A Blind Deconvolution Algorithm for Simultaneous Image Restoration and System Characterisation.

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ABSTRACT

The restoration of a blurred image in a practical imaging system is critically dependent on the system point spread function. Measurement of the point spread function is often a difficult and time consuming process, and the measurement environment itself is somehow artificial. Also, it is frequently the case that an observed image and the point spread function are not measured simultaneously under the same conditions. An iterative blind deconvolution algorithm is presented here which is capable of restoring an image without the need for an exact estimate of the point spread function. The ideal image and the point spread function can be estimated simultaneously by imposing appropriate *a priori* constraints. Typical experimental results are presented and discussed.

1 INTRODUCTION

3D optical microscopy has many biological applications, and in particular it is used in our research to study plant cell architectures. Particular components within cells, for instance specific genes or proteins are labelled by fluorescent probes. Focal sectioning is then applied, using conventional wide field or confocal laser scanning microscopes, to image a series of 2D slices through the specimen. Vast amount of data is collected, typically between 60 to 90 image slices (each slice up to 512x512 pixels), and then processed on a supergraphics workstation. The image data obtained in this way is noisy and also blurred by the point spread function (PSF) of the optical system used. For correct scientific interpretation and analysis of a typical image obtained in this way it is essential that the image is further processed to remove these aberrations, and hence restore the ideal (source) image. The solution to this problem is not unique as small perturbations in the observed data could lead to different solutions. Restoration by traditional linear techniques results in artefacts such as oscillations or 'ringing' around sharp changes in intensity in the image, and generation of negative pixel values. We have developed several robust non-linear restoration algorithms which overcome these shortcomings and produce high quality restored images [1-4]. However these algorithms are dependent on the availability of an accurate PSF model. Modelling and characterisation of the PSF [3] is difficult as the environment for measuring PSF is not ideal, and the measurements themselves are often tricky, laborious and time consuming and sometimes impossible to perform. Therefore restoration by blind deconvolution without relying on the availability of a PSF model would be of considerable advantage.

Although blind deconvolution has been applied to areas such as speech, telecommunications, astronomy and so on, see for example [5-7], there appears to be relatively little work in the literature for optical microscopy applications. A novel blind deconvolution algorithm for restoration of optical microscopy images is proposed in this paper.

Given an observed image and a number of constraints, this algorithm is capable of estimating simultaneously the ideal image and PSF of the imaging system. Estimation of the PSF offers an opportunity for modelling the imaging system without performing time consuming and laborious measurements in an artificial environment.

2 THE ALGORITHM

We now describe an overview of the proposed blind deconvolution algorithm.

Let f(x,y) be the ideal image, h(x,y) the PSF of the imaging system, g(x,y) the observed image and n(x,y) the Gaussian noise. The assumed imaging system models in spatial and frequency domains are defined in equations (1a) and (1b).

$$g(x,y)=\int_{x=-\infty}^{+\infty}\int_{y=-\infty}^{+\infty} f(i,j)h(x-i,y-j)\,di\,dj+n(x,y) \tag{1a}$$

$$G(u,v)=F(u,v)H(u,v)+N(u,v) \tag{1b}$$

Upper case letters denote the Fourier transformed quantities. The proposed algorithm estimates the ideal image and PSF, given the observed image and *a priori* knowledge of constraints. The PSF was assumed to be space invariant. This is a reasonable assumption, based on our experience of modelling PSFs for the imaging system [3].

Figure 1 shows a simplified structure of the blind deconvolution algorithm. An initial estimate of the ideal image is supplied, which is then Fourier transformed and used along with the

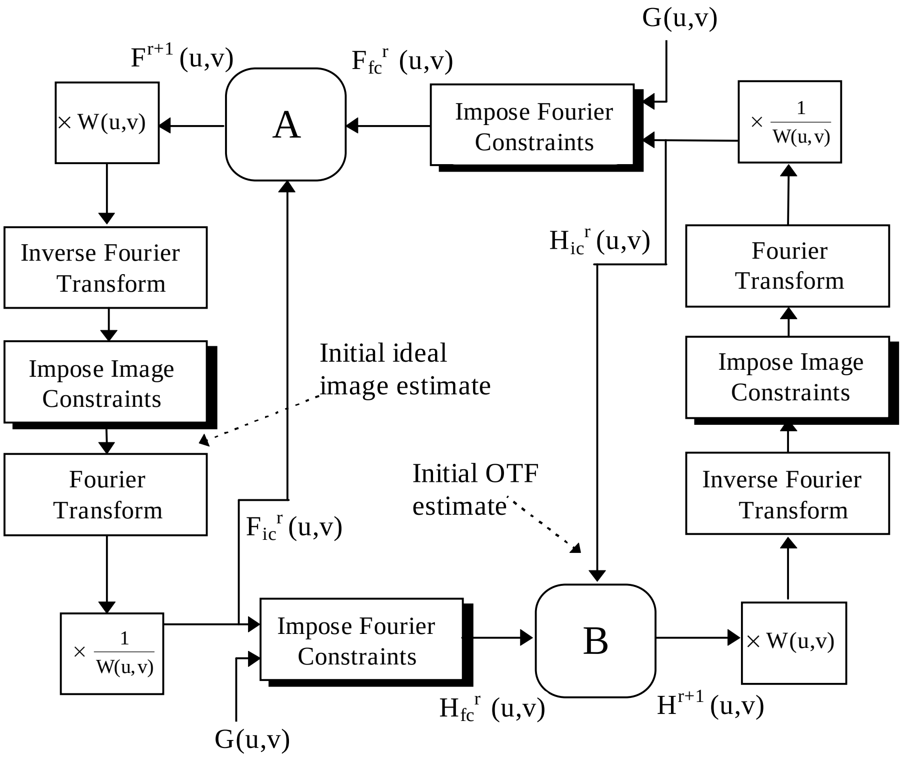


Figure 1. The main structure of the blind deconvolution algorithm

observed image transform to form an estimate of the optical transfer function (i.e. the Fourier transform of PSF) according to (2).

$$H_{fc}(u,v) = \frac{G(u,v)}{F_{ic}(u,v)} \quad (2)$$

$H_{fc}(u,v)$ approximately meets the Fourier constraints since it is an estimate which, in the absence of noise, conforms to the model of the imaging system being used. $F_{ic}(u,v)$ is an estimate of the ideal image spectrum approximately meeting the image constraints. $H_{fc}(u,v)$ is then inverse Fourier transformed to give an estimate of the PSF, upon which we 'Impose image constraints'. In the simplest case this consists of a positivity constraint on pixel values. Other constraints could, for example include forcing the PSF to be smaller than a pre-defined size. As we progress through the system, so the image and Fourier constraints are imposed upon the ideal image estimate in a manner similar to that described for the PSF and its Fourier transform, OTF .

2.1 CONFORMANCE MEASURES

Two measures of constraint conformance are used in the proposed algorithm to provide flexibility and improve performance.

$$E_{ic}(f_{fc}) = \sum_{i\in\gamma} \sum_{j\in\gamma} \left[f_{fc}(i,j)\right] \quad (3)$$

$$E_{fc}(F_{ic}) = \sum_{l=1}^{N_U} \sum_{m=1}^{N_V} \left|F_{fc}(l,m) - F_{ic}(l,m)\right| \quad (4)$$

Equations (3) and (4) are measures of the conformance of the ideal image to the spatial and Fourier constraints. $f_{fc}(i,j)$ is an estimate of the ideal image approximately meeting the Fourier constraints, γ a set containing any negative pixels within $f_{fc}(i,j)$, and $F_{fc}(l,m)$, an estimate of the ideal image spectrum which approximately meets the Fourier constraints. Similar measures to (3) and (4) are used to assess conformance to the constraints applicable to the PSF.

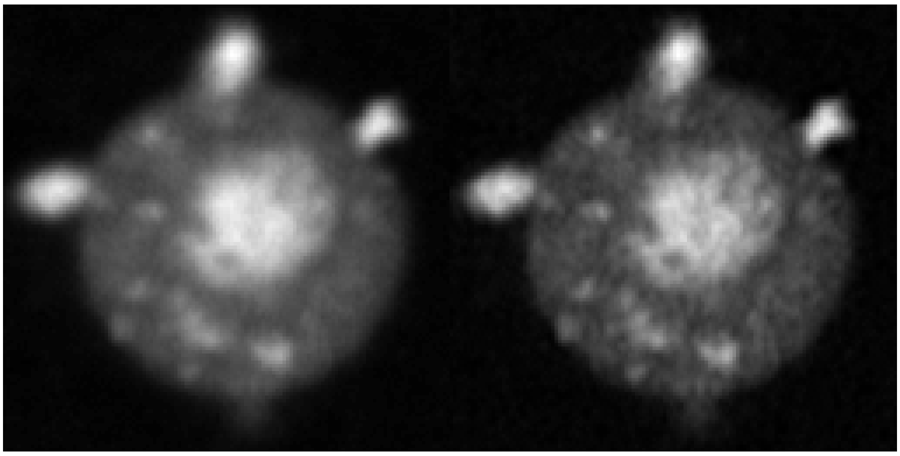
2.2 AVERAGING BLOCKS

Each iteration of the algorithm provides two estimates of the ideal image, $f_{ic}(x,y)$, $f_{fc}(x,y)$, and two estimates of the PSF. The constraint conformance measures are then used to weight and combine these estimates. The general manner by which this is carried out can be seen in Figure 1. The main point to notice is the inclusion of the two averaging blocks A and B. These have a dual purpose. Firstly, they overcome the problems associated with the inverse filter arrangement in the 'Impose Fourier constraints' blocks. Secondly, they add together the two appropriately weighted estimates to form a new estimate. The weighting is chosen so as to include a larger proportion of the image which best conforms to the constraints. The resulting system is fast, and most important of all, capable of taking into account the effect on total constraint conformance caused by the modifications designed to improve conformance to a single constraint.

3 RESULTS

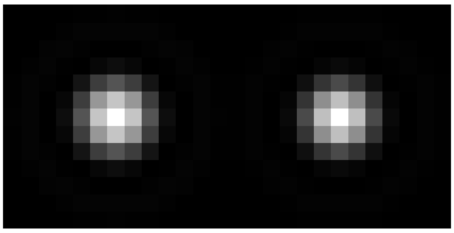
We have applied the blind deconvolution algorithm to synthetic images and real confocal images. Some typical results are presented here. Figure 2 shows the restoration of a confocal image by this algorithm. The initial ideal image estimate was provided by Wiener filtering the observed image.

The images in Figure 3 show the ability of our algorithm to estimate the point spread function of the imaging system. Figure 3a shows an accurately measured and modelled PSF using the techniques described in [3]. Figure 3b shows an estimate generated by our algorithm, which agrees well with Figure 3a. Note that the images shown in Figure 3 are magnified, close-ups of the centres of the PSFs. The algorithm generally performs better for images with moderate to high signal to noise ratios.



(a) Ideal Image (b) Restored Image

Figure 2. Image restoration by the blind deconvolution algorithm



(a) Measured PSF (b) Estimated PSF

Figure 3. PSF estimate by the blind deconvolution algorithm

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