Non-uniform Motion Deblurring Using Normalized Hyper Laplacian Prior

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Abstract. Non-uniform motion deblurring is a hard topic for image processing. Non-uniform blur is often caused by camera motion in 3D while taking photos. Existing non-uniform deblurring methods formulate the blur as a linear combination of homographic transforms of a clear image. But they are computationally expensive and require large memory because the amount of the unknown variables are large. In this paper we use patch-wise method for the deblurring process. The patch-wise method are proved to be an effective method for non-uniform motion deblurring. The key issues are the accuracy of kernel estimation and the substitution of the erroneous kernels. In this paper, we use normalized smoothing term for the blur kernel estimation because it is effective and stable. When the erroneous kernels are conformed, we use a minimization method using neighborhood information for estimating the kernels. Experiments demonstrate the validity of the proposed method.

Keywords: Non-uniform motion deblur · Normalized hyper laplacian prior · Variational method · Patch -wise method

1 Introduction

The image is often blurred with the camera shake while taking photos. Deblurring from a single image is an ill posed question because the blur kernel and the clear image are not known.

In the last decade, significant progress has been made for removing uniform blur from a single image. There are many successful deblurring algorithms for uniform blur. When camera motions only contain translations, these algorithm can achieve good results. However, in real case, camera shake includes translation and camera rotations. So this procedure is also called non-uniform blur. That is to say, the blur kernels are not the same at different points. This is a hard work for the researchers. Several non-uniform deblurring algorithms have been proposed, which model the blur as an integration of the clear scene under a sequence of planar projective transforms. The drawbacks of these algorithm are that they require a large memory and are computational expensive.

For reducing the memory and computation requirement, patch-wise deblurring algorithms are proposed. The idea is that in a small neighborhood the blur kernels are

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similar. In these methods, images are divided into patches and the blur kernels are estimated from each patch using a uniform deblurring algorithm. Then using estimated blur kernels the clear image can be recovered. There are two main steps: The first step is dividing the image into overlapped patches and obtaining the blur kernels using uniform motion deblurring algorithm. The second step is to verify erroneous kernels and estimate the kernels again.

To obtain accurate blur kernels efficiently, we use normalized smoothing term in the energy function. We select normalized hyper laplacian prior as the normalized smoothing term. The hyper laplacian prior can model the heavy-tailed distribution of the natural image gradient which is an important prior for clear image processing. The normalized hyper laplacian prior can lead the energy decreasing while solving the equation. So using normalized hyper laplacian prior , we needn't use additional steps for kernel estimation.

To detect the erroneous kernels, we use the error residue to measure the accuracy. We calculate all the error between the blurred image and the image convolve with the calculated kernel. After detecting the poorly estimated blur kernels, previous works replace the rejected kernels with the average of their neighboring kernels. However, simply averaging the kernels causes the substituted kernel inaccurate and may lead to artifacts in the deblurred images. For the erroneous kernels, we use the neighborhood information to recaluate the kernels. We build a new energy function by incorporating neighborhood information with an stable kernel. Then the estimated kernel is stable.

The organization of this paper goes as follows. In Section 2, we will introduce the related work for motion deblurring. The new proposed method and the solving procedure is introduced in section 3. Then some numerical examples are shown in Section 4. Section 5 makes some concluding remarks.

2 Related Work

We briefly introduce the uniform and non-uniform motion deblurring algorithms. We deblur an image without any additional information. The uniform blur means that the kernels are the same in the image. The non-uniform blur means the kernels varies according to the location. The uniform deblurring algorithms were extensively studied in the past few years and achieved great success.

By convention, the invariant motion blurred image can be expressed as follows :

$$f = k * u + n \tag{1}$$

where k , u and n denote the blur kernel, the original unblurred image and the noise respectively, f denote the blurred image. $*$ is the convolution operation. The uniform motion deblurring is well studied. Chan [1] firstly proposed using variational method for solving the question of blind deconvolution by using total variation method. He used total variation terms for restricting both the blur kernel and image gradients. The method laid the foundation of deblurring by variation method. After Chan's method, Fergus [2] using the heavy tailed probabilistic distribution for image gradients because he observed that natural image's gradient obeys this rule but the blurred image doesn't fit the law. His method is the first successful one for real case deblurring using variational method. Shan [3] presented an analysis of the reasons of common artifacts found in current deblurring methods. Then he computed deblurred image using a unified probabilistic model of both blur kernel estimation and clear image restoration. He incorporated first and second derivatives into his proposed model and make the deblurring image clear from ring artifact. Levin [4] points out that some deblurring methods can fail because the detail sections have negative effects on the process by comparing the methods in [2] and [3]. After this discovery, many researchers used additional method such as shock filter for reducing the effort of little details. Hui [5] proposed a method for identifying motion blurs form image gradients. Using the gradients, he will estimate the blur kernels. Cho [6] proposes a fast deblurring method by accelerating both latent image and kernel estimation by introducing a novel prediction step and working with image derivatives rather than pixel values. In the auxiliary step, he use bilateral filter for enhancing strong edges and eliminating tiny edges. For further accelerating the implementation, GPU is used for speed-up the method which makes the method fast enough for practical usage. Xu [7] use large gradients selection for reducing the negative effect of the tiny gradient. Then, kernel refinement procedure is used by the fact that motion caused blur kernel is spatially continuous. His method is a stable one for estimating blur kernels. Hong [8] used nonlinear diffusion method for motion deblurring. Then, the blur kernel correction is done by the consumption that blur path should be curve with single point width. Xu [9] proposed using L0 sparse prior [12] for gradient restriction. The L0 term has the ability of enhancing large gradient and eliminating small edges. This feature can make the method doesn't need additional steps for kernel estimation.

When the blur kernels are spatial variant, the blur image can be written into a matrix form:

$$f = Ku + n \tag{2}$$

K represents the matrix form of k. Gupta et al. model the blur matrix as a motion density function and the blur image f as the summation over images taken from different poses.

$$f = \sum_i a_i K_i u + n \tag{3}$$

where a_i is the weighting coefficient. There are little work on the non-uniform motion deblurring.

There has been relatively little work on spatially varying blind motion blurring. Levin et al. [14] proposed a spatially varying motion deblurring method by segmenting the image into different areas through the depth information and then deblurred each region. Whyte et al. [16] proposed a new model for non-uniform motion deblurring. In his method, he model the spatially varying motion blur by 3D rotational camera motion model. Gupta et al. [17] proposed model the spatially variant motion blur by the motion density function which can represent a different set of 3D camera motions. Then the calculated motion density function can model the spatially varying kernel function. Harmeling et al. [18] built on a framework for space-variant filtering by Hirsch et al. [20] and a fast algorithm for single image blind deconvolution for space-invariant filters by Cho and Lee [6] to construct a method for blind deconvolution in the case of space-variant blur. Hirsch et al. [19] proposed a framework of the efficient filter flow for deblurring images with spatially varying motion blurring effects. In his method, he assume that in every small area the motion blur can be deemed as an uniform blur. Ji [20] proposed two-stage approach for blind spatially-varying motion deblurring. First, he calculated the blur kernels by patch based method. Then he recovered the clear image by using a robust non-blind deblurring method.

3 Proposed Method

In this paper, we also use patch-wise deblurring method for spatially varying blur image. To obtain accurate blur kernels efficiently, we use patch wise normalized hyper laplacian prior in the energy function. After detecting the erroneous kernels, we use the neighborhood information to re-estimate the erroneous kernels. Because the patch based method is first proposed by Hirsch so we will introduce the efficient filter flow first.

3.1 Framework of Efficient Filter Flow

Hirsch *et al.* [19] proposed a framework of the EFF (Efficient Filter Flow) for handling smoothly space-variant convolutions. He found that a spatially variant filtering can be implemented by chunking a signal into overlapping patches, then he filtered each patch with a spatially invariant PSF, finally assembling the filtered image from the filtered patches using the overlap-add method. The framework of the EFF aims to extend a uniform moton deblurring to a non-uniform motion deblurring and is defined as:

$$f_i = \sum_{r=1}^{p}\sum_{j=1}^{s} k_j^{(r)} w_{i-j}^{(r)} u_{i-j}^{(r)}, \text{ for } 1 \le i \le m \tag{4}$$

where p is the number of the overlapping patches, $k_j^{(r)}$ is the blur kernel of the r-th patch ($1 \le r \le p$), and is a window function to fade the r-th patch in and masking the others out. The sum of the weights at each pixel should be equal to one, *i.e.*, $\sum_{r=1}^{p} w_i^{(r)} = 1$, for $1 \le r \le m$ .Without the normalization, there will be artifacts in the overlapping areas.

As indicated in Eqn. (3), the EFF is linear in u and in k, where k is a vector stacked by p PSFs $k^{(1)}, \ldots, k^{(p)}$. It implies there are matrices K and U such that $B = Ku = Uk$. According to [19], the matrices are expressed as

$$K = Z_b \sum_{r=1}^{p} C_r^T F^{-1} Diag(FZ_k k^{(r)}) FC_r Diag(w^{(r)}) \quad (5)$$

$$U = Z_b \sum_{r=1}^{p} C_r^T F^{-1} Diag(FC_r Diag(w^{(r)}) l) FZ_k B_r \quad (6)$$

where Z_b is a matrix that appends zeros to the valid part of the space-variant convolution such that its size matches the full size of an input image u, C_r is a matrix that crops the r -th patch from the input image, is the Discrete Fourier Transform matrix, Diag(v) is a diagonal matrix with along its diagonal, is a matrix that appends zeros to such that its size matches the patch size, and is a matrix that crops the r-th PSF from the vector k.

Eqn. (6) implies that the patches are firstly recovered locally and then assembled into a latent image. Eqn. (7) implies that each PSF can be estimated from the corresponding patch locally. It indicates that space-variant convolutions can be implemented in the EFF as efficiently as space-invariant ones. In the next section, we will introduce our method under the framework of EFF.

3.2 Normalized Hyper Laplacian Prior in EFF

In the deblurring process, the image gradient's amplitude will became bigger while the image get more clearer. This phenomenon makes the traditional methods failed. So additional steps such as shock filter and bilateral filter should be added for the kernel estimation. Krishnan [11] proposed using normalized total variation term [10] for the motion deblurring. The energy is decreasing in the deblurring processing by using the normalized total variation term. So he needn't use additional filters for the deblurring. In this paper, we use hyper laplacian prior for motion deblurring. The hyper laplacian prior is a good model for reflecting the clear image's gradient distribution which is expressed as heavy tailed distribution. The energy function incorporating normalized hyper laplacian prior can be expressed as:

$$E(\nabla u, k) = \sum_{r=1}^{p} \left(\frac{1}{2} \int_\Omega \left(k^{(r)} * \nabla u^{(r)} - \nabla f^{(r)}\right)^2 dx + \lambda_1 \frac{\int_\Omega \left|\nabla u^{(r)}\right|^p dx}{\int_\Omega \left|\nabla u^{(r)}\right|^2 dx} + \lambda_2 \int_\Omega \left|k^{(r)}\right| dx \right), (0.5 \le p \le 0.8) \quad (7)$$

The first term in the energy equation is the data fidelity term where k , u and f denote the blur kernel, the recovered image and the blurred image respectively, $*$ is the convolution operation. In this paper, we use the residual error of the deblurred image's gradient and the kernel convolved with the gradient of the image for the data fidelity. This term is easy for energy resolving because the smoothing term also containing the gradient operation. r denotes the r th patch. The second term is the normalized hyper laplacian item. This term can make the energy decreasing while in the deblurring process. The third term is the restriction term of the blur kernel. The absolution operator make the kernel sparse. For convenience, we let $x = \nabla u$, $y = \nabla f$.

The energy function can be rewritten as:

$$E(x,k)=\sum_{r=1}^{p}\left(\frac{1}{2}\int_{\Omega}\left(k^{(r)}*x^{(r)}-y^{(r)}\right)^2dx+\lambda_1\frac{\int_{\Omega}\left|x^{(r)}\right|^p dx}{\int_{\Omega}\left|x^{(r)}\right|^2 dx}+\lambda_2\int_{\Omega}\left|k^{(r)}\right|dx\right)(0.5\le p\le 0.8)\quad(8)$$

After dividing the image into overlaped patches, we use the following energy equation for solving the blur kernels.

$$E(x^{(r)},k^{(r)})=\frac{1}{2}\int_{\Omega}\left(k^{(r)}*x^{(r)}-y^{(r)}\right)^2dx+\lambda_1\frac{\int_{\Omega}\left|x^{(r)}\right|^p dx}{\int_{\Omega}\left|x^{(r)}\right|^2 dx}+\lambda_2\int_{\Omega}\left|k^{(r)}\right|dx\quad(9)$$

We use iterative minimization method for solving the above equation.

Fixing $k^{(r)}$ for solving $x^{(r)}$, the relative energy function is:

$$E(x^{(r)})=\frac{1}{2}\int_{\Omega}\left(k^{(r)}*x^{(r)}-y^{(r)}\right)^2dx+\lambda_1\frac{\int_{\Omega}\left|x^{(r)}\right|^p dx}{\int_{\Omega}\left|x^{(r)}\right|^2 dx}\quad(10)$$

In above equation, because the denominator containing x, so the energy is not convex and the energy solving is a hard work. In the iteration of energy solving, because the item of $\int_{\Omega}|x|^2 dx$ doesn't change dramatically, we can use the value of the last step. So the Euler-Lagrange equation can be written as:

$$k'^{(r)}*\left(k^{(r)}*x^{(r)}-y^{(r)}\right)+\lambda_1\frac{p\left|x^{(r)}\right|^{p-1}}{\int_{\Omega}\left|x^{(r)}\right|^2 dx}\frac{x^{(r)}}{\left|x^{(r)}\right|}=0\quad(11)$$

where $k'^{(r)}(x,y)=k^{(r)}(-x,-y)$, in other word k' is the centrosymmetric matrix of k.

$x^{(r)}$ is not easy to be solved, so we rewrite the equation in the following form.

$$x^{(r)}-x^{(r)}+k'^{(r)}*\left(k^{(r)}*x^{(r)}-y^{(r)}\right)+\lambda_1\frac{p\left|x^{(r)}\right|^{p-1}}{\int_{\Omega}\left|x^{(r)}\right|^2 dx}\frac{x^{(r)}}{\left|x^{(r)}\right|}=0\quad(12)$$

$$x^{(r)k+1} = x^{(r)k} - k'^{(r)} * (k^{(r)} * x^{(r)k} - y^{(r)}) - \frac{\lambda_1 p \left| x^{(r)k} \right|^{p-1}}{\int_\Omega \left| x^{(r)k} \right|^2 dx} \frac{x^{(r)k+1}}{\left| x^{(r)k+1} \right|} \tag{13}$$

The $x^{(r)}$ can be got by using soft shrinkage-thresholding [13]:

$$x^{(r)k+1} = \max\left(abs\left(x^{(r)k} - k'^{(r)} * (k^{(r)} * x^{(r)k} - y^{(r)})\right) - \frac{\lambda_1 p \left| x^{(r)k} \right|^{p-1}}{\theta \int_\Omega \left| x^{(r)k} \right|^2 dx}, 0 \right) \cdot sign\left(x^{(r)k} - k'^{(r)} * (k^{(r)} * x^{(r)k} - y^{(r)})\right) \tag{14}$$

For calculate k, the energy function is:

$$E(k^{(r)}) = \frac{1}{2} \int_\Omega \left(k^{(r)} * x^{(r)} - y^{(r)}\right)^2 dx + \lambda_2 \int_\Omega \left| k^{(r)} \right| dx \tag{15}$$

The Euler-Lagrange equation is:

$$x'^{(r)} * \left(x^{(r)} * k^{(r)} - y^{(r)}\right) + \lambda_2 \frac{k^{(r)}}{\left| k^{(r)} \right|} = 0 \tag{16}$$

Because the dimension of x is much larger than k, we use unconstrained iterative re-weighted least squares (IRLS) [14] for solving k for the calculation precision. Then a projection is followed by the contraints which is setting negative elements to 0 and renormalizing the elements to [0,1].

Although the proposed method can make the energy decreasing while in the deblurring processing, we will use multiscale method which is a common approach for motion deblurring for avoiding the kernels falling into local minimization.

After the blur kernels are estimated, we choose to use the TV[15] model as non-blind deconvolution method, since it is fast and robust to small kernel errors.

$$E\left(u^{(r)}\right) = \frac{1}{2} \int_\Omega \left(k^{(r)} * u^{(r)} - f^{(r)}\right)^2 dx + \lambda \int_\Omega \left| \nabla u^{(r)} \right| dx \tag{17}$$

3.3 Removing Poorly Estimated Blur Kernels

In the patch based non-nuniform deblurring procedure, there are always erroneous initial estimation of local kernels because the edges are not efficient for kernel estimation. So after the initial kernel estimation, we will detect erroneous kernels. We use the method proposed by Ji [20] for the reason of simplicity and efficient. For each patch P_i, let k_i denote the kernel obtained from the previous step. We use the residual $r_i = \left(k_i * u_i - f_i\right)^2$ to measure its accuracy and set the accuracy threshold by $\varepsilon = \frac{3}{2} \times median\{r_1, r_2, \ldots, r_n\}$. Then any local kernel whose residual r_i larger than the accuracy threshold is considered as wrongly estimated kernel and discarded.

3.4 Re-estimating Erroneous Local Kernels

Several method for re-estimating erroneous kernels only use the estimated kernels in the neighborhood. To re-estimate the discarded local blur kernels, we need some additional information outside these regions to help the estimation of blur kernels as these regions by themselves do not have sufficient image content for a reliable kernel estimation.

We use a minimization method using neighborhood information for estimating the kernels. It is observed that the blur kernels of neighboring regions changes not dramatically. This motivates us to combine the local image information and the correlation among the kernel to estimate and the available kernels in its neighborhood. We incorporating the neighborhood information into the energy equation and the equation can be written as:

$$E(k^{(r)}) = \sum_{\substack{i=1 \\ i \neq r}}^{m} \left(\frac{1}{2} \int_{\Omega} \left(k^{(r)} * u^{(i)} - f^{(i)} \right)^2 dx + \lambda \int_{\Omega} \left| k^{(r)} \right| dx \right) \tag{18}$$

In the above equation, m is the number of the patches used for re-estimating kernels. In our experiment, we set m as 4. That is to say, we use the north, south, east and west neighbors of re-estimating erroneous kernels.

The Euler-Lagrange equation is:

$$\sum_{\substack{i=1 \\ i \neq r}}^{m} u'^{(i)} * \left(u^{(i)} * k^{(r)} - f^{(i)} \right) + \lambda \frac{k^{(r)}}{\left| k^{(r)} \right|} = 0 \tag{19}$$

Because the dimension of u is larger than k, we also use unconstrained iterative reweighted least squares (IRLS) [14] for solving k. Using the estimated kernels, we will get the patch-based clear images.

4 Numerical Experiments

To validate the effect of our proposed method, we use several images selected from several papers as experiments. The deblurred images and the calculated kernels are also shown in the experiments. Figure 1 shows an elephant and several people standing before a church. We divide the image into 7*5 patches. From the deblurred kernel, we can see that the image is blurred with camera rotation. The deblurred image is clear and has no ringing artifacts. In the following two experiments, using the same procedure, we also get the clear image and the corresponding kernels.

To prove the effect of our method, we also compare our method with the method of Jia [7]. Figure 2 shows the results using the proposed non-uniform method. From the results, we can find that our method can reasonable results. The estimated blur kernel is reasonable for motion camera's trajectory. The blur kernel is sparse because only on the motion path, the elements are not zero. This finding conforms the sparse prior of the kernel. The divided patches have different blur kernels and the neighborhood kernels are changing smoothly. These phenomena also proved that patch-based non-uniform deblurring method is useful.

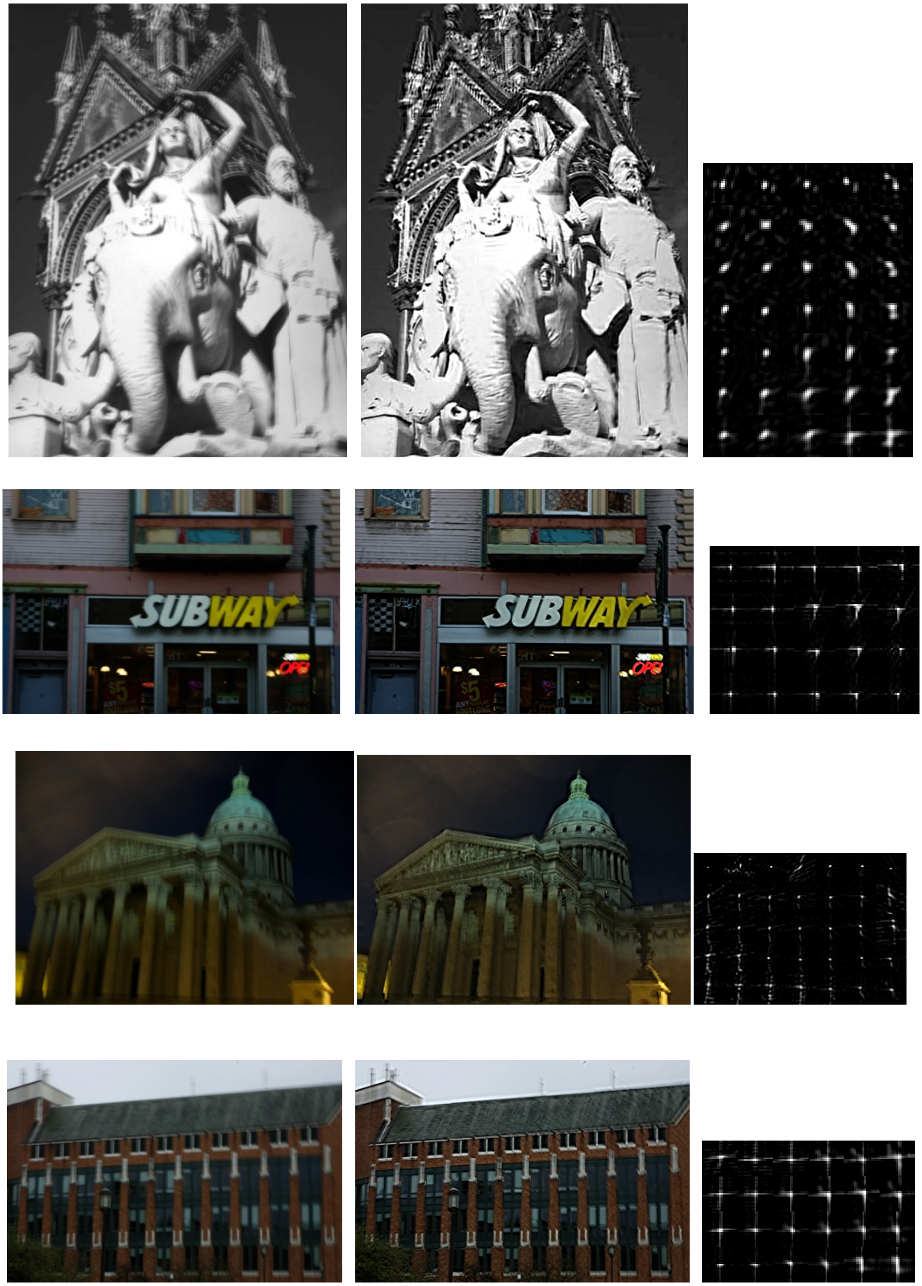

Fig. 1. Non-uniform motion deblur using the proposed method. (From left to right: the blurry images; our results; and our refined PSFs after using the strategy of identifying and replacing the poorly estimated kernels.)

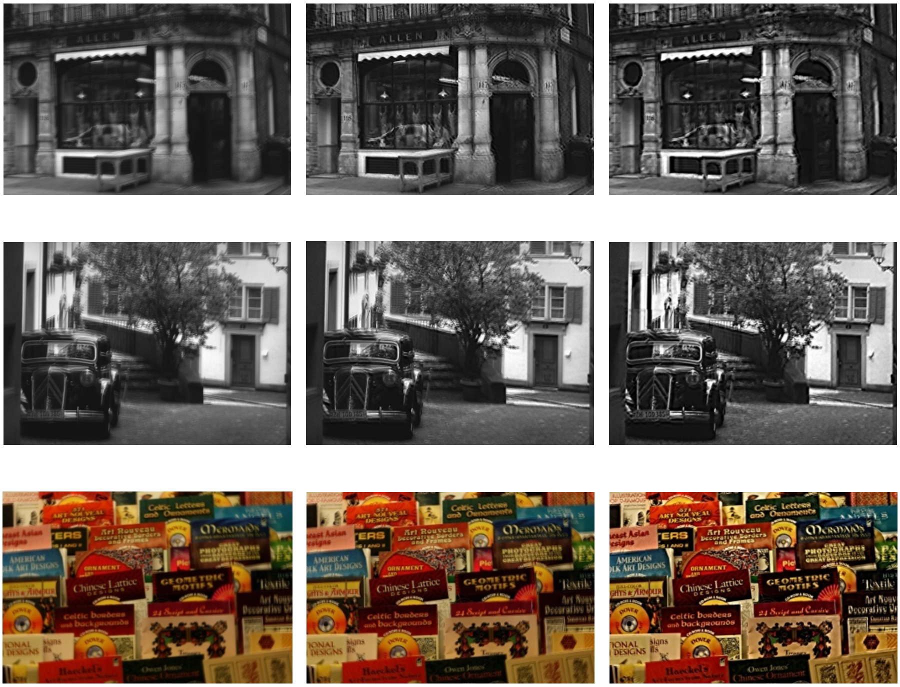

Fig. 2. Comparison with the approach of Jia [7]. For every experiments, from left to right are the blurry images; results of Jia; our results.

5 Conclusion

In this paper, we have presented a novel patch-wise motion deblurring method for non-uniform deblurring. In every patches, we use normalized hyper laplacian prior for kernel estimation and image recovery. Our deblurring method can easily get the real result under multiscale framework. In some patches, the initial kernels estimation are not accurate, so we use residues for the erroneous kernel estimation. Then we use the information of the neighborhood for re-estimating the erroneous local kernels. From the experiments, we can see that our method get proper results.

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