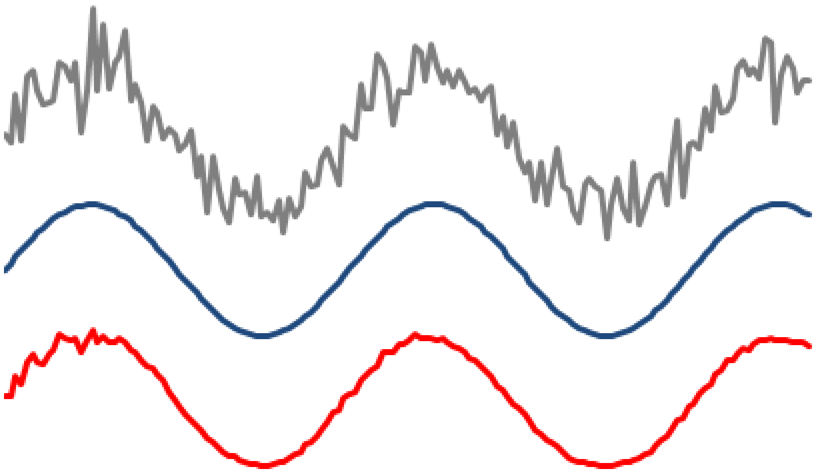

Denoising magnetometer data

(Carpați workshop, Bâlea Lac, 15. September 2015)

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Overview:

* Denoising techniques for 2D imaging
* A new denoising method for 1D timeseries

Comparison of algorithms

Most common and advanced methods for denoising:

	Local	Non-local
Averaging	Smoothing Yaroslavsky neighborhood	Total variation (entropy) NL-means
Fitting	Gaussian convolution Wavelet	-/-
Frequency domain	-/-	Fourier-Wiener DCT-empirical Wiener

Most common methods for denoising:

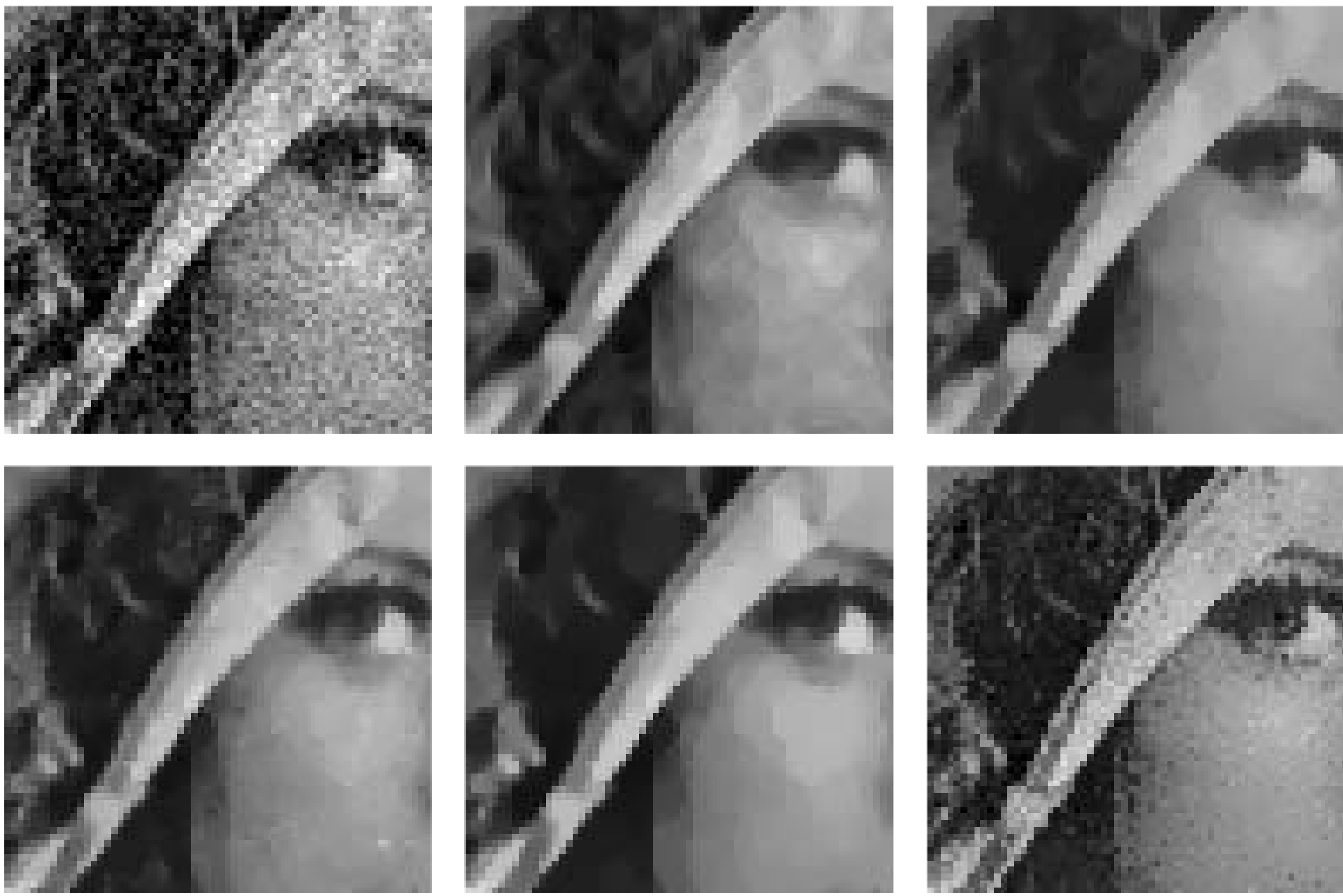
- Gaussian convolution:

(Buades et al. 2005)

Comparison of algorithms

Most common methods for denoising:

- Total variation (TV) minimization / entropy reduction:



<u>left to right</u>:

noisy image

Anisotropic

Total variation

Tadmor-Nezzar-Vese iterated TV

Osher et al. iterated TV

Yaroslavsky neighborhood

(Buades et al. 2005)

Most common methods for denoising:

- Fourier filtering & Wavelet analysis:

<u>left to right</u>:

noisy image

Fourier-Wiener

DCT-empirical Wi.

Wavelet soft thresholding

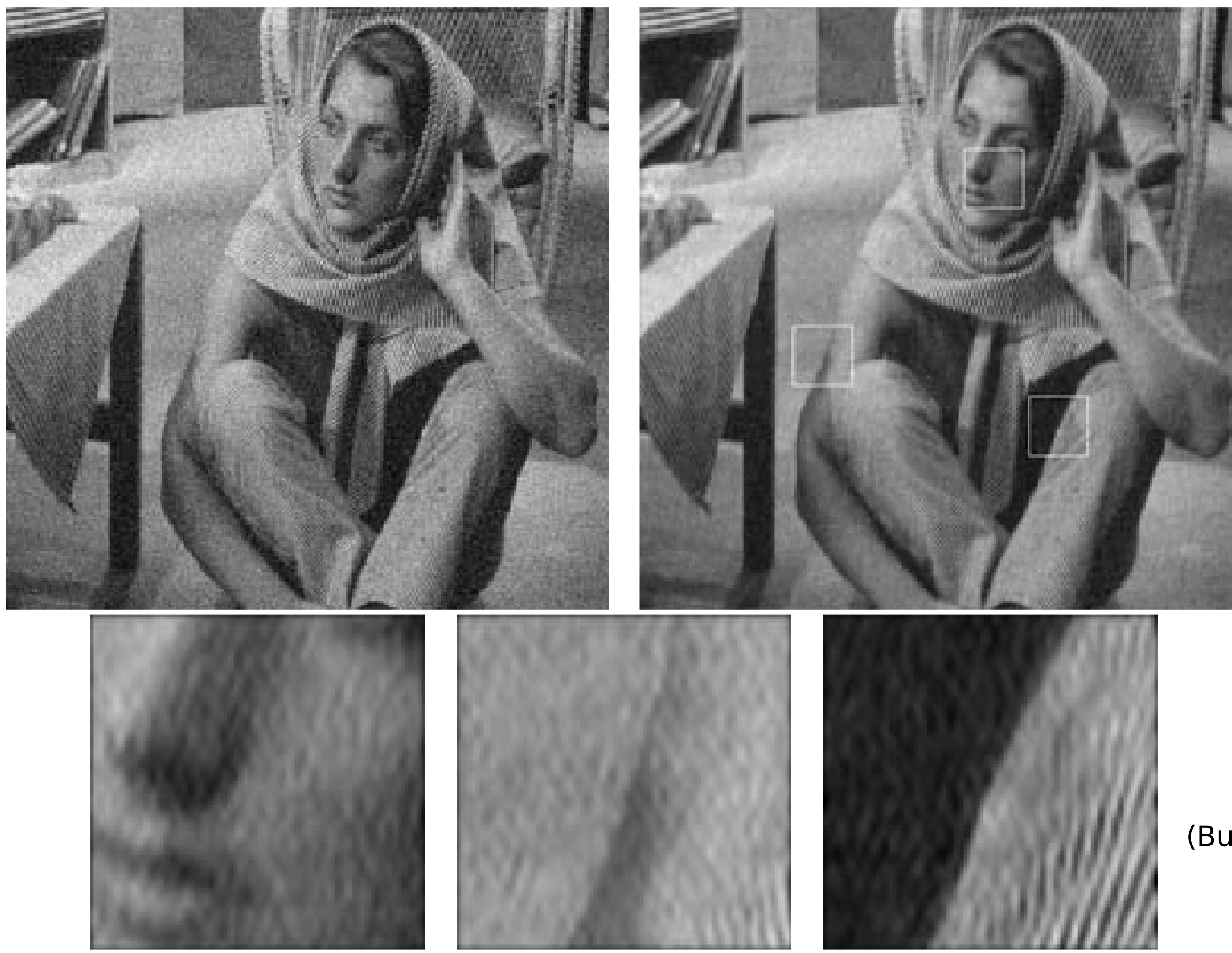
Wavelet hard thr.

translation invariant Wavelet hard thr.

(Buades et al. 2005)

Most common methods for denoising:

- Frequency filtering (Fourier-Wiener filter):



(Buades et al. 2005)

Most common and advanced methods for denoising:

	Local	Non-local
Averaging	Smoothing Yaroslavsky neighborhood	Total variation (entropy) **NL-means**
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Frequency domain	-/-	Fourier-Wiener DCT-empirical Wiener

Blue: loss of resolution – versus – low performance

Orange: introduction of artefacts

Non-local averaging

Non-local averaging

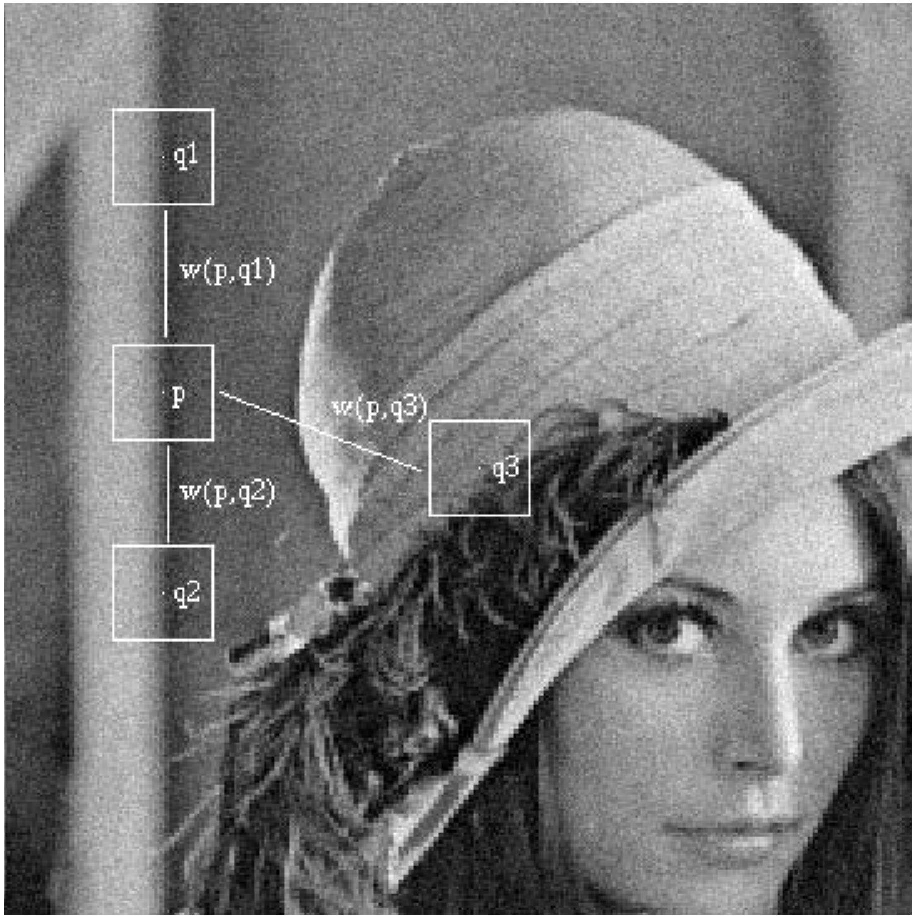
Noisy image: $v = \{ v_p | p \in \Omega \}$

Pixels: $p, q \in \Omega$

Algorithm: $NL[v](p) = \sum_{q \in \Omega} w(p,q) v(q)$

with: $\sum_{q \in \Omega} w(p,q) = 1 \; \forall \; p$

and: $0 \leq w(p,q) \leq 1$



(Buades et al. 2005)

Similarity:

$$w(p,q) = \frac{\exp\left(-\frac{1}{h^2} \| N_p - N_q \|\right)}{\sum_{k \in \Omega} \exp\left(-\frac{1}{h^2} \| N_p - N_k \|\right)}$$

Non-local averaging

Holiday image data:

Input image

(Buades et al. 2005)

Holiday image data:

Artificial noise added

(Buades et al. 2005)

Holiday image data:

Denoised image

(Buades et al. 2005)

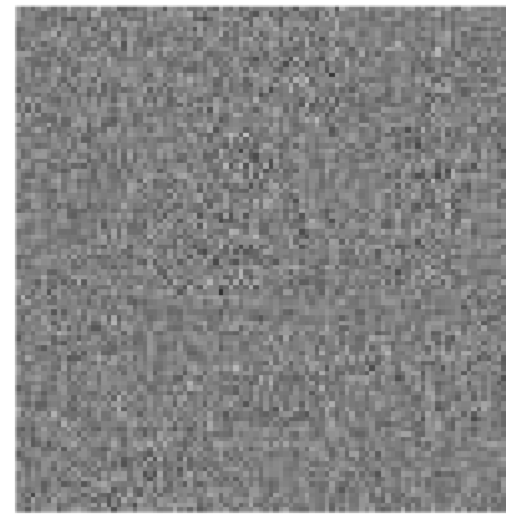
Non-local averaging

Difference plots:

Noisy image

Gaussian convolution

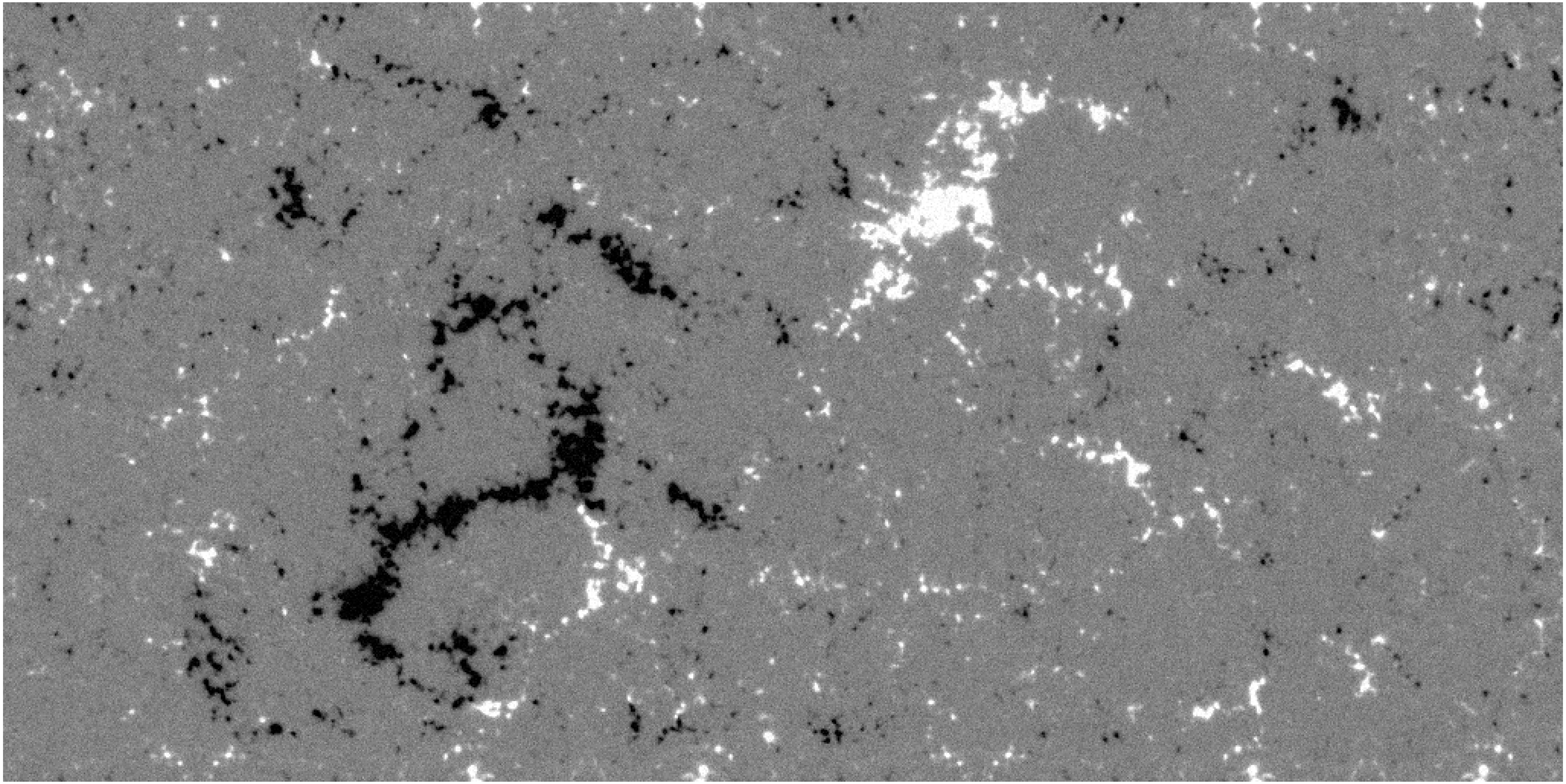
NL-means



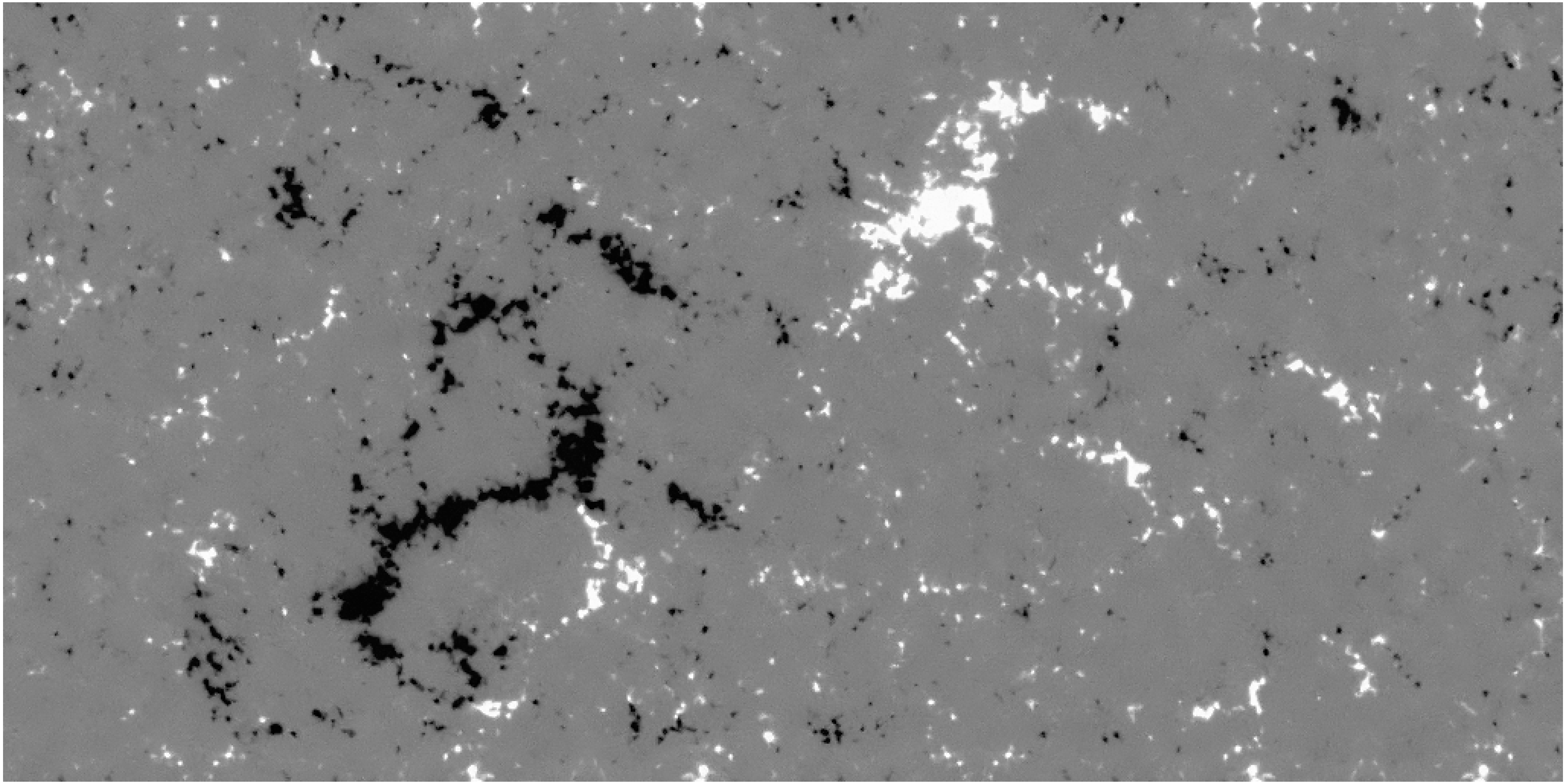
(Buades et al. 2005)

Denoising 2D imaging magnetogram

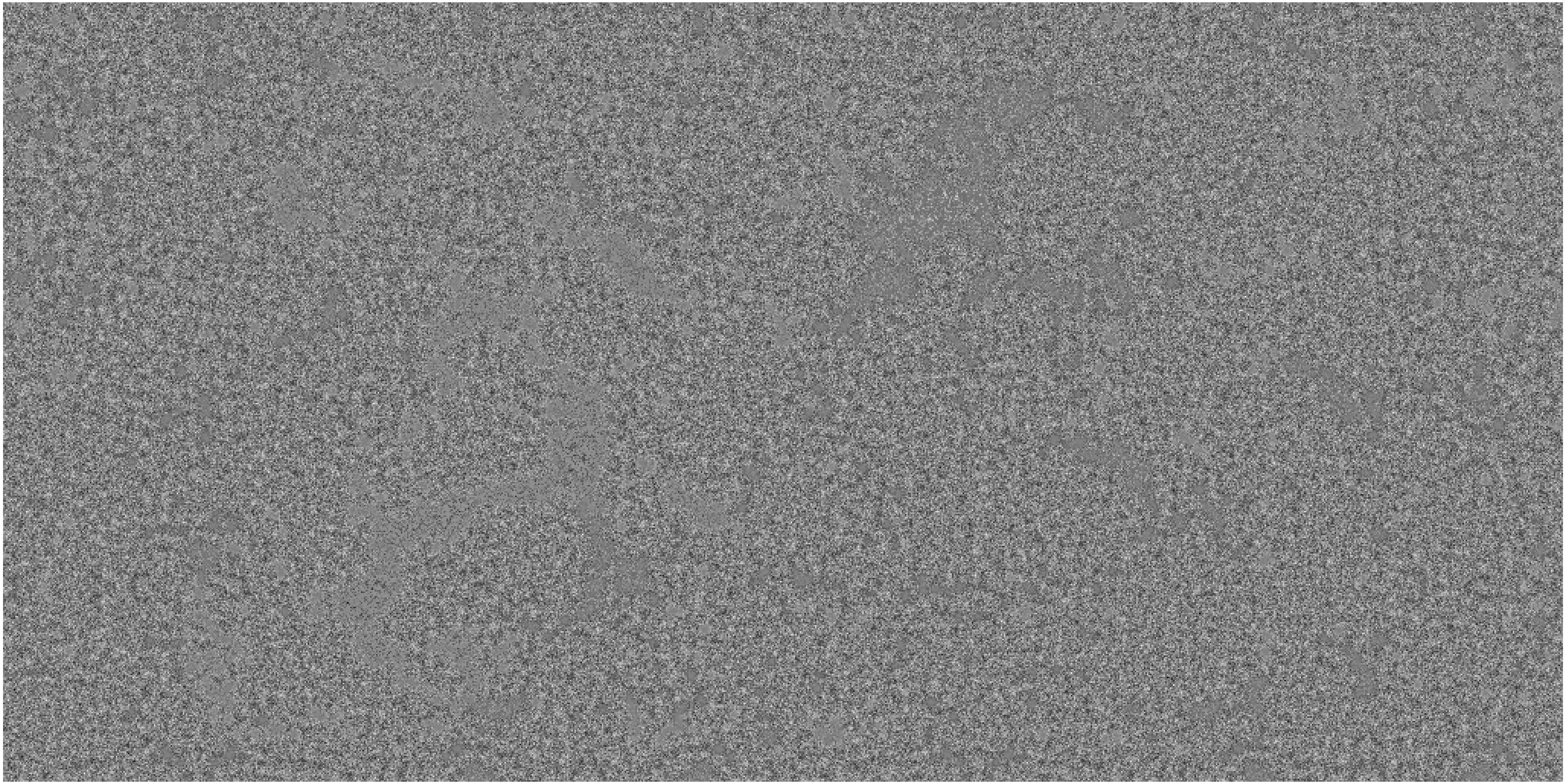
Hinode magnetogram (noisy):



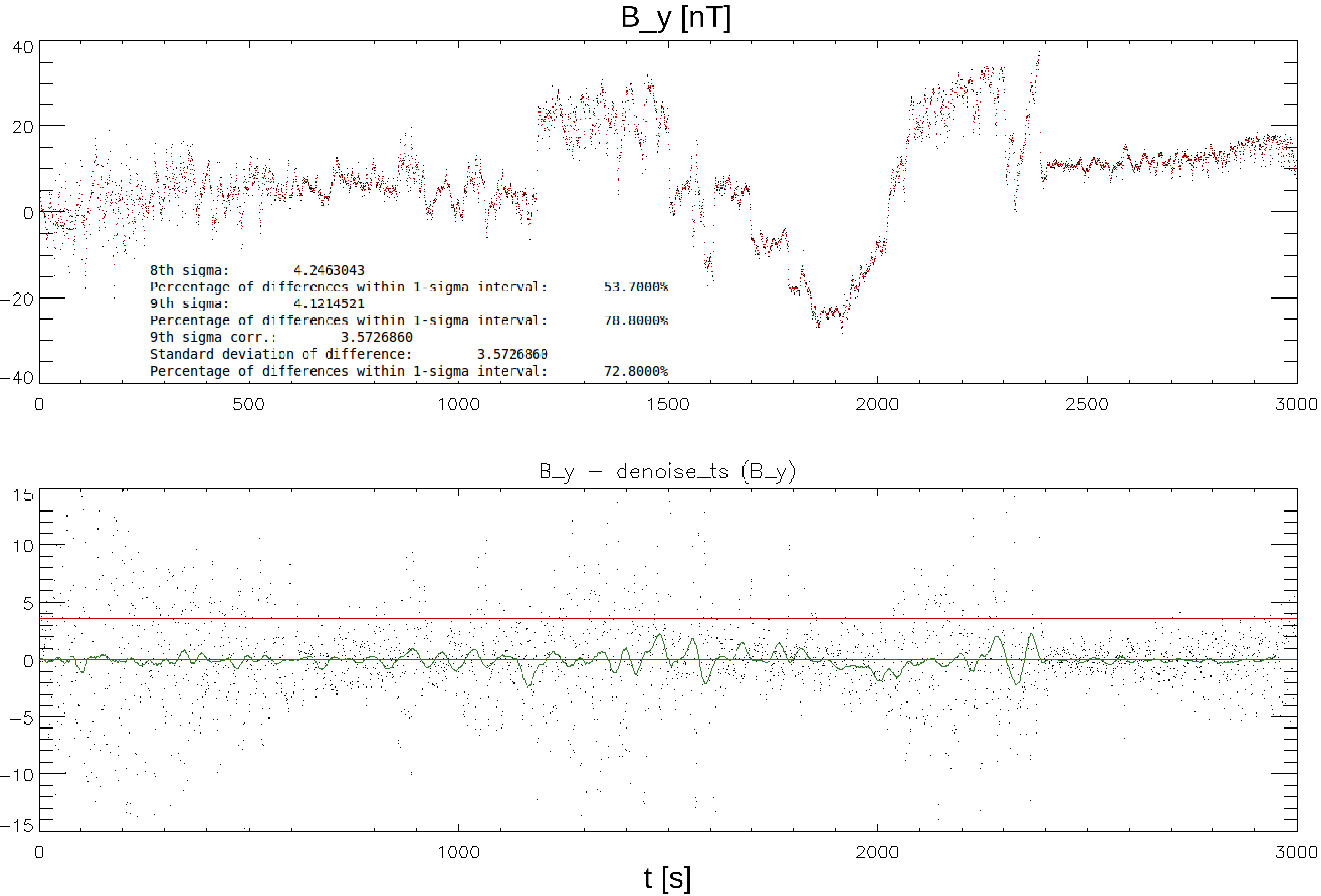
Hinode magnetogram (denoised with NL-means):



Hinode magnetogram (difference plot):

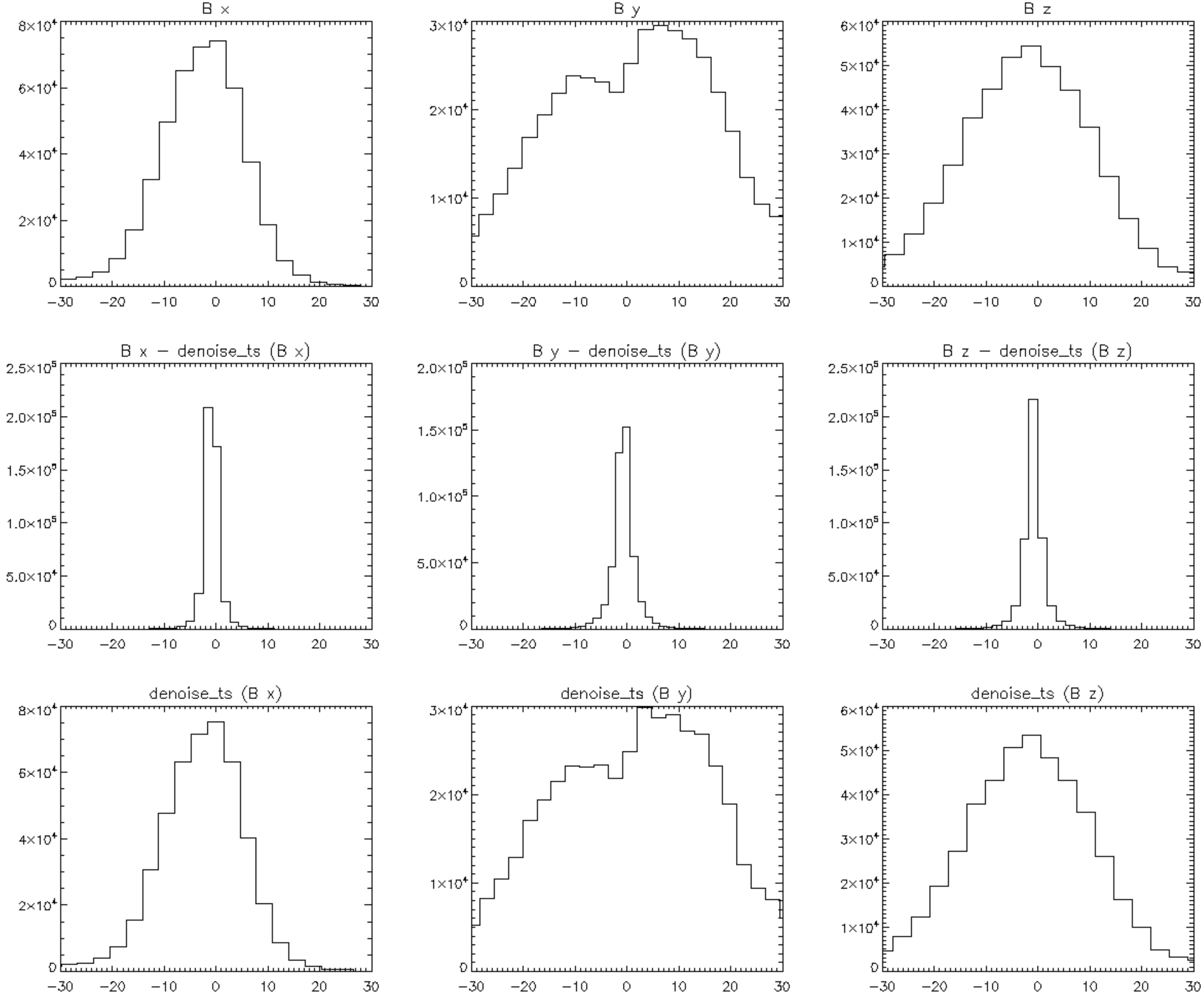


Denoising 1D-timeseries data (e.g. Cluster, MMS magnetometer)



B_y [nT]
8th sigma: 4.2463043
Percentage of differences within 1-sigma interval: 53.7000%
9th sigma: 4.1214521
Percentage of differences within 1-sigma interval: 78.8000%
9th sigma corr.: 3.5726860
Standard deviation of difference: 3.5726860
Percentage of differences within 1-sigma interval: 72.8000%
40
20
0
−20
−40
0
500
1000
1500
2000
2500
3000
B_y − denoise_ts (B_y)
15
10
5
0
−5
−10
−15
0
1000
2000
3000
t [s]

B [nT]



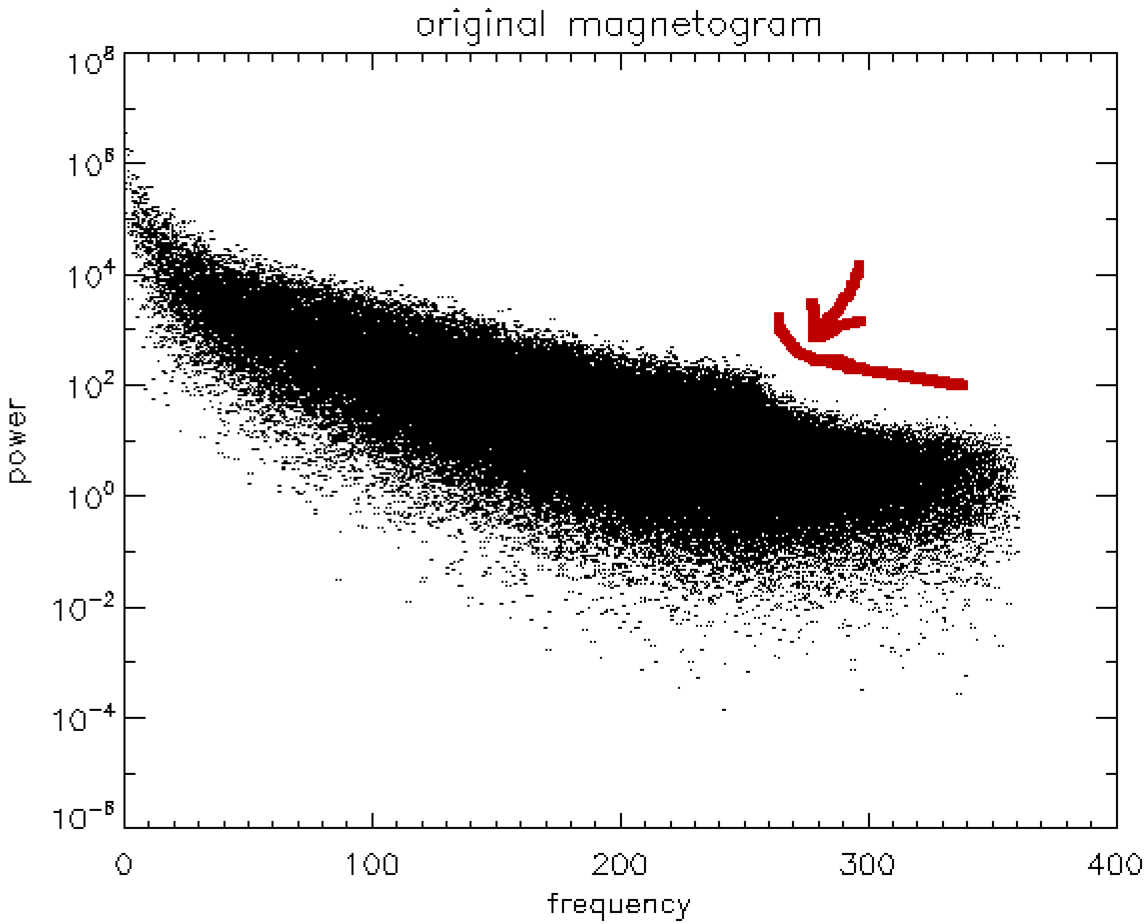

```
1st sigma:       8.82867
2nd sigma:       4.70288
3rd sigma:       4.70288
4th sigma:        2.3088144
5th sigma:        1.8288614
6th sigma:        1.8110390
7th sigma:        1.6962064
```

```
sigma B_y:
1st sigma:       17.6623
2nd sigma:       9.90398
3rd sigma:       9.90398
4th sigma:        3.8232615
5th sigma:        2.6719532
6th sigma:        2.7195409
7th sigma:        2.5529399
```

```
sigma B_z:
1st sigma:       14.0852
2nd sigma:       7.50026
3rd sigma:       7.50026
4th sigma:        3.4408310
5th sigma:        2.5290380
6th sigma:        2.5457214
7th sigma:        2.4118983
```

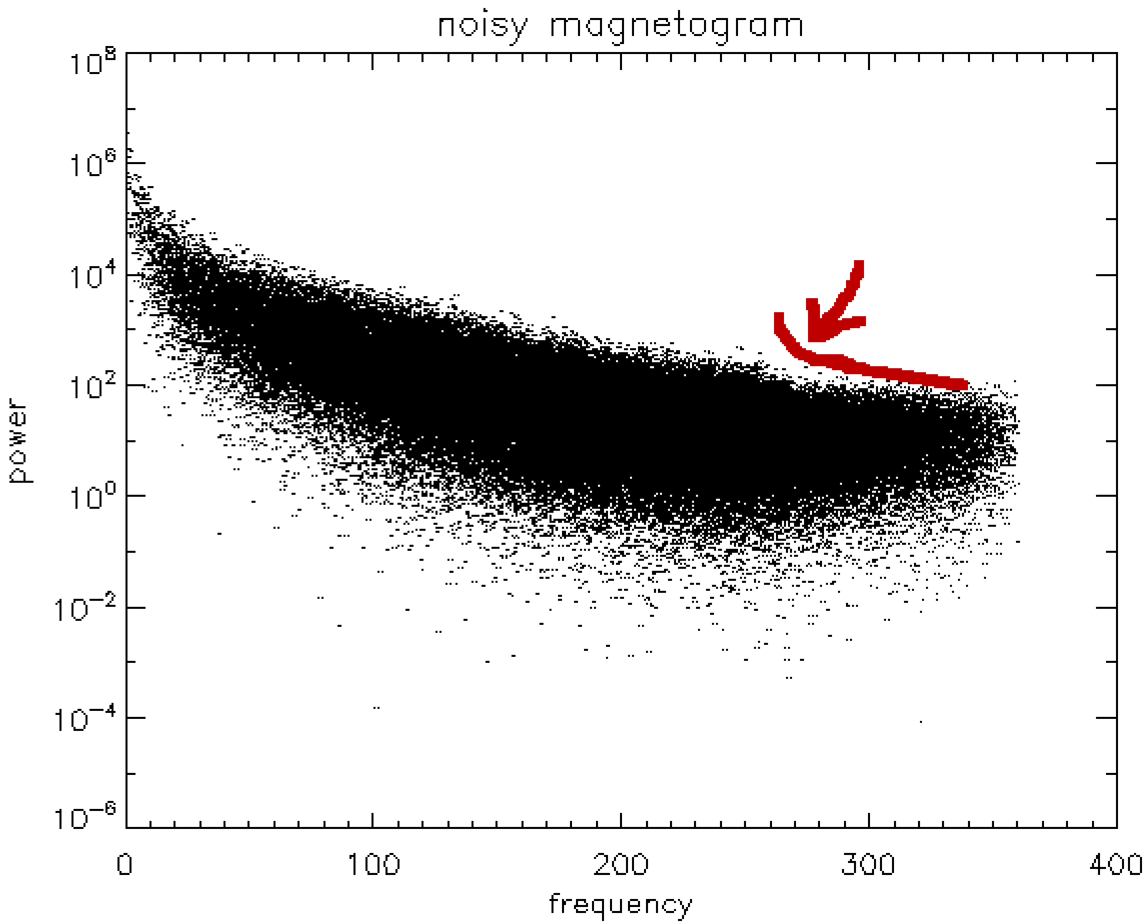
Denoising 1D-timeseries data (e.g. Cluster, MMS magnetometer)

Power spectrum – original data:



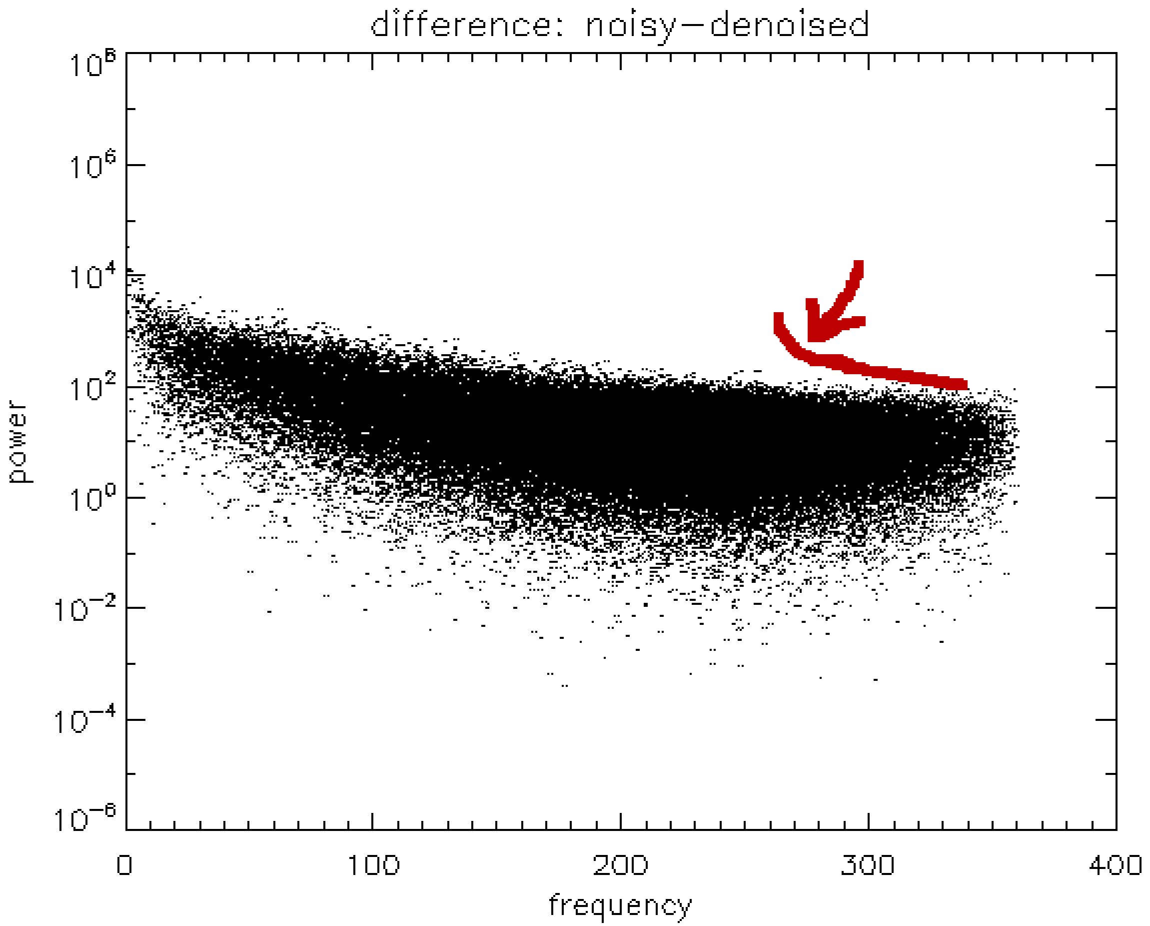
Denoising 1D-timeseries data (e.g. Cluster, MMS magnetometer)

Power spectrum – noise added to original data:



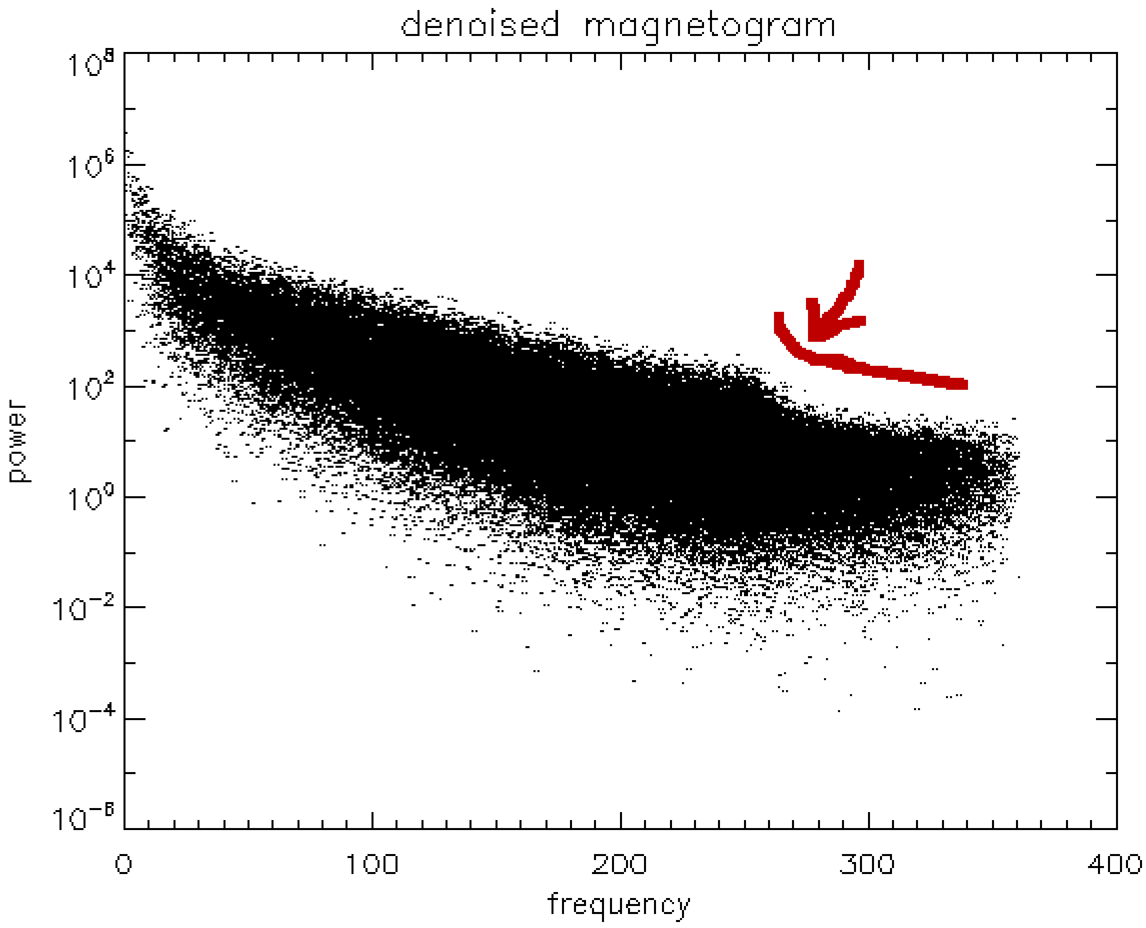
Denoising 1D-timeseries data (e.g. Cluster, MMS magnetometer)

Power spectrum – difference between noisy and denoised:



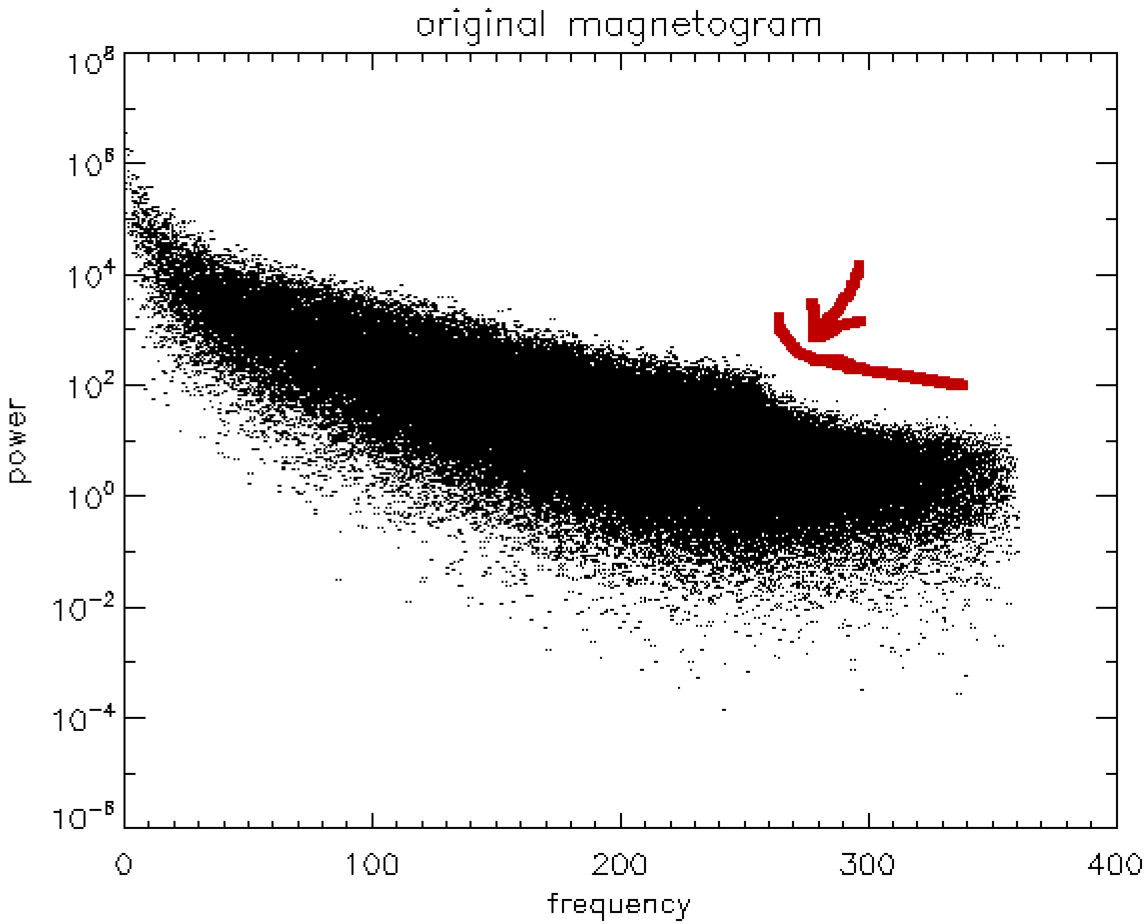
Denoising 1D-timeseries data (e.g. Cluster, MMS magnetometer)

Power spectrum – denoised data:



Denoising 1D-timeseries data (e.g. Cluster, MMS magnetometer)

Power spectrum – original data:



Conclusions

NL-means:

* no artefacts introduced

* no harm is done, where there is uncertainty

* no loss of resolution

* non-local method

* can be applied early in the data processing pipeline (even for movies)

* maybe even suitable for 1D-time series

  (use Kalman filtering for correlated 1D-time series)

=> deserves consideration

References:

Buades et al., Multiscale Modeling and Simulation, Vol. 4 (2), 2006

Buades et al., Int. J. Comput. Viz., Vol. 76, 2008

Online demo: http://mw.cmla.ens-cachan.fr/megawave/demo/nlmeans/