# Newtonian-noise Cancellation in Virgo

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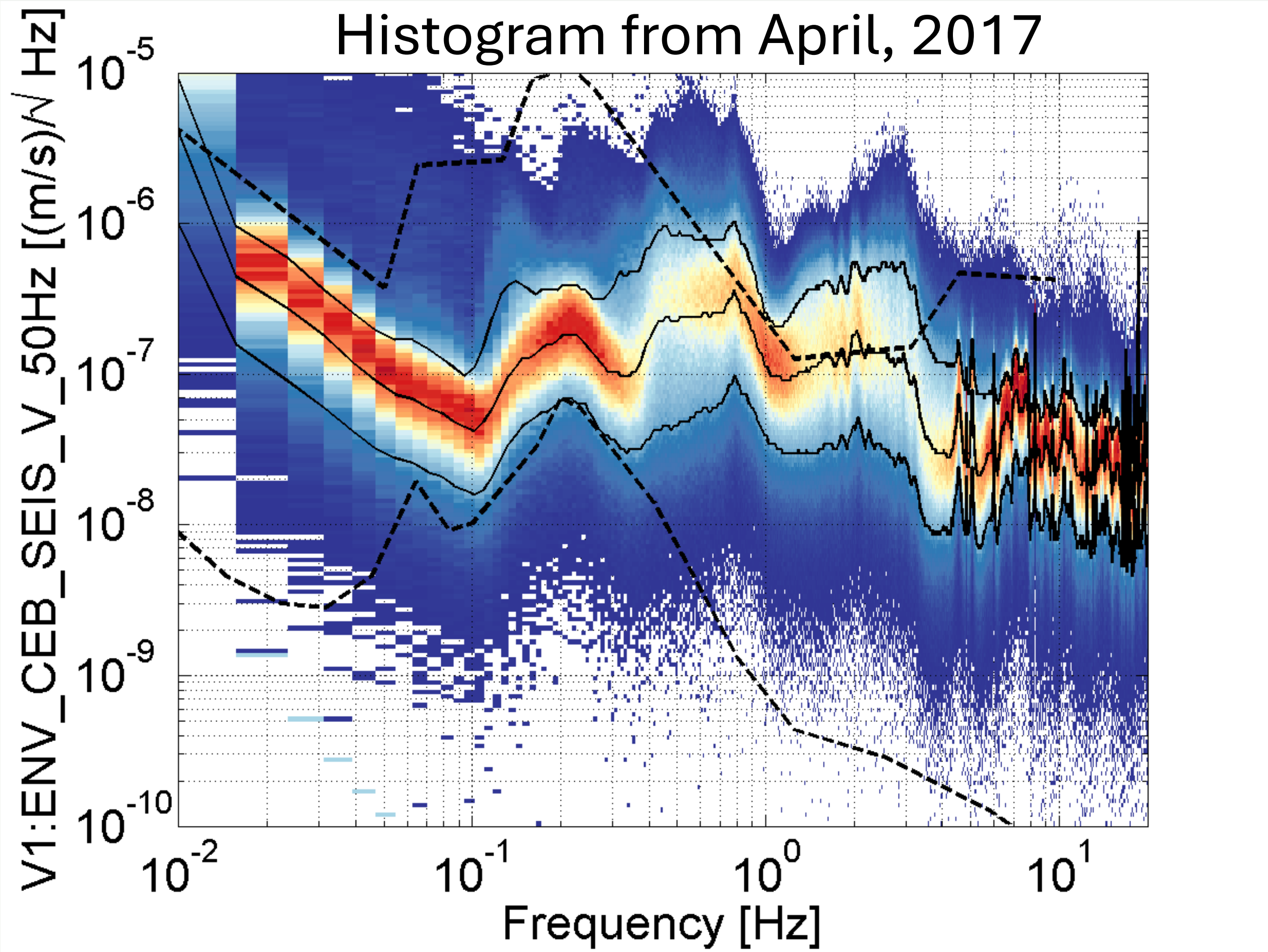
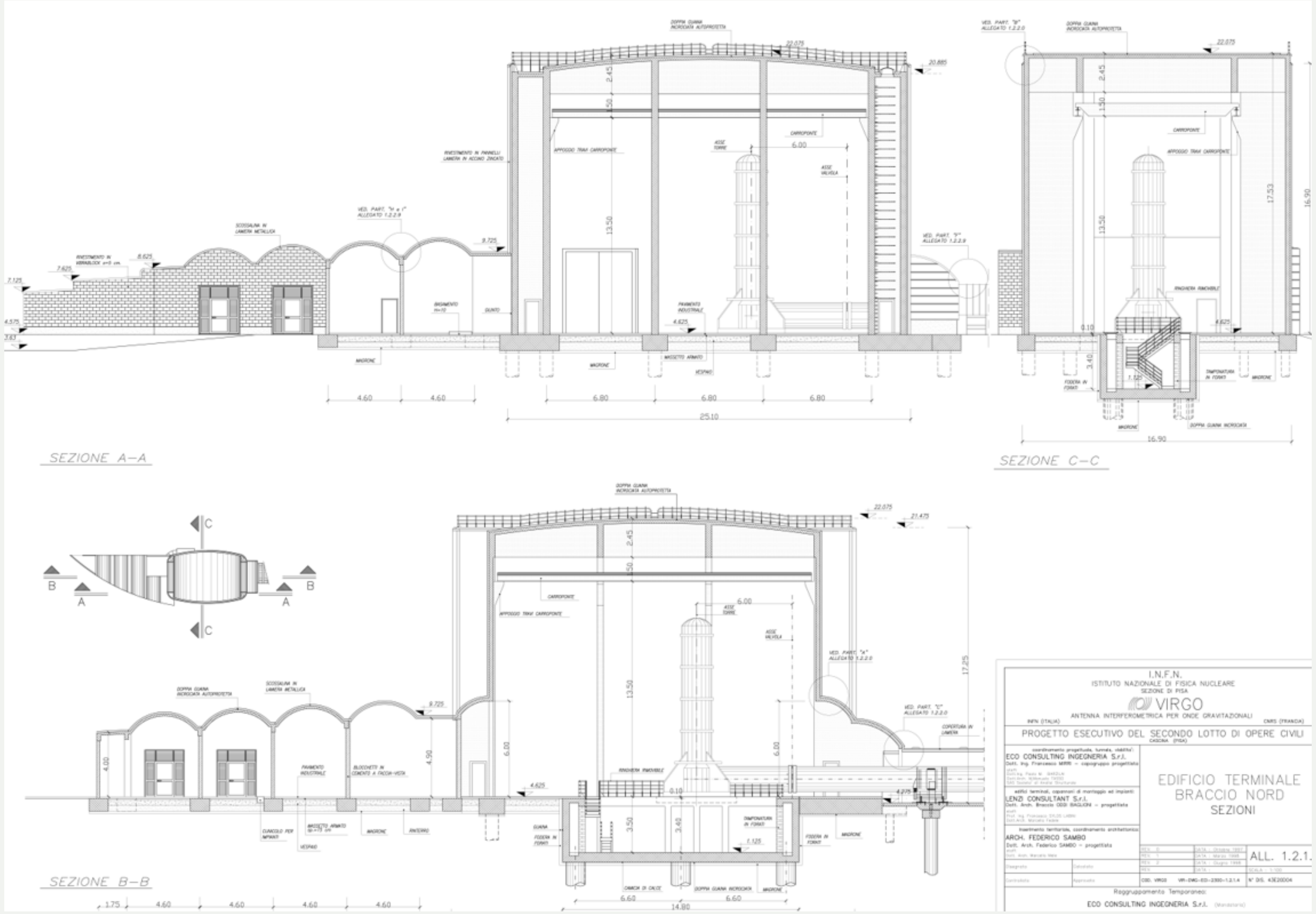
# Virgo Seismic Noise

- There is strong ground displacement at the Virgo site
- The need for a seismic Newtonian-noise cancellation (NNC) system as part of a future detector upgrade was clear

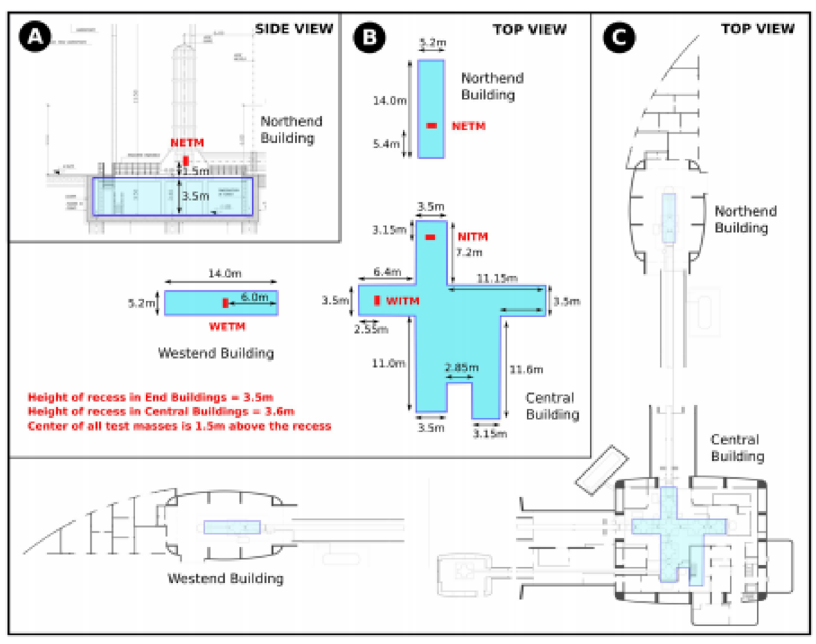


# Virgo End Buildings

- If possible, we like to work with simple NN models as we did for LIGO
- However, the Virgo site has a complex structure with clean rooms under the test masses.
- We already knew from a past study (Harms & Hild, CQG 31 185011, 2014 ) that such free space below test masses can reduce NN significantly

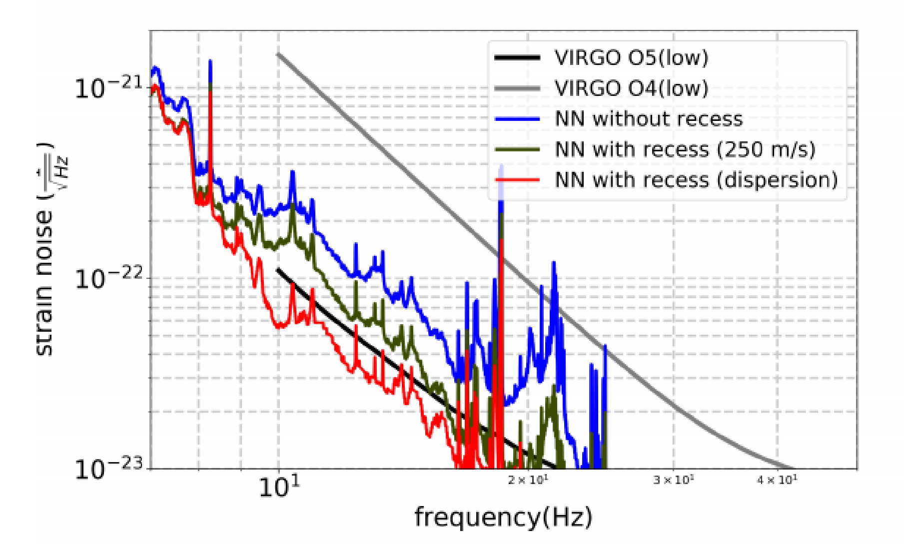


# Simplest numerical models



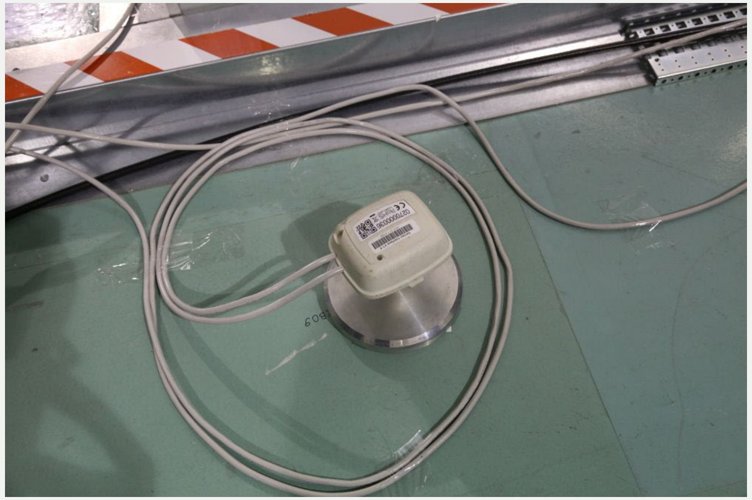

## Method

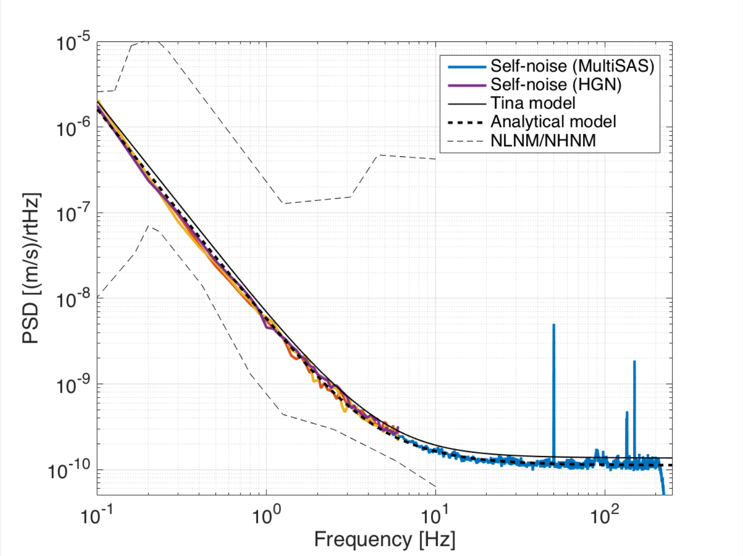
- Propagate plane Rayleigh waves through FEM with correct surface topography;
- Integrate over FEM to obtain NN;
- Neglects scattering of Rayleigh waves

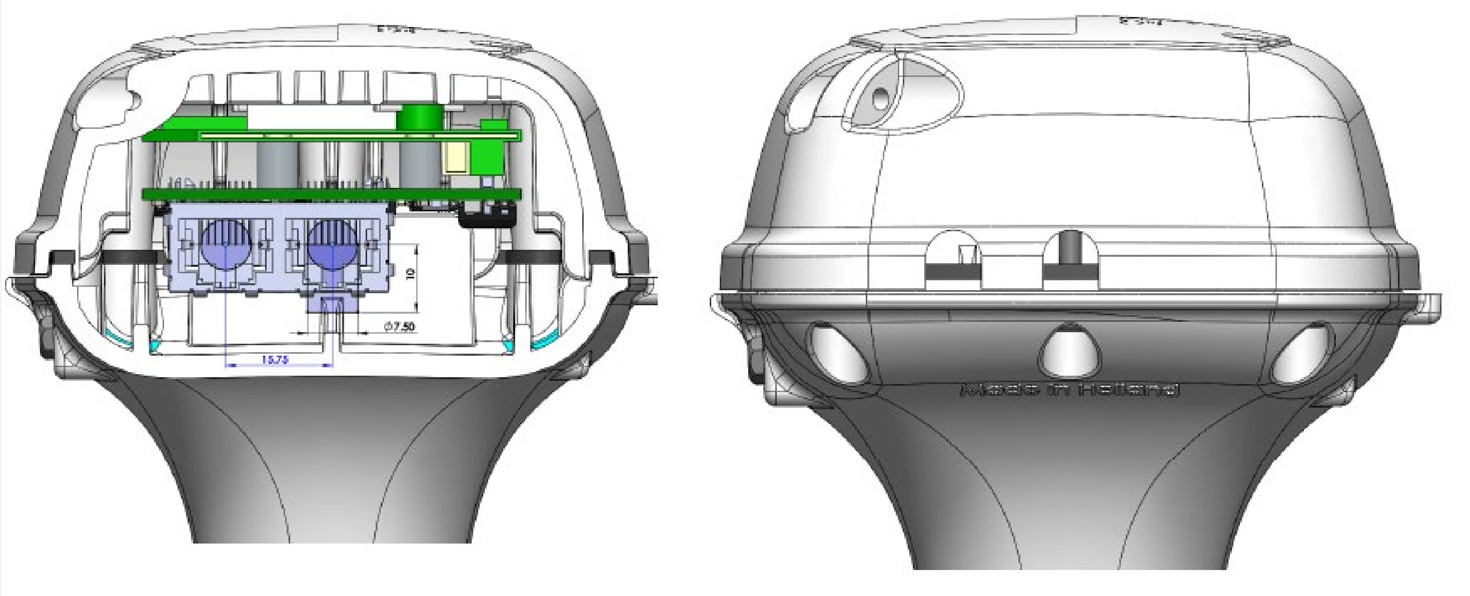



Singha et al 2021 Class. Quantum Grav. 38 245007

# Geophones for NN Array



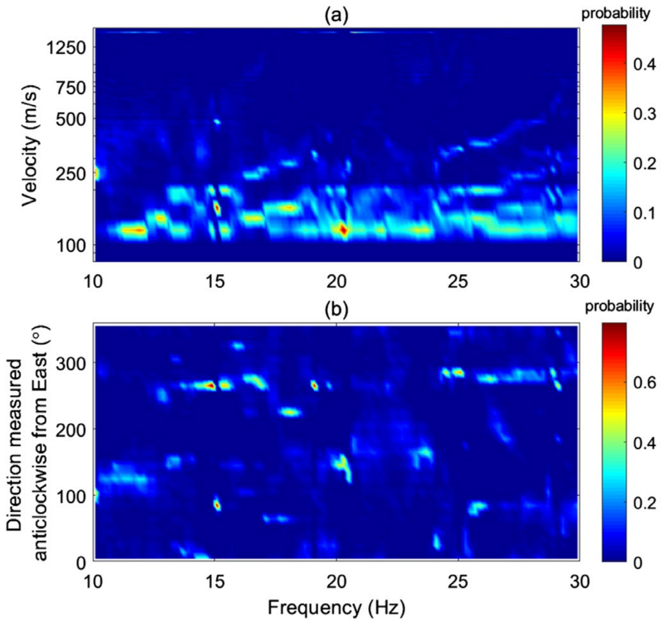


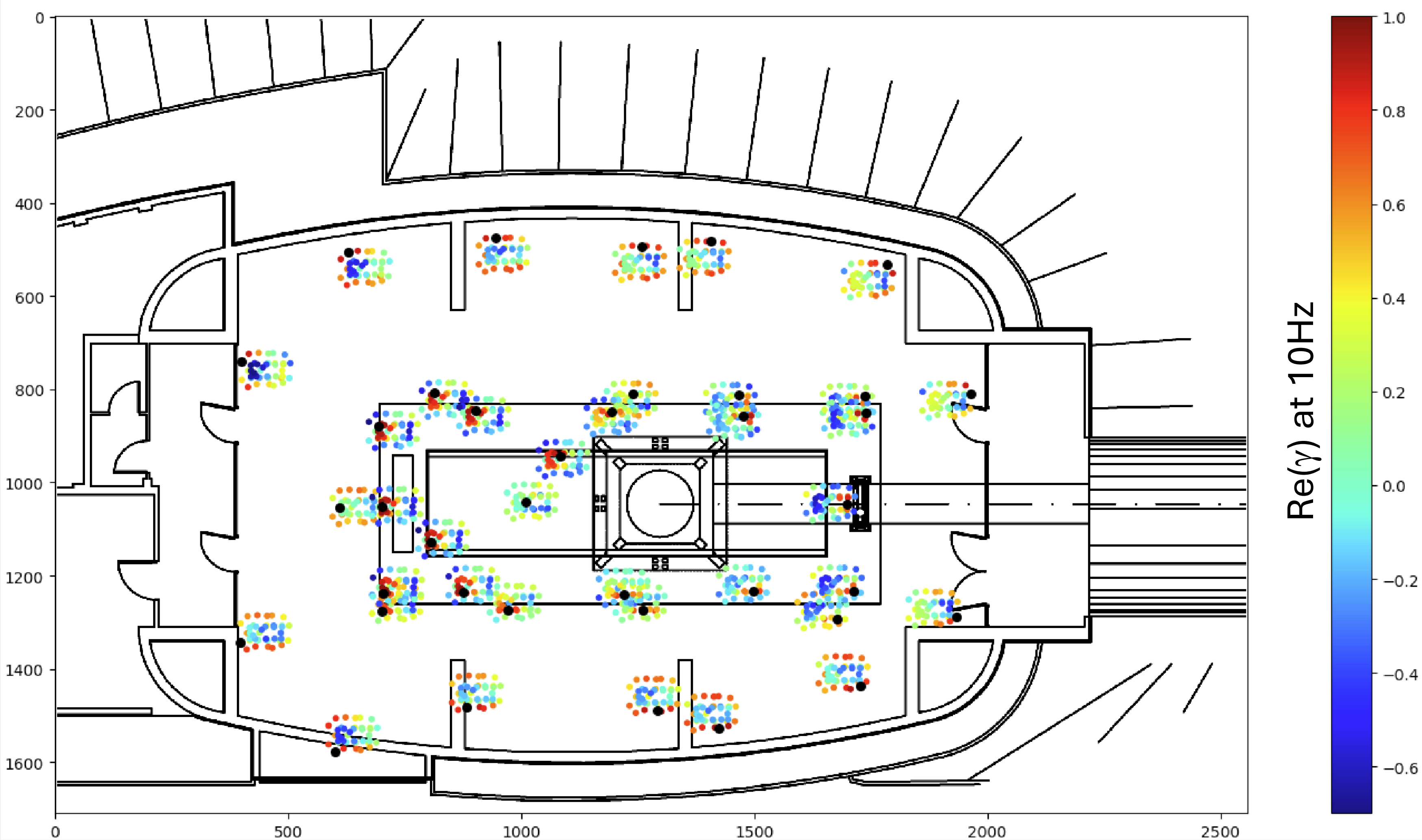




120 InnoSeis vertical geophones were deployed with modified mounts for indoor deployment.

Sensor electronics were modified by Polgraw to be compatible with Virgo central data acquisition and distributed timing signal.

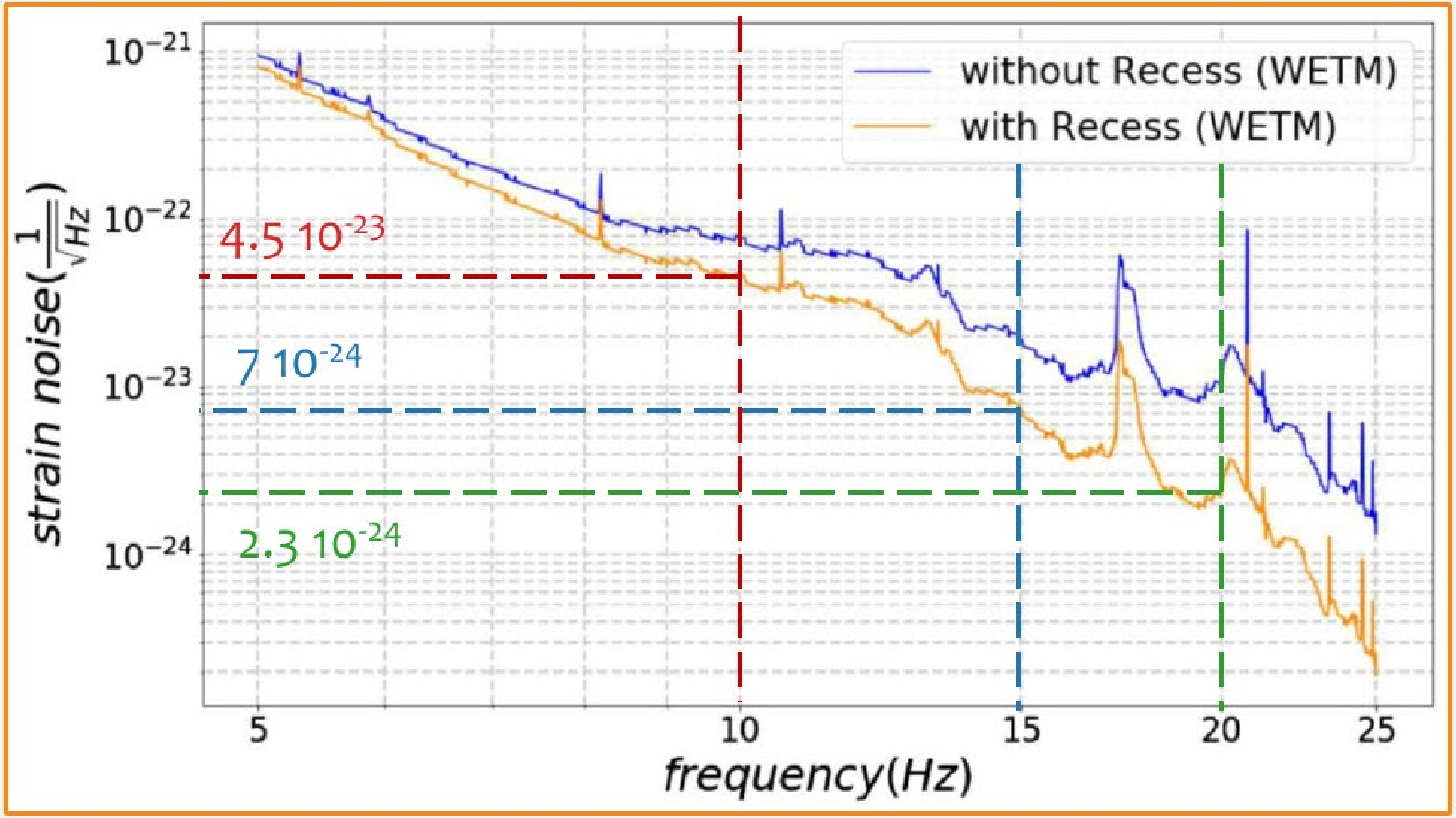
# Seismic Correlations at Virgo




Seismic field at Virgo is strongly inhomogeneous and anisotropic.

# Do NN estimates converge?

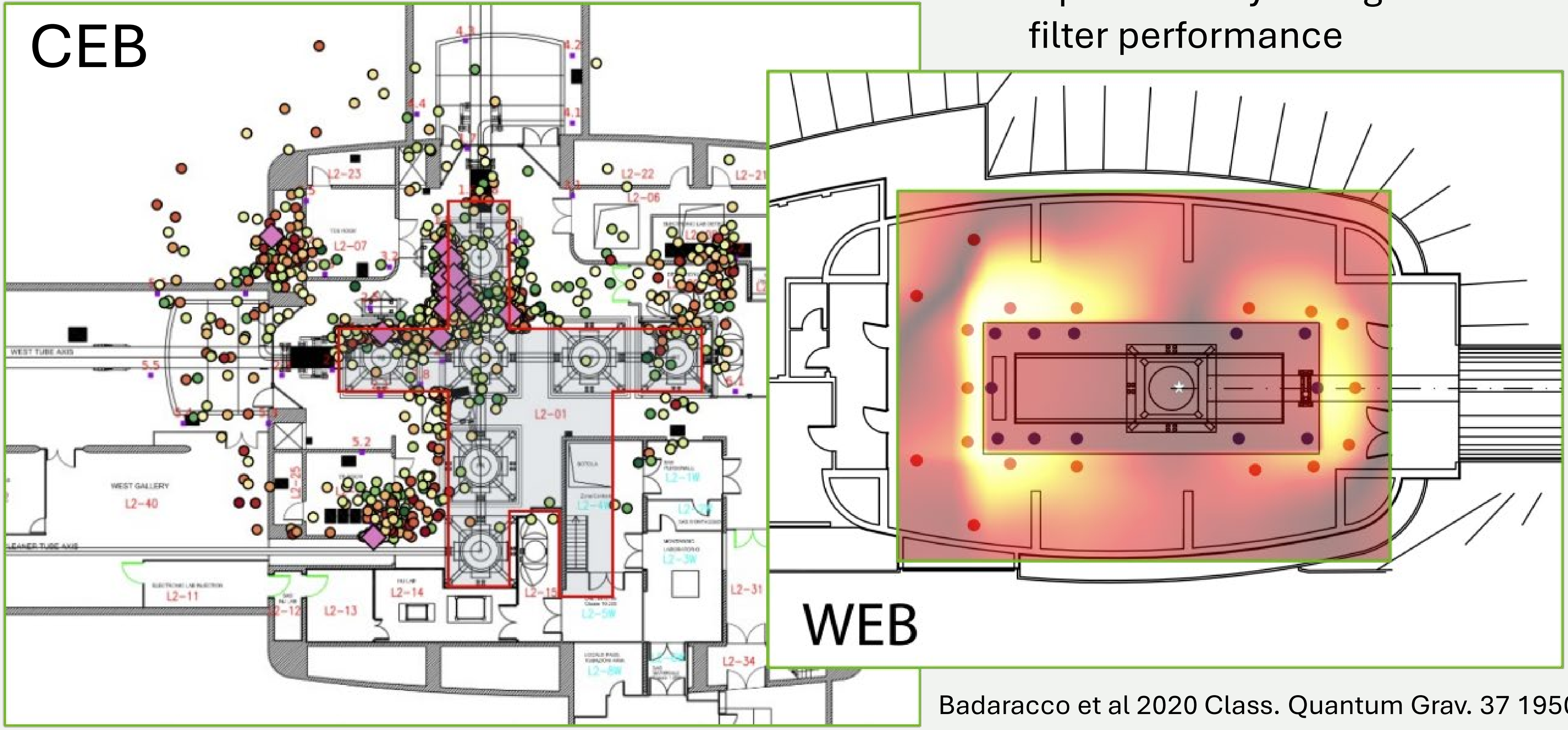



WEB NN predictions based on FEM (Singha et al) and correlation model (Badaracco et al), both using accurate WEB topography, match very well.

# Array optimization

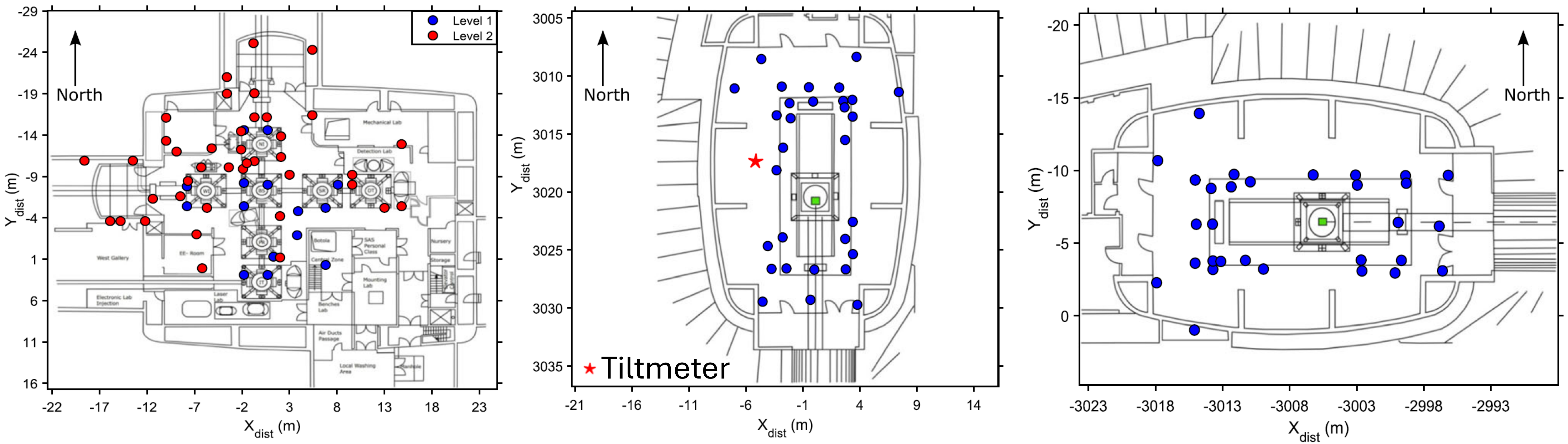
## Method

- Use observed seismic correlations to construct a surrogate Wiener filter
- Optimal array configuration maximizes filter performance




Badaracco et al 2020 Class. Quantum Grav. 37 195016

# Final Array Configurations



# Noise Cancellation

Time step k

$$e(k) = y(k) - \mathbf{h}(k)\mathbf{x}(k)$$

Noise residual

Sample of the target channel

Coefficients of a linear filter

Present and past samples of witness channels

- y(k) is a sample of the Virgo GW data, which includes NN
- h(k)x(k) is the NN estimate based on seismic data x(k)

# Wiener Filter

$$\mathbf{h}(k) = \mathbf{P}\mathbf{S}^{-1}$$

**S** is a correlation matrix between witness channels.

It has size (N M) x (N M).
N is the number of witness channels.
M is the number of past samples to be mapped with the filter.

**P** is a correlation vector between witness channels and the target channel.

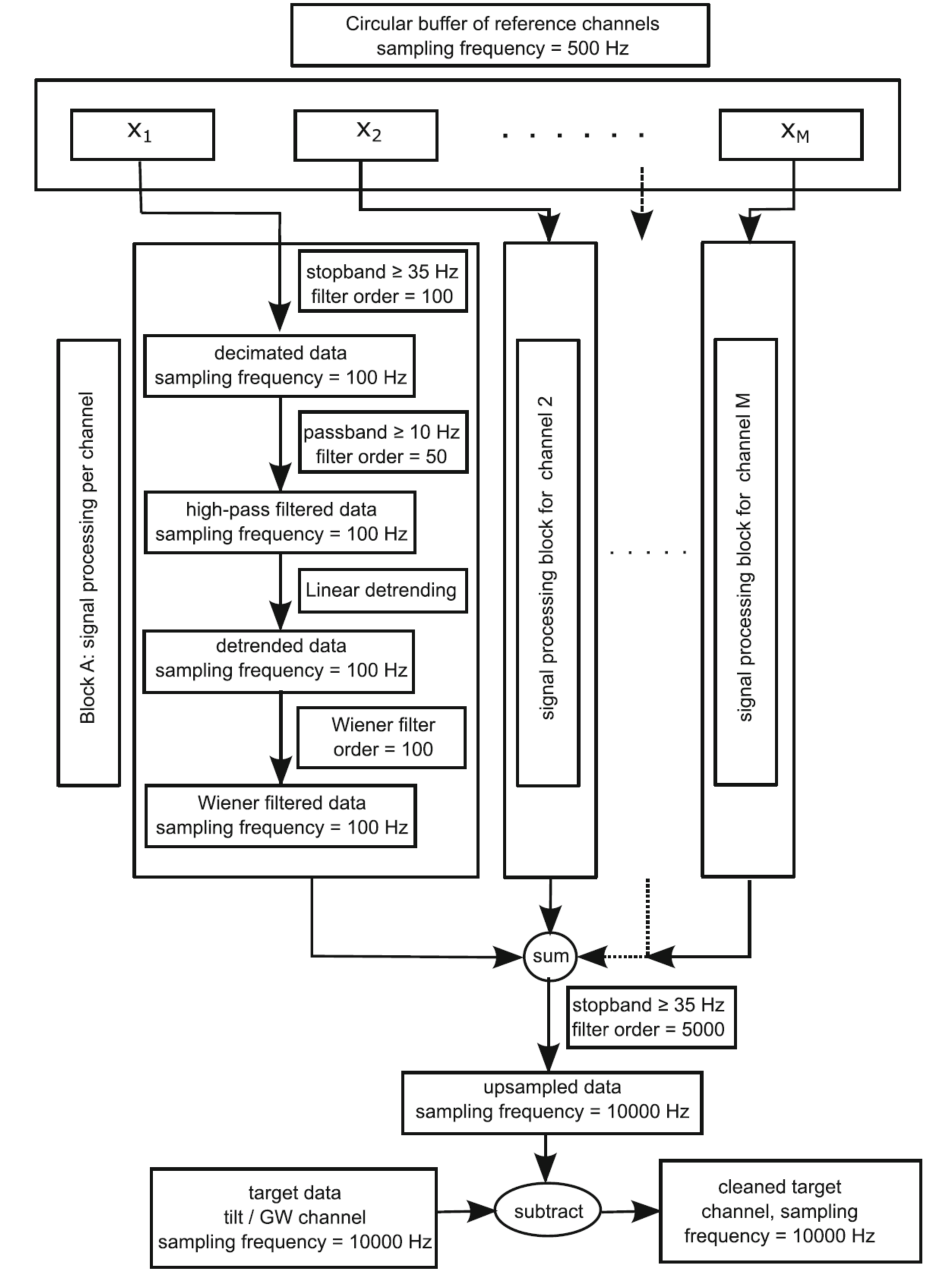
It has size 1 x (N M).

The Wiener filter is the optimal noise-cancellation filter when the relation between the measured degrees of freedom is linear.

# NNC Pipeline

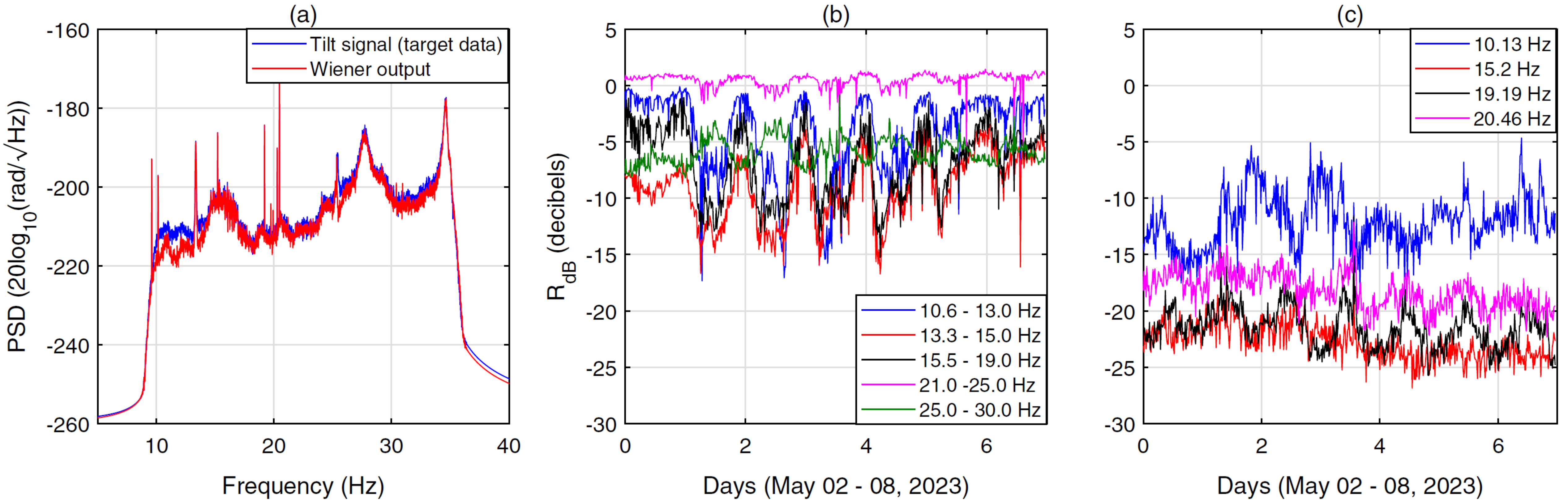
Several auxiliary data-processing steps are required in practice:

- Decimation, upsampling
- Low-pass, band-pass
- Detrending




Koley et al, Eur. Phys. J. Plus (2024) 139:48

# Static Wiener Filter

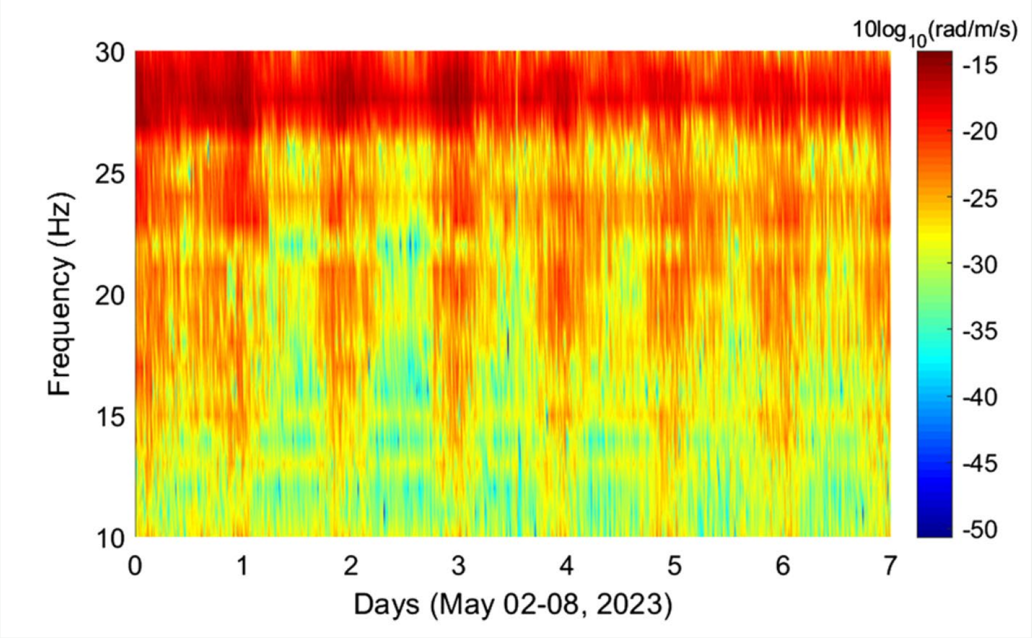



Koley et al, Eur. Phys. J. Plus (2024) 139:48

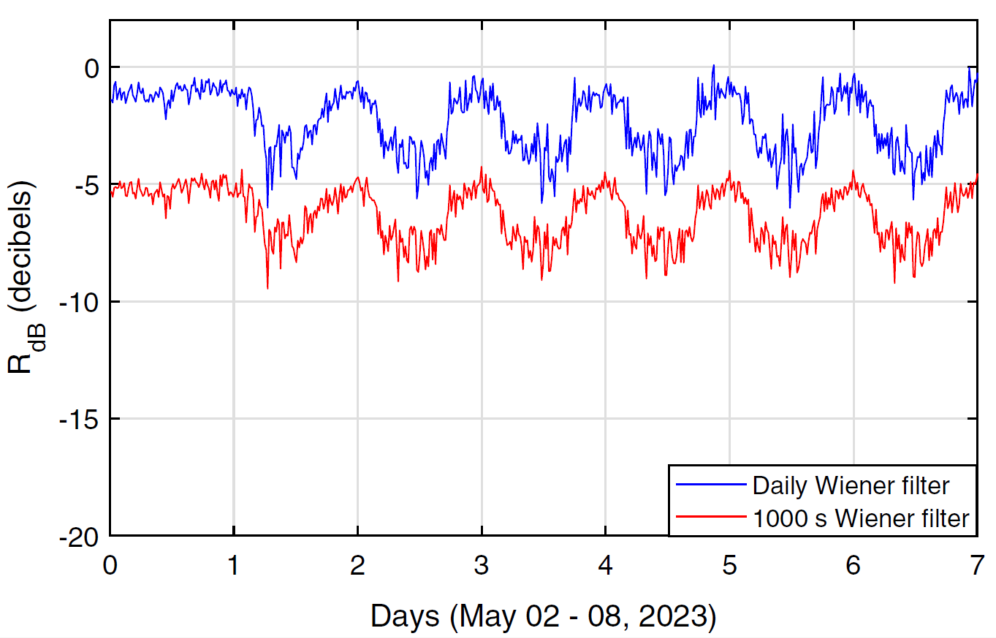
Test: cancel signal of a tiltmeter using geophone data

# Regularly Updated Wiener Filter

Transfer function of the Wiener filter relative to one of the geophones




Filter averaged over a day vs filter updated every 1000s.

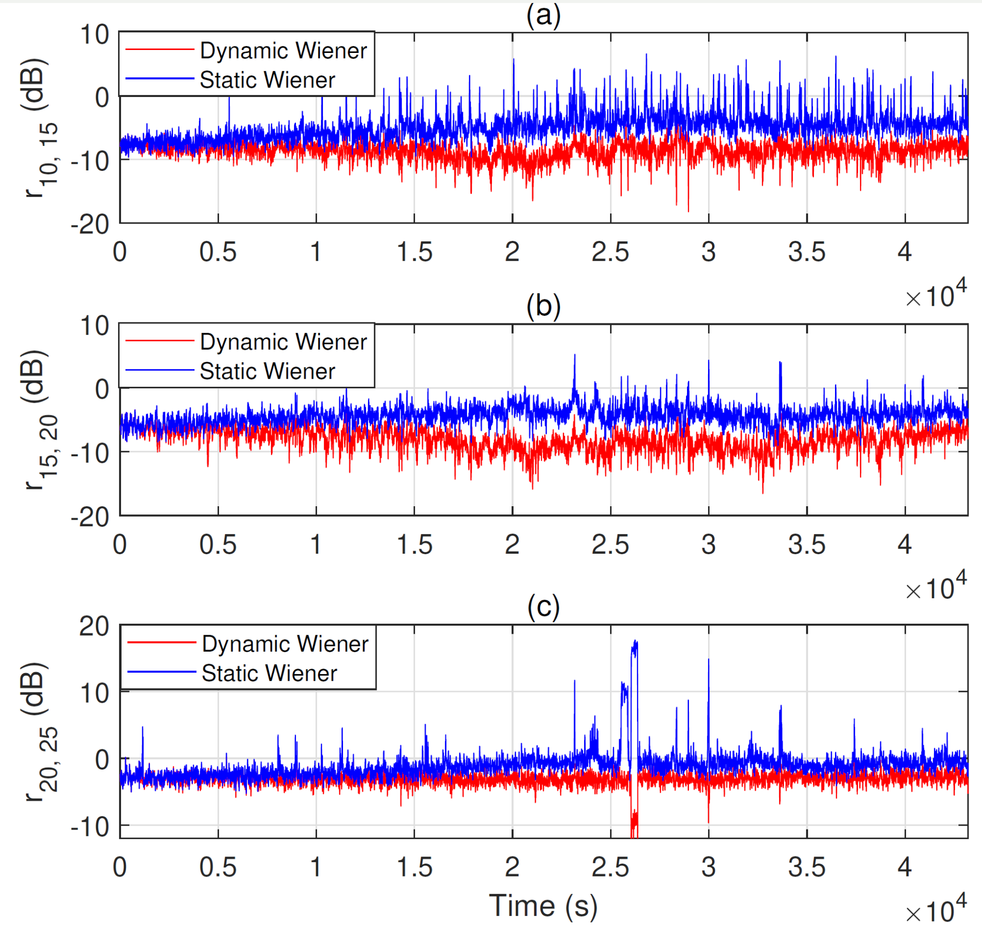



Koley et al, Eur. Phys. J. Plus (2024) 139:48

# Regularly Updated Wiener Filter

Calculating a static Wiener filter with 1000s of data and applying it to 12 hours of data vs updating a Wiener filter every 1000s.

Noise-cancellation performanceof the static filter becomes worse over time due to diurnal cycles of the seismic field.




Koley et al, Adaptive NNC (2024) [under preparation]

# Adaptive Wiener Filters

LMS

$$\mathbf{h}_n = \mathbf{h}_{n-1} + \mu \mathbf{X}_n^\dagger \left( y_n - \mathbf{h}_{n-1}\mathbf{X}_n \right)$$

$$\mathbf{h}_n = \mathbf{h}_{n-1} + \mu \mathbf{X}_n^\dagger \mathcal{E}_n$$

NLMS

$$\mathbf{h}_n = \mathbf{h}_{n-1} + \alpha \frac{\mathbf{X}_n^\dagger \mathcal{E}_n}{\mathbf{X}_n^\dagger \mathbf{X}_n + \delta_{\rm NLMS}}$$

IPNLMS

$$\mathbf{h}_n = \mathbf{h}_{n-1} + \alpha \frac{\mathbf{X}_n^\dagger \mathbf{G}_{n-1} \mathcal{E}_n}{\mathbf{X}_n^\dagger \mathbf{G}_{n-1} \mathbf{X}_n + \delta_{\rm IPNLMS}}$$

RLS

$$\tilde{\mathbf{C}}_n = \mathbf{X}_n^\dagger \lambda^{-1} \mathbf{R}_{n-1}^{-1}$$
$$\gamma_n^{-1} = 1 + \tilde{\mathbf{C}}_n \mathbf{X}_n$$
$$e_n^p = y_n - \mathbf{h}_{n-1}\mathbf{X}_n$$
$$\mathbf{h}_n = \mathbf{h}_{n-1} + \gamma_n e_n^p \tilde{\mathbf{C}}_n$$
$$\mathbf{R}_n^{-1} = \lambda^{-1}\mathbf{R}_{n-1}^{-1} - \tilde{\mathbf{C}}_n^\dagger \gamma_n \tilde{\mathbf{C}}_n$$

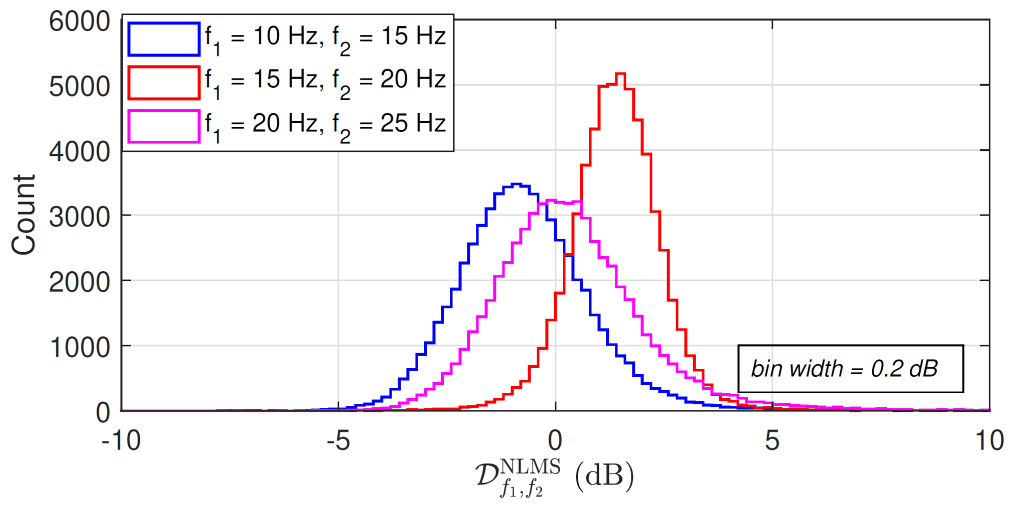
Requirements

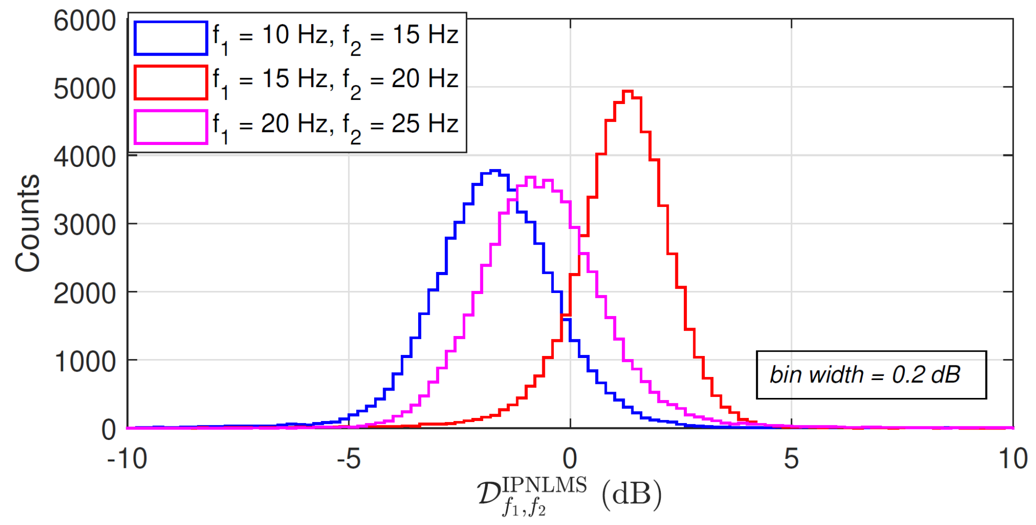
1) Fast convergence
2) Long-term stability
3) Low noise residuals over a broad band (10Hz – 25Hz in Virgo)
4) Computationally not too demanding for real-time applications

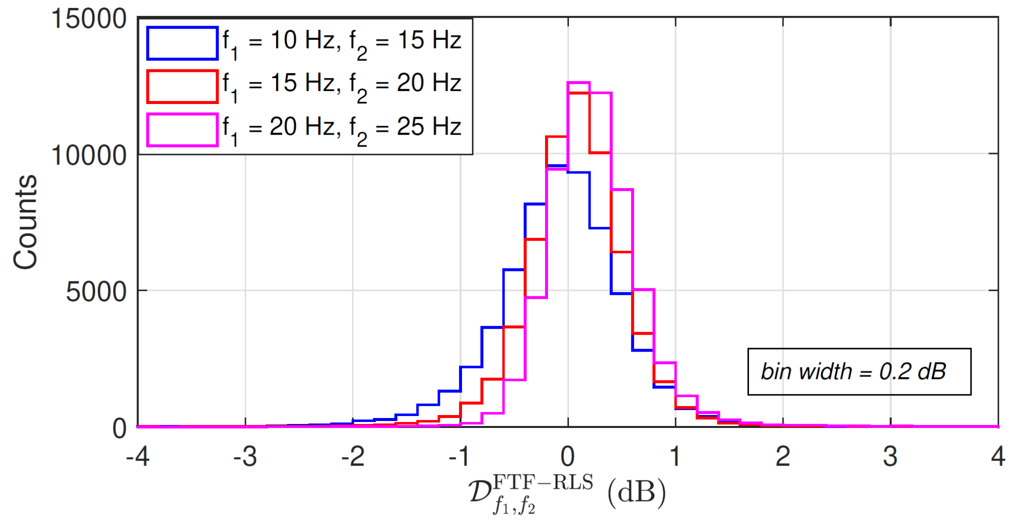
# Comparison of AWF Performance

The regularly updated Wiener filter is tough to beat.

It seems that the ideal adaptive filter is still out their to be found




Koley et al, Adaptive NNC (2024) [under preparation]

# Two Simple Limits of Wiener Filtering

$$\mathcal{B}_{\rm stat}(f) = \frac{\langle |y(f)|^2\rangle^0}{\nu} NM$$

Minimum residual set by filter bias due to statistical errors in estimation of coefficients.

Depends on
- number of filter coefficients (NM),
- number of averages ν used to calculate the Wiener filter,
- the spectrum $<y^2>$ of the target channel.

$$\mathcal{B}_{\rm sens}(f) = S(f)\mathbf{h}^0(f)\cdot\left(\mathbf{h}^0(f)\right)^\dagger$$

Minimum residual set by the sensor noise in the witness channels.

Depends on
- sensor noise PSD S(f),
- and how this noise is mapped into the target channel by the Wiener filter **h**.

Koley et al, Adaptive NNC (2024) [under preparation]

# Implications for Time-varying Filters

$$\mathcal{B}_{\rm stat}(f) = \frac{\langle |y(f)|^2\rangle^0}{\nu} NM$$

**Fundamental constraint**

If you want to adapt to changes occurring over a time τ for cancellation of noise at frequency f, then you have at most ν=τf averages.

**Example**

If you have N=30 sensors and you use M=100 past samples of each channel, then for a factor 3.2 noise reduction in amplitude, you need ν=30000 averages to calculate the WF.

If this noise reduction is to be achieved at 10Hz, you need >3000s of training data / adaptation time scale.

# Similarities to Modeled Transient Subtraction

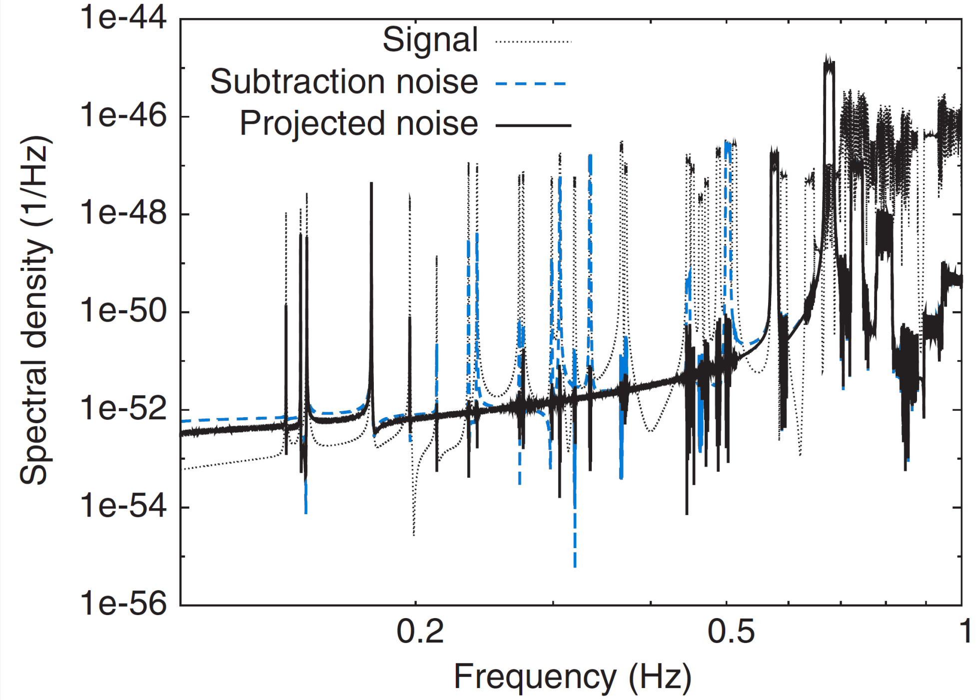
Cutler & Harms, Phys. Rev. D 73, 042001 (2006)

$$4\int_0^\infty \mathrm{d}f\,\frac{|\tilde{y}(f)-\hat{y}(f)|^2}{S(f)} = M \quad \Longleftrightarrow \quad \mathcal{B}_{\rm stat}(f) = \frac{\langle|y(f)|^2\rangle^0}{\cancel{\nu}}NM$$

Generally nonlinear model of a transient with M parameters

- This bound represents the case of a matched-filter likelihood analysis.
- We never reach this bound with our transient noise models.

Payne et al, Phys Rev D 106,104017 (2022)




Harms et al, Phys. Rev. D 77, 123010 (2008)

# Possible Future Developments

How can we do better than WF and LIGO/Virgo style parameterized, nonlinear transient modeling?

«repeated wave» scenario

- Properties of the seismic field repeat so that a filter calculated once can be applied later again and thereby be improved over time using the new data. This could reduce the statistical bound for NNC with nonstationary fields.
- Machine learning might be a method to identify and process these scenarios automatically.