Impact of planetary ephemerides on gravitational wave searches with Pulsar Timing Arrays

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Pulsars



Pulsars

A full zoology !

- Canonical pulsars
- Millisecond pulsars
- Magnetars
- Young pulsars
- X-ray pulsar
- Gamma-ray pulsar
- Spiders



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Pulsar timing

Determinate times of arrival (TOAs)



A. Chalumeau

cf. McKee

Pulsar timing

Build a timing model and get residuals



A. Chalumeau

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Year

Pulsar Timing Arrays

Probe very low-frequency gravitational waves effects in a combined set of residuals of a full array of pulsars !

PTA_NRAO_Outreach_animation



Pulsar Timing Arrays



Gravitational wave background (GWB) upper-limits







Our motivations

GWB Amplitude PDF vs. Solar-system ephemerides (SSEs) DE435 DE42DE436 DE430 10^{0} PDF 10^{-1} Arzoumanian et al. 2018] 10^{-2} NANOGrav 11-year dataset 10^{-3} -17-16-15-18-14 $\log_{10} A_{\rm GWB}$

Problem : GWB results seem dependent of the chosen ephemeris model !

Possible to fix it by modelling some SSE parameters

BAYESEPHEM model (11 params) to « unfix » ephemeris parameters

GWB constraint gets robust against SSE errors

But modelling SSE errors can absorb some of the GWB signal

Solar system ephemerides

Pos. & vel. predicted from numerical integration of eq. of motions fitted to the observational data



Various solutions given by various collaborations ! JPL, IMCCE (INPOP),...

- Different data
- Different uncertainties
- → Different models (i.e. eq. & params)



A. Chalumeau

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Work with INPOP data (cf. A. Fienga)



A first approach – SSE perturbation

INPOP data (cf. A. Fienga)

- Covariance matrix of orbital parameters
- Linear model coefficients

 Linear approximation + perturbation of planet positions (EMB & 4 outer planets) at initial conditions

$$\vec{x}_{new}(\vec{\theta}) = \vec{x}_{ref}(\vec{\theta}) + \frac{\partial \vec{x}_{ref}(\vec{\theta})}{\partial \vec{\theta}} \delta \vec{\theta}$$



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Max & min values of post-fit residuals of J1909-3744 after perturbations at 1σ (2000 perturb.)



A. Chalumeau

Model SSE uncertainties as gaussian process

Description of SSE noise as <u>Gaussian process</u> in residuals with the PTA analysis Bayesian framework software : <u>enterprise</u> (cf. M. Vallisneri)

Method(s)

Marginalize over the SSE parameters (orbital elements)



Perform a GW searches

Sample for SSE parameter uncertainties & GW parameters together

Get SSE uncertainties params by marginalizing over other signals Get constraints on priors that take into account possible <u>systematic biases</u> Add SSE errors into a full noise model using <u>dipolar correlations</u>

Conclusions

- SSE studies very important to increase PTA sensibility
- Need to take into account ephemeris uncertainties in GW analysis
- Possible to model ephem uncertainties as Gaussian process
 Next steps :
 - Study systematics between SSEs (importance of probing several ephemeris solutions)
 - Find an optimal model for ephemeris uncertainties which takes into account dipolar spatial correlations

Thank you for your attention

A timing model

J1909-3744 53368-56794

425

0.13

Effect of param errors on residuals









PSR name

MJD range

Number of TOAs rms timing residual (us)

Reference epoch (MJD)	55000
Measured parameters	
Right ascension, α Declination, δ Proper motion in α (mas yr ⁻¹) Proper motion in δ (mas yr ⁻¹) Period, <i>P</i> (ms) Period derivative, $\dot{P} (\times 10^{-20})$ Parallax, π (mas) DM (cm ⁻³ pc) DM1 (cm ⁻³ pc yr ⁻¹) DM2 (cm ⁻³ pc yr ⁻²)	19:09:47.433 5737(7) -37:44:14.515 61(3) -9.519(3) -35.775(10) 2.947 108 069 766 629(7) 1.402 518(14) 0.87(2) 10.3925(4) -0.000 32(3) 0.000 04(1)
Orbital period, P_b (d) Epoch of periastron, T_0 (MJD) Projected semimajor axis, x (lt-s) Longitude of periastron, ω_0 (deg) Orbital eccentricity, e $\kappa = e \times \sin \omega_0$ $\eta = e \times \cos \omega_0$ Time of asc. node (MJD) Orbital period derivative, \dot{P}_b First derivative of x , \dot{x} Sine of inclination angle, sin i Companion mass, m_c (M_{\odot})	$\begin{array}{l} 1.533 \ 449 \ 474 \ 329(13) \\ 53 \ 114.72(4) \\ 1.897 \ 990 \ 99(6) \\ 180(9) \\ 1.22(11) \times \ 10^{-7} \\ -2.3(1900) \times \ 10^{-10} \\ -1.22(11) \times \ 10^{-7} \\ 53 \ 113.950 \ 741 \ 990(10) \\ 5.03(5) \times \ 10^{-13} \\ 0.6(17) \times \ 10^{-16} \\ 0.997 \ 71(13) \\ 0.213(3) \end{array}$

- Astrometric parameters •
- **Rotational parameters** •
- **Dispersion measure** •
- **Orbital parameters** ٠
- + solar system ephemerides and clock correction

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2015

Transformation to the SSB

From the topocentric to the quasi-inertial solar system barycenter frame



Gaussian processes

« Collection of random variables such that every finite collection of these has a multivariate normal distribution »



A. Chalumeau

Marginal likelihood of data (n TOAs) with GP noise description subject to Gaussian measurement noise ε_i with covariance matrix N

$$\log p(y|\theta, \text{GP}) = -\frac{1}{2}y^T (N + \sum_{(A)} K^{(A)})^{-1} y - \frac{n}{2} \log(2\pi) - \frac{1}{2} \log \det \left(N + \sum_{(A)} K^{(A)} \right)$$

Gaussian process covariance matrices

Gaussian process « duality »

$$p(y_{i}|w_{\mu}, \text{GP}) = \frac{e^{-\frac{1}{2}\sum_{i,j} \left(y_{i} - \sum_{\mu} \phi_{\mu}(x_{i})w_{\mu}\right)(N_{ij})^{-1} \left(y_{j} - \sum_{\mu} \phi_{\mu}(x_{j})w_{\nu}\right)}{\sqrt{(2\pi)^{n} \det N}} \times \frac{e^{-\frac{1}{2}\sum_{\mu\nu} w_{\mu}(\sum_{\mu\nu})^{-1}w_{\nu}}}{\sqrt{(2\pi)^{m} \det \Sigma}}$$
$$p(y_{i}|\text{GP}) = \frac{e^{-\frac{1}{2}\sum_{i,j} y_{i} \left(N_{ij} + K_{ij}\right)^{-1}y_{j}}}{\sqrt{(2\pi)^{n} \det (N + K)}}, \quad \text{with} \quad K_{ij} = k(x_{i}, x_{j}) = \sum_{\mu\nu} \phi_{\mu}(x_{i}) \sum_{\mu\nu} \phi_{\nu}(x_{j}),$$

Marginal likelihood of the data given the Gaussian process

A. Chalumeau