Chinese Pulsar Timing Array Upper Limits on Microhertz Gravitational Waves from Supermassive Black-hole Binaries Using PSR J1713+0747 FAST Data Postprint

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Date: 2025-04-28T11:57:59+00:00

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Full Text

Preamble

Research in Astronomy and Astrophysics, 25:035022 (11pp), 2025 March

https://doi.org/10.1088/1674-4527/adb5d6
CSTR: 32081.14.RAA.adb5d6

Chinese Pulsar Timing Array Upper Limits on Microhertz Gravitational Waves from Supermassive Black-hole Binaries Using PSR J1713+0747 FAST Data

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Received 2024 March 13; revised 2024 December 29; accepted 2025 February 11; published 2025 March 26

Abstract

We derive gravitational-wave (GW) strain upper limits from resolvable supermassive black-hole binaries using data from the Five-hundred-meter Aperture Spherical radio Telescope, in the context of the Chinese Pulsar Timing Array project. We focus on circular orbits in the Hz GW frequency band between 10^{-7} and 3×10^{-6} Hz. This frequency band is higher than the traditional pulsar timing array band and is less explored. We used data from the millisecond pulsar PSR J1713+0747 observed between 2019 August and 2021 April. A dense observation campaign was carried out in 2020 September to allow for Hz band coverage. Our sky-averaged continuous source upper limit at the 95% confidence level at 1 Hz is 1.26×10^{-12}, while the same limit in the direction of the pulsar is 4.77×10^{-13}.

Key words: (stars:) pulsars: general – gravitational waves – methods: statistical – methods: observational – methods: data analysis

1. Introduction

The primary work in searching for gravitational waves (GWs) at nHz frequencies over the last decades has been conducted using radio pulsars, particularly through the employment of pulsar timing arrays (PTAs; Foster & Backer 1990). PTAs are ensembles of millisecond pulsars (MSPs) at different sky locations. MSPs are chosen for GW searches due to their remarkably stable rotations (see, e.g., Verbiest et al. 2009), which allow for high-precision recording of pulse arrival times (times-of-arrival; ToAs) with precision reaching tens of nanoseconds, as is the case with the data in this paper. By comparison, the canonical pulsar population, comprising younger pulsars, exhibits substantial rotational irregularities (Hobbs et al. 2010; Parthasarathy et al. 2019). These manifest as regular glitches, nulling and mode changes, and strong stochastic irregularities known as timing noise, also referred to as red noise (RN) or spin noise, which reduce sensitivity to GW signals (see, e.g., Caballero et al. 2016). In contrast, MSPs have very smooth and regular rotations that result in very small levels of stochastic timing noise (e.g., Verbiest et al. 2009; Caballero et al. 2016; Lentati et al. 2016), and only a couple of glitches have been previously observed in

MSPs (Cognard & Backer 2004; McKee et al. 2016). Profile changes in MSPs are generally subtle, appearing as profile instabilities that can be addressed in standard timing methods (e.g., Kramer et al. 1999; Liu et al. 2015; Shannon et al. 2016; Kerr et al. 2020). Profile changes that are severe and significantly affect the long-term timing of MSPs are rare, but PSR J1713+0747 has recently exhibited such a change, which led to the limitation in the total data set used in this study (see Section 2).

PTAs are most sensitive in the nHz part of the GW spectrum, where the primary goal is to observe GWs emitted by supermassive black-hole binaries (SMBHBs). In addition to GWs from resolvable SMBHBs (see, e.g., Thorne 1989; Jenet et al. 2004; Sesana & Vecchio 2010; Lee et al. 2011), PTAs are also sensitive to stochastic GW background (GWB) signals. Such stochastic signals may result from the superposition of GWs from the cosmic population of SMBHBs (Rajagopal & Romani 1995; Jaffe & Backer 2003), cosmic strings (Kibble 1976; Sanidas et al. 2012), and relic GWB from quantum fluctuations in the early Universe, particularly from the inflationary era. Recently, the Chinese Pulsar Timing Array (CPTA; Lee 2016) and other PTA groups have reported statistical evidence for the existence of a nHz GWB (Agazie et al. 2023; EPTA Collaboration et al. 2023; Reardon et al. 2023; Xu et al. 2023), though no individual PTA has yet detected a single GW source.

The observational GW frequency window for PTAs is determined by the total timespan of the data set, T, and the observational cadence, Δt. The upper frequency limit is determined by the Nyquist theorem for regular sampling. For irregular sampling, which is the case for real pulsar timing data, the upper frequency limit can be much higher than the "traditional" Nyquist principle would suggest (based on arguments similar to those of Koen 2006). In practical PTA GW detection, the interesting upper frequency limit is mainly determined by the data sensitivity. The lower recoverable frequency is $1/T$, as any power in the pulsar ToAs below this frequency is effectively absorbed by the quadratic term of the pulsar's rotational-frequency derivative (see Lee et al. 2012). This term accounts for the slowing-down of the pulsar rotation as it loses rotational energy through emitted radiation and is always present in timing models of radio pulsars.

Typical pulsar data sets have decadal timespans for a large number of pulsars and have the highest GW sensitivity at the lowest frequencies of the spectrum. Single-telescope data seldom achieve cadence below \$ \$1 week, but multi-telescope data combination can achieve daily cadence. In this way, PTAs can probe single-source GWs (SSGWs) up to the Hz band. So far, the Hz regime for SSGW from SMBHBs with pulsar timing has been explored using single-pulsar data (Dolch et al. 2014; Yi et al. 2014; Perera et al. 2018). As a consequence, these studies can only provide GW amplitude strain upper limits, as GW detection requires observations by multiple pulsars. The current paper also places an upper limit using single-pulsar data.

PSR J1713+0747 is one of the most observed and thoroughly studied MSPs.

Due to its sky location that permits observations from both the Northern and Southern Hemispheres, its long-term stability, and its high brightness that results in high ToA measurement precision, PSR J1713+0747 has always been a primary PTA target for GW search efforts. It has been continuously observed by the three founding PTAs and has also been the subject of the International Pulsar Timing Array (IPTA) 24 hr global observing campaign (Dolch et al. 2014), with nine participating telescopes observing the source, allowing rare investigations of noise properties on intermediate timescales.

In this paper, we use PSR J1713+0747 data from the Five-hundred-meter Aperture Spherical radio Telescope (FAST; Jiang et al. 2019) in China to place new and independent upper limits for the strain amplitude of SSGWs from circular SMBHBs in the Hz regime.

The rest of the paper is organized as follows: In Section 2, we describe the data used for the study. In Section 3, we present the pulsar timing model and the data's noise properties, while in Section 4 we derive the SSGW strain upper limits. Finally, we discuss our conclusions in Section 5.

2. Data

PSR J1713+0747 was observed using the 19-beam receiver of the FAST radio telescope from 2019 August to 2021 April with a cadence of about 1 week, and we conducted a dense observation campaign with nearly 2 day cadence in September 2020. Since this pulsar was found to show a profile-changing event (Xu et al. 2021), the data after 2021 April 16 are not included in this work. The receiver is centered at 1.25 GHz with a bandwidth of 500 MHz. We used the ROACH2 system to record the data in search mode with a 49.152 s sampling time and 4094 channel mode. Each observation was typically 20–30 minutes, although some were longer, up to 3 hr. In total, we include 56.2 hr of observations. The data were off-line folded every 30 s using the standard pulsar data reduction software DSPSR (van Straten & Bailes 2011), and the polarization calibration was performed with the pulsar analysis software package PSRCHIVE (Hotan et al. 2004) using the single-axis model.

Following polarization calibration, any data corrupted by radio frequency interference (RFI) were removed manually. The clean data were finally time-integrated every 15 or 20 minutes and the whole band was split into 16 subbands to allow for frequency-dependent noise measurement and corrections, e.g., dispersion measure (DM) variation. The subband ToAs were generated following the Fourier-domain algorithm (Taylor 1992) with the PAT routine in PSRCHIVE. ToAs with signal-to-noise ratio (S/N) lower than 8 were removed from the subsequent analysis. In total, 3436 ToAs from 65 observation sessions were used in this paper.

3. Pulsar Timing Model and Noise Properties

The initial timing analysis of the data was performed using TEMPO2 (Hobbs et al. 2006), providing a phase-coherent timing solution. As TEMPO2 uses a linearized model and the solution is calculated via least-squares fit, the presence of any RN can bias the estimated values and uncertainties of the timing parameters (Coles et al. 2011; van Haasteren & Levin 2013). We followed a Bayesian approach using TEMPONEST (Lentati et al. 2014) for the noise analysis, searching for noise components that are standard in pulsar timing (see, for example, Lentati et al. 2016; see further details in the next section). We used Bayesian model selection using Bayes factors to determine how many components are supported by the data. Detailed timing and noise analyses are presented for PSR J1713+0747 and all MSPs timed by the CPTA in separate papers (Chen, S. et al. 2025, in preparation; Xu, H. et al. 2025, in preparation).

Figure 1 [Figure 1: see original paper] shows the timing residuals from a generalized-least-squares fit of the timing model including the noise model, as well as the same residuals after subtracting the stochastic effects of the interstellar medium (see next section). The latter residuals have a root mean square (rms) of only 93 ns.

3.1. Noise Model

In general, for a one-dimensional (1D) time series, noise can be divided into time-uncorrelated and time-correlated noise. The former are referred to as white noise parameters and include: (i) EFAC, a corrective multiplying factor on the ToA uncertainties calculated during the ToA estimation (Taylor & Weisberg 1982); (ii) EQUAD, a factor added in quadrature to the ToA uncertainties (Ekers & Moffet 1968; Shannon & Cordes 2010), which tracks effects of pulse phase jitter; and (iii) ECORR (Arzoumanian et al. 2016), which models pulse jitter effects that are specifically correlated in subband ToAs across the observing bandwidth. The interested reader can find more details in the CPTA pulsar-noise paper (S. Chen et al. 2025, in preparation).

The time-correlated noise components included are: (i) red (achromatic) noise, stochastic noise presumably associated with pulsar spin irregularities (Shannon & Cordes 2010); and (ii) stochastic DM variations (see You et al. 2007). DM is the column density of free electrons between the pulsar and Earth, causing a delay $\delta\tau_{\mathrm{dm}}$ in the radio signal proportional to ν^{-2} (where ν is the observing frequency), following the dispersion law of cold plasma (e.g., Landau & Lifshitz 1960). These types of stochastic, correlated noise are typically assumed to be wide-sense stationary signals and are modeled in the time-frequency domain (Lentati et al. 2013). Following the literature, we use a power-law spectrum for RN of the form $S(f) = A^2 f^{-\gamma}$, where $S(f)$ is the power spectral density, A is the spectrum's amplitude, and γ is the spectral index.

3.2. Bayesian Parameter Estimation and Model Selection

We use Bayesian inference to perform parameter estimation, where model selection is based on Bayes evidence comparison as previously described (Lentati et al. 2016; Chalumeau et al. 2022). We employed the software package TEMPONEST to perform the Bayesian noise modeling. Here, we give a brief mathematical description of the process, which is also (partially) applied in the calculations of the SSGW amplitude limits discussed in the next section.

Bayes' theorem relates the posterior distribution (i.e., the distribution of inferred parameters given the data) and the likelihood (i.e., the distribution of data given the model) as:

$$P(\lambda|\Delta, H) = \frac{L(\Delta|\lambda, H)p(\lambda|H)}{Z(\Delta|H)}$$

where Δ denotes our data, H denotes the hypothesis (i.e., the model), and λ denotes the model parameters. P is the posterior distribution, L is the likelihood function, p is the prior distribution, and Z is the Bayesian evidence.

The likelihood function of pulsar timing was assumed to be Gaussian (van Haasteren et al. 2009), i.e.:

$$L(\Delta|\lambda, H) = \frac{1}{\sqrt{(2\pi)^n \det C}} \exp\left[-\frac{1}{2}(t - t_{\mathrm{tm}})^T C^{-1}(t - t_{\mathrm{tm}})\right]$$

where t is the recorded ToA, t_{tm} is the ToA predicted by the timing model, $(t - t_{\mathrm{tm}})$ corresponds to the timing residuals, C is the total noise covariance matrix, and n is the number of ToAs in the data.

The prior distribution represents our prior knowledge or belief about the distribution of unknown parameters. This choice can add information to the parameter estimation and can lead to erroneous results if our belief regarding the parameter distribution is informative but wrong. Theoretically, Jeffreys prior represents the least informative choice. However, its formal calculation can be difficult and approximations are used. For example, for scale-invariant parameters such as the amplitude of the power-law RN spectrum, we use a uniform prior (flat) in log space as an uninformative prior (Gregory 2005), while one would use a uniform prior in linear space to estimate conservative upper limits.

The evidence Z is accurately estimated when we want to perform model comparison and selection to decide which model better fits the data. The evidence is the integrated likelihood over the prior, and for N parameters is defined as:

$$Z = \int L(\Delta|\lambda, H)p(\lambda|H)d^N\lambda$$

Larger Z values signify more favorable models. As a metric to choose whether a more complicated model is required, Z should be larger than a threshold. We can measure this using the posterior odds ratio for two models, e.g., H_0 and H_1, where the ratio of the evidences $\mathcal{B}_{10}$ is called the Bayes factor. As the prior distributions for all models we discuss in model selection analysis in this paper are the same, the Bayes factor is equal to the posterior odds ratio. As a rule of thumb, a threshold of $\mathcal{B}_{10} > 3$ is taken in the current paper following Kass & Raftery (1995) to choose the preferred model.

3.3. Noise Analysis

In the noise analysis, we used the priors shown in Table 1 and employed TEMPONEST's importance nested sampling algorithm to perform posterior and evidence computation (see Skilling 2004; Feroz & Hobson 2008). Our model selection process uses Bayes factors to select our preferred noise model from a set of nested models, where the simplest models only include EFAC. We proceed by trying models with white-noise parameters only: EFAC+EQUAD, EFAC+ECORR, and EFAC+EQUAD+ECORR. The analysis results suggested that all three terms were required.

To test whether the data support red and/or DM stochastic noise, we first assume EFAC+RN and EFAC+DM models with increasing number of frequency bins to find the optimal number of frequency bins for the RN and DM power-law spectrum models using Bayes factor evaluations. Once that number was defined, we tested the EFAC+RN, EFAC+DM, and EFAC+RN+DM models with the respective optimal numbers of frequency bins. The analysis suggested that the data are sufficiently modeled using white noise+DM noise and that there is not sufficient support to add the RN noise component. We note that this does not mean that an RN component, including a GWB, is not present. It means that if present, the current data set is not sufficient to detect it with high statistical significance, and therefore model selection prefers the simpler model that does not include it. This is expected for a GWB from GW-driven SMBHBs whose stochastic signal has a spectral index of $-13/3$, as a longer data span would be required to detect it: see, for example, Jenet et al. (2005), where (simulated) data similar to CPTA data require $ $3 yr for such a GWB detection depending on the exact pulsar number and noise properties, and Xu et al. (2023) for the case of CPTA data.

The detected DM noise in the current data is a shallow power-law with spectral index of $ $1.7 (see Table 2), thus allowing its detection at higher frequencies where our data are more sensitive. We confirmed that from all the white-noise models with DM noise added, the most supported model is the EFAC+EQUAD+ECORR+DM model. We then confirmed that changing the number of frequency bins for the RN does not improve the support to add the RN in the EFAC+EQUAD+ECORR+DM model, and that the optimal number of DM noise frequency bins (43) remains the same as in the case of the simpler EFAC+DM model. Thus, the DM power-law signal spans the frequency spectrum from $1/T$ (1.9×10^{-8} Hz) to the highest frequency of $1/43$ day^{-1} (2.7×10^{-7} Hz).

Table 1. Ranges and Types for the Priors Used in the Single-pulsar Noise Analysis of PSR J1713+0747

Parameter	Range	Prior Type
EFAC	[0.1, 5]	log-Uni
$\log_{10}$(EQUAD)	[-9, -5]	log-Uni
$\log_{10}$(ECORR)	[-9, -5]	log-Uni
$\log_{10}(A_{DM})$	[-20, -8]	log-Uni
γ_{DM}	[0, 7]	Uni
$\log_{10}(A_{RN})$	[-20, -8]	log-Uni
γ_{RN}	[0, 7]	Uni

Note. The prior types Uni and log-Uni correspond to uniform priors in linear and logarithmic space, respectively.

Table 2. Overview of the Results from the Single-pulsar Noise Analysis of PSR J1713+0747, for the Optimal Noise Model (See Main Text for Details)

Parameter	Median	ML Value
EFAC	1.06	1.06
$\log_{10}$(EQUAD)	$-7.531^{+0.002}_{-0.002}$	-7.533
$\log_{10}$(ECORR)	$-7.159^{+0.003}_{-0.003}$	-7.162
$\log_{10}(A_{DM})$	$-12.176^{+0.020}_{-0.020}$	-12.196
γ_{DM}	$1.70^{+0.15}_{-0.15}$	1.68

Note. The table lists the median values of the 1D marginalized posterior distribution for each parameter, with the (asymmetric) 68% uncertainties, as well as the maximum likelihood (ML) values.

Here, we present the results from the optimal model's noise analysis. Figure 2 [Figure 2: see original paper] is the corner plot showing the two-dimensional (2D) and marginalized 1D histograms of the noise parameters. We note that while EFAC and EQUAD appear correlated, ECORR does not correlate with either EFAC or EQUAD. On the other hand, all three parameters show correlation with the spectral index of DM. This occurs due to the very shallow DM power-law, i.e., because the DM signal has significant power at higher frequencies. Table 2 gives the median and maximum likelihood values of the noise-parameter posterior distributions.

4. Continuous Gravitational-wave Strain Upper Limits

In the context of PTAs, the problem of SMBHB GW detection has been discussed extensively (e.g., Jenet et al. 2004; Lee et al. 2011; Sesana 2013). In general, GWs from a SMBHB have two terms, which we refer to as the "Earth term" and the "pulsar term," which quantify the spacetime distortion of the passing GW at the Earth's and at the pulsar's vicinities, respectively. The two-component SSGW signal is a direct result of the large (thousands of years) time-delay between the pulsar and Earth. In this work, we focus on the case of monochromatic GWs and neglect the evolution of the GW source. We adopt the mathematical framework described in Lee et al. (2011). The monochromatic GW is then described by seven parameters: the GW strain amplitude (A), the two GW-source position sky coordinates (right ascension [RA] and declination [DEC]), the GW angular frequency ($\omega_{\rm gw}$), the orbital inclination angle (ι), the orientation angle of ascending node (ψ), and the GW initial phase (ϕ_0) at reference epoch t_0. The term "monochromatic" refers to signals where we have the condition $\delta f \ll \omega_{\rm gw}/2\pi$, where δf is the difference between the frequencies of the Earth and pulsar terms.

As only one pulsar is considered, our SSGW analysis is limited to the derivation of robust upper limits for the GW strain amplitude. We employed two methods to estimate the upper limits: (1) analytic calculations based on the Cramér–Rao lower bound (CRLB) and (2) Bayesian inference analysis. In contrast, the CRLB calculations require less computational resources and are used to cross-check the Bayesian result, as the CRLB provides the theoretically best possible result (Fisz 1963) and the Bayesian inference result must be "worse" than the CRLB in any case (see discussion in Lee et al. 2011; Caballero et al. 2016). We are interested in two results: (i) the sky-averaged limit and (ii) the limit in the best sky location (the pulsar direction). Because we only use one pulsar, our analysis is insensitive to the sky direction opposite to the pulsar position (henceforth the anti-pulsar direction), while it is optimal around the direction of the pulsar. For this reason, when computing the all-sky upper limit, we exclude an area around the anti-pulsar direction (see Section 4.2). All of the SSGW analysis was performed using the PTA data analysis package FORTYTWO (Caballero et al. 2016), which performs pulsar-timing noise and GW analysis.

4.1. Cramér–Rao Lower-bound

The calculation of GW sensitivity curves for PTA data using the CRLB was previously described in Lee (2016) and Caballero et al. (2016). The CRLB is defined as the inversion of the Fisher information matrix, $\mathcal{I}$. Given the likelihood function $L(\lambda, x)$, where x is the data and λ are the model parameters, the CRLB is described by:

$$\mathrm{Cov}(\lambda) \geq \mathcal{I}^{-1}$$

where the indices i and j denote different parameters, $\mathrm{Cov}(\lambda)$ is the covariance of the parameters λ, and $\mathcal{I}_{ij}$ is defined as:

$$\mathcal{I}_{ij} = -\left\langle \frac{\partial^2 \ln L}{\partial\lambda_i \partial\lambda_j} \right\rangle$$

For Gaussian likelihood functions like the pulsar timing likelihood, $\mathcal{I}$ can be analytically calculated and the result is known as the Slepian–Bangs formula (Slepian 1954; Bangs 1971):

$$\mathcal{I}_{ij} = \frac{1}{2}\mathrm{tr}\left[C^{-1}\frac{\partial C}{\partial\lambda_i}C^{-1}\frac{\partial C}{\partial\lambda_j}\right] + \frac{\partial\mu^T}{\partial\lambda_i}C^{-1}\frac{\partial\mu}{\partial\lambda_j}$$

Here, β_i are the model parameters describing the covariance matrix, λ_i are the parameters describing the unknown waveform S, and tr is the matrix trace.

In the context of SSGW in this paper, we use the reduced likelihood function with the timing parameters marginalized (van Haasteren et al. 2009), where we separate the timing residuals into those induced by stochastic processes, δt_s (for example RN or a stochastic GWB), and the deterministic residuals induced by the SSGW, $S(\lambda)$, such that $\delta t = \delta t_s - S(\lambda)$. In our specific problem, λ is the set of seven parameters required to describe the monochromatic SSGW. When focusing on the SSGWs, the terms with partial derivatives of C are zero and the equation reduces to:

$$\mathcal{I}_{ij} = \frac{\partial S^T}{\partial\lambda_i}C^{-1}\frac{\partial S}{\partial\lambda_j}$$

For the CRLB calculations, the noise covariance matrix C is fixed using the maximum likelihood values of the noise components, as derived from the pulsar noise analysis. We run 1000 analyses by selecting random values from uniform distributions for the six SSGW parameters (excluding the amplitude) and calculate the covariance of the amplitude. The sky-position-parameter range is set accordingly depending on whether we are interested in the full sky-averaged amplitude limits or the "best-sky" limits. Figure 3 [Figure 3: see original paper] shows both results. Note that by default, the estimated CRLB corresponds to the 1σ uncertainty, as we are dealing with a Gaussian likelihood. From this result, we may expect the sky-averaged and best-sky upper limits to differ by a factor of a few. In the frequency range 10^{-7}–10^{-6} Hz, the average difference is a factor of 3.35, while specifically at frequency 1 Hz, the difference is a factor of 2.2.

We also note that for frequencies below 10^{-7}, due to the limited timespan, the sensitivity drops sharply and becomes non-comparable to previously published results. For this reason, we opted to only include frequencies above 10^{-7} in the Bayesian analysis, saving computational resources and time.

4.2. Bayesian Inference

Our main SSGW analysis follows the Bayesian inference principles outlined in Section 3.2. As we are only interested in amplitude upper limits, we do not need to perform any model selection. We perform two analyses. First, as in the derivation of the CRLB, we perform a fixed-noise analysis using the maximum likelihood noise-parameter values. This allows direct comparison of the methods. In addition, we perform a complementary analysis with varying noise for five key GW frequencies: 0.1, 0.3, 0.5, 1, and 2 Hz. This allows derivation of the most conservative upper limit at our reference frequency of 1 Hz. We use uniform priors for the amplitude with a wide range to derive robust upper limits. The prior ranges are presented in Table 3 .

The sky-averaged results are derived by averaging the upper limits derived in 400 sky cells, formed by a 20 × 20 grid equally spaced in RA and cos(DEC). As explained earlier, motivated by the CRLB results, we limit our analysis to the GW frequency range of 10^{-7}–3×10^{-6} Hz. The amplitude upper limit is evaluated at each GW frequency with a fixed frequency analysis, using a frequency grid uniform in $\log_{10}$ for a total of 180 frequencies per sky cell. The best-sky limit was calculated with a single analysis where the RA and DEC priors were set at $±$10° around the pulsar position coordinates.

Table 3. Ranges and Types for the Priors Used in the Bayesian SSGW Upper-limit Analysis

Parameter	Prior Range	Prior Type
A_{SSGW}	$[10^{-20}, 10^{-10}]$	log-Uni
RA*	$[0, 2\pi]$	Uni
cos(DEC)*	[-1, 1]	Uni
ω_{gw}	$[10^{-7}, 3 \times 10^{-6}]$	Fixed from grid
ι	$[0, \pi]$	Uni
ψ	$[0, 2\pi]$	Uni
ϕ_0	$[0, 2\pi]$	Uni

Note. The prior types Uni and log-Uni correspond to uniform priors in linear and logarithmic space, respectively. The sky coordinates RA and cos(DEC) are marked with an asterisk (*) to signify that the quoted range is the total covered, but each analysis used only the coordinate range corresponding to each sky cell. The GW angular frequency ω_{gw} is fixed for each analysis, each time using a value from the pre-calculated grid.

We first make a comparison between the Bayesian and CRLB estimates. Figure 4 [Figure 4: see original paper] shows the two results. As expected, the results are compatible and, in fact, almost identical, which suggests that the Bayesian result approaches that of a fully efficient estimator (Fisz 1963).

Figure 5 [Figure 5: see original paper] presents the results from the Bayesian analyses. It compares the sky-averaged with the best-sky 95% upper limits of the amplitude for the full 180-frequency spectrum using fixed-noise analysis. In addition, we plot the results for the varying-noise, full-sky analysis for the five key frequencies, noting the corresponding 95% amplitude upper limits. At the reference GW frequency of 1 Hz, the most conservative sky-averaged upper limit using the varying pulsar-noise analysis is 1.26×10^{-12}. The corresponding best-sky limit is 4.77×10^{-13}. For the fixed-noise analysis, the same sky-averaged and best-sky limits are 1.01×10^{-12} and 4.77×10^{-13}, respectively.

In order to further highlight the effect of using a single pulsar, in which case the sensitivity to GWs tends to zero in the anti-pulsar direction, we note that the sky-averaged amplitude limit in the half-sky containing the pulsar direction is 7.01×10^{-13}, in contrast to 1.41×10^{-10} in the half-sky of the anti-pulsar direction.

4.2.1. High-resolution Sky Map at 1 Hz We repeat the Bayesian analysis on a finer 40×40 grid of 1600 sky cells at our reference GW frequency of 1 Hz to create a high-resolution sky map of the SSGW strain amplitude upper limit. We use the fixed-noise approach to reduce computational cost, as the numerical results are identical to those using the 20×20 case, and thus the sky map serves primarily as a visual representation of the upper limit as a function of sky location. The sky map is presented in Figure 6 [Figure 6: see original paper] and shows very clearly the dipolar sensitivity of the single-pulsar GW detector: the sensitivity is maximized in the pulsar direction and approaches zero in the opposite direction, which leads to a difference of multiple orders of magnitude in sensitivity between the two respective sky hemispheres.

5. Conclusion

We have used CPTA data collected with the FAST radio telescope from the MSP PSR J1713+0747 to derive robust upper limits on the strain amplitude of monochromatic SSGW from GW-driven SMBHBs in circular orbits in the Hz regime. This is one of the most observed MSPs in the context of PTAs, due to its brightness that enables high-precision ToA measurements and low levels of time-correlated noise. As it is observable from both Northern and Southern Hemispheres, it has been a source used for various studies, including noise analysis at very high frequencies, scintillation, and pulse jitter studies. So far, it has provided the best SSGW strain amplitude limits at Hz frequencies. Due to their very high measurement precision, the CPTA FAST data are especially suitable for SSGW studies, and we can probe the Hz regime thanks to dense observation campaigns that give the data set a best cadence of 1–2 days. Due to the recent profile-change event of PSR J1713+0747 in 2021 April, the data beyond this date are not suitable for this study and are excluded. As the FAST observations began in mid-2019, our data set has a timespan of only 1.67 yr, which causes some limitations in sensitivity to SSGW across the spectrum, especially at frequencies below 10^{-7} Hz. However, the high ToA precision offsets this loss and allows us to derive upper limits comparable to the previously published European Pulsar Timing Array (EPTA) limits (Perera et al. 2018) that used 4.3 yr of data with roughly daily cadence.

Using Bayesian inference with the analysis software package FORTYTWO, we derived a sky-averaged strain amplitude upper limit of 1.26×10^{-12} at 1 Hz at the 95% confidence level, and a limit of 4.77×10^{-13} in the direction of PSR J1713+0747, where the sensitivity is maximum. We also produced a high-resolution sky map of the amplitude limit by running the analysis on a fine grid of 1600 sky cells.

By comparison to Perera et al. (2018), the sky-averaged limit is $ $3.5 times higher, and the best-sky limit is $ $2.2 times higher. This is primarily due to the shorter timespan in CPTA data, caused by the profile change that limits the data set. Figure 7 [Figure 7: see original paper] (left panel) shows the effect of the short timespan using simulated PSR J1713+0747 data. The two data sets have properties similar to the CPTA data (i.e., ToA uncertainty of 50 ns and a 2 day cadence). White noise includes only radiometer noise to exclude jitter effects. The first data set has the timespan of the present CPTA data (1.67 yr) and the second has a timespan equal to the data in Perera et al. (2018) (4.32 yr). Because of the short timespan and the $1/T$ limit near the 1 yr^{-1} frequency spike, the shape of the sensitivity curve for the first case rises at such high frequency that it affects the sensitivity in the Hz regime. By comparison to the second curve, the sky-averaged limit is 2.2 times higher. Note that this is the same difference for the best-sky limit when comparing the two real data sets, which satisfy the exact same condition ($±$10° around the pulsar position). The exact area around the opposite direction to the pulsar excluded in the sky-averaged result in Perera et al. (2018) is not mentioned, and therefore we cannot make an exact comparison. Nevertheless, the simulations show that the majority of the difference between the two results is explained by the short CPTA timespan. Details on sensitivity effects from other mechanisms, such as jitter, are deferred to future work. We note, however, that the majority of CPTA pulsar data are not jitter-limited but radiometer-noise limited.

In the current study, we only used data from a single pulsar, PSR J1713+0747, to prove the concept and verify the validity of the analysis software. Such GW sensitivity is ten times worse than the Cassini spacecraft tracking experiment (Armstrong 2006) at a similar frequency band (see Figure 7). In future studies, data from multiple pulsars can be combined. The SSGW sensitivity increases with a rough scaling of $N^{-1/2}$, where N is the total number of pulsars. We expect that a future combination of CPTA data (50+ pulsars) will lower the current upper limit by about an order of magnitude. Since most CPTA pulsars are radiometer-noise limited, we compute a first estimate of the improvement in SSGW upper limits we can achieve when including the rest of the CPTA data in the analysis, without being concerned about jitter effects. In Figure 7 (right panel), we show an estimate of the upper limit assuming the use of the average of the 40 pulsars with timing precision at brighter CPTA sources (Xu, H. et al. 2025, in preparation). We assume timespans of 3.4 yr (timespan of CPTA first data release), 10 yr, and 20 yr. For simplicity, we assume the pulsars are isotropically distributed in the sky. We assume that all pulsars except PSR J1713+0747 can contribute beyond the 1.67 yr limitation and therefore counteract the corresponding sensitivity loss of \$ \$2 discussed above. One can expect further improvement over time with dense observing campaigns for various pulsars, as was done for PSR J1713+0747, and with the addition of more pulsars to PTA target lists. The longer data span will also further aid us in probing the lower frequency band, i.e., $f < 10^{-8}$ Hz. We can thus expect an upper limit at the level of $\sim 10^{-14}$ in the near future for the SSGW, resulting in pulsar timing likely becoming the most sensitive Hz GW detector.

Acknowledgments

Observations for CPTA are supported by the FAST Key Project. FAST is a Chinese national mega-science facility, operated by the National Astronomical Observatories, Chinese Academy of Sciences. This work is supported by the National SKA Program of China (2020SKA0120100), the National Natural Science Foundation of China (NSFC, Grant Nos. 12041303 and 12250410246), the CAS-MPG LEGACY project, and funding from the Max-Planck Partner Group. K.J.L. acknowledges support from the XPLORER PRIZE and 20 yr long-term support from Dr. Guojun Qiao. H.X. is supported by the Major Science and Technology Program of Xinjiang Uygur Autonomous Region No. 2022A03013-4. The data analyses were performed with computer clusters DIRAC and C*-SYSTEM of PSR@pku and computational resources provided by the PARATERA company.

H.X., S.Y.C., Y.J.G., J.C.J., B.J.W., J.W.X., Z.H.X., R.N.C., and K.J.L. are the core team that performed the data analysis for this paper. H.X. worked on data reduction, timing, and data analysis; R.N.C. and Z.H.X. performed the noise and SSGW analysis; B.J.W. carried out single-pulse studies; J.C.J. and J.W.X. calibrated polarization data; Z.H.X. and R.N.C. searched for GW single sources; Y.H.X. studied scintillation processes.

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Note: Figure translations are in progress. See original paper for figures.