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ON ALGORITHMS FOR AUTOMATIC DEBLURRING FROM A SINGLE IMAGE*

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Abstract

In this paper, we study two variational blind deblurring models for a single image. The first model is to use the total variation prior in both image and blur, while the second model is to use the frame based prior in both image and blur. The main contribution of this paper is to show how to employ the generalized cross validation (GCV) method efficiently and automatically to estimate the two regularization parameters associated with the priors in these two blind motion deblurring models. Our experimental results show that the visual quality of restored images by the proposed method is very good, and they are competitive with the tested existing methods. We will also demonstrate the proposed method is also very efficient.

Mathematics subject classification: 65J22, 65K10, 68U10.
Key words: Blind deconvolution, Iterative methods, Total variation, Framelet, Generalized cross validation.

1. Introduction

The blurring of images often occurs from the motion of objects, unfocused cameras and calibration errors with imaging devices. Mathematically, the forward model of the blurring process is stated as follows:

$$f = p * g. \tag{1.1}$$

Here f is the observed image, g is the original image, p is the blur kernel which is also known as point spread function, $*$ represents the convolution operator. Recovering g from problem (1.1) with known p is called non-blind deconvolution problem which is a mathematically ill-posed problem. When p is also unknown, the problem is called blind deconvolution which is even more ill-posed. A survey and a book on blind image deconvolution can be found in [1] and [2] respectively.

In this paper, we consider blind motion deblurring problem. Motion blur appears when there is a relative motion between the camera and the scene during exposure. In the literature, there are several deblurring techniques by making use of information from multiple motion blurred images [3–8]. For single-image blind motion deblurring, some parametric models for the motion blur kernel are studied and considered in [9, 10]. In [11], Fergus et al. employed

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ensemble learning to recover a motion blur kernel with some image priors. In [12], Tai et al. introduced a new Projective Motion Blur Model that treats the blurred image as an integration of a clear scene under a sequence of projective transformations that describe the cameras path. In [13–16], researchers proposed some efficient and high-quality kernel estimation methods based on using different approaches. In [14], Jia formulated the kernel estimation as solving a Maximum a Posteriori (MAP) problem with the defined likelihood and prior on transparency. In [15], Shan et al. computed a deblurred image using a unified probabilistic model of both motion blur kernel estimation and unblurred image restoration. They developed a model of the spatial randomness of noise in the blurred image, as well a new local smoothness prior that reduces ringing artifacts by constraining contrast in the unblurred image wherever the blurred image exhibits low contrast. In [16], Xu et al. proposed an efficient and high-quality kernel estimation method based on using the spatial prior and the iterative support detection kernel refinement, which avoids hard threshold of the kernel elements to enforce sparsity. However, these algorithms are required to input some values of parameters so that motion blur kernels can be recovered and image details can be enhanced properly.

The main aim of this paper is to develop algorithms for automatic deblurring from a single image. We study two variational blind deblurring models for a single image restoration. The formulation is given as a minimization problem with some regularization terms on p and g:

$$\min_{p,g} E(p,g) \equiv \Phi(p * g - f) + \lambda_1 R_1(p) + \lambda_2 R_2(g), \tag{1.2}$$

where $\Phi(p*g-f)$ is the data fidelity term, $R_1(p)$ and $R_2(g)$ are the regularization terms for p and g respectively, and λ_1 and λ_2 are the two positive regularization parameters which are used to balance the data fidelity term and the two regularization terms. One of the useful regularization approaches is the total variation (TV) regularization method [17–20]. In this approach, the data fidelity term is usually l^2 norm for image intensity fitting; and the regularization terms are both measured by the total variation. According to the experimental results in [18, 21], we find that the use of total variation as a prior to general blur kernels may not be effective. However, it has been observed for blind motion or out-of-focus deblurring problems [18] that these blur kernels can be recovered and image details can be enhanced very well. Recently, another popular regularization method is to determine a sparse representation of image and blur under tight frame systems [22–24]. These methods are able to recover high-quality images from given blurred images.

According to (1.2), the regularization parameters must be determined properly so that deblurring algorithms can be used to provide good recovered images and blurs. In [18, 22–24], methods are not given for searching suitable regularization parameters. The main contribution of this paper is to show how to employ the generalized cross validation (GCV) method [25] efficiently and automatically to estimate the two regularization parameters λ_1 and λ_2 associated with the priors in blind motion deblurring models. In this paper, we consider two types of regularization terms and compare their performance. One type is to use the total variation for R_1 and R_2. The other type is to employ tight frame systems for R_1 and R_2. Our experimental results show that the visual quality of restored images by the proposed method is very good, and it is competitive with the tested existing methods. We will demonstrate the proposed method is also very efficient.

This paper is organized as follows. In Section 2, we present models using the total variation regularization and the frame-based regularization. In Section 3, we propose the two blind deblurring algorithms by employing the generalized cross validation (GCV) method to estimate