Blur kernel estimate in single noisy image deblurring
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ABSTRACT
Restoring blurred images is challenging because both the blur kernel and the sharp image are unknown, which makes this problem severely underconstrained. Recently many single image blind deconvolution methods have been proposed, but these state-of-the-art single image deblurring techniques are still sensitive to image noise, and can degrade their performance rapidly especially when the noise level of the input blurred images increases. In this work, we estimate the blur kernel accurately by applying a series of directional low-pass filters in different orientations to the input blurred image, and effectively constructing the Radon transform of the blur kernel from each filtered image. Finally, we use a robust non-blind deconvolution method with outlier handling, which can effectively reduce ringing artifacts, to generate the final results. Our experimental results on both synthetic and real-world examples show that our method achieves comparable quality to existing approaches on blurry noisy-free images, and higher quality outputs than previous approaches on blurry and noisy images.

Blur kernel estimate, Single noisy image, Blind deconvolution, Image deblurring

1. INTRODUCTION
Image blur is an inevitable problem in consumer-level photography, remote sensing and astronomical imaging etc. It arises when the image formation process is interfered by many factors such as a relative motion between a camera and a scene, using longer exposure times or the effect of atmospheric turbulence. Although many techniques have been proposed to deal with image blur, most of the existing deblurring methods concentrate at recovering the entire image with the assumption of low noise levels. As a result, removing deblurring from a degraded and noisy image is still a challenge due to the ill-posedness of image deblurring. In this work, however, we do not make this assumption and would like to achieve the aim of restoring a sharp image from a blurry and noisy input.

Image deblurring has always been a very popular topic in computer graphics and vision research, and many excellent methods have been developed to improve the quality of deblurred images and accelerate the computation speed. Software-based methods use image priors and kernel priors to constrain an optimization for the blur kernel and the latent image. Early approaches such as Weiner filtering and Richardson-Lucy (RL) deconvolution are simple and efficient, but tend to suffer from unpleasant ringing artifacts that appear near strong edges. Recently, many single image blind deconvolution techniques have been proposed.1,2,3,4,5,6,7,8 Although these methods can produce excellent deblurring results, they generally necessitate intensive computation and assume that the input image is noise-free. It usually takes more than several minutes for the methods to deblur a single image of moderate size. Furthermore, most of these best-performing methods are known to be very sensitive to noise, whose performance degrades rapidly when the noise level increases. Another software-based approach is to use multiple frames to estimate blur. Hardware-based methods take advantage of additional, specialized hardware, such as the hybrid imaging system consisted of a low-resolution video camera and a high-resolution camera,9 and fluttered shutter in computational photography.10 However, such hardware systems are still expensive, and unfortunately they are not commonly available. In contrast to all these methods, our technique emphasizes on estimating the correct blur kernel in single noisy image deblurring, and requires no additional hardware.
To overcome the sensitivity to noisy inputs in single image deblurring, Tai and Lin\textsuperscript{11} first use an existing denoising package as preprocessing, and then estimate the blur kernel and the latent image from the denoised result. However, applying existing denoising methods is likely to damage the detailed blur information that one can extract from the input image, thereby leading to a biased kernel estimation. Zhong and Cho\textsuperscript{8} apply a series of directional filters at different orientations to the input image so that the noise level can be greatly reduced, then estimates an accurate Radon transform of the blur kernel from each filtered image, and finally reconstruct the blur kernel by using inverse Radon transform. However, this approach is based on edge prediction and so necessitates stronger edge components in the input blurry image. Meanwhile, estimated latent images also contain some over-smoothing and color noise artifacts by using this technique.

In this paper, we do not try to recover the blur kernels directly, but rather first apply a series of directional low-pass filters in different orientations to the input blurred image, and then effectively constructing the Radon transform of the blur kernel from each filtered image. Finally, we use a robust non-blind deconvolution method with outlier handling, which can effectively reduce ringing artifacts, to generate the final results. Our experimental results on both synthetic and real-world examples show that our method achieves comparable quality to existing approaches on blurry noisy-free images, and higher quality outputs than previous approaches on blurry and noisy images.

2. MOTIVATION

In this section, we first analyze the impact of using existing denoising techniques as preprocessing on kernel estimation, before explaining our method.

2.1 Image blur model

Let $l$ be the latent image and $b$ be the recorded blurred image. In single image deblurring, the blurred image $b$ is commonly modeled as a convolution of the latent image with a kernel $k$ and the addition of some noise $n$:

$$b = l \ast k + n$$

where $\ast$ is the convolution operator. For simplicity, commonly let unknown noise $n$ be Gaussian noise, $n \sim N(0, \sigma^2)$. Solving $l$ and $k$ from input $b$ is a severely ill-posed problem, and the additional noise $n$ makes this problem even more challenging.

Assuming that $l$ is known, a common approach to solve for $k$ is:

$$k = \arg \min_k \{ \| b - k \ast l \| + \rho(k) \}$$

where $\rho(k)$ is the additional regularization term that imposes smoothness on $k$.

2.2 Defect of denoising as preprocessing

For employing denoising as preprocessing in single noisy image deblurring, Zhong and Cho\textsuperscript{8} analyze the negative impact. Let us suppose that Gaussian filter is used to the blurry image to reduce the noise amplitude, convolving with a Gaussian $G_g$ decreases the noise level. However, the kernel estimation then becomes:

$$k_g = \arg \min_{k_g} \| b \ast G_g - l \ast k_g \|^2$$

$$= \arg \min_{k_g} \| k \ast G_g + n \ast G_g - l \ast k_g \|^2$$

$$= \arg \min_{k_g} \| (k \ast G_g - k_g) + n \ast G_g \|^2$$

$$\approx \arg \min_{k_g} \| (k \ast G_g - k_g) \|^2 = k \ast G_g$$

where $k$ is the blur kernel for the original input image and $k_g$ is the optimal solution after Gaussian denoising. Eq.3 shows that the estimated kernel $k_g$ is a blurred version of the actual kernel $k$. Further, since $G_g$ is low-pass filter, the high frequencies of $k$ are lost and recovering them from $k_g$ would be very difficult, if possible at all. This result comes from the initial noise reduction and is independent of the kernel estimation method. Zhong et al. also shows that although more sophisticated denoising methods are better at preserving high frequencies, they still have the same negative impacts on kernel estimation.
3. APPROACH

The previous section has shown that denoising filters have negative impacts on kernel estimation. In this section, we present a complete method to remove deblurring from a single noisy and blurry image, including accurate kernel estimation by using directional filters, the Radon transform and robust non-blind deconvolution with outlier handling.

3.1 Directional filters

Zhong et al.\(^8\) have shown that directional low-pass filters can be used to an image without affecting its Radon transform, while decreasing its noise level. Considering the directional low-pass filter \(f_\theta\), according to Eq.3, the kernel that we estimate from the filtered image \(b_\theta = b \otimes f_\theta\) is \(k_\theta = k \otimes f_\theta\). Since \(f_\theta\) filters only along the direction \(\theta\), it has nearly no influence on the blur information in the orthogonal direction. So we use Radon transform to projected the filtered image \(b_\theta\) to the line \(\rho = x \sin \theta + y \cos \theta\):

\[
R_\rho(\rho) = \int \int k(x, y) \delta(\rho - x \sin \theta - y \cos \theta) dx dy
\]

where \(k(x, y)\) indicates the value at the coordinate \((x, y)\) on kernel \(k\), \(\theta\) and \(\rho\) are respectively the angle and offset of projection line. Thus, the projection of kernel \(k_\theta\) along the projection direction \(\theta\) is:

\[
R_\rho(\rho) = R_\rho(k \otimes f_\theta) = R_\rho(k) \otimes R_\rho(f_\theta) = R_\rho(k)
\]

where \(R_\rho(\cdot)\) is the Radon transform operator to the direction \(\theta'(\theta' = \theta + \pi/2)\), \(R_\rho(f_\theta)\) is a 1D delta function. Eq.5 shows \(f_\theta\) has no impact on the Radon transform of the blur kernel to the orthogonal direction of the filter.

3.2 Blind kernel estimation

Based on the analysis in Sec.3.1, we apply a directional filter \(f_\theta\), estimate the combined blur kernel \(k_\theta\), and the project it along the orthogonal direction of the filter to get corresponding 1D Radon transform. Then this process is repeated to get a set of projections in different direction. Finally, 2D kernel is computed by using the inverse Radon transform. We generate the final latent images by using the estimate kernel and the non-blind deconvolution method with outlier handling. Algorithm 1 outlines the process of removing a single noisy and blurry image.

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**Algorithm 1: Overall Algorithm**

**Require:** Observed blurry image \(b\), Maximum kernel size \(h\).

Create the pyramid \(\{b_0, b_1, ..., b_n\}\) by down-sampling the input blurry and noisy image \(b\), where \(b_0 = b\).

1. Apply an existing non-blind approach to estimate \(k_i\) and \(l_i\) for \(b_i\), \(i = n, n-1, ..., 1\).
2. Upsample \(l_i\) to generate initial \(l_0\).
3. Do

   4. Apply \(N\) directional filters to the input image \(b_0\), each filter has a direction of \(i \cdot \pi / N, i = 1, ..., N\), where \(N\) is the number of directional filters.
   5. For each filtered image \(b_\theta\), use \(l_0\) as the latent image to estimate \(k_\theta\).
   6. For each optimal kernel \(k_\theta\), compute its Radon transform \(R_\rho(k_\theta)\) as in Eq.5, along the direction \(\theta' = \theta + \pi/2\).
   7. Reconstruct \(k_0\) from the series of \(R_\rho(k_\theta)\) using inverse Radon transform.
   8. Update \(l_0\) based on the new \(k_\theta\) using outlier handling based non-blind deconvolution approach.

   while \(k_0\) has no convergence.

9. With the final estimated kernel \(k_0\), apply the outlier handling based deconvolution method\(^3\) to generate the final output \(l_0\).
4. EXPERIMENTAL AND RESULTS

We run our deblurring experiments in Matlab on an Intel dual-core 2.4GHz PC with 4GB RAM. For all the experiments, we use the same settings as Zhong and Cho’s experiments\(^8\) to estimate blur kernels. Because Zhong and Cho’s method is the most related work to ours since it also seeks to handle noisy images, we focus on comparing this method with our approach. We first ran comparisons on synthetic images (Fig.1), where the latent sharp images that come from Cho’s shared examples\(^3\) and Kodak dataset\(^1\), were blurred using two blur kernel shared by Levin et al.\(^5\). We then added Gaussian noise with zero mean and standard deviations of 0.05 for a \([0,1]\) intensity range. The comparison shows that visually our estimated latent images contain more details and less ringing artifacts. We also evaluate the results quantitatively by computing the Peak Signal-to-Noise Ratio (PSNR) and Structural SIMilarity (SSIM) (Table 1).

We next compared our method and Zhong and Cho’s method\(^8\) on real-world images shown in their paper, and the results are shown in Fig.2. The close-ups in the yellow rectangle show that our method achieves comparable quality to Zhong and Cho’s approach. However, our results have less noticeable ringing artifacts.

![Figure 1](http://proceedings.spiedigitallibrary.org/)

Figure 1. Comparing Zhong and Cho’s method and our method on synthetic data. (a) The original images. Top-left: soldier; middle-left: kodim08; bottom-left: kodim24. (b) Synthetic input blurred images with 5% noise and the ground-truth blur kernels (overlayed). (c) Estimated latent images by applying Zhong and Cho’s method. (d) Results of our method.

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<tr>
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<th>PSNR</th>
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Table 1. The comparison experiments of our method and Zhong and Cho’s method on synthetic blurry images with 5% noise. The performances are evaluated by PSNR and SSIM.
5. CONCLUSION

Most of the state-of-the-art single image deblurring approaches are sensitive to image noise. In this paper, we propose a single image blind deconvolution approach that includes blur kernel estimation method using noise handling and non-blind deconvolution method with outlier handling. We first estimate the blur kernel accurately by applying a series of directional low-pass filters in different orientations to the input blurred image, and effectively constructing the Radon transform of the blur kernel from each filtered image. Finally, we use a robust non-blind deconvolution method with outlier handling, which can effectively reduce ringing artifacts, to generate the final results. The effectiveness of the proposed approach is demonstrated on several comparisons on synthetic and real-world data.

REFERENCE