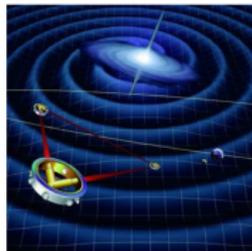


DE LA RECHERCHE À L'INDUSTRIE

cea



## Sparse data inpainting for gapped data in LISA



| Aurore BLELLY

March 30, 2021

## Introduction

### LISA mission

LISA Data  
Work Hypothesis

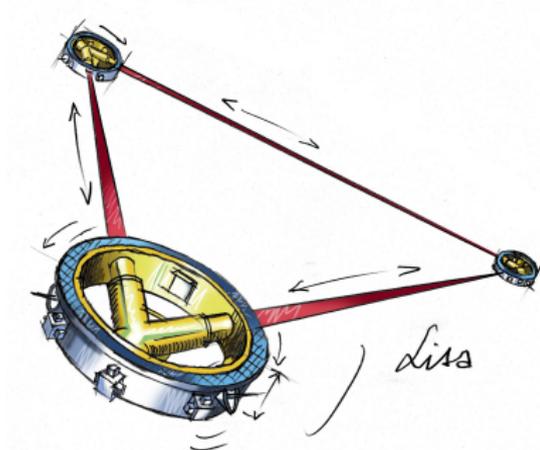
### Sparse Data inpainting

Joint Estimator  
Algorithm

### Results

### Conclusion

- 3 satellites 2.5 millions km one from another
- Follows the movement of the Earth on its orbit
- Probes a **frequency range that is still unexplored**  
⇒ high potential for **new discoveries**
- Launching: 2034



1

<sup>1</sup>[https://www.esa.int/Science\\_Exploration/Space\\_Science/LISA](https://www.esa.int/Science_Exploration/Space_Science/LISA)

## Introduction

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## Sparse Data

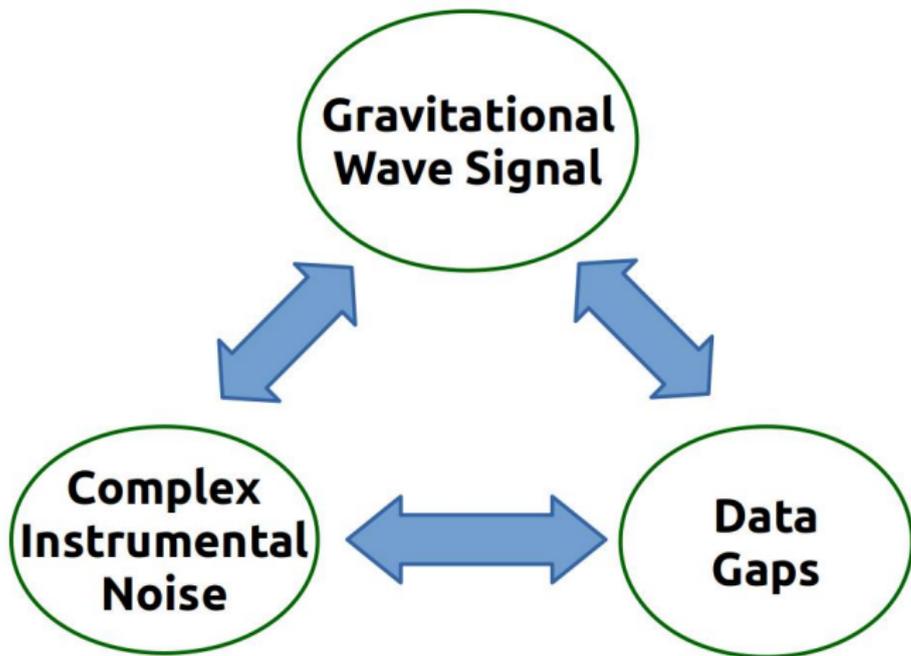
### Inpainting

Joint Estimator

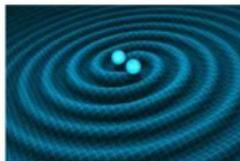
Algorithm

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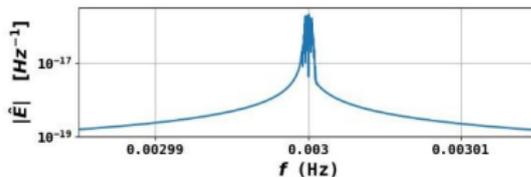
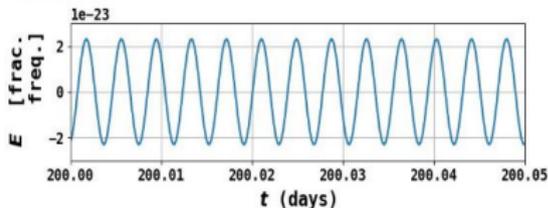


## Gravitational Wave Signal



Focus on GBs :

- $10^6$  expected sources
- Goal : identify  $\sim 20.000$
- Low SNR = long observation required
- **Nearly mono-frequency signal**



## Introduction

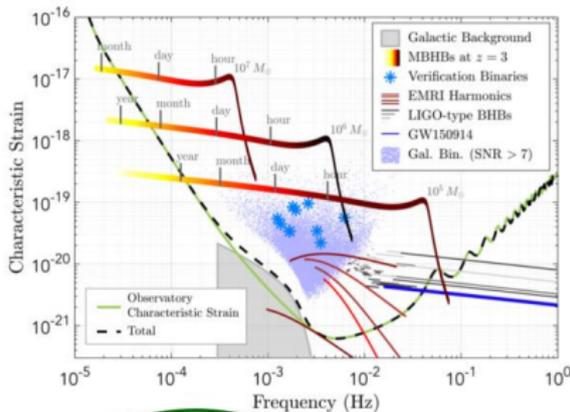
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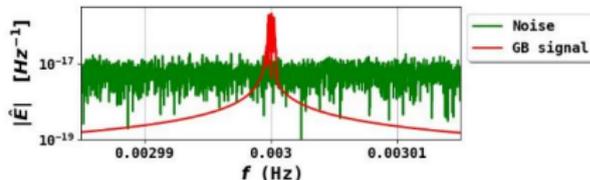
## Conclusion



## Noise characteristics :

- **Known expected distribution**
- For now, simplified hypothesis (Gaussianity)
- Noise level impacts the ability to detect a source

**Complex Instrumental Noise**



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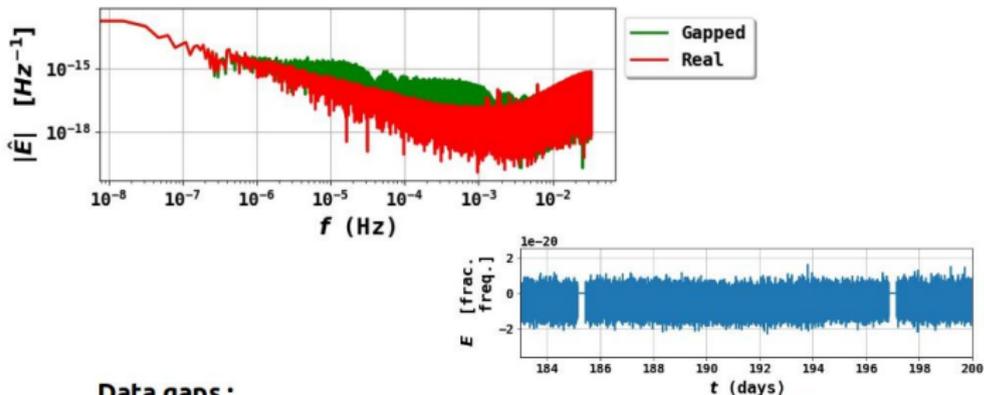
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### Data gaps :

- Maintenance or unplanned
- Various durations/frequencies :
  - Planned : 7 hours / 2 weeks
  - Unplanned : a few seconds => several days
- **Impact expected noise distribution**
- **Impact** quality of identification

**Data Gaps**

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- **Goal:** Mitigating the impact of gaps in LISA data by filling the gaps with as little new information as possible.
- **State of the art:** Data augmentation method <sup>2</sup> : based on sampling and MCMC.
- **Strategy:** Using the **waveform expected structure** instead of **parametric description**.

⇒ **Non-parametric** method, no GB identification.

---

<sup>2</sup>Q. Baghi, I. Thorpe, J. Slutsky, J. Baker, T. Dal Canton, N. Korsakova, N. Karnesis, *Gravitational-wave parameter estimation with gaps in LISA: a Bayesian data augmentation method*, 2019

Prior hypothesis:

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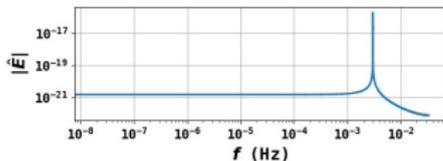
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- Simple representation in Fourier basis (**Sparsity prior**)



Prior hypothesis:

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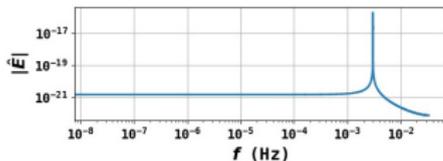
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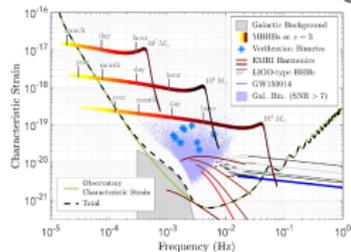
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- Simple representation in Fourier basis (**Sparsity prior**)



- Noise is Gaussian with known PSD  $\Sigma$  for ungapped data



Prior hypothesis:

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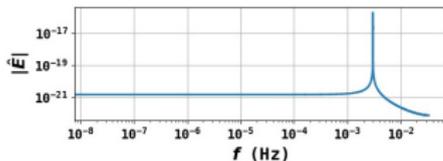
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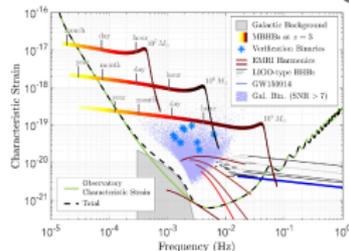
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- Gap time is known: 

# Sparse Data Inpainting

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- $M$  is the data mask: 
- $(S, N)$  the joint estimate of **ungapped** signal and noise

$$(S, N) =$$

<sup>3</sup>*Sparse data inpainting for the recovery of Galactic-binary gravitational wave signals from gapped data*,  
A. Blelly, J. Bobin, M. Moutarde [IN PROGRESS]

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With  $Y$  the gapped measurement;  $\Sigma$  the noise PSD and  $\gamma$  the detection threshold.

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With  $Y$  the gapped measurement;  $\Sigma$  the noise PSD and  $\gamma$  the detection threshold.

- **Resolution:** alternates between signal estimation and noise estimation.

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## Introduction

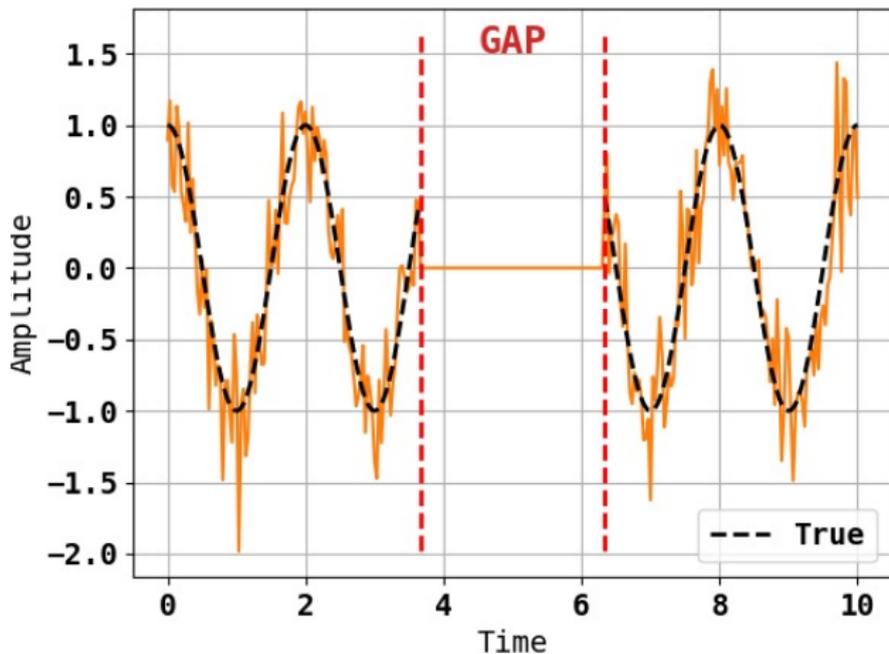
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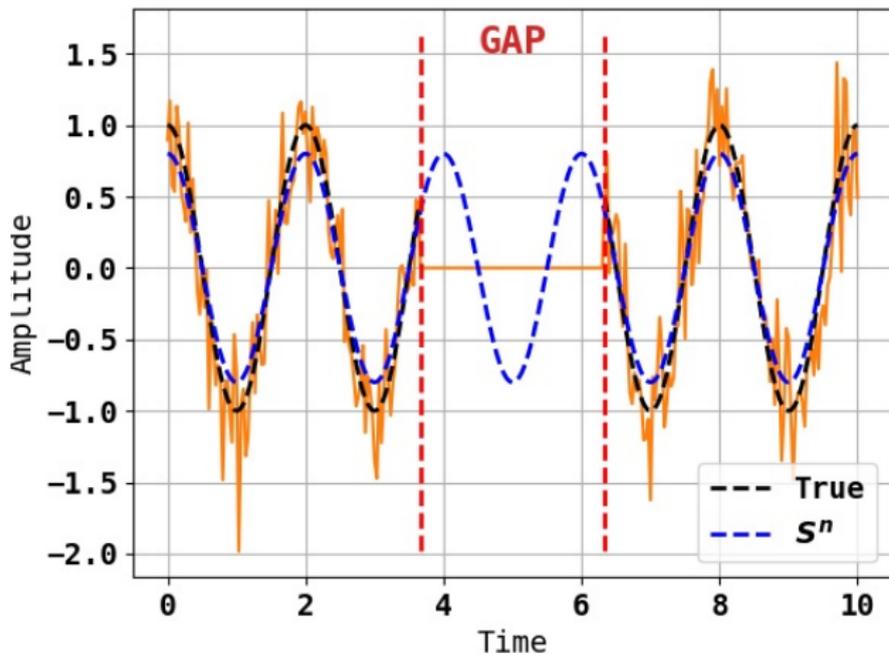
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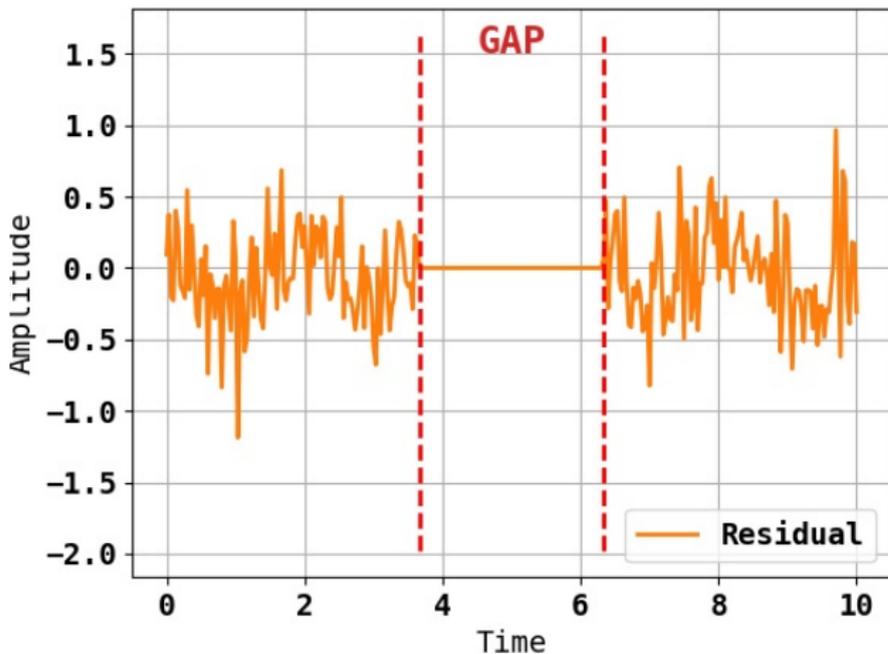
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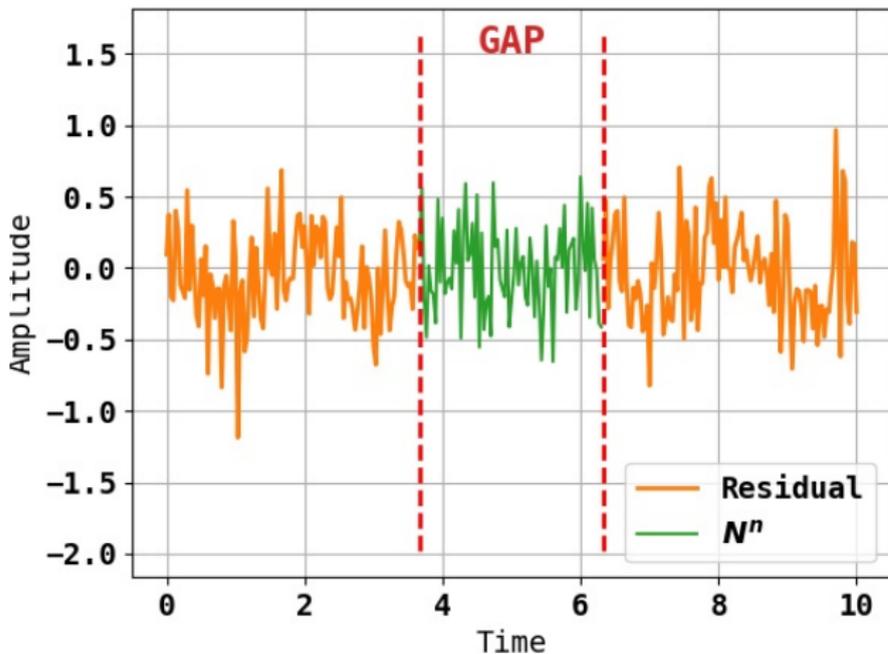
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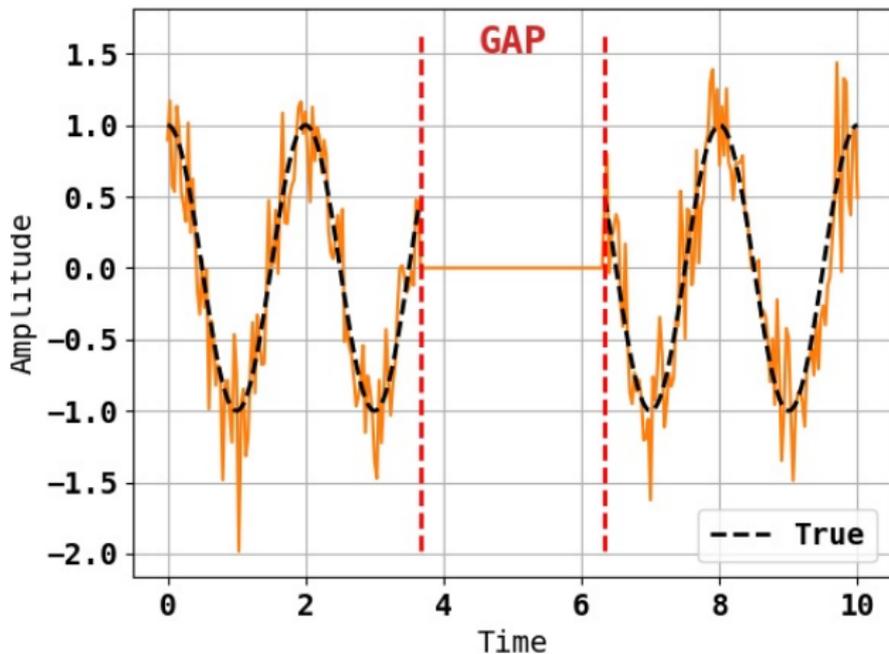
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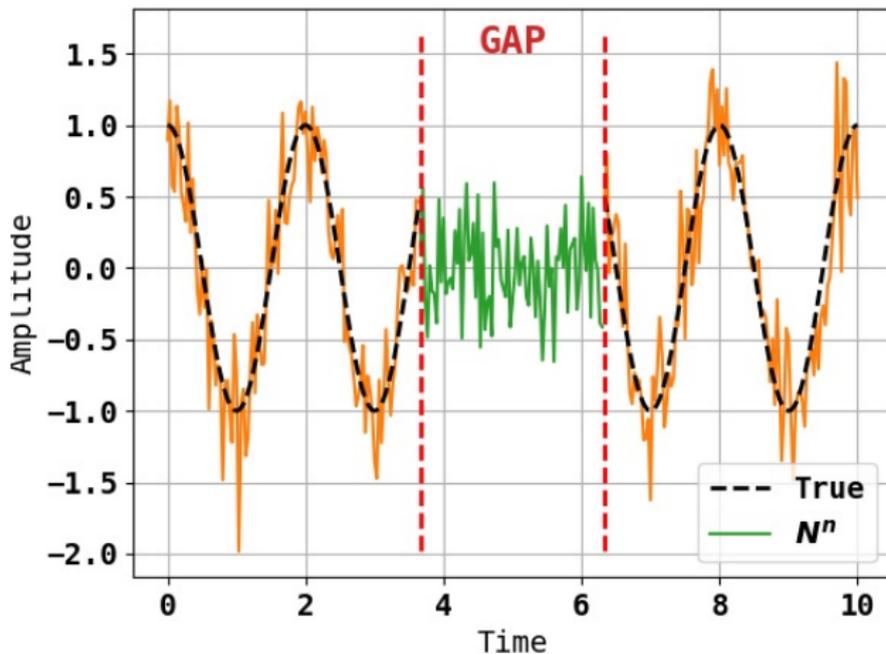
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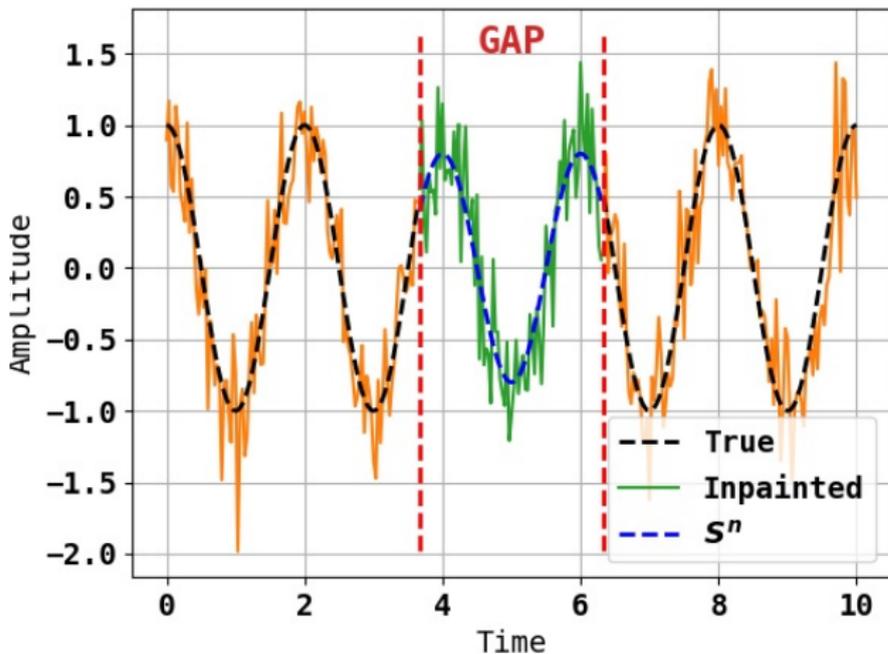
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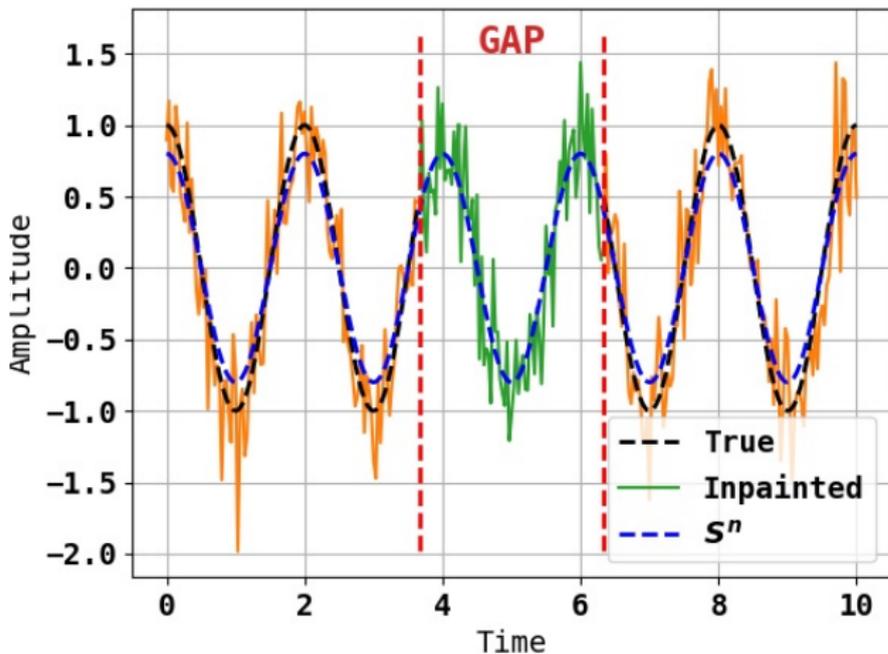
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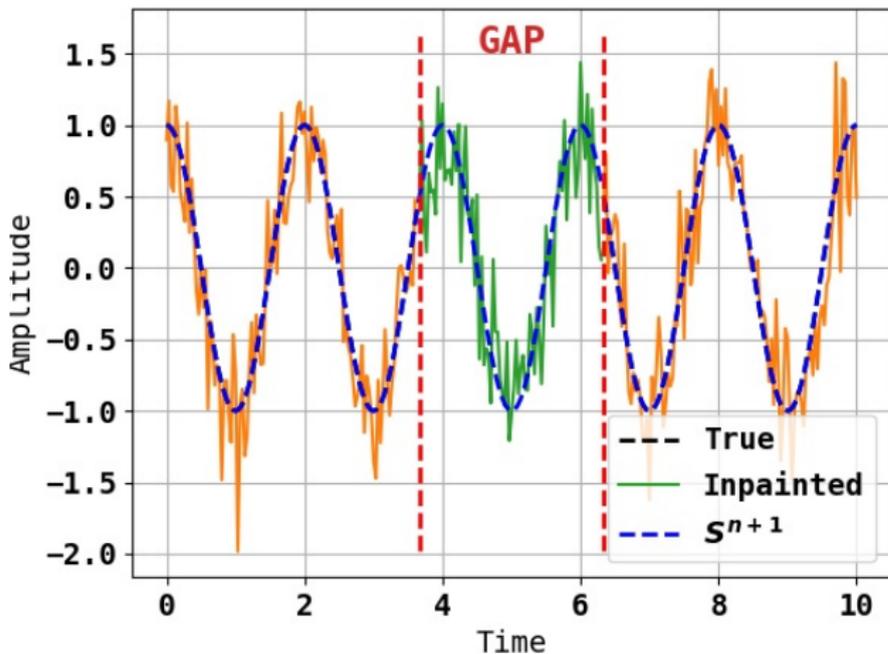
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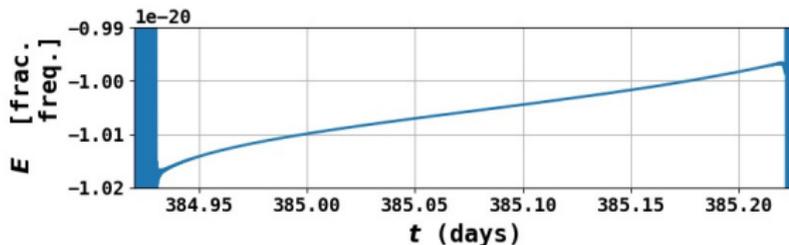
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Classical Inpainting (**C.I.**): only retrieves lower-frequency noises



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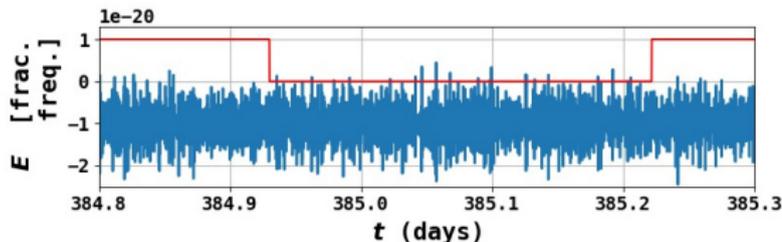
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Modified Inpainting (**M.I.**): restores higher frequency noises using a stochastic component



# Results

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The performances of our algorithms are assessed on three main outcomes:

- 1 the detection capacity (comparatively to the ungapped case)
- 2 the recovered noise statistics
- 3 the quality of extracted signal

On 3 types of gaps:

**Small (S)**: 10min/day

**Medium (M)**: 7hours/2 weeks

**Large (L)**: 3 days / 12 days

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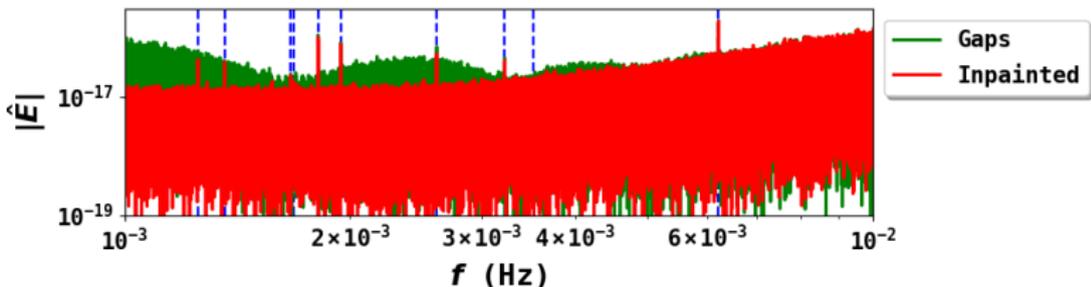
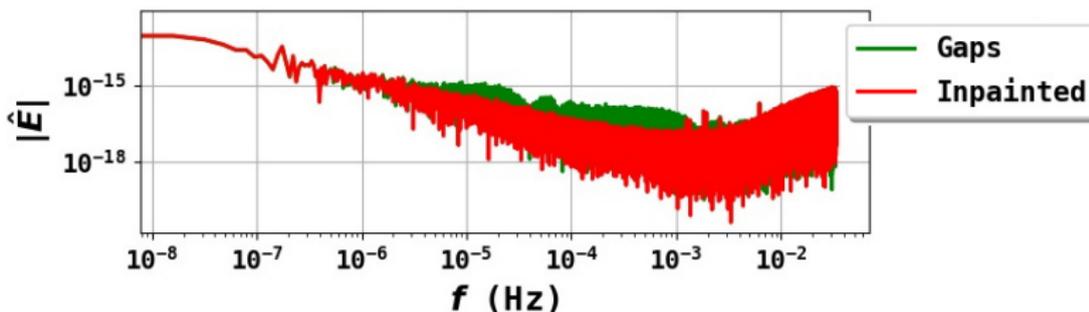
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## ■ LDC 1-3: 10 Verification galactic binaries

<sup>4</sup><https://lisa-ldc.lal.in2p3.fr/>

## Introduction

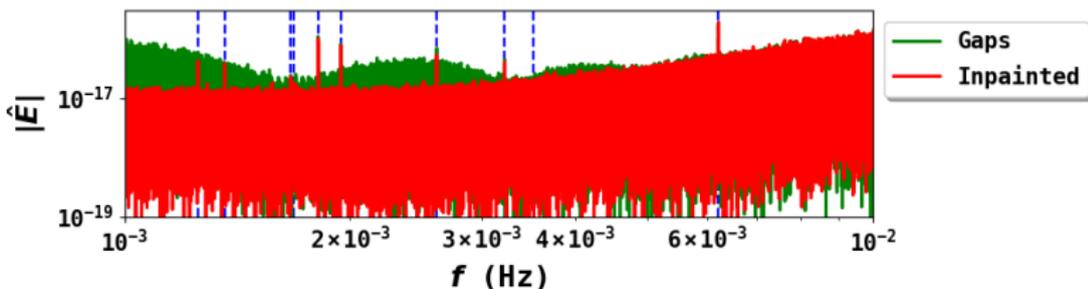
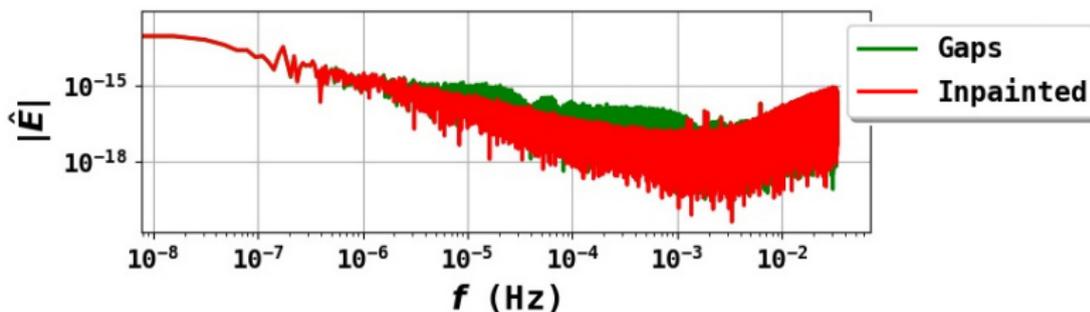
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⇒ Impact of the gaps on the data is strongly mitigated

⇒ Contamination of the signal by noise is limited

<sup>4</sup><https://lisa-ldc.lal.in2p3.fr/>

Introductio

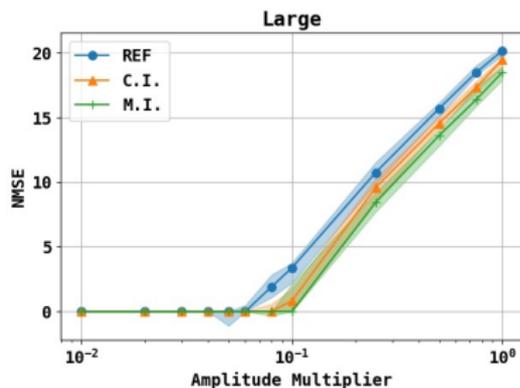
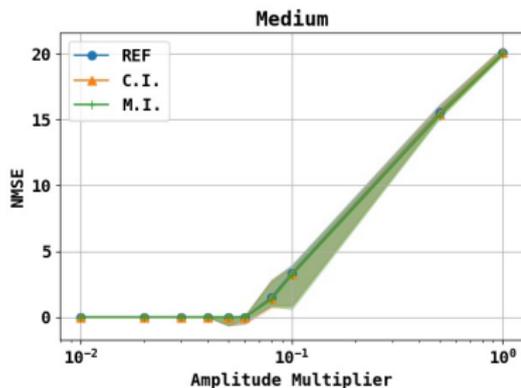
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Single GB, quality of extracted signal with input amplitude

	S/M	L
C.I.	Same as ungapped	Quality loss
M.I.	Same as ungapped	Quality loss

Introductio

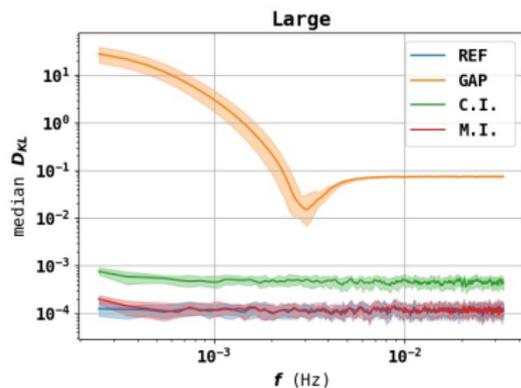
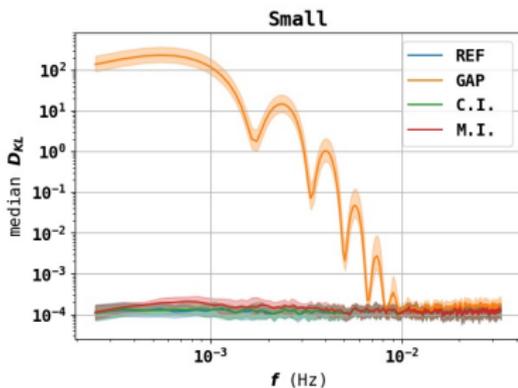
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The Kullback-Leibler Divergence measures a discrepancy between the expected and the recovered noise distributions.

	S/M	L
C.I.	Good	Cannot make up for power loss
M.I.	Good	Good

# Conclusion

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- **Efficient reconstruction** of signal and noise
- Works as well with a **large unknown number of separated sources**.
  - Worked on LDC1-3 with 28% of missing data <sup>5</sup>
- **Flexible framework** which could be adapted to:
  - Other types of sources.
  - Sources separation.
  - Noise distribution estimation.
- Fast:  $\sim 1$  hour for 2 years of data on a laptop

**Future work:** improving waveform representation (machine learning, non-parametric)

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<sup>5</sup> *Sparse data inpainting for the recovery of Galactic-binary gravitational wave signals from gapped data*,  
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