

Recovering Primordial Stochastic Gravitational Wave Backgrounds in the LISA Global Fit

with Tyson B. Littenberg

Robert Rosati

7 June 2023

NASA Posdoctoral Program Marshall Space Flight Center

- LISA will see a lot of things
- (Explain data analysis??)
- Explain the Global Fit
- Eventual and current stochastic search strategy
- List current template bank
- Simulated data results
- Real global fit residuals

What will LISA see?

- Discrete sources [Baker+ 2019]
 - $\mathcal{O}(10^4)$ galactic binaries
 - Extreme mass-ratio inspirals
 - Black hole binaries
- Stochastic sources [Cornish, Romano 2015]
 - Unresolved GBs (Galactic foreground)
 - Unresolved BBHs (Extragalactic background)
 - Primordial sources?





What does the data look like?



Assuming Gaussian noise:

$$L(\mathbf{d}|\vec{\lambda}) = \frac{1}{\sqrt{(2\pi)^N |\mathbf{C}|}} e^{-\frac{1}{2}(\mathbf{d}-\mathbf{h})\mathbf{C}^{-1}(\mathbf{d}-\mathbf{h})}$$

Very challenging data analysis problem – easily $10^5\ \rm parameters$ In principle, could split for each source

$$\log L = \langle d|h \rangle - \frac{1}{2} \langle h|h \rangle = \sum_{i}^{M} \log L_{i} - \frac{1}{2} \sum_{i \neq j} \langle h_{i}|h_{j} \rangle$$

Blocked Gibbs sampling



Wheel





Current GLASS noise model



- Current residual is fit with independent Akima splines in TDI A and E channel
- Number of control points is varied (RJMCMC)
- Ignores null channel!

How do we detect an SGWB?

Use the covariance matrix, C. In the equal arm case $(i, j \in \{A, E, T\})$

$$C_{ij} = \delta_{ij}(N_i + R_i S_i)$$

$$A = \frac{Z - X}{\sqrt{2}}$$
$$E = \frac{X - 2Y + Z}{\sqrt{6}}$$
$$T = \frac{X + Y + Z}{\sqrt{3}}$$



[Smith, Caldwell 1908.00546]

Many caveats! See Baghi+ 2302.12573, talks including Marc Lilley and Olaf Hartwig

Use stochastic templates

 Physically motivated background shapes – matched filtering in frequency domain [comish,

Romano 2016]

- Decompose overlapping signals
- Automatic parameter inference and exclusion
- Work in time/frequency

[Digman, Cornish 2206.14813]



Prototype SGWB Recovery pipeline

Language	files	blank	comment	code
Python	27	481	885	5448
Jupyter Notebook	4	Θ	1664	655
с	1	52	143	454
make	1	Θ	Θ	3
SUM:	33	533	2692	6560

- Likelihood, templates, noise model implemented in C
- Use simple two-parameter noise model
- Data synthesis, bookeeping, sampling, plotting in Python
- Use Eryn parallel-tempered sampler [Karnesis+ 2303.02164]
- Use STFTs



- Non-stationarity!
- Confusion noise is (close to) cyclo-stationary
- Instrument noise
- Isotropic SGWB posteriors modeled with GMMs

Gaussian Mixture Models



Gaussian Mixture Models



GMM comparison



Stationary "confusion noise" + powerlaw injection



Real global fit residual + powerlaw injection



- Primordial SGWBs can be constrained in presence of non-stationary components
- Modeling the non-stationarity helps constrain primordial signals
- Analytic model for confusion noise doesn't match
- Likely other un-modeled populations too [Littenberg, Breivik in prep]
- Anisotropies not fully exploited (BLIP [Banagiri+ 2103.00826])

- Explore covariances in cosmological templates
- Expand the template library
- Inference during future GLASS runs
- Work with a better noise model?
- Switch to wavelet domain
- Use normalizing flows?

Confusion QQ plot



Injection simulating confusion noise



Real global fit residual, powerlaw upper limit (One STFT)



$$\begin{split} \Omega_{\rm GW}(k) &= \\ c_g \Omega_{r,0} \int_0^{1/\sqrt{3}} \mathrm{d} d \int_{1/\sqrt{3}}^\infty \mathrm{d} s \, P_\zeta \left[\frac{\sqrt{3}k}{2} (s+d) \right] P_\zeta \left[\frac{\sqrt{3}k}{2} (s-d) \right] T(d,s) \\ T_{\rm RD}(d,s) &= 36 \frac{(d^2 - 1/3)^2 (s^2 - 1/3)^2 (d^2 + s^2 - 2)^4}{(s^2 - d^2)^8} \times \\ \left[\left(\log \frac{1 - d^2}{|s^2 - 1|} + \frac{2(s^2 - d^2)}{d^2 + s^2 - 2} \right)^2 + \pi^2 \theta(s-1) \right] \\ c_g \Omega_{r,0} h^2 &= 1.6 \times 10^{-5} \end{split}$$

