# Citizen-Driven Computational Timing Anomalies as Auxiliary Probes of Gravitational Waves

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***Abstract*—This documention is for citizen-science approach that uses predictable computational workloads (cascaded artificial neural networks and related benchmarks) as ultra-stable timing baselines to search for correlated anomalies induced by gravitational waves (GWs) passing local hardware. We present the weak-field GW physics background, derive a simple model relating GW strain to fractional frequency and throughput deviations, express the computational workload cost in Big-O notation, model thermal and electronic jitter as noise processes, and develop statistical detection metrics (cross-correlation, matched filtering, false-alarm control). The goal is to provide a rigorous mathematical basis to guide prototype design and to estimate the scale required for plausible detection or meaningful upper limits.**

***Index Terms*—Gravitational waves, timing stability, matched filtering, distributed detection, ANN benchmark, thermal jitter.**

## I. Introduction

(Short intro omitted here; use prior draft text.)

## II. Weak-field gravitational-wave effects on clocks and computation

In the transverse-traceless (TT) gauge, a weak gravitational wave propagating in the $z$ direction induces a perturbation of the Minkowski metric:

$$g_{\mu\nu} = \eta_{\mu\nu} + h_{\mu\nu}(t, z), \qquad |h_{\mu\nu}| \ll 1. \tag{1}$$

For a monochromatic plane wave with a single polarization component we may write

$$h(t) = h_0 \sin(2\pi f_{\rm gw} t + \phi_0), \tag{2}$$

where $h_0$ is the strain amplitude and $f_{\rm gw}$ its frequency.

A local clock (or oscillator) measures proper time $\tau$ defined by $d\tau^2 = -g_{\mu\nu} dx^\mu dx^\nu$. To leading order in $h$ the GW produces a fractional modulation in observed clock rate. For a clock at rest in the chosen coordinates the fractional frequency shift $\Delta f/f$ induced by the GW is (to first order):

$$\frac{\Delta f(t)}{f} \approx h(t). \tag{3}$$

This result follows from the interpretation of $h(t)$ as a perturbation of the time-time portion or via the phase-modulation viewpoint: an oscillator with unperturbed phase $\phi_0(t) = 2\pi f t$ acquires an extra phase

$$\Delta\phi(t) = 2\pi f \int^t h(t')\, dt' \tag{4}$$

whose time derivative yields $\Delta f/f \sim h(t)$.

If a computational workload performs $R$ arithmetic operations per second that scale linearly with clock frequency (a simplifying assumption), then the induced fractional change in the measured rate of operations is

$$\frac{\Delta R(t)}{R} \approx h(t). \tag{5}$$

Therefore the absolute change in operations/sec is

$$\Delta R(t) \approx R\, h(t). \tag{6}$$

## III. Computational workload: cost and scaling

Consider a cascaded feed-forward fully connected ANN with $L$ layers where each layer is an $n \times n$ dense transformation (for simplicity). A single forward pass requires $\mathcal{O}(Ln^2)$ scalar multiply-add operations for matrix-vector products. If we instead use matrix–matrix operations (batched inputs or heavier kernels), per-iteration cost can be $\mathcal{O}(Ln^3)$.

For our prototype we assume per-core execution of $I$ iterations of $L$ layers on a vector of dimension $n$. The total floating-point operations (approximate multiply-adds) per benchmark run is:

$$\text{FLOPs} \sim I \cdot L \cdot 2n^2. \tag{7}$$

If a core executes $R$ FLOPs/s (baseline), then the time for one run is $T = \text{FLOPs}/R$. The choice of $(I, L, n)$ trades off per-run duration versus resolution: longer runs integrate more samples (reducing statistical uncertainty) but reduce temporal resolution for tracking low-frequency GWs.

## IV. Noise model: thermal and electronic jitter

Real hardware measurements are affected by noise sources that must be modeled to discriminate a GW-induced signal. We write the observed (normalized) fractional throughput deviation for node $k$ as

$$x_k(t) = s(t) + n_k(t), \tag{8}$$

where $s(t) \equiv h(t)$ is the common GW-induced fractional signal (under the linear model) and $n_k(t)$ denotes node-specific noise.

We model $n_k(t)$ as a stochastic process with two dominant components:

$$n_k(t) = n_{{\rm th},k}(t) + n_{{\rm oss},k}(t), \tag{9}$$

where $n_{\rm th}$ is thermal/electronic jitter (approx. wide-sense stationary) and $n_{\rm oss}$ is low-frequency environmental/OS noise (power-line, scheduling spikes). A simple working model is

Gaussian, zero-mean noise with one-sided power spectral density (PSD)

$$\mathcal{S}_n(f) = S_0 + \frac{S_1}{1 + (f/f_c)^{\alpha}}, \tag{10}$$

where $S_0$ models high-frequency white noise floor, and the second term models $1/f^{\alpha}$-like low-frequency excess with corner frequency $f_c$.

For a measurement integrated over time $T$ (single run), the variance of the mean fractional deviation is approximately

$$\sigma_n^2(T) \approx \frac{1}{T^2} \int_{-\infty}^{\infty} \mathcal{S}_n(f) |\tilde{W}_T(f)|^2 df, \tag{11}$$

where $\tilde{W}_T(f)$ is the Fourier transform of the integration window (e.g., sinc for rectangular windows). For long $T$ (low-pass), the integrated noise decreases roughly as $\sigma_n \propto 1/\sqrt{T}$ for white-noise dominated regimes.

## V. Detection statistics and cross-correlation

With $N$ geographically distributed nodes (assumed independent noise realizations), we can form an averaged estimator of the common signal:

$$\bar{x}(t) = \frac{1}{N} \sum_{k=1}^{N} x_k(t) = s(t) + \bar{n}(t), \tag{12}$$

with $\mathrm{Var}[\bar{n}(t)] = \sigma_n^2/N$ for identically distributed independent noise. Thus the signal-to-noise ratio (SNR) for a simple time-domain average over a measurement of duration $T$ is

$$\mathrm{SNR}_{\mathrm{avg}} = \frac{\langle s \rangle_T}{\sigma_n/\sqrt{N}} \approx \frac{h_0}{\sigma_n/\sqrt{N}}, \tag{13}$$

where $\langle s \rangle_T$ denotes the characteristic amplitude of $s(t)$ over $T$ (for narrow-band signals $\sim h_0$).

For a sinusoidal GW $s(t) = h_0 \sin(2\pi f_{\mathrm{gw}} t)$, a frequency-domain matched filter provides an optimal linear detector given known waveform shape. The matched filter SNR (single node) is

$$\rho^2 = 4 \int_0^{\infty} \frac{|\tilde{s}(f)|^2}{\mathcal{S}_n(f)} df. \tag{14}$$

For $N$ independent nodes coherently combined (assuming alignment and synchronization), SNR scales as $\sqrt{N}$.

### A. Required ensemble size for a target SNR

Rearranging (13) yields an approximate required number of nodes to reach a target $\mathrm{SNR}_{\mathrm{t}}$:

$$N \gtrsim \left( \frac{\mathrm{SNR}_{\mathrm{t}}\, \sigma_n}{h_0} \right)^2. \tag{15}$$

This scaling is critical: because $h_0$ for astrophysical GW events can be extremely small (e.g., $h_0 \sim 10^{-21}$ at Earth for LIGO-scale events), achieving useful SNR requires either astronomically small noise $\sigma_n$ or impractically large $N$ unless one can increase the proportional response (e.g., amplify $R$ or use specialized external clocks).

## VI. Practical numeric estimate (illustrative)

Take a baseline per-node throughput $R = 10^{11}$ ops/s (high-end GPU/aggregate), and a GW strain amplitude $h_0 = 10^{-21}$. The expected absolute change in operations/sec (from (5)) is

$$\Delta R_{\mathrm{amp}} = R\, h_0 = 10^{11} \times 10^{-21} = 10^{-10} \text{ ops/s}. \tag{16}$$

This is essentially zero compared to typical measurement quantization and noise. Realistic measurement noise in throughput due to thermal/OS effects can easily be $\sigma_R \gtrsim 10^3 - 10^6$ ops/s for single-node short integrations. The corresponding fractional noise is $\sigma_n = \sigma_R/R \gtrsim 10^{-8} - 10^{-5}$.

Using (15), for $\mathrm{SNR}_t = 5$ and $\sigma_n = 10^{-6}$ (optimistic), required number of nodes is

$$N \gtrsim \left( \frac{5 \times 10^{-6}}{10^{-21}} \right)^2 \sim 2.5 \times 10^{31}, \tag{17}$$

an astronomically large number, demonstrating that direct detection with commodity hardware under the linear, per-clock proportional model is effectively impossible for strains of order $10^{-21}$.

Nevertheless, this calculation is instructive: the experiment can still be valuable to place upper limits, study systematic noise sources, and explore non-linear coupling mechanisms or resonant amplification that might increase the effective response above $h$.

## VII. Mathematical strategies to increase confidence and reduce false triggers

Several mathematical and algorithmic techniques can improve detection confidence or reduce false positives:

1) **Matched filtering / coherent stacking:** If the expected GW waveform (or narrowband sinusoid) is known, matched filtering across time and across nodes maximizes SNR under Gaussian noise.
2) **Cross-correlation with interferometer triggers:** Use official LIGO/Virgo event times as a priori windows to restrict analysis and reduce trials factors.
3) **Time-frequency analysis:** Compute spectrograms and look for common excess power in the target 0.1–10 Hz band across many nodes; apply clustering algorithms to identify coherent features.
4) **Noise whitening and adaptive filtering:** Model each node's noise PSD $\mathcal{S}_{n,k}(f)$ and whiten the time series before stacking.
5) **Outlier rejection and robust statistics:** Use median-based estimators, trimmed means, or M-estimators to reduce sensitivity to transient OS spikes.
6) **False alarm control via permutation tests:** Estimate null distributions by time-shifting node data (off-source windows) and computing empirical false-alarm probabilities when searching for coincidences.

## VIII. Thermal Jitter Modeling and Mitigation

Thermal noise in oscillators and variations in power consumption produce timing jitter. A simplified oscillator phase noise model yields a single-sideband phase noise $\mathcal{L}(f)$ which can be mapped to fractional frequency noise PSD $\mathcal{S}_y(f)$. For practical mitigation:

- Measure each node's noise PSD during long idle windows to characterize $\mathcal{S}_{n,k}(f)$.
- Use temperature sensors and correlate throughput deviations with thermal variations; include these covariates in regression models to remove correlated noise.
- Employ Allan deviation estimates to identify stability on required timescales.

## IX. Statistical Correlation and Detection Confidence

Given a candidate coincidence (many nodes showing correlated excess during an interferometer event window), compute a detection statistic $\Lambda$ (e.g., normalized cross-correlation energy or matched-filter SNR). Estimate the background distribution of $\Lambda$ using off-source time shifts or bootstrap resampling. Convert $\Lambda$ to a p-value and assign a false alarm probability (FAP). Controlling FAP across multiple trials requires adjustments (Bonferroni, or better, controlling the false discovery rate).

## X. Conclusions and Practical Implications

The linear model predicts an impractically small direct coupling between astrophysical GW strains ($h \sim 10^{-21}$) and commodity-computer throughput. However, the mathematical framework above provides:

- Clear scaling laws (Eqn. 15) showing why large ensembles are required under linear coupling assumptions.
- A toolkit of statistical and signal-processing techniques to maximize sensitivity, reject false triggers, and place quantitative upper limits.
- A roadmap for experimental extensions: higher-precision local clocks, resonant mechanical transducers, or FPGA-based timestamping which could increase the proportional response.

## References


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