GPU-Based Chaotic Oscillator as Local State Detector

Validated Physics for Tamper Detection and Thermal Sensing

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Abstract

We present a validated GPU-based chaotic oscillator system that functions as a local state detector. Through systematic null hypothesis testing, we establish three primary capabilities: (1) tamper/workload detection via k_{eff} mean shift ($p = 0.007$), (2) thermal state sensing via k_{eff} variance ($r = -0.97$ correlation with GPU temperature), and (3) sensitivity regime prediction via internal correlation r_{ab} ($r = -0.999$).

The system operates optimally at coupling strength $\epsilon = 0.003$, achieving 562× signal improvement over weaker coupling while maintaining 64% time in the sensitive transient regime. The scaling law $\tau \propto \epsilon^{-1.06}$ enables predictive control of thermalization dynamics. Frequency analysis confirms the detector is sensitive to slow changes (< 0.5 Hz, 88.6% of signal power), making it suitable for thermal drift, workload state changes, and gradual system monitoring.

The Leggett-Garg inequality test yields $K_3 = 1.0$, confirming classical dynamical system behavior. All findings are validated through statistical testing with reported p-values and effect sizes.

Code availability:

- CIRISOssicle: https://github.com/CIRISAI/CIRISOssicle
- CIRISArray: https://github.com/CIRISAI/CIRISArray
- RATCHET framework: https://github.com/CIRISAI/RATCHET

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1 Introduction

Coupled chaotic oscillators exhibit rich dynamical behavior that can be harnessed for sensing applications. We present a GPU-implemented chaotic oscillator system that serves as a local state detector, capable of sensing computational workload changes and thermal state through distinct measurement channels.

The system consists of three coupled logistic map oscillators arranged with phase offsets, requiring only 768 bytes of state. Despite this minimal footprint, the detector achieves statistically significant detection of local GPU state changes through careful optimization of coupling parameters and operating regime.

1.1 Contributions

This work makes five validated contributions:

1. **Tamper detection**: The k_{eff} metric detects workload changes with $p = 0.007$ statistical significance.
2. **Thermal sensing**: The k_{eff} variance correlates with GPU temperature at $r = -0.97$, enabling thermal state monitoring through a novel channel.
3. **Sensitivity prediction**: The internal correlation r_{ab} predicts detection sensitivity with $r = -0.999$ correlation, enabling adaptive operation.
4. **Coupling optimization**: Systematic sweep identifies $\epsilon = 0.003$ as optimal, achieving $562\times$ signal improvement while maintaining sensitivity.
5. **Scaling law**: The relationship $\tau \propto \epsilon^{-1.06}$ enables predictive control of system dynamics.

2 System Architecture

2.1 Oscillator Design

The detector consists of three coupled logistic map oscillators:

$$x_{n+1}^{(i)} = r_i \cdot x_n^{(i)} \cdot (1 - x_n^{(i)}) + \epsilon \sum_{k \neq i} (x_n^{(k)} - x_n^{(i)}) \cos(\theta_k - \theta_i) \tag{1}$$

where $r_i \in \{3.70, 3.73, 3.76\}$ (chaotic regime), ϵ is the coupling strength, and $\theta_i = i \cdot 1.1$ defines the twist angle between oscillators.

2.2 The k_{eff} Metric

We quantify oscillator state using the effective sample size:

$$k_{\text{eff}} = \frac{k}{1 + \rho(k-1)} \tag{2}$$

where k is the number of correlation pairs and ρ is the mean correlation. This metric captures effective independence of sensing channels.

2.3 The r_{ab} Metric

The internal correlation between oscillator channels a and b:

$$r_{ab} = \text{Corr}(x^{(a)}, x^{(b)}) \tag{3}$$

serves as a direct indicator of oscillator synchronization state and, as we demonstrate, a powerful predictor of detection sensitivity.

3 Validated Capabilities

3.1 Tamper and Workload Detection

The k_{eff} mean responds to GPU workload changes with high statistical significance.

Metric	Value	Interpretation
p-value	0.007	Highly significant
Effect size	-0.006 mean shift	Detectable change
Detection threshold	$3\sigma = 0.009$	Validated

Table 1: Tamper detection validation results.

The detection mechanism operates through perturbation of oscillator dynamics by computational activity on the GPU, manifesting as shifts in the k_{eff} distribution.

3.2 Thermal State Sensing

A key finding: k_{eff} variance correlates strongly with GPU temperature.

Metric	Correlation	Interpretation
k_{eff} mean vs Temperature	$r = 0.01$	No correlation
k_{eff} variance vs Temperature	$r = -0.97$	Strong inverse

Table 2: Thermal sensing validation. Variance is the thermal channel.

Physical interpretation: As GPU temperature increases, oscillator dynamics thermalize faster, reducing variance. This provides a novel thermal sensing channel independent of direct temperature measurement.

Validation test:

- Temperature change: 46°C $\rightarrow$ 48°C (+2°C)
- Variance change: $0.058 \rightarrow 0.042$ ($\downarrow$27%)

3.3 Sensitivity Prediction via r_{ab}

The internal correlation r_{ab} predicts detection sensitivity with near-perfect accuracy.

Regime	r_{ab} Range	Sensitivity	Response
TRANSIENT	< 0.95	$20\times$ baseline	0.91 units
TRANSITIONAL	$0.95 - 0.98$	Decaying	Variable
THERMALIZED	> 0.98	$1\times$ baseline	0.04 units

Table 3: Sensitivity regimes defined by r_{ab}.

The correlation between r_{ab} and sensitivity is $r = -0.999$, enabling:

- Adaptive reset timing based on r_{ab} threshold
- Real-time sensitivity estimation
- Optimal operating point maintenance

4 Coupling Optimization

Systematic coupling strength sweep revealed an optimal operating point.

4.1 Coupling Sweep Results

ϵ	τ (s)	% Transient	k_{eff} σ	Behavior
0.0003	N/A	100.0%	0.03	Never thermalizes
0.0010	N/A	100.0%	0.25	Never thermalizes
0.0030	**12.8**	**63.8%**	**0.75**	**Optimal**
0.0100	3.7	18.8%	1.61	Fast thermalization
0.0300	1.2	6.0%	2.67	Very fast
0.0500	0.7	3.5%	3.14	Near instant
0.1000	0.3	1.5%	3.17	Instant

Table 4: Coupling strength sweep results. Optimal at $\epsilon = 0.003$.

4.2 Optimal Operating Point

At $\epsilon = 0.003$:

- **562× signal improvement** over default ($\epsilon = 0.0003$)
- **64% time in TRANSIENT regime** (high sensitivity)
- $\tau = 12.8$s **thermalization time** (manageable reset interval)
- **Variance ratio**: TRANSIENT 0.67 vs THERMALIZED 0.0002 (2724×)

4.3 Scaling Law

Thermalization time follows a power law:

$$\tau = \tau_0 \cdot \left(\frac{\epsilon}{\epsilon_0}\right)^{-1.06} \tag{4}$$

Measured values:

- At $\epsilon = 0.003$: $\tau \approx 12.8$s
- At $\epsilon = 0.010$: $\tau \approx 3.7$s
- At $\epsilon = 0.030$: $\tau \approx 1.2$s
- At $\epsilon = 0.050$: $\tau \approx 0.7$s

5 Frequency Response Characterization

Spectral analysis reveals the detector's frequency sensitivity profile.

5.1 Power Distribution

Frequency Band	Power	Interpretation
< 0.1 Hz	45.7%	τ thermalization dynamics
$0.1 - 0.5$ Hz	42.9%	Harmonics of τ
$0.5 - 2$ Hz	8.8%	Diminishing sensitivity
> 2 Hz	2.7%	Noise floor

Table 5: Frequency sensitivity profile. 88.6% of power below 0.5 Hz.

5.2 Implications

The detector is optimized for **slow-change detection**:

- Sensitive to: < 0.5 Hz (periods > 2 seconds)
- Dominated by: τ thermalization dynamics ($\sim$13s period at $\epsilon = 0.003$)
- Ideal applications: thermal drift, workload state changes, gradual system monitoring

6 Classical Dynamics Confirmation

The Leggett-Garg inequality (LGI) test probes whether the system exhibits classical or quantum-like correlations.

6.1 LGI Test Results

$$C_{12} = 1.0000 \tag{5}$$
$$C_{23} = 1.0000 \tag{6}$$
$$C_{13} = 1.0000 \tag{7}$$
$$K_3 = C_{12} + C_{23} - C_{13} = 1.0000 \tag{8}$$

Classical bound: $K_3 \leq 1$. Quantum bound: $K_3 \leq 1.5$.

Result: $K_3 = 1.0$ (exactly at classical boundary)

The system exhibits classical dynamical behavior with perfect temporal correlations, consistent with deterministic chaotic dynamics.

7 Implementation

7.1 Recommended Configuration

```
from ciris_sentinel import Sentinel, SentinelConfig

config = SentinelConfig(
    epsilon = 0.003,              # Optimal coupling
    noise_amplitude = 0.001,      # Stochastic resonance optimal
    use_r_ab_reset = True,        # Reset when r_ab > 0.98
    r_ab_reset_threshold = 0.98, # Thermalized threshold
    r_ab_sensitive_threshold = 0.95,  # TRANSIENT threshold
    detection_threshold = 0.009, # 3 validated
)
```

```
sensor = Sentinel(config)
state = sensor.step_and_measure_full()
# Returns: k_eff, variance, dk_dt, sensitivity_weight, r_ab,
#          regime, sensitivity_multiplier, time_since_reset
```

7.2 Detection Channels

Channel	Metric	Correlation	Use Case
Tamper/workload	k_{eff} mean	$p = 0.007$	State change detection
Thermal state	k_{eff} variance	$r = -0.97$	Temperature monitoring
Sensitivity	r_{ab}	$r = -0.999$	Adaptive operation

Table 6: Three validated detection channels.

8 Conclusion

We have presented a validated GPU-based chaotic oscillator system with three distinct sensing capabilities:

1. **Tamper detection** via k_{eff} mean ($p = 0.007$)
2. **Thermal sensing** via k_{eff} variance ($r = -0.97$)
3. **Sensitivity prediction** via r_{ab} ($r = -0.999$)

The system operates optimally at coupling strength $\epsilon = 0.003$, achieving $562\times$ signal improvement while maintaining 64% time in the sensitive regime. The scaling law $\tau \propto \epsilon^{-1.06}$ enables predictive control of dynamics.

The detector functions as a slow-change sensor (sensitive to < 0.5 Hz), making it suitable for monitoring gradual system state evolution including thermal drift and workload changes.

All findings are established through null hypothesis testing with reported statistical significance, providing a solid foundation for practical deployment.

References

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A Validated Parameters Summary

Parameter	Value	Source
Optimal coupling (ϵ)	0.003	Coupling sweep
Optimal noise (σ)	0.001	Stochastic resonance
Thermalization time (τ) at $\epsilon = 0.003$	12.8 s	Measured
Scaling exponent	-1.06	Power law fit
Detection threshold	0.009	3σ validated
TRANSIENT threshold (r_{ab})	< 0.95	Sensitivity analysis
Reset threshold (r_{ab})	> 0.98	Regime analysis
Tamper detection	$p = 0.007$	Null hypothesis test
Thermal correlation	$r = -0.97$	Regression
Sensitivity prediction	$r = -0.999$	Regression
Signal improvement	562$\times$	vs $\epsilon = 0.0003$
TRANSIENT/THERMALIZED ratio	2724$\times$	Variance comparison
LGI result (K_3)	1.0	Classical boundary

Table 7: Complete validated parameters.