J. Vis. Commun. Image R. 25 (2014) 814–821

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Blind image deblurring via coupled sparse representation

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ARTICLE INFO

Article history:
Received 31 May 2013
Accepted 3 February 2014
Available online 15 February 2014

Keywords:
Blind deblurring
Sparse representation
Coupled dictionary
Image patch
Deconvolution
Blur kernel
Total variance
Sub-pixel resolution

ABSTRACT

The problem of blind image deblurring is more challenging than that of non-blind image deblurring, due to the lack of knowledge about the point spread function in the imaging process. In this paper, a learning-based method of estimating blur kernel under the ℓ_0 regularization sparsity constraint is proposed for blind image deblurring. Specifically, we model the patch-based matching between the blurred image and its sharp counterpart via a coupled sparse representation. Once the blur kernel is obtained, a non-blind deblurring algorithm can be applied to the final recovery of the sharp image. Our experimental results show that the visual quality of restored sharp images is competitive with the state-of-the-art algorithms for both synthetic and real images.

1. Introduction

Blurred images occur when the image acquiring process is influenced by the relative movement between the camera and objects during the exposure time [20]. A clean image from a blurred image can be obtained through solving the problem of image deblurring, which is one of challenging problems in image restoration. Image deblurring has been extensively studied in recent years [4,21].

In general, the degradation process of the blurred images is often modelled as a convolution followed by a noising process,

$$Y = \mathbf{k} \otimes X + n \tag{1}$$

where Y is a blurred image, i.e. observed image, X is a sharp image, i.e. unknown latent (clean/sharp) image, $\mathbf{k}$ is a spatial-invariant kernel, i.e. point spread function (PSF) and n is independent white Gaussian noise added to the convoluted image. The problem of image deblurring is to recover the latent image X from the observed blurred one Y, which is also regarded as a deconvolution processing.

The process of image deblurring falls into two categories. If the blur kernel $\mathbf{k}$ is known or well estimated, then the restoration of X from Y is considered as a non-blind deconvolution problem. If, on the other hand, there is very little or no information about the blur kernel $\mathbf{k}$, the problem is regarded as blind deblurring. Unfortunately, in most of the real-world cases, we have no knowledge of the exact kernel $\mathbf{k}$ for a blurred image. Thus, most of the time, we have to face the challenging blind deconvolution problems [2,24,26]. This results in well-known,, but ill-posed and difficult problems. In this paper, we focus on the issue of blind image deblurring.

Recently, many methods have been proposed to solve this kind of problems [5]. These methods can be roughly divided into two classes based on the ways of how blur kernels are identified or learned. In the first class, a blur kernel is identified independently from a single blurred image [14]. In the second class, both the blur kernel and latent (clean or sharp) image are estimated simultaneously via a learning process [5,6]. In most of the methods of the second class, a *prior* knowledge [9,14,17] about both latent image and blur kernel is exploited, for example in total variation and Bayesian paradigms [2,24]. Once the blur kernel is well estimated, the problem can be simplified into a non-blind deconvolution issue, which can be effectively solved by the popular sparse representation methods [3,29,31].

However, many hidden mappings between the blurred images and the latent images are not well exploited during estimating blur kernels [8,10]. For example, a motion blurred image [10] usually retains information about motion which gives us clues to recover motion from this blurred image by parameterizing the blurring model. The sparse representation of image is more helpful in estimating an appropriate blurring kernel and its relevant latent image [8]. The advancements in sparse representation of signals [7,12]

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http://dx.doi.org/10.1016/j.jvcir.2014.02.003

and learning their sparsifying dictionaries [1] make it more effective in solving the image restoration problems.

In this paper, we focus on the spatially invariant blurring issue. Our goal is to recover the true blur kernel based on the assumption that there exists a coupled sparse representation between the blurred and sharp (latent) image patch pairs under their own dictionaries, respectively. This type of hidden mappings is helpful in estimating the unknown blur kernel. Then, with the estimated blur kernel, we can recover the latent image by a variety of non-blind deconvolution methods. The main contribution of this paper to the literature is summarized as the integration of the sparse representation of blurred image and its corresponding latent patch into a unified framework for optimization. Specifically, in addition to requiring that the coding coefficients of each local patch are sparse, we also enforce the compatibility of sparse representations between the blurred and latent image patch pair with respect to their own dictionaries. Once the blur kernel is learned, we restore the latent clean image by imposing a sparse prior regularization over the image derivatives as done in [18]. This regularization allows a robust recovery even for a possibly lower accurate kernel estimate and is an effective way to solve the non-blind deconvolution issue.

This paper is organized as follows. In Section 2, we briefly review the related works on the approaches of blind image delurring. The blind image deblurring based sparsity prior is proposed in Section 3. The extensive experimental results are provided in Section 4. The conclusion is drawn in Section 5.

2. Related works

Due to its inherently ill-posed problem, a blind image deblurring process needs to be regularized by image priors for better solution. We briefly review a variety of approaches on blind image delurring in the following.

Generally, natural image statistics can be used as appropriate image priors, e.g., in constraining the output of local derivative operators. Among many priors, the Gaussian smoothness penalty is the simplest one, which has been widely used in blind image deconvolution [9,14,17]. Fergus et al. [14] first estimated a blur kernel using a prior on gradient distribution of natural images in a variational Bayes framework [2,24]. In [9], a computationally efficient Gaussian prior is applied to estimate the latent image. However, since images may be highly non-Gaussian, these Gaussian prior based approaches may favor noisy or dense kernel estimates. Therefore, given that the distribution of image derivatives is well modeled by a hyper-Laplacian, a non-blind deconvolution approach proposed in [18] provides competitive performance with several orders of fast speed.

Instead of using statistical priors, Joshi et al. [17] proposed an algorithm to estimate blur functions at sub-pixel resolution, which is fulfilled by estimating regions of a sharp image from a single blurred image. For spatially non-uniform blur, Gupta et al. [15] proposed a spatially invariant deconvolution method, where the blurring was represented as motion density function (MDF) to compute initial estimates of the latent image.

Recently, the advancements in sparse representation of signals [7,12] and in learning their sparsifying dictionaries [1] have made it easier to solve the image delurring problem [14,16,26]. Shan et al. [26] applied the sparse priors for both the latent image and blur kernel under an alternating-minimization scheme. Cai et al. [8] exploited a framelet and curvelet system to sparsely represent both blur kernel and sharp image. Finally, a sparse representation based on incremental iterative method was established for blurred image restoration [30]. Although the above methods have achieved impressive progress on blind deblurring, the quality of the recovered sharp image is far from perfect. In [22], Lin et al. proposed a framework, called Coupled Space Learning, to learn the relations between the image patches lying in different spaces. In statistical learning, the relationship between two image patch pairs can be regarded as the mapping between two vector spaces associated with two image styles. Inspired by this observation, we integrate the couple concept into the spare representation framework and propose a novel method to learn the unknown blur kernel for image blind deblurring.

3. Learning-based blind image deblurring method

3.1. Conceptual framework

Consider a patch $\mathbf{x}$ extracted from a latent image X and assume that $\mathbf{x}$ can be well represented as a sparse linear combination over an appropriate dictionary $\mathbf{D}$. This dictionary $\mathbf{D}$ may be trained from those true sample patches extracted from training images. In general, we assume

$$\mathbf{x} \approx \mathbf{D}\boldsymbol{\alpha}, \ \|\boldsymbol{\alpha}\|_0 \ll m \quad \text{with} \quad \boldsymbol{\alpha} \in \mathbb{R}^m. \tag{2}$$

Such a sparse representation can be helpful in image processing tasks [7,12,30]. For example, the sparse representation approach has been widely used in image denoising [13]. The idea is based on the assumption that all the image patches can be adequately approximated by a sparse linear combination of a learned patch dictionary. Let R_i denote the extraction operator for a patch $\mathbf{x}_i$ from the given image X at location i, i.e., $\mathbf{x}_i = R_i X$. Assume that all the patches $\{\mathbf{x}_i\}$ of the given image X permit a sparse representation with a set of sparse coefficients $\Lambda = [\boldsymbol{\alpha}_i]$ under a known dictionary $\mathbf{D}$, then the reconstruction of X^* from the sparse coefficients can be formulated as an over-determined system and its straightforward least-square solution is given as follows [13],

$$X^* \approx \mathbf{D} \circ \Lambda = \left(\sum_i R_i^T R_i\right)^{-1} \sum_i \left(R_i^T \mathbf{D}\boldsymbol{\alpha}_i\right)$$

This idea can be generalized to our deblurring problem, as proposed below. Let us consider the blurring model in (1). Suppose the sharp latent image patches admit a well defined sparse representation under a dictionary as defined in (2), then based on the linearity of convolution process one can expect a similar sparse representation of the corresponding blurred image patches as defined in the following model,

$$\mathbf{y} \approx \mathbf{k} \otimes \mathbf{D}\boldsymbol{\alpha} = \widetilde{\mathbf{D}}\boldsymbol{\alpha}, \ \alpha \in \mathbb{R}^m, \|\boldsymbol{\alpha}\|_0 \ll m \tag{3}$$

where $\widetilde{\mathbf{D}} = \mathbf{k} \otimes \mathbf{D}$ is regarded as the blurred dictionary under the deblurring process $\mathbf{k}$.

Actually Eqs. (2) and (3) implicitly suggest a hidden relation [22] between the blurred image and the corresponding latent one as a set of the same sparse coefficients is utilized in the model. In real applications, it is reasonable for the sparse representation between blurred image and latent image to be equal by enforcing such coherence of the sparse coefficients, similar to the basic idea in [23,28]. Hence our hypothesis is that similar patch pairs will demonstrate similar sparse decomposition. Thus our approach for the blind deblurring problem is to formulate a coupled sparse representation framework, and then to obtain the blur kernel by using a learning-based minimization strategy and recover the latent image via non-blind deconvolution method.

One of significant difference from [23] is that we offer a learning procedure for blur kernel with certain prior knowledge through the addition of a regularizer term. In summary, our method consists of two stages. The first stage is to estimate the blur kernel from the blurred input $\mathbf{y}$ where the kernel estimation is performed on the high frequency part of the image. This is reasonable since blurring