P5.1

Image Stacking Tools for Modern Surveys

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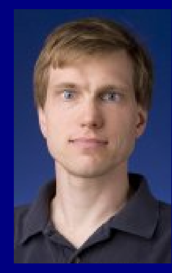


Abstract

Modern imaging observation programs often collect many exposures for each area of sky observed. Although simple methods for generating a single, high quality exposure from collections of overlapping images are well understood and tools that implement them are commonplace, many modern exposure sets, such as those from the Sloan Digital Sky Survey (SDSS) and those expected from the Dark Energy Survey (DES), have complicating properties that these tools do not address optimally. These exposures may have different point spread functions, so direct co-addition or image stacking will not result in an image with either an optimal PSF or noise. They may have significantly different distortion in their mapping of pixel to celestial coordinates. If the generated image is to be used for object detection, exposures through different filters should be combined into a single image, so that objects below the detection threshold in any given filter may still be detected. I present progress on a set of tools designed to combine multiple exposures in a manner optimal for object detection, integrating distortion removal and registration, coaddition, and noise suppression into a single step. I also introduce a method for using cross correlation between exposures to estimate the statistical properties of undetected sources for use in combining images.

Image restoration: resampling, coaddition, and noise suppression

A typical procedure for combining multiple exposures of the same field includes several steps:

1. Resampling for alignment and distortion removal (for example using a Lanczos sinc kernel)
2. Weighted addition of aligned pixels

This coadded image is itself commonly used for interactive examination and other purposes. When preparing an image for object detection, a third step is used:

3. Noise suppression through application of a matched filter (usually through convolution by the PSF)

This approach has several flaws:

1. The ideal interpolation kernel, the sinc function, must be truncated for practical reasons
2. When not all exposures have identical point spread functions, different Fourier frequencies should be given different weights in the coaddition, but the addition of unfiltered exposures in image space does not allow this.
3. Two linear kernels are applied (one for resampling, and another for noise suppression), but this can be done in one step because addition is commutative.
4. Convolution by the PSF is only a proper matched filter when there are no extended sources.

Nick Kaiser advocates convolution by the PSF between alignment and addition, addressing the second flaw.

Alternatively, we can consider the derivation of a single, noise suppressed image from a collection of exposures as a single linear image restoration problem.

1. Each step above is a linear filter, so the above procedure can be expressed as a single linear restoration.
2. The optimal solution for producing a least squares best fit of the sky is a Wiener filter.
3. The optimal solution for object detection is a matched filter.

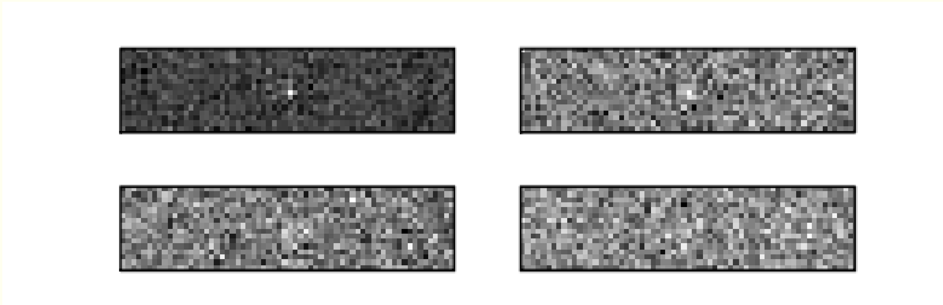
In other words, if we use a kernel derived either from a Wiener or matched filter as our interpolation kernel in the initial resampling, the relative weighting of the Fourier frequencies will be optimal and the noise suppression step prior to object detection will be unnecessary. Using the PSFs as our interpolation kernels addresses flaws one through three in the above list.

When an image consists of randomly distributed sources at low signal to noise, the Weiner filter and matched filter are the same. If the sources are point sources, this filter will be the PSF. In all cases, we can generate an image analogous to that produced after addition in the traditional approach using a high pass filter.

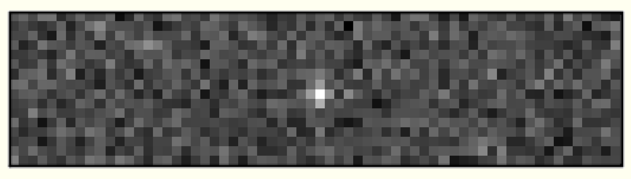
The Wiener and matched filters suffer a common disadvantage; derivation of either requires that we know the power spectra of the images of the objects we have not yet detected. One approach, which leads to the fourth flaw listed above, is to assume that they are point sources. An alternate approach which addresses this issue is to use the cross correlation between different exposures; see the "Statistics of Undetected Objects" panel.

Stacking of simulated data

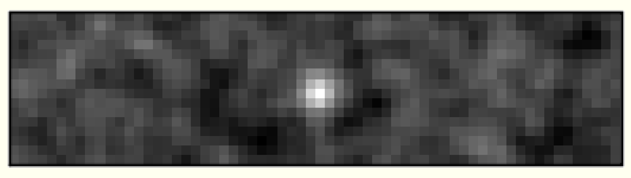
These four images each contain a simulated point source. The ratio of the total flux of the point source to the stardard deviation of the noise is the same in each image, but the width of the point source varies signficantly between images.



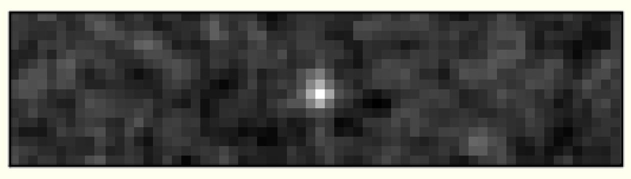
When the three sharpest images are added, the peak is 7.8 times the sky standard deviation.



When a matching filter is applied to the coadded image, the peak is then 9.7 times the sky standard deviation.

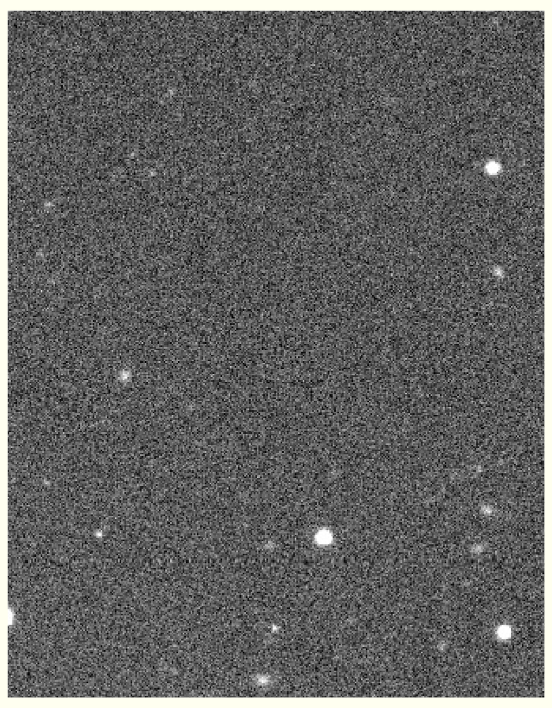


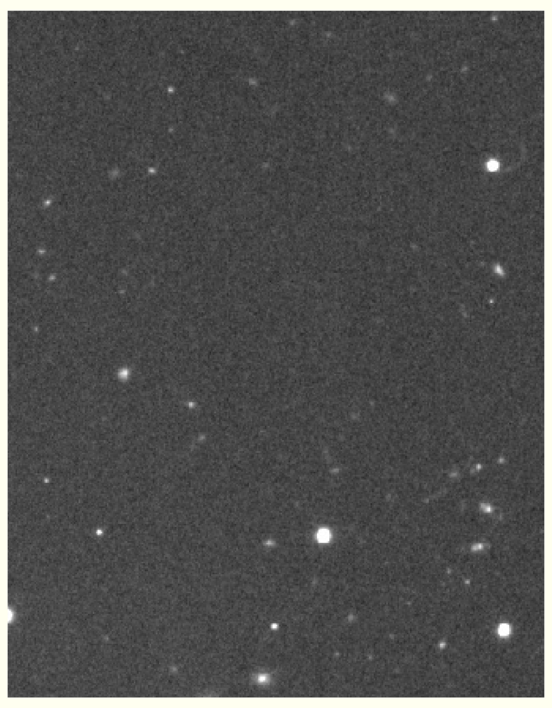
When a matching filter is applied to each individial exposure and the results added, the peak that is 12.3 times the sky standard deviation.

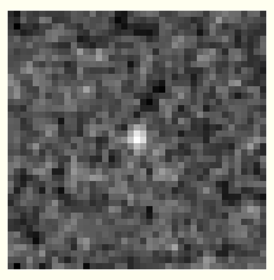


Stacking of SDSS frames

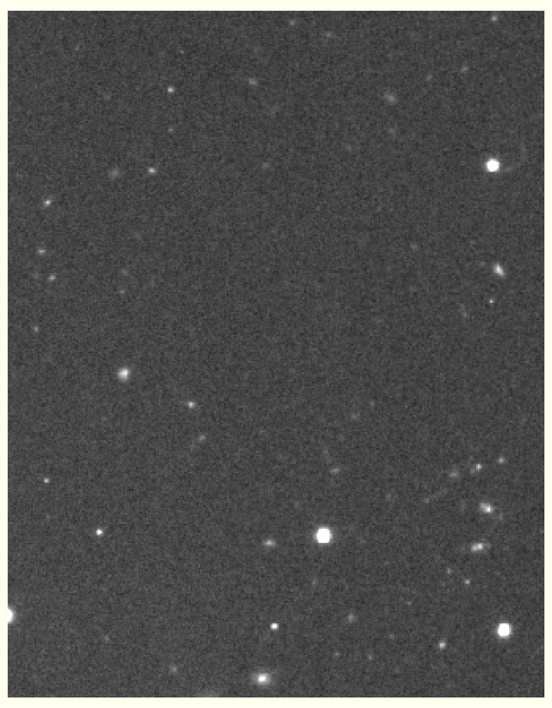
I also applied these coaddition techniques to real data from the SDSS. These frames show two of the eight sections of a scan used to produce the coadded images.

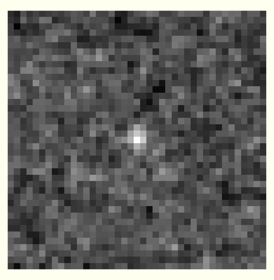






This images show the result of registering and adding the set of 8 SDSS frames and convolving it by the point spread function of the coadded image, a typical first step in object detection applications. (When the objects are randomly distributed point sources and we are optimizing for detection of objects at low signal to noise, the Weiner filter becomes the PSF.) The peak of the sample star is 6.7 times the standard deviation of sky pixels.





If each exposure is convolved by its own point spread fuction before they are added, the result is a slight improvement in signal to noise; the peak in this sample star is 7.5 times the standard deviation of sky pixels.

References

Kaiser, Nick, "Addition of Images with Varying Seeing," 2001
Szalay, A. S., Connolly, A. J., & Szokoly, G. P. 1999, AJ, 117, 68

Coaddition of exposures in different filters

Sets of exposures on a given region of the sky will often include images taken through multiple filters. An ideal combined exposure to be used for object detection will take advantage of the signal present in all filters. If multiple exposures are to be added optimally, each image must be weighted according to the signal to noise of the objects to be detected. When exposures taken using different exposures are to be added to each other, this weighting depends on the color of the objects. This is a challenge, because it requires knowledge of the colors of the objects before they are detected. Furthermore, not all objects will be of the same color.

This problem can be addressed in two ways, or using a combination of the two.

1. Instead of adding the images in different filters, Szalay, Connolly, and Szokoly (1999) measure the goodness of fit of the sky to the pixels in the exposures from all filters. This can be accomplished in practice by adding the images in quadrature, which results in an image of the goodness of fit.
2. One can use the cross correlation between exposures (after masking of detected objects) in different filters to measure the flux weighted mean colors of undetected objects.

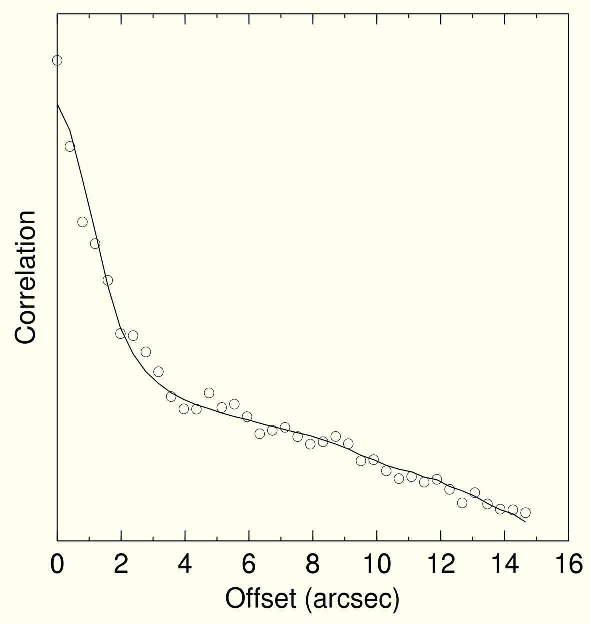
Szalay et al. also present an "optimal subspace filtering" based refinement on their approach, which uses knowledge of the colors of objects to reduce the degrees of freedom that need to be considered in the goodness of fit. The goodness of fit and cross correlation methods can be combined by using the cross correlation to determine the optimal subspace.

Statistics of undetected objects

One of the classic disadvantages of the Wiener filter is that it requires an approximation of the power spectrum of the true signal. In this application, a flat spectrum (corresponding to a random distribution of point sources) is a reasonable first approximation, but we can improve upon this using the cross correlation between different exposures: if the noise in one exposure is not correlated with the noise in a second, then the mean power contributed by the noise to the cross correlation of the two will be zero, and the result can be used to approximate the Wiener filter; correlation between images comes from the signal only.

Note that, as the signal to noise of the image being added varies, so does the cross correlation; the magnitude of the correlation incorporates an estimate of the proper weighting. Note that this even works when the images were taken through different filters. In that case, the weighting is appropriate for the flux weighted mean color of undetected objects.

When the objects we are attempting to detect in coadded images are randomly distributed point sources at low signal to noise, Wiener filtering can be well approximated by convolution by the point spread function. This can be tested by fitting the cross correlation between two exposures to the cross correlation between PSFs. In the figure to the right, the line shows the cross correlation between models of the point spread functions of two exposures, and the circles show the cross correlation between the images themselves after bright objects are masked.



Implementation

I have explored the coaddition methods described here using a set of Python and bash scripts that coadd SDSS data. Development of a production implementation is underway. It will work as either a stand alone utility or when integrated into the Dark Energy Survey pipeline, and be tested using the imsim 3 simulation of DES data. The implementation is in ANSI C, and can be compiled and installed using the ubiquitous GNU autoconf utilities.