

Random projections for gravitational waves detection

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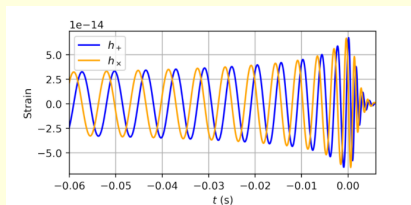
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- ▶ CBC search
- ▶ Matched filtering : correlation of a template with data
- ▶ Template banks :
~ 500000 templates (will get larger in the future)
- ▶ "Real-time search" : need to accelerate the process



Example of a CBC template

Singular Value Decomposition for template banks

H is the matrix containing the templates ($T \times N$)

$$\begin{matrix} T \\ \left[\begin{array}{c} \text{---} \\ \vdots \\ \text{---} \end{array} \right] \\ H \end{matrix} = \mathbf{U} \begin{matrix} \left[\begin{array}{c} \sigma_1 \\ \vdots \\ 0 \end{array} \right] \\ \Sigma \end{matrix} \begin{matrix} \left[\begin{array}{c} \text{---} \\ \vdots \\ \text{---} \end{array} \right] \\ V \end{matrix}$$

Issues with SVD :

- ▶ Impossible to do when the matrix is too big : complexity $\mathcal{O}(NT^2)$
- ▶ Choice of the number of reduced templates ?

Overall goal : reducing the computational time on the matched filtering portion.

- ▶ Using random projections instead of SVD for the dimensionality reduction
- ▶ Investigating the use of the OPU for doing random projections
- ▶ Tackling the reconstruction cost

In light of these goals, we also tried to implement these techniques into the PyCBC pipeline.

Random projections

Possible solution : random projections

$$\begin{bmatrix} \text{---} \\ \text{---} \\ \vdots \\ \text{---} \end{bmatrix} \begin{bmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{bmatrix} = \mathbf{QR} \quad \mathbf{Q}^T \mathbf{H} = \begin{bmatrix} \text{---} \\ \text{---} \\ \vdots \\ \text{---} \end{bmatrix}$$

$\mathbf{H} \quad \quad \quad \mathbf{\Omega} \quad \quad \quad \mathbf{B}$

"Autorank" algorithm : projecting successively on small spaces (dimension ~ 5) until we reach a small enough error.

Complexity : $O(Ntl)$

Reproducing the results of Reza et al.[2]:

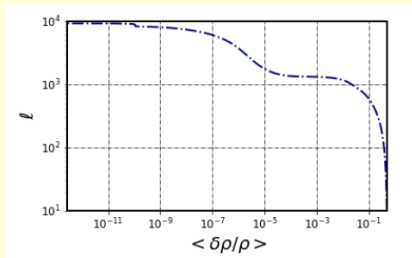
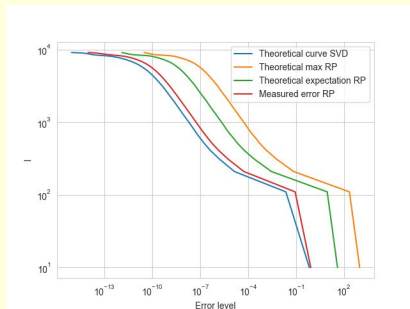
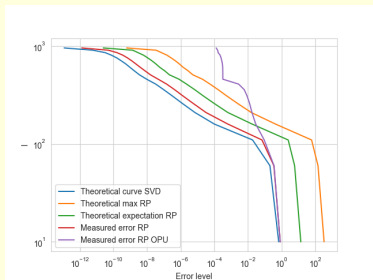
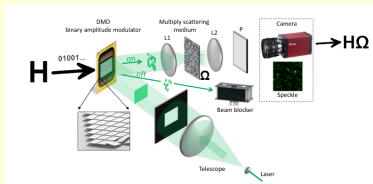


Figure 2 of Reza et al.



Similar figure with our implementation

For a 10^{-3} error on the SNR, 160 reduced templates (against 140 for the SVD). But 54,6s of execution time for the SVD and only 8,9s for RP.



Results for the OPU with 8 bits precision

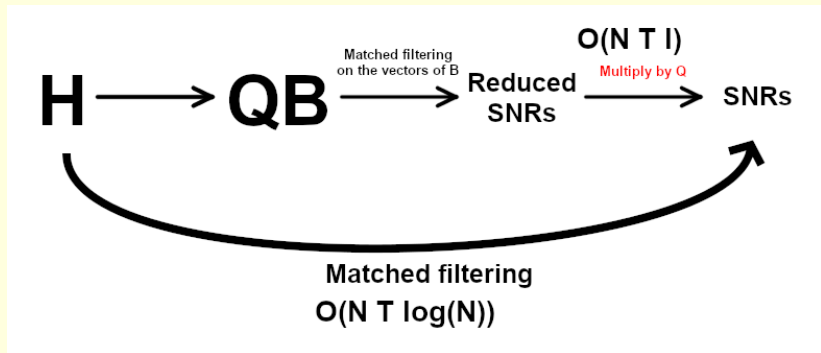
Optical Processing Unit :

Hardware developed by LightOn to perform random projections using photon diffusion

Not well matched for our purposes :

- ▶ Using low precision encoding of the data greatly reduces the performance
- ▶ Using high precision leads to high computational time allowed to the encoding.

The reconstruction cost issue



Reconstruction cost is actually higher than the matched filtering cost : how can we reduce it ?

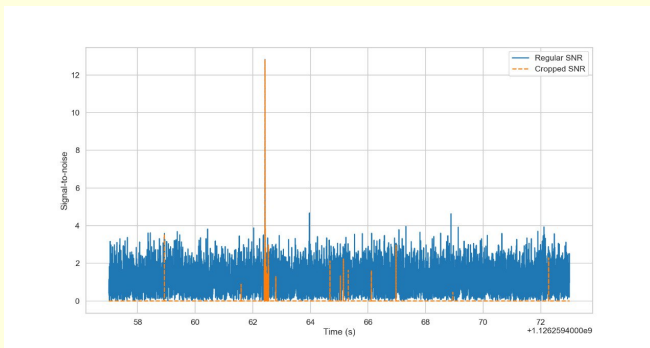
We want to avoid reconstructing everything. [1] proposes a hierarchical approach, reconstructing only a part of the SNR.

Two levers for acting on the reconstruction cost

- ▶ Reducing N : reconstructing only some part of the timeseries $\rightarrow \mathcal{O}(nTl)$
- ▶ Reducing T : reconstructing only some templates $\rightarrow \mathcal{O}(Ntl)$

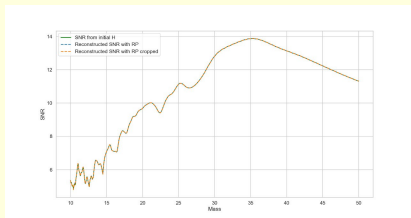
Reducing N ("cropping")

Main idea : identifying the regions in the reduced templates SNRs above a certain threshold, and reconstruct only those.

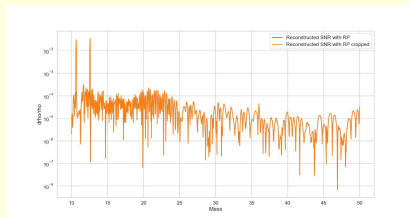


Reducing N : results

Toy example : uniform template bank, GW150914 event



Peak SNR for each template

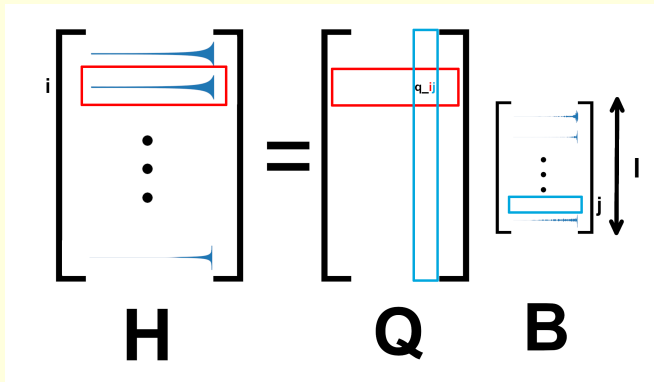


Difference between the peak SNRs and the true ones, with and without the cropping

Only 364 timesteps out of 114688 are reconstructed : reduces operation count by $\times 300$!
SNR error below 10^{-2} : suitable for detection.

Reducing T

Main idea : looking at the coefficient of the Q matrix to see which templates are relevant to reconstruct, based on which reduced template(s) have the highest peak SNR.



I implemented the random projections within the PyCBC pipeline, along with the cropping method.

- ▶ Still issues with implementation preventing to fully get the theoretical computational gain
 - ▶ numpy memory access when slicing is a significant cost
 - ▶ need to change how the χ^2 is computed
- ▶ Few errors compared to regular methods
 - ▶ 1 trigger/4900 missed with random projections
 - ▶ 11 triggers/4900 missed with RP + cropping ($\times 56$ reduction factor)



Takeaways :

- ▶ Random projections are a viable alternative to SVD for dimensionality reduction in the context of GW
 - ▶ Promising for subsolar masses search or 3rd generation
- ▶ Reconstruction cost is a large obstacle but it can be overcome

Perspectives :

- ▶ Solving the remaining issues with the PyCBC implementation
- ▶ Making a sensitivity analysis

References

-  Rahul Dhurkunde, Henning Fehrmann, and Alexander H. Nitz. Hierarchical approach to matched filtering using a reduced basis.
Physical Review D, 105(10), may 2022.
-  Amit Reza, Anirban Dasgupta, and Anand S. Sengupta. Random projections in gravitational-wave searches from compact binaries ii: efficient reconstruction of the detection statistic.
2021.