

Robert Lupton LSST Pipeline Scientist HSC pixels meet LSST Pipelines

200

2017-06-13

HSC's Pixels





HSC's 1.8 deg² Field of View





Cosmos





Cosmos



2.0 1.5 1.0 0.5 0.0 0 < z < 0.25 0.25 < z < 0.5 Ŀ т 2.0 1.5 1.0 0.5 0.0 0.5 < z < 0.75 0.75 < z < 1 Ó ź 0 2 g - r





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Strategy



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I'm pretty confident that we'll have come out ahead by the time the HSC 'SSP' survey is done.

LSST Pipelines



Create the tasks

```
In [6]: schema = afwTable.SourceTable.makeMinimalSchema()
        algMetadata = dafBase.PropertyList()
        config = CharacterizeImageTask.ConfigClass()
        config.psfIterations = 1
        if False:
            config.measurePsf.psfDeterminer.name = "pca"
        else:
            config.measurePsf.psfDeterminer.name = "psfex"
        charImageTask =
                                CharacterizeImageTask(None, config=config)
        config = SourceDetectionTask.ConfigClass()
        sourceDetectionTask =
                                SourceDetectionTask(schema=schema, config=config)
        sourceDeblendTask =
                                SourceDeblendTask(schema=schema)
        config = SingleFrameMeasurementTask.ConfigClass()
        config.slots.apFlux = 'base CircularApertureFlux 12 0'
        sourceMeasurementTask = SingleFrameMeasurementTask(schema=schema, config=config,
                                                            algMetadata=algMetadata)
```

LSST Pipelines



Process the data

```
In [7]: butler = dafPersist.Butler("/Volumes/RHLData/hsc-v13_0")
In [8]:
dataId = dict(visit=29352, ccd=50)
exposure = butler.get('calexp', dataId)
tab = afwTable.SourceTable.make(schema)
result = charImageTask.characterize(exposure)
psfCellSet = result.psfCellSet  # we'll look at this data structure later
result = sourceDetectionTask.run(tab, exposure)
sources = result.sources
sourceDeblendTask.run(exposure, sources)
sourceMeasurementTask.run(exposure, sources)
sources.writeFits("outputTable.fits")
exposure.writeFits("outputTable.fits")
```



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 - flat fielding etc.
 - source detection
 - astrometric/photometric calibration
 - PSF estimation
 - deblending
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 - flat fielding etc.
 - source detection
 - astrometric/photometric calibration
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 - measurement
- Relative calibration (photometric and astrometric) of all visits on the scale of the focal plane. We're currently using PanSTARRS catalogues, but will soon switch to Gaia (at least for astrometry, maybe photometry)



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refPSFImagePeakNorm BrighterFatterKernelNewAvIsolcatMatched

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(a) The difference ϵ_1 of ellipticity of stars and the average (b) The difference ϵ_2 of ellipticity of stars and the average star both with and without the correction. star both with and without the correction.

PSF Estimation



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- psfEx++?
- piff?
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- Wavefront-based estimation?



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- Wavefront-based estimation?
- Your Code?





Data





Model





Residual

















 e_1, e_2

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Processing Flow



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The PSF is discontinuous at CCD and field boundaries and wherever you've masked pixels, so we add up all the contributing PSFs for each object to define its personal PSF "coaddPsf" – I first heard this suggested by James Jee.



- Coadd source detection:
 - The primary detection is on the scale of the PSF resulting in a set of pixels — a Footprint. Each Footprint has one or more Peaks and these sets of Peaks define our objects.



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 - The primary detection is on the scale of the PSF resulting in a set of pixels — a Footprint. Each Footprint has one or more Peaks and these sets of Peaks define our objects.
- Association and deblending:
 - Synthesize a list of unique objects by merging Peaks from each band.
 - Output a list of uncharacterized deblended (*i.e.* isolated) 0bjects.

Deblender



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Processing Flow



- Object characterization on coadds: Measure Object properties such as:
 - centroids
 - adaptive moments
 - PSF and Kron/Petrosian fluxes
 - "fibre" aperture fluxes
 - simple "cmodel" galaxy models
 - "HSM" shapes

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- Forced Photometry:

Measure fluxes for every Object on every visit keeping all non-photometric parameters fixed



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- PSF match, then clip. But faint features still survive.
- Use a direct mean of the pixel values. But this allows the junk to leak into the coadd.
- Make use of the differences between images to remove the junk, then use a mean



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- Make a heavily clipped coadd
- Calculate a direct mean coadd
- Subtract the coadds
- Detect the junk (and cores of bright objects) on the difference
- Remove the junk that's in only one image (leaving the cores of bright objects)



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- Subtract the coadds
- Detect the junk (and cores of bright objects) on the difference
- Remove the junk that's in only one image (leaving the cores of bright objects)
- Calculate a direct mean of what's left, a "Safe Clipped Coadd"

PSF Matched Coadds



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- As Nick Kaiser pointed out in 2001 (PSDC-002-011-00), and Zackay, Ofek, and Gel-Yam recently rediscovered, you can build a coadd with optimal properties by down-weighting components that are suppressed by the images' PSFs, and then flattening the noise.
- We don't currently use these coadds for HSC (it's a bit complicated with a spatially varying PSF)

Safe-Clipping Coadds





PSF-matched Coadds





Does Clipping Really Matter?



Does Clipping Really Matter?



Courtesy Bob Armstrong σ Clipped



Does Clipping Really Matter?



Courtesy Bob Armstrong Mean



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"Take the code to the data"



For 20 years we've been saying that we should "take the code to the data"



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Unfortunately SQL isn't a very expressive language. Recently many people have realised the *Jupyter Notebooks* provide a way that people can really compute close to the data. I think it's time to move to the next phase:

Keep the Code with the Data



Get HSC calibrated exposure

```
In [5]: dataId = dict(tract=9348, patch='7,6', filter='HSC-I')
exp = butler.get('deepCoad_calexp',dataId)
display_image(exp.getMaskedImage().getImage().getArray(), figsize=(8,8));
```





Make cutout

```
In [6]: bbox = afwGeom.BoxXI()
bbox.include(afwGeom.Point2I(2700, 3600))
bbox.include(afwGeom.Point2I(3330, 4000))
exp_cutout = exp.Factory(exp, bbox, afwImage.LOCAL)
mi = exp_cutout.getMaskedImage()
mask = mi.getMask()
mask.removeAndClearMaskPlane('CR', True)
display image(mi.getImage().getArray());
```





Smooth at PSF scale

```
In [7]: psf = exp.getPsf()
sigma = psf.computeShape().getDeterminantRadius()
ngrow = int(3*sigma)
mi_smooth = smooth_gauss(mi, sigma)
print('psf fwhm = {:.2f} arcsec'.format(sigma*0.168*2.355))
```

```
psf fwhm = 0.52 arcsec
```

Image thresholding

+ Find high-threshold sources that are 6 σ above the background and create a mask plane

```
In [8]: high_thresh = 6
fpset_high = afwDetect.FootprintSet(
    mi_smooth, afwDetect.Threshold(high_thresh, afwDetect.Threshold.STDEV), 'HIGH_THRESH', 1)
fpset_high = afwDetect.FootprintSet(fpset_high, ngrow)
fpset_high.setMask(mask, 'HIGH_THRESH')
```

+ Find low-threshold sources that are 1.5 σ above the background and create a mask plane



Visualize segmentation maps

- · low-threshold footprints are purple
- · high-threshold footprints are yellow

```
In [10]: seg_high = fpset_high.insertIntoImage(True).getArray().copy().astype(float)
    seg_low = fpset_low.insertIntoImage(True).getArray().copy().astype(float)
    seg_low[seg_low=0] = np.nan
    seg_high[seg_high=0] = 1.0
    seg_high[seg_high=0] = np.nan
    ax = display_image(mi.getImage().getArray())
    kws = dict(cmap='plasma', vmin=0, vmax=1, origin='lower')
```

```
ax.imshow(seg_low*0.2, alpha=0.4, **kws)
ax.imshow(seg high*1.0, alpha=0.8, **kws);
```













