

Detector Statistics, Multiscale filtering, and Coronal Imagery

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August 29, 2014

This demo session covered two related topics in coronal image processing and filtering also covered in my poster, ‘Detector Statistics and Interpretation of Image Data’.

1 Temporal filtering

The dynamics of the solar corona occur on widely varying time scales - much of the emission occurs relatively slowly, over periods of hours or even days, while some of the most interesting dynamic events (e.g., flares) occur over periods of minutes or tens of minutes. Given this, it is desirable to filter image time series to show this short-period variation, especially when it is relatively faint. The standard method of doing this is by running difference images, but these are strongly affected by instrument noise. I demonstrate a much cleaner temporal filtering method, utilizing a running median and taking the instrument noise statistics into account:

- Median filter the time series around each 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).

An animation showing the application of this method to a sequence of AIA data is embedded in Figure 1, and can be seen when this document is viewed with Adobe Reader.

2 Multiscale Image Decomposition & Background Estimation

The corona is composed of spatial structures which also have widely varying scales, from diffuse emission covering tens of megameters, down to well under the pixel scale of modern EUV imagers (tenths of megameters). Given this variety of structures, the ability to decompose a coronal image into a set of ‘subimages’, each showing a different coronal scale would be very useful. A variety of methods for decomposition exist, Fourier and Wavelet methods being two of the most important categories. However, any such method imposes its own assumptions on the data (the problem in general is ill-posed, as there are more degrees of freedom than there are data points). If these assumptions do not adhere to the known physical characteristics of the corona however, there’s no guarantee that the decomposition will correspond to the coronal structures being observed.

One of the principal characteristics of these structures is that they are all optically thin. Thus, images of the corona are a superposition of the contributions from each structure along the line of sight, and all of these contributions are positive. In other words, in the true physical decomposition of a coronal image, each ‘subimage’ containing only a subset of the spatial scales present in the full image will be everywhere non-negative, and it must be everywhere less than or equal to (modulo detector noise) the full image. This positivity can provide a powerful (and important) constraint on decompositions of coronal images. It is not enforced by the Fourier and Wavelet methods mentioned above, so I am looking for some other method. To illustrate the results such a method might produce, I give a crude ‘toy’ deconstruction method combining convolutional smoothing and an iteration:

1. Smooth the image, minus a correction (set to zero at the first iteration), at a given radius using a convolutional filter such as a Boxcar or Gaussian.

Figure 1: Animation showing results of temporal filtering of an AIA 193 Å image sequence, as described in the text. May not show up in all PDF viewers (Adobe Reader is known to work) - Figure 2 shows a static fallback image.

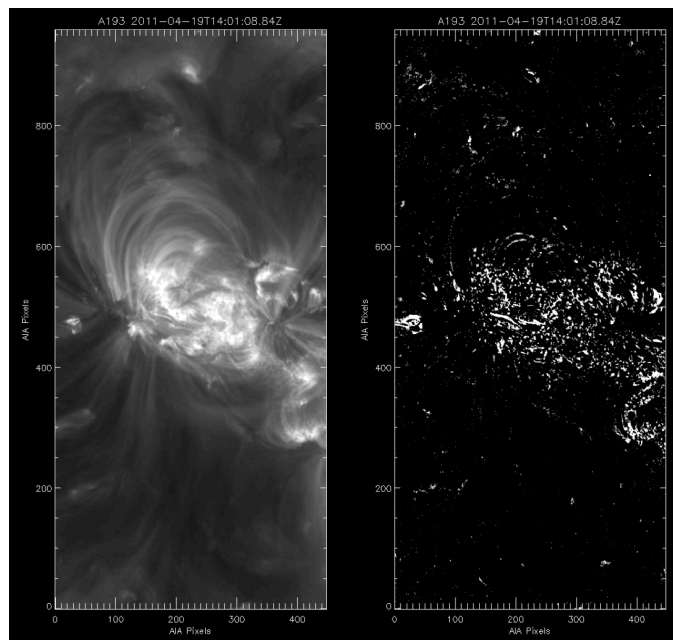


Figure 2: Frame showing statistically significant residuals after applying a temporal median filter (width is 15 frames or 30 minutes).

2. Subtract the smoothed image from the original, and threshold at zero. This is the new correction.
3. Repeat from step 1 until some stopping condition is met (e.g., 10 iterations).

The smoothing ensures that the resulting image has no features smaller than the smoothing scale, and the iteration minimizes areas where the smoothed image is greater than the original ('negative' residuals) . The greater the number of iterations, the more these areas will be minimized. However, each iteration also applies additional smoothing to those areas, and the resulting image will be smoothed with variable scale depending on how many iterations are required to remove the negative residuals in any given area. Many iterations are required in areas where there are a large range of spatial scales, so the effects of this additional, variable smoothing can be pronounced. For that reason, this method is presented as an illustrative example rather than an acceptable solution to the problem, although it is possible that a more useful method can be developed from it.

Results of the method for several smoothing radii are shown in Figure 3, and compared with those of a Gaussian blur. Additional discussion can be found on my poster, 'Detector Statistics and Interpretation of Image Data'.

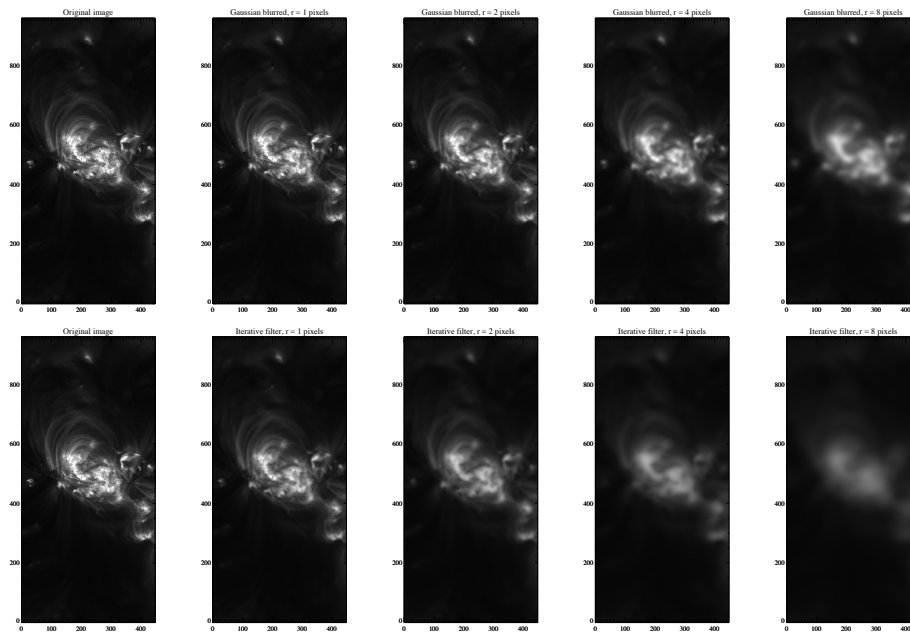


Figure 3: Top row: Gaussian blur of example AIA 193 Å image. Bottom (semi)-positivity-enforcing filtering of same image. Original image shown on left.