CitizenGW-Compute: Turning Computational Operations into a Gravitational Wave Sensor (P-II)

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Abstract

We propose a citizen science framework to explore gravitational wave (GW) properties by exploiting modern computing systems as auxiliary detectors. Instead of measuring fractional deviations in raw clock frequency, which are minuscule (order 10^{-12} Hz for GHz clocks), we leverage the computational rate (operations per second) as an amplification mechanism. This approach scales deviations by factors of 10^3 to 10^6, potentially rendering otherwise undetectable effects into measurable statistical signals. The framework includes dummy artificial neural network (ANN) workloads, distributed logging across commodity PCs, and extensions to high-performance computing (HPC) clusters such as EAGLE, with real-time correlation against LIGO/Virgo alerts.

1 Introduction

Gravitational waves (GWs) induce minute spacetime perturbations. Current detectors (LIGO, Virgo) are highly specialized laser interferometers optimized for 10–10^3 Hz bands. Here, we explore whether distributed computing systems—with stable clocks, GPUs, and CPUs—could serve as complementary sensors by monitoring deviations in computational throughput.

2 Theoretical Framework

2.1 Weak-field approximation

In linearized general relativity, the spacetime metric is approximated as:

$$g_{\mu\nu} = \eta_{\mu\nu} + h_{\mu\nu}, \quad |h_{\mu\nu}| \ll 1, \tag{1}$$

where $h_{\mu\nu}$ is the GW perturbation. For a monochromatic GW of strain amplitude $h \sim 10^{-21}$, the fractional frequency shift on a stable clock is

$$\frac{\Delta f}{f} \sim h(t). \tag{2}$$

For a GHz-scale clock ($f \sim 10^9$ Hz), this yields

$$\Delta f \sim 10^{-12} \text{ Hz}, \tag{3}$$

far below detection thresholds.

2.2 Principle of Amplification

We propose shifting from frequency f to computational throughput R (operations per second). If each core performs A operations per cycle, then

$$R = Af. \tag{4}$$

The fractional effect is

$$\frac{\Delta R}{R} \sim h(t), \quad \Delta R \sim Rh(t). \tag{5}$$

Thus,

$$\Delta R \sim Afh(t). \tag{6}$$

3 Numerical Worked Examples

3.1 Consumer-grade example

Consider a single core with $f = 10^9$ Hz and per-cycle arithmetic capacity $A = 10^4$. Then

$$R = Af = 10^{13} \text{ ops/s}, \tag{7}$$

$$\Delta R = Rh = 10^{13} \times 10^{-21} = 10^{-8} \text{ ops/s}. \tag{8}$$

If $A = 10^6$ (GPU-like logical throughput) the absolute change becomes 10^{-6} ops/s though the fractional remains 10^{-8}.

3.2 HPC-scale example (EAGLE/Azure)

Assume aggregate throughput $R_{\text{tot}} = 10^{17}$ FLOP/s and $h = 10^{-21}$. Then

$$\Delta R_{\text{tot}} = R_{\text{tot}} h = 10^{-4} \text{ FLOP/s}. \tag{9}$$

Per-node expectation with $N_{\text{CPU}} = 1.5 \times 10^5$ is

$$\Delta R_{\text{per}} = \frac{\Delta R_{\text{tot}}}{N_{\text{CPU}}} \approx 6.7 \times 10^{-10} \text{ FLOP/s}. \tag{10}$$

Coherent stacking across nodes improves SNR by $\sqrt{N}$, but absolute rates remain extremely small compared to telemetry quantization and environmental noise.

4 Computational Cost: Big-$\mathcal{O}$

For a cascaded ANN with L dense layers and layer width n, and I inference iterations, the flop count is approximately

$$\text{FLOPs} = I \cdot L \cdot 2n^2 = \mathcal{O}(ILn^2). \tag{11}$$

If using batched matrix–matrix kernels cost can approach $\mathcal{O}(ILn^3)$ depending on blocking and algorithmic choices. Given per-core throughput R, the run time is

$$T_{\text{run}} \approx \text{FLOPs}/R. \tag{12}$$

Longer runs reduce fractional variance via averaging but reduce temporal sampling resolution.

5 Resolving Power and Bandwidth Dependencies

5.1 Definitions

Define:

- f: per-core clock frequency (Hz).
- A: ops-per-cycle amplification factor (dimensionless).
- $R = Af$: per-core operations/sec.
- $y(t) = (R_{\text{meas}}(t) - R)/R$: fractional throughput time series.
- $S_y(f)$: one-sided PSD of $y(t)$.
- T: coherent integration time.
- B: effective analysis bandwidth (Hz).
- N: number of independent nodes.

5.2 Per-core resolving power

We define per-core resolving power at frequency f_{gw} as

$$\eta_{\text{core}}(T; f_{\text{gw}}) = \frac{1}{\sigma_y(T; f_{\text{gw}})}, \tag{13}$$

where, for white fractional noise, $\sigma_y(T; f_{\text{gw}}) \simeq \sqrt{S_y(f_{\text{gw}})/(2T)}$.

5.3 Network resolving power

Assuming independent noise realizations,

$$\eta_{\text{net}}(T; f_{\text{gw}}) = \sqrt{N}\, \eta_{\text{core}}(T; f_{\text{gw}}). \tag{14}$$

5.4 Sensitivity vs. bandwidth

For a band-limited estimator of ENBW B, variance scales as $\sigma_y^2 \propto S_y B/T$. Narrowing B improves sensitivity as $\sigma_y \propto \sqrt{B/T}$ at the cost of responsiveness.

6 Narrowband Tuning: Digital Antenna / Lock-in Amplifier Analogy

To focus sensitivity at a target narrowband f_0, implement a deterministic gating waveform $g(t)$ (sinusoid, multi-tone, PRBS) that modulates the computational load. The measurement chain is:

1. Acquire $y(t)$ while applying $g(t)$.
2. Multiply $y(t)$ by a coherent reference $\cos(2\pi f_0 t)$ (mixing/heterodyne).
3. Low-pass filter the product with cutoff B and integrate for T.

The resulting demodulated output behaves like a lock-in amplifier: the effective SNR scales as

$$\text{SNR} \propto \frac{h_0 \sqrt{T}}{\sqrt{S_y(f_0) B}}. \tag{15}$$

Design choices for $g(t)$ determine the effective "Q" (selectivity) of the digital antenna and its trade-off between gain and cyclostationary noise.

7 HPC / Cloud Extension: Practical Considerations

For a production-level experiment on EAGLE or Azure:

- Reserve nodes and ensure job start/stop synchronization (scheduler barriers, job arrays).
- Pin CPU frequency states (disable DVFS), fix SMT/Hyper-Threading, and isolate cores where possible.
- Instrument each node with high-resolution timers, temperature sensors, and interrupt counters.
- Run deterministic kernels with prebuilt weights and fixed data to avoid variability.
- Collect fractional throughput $y_i(t)$ at a chosen sampling cadence and forward to an aggregation node for whitening and coherent stacking.

A practical coherent estimator is the inverse-PSD weighted average in Fourier space:

$$\hat{h}(f) = \frac{\sum_{i=1}^{N} \tilde{y}_i(f)/S_{y,i}(f)}{\sum_{i=1}^{N} 1/S_{y,i}(f)}. \tag{16}$$

Assuming $S_{y,i} \approx S_y$ this reduces to the arithmetic mean in the frequency band of interest.

8 Scaling Laws with A and N

Recall $R = Af$ and $\Delta R = Rh$. While increasing A increases absolute ΔR, fractional detectability depends on S_y. For design decisions the useful scaling is:

$$h_{\min} \sim \frac{\kappa}{\sqrt{N}} \sqrt{\frac{S_y(f_{\mathrm{gw}})B}{T}}, \tag{17}$$

where κ accounts for windowing and mismatch factors. Increasing N or T, or reducing S_y and B, lowers detectable $h_{\min}$.

9 Hypothetical Ultra-High-Frequency Timebase

If a timebase at $f_\gamma = 10^{18}$–10^{20} Hz were available, then

$$\Delta f_\gamma = f_\gamma h. \tag{18}$$

For $f_\gamma = 10^{19}$ Hz and $h = 10^{-21}$, $\Delta f_\gamma = 10^{-2}$ Hz. If such devices achieved a fractional PSD $S_{y,\gamma}$ comparable to the best optical clocks, then detection becomes feasible at much smaller N and shorter T. This remains hypothetical but indicates frequency scaling benefits.

10 Statistical Correlation, Background Estimation and False-Alarm Control

The analysis pipeline should include:

1. Per-node noise characterization (estimate $S_{y,i}(f)$ using long off-source runs).
2. Whitening by dividing by $\sqrt{S_{y,i}(f)}$ in Fourier space.
3. Coherent stacking across nodes with inverse-PSD weights.
4. Background estimation by time-shifted coincidence trials (circular shifting node streams by offsets larger than causal windows) to compute false-alarm rates.
5. Multiply-trial correction using pre-defined band/session selections or FDR procedures.

11 Conclusion

The computational-amplification idea is internally consistent and offers a way to amplify absolute changes induced by GWs by using large aggregate computational throughput. Practical detection of astrophysical strains requires dramatic reductions in fractional noise or very large, well-synchronized ensembles in controlled environments (HPC/cloud). Nonetheless, this framework is scientifically useful for upper limits, noise studies, and citizen-science engagement. HPC-triggered narrowband experiments aligned with LVK alerts are the most promising near-term experimental path.

References

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