Iterative blind deconvolution of adaptive optics images

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Adaptive optics (AO) technique has been extensively used for large ground-based optical telescopes to overcome the effect of atmospheric turbulence. But the correction is often partial. An iterative blind deconvolution (IBD) algorithm based on maximum-likelihood (ML) method is proposed to restore the details of the object image corrected by AO. IBD algorithm and the procedure are briefly introduced and the experiment results are presented. The results show that IBD algorithm is efficient for the restoration of some useful high-frequency of the image.

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The atmospheric turbulence severely limits the resolution of astronomical telescopes. Without correction, the angular spatial resolution is limited to the ratio wavelength over friel’s parameter. In the past 30 years various techniques have been proposed to overcome this limitation and to effectively reach the diffraction limit of the telescopes. Adaptive optics (AO) is a powerful way, providing a real time compensation of the turbulence. The correction is however shown to be only partial. Therefore post-processing techniques such as iterative blind deconvolution (IBD) and myopic deconvolution can still be required to restore the fine details of the long exposure images. In this paper, an IBD algorithm based on maximum-likelihood (ML) method is proposed to restore the AO corrected images.

There are several algorithms of IBD, such as the Richardson-Lucy (R-L) restoration algorithm, the strict a priori constraint ML IBD algorithm, etc. The R-L algorithm is an iterative technique used heavily for the restoration of astronomical imagery. It attempts to maximize the likelihood of the restored image by using the expectation-maximization (EM) algorithm.

An observed image $g(x, y)$ can be described in Fig. 1 as a convolution of the object intensity distribution $f(x, y)$ by a point-spread function (PSF) $h(x, y)$ plus a noise function $n(x, y)$, where $(x, y)$ is the spatial coordinate and $n(x, y)$ is an additive zero mean noise, and the convolution operator

$$g(x, y) = f(x, y) \otimes h(x, y) + n(x, y)$$

The corrected image must be deconvolved to restore the fine details of the observed object. Since the noise $n(x, y)$ exists, the solution of Eq. (1) becomes an ill-posed inverse problem. Most deconvolution techniques boil down to minimization (or maximization) of a criterion, like ML and maximum a posteriori (MAP). R-L algorithm is one of the ML algorithms.

The iterative R-L algorithm can be succinctly expressed as

$$f_{k+1} = f_k \left( h \ast \frac{g}{h \otimes f_k} \right) = \Phi(f_k), \quad (2)$$

$$h_{k+1} = h_k \left( h \ast \frac{g}{h \otimes f_k} \right) = \Phi(h_k), \quad (3)$$

where $\hat{f}_k$ is the estimate of $f$ after $k$ iterations, * is the correlation operator, and the function $\Phi(\cdot)$ is called the R-L function. The image $h \otimes \hat{f}_k$ is referred to as the redffused image.

Since the restoration may take over 1000 iterative steps and a long time, it is important to bring acceleration methods into this R-L algorithm to reduce the time required to achieve a certain level of restoration without introducing unwanted artifacts. A simple way to increase the speed of convergence is shown below. Representing Eqs. (2) and (3) as

$$\tilde{y}_k = x_k + \lambda \cdot d_k, \quad (4)$$

$$\left\{ \begin{array}{l} d_k = x_k - x_{k-1} \\ x_{k+1} = y_k + \tilde{y}_k \\ y_k = \Phi(\tilde{y}_k) - y_k \end{array} \right., \quad (5)$$

$$\lambda_k = \frac{\sum g_{k-1} \cdot g_{k-2}}{\sum g_{k-2} \cdot g_{k-2}}, \quad 0 < \lambda < 1, \quad (6)$$

where $x_k$ is the iterated point, $y_k$ is the predicted point, $h_k$ is the direction vector, and $\lambda_k$ is the acceleration parameter.

The general iterative loops using the formulas above is shown in Fig. 2.

These general IBD loops are proposed on some AO corrected images. Both images are taken under parameters of wavelength $\lambda = 0.8 \mu m$, aperture $D = 1.06 m$. According to the full-width at half-maximum criteria, in which
the diffraction limit is computed by function $\frac{\lambda}{D}$, the diffraction limited resolution of the system is about $0\arcsec.155$, the pixel scale of the imaging system is $0\arcsec.037$.

Figure 3 shows the deconvolution result of AO image of star FK5–545 captured on May 8, 2004. The horizontal and vertical resolutions of the AO-corrected long exposure image (Fig. 3(a)) are $0\arcsec.298$ and $0\arcsec.308$, respectively. The corresponding deconvolution results (Fig. 3(b)) after 5 iterations using R-L algorithm are $0\arcsec.179$ for horizontal resolution and $0\arcsec.247$ for vertical resolutions, respectively.

Figure 4 shows the deconvolution result of AO image of bi-star HE 42 captured on January 5, 2005. The bi-star can be evidently resolved after AO correction. The horizontal and vertical resolutions of the AO-corrected long exposure image (Fig. 4(a)) are $0\arcsec.206$ and $0\arcsec.221$, respectively. After 4 iterations using R-L algorithm (Fig. 4(b)) the maximum brightness value of the bi-star increases from 23876 to 42622, and the bi-star can be recognized more easily.

The R-L IBD algorithm we proposed has successfully restored the AO images given. This algorithm is efficient for the restoration of some useful high-frequency of the object. The effect of these images has been improved. The resolution after several IBD restoration steps has approached the diffraction limit of the system.

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References