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Detecting and Identifying Single Event Transients using IRES and Machine Learning

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RESEARCH DIALOGUES 2020

Detecting and Identifying Single Event Transients using IRES and Machine Learning

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Research Question

How can radiation effects on embedded systems, particularly systems in space, be mitigated by leveraging IRES and machine learning?

Introduction

A method of detecting and classifying single event transients (SETs) in devices and integrated circuits (ICs) using Ionizing Radiation Effects Spectroscopy (IRES) [1][2] and machine learning is presented. IRES is leveraged as a non-invasive interrogation (i.e., requiring only output waveforms) of single-event effects (SEE), revealing vulnerable circuit nodes identified through statistical measures of signal features that compose an IRES image. Machine learning (ML) via a k-Nearest Neighbors (KNN) algorithm is then used to classify nominal data and event data, as well as potentially identify specific circuit nodes of SETs.

1

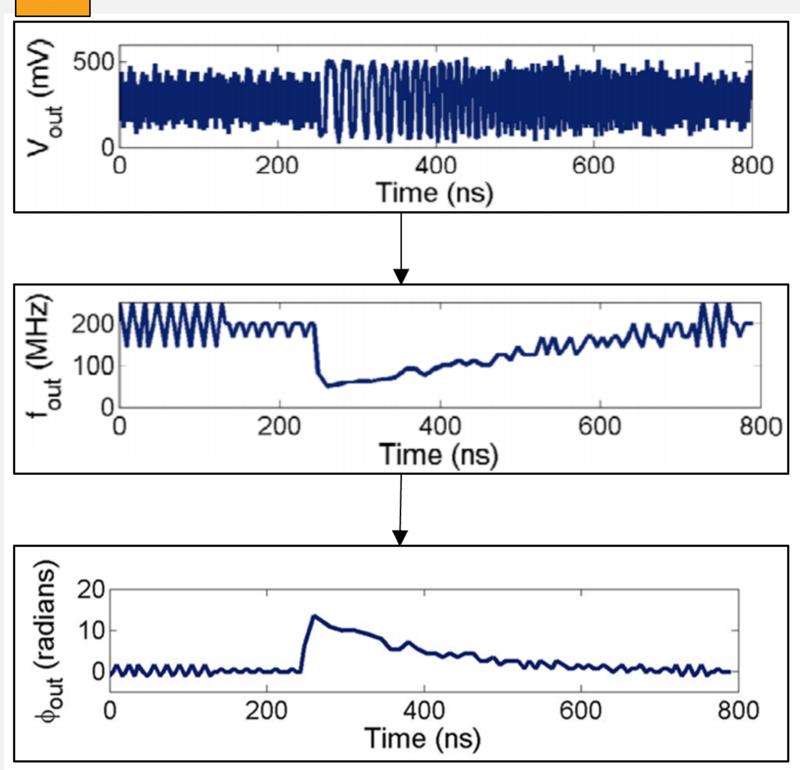

Fig. 1. Example of an output frequency/phase transient following a laser perturbation in the CP sub-circuit of the PLL fabricated in a 130 nm CMOS technology. [3]

Methodology

1. Signal Collection and Detection
2. IRES Image Generation
3. k-Nearest Neighbors
4. Data Classification

2

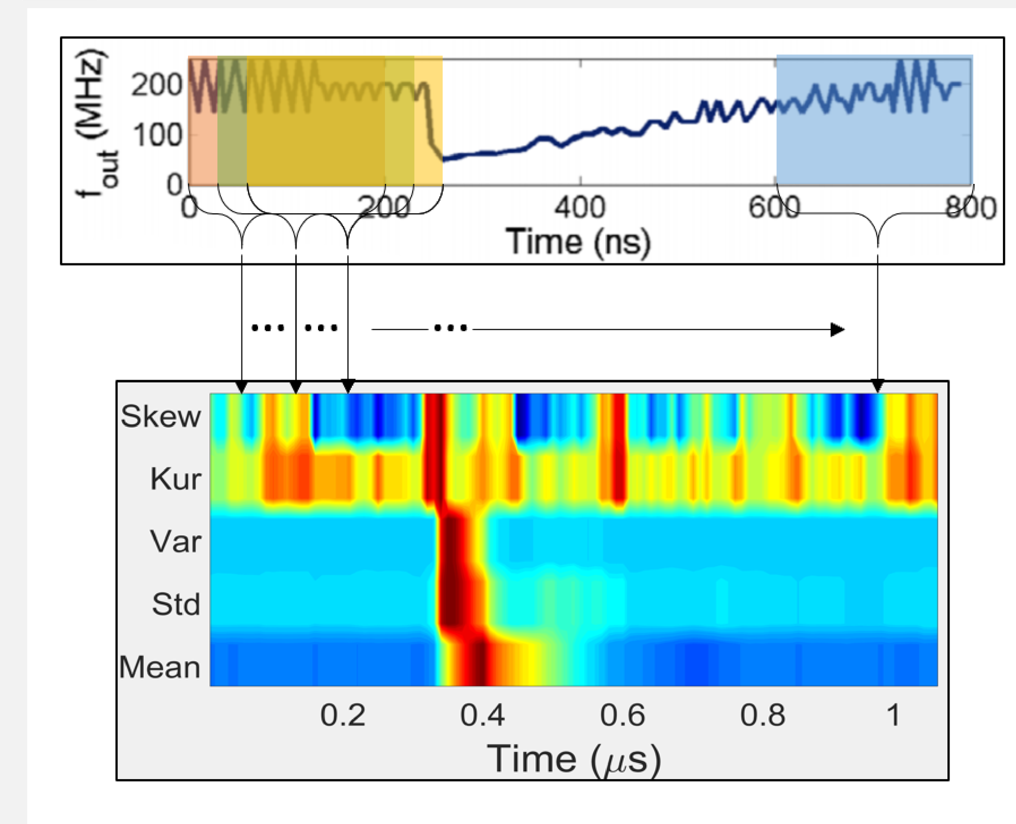

Fig. 2. Example of output frequency IRES analysis and image generation, where the change in frequency correlates to the distinct aberration in the IRES image.

4

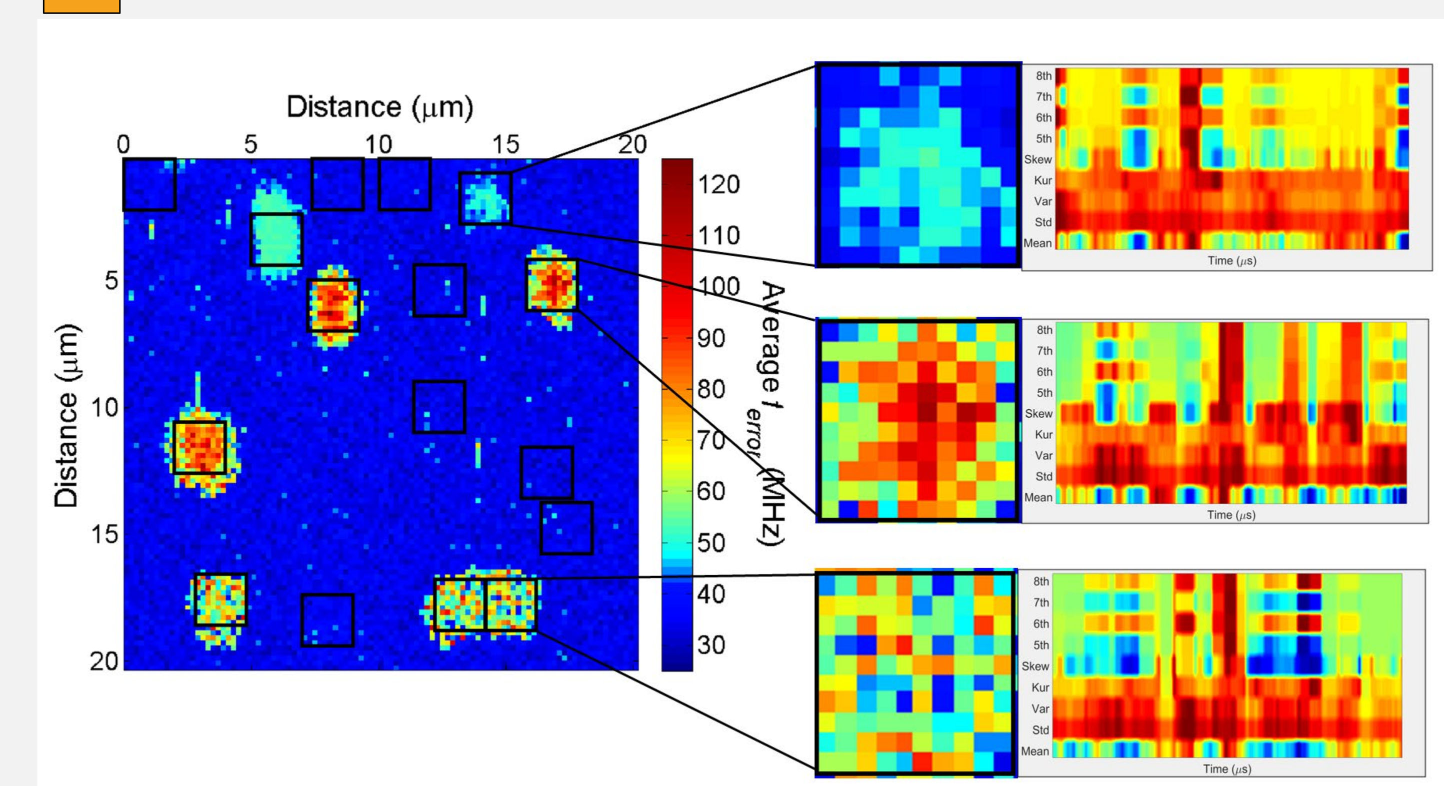

Fig. 3. The process of selecting nominal and event patches and performing IRES analysis to generate data for the KNN classifier. (Note: the IRES images in this figure are shown with additional moment generating function outputs.).

Results

TABLE I

Legend for the output confusion matrix.

Confusion Matrix Legend	Statical Measure	
Signal Transformation (#Sample Sets)	True Reject #	False Reject #
	False Accept #	True Accept #

Confusion Matrix Legend	Statical Measure	
Signal Transformation (#Sample Sets)	True Reject %	False Reject %
	False Accept %	True Accept %

TABLE II

Output confusion matrix results for the 3 types of signal transformations with individual and all statistical measures using 9 out of 10 sample sets. (Bold indicates performance greater than 95%).

	Mean		Std.Dev.		Variance		Kurtosis		Skewness		All	
c2m (9)	1151	449	**1542**	**58**	**1525**	**75**	1150	450	1279	321	**1564**	**36**
	350	1250	**61**	**1539**	**73**	**1527**	347	1253	254	1346	**29**	**1571**
c2c (9)	959	641	**1541**	**59**	**1552**	**48**	1231	369	1177	423	**1522**	**78**
	566	1034	**60**	**1540**	**68**	**1532**	326	1274	342	1258	**96**	**1504**
f (9)	**1578**	**22**	**1584**	**16**	**1598**	**2**	1212	388	1244	356	**1594**	**6**
	15	**1585**	**9**	**1591**	**0**	**1600**	320	1280	281	1319	**8**	**1592**

	Mean		Std.Dev.		Variance		Kurtosis		Skewness		All	
c2m (9)	71.9375	28.0625	**96.375**	**3.625**	**95.3125**	**4.6875**	71.875	28.125	79.9375	20.0625	**97.75**	**2.25**
	21.875	78.125	**3.8125**	**96.1875**	**4.5625**	**95.4375**	21.6875	78.3125	15.875	84.125	**1.8125**	**98.1875**
c2c (9)	59.9375	40.0625	**96.3125**	**3.6875**	**97**	**3**	76.9375	23.0625	73.5625	26.4375	**95.125**	**4.875**
	35.375	64.625	**3.75**	**96.25**	**4.25**	**95.75**	20.375	79.625	21.375	78.625	**6**	**94**
f (9)	**98.625**	**1.375**	99	1	**99.875**	**0.125**	75.75	24.25	77.75	22.25	**99.625**	**0.375**
	0.9375	**99.0625**	**0.5625**	**99.4375**	**0**	**100**	20	80	17.5625	82.4375	**0.5**	**99.5**

(a)

(b)

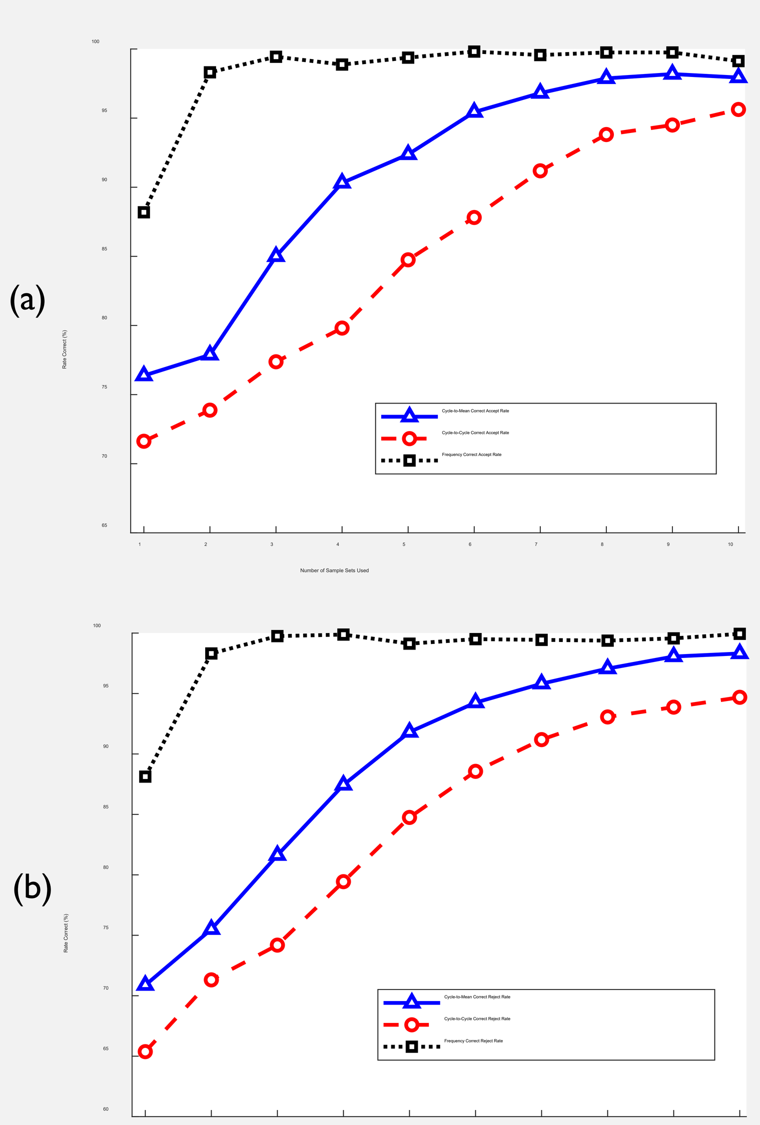

Fig. 4a. The correct acceptance rate at which additional sample sets affect classification accuracy for frequency, cycle-to-mean, and cycle-to-cycle signal transformations.

Fig. 4b. The correct rejection rate at which additional sample sets affect classification accuracy for frequency, cycle-to-mean, and cycle-to-cycle signal

- 10 sample sets processed linearly as independent measurements however, they are features in themselves and provide a better description of the data when used as such, thus improving classification.
- Greater than 95% classification is achievable for all signal transformations when all statistical measures and 9 of 10 sample sets are used.
- Event data requires a better description to be uniquely classifiable. Achieved by inclusion of additional statistical measures (5th, 6th, 7th, and 8th moments).
- Additional features boost classification capabilities in the "nominal versus event" case (greater than 99% rate using single features) but have a marginal effect on "event versus event" classification
- The frequency signal transformation requires the least input data (2 of 10 sample sets) to achieve a greater than 98% classification rate Variance and standard deviation in classification of nominal and event data with greater than 95% in all signal transformations.
- Mean also performs well when used as the single metric for classification for the frequency metric; least discriminating feature with cycle-to-mean and cycle-to-cycle signal transformations (~75% and ~62% respectively).

Conclusions

The introduction of ML to the SET analysis process adds to the utility of IRES by being able to manifest nuance contained in the output data. This utility is further improved by the introduction of higher moment generating functions to the IRES analysis. The long-term goal of this research is to establish the statistical relationships that characterize SETs and implement this knowledge gained to create an on-chip architecture that can perform IRES-KNN analysis. This milestone would be a significant step in mitigating the devastating effects radiation can have on electrical circuits and systems.

References

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