Streaming Multiframe Deconvolution of Atmospherically Distorted Images on GPUs

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Motivation

Atmospheric distortion is an issue in various fields relying on long-distance imaging, especially in astronomy. Earth-based telescopes face the challenge of peering though the ever-changing and blur-inducing atmosphere. This can be especially detrimental to observations of small and faint objects. The point spread function (PSF) defining this blur is unknown, hard to predict and varies wildly making recovery more difficult.

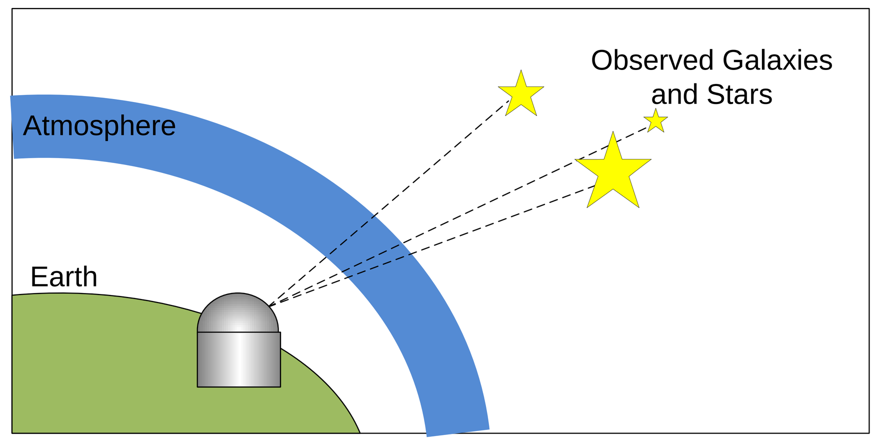


Figure 1: Earth-based telescopes have the disadvantage of peering through earth's ever-changing and blur inducing atmosphere. This is especially detrimental for faint and distant observations.

Modern telescopes produce high volumes of extremely large images, upwards of 100PB in 10 years, yielding an even more compute intensive and time consuming reconstruction. The current "State-of-the-Art" images are commonly Co-Add images made by overlaying multiple faint observations to create one higher quality image, see Fig. (2) These Co-Add images are very noisy and missing detail. More advanced reconstruction is computationally complex and therefore slow and laborious. We need GPU-accelerated, statistically sound and extensible tools to keep up with, explore and deblur these images in real time.

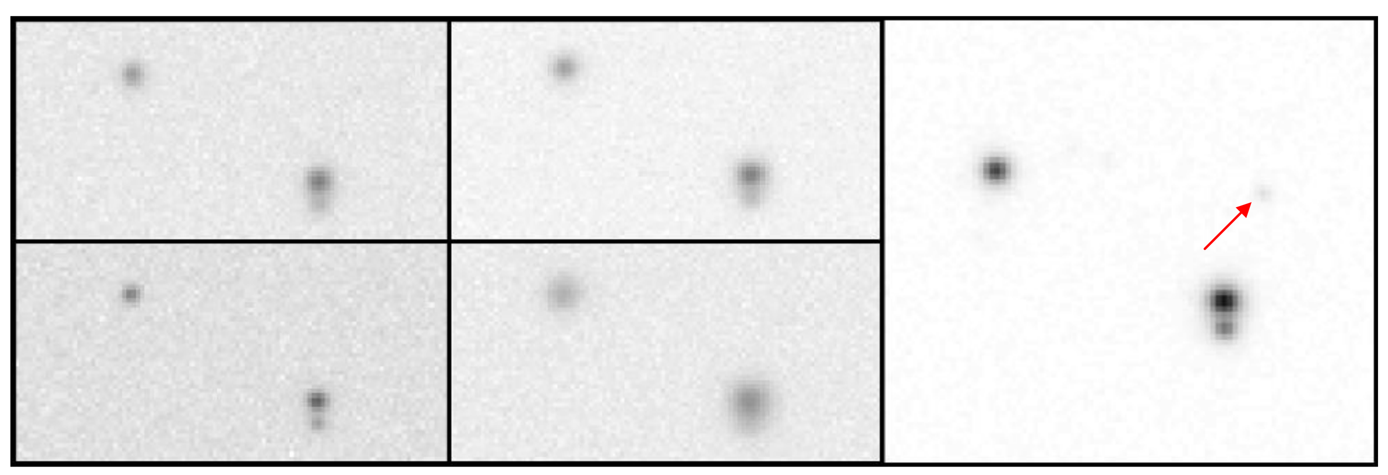


Figure 2: [Image: SDSS Stripe 82] *Left: faint and blurry Single Frame Observations, very low Signal-to-Noise; Right: Blurry* Co-Add Image, higher Signal-to-Noise ratio, hard to identify objects

Problem

The general problem can be defined as shown in Eq. (1), where y_t and f_t are the observed image and the Point Spread Function defining the blur at time t. x is the underlying "true" image which we assume to be constant across all observed frames. In case there are moving objects, these can be masked. The observed image y_t consists of the "true" image, x, which has been convolved with an unknown blur f and some noise ϵ_t. Initially both x and f_t are unknown but can be constrained to being at least non-negative, which allows us to use methods for Non-Negative Matrix factorization.

To recover the "true" image we need to deconvolve the PSF and the observed image. The better our estimate for the PSF is, the more precise our model of the underlying "true" image will be. In order to get a good estimate of the PSF, we extract information from each of a series of single frames and iteratively apply/update it to our model.

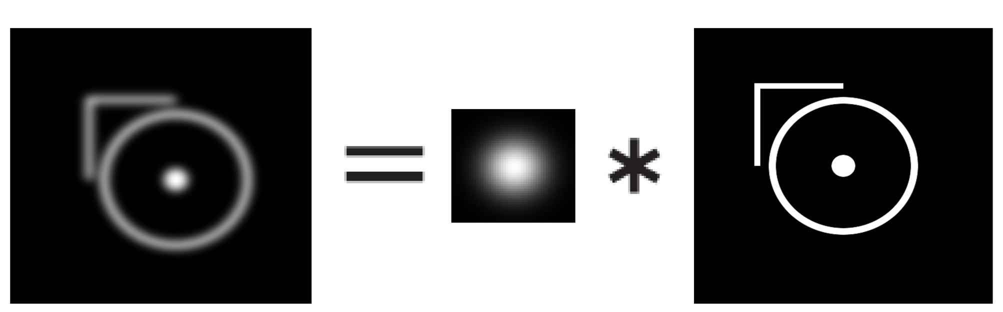


Figure 3: The blurry observed image on the *left* is a composition of the blur function or PSF(*center*) and the underlying "true" image on the *right*.

Methods & Implementation

Our approach mainly focuses on the Gaussian-based Multiframe Blind Deconvolution (MFBD) as described by Stefan Harmeling [1]. We have also experimented with the Poisson-likelihood based Richardson-Lucy deconvolution as described by Rick White [3].

$$y_t = f_t * x + \epsilon_t$$

Equation 1: *Where y is the observed image, f is the PSF and x is the true image*

$$f_t = \operatorname{argmin}_{f \geq 0} \|y_t - F x_t\|^2$$

Equation 2: Function to be minimized for every observed image

$$x_{t+1} = x_t \odot \frac{F^T y_t}{F^T F x_t}$$

Equation 3: Gaussian based update formula as described by Harmeling et al

To estimate our PSF we need find the f which minimizes the residual between the observed image and our model image, see Eq. (2). With this PSF we update the model image via our multiplicative update formula, see Eq. (3). This process is repeated for every observed image. The model is thereby iteratively updated with new information from every image.

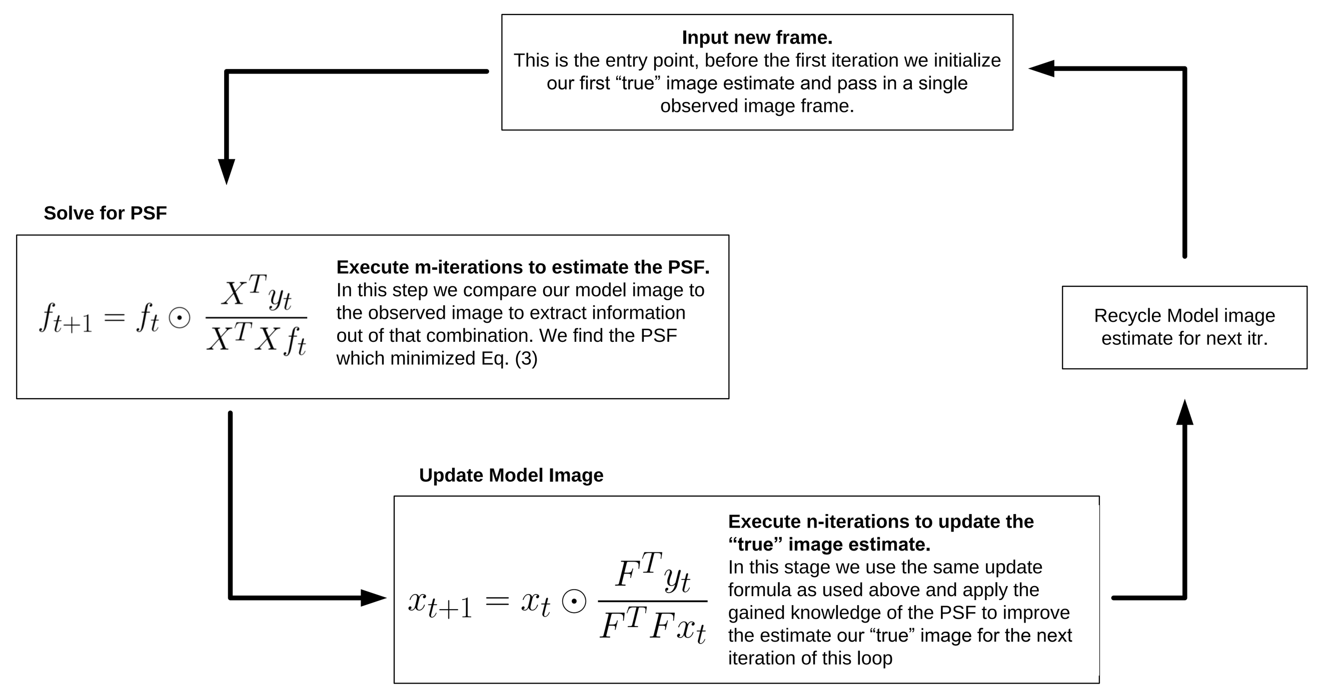


Figure 4: Multiframe Blind Deconvolution Iteration steps

The simple update formula as described by Stefan Harmeling et al. in [1] and [2] work well on clean images void of defects and background subtraction issues. In order to combat issues with real data, we added two main enhancements to the update formula, see Eq. (4). We introduce a clipping parameter as well as a weighting matrix. The clipping, $\mathbb{C}$, limits the effect a single update may have on our model and thereby prevents bad images or failed PSF estimates from breaking our algorithm. The weighting matrix, W, lets us introduce both masks as well as robust statistics weighting, which prevents bright sources from dominating the residual and therefore converging before the rest of the image has converged.

$$x_{t+1} = x_t \odot \mathbb{C}\left[\frac{F^T W y_t}{F^T W F x_t}\right]$$

Equation 4: Enhanced update formula, adding Clipping and Weighting, see [4]

Our general goal on point sources (Stars) is to shrink the overall diameter of the PSF while pulling more flux into the center. Fig. (5) shows a typical point source, comparing the Co-added image with our result. Note the change in diameter of the PSF as well the intensity of the center. Fig. (5) shows a series of cross sections of the same point source shown in Fig. (6).

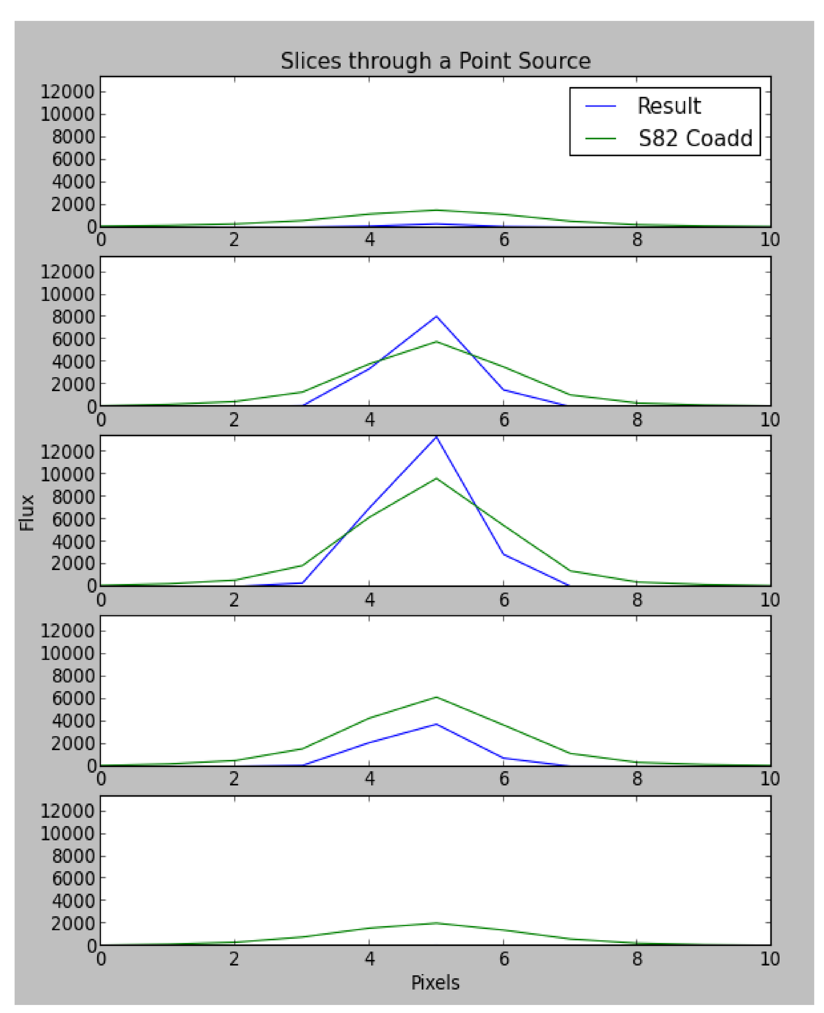


Figure 5: Cross section of the flux accumulated in each pixel across the point sources of Fig. (6)

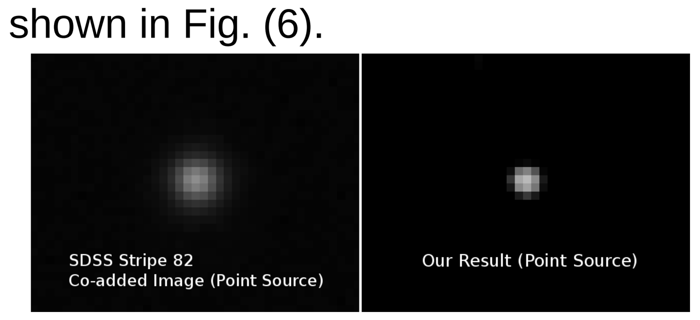


Figure 6: Comparison of point sources, between the official Stripe 82 Co-add and our result

Results & Future Work

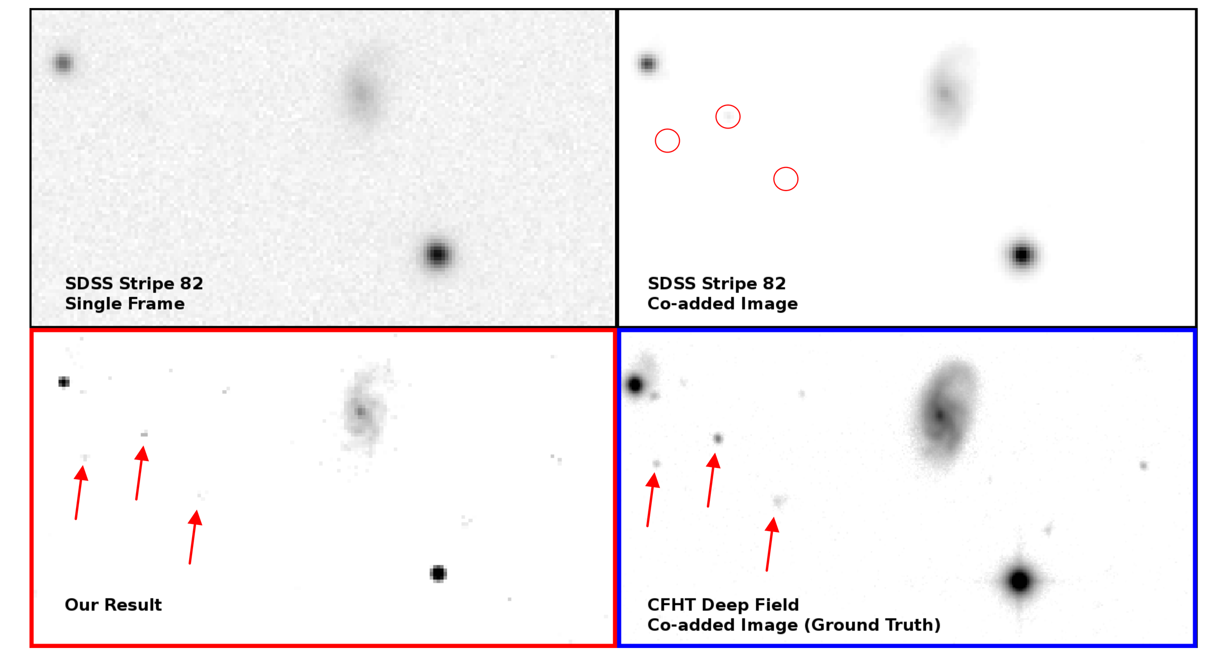
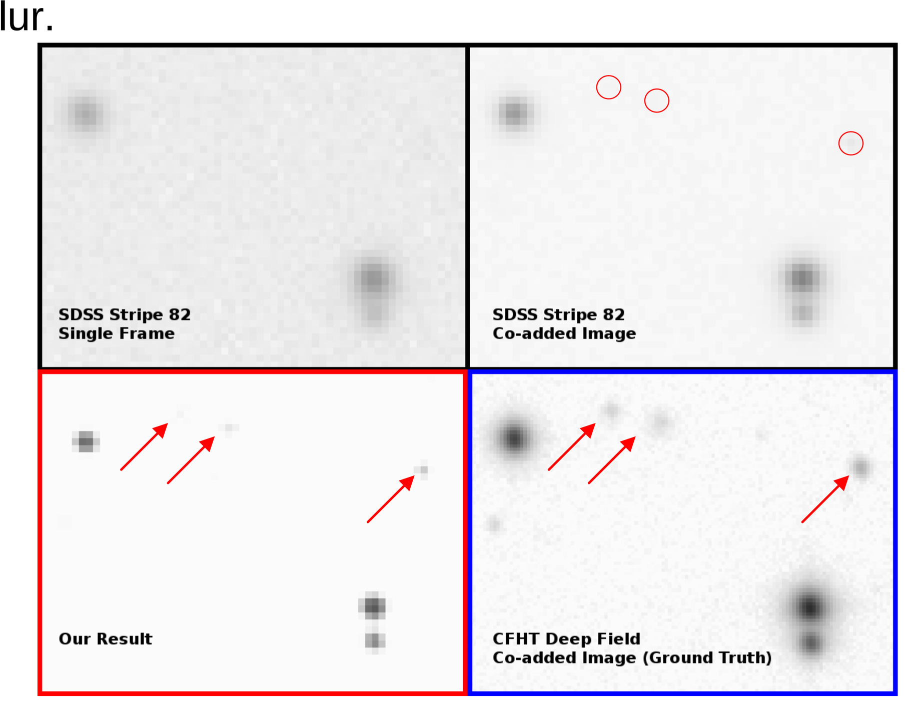


Figure 8: *Top:* SDSS Stripe 82 Single Frame; SDSS Stripe 82 Official Co-add (Annis et al.) *Bottom:* Our Result, based on Stripe 82 Frames; CFHT Deep Field as "ground truth". Images have been scaled to same total flux.

Our results show a large improvement in PSF size over the current State-of-the-Art co-add for both point sources and galaxies while suppressing background noise. Our process allows us to sharpen existing sources and exposing sources that previously were too faint to see. During development we found sources/artifacts which did not correspond to anything we could identify in the co-adds, but further inspection and comparison to CFHT, a larger and deeper survey, has let us conclude that the vast majority of those artifacts are actually real sources. Our method also unveils structures, such as spiral arms, in Galaxies previously hidden within the blur.



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Our tool is built with python and relies on pyCUDA for GPU-acceleration. We achieved an over 40x speedup over the previous CPU version, currently it takes approximately 5 minutes to process 70 images. Depending on parameter adjustments and input images, the run time will vary as the number of iterations will vary to reach convergence.

Currently we are working on super resolution which promises higher shape and location precision of sources. Another upcoming feature is multi-parameter background estimation. This adds only a few more parameters to solve for, but will allow us to automatically detect and remove gradient backgrounds. Beyond these algorithmic improvements, there are also some regions of the code that could be vastly sped up with more GPU optimizations.

References

[1] Harmeling, Stefan, et al. "Online blind image deconvolution for astronomy." (2009).

[2] Harmeling, Stefan, et al. "Multiframe blind deconvolution, super-resolution, and saturation correction via incremental EM." Image Processing (ICIP), 2010 17th IEEE International Conference on. IEEE, 2010.

[3] White, Richard L. "Image restoration using the damped Richardson-Lucy method." 1994 Symposium on Astronomical Telescopes & Instrumentation for the 21st Century. International Society for Optics and Photonics, 1994.

[4] Lee, M. A., and T. Budavári. "Cross-Identification of Astronomical Catalogs on Multiple GPUs." Astronomical Society of the Pacific Conference Series. Vol. 475. 2013.

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