BERRY: Bit Error Robustness for Energy-Efficient Reinforcement Learning-Based Autonomous Systems

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Background & Motivation

❖ **Background: A growing demand for on-device auto. system**

✓ Two bottlenecks: size-weight-and-power constraint + safety-critical

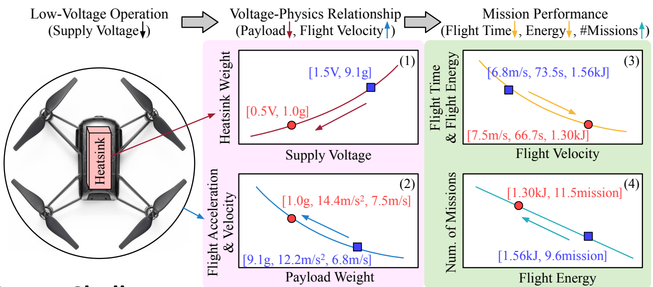
✓ Lowering operating voltage: reduce energy quadratically but induce bit errors bringing reliability concern

❖ **A Startling Observation**

✓ Processing energy (3%) vs. Mechanical energy (97%) in auto. system

✓ Processing energy has huge impacts on auto. system energy

✓ Low voltage -> Low payload -> high safe flight velocity



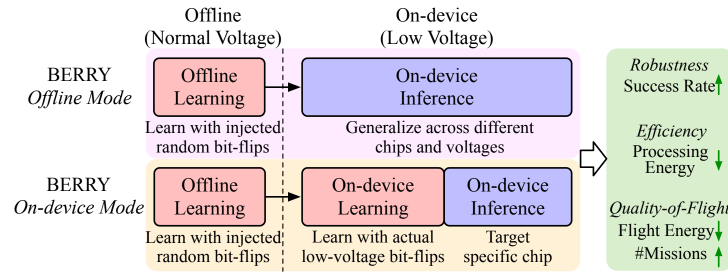
❖ **Target Challenge**

✓ Enable aggressive energy-saving yet computational-safe auto. system under low-voltage (performance-efficiency-resilience co-optimization)

Proposed BERRY Framework

❖ **The Proposed Framework: Bit-Error Robustness for Energy-Efficient RL-Based Autonomous System (BERRY)**

✓ Robust learning framework, applies error-aware training to optimize system robustness, thus boosting processing efficiency and improving mission-level performance under low operating voltage.



❖ **Key Features:**

✓ For the first time, demonstrate the practicality of robust low-voltage operation on unmanned aerial vehicles (UAVs)

✓ Support both offline and on-device robust learning

✓ Generalize across devices, voltages, environments, models, tasks, algorithms, UAV types, etc

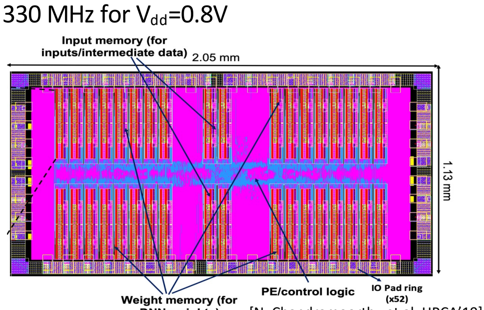
SRAM Macro

❖ **SRAM Macro**

✓ 2.05mm x 1.13mm in 14nm tech node

✓ 128 KB weight memory, 16 KB input memory

✓ 330 MHz for V_{dd}=0.8V



[N. Chandramoorthy et al. HPCA'19]

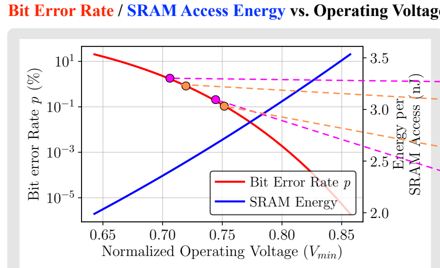
Voltage, Energy, Bit Error Silicon Measurement

❖ **Energy and Low-Voltage Operation**

✓ Reducing voltage leads to energy savings but exponentially increasing bit error rates

✓ Normalized to min error-free voltage

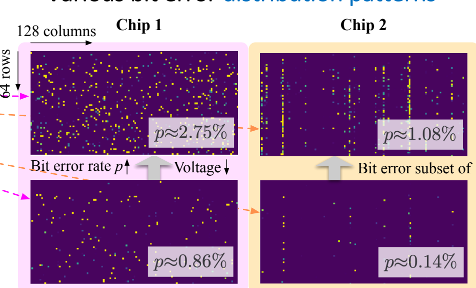
Bit Error Rate / SRAM Access Energy vs. Operating Voltage



❖ **Exemplary SRAM Bit Error Patterns**

✓ Inclusive fault model: bit errors under high voltage are subset of lower voltage

✓ Various bit error distribution patterns

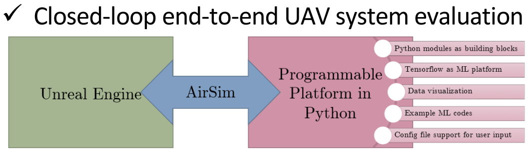


[D. Stutz et al. MLSys'21]

Evaluation Results

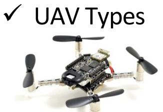
❖ **Evaluation Setups**

✓ Closed-loop end-to-end UAV system evaluation



✓ Environments: sparse, medium, dense

✓ UAV Types



Bitcraze Crazyflie

Nano-UAV
27g takeoff weight
15g max payload
250mAh battery

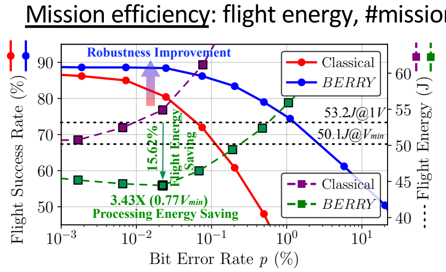
DJI Tello

Micro-UAV
80g takeoff weight
70g max payload
1100mAh battery

❖ **Resilience-Efficiency Improvement**

✓ **Observation:** improve resilience, processing efficiency, and mission efficiency over classical RL system

✓ **Metric**: Resilience: mission success rate
Processing efficiency: processing energy
Mission efficiency: flight energy, #mission



❖ **On-Device BERRY Robust Learning**

✓ **Observation:** on-device BERRY enables more energy savings, improved resilience with lower operating voltage over offline BERRY

✓ Learn bit errors directly at low-voltage chips

✓ Trade off learning-consumed on-the-fly energy and mission efficiency

Low-Voltage Operation				**Operating Efficiency**	**Robustness**	**Quality-of-Flight**	
Num. of Learning Steps		Operating Voltage	Learning Energy (J)	Energy Savings	Success Rate (%)	Flight Energy (J)	Num. of Missions*
On-Device BERRY	4000	$0.77V_{min}$	1849	3.43×	84.6	264.2	48.19
		$0.70V_{min}$	1807	4.16×	82.4	266.5	46.52
	6000	$0.77V_{min}$	2775	3.43×	85.0	260.9	49.03
		$0.70V_{min}$	2711	4.16×	84.8	**255.1**	**50.01**
Offline BERRY		$0.77V_{min}$	-	3.43×	84.4	265.5	47.84
		$0.70V_{min}$	-	4.16×	63.8	375.6	25.56
Baseline		$1V$	-	1×	85.2	294.7	43.50

* Does not include on-device learning flight energy, evaluated for missions after learning.

Paper   Website

Acknowledgments

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