

Towards automated selection of reference images for difference imaging analysis

Leo Huckvale¹, Eamonn Kerins¹ & Stuart Sale²

(1) Jodrell Bank Centre for Astrophysics, University of Manchester, (2) Pontificia Universidad Católica de Chile

E-mail: leo.huckvale@postgrad.manchester.ac.uk

Abstract

We present an algorithm for selecting an ideal reference image for use in difference imaging analysis (DIA). This is thus far an unsolved problem in DIA. Our algorithm is based on a numerical simulation of a stellar Gaussian point spread function (PSF) in the context of the “stamp” used in DIA for the derivation of the convolution kernel. Our goal is to automatically select reference images based on their characteristics by finding an optimal balance of seeing, pixelisation and sky background level. We attempt to find this optimisation using the estimated Gaussian width of a simulated PSF as a measure of how well it may be characterised by the kernel.

Difference imaging analysis

Difference imaging analysis (DIA) is an efficient photometric method in crowded fields, such as the Galactic bulge regions covered by the VISTA Variables in the Via Lactea (VVV) survey. DIA uses image subtraction to compare the brightness of sources from a set of images observed over a number of epochs. Unresolved background stars and stars which do not change much in brightness do not appear in the residual images. To achieve correct subtraction, all images must first be geometrically aligned to the same coordinate system (that of a coordinate reference image). Subtraction with each target image should be made with a well-chosen reference image. In each subtraction, the reference image is convolved and photometrically aligned to match the seeing and background level, respectively, of the target image. The reference image, R , and target image, T , can be treated as matrices. The convolution kernel, k , can then be derived (via its inverse) by minimising the residuals in the difference image, given by:

$$\sum (R \otimes k - T)^2$$

Using this method, it is important to choose a reference image, or stack of reference images, with well-resolved stars (small seeing) and a high signal-to-noise ratio. This is the *Optimal Image Subtraction* process devised by Alard & Lupton (1998) and Alard (2000) and implemented in the *ISIS* pipeline (which can be obtained from <http://www2.iap.fr/users/alard/package.html>). In this case, Alard & Lupton (1998) suggest using the best seeing image (or stack of best seeing images) for the reference.

Wozniak (2008) gives a “rule-of-thumb” minimum seeing of 2.5 pixels in both reference and target image so that the PSF is sampled above the spatial Nyquist frequency. Below this limit, pixelisation of the PSF may have a significant effect on the derivation of the kernel. The effect of seeing should also not be considered irrespective of the background. For example, the PSF in a broad seeing, low background image might be better sampled than the PSF in an image of seeing < 2.5 pixels with a higher background. The seeing also cannot be considered independently of the size of the pixel grid (the “stamp”) over which the kernel is determined. A PSF approaching the size of the stamp may not be measured accurately. Where the stellar point-spread functions are largely undersampled in the images (seeing ~ 2 pixels), as in the VVV data, there is some argument to be made for an alternative method, using the worst seeing image as a reference. The rationale here is that in a worse seeing image, the PSF will be better sampled and thus the convolution kernel will be more accurately derived. In this scenario, we would use the minimisation of:

$$\sum (T \otimes k - R)^2$$

The selection of a suitable reference image is thus a problem of optimisation between the seeing, pixelisation, and the sky background level.

Image simulation

To explore the problem of good reference image selection, we constructed a simulation to test the accuracy with which the width of a basic Gaussian PSF could be estimated from a set of 200 simulated stamps. Each stamp is initially created as a 2D numerical array with a simulated stellar PSF. Each pixel of the array is taken as the value of the 2D Gaussian at the coordinates of that pixel. The center of the Gaussian is given a random sub-pixel offset to simulate the random distribution of stars in a real image. A background level is added to the Gaussian PSF before replacing the elements of the array with their Poisson deviates to simulate photon noise. The Gaussian width of the array is then estimated by a weighted average, using the pixel values as weights to the pixel coordinates. This gives an estimate of the width of the underlying Gaussian PSF. This stamp simulation is repeated for a set of 200 stamps to simulate a whole image. The variance of the set of 200 estimated widths is then calculated (variance with respect to the true input width of the underlying PSF) as a measure of the (in)accuracy with which the width of the PSF is determined in that simulated image. This variance is derived repeatedly for several trial simulations to obtain a mean variance. The trials cease when the difference between the mean variance derived at one trial and that derived at the last falls below 5% five times. This is to account for any spread in the measured variance with each different simulation of 200 stamps. This process is repeated for several data points in a space of seeing and background level inputs to produce a contour plot. At each data point is plotted the ratio, ϵ , of the root mean variance of the estimated widths to the true width of the underlying Gaussian (as derived from the seeing). Figure 1 shows such a plot, generated using a stamp of size 31x31 pixels for a range of seeing and background values. The horizontal axis is the log of the ratio of the background counts per pixel to the total (integral) counts in the underlying Gaussian PSF. As the background counts per pixel are entered as a ratio of the total PSF count, the contours do not change significantly for different input total PSF counts, but a large count (20000) gives better contrast between high and low regions (perhaps due to better sampling). The contours are on a log scale.

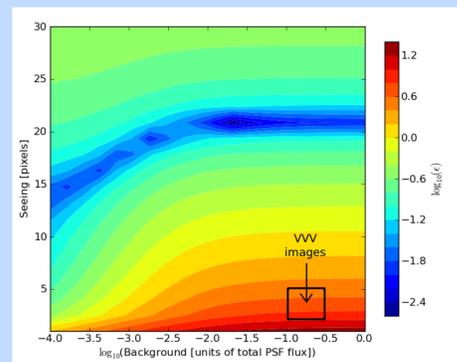


Figure 1:

Contour plot of our metric, ϵ , for the accuracy of estimating the width of a pixelated, noisy Gaussian PSF in a simulated stamp. ϵ is the ratio of the root mean variance of the estimated width determined from several trials, each of 200 stamp simulations, to the input width of the underlying Gaussian (as derived from the input seeing). The background axis is given in terms of the log of the ratio of the background counts per pixel to the total counts in the input Gaussian. The contour levels are shown on a log scale. The region in which we expect much of the VVV data to be is shown.

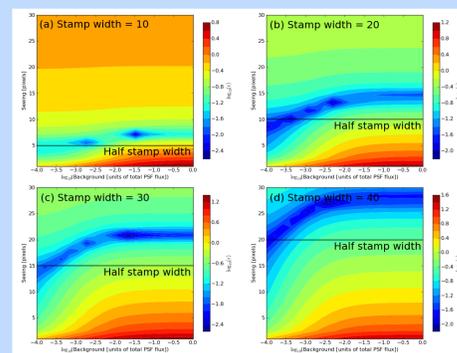


Figure 2:

Contour plots produced for a range of stamp sizes: a) 11x11, b) 21x21, c) 31x31 and d) 41x41. The half stamp width is shown in each case. Note the cut-off in ϵ for seeing values above the half stamp width. This is probably due to the Gaussian width algorithm finding the stamp size, rather than the width of the PSF which is swamped by noise.

Results

The plot in Figure 1 shows various subtle effects on the accuracy of the PSF width determination. ϵ increases significantly below the “rule-of-thumb” minimum seeing of 2.5 pixels at all except very low backgrounds. A minimum at seeing ~ 12 pixels, background $\sim 10^{-4}$, suggests a region in which determination of the PSF width could be more accurate, although this blends into another minimum, which corresponds to the half stamp width. Indeed, running the simulation for different stamp widths shows how this minimum changes (see Figure 2). This region probably corresponds to the point where much of the PSF bleeds off the edge of the stamp, and the accuracy is due only to the fact that the PSF width is near to the half stamp width. At seeing below the half stamp width (< 15 pixels) the contours begin to fall off below a background level of 10^{-1} .

Discussion and future work

The minimum towards low background (10^{-4}) and moderate seeing (~ 12 pixels) in Figure 1 suggests an optimal region for accurate measurement of the PSF (and thus the kernel). The test of this method will be its application to real images and the resultant difference images and DIA lightcurves. This work is ongoing - specifically the correct characterisation of the images in the context of the contour plot. The ratio of background per pixel counts to the total counts in the PSF was chosen to generalise the plot (rather than using absolute values). However, defining this quantity in terms of each real image is non-trivial. Once a set of images have been characterised and plotted on top of the contours, it will be possible to test the strength of this method by two tests. The first will compare the residuals in difference images produced from single reference images chosen at successive distances from the minimum. The second will also compare the residuals in difference images, but this time stack different sets of images to produce a variety of reference images. From this we will see, for example, if it is possible to produce a better reference image (on a lower contour) from several worse images (on a higher contour). Early attempts at DIA carried out on the VVV science verification data indicates that VVV images may in fact be best reduced using the worst seeing image as the reference, rather than the best. This has the advantage of being able to use all of the data (of better seeing) in the DIA pipeline.

References

- Alard, C. and Lupton, R.H., (1998), *Astrophysical Journal*, **503**, 325
 Alard, C. (2000), *Astronomy & Astrophysics Supplement Series*, **144**, 363-370
 Wozniak, P. (2008), *Proceedings of The Manchester Microlensing Conference: The 12th International Conference and ANGLÉS Microlensing Workshop*