



The detector statistics of CCD-based imagers are fairly well understood and are straightforward to model as a combination of read and Poisson (photon counting) noise. I demonstrate how an understanding of these statistics can be employed to spatially or temporally process solar images, clearly distinguishing instrument noise from dynamics and structure on the Sun.

Understanding and taking advantage of the statistics of the data is vital to getting the most out of the data. More specifically, it ensures that the interpretation of the data is due to signal, not noise.

This is often ignored when analyzing solar image sequences, even though noise statistics are fairly simple:

- ▶ Mostly shot noise,  $\sigma_I \propto \sqrt{I}$ .
- ▶ Small additive Gaussian read noise.
- ▶ One or two other minor sources may be present - ignored here for simplicity.

Combined with very modest assumptions about the image sequence in question, applying basic understanding of these statistics can cast much new light on the data. I show examples of both spatial and temporal filtering. AIA data is used for both examples.

## Temporal Filtering:

- ▶ Median filter the time series around each pixel with a given width (i.e., in time).
- ▶ Use median to estimate detector statistics for the pixel.
- ▶ Compute difference between median and actual data value, compare to error.
- ▶ Form image of residuals:
  - ▶ Intensity of image shows statistical significance of deviation from median.
    - ▶ Insensitive to monotonically varying intensity;
    - ▶ Requires 'impulsive' intensity variation.
  - ▶ Sequence of images can be used to form animation (see tablet or ask for demo).

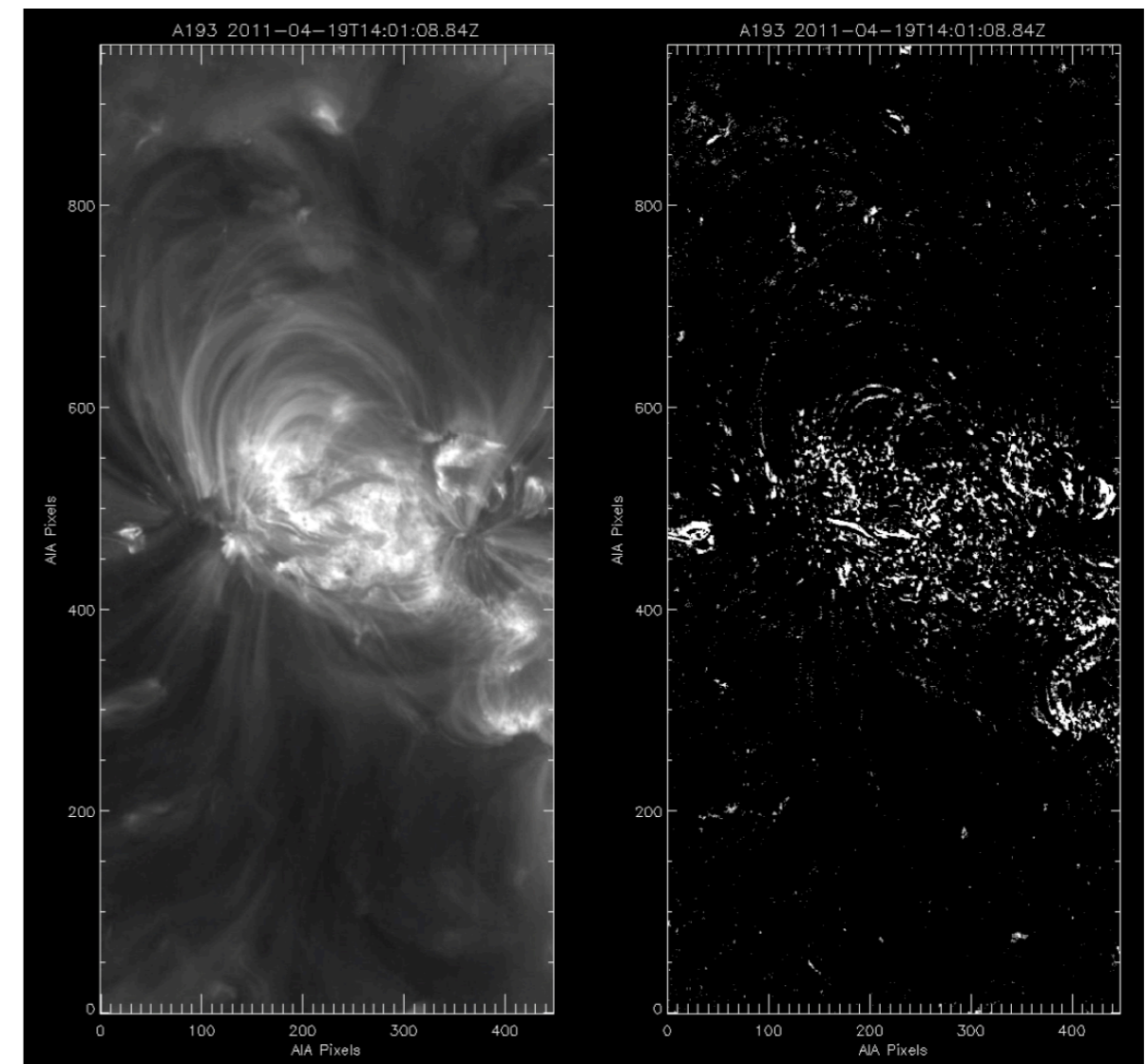


Figure: Frame showing statistically significant residuals after applying a temporal median filter (width is 15 frames or 30 minutes).

## Spatial Filtering:

- ▶ Similar to temporal filtering, but in 2 spatial dimensions, across a single image
- ▶ Filtering is applied with several spatial scales
  - ▶ Modified Gaussian blur (described below)
  - ▶ Can be used to show variation at each scale (image below).
  - ▶ Use coarsest spatial scale consistent with original image, given detector noise.
  - ▶ Alternatively, can be combined into one image:
    - ▶ A form of noise reduction (e.g., AIA 94 Å image on right).

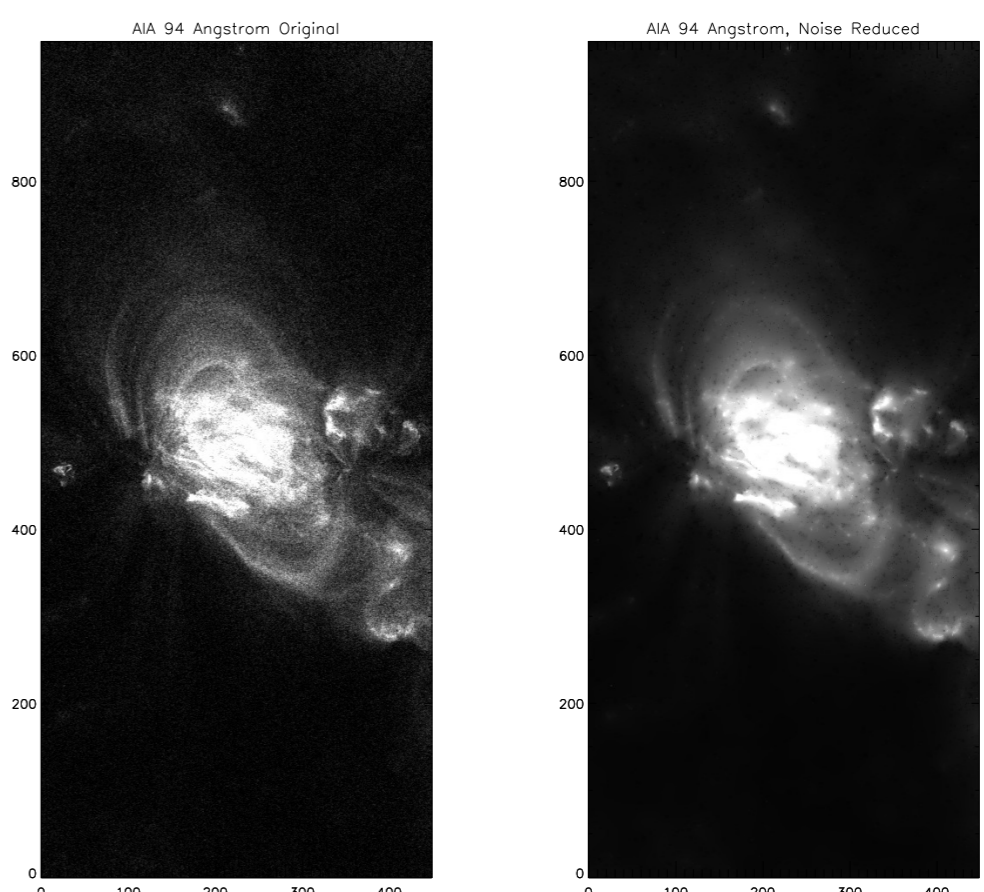


Figure: Multiscale noise reduction applied to an AIA 94 Å image.

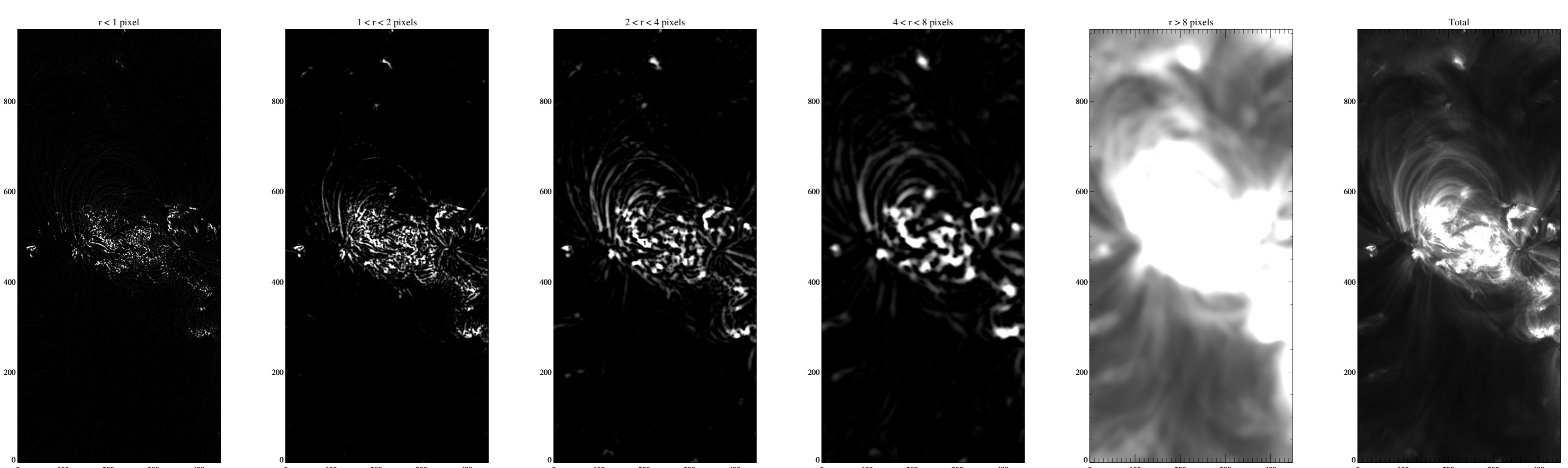


Figure: Example of multiscale (semi)-positivity-enforcing decomposition of AIA 193 Å image. Rightmost image shows sum of other images.

## Modified Gaussian Blur (work in progress)

- ▶ The standard Gaussian blur smooths all length scales to smaller than its radius.
  - ▶ Contributions from small scale positive features are still present, just spread out
- ▶ We'd like something similar which leaves out smaller scales entirely:
  - ▶ Start with Gaussian blurred image,  $I_B$  and original,  $I$ .
  - ▶ Parts of image which are greater than blurred image are from smaller features.
  - ▶ Let  $I_+ = I - I_B$ , and set its negative values equal to 0.
  - ▶ Gaussian blur  $I_+$ , and make it the new  $I_B$ .
  - ▶ Iterate.
- ▶ Result is image with greatly reduced contribution from scales less than the Gaussian blur radius.

## What's next?

- ▶ Much of this is similar to wavelet filtering;
  - ▶ Not normally applied to time domain in this manner
  - ▶ Photon counting does not normally play a role
- ▶ The corona is optically thin:
  - ▶ Superposition of features on many scales, each positive-definite.
- ▶ Wavelet decompositions susceptible to negative ringing
  - ▶ Median somewhat less prone than convolutional methods
- ▶ A positive-definite decomposition should be possible:
  - ▶ Can do multidimensional fitting (e.g., Powell's); very slow.
  - ▶ Want to do it quickly and robustly, using detector statistics.
- ▶ Iteration + (Gaussian) convolution shows some promise, but limitations are unclear. Reinventing the wheel?