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ScienceDirect
Optics Communications 266 (2006) 456–464
OPTICS COMMUNICATIONS
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Single frame blind image deconvolution by non-negative sparse matrix factorization

Ivica Kopriva [a,d,*], Dennis J. Garrood [b], Vesna Borjanović [b,c]

[a] Department of Electrical and Computer Engineering, The George Washington University, 801 22nd Street, NW, Washington, DC 20052, USA
[b] International Technology Center, 8100-120 Brownleigh Drive, Raleigh, NC 27617, USA
[c] Department of Applied Physics, Faculty of Electrical Engineering and Computing, University of Zagreb, Vukovarska 39, 10000 Zagreb, Croatia
[d] Department for Laser and Atomic Research Development, Institute Ruđer Bošković, P.O. Box 1016, 10001 Zagreb, Croatia

Received 19 December 2005; received in revised form 23 March 2006; accepted 5 May 2006

Abstract

Novel approach to single frame multichannel blind image deconvolution has been formulated recently as non-negative matrix factorization problem with sparseness constraints imposed on the unknown mixing vector that accounts for the case of non-sparse source image. Unlike most of the blind image deconvolution algorithms, the novel approach assumed no *a priori* knowledge about the blurring kernel and original image. Our contributions in this paper are: (i) we have formulated generalized non-negative matrix factorization approach to blind image deconvolution with sparseness constraints imposed on either unknown mixing vector or unknown source image; (ii) the criteria are established to distinguish whether unknown source image was sparse or not as well as to estimate appropriate sparseness constraint from degraded image itself, thus making the proposed approach completely unsupervised; (iii) an extensive experimental performance evaluation of the non-negative matrix factorization algorithm is presented on the images degraded by the blur caused by the photon sieve, out-of-focus blur with sparse and non-sparse images and blur caused by atmospheric turbulence. The algorithm is compared with the state-of-the-art single frame blind image deconvolution algorithms such as blind Richardson–Lucy algorithm and single frame multichannel independent component analysis based algorithm and non-blind image restoration algorithms such as multiplicative algebraic restoration technique and Van-Cittert algorithms. It has been experimentally demonstrated that proposed algorithm outperforms mentioned non-blind and blind image deconvolution methods.

PACS: 07.05.Pj; 42.30.Wb; 87.57.Gg; 42.69.Bz

Keywords: Image restoration; Blind deconvolution; Non-blind deconvolution; Non-negative sparse matrix factorization; Independent component analysis

1. Introduction

The goal of image deconvolution is to reconstruct the original image from an observation degraded by spatially invariant blurring process and noise. Neglecting the noise term the process is modeled as a convolution of a blurring kernel $h(s,t)$ with an original source image $f(x,y)$ as:

$$g(x,y)=\sum_{s=-K}^{K}\sum_{t=-K}^{K}h(s,t)f(x+s,y+t) \tag{1}$$

where K denotes the size of the blurring kernel. If the blurring kernel is known, a number of so-called non-blind algorithms is available to reconstruct original image $f(x,y)$ [1]. However, it is not always possible to measure or obtain information about the blurring kernel, which is why blind deconvolution (BD) algorithms are important. Comprehensive comparison of BD algorithms is given in [1]. They can be divided into those that estimate the blurring kernel $h(s,t)$ first and then restore original image by some of the

* Corresponding author. Tel.: +1 2029945508; fax: +1 2029945171.
E-mail address: ikopriva@gmail.com (I. Kopriva).

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doi:10.1016/j.optcom.2006.05.010

non-blind methods [1], and those that estimate the original image $f(x, y)$ and the blurring kernel simultaneously. In order to estimate the blurring kernel a support size has either to be given or estimated. Also, quite often *a priori* knowledge about the nature of the blurring process is assumed to be available in order to use appropriate parametric model of the blurring process [2]. It is not always possible to know the characteristic of the blurring process. Methods that estimate blurring kernel and original image simultaneously use either statistical or deterministic priors of the original image, the blurring kernel and the noise [2], which leads to a computationally expensive maximum likelihood estimation usually implemented by expectation maximization algorithm. In addition to that, exact distributions of the original image required by the maximum likelihood algorithm are usually unknown. One of the most representative algorithms from this class is the blind Richardson–Lucy (R–L) algorithm originally derived for non-blind deconvolution of astronomical images in [3,4], and later on formulated in [5] for BD and then modified by iterative restoration algorithm in [6]. This version of blind R–L algorithm is implemented in MATLAB© command *deconvblind*. It will be used in Section 3 for the comparison purpose during experimental performance evaluation of the to be introduced yet non-negative matrix factorization (NMF) based blind image deconvolution method. In order to overcome difficulties associated with the "standard" BD algorithms an approach was proposed in [7] based on quasi maximum likelihood with an approximate of the probability density function. It however assumed that original image has sparse or super-Gaussian distribution. This is generally not true because image distributions are mostly sub-Gaussian. To overcome that difficulty it was proposed in [7] to apply sparsifying transform to blurred image. However, design of such a transform requires knowledge of at least the typical class of images to which original image belongs in which case training data can be used to design sparsifying transform. Multivariate data analysis methods such as independent component analysis (ICA) [8] might be used to solve BD problem as a blind source separation (BSS) problem where unknown blurring process is absorbed into what is known as a mixing matrix. The advantage of the ICA approach would be that no *a priori* knowledge about the origin and size of the support of the blurring kernel is required. However, multi-channel image required by ICA is not always available. Even if it is, it would require the blurring kernel to be non-stationary, which is true for the blur caused by atmospheric turbulence [9], but it is not true for the out-of-focus blur for example. Therefore, an approach to single frame multi-channel blind deconvolution that requires minimum of *a priori* information about blurring process and original image would be of great interest. Single frame multi-channel representation was proposed in [10]. It was based on a bank of 2D Gabor filters [11] used due to their ability to realize multi-channel filtering. ICA algorithms have been applied in [10] to multichannel image in order to extract the source image and two spatial derivatives along x and y directions. There is however critical condition that source image and their spatial derivatives must be statistically independent. In general this is not true as already observed in [12]. Consequently, quality of the image restoration by proposed single frame multi-channel approach depends on how well each particular image satisfies statistical independence assumption. Therefore, an extension of the ICA approach formulated in [10] is given in [13] where it has been shown that single frame multichannel BD can be formulated as NMF problem with sparseness constraints imposed on the unknown mixing vector. Consequently, no *a priori* knowledge about either the origin or the size of the blurring process is required. Because NMF is deterministic approach no *a priori* information about the statistical nature of the source image is required as well. We present here generalized NMF approach to blind image deconvolution with sparseness constraints imposed on either unknown mixing vector or unknown source image. The criteria are provided to distinguish whether source image was sparse or not as well as to estimate appropriate sparseness constraint from degraded image itself making the proposed approach completely unsupervised. The rest of the paper is organized as follows. We introduce briefly in Section 2 non-blind Van-Cittert [14] and multiplicative algebraic restoration technique (MART) [17,18] image restoration algorithms, blind R–L algorithm [5,6], ICA approach to single frame multichannel BD [10]. We describe in more details generalized NMF approach to single frame multichannel BD with sparseness constraints originally given in [13]. Comparative experimental performance evaluation is given in Section3 for images degraded by photon sieve, sparse and non-sparse images degraded by out-of-focus blur and images degraded by atmospheric turbulence. Conclusion is presented in Section 4.

2. Basic overview of the compared non-blind and blind image deconvolution algorithms

Before proceeding to description of the to be compared non-blind and blind image deconvolution algorithms we shall rewrite image observation model given by Eq. (1) in the lexicographical notation:

$$\mathbf{g} = \mathbf{Hf} \tag{2}$$

where $\mathbf{g}, \mathbf{f} \in Z_{0+}^{MN}$, $\mathbf{H} \in R_{0+}^{MN \times MN}$ assuming image dimensionality of $M \times N$ pixels. Observed image vector $\mathbf{g}$ and original image vector $\mathbf{f}$ are obtained by the row stacking procedure. The matrix $\mathbf{H}$ is block-circulant matrix [14], and it absorbs into itself the blurring kernel $h(s, t)$ assuming at least size of it, K, to be known.

2.1. Non-blind Van-Cittert and MART algorithms

Van-Cittert algorithm solves image restoration problem through the following iterative procedure [14]:

$$\hat{\mathbf{f}}^{(k+1)} = \hat{\mathbf{f}}^{k} + \varepsilon \mathbf{H}^{\mathrm{T}}(\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}^{k}) \tag{3}$$