Detector Characterization of the 40m Interferometer

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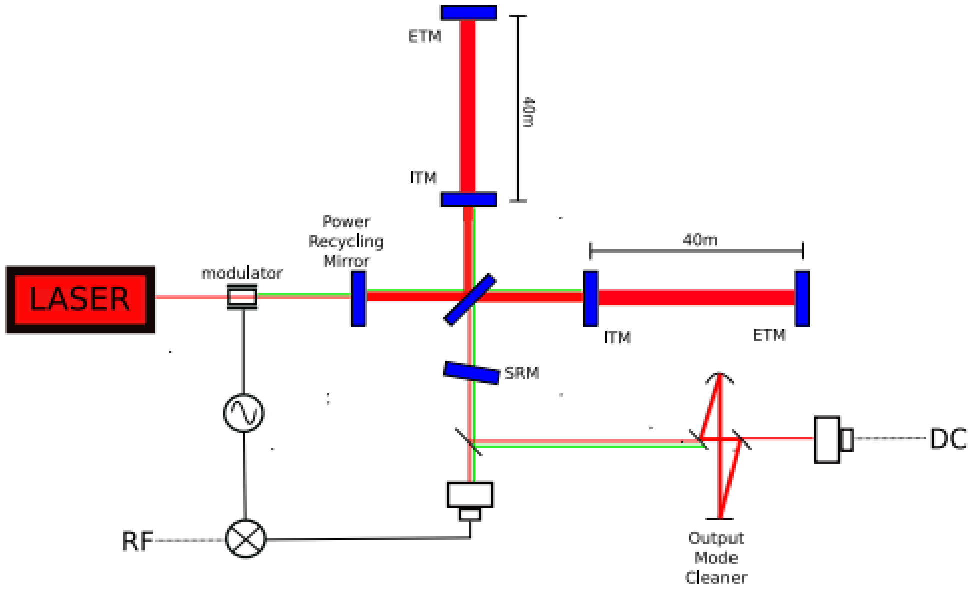
LIGO-T1500123

Overview

- Detector Characterization- an effort to identify, understand, and eliminate noise
- Two projects to monitor and understand noise in interferometric GW detectors
- **Summary Pages**
  - Implemented new features to enhance real-time monitoring of the detectors
- **Gaussianity Tests of Noise Sources**
  - Provide a method to determine Gaussianity of noise at particular frequencies
  - Gaussianity allows us to characterize distributions which are not clearly discernible in PSDs
- Can include **Gaussianity tests** in the **summary pages**

40m Prototype Interferometer

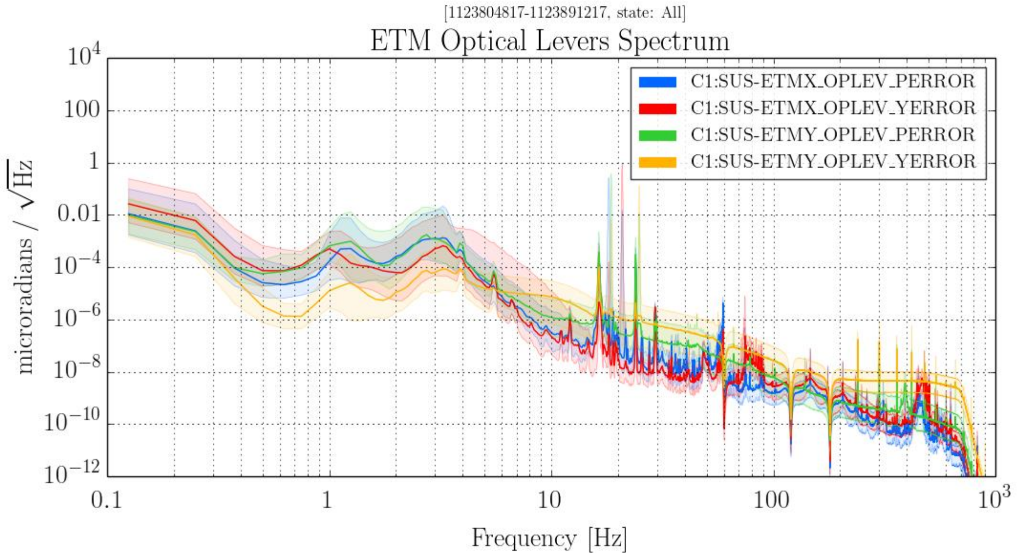
- 1% scaled prototype of LIGO detectors
- Housed at Caltech
- Perfect playground to test new ideas and innovations
- Innovations tested at the 40m prototype can be implemented at the main detectors

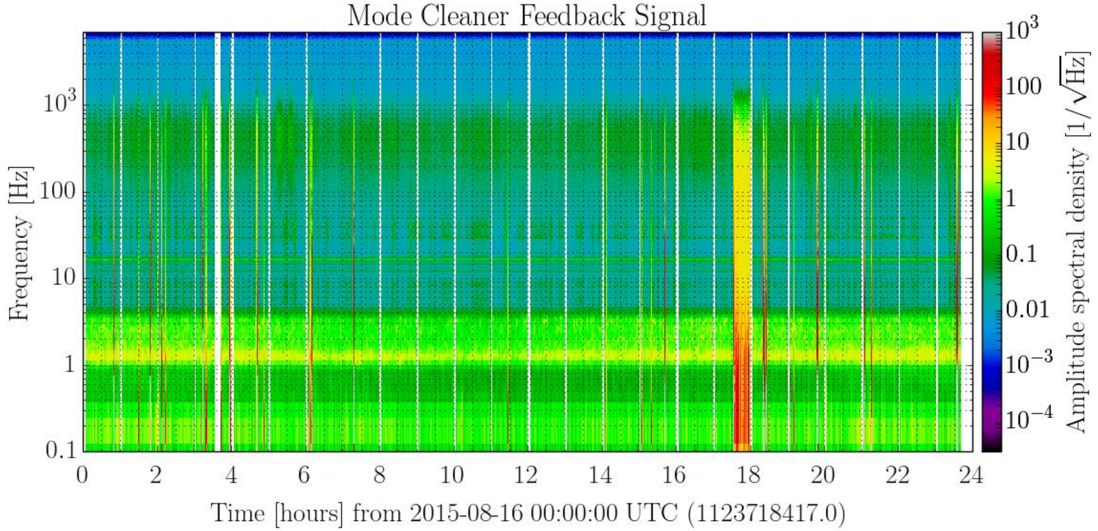


Ward et al. 2008

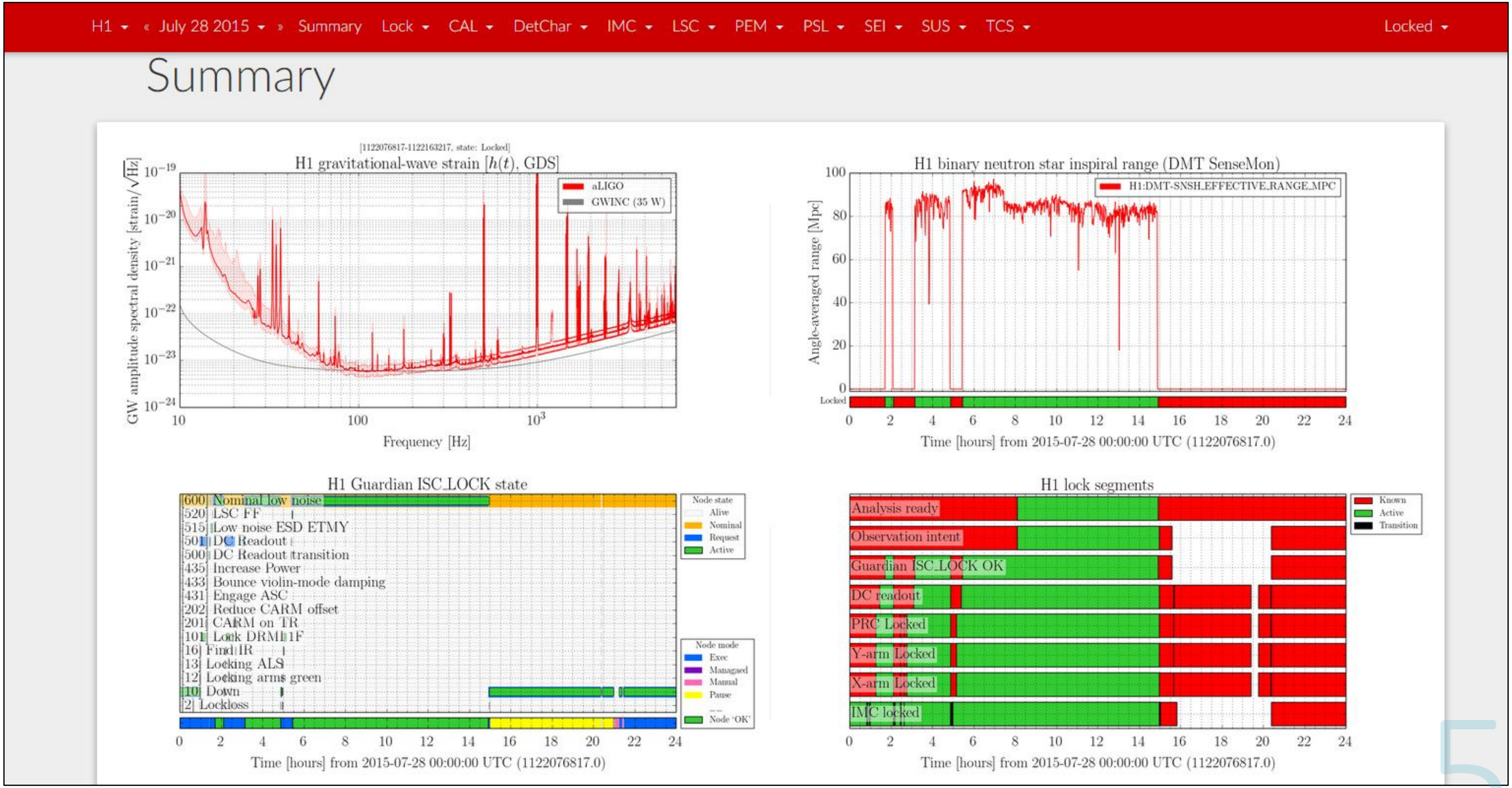
Summary Pages

- Near real-time detector monitoring tool
- Updated every 30 minutes
- Include time-series, spectra, and spectrograms of different channels
- Summary pages available for Livingston, Hanford, and Caltech (C1) detectors
- Made many changes to the 40m summary pages throughout the summer

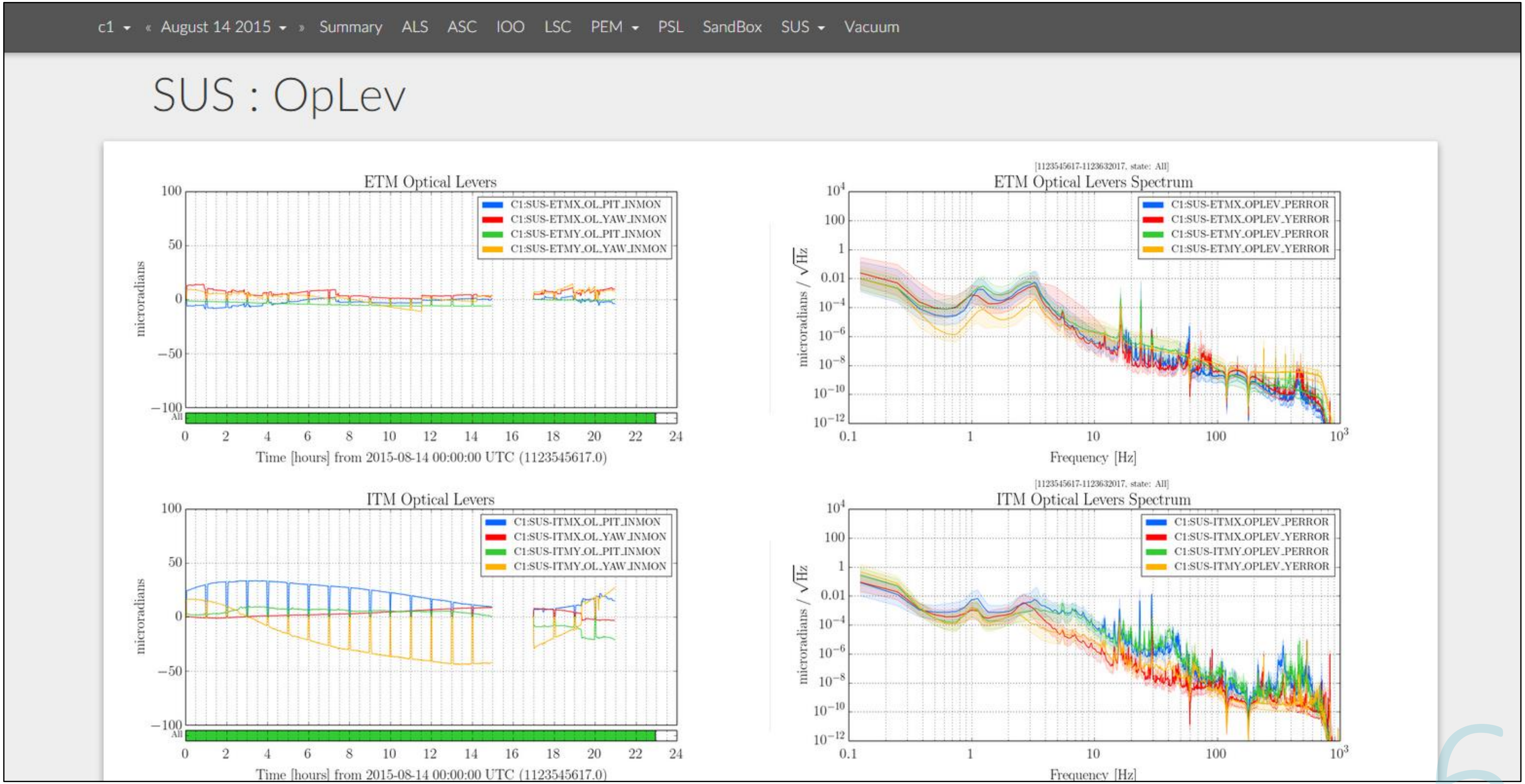




LIGO site summary pages have many features implemented



This summer, I have worked to bring the 40m summary pages to the quality of the site pages



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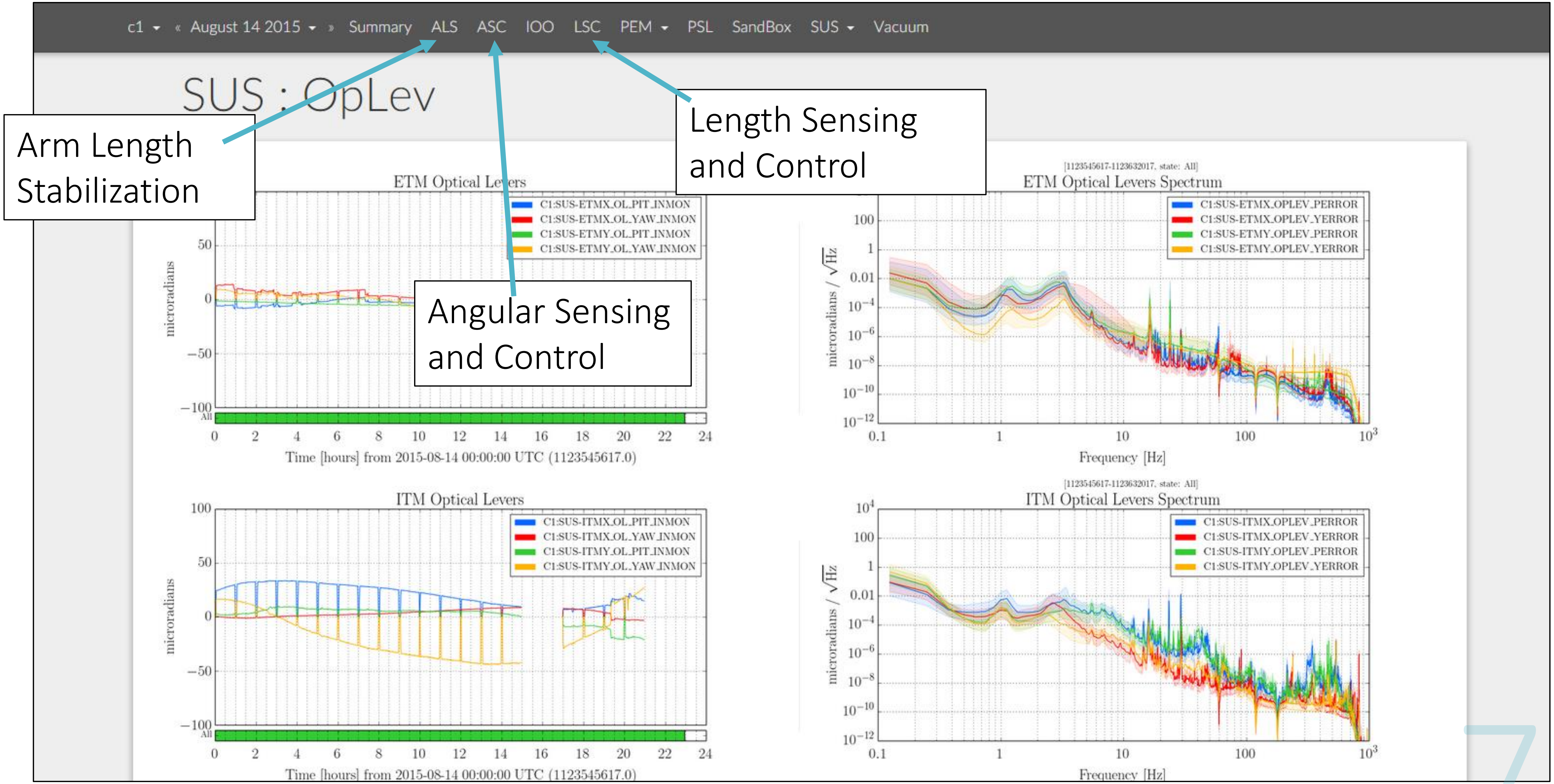

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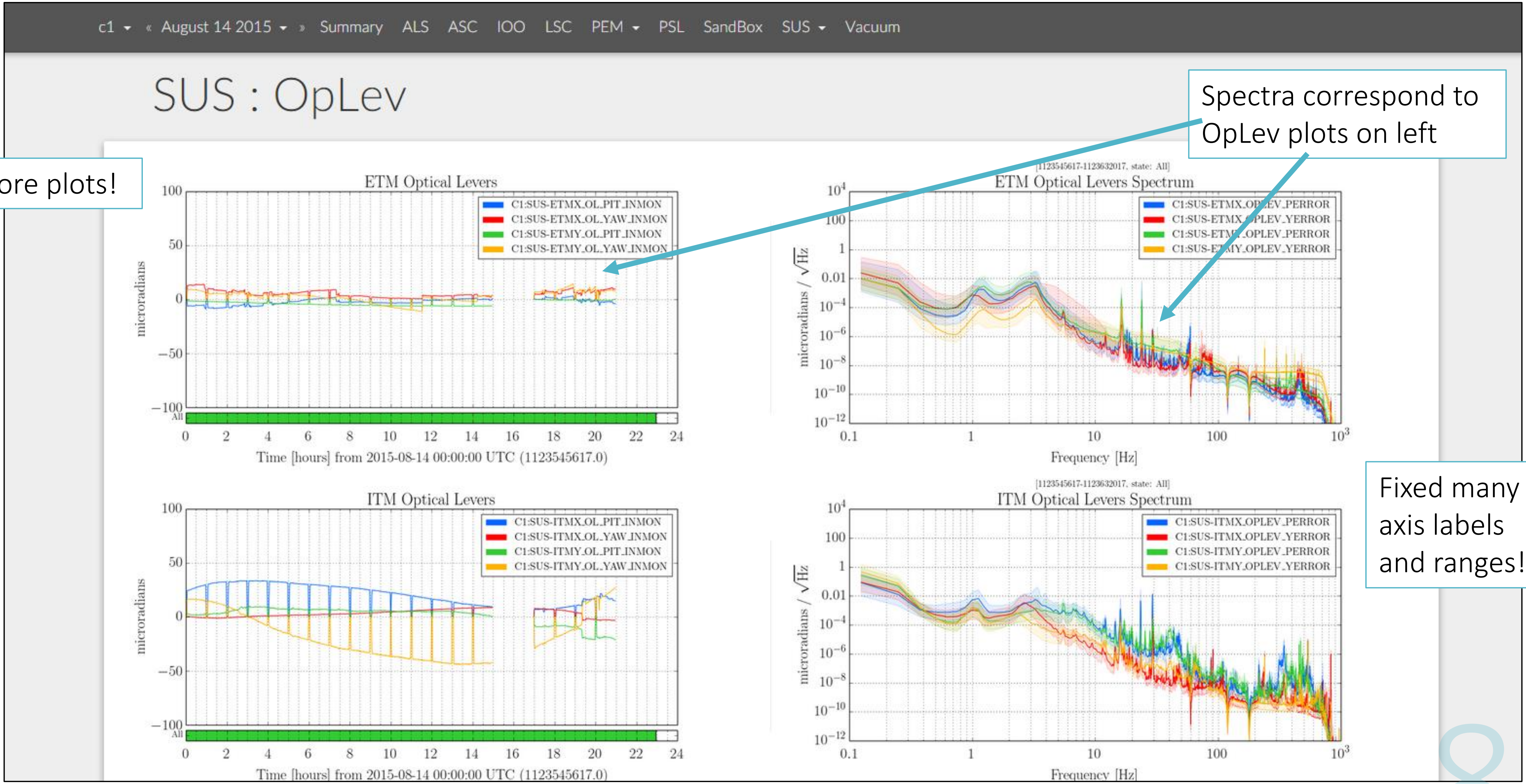
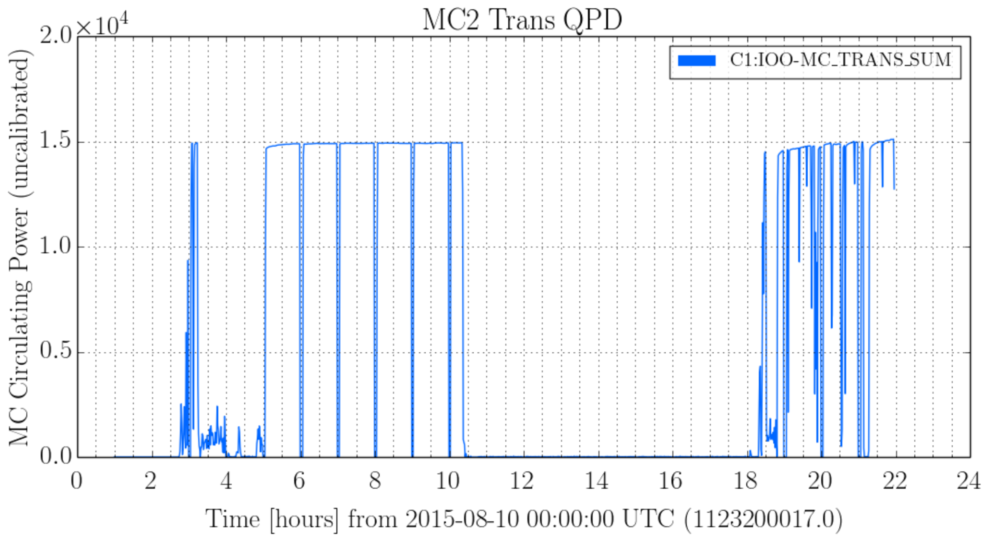
More plots!

Spectra correspond to OpLev plots on left

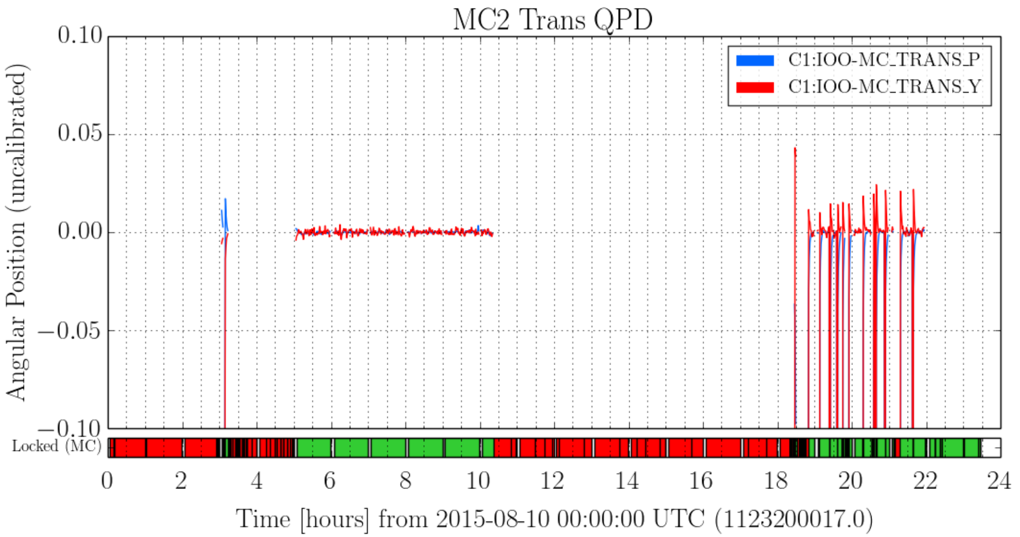


Fixed many axis labels and ranges!

States



Red: MC unlocked
Green: MC locked

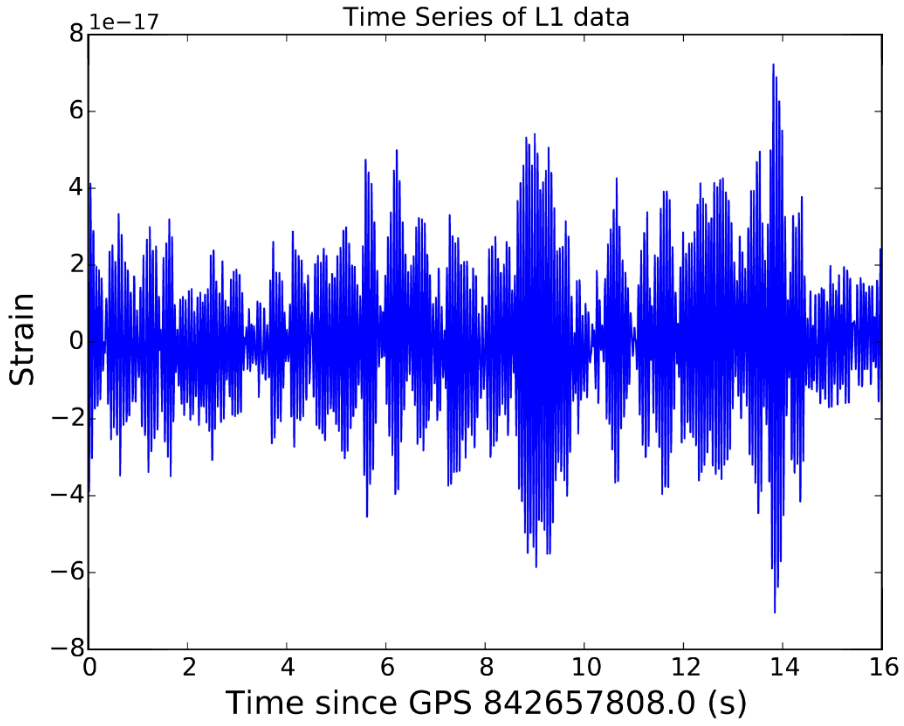


- Added triggered states to only show data for times at which the Mode Cleaner (MC) is locked
- Here, MC is locked when the channel C1:IOO-MC_TRANS_SUM $\geq 10^4$
- User can toggle between displaying all states and only locked states
- This can be incorporated for many other channels

Gaussianity Tests of Noise Sources

- Detectors are constantly inundated with noise
- We can characterize signals as Gaussian or non-Gaussian based on their statistical nature
- How does this help a data analyst?
  - Non-Gaussian noise contaminated GW signals
  - By characterizing non-Gaussian noise, we can eventually reduce it
- How does this help a detector developer?
  - Allows us to identify particular noise coupling mechanisms in signals
  - Receive more information about noise coupling than available in PSDs

Gaussianity Tests with S5 L1 Data



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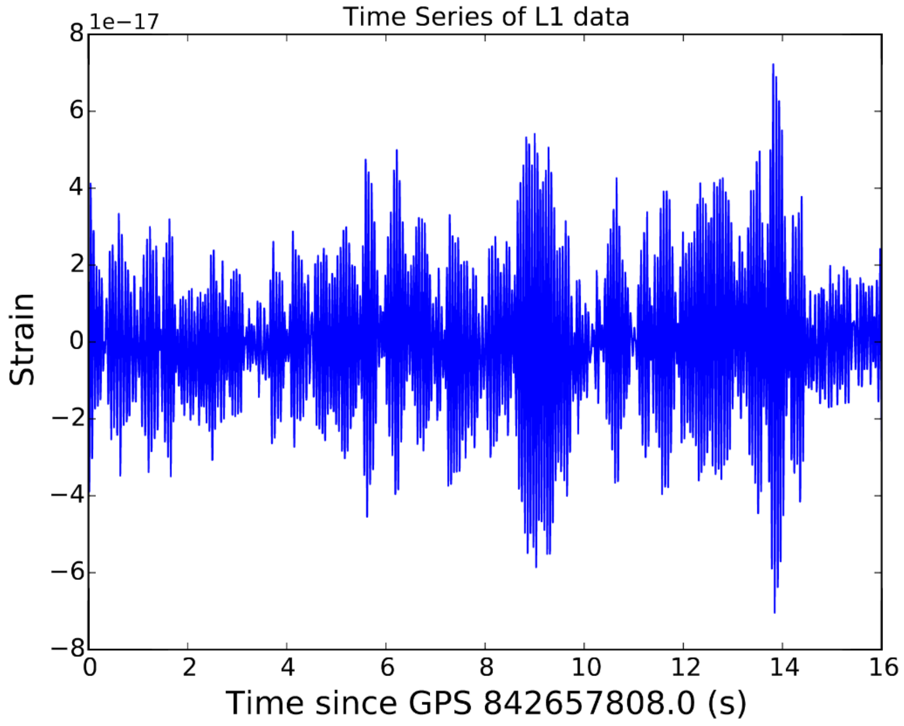

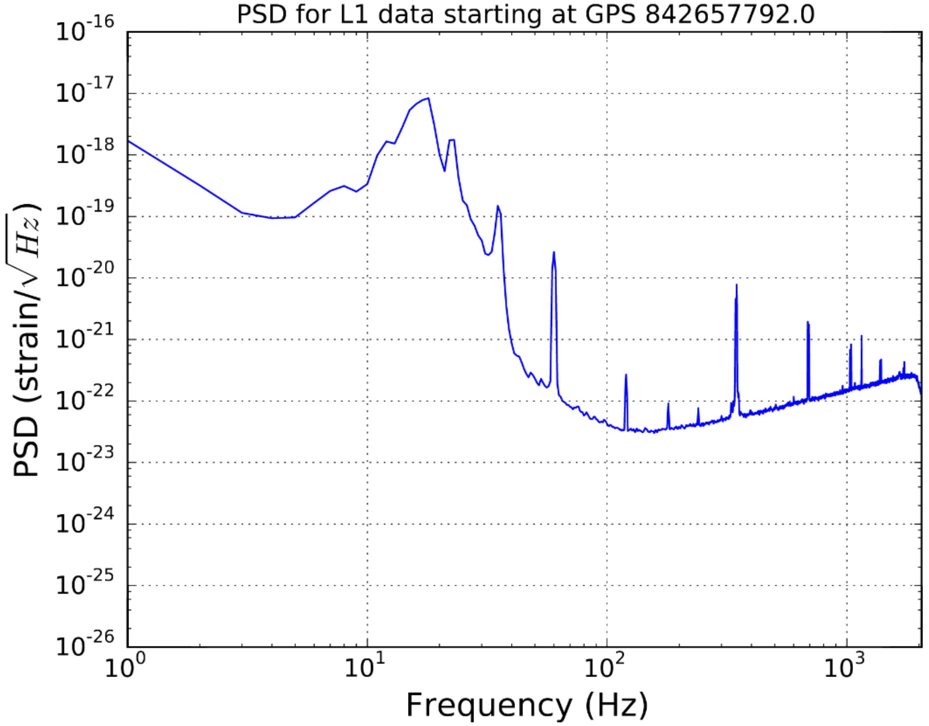

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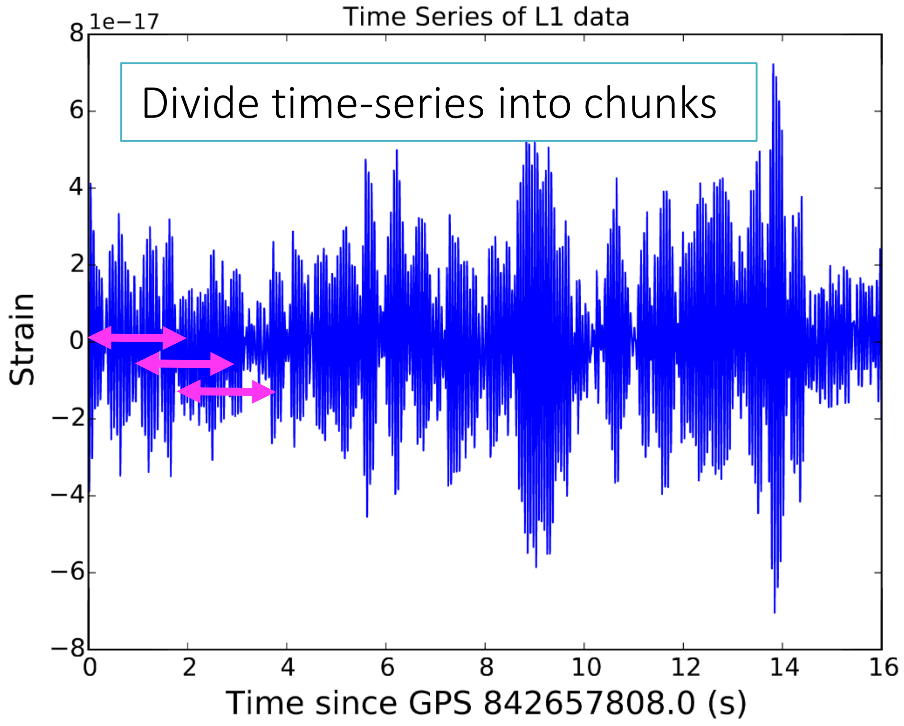

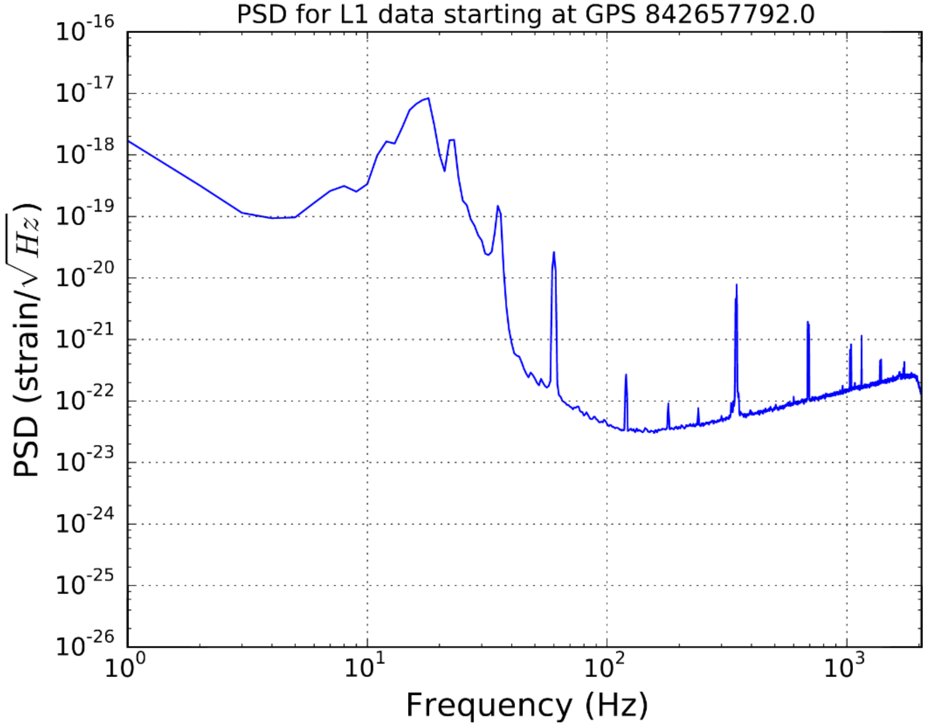

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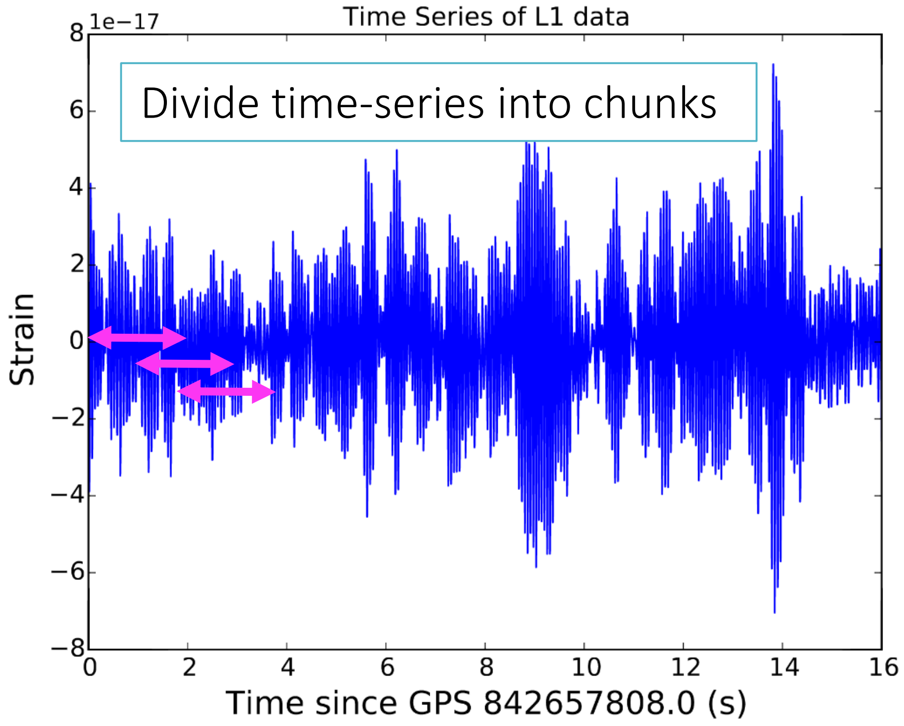
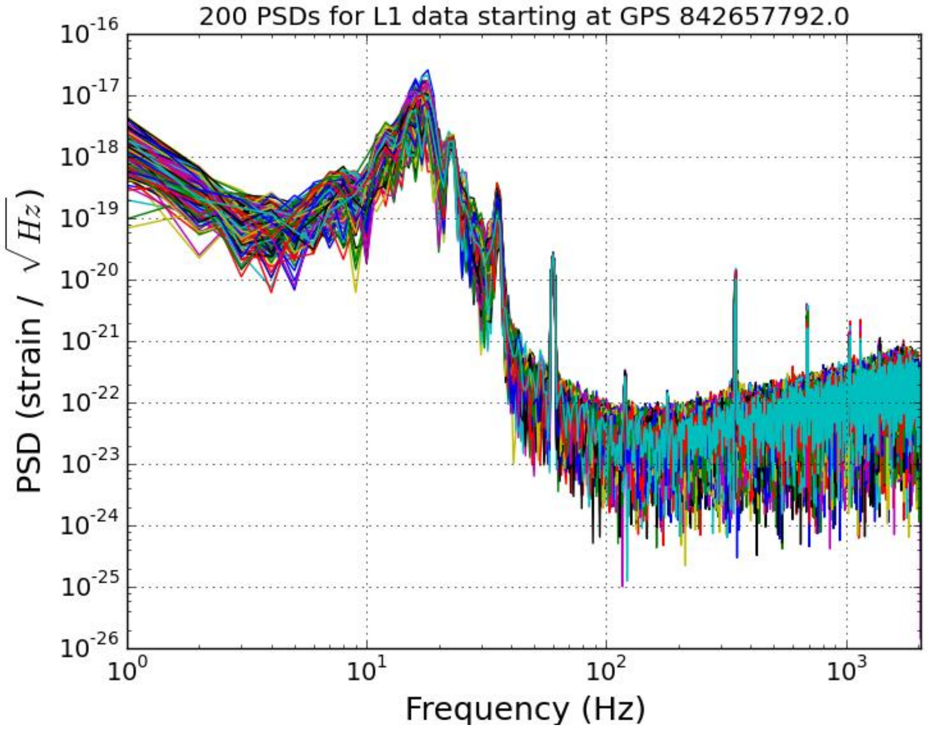


Make a PSD for each chunk



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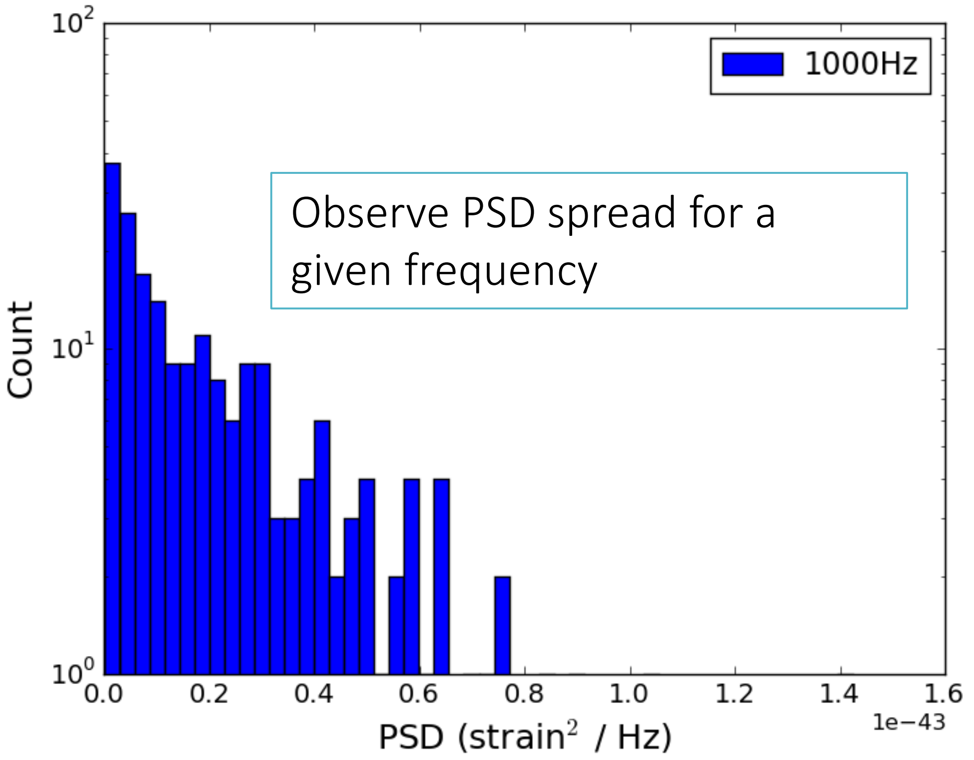
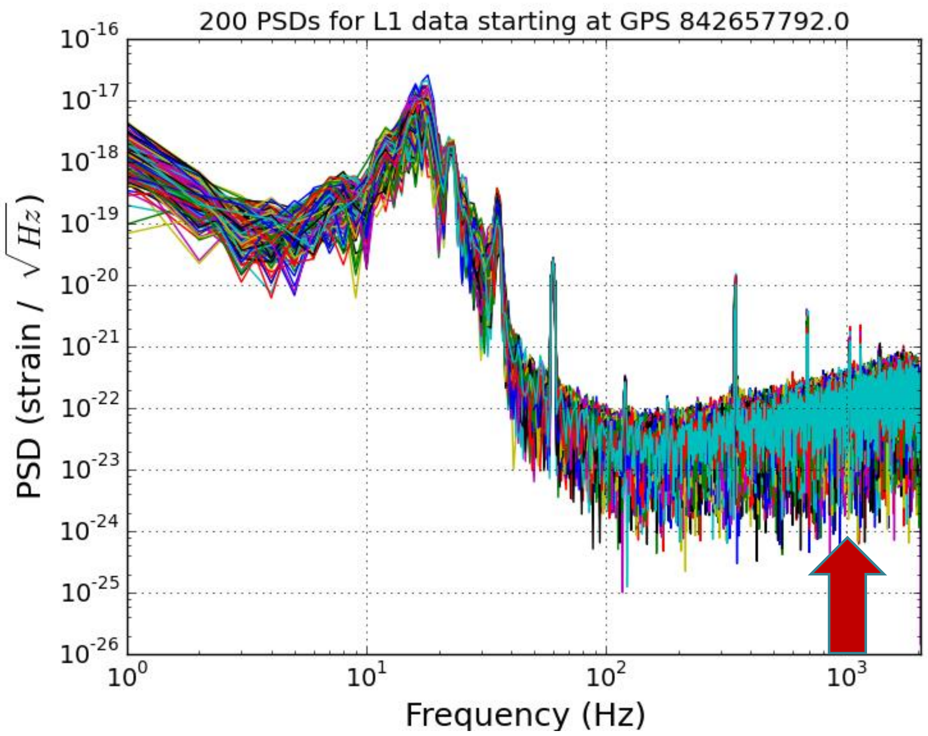


Observe PSD spread for a given frequency



Exponential decay suggests a Gaussian distribution

Formalism

- Mathematically characterize Gaussianity of PSD spread at a given frequency following the method in Ando et al. (2003)

Long-term average: $P_0 \cong \overline{P_j}$

Instantaneous average: $P_1 = \frac{1}{k}\sum_{j=1}^{k} P_j$

Instantaneous average: $P_2 = \frac{1}{k}\sum_{j=1}^{k} (P_j)^2$

$\overline{P_j}$: PSD values for 5620 chunks (larger number)

P_j : PSD values for 200 chunks (smaller number)

$$c_1 = \frac{P_1}{P_0} - 1$$

$$c_2 = \frac{1}{2}\left(\frac{P_2}{P_1^2} - 2\right)$$

c_1 and c_2 are produced from a Laguerre expansion of the probability density function of the PSD

A power distribution is Gaussian when c_2 is zero.

How do we determine Gaussianity?

Gaussianity Tests with PSDs

$$\widetilde{x}(f) = \int_{-\infty}^{\infty} x(t) e^{-i2\pi f t} dt$$

PSD: $\lim_{T\to\infty} \frac{1}{T} |\widetilde{x}_T(f)|^2$

$$c_1 = \frac{P_1}{P_0} - 1$$

$$c_2 = \frac{1}{2}\left(\frac{P_2}{P_1^2} - 2\right)$$

Rayleigh Statistics

$$R(f) = \frac{\sigma[|\widetilde{x}_T(f)|^2]}{\mu[|\widetilde{x}_T(f)|^2]}$$

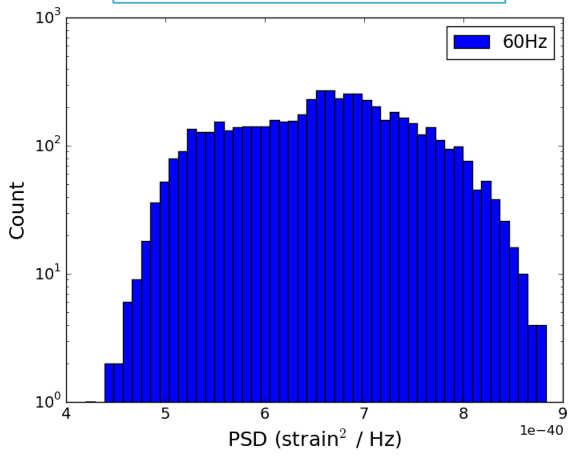
- R=1: Gaussian
- R>1: Coherent variation
- R<1: Glitchy
- Based on exponential distributions

$$c_2 = \frac{1}{2}(R^2 - 1)$$

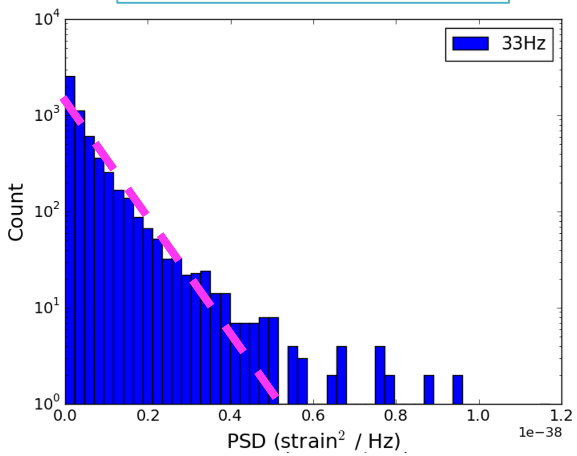
Gaussianity Plots

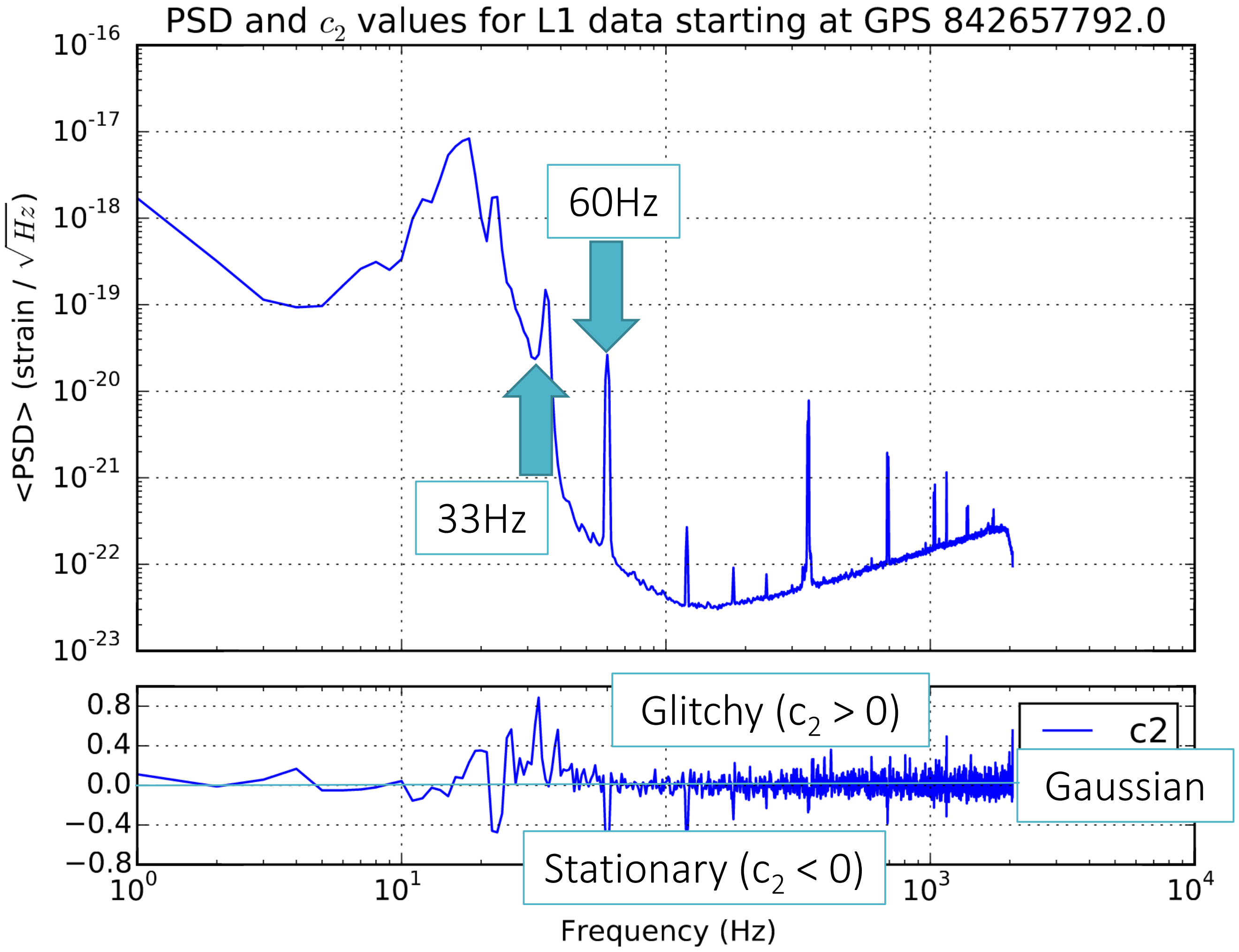
- Select frequencies at which c_2 deviates from Gaussianity
- Plot histograms for PSD distribution at these frequencies

60Hz: Stationary



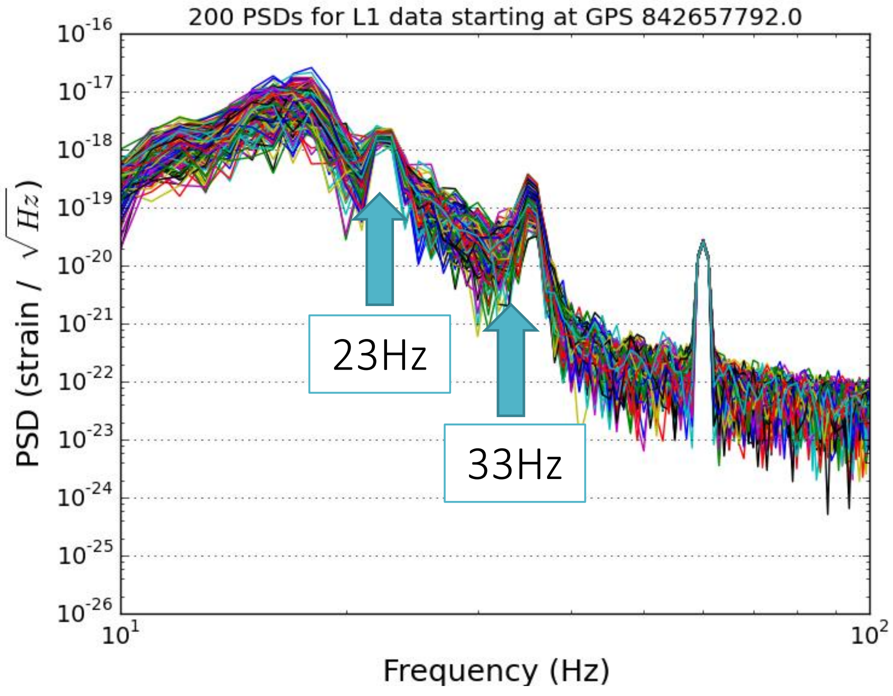
33Hz: Glitchy



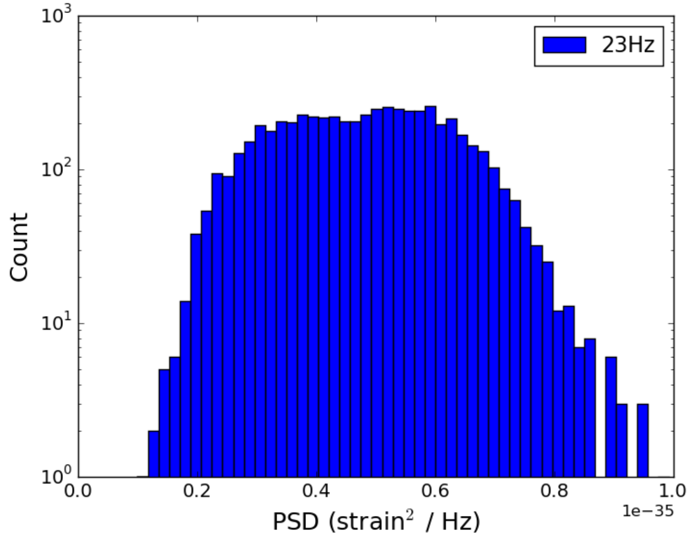


How is this useful?

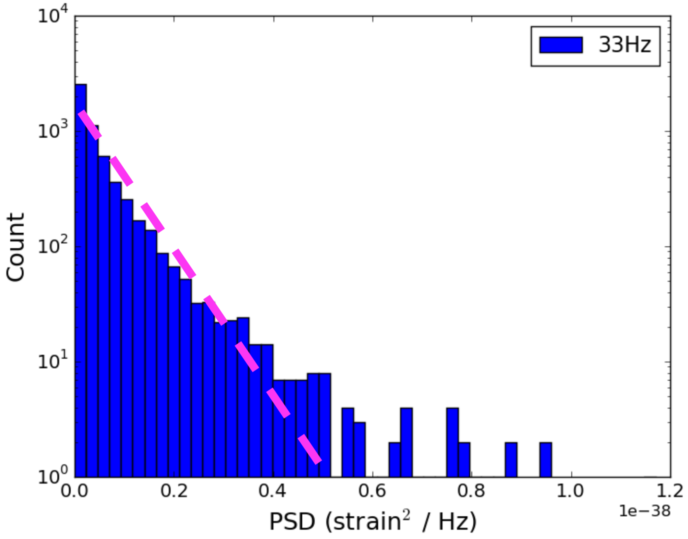
- From the plot of several PSDs, we see no difference in distribution at 23Hz and 33Hz
- Through our formalism, we find significantly different c_2 values at these two frequencies



c_2 = -0.474



c_2 = +0.888



Conclusion

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Thank You ☺

Questions?

References

1. Ward, RL et al. *DC Readout Experiment at the Caltech 40m Prototype Interferometer*. Class. Quantum Grav. 25, 114030 (2008).
2. Izumi, K. et al. *Multicolor cavity metrology*. J. Opt. Soc. Am. 29, 10, 2092 (2012).
3. Davison, E. *Detector Characterization Tools for Interferometer Commissioners*. LIGO SURF 2012.
4. Ando, M. et al. *Methods to characterize non-Gaussian noise in TAMA*. Class. Quantum Grav. 20, S697 (2003).
5. Sutton, P. & P. Saulson. *RayleighMonitor Overview*. LIGO-G040422-00-Z.
6. Finn, L., Gonzalez, G. & P. Sutton. *RayleighMonitor: A Time-Frequency Gaussianity Monitor for the DMT*. LIGO-G020133-00-Z (2002).

Summary Page Links

- Caltech 40m: https://nodus.ligo.caltech.edu:30889/detcharsummary/
- Livingston: https://ldas-jobs.ligo-la.caltech.edu/~detchar/summary/
- Hanford: https://ldas-jobs.ligo-wa.caltech.edu/~detchar/summary/

Summary Pages Code

```
[tab-DARM]
name = Differential and Common ARM motion
1 = L1:OAF-CAL_DARM_DQ spectrum
1-title = DARM
1-legendloc = 'upper right'
1-ylabel = r'Amplitude spectral density [m$/
\sqrt{\mathrm{Hz}}$]'
```

```
[channels-LSC]
channels = L1:LSC-MICH_IN1_DQ,
           L1:LSC-PRCL_IN1_DQ,
           L1:LSC-SRCL_IN1_DQ
resample = 4096
stride = 45
fftlength = 2
fftstride = 1
frequency-range = 1,1024
asd-range = 5e-4,10
```

40m Interferometer Subsystems

Name	Subsystem Details
Length Sensing and Control (LSC)	Mirror position control and gravitational wave signal channel.
Angular Sensing and Control (ASC)	Mirror angular control.
Arm Length Stabalization (ALS)	Monitor x and y arm length.
Pre-Stabilized Laser (PSL)	Optical cavities for laser stabilization in frequency and spacial distribution.
Input and Output Optics (IOO)	Similar to PSL.
Suspensions (SUS)	Sensors for mirror positions and angles. Optical lever system which provides additional angular sensing signals.
Physical Environmental Sensors (PEM)	Seismic and acoustic noise.
Vacuum System (VAC)	Vacuum status monitoring.

Welch’s Method for PSD Calculation

We create a PSD of the dataset to provide more information about the frequency content of the time-series. We use the Python function, matplotlib.mlab.psd() to compute the PSD. This function uses Welch's average periodogram method to approximate a PSD. The time-series is divided into several segments of length NFFT, and the fast Fourier transform is calculated for each segment, then squared, and then averaged for all segments to produce the PSD. We define the sampling frequency to be the inverse of the time between consecutive data sampling. The NFFT segment length is also set to this sampling frequency value. We select a Hanning window function, which maps each segment's values onto the Hanning function of length NFFT. As the Hanning function eliminates datapoints at the endpoints of segments, we define an overlap of half of NFFT which recalculates the PSD using the same segments shifted over by half their lengths.

```
psd(x, NFFT=256, Fs=2, detrend=mlab.detrend_none,
    window=mlab.window_hanning, noverlap=0, pad_to=None,
    sides='default', scale_by_freq=None)
```

Statistical Concepts

A.1 Arithmetic Mean

The arithmetic mean represents an unweighted average of a set of n values.

$$\mu = \overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

A.7 Fourier Transform

The Fourier transform provides a continuous Fourier series from $-\infty$ to ∞ for a given function. The Fourier transform of $f(t)$ is,

$$g(\omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty} f(t)e^{-i\omega t}dt, \quad (21)$$

and the inverse Fourier transform is,

$$f(t) = \int_{-\infty}^{\infty} g(\omega)e^{i\omega t}d\omega. \quad (22)$$

Laguerre Expansion

I provide a statistical background for Laguerre exponential expansions, following the method defined in Ando et al. [13]. We define a probability density function, $P(\zeta)$, given the following Rayleigh distribution:

$$\Phi(\zeta) = e^{-\zeta}, \tag{28}$$

where ζ is a function of Gaussian variables x and y,

$$\zeta = \frac{1}{2}(x^2 + y^2). \tag{29}$$

We derive ζ by first defining a heterodyne signal. We focus on the signal component at $f_0 = \omega_0/2\pi$ with frequency resolution df = 1/T. We define this signal component as

$$v(t) = A_x \cos\omega_0 t + A_y \sin\omega_0 t, \tag{30}$$

for $f_0 \gg$ df. The variables, A_x and A_y, change at a much slower rate than the frequency of oscillation, ω_0. We can then calculate the instantaneous power of the signal to be

$$P(t) = \frac{1}{T}\int_t^{t+T} v(t')^2 dt', \tag{31}$$

which is equivalent to

$$P(t) = \frac{1}{2}\left(A_x(t)^2 + A_y(t)^2\right). \tag{32}$$

We hope to test the Gaussianity of the independent variables, A_x and A_y, with an instantaneous power of P(t). If we replace A_x with x, A_y with y, and $P(t)$ with ζ, we reproduce Equation 28. Given that $P(\zeta)$ is perturbed from an exponential distribution, we represent the probability density function as a series expansion:

$$P(\zeta) = \bar{c_0}\Phi(\zeta) + \bar{c_1}L_1(\zeta)\Phi(\zeta) + \bar{c_2}L_2(\zeta)\Phi(\zeta) + \cdots. \tag{33}$$

$L_n(\zeta)$ describes the Laguerre polynomials for ζ, following the pattern

$$L_n(\zeta) = e^{\zeta}\frac{d^n}{d\zeta^n}(\zeta^n e^{\zeta}). \tag{34}$$

The first few Laguerre polynomials are explicitly described as $L_0 = 1$, $L_1 = 1 - x$, and $L_2 = \frac{1}{2}(x^2 - 4x + 2)$. Laguerre polynomials satisfy a condition for orthogonality:

$$\int_0^\infty L_m(\zeta)L_n(\zeta)\Phi(\zeta)d\zeta = \delta_{mn}. \tag{35}$$

The coefficients $\bar{c_n}$ can be calculated with

$$\bar{c_n} = \int_0^\infty L_n(\zeta)P(\zeta)d\zeta, \tag{36}$$

resulting in coefficients such as $\bar{c_0} = 1$, $\bar{c_1} = 1 - \bar{\zeta}$, and $\bar{c_2} = \frac{1}{2}(\bar{\zeta}^2 - 2)$.

Correlation between R and c_2

For a given PSD, we expect P_1 to be the mean:

$$P_1 = \mu \left[\frac{1}{T} \left| \widetilde{x}_T(f) \right|^2 \right], \tag{10}$$

and P_2 to follow the distribution,

$$P_2 = \left(\sigma \left[\frac{1}{T} \left| \widetilde{x}_T(f) \right|^2 \right] \right)^2 + P_1^2. \tag{11}$$

From this, we derive the equation for R in terms of P_1 and P_2:

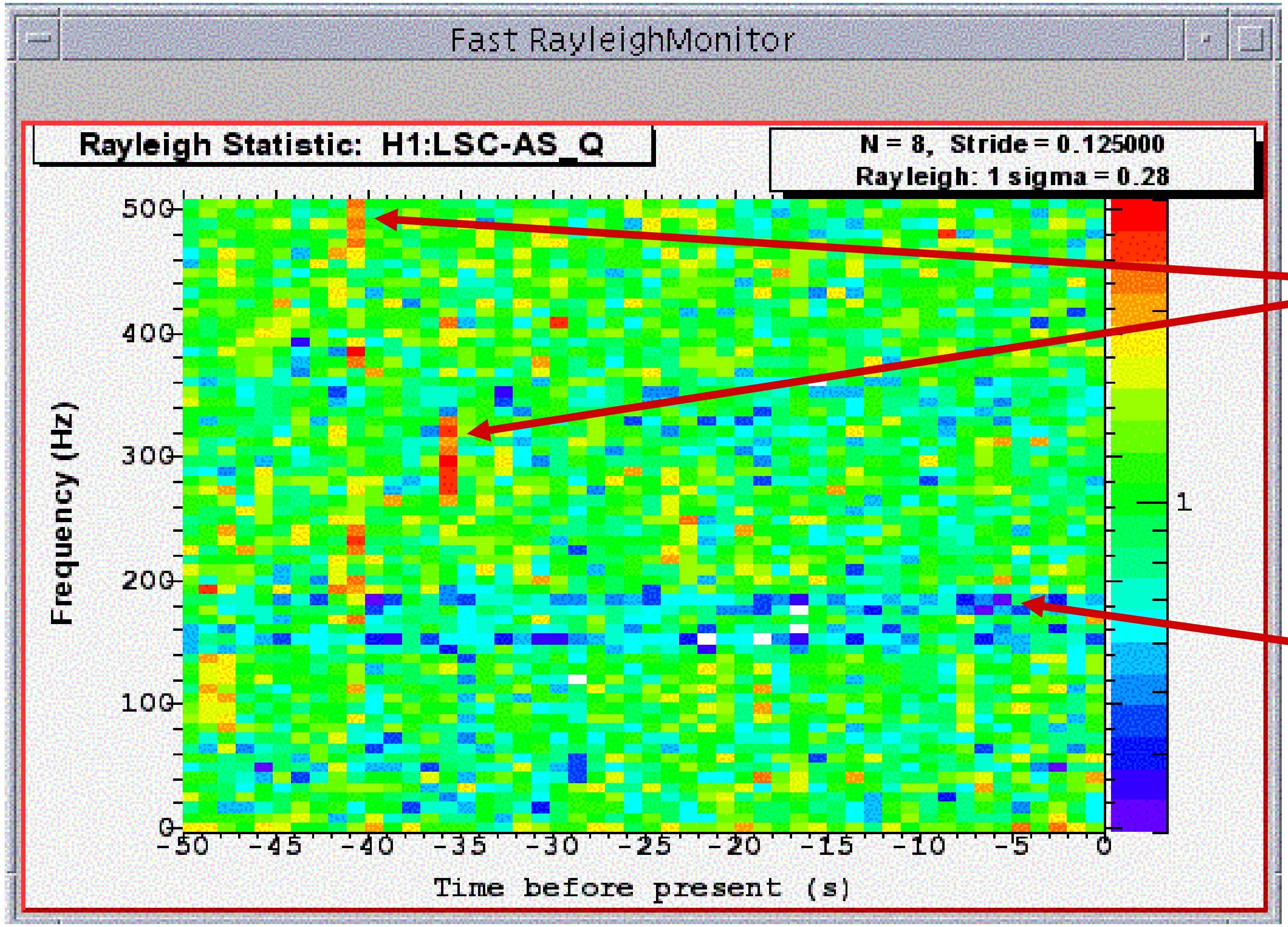
$$R^2 = \frac{P_2 - P_1^2}{P_1^2} = \frac{P_2}{P_1^2} - 1. \tag{12}$$

It is then evident that,

$$c_2 = \frac{1}{2}(R^2 - 1), \tag{13}$$

Slide adapted from Sutton & Saulson G040422-00-Z

Rayleighgrams



Same data, Rayleighgram.

Sub-second glitches (not obvious in power spectrum)

Coherent noise around 150, 180Hz.

Plot Including c_1 Statistics