Difference-imaging photometry with pySIS3

Michael D Albrow

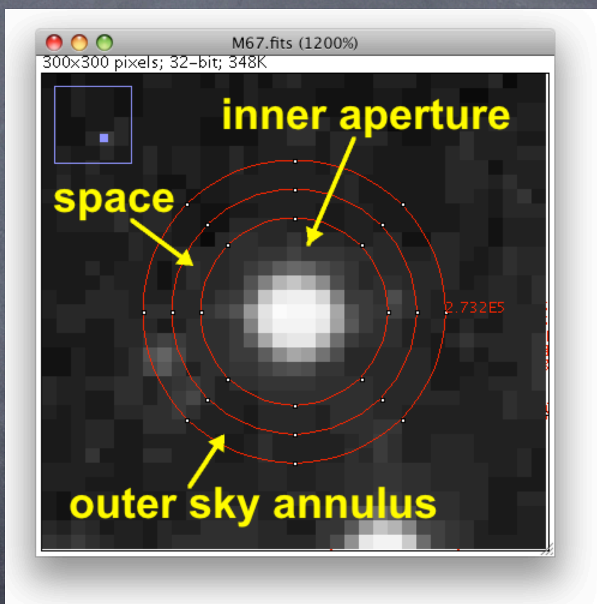
Department of Physics and Astronomy

University of Canterbury

Aperture photometry

Add up the light from a star within a defined circular region called the aperture.

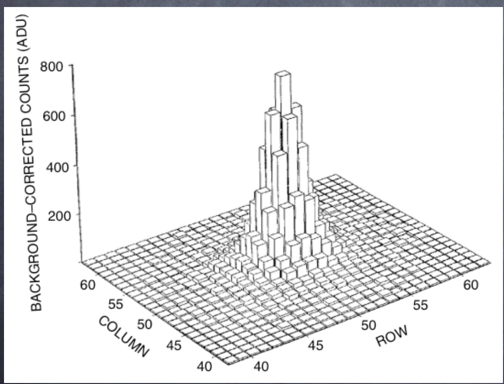
An outer annulus is used to measure the background light.



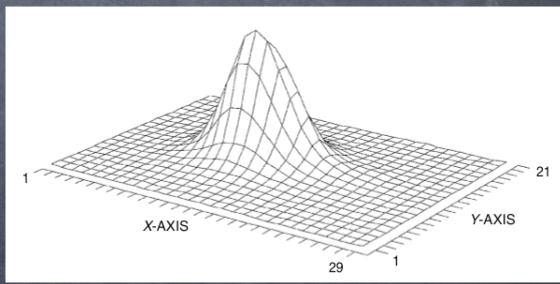
PSF photometry

In crowded star fields, aperture p
unsuccessful, since it relies on sta
order to get measurements of the
that are not contaminated by oth
involves fitting a model PSF to th

The model chosen can be an analytic function (such as a Gaussian) or can be some numerical representation. The stellar flux is determined by integrating the fitted model PSF.



star

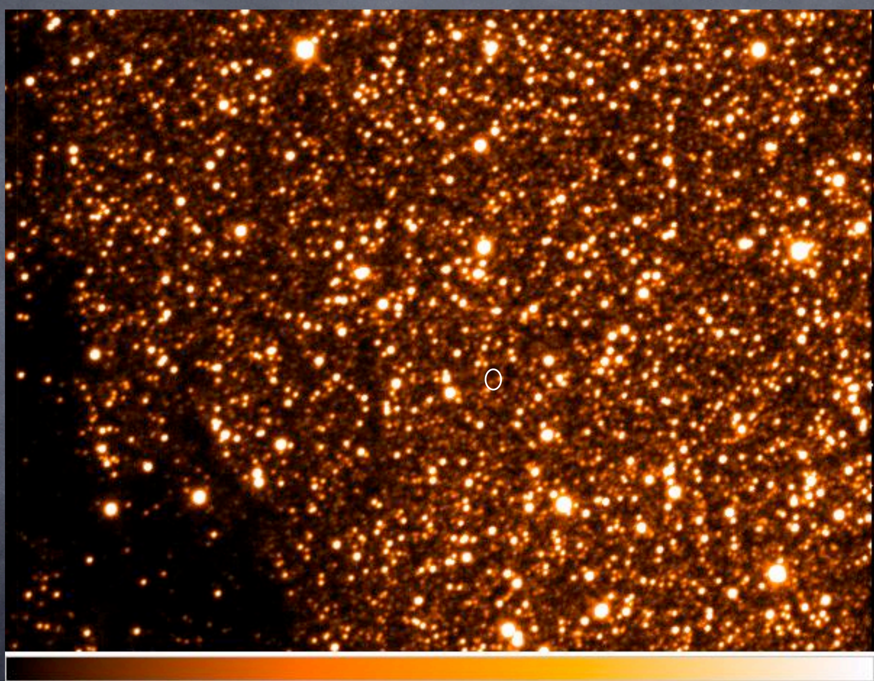


model

Our fields are very crowded

OGLE 2005-BLG-390

image from PLANET Danish 1.5 m telescope, La Silla, Chile

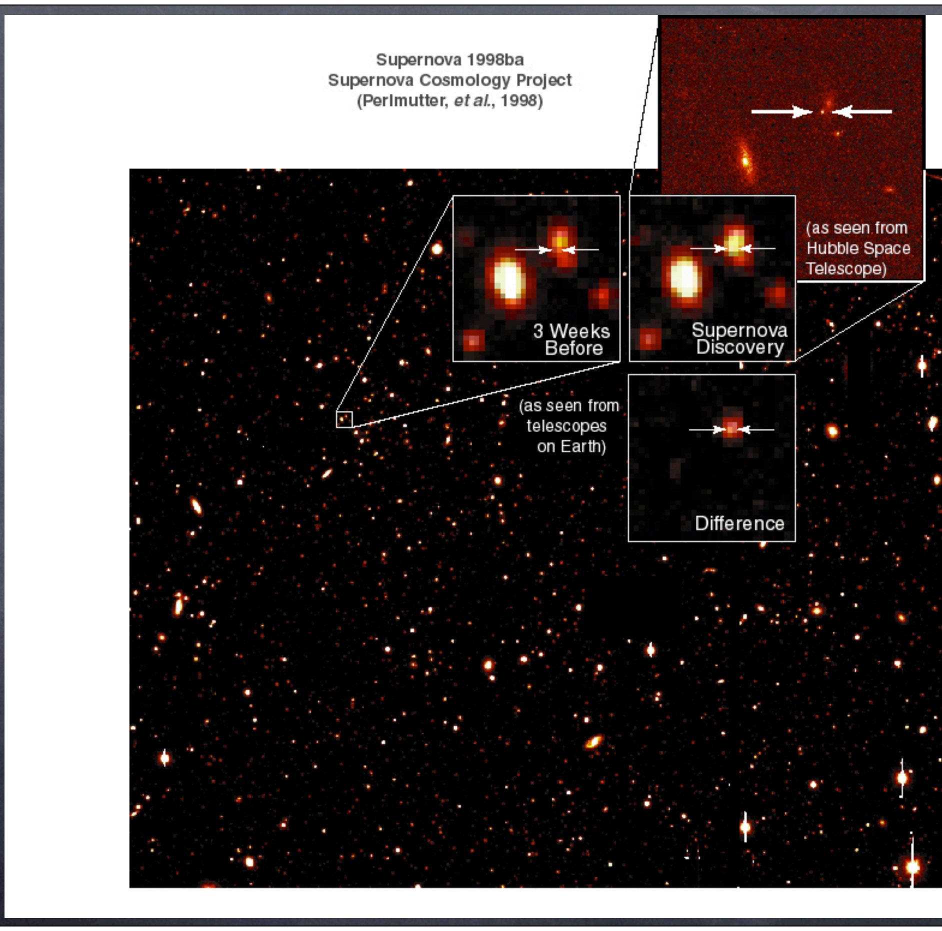


Difference image photometry

This is a relatively new method for detecting and measuring variable stars in very crowded fields. The idea is to subtract two CCD images, taken at different times. All the constant-brightness objects should disappear, leaving behind things that have changed in brightness.

Difference image photometry

The major difficulty is that the images must first be processed so that they have the same PSF before doing the subtraction. Generally this involves convolving (blurring) the best-seeing image, R, to match the other one, T.



Difference-Imaging

If we have a reference image, R, and a series of target images, T^α, then we define the difference image

$$D^\alpha \equiv R \otimes K^\alpha - T^\alpha$$

K^α is called a convolution kernel.

Convolution Kernel

Analytic - e.g. sum of a few fixed width gaussians multiplied by polynomials (Alard 2000). (Almost) complete image registration required.

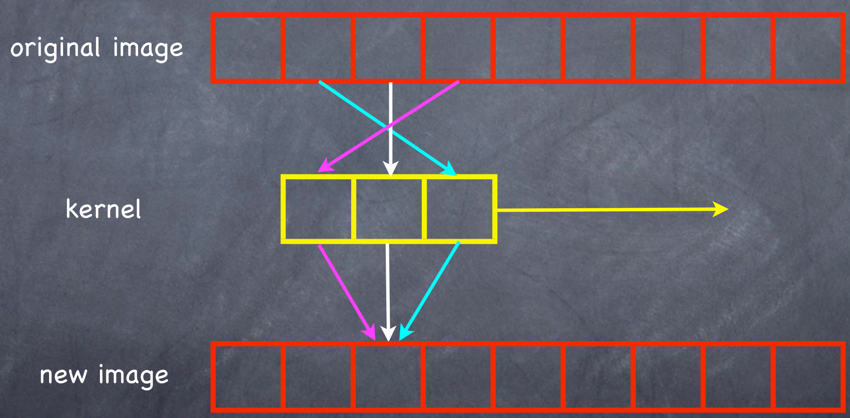
Numerical - grid of pixels (Bramich 2008). Registration by integer pixel shifts OK. Can cope with weird PS

pysis available - useful for crowded field transit searches

In either case the kernel can be allowed to vary smoothly across the image.

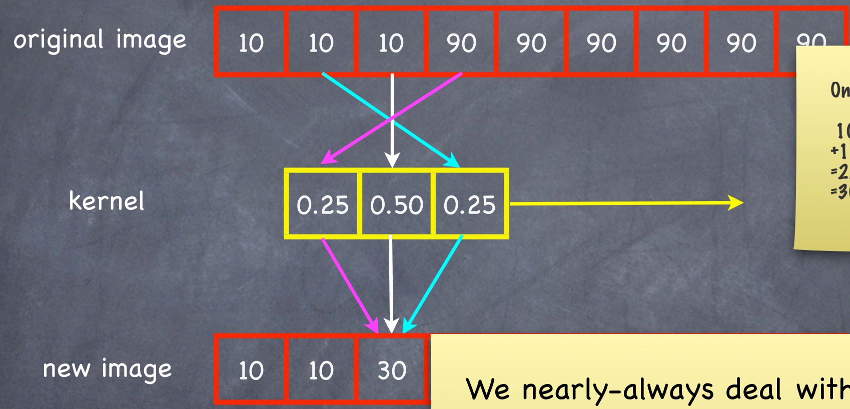
Convolution

First we will consider what happens in one dimension. The basic process is:



Convolution

An example:



On whiteboard:

10x0.25
+10x0.5+90x0.25
=2.5 + 5.0 + 22.50
=30

We nearly-always deal with symmetric kernels and in such cases the inverted order of the pixel-matching between the original image and the kernel can be ignored.

In this case, a sharp transitio
softened (blurred) by the ker
influence of the Earth's atmos

The identity kernel

Lets look at some examples of convolution kernels and what they are used for. You will use some of these in your tutorial and assignment next week.

Imagine we have an 'image'

$$o = [\ 0\ 0\ 100\ 0\ 0\ ]$$

and we convolve it with a kernel

$$k = [\ 0\ 1\ 0\ ]$$

then

$$k \otimes o = [\ 0\ 0\ 100\ 0\ 0\ ]$$

[0 1 0] is an identity operator - all it does is make a copy of an image.

The kernel as a shift operator

Do this one explicitly on the whiteboard - shows why the kernel gets reversed during the convolution process.

Imagine we have an 'image'

$$o = [\ 0\ 0\ 100\ 0\ 0\ ]$$

and we convolve it with a kernel

$$k = [0\ 0\ 1]$$

then

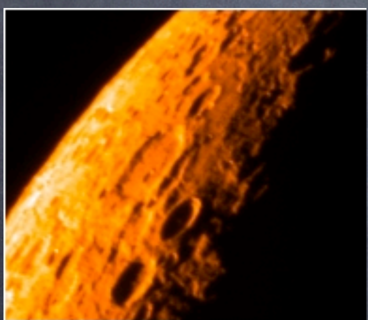
$$k \otimes o = [\ 0\ 0\ 0\ 100\ 0\ ]$$

[0 0 1] is a shift operator – it makes a copy of an image with all pixels shifted one position to the right.

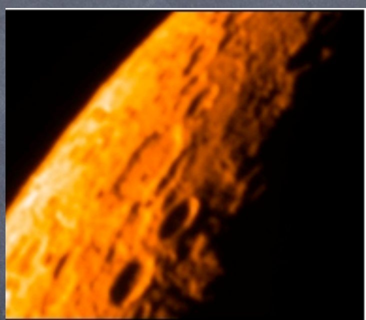
1	1	1
1	1	1
1	1	1

1	1	1
1	2	1
1	1	1

original image

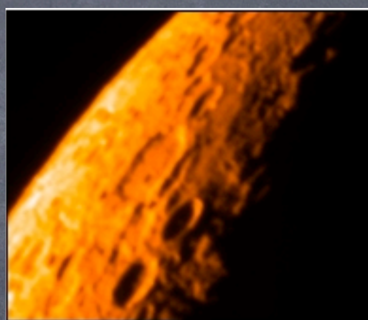


boxcar blur kernel



Severe loss of small scale detail

50% blur kernel

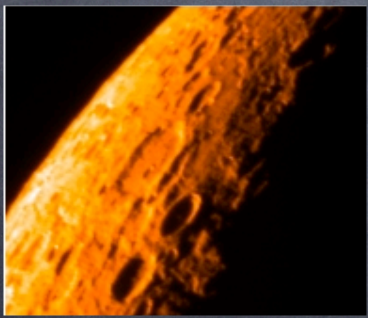


Preserves more detail while still softening image

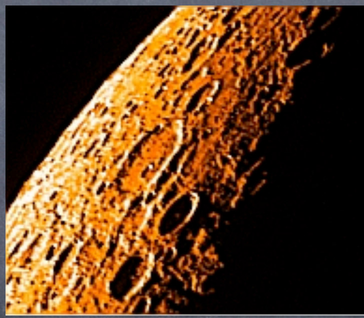
-1	-1	-1
-1	9	-1
-1	-1	-1

0	-1	0
-1	5	-1
0	-1	0

original image

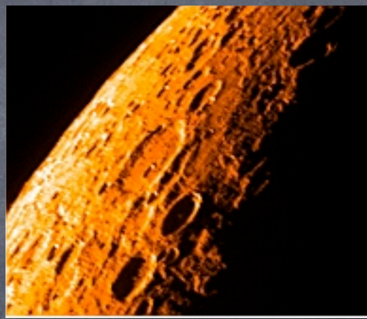


classic sharpening kernel



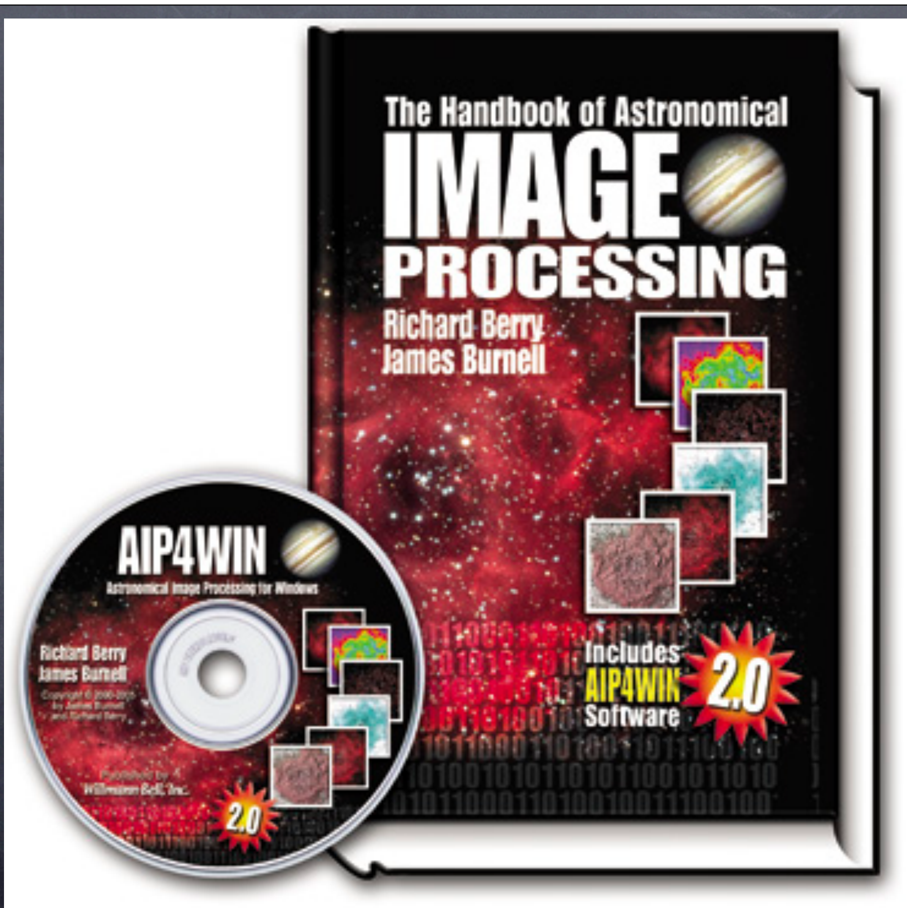
Strong enhancement
of fine-detail contrast

crispening kernel



Milder degree of contrast
enhancement

But note that it looks noisier



Difference-Imaging

If we have a reference image, R, a[...] target images, T^{α}, then we define t[...] image

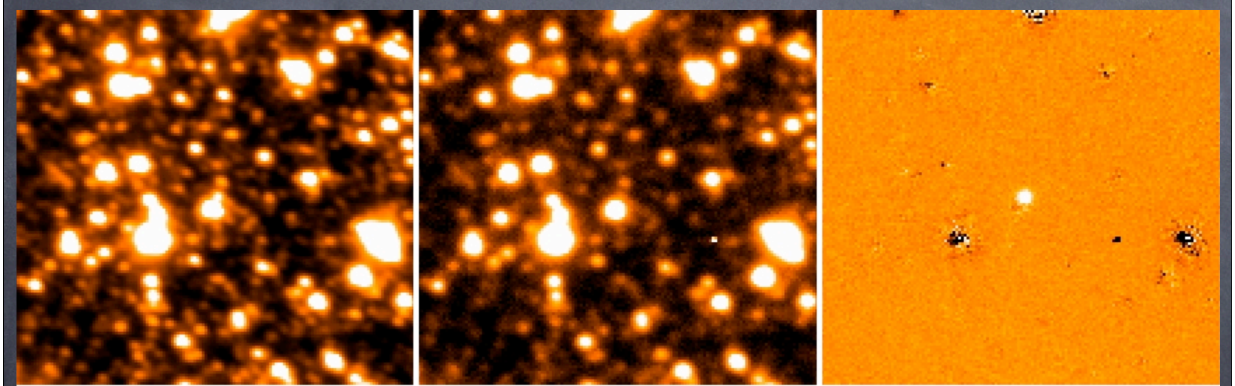
$$D^{\alpha} \equiv R \otimes K^{\alpha} - T^{\alpha}$$

Back to difference imaging

Now we are dealing with the situation where we don't know the kernel

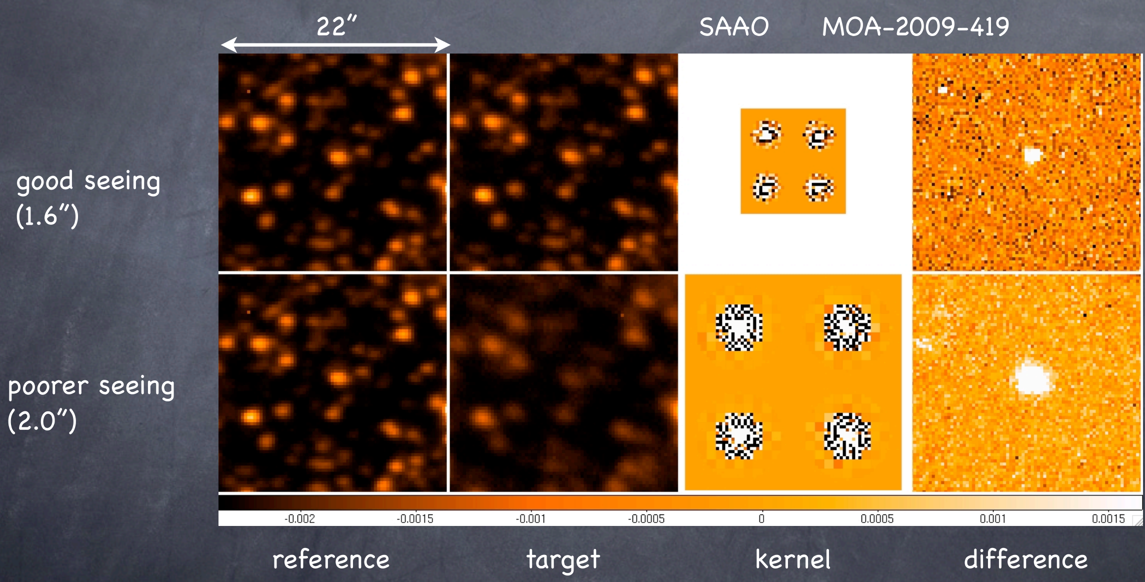
K^{α} is a convolution kernel computed to minimize

$$\chi^2 = \sum_{ij} \left(\frac{D_{ij}}{\sigma_{ij}} \right)^2$$



R T D

What do the kernels look like?



Photometry

The microlens flux in the difference image is measured by optimal PSF photometry:

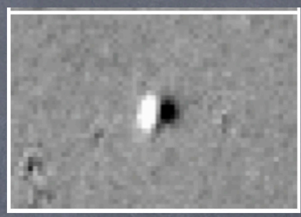
Compute the PSF of the reference image by coadding bright stars.

Convolve the reference PSF with the kernel.

Interpolate the convolved PSF at the subpixel lens coordinates.

Evaluate the flux as $f = \sum_{ij} \frac{pd/\sigma^2}{p^2/\sigma^2}$

Refining the lens coordinates



Use the pattern of photometric residuals.

Expand the PSF model:

$$\boldsymbol{P} = \boldsymbol{P}_0 + \Delta x\, \boldsymbol{P}_x + \Delta y\, \boldsymbol{P}_y$$

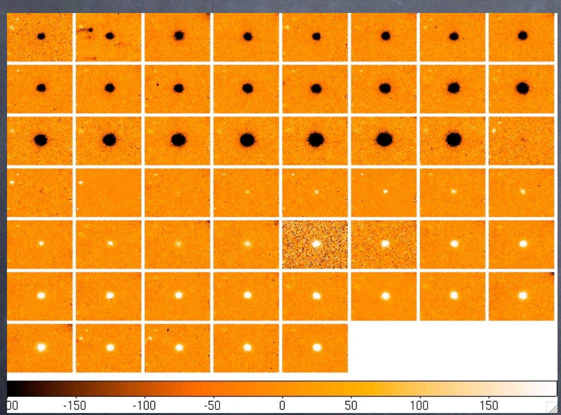
After some arithmetic, the coordinate correction is given by

$$\Delta x = \frac{\sum_j \Delta F \left\langle \boldsymbol{D} - \Delta F\, \boldsymbol{P}_0 \,\middle|\, \boldsymbol{P}_x - \frac{\langle \boldsymbol{P}_x | \boldsymbol{P}_y \rangle}{|\boldsymbol{P}_y|^2} \boldsymbol{P}_y \right\rangle}{\sum_j (\Delta F)^2 \left(|\boldsymbol{P}_x|^2 - \frac{\langle \boldsymbol{P}_x | \boldsymbol{P}_y \rangle^2}{|\boldsymbol{P}_y|^2} \right)}$$

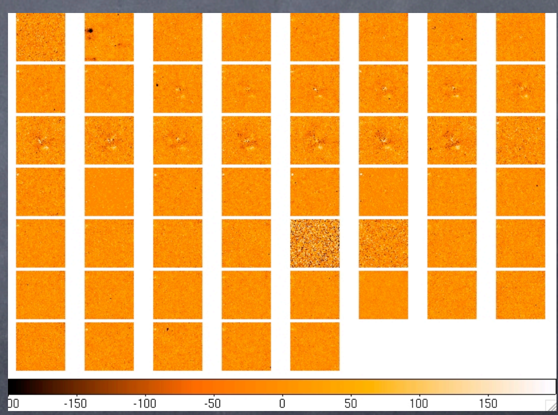
This depends on the flux, so the corrections must be iterated. Convergence to a few thousandths of a pixel usually takes only a few iterations.

Diagnostics

To verify the photometric performance, we always write out the photometric residual images and compare them with the difference images. e.g.



difference images



difference images after subtraction of fitted PSF