Difference Imaging in Wide Field Surveys

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Outline

1. What is difference imaging and why do we want to use it?
2. How to implement a spatially varying numerical kernel
3. How to implement difference imaging on a GPU
4. Large Images

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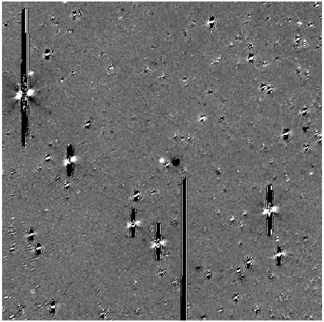
What is difference imaging?

- method to detect transient events (including microlensing)
- method to get quality time series photometry of transient events (and variable stars)



MOA implementation

- MOA camera: $10 \times 2048 \times 4096$ CCD mosaic
- Exposure time: 60 secs (for Bulge fields) – generate difference images for all frames in an exposure
  – get positions of possible transients
  – generate "quicklook" photometry for all transients in the list
- All done in real time, i.e before the next exposure finishes
- This approached has worked well for MOA

New Generation Wide Field Surveys

Can we do the same for new generation surveys

- KMT
  - Camera: $4 \times 9\mathrm{K} \times 9\mathrm{K}$
- LSST
  - Camera: $189 \times 4\mathrm{K} \times 4\mathrm{K}$

Important issues

- Can difference imaging be done fast enough for real-time?
- Can it work on large images

Principles of Difference Imaging

- Given two images, r and i, of the same field taken at different times, one constructs a difference image by

$$d(x, y) = i(x, y) - (r * k)(x, y) - b(x, y)$$

- Solve for the “convolution kernel”, k, and the differential background, b
- Both k and b are spatially varying
  – major issue for large images!

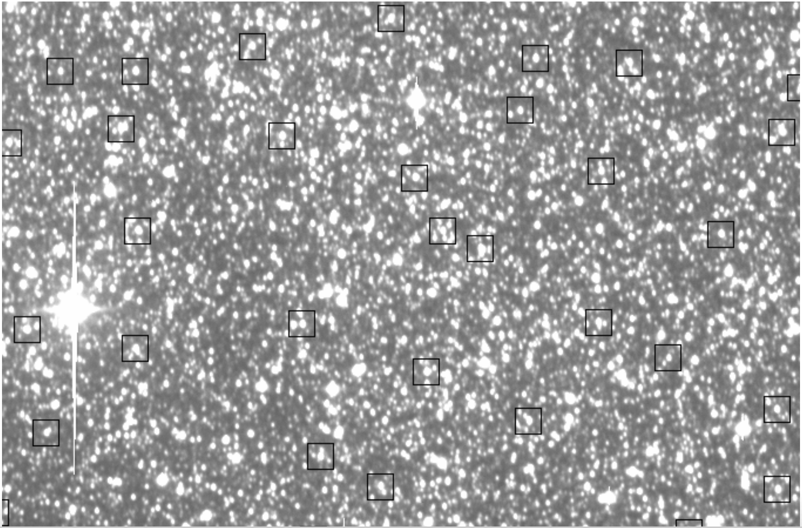
Classic Method

- Model kernel as a linear combination of smooth analytic basis functions (Alard &Lupton 1998)
- Model spatial variation of kernel by 2D polynomial (applied to each coefficient)
- Model background as 2D polynomial

Numerical trick by Alard (1999)

- Kernel is constant on over its own size
- Select a number of “stamps” across the image
- Build zero order matrices for each stamp
- Expand into linear system for the whole image by combining zero order linear systems for each stamp with the basis functions for the spatial variations

Stamps



Classic Method

- Size of the linear system:
  $N = 1 + (N_{\mathrm{k}} - 1)N_{\mathrm{s}} + N_{\mathrm{b}}$
- Typically
  $N_{\mathrm{k}} = 49$ (kernel basis functions)
  $N_{\mathrm{s}} = 6$ (functions to model spatial variations in k
  $N_{\mathrm{b}} = 6$ (functions to model background)
  $N = 295$
- All takes <10 seconds on a modern PC for a single 2K $\times$ 4K image
  – Fast enough? Maybe.

Numerical Kernel

- Treat kernel as a numerical table and solve for each entry (Bramich 2008)
- Used extensively for follow-up observations (small telescopes, small CCDs)
  – weird kernel shapes, not necessary to interpolate (Albrow 2009)
- More computationally expensive than the classic method
- Can we use the numerical kernel for wide field surveys?
  – Need to allow for for spatially varying kernel
  – Need a reasonable computation time

Outline

Spatially varying numerical kernel

- A spatially varying numerical kernel can be implemented using the principles of the classic method
- The basis function set is just a grid of delta functions.
- Modify slightly to apply flux conservation rule:

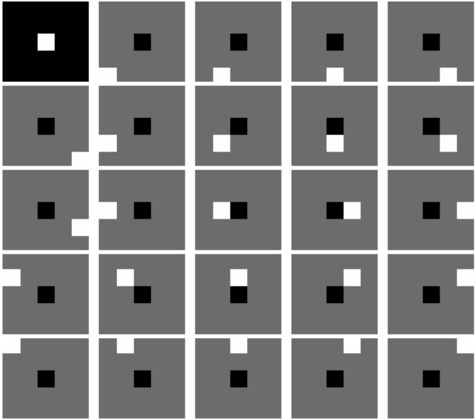
$$k(x, y) = c_0\delta(x, y) + \sum_n c_i \left[\delta(x - j, y - i) - \delta(x, y)\right]$$

  The c_i are spatially dependent (modelled using 2d polynomial set), but the photometric scaling is always given by c_0
- Also include background

$$b(x, y) = \sum_n c_n x^i y^j$$

Spatially varying numerical kernel

A numerical 5×5 kernel basis set



Linear system becomes largel

- For a 17×17 numerical kernel, we need to build a 289×289 zero order matrix for each stamp
- Degree 2 polynomial for spatial variations in the kernel (6 basis functions)
- Degree 2 polynomial for background (6 basis functions)
- Total size of linear system $N = 1 + 288 \times 6 + 6 = 1735$

Can we speed things up?

Outline

NVIDIA GeForce GTX 480

Programming a GPU

GPU architecture supports Single Instruction Multiple Thread programming model

- executes instruction for all threads in the warp, before moving onto next instruction
- divergence occurs when threads in a warp follow different control flows. Sequential passes are then needed which can affect performance
- but SIMT approach is ideal for most image processing operations

Examples

- Zero order matrices

$$Q_{sij} = \sum_{(x,y)\epsilon S_s} [r(x - x_i, y - y_i) r(x - x_j, y - y_j) - r(x,y) r(x,y)]$$

each thread works on its own s, i, j

- Expanding zero order matrices

$$M_{ij} = \sum_{\text{stamps}} F(s, s_i) F(s, s_j) Q(s, k_i, k_j)$$

one thread per i and j

- Convolution

$$(r * k)(x, y) = \sum_{(x_k, y_k)} r(x_k, y_k) k(t, x_i, y_i)$$

one thread per pixel x, y (t is “tile” index)

Performance

2 K $\times$ 4 K image
17 $\times$ 17 spatially variable numerical kernel

	CPU	GPU
Build zero order system	30 secs	2 secs
Expand over stamps	6 secs	72 ms
Solve linear system	10 secs	10 secs
Build difference image	5 secs	91 ms

Outline

Dealing with large images

Work in progress

- For large images, 2nd order polynomials may not be be able to model high frequency spatial variations in the kernel and background
- One approach is to divide image into tiles and solve separately for each.
- May have issues with continuity across the tile boundaries
- Can we force continuity conditions on the polynomial models?

Hermite polynomials

- Form a set of 16 2D polynomials, $h_{ij}(u, v) = h_i(u)h_j(v)$ from the 1D Hermite blending functions
  $h_1(u) = 1 - 3u^2 + 2u^3$
  $h_2(u) = u - 2u^2 + u^3$
  $h_3(u) = 3u^2 - 2u^3$
  $h_4(u) = -u^2 + u^3$
  where $u = (x - x_i)/w$, $v = (y - y_i)/w$ for tile i
- each tile has its own 16 2D polynomial set
- but coefficients are shared at each node of the tile

Hermite polynomials

- for any arbitrary set of coefficients, the resulting surface satisfies at the tile boundaries:
  C_0: functions continuous
  C_1: 1st derivatives contuous
- total of $4(N_x + 1)(N_y + 1)$ coefficients
- could use this basis set to model spatial variations in the kernel, and background
- end up solving a single large linear system

Tiling