A Seizure-detection IC Employing Machine Learning to Overcome Data-conversion and Analog-processing Non-idealities

J. Zhang, L. Huang, Z. Wang and N. Verma, Princeton University

PRINCETON UNIVERSITY

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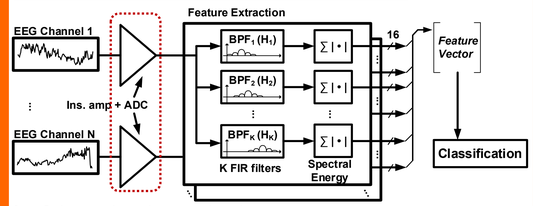
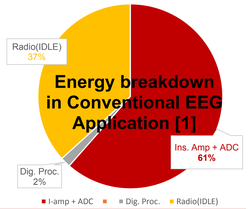
CONVENTIONAL SEIZURE –DETECTOR [1]

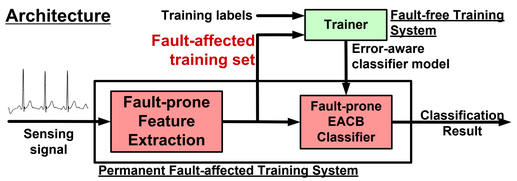


In Seizure detection, and other biomedical applications, high quality signal analysis first requires sensor outputs to be acquired with high accuracy. Given the low amplitude of signals, high impedance of electrodes, and prominence of artifacts (stray coupling, electrode interfacing/movement), the analog front end (instrumentations amplifiers and ADCs) often dominate energy.

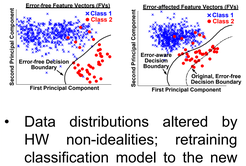


Use machine-learning algorithms to relax analog front-end

Data-Driven Hardware Resilience (DDHR) [2]

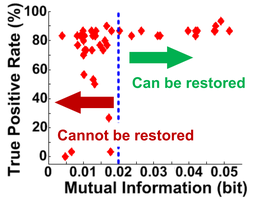


Error-aware Modelling



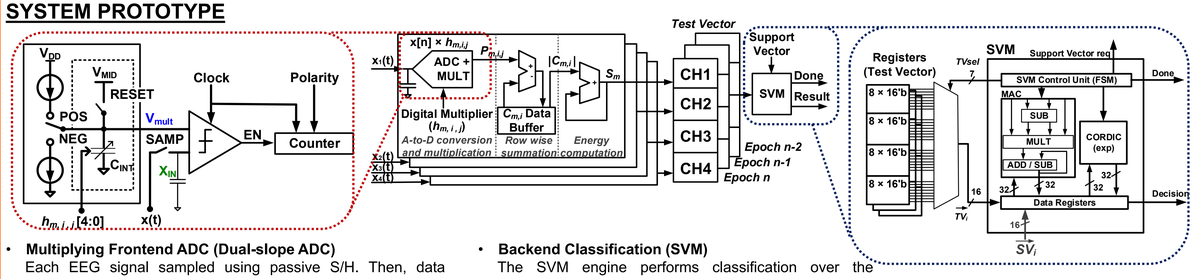
- Data distributions altered by HW non-idealities; retraining classification model to the new distributions yields an **Error-Aware Model, limited by information loss**

Fundamental Limitation



[1] N. Verma, A. Shoeb, J. Bohorquez, J. Dawson, J. Guttag, and A. P. Chandrakasan, "A micropower EEG acquisition SoC with integrated feature extraction processor for a chronic seizure detection system," IEEE J. Solid-State Circuits, vol. 45, no. 4, pp. 804–816, Apr. 2010.
[2] Z. Wang, K. H. Lee, and N. Verma, "Overcoming computational errors in sensing platforms through embedded machine-learning kernels," IEEE Trans. VLSI Syst., DOI: 10.1109/TVLSI.2014.2342153.

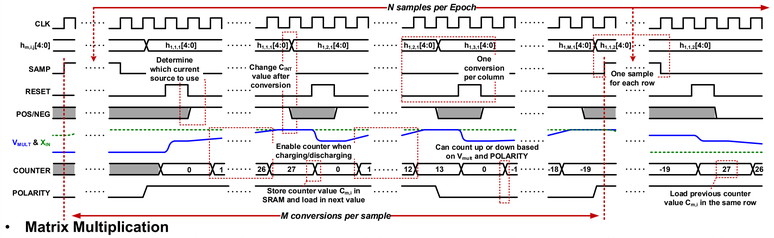
SYSTEM PROTOTYPE



- **Multiplying Frontend ADC (Dual-slope ADC)**
  Each EEG signal sampled using passive S/H. Then, data conversion is performed by measuring the time (number of cycles) needed to charge/discharge a variable integration cap C_{INT} to the sampled voltage X_{IN}. The variable cap effectively enables multiplication during conversion.

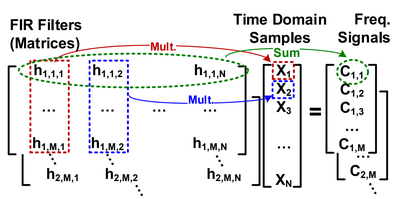
- **Backend Classification (SVM)**
  The SVM engine performs classification over the computed feature vector by using a model that is preloaded from training. The on-chip SVM is capable to implement a linear kernel, polynomial kernel, and a radial-basis function (RBF) kernel.

ADC OPERATION WAVEFORM

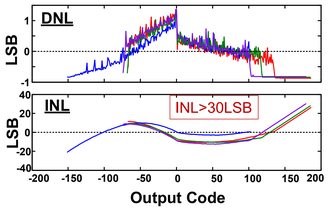


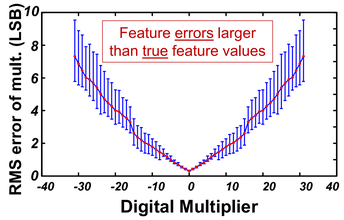
- **Matrix Multiplication**
  One sample can be used for multiple conversions. Between conversions, the charge on C_{INT} will be reset to V_{MID}. For matrix multiplication, conversion is performed column-by-column as input samples are acquired. Row-wise summation is performed by store/load each intermediate result in a buffer (SRAM).

MATRIX MULTIPLICATION



ADC PERFORMANCE

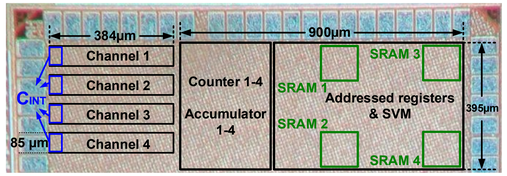




- **Severe Non-linearity**
  Such implementation of ADC in 32nm technology suffers from severe nonlinearity. DNL is 1.5 LSB and INL is >30 LSB at 8-b level

- **High RMS Error**
  The nonlinearity leads to large RMS error of the features; when normalized to the ideal feature values, the RMS error is measured to be 1.16, indicating errors larger than the feature values themselves.

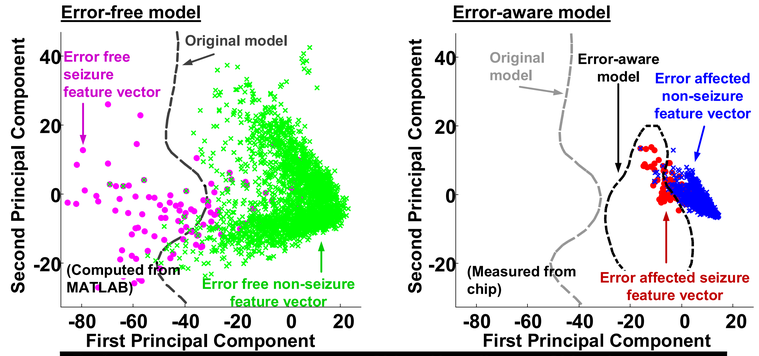
DIE PHOTO



CHIP SUMMARY

Technology	32nm CMOS SOI	Sample Rate	Up to 5kHz (typ. 64Hz)
Supply Voltage	Analog: 0.9 V Digital: 0.9 V SRAM: 0.9 V	ADC ENOB	2.8-3.6 (f_{in} = 100 Hz)/ 2.1-2.6 (f_{in} = 1k Hz)
		ADC INL/DNL	20.8-30.1/1.2-1.4 (LSB)
ADC Resolution	8 bits	Energy / Feature Vector	12.04 uJ / Feature Vector
Input Range	200 mV - 700 mV	Energy / class.	1.35 uJ / class.

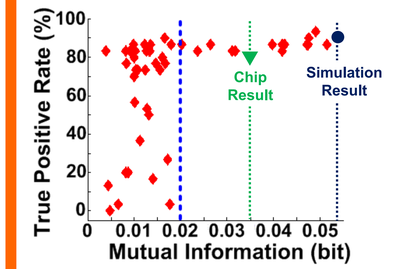
CHIP RESULT



Performance Summary	Ideal Performance	Chip w/ baseline model	Chip w/ error-aware model
Sensitivity	5/5	5/5	5/5
Latency	2.0 sec.	3.6 sec.	3.4 sec.
Specificity*	8	443	4

- **Restored performance**
  Using baseline model to classify error affected data will cause high false alarm rate. Despite the feature errors, the error-aware model restores the system performance to nearly the ideal level.

CONCLUSION



- **Mutual Information Preservation**
  The analog frontend downgrade the mutual information from ~0.055 bits to 0.035 bits.
  However the mutual information still remains in the range where effective classification can be performed.

- **Limitation of error resilience**
  The performance is limited fundamentally by how well the error affected data retains information for distinguishing class membership [2]. Mutual Information (MI), uses Shannon entropy to calculate the difference between the overall uncertainty of a class label and the conditional uncertainty of the label-DDHR systems are shown to be limited by MI.

This project explores the possibility of greatly relaxing the precision requirements of analog frontend circuits by taking advantage of algorithmic capabilities to model how information is represented in the resulting outputs. The performance can be successfully restored in the presence of severe errors.

ACKNOWLEDGEMENT

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The mutual information calculation is done by J. Alexander Bae.