University of Central Florida

IEEE Computer Society Annual Symposium on VLSI

MRAM-based Stochastic Oscillators for Adaptive Non-Uniform Sampling of Sparse Signals in IoT Applications

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Session 12, Conference Room 223

Tuesday, July 16, 2019, 10:00 AM - 10:40 AM

ISVLSI 2019

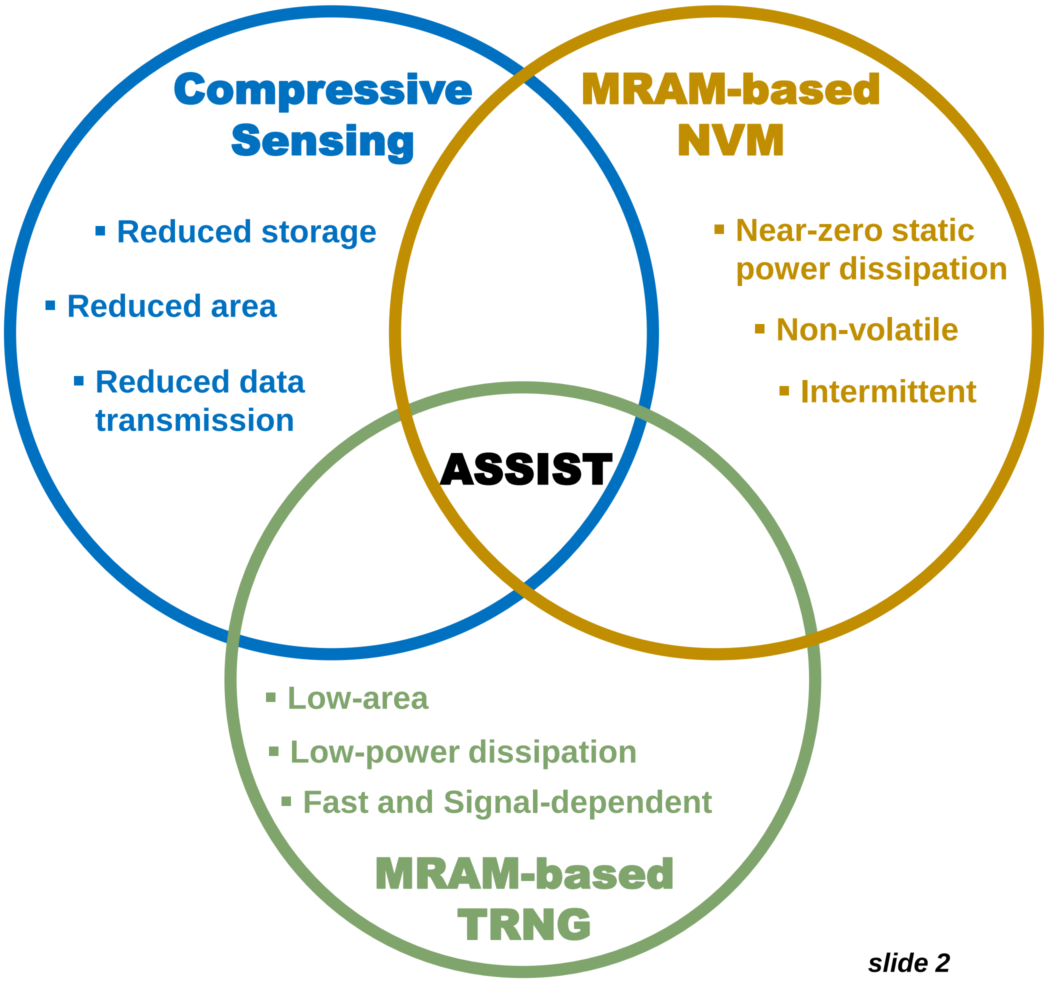
This work was supported by the **Center for Probabilistic Spin Logic for Low-Energy Boolean and Non-Boolean Computing** (**CAPSL**), one of the Nanoelectronic Computing Research (**nCORE**) Centers as task 2759.006, a Semiconductor Research Corporation (**SRC**) program co-sponsored by **NSF** through CCF-1739635 and ECCS-1810256.

Motivation

Need for CS solutions considering device-level constraints for IoT

- Maximize signal sensing and reconstruction performance while **reducing energy consumption for Internet of Things (IoT) applications**
- Solutions like **Compressive Sensing (CS)** reduces number of samples per frame to **decrease energy, storage, and data transmission overheads**
- Non-uniform CS in hardware requires Random Number Generator (RNG)
  - True RNGs (TRNGs)
  - Pseudo RNGs (PRNGs)

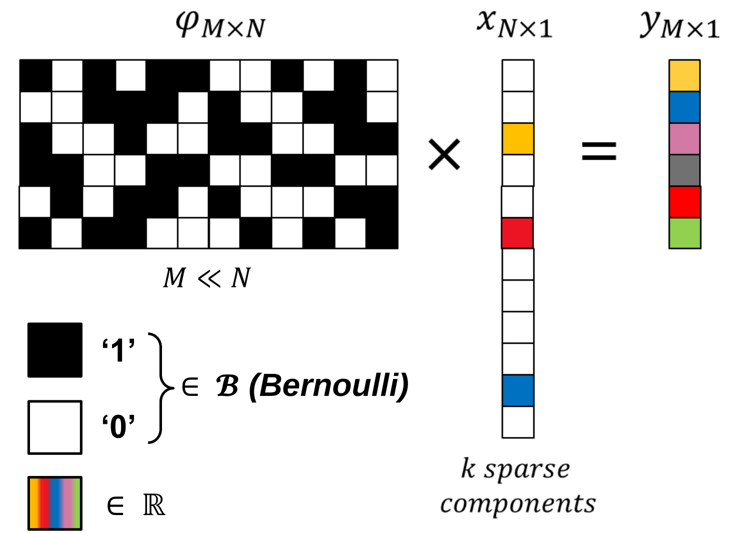
Adaptive Sampling of Sparse IoT signals via STochastic-oscillators (ASSIST)

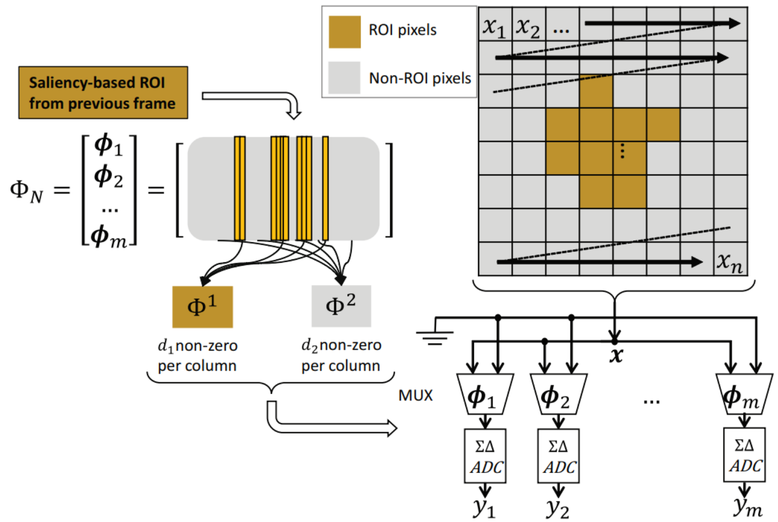


Background

Compressive Sensing (CS) and Region of Interest (RoI)

- Sparse signals are common in applications such as sensors and wireless spectrum sensing
- In real-world applications, **signals may contain a Region of Interest (RoI)** and uniform sampling is not efficient
- CS can be applied to RoI of signals, image, video, etc. identified by methods in literature*
- Signal's **sparsity may be non-uniform**
- Cornerstone to achieving high-accuracy and efficient CS is utilization of **adaptive measurement matrix** that **changes according to signal characteristics** extracted from previous time frames





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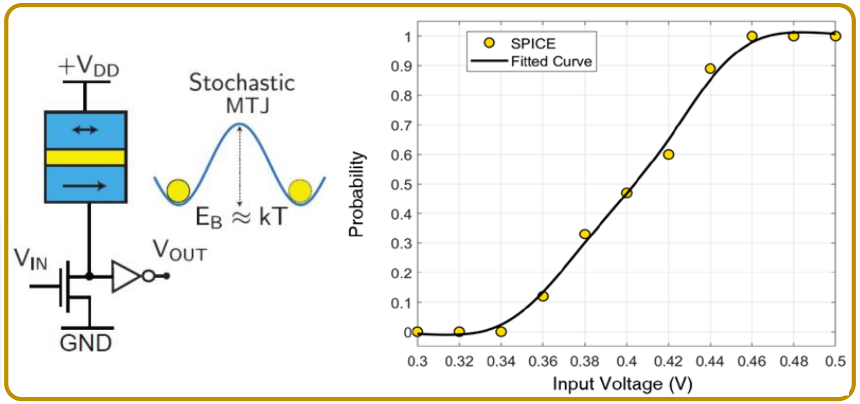
ASSIST Approach

MRAM-based Stochastic Bitstream Generator as TRNG

✓ MRAM-based Stochastic Oscillator (MSO)

Parameters of MSO

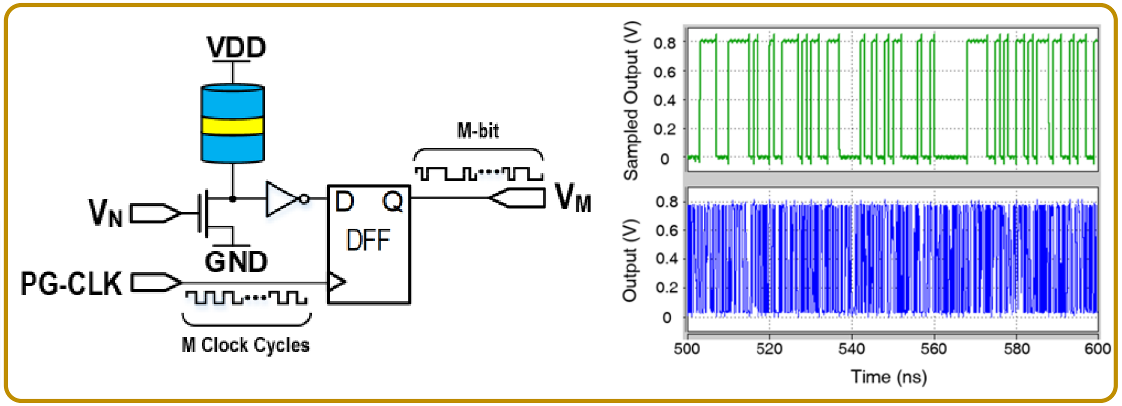
Parameters	Value
Saturation magnetization (CoFeB) (M_s)	$1100emu/cc$
Free Layer diameter, thickness	$22nm$, $2nm$
Polarization	0.59
TMR	110%
MTJ RA-product	$9\Omega - \mu m^2$
Damping coefficient	0.01
Temperature	$26.85°C$



- Due to low energy-barrier, MTJ's resistance level fluctuates between AP and P states
- Probability of output being '1' can be controlled using V_{IN}

✓ MRAM-based Stochastic Bitstream Generator

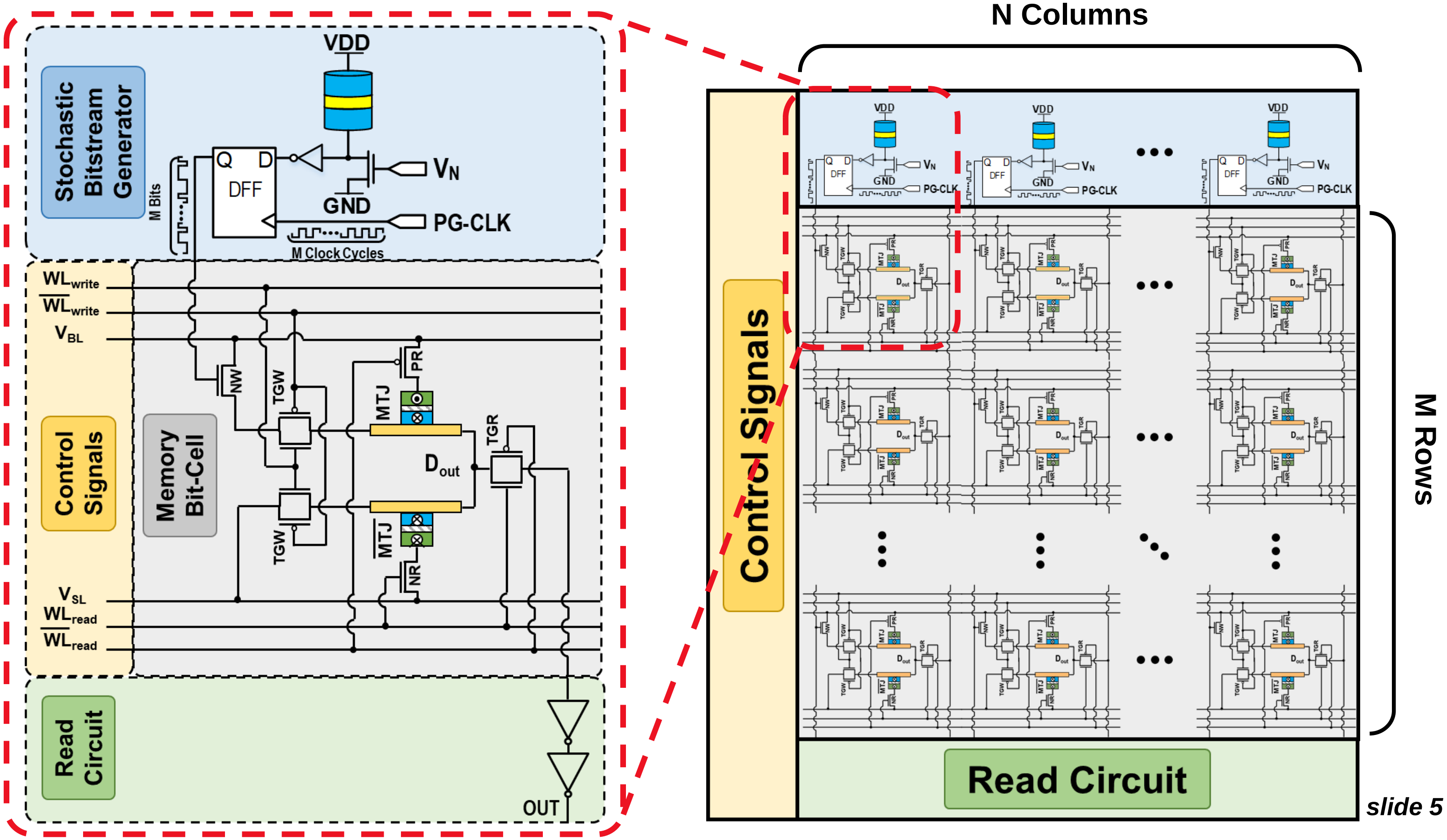
- Power-Gated Clock (PG-CLK) controls number of MSO outputs
- V_N can be used to adaptively adjust number of '1's in V_M



ASSIST Approach

MRAM-based NVM for Storing CS Measurement Matrix

- Non-volatile complementary SHE-MRAM array offers wide read margin, increased reliability, and clockless read
- MRAM-based stochastic bitstream generator for columns
- Adjust V_M to modify number of rows to account for signal's sparsity rate
- Adjust V_N to increase accuracy of RoI sensing and reconstruction

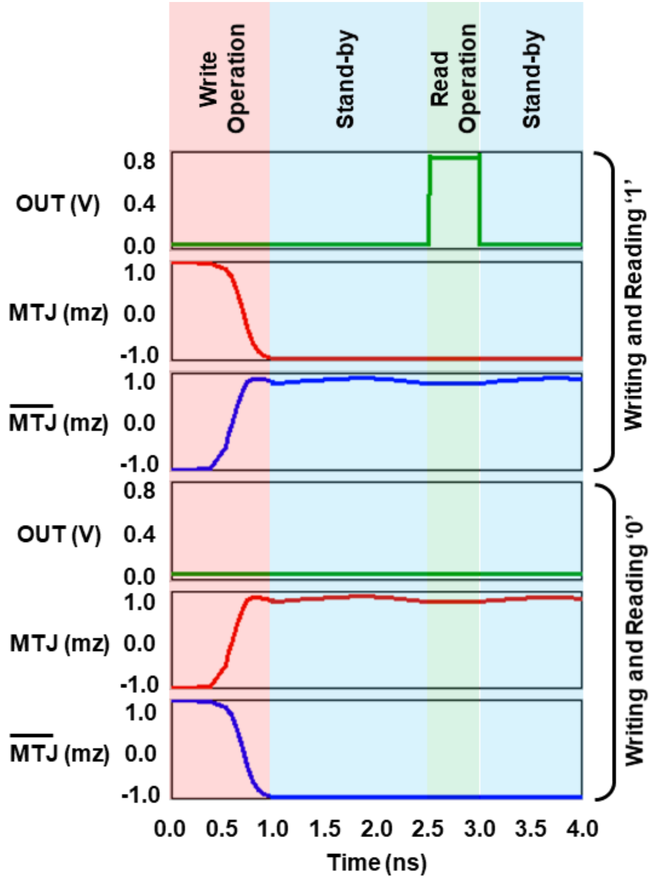


Simulation Results

MRAM-based Stochastic Oscillator and MRAM-based NVM

- NVM bit-cell requires **155.2fJ write energy** and **21.9fJ read energy**, on average
- NVM bit-cell **standby energy is 36.4aJ**
- MSO **reduces energy consumption per bit by 9-fold** and **reduces area by 3-fold**, on average, compared to state-of-the-art TRNGs

Design	Technology (V_{DD})	Energy_{norm}	Area_{norm}
[1]	28nm (1.0V)	0.3X	1.25X
[2]	28nm (1.0V)	8.9X	4.8X
[3]	28nm (1.0V)	17.4X	3.7X
This Work	14nm (0.8V)	1X	1X



[1] D. Vodenicarevic, et al., "Low Energy Truly Random Number Generation with Superparamagnetic Tunnel Junctions for Unconventional Computing," Physical Review Applied, vol. 8, p. 054045, 11 2017.

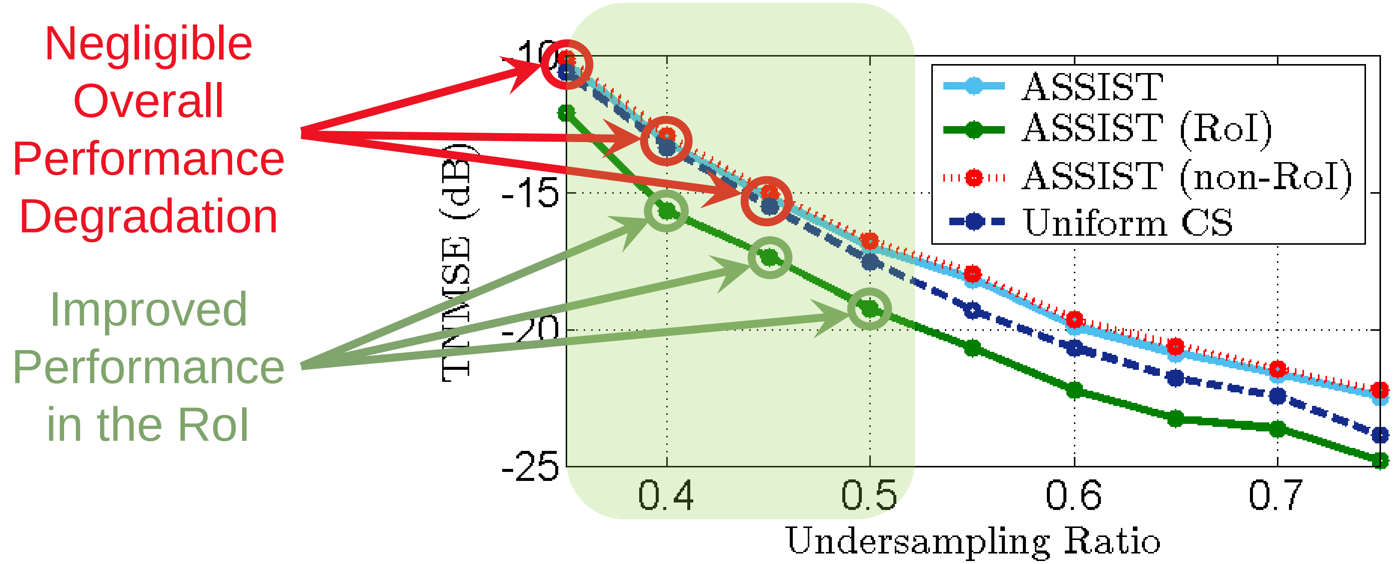
[2] Y. Qu, et al., "A True Random Number Generator Based on Parallel STT-MTJs," in Proceedings of the Conference on Design, Automation & Test in Europe (DATE '17), pp. 606–609, 2017.

[3] Y. Wang, et al., "A Novel Circuit Design of True Random Number Generator Using Magnetic Tunnel Junction," in IEEE/ACM International Symposium on Nanoscale Architectures (NANOARCH), pp. 123–128, 2016.

Simulation Results

ASSIST Approach via CS with RoI

- ASSIST **decreases** Time-Averaged Normalized Mean Squared Error **(TNMSE) of RoI coefficients up to 2dB*** at cost of reduced performance on total recovery error
  - N = 200 and various undersampling ratios, M/N
  - Sparsity level of k/N = 0.1 and RoI occupying 10% of entire signal
- For smaller undersampling ratios, ASSIST incurs no performance degradation compared to uniform CS for non-RoI entries



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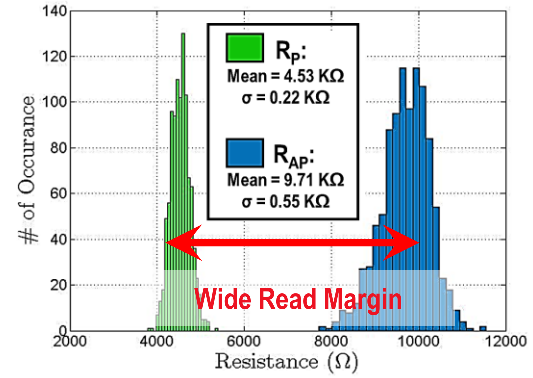
Simulation Results

Process Variation Reliability Analysis of MRAM-based NVM

1,000 Monte Carlo simulations considering:

- 10% variation on threshold voltage of CMOS transistors
- 1% variation on width and length of CMOS transistors
- 10% variation for MTJ's dimensions

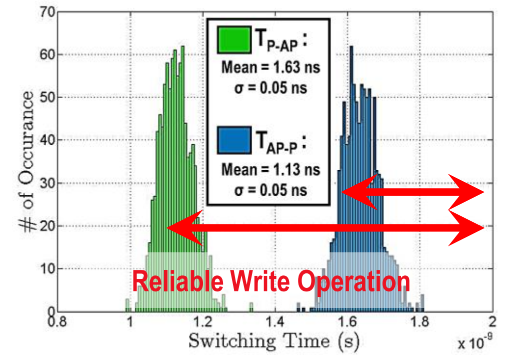


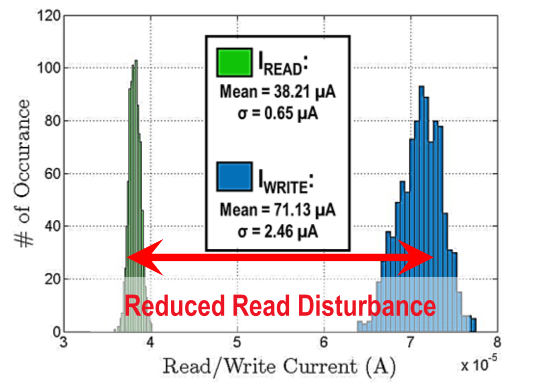
Results:

1) since states of MTJs are Complementary, they provide large sense margin, resulting in **<0.001% read errors**

2) Complementary SHE-MRAM provides reliable write performance resulting in **<0.001% write errors**

3) Complementary SHE-MRAM **does not suffer from read disturbance error** due to small read current compared to write current

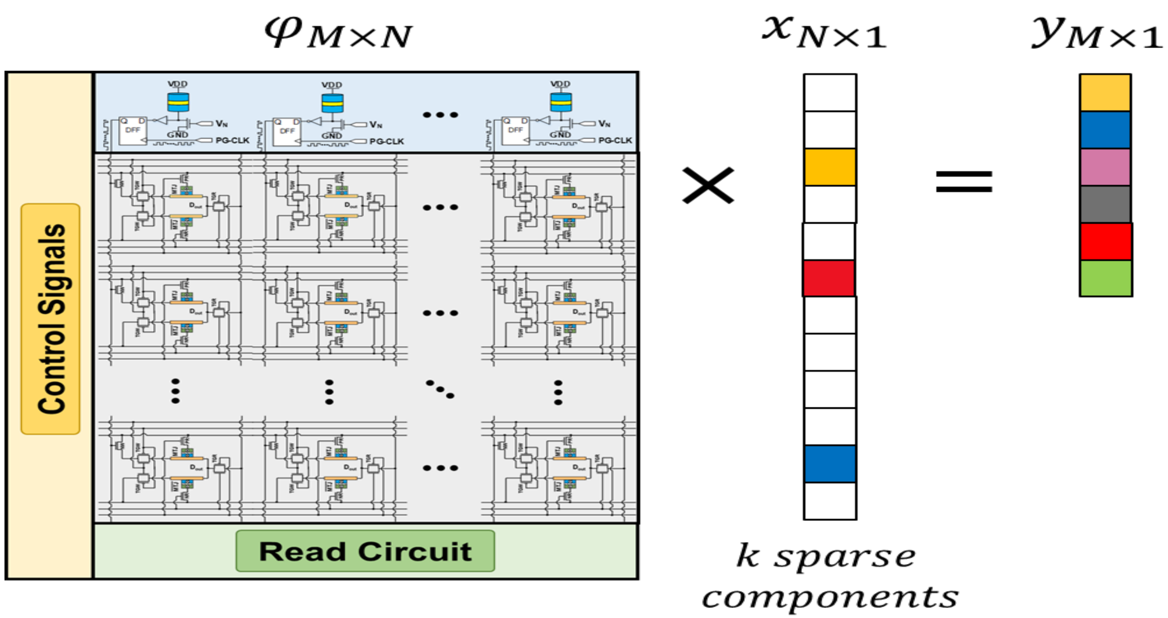




Conclusion

ASSIST for Low-Power and Area-Efficient IoT Applications

- **ASSIST** offers a spin-based non-uniform CS **circuit-algorithm solution** that **considers signal dependent and hardware constraints**
- **MRAM-based Stochastic Oscillator** as a TRNG provides **3-fold area improvement** while achieving **9-fold reduction in energy consumption per bit** compared to similar TRNGs in the literature
- In **ASSIST**, sensing energy is distributed less wastefully by **assigning more sensing energy to coefficients in RoI**
- Our **circuit-algorithm simulation** results indicate **non-uniform recovery** of original signals with **varying sparsity rates and noise levels**

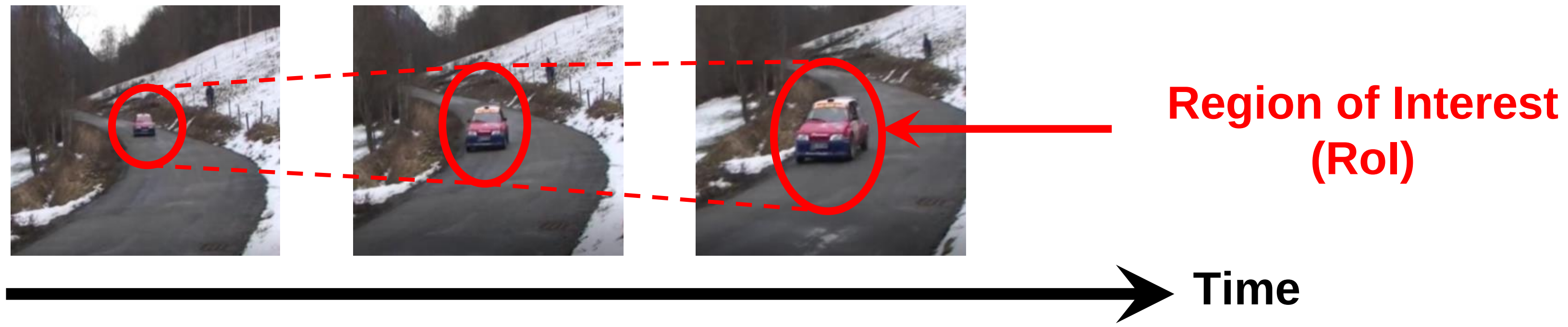


BACKUP

Background

Adaptive Non-uniform CS with Bayesian Data Analysis and Inference

- Importance level of the coefficients and **RoI** are **inferred using a Bayesian data mining** framework**
- Design **measurement matrix** such that **more important coefficients** with **more sensing energy** can be recovered
- Exploit **temporal and spatial correlation** to **design measurement matrix** at each step to sample more intelligently
- Bayesian Inference: Given the effect/output find the cause/input
- Using Bayesian inference, we predict the RoI from history of signal at each frame



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