Automating detection of near-Earth asteroids with LISA

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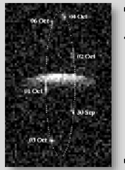
Automating detection of NEA with LISA

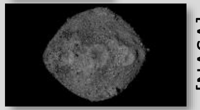
- Known NEA masses
- Modelling NEA encounters
- Simulating LISA telemetry
- Neural networks used
- Interim results
- Summary and remaining tasks

Known NEA masses [1]

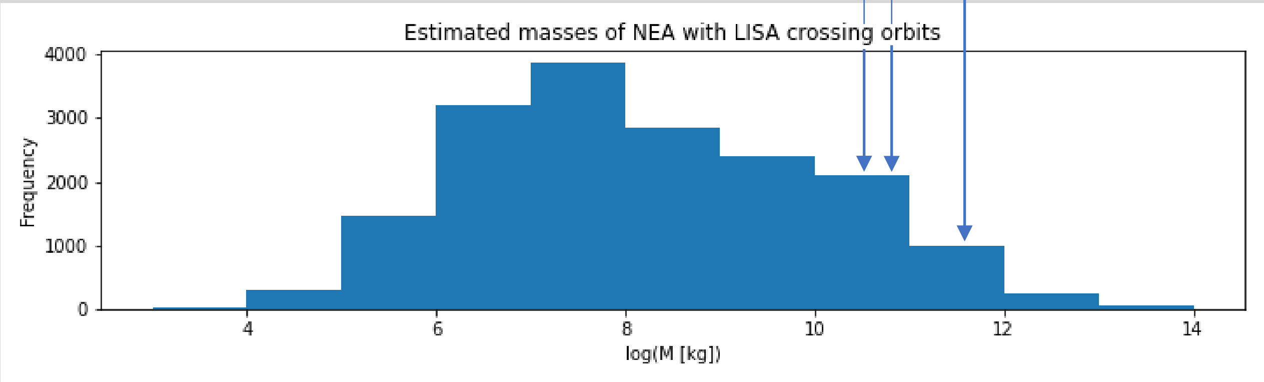
Asteroid	GM ($km^3\ s^{-2}$)	σ ($km^3\ s^{-2}$)
185851	3.224×10^{-8}	3×10^{-9}
162173 Ryugu	3.00×10^{-8}	0.04×10^{-8}
101955 Bennu	4.8904×10^{-9}	0.009×10^{-9}
25143 Itokawa	2.1×10^{-9}	0.063×10^{-9}


[NAIC-Arecibo]


[JAXA]


[NASA]


[JAXA]



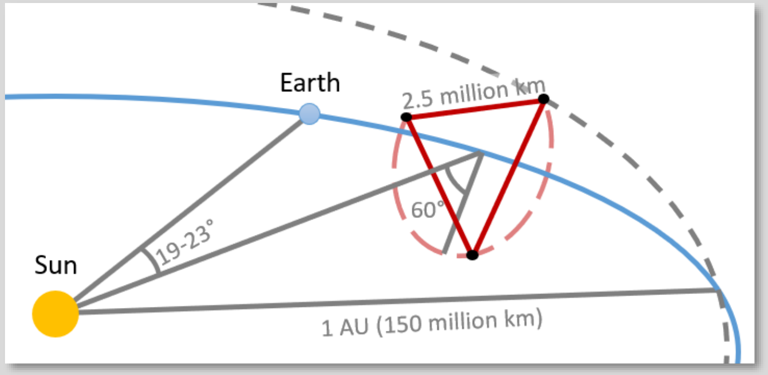
Gravitational measurements [2]

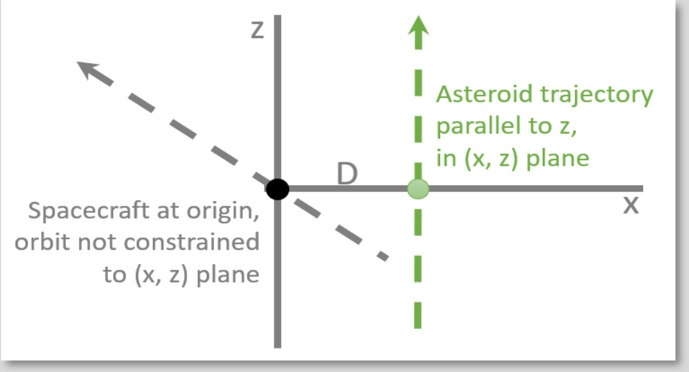
- Asteroid-asteroid / -planet
- Spacecraft fly-by / orbit
- Binary asteroids' orbits

Estimation methods

- Yarkovsky effect [3]
- Absolute magnitude + albedo + shape + density

Modelling NEA encounters





$$\vec{v}(t) = \frac{GM}{DV}\begin{bmatrix} 1 + \dfrac{Vt/D}{\sqrt{1 + V^2t^2/D^2}} \\ 0 \\ -\dfrac{Vt/D}{\sqrt{1 + V^2t^2/D^2}} \end{bmatrix}$$ [4]

Then, for any combination of incident angles (χ,ψ,ω) about X, Y and Z axes:

$$\vec{v_i}(t) = \frac{GM}{DV} R_Z(\omega) \cdot R_Y(\psi) \cdot R_X\,(\chi) \cdot R_Z(\beta_i) \cdot \begin{bmatrix} 1 + \dfrac{Vt/D}{\sqrt{1 + V^2t^2/D^2}} \\ 0 \\ -\dfrac{Vt/D}{\sqrt{1 + V^2t^2/D^2}} \end{bmatrix}$$

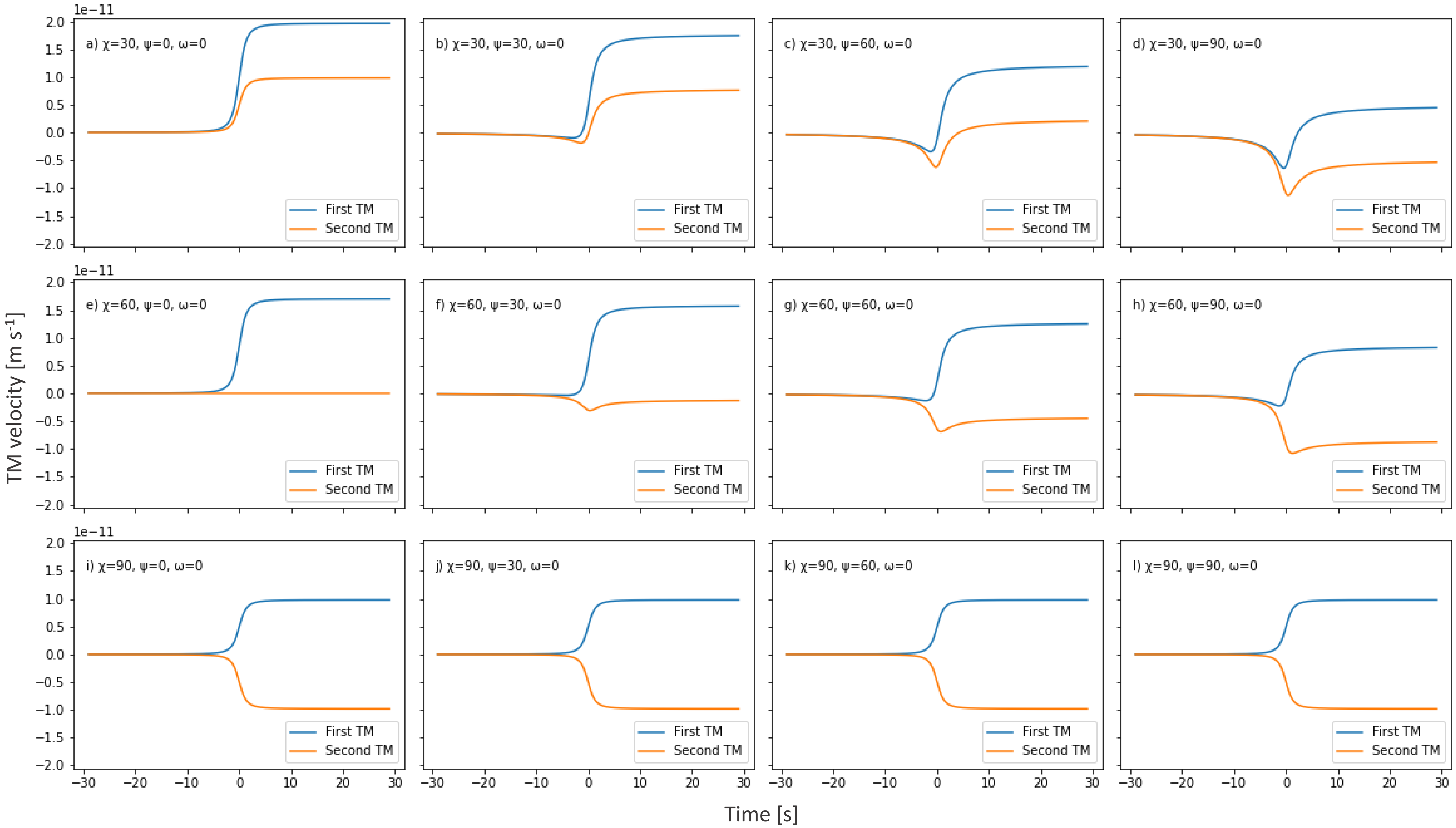
Where:

$$R_Z(\beta_i) = \begin{bmatrix} \cos\beta_i & \sin\beta_i & 0 \\ -\sin\beta_i & \cos\beta_i & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

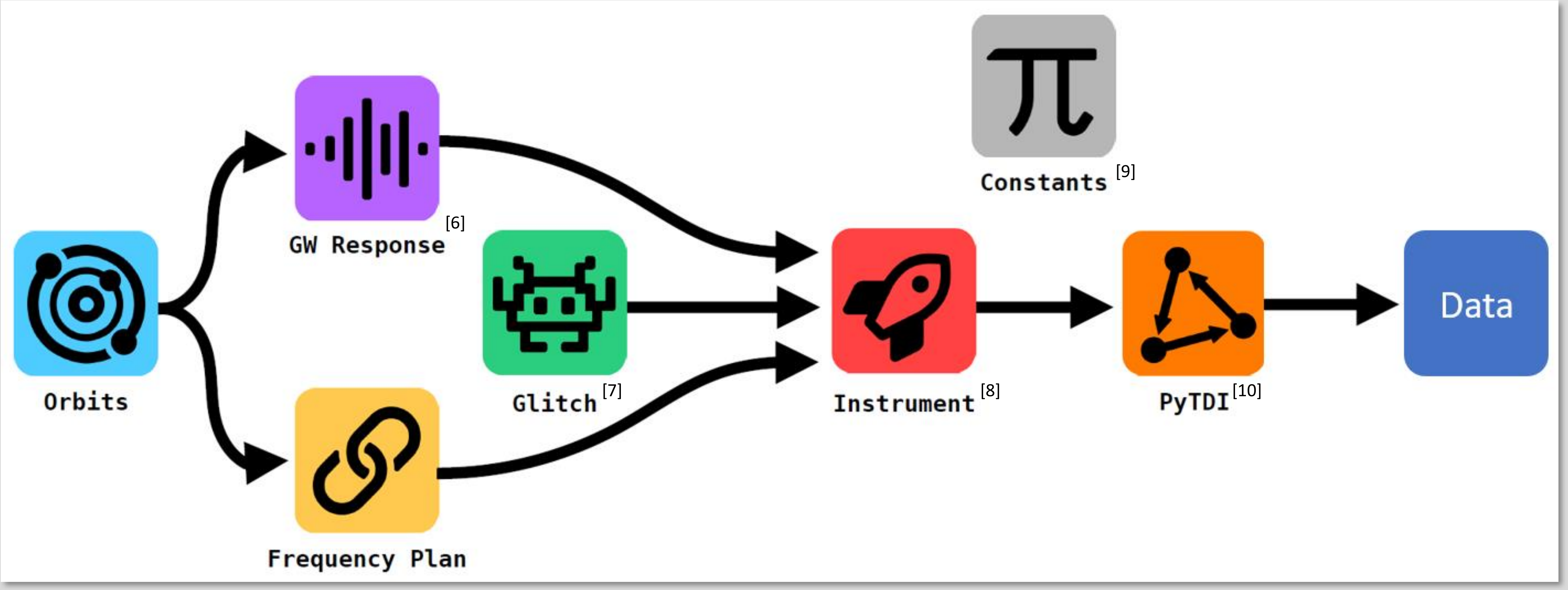
And the two test masses have:

$$\beta_i = \pm\pi/6$$

[5]

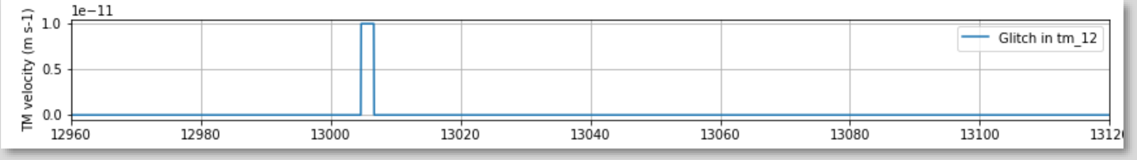

1e−11
a) χ=30, ψ=0, ω=0
b) χ=30, ψ=30, ω=0
c) χ=30, ψ=60, ω=0
d) χ=30, ψ=90, ω=0
e) χ=60, ψ=0, ω=0
f) χ=60, ψ=30, ω=0
g) χ=60, ψ=60, ω=0
h) χ=60, ψ=90, ω=0
i) χ=90, ψ=0, ω=0
j) χ=90, ψ=30, ω=0
k) χ=90, ψ=60, ω=0
l) χ=90, ψ=90, ω=0
First TM
Second TM
TM velocity [m s-1]
Time [s]

Simulating LISA telemetry



Simulating LISA telemetry: rectangular

Glitch



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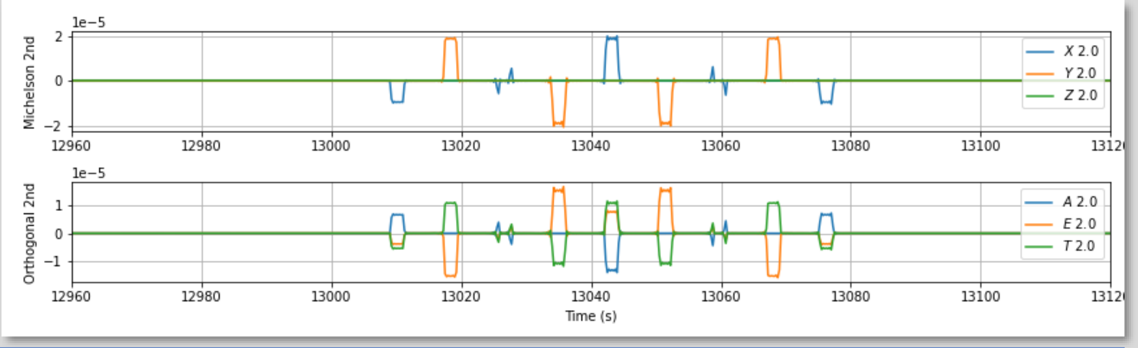
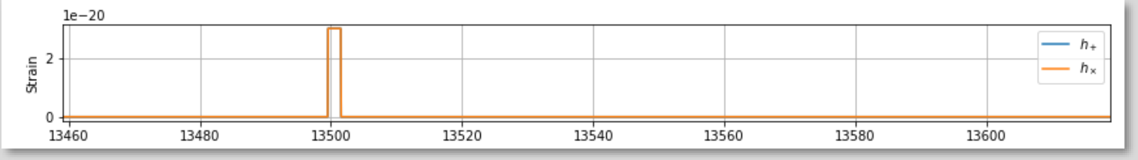


GW burst



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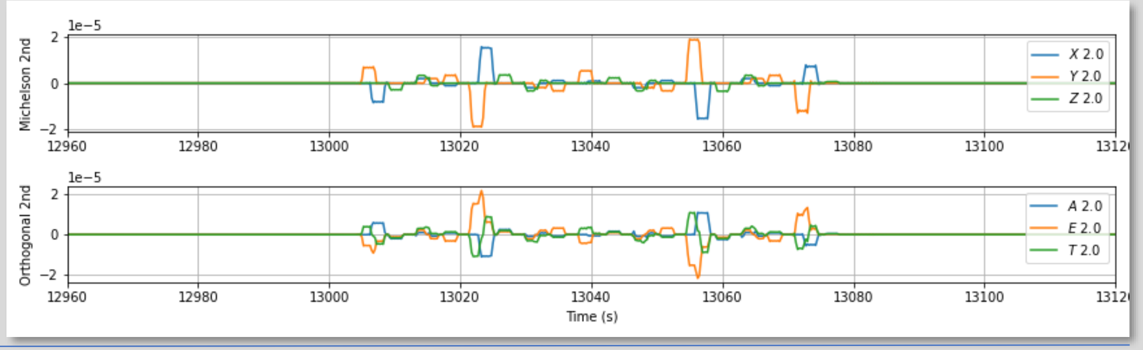
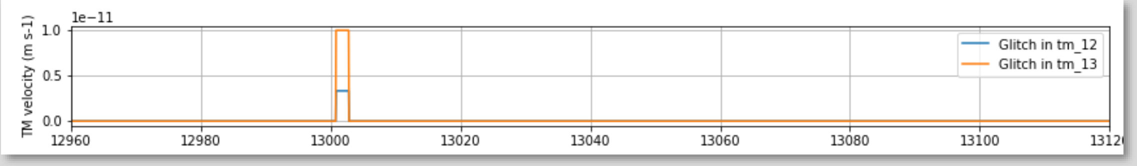


NEA encounter



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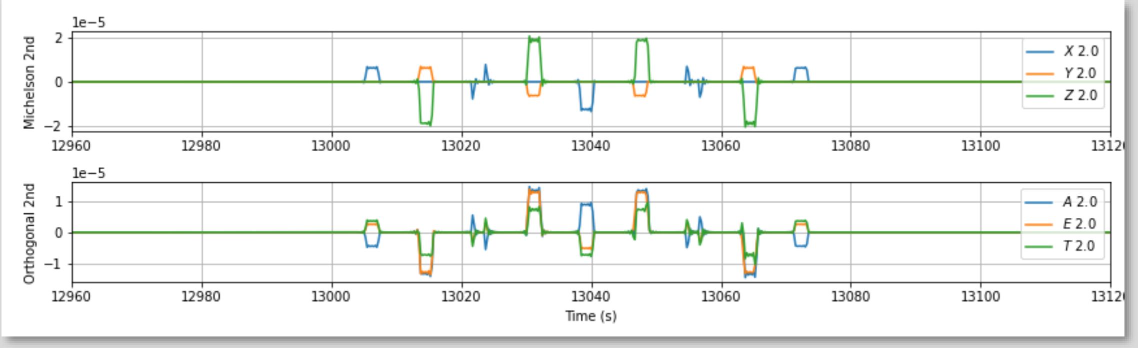
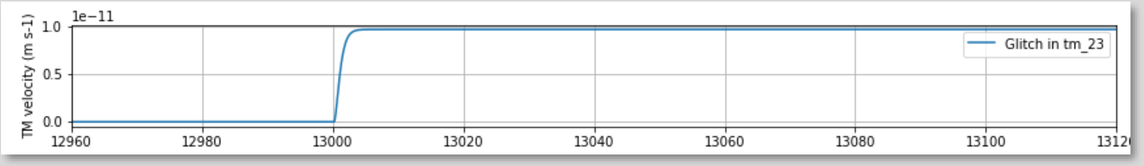


Simulating LISA telemetry: various

Glitch



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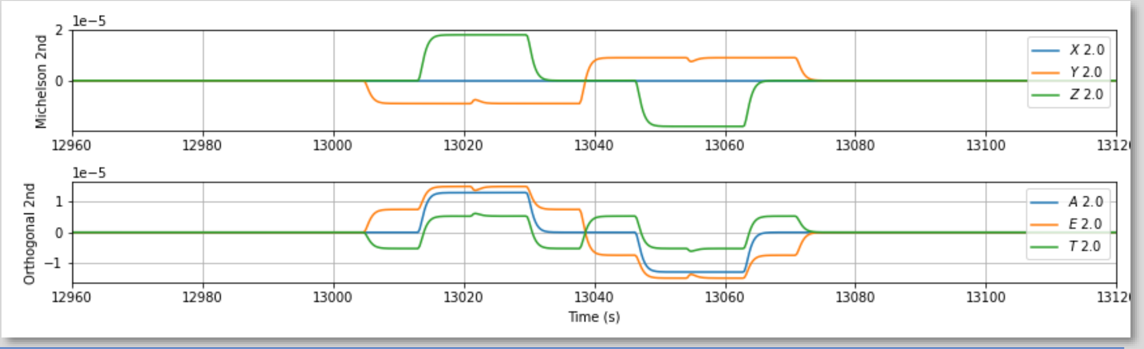
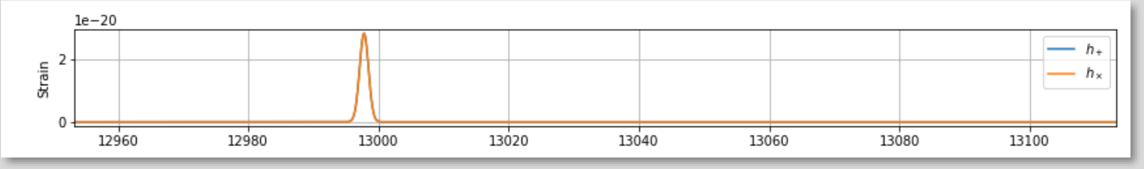


GW burst



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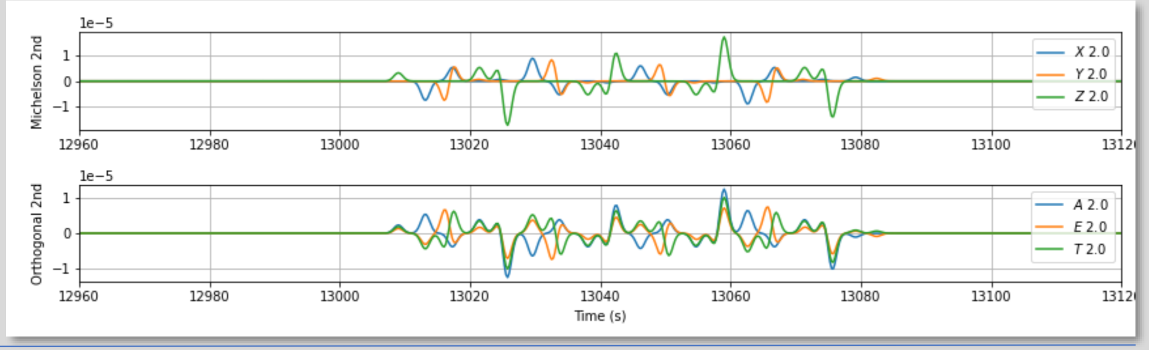
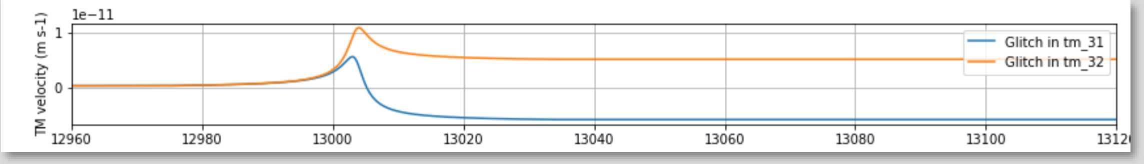


NEA encounter



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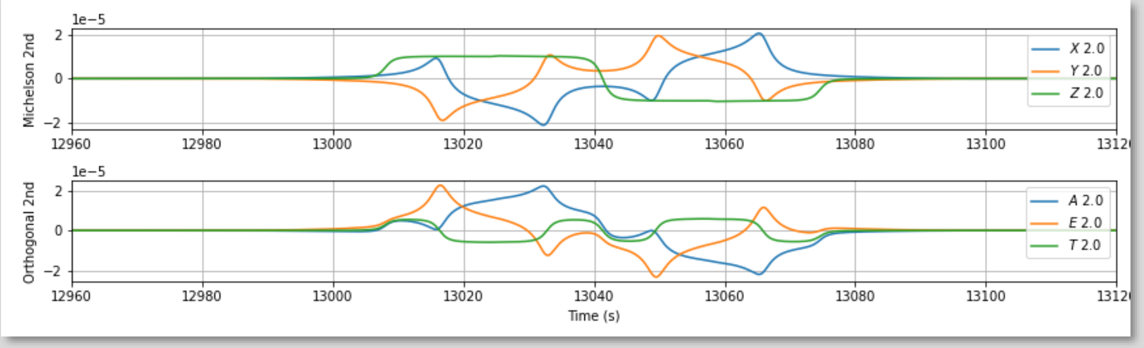


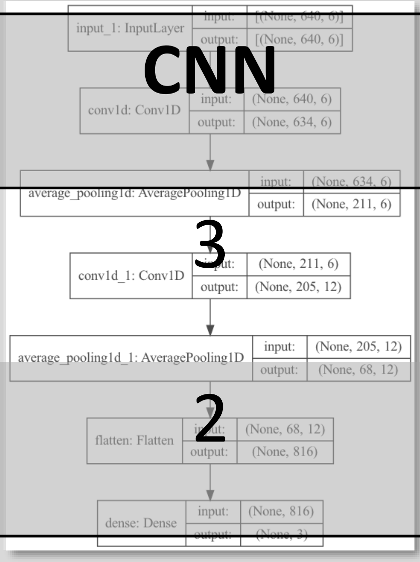
Simulating LISA telemetry: datasets

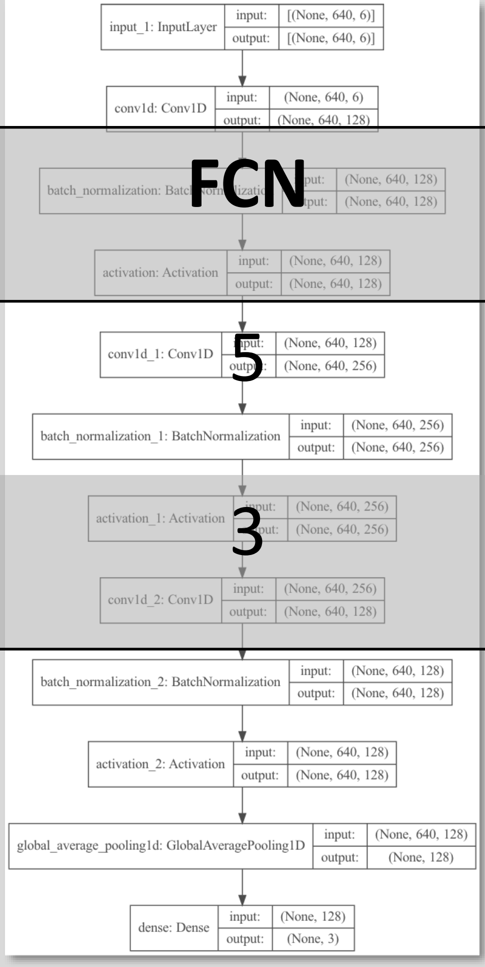
#	Rectangular shapes and no instrument noise
1	Fixed duration, amplitude and sky location.
2	Durations and amplitudes drawn from normal distributions.
3	GW bursts uniformly distributed across the sky.

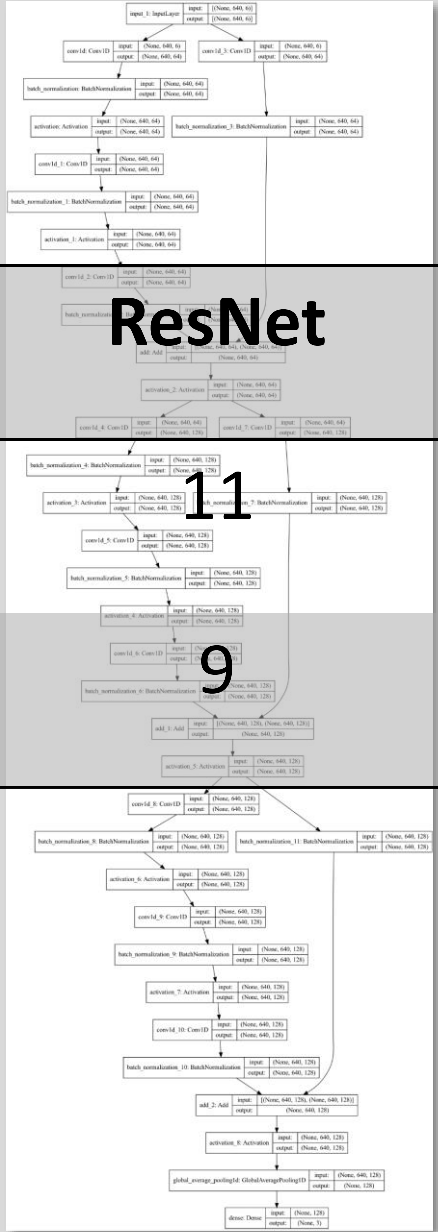
#	Different shapes for each instance type
4	LISA Glitch shapelet. GW bursts use a gaussian shape. Fixed NEA mass, velocity and impact parameter over all incident angles.
5	NEA mass and velocity distributed uniformly over a range of values.
6	With instrument noise added.
7	NEA mass, velocity and impact parameter distributed over wider ranges.

Neural networks [11,12]

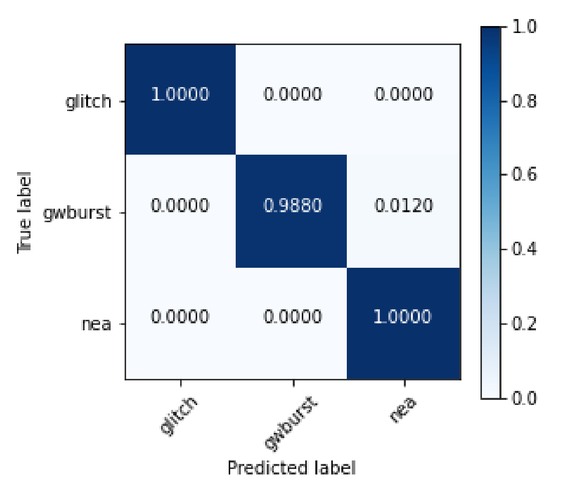
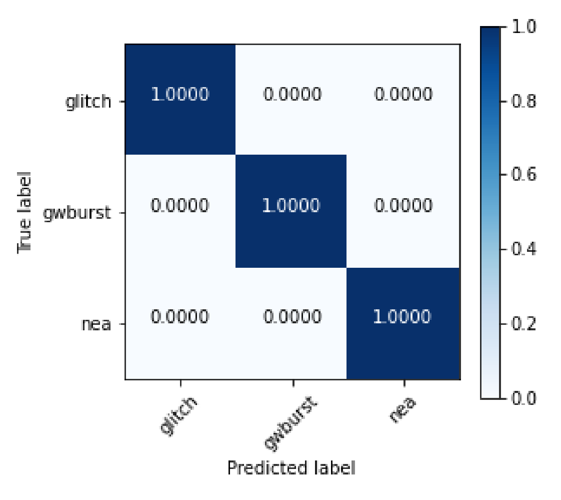
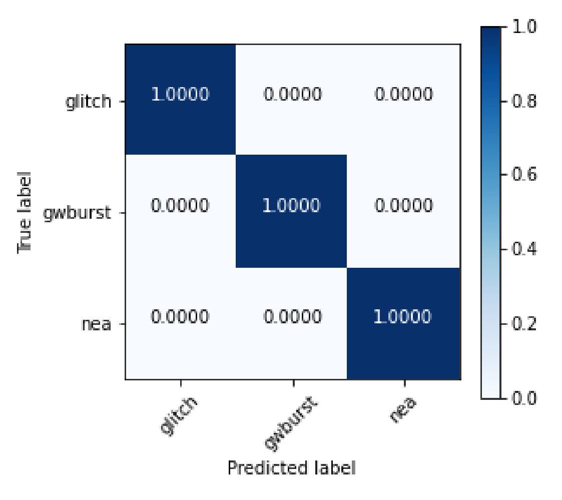
Model	CNN	FCN	ResNet
Layers	3	5	11
Convolutions	2	3	9





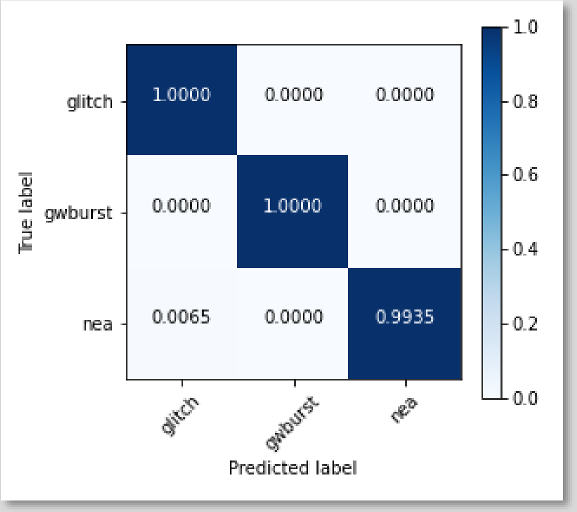
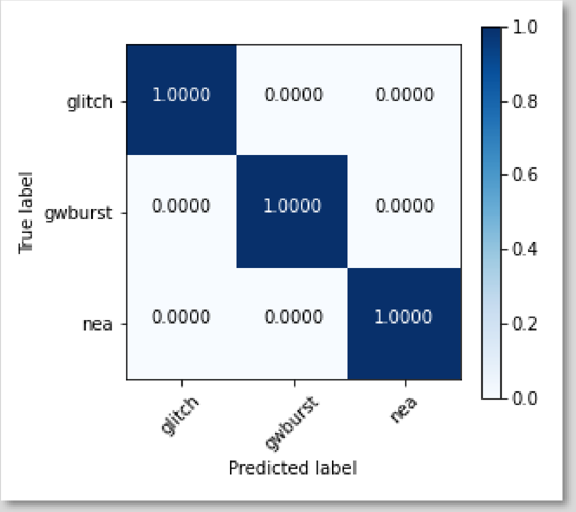
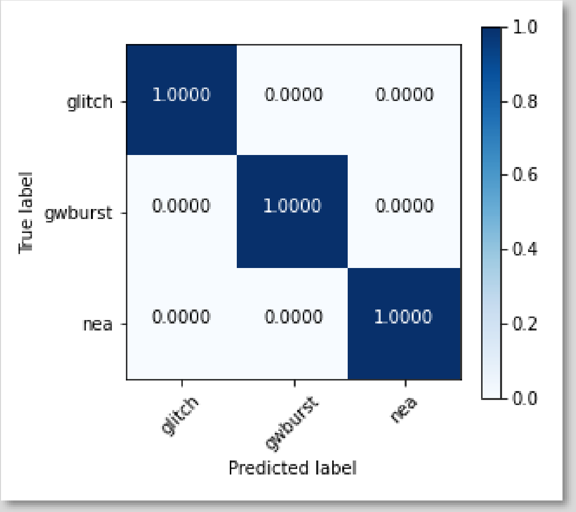


Interim results: rectangular

Dataset 3	**CNN**	**FCN**	**ResNet**
Trained and tested on rectangular signals. Range of durations and amplitudes. GW bursts uniformly and randomly distributed across the sky.			

Interim results: various

<table>
<tr><th>Dataset 5</th><th>CNN</th><th>FCN</th><th>ResNet</th></tr>
<tr><td>Trained and tested on various signal shapes.

Range of durations and amplitudes, NEA encounters with range of values, GW bursts uniformly and randomly distributed across the sky.</td><td>
</td><td>
</td><td>
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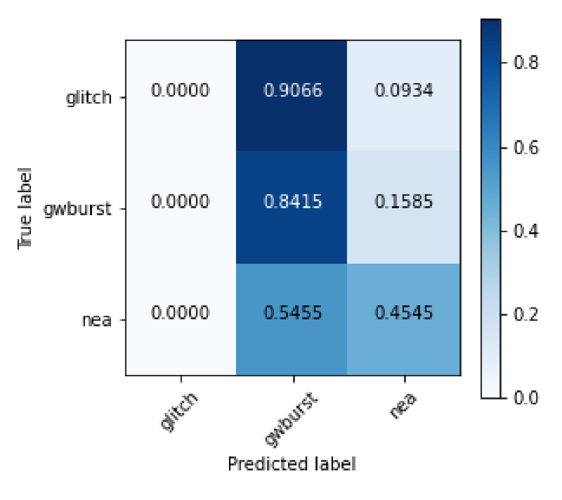
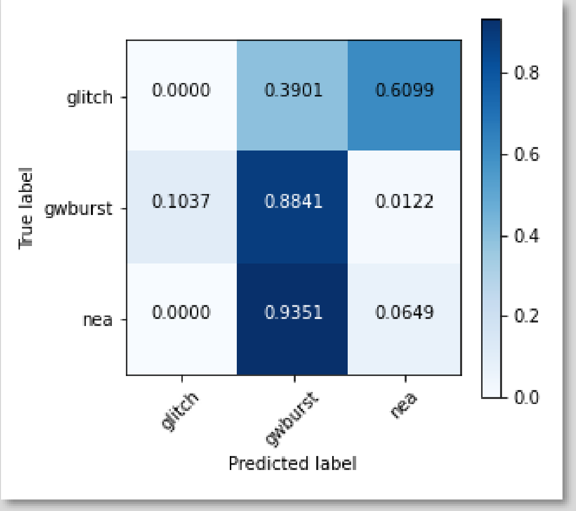
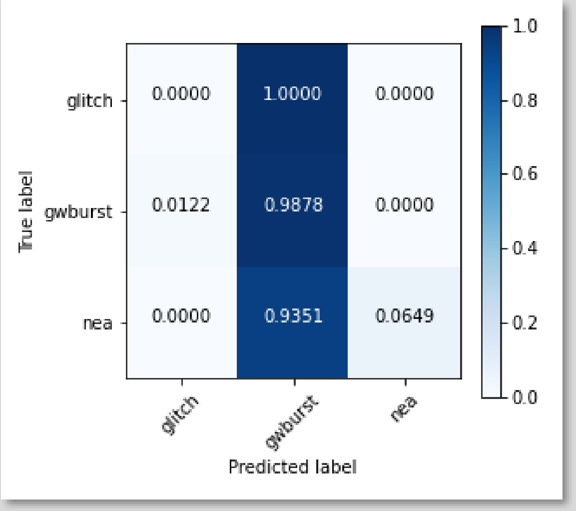
Interim results: cross-testing

Dataset	CNN	FCN	ResNet
Trained on rectangular signals (dataset 3). Tested on various shapes (dataset 5). NEA encounters and GW bursts uniformly and randomly distributed across the sky.			

Summary, so far…

- NEA encounters can be differentiated from glitches and GW bursts
- Neural networks trained on rectangular shaped signals did not successfully differentiate between different shapes
- CNN was the most efficient neural network

Remaining tasks

- Add noise to LISA simulations
- Use a wider range of NEA parameters

Thank you to LECS and LISA Consortium

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[2] Bottke, W., Cellino, A., Paolicchi, P. and Binzel, R. (eds.) (2002) Asteroids III, University of Arizona Press.

[3] Vokrouhlicky, D. and Bottke, W.F. (2012) “Yarkovsky and YORP effects,” Scholarpedia, 7(5), p. 10599. DOI: 10.4249/SCHOLARPEDIA.10599.

[4] Vinet, J. Y. (2006) “LISA and asteroids,” *Classical and Quantum Gravity*, IOP Publishing, vol. 23, no. 15, p. 4939. DOI: 10.1088/0264-9381/23/15/012.

[5] Purdue, P. and Larson, S.L. (2007) “Spurious acceleration noise in spaceborne gravitational wave interferometers,” Classical and Quantum Gravity, 24(23), p. 5869. DOI: 10.1088/0264-9381/24/23/010.

[6] Bayle, J.-B., Baghi, Q., Renzini, A. and le Jeune, M. (2022) “LISA GW Response,”. DOI: 10.5281/ZENODO.6423436.

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[8] Bayle, J.-B., Hartwig, O. and Stabb, M. (2022) “LISA Instrument,”. DOI: 10.5281/ZENODO.6447390.

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[12] Bayle, J.-B. (2019) “Simulation and Data Analysis for LISA (Instrumental Modeling, Time-Delay Interferometry, Noise-Reduction Performance Study, and Discrimination of Transient Gravitational Signals),”. Available at https://hal.archives-ouvertes.fr/tel-03120731.

https://www.open.ac.uk/postgraduate/qualifications/f77

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