern Recognition, 8183 (2018).

[15] G. Gong and K. Zhang, Local Blurred Natural Image Restoration Based on Self-Reference Deblurring Generative Adversarial Networks, IEEE International Conference on Signal and Image Processing Applications, 231 (2019).

[16] Zuo W and Lin Z, IEEE Transactions on Image Processing **20**, 2748 (2011).

[17] He K, Sun J and Tang X, Single Image Haze Removal Using Dark Channel Prior, IEEE Computer Vision and Pattern Recognition, 1956 (2009).

[18] Zhang Z, Li Q, Xu Z and Feng H, Opt. Precision Eng. **27**, 181 (2019). (in Chinese)

[19] Qiu X and Dai M, Opt. Precision Eng. **25**, 2490 (2017). (in Chinese)

[20] Tang J, Shu X, Qi G J, Li Z, Wang M, Yan S and Jain R, IEEE Transactions on Pattern Analysis and Machine Intelligence **39**, 1662 (2017).

[21] Wang Y, Yang J, Yin W and Zhang Y, SIAM Journal on Imaging Sciences **1**, 248 (2008).

[22] Tai Y W, Tan P and Brown M S, IEEE Transactions on Pattern Analysis and Machine Intelligence **33**, 1603 (2010).

[23] Krishnan D and Fergus R, Fast Image Deconvolution Using Hyper-Laplacian Priors, International Conference on Neural Information Processing Systems, 1033 (2009).

[24] Wang Z, Bovik A C, Sheikh H R and Simoncelli E P, IEEE Transactions on Image Processing **13**, 600 (2004).

[25] Shearer P, Gilbert A C and Iii A O H, Correcting Camera Shake by Incremental Sparse Approximation, IEEE International Conference on Image Processing, 572 (2013).