Transient Discovery using Image Differencing

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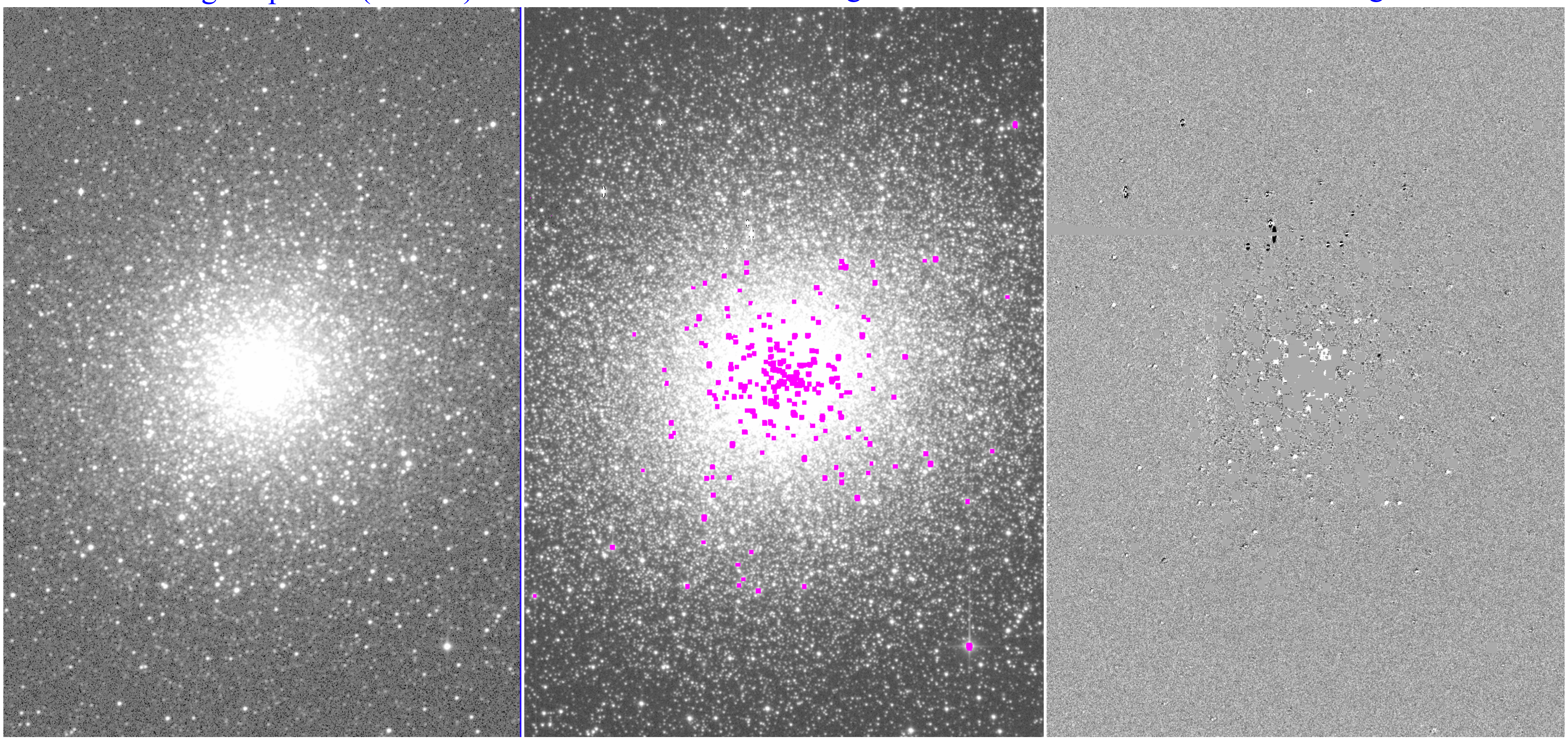
Definitions & Introduction

- **Image differencing**: discover transients by suppressing everything that's static in space and time
- **Transients:** any object that has varied in flux, or "suddenly" appeared or disappeared, or has moved (e.g., asteroid) in a new image exposure relative to some historical image (benchmark image)
- New exposure image: **"science image"** or simply **"new image"**
- Historical (benchmark) image: **"reference image"**
  - a stack (co-add) of several or more high-quality historical science exposures
  - has higher signal-to-noise ratio than a single exposure image

E.g., M13 globular cluster

- **Enormous benefit:** image-differencing suppresses regions with high-source confusion
- Improves ability to discover flux variables and transients

Science image exposure (R-filter) – Reference image = Difference image

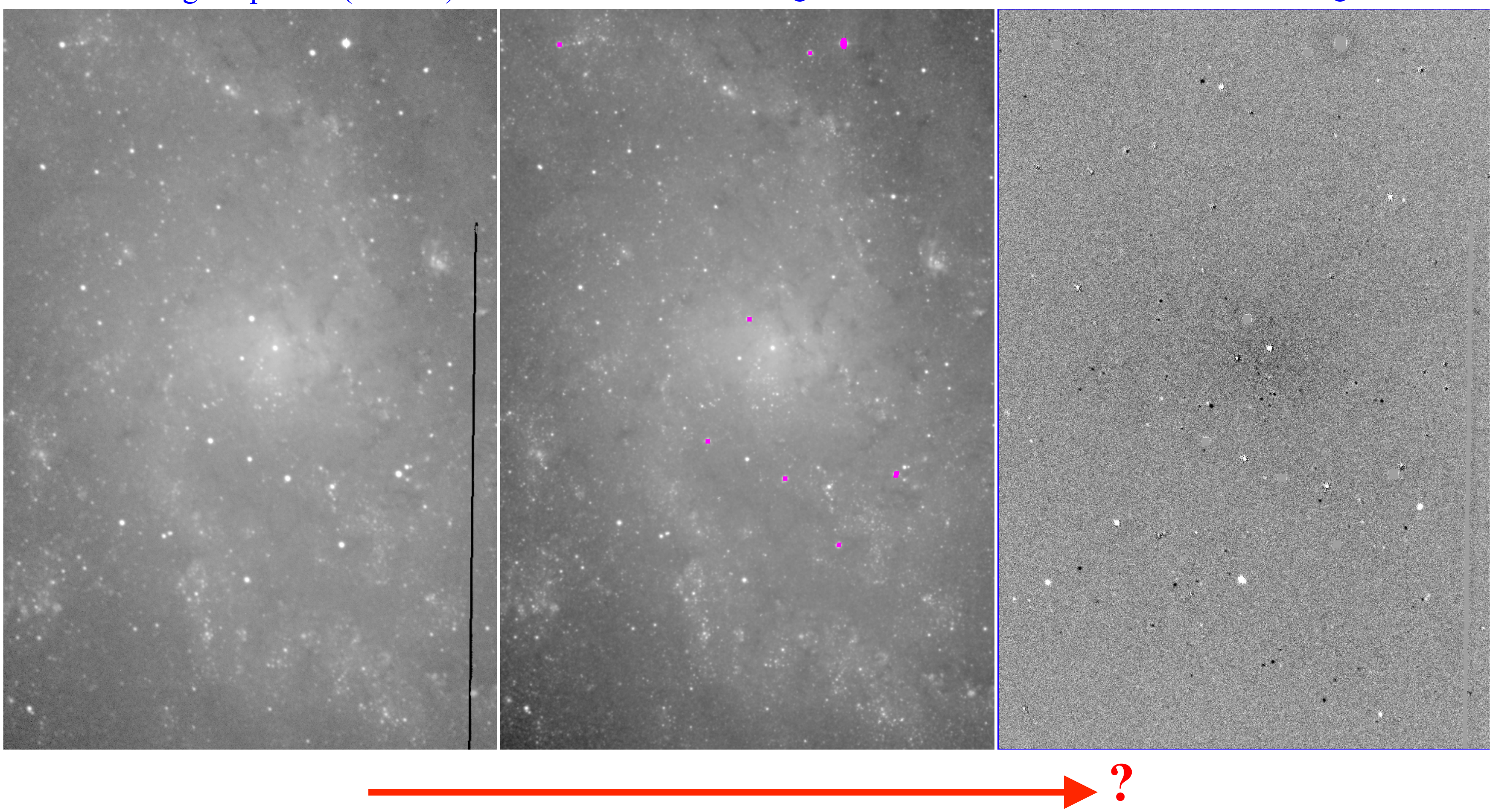


- Bad / saturated pixel regions: colored magenta (zeroed in difference)

E.g., M33 galaxy core

- **Another benefit:** image-differencing suppresses regions with complex backgrounds and emission: enhancing discovery potential, but also photometric accuracy of transient / variable candidates

Science image exposure (R-filter) – Reference image = Difference image



Software and methods (incomplete synopsis)

- At least four different methods exist: slightly differ in what is being optimized in the end: PSF-matching between *sci* and *ref* images and/or transient point-source detection in final difference

~ similar algorithms

- Alard & Lupton (1998); Alard (2000): **ISIS** package
- Woźniak (2000): **DIAPL** package
- Becker (2012): **HOTPANTS**: **H**igh **O**rder **T**ransform of **P**SF **AN**d **T**emplate **S**ubtraction
- Yuan & Akerlof (2008): package may exist (Robert Quimby)?

- Bramich et al. (2008, 2016): **DANDIA**

- Zackay, Ofek, Gal-Yam (2016): **ZOGY** (the next generation!)

- Masci et al. (2016): **PTFIDE:** PTF Image Differencing & Extraction
  - designed specifically for PTF / iPTF at IPAC, Caltech
  - complements other image-differencing software currently running at NERSC (HOTPANTS)
  - an extension of the method presented in Bramich (2008)

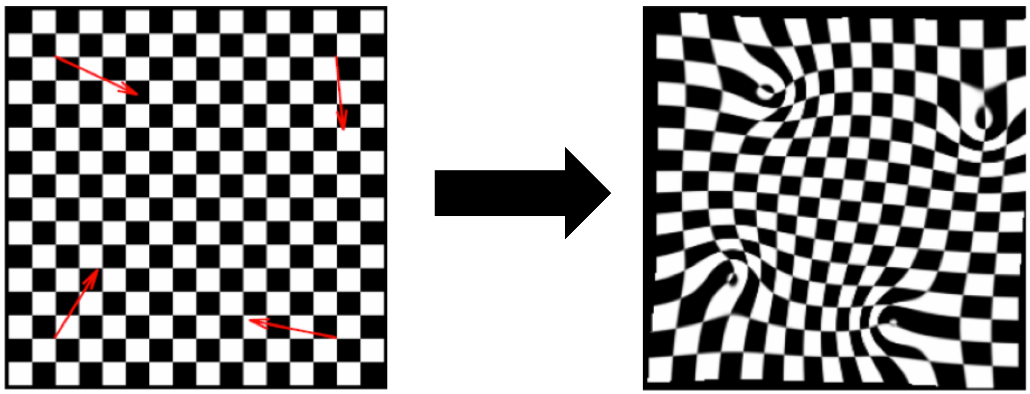
Basic processing steps in PTFIDE

1. **INPUTS:** science image; reference image (both astrometrically and photometrically calibrated); processing parameters
2. Throughput (gain) matching of input images: use either extracted relative source photometry or photometric zeropoints
3. Reproject and resample reference image onto science image frame using refined astrometric solutions
4. Match spatially varying backgrounds on large scales
5. Derive Point Spread Functions for science image and reprojected/resampled reference image
6. Derive spatially dependent PSF-matching Convolution kernel
7. Apply PSF-matching kernel to match PSF shapes in input images
8. Compute difference image with accompanying uncertainty & mask images
9. Extract transient candidates with photometry
10. Quality assurance metrics on difference image and individual extracted transient candidates
11. Machine-learned and human vetting (not in PTFIDE software)

Reference image to science frame reprojection

- Reference image is "warped" (and resampled) onto science image grid using science image distortion polynomial
- Camera (field-of-view) distortion is calibrated upstream as part of astrometric calibration

ref image grid



sci image grid

- Astrometric / distortion calibration of input science image is crucial!
- If wrong (even slightly), astrometry of reprojected reference image will also be wrong and residuals will result in difference image (more later)

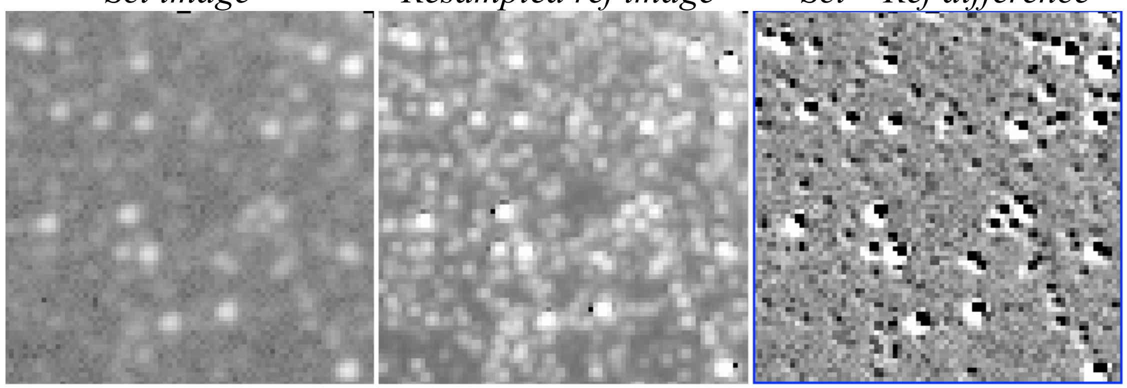
Example difference after *ref* to *sci* reprojection

PTFIDE also refines the astrometry of input science image (relative to the reference image)

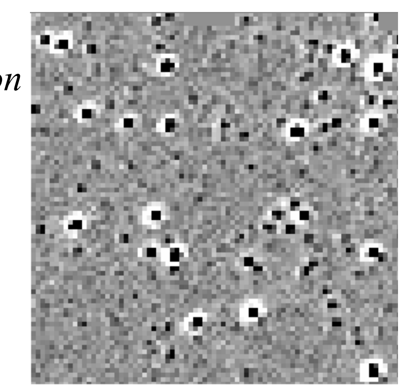
- ➢ only applies constant global Δx, Δy corrections to *sci* image pointing before *ref* reprojection

Sci image | *Resampled ref image* | *Sci – Ref difference*

zoom on M13
cluster field



with Δx, Δy correction

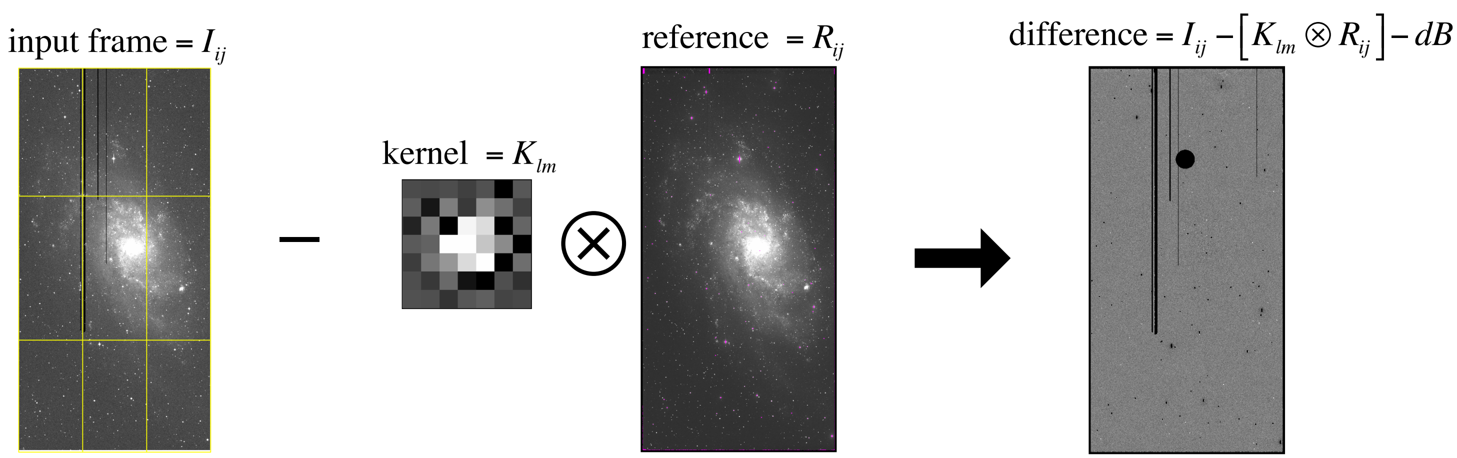


Generic PSF-matching model

- **Goal:** match the seeing profiles in the (resampled) *ref* and (gain-matched) *sci* images
- We assume the science image I can be modeled from a higher S/N, better "seeing" reference image R, a PSF-matching convolution kernel K, differential background dB, and noise term:

$$I_{ij} = \left[K(u,v) \otimes R_{ij} \right] + dB + \varepsilon_{ij}$$

- **Unknowns:** PSF-matching kernel $K(u,v)$ to convolve with better seeing image, and dB



(single chip with **M33**)

- Since seeing is a slow-varying function of position, solve for PSF-matching kernel over a 3 x 3 grid

Derivation of PSF-matching kernel

- PSF-matching entails finding an optimum convolution kernel K by minimizing some cost function, e.g., chi-square:

$$\chi^2 = \sum_{i,j}\left[\frac{I_{ij} - M_{ij}}{\sigma_{ij}}\right]^2 \equiv (I - M)^T \Omega_{\text{cov}}^{-1} (I - M)$$

where M is the "model" image: $$M_{ij} = \left[K(u,v) \otimes R_{ij}\right] + dB$$

- We discretize the kernel $K(u,v)$ into a 9 x 9 pixel image (a 2D array of delta functions) and then estimate the 81 pixel values therein (coefficients K_{lm}):

$$K(u,v) = K_{lm}\delta(u-l)\delta(v-m)$$

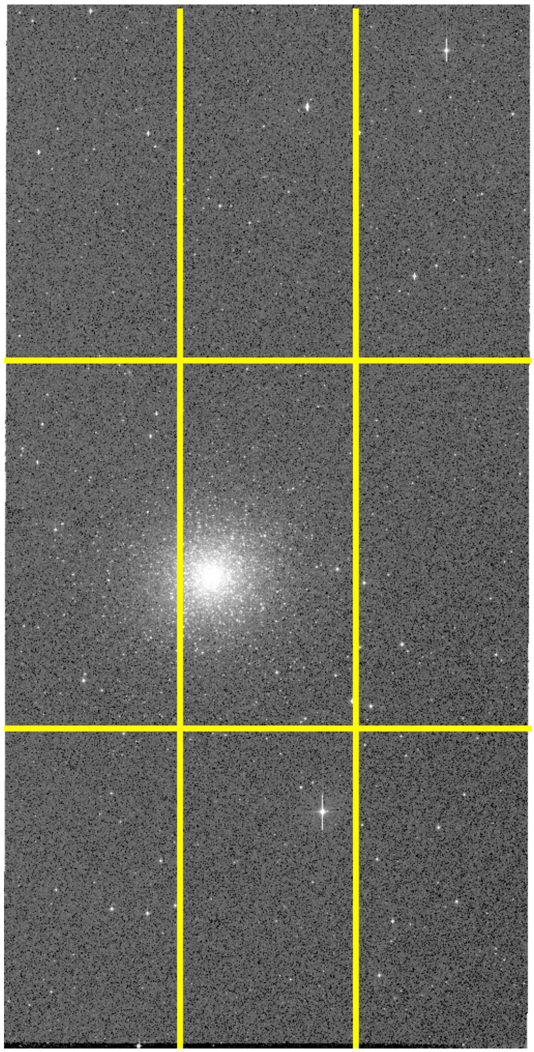
- Model image can then be written:

$$M_{ij} = dB + \sum_l \sum_m K_{lm} R_{(i+l)(j+m)}$$

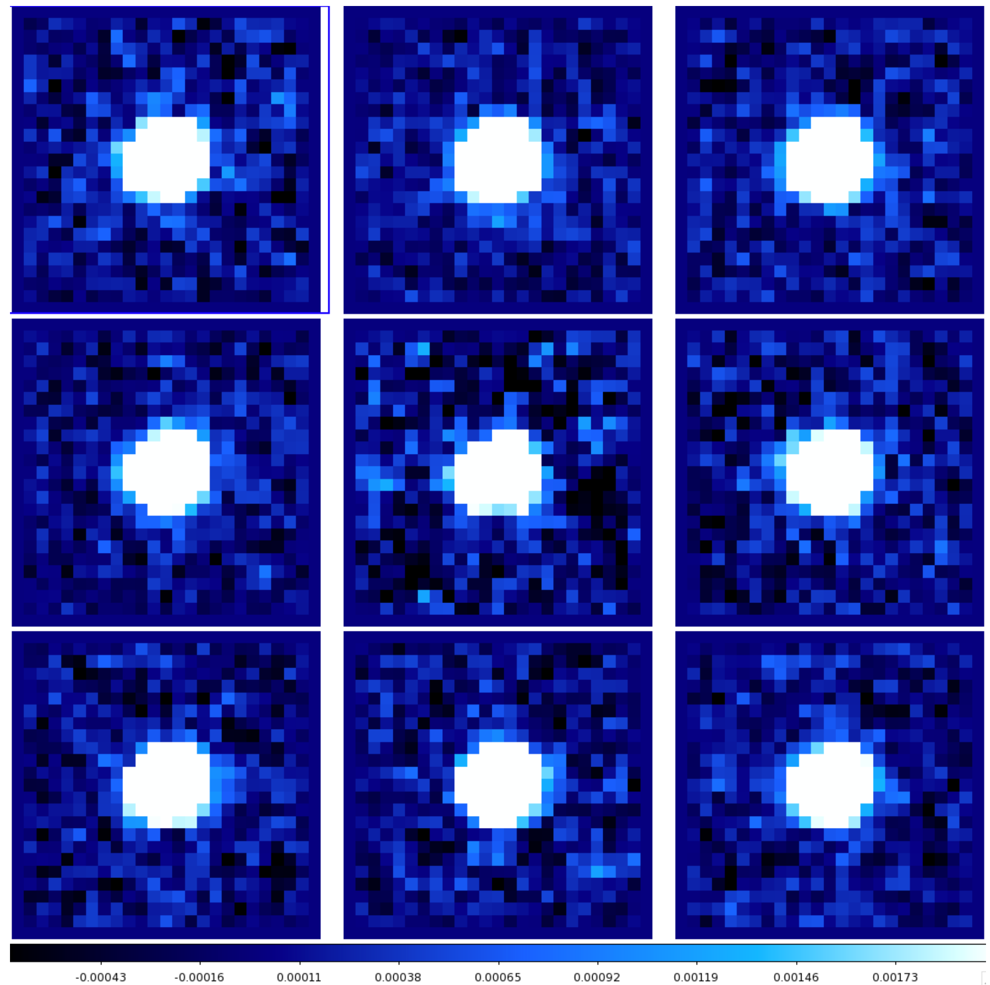
- Solve for the coefficients K_{lm} using linear-least squares.

Input PSF-images from *sci-image* for deriving PSF-matching kernel

science *image exposure with M13*

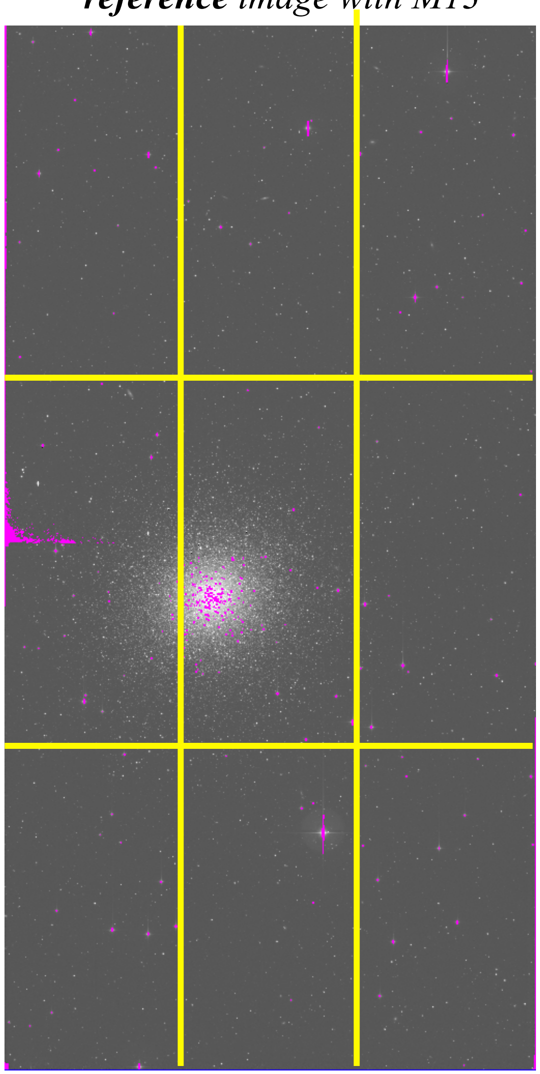


PSFs over ***sci-image*** *partitions*

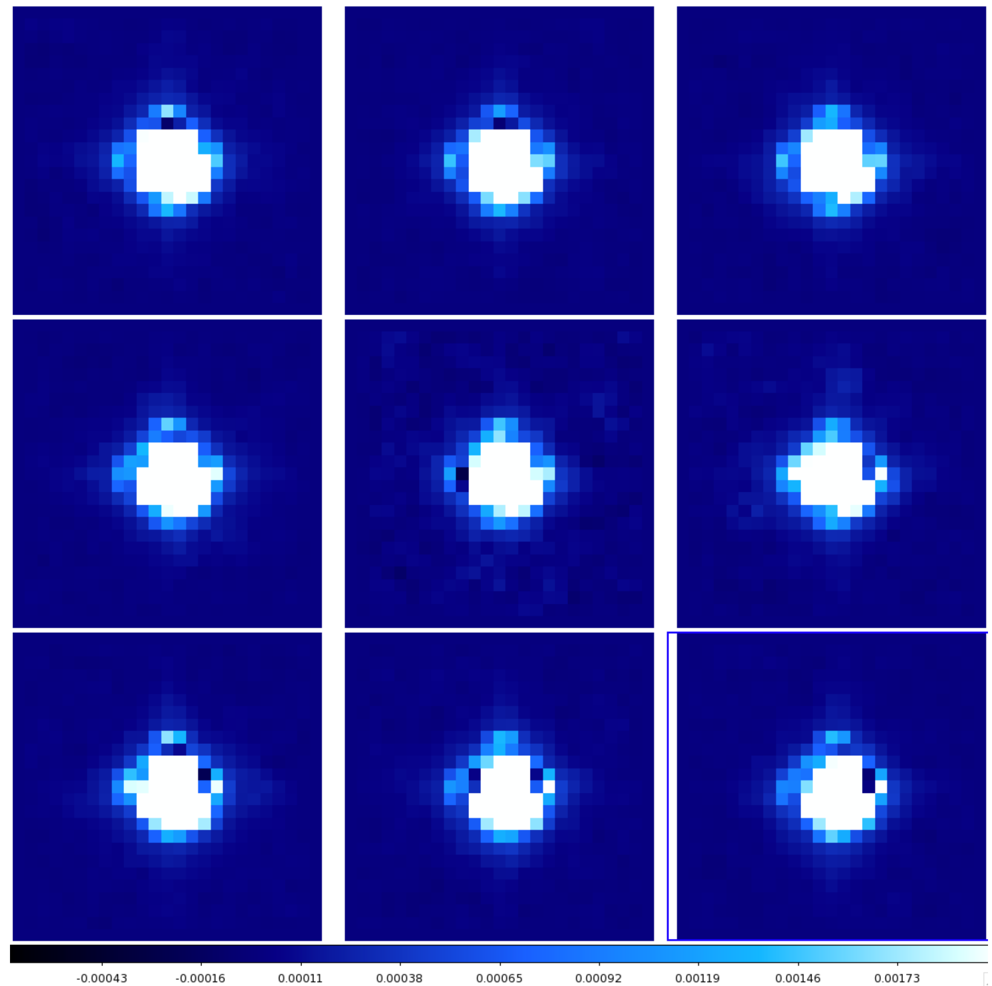


Input PSF-images from *ref-image* for deriving PSF-matching kernel

reference *image with M13*

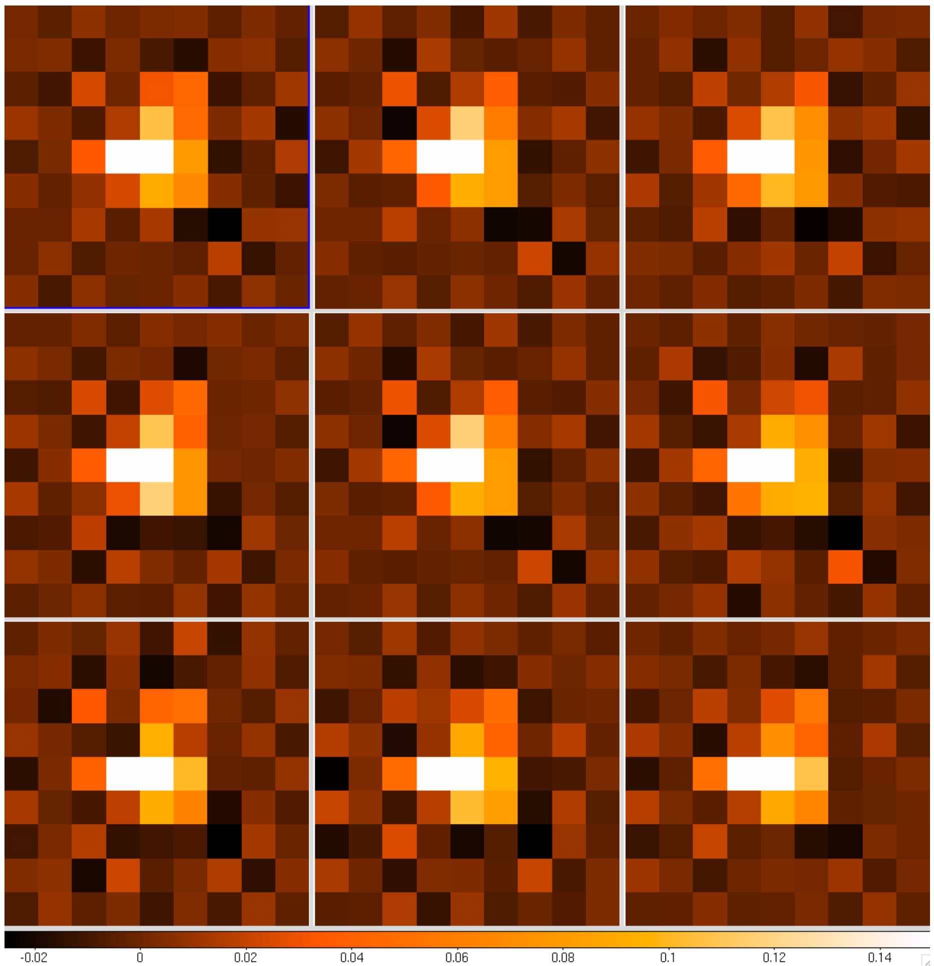


PSFs over ***ref-image*** *partitions*



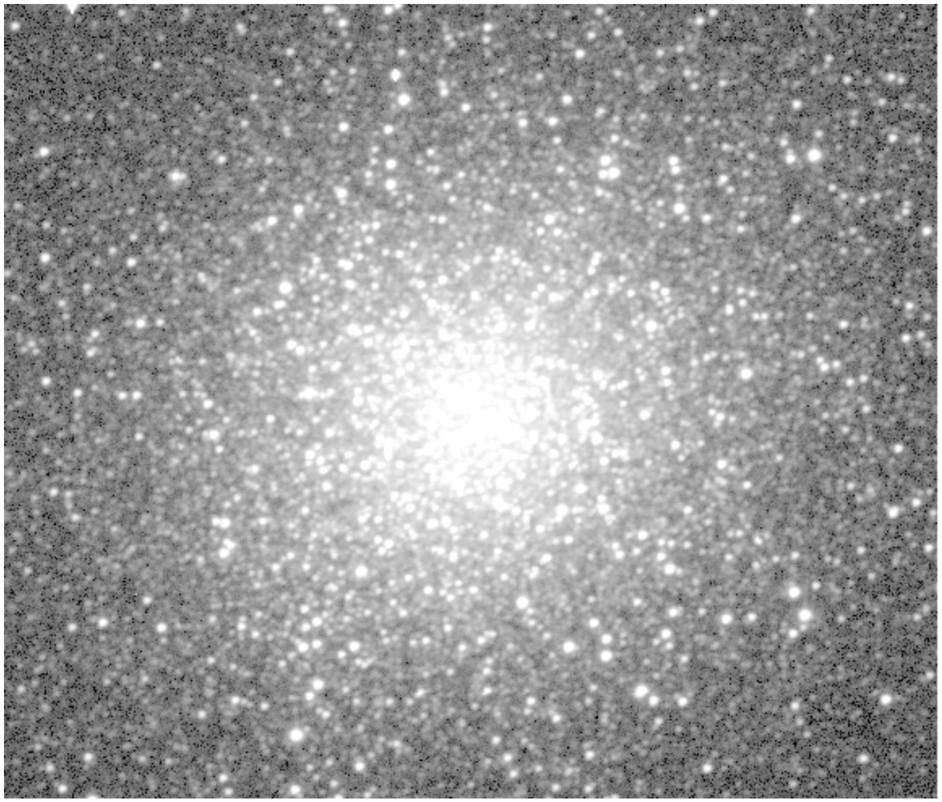
Final solutions for PSF-matching kernels

Convolution kernels for the 9 image partitions to match the *sci* and *ref* image PSFs for the M13 test case

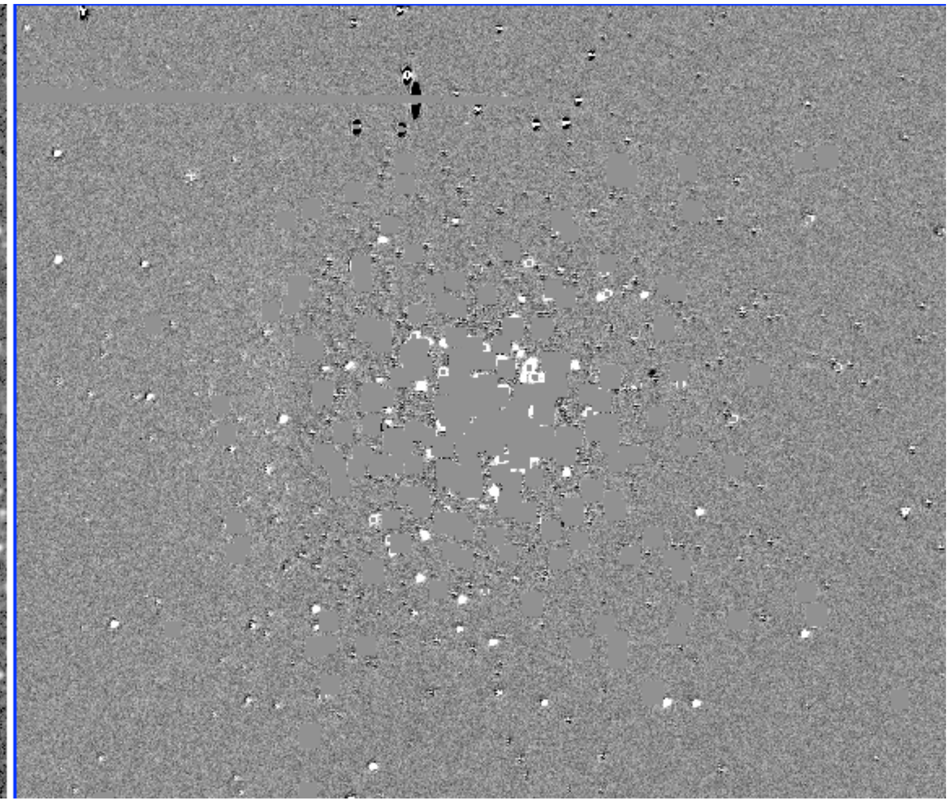


Final difference image:
zoom on M13 globular cluster

science image exposure (~ 9' x 9' *zoom*)



sci – *K* (x) *ref difference image*



Lots of RR-Lyrae variables!

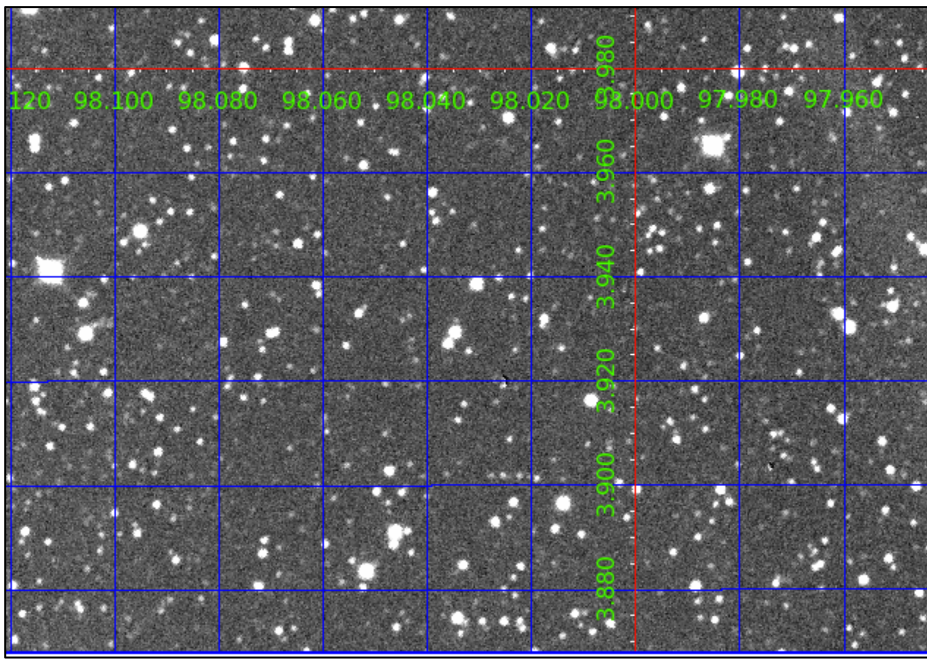
For an animation of this field across multiple epochs, see:
http://web.ipac.caltech.edu/staff/fmasci/home/idemovies/d4335ccd8f2movie.html

“Good” difference in Galactic Plane

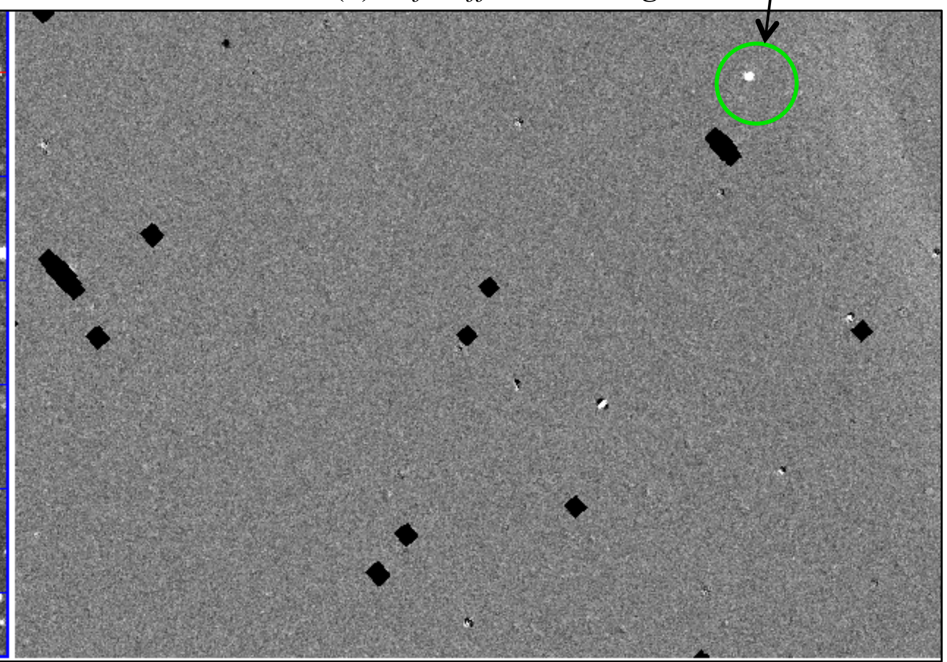
When upstream astrometric/distortion calibration is near perfect, it works!

known variable

science image exposure (~ 10’ x 7’ *zoom*)



Sci – K (x) *Ref difference image*

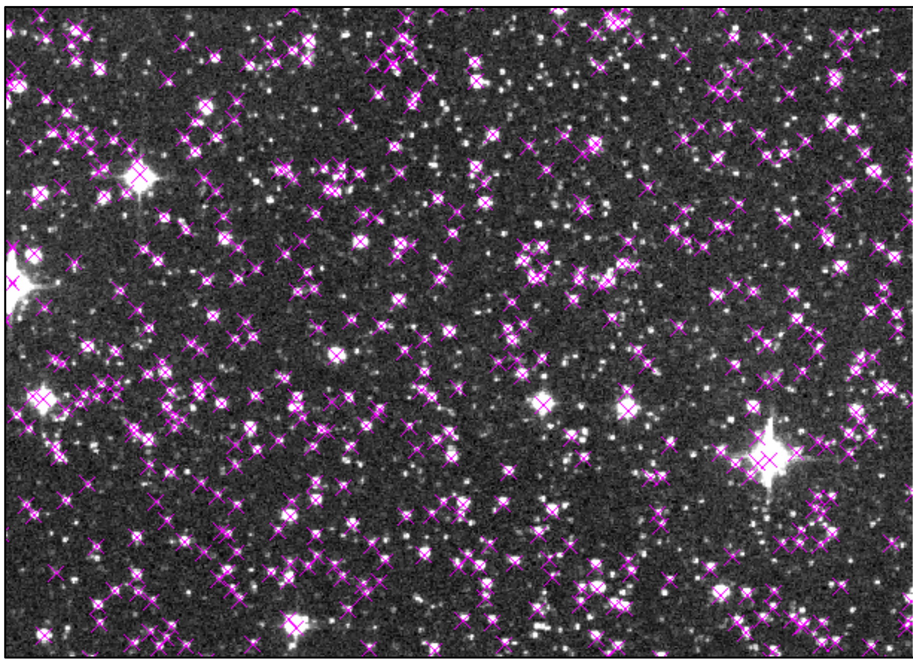


coordinate grid is galactic

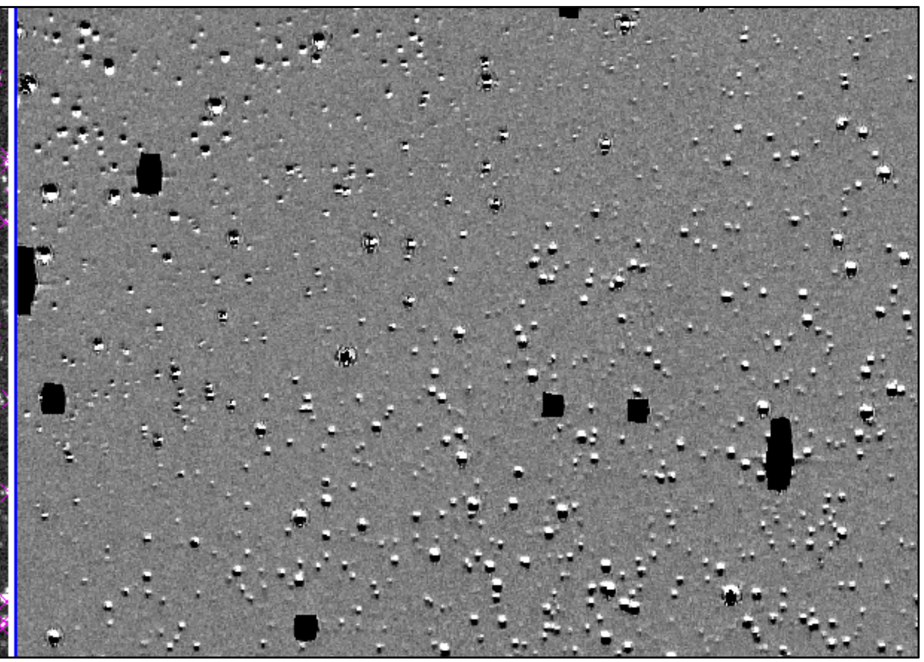
When things go wrong:
e.g. “bad” difference in Galactic Plane

When upstream astrometric / distortion calibration is “slightly” wrong (even 1-pixel from image edge-to-edge!)

science image exposure (~ 12’ x 8’ *zoom*)



Sci – K (x) *Ref difference image*



magenta crosses: 2MASS positions

Candidate extraction and photometry

- Candidate transients are detected on difference images and their fluxes measured using both PSF-fitting and aperture photometry

- Difference-image photometry provides “AC photometry” or “relative photometry”.

- Absolute photometry for lightcurve generation is sometimes referred to as “DC photometry”, e.g., if have a variable star with a time-average reference baseline flux f_{ref} , then:

$$mag_{DC} = ZP - 2.5\log_{10}\left[f_{AC} + f_{ref}\right]$$

- Where fluxes f_{AC} and f_{ref} pertain to the same photometric zeropoint (ZP)

Summary

- Image differencing using ground-based image data is hard!

- Must first perform all instrumental calibrations as accurately as possible, particularly astrometry.

- Matching PSFs across images is a challenge. Is PSF-matching the right thing to do?
  - ➢ thought: design the instrumentation/hardware to optimize transient discovery instead of implementing or adapting software to work on existing facilities

- Goals:

  -- minimize image artifacts (subtraction residuals)

  -- maximize completeness according to survey strategy

  -- maximize Signal-to-Noise ratio of real transients

- PTFIDE has evolved considerably: benefited from lots of eyes on the science products

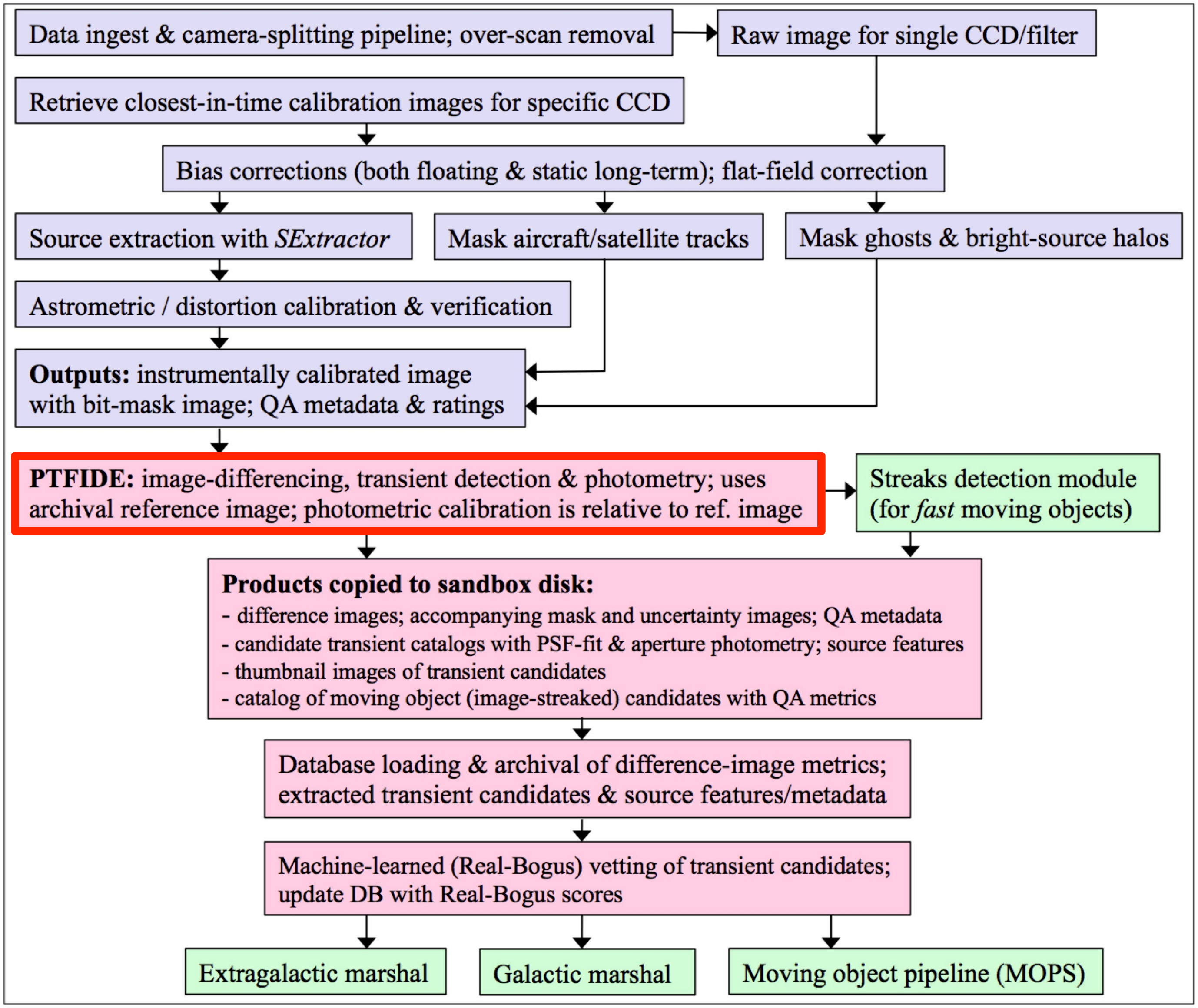
Further reading

- More details on the method used in PTFIDE:
  Masci et al., 2016, to appear in PASP, preview
  http://web.ipac.caltech.edu/staff/fmasci/home/masci_ptfide.pdf

- Different method based on optimizing transient detection in a difference image directly (which is the ultimate goal!):
  Zackay, Ofek, & Gal-Yam (the "ZOGY" method), 2016, submitted to ApJ
  http://arxiv.org/pdf/1601.02655v2.pdf

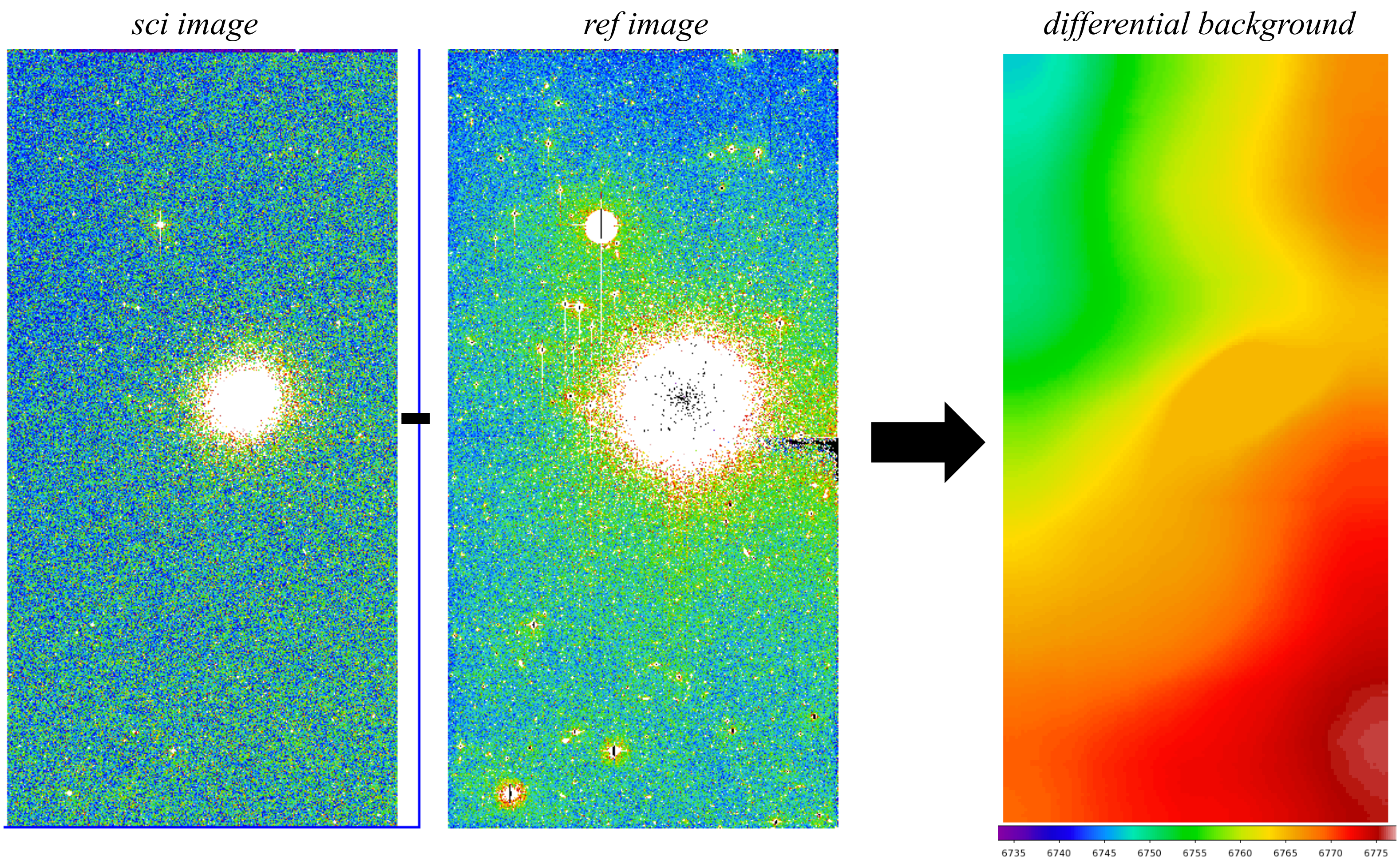
Back up slides

The bigger picture:
"real-time" pipeline at IPAC/Caltech

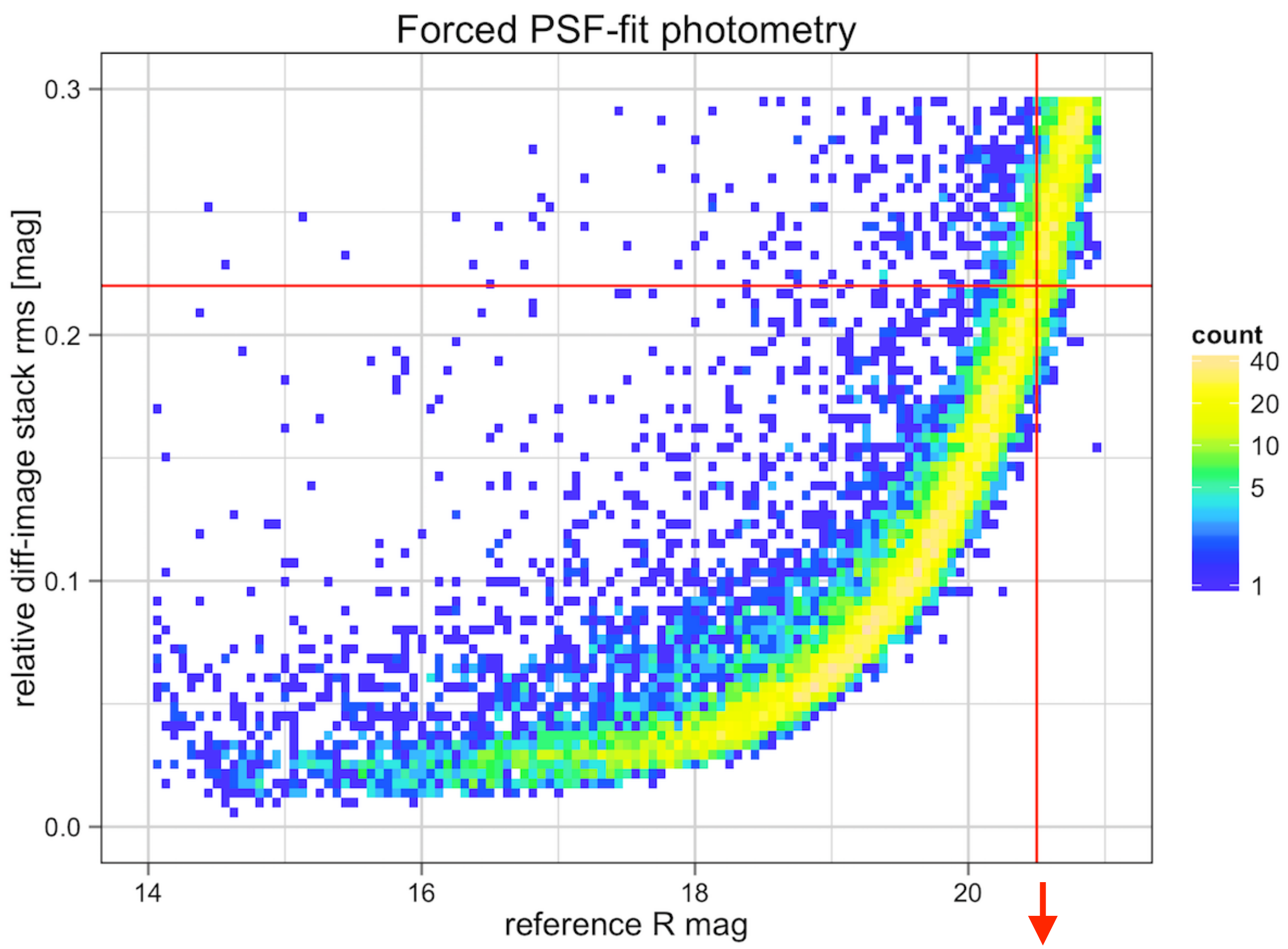


Pre-conditioning step
(prior to PSF-matching)

- Compute low-pass filtered, smoothly-varying differential background and correct science image to match reference image background: $sci_{new} = sci_{old} - \langle sci_{old} - ref_{resampled} \rangle_{filt}$
- Helps improve photometric accuracy on difference images later



Photometric sensitivity in PTFIDE
PSF-fit photometry on diff. images



5σ limit ~ 20.5 mag

Machine-learned candidate classification: real or bogus?

- **Definitions:**
  RB = Real or Bogus candidate, above some probability threshold
  FPR = False Positive Rate: fraction of bogus transients incorrectly classified as real (max tolerable = 1%)
  FNR = False Negative Rate: fraction of real transients incorrectly classified as bogus

Performance analysis as of ~ May 2015 (Umaa Rebbapragada & Gary Doran, JPL):

- **Measure FNR at 1% FPR**
- **NERSC:**
  - **RB2: 7.7% (Brink et al. 2012)**
  - **RB4: 17.0%, RB2 had 42% on same set**
  - **RB5: 5% (LANL)**
- **PTFIDE:**
  - **3%**

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