State of the Art in Difference Imaging & Lessons Learned from Pan-STARRS

Eugene Magnier
Pan-STARRS / IfA
Typical Transient / Asteroid Analysis Pipeline

detrend
Typical Transient / Asteroid Analysis Pipeline

detrend → warp
Typical Transient / Asteroid Analysis Pipeline

detrend

warp

PSF match & subtract
Typical Transient / Asteroid Analysis Pipeline

- detrend
- warp
- PSF match & subtract
- cosmic ray
- garbage rejection
Typical Transient / Asteroid Analysis Pipeline

detrend → warp → PSF match & subtract → cosmic ray → garbage rejection → identification & classification → exciting object
Typical Transient / Asteroid Analysis Pipeline

1. Detrend
2. Warp
3. PSF match & subtract
4. Garbage rejection (cosmic ray)
5. Identification & classification (exciting object)
6. Follow-up observations
Typical Transient / Asteroid Analysis Pipeline

1. **Detrend**
   - Initial data with multiple points

2. **Warp**
   - Process to align data

3. **PSF Match & Subtract**
   - Remove background light using Point Spread Function

4. **Garbage Rejection**
   - Remove cosmic rays and noise

5. **Exciting Object!**
   - Identified as an interesting phenomenon

6. **Identification & Classification**
   - Further analysis to confirm findings

7. **Follow-up Observations**
   - Additional observations to verify finding

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*Image credit: Magnier - Rubin Algorithms Workshop - 2020.03.17*
Typical Transient / Asteroid Analysis Pipeline

- detrend
- warp
- PSF match & subtract
- cosmic ray
- garbage rejection
- exciting object!
- identification & classification
- follow-up observations
Image Difference Algorithm History

- 1990 : Ciardullo et al 1990 discussed early implementation
- 1995 : Phillips & Davis : fourier-space calculation of kernel
- 1996 : Tomaney & Crotts : fourier-space kernel
- 1998 : Alard & Lupton : real-space kernels (Gaussians * polynomials)
- 2008 : Bramich : pixel kernel basis function
- 2008 : Miller et al : pixel kernel basis function
- 2008 : Yuan & Akerlof : A/L-style cross-convolution
- 2016 : Zackay et al : fourier-space cross-convolution & noise whitening
- 2017 : Reiss & Lupton : real-space A/L with ZOGY-style whitening
- 2017 : Sedaghat & Mahabal : CNN implementation
Pre-History

- 1990 - Ciardullo et al: mentioned early implementation
- 1995 - Phillips & Davis: describe fourier-space calculation of kernel
- 1996 - Tomaney & Crotts: use fourier-space kernel for microlensing

\[ I = R \otimes k \]

\[ \tilde{I} = \tilde{R} \times \tilde{k} \]

- measure \( k \) on bright, isolated star(s)
- apply to reference image
- suppress noisy high-frequency modes with Gaussian fit

\[ \tilde{k} = \frac{\tilde{I}}{\tilde{R}} \]
Optimal Image Subtraction

- 1998: Alard & Lupton: kernel built from Gaussians

\[ I = R \otimes k \]

Fit for kernel in real space

\[ k = \sum_{n, i, j} a_n u^n v^j e^{-(u^2 + v^2) / 2\sigma^2_n} \]

- measure \( k \) on all / many star(s)
- apply to reference image
- coefficients can vary in 2D to follow PSF variations
- HOTPANTS (Becker 2015) perhaps most popular

Many papers on the implementation details:

- Israel et al 2006
- Becker et al 2012
- etc..
Pixel Basis Function

- 2008: Bramich
- 2008: Miller et al

\[ I = R \otimes k \]

Fit for kernel in real space

\[ k = \sum_{n} a_n \delta_n(u, v) \]

- measure \( k \) on bright star(s)
- apply to reference image
- coefficients can vary in 2D to follow PSF variations
Cross-convolution

- 2008: Yuan & Akerlof: A/L-style cross-convolution

\[ R \otimes k_R = I \otimes k_I \]
\[ D = R \otimes k_R - I \otimes k_I \]
\[ Q = \sum D^2 + \lambda \sum (u^2 + v^2)^2 \left[ k_R^2 + k_I^2 \right] \]

- measure \( k \) on all / many star(s)
- apply to reference image
- coefficients can vary in 2D to follow PSF variations
- target & reference can both be 'larger'
Back to the Fourier?

- 2016: Zackay et al (ZOGY): Fourier-space cross-convolution & noise whitening

\[ R \otimes k_R = I \otimes k_I \]

\[ \tilde{D} = \frac{\tilde{P}_I \tilde{R} - \tilde{P}_R \tilde{I}}{\sqrt{\sigma_R^2 |\tilde{P}_I|^2 + \sigma_I^2 |\tilde{P}_R|^2}} \]

- \( D \otimes P_D \) is defined as optimal matched filter
- noise whitening removes pixel correlations
- Reiss & Lupton 2017 describe real-space version
Machine Learning to the Rescue

- 2017: Sedaghat & Mahabal: Convolutional NN implementation
Typical Transient / Asteroid Analysis Pipeline

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2. **Warp**
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4. **Garbage rejection**
   - **Cosmic ray**
5. **Identification & classification**
   - **Exciting object!**
6. **Follow-up observations**
Garbage Rejection: Typical Sources

- cross-talk
- glows
- persistence
- non-linearity
- ghosts
- glints
- diffraction spikes
- vignetting changes
- cosmic rays
- dipoles
- variance mis-estimation
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Garbage Rejection: Pan-STARRS Asteroid Science

- Statistics used in Pan-STARRS IPP -> MOPS cuts
  - second moments (Mxx, Myy)
  - flux & S/N in both positive and negative images
  - number of masked & unmasked pixels in diff image
  - positive and negative pixel values in diff image
- Cuts based on collection of false positives, known asteroids
  - Reduce false positive by 70% - 90%
- Raw false positive rate is > 99% - 99.9%
  - *we rely heavily on human vetting for asteroids*
  - ~20,000 - 40,000 detections vetted *per night*
Garbage Rejection: Pan-STARRS Transient Science

- Initial cut based on source statistics
- Machine learning classifier(s) on pixels
  - Wright et al 2015: Medium-Deep field data
    - compared NNet, Random Forest, SVM
    - settled on Random Forest based on tests
      - Purity: 99%, Missed Detection Rate: 6.2%
  - Wright et al 2017: individual exposures
    - Convolutional NNet for initial classification
      - Purity: 42%, Missed Detection Rate: < 1%
    - Human vetting by Supernova Hunters
      - ~20,000 - 30,000 classifications of ~6000 detections per week
    - Final selection based on combined score
Sanchez et al 2019: Comparison of techniques

- circles: real data
- horizontal lines: results pre-ML classification
- whiskers: ranges for simulation results with ML classifications

[Diagram with box plots and annotations]

Classification & Follow-up

Near-Earth Asteroid Discoveries by Survey
~140m and larger NEAs (as of 2020-Mar-13)

Number Discovered

Discovery Date

https://cneos.jpl.nasa.gov/stats/

Alan Chamberlin (JPL/Caltech)
Classification & Follow-up

- **PS1 Supernovae**
- **All Supernovae**

![Bar chart showing the number of supernovae discovered from 2010 to 2020, with a significant increase in the late 2010s.](chart.png)
Classification & Follow-up

![Graph showing SN Alerts in 2019 vs Maximum Magnitude for different surveys: ZTF, PS1, ATLAS, ALeRCE, and Gaia. The graph displays the number of alerts for each survey at different magnitude levels.](image-url)
Classification & Follow-up

![Graph showing SN classifications in 2019 for different telescopes: ZTF (1143), PS1 (85), ATLAS (483).]
Conclusions & Lessons Learned

- Template quality matters a lot
- Image differencing is sensitive to tuning
- Cross-convolution was critical for
  - warp-warp subtractions
  - improving image quality vs infrequent template updates
- Mask / eliminate artefacts as much as possible
- Machine learning is helping but human vetting is still needed
- Triage targets for science follow-up