Digital Signal Processing 47 (2015) 116–127

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Variational Bayesian Blind Image Deconvolution: A review ☆

Pablo Ruiz [a], Xu Zhou [b,*], Javier Mateos [a], Rafael Molina [a], Aggelos K. Katsaggelos [c]

[a] Departamento de Ciencias de la Computación e I. A. E.T.S. Ing. Informática y Telecomunicación, Universidad de Granada, 18071 Granada, Spain
[b] Image Processing Center, Beihang University, 100191 Beijing, China
[c] Department of Electrical Engineering and Computer Science, Northwestern University, Evanston, IL 60208, USA

ARTICLE INFO

Article history:
Available online 4 May 2015

Keywords:
Blind deconvolution
Image deblurring
Image restoration
Variational Bayesian
Bayesian modeling

ABSTRACT

In this paper we provide a review of the recent literature on Bayesian Blind Image Deconvolution (BID) methods. We believe that two events have marked the recent history of BID: the predominance of Variational Bayes (VB) inference as a tool to solve BID problems and the increasing interest of the computer vision community in solving BID problems. VB inference in combination with recent image models like the ones based on Super Gaussian (SG) and Scale Mixture of Gaussians (SMG) representations have led to the use of very general and powerful tools to provide clear images from blurry observations. In the provided review emphasis is paid on VB inference and the use of SG and SMG models with coverage of recent advances in sampling methods. We also provide examples of current state of the art BID methods and discuss problems that very likely will mark the near future of BID.

1. Introduction

Thousands of millions of pictures are taken everyday. If the claim in [1] is right, 880 billion photos were taken in 2014. Every minute, 27,800 pictures are uploaded to Instagram, 208,300 photos are uploaded to Facebook and more than one thousand to Flickr, and the trend, with a digital camera in every mobile phone, is probably exponentially increasing. The quality of these pictures varies widely from professional to amateur, in which case in many instances the images are taken under adverse conditions, such as low lighting or with motion between the camera and the scene, thus resulting in blurred images. While in some cases the introduction of blur in photography is intentional, being a powerful element of visual aesthetics, in most cases it is an undesirable effect degrading the quality of the image. Examples of the intentional introduction of blur includes the silky water effect obtained by using a long exposure when photographing a water flow (Fig. 1(a)), the bokeh effect obtained in parts of the scene lying outside the depth of field (Fig. 1(b)) and used to focus the attention of the viewer on a specific subject, or the motion blur effect (Fig. 1(c)) used to provide a sense of speed. Unintentional blur is caused by a number of causes, the most important ones being: camera or subject motion while the shutter is open (Fig. 1(d)) which leads to motion blur, out-of-focus (Fig. 1(e)) that blurs the whole the image or relevant parts of it or, simply, the presence of the atmosphere (Fig. 1(f)) as is the case with astrophotography.

Not only commercial photography is affected by blur. Modern science makes an intensive use of images in areas such as astronomy, remote sensing, medical imaging and microscopy and, in all of them, imperfections and characteristics of the capture system lead to images degraded during the observation process by blur, noise, and other degradations that diminish the quality and, hence, the value of the captured images.

Image deconvolution is a mature topic that aims at recovering the underlying original image from its blurred and noisy observations. Sometimes, the blur is completely or partially known or can be estimated prior to the deconvolution process. For instance, in astronomical imaging, an accurate representation of the blur can be obtained by imaging a single star first before photographing the astronomical object of interest. In contrast, blind image deconvolution (BID) tackles the restoration problem without knowing the blur in advance, leading to one of the most challenging image processing problems, since many combinations of blur and "true" image can produce the observed image. To start with, deconvolution is an ill posed problem in the Hadamard sense [2], that is, small variations in the data result in large variations in the solution. The problem is exacerbated in the BID problem, since in

☆ This paper has been partially supported by the Spanish Ministry of Economy and Competitiveness under project TIN2013-43880-R, the European Regional Development Fund (FEDER), the CEI BioTic at the Universidad de Granada, the National Natural Science Foundation of China (61233005) and the Department of Energy (DE-NA0002520).

* Corresponding author.
E-mail addresses: mataran@decsai.ugr.es (P. Ruiz), xuzhou@buaa.edu.cn (X. Zhou), jmd@decsai.ugr.es (J. Mateos), rms@decsai.ugr.es (R. Molina), aggk@eecs.northwestern.edu (A.K. Katsaggelos).

http://dx.doi.org/10.1016/j.dsp.2015.04.012
1051-2004/

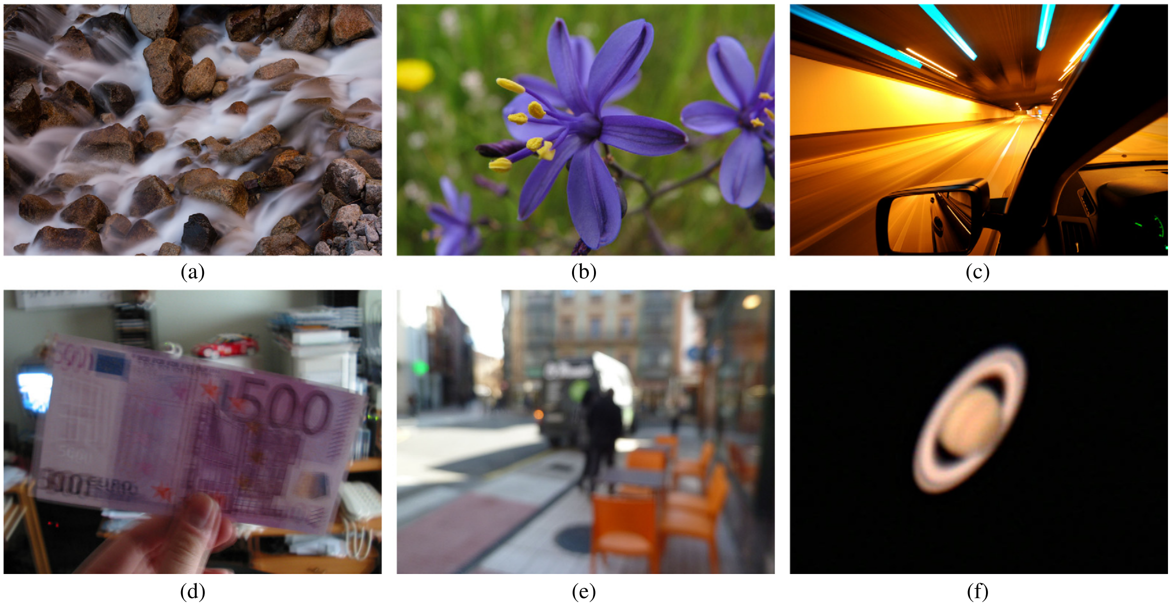

Fig. 1. Blurred pictures due to intentional blur: (a) silky water effect by Geraint Rowland (https://www.flickr.com/photos/geezaweezer/15327097294), (b) bokeh by Rodrigo Gomez (https://www.flickr.com/photos/rgomez74/2970906336), (c) motion blur by Ernest (https://www.flickr.com/photos/viernest/3380560365). Blurred pictures due to unintentional blur: (d) camera motion by tunguska (https://www.flickr.com/photos/tunguska/103472115), (e) out of focus by Nacho (https://www.flickr.com/photos/gonmi/8193430914), (f) atmosphere by Mike Durkin (https://www.flickr.com/photos/madmiked/43831827).

addition, small variations in the estimated blur can lead to large variations in the restored image.

BID is an underdetermined nonlinear inverse problem, which requires the estimation of many more unknown variables than the available observed data. To find meaningful solutions, not only prior information about the unknowns is crucial, but also a good and sound estimation approach. In this paper, we provide a comprehensive survey of BID methods reported since the publication of the review [3], with a focus on Bayesian approaches. In our opinion, since the publication of [3], Variational Bayes (VB) inference has emerged as a dominant approach for the solution of BID problems. VB inference in combination with recently introduced image models, like the ones based on Super Gaussian (SG) and Scale Mixture of Gaussian (SMG) representation, has led to the development of very general and powerful tools to obtain clear images from blurry observations. We review the recent BID literature with an emphasis on VB inference and the use of SG and SMG models but without ignoring recent advances in sampling methods. We also provide examples of current state of the art BID methods and discuss problems that very likely will mark the near future of BID. The paper is organized as follows. In Section 2, we briefly introduce the BID problem as well as the prior models. Section 3 shows the variational Bayesian methodology and its advantages over other inference approaches. We also present two representation models for variational inference, followed by the final BID algorithm. Section 4 discusses some important outstanding challenges regarding the applications of VB based BID methods and BID as a whole research field. Experimental results are presented in Section 5.

2. Bayesian problem formulation

2.1. Bayesian framework for BID

In BID the image formation model is usually assumed to be:

$$\mathbf{y} = \mathbf{x} \otimes \mathbf{h} + \mathbf{n} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where $\mathbf{y} \in \mathbb{R}^N$ is the observed blurred image (a column vector of N pixels), $\otimes$ represents the convolution operation, $\mathbf{x} \in \mathbb{R}^N$ is the unknown original image, $\mathbf{H} \in \mathbb{R}^{N\times N}$ is the convolution matrix obtained from the also unknown blur kernel $\mathbf{h} \in \mathbb{R}^K$ and $\mathbf{n} \in \mathbb{R}^N$ is a noise term which is assumed to be i.i.d. Gaussian with variance β^{-1}. As discussed in Section 4.4, other degradation models than the Linear and Spatially Invariant model above are also utilized.

Notice that although the BID problem is defined here in the image domain, it can also be easily formulated in transformed domains, such as the derivative, wavelet, and curvelet domains. The use of the filter space has gained popularity recently, however, there are still some open questions which need to be addressed before deciding which one is the right domain to work on, see Section 4.1.

From a Bayesian perspective, given the observed blurred image $\mathbf{y}$, the goal is to infer the latent (hidden) variables $\mathbf{z} = \{\mathbf{x}, \mathbf{h}\}$ and possibly the model parameters denoted by Ω. The image degradation model in Eq. (1) can be written as:

$$\mathrm{p}(\mathbf{y}|\mathbf{z}, \beta) = \mathcal{N}(\mathbf{y}|\mathbf{H}\mathbf{x}, \beta^{-1}\mathbf{I}), \tag{2}$$

where β is the precision parameter of the observation model, and possibly one of the model parameters to be estimated.

It is well known that the inverse problem of Eq. (1) is ill-posed [3]. Therefore, additional information on the latent variables and model parameters must be provided. The Bayesian paradigm introduces this necessary information for the BID problem as a prior distribution $\mathrm{p}(\mathbf{z}|\Omega)$, which models the information on $\mathbf{z}$, and a prior $\mathrm{p}(\Omega)$ on the model parameters. Sometimes the prior on the model parameters is called hyperprior and the elements of Ω are called hyperparameters.

With these ingredients, the global modeling of the BID problem can be written as

$$\mathrm{p}(\mathbf{z}, \Omega, \mathbf{y}) = \mathrm{p}(\mathbf{y}|\mathbf{z}, \Omega)\mathrm{p}(\mathbf{z}|\Omega)\mathrm{p}(\Omega). \tag{3}$$

Before describing how inference is performed, we will now review the image, blur and hyperparameters priors proposed for the BID problem since the publication of [3].