Image Deblurring based on the Light Streak Shape

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Abstract. Deblurring images captured from low-illumination conditions is a challenging task because these images contain fewer useful structures for kernel estimation. However, these images usually contain some light streaks which are benefit for us to estimate the blur kernel. On one hand, these light streaks can provide us a good initial value for a non-convex problem in kernel estimation. On the other hand, they record the track of the blur kernel at the moment of images taken. Therefore, we propose a new prior for kernel estimation based on light streaks in this paper. And in order to ensure the shape of the blur kernel to be similar to that of light streaks during the updating, a new method is proposed to refine the shape of light streaks. With the help of the refined shape, our kernel estimation process does not require heuristic coarse-to-fine strategy which is widely used in image deblurring methods. Quantitative experimental results show the effectiveness of the proposed method. In addition, we also demonstrate that the proposed method can be applied to the existing deblurring methods to achieve better performance.

Keywords: image deblurring, low-illumination, light streaks, kernel estimation, kernel shape, kernel sparsity.

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1 Introduction

Blind deblurring is the problem of recovering a sharp version from a blurred input image when the blur parameters are unknown. Because the number of unknowns exceeds the number of observed data, it is an ill-posed problem. It has many important applications in computer vision fields, such as video surveillance and licence plate recognition. Therefore, image deblurring has recieved lots of attention in recent years.

The goal of image deblurring is to restore the latent image from a given blurred image. Although the existing deblurring methods[1–8] can successfully recover a reliable intermediate latent image for blur kernel estimation, most of them are designed for natural images which are captured in suitable light conditions. The light conditions enough to display most of edge structure in the scene. These methods have difficulty in dealing with the images captured from low-illumination conditions. Because most of them need rich salient edge structures to estimate the blur kernel.

In low-illumination conditions, the camera requires long exposure time to adapt the radiance of the scene. On one hand, the camera is easier to shake than in daytime because the longer exposure time, which is the main reason for those blurred images appearing in the internet. On the other hand, the presence of bright highlights arises the limitation that the radiance of the scene exceeds the range of the camera's sensor which leaves bright highlights clipped at the maximum output value.[9] In addition, because of the impacts of light blubs, flash lights and reflected lights in low-illumination conditions, most of pictures captured by the imaging device contain little useful structure information for kernel estimation.[10] Although these light streaks often contain sharp, strong edges, ~~treating them as structure edges are not correct~~.[10] We observe that some light points in the clear image would become light streaks after image blurring. And these light streaks describe the camera path which can help us to explore the shape of blur kernels.

To recover a clear image, the estimation of kernel is of great concern. With the selected edge maps, some researchers[3,8] applied the L_2-norm to obtain the kernel quickly, but they could not ensure the sparsity of the estimated kernel. Although Shan *et al.* [2] employed the L_1-norm to ensure the sparsity of kernel, they had difficulty in removing the noise of kernel. Xu and Jia[11] used an iterative support detection to remove noise for estimating the kernel. Goldstein and Fattal[12] recovered the blur kernel based on statistical irregularities of their power spectrum exhibits. But those two methods[2,12] could not ensure the shape of the estimated kernel was similar to the real one. Theoretically, a good blur kernel should be sparse and less noise in the statistical sense.[5,11] Of course that would be better if we could know the shape of blur kernel. In low-illumination conditions, we could make full use of the shape and intensity information of these light streaks to estimate the blur kernel for meeting these conditions. Firstly, the light streak which is occupying a small patch ensures the sparsity. Secondly, we could use its shape to remove the noise effectively.

Fig 1 The respective updating process of masks in different two pictures (Fig. 5.2 (a) and 5.2 (a)).

Motivated by light streaks, we propose a novel shape prior to constrain the blur kernel. As there is often more than one light streak in image, and each patch with light steak has different backgrounds which disturb us to refine the shape of light streaks. We also know that the average light streak~~(adding all the detected light streaks and divided it by their numbers)~~ is able to enhance the shape of light streak and reduce the influences of backgrounds. Therefore, we first use the average light streak as the prior for kernel estimation in our paper. Then based on the fact that the light streak patches have higher intensities than the background in a local neighborhood, we propose a method to obtain the shape of light streak and use it to guide the blur kernel estimation. We develop a simple and effective deblurring algorithm which is able to deal with the high saturate~~d~~ areas with bright pixels, thus avoiding the influence of over-expose pixels.

As described above, our method can ensure the blur kernel sparse and connected in a reasonable way. Compared with the state-of-the-art methods,[3,5,10,13] our approach has the best performance and obtains the most accurate blur kernel. Figure 1 shows the updating process of shape which ensures that the blur kernel has the similar shape with that of light streak. The corresponding deblurring results are shown in Fig. 5.2 (f) and 5.2 (f).

2 Related Work

In recent years, single image deblurring has made great progress. Researches studied image deblurring not only in good conditions[1–4], but also in low-illumination conditions.[9,10,13]

Some researchers[14,15] used the Gaussian prior to estimate the image gradient. However, the gradient of the natural image did not obey the Gaussian distribution.[1,2] Fergus *et al.* [1] proposed a zero-mean Mixture of Gaussian to obtain the latent image. Shan *et al.* [2] used a Laplacian distribution to approximate the heavy-tailed natural image prior. Recently, sparse representation had been successfully employed in image blind deblurring.[6,16,17] However, these methods could not deal with the images obtained in low-illumination conditions very well. Firstly, their models were not suitable for the over-expose pixels. Secondly, these approaches mainly relied on the strong structure edges[3,7,18] which were not obvious in low-light conditions to estimate the blur kernel. Furthermore, their methods also had difficulty in handling with the ringing artifacts caused by the high light areas.

In order to deal with the above limitations, researchers proposed some ideas for image deblurring in low-illumination conditions. Hameling *et al.* [19] and Whyte *et al.* [9] abandoned those saturated pixels and used the remaining pixels to estimate the blur kernel. However, they ignored the light streak information. The region with light streak was used by Hua and Low[13] to estimate the blur kernel, but they needed to manually select the region that contained the light streak. In addition, since they discarded the whole information of the image, the estimation of blur kernel might not be optimal. Cho *et al.* [20] regarded these light streaks as outliers and proposed a robust method to handle with them, effectively abate the ringing artifacts. Pan *et al.* [17] found that the method of deblurring text images also had a role in deblurring low-light images.

Hu *et al.* [10] proposed a method which can automatically detect the light streaks. Their method is based on the following facts: (1) Those light streak patches have higher intensities than the background in a local neighborhood. (2) The high intensity pixels should have a very sparse distribution. (3) The light streaks should be located near the center of a patch. They used some disks which had different size and intensity as the latent images for these light streaks during the deconvolution to obtain an initial kernel estimation. Then an energy function was used to update kernel, disks and latent image, respectively. During the updating, they used the $L_{0.8}$-norm as the gradient prior of the latent image and L_1-norm to ensure the sparsity of the kernel. However, their method could not deal with the light streaks with a lot of interference from the backgrounds or adjacent light streaks. They also did not utilize the shape information of light steaks. In addition, due to the contrast of night images, $L_{0.8}$-norm might not be fit for fitting the gradient distribution of night images.

Considering these reasons, we propose a novel method for image deblurring. Firstly, we adapt the method[10] to detect the region that contains the light steak. Secondly, we utilize a shape prior for kernel estimation. The shape prior can not only remove the interference in the light steak patches, but also ensure the shape of blur kernel be similar to that of light streaks. Thirdly, we use the L_0-regularized prior based on intensity and gradients as the estimation of latent image intensity and gradient basing the paper.[17] Finally, we adapt the method[10] to remove the ringing artifacts. The experimental results demonstrate that the proposed method performs well.

3 Image deblurring via the shape of light streak

Intuitively, light streaks in the image play an important role in estimating the shape of blur kernel in low-illumination conditions. Because light streaks describe the camera path which enable us to know the shape of blur kernel. In this paper, we use the average light streak as the initial kernel and employ a mask which can be obtained though the average light streak, to remove the noise of the estimated kernel. Different from the previous method,[10] we develop a simple and effective method by using the shape prior.

3.1 Single image deblurring

In general, the image blur[14] is defined as

$$B = L * K + N \,,$$

where L is an original clear image, K is the blur kernel which is also called the point spread function (PSF), B is an observed image, N is the unknown noise and $*$ represents the convolution operator. However, this formulation is insufficient[9,19,20] to model the deblur process of images with high saturated areas obtained in low-illumination conditions. As the tonal modulation of the camera makes the bright highlights clipped at the maximum output value,[9] we modify the convolution model as the following nonlinear form

$$M \odot B = L_m * K + N \,,$$

where M is defined the mask of image region that is not saturated, B represents the blurred image, L_m is the latent image restored by the item $M \odot B$, K is the blur kernel needed to be carefully estimated, N is the additional noise and $\odot$ operator represents the Hadamard production of matrix, also can be treated as the dot product of matrix.

The nonlinear model is difficult to solve. To handle this NP-hard problem, researchers often impose some reasonable prior knowledge on the solution domain. In low-illumination conditions, the number of salient image features that can be used to deblur is often limited, as shown in Fig. 5.2 (b-c) and Fig. 5.2 (b-c). The classical methods[3,5] cannot achieve good results in low-illumination conditions which can be seen from the blur kernel estimated by their approaches. As Hua and Low[13] and Hu *et al.* [10] pay attention to the light streak information, their methods can achieve acceptable results. However they do not make full use of the light streak information. Most importantly, the shape of light streak is not utilized in their model explicitly. In this paper, we propose a shape prior of kernel based on the light streaks which can be expressed as

$$P = \lambda||\nabla L_m||_0 + \sigma||L_m||_0 + \beta||K||_2^2 + \gamma||K - S||_2^2\,, \tag{1}$$

where λ, σ, β, γ are trade-off parameters, ∇L_m is the image gradient, ~~$||\cdot||_2^2$ is the L_2-norm which can be defined as the sum of squares of all elements,~~ $||\cdot||_0$ is the L_0-norm which can be defined as the number of non-zero values, S is shape prior which can be calculated by ~~the average~~ light streak ~~patch~~ and P is the regularized item.

With this prior, our deblurring model is formulated as:

$$\min_{L,K} \; ||M \odot L * K - M \odot B||_2^2 + P\,, \tag{2}$$

where P is the Eq. (1).

Our model contains five items. The first item is used to describe the noise. The second and third items are L_0-norm that can express the sparsity of low-light nature image. This sparsity includes two aspects. One is the big-tail gradient prior and the other represents the proximity of the image intensity in low-illumination conditions. The fourth item is the L_2-norm of the kernel, which can stabilize the blur kernel estimation. The fifth item constrains the domain of kernel, which makes the kernel similar to the light streak. The fifth item is just one part of our shape prior. To precisely obtain the shape of kernel, we also use a mask which can be refined from the light streak to guide the estimation of kernel. ~~We call that mask shape mask which is the other part of our shape prior.~~ After the kernel is estimated, we can use it to restore the latent image on the whole blurred image.

In the next section we will first introduce how we get M (the mask of image region) that is not saturated and S (the initial light steak patch) in preprocessing. Then M will be fixed in our algorithm.

3.2 Preprocessing for M

To solve the problem on tonal modulation of camera, we use a clipping function $f(x)$, which is defined as

$$f(x) = \begin{cases} x, & if\ 0 \leq x \leq \tau \\ 0, & x > \tau \end{cases},$$

where τ is the 0.97 times the maximum output value of a camera in our experiments. We ~~assure~~ that all saturated pixels can meet the above conditions. Then based on the $f(x)$, M can be defined as

$$M(x) = \begin{cases} 1, & if\ f(x) = x \\ 0, & otherwise \end{cases}.$$

From the definition, we know that the values of M only contain 0 and 1. Therefore, Hadamard production of matrix is used to drop the saturated pixels based on the value of τ. At the same time, we use minimum rectangular boxes to cover the saturated areas(such as street lamp) which can be obtained by the value of τ. These boxes just cover these areas. To avoid the effect of edge of the high light areas, we set the values of M in these boxes to 0. In addition, we throw away a half of size of kernel pixels away from the boundary of the rectangular boxes to further avoid the error of convolution operator during the kernel estimation. In our experiments, we find that the regions with high light streaks are useful for estimating the blur kernel when using our shape prior. Therefore, we set the value of M in these regions to 1 when their area approximate that of blur kernel which can be calculated by their size.

3.3 Preprocessing for S

First, ~~we employ~~ the ~~detecting light streak~~ method[10] to obtain a set of light steak. Their method is based on the intensity and sparsity of light steak. For understanding more detail, you can refer to the paper.[10] Then we obtain an average light streak by using the first n light streaks. This preprocessing method is able to enhance the shape of light streak and reduce the influence of backgrounds. Hence it can guide the estimation of kernel and refine the shape of light streak more accurately. Once we get the average light steak, ~~we use~~ the method of ~~paragraph~~ 4.2 to obtain the shape mask. Then S will be got by the dot product of shape mask and average light streak.

In our experiments, we just set $n = 5$. If the number of light streaks is less than 5, we use all of them to get the average light streak. If there is no light streak found, we ~~make~~ the middle value of S ~~be~~ 1, others ~~be~~ 0. ~~Beyond that,~~ we ~~let~~ all the elements in the shape mask ~~be~~ 1.

After we obtain M and S, the proposed method can be solved by an effective alternating minimization methods.

4 Optimization

We obtain the solution of Eq. (2) by alternatively solving

$$\min_{L} \ \|M \odot L * K - M \odot B\|_2^2 + \lambda \|\nabla L_m\|_0 + \sigma \|L_m\|_0 \,, \tag{3}$$

and

$$\min_{K} \|M \odot L * K - M \odot B\|_2^2 + \beta \|K\|_2^2 + \gamma \|K - S\|_2^2. \tag{4}$$

These two sub-problems can be solved easily.

4.1 Intermediate latent image estimation

As M can be obtained in the preprocessing, Eq. (3) can be written as

$$\min_{L_m} \ \|L_m * K - B_m\|_2^2 + \lambda \|\nabla L_m\|_0 + \sigma \|L_m\|_0 \,, \tag{5}$$

where $L_m = M \odot L$, $B_m = M \odot B$.

Based on the L_0 gradient minimization method,[21] we can rewrite Eq. (5) with the auxiliary variables $g = (g_h, g_v)^T$ and u.

$$\min_{L_m, g, u} \ ||L_m * K - B_m||_2^2 + \mu ||\nabla L_m - g||_2^2 + \lambda ||g||_0 + \eta ||L_m - u||_2^2 + \sigma ||u||_0 \,. \tag{6}$$

When μ and η are close to ∞, the solution of (6) will approximate to that of (5). With these auxiliary variables, Eq. (6) can be efficiently solved through alternatively minimizing L_m, g and u by fixing other variables, independently. In our experiments, u and g are set to zero.

In each iteration, L_m is obtained by solving the following least squares minimization problem,

$$\min_{L_m}\|L_m * K - B_m\|_2^2 + \mu\|\nabla L_m - g\|_2^2 + \eta\|L_m - u\|_2^2 \,. \tag{7}$$

With the help of Fast Fourier Transform(FFT), L_m can be easily obtained.

$$L_m = F^{-1}\left(\frac{\overline{F(K)}F(B) + \eta F(u) + \mu\overline{F(\nabla)}F(g)}{\overline{F(K)}F(K) + \eta + \mu\overline{F(\nabla)}F(\nabla)}\right), \tag{8}$$

where $F(\cdot)$ denotes FFT, $F^{-1}(\cdot)$ is the inverse FFT, $\overline{F(\cdot)}$ represents the complex conjugate operation, $\nabla = (\nabla_x, \nabla_y)^T$, ∇_x and ∇_y denote the differential operations along the x and y axes of the image.

Then given L_m, we can obtain g and u by the following two formulations

$$\min_{g} \quad \mu||\nabla L_m - g||_2^2 + \lambda||g||_0 \,, \tag{9}$$

and

$$\min_{u} \quad \eta||L_m - u||_2^2 + \sigma||u||_0 \,. \tag{10}$$

Note that Eqs. (9) and (10) are pixel-wise minimization problems. With the method proposed in the paper,[21] we can solve g and u,

$$g(x) = \begin{cases} \nabla L_m, & if\ |\nabla L_m|^2 \geq \frac{\lambda}{\mu} \\ 0, & otherwise \end{cases} , \tag{11}$$

and

$$u(x) = \begin{cases} L_m, & if\ |L_m|^2 \geq \frac{\sigma}{\eta} \\ 0, & otherwise \end{cases}. \tag{12}$$

The pseudocode for solving Eq. (6) is described in Algorithm 1.

Algorithm 1 Energy minimization for Solving (6)

Input: Blur image B, blur kernel K and the mask of not saturated image region M.
Initialize: $L_m = B_m = B \odot M$, $\mu = 2\lambda$.
while $\mu < \mu_{max}$ **do**
  Estimating latent image L_m by (8).
  $\eta = 2\sigma$.
  while $\eta < \eta_{max}$ **do**
    Estimating g by (11).
    Estimating u by (12).
    Updating $\eta = 2\eta$.
  end while
  Updating $\mu = 2\mu$.
end while
Output: Latent image L_m

4.2 *Intermediate blur kernel estimation*

As M can be obtained in the preprocessing, Eq. (4) can be written as

$$\min_K \|L_m * K - B_m\|_2^2 + \beta\|K\|_2^2 + \gamma\|K - S\|_2^2 \,. \tag{13}$$

Based on the study of the paper,[3,22] the intensity values are not accurate for estimating the blur kernel. So we solve the Eq. (13) in the gradient space, which can be written as

$$\min_K \|\nabla L_m * K - \nabla B_m\|_2^2 + \beta\|K\|_2^2 + \gamma\|K - S\|_2^2 \,. \tag{14}$$

After L_m, B_m and S are obtained, the Eq. (14) can be efficiently computed by $FFTs$.[3] Although adding the approximating prior of kernel, we still convert it to solve the linear equations,

$$(\overline{F(\nabla L_m)}F(\nabla L_m) + \beta + \gamma)F(K) = \overline{F(\nabla L_m)}F(\nabla B_m) + \gamma F(S)\,.$$

The above equation can be solved by the conjugate gradient method.[3]

After we obtain the kernel K, the elements which are outside the shape of light streaks to set to 0. Then, a new kernel is generated by normalizing K so that the sum of its elements is 1.

4.3 Intermediate blur kernel mask

In order to make the blur kernel become connected and sparse, we apply a mask which can be refined from the light streak to update the kernel. ~~That mask is called the shape mask of kernel~~.

As the intensity of kernel can be regarded as a response of the latent images, we believe that the area where big values are gathered has an advantage in deblurring. In this paper, we use a relative approach to choose the proper region that can ensure the connection and sparsity of blur kernel. We first define a ratio as

$$thl = \frac{norm(A_i)}{norm(C)}\,, \tag{15}$$

where C and A_i are vectors which have 3 elements and $norm(\cdot)$ defines the 2-norm of vector. The elements in C are the three biggest values in the 3×3 patch which contains the maximum value in current kernel. The elements in A_i are the three biggest values in any 3×3 patch in current kernel.

The ratio can be regarded as an appearance prior of good blur kernel region. If the ratio is greater than a given threshold, we choose this region as one part of shape, otherwise we discard it. Then we determine whether these regions are connected in a 8-neighborhood around a pixel. If these regions are not connected but are sparse, we reduce the threshold. After we get the proper area, we normalize the sum of its elements to 1.

The reason we use three biggest values is it can avoid the effect of isolated big value in current blur kernel. Furthermore, the connection of blur kernel is ensured in a 8-neighborhood.

Given a kernel K, we can get the mask M_s by

$$M_s(x) = \begin{cases} 1, & if\ thl \geq \tau \\ 0, & otherwise \end{cases},$$

where x is a 3×3 small patch. thl can be calculated from P by Eq. (15). Algorithm 2 shows the main steps for estimating the blur kernel and restoring the latent image.

Algorithm 2 Alternating energy minimization for solving blur kernel and latent image

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Input: Blur image B, mask of unsaturated area M and shape prior S
Initialize: $iter = 0$, $B_m = B \odot M$, $K = S$,$\beta = 2$, $\lambda = \sigma = 10^{-3}$, $\gamma = 8$ and $thl = 0.2$ for most.
for $iter = 1 \rightarrow 5$ **do**
  $iter = iter + 1$.
  Estimating L_m by Algorithm 1.
  Estimating K by the conjugate gradient method.
  Updating K by M_s.
  Updating $\lambda = max\{\frac{\lambda}{1.1}, 1e^{-4}\}$, $\sigma = max\{\frac{\sigma}{1.1}, 1e^{-4}\}$ and $\gamma = max\{\frac{\gamma}{1.1}, 1e^{-4}\}$.
end for
Return: Kernel K
Output: Latent image L using K and B

4.4 Removing artifacts

After we estimate the blur kernel, a non-blind deconvolution method is employed to restore the latent image. As the images obtained in low-illumination conditions have lots of saturated pixels, these pixels should be reasonably handled to avoid emerging severe ringing artifacts.

Handling outliers have achieved a considerable development in non-build deconvolution in rencent years. Cho *et al.* [20] used expectation-maximization (EM) method to solve the blur model that models saturated pixels as outliers. Whyte *et al.* [9] used modified Richardson-Lucy (RL) and a saturation function to build a blur model. Hu *et al.* [10] derive a new deconvolution algorithm by combining the advantages of these two methods. Their method was more effective at suppressing ringing artifacts. For understanding more detail, you can refer to the paper.[10]

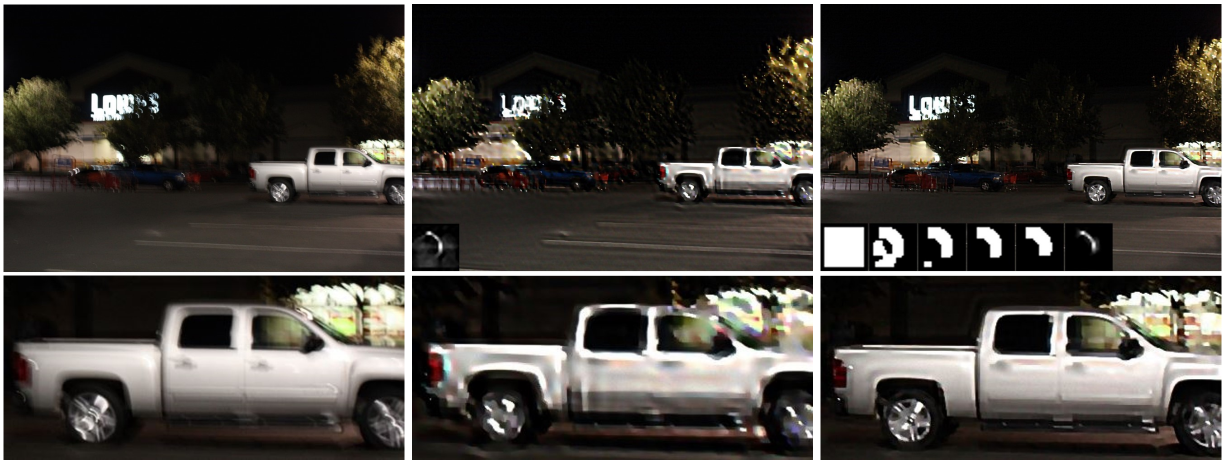
Compared with other approaches, we use the method[10] to restore our latent image during the final deconvolution. Although our method does not use the image pyramid algorithm, we still can obtain very good results by the guide of shape prior.

5 Experimental results

The success of recent deblurring methods depends on ~~the edge selection~~ explicitly (*e.g.* , spatial filtering[3,11]) or implicitly (*e.g.* , edge re-weighting[2,5]). Our proposed method is different from existing methods as it does not choose the edge feature (*e.g.* , spatial filtering or edge re-weighting), especially for estimating the blur kernel.

We apply a mask which can be refined from the light streak to update the kernel. This approach can ensure the connection and sparsity of the blur kernel. In the process of intermediate estimations, the optimization problems can be easily solved by our method. Eqs. (11) and (12) remove the small intensity pixel values while strong edges are left.

All the experiments are carried out on a desktop computer with an Intel Core i7-4790k processor and 32 GB RAM. The execution time for a 1084×683 image is round 106 seconds on MATLAB R2012b. In our experiments, we set $\beta = 2$, $\lambda = \sigma = \gamma = 5e{-}3$, $thl = 0.2$ for most. We



(a) (b) (c)

Fig 2 The effectiveness of shape prior. (a) The Original image(Top). (b) The result without shape prior(Top). (c) The result with shape prior(Top). The middle of (c) depicts the updating process of mask. The bottom is the cropped regions from (a)-(c).

empirically set $\beta_{max} = 2^3$ and $\mu_{max} = 1e{+}5$ in Algorithm 1. ~~The results of others use the default parameters in their papers.~~

5.1 The effectiveness of the shape prior

As the behavior of people taking photos, blur kernel is connected. Therefore, blur kernel with many branches should not be correct. In our section of intermediate blur kernel mask, we propose a relative evaluation criteria which is very effective and reasonable to make the kernel become sparse and connected. And the mask can clip the isolated big noise in the kernel.

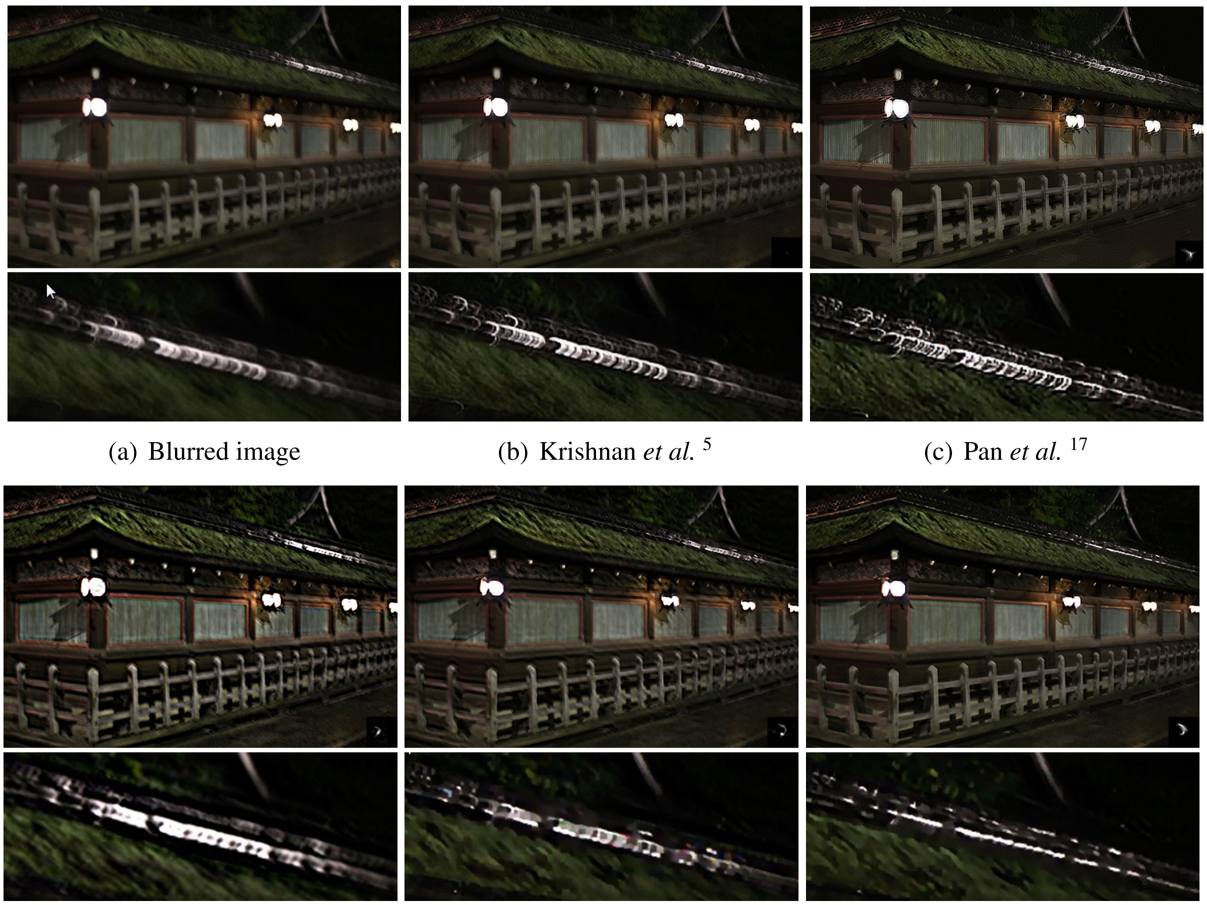
Figure. 1 and 2 show the effectiveness of our shape prior. From Fig. 1, we can obtain two obvious information. One is that the shape of mask approximates that of blur kernel. The other is that the mask prune the ”inveracious” value (noise or isolated big value) during the kernel estimation. Figure. 2 (b) depicts that there are serious distortion and ringing artifacts if we do not use the shape prior of light steaks. As a comparison, Figure. 2 (c) witnesses the improving results after we adopt the shape prior. The middle of Fig. 2 (c) also describes the updating process of masks, which verifies the blur kernel has the similar shape with that of light streak.

5.2 *Comparisons on real images*

The proposed algorithm and other methods are tested on the real images to demonstrate the performance of our method on some real-world examples.

The results are shown in Fig. 5.2 and 5.2. Figure 1 shows the updating process of their masks which demonstrate the blur kernel has the similar shape to that of light streak. Since low-illumination images do not contain sufficient salient edges for kernel estimation and also have some high light areas, the methods proposed by Krishnan *et al.* [5] cannot achieve acceptable results. Pan *et al.* [17] have a better effect, but they can not deal with the light streaks ~~well.~~ Although Hua and Low[13] and Hu *et al.* [10] can also obtain better results, their results have severe ringing artifacts and a little distortion. Furthermore, the blur kernels estimated by their methods are not optimal. Because Hua and Low discard the information of the whole image. Hu *et al.* [10] only use the disks which have different size and intensity seriously hampers the initial kernel estimation basing the disks, so their method cannot obtain good result.

Compared with other methods, our approach performs well. The cropped region from the Fig. 5.2(a) demonstrates the accuracy of the blur kernel estimated by our method. Because they all shrink to points very well over other approaches after deconvolution. And our approach can also effectively suppress the ringing artifacts from the result of handrail. In the Fig. 5.2(a), the red and blue box~~es~~ area shows~~s~~ us the not obvious light streak but with too much interference. ~~However,~~ Fig. 5.2(f) shows our method can effectively handle ~~with~~ the blurred image with light streaks having too much noise~~.~~ ~~Other~~ methods have difficulty in dealing with this condition. The results of Hua and Low[13] and Pan *et al.* [17] have severe ringing artifacts. Hu *et al.* [10] get a bad blur



(a) Blurred image (b) Krishnan *et al.* [5] (c) Pan *et al.* [17]

(d) Hua and Low[13] (e) Hu *et al.* [10] (f) Our results

Fig 3 Comparisons~~ with other methods~~ on a blurred image from.[13] The bottom of (a)-(f) ~~is the cropped~~ regions from original image, the results of [5,10,13,17] and ours. From the cropped region, the light streaks shrink to points ~~very well~~ over other approaches after deconvolution. in addition, our method can also effectively suppress the ringing artifacts ~~from the result of handrail~~.

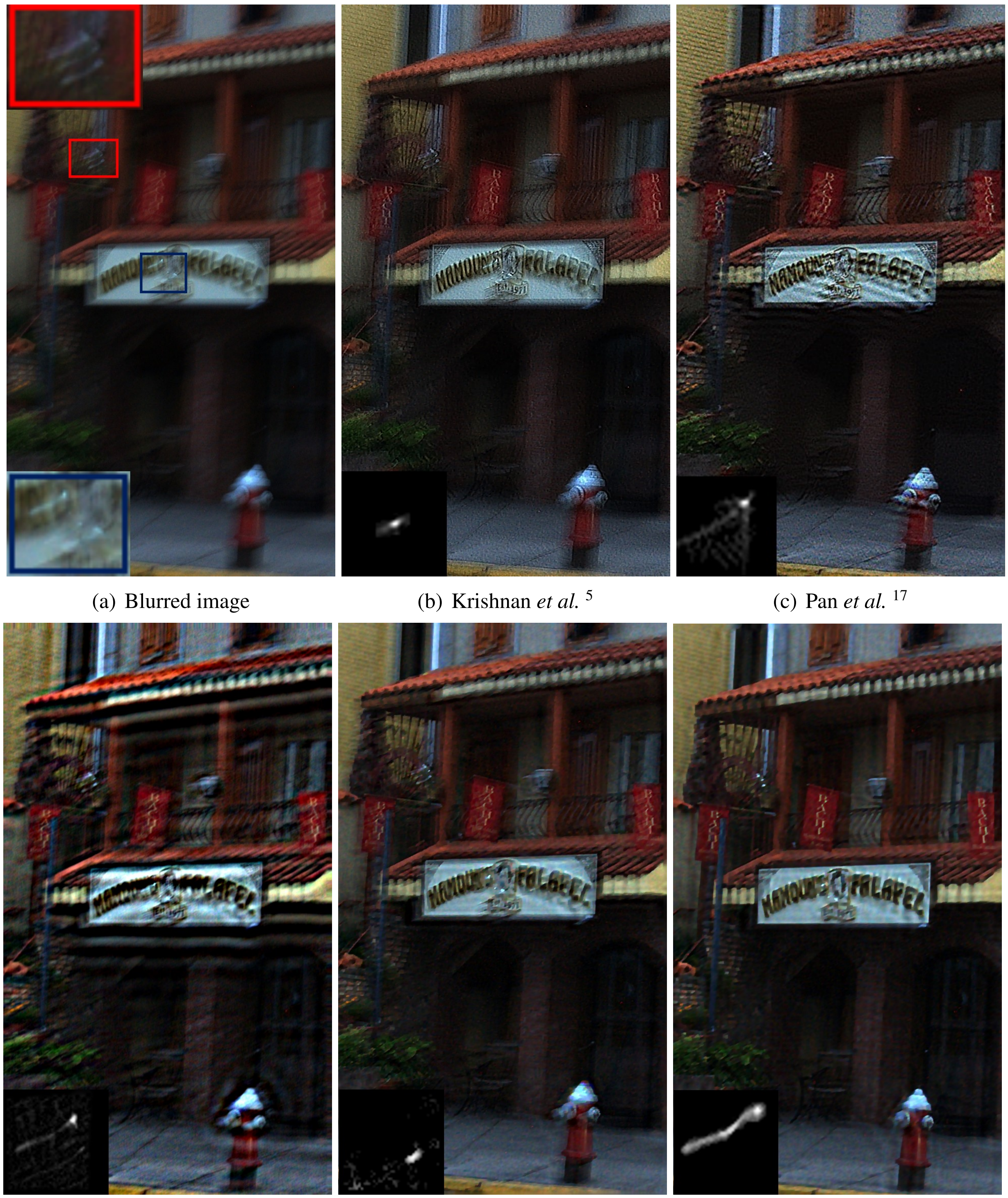
kernel.

Table 1 Quantitative comparisons using kernel similarity(KS).

	Pan *et al.* [17]	Hu *et al.* [10]	Ours
KS	0.6294	0.7163	**0.7603**

5.3 Comparisons on synthetic images

We also test ~~our~~ proposed method on ~~this~~ dataset provided by the paper.[10] This dataset contains 154 low-light ~~iamges~~ in RAW format covering a variety of scenes. The experimental results suggest



(a) Blurred image (b) Krishnan *et al.* [5] (c) Pan *et al.* [17]

(d) Hua and Low[13] (e) Hu *et al.* [10] (f) Our results

Fig 4 Comparison~~s~~ with other methods. A blurred image with too much interference in the light streak region (red ~~box~~ and blue box are enlarged from the corresponding cropped regions). Our approach performs better in the kernel estimation and deblurred image.

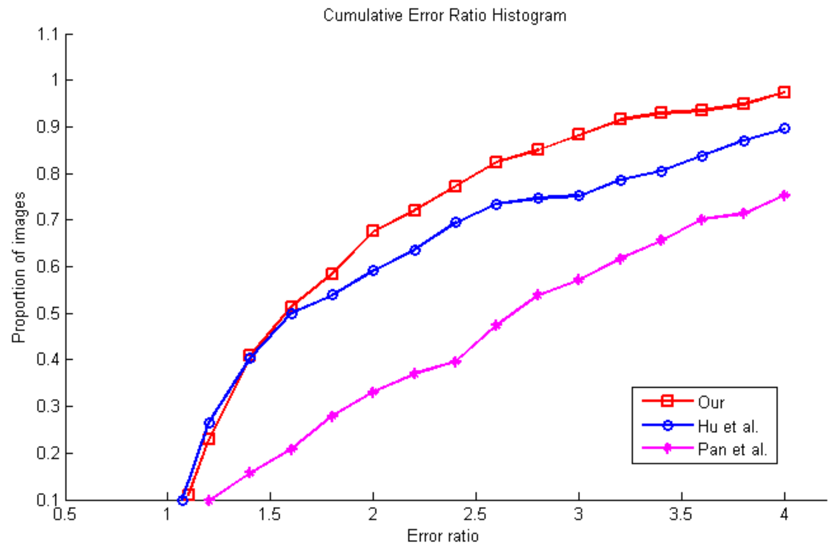
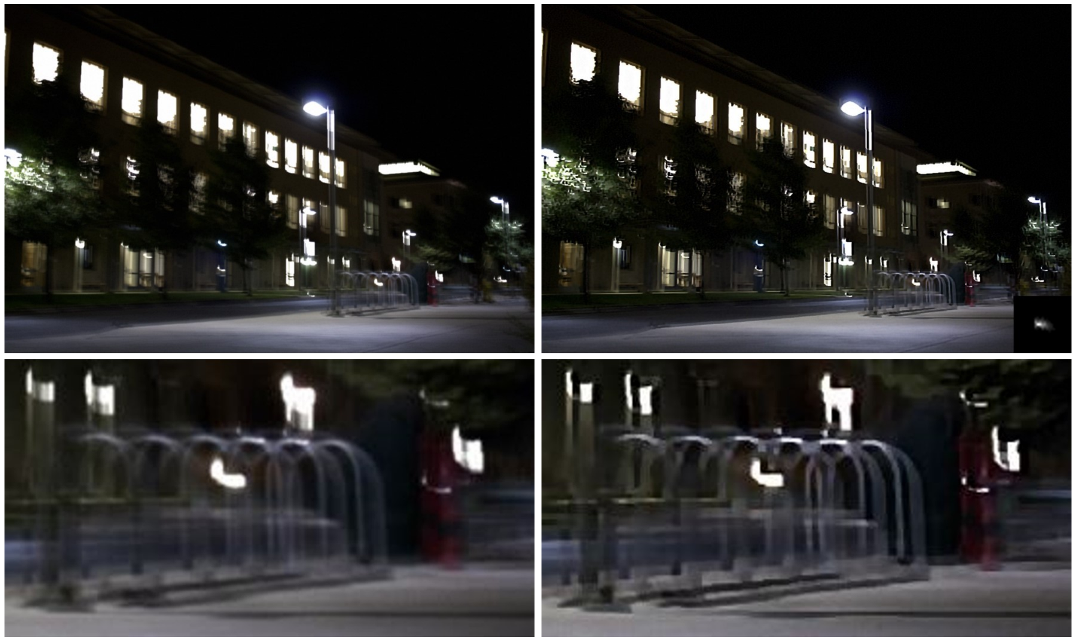


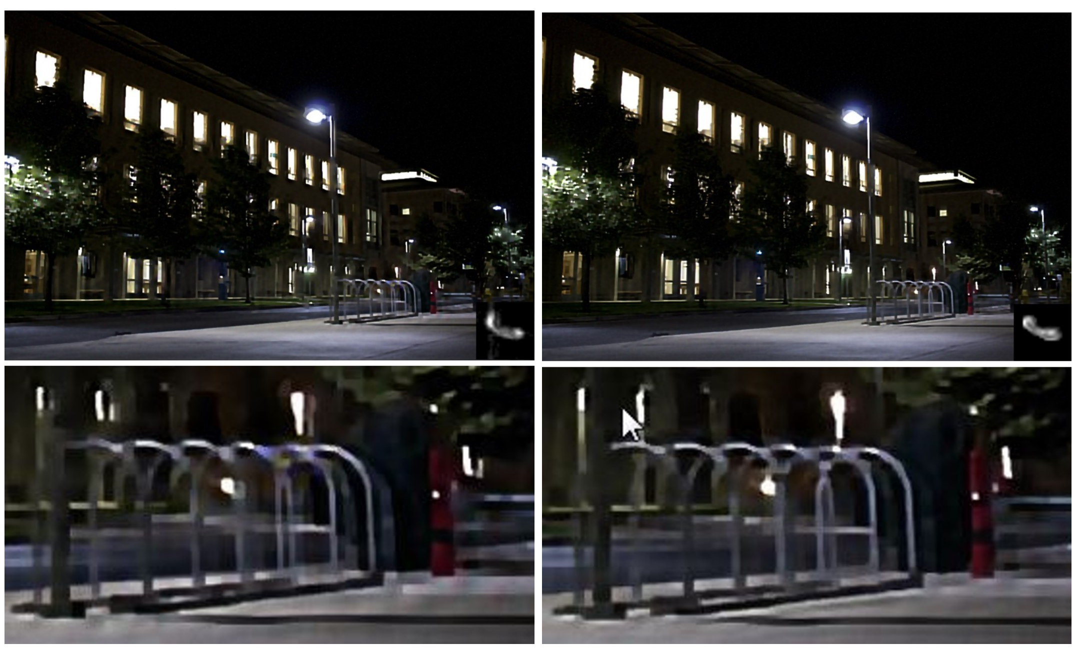
Fig 5 Cumulative error ratio histogram on the synthetic dataset.

that our results have better visual quality than those generated by other methods, ~~due to more accurate kernel estimation.~~

Figure. 5.2 shows a quantitative comparison between the different methods on the dataset[10] using the deconvolved-image metric introduced in.[4] This metric ~~consists of an error ratio given by~~ $||I_{out} - I_{gt}||^2/||I_{k_{gt}} - I_{gt}||^2$, where I_{out} is the the image deblurred by the estimated kernel, $I_{k_{gt}}$ is the image obtained by deconvolving with the ground-truth kernel and I_{gt} is the ground-truth image. The metric indicates the percentage of images ~~with~~ ratios below a specified ratio. We plot the cumulative histograms of the error ratios for ~~these algorithms~~[10,~~17~~] ~~and ours.~~ ~~We also compute the average kernel similarity[23] of each estimated kernel, and their results are shown in Table 5.2.~~ Figure. 5.2 shows the performance in synthetic image. These results demonstrate that the proposed method ~~have a better preformance than others.~~



(a) Original image (b) Pan *et al.* [17]



(c) Hu *et al.* [10] (d) Our results

Fig 6 Comparisons with other methods on a blurred image. The bottom of (a)-(d) ~~is~~ the ~~cropped~~ regions from original image, the results of [10,17] and ours.

(a) (b) (c)

Fig 7 Performance improvement in text image. (a) Original image. (b) The result without the shape mask. (c) The result with our shape mask.

5.4 Improving existing deblurring methods

The proposed method can be applied to the existing deblurring methods and to improve their performance.

We use the shape mask which restricts the domain of kernel to the final step of iteration in every layer image pyramid algorithm. Though experiments, this approach eliminates the isolated noise of kernel indeed. For fair comparison with the method,[17] all the parameters are the same. We only add a parameter, namely the threshold when we choose the kernel mask. From Fig. 7 we can see that although their method can obtain good result, the result becomes more ideal after the shape mask is added. Since their work focuses on the text image deblurring, their method will not generate good result on other images, see Fig. 8 (b). But after our mask restriction is added, the ringing artifacts are reduced and the image quality is improved, see Fig. 8 (c).

6 Conclusion

This paper presents a new method which uses the shape of light streak to constrain the estimation of blur kernel. To obtain a better blur kernel, we consider two aspects. One is the prior of average

(a) (b) (c)

Fig 8 Performance improvement in non-text image. (a) Original image. (b) The result without the shape mask. (c) The result with our shape mask.

light steak in our model, and the other is the mask which is used to refine the shape of blur kernel in our algorithm. In addition, we develop a new optimization method to solve the proposed deblurring model. The reasonableness of initial estimation of blur kernel guides a good result. The proposed algorithm is based on the alternative minimization method which ensures each sub-problem has a closed-form solution. Experimental results demonstrate that the proposed method can successfully restore the latent image. Since the proposed method is mainly based on the light streaks, it would fail if the light streaks are not available. Our future work will focus on developing a better deblur method for low-light images and find a way to learn the shape of blur kernel effectively.

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