SPACE-VARIANT DEBLURRING USING ONE BLURRED AND ONE UNDEREXPOSED IMAGE

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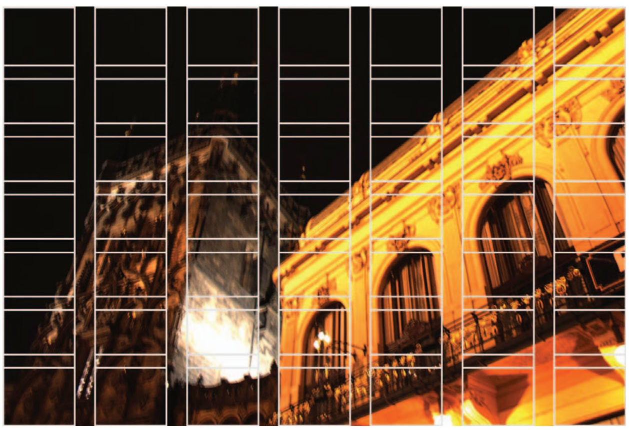
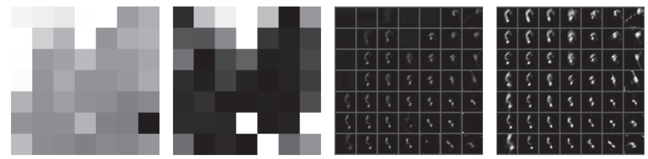


Fig. 1. This night photo was taken from hand at ISO 100 and shutter speed 1.3s. Another photo of the same scene was taken at ISO 1600 and 2 stops under-exposure to achieve the hand-holdable shutter time $1/50$s. The proposed algorithm combines them to get a low-noise sharp photo.



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

Fig. 2. The $49 = 7 \times 7$ kernels (c) were computed in the corresponding squares shown in white in Fig. 1. Incorrect kernels are detected as those with energy (a) or entropy (b) above a threshold (bright squares). We replace them by the average of adjacent kernels, resulting in a new set of kernels (d). Details in Section 5.2.

ABSTRACT

We propose a practical method to remove photo blur due to camera shake, which is a typical problem when taking photos in dim lighting conditions such as indoor or night scenes. We use a pair of images, one of them blurred and the other one underexposed or noisy because of high ISO setting. Existing methods assume convolution model, that is the same blur in the whole image. It is seldom true in practice, especially for wide angle lens photos. We apply a space-variant model of blurring valid in many real situations. Results are documented by a photograph of a night scene.

1. INTRODUCTION

The blur caused by camera shake is a serious problem for photographers. Especially when taking photographs under low light conditions, the camera needs a long exposure time to gather enough light to form the image, which leads to objectionable blur. To mitigate this problem, producers of digital cameras introduced hardware-based stabilizers, which help remove the blur at the expense of higher cost, weight and energy consumption of the device.

A system removing the blur in software would be an elegant solution. Previous work in this direction is overviewed in the following section and the rest of this paper describes our method overcoming the main disadvantage of existing methods – assumption of homogenous blur in the whole image.

2. RELATED WORK

Estimation of the sharp image based on only one blurry image is not an easy task. To simplify the problem, the blur is usually assumed to be homogenous in the whole image. In this case the blur can be modeled by *convolution* of the sharp image with a *point spread function* (PSF) and therefore the reverse problem to find the sharp image is called *deconvolution*. If the PSF is not known, the problem is called *blind deconvolution*. Solutions of blind deconvolution problems from only one image are highly ambiguous and to find a stable solution some additional knowledge about both the image and blur is required. For the present, probably the most stable blind deconvolution method is that of Fergus *et al.* [1].

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Fig. 3. Details of the image. From left to right – the blurred image, noisy image, the result of deconvolution by the kernel valid in the image center, our result.

Another approach, extensively studied in the past years, is to use multiple images capturing the same scene but blurred in a different way. This setup is easy to arrange with a handheld camera. If the camera takes two or more successive images, each of them exhibits different blurring due to basically random motion of cameraman's hand. Multiple images permit estimation of the blurs without any prior knowledge of their shape, which is hardly possible in single image blind deconvolution [6].

One particular multi image setup attracted considerable attention only recently. Taking images with two different exposure times (long and short) results in a pair of images, one sharp but underexposed and another one correctly exposed but blurred [5, 7, 3, 9]. Instead of the underexposed image we can also take an image at high ISO. Both can be easily achieved in continuous shooting mode by exposure and ISO bracketing functions of DSLR cameras. Most papers [7, 3, 9] use the image pair to estimate the blur and then deconvolve the blurred image.

None of the aforementioned methods is general enough to be applicable to full uncropped photos. The reason is that the blur is not constant throughout the image, especially in the case of lenses with a shorter focal length ($<$ 50mm). In addition, it often happens that camera motion has a considerable rotation component about the optical axis and then the blur is space-variant even for tele lenses. Another effect modifying blurs is lens distortion. All these effects are accentuated in regions close to image borders. Therefore a space-variant approach is necessary for artifact-free results.

Space-variant restoration was already considered in astronomy and microscopy but there is almost no work applicable on image stabilization. Only recently in [8] is the space-variant blur considered for a camera moving without rotation, but this assumption does not correspond to the real trajectory of a handheld camera.

3. CONTRIBUTIONS

In this paper we propose a method to remove blur from photographs taken from hand. As in [7, 9] we consider two images of the same scene, one of them blurred and the other one sharp but underexposed or noisy. We assume that no parts of scene are moving relative to each other during the exposure and so the only source of blur is camera motion.

We consider a space-variant blur model. It improves significantly applicability of the algorithm, especially for wide angle lens photos. We apply a robust procedure to estimate PSFs. For image restoration, we use a constrained least square method with total variation regularization to improve image quality. Unlike previous papers, which consider only shift or very small rotation between images, we work with general projective transform and apply a robust registration procedure to estimate it.

4. SPACE-VARIANT MODEL OF MOTION BLUR

It is well known that homogenous blurring can be described by convolution. Unfortunately it is not true in the case of motion blur due to camera shake, especially if the focal length of the lens is short. The blur is typically different in different parts of the image and is a complex function of camera motion and depth of scene [8]. In Fig. 2 (c), we can see convolution kernels estimated in $49 = 7 \times 7$ different places of Fig. 1. Notice, for example, the difference between the upper-left and bottom-right kernels in Fig. 2 (d).

Nevertheless, the blur can be described by more general linear operation

$$\mathbf{z} = \mathbf{u} *_v \mathbf{h}\,[x, y] = \int \mathbf{u}(x-s, y-t)\mathbf{h}(x-s, y-t; s, t)\, dsdt, \tag{1}$$

where $\mathbf{u}$ is an original image, $\mathbf{h}$ is called the *point-spread function* (PSF) as in the case of convolution and $\mathbf{z}$ is the blurred image. We can look at (1) as convolution with a kernel that changes with its position in the image. The subscript v is used to distinguish from ordinary space-invariant convolution often denoted by asterisk.

Because the rotational motion of the camera is usually dominant, the blur is independent of depth and the PSF changes in a continuous gradual way. Therefore the blur can be considered locally constant and can be locally approximated by convolution. We make use of this property and do not estimate blur kernels in all pixels. Instead, we divide the image into rectangular windows and estimate only a small set of kernels $\mathbf{h}_{i,j}$ ($i, j = 1..7$ in our example). The estimated kernels are assigned to centers of the windows where they were computed. In the rest of the image, the PSF $\mathbf{h}$ is approximated by bilinear interpolation from the four adjacent blur kernels.

5. ALGORITHM

For input, the algorithm requires a pair of images, one of them blurred and another noisy but sharp. The algorithm works in three phases:

1. Robust image registration (Section 5.1)
2. Estimation of convolution kernels on a grid of sub-windows, followed by detection and adjustment of the incorrectly estimated kernels (Section 5.2)
3. Restoration of the sharp image (Section 5.3)

5.1. Image registration

In the first step, we need a robust registration procedure working with precision significantly better than the considered size of blur kernels. We assume that the change of camera position is negligible with respect to scene distance and consequently it can be approximated by a projective transform independent of scene depth. Misalignments due to lens distortion do not harm the algorithm because they are compensated by the shift of the corresponding part of the space-variant PSF.

For the purpose of this algorithm, we apply a RANSAC based [2] approach to estimate the homography matrix. Then we transform the blurred image accordingly. The transformed image will be denoted by $\hat{\mathbf{z}}$.

5.2. Estimation of convolution kernels

In the second step of the algorithm we estimate blur kernels $\mathbf{h}_{i,j}$ on a grid of sub-windows, where the blurring can be locally approximated by convolution. Solution of this problem can be estimated in least squares sense as

$$\mathbf{h}_{i,j} = \arg\min_{\mathbf{k}} \|\mathbf{d}_{i,j} * \mathbf{k} - \hat{\mathbf{z}}_{i,j}\|^2 + \alpha\|\nabla\mathbf{k}\|^2, \qquad \mathbf{k}(s,t) \geq 0, \tag{2}$$

where $\hat{\mathbf{z}}_{i,j}$ is a section of the transformed blurred image $\hat{\mathbf{z}}$ and $\mathbf{d}_{i,j}$ the corresponding part of the noisy image. Blur kernel $\mathbf{h}_{i,j}(s,t)$ is an estimate of $h(x_0, y_0, s, t)$, (x_0, y_0) being the center of the current window $\mathbf{z}_{i,j}$ and $\|.\|$ is the L_2 norm.

The kernel estimation procedure, described above, can fail. We identify such kernels and replace them by the average of adjacent (valid) kernels.

There are basically two reasons why kernel estimation fails. The first reason are textureless regions. To identify them, we compute the entropy of the kernels and take those with the entropy above some threshold. In our examples, entropies of all 49 individual kernels are shown as greyscale levels of corresponding squares in Fig. 2 (b). The other case of failure is pixel saturation caused by light levels above the sensor range. This situation can be identified by computing the kernel energy, i.e. the sum of kernel values. For valid kernels the energy should be one. Therefore, we simply remove kernels whose sum is too different from unity, again above some threshold (Fig. 2 (a)). These two thresholds must be set by user.

5.3. Restoration

For the restoration step, we use an energy minimization approach with total variation (TV) as an image regularization term, which belongs to the category of constrained least squares estimators [8]. It has better convergence properties and less artifacts than Richardson-Lucy algorithm used in [9] and removes noise efficiently without oversmoothing edges.

The restoration phase of the proposed algorithm can be described as minimization of the functional

$$E(\mathbf{u}) = \frac{1}{2}\|\mathbf{u} *_v h - \hat{\mathbf{z}}\|^2 + \lambda \int |\nabla \mathbf{u}| \tag{3}$$

with respect to unknown sharp image $\mathbf{u}$, where the second term is the total variation of the image.

Its derivative can be written as

$$\partial E(\mathbf{u}) = (\mathbf{u} *_v h - \hat{\mathbf{z}}) \circledast_v h - \lambda \operatorname{div}\left(\frac{\nabla \mathbf{u}}{|\nabla \mathbf{u}|}\right), \tag{4}$$

where $\circledast_v$ is the operator (adjoint to $*_v$)

$$\mathbf{u} \circledast_v \mathbf{h}\,[x, y] = \int \mathbf{u}(x - s, y - t)\mathbf{h}(x, y; -s, -t)\, ds dt. \tag{5}$$

To minimize functional (3) we use half-quadratic iterative approach reducing this problem to a sequence of linear subproblems [8]. Operations $*_v$ and $\circledast_v$ can be speeded up by Fourier transform [4].

6. EXPERIMENTS

Taking into account available space, we show only one practical example to illustrate mainly that space-variant approach is indispensable, if the restoration has to be free of artifacts. For this purpose, we compare our result (fourth column of Fig. 3) with the result of deconvolution by a constant kernel valid in the central part of the image (third column of Fig. 3). For the deconvolution we use again the least squares approach with TV regularization [6].

We took a night photo of a historical building Fig. 1 at ISO 100 with shutter speed 1.3s. The same photo was taken at ISO 1600 with 2 stops under-exposure to achieve a hand-holdable shutter time $1/50$s. The kernels were estimated in $49 = 7 \times 7$ rectangular windows shown in white in Fig. 1. Figures 2 (c) and (d) illustrate the importance of the kernel adjustment step of the algorithm, that handles the cases of pixel saturation or weak texture. To help reader recognize differences in quite large photograph (1154×1736 pixels), we show details in Fig. 3. The images were taken by an 8 megapixel DSLR camera and the described algorithm was applied separately on all channels of RAW image.

7. SUMMARY

In this paper, we propose a method to remove blur from photographs taken from hand. We use a pair of blurred and noisy images. The main contribution is extension to space-variant model of blur, removing artifacts typically arising in outer areas of an image for convolution based methods. The restoration phase could be further improved by incorporating a term related to the noisy image.

For the present, the method needs a partial user assistance, mainly to set thresholds for detection of wrong blur kernels. The rest of parameters (maximal support of PSF, regularization parameters α, λ) can be estimated based on the shutter speed and experience of the photographer.

8. REFERENCES

[1] Rob Fergus, Barun Singh, Aaron Hertzmann, Sam T. Roweis, and William T. Freeman. Removing camera shake from a single photograph. *ACM Trans. Graph.*, 25(3):787–794, 2006.

[2] Martin A. Fischler and Robert C. Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Commun. ACM*, 24(6):381–395, 1981.

[3] S. H. Lim and D. A. Silverstein. Method for deblurring an image. US Patent Application, Pub. No. US2006/0187308 A1, Aug 24 2006.

[4] James G. Nagy and Dianne P. O'Leary. Restoring images degraded by spatially variant blur. *SIAM J. Sci. Comput.*, 19(4):1063–1082, 1998.

[5] Q. R. Razligh and N. Kehtarnavaz. Image blur reduction for cell-phone cameras via adaptive tonal correction. pages I: 113–116, 2007.

[6] Filip Šroubek and Jan Flusser. Multichannel blind deconvolution of spatially misaligned images. *IEEE Trans. Image Process.*, 14(7):874–883, July 2005.

[7] M. Tico, M. Trimeche, and M. Vehvilainen. Motion blur identification based on differently exposed images. In *Proc. IEEE Int. Conf. Image Processing*, pages 2021–2024, 2006.

[8] Michal Šorel and Jan Flusser. Space-variant restoration of images degraded by camera motion blur. *IEEE Trans. Image Process.*, 17(2):105–116, February 2008.

[9] Lu Yuan, Jian Sun, Long Quan, and Heung-Yeung Shum. Image deblurring with blurred/noisy image pairs. In *SIGGRAPH '07: ACM SIGGRAPH 2007 papers*, page 1, New York, NY, USA, 2007. ACM.