

# Deconvolution

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See Aster and Borchers, Time Series Analysis, chapter 6.

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For example, if we obtain a seismogram, that's our observable,  $d(t)$ . And we have the impulse response of our seismometer,  $g(t)$ . We then wish to find the ground motion input,  $m(t)$ .

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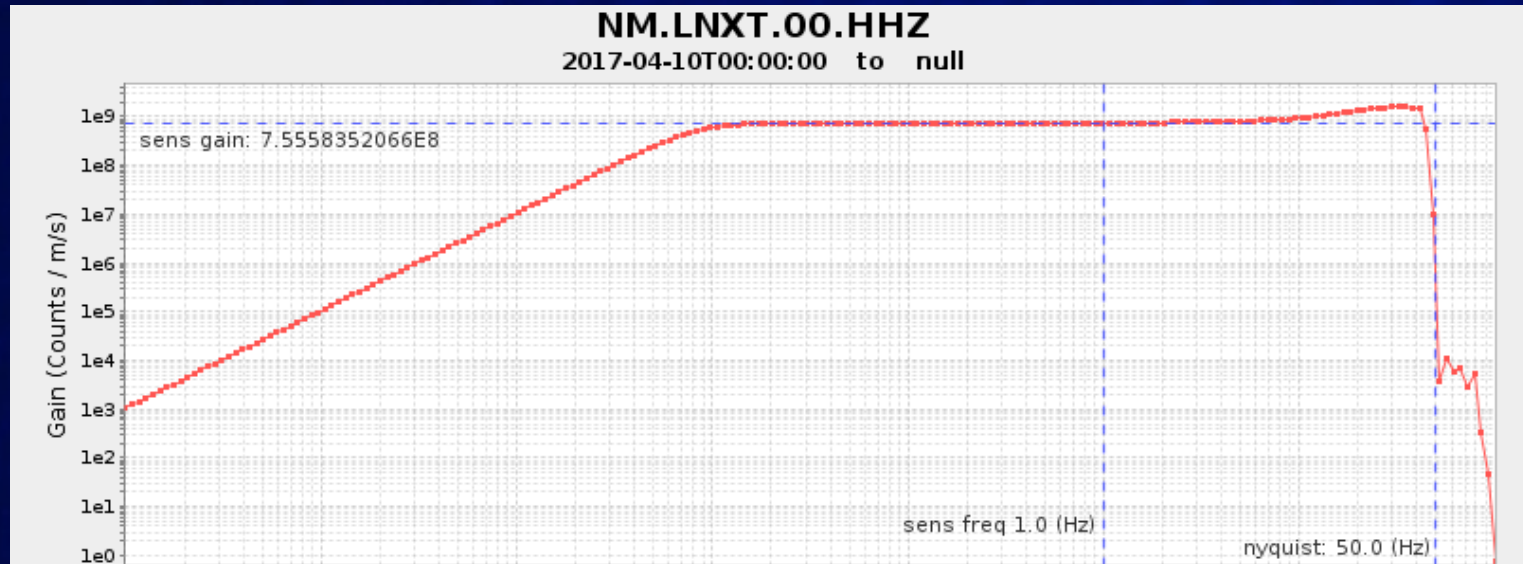
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$$M_k = \frac{D_k}{G_k \Delta t} \quad \longrightarrow \quad \text{Spectral Division}$$



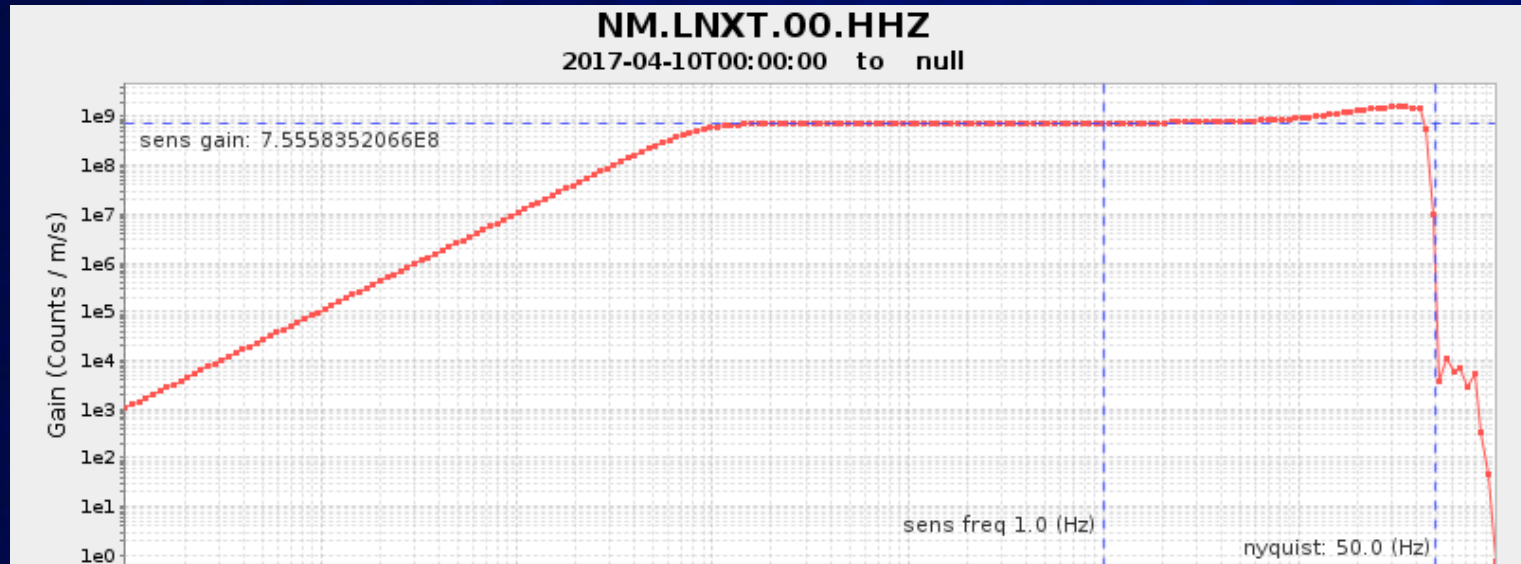
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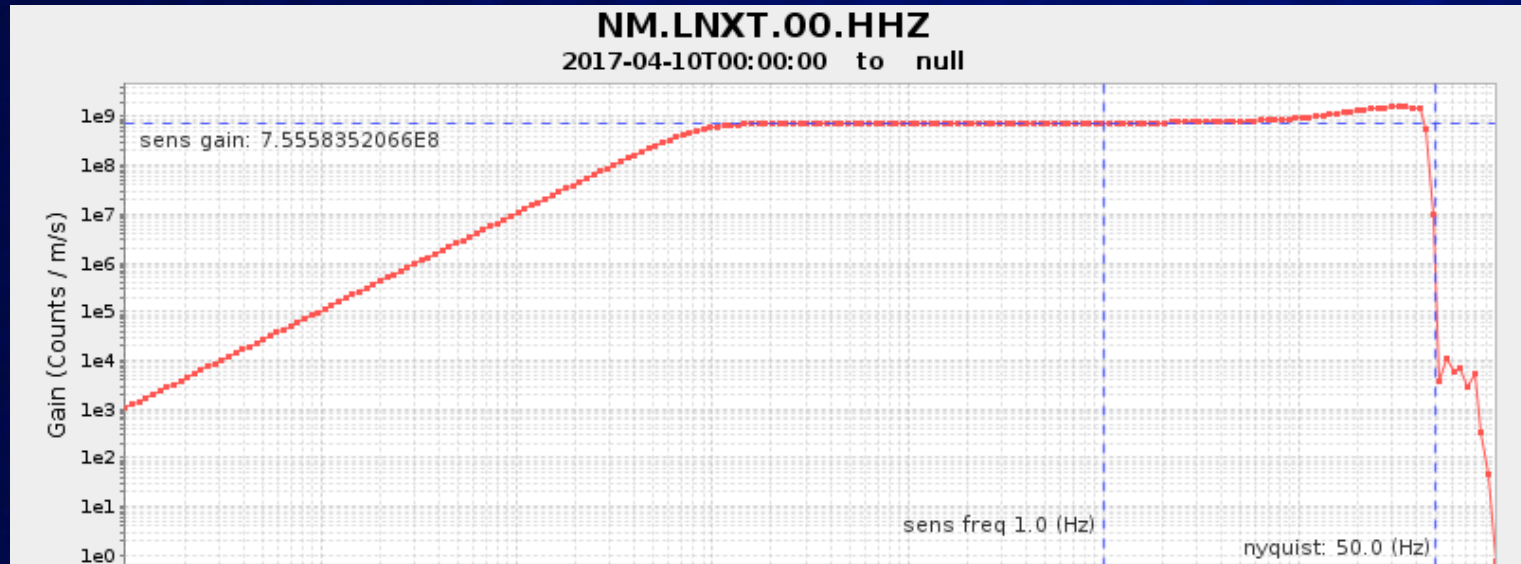
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We record some frequencies with poor fidelity (e.g. the gain of the instrument at those frequencies is very small).

And using spectral division, we divide by small numbers at those frequencies.

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What if the noise is added after the convolution (e.g. instrument noise)?

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Remember we're trying to deconvolve the instrument response (G) from the data (D) to get the input ground motion (M). Where G is small, we amplify the noise.

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We wish to keep the denominator from getting small so we add a small constant to it.

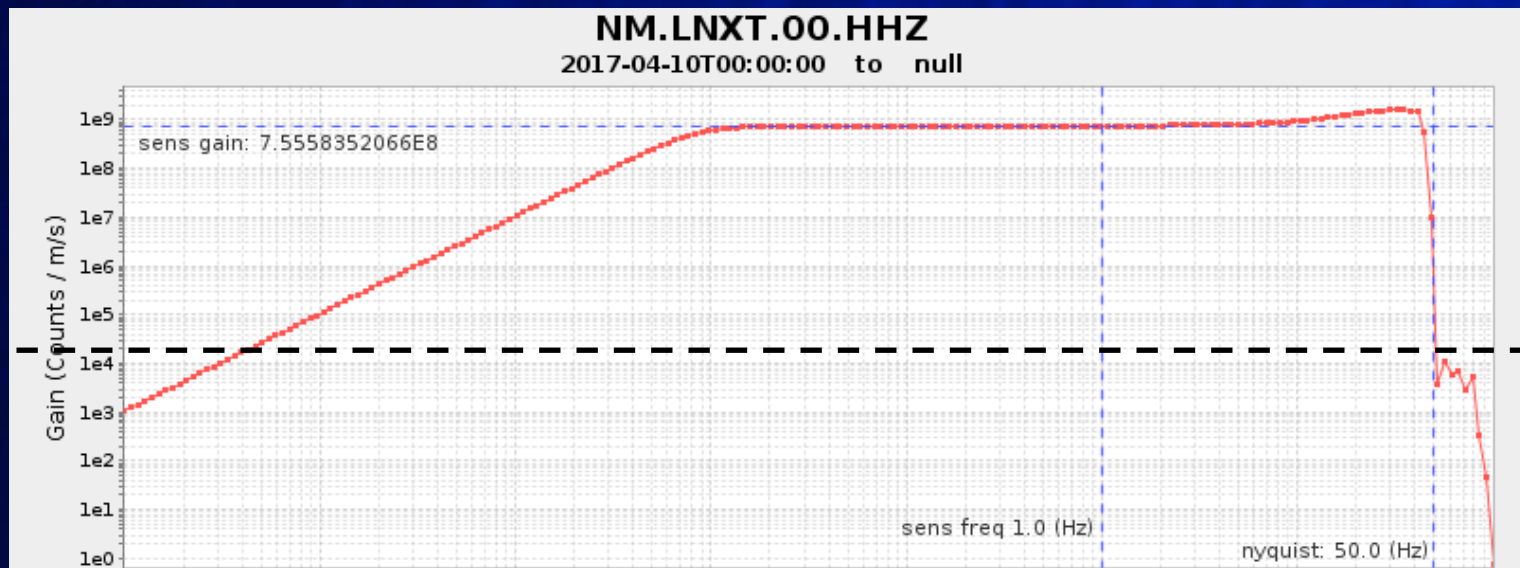
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When  $G$  is large,  $\lambda$  will have a small effect.

When  $G$  is small,  $\lambda$  will have a larger effect.

When  $G = -\lambda$ , we have a problem.

 $\lambda$ 

 $\lambda$



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But be careful of 0.

$$\hat{G}(f) = \begin{cases} G(f), & |G(f)| > w \\ \frac{wG(f)}{|G(f)|}, & 0 < |G(f)| \leq w \\ w, & G(f) = 0 \end{cases}$$

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If you know  $N(f)$  (e.g. the average instrument noise say from an ASL study for your system) then that can define  $w$ .

As an example, let the input be,  $m(t) = te^{-t}$

And the linear system be,  $g(t) = e^{-5t} \sin(10t)$

Run matlab program deconvdemoA to demonstrate recovering  $m(t)$  in the presence of noise using water level regularization.

Another more elegant method is Tikhonov regularization.

$$\hat{M}_k = \frac{G_k^* D_k}{(G_k^* G_k + \lambda) \Delta t}$$

When  $|G_k| \gg \lambda$ ,  $M_k = \frac{D_k}{G_k}$

When  $|G_k| \ll \lambda$ ,  $M_k$  is reduced rather than amplified.

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One could also use average pre-event noise and average event amplitude or some similar scheme to choose  $\lambda$

Run matlab program deconvdemoB

