Diagnostic Test Generation for Fault Localization in Printed Neuromorphic Circuits

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***Abstract*—Printed electronics (PE) enable lightweight, flexible, and low-cost devices for the Internet of Things (IoT) and wearable applications. Compared to conventional silicon-based electronics, PE trades peak performance for advantages in cost efficiency, mechanical flexibility, and large-area fabrication. However, its manufacturing processes remain unreliable and are prone to structural defects and variation due to inherent limited control in additive manufacturing. Printed neuromorphic circuits (pNCs) leverage the benefits of PE for on-demand analog edge computation in target applications but remain vulnerable to such defects. Diagnostic testing is therefore essential not only for detection but also for localizing faults to specific subcircuits and regions in the layout, a step critical for guiding yield improvement and reducing the cost of downstream inspection. We propose a diagnostic test pattern generation (DTPG) framework for fault localization in pNCs under black-box access. While ATPG is typically formulated as an optimization problem for fault detection, our approach extends this formulation by explicitly optimizing for fault distinguishability. On ten UCI datasets, the framework achieves up to 20.7% higher diagnostic coverage with a reduction of up to 3.6 times the number of undetectable subcircuits than detection-only test sets, while constraining the number of patterns to reduce storage overhead. These results demonstrate effective fault localization and establish a foundation for finer-grained, component-level diagnosis in future work.**

***Index Terms*—diagnostic test pattern generation, printed electronics, neuromorphic computing**

I. Introduction

Printed electronics (PE) enable low-cost, lightweight, and flexible hardware for edge applications where conventional silicon-based hardware is economically or mechanically impractical (e.g., smart packaging, wearables, large-area IoT) [1]–[4]. However, unlike mature silicon fabrication, additive printing processes suffer from limited resolution and higher variability, leading to opens/shorts and parameter drift that degrade functionality and lifetime.

For the target application domain of PE, printed neuromorphic circuits (pNCs) enable on-demand analog edge computing by offering bespoke mapping of machine learning models to analog hardware for low hardware footprint, but their reliability is challenging: pNCs are highly sensitive to defects, as they rely on dense interconnectivity, analog signal fidelity, and temporal stability and pNCs typically expose only black-box I/O without digital Design-for-Test (DfT) (e.g., scan chains). This motivates compact *diagnostic* strategies that not only detect faulty behavior but also *localize* faults to actionable primitives.

Digital Automatic Test Pattern Generation (ATPG) and Diagnostic Test Pattern Generation (DTPG) has a long history [5]–[9], but logic-level formulations do not translate to analog pNCs. Analog diagnosis often relies on data-driven classifiers [10]–[14], which typically assume internal node access and are not tailored to catastrophic open/short defects prevalent in PE. Recent gradient-based ATPG achieves detection for pNCs under black-box access [15], but does not explicitly optimize localization by separating fault candidates across primitives.

Therefore, we propose an optimization methodology for **diagnostic test generation for fault localization in pNCs** to pinpoint faulty subcircuits or primitive in terms of pNC. We consider pNCs composed of reusable primitives such as resistor crossbars for weighted summation and printed nonlinear blocks (e.g., *p-inv*, *p-tanh*) for signed weights and activation [16]–[18]. Faults in PE are dominated by catastrophic opens/shorts and process variability [19], [20]. We focus on catastrophic primitive-level faults under a single-fault assumption and characterize their behaviors via SPICE-based transfer-function approximations for efficient evaluation [15], [21]. The work makes two main contributions:

- **Diagnostic objective for localization:** We extend gradient-based ATPG to a diagnostic setting by jointly optimizing (i) fault detection and (ii) primitive-level separability among faulty behaviors.
- **Compact test sets under a fixed budget:** We constrain test set size for practical storage limits. Under the same budget, we achieve **20.7%** higher diagnostic coverage and a **3.6**$\times$ reduction in undetected primitives (under the generated test set) compared to detection-only ATPG.

II. Proposed Diagnostic Test Generation

Moving beyond fault detection, this work addresses the challenge of high-precision, subcircuit-level fault localization in pNCs. Catastrophic defects in pNCs often produce highly similar output behaviors, making them indistinguishable under

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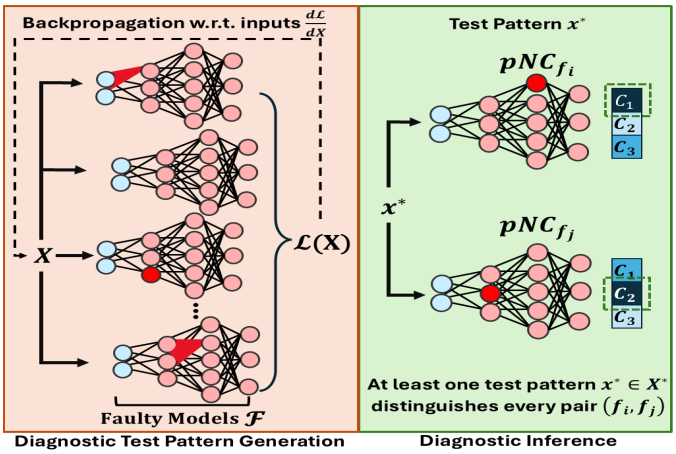

Fig. 1: Overview of the proposed diagnostic test pattern generation framework.

conventional ATPG. To overcome this, we propose a DTPG framework that explicitly optimizes fault distinguishability under practical test-set size constraints. We therefore formalize DTPG as an optimization problem with limited test-set size.

As shown in Fig. 1, given black-box access to a fault-free pNC $y(\cdot)$ and a set of single-fault instances $\{y^f(\cdot)\}_{f\in\mathcal{F}}$, we seek a compact test set $\mathcal{X}^\star = \{\mathbf{x}_1, \ldots, \mathbf{x}_m\}$ of fixed size m that (i) detects faults and (ii) improves *coarse localization* by separating faults originating from different primitives. We directly optimize the test inputs $\mathcal{X}$ subject to valid input bounds $\mathbf{x}_k \in [\mathbf{x}_{\min}, \mathbf{x}_{\max}]$ (element-wise) and a fixed budget.

A. Diagnostic Objective Function

For an input x, let $y^0_{\mathbf{x}}$ be the fault-free output and $y^f_{\mathbf{x}}$ the output under fault f. We optimize a joint objective:

$$\mathcal{L}(\mathcal{X}) = \max_{\mathbf{x}\in\mathcal{X}} \{\mathcal{L}_{\text{det}}(\mathbf{x}) + \lambda\, \mathcal{L}_{\text{loc}}(\mathbf{x})\}\,, \tag{1}$$

where $\lambda > 0$ balances detection and localization. The detection term $\mathcal{L}_{\text{det}}(\mathcal{X}) = \mathbb{E}_{f\sim\pi}\left[\max_{\mathbf{x}\in\mathcal{X}} d\big(y^0_{\mathbf{x}}, y^f_{\mathbf{x}}\big)\right]$, encouraging at least one test input to separate each fault from the fault-free behavior.

Let p_f map a fault to its primitive. We encourage separability between faults from different primitives with the localization term: $\mathcal{L}_{\text{loc}}(\mathcal{X}) = \mathbb{E}_{f,f'\sim\pi}\left[(-1)^{[p_f=p_{f'}]} \max_{\mathbf{x}\in\mathcal{X}} d(y^f_{\mathbf{x}}, y^{f'}_{\mathbf{x}})\right]$. We use $d(\cdot,\cdot)$ as either ℓ_2 distance or KL divergence between output vectors.

B. Optimization and Fault Sampling

We initialize $\mathcal{X}$ from valid samples and optimize Eq. 1 the Adam [22] optimization method. The expectations in $\mathcal{L}_{\text{det}}$ and $\mathcal{L}_{\text{loc}}$ are approximated via Monte Carlo sampling of faults (we use uniform $\pi(f)$; non-uniform priors can be incorporated without changing the framework).

C. Diagnostic Metrics

Diagnostic coverage. A primitive is detectable under $\mathcal{X}$ if there exists a fault f in that primitive and an input $\mathbf{x} \in \mathcal{X}$ such that $y^0_{\mathbf{x}} \neq y^f_{\mathbf{x}}$. Among detectable primitives, a pair of primitives is distinguishable under $\mathcal{X}$ if their induced faulty signatures do not overlap. We report:

$$\text{DiagCov}(\mathcal{X}) = \frac{\#\{\text{distinguishable detectable primitive pairs}\}}{\#\{\text{detectable primitive pairs}\}}. \tag{2}$$

Undetected primitives. We additionally report the number of primitives that are *undetected under* $\mathcal{X}$, i.e., no fault within the primitive has a different output from pNC with that fault-free primitive for any $x \in X$.

TABLE I: Per-dataset diagnostic performance at $|X| = 50 \times |T|_{\min}$.

Dataset	**Proposed** Cov (%)	**Proposed** Undet (%)	Data-driven Cov (%)	Data-driven Undet (%)	ATPG(det.) Cov (%)	ATPG(det.) Undet (%)
AcuteInf	70.6	15.0	38.0	5.0	46.4	60.0
BreastCa	64.9	0.0	64.5	0.0	74.6	66.7
Energy-1	83.3	4.0	71.3	24.0	64.1	28.0
Energy-2	84.0	0.0	60.5	20.0	67.8	24.0
Iris	72.5	14.3	65.0	23.8	71.9	14.3
Mammo	40.0	35.0	38.5	35.0	50.0	35.0
PenDig	84.9	2.1	83.2	2.1	79.5	72.9
Seeds	84.6	8.0	72.8	4.0	68.1	4.0
TicTac	34.6	4.3	41.1	4.3	28.6	4.3
VertCol	83.2	4.7	60.0	0.0	79.5	4.7
Avg	**71.8**	**8.7**	59.5	11.8	63.1	31.2

III. Evaluation

A. Setup

We assume a single-fault model and characterize catastrophic opens/shorts at the primitive level. Fault behaviors for *p-tanh* and *p-inv* are pre-characterized via SPICE (Cadence Virtuoso) using the nEGT P-PDK [23], yielding 12 fault subtypes for *p-tanh* and 18 for *p-inv*; crossbar resistor faults are modeled by a ternary mask M_g. We evaluate ten pNCs models trained on UCI datasets [24].

B. Results

We compare against (i) a *data-driven sensitivity* baseline that selects high-gradient training samples as tests, and (ii) a detection-only gradient-based ATPG baseline adapted to optimize a fixed-size set (i.e., without $\mathcal{L}_{\text{loc}}$) [15]. All methods use the same test budget $|X| = 50 \times |T|_{\min}$, where $|T|_{\min}$ is the lower bound on the number of patterns required to distinguish primitives.

As shown in Table I, at the same test budget, the proposed DTPG improves average diagnostic coverage by **+20.7%** over the data-driven baseline and by **+13.8%** over detection-only ATPG, while reducing undetected primitives by **1.4**× and **3.6**×, respectively. Crucially, DiagCov must be interpreted alongside Undet. since high coverage can be inflated if many primitives remain undetected. These results indicate that our localization objective improves both distinguishability and the fraction of primitives that become observable under the compact test set.

IV. Conclusion

We proposed a black-box DTPG method for coarse primitive-level localization in pNCs using a compact, optimized test set. At a fixed test budget, it improves average diagnostic coverage by **20.7%** and reduces undetected primitives by **3.6**× versus detection-only ATPG.

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