A Wiener Filter Version of Blind Iterative Deconvolution

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I. Introduction

Over the last decade, great progress has been made in high angular resolution imaging at optical and infrared wavelengths. Techniques have been developed which allow nearly diffraction-limited image recovery from images which have been severely degraded by atmospheric turbulence and telescope aberrations. Imaging at radio frequencies has also led to the development of a number of new and powerful image processing algorithms for handling the data from large telescope arrays. Techniques such as CLEAN (Hogbom, 1974), MEM (Gull and Daniell, 1978) and Gerchberg-Saxton (Gerchberg and Saxton, 1972) have proven to be useful, not only for radio map reconstruction, but also for a wide range of other astronomical imaging applications. Blind Iterative Deconvolution (BID) is a technique which was originally proposed for the correction of the effects of atmospheric turbulence on astronomical images. In this technique, both the restored image and the degrading point spread function (PSF) may be recovered from a single high-signal-to-noise ratio short exposure (speckle) image.

At the Center for Astrophysics, we have implemented a modified version of BID using the general approach proposed by Ayers and Dainty (1988). The basic approach is to alternately deconvolve the original data by the PSF and then by the restored image. A set of physical constraints are applied after each iteration. The iterations are continued until an image and PSF are found which give the original data when convolved (with each other) and which adhere to the physical constraints. BID is most useful for cases where the PSF is poorly known or time dependant. It has a number of features which should be important for a wide variety of scientific problems, such as the blurred images from HST. We have performed a number of numerical and experimental tests with the algorithm and have found that, in many cases, it provides remarkable reconstructions from severely degraded imagery.

II. Blind Iterative Deconvolution

Blind Iterative deconvolution (BID) combines constrained iterative techniques such as those developed for phase retrieval (Gerchberg and Saxton 1972, Fienup 1978) with blind deconvolution (Lane and Bates 1987). One starts with an image which is degraded by some blurring function. A necessary condition for the algorithm to work is that the blurring function be invariant over the entire image field to be restored (stationarity). It is also assumed that the degradation has been a linear operation. The general approach is then to find a pair of functions whose convolution gives the input image within a set of physical constraints. These constraints include positivity in the two convolved functions, the image and psf support (non-zero) region and the signal-to-noise ratio in the Fourier transform (FT). While it has not been proven that the derived functions are unique, complicated images appear to converge on only one sensible solution. A flow diagram for the technique is given in figure 1. One starts with a degraded image and an initial estimate of the point spread function (PSF). The initial PSF can be randomly chosen, however the number of iterations required to converge on an acceptable answer is highly dependant on how close the first estimate of the PSF is to the actual PSF. Both inputs are Fourier transformed and a deconvolution is performed by constructing a Wiener filter from the FT of the PSF. The technique of Wiener (or Optimum) filtering damps the high frequencies and minimizes the mean square error between each estimate and the true spectrum. Denoting the FT by lower case letters this filtered deconvolution takes the form:

$$o(u,v) = \frac{i(u,v).\phi(u,v)}{p(u,v)}$$

where the Weiner filter used in our computations, $\phi(u,v)$, is given by:

$$\phi(u,v) = \frac{p(u,v).p^*(u,v)}{|p(u,v)|^2 + |n(u,v)|^2}$$

$p(u,v)$ and $n(u,v)$ are the PSF and noise spectra respectively. $n(u,v)$ usually can be replaced with a constant estimated from a high frequency region in the spectrum where the object power is small.

The result is transformed back to image space and positivity and support constraints are applied. After the support constraint is applied,the negatives in the image are set to zero. The negatives are then summed and uniformly subtracted within the support region in order to preserve the total power in the image. After subtraction, some areas of the image may become negative. If this is the case, the negatives are again truncated, summed and subtracted. This procedure is repeated until the restored image is all positive. The ratio of positives to negatives in the image is also used as a diagnostic of convergence. The FT of the original degraded image is then deconvolved by the FT of the restored image obtained from the first iteration. The result is transformed back to image space. Again, positivity and support constraints are enforced. The result is a new estimate of the PSF. The iteration continues until a stable solution is found. A damping factor is used to stabilize the iteration, particularly important when the PSF estimate is still inaccurate. About 20% of the image (or PSF) from the previous cycle is averaged with the new image (or PSF) in the early stages of the process. This percentage is reduced when the iteration has nearly converged.

Two criterion have been found to be very useful in determining the completion of the iteration: the ratio of positive power to negative power in the restored image and psf; and the rms difference between iterations. Both criteria drop irregularly in the first few cycles of the iteration, but they both level off and stabilize when the operation is close to convergence. After examination of the output image and the PSF, the results may be fed back into the loop for continued iterations.

There are a number of parameters which must be chosen in order to ensure convergence and an optimum result. Probably the most important are estimates of the signal-to-noise ratio in the data for construction of the Wiener filter and the region of the support constraint. It is also very important that the image and PSF remain aligned with the support constraint, to avoid truncation. This is done by centering the initial image and PSF, calculating the two support regions, and then recentering the PSF after each iteration.

III. Reconstructions Using Iterative Deconvolution.

The work on BID already undertaken at CfA has produced an algorithm that has been tested with computer simulations and also applied to some real data. Results of the simulations are shown in Figs. 2. Fig. 2a shows the input diffraction limited image of 8 point sources, the bottom right- hand "point" being two unresolved points. This image was convolved with the PSF in Fig. 2b (a simulated atmospheric PSF) and then degraded by photon noise. The level of photon noise was set by assuming that the image was recorded with a one second exposure with a 2.4 meter telescope, that the stars were 12th magnitude, that the detector had 30% quantum efficiency and that the optical efficiency was 50%. The resulting input (speckle) image is shown in Fig. 2c. The starting guess for the PSF (Fig. 2d) used in the first cycle of BID was a gaussian with random noise and a half power width approximately the same as the "seeing". In most real situations, there is usually some reasonable estimate of the PSF which, when used as a first guess, should improve the rate of convergence. Here, a randomly chosen PSF was used to demonstrate the dramatic evolution of the reconstructed PSF towards the actual degrading PSF, despite the quasi-random starting estimate. The image and PSF obtained from BID after 250 cycles are shown in Figs. 2e and 2f. Comparison of these with Figs. 2a. and 2b. show a dramatic recovery of both the morphology and relative intensities present in the diffraction limited image and PSF. The dramatic convergence towards a solution is seen in Fig 3. Here the percentage of negatives is plotted against the number of iterations. After 180 iterations BID has converged on a stable solution. However, a roughly constant percentage of negatives remains, which adds a constant level to the reconstructed image. Rescaling the restored image to preserve the total integrated power in the original image removes this level.

Some initial attempts have been made to use the technique on real optical CCD data. Figs. 4a and 4b show results of BID processing on CCD images of supernova SN1987A recorded with a 30Åwide, Hα filter at the CTIO 4-meter telescope in January, 1990. Fig. 4a shows the original image of the supernova, its two companions, and the extended nebulosity during the pre-supernova red supergiant phase of the precursor star. The wide companion is separated by 2.9 arcseconds from the SN. Fig. 4b is the BID reconstruction, using a single star in a close field as the first guess at the PSF, after only 10 cycles of processing. Clearly the image has been sharpened, though only limited resolution recovery is possible due to the long exposure atmospheric transfer function cutoff. These results demonstrate the power of the technique, and Fig. 4c shows that one obtains rapid convergence if a good initial estimate of the PSF is available. Excellent results have also been obtained on X- ray (Standley et al, 1990) and EUV Solar images from Skylab (Karovska and Habbal, 1990). Tests of BID on WF/PC simulation data were also impressive in their recovered resolution and fidelity to the original data.

IV. Summary

Blind Iterative Deconvolution shows great promise as an image enhacement technique for astronomical images with unknown or poorly known degradations. BID provides not only improved spatial resolution but also allows extraction of the PSF of the degrading process. Since it always Wiener filters the original data, it never walks away from a data dependant, linear solution. A detailed comparison of BID with MEM and other iterative deconvolution techniques is also of great interest. BID may prove to have important application to the processing of HST images (and spectra) since precise measurements of the PSF for all fields may be difficult. While initial tests indicate that it degrades gracefully with noise (producing a noisey, but undistorted image), detailed characterization and rigorous analysis of the technique is required before it can be used for scientific purposes.

References.

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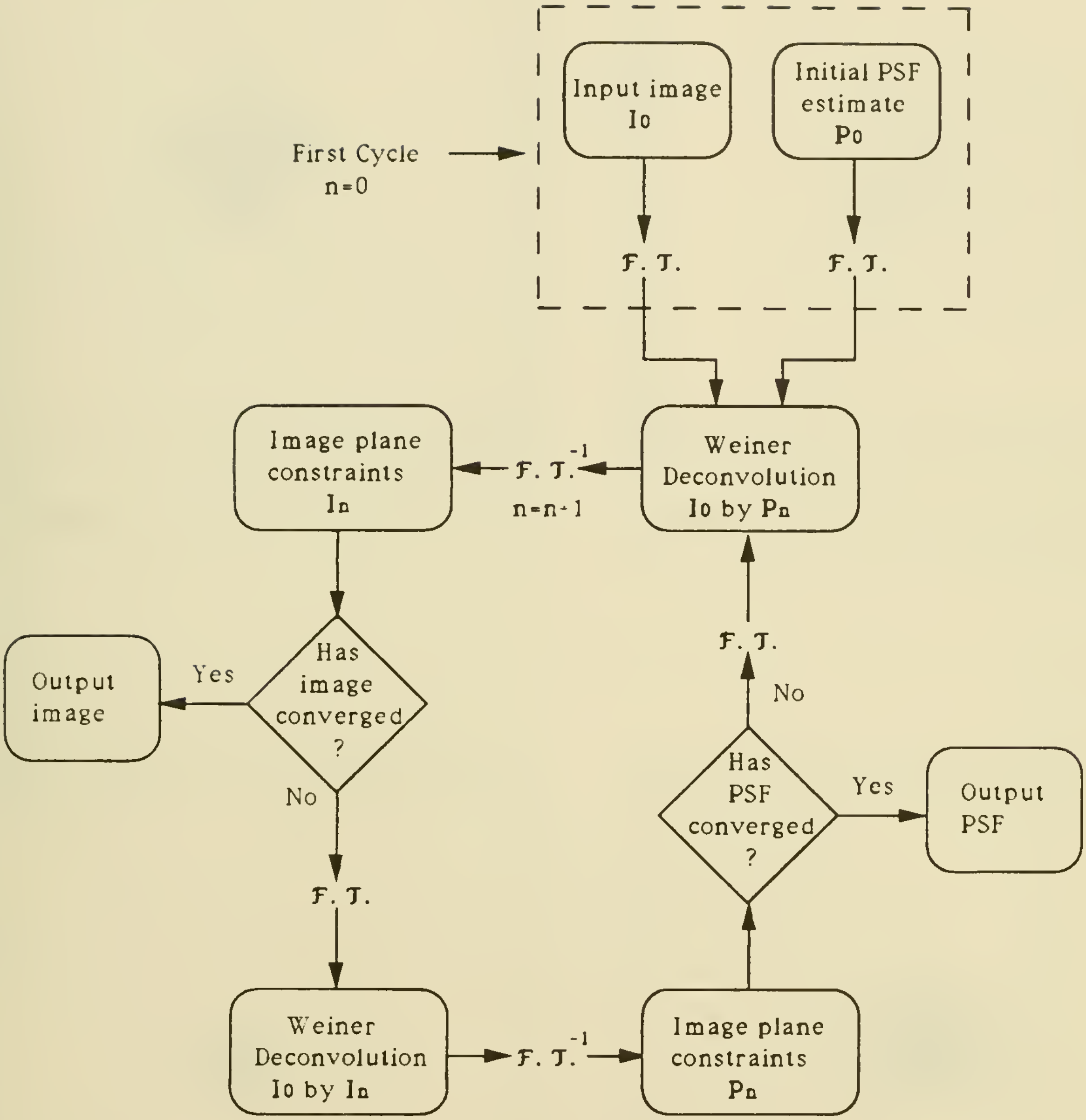

Fig. 1 Flow Diagram of the Blind Iterative Deconvolution Algorithm.

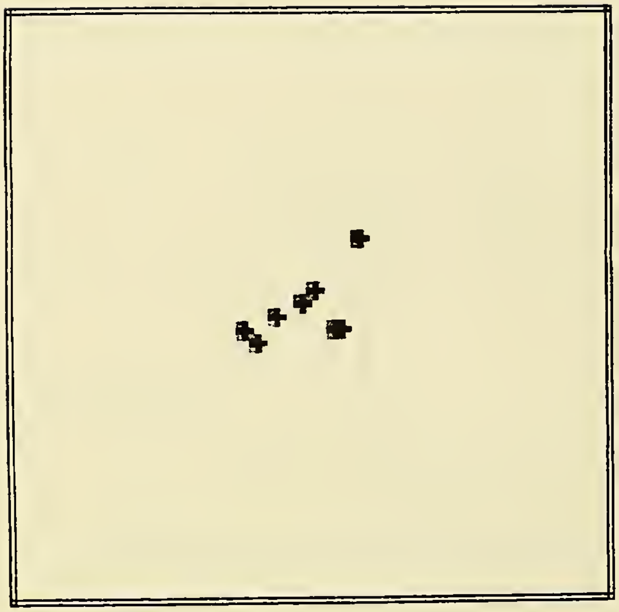

Fig. 2a. The Diffraction Limited Input Image.

Fig. 2b. The Degrading PSF

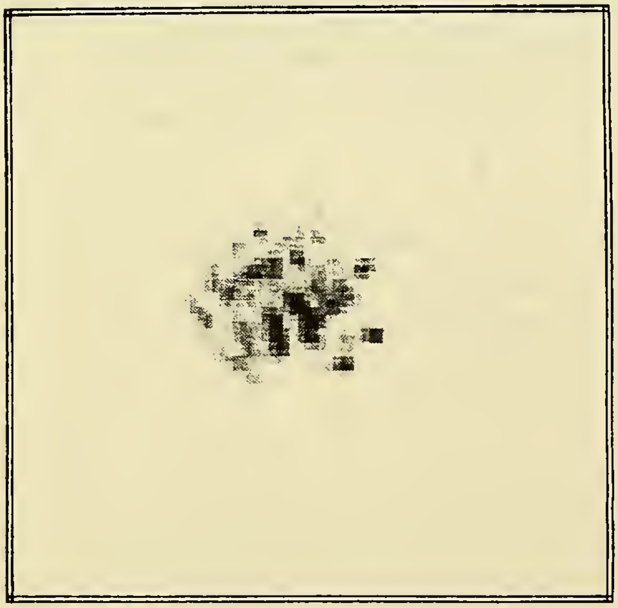

Fig. 2c. The Degraded Image. Convolution of 2a. with 2b. Including Photon Noise.

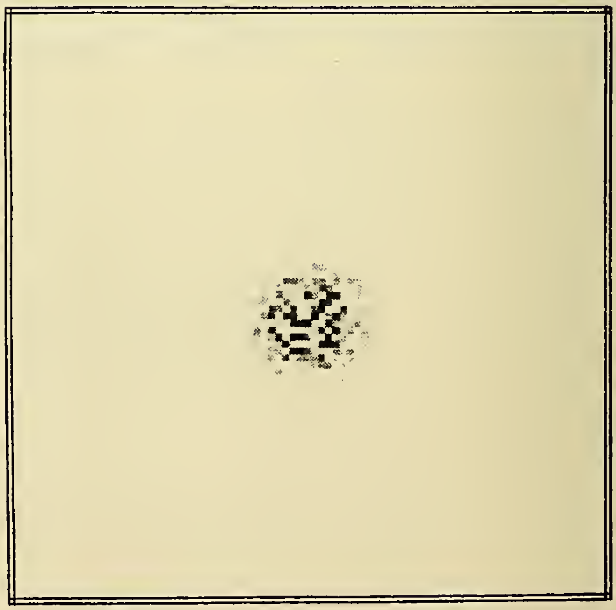

Fig. 2d. The Starting PSF (P_0) for BID.

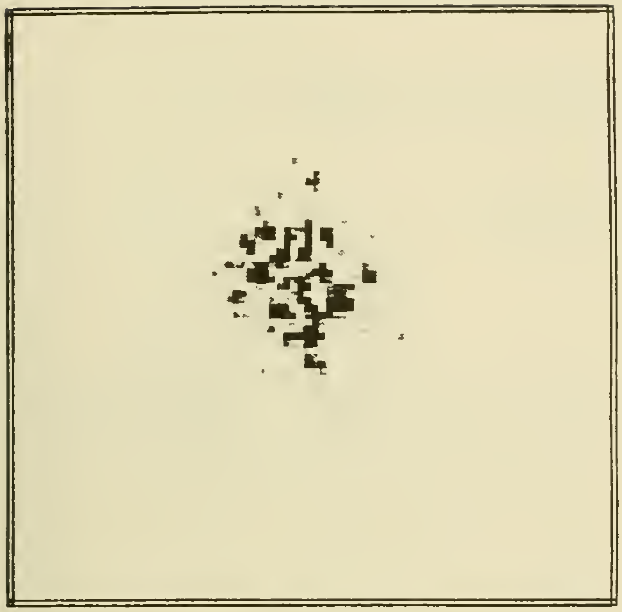

Fig. 2e. The Reconstructed PSF After 250 Cycles.

Fig. 2f. The Reconstructed Image After 250 Cycles.

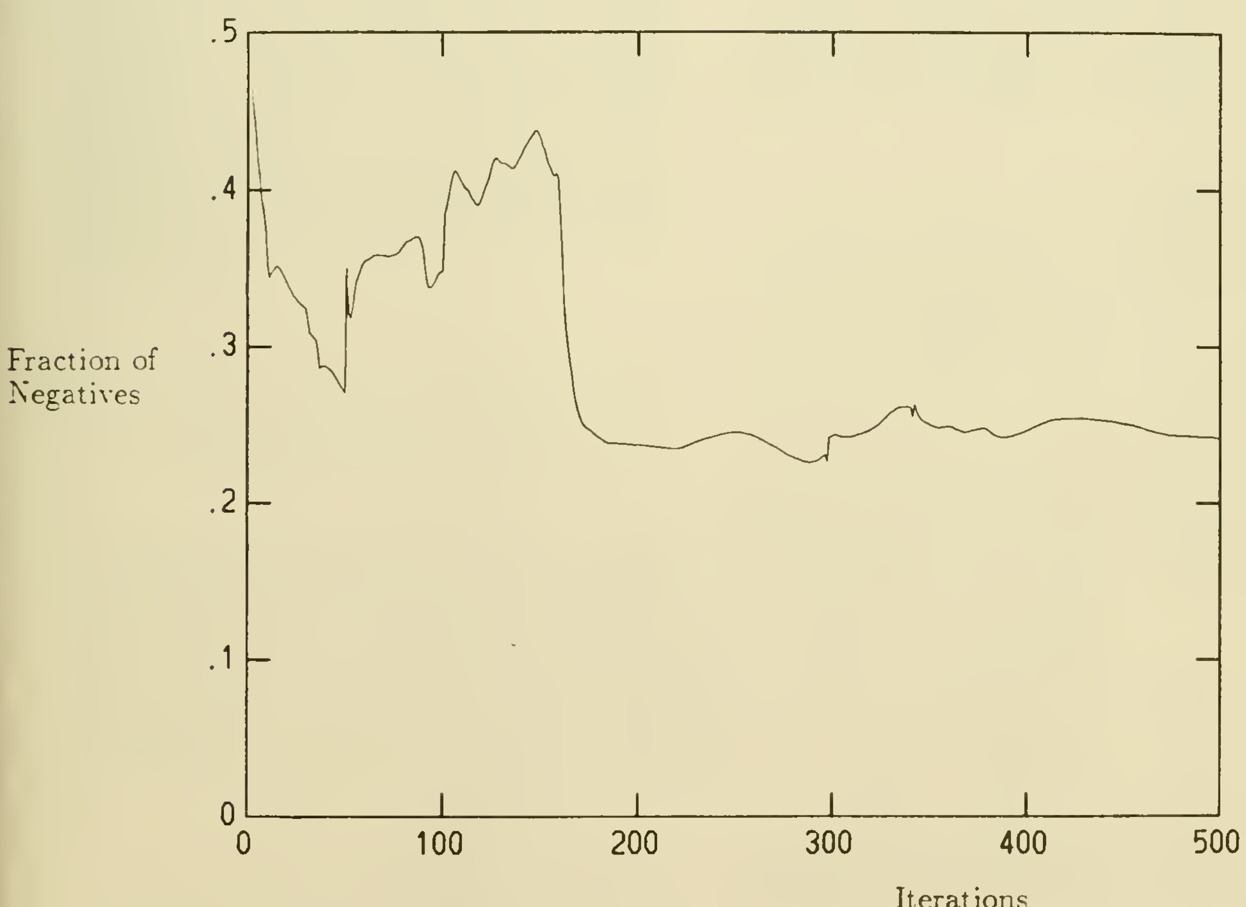

Fig. 3. The Convergence of BID for the 8 Point Image.

Fig. 4a. A 30Å, Hα CCD Image of SN1987A

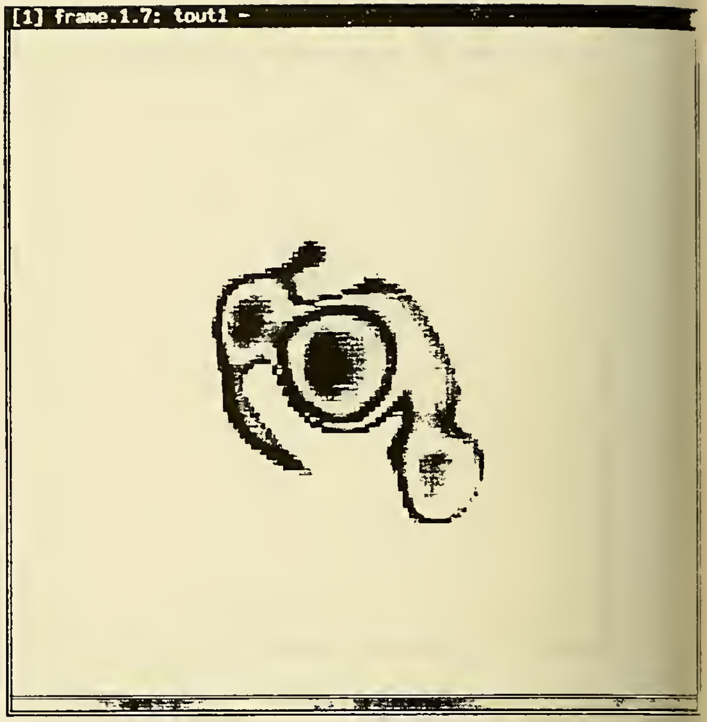

Fig. 4b. The Reconstruction of the SN1987A Image.

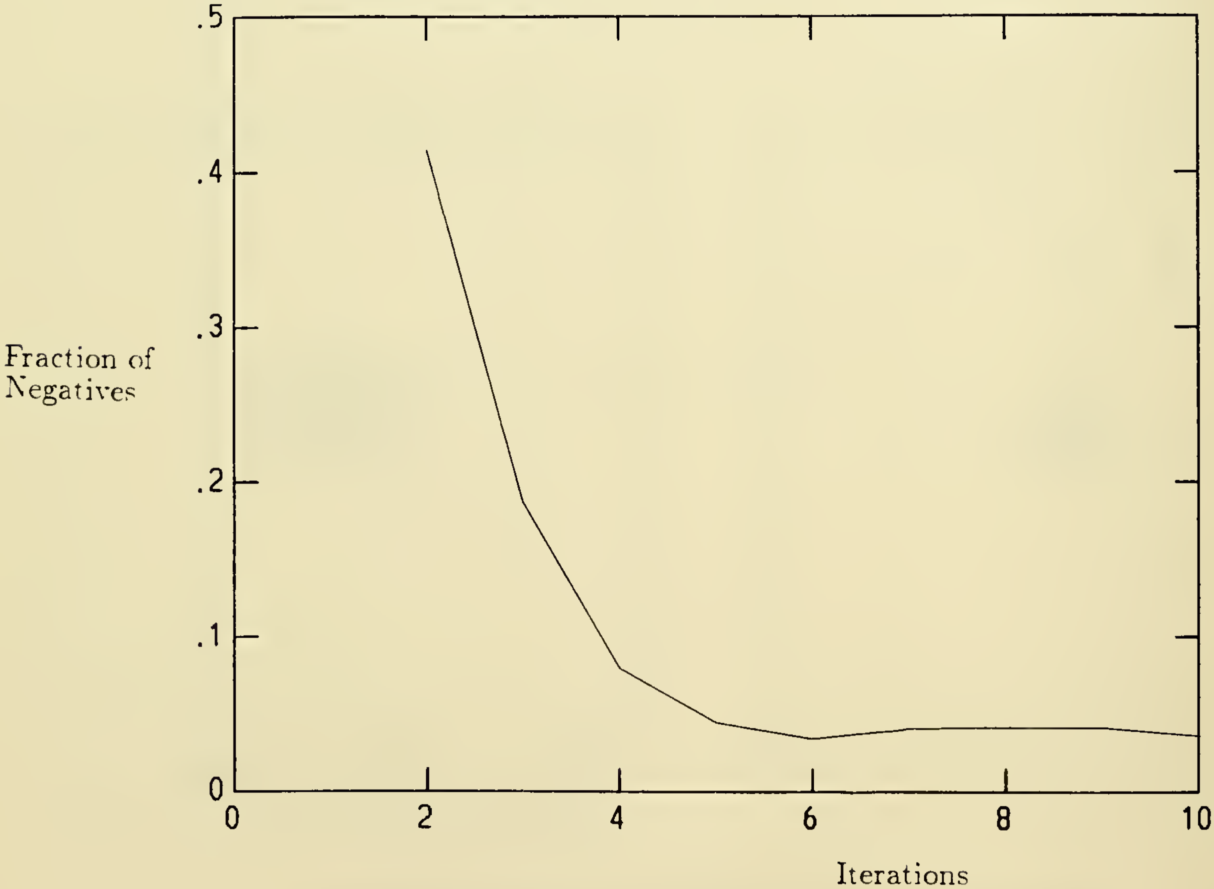

Fig. 5. The Convergence of BID for the SN1987A Image.