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A computational photography algorithm for quality enhancement of single lens imaging deblurring

Weili Li [a,*], Yu Liu [a], Xiaoqing Yin [b], Bin Wang [a], Maojun Zhang [a]

[a] College of Information Systems and Management, National University of Defense Technology, Deya Road, Changsha 410000, China
[b] Facility Design and Instrumentation Institute, China Aerodynamics Research and Development Center, Mianyang 621000, China

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ABSTRACT

Modern single lens reflex lenses typically consist of up to two dozen individual optical elements, the complexity of which is necessary to compensate for geometric and chromatic aberrations. This paper adopts one single lens to capture images instead of complex lenses, and computational photography technique is employed to remove corresponding imaging artifacts. We initially estimate the space-variant point spread function of the single lens by combining l_1/l_2 image and sparse kernel priors. A fast non-blind deconvolution method with hyper-Laplacian prior is then performed to recover clear image. Experimental results show that the proposed method is at par with state-of-the-art non-blind deconvolution approaches, especially with regards its speed that is much faster than that of existing methods.

1. Introduction

All single lens elements with spherical surfaces suffer from optical aberrations, such as geometric distortions, chromatic aberration, spherical aberration, and coma [1]. Therefore, they cannot be directly used in high-quality photography. Modern single lens reflex (SLR) cameras combine different lens elements to optimize light efficiency and cancel out these aberrations. Despite their better geometric imaging properties than earlier lenses, modern lenses design face high cost and weight problems.

Computational photography has revolutionized photography in recent years by presenting an integrative technology that combines computer and software technologies with modern sensors and optics to create new imaging systems and image applications [2]. Inspired by this idea, this paper proposes an alternative way of capturing high-quality photographs without complex combined lenses. Only one simple single lens (plano-convex lens) is used for imaging, as shown in Fig. 1, and then the ensuing aberrations are corrected computationally.

The primary challenge in achieving the goal is the estimation of the complicated PSF caused by single lens aberrations. Proper image and kernel priors are necessary to improve estimation accuracy. Considering realistic implementation, both the deblurring performance and deconvolution efficiency are important. Recently, Schuler [3] and Heide [4] designed single lens cameras, and obtained clear images by implementing certain algorithms. However, the methods presented by Schuler and Heide require complex calibration in estimating PSF and are time-consuming in deblurring the image, which are impractical in realistic implementation.

In this paper, the l_1/l_2 image and sparse kernel priors are combined to estimate space-variant PSF in blind deconvolution. Such combination can improve estimation accuracy and present PSF calibration. Fast non-blind deconvolution method based on hyper-Laplacian prior [5] is then applied to acquire a clear image. Experimental results show that the proposed method can enhance deblurring performance and increase the processing speed.

The reminder of the paper is organized as follows: Section 2 reviews related work. Section 3 introduces the blind deconvolution method for PSF estimation. Section 4 describes the fast non-blind deconvolution method to recover clear image. In Section 5, experiments are implemented and the experimental results are shown. Finally, Section 6 concludes this article.

2. Related work

2.1. Image deconvolution

Image deconvolution is a classic problem in image processing. According to whether the blur kernel is known, the problem can be classified as blind and non-blind deconvolution. The most basic non-blind deconvolution methods include frequency-space division, the Wiener filter [6] and the Richardson–Lucy algorithm [7,8]. The Richardson–Lucy algorithm has been extended in many ways,

* Corresponding author. Tel.: +86 13778017046.
E-mail addresses: liweili6563@gmail.com (W. Li), jasonyuliu@nudt.edu.cn (Y. Liu), yinxiaoqing89@gmail.com (X. Yin), nudtwangbing@163.com (B. Wang), zmjbar@163.com (M. Zhang).

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0030-4026/

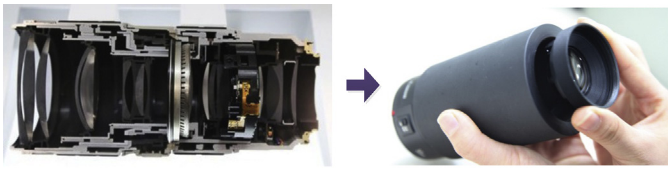

Fig. 1. (a) Complex modern camera lens with combined optical elements (b) our self-made camera lens with a single plano-convex lens (with focal length 120 mm, *f*/4.5).

such as residual deconvolution [9] and Bilateral Richardson–Lucy [10]. Popular blind deconvolution methods in recent years mainly include those that are based on maximum a posterior (MAP) [11,12], variational Bayesian [13,14] and edge prediction [15,16].

2.2. Prior regularization

Given that image deconvolution is an ill-posed problem, additional prior knowledge of the original image or the blur kernel is necessary. Additional prior can disambiguate potential solutions, obtain an accurate blur kernel and accelerate the convergence process.

A few well-known models of image prior include total variation [17], hyper-Laplacian [5], Gaussian scale mixtures [18].

Some probabilistic priors on image statistics are used to derive the blur kernel, such as image gradient distribution [16], alpha-matte constraint [19] and edge profile [20].

Several common assumptions on the blur kernel that constrain its form are non-negativity, energy-conserving, sparsity and smoothness. If some information of the blur kernel is known, the parametric model can be used directly. Main blur kernel types include atmospheric, out-of-focus and motion blur [21].

2.3. Correction for aberration

The use of deconvolution algorithms to correct aberrations dates back at least to the original development of the Richardson–Lucy algorithm. Renewed interest has been given in solving such problems by modern techniques, including the removal of color fringing [22] and chromatic aberrations [20] as well as deconvolution for spatially varying PSFs [23], for images obtained using complex optical systems.

Schuler [3] and Heide [4] attempted to address the aberration correction problem in simple lens imaging. Schuler used point light sources to measure PSF as a function of image location and solved demosaicing and deconvolution problems simultaneously by working in YUV color space. Heide used a convex cross-channel prior that can be implemented efficiently and with guaranteed global convergence. Heide also introduced a convex optimization framework for this prior, which is a key component in achieving ideal image quality in the presence of large blur kernels.

3. Blind deconvolution for PSF estimation

PSF estimation can be posed as a blind deconvolution problem, in which only the blurred image y is given. In this paper, blurring caused by single lens aberrations and chromatic aberrations is considered. The blurred image y can be described as a convolution of the latent sharp image x with the latent blur kernel k as follows:

$$y = k \otimes x \tag{1}$$

where $\otimes$ is the convolution operator.

This section mainly introduces the approach for space-variant PSF estimation in multi-scale implementation. This problem is generally solved in the derivative space by the MAP method. We combine the l_1/l_2 image and sparse kernel priors, and optimize the MAP score using the expectation-maximization framework.

3.1. MAP$_\mathrm{k}$ blind deconvolution

The straightforward approach for blind deconvolution is to search the MAP$_{x,k}$ solution by

$$\left(\hat{x}, \hat{k}\right) = arg\max p(x, k|y) = arg\max p(x, y, k) \tag{2}$$

MAP$_{x,k}$ pair should minimize the convolution error and have spare derivatives. Considering that a simultaneous MAP estimation of both image and kernel is ill-posed, estimating the kernel alone is a better choice. Given that the number of parameters to estimate is smaller than that of image pixel measured, Levin [24] proposed a simple and practical MAP$_k$ algorithm that marginalizes over all latent images.

$$\hat{k} = arg\max p(k|y) = arg\max \int p(x, y|k)\,\mathrm{d}x \tag{3}$$

As shown in Eq. (3), to optimize the MAP$_x$ score, Levin considered an expectation-maximization framework that treats the latent image as a hidden variable and marginalizes over it. This algorithm alternatives between two main steps. The E-step solves a non-blind deconvolution problem and estimates the mean image by the current kernel, with its surrounding covariance. The M-step determines the best kernel using the image. This step calculates the mean of estimated image and the covariance surrounding it. The algorithm is finally defined as follows:

(1) E-step: Considering $p(x) = p(x|y, k)$, compute the mean μ and the covariance C of $q(x)$, which represent the mean image indicated by a kernel and the covariance surrounding it.
(2) M-step: k is found by minimizing.

$$E_q\left[||k \otimes x - y||^2\right] \tag{4}$$

Given that Eq. (4) integrates a quadratic term, the mean and covariance computed in the E-step provide sufficient statistics of $q(x)$ that is required for the minimization.

3.2. Prior regularization

Our goal is to estimate x and k from the blurred input y. Since there are many possible combinations of x and k which can explain the y observation, blind deconvolution is a highly ill-conditioned problem that requires certain prior regularization to solve it.

3.2.1. Image prior

The major drawback of existing image prior in blind deconvolution is that the minimum of the resulting cost of function does not correspond to the true sharp solution. In this paper, we use the image regularization l_1/l_2 introduced by Krishnan [25], which provides the lowest cost for the true sharp image and allows a simple cost formulation to be used for blind deconvolution model.

The scale-variant l_1 norm is widely used to impose signal sparsity, the norm of which can be minimized by simply reducing the signal. In an image setting, l_1 norm is typically used to penalize high frequency bands. Given that image noise is present in these bands, enhancing l_1 norm and minimizing the norm is a method of denoising the image. However, in the case of image blur, the opposite situation holds because blur attenuates the high frequency bands, thus reducing their l_1 norm. Consequently, in a blind deconvolution setting where the kernel is only loosely constrained, minimizing l_1 norm on the high frequencies of the image will result in a blurry image. The simplest interpretation of the l_1/l_2 function is that it is a normalized version of l_1, thus making it scale-invariant. If applied