A New Multichannel Blind Deconvolution Method and its Application to Solar Images

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Abstract

A new method of the multichannel blind deconvolution is introduced. The algorithm is simple, computationally efficient and does not need any statistical presumptions about the image. Any a priori knowledge about the PSF and the original can be incorporated very easily. The numerical simulations and experiments give promising results comparing to other restoration methods.

1. Introduction

In the real restoration problems the blur is unknown or not exactly known. Thus we first need to estimate the blur or restore the image and identify the blur simultaneously. In many applications the multichannel images blurred in different ways are available. Examples of such a sensor "diversity" include astronomy, remote sensing, electron microscopy and broadband imaging.

The case when the blur is completely unknown the problem is called multichannel blind deconvolution. This blind case is a hard problem in comparison to the case of known or partially known blur. An attempt to solve this task has been reported for example by Harikumar and Bresler [2], Giannakis [1] and others. Usually these methods use statistic presumptions and parametric models for the unknown image and blur. These statistical presumptions are valid only approximately for real images. Additional drawback of many restoration methods is their heavy computational burden or they do not work properly if the noise is present.

In this paper a new computationally effective method for multichannel blind deconvolution is proposed. The method is a generalization of iterative deconvolution scheme introduced by Ayers and Dainty [3] for single images. The advantages of our method are, among others, good convergence properties, the possibility to incorporate any a priori knowledge about the images and blur and the good quality of the results.

2. Multichannel restoration theory

In multichannel deconvolution we usually use the following degradation model.

$$g_i(x,y) = f(x,y) * h_i(x,y) + n_i(x,y),\ i = 1,\ldots,N$$

where $g_i(x,y)$ describe observed images in each channel, $f(x,y)$ is an original image, $h_i(x,y)$ are PSFs of the channels and $n_i(x,y)$ represent the noise. One of the possible ways how to deal with multichannel data is merging the several channels into one image. In our method we propose to represent several two dimensional signals as a three dimensional one. That is achieved by stacking the 2-D images along the additional third axis. Then we may use following three dimensional model which looks similar as the two dimensional one for a single image:

$$\bar{g}(x,y,z) = \bar{f}(x,y,z) * \bar{h}(x,y,z) + \bar{n}(x,y,z).$$

This model is clearly more general then the previous one. It allows us to describe even more complex problems then just multichannel image convolution such as continuous change of PSF in time in one channel. Suppose we define 3-D convolution in the equivalent way as the two dimensional one. Then the following equations must hold for all possible values of x, y.

$$\begin{aligned}
\bar{g}(x,y,z) &= \begin{cases} g_z(x,y) & \text{if } z = 1,2,\ldots,N \\ 0 & \text{otherwise} \end{cases} \\
\bar{f}(x,y,z) &= \begin{cases} f(x,y) & \text{if } z = 1, \\ 0 & \text{otherwise} \end{cases} \\
\bar{h}(x,y,z) &= \begin{cases} h_z(x,y) & \text{if } z = 1,2,\ldots,N \\ 0 & \text{otherwise} \end{cases}
\end{aligned}$$

This 3-D notation enables us consider the multichannel data as one 3-D image.

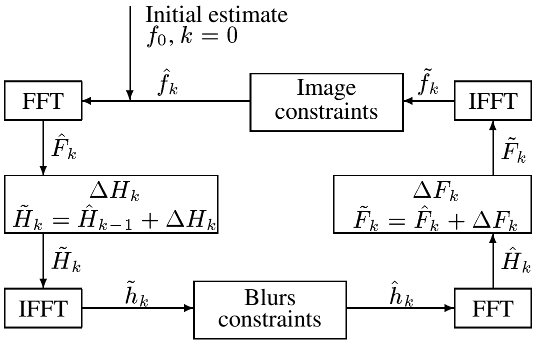

Figure 1. One iteration of the algorithm.

To restore the multichannel images we propose the following iterative procedure. The basic idea is presented in Fig. 1. At the very beginning the algorithm makes a guess for the true image or for the PSF. After that it alternates between image and Fourier domains, enforcing known constraints in each. These constraints are based on the a priori information about the original image and the PSF. One of the typical constraint on the image is nonnegativity. For the PSF, constraints on the size of the support and nonegativity are often used. We use an incremental Wiener filter (see [5]) for computing of the new estimates of image and/or the PSF.

The incremental Wiener filter for computing of ΔF_k and ΔH_k is defined as follows:

$$\Delta F_k = \frac{(G - \hat{F}_k \hat{H}_k)\overline{\hat{H}_k}}{|\hat{H}_k|^2 + \varphi} \quad \Delta H_k = \frac{(G - \hat{F}_k \hat{H}_{k-1})\overline{\hat{H}_{k-1}}}{|\hat{H}_{k-1}|^2 + \varphi}.$$

The bar denotes a complex conjugate, constant φ represents the noise/signal ratio. φ may be determined according to a prior knowledge of the noise corruption level in the images. It may be shown that the use of this incremental filter instead of ordinary Wiener filter improves the convergence properties of the algorithm in the sense that it decreases the number of iterations necessary for convergence and decreases the possibility of oscillations. Sometimes in order to achieve the best convergence properties it is useful to let the parameter φ change from higher SNR values to lower ones during the iteration process. It has been shown experimentally that this approach ensures convergence if the oscillations occur.

Following constraints are imposed on the image.

1. $\hat{f}_k(x,y,z) \in < v_{min}, v_{max} >$ if $z = 1$,
2. $\hat{f}_k(x,y,z) = 0$ if $z \neq 1$,
3. $\hat{f}_k(x,y,z) \geq 0$

where v_{min}, v_{max} describe the minimum and maximum pixel value expected in the image (for example 0-255). Second condition implies directly from our 3-D model. Clearly, the correct restoration filter is the one that deconvolves N input channels into just one output channel. In a frequency domain this constraint can be expressed as $\hat{F}_{u,v}(w) = \delta(w)$, where $\hat{F}_{u,v}(w) = F(u,v,w)$ for a fixed u, v and $\delta(w)$ is a Dirac function. It means that the subsequent ratio of Fourier transforms $\hat{H}_1, \ldots, \hat{H}_N$ of point spread functions must be equal to subsequent ratio of corresponding $G_1, \ldots, G_N$. This is the way the method takes advantage of the existence of multiply blurred image.

On the blurs we impose nonnegativity and support constraints. That is

1. $\hat{h}_k(x,y,z) = 0 \quad$ if $(x,y,z) \notin S_h$,
2. $\hat{h}_k(x,y,z) \geq 0$,

where S_h is a support of the 3-D blur which is a composite of the supports of PSFs of all channels.

Of course there are many other possible constraints but the presented ones are strong enough to ensure a good convergence of the algorithm and at the same time they are not too strict and can be quite easily met in practice. In real situation it is sometimes difficult to estimate the sizes of supports of the point spread functions. Then we propose to use the strategy of *support pruning* (see [4]). This strategy works very well in most cases.

3. Experiment on artificial data

We present here the result obtained on computer generated multichannel data. As the input we use a picture of the size 128×128 pixels. This image was blurred with three different masks of the size 13×13 pixels. The first one was a gaussian (Fig. 2a), the second one simulates defocusation (see Fig.2b) and the third one simulates vertical motion blur (see Fig.2c). The gaussian zero mean noise was added to all channels with SNR=50dB. The picture in Fig. 2d shows the result of the restoration procedure. This result has been obtained after 200 iterations when the algorithm was stopped.

Other our experiments showed that the quality of the estimate of the original image strongly depends on the diversity of the blurs. The more diverse the blurs are the better results we obtain. This is in correspondence with the reports of other authors ([1, 2]).

4. Experiment on real astronomical data

The second experiment tested the possibility of using the presented algorithm for restoring one single image of

Figure 2. Degraded images and the restored one. a - upper left, b - upper right, c - lower left, d - lower right

sunspots. In this experiment we used subimages of one degraded image as different input channels. If the PSF is spatially invariant then it is common to all subimages of the original image.

The original image acquired by the telescope (see Fig. 3) was partitioned into small frames that were large enough comparable to the PSF support. In order to reduce boundary effects these subimages were windowed. One frame represents one individual channel. With the subimages as the channels the algorithm computed the estimate of the blur. Having this $\hat{h}(x, y)$ we could suppress the impact of non-ideal observational conditions.

The size of subimages was 128×128 pixels. For further processing only five subimages were chosen, because the others contained mostly background. The regions that contain as much edges or other features as possible are the most significant for the estimation of PSF.

5. Conclusion

A new computationally effective method for multichannel blind deconvolution has been presented in this paper. Our experiments on the test images indicate, that the convergence properties of the method and the reliability of the restored images are satisfactory in most cases.

We also successfully applied this method to the removal of atmospheric turbulence blur in astronomical images, particularly in the images of sunspots. In that way, we extracted an information about the observed phenomenon which is of higher quality than the information obtainable from each individual image. This fact can significantly improve further analysis and astrophysical interpretation of the data.

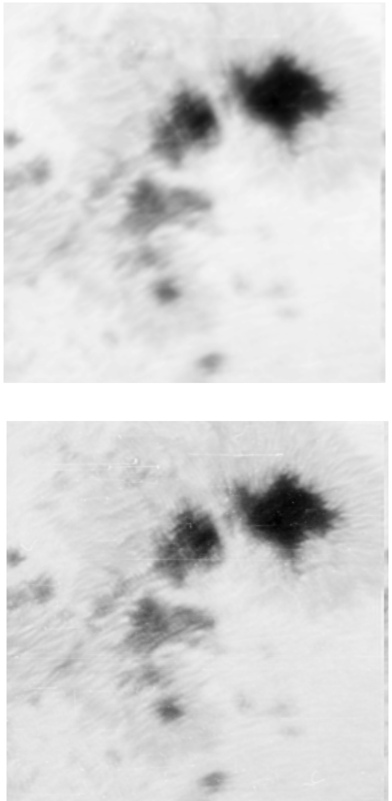

Figure 3. The observed (upper) and restored (lower) images

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