Characterizing Anisotropic Stochastic Gravitational Wave Backgrounds and Foregrounds with the Bayesian LISA Pipeline (BLIP)

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with Sharan Banagiri, Jessica Lawrence, Steven Rieck, Malachy Bloom, Joe Romano, and Vuk Mandic

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Stochastic Gravitational Wave (GW) Signals:

The stochastic confusion noise arising from the superposition of many **unresolved** gravitational wave sources on the sky ^[1,2]



Stochastic GW Signals in LISA

Cosmological

Arise from the early universe

- Inflation ^[3]
- Phase transitions ^[4]
- Cosmic Strings ^[5]

Expected to be **isotropic** at scales accessible by LISA

Arise from the superposition of many individual astrophysical events (e.g. unresolved white dwarf binaries^[6,7])

Expected to reflect the spatial distributions of their component sources and may be **anisotropic**

Astrophysical

Stochastic GW Signals in LISA



Anisotropic

One scientist's noise is another's signal!

Anisotropic astrophysical signals embed **spatial** and **frequency** information about their source **populations**.

Astrophysical

The Bayesian LISA Pipeline (BLIP)

A Python pipeline for end-to-end simulation and Bayesian analysis of stochastic signals with LISA

- Simulation of time-domain data, Fourier domain analysis
- Flexible, modular GW signal, injection, and likelihood models
- Simultaneous noise and signal characterization

All-sky **isotropic** and **anisotropic** stochastic searches



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Post-doc at <u>No</u>rthwestern

github.com/sharanbngr/blip



The Bayesian LISA Pipeline (BLIP)

JOURNAL ARTICLE

Mapping the gravitational-wave sky with LISA: a Bayesian spherical harmonic approach

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Assume frequency and spatial dependence are separable (expected!)

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$$\mathcal{P}(\mathbf{n}) = \frac{1}{\sqrt{4\pi a_{0,0}}} \sum_{\ell,m} a_{\ell,m} Y_{\ell,m}(\mathbf{n}),$$

Standard spherical harmonic expansion of GW power on the sky. But $\mathcal{P}(n)$ must be non-negative everywhere on the sky...

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$$\mathcal{S}(\mathbf{n}) = \left[\sum_{\ell,m} a_{\ell,m} Y_{\ell,m}(\mathbf{n})\right]^{1/2} = \sum_{\ell,m} b_{\ell,m} Y_{\ell,m}(\mathbf{n}).$$

Defining $S(\mathbf{n})$ as the square root of the spherical harmonic expansion fulfills this condition as long as $S(\mathbf{n})$ is real – or, equivalently, $b_{l,-m} = (-1)^m b_{l,m}^*$

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We can then infer each $b_{l,m}$ up to some desired $l_{max}^b = \frac{1}{2} l_{max}^a$, quickly liaising between our $b_{l,m}$ parameterization and the power on the sky in the $a_{l,m}$ s via **Clebsch-Gordon coefficients**

Science with BLIP

BLIP is a *tool*.

... so what can we do with it?

Explore & characterize BLIP's abilities and limitations.

Test our capabilities with known signals in LISA.

Investigate detectability of potential new sources!

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Angular Resolution of the Anisotropic Search



Main takeaway: BLIP's anisotropic search is *currently* computationlimited (primarily), not SNR-limited \rightarrow need to optimize!

New Capability

Population Injections

BLIP can now take in a GW source population synthesis catalogue and inject/recover the associated spectral and spatial power distribution.

This allows for realistic investigations of population-derived anisotropic stochastic signals.

The Milky Way Foreground



Recovery Shown:

- 1 year of data
- Injected pop. synth. catalogue from Korol+2021 ^[9]
- Broken power law spectral model (3 parameters)
- Acceleration + position noise model (2 parameters)

•
$$l_{\text{max}}^a = 8$$
 (so $l_{\text{max}}^b = 4$; 24 b_{lm} parameters)



The Large Magellanic Cloud (LMC)!



Recovery Shown:

- 2 years of data
- Injected LMC pop. synth. catalogue from Keim+2022 ^[10]
- Power law spectral model (2 parameters)
- Acceleration + position noise model (2 parameters)

•
$$l_{\text{max}}^a = 4$$
 (so $l_{\text{max}}^b = 2$; 8 b_{lm} parameters)



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Population studies: what's next?



Marginalized posterior skymap of $\Omega(f = 1mHz)$



Hierarchical Parameter Estimation



& more?

Stellar

Spatial distribution models

Where do we go from here?

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Simultaneous characterization.

Simultaneous inference of **isotropic + anisotropic** sources.

Simultaneous inference of multiple anisotropic sources.

Integration of the BLIP stochastic search with global fit efforts.

Summary

- ♦ Ability to inject realistic, population synthesis catalogue-derived signals, allowing us to investigate both known and novel stochastic sources in LISA.
- ♦ Large numbers of spherical harmonic parameters needed at high $l_{max} \rightarrow$ **need to optimize sampling** to improve angular resolution.
- ♦ Successful characterization of a realistic galactic foreground signal.
- The stochastic signal from unresolved white dwarf binaries in the Large Magellanic Cloud may be within reach of LISA!

References

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Extra Slide: Clebsch-Gordon Expansion

$$\sum_{L,M} a_{L,M} Y_{L,M} = \left(\sum_{\ell,m} b_{\ell,m} Y_{\ell,m}(\mathbf{n}) \right)^2.$$

$$\sum_{L,M} a_{L,M} Y_{L,M} = \sum_{\ell,m} \sum_{\ell',m'} b_{\ell,m} b_{\ell',m'} Y_{\ell,m}(\mathbf{n}) Y_{\ell',m'}(\mathbf{n}).$$

$$Y_{\ell,m}(\mathbf{n})Y_{\ell',m'}(\mathbf{n}) = \sum_{L=L_{\min}}^{L_{\max}} \sqrt{\frac{(2\ell+1)(2\ell'+1)}{4\pi(2L+1)}} \times C_{\ell m,\ell'm'}^{LM} C_{\ell 0,\ell'0}^{L0} Y_{L,M}(\mathbf{n}).$$

$$\sum_{L,M} a_{L,M} Y_{L,M}(\mathbf{n}) = \sum_{L,M} \left(\sum_{\ell m} \sum_{\ell' m'} b_{\ell,m} b_{\ell',m'} \beta_{L,M}^{\ell m,\ell'm'} \right) \times Y_{L,M}(\mathbf{n}).$$

• M = m + m'

•
$$L_{\min} = \min(|\ell - \ell'|, |m + m'|)$$
 and $L_{\max} = \ell + \ell'$

• L is an integer

For compactness, let us define $\beta_{\ell m,\ell'm'}^{L,M}$ such that:

$$\beta_{\ell m,\ell'm'}^{L,M} = \sqrt{\frac{(2\ell+1)(2\ell'+1)}{4\pi(2L+1)}} C_{\ell m,\ell'm'}^{LM} C_{\ell\,0,\ell'\,0}^{L0}, \qquad (3.7)$$

when the selection rules are satisfied, but $\beta_{\ell m,\ell'm'}^{L,M} = 0$ otherwise.

Extra Slide: Spectral Models

Power law:

$$\Omega(f) = \Omega_{\text{ref}} \left(\frac{f}{f_0}\right)^{\alpha},$$

Broken power law from Boileau et al. (2021)



Extra Slide: Foreground Corner Plot (full)



Extra Slide: Foreground Corner Plot (spectral)



Extra Slide: Foreground Corner Plot (spatial)



Extra Slide: LMC Corner Plot (full)



Extra Slide: LMC Corner Plot (spectral)



Extra Slide: LMC Corner Plot (spatial)

