Contrib. Astron. Obs. Skalnaté Pleso **41**, 149 – 155, (2011)

Denoising observational data

Ph.-A. Bourdin[1,2]

[1] *Max-Planck-Intitute for Solar System Research,*
Max-Planck-Str. 2 D-37191 Katlenburg-Lindau, Germany
(E-mail: Bourdin@MPS.mpg.de)
[2] *Kiepenheuer-Institut für Sonnenphysik,*
Schöneckstr. 6,
D-79104 Freiburg, Germany

Received: January 3, 2011; Accepted: April 16, 2011

Abstract. Reducing noise caused by the instrumentation in observational data is a crucial step in data post-processing. A method is searched for that conserves most of the instrumental resolution and introduces as few methodical artefacts as possible. With such a method integrated in an observation sites software tool-chain, the resources spent for the generation of observational data will more likely find their way into resulting scientific publications; otherwise, for data post-processing often methods are used, which just smear out the noise, introduce artefacts, or decrease the provided resolution in space or time. A short review of different techniques is given here, and a non-local averaging method is applied to Hinode magnetograms and G-band data. The presented method fits the needs for various kinds of observational data.

Key words: Techniques: image processing

1. Introduction

Any modern telescope or observational instrument is nowadays equipped with digital sensors, in particular CCDs for imaging. A resolution element of a CCD basically counts photons and provides 2D pixel data with some kind of noise on each pixel. The cause for the noise might lie in the CCD or other parts of the instrument, but usually the noise can be treated as it would have come from only one source. Good CCD cameras often use 16 bit unsigned integers and can reach photon counts up to $2^{16} - 1 = 65535$. Typical signal-to-noise ratios combined with reasonable exposure times of such CCDs are usually resulting in a noise count of 10 or more, where a Gaussian distribution of the photon noise can be assumed. Therefore denoising methods can be tested, by adding Gaussian noise to a known image, run the denoising method, and compare the resulting images with the original ones. Presented here are excerpts from a well written review article (Buades *et al.*, 2006) as well as an analysis of a non-local averaging method (Buades *et al.*, 2005) applied to solar observations, such as Stokes-V images from the Hinode satellite as well as G-band images from the Dutch Open Telescope (DOT).

2. Common methods for denoising

As a young scientist or PhD student, who has to post-process observational data for the first time, the obvious methods to get rid of noise are smoothing the data in space, time-averaging aligned image data, or simply reducing the resolution to the maximum possible, so that the noise cannot be seen. All of those methods basically mean not removing any noise, but smearing it out in space or time. Another possibility is to try a Gaussian convolution method, which tries to locally fit the image by Gaussian curves. This method also smooths an image, lowers the resolution, and cannot maintain sharp contrasts, as it can be seen in difference plots of a noisy and its denoised image. More advanced methods are needed to make better use of the provided resolution, cadence or other kinds of data qualities.

In principle, denoising methods can be divided into local and non-local methods. Where averaging methods are now available in local and non-local variants, any fitting method is local and any frequency domain (Fourier transform based) method is non-local. The advantage of non-local methods is clearly the possibility to profit from self-similarities of any scale, where local methods have the dilemma of delivering performance by using larger amounts of pixels versus maintaining resolution by using less amounts of pixels.

Fitting methods (*e.g.*, wavelets) use subfields of an image to fit a set of base functions to the shape of the image. Because such sets are discrete and finite, the fit is usually not representing the true shape of the image and it introduces artefacts at the borders of the subfields. Total variation (TV) minimization, iterated TV, anisotropic filtering, and entropy reduction methods are usually producing an oil-painting effect or deliver low denoising performance.

Frequency domain methods (*e.g.*, Fourier-Wiener and DCT-empirical Wiener filters) are introducing artefacts, which are then uniformly visible, *e.g.*, as wiggles in large parts of the denoised image. Furthermore, no clear distinction can be made between high frequencies resulting from noise or from true sharp contrasts on a low spatial scale. Some smoothing can therefore not be avoided. A more in-depth discussion of all these methods can be found in the mentioned review article (Buades *et al.*, 2006).

3. A non-local averaging method

The NL-means algorithm features the advantages of a non-local method, without introducing artefacts. This is achieved by building, to get one pixel of the denoised image, a superposition (or an average) of all pixels in the image, weighted by the similarity between the surrounding area of the to-be-denoised pixel and the surrounding area of every other pixel in the whole image. Where there is a strong similarity, the contribution to the average is strong; where there is no similarity, the contribution is negligible. Furthermore, a small fixed fraction of the original image is added to the result, to maintain the original image in areas, where there is less similarity to other areas. This conserves unique features in a noisy image, if they are significantly above the noise level (like, *e.g.*, a G-band bright feature). A full description of the algorithm can be found in (Buades *et al.*, 2005).

For better denoising performance, the surrounding areas around pixels (windows) can be varied in size and shape. A smooth window shape can be achieved by using a quadratic window with a Gaussian kernel multiplied to it. The half-width of the Gaussian kernel should match at least two optical resolution elements, which can be more than two pixels, depending on the instrument. For faster computation the window size should be kept small, since every possible relation between two pixels of the image needs to be computed. Nonetheless, using parallel programming techniques, it is possible to denoise a 1 k×1 k pixels image within a few seconds on an off-the-shelf server hardware with 8 CPU cores. The computation domain for one CPU core should be sized such that all necessary image data fits into the L2-cache; for larger images, more CPU cores are needed. A special feature of the NL-means algorithm is the fact that it can easily be applied also to time series of images without previous alignment, since the algorithm is by itself looking for self-similarities and can use windows from other frames of the time series for averaging. This is described in the movie denoising article of the same authors (Buades *et al.*, 2008).

4. Application to solar observations

Fig. 1 shows a Hinode/NFI Stokes-V map of a small active region (pixel value range is -128 to 127), which has been used to test NL-means by adding Gaussian noise with a standard deviation of 10. This corresponds to a high noise level, compared to the original Hinode data. The denoising result shows most of the features of the original image, except some small-scale low-signal features, which are anyway not above the given noise level. The difference plot shows that very little of the actual structure of the original image has been falsely recognized as noise. The astounding result is that the algorithm worked that well because one cannot say that the original image would present much self-similarity, but nonetheless quiet Sun areas between the strong polarities have been well denoised. Furthermore, one could say that there is a loss of "visible by eye"-features in the quiet Sun area, but one has to notice that these features might be recognized by our brain as "visible", but may not be mathematically significant, because they are below the noise level. So, one could see this effect as a benefit instead of a defect, because by applying this denoising method we give our selective recognition a simple proxy for the significance of certain features.

A remarkable result is shown in the histograms in Fig. 2, where one can see again the original, noisy, denoised, and difference images in the same order as in Fig. 1. Even though the algorithm only knows the noisy image with a

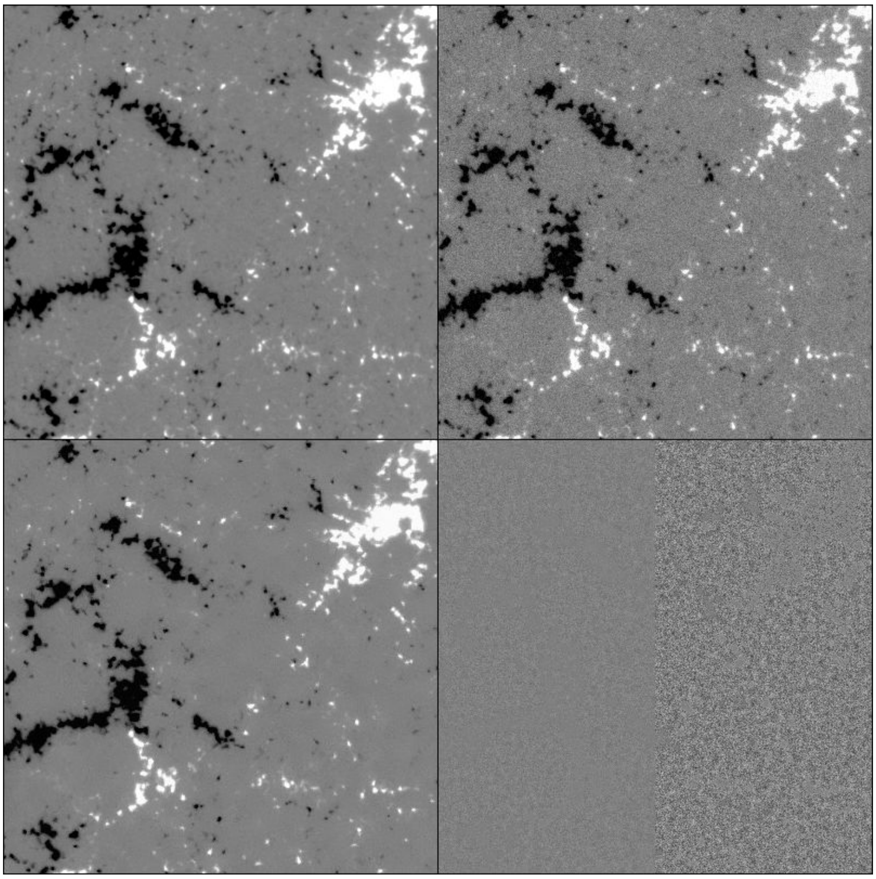

Figure 1. A Hinode/NFI Stokes-V map of a small active region. The peak polarities have values of around 1200 Gauss, in this image the saturation level is at 300 Gauss and corresponds to a pixel value of 127. The upper left pane shows the original image, in the upper right pane a Gaussian noise with a standard deviation of 10 was added. The lower left pane shows the denoised image as denoised with the NL-means algorithm. The lower right pane shows the difference of the noisy and the denoised image; in the right half the contrast has been improved by a factor of 3 for better visibility.

relatively flat histogram, the method is capable of recovering an image that has a histogram very close to the original one. In the histogram of the removed noise one can recognize its standard deviation.

Tab. 1 shows the bias of the denoising algorithm for different noise levels. The mean value of the original image is 2.06 and the standard-deviation is 32.9 as it can be seen in Tab. 2, where the standard deviation and mean value are given for the noise level 10 images, too. It is found that the bias in that case is

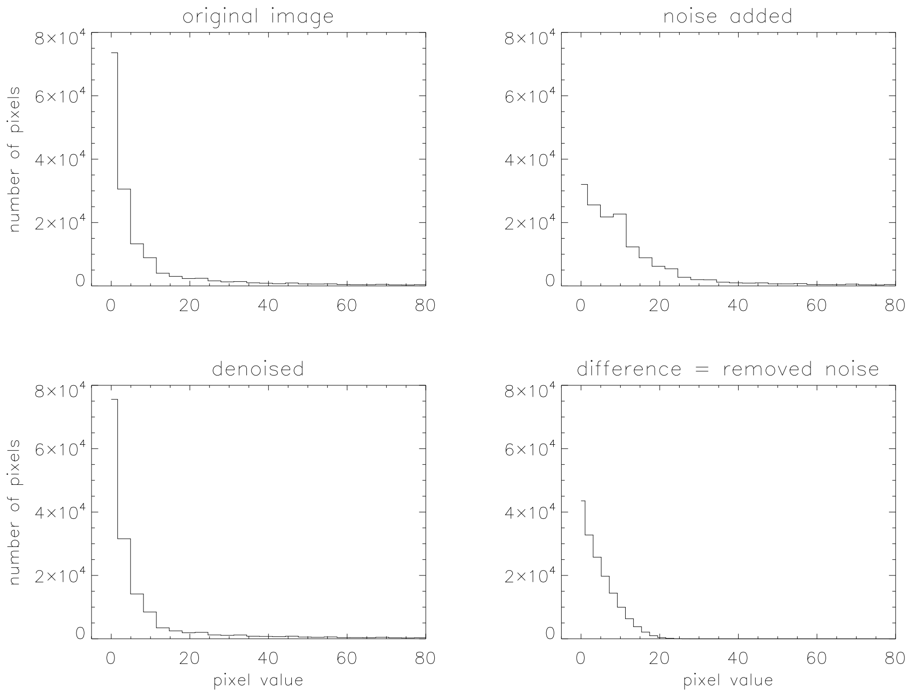

Figure 2. Histograms of corresponding images shown in Fig. 1 in the same ordering.

Table 1. Bias of the NL-means denoising method for different noise levels.

noise level	bias
0	0.008
5	0.009
10	0.016
15	0.032
20	0.029

Table 2. Standard deviation and mean value of the images in Fig. 1.

image	standard deviation	mean value
original	32.9	2.061
noisy	33.7	2.060
denoised	32.0	2.044
difference	7.2	0.016

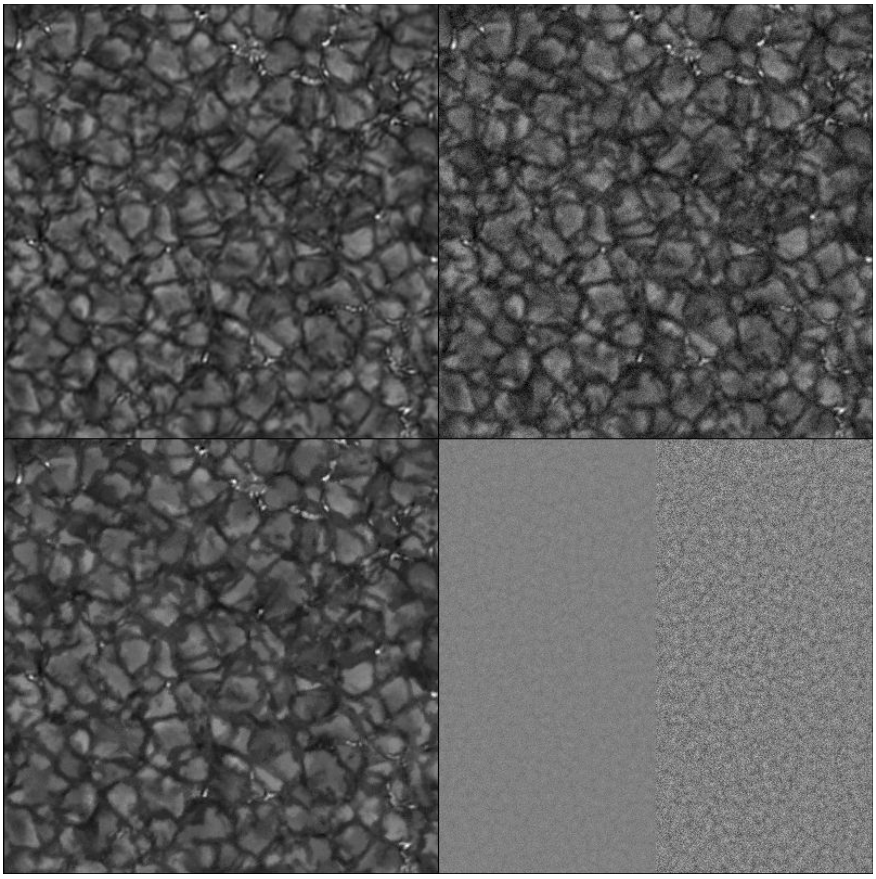

Figure 3. A G-band image of solar granulation and bright features as taken from the Dutch Open Telescope (DOT) after speckle reconstruction. The panels are in the same order as in Fig. 1, a Gaussian noise of level 10 has been used to test the NL-means denoising method.

around 0.8 % of the mean value and below 1.6 % at noise levels of 15 and 20. Levels above 10 are already much higher than the noise level one would expect in the provided original image data.

Fig. 3 shows the same method applied to a G-band image with a noise of level 10 added to it. Basically, the same findings as above are seen. In the intergranular lanes we see the biggest differences to the original images, because some of the original contrast is hidden in the noise level and gets flattened out. One should also notice the conservation of G-band bright features without introduction of artefacts and without any loss of spatial resolution. With a more realistic (lower) noise level and with 16-bit data, better results are achievable.

5. Conclusion

NL-means should be considered as denoising tool for solar observational data. Losses of image features during denoising are usually only because the features are anyway not above the level of significance. Where there is no possibility to improve image quality, NL-means would also not do much harm. Integration of such a denoising method in the observation sites software tool-chain could improve the throughput of valuable image quality from the detector into the scientific publication.

Acknowledgements. Hinode is a Japanese mission developed and launched by ISAS/JAXA, with NAOJ as domestic partner and NASA and STFC (UK) as international partners. It is operated by these agencies in co-operation with ESA and NSC (Norway). The DOT was built by the Sterrekundig Instituut Utrecht, the Physics Instrumentation Group of Utrecht University, and the Central Workshop of Delft Technical University. The DOT completion, installation and verification are funded by the Stichting Technische Wetenschappen (STW) of the Netherlands Organization for Scientific Research (NWO). The current installation at La Palma proceeds under the umbrella of the Instituto de Astrofísica de Canarias.

References

Buades, A.; Coll, B.; Morel, J.M.: 2005, *ICASSP '05 Proceedings, IEEE Int. Conf.*
Buades, A.; Coll, B.; Morel, J.M.: 2006, *Multiscale Modeling and Simulation* **4**, 2
Buades, A.; Coll, B.; Morel, J.M.: 2008, *Int. J. Comput. Viz.* **76**