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Robust penalty-weighted deblurring via kernel adaption using single image ☆

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ABSTRACT

Image blind deconvolution is well known as a challenging, ill-posed problem due to the uncertainty of the blur kernel and the noise condition. Based on our observations, blind deconvolution algorithms tend to generate disconnected and noisy blur kernels, which would yield a serious ringing effect in the restored image if the input image is noisy. Therefore, there is still room for further improvement, especially for noisy images captured under poor illumination conditions. In this paper, we propose a robust blind deconvolution algorithm by adopting a penalty-weighted anisotropic diffusion prior. On one hand, the anisotropic diffusion prior effectively eliminates the discontinuity in the blur kernel caused by the noisy input image during the process of kernel estimation. On the other hand, the weighted penalizer reduces the speckle noise of the blur kernel, thus improving the quality of the restored image. The effectiveness of the proposed algorithm is verified by both synthetic and real images with defocused or motion blur.

1. Introduction

Taking images with a hand-held camera may be a challenge since the camera will be more sensitive to shaking, and the camera autofocus system will become less accurate when there is less contrast or when the light level drops. Therefore, under one of these two conditions, the quality of images will be degraded dramatically by motion or defocus blur. In our research, we aim to deblur images captured under the above conditions.

Mathematically, the problem can be formulated using a space-invariant model, if there is no in-plane rotation during the process of image acquisition. Given a blurred and noisy image, the general space-invariant degradation model can be described as

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

where k represents an unknown blur kernel, n is the unknown independent and identically Gaussian (IID) noise with random variance [12,13,29,9,21,26,2,27,4,32,46]. Under low-light conditions, the photon shot noise follows a Poisson distribution [47]. However, this Poisson distribution can normally be approximated as Gaussian except at very low intensity levels which is not applicable in this paper. Hereafter, we use Gaussian to approximate the noise model under low-light conditions.

If the blur kernel k of the image can be recorded with an assistant hardware, non-blind deconvolution [21,18,23,51] can be applied to recover the ideal image u. Since non-blind deconvolution is sensitive to the unknown noise n, it is also considered an ill-posed [48] problem. However, in most cases, the blur kernel k is also unknown. Therefore, blind deconvolution is required to recover the information in the blurred image as seen in Fig. 1. The key challenge in solving this ill-posed problem is that none of the variables on the right-hand-side of Eq. (1), i.e. the original image u, the blur kernel k, or the noise n, is known. Furthermore, the estimated blur kernel k is severely degraded as the noise level of the input image increases.

In this paper, we aim to recover defocused or motion blur-degraded images in a robust fashion, and further demonstrate that the proposed algorithm is also effective in processing images taken under poor illumination conditions. We refer to it as the weighted anisotropic diffusion regularized blind deconvolution (wADBD). The contribution is threefold. First, based on extensive experimental studies, we hypothesize that the ringing effect often seen in the recovered image is due to the discontinuity in the estimated blur kernel, which in turn is caused by the noise in the input image. Second, based on the hypothesis, we speculate that by adding a diffusion prior, specifically, the anisotropic diffusion prior, to regularize the kernel estimation process, a more connected kernel can be

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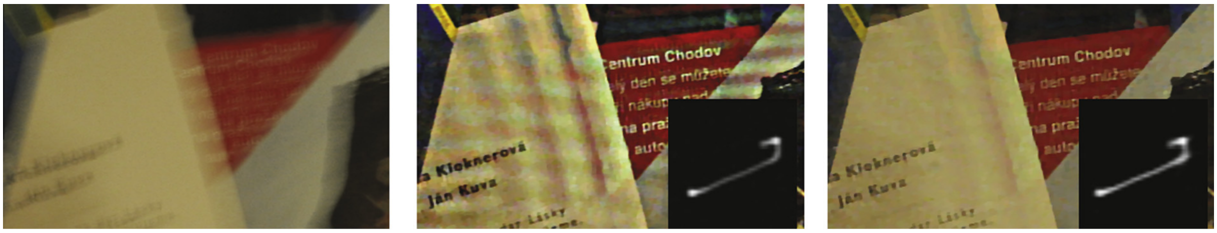

(a) (b) (c)

Fig. 1. Single image blind deconvolution example. Full results are shown in Fig. 12. (a) Cropped input motion blurred image from the data set of [33] acquired by [34]. (b) Cropped recovered image using the algorithm of Kotera et al. [17]. (c) Cropped recovered image from the proposed algorithm.

generated to reduce the ringing effect on the restored image. Third, in order to better control the degree of diffusion in the prior, a weight needs to be applied to the prior to balance between the amount of blur and the amount of discontinuity in the kernel estimation. Experimental results validate the effectiveness of the proposed wADBD.

This paper is organized as follows: Section 2 discusses related work in blind image deconvolution. Section 3 explains the fundamental framework and studies priors used in some state-of-the-art algorithms. The proposed algorithm is described in Section 4. In Section 5, the proposed algorithm is validated using both synthetic images and real defocused and motion blurred images. Section 6 concludes the paper.

2. Background and related work

Blind deconvolution can be dated back to the early 1970s [16,20] and has been involved in numerous applications such as astronomical imaging processing, remote sensing, photography [26,1], etc. However, most of the methods are only applicable in special situations, e.g., the input image has a constant black background [3,14]. The robust estimation of blur kernel seemed too difficult a problem to conquer [35] until 2006, when natural image statistics was applied to the blind deconvolution problem [8,22,24], which inspired the subsequent works.

Lately, efficient state-of-the-art single-image blind deconvolution approaches have been proposed to recover images from motion or defocus blur caused by handheld photography in different directions. These approaches had achieved impressive results. MAP (Maximum a Posterior) is considered one of the most effective solutions to blind deconvolution. The downside, however, is that it favors the delta kernel during the procedure of blur kernel estimation. Levin et al. [24] investigated into the MAP approaches, and adopted a marginalized posterior method to overcome the drawback of traditional MAP algorithms. Useful prior assumptions are most important for MAP. Kotera et al. discussed the relationship between MAP and the regularization strategy and adopted a heavy-tailed prior [17]. The gradients of the blur kernel and the ideal image are well known to be sparse. Several methods took advantage of this property as priors to regularize the image or blur kernel [15,6,44]. Regularization schemes like the l_0, l_1 and l_2 norms, have also been successfully employed [26,4,19,45,31]. For example, Zhou et al. [50] used a nondimensional Gaussianity measure to force sparsity of a boundary and incorporated a Dirichlet distribution to approximate the posterior distribution of the blur kernel.

Most single image deconvolution methods [8,24,6,44,31] seek to solve the problem with the assumption that the input image is at a low noise level. However, when light conditions are poor, the image becomes difficult to observe. To fix this problem, one can either set a higher ISO or extend the exposure time of the camera. However, both solutions would increase the noise or blurriness of the image. When the noise level of the image increases, the image properties will be influenced. For example, the edges may no longer be sparse. As stated in previous research [35,31,49], it is difficult to predict the shape of the kernel for a noisy input image. Additionally, the ringing effect becomes a significant problem when solving the blind deconvolution for a noisy image. Shan et al. [31] analyzed the cause of the common artifacts and introduced a sparse image prior in their method. Tai and Lin [38] proposed a new noise-related regularization term in the kernel estimation step to suppress the noise in the restored ideal image. Zhong et al. [49] proposed a novel approach for noisy input images only, which applied a directional low-pass filter to handle the noise during the deconvolution process. Since the success of algorithms depends on the noise level of the input image and the noise level is difficult to predict, there remains room for performance improvement.

3. Fundamentals of blind deconvolution

3.1. Fundamental framework

For single blind deconvolution, the ideal image u and blur kernel k are solved only by a single given image g. The common probabilitic model can be built using Bayes' theorem

$$p(u,k|g) = \frac{p(g|u,k)p(u)p(k)}{p(g)}. \tag{2}$$

Since $p(g)$ is fixed, the formula can be simplified as

$$p(u,k|g) \propto p(g|u,k)p(u)p(k). \tag{3}$$

Taking the logarithm on both sides of Eq. (3), the function can be written as

$$\ln p(u,k|g) \propto \ln p(g|u,k) + \ln p(u) + \ln p(k). \tag{4}$$

Note that $p(g|u,k)$ is proportional to the probability of image noise, which is normally assumed as an IID Gaussian noise and can be modeled as

$$p(g|u,k) \propto e^{-\frac{\|u*k-g\|^2}{2\sigma^2}}, \tag{5}$$

where $\|.\|$ denotes the l_2 norm. Importing Eq. (5) into Eq. (4), we get

$$\ln p(u,k|g) \propto -\frac{\|u*k-g\|^2}{2\sigma^2} + \ln p(u) + \ln p(k). \tag{6}$$

To solve u and k, we can maximize the cost function $\ln p(u,k|g)$, which is equivalent to minimizing the negative of this function. In addition, we set $R_u(u) = -\ln p(u)$ to be the regularization term for image u, and $R_k(k) = -\ln p(k)$ to represent the prior regularization term for blur kernel k. The objective function can then be defined as

$$\min_{u,k} \frac{\gamma}{2}\|u*k-g\|^2 + R_u(u) + R_k(k). \tag{7}$$

The primary challenge is to find useful regularization terms for image u and kernel k. Fig. 2 shows the system diagram of blind