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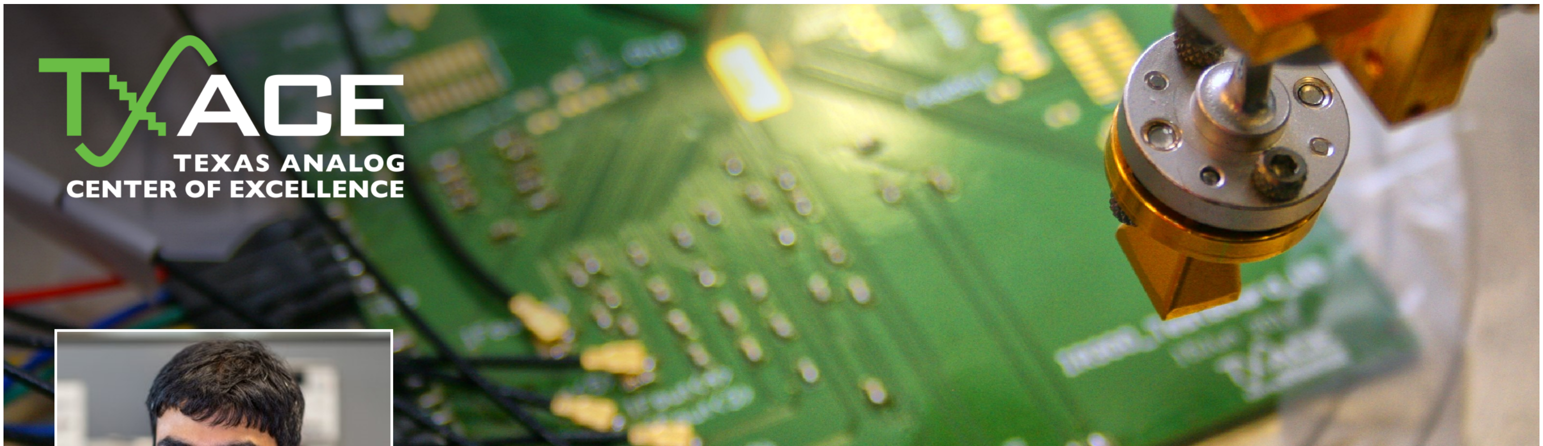

Unsupervised Learning-based Early Anomaly Detection in Automotive AMS Circuits

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BIO

Kanad Basu received his Ph.D. from the department of Computer and Information Science and Engineering, University of Florida. His thesis was focused on improving signal observability for post-silicon validation. Post-PhD, Kanad worked in various semiconductor companies like IBM and Synopsys. During his PhD days, Kanad interned at Intel. Currently, Kanad is an Assistant Professor at the Electrical and Computer Engineering Department of the University of Texas at Dallas, where he leads the Trustworthy and Intelligent Embedded Systems (TIES) lab. Prior to this, Kanad was an Assistant Research Professor at the Electrical and Computer Engineering Department of NYU. He has authored 1 book, 2 US patents, 2 book chapters and several peer reviewed journal and conference articles. He has graduated 1 PhD student and currently, his lab has 8 PhD students. Kanad was awarded the "Best Paper Award" at the International Conference on VLSI Design 2011 and an honorable mention award at the same conference in 2021. Several News agencies have covered his research including NBC Austin and CBS Dallas-Fort Worth. Kanad's current research interests are hardware and systems security, functional safety, deep learning hardware and quantum computing. Undergraduate and graduate teams mentored by Kanad has won several national and international cybersecurity competitions. His research is supported by NSF, SRC, DARPA and Ford Motors. His research team is part of TxACE (Texas Analog Center of Excellence) and CHEST IUCRC.

ABSTRACT

With the proliferation of safety-critical applications in the automotive domain, it is imperative to guarantee the functional safety of circuits and components constituting automotive systems, e.g., the electrical and/or electronic subsystems in automotive vehicles. Analog and Mixed-Signal (AMS) circuits, prevalent in such systems, are more susceptible to faults than their digital counterparts, due to parametric perturbations, noise, environmental stress, among others. However, their continuous signal characteristics provide an opportunity for early anomaly detection, which in turn, facilitates the deployment of safety mechanisms to prevent eventual system failure. Towards this end, we propose a novel unsupervised machine learning-based framework to perform early anomaly detection in AMS circuits. Our approach involves anomaly injection in various circuit locations and individual components to develop a comprehensive anomaly model, feature extraction from observation signals, and clustering algorithms to facilitate anomaly detection. To this end, we propose a novel centroid selection technique for the unsupervised learning algorithms, which is tailored for detecting anomalies in AMS circuits. This approach furnishes high fidelity anomaly detection by identifying the ideal cluster centers corresponding to anomalous and non-anomalous signals. Furthermore, time series-based analysis is proposed to improve and expedite the anomaly detection performance. We evaluated our solution using a case study of two AMS circuits commonly present in automotive systems-on-chips. Our experimental results exhibit that the proposed approach furnishes up to 100% accuracy. Additionally, the time series-based technique reduces the anomaly detection latency by 5X, thereby demonstrating the efficacy of our solution.

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