

ADA 14 -- 9am Thu 13 Oct 2022

Periodogram Analysis (continued)
 Quasi-Periodic Oscillations
 Dynamic Power Spectra (GW detection)
 White/Red Noise (Wavelets, Splines)

262

Periodogram of a Sinusoid + Spike

Single high value is sum of cosine curves all in phase at time t_0 :

$$X(t) = \mu + A \sin(\omega_0 t) + \Delta \delta(t - t_0) \pm \sigma$$

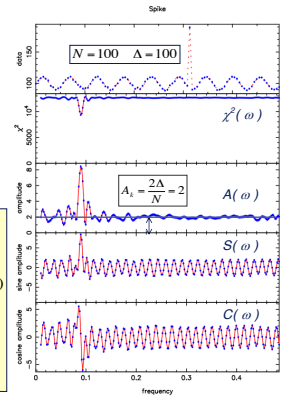
This spike raises the amplitude uniformly at all frequencies.

$$S_k = \frac{\Delta \sin(\omega_k t_0) / \sigma^2}{\sum_{i=1}^N \sin^2(\omega_i t_0) / \sigma^2} = \frac{2\Delta}{N} \sin(\omega_k t_0)$$

$$C_k = \frac{\Delta \cos(\omega_k t_0) / \sigma^2}{\sum_{i=1}^N \cos^2(\omega_i t_0) / \sigma^2} = \frac{2\Delta}{N} \cos(\omega_k t_0)$$

$$A_k^2 = S_k^2 + C_k^2 = \left(\frac{2\Delta}{N}\right)^2$$

Note: $\langle \sin^2 \rangle = \langle \cos^2 \rangle = 1/2$



263

Periodogram of a Sinusoid + White Noise

- White Noise is generated by sampling a Gaussian random number at each time.

$$X_i \sim G(\mu, \sigma^2)$$

- Or, use a Gaussian random number for each sine and cosine amplitude.

$$C_0 = \mu, \quad C_k, S_k \sim G(0, 2\sigma^2/N)$$

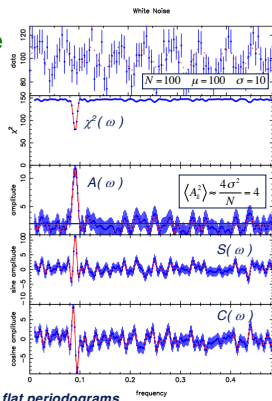
$$C_k = \frac{\sum_{i=1}^N (X_i - \mu) \cos(\omega_k t_i) / \sigma^2}{\sum_{i=1}^N \cos^2(\omega_k t_i) / \sigma^2} \quad \langle C_k \rangle = 0$$

$$\langle C_k^2 \rangle = \text{Var}[C_k] = \frac{1}{\sum_{i=1}^N \cos^2(\omega_k t_i) / \sigma^2} = \frac{2\sigma^2}{N}$$

$$A_k^2 = C_k^2 + S_k^2 \sim \frac{2\sigma^2}{N} \chi_2^2 \quad \langle A_k^2 \rangle = \frac{4\sigma^2}{N}$$

Parseval's theorem: $\langle \sum_{k=1}^{N/2} A_k^2 \rangle = 2\sigma^2$

Note: Both white noise and a spike have flat periodograms.



264

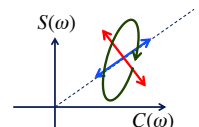
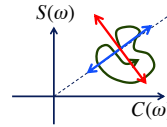
Unstable or "Quasi-Periodic" Oscillations

$$X(t) = [A_0 + A(t)] \sin(\omega_0 t + \Phi_0 + \Phi(t))$$

Amplitude modulation: $A(t)$

Phase modulation: $\Phi(t)$

Special case:



Unstable oscillation has a broader periodogram peak.

Amplitude drifts -> sidelobes

Phase drifts equivalent to frequency ω changing with time.

$$A(t) = A \sin \Omega t + B \cos \Omega t$$

$$\Phi(t) = \alpha \sin \Omega t + \beta \cos \Omega t$$

265

Amplitude Modulation

Set $A_0 = 1$ and $\Phi_0 = 0$.

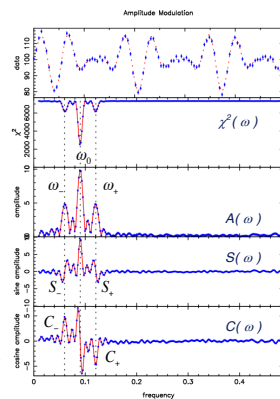
Oscillation frequency ω_0 with slow amplitude modulation at lower frequency Ω .

$$X(t) = (1 + A \sin \Omega t + B \cos \Omega t) \sin \omega_0 t$$

$$= \sin(\omega_0 t) + (A/2) [\cos(\omega_0 t) - \cos(\omega_0 t)] + (B/2) [\sin(\omega_0 t) + \sin(\omega_0 t)]$$

Note: **sidelobes** at $\omega_{\pm} = \omega_0 \pm \Omega$.

Sine amplitudes in phase: $S_+ = S_-$
 Cosine amps anti-phased: $C_+ = -C_-$



266

Phase Modulation

Oscillation frequency ω_0 with slow phase modulation at lower frequency Ω :

$$X(t) = \sin(\omega_0 t + \alpha \sin \Omega t + \beta \cos \Omega t)$$

Note: $\sin(x + \Delta x) = \sin x + \Delta x \cos x$:

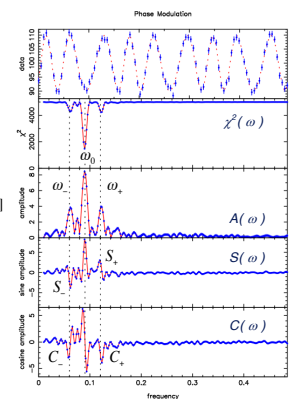
$$X(t) = \sin(\omega_0 t) + (\alpha \sin \Omega t + \beta \cos \Omega t) \cos \omega_0 t$$

$$= \sin(\omega_0 t) + (\alpha/2) [-\sin(\omega_0 t) + \sin(\omega_0 t)] + (\beta/2) [\cos(\omega_0 t) + \cos(\omega_0 t)]$$

Again, **sidelobes** at $\omega_{\pm} = \omega_0 \pm \Omega$ but now with

Sine amps anti-phased: $S_+ = -S_-$

Cosine amps in phase: $C_+ = C_-$



267

Phase relations for Sidelobes

Both Amplitude and Phase Modulation:

$$X(t) = (1 + A \sin \Omega t + B \cos \Omega t) \sin(\omega_0 t + \alpha \sin \Omega t + \beta \cos \Omega t)$$

$$\approx \sin(\omega_0 t) + S_- \sin(\omega_- t) + C_- \cos(\omega_- t)$$

$$+ S_+ \sin(\omega_+ t) + C_+ \cos(\omega_+ t)$$

$$\omega_{\pm} = \omega_0 \pm \Omega, \quad S_{\pm} = \frac{B \pm \alpha}{2}, \quad C_{\pm} = \frac{\beta \mp A}{2}$$

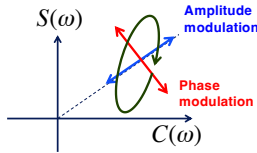
Amplitude and Phase Modulation Spectra:

$$A(\Omega) = C_-(\Omega) - C_+(\Omega)$$

$$B(\Omega) = S_-(\Omega) + S_+(\Omega)$$

$$\alpha(\Omega) = S_+(\Omega) - S_-(\Omega)$$

$$\beta(\Omega) = C_+(\Omega) + C_-(\Omega)$$



268

Dynamic Power Spectrum

For periodic oscillations with amplitude and phase that vary with time.

Data: $X_i \pm \sigma_i$ at $t = t_i$

Model: $\mu(t) = X_0(t) + S(t) \sin(\omega t) + C(t) \cos(\omega t)$

Like Running Optimal Average, but including Sin and Cos amplitudes in the fit to each time window.

3 Patterns: 1, $s_i = \sin(\omega t_i)$, $c_i = \cos(\omega t_i)$

Iterated Optimal Scaling:

$$\hat{X}_0(t) = \frac{\sum (X_i - \hat{S}_i - \hat{C}_i c_i) w_i(t)}{\sum w_i(t)}$$

$$\hat{S}(t) = \frac{\sum (X_i - \hat{X}_0 - \hat{C}_i c_i) s_i w_i(t)}{\sum s_i^2 w_i(t)}$$

$$\hat{C}(t) = \frac{\sum (X_i - \hat{X}_0 - \hat{S}_i s_i) c_i w_i(t)}{\sum c_i^2 w_i(t)}$$

$$\hat{A}^2(t) = \hat{C}^2(t) + \hat{S}^2(t)$$

$$w_i(t) = \frac{G(t - t_i)}{\sigma_i^2}$$

$$G(t) = \exp\left\{-\frac{t^2}{2\Delta^2}\right\}$$

Time-resolution set by parameter Δ .

Iterate (patterns not orthogonal).

269

Dynamic Power Spectrum

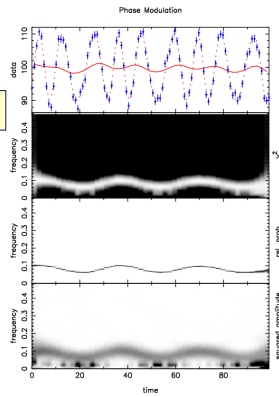
Phase modulation is equivalent to a wandering frequency.

Badness-of-Fit: $\chi^2(\omega, t)$

Probability: $P \sim \exp\{-\chi^2/2\}$

Power density: $A^2(\omega, t)$

Note: the probability peak is much sharper than power density peak.



270

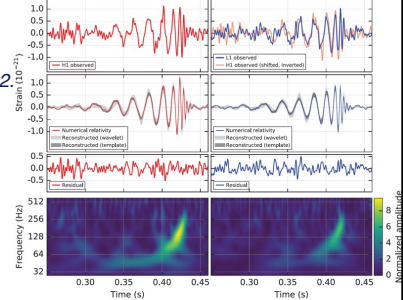
Example of Dynamic Power Spectra

Gravitational Waves from a Binary Black Hole Merger

Hanford, Washington (H1) Livingston, Louisiana (L1)

Abbott et al. (2016)
Phys Rev L 116, 1102

2017 Nobel Prize:
R. Weiss (MIT),
K. Thorne, B. Barish (Caltech)

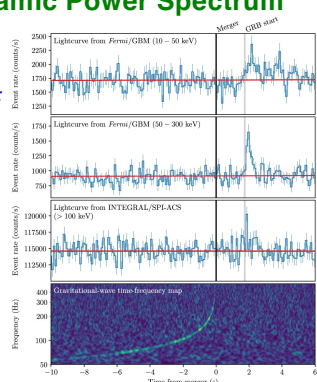


271

Example 2: Dynamic Power Spectrum

Gravitational Waves and Gamma Rays from a Binary Neutron Star Merger:
GW170817 and GRB 170817A.

Abbott et al. (2017)
ApJL 848, L13.



272

Summary: Fourier Analysis

$$\text{model: } \mu(t) = \mu_0 + \sum_k c_k \cos \omega_k t + s_k \sin \omega_k t$$

$$\text{even spacing: } t_i = t_0 + i \Delta t \quad T = N \Delta t \quad i = 1, 2, \dots, N$$

$$\text{Fourier frequencies: } \omega_k = k \Delta \omega = 2\pi/P_k \quad P_k = T/k \quad k = 0, 1, \dots, K_{\max} = N/2$$

$$\text{Nyquist frequency: } \omega_{\text{Nyq}} = \pi / \Delta t = 2\pi/P_{\text{Nyq}} \quad P_{\text{Nyq}} = 2\Delta t$$

$$\text{Orthogonal basis: } \underline{C}_k = \cos \omega_k t \quad \underline{S}_k = \sin \omega_k t$$

$$\text{Model: } \underline{\mu} = \mu_0 \underline{C}_0 + \sum_{k=1} (c_k \underline{C}_k + s_k \underline{S}_k)$$

Exact fit possible by using N parameters to fit N data points.

$$\text{Badness-of-fit: } \chi^2 = \|\underline{X} - \underline{\mu}\|^2$$

$$\text{Optimal fit: } \hat{\mu}_0 = \frac{\underline{X} \cdot \underline{C}_0}{\underline{C}_0 \cdot \underline{C}_0} \quad \hat{c}_k = \frac{\underline{X} \cdot \underline{C}_k}{\underline{C}_k \cdot \underline{C}_k} \quad \hat{s}_k = \frac{\underline{X} \cdot \underline{S}_k}{\underline{S}_k \cdot \underline{S}_k}$$

$$\text{Power spectrum: } P(\omega_k) \Delta \omega = \hat{A}_k^2 = \hat{c}_k^2 + \hat{s}_k^2$$

Decomposes lightcurve into frequency components.



273

Wavelet Analysis - Wavelet Basis Functions

Fourier basis isolates in **frequency** but not in **time**.
Delta basis isolates in **time** but not in **frequency**.
Wavelet basis isolates in both **frequency** and **time**.

Exact fit possible by using N parameters to fit N data points.

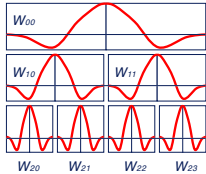
$$W_{k,j}(x) = W[2^k(x-j)]$$

$$j = 0, \dots, (2^k - 1)$$

At each new level, $k \rightarrow k+1$:
 Double the wavelet frequency.
 Double the number of wavelets.
 Complete orthogonal basis.
 (Used e.g. for data compression)

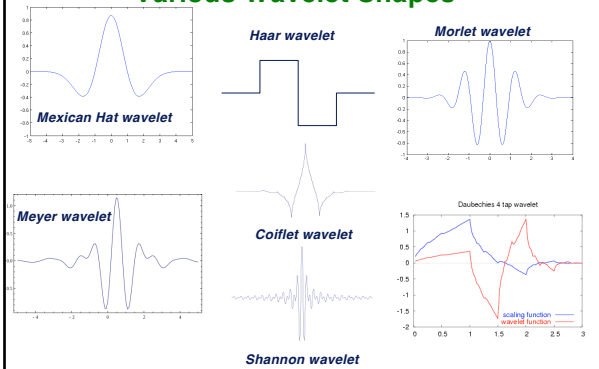
Many wavelet shapes possible. e.g. "Mexican Hat" wavelet:

$$W(x) = (1 - x^2) \exp(-x^2 / 2)$$



274

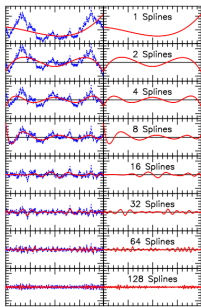
Various Wavelet Shapes



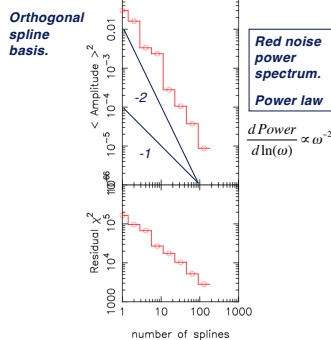
275

Spline Decomposition - Red Noise

Fit and subtract sequence of cubic splines.



Red Noise: Random walk

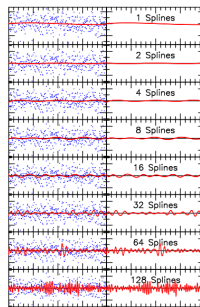


Red noise power spectrum.
 Power law

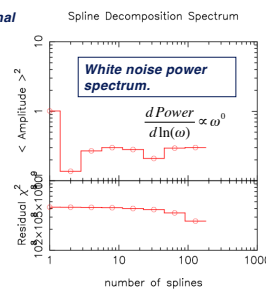
276

Spline Decomposition - White Noise

Fit and subtract sequence of cubic splines.



White Noise: Independent noise at each time



Spline Decomposition Spectrum
 White noise power spectrum.
 $\frac{dPower}{d\ln(\omega)} \propto \omega^0$

277

Fini -- ADA 14

278