DUAL DEBLURRING LEVERAGED BY IMAGE MATCHING

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ABSTRACT

Existing dual image deblurring methods usually model blurred image pairs being taken from exactly the same viewpoint and restore a single clear image. This imposes a strong assumption that the latent clear images of both images must be completely identical. In contrast to this restricted scenario, we assume that the restored pair are different, but can be approximated by image warping due to small viewpoint change. This allows us to deblur each image individually, but still being able to make use of the matched areas in image pairs. Our deblurring algorithm iteratively performs a two-directional dual image deblurring, which uses the Split Bregman method, and matches the latent clear image pairs by a homography. Experiments show that the proposed algorithm automatically recovers clear images from blurred image pairs in the same scene. Statistics suggest that the method is robust to viewpoint change and different noise levels.

1. INTRODUCTION

Blind image deblurring aims at restoring clear latent images and blur kernels simultaneously. Recently, dual image deblurring has received more attention in image processing community [1, 2, 3, 4, 5, 6]. These methods make use of the redundant information in image pairs in optimization, and provide more effective restoration results.

However, most existing dual image deblurring methods assume both input images are taken from exactly the same viewpoint, and attempt to restore a single clear image. This strict assumption limits the applications in many situations, where viewpoints of these images may vary reasonably. For example, consecutive images from handheld cameras may be contaminated by different linear blur kernels and noises.

This mismatch in image pairs may significantly influence kernel estimations in dual deblurring methods, subsequently degrade the recovered results, and result in severe artifacts [7]. This cannot be handled by easy solutions such as aligning two blurred images, because the projective transformation from one image to the other leads to a non-uniformly blurred image, resulting in severe artifacts in deblurring.

To avoid the distortion of projecting blur kernels, we propose to deblur the image pair to two latent clear images in their original image planes. Further, we assume these two clear latent images are approximated by a homography. Our goal is to deblur each image individually, but iteratively estimate the homography between latent images and use the matched area to improve the deblurring results.

Therefore, our novel objective function minimizes the reconstruction error of blur images and the matching penalty between two latent images. This penalty can be regarded as a relaxation in optimization, making the solving procedure avoid local minima and achieve better performance.

Our approach has two alternate procedures. A local feature based image matching method accounts for warping one latent image to another, and vice versa. In the alternate step, we extend an iterative blind dual image deblurring method to handle matching penalty, and simultaneously estimate the blur kernels and recover latent clear image pair. This procedure assumes uniform camera blur over input images.

We demonstrate the performance on both synthetic and real images. Experiments suggest that our method achieves better restorations and image matchings are well recovered.

2. RELATED WORK

Early works on blind image deblurring usually focus on single image restoration [8, 9]. A typical approach is to formulate the blind deconvolution as a minimization problem, regularized by additional priors on both clear images and blur kernels. Fergus *at el.* [8] and Shan *at el.* [9] used a heavy-tailed gradient distribution as a statistic prior of nature images. Chan *at el.* [10] used TV (Total Variation) norm as regularization term to solve blind deblurring problem.

However, recovering clear image from single images can be challenging, because the blind restoration process is ill-posed. It may be more promising to perform blind image deblurring using multiple images captured in the same scene [11, 12] . The blurred image pairs are modeled as being captured with exactly the same contents but different luminances or noises, and smeared by different motion blurs.

Yuan *et al.*[2] proposed a dual deblurring method using blurred/noisy pair. They used the built-in *exposure bracketing* function of DSLR to obtain blurred/noisy image pairs with small translations. The denoised image was used as a initialization of the latent sharp image. Li *et al.* [13] generated panoramas from consecutive frames picked out from video, which ensures the motion between two images is relatively small. Cai *et al.*'s method [1] also depended on aligned image pair. They simultaneously estimated blur kernels from multiple blurred images. A framelet based prior of blur kernels was introduced and lead to a deblurring algorithm robust to matching error. Compared to these methods, we allow alignment error and focus on deblurring of unaligned blurred image pair.

3. DUAL IMAGE DEBLURRING

Image blur is modeled as a convolution between a latent sharp image and a blur kernel. Given two blur images from similar viewpoints, we assume they are smeared by different uniform blur kernels independently as follows:

$$B_1 = I_1 * k_1 + n_1 \tag{1}$$

$$B_2 = I_2 * k_2 + n_2 \tag{2}$$

where B_i denotes the blurred images, I_i denotes the latent sharp counterparts, k_i is blur kernels, and n_i is additive noise, $i \in \{1, 2\}$.

Existing dual deblurring methods usually make assumption that $I_1 = I_2$. We relax this strict constraint by introducing a divergence penalty term between them in Sec. 3.1. Separately modeling latent image pair allow each of the blurring process obey spacial-invariant blur kernel assumption in the deconvolution process.

3.1. Blind Image Dual Deblurring

We first define the divergence penalty between two latent images, and then present our deblurring procedure.

Divergence Penalty Denote H as the projective transformation between this clear image pair, we have

$$I_{t2} = H(I_1), \tag{3}$$

$$I_{t1} = H^{-1}(I_2). \tag{4}$$

where and H^{-1} denotes the inverse projection.

We evaluate the matching error by a divergence evaluation term of the match area, E_q, which is defined as follows:

$$E_q(I_1, I_2) = \|I_1 - H(I_2)\|_2 = \|I_2 - H^{-1}(I_1)\|_2 \tag{5}$$

where $\|\cdot\|_2$ denotes l_2-norm. Intuitively, this is a two-directional measurement. The two formulation of E_q is intrinsically the same, subject to boundary conditions. The two directional measurement allow us to separate the deblurring process in our modeling.

Two-direction dual image deblurring framework We present a two-direction dual image deblurring framework. The primary idea is that when solving I_1 we firstly calculate I_{t2} using Eq. 3 and use the matched area as side information, and vice versa. In this method, I_1 and I_2 will be optimized alternatively.

Combining the two-direction divergence penalty term, we can estimate blur kernel pair by minimizing

$$\begin{aligned} E(k_1, k_2) &= \|I_1 * k_1 - B_1\|_2 + \lambda_1 E_f(I_1) + \lambda_2 E_k(k_1) \\ &+ \|I_2 * k_2 - B_2\|_2 + \lambda_1 E_f(I_2) + \lambda_2 E_k(k_2) \\ &+ E_q(I_1, I_2), \end{aligned} \tag{6}$$

where $E_f(I_i)$ denotes priors of clear images, $E_k(k_i)$ denotes priors of blur kernels, and λ_1, λ_2 are weighted parameters. By modeling I_1, I_2 separately, we simultaneously solve the two single blind deburring problems for B_i. We also minimize matching error between latent clear images.

Sparsity Priors To optimize I_1, I_2 and k_1, k_2 simultaneously in Eq. 6, we adopt the framelet system and sparsity constrains proposed in [1], and use l_1-norm based optimizations for both blur kernel k_i and clear image I_i. To use the framelet system, we transform I_1, I_2 and k_1, k_2 to their corresponding framelet coefficients using

$$I_i = Dv_i, \tag{7}$$

$$k_i = Au_i, \tag{8}$$

where D and A are framelet transforms of clear images and blur kernels, respectively.

We apply Split Bregman iteration [14] to solve I_i and k_i alternatively. Our iterative dual image deblurring algorithm is formulated as follows:

1. Given I_1, I_2, we solve u_1, u_2 separately by minimizing

   $$\|I_i * (Au_i) - B_i\|_2 + \lambda_2 \|u_i\|_1, i \in \{1, 2\}, \tag{9}$$

   where $\|\cdot\|_1$ denotes l_1-norm. Then we can reconstruct k_1, k_2 using Eq. 8.

2. Given I_2 and k_1, we solve v_1 by minimizing

   $$\|(Dv_1) * k_1 - B_1\|_2 + \|(Dv_1) - H(I_2)\|_2 + \lambda_1 \|v_1\|_1. \tag{10}$$

   Then I_1 is reconstructed using Eq. 7.

3. Given I_1 and k_2, we solve v_2 and I_2 using similar procedure with Step 2.

The sub-problem in Eq. 9 corresponds to a l_1-regularized problem. Eq. 10 is least square minimization problem, which is efficiently solved by iteratively applying conjugate gradient algorithm. Please note our algorithm handles a special case where both images are taken from the same viewpoint.

3.2. Image Matching

We use a feature based technique to match images. To find the geometric transformation between two images, a set of SIFT features [15] are detected for each image. Then, we adopt the RANSAC-based approach to robustly find a set of matched features. Since RANSAC does not guarantee to minimize matching error, we use the divergence penalty term in Eq. 5 as the criteria of warping error, and we repeatedly perform the re-matching until the divergence penalty converges.

Fig. 1 shows two blurred images, their intermediate results, and their warping. These image from the "graffiti" sequence [16] are blurred by real kernels from the work in [17]. One can also see that the clear latent images are more accurate to match. Therefore, our method has better results both in terms of matching accuracy and deblurring performance.

When the overlapped region is flat, i.e. hardly to find any feature to match, our method may become weak since the initialization matching depends on SIFT features. But take into the consideration that current deblurring methods are not very promising on flat images, this should not be a big problem in our algorithm.

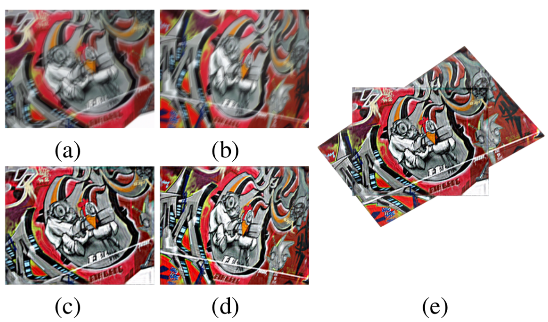


Fig. 1. Feature-based image warping. (a) and (b) are two blurred images, (c) and (d) are their deblurred results (3rd iteration), respectively. (e) is the warping from (d) to (c).

4. EXPERIMENTS AND RESULTS

We present our dual deblurring experiments in this section. Firstly, we demonstrate that our deblurring algorithm is applicable to small matching error using synthetic images. Then, we statistically show that our method is robust to translation, rotation, and more general, affine transformation. Finally, we use real image pairs to demonstrate the effectiveness of our method. The optimal parameters to achieve best performance on different images may vary. For fairly comparison purpose, we used 300 iterations and fixed kernel size (64×64) for all images in both dual deblurring and single image deblurring.

Please note that other dual deblurring methods require images from exactly the same viewpoint, so it may be fair for us to generate our own synthetic data and real dataset, and compare to a single image deblurring method. Therefore, we chose a single image deblurring algorithm proposed by Cai *et al.* [1] for comparison. We conduct our dual image deblurring method on image pairs, where we use the divergence penalty term to regularize both images. In single image deblurring comparison, we only used the first image in the pair.

4.1. Synthetic Images

We first show that our method handles small matching error. The two blurred images were generated (Fig. 2a and 2b) using synthetic motion blurs over the clear image (Fig. 2c) with the parameters $(9\,\text{pixel}, 90°)$ and $(11\,\text{pixel}, 45°)$, respectively. Both images were degraded by 20 dB Gaussian noise. The second image was rotated by a small angle $(0.5°)$.

Fig. 2d and 2e show the deblurring results of our approach. One can see that estimated blur kernels of our method are very similar with the ground truth. In comparison with the single deblurring result shown in Fig. 2f, images generated by our method are clearer.

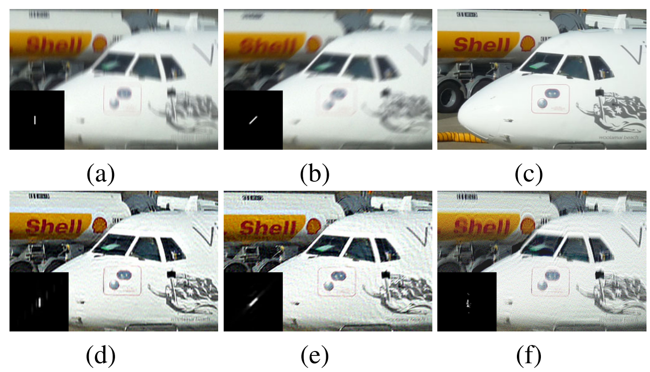


Fig. 2. Dual deblurring results on synthetic images. (a)(b) Two blurred inputs. (c) Ground truth image. (d)(e) Results of our approach. (f) Results of single image deblurring. The synthetic and estimated motion blur kernels are overlaid in the bottom left corner.

4.2. Statistical results

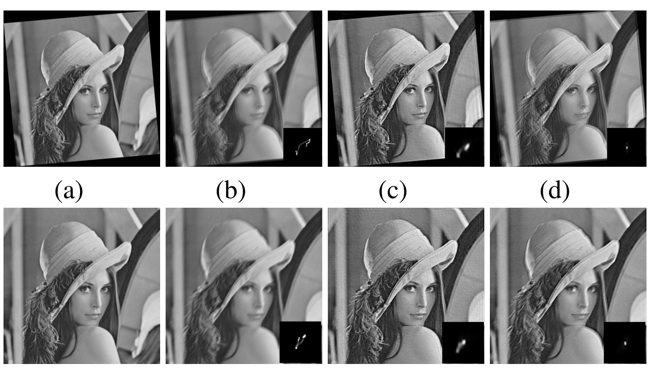
We statistically show our dual deblurring is robust to rotation, translation, and homography transformation. We used the following three sets of images: 1) two pairs in the "graffiti" sequence for affine transformation, 2) two pairs of rotated "Lena" ($\pm 5°$), 3) two pairs of shifted Cameraman. Different noise levels (20 to 60 dB) were added for all images.

Fig. 4 shows an example. Fig. 4b and 4f were generated by convolving the input pairs Fig. 4a and 4e by two large kernels from [17], and the images were degraded by 20 dB noise. Our restored results are shown in Fig. 4c and 4g, and Fig. 4e and 4h are the single image deblurring results, respectively.

We further computed the average error per pixel with respect to different noise levels for the whole test set (Fig. 5).

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

Fig. 3. Dual deblurring result. (a)(b) The input blurred pair. (c)(d) Results for our dual deblurring approach. (e) Results for single image deblurring method from Cai *et al.* . Estimated blur kernels are overlaid on the bottom right corner of each image.



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

(e) (f) (g) (h)

Fig. 4. A dual deblurring example. See text for description.

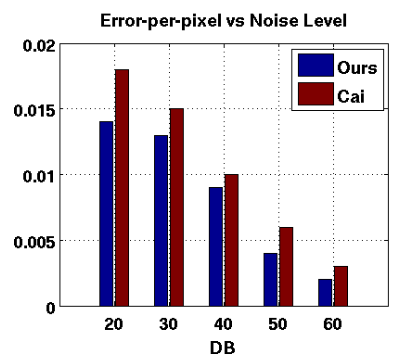


Fig. 5. Statistical performance evaluation.

One can see that the errors of our method are consistently lower. The error generally decreases as noise become smaller. This experiment suggests our method is robust and handles a number of geometric transformation.

4.3. Real Images

In this section, we present deblurring results of real images. All images in this experiment were taken by DSLR camera, using 0.1s shutter speed and indoor lighting environment.

Fig. 3 shows our results on real blurred image pairs. The first two columns (Fig. 3a and 3b) show unaligned blurred image pairs, and Fig. 3c and 3d are the recovered clear images using our method. Results for single image deblurring are shown in Fig. 3e. All estimated blur kernels are overlaid on the bottom right corners, respectively.

Compared to the results of single image deblurring, our approach produced clearer and sharper images with higher visual quality and less artifacts.

5. CONCLUSION

We present a robust algorithm for deblurring a pair of individually captured blurred images. In contrast to previous methods, our approach jointly models two latent clear images using an iterative optimization algorithm. In each iteration, deblurring and matching are performed alternatively. Experiments show that our dual image deblurring method recovers clear results on image pairs and handles matching error.

6. REFERENCES

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