Application of Non-Linear Noise Regression in the Virgo Detector

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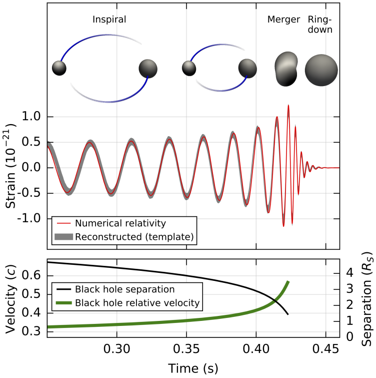
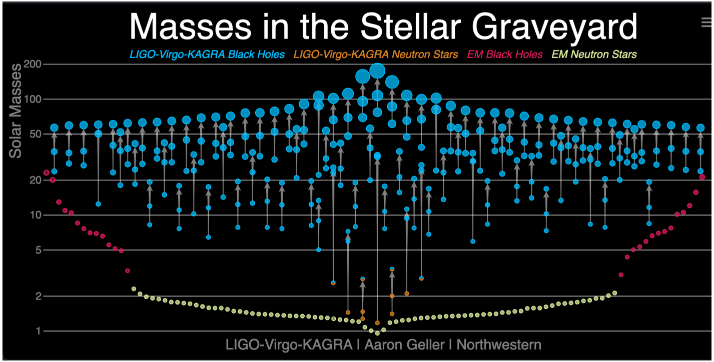
Gravitational Wave Window

First Direct Detection of Gravitational Waves



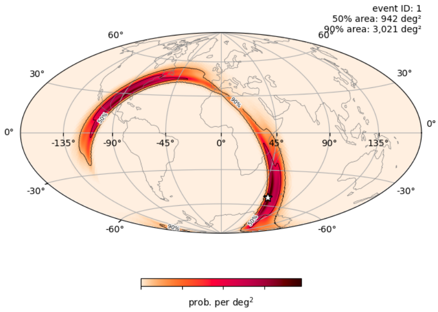
source : Abbott et al. 2016

Over 200 Compact Binary Mergers Detected Since 2015 (O4a End)



Nonlinear Noise : Undetectable GW Signals

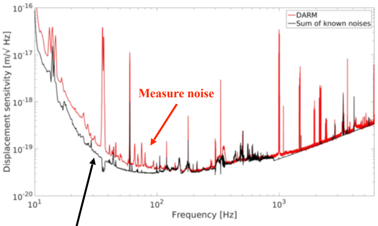
1. Many other signals are hidden below detector noise thresholds
   - Stationary and non-stationary noise (Environmental & Technical sources...)
   - GW signals are often too weak compared to background noise
2. Reducing gravitational wave detector noise
   - Reducing the sky localization area
   - Improving the signal-to-noise ratio (S/N)
   - Detect more events



Simulated data were used from Kiendrebeogo et al. 2023

Noise sources : Reality vs. Expectations

LHO, July 4, 2017 (credit : Ormiston et al. 2020)



Expected noise from known sources

Some noises sources tracked by witness sensors

NonSENS: applied deep neural networks for noise modeling

- **Main Noise Sources**:
  - **Environmental noise:**
    - **Atmospheric fluctuations**
    - **Seismic disturbances detector materials**
  - **Instrumental noise**:
    - **Detector design aspects**
  - **Fundamental noise:**
    - **Limitations inherent to detector materials**
    - **Quantum and thermal fluctuations**
- **Denoising Technique – DeepClean**
  - **Uses witness sensors data to:**
  - **Estimate and subtract complex noise** (non-linear, non-stationary)
  - **Enhance sensitivity to gravitational wave signals**
- **DeepClean**: **Uses data from witness sensors to estimate and subtract stationary and non-stationary noise from gravitational wave data.**
- **Other Algorithmes** : **Wiener filtering**, **Adaptive Feed-Forward** and **NonSENS:** Non-Stationary Estimation of Noise Subtraction (Vajente et al. **2020**)

Classification of Noise : Removable and Non-Removable

Interferometer readout   Possible signal   Detector noise

$$h(t) = s(t) + n(t)$$

$$\boxed{n_{NR}(t) + n_R(t)}$$

Non-removable (Fundamental noise)
Eg: photon shot, thermal noise
Reduced only with upgraded design

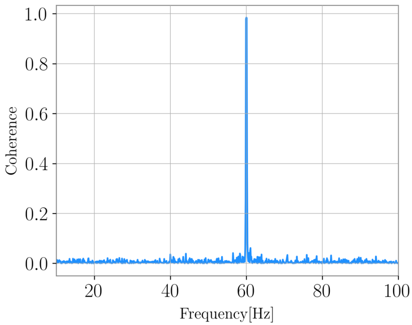
Removable noise:
Eg : environmental and technical noise

Independently tracked by witness channels $w_i(t)$

BruCo algorithm (Acernese et al . 2023) : *is used for the statistical measure of the coherence between witness channels and h(t)*

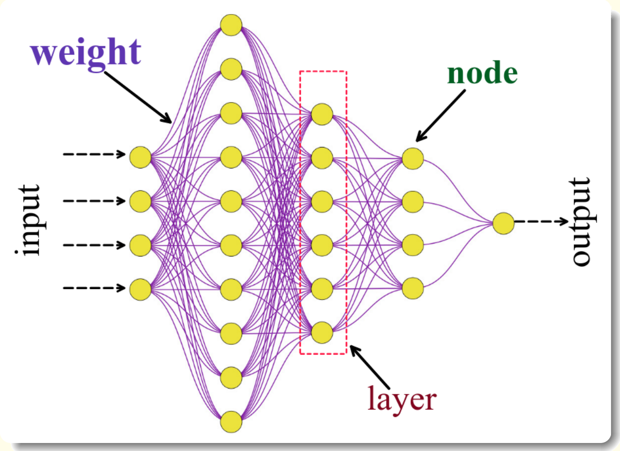
More than 1000 witness channels, denoted $w_i(t)$, independently measure the noise interfering with the potential signal. This makes $n_R(t)$ a complex noise.

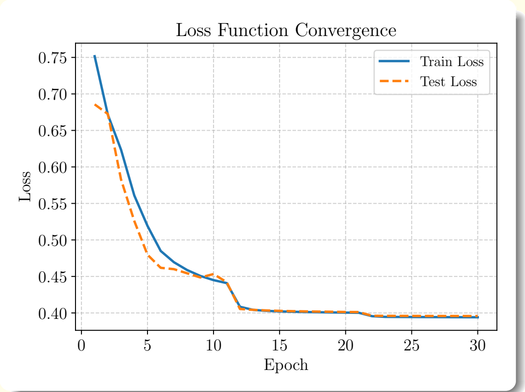
Coherence : LLO magnetometer and h(t)



Coherence monitoring : Reissel et al. 2025

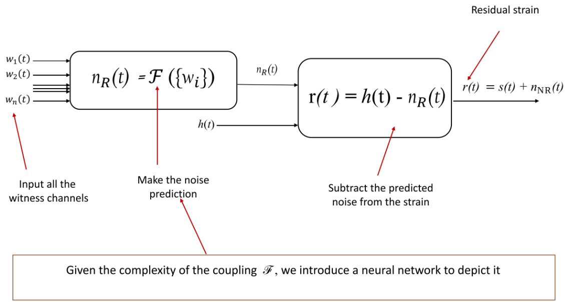
Operation of a Neural Network



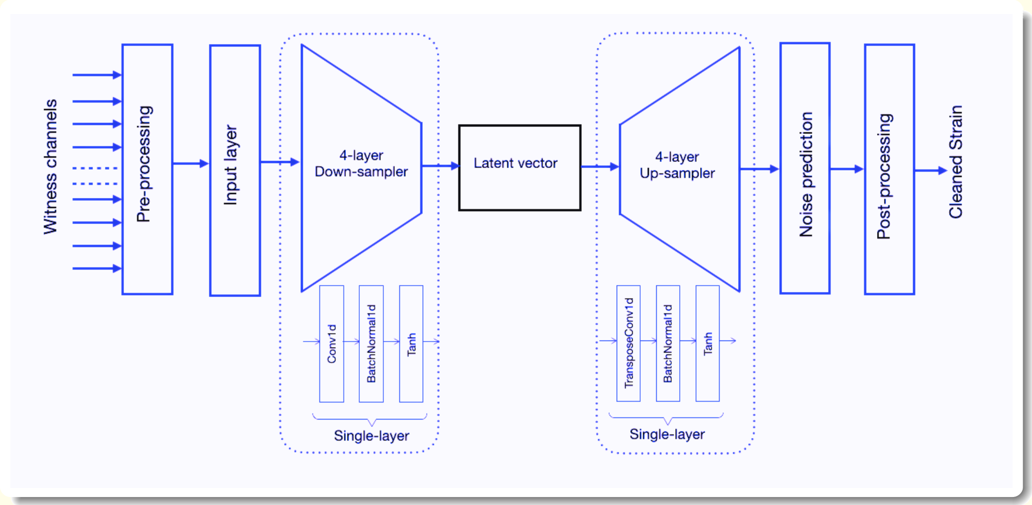


Purpose of DeepClean Denoising

1. Formalism
   - $h(t)$ is the target signal, V1 :Hrec_hoft_raw_20000Hz
   - $w_i(t)$ is the witnessed noise, equivalent to $n_R(t)$ in $h(t)$.
2. Several thousands witness sensors are used in Virgo
3. `DeepClean` : Reduces noise $n(t)$ and enhances $s(t)$ using $w_i(t)$
4. DeepClean algorithm Ormiston et al. 2020 and Saleem et al. 2023
   - 1-D Convolutional Neural Network (CNN)
   - Taking input from a set of user witeness channels
   - the output is the predicted noise



DeepClean Flowchart



Analysis Data : Virgo O3b Observation Campaign

1 Target signal description

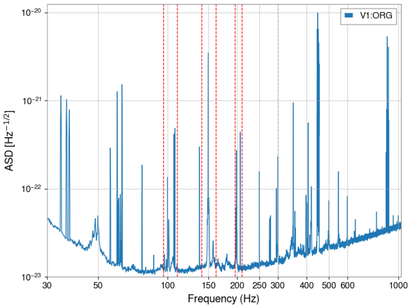
- Analyzed signal : $h(t)$ (V1 : Hrec_hoft_raw_20000Hz)
- Data duration : 2 days, 18 hours, and 15 minutes (from February 7, 2020, 16:19:27 UTC to February 10, 2020, 10:35:01 UTC)

2 Model preparation and training

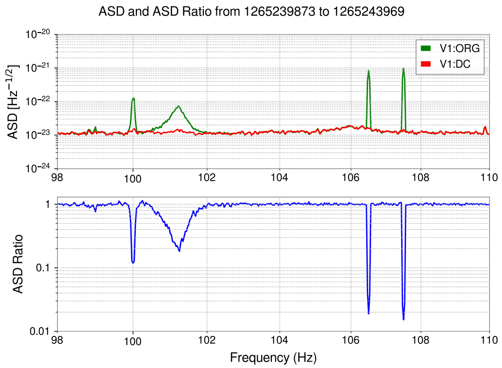
- Data segments used for training : 4096 s over 100,000 s (≈ 28 *hours*) intervals
- Training on 3 frequency bands : 98–110 Hz, 142–162 Hz, and 197–208 Hz
- Objective : reduce non-stationary and non-linear noise

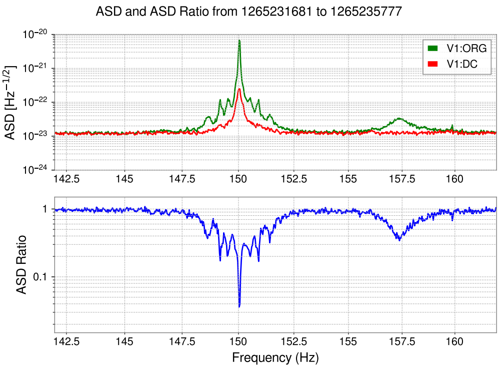
3 Results and denoising effectiveness

- Significant improvement in amplitude spectral density (ASD)
- Increased S/N
- Improved detection range for BNS inspirals



ASD : Before and After DeepClean





Improving BNS Inspiral Range

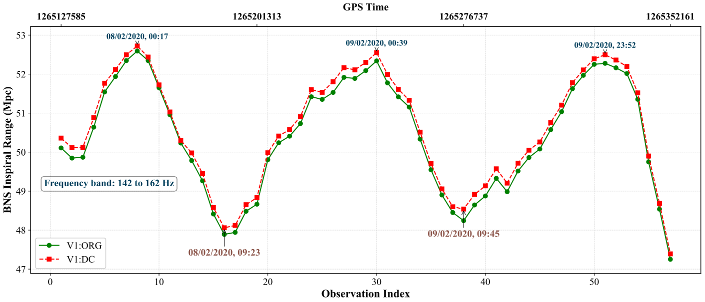
What is the BNS inspiral range ?

- Average distance at which a BNS system ($m_1 = m_2 = 1.4M_\odot$)
- Can be detected by GW detectors with an SNR of 8

BNS inspiral range gain

- 98–110 Hz : increase of 0.2 Mpc ($\approx$ 0.39%)
- 142–162 Hz : gain of 0.18 Mpc ($\approx$ 0.37%)
- 197–208 Hz : increase of 0.02 Mpc ($\approx$ 0.05%)

BNS Range (Cleaned vs. Uncleaned) : 142–162 Hz



142–162 Hz : Gain of 0.18 Mpc $\approx$ 0.37%

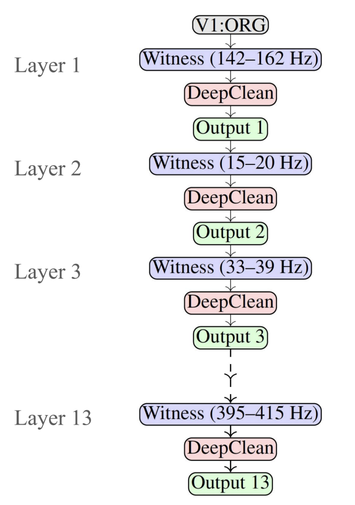
Multi-training Process

Key Points

- Frequency bands : 15–415 Hz
- 225 witness channels
- 13 sequential layers
- Each layer output → Next layer input

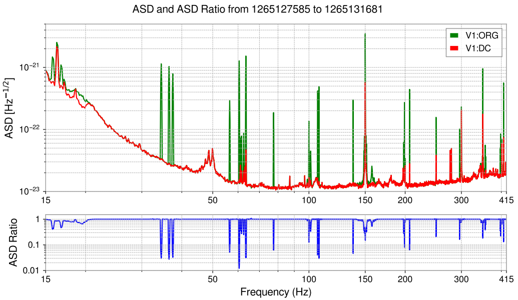
Advantages

- Efficient noise reduction per frequency band.
- Optimized model accuracy through segmented training.

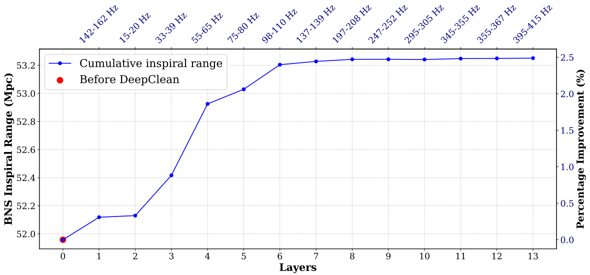


ASD and Cumulative BNS Inspiral Range

Comparison of ASD and BNS Range Before / After Cleaning



BNS Range Increased to 1.3 Mpc



Improvement in BNS range is more significant in the 55–56 Hz

Parameter Estimation : Preserving GW Signal Integrity

BBH Injection Signals

- 128 BBH signals injected into 4096 s of Virgo data
- ISCO frequencies : 15–415 Hz, spaced 32 s apart
- Each BBH signal has 15 independent parameters to estimate

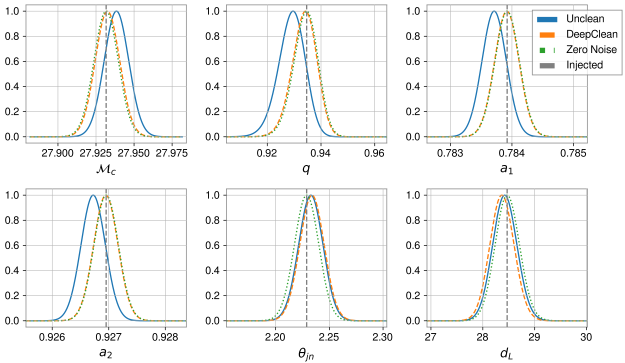
Parameter Estimation (PE)

- One-at-a-time estimation to compute the likelihood (Bilby)
- Example of 6 PE : $\mathcal{M}_c$, q, a_1, a_2, θ_{jn}, d_L
- All other parameters fixed to injected values

Results

- Uncleaned parameters : offsets due to non-gaussian noise
- With `DeepClean` : posteriors closer to true values

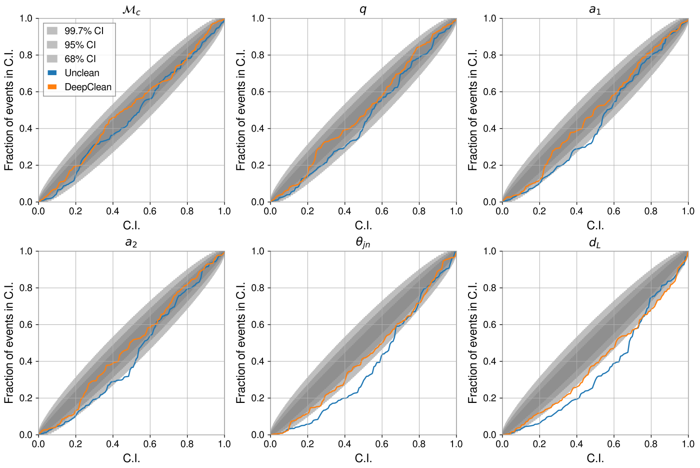
Posteriors of single-parameter PE analysis from multi-training : one injection



A “one-at-a-time” parameter estimation approach (15–415 Hz).

Parameter Estimation : PP plots from all 128 injections

The pp plots of the six parameters with unclean and DeepClean strain



Conclusion

Key Takeaways

- **Noise Reduction with DeepClean :** Previously applied to LIGO (Ormiston et al. 2020 ; Saleem et al. 2023) ; now also shown to remove noise effectively in Virgo (Look for our papers on arXiv soon)
- **Multi-Band Training :** Training across several frequency ranges (instead of just one) significantly improves noise subtraction performance.
- **Efficient Validation :** A "one-at-a-time" parameter estimation approach cuts down on computing costs when verifying noise removal.
- **Real-Time Processing :** Plans for O5 include integrating DeepClean online, enhancing Virgo's immediate sensitivity for pre-merger GW detection.

Achievements & Next Steps

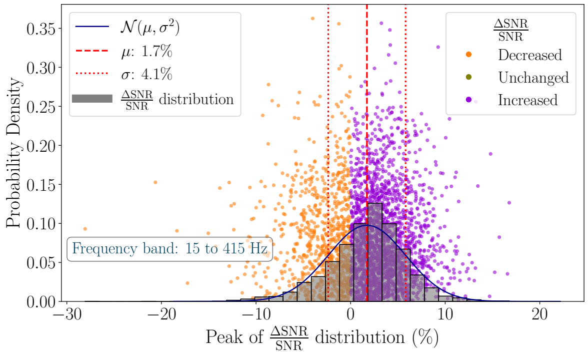
- **Improved Sensitivity :** Our multi-band method delivers better strain sensitivity, especially around the 150 Hz region.
- **Computational Demands :** Handling multiple frequency bands and large data sets requires significant resources, leading us to explore more memory-efficient architectures.
- **Data Handling :** The `VirgoTool` Python package can reduce data-access times, but cluster-integration challenges remain. Future work aims to merge its capabilities into `gwpy` for broader accessibility.

Thank you for your Attention

Questions ?

Signal-to-noise Ratio Analysis

$\frac{\Delta SNR}{SNR}$ for injections across the 15–415 Hz frequency band



Statistical analysis of SNR differences over frequency bands

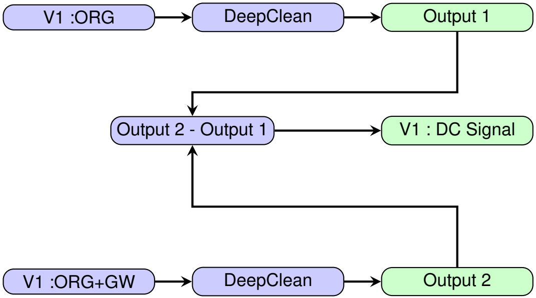
Frequency band	μ (%)	σ (%)	$\frac{\Delta SNR}{SNR}$ (%) at 1σ
Single training			
98–110 Hz	0.8	1.4	-0.62%–2.15%
142–162 Hz	-0.3	2.7	-3.05%–2.42%
197–208 Hz	0	0.4	-0.35%–0.36%
Multi-training			
15–415 Hz	1.7	4.1	-2.36%–5.81%

Preserving GW signal integrity

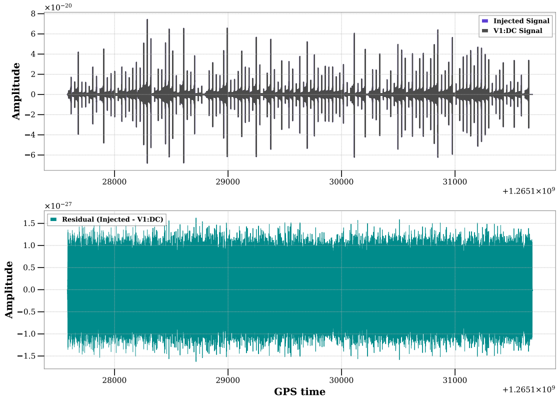
Key observations

- Injection of 128 GW signals in a 4096 s of data
- Post-process signal - Injected signal $\approx 10^{-27}$
- Normalized root mean square = $1.2 \times 10^{-5} \ll 1\%$

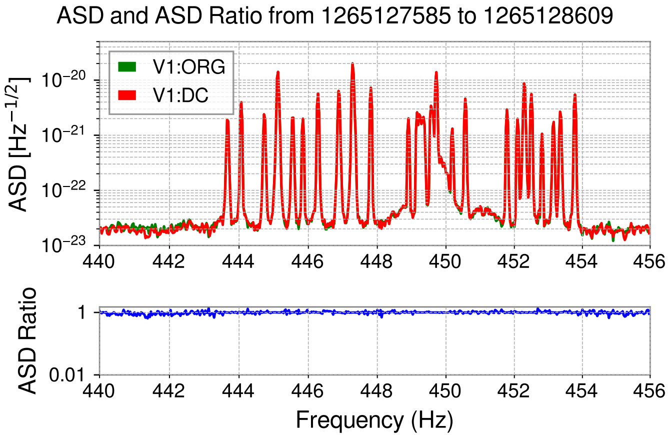
Data Processing Workflow



Residual analysis



Violin mode


ASD and ASD Ratio from 1265127585 to 1265128609
V1:ORG
V1:DC
ASD [Hz$^{-1/2}$]
10^{-20}
10^{-21}
10^{-22}
10^{-23}
440
442
444
446
448
450
452
454
456
ASD Ratio
1
0.01
Frequency (Hz)