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Blind image motion deblurring with L_0-regularized priors ☆

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ABSTRACT

Blind motion deblurring from a single image has always been a challenging problem. This paper proposes a blind image motion deblurring method which adopts L_0-regularized priors both in kernel and latent image estimation. A sparse and noiseless kernel and reliable intermediate latent images are generated with this prior constraint. An alternating minimization method is adopted to ensure that latent image and kernel estimation converge at an acceptable time. The proposed method is easy to implement since it does not require any complex filtering strategies to select salient edges which are critical to the explicit salient edges selection methods. The experimental results demonstrate that the proposed method is superior because of the better performance when compared with other state-of-the-art methods and the encouraging results obtained on some challenging examples.

1. Introduction

Single image blind deblurring has been extensively discussed in recent years due to its wide range of applications. Such as facial deblur, Liao and Lin [1] decomposed an intrinsic sharp face image into the eigen-face subspace and adopted a Gaussian prior to regularizing the estimated intrinsic face image. Zhang et al. [2] used the Joint Restoration and Recognition method, which combines restoration and recognition within sparse learning. Pan et al. [3] proposed a face image deblurring method which is based on the contour of faces. While in medical imaging field, the Computed Tomography (CT) medical images are degraded by blurring due to many reasons, like the low resolution of the imaging system, data loss in acquisition and noise. Recently, many deblurring methods have been proposed to better visualize miniature-sized features of the CT image. Jiang et al. [4] proposed a deblurring method for spiral CT image based on edge signal-to-noise ratio, which improved the identification of cochlear CT details significantly. Wang et al. [5] made an improvement to Jiang et al. [4] by using the Wiener filter, which improved the image quality and accelerated the speed of deblurring algorithm. Alameen and Sulong [6] proposed a fast deblurring method for CT medical images using a novel kernel set. Gou et al. [7] proposed a low-rank decomposition-based method for CT image sequence restoration, which achieved higher contrast, sharper organ boundaries and richer soft tissue structure information, compared with existing CT image restoration methods.

This paper focuses on motion deblurring problem, and the process of motion blur is generally modeled as a latent image convolved with a motion blur kernel as follow

$$y = x * k + \sigma \quad (1)$$

where y denotes blurred image, k is blur kernel, latent image x indicates the image we would have captured if the camera had remained perfectly still, $*$ represents the convolution operation and σ is image noise. Our purpose is to reconstruct x from y without specific knowledge of k.

Previous single-image blind motion deblurring methods [8–10] work partly due to the use of various latent image and kernel priors. Cho and Lee [10] and Xu and Jia [11] used Gaussian prior in their methods, but this prior cannot keep the sparsity of the estimated kernel and the image structures, which leads to noisy and dense estimated results. Since natural image gradients do not satisfy the Gaussian distribution but the heavy-tailed distribution [12], Fergus et al. [8] developed a method that incorporates zero-mean mixture of Gaussian for deblurring, Shan et al. [9] proposed a parametric model to approximate the heavy-tailed distribution of natural image gradients, Krishnan and Fergus [13] and Levin et al. [14] both adopted Hyper-Laplacian prior in estimation.

Image structure edges play an important role in kernel estimation. The strategy combining shock filter with filter methods such as bilateral filter has been extensively adopted in [10,11,15–17]. However, not all edges are helpful in kernel refinement [10,11]. Xu and Jia [11] proposed an effective mask computation algorithm to select useful edges adaptively in kernel estimation. Recently, a

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novel L_0-regularized [18] constraint method has been adopted in natural [9,18] and text motion deblurring [19], since L_0-regularized prior has a good interpretation for sparsity of natural image gradients and also a good effect on noise and ring-artifact suppression.

When it comes to the motion blur, the kernel k indicates the trace of sensor and shows great sparseness. Some methods [9,20] used kernel constraint $\|k\|_1$, which could preserve the sparse property of kernel effectively. However, it sometimes induced noise [15]. Most kernel estimation models [10,11] adopted quadratic kernel constraint $\|k\|_2^2$ which could help to reduce kernel noise and enable fast kernel estimation by using Fast Fourier Transform (FFT). However, this prior constraint often leads to a dense kernel. Xiao et al. [21] developed a stochastic optimization method, which does not require the explicit computation of the gradient of the objective function and uses only efficient local evaluation of the objective. Thus, new priors can be implemented and tested very quickly by using their method. Since kernel size is an important parameter in image deblurring approaches, and it is often manually selected. Liu et al. [22] proposed an approach for automatically estimating the kernel bound of the blurred images, which focuses on kernel size selecting.

Inspired by this, we propose a natural image motion deblurring model based on L_0-regularized prior and introduces an efficient optimization algorithm. Firstly, we adopt an L_0-regularized prior in latent image estimation, therefore complex filter or explicit edges selection methods are no more needed in our method. Secondly, we introduce an L_0-regularized constraint in kernel estimation, which could ensure estimated kernel sparse and continuous. Thirdly, we apply an alternating minimization method [23] that makes latent image and kernel estimation converge at an acceptable time. Finally, we employ a standard Total Variation non-blind deblurring method to guarantee a detailed restored image.

The rest of this paper is organized as follows. Section 2 demonstrates the proposed method and describes the implementation in detail. Section 3 shows the experimental results and compared with other state-of-the-art methods. Conclusions are drawn in Section 4.

2. The proposed method

Previous works [8–10,20] demonstrate that regularization term is important in both kernel and latent image estimation. Krishnan et al. [20] performed kernel estimation on the high frequencies of the image and they used differential filters $\nabla_h = [1, -1]$ and $\nabla_v = [1, -1]^T$ to generate a high-frequency version $\nabla y = (\nabla_h y, \nabla_v y)^T$. They modeled the deblurring problem as

$$\min_{x,k} \psi\|\nabla x * k - \nabla y\|_2^2 + \|\nabla x\|_1/\|\nabla x\|_2^2 + \varphi\|k\|_1 \tag{2}$$

where ψ and φ are weights, $\|k\|_1$ is L_1 norm of $k, \nabla x$ is the latent image x in the high-frequency space, $\nabla x = (\nabla_h x, \nabla_v x)^T, \|\nabla x\|_1$ and $\|\nabla x\|_2^2$ are L_1 and L_2 norm for ∇x, respectively. In this model, $\|\nabla x\|_1/\|\nabla x\|_2^2$ function would produce multiple local minima, and this function is non-convex thus very hard to be optimized directly. $\|k\|_1$ norm has a good sparse representation, but it would result in a noisy kernel. Pan and Su [24] introduced a sparse $\|\nabla x\|_0$ regularization and applied a Gaussian prior $\|k\|_2^2$ in their model

$$\min_{x,k} \|\nabla x * k - \nabla y\|_2^2 + \gamma\|\nabla x\|_0 + \varphi\|k\|_2^2 \tag{3}$$

where γ is weight, $\|k\|_2^2$ is L_2 norm of $k, \|\nabla x\|_0$ is the L_0 norm of ∇x that counts the number of non-zero values of ∇x. $\|k\|_2^2$ has a good noise suppression effect and the quadratic format makes the kernel estimate faster by using *FFT*. However, the Gaussian prior $\|k\|_2^2$ used in this model would result in a dense kernel.

Summarizing the preceding discussions, various constraint functions have been proposed to approximate $\|\nabla x\|_0$ and $\|k\|_0$ which have a good natural interpretation for the sparsity of image gradients and kernel intensities, respectively. However, an L_0 regularization term would result in a non-convex problem which is very difficult to be optimized. Pan et al. [19] introduced a highly efficient alternating minimization method which could effectively solve this problem. We introduce the $\|\nabla x\|_0$ and the $\|k\|_0$ constraints into the deblurring model as

$$\min_{x,k} \|x * k - y\|_2^2 + \gamma\|\nabla x\|_0 + \varphi\|k\|_0 \tag{4}$$

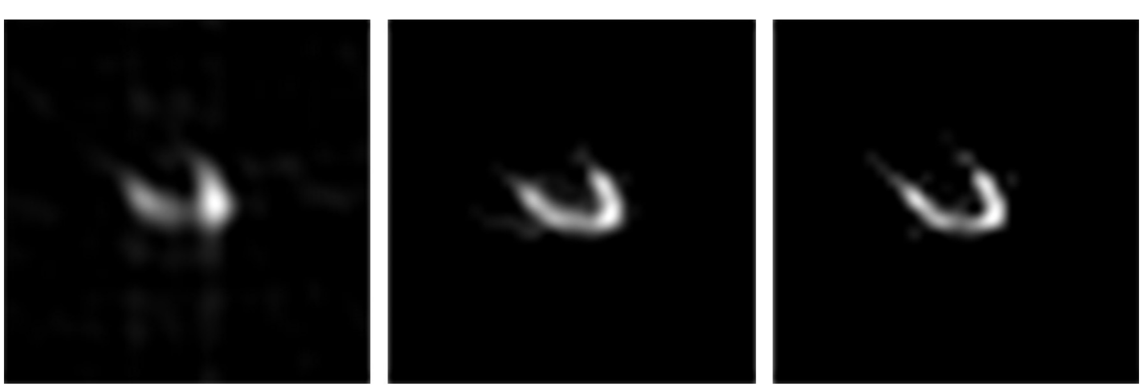
The optimization method proposed by Pan et al. [19] is applied to solve the model, which works by solving the following two sub-problems alternately

$$\min_{x} \|x * k - y\|_2^2 + \gamma\|\nabla x\|_0 \tag{5}$$

and

$$\min_{k} \|x * k - y\|_2^2 + \varphi\|k\|_0 \tag{6}$$

In Fig. 1, the kernel in Fig. 1(a) is estimated by using the model Eq. (2) which is employed by Krishnan et al. [20]. Kernel in Fig. 1(c) is obtained by using the proposed model Eq. (4) where a sparse $\|k\|_0$ prior is adopted. Kernel in Fig. 1(b) corresponds to model Eq. (3) which can be easily testified by changing $\|k\|_0$ to $\|k\|_2^2$ in



(a) (b) (c)

Fig. 1. Comparisons of results with different kernel priors. The kernel shown in (a) is estimated by using the model Eq. (2) that is employed by Krishnan et al. [20], and the kernel shown in (b) and (c) are obtained by using model Eqs. (3) and (4), respectively.