Image Subtraction & Transient Detection Techniques

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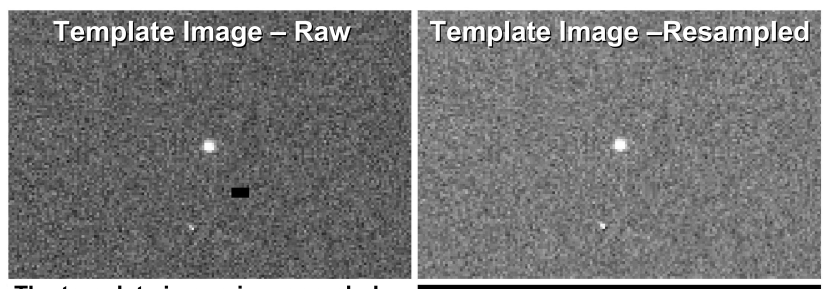
Large Synoptic Survey Telescope

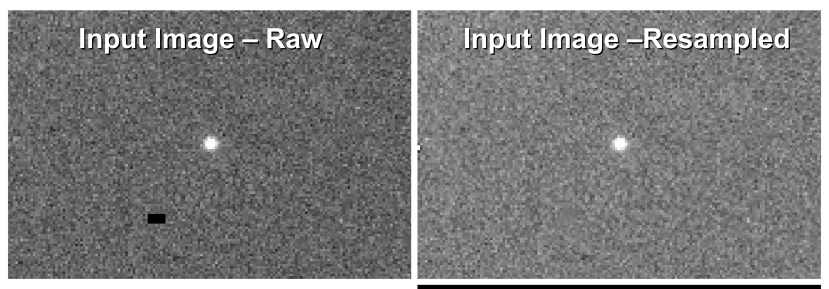
The process of image subtraction drastically changes the characteristics of the signal and noise in the images being analyzed. One or both images are resampled to a fiducial astrometric system; one image is additionally convolved to match PSFs; and one image is subtracted from the other. Without careful propagation of image artifacts and noise, the output image may be littered with false positives and have a poorly defined measure of significance. We outline improvements made to the SuperMACHO/ESSENCE pipeline that have helped us improve the quality of our difference images. These improvements are a significant step along the route to robust image subtraction algorithms for the LSST variability pipeline.

Masking : Bad pixels

In difference imaging, the primary goal is the determination of the convolution kernel that matches PSFs. This requires comparing pixel regions found in both images, which should optimally contain an object or set of objects at high S/N. If there are bad pixels (or variable objects) in these regions, the process can fail. It is of utmost importance to know the quality of the input images and to use only pristine pixels in this calculation. In addition, bad or saturated pixels leave a large footprint in resampled images, and an even larger footprint in difference images where they have been convolved twice. We explicitly propagate the influence of bad pixels through our pipeline, using a bit-wise image mask that tells us if a pixel was found in the detector's bad pixel mask, was saturated, or received flux from any such pixel during the convolution steps. Our object detection algorithms have been modified to use these masks.

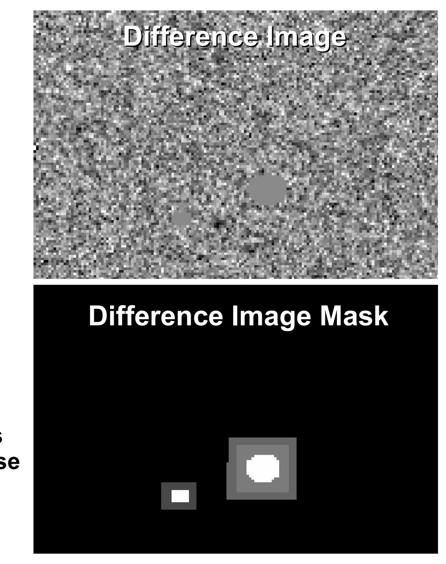


The template image is resampled to an astrometric reference frame. This process extends the footprint of bad pixels. In the mask image at right, the *white* area represents the region where bad pixels dominate the convolution. These will be masked out in the difference image. The *grey* area represents less contaminated pixels. These will not be masked in the difference image, but will be excluded from the difference imaging kernel fitting. Note the bad pixel region is interpolated over in the resampled image.



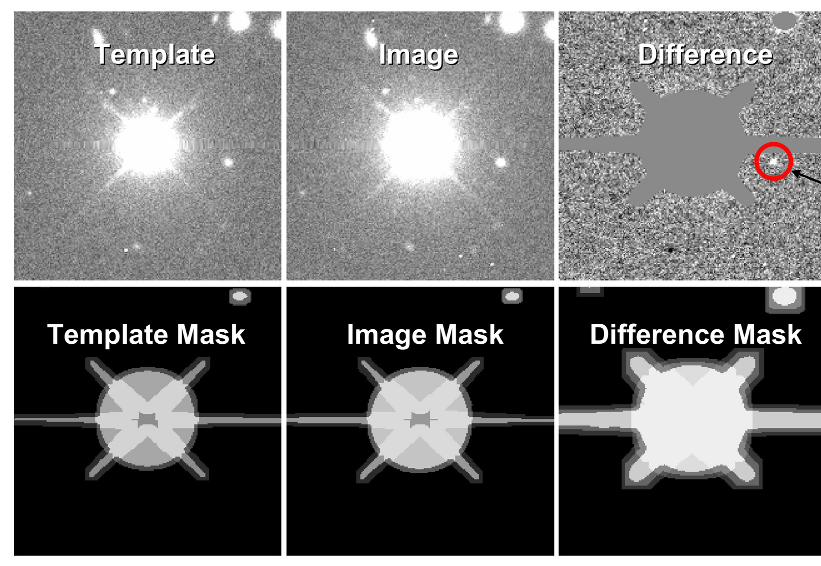
The input image is resampled to the same astrometric reference frame. Due to pointing differences, the bad pixel region lands on a different part of the sky. Mask levels are the same as in the template image.

The difference image contains artifacts from both images. In addition, one set of artifacts are convolved with the difference imaging kernel. In this case, the template was convolved before subtraction from the input image. Note the mask from the template is spread, yielding 3 shades of grey. The whitest regions represent regions dominated by bad pixels during the convolution. These are masked out in the difference image and in object detection. The middle and outer regions correspond to destination pixels that received *any* flux from masked pixels during the convolution (2 levels for the 2 levels of masking in the input image). These are suspect but not masked out in the difference image, allowing us sensitivity to variability near bad pixels. We increase the noise in these pixels accordingly.



Masking : Diffraction spikes

Features around saturated stars lead to significant numbers of residuals in difference images. To compensate, additional bits are added to our mask to model haloes and diffraction spikes. The image on the right shows the resampled template and input images and their masks, as well as the difference image and its mask.

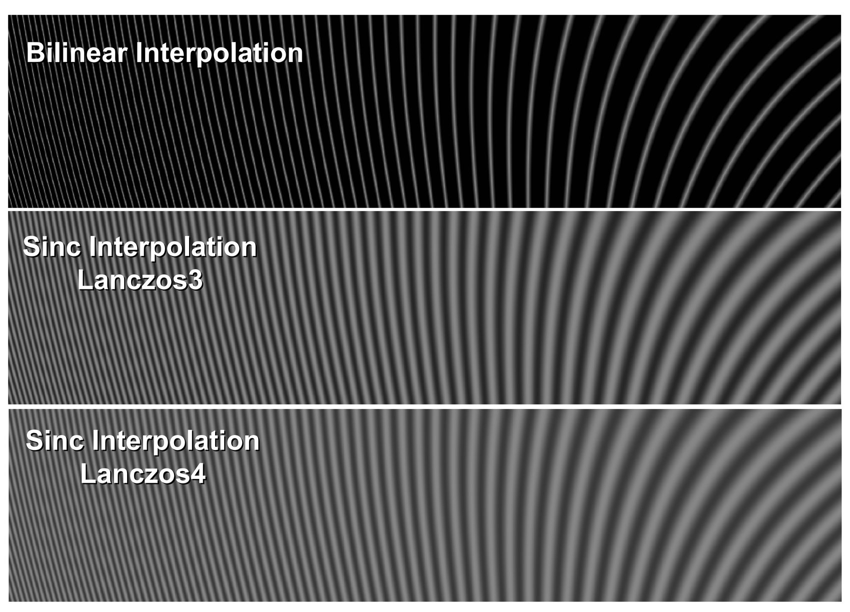


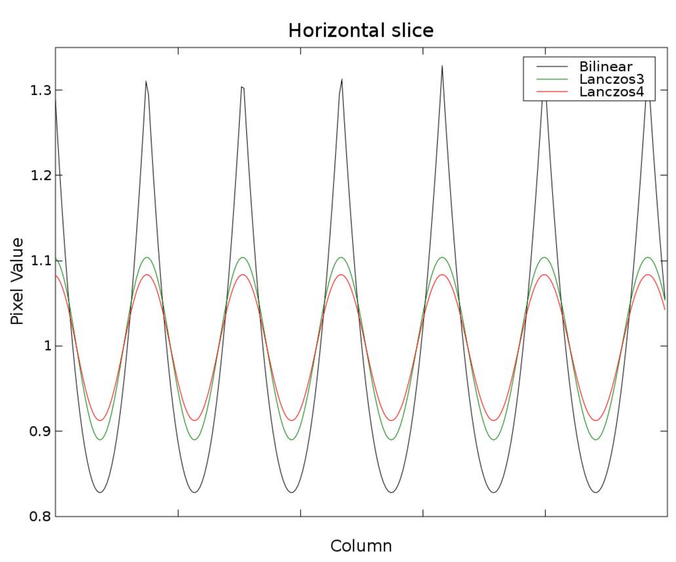
ESSENCE SN 2004-G-29

Noise propagation :

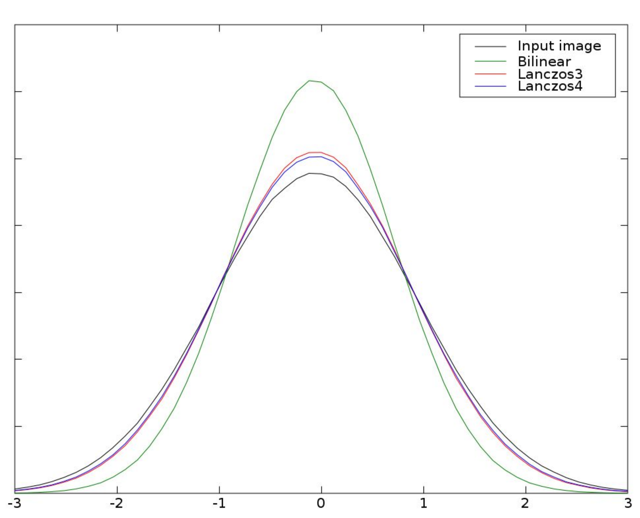
The propagation of noise is important to quantify detection limits in the difference images. The resampling and difference imaging stages both accept input noise images, and produce output noise images. Object detection stages use this information to determine the significance of detected objects. We currently ignore pixel covariance.

Result of resampling a FITS file whose pixels are all the same value. The process was done using the Swarp package, which uses WCS information in each header for the transformation. The input image had TNX-format WCS distortions, and was flattened out to a TAN projection. All figures have the same scaling. A horizontal slice through these images is seen to the right, which indicates that the Sinc resampling yields less systematic distortions (although at the expense of a larger footprint). The observed features also reflect the spatial distortions of the PSF introduced by the resampling process, which must be minimized for the image subtraction stage.

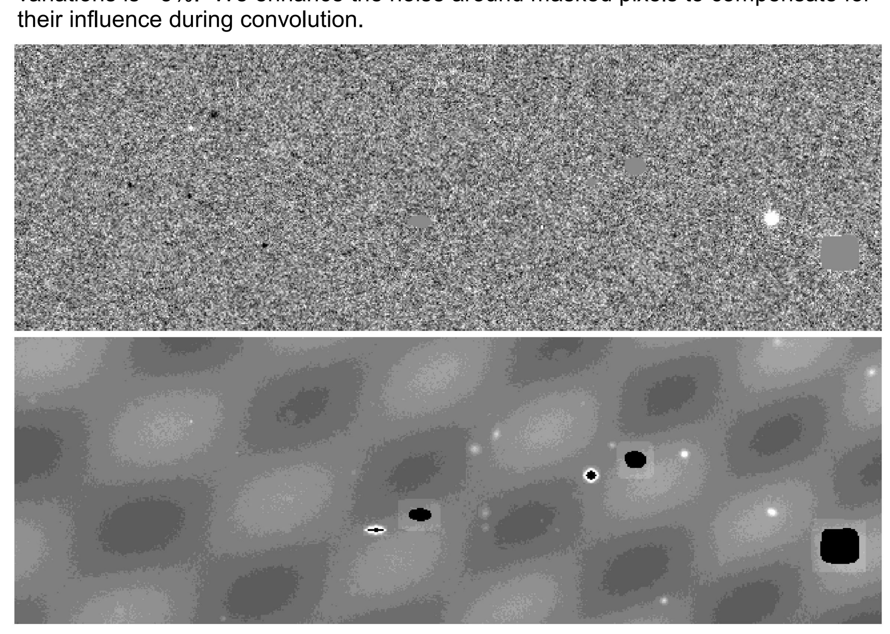




Histogram of pixels in an input image containing purely Gaussian noise, and in output images resampled with a variety of algorithms. The input and output coordinate systems are the same as in the figures to the left. Note the Lanczos4 resampling kernel distorts the image statistics the least.

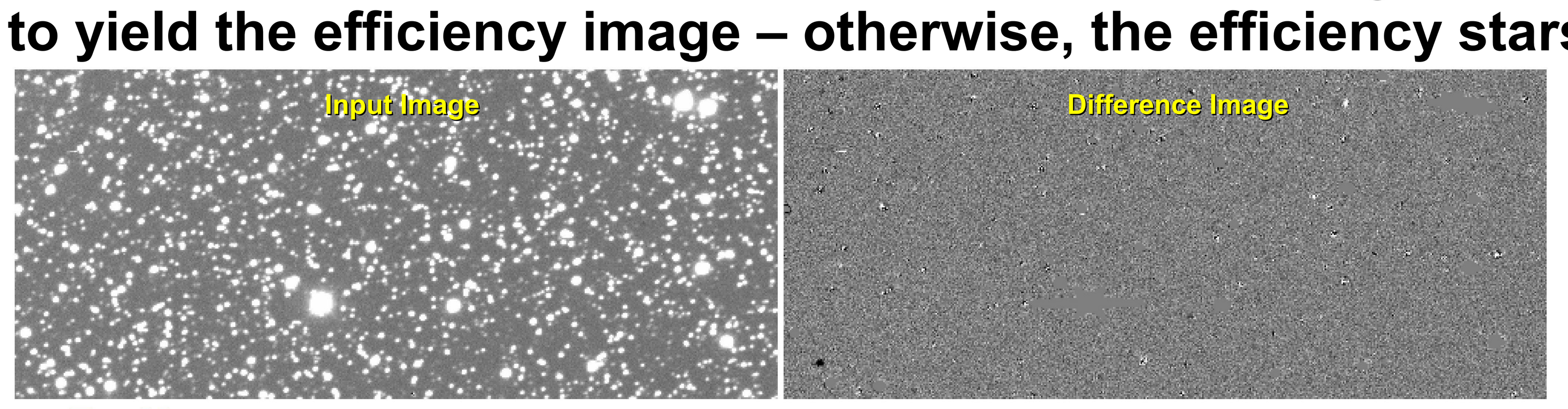


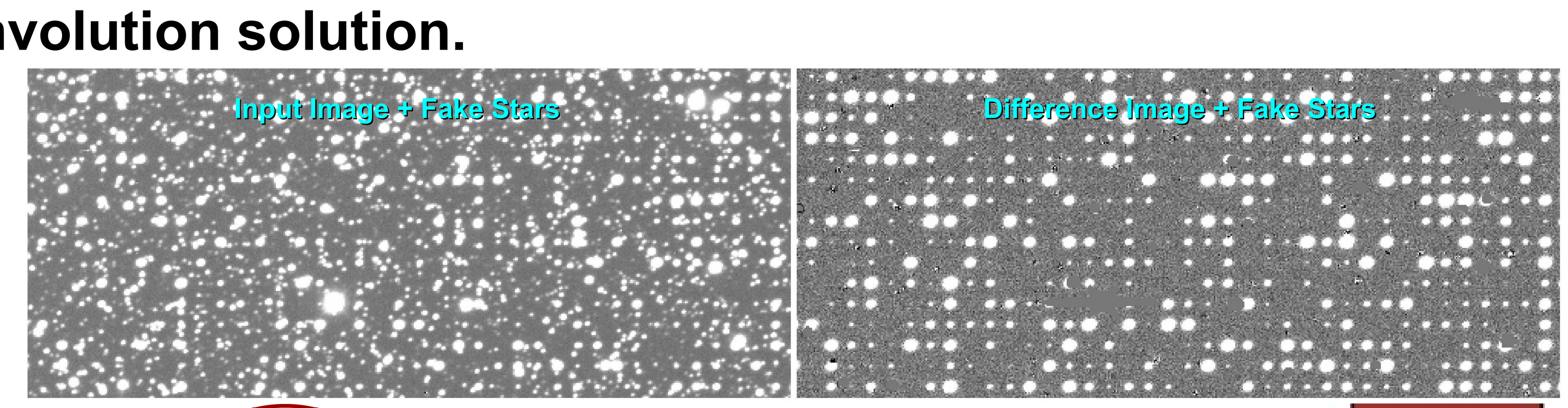
Difference and associated noise images. The amplitude of the systematic noise variations is ~5%. We enhance the noise around masked pixels to compensate for their influence during convolution.



Efficiency analysis :

The determination of image detection efficiencies requires the addition of fake stars and an inventory of fraction recovered as a function of brightness. To enable this for our image subtraction pipeline, we save the convolution coefficients in the FITS header of the difference image. In this way, we can use the same kernel that determined the original difference image to yield the efficiency image – otherwise, the efficiency stars may dominate the convolution solution.





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