Robust Kernel Estimation for Single Image Blind Deconvolution

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Abstract

Most of the state-of-the-art algorithms of restoring single blurred image are sensitive to image noise and artifacts. Our idea is to learn an adaptive filter for blind deconvolution to remedy this problem. We use this auxiliary filter to progressively suppress image noise in early stage of kernel estimation, leading to a robust kernel estimation algorithm. Our approach can naturally handle image noise and improve performance of single image blind deconvolution. Experiments suggest that our approach is more robust than other methods in restoration of blurred images.

1. Introduction

In consumer level cameras, motion blur caused by camera shake is often unavoidable in low illumination photography conditions. Automatically restoring these blurred photos to clean and artifact-free images is attractive and practically useful, and this becomes an operation called image deblurring or image deconvolution.

Most of state of the art algorithms focus on high quality images. However, large amount of blurred images are in low quality due to various degradations, such as noise and compression artifacts. Current available deconvolution algorithms cannot properly handle image noise. Estimation of blur kernels and restoring such low quality images can be challenging.

Image noise is the main cause of error in kernel estimation and artifacts in recovered images. Fig.1 shows that noise leads to kernel estimation errors and produces deblurring artifacts in result image. We generated a synthetic noiseless blurred image (Fig.1b) using real blur kernel, and then compressed the blurred image using JPEG (Quality=80) to obtain a noisy correspondence. Fig.1c and 1d show blind deconvolution results of noiseless and noisy image, respectively, using a recently proposed method [5]. Artifacts are obvious in the result of noisy image. Thus, finding a robust kernel estimation method is necessary.

Linear filtering is a common approach in image denoising, especially when no knowledge is given about the noise. Our approach is to suppress noise by smoothing the input image with a learned linear filter. Instead of using manually designed pre-processing filters, we proposed a method that automatically learns this auxiliary filter, simultaneously with kernel estimation procedure. The auxiliary filter is adaptive to input images. It is able to automatically handle image noise and lead to a robust kernel estimation algorithm. Fig.1e shows effectiveness of our approach in deblurring noisy image.

2. Related work

Blind image deconvolution is a challenging ill-posed problem. Errors in kernel estimation result can cause significant ringing artifacts in restored image. Many previous works on blind deconvolution primarily focus on image priors. Fergus et al. [3] used mixture of Gaussian model as global probabilistic constraint of edge distribution. Krishnan et al. [5] proposed a normalized sparsity measurement which favors nature clear image more than blurred ones.
Due to the highly ill-posed nature of the problem, standard maximum a posteriori based methods do not work well. Numbers of complex techniques has been proposed to enhance performance of blind deconvolution. Cho et al. [1] used shock filter to gain estimation of clear images. Xu et al. [10] used a selective edge map to help kernel estimation.

The performance of image deconvolution is highly sensitive to noise, which is the main cause of artifacts in recovered image for both blind and non-blind deconvolution methods. Several methods have been proposed to handle noise in deconvolution. Shan et al. [8] modeled image noise by minimizing errors caused by inaccurate blur kernel estimation. Cho et al. [2] explicitly modeled outliers such as saturated pixels and non-Gaussian noise. They classified outlier pixels using expectation-maximization algorithm and excluded these pixels in deconvolution to prevent artifacts.

### 3. Robust blind deconvolution approach

Blurred image $g$ can be modeled as a convolution of the true clear image $a$ and a blur kernel $h$ plus noise $n_0$:

$$ g = a * h + n_0, \quad (1) $$

where $(*)$ is convolution operator. Blind deconvolution techniques aim at solving $a$ from its blurred correspondence $g$ without knowledge of $h$.

To suppress the noise term in Eq.1, we solve blind deconvolution problem by smoothing the input image with a learned filter. Our approach is to convolve both side of Eq.1 with an auxiliary filter $f$, then the equation can be expressed as:

$$ g * f = a * h * f + n_0 * f = a * k + n \quad (2) $$

where $f$ is the auxiliary filter, $k = h * f$ is the smoothed kernel. For simplicity we use $k$ as the blur kernel directly. Assuming noise term $n$ is gaussian will lead to a least-square-error minimization approach to solve Eq.2 by minimizing $\|g * f - a * k\|_2$. We will show how to perform this optimization in Sec.3.1. Our algorithm learns filter $f$ simultaneously with the blur kernel $k$, and recovers the latent clean image $a$.

Our approach is particularly useful in handling noise in image gradients. Many deconvolution methods solve the problem in image gradients [1, 5, 10], which makes them very sensitive to noise. Our solution naturally handles this issue. The adaptive filter automatically suppresses noise in these methods and improves their performances. In this paper, we choose [5] as our solver.

### 3.1. Kernel estimation

Our aim is to solve blind deconvolution problem defined in Eq.2. We firstly perform kernel estimation on image high frequencies using our newly proposed model. This can be solved using a robust optimization approach. Clear image is restored using a non-blind deconvolution module.

We firstly perform kernel estimation on image derivatives. This is performed by minimizing the following energy function:

$$ E(k) = ||\partial_x a * k - \partial_x g * f||_2^2 + \lambda_1 ||\partial_a a||_1 \nonumber$$

$$ + \lambda_2 ||k||_1 + \lambda_3 ||f||_1. \quad (3) $$

where $\| \cdot \|_1, \| \cdot \|_2$ denotes $l_1$ and $l_2$ norms, $\lambda_1, \lambda_2, \lambda_3$ are weights that control image and kernel regularization terms, and $\partial_x = [\partial_x, \partial_y]$ denotes image gradients along $x$ and $y$ directions. Here, we use high pass filters $[-1, 1]$ and $[-1, 1]^T$ to compute image gradients.

Our model of the deconvolution process (Eq.3) is non-convex when $a$, $k$, and $f$ are unknowns. Therefore, iterative methods are frequently adopted to solve these variables in an alternative manner. This amounts to solve the following three optimizations alternately:

1. Given $k$, $f$ and $g$, solve $a$ as follows:

$$ \arg \min_a ||\partial_x a * k - \partial_x g * f||_2^2 + \lambda_1 ||\partial_a a||_1 \nonumber$$

$$ + \lambda_2 ||k||_1 + \lambda_3 ||f||_1. \quad (4) $$

2. Given $a$, $f$ and $g$, solve $k$ as follows:

$$ \arg \min_k ||\partial_x a * k - \partial_x g * f||_2^2 + \lambda_2 ||k||_1, \quad (5) $$

3. Given $a$, $k$ and $g$, solve $f$ as follows:

$$ \arg \min_f ||\partial_x a * k - \partial_x g * f||_2^2 + \lambda_3 ||f||_1. \quad (6) $$

Though solving Eq.3 involves a complicate non-convex optimization with large number of variables. The sub-optimization problems Eq.5 and Eq.6 are convex. Although the sub-optimization problem in Eq.4 is non-convex due to the normalized sparse prior, it can be transformed to a convex $l_1$ constrain formulation by fixing the $l_2$ norm denominator from previous iteration. Please refer to [5] for details. We also add physical validate constrains on both $k$ and $f$, which include $k \geq 0, \sum_i k_i = 1; f \geq 0, \sum_i f_i = 1$.

Here we describe how the additional filter $f$ can facilitate kernel estimation procedure. As we mentioned before, the performance of kernel estimation is subject to noise in images. The smoothing filter $f$ can reduce
the effect of noise and estimation errors. To achieve a better estimation of \( k \) in the first several iterations, we initialize filter \( f \) as an isotropic Gaussian filter with the same size as \( k \). Then during the estimation procedure, we gradually shrink down size of \( f \) and increase the weight of sparsity regularization term of \( f \). A larger weight of sparsity term makes the filter \( f \) favors a delta function and leads to a more precise result of \( k \).

### 3.2. Image restoration

Once we have the blur kernel estimation, we can restore the blurred image using any non-blind deconvolution methods. In our implementation, we used a recently proposed deconvolution method [4]. This algorithm uses a lookup table technique for computation acceleration, which is much more effective than other deconvolution algorithms while producing reasonable good results in image deblurring.

### 3.3. Multi-scale approach

Most of blind deconvolution methods need to be designed properly to avoid degenerate solutions such as \( a = g; k = \delta \). Hence, we performed kernel estimation using a coarse-to-fine method similar to other blind deconvolution methods [2, 3, 10].

![Figure 2. Multi-scale kernel estimation. Without linear filtering (top) and with linear filtering (bottom). Kernel sizes of different scales are shown below. Images are color coded, best viewed in color.](image)

We build multi-scale pyramids for both images and kernels (both \( k \) and \( f \)). For the coarsest level, we set kernel size as \( 3 \times 3 \), then each level can be generated by up-sampling the previous level by factor \( \sqrt{2} \). Fig.2 illustrate the auxiliary filter improved kernel estimation results in first several stages. From coarse to fine (left to right in Fig.2), our method progressively suppresses noise and weak image edges that are less helpful to kernel estimation, while still maintaining main image structures and strong edges. This produced a stable and fast kernel estimation results in coarse levels. Our strategy results in a significant difference in image restoration (Fig.5d and 5e, respectively).

![Figure 3. Example results of comparison.](image)

(a) Clear (c) Levins (e) Cho
(b) Blurred (d) Ours (f) Krishnan

### 4. Experiments

#### 4.1. Robustness evaluation

To demonstrate our approach outperforming state-of-the-art methods in robustness, we evaluated our results on Levin et al.’s blur image dataset [6] against three other methods. The dataset has 4 different images with size \( 255 \times 255 \), and each blurred with 8 different kernels, which makes 32 images in total. Fig.3a and 3b show example images of the dataset. We used both pixel wise errors and Universal Quality Index (UQI) [9] for robustness evaluation. We first computed pixel wise difference of each restored image against ground truth, and averaged errors over each image. For UQI measurements, we used the authors’ matlab implementation. The accumulative percentages of image with regard to average pixel errors and “1-Quality” are shown in Fig.4. Higher percentage in smaller avg. error range or larger UQI quality range means algorithm produced better results on more images, which reveals the robustness of our approach. See sample results in Fig.3c-3f.

![Figure 4. Error ratios comparison of four methods on Levin’s dataset.](image)
4.2. Image deconvolution results

We then performed blind image deconvolution on images with noise and compression artifacts. The test images were captured using hand-held DSLR with 0.3s shutter speed. To get noisy inputs, all test images are resized to $800 \times 533$ pixels and JPEG compressed (Quality=80). We compared our deblurring results with three state-of-the-art methods including Levin et al. [7], Cho et al. [1], and Krishnan et al. [5]. Fig.5 shows the restored results and estimated kernels of all four methods. Close-up patches highlighted our results with original inputs. Notice the highlight in bird’s eye revealed true blur kernel shape, which shows that our method correctly estimated blur kernels and recovered details. Benefited from the auxiliary filter, our algorithm produced robust kernel estimation results, which were similar with the true blur kernels.

5. Conclusion

We proposed an improved kernel estimation method for single image blind deconvolution. By adding an adaptive linear filter, our method progressively suppressed noise in early stage of kernel estimation, and achieved more robust estimation results. Recovered images using our method are clean and with less deblurring artifacts. Experiment results showed our algorithm is more robust than state-of-the-art algorithms, and has better performance in blind image deconvolution.

References