Optics and Lasers in Engineering 100 (2018) 161–169

Contents lists available at ScienceDirect

Optics and Lasers in Engineering

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

Multi-kernel deconvolution for contrast improvement in a full field imaging system with engineered PSFs using conical diffraction

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ARTICLE INFO

Keywords:
Deconvolution
Image enhancement
Optical transfer functions
Optical devices
Crystal optics
Diffractive optics

ABSTRACT

The problem of restoration of a high-resolution image from several degraded versions of the same scene (deconvolution) has been receiving attention in the last years in fields such as optics and computer vision. Deconvolution methods are usually based on sets of images taken with small (sub-pixel) displacements or slightly different focus. Techniques based on sets of images obtained with different point-spread-functions (PSFs) engineered by an optical system are less popular and mostly restricted to microscopic systems, where a spot of light is projected onto the sample under investigation, which is then scanned point-by-point. In this paper, we use the effect of conical diffraction to shape the PSFs in a full-field macroscopic imaging system. We describe a series of simulations and real experiments that help to evaluate the possibilities of the system, showing the enhancement in image contrast even at frequencies that are strongly filtered by the lens transfer function or when sampling near the Nyquist frequency. Although results are preliminary and there is room to optimize the prototype, the idea shows promise to overcome the limitations of the image sensor technology in many fields, such as forensics, medical, satellite, or scientific imaging.

1. Introduction

Restoration of a high-resolution image from one or more low-resolution or degraded versions is an interesting problem that has been receiving attention in the last years in the fields of optics, image processing and computer vision. This process has been called many times *super-resolution image reconstruction*, term still widely used in the field of image processing, but which has been questioned lately, as it properly refers to those optical techniques aimed at transcending the diffraction limit. Some authors make the distinction between *geometrical* super-resolution for the former, and refer to the later as *optical* (or sometimes *true*) super-resolution.

In any case, in this paper we refer to those techniques aimed at improving the spatial resolution (contrast and details in the high frequencies) in an image which has been degraded by the optical system, such as slight defocus, aperture diffractions, blurring due to motion, or simply due to the optical transfer function (OTF) of the imaging lens. These techniques are of utmost interest in many different fields, ranging from surveillance, forensic or medical applications to satellite or scientific imaging, and their aim is to overcome the limitations of the image sensor technology [1].

There are two different approaches: using a single image and using multiple images. Single-image techniques are usually based on some kind of interpolation or kernel-regression (see, for instance [2]), although lately some alternatives using example-based learning have been reported. A complete survey of these techniques is out of the scope of this paper, but there are many excellent reviews such as van Ouwerkerk's [3]. Nevertheless, single-image methods tend to either generate unpleasant results or be computationally expensive mostly due to the lack of input images [4].

Multi-image techniques, on the other hand, attempt to generate the high-resolution image by combining the information given by a set of degraded images of the same scene provided those images are shifted by a sub-pixel distance or are taken under different optical conditions. These different conditions result in different Point Spread Functions (PSFs). References [1,5] include excellent reviews of these techniques. Most of the research in this area focuses on the first category, as the motion can be easily obtained either mechanically or due to vibration of the camera or motion of the object being examined. As examples of this line of research Lin et al. [6] propose an algorithm to obtain the enhanced image from a set of images degraded only by optical blur and noise, while preserving high-frequency details; Li et al. [7] propose a multi-kernel regression learn-based method; Sajjad et al. [8] use a set of pre-defined kernels and an edge-directed algorithm for cost-efficient restoration; Shi et al. [9] propose two methods using small-kernels for efficient image processing in a micro-scanning imaging system; Rav-Acha

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http://dx.doi.org/10.1016/j.optlaseng.2017.08.008
Received 6 June 2017; Received in revised form 13 July 2017; Accepted 9 August 2017

and Peleg [10] propose a method that uses several images with motion blur in different directions to restore the original, just to name a few.

As this problem is ill posed, errors in the estimation of the kernels result in poor quality images. Therefore, some proposals include adaptive methods such as the one by Maiseli et al. [4], in which the regularization term updates accordingly to local image features, or estimate the PSF directly from the input image. These are called *blind* methods, and good examples are described in [11] and [12], both for single-image techniques; and [13] where the authors propose a blind method using multiple images obtained with a system employing adaptive optics.

Nevertheless, techniques based on sets of images obtained with different PSFs but no motion are much less popular and mostly restricted to microscopic systems where it is possible to engineer the shape of the illuminating point source, and therefore, scan the specimen under examination with different PSFs. This approach leads to "*true*" super-resolution techniques, as reported by Simon and Haeberlé in [14] for confocal fluorescence microscopy combining laterally interfering focused beams, or Rosen et al. in [15] or Caron et al. in [16] for standard confocal microscopy using conical diffraction.

In this paper, we use the concept of PSF shaping and apply the same idea on a novel full-field imaging system. The optical setup is based conical diffraction too, but it is mounted on the acquisition branch of the image sensor, and can be fit inside a standard F-mount. In [17] we reported the theoretical background and described the setup of a general-purpose prototype built to evaluate the possibilities of the conical diffraction effect in full-field imaging. This device can, in one of its operating modes, shape the PSF for the whole image acquired by the sensor in one frame-time, so it is applicable in full-scene imaging devices and for a broad range of working conditions.

The rest of the paper is structured as follows. Section 2 outlines the theory behind the image restoration using multiple images obtained with different PSFs and describes the optical setup of the sensor. Section 3 shows the results from both simulations and real images, which are discussed in Section 4. Finally, Section 5 draws some conclusions.

2. Materials and methods

2.1. Reconstruction method

The problem of calculating an approximated version of the original image, from the recorded image is called deconvolution. It was Ghiglia back in 1984 [18] who first proposed a multi-kernel approach to this problem by combining the information acquired from different images with different transfer functions. The idea behind this method is to recover the information lost due to the zeros present in the transfer functions if they are located at different positions.

For simplicity, let us consider a linear imaging system. The recorded image $I(x, y)$ can be expressed as the convolution of the original image $O(x, y)$ and the PSF of the imaging sensor $h(x, y)$ plus an additive noise $b(x, y)$:

$$I(x, y) = O(x, y) * h(x, y) + b(x, y). \tag{1}$$

This equation can be rewritten in the frequency domain by taking the Fourier Transform (FT), denoted by ˆ:

$$\hat{I}(\omega_x, \omega_y) = \hat{O}(\omega_x, \omega_y) \times \hat{H}(\omega_x, \omega_y) + \hat{b}(\omega_x, \omega_y), \tag{2}$$

where $\hat{H}$ is the modulus of the OTF (also known as the modulation transfer function – MTF) and acts as a filter, transmitting only partially the object spatial frequencies. In the multi-kernel approach, we have a set of images of the same scene each one obtained with a different PSF (kernel), so that:

$$\hat{I}_k(\omega_x, \omega_y) = \hat{O}(\omega_x, \omega_y) \times \widehat{H_k}(\omega_x, \omega_y) + \hat{b}(\omega_x, \omega_y). \tag{3}$$

The reconstruction problem (finding an estimation of O from the set of I_k), with or without a-priori information about H_k, is ill posed so small variations in the input can cause very large variations in the output, rendering the solution unacceptable. In 2000, Goudail et al[19] proposed to use an algorithm based on the Tikhonov filter regularized by a Laplacian function based on the works of Reeves and Mersereau [20], using:

$$\hat{O}'(\omega_x, \omega_y) = \frac{\sum_{k=1}^{n} \widehat{H_k}^*(\omega_x, \omega_y) \times \hat{I}_k(\omega_x, \omega_y)}{\sum_{k=1}^{n} |\widehat{H_k}(\omega_x, \omega_y)|^2 + \lambda |L(\omega_x, \omega_y)|^2}, \tag{4}$$

where $\hat{O}'$ is the estimated FT of the object, $\widehat{H_k}$ are the FT of the PSFs (kernels), $\hat{I}_k$ are the FT of the images obtained for each kernel k (n is the total number of kernels), and L is the transfer function of a classical Laplacian filter, being λ a weight parameter. The operator * denotes the complex conjugate. This is the same approach followed by Simon and Haeberlé [14].

There are other methods for deconvolution such as the well-known Richardson-Lucy iterative method [21,22], which is non-linear and, therefore, could potentially produce better results. However, its iterative nature may result in problems with the stop criterion. For the sake of simplicity, we will concentrate on the regularized Tikhonov algorithm in this study.

As an important note, image contrast can be defined in several different ways, depending on the situation. Along this paper, we use the definition which considers contrast as the ratio between the luminance difference and the average luminance, which could be calculated for instance -Michelson contrast- as $(I_{max} - I_{min})/(I_{max} + I_{min})$. The contrast of a given feature inside an image is given as a percentage of the global image contrast. All the image results are shown after performing a linear scaling of the data to the full range of the grey colormap, which does not alter this value. Therefore, a black pixel represents the minimum value in the image and a white pixel represents the maximum, unless specifically stated, in which case a scale bar will be displayed alongside the image.

2.2. Prototype for multiple PSF imaging

To obtain images of the same scene with different PSFs, a prototype based on conical diffraction principle has been employed.

A light beam traveling along one of the optic axes of a biaxial crystal, such as LBO (lithium triborate - LiB_3O_5) or KTP (potassium titanyl phosphate - $KTiOPO_4$), spreads into a narrow hollow cone due to internal conical diffraction and emerges as a hollow cylinder. See, for instance, [23] for a complete description of this phenomenon. For the usual configuration, a set of concentric rings with different amplitude and radial positions are observed at the focal image plane. These are the well-known Poggendorff Rings. The semi angle of the cone depends on the principal refractive indices of the crystal.

However, for thin crystals (0.4 mm instead of the usual thickness of 25–30 mm reported in most of the literature), the radius of the emerging cylinder, R_o, is smaller than the entry beam size and the Poggendorff Rings do not develop, but the emerging beam has a varying polarization state, which generates interesting and usable optical effects.

Under paraxial approximation and for a uniformly polarized and circularly symmetric input beam of wavenumber k, the electrical field at the focal plane is (in polar coordinates ρ, ϕ):

$$\boldsymbol{E} \propto \begin{pmatrix} \boldsymbol{B}_o(\rho) + \boldsymbol{B}_1(\rho)\cos\phi & \boldsymbol{B}_1(\rho)\sin\phi \\ \boldsymbol{B}_1(\rho)\sin\phi & \boldsymbol{B}_o(\rho) - \boldsymbol{B}_1(\rho)\cos\phi \end{pmatrix} \boldsymbol{P}, \tag{5}$$

where $\boldsymbol{P}$ is the polarization vector and $\boldsymbol{B}_o, \boldsymbol{B}_1$ are defined as:

$$\boldsymbol{B}_o(\rho) = k \int dU\ U a_o(\mathrm{U}) \cos(kR_oU) J_o(kU\rho),$$
$$\boldsymbol{B}_1(\rho) = k \int dU\ U a_o(\mathrm{U}) \sin(kR_oU) J_1(kU\rho), \tag{6}$$

where the function $a_o(\mathrm{U})$ represents the incident light distribution in Fourier space and J_o and J_1 are the Bessel functions [15].