A Compressed-Sensing Sensor-on-Chip Incorporating Statistics Collection to Improve Reconstruction Performance

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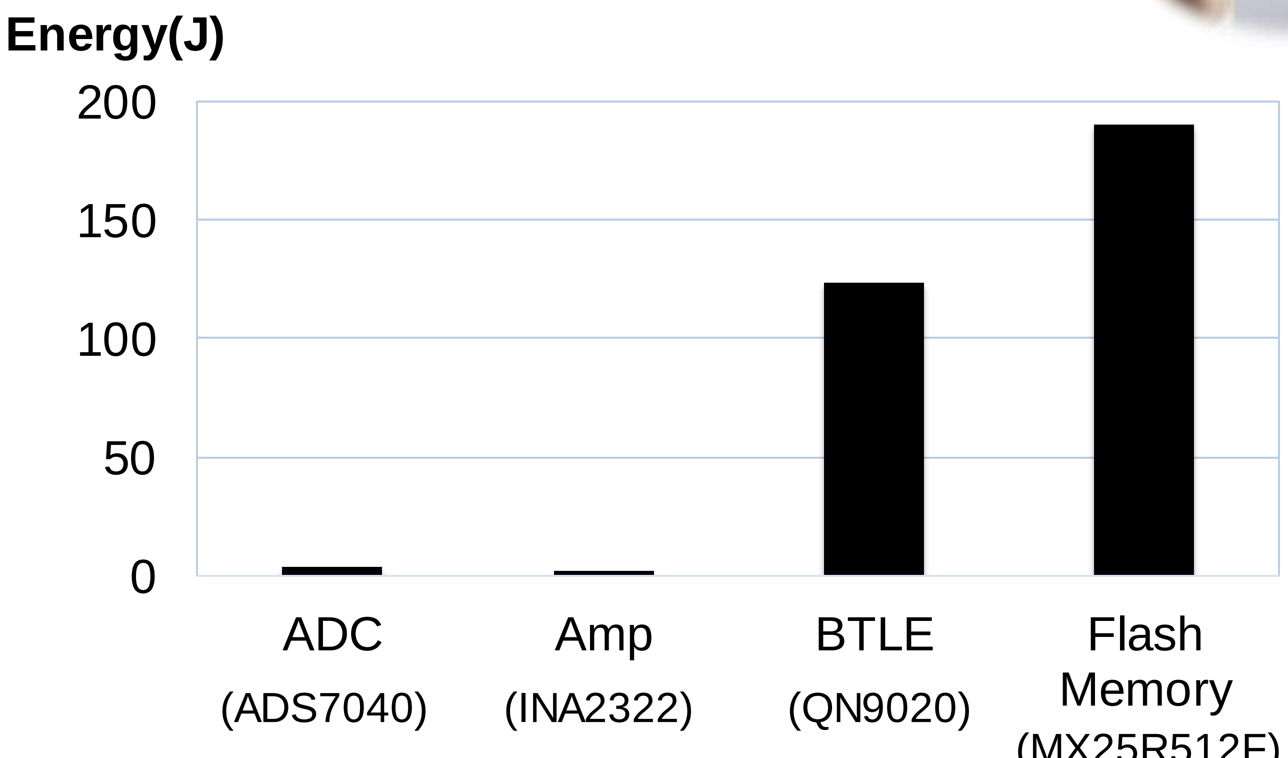
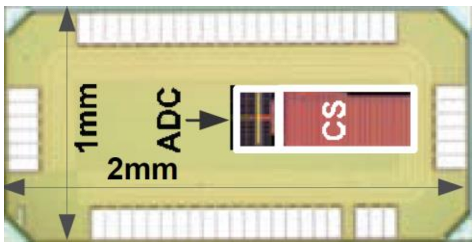
Problem Statement: Too much data!

8bit × 200Hz × 14days = 2 Gb

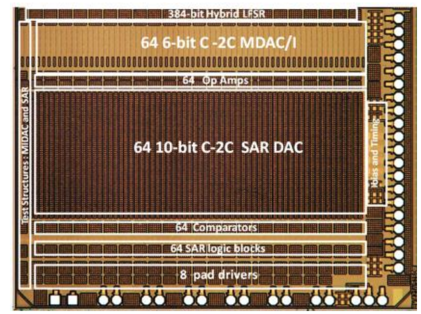


Previous Sensor Solution

- Compressed Sensing (CS)



F. Chen,
CICC 2010



D. Gangopadhyay,
JSSC 2014

+ Easy to Perform
+ Multiple Sensors Usage
- A-priori Compression Rate [1]
- Error in Reconstruction

[1] V. Behravan, et al., "Rate-Adaptive Compressed-Sensing and Sparsity Variance of Biomedical Signals", BSN 2015.

Goal of This Work

- Introduce: Intelligent Compressed Sensing (CS)

  1- Generate statistics collection (SC) of sensor data

  2- Fuse SC data with CS during reconstruction

- Demonstrate: 10-20dB improvement in Signal to Error Ratio (SER)

Outline

I. Introduction to Compressed Sensing / Sparsity

II. Reconstruction Algorithms

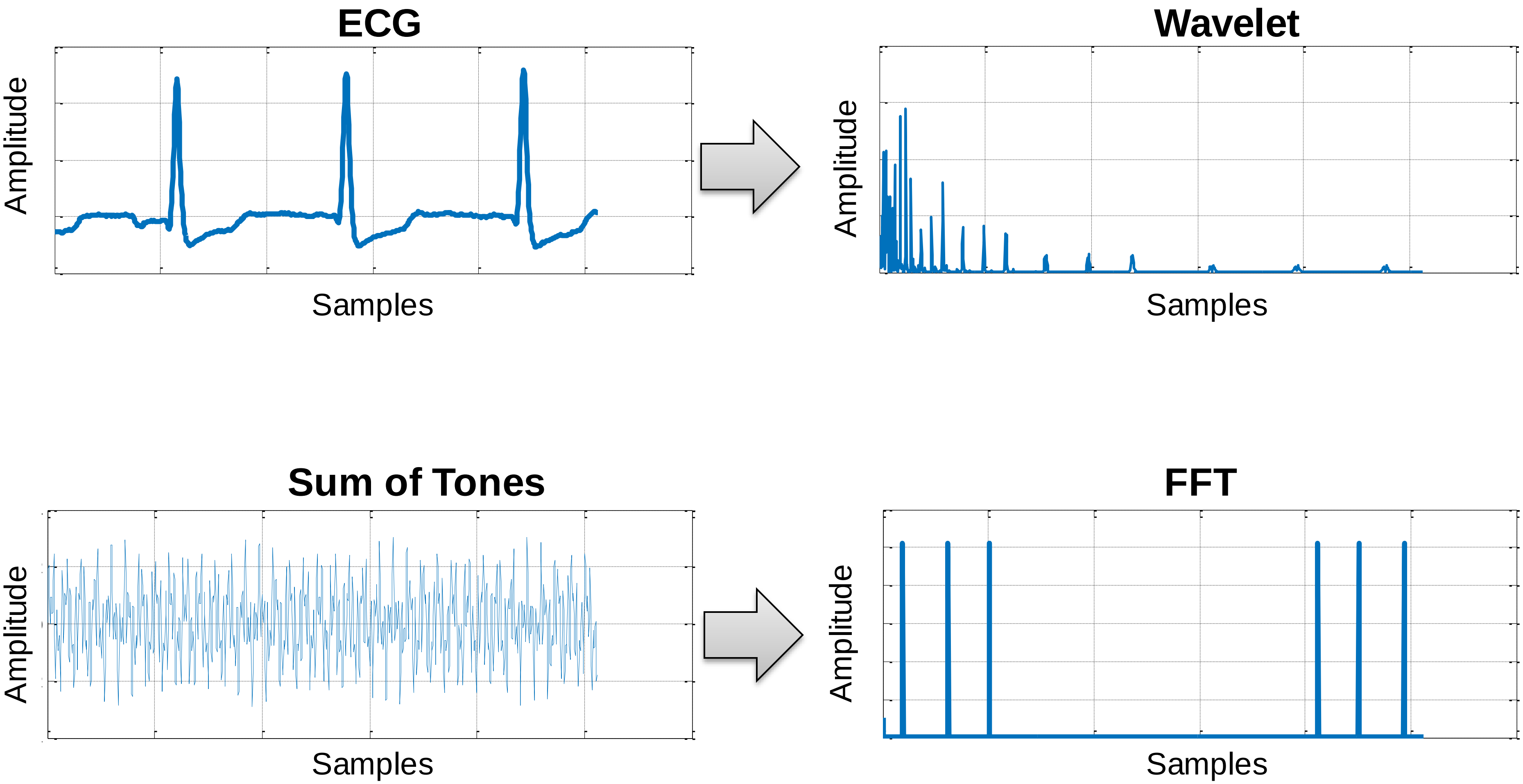
III. Proposed: Intelligent Compressed Sensing

IV. Block Diagram of SoC

V. Measurement Results

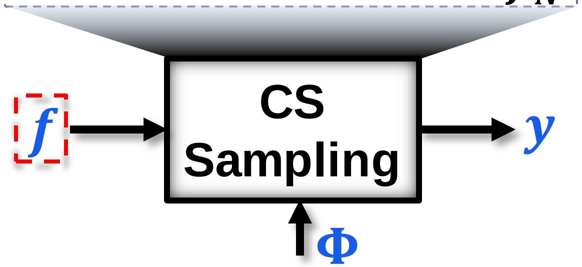
VI. Performance Summary

Sparsity

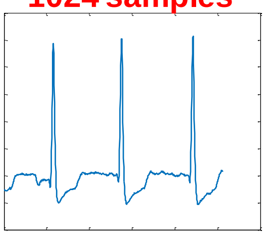

ECG
Amplitude
Samples
Wavelet
Amplitude
Samples
Sum of Tones
Amplitude
Samples
FFT
Amplitude
Samples

Introduction to CS

$$\begin{bmatrix} y_1 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1 & \cdots & 1 & 1 \\ 1 & 1 & 0 & \cdots & 1 & 0 \\ \vdots & & & \mathbf{\Phi} & & \vdots \\ 0 & 0 & 1 & \cdots & 0 & 1 \end{bmatrix} \begin{bmatrix} f_1 \\ \vdots \\ f_N \end{bmatrix}$$

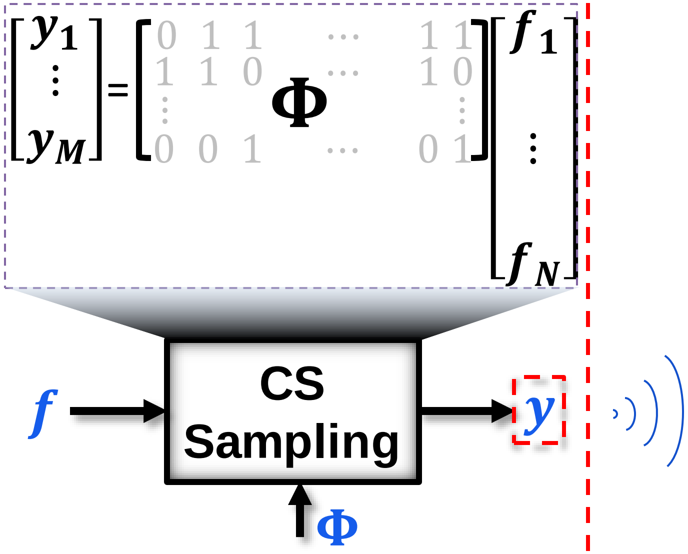


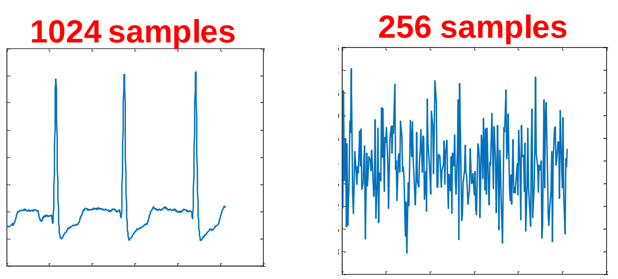
1024 samples



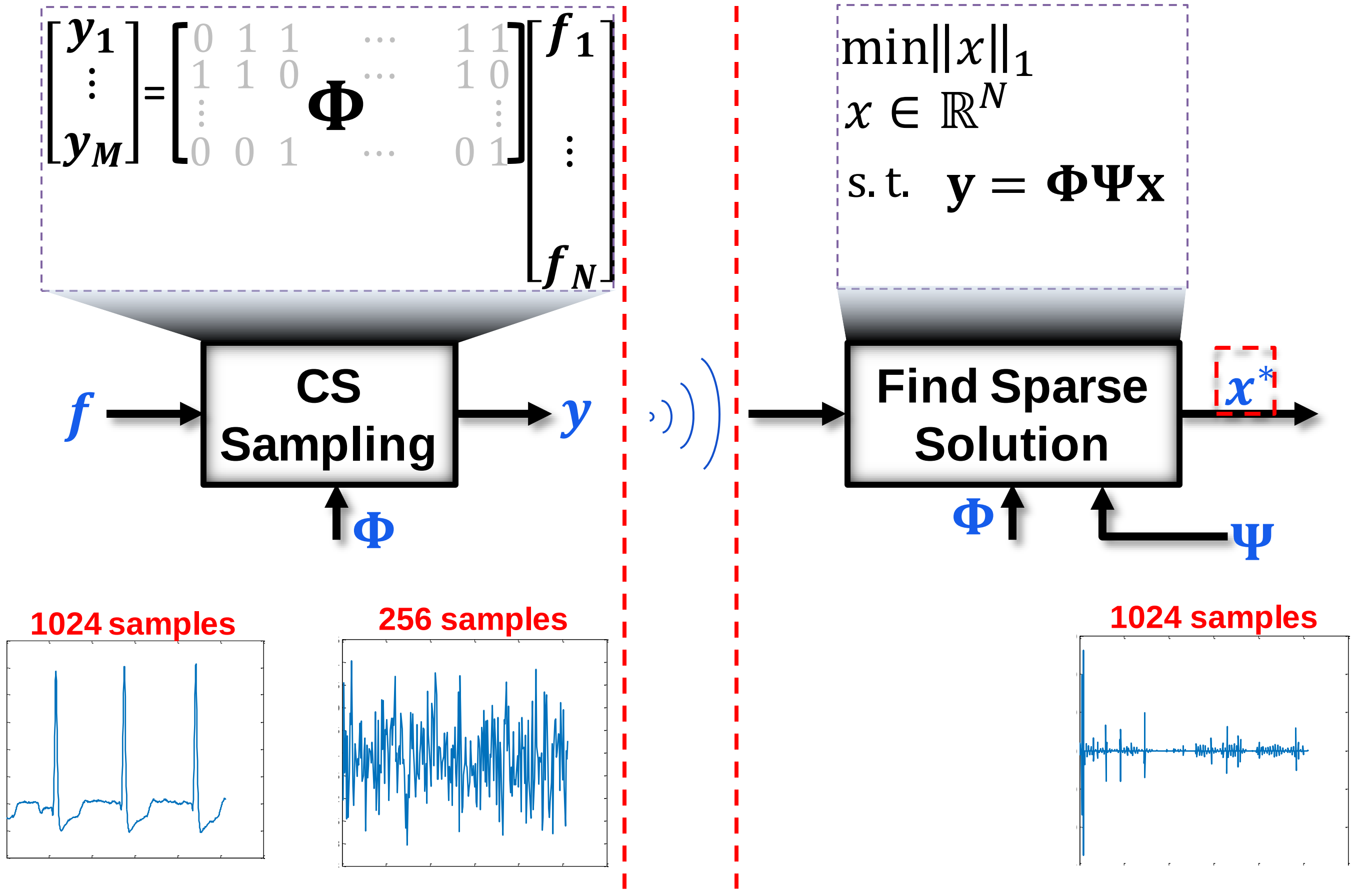
Compression on Sensor Node

Introduction to CS

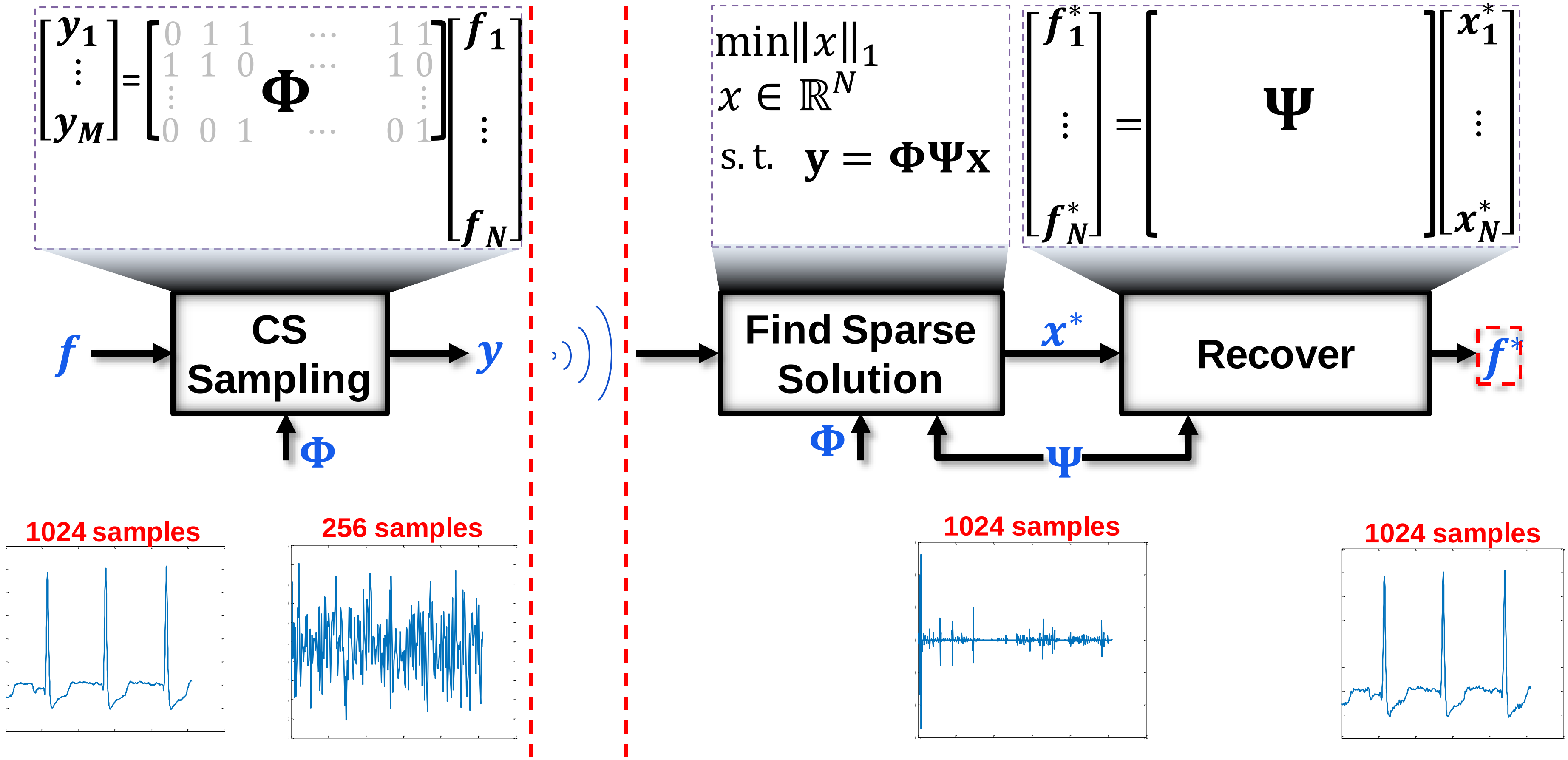




Introduction to CS



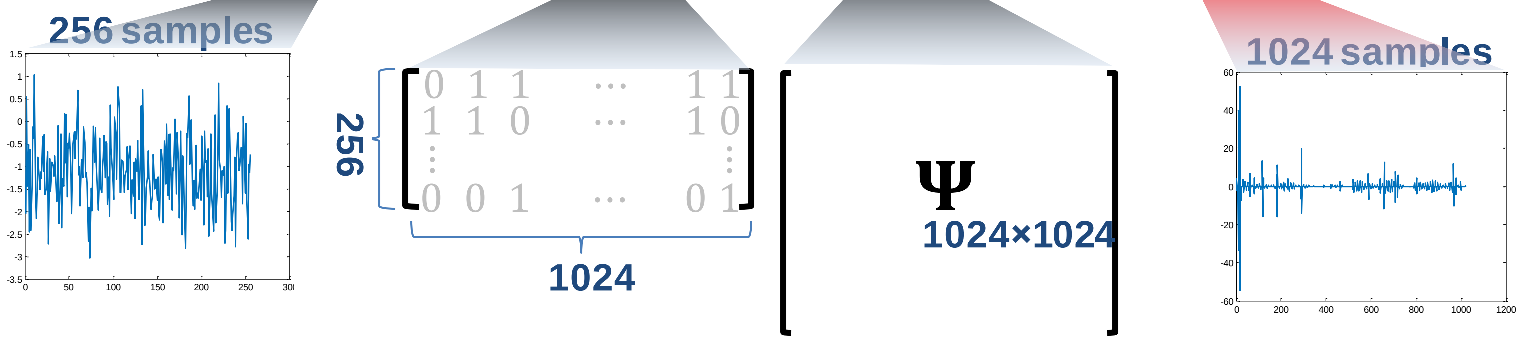
Introduction to CS



$$\text{Compression Factor} = \frac{1024}{256} = 4$$

Reconstruction Algorithm

$$\mathbf{y} = (\mathbf{\Phi} \times \mathbf{\Psi}) \times \mathbf{x}$$



- Infinite solutions
  - Set of 256 equations with 1024 unknown
- Unique solution if x is sparse
  - An Optimization Problem

Reconstruction Algorithm:GPSR[1]

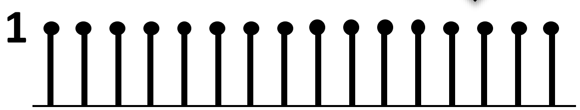
$$\mathrm{x} = arg\min_{x}(\sum abs(\boldsymbol{x}) \quad + 0.5 \times \|\boldsymbol{y} - \boldsymbol{\Phi\Psi x}\|_2^2)$$

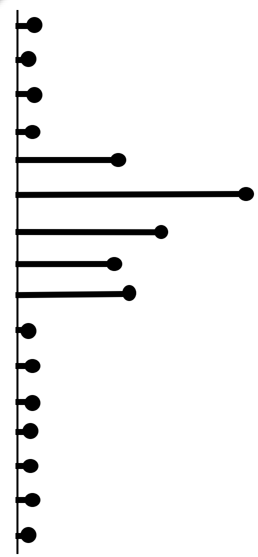
[1] M. Figueiredo, et al., “Gradient Projection for Sparse Reconstruction: Application to Compressed Sensing and Other Inverse Problems, ” IEEE J. Sel. Topics in Signal Processing, Dec. 2007.

Proposed Method

$$\mathrm{x} = arg \min_{x}\left(\boxed{\sum abs(\boldsymbol{x})} + 0.5 \times \|\boldsymbol{y} - \boldsymbol{\Phi\Psi x}\|_2^2\right)$$

$$\mathrm{x} = arg \min_{x}\left(\boxed{W \times abs(\boldsymbol{x})} + 0.5 \times \|\boldsymbol{y} - \boldsymbol{\Phi\Psi x}\|_2^2\right)$$





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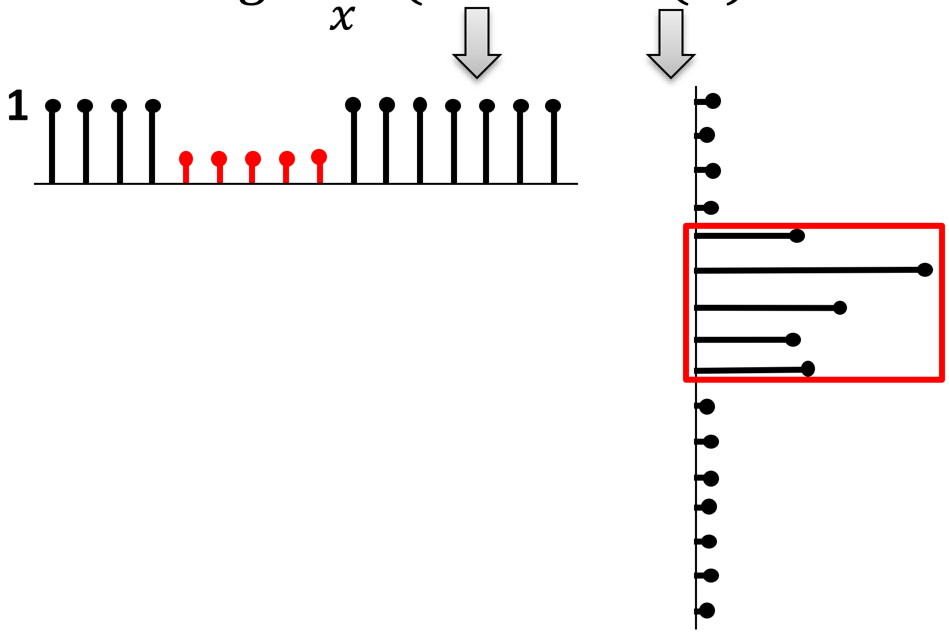

Construct W based on statistics of input data

Proposed Method

$$x = arg\min_{x}\left(\sum abs(\boldsymbol{x}) \quad + 0.5 \times \|\boldsymbol{y} - \boldsymbol{\Phi\Psi x}\|_2^2\right)$$

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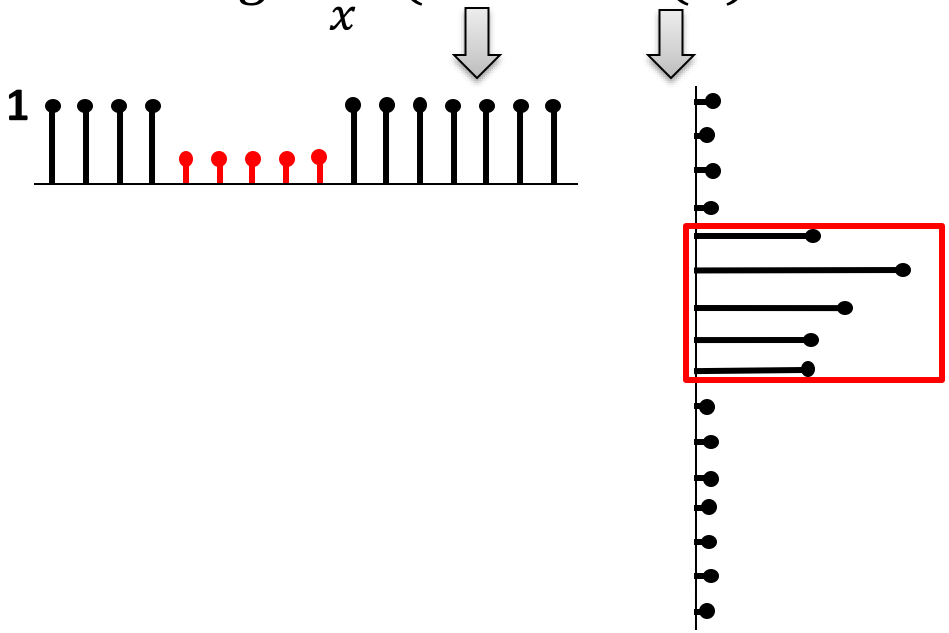
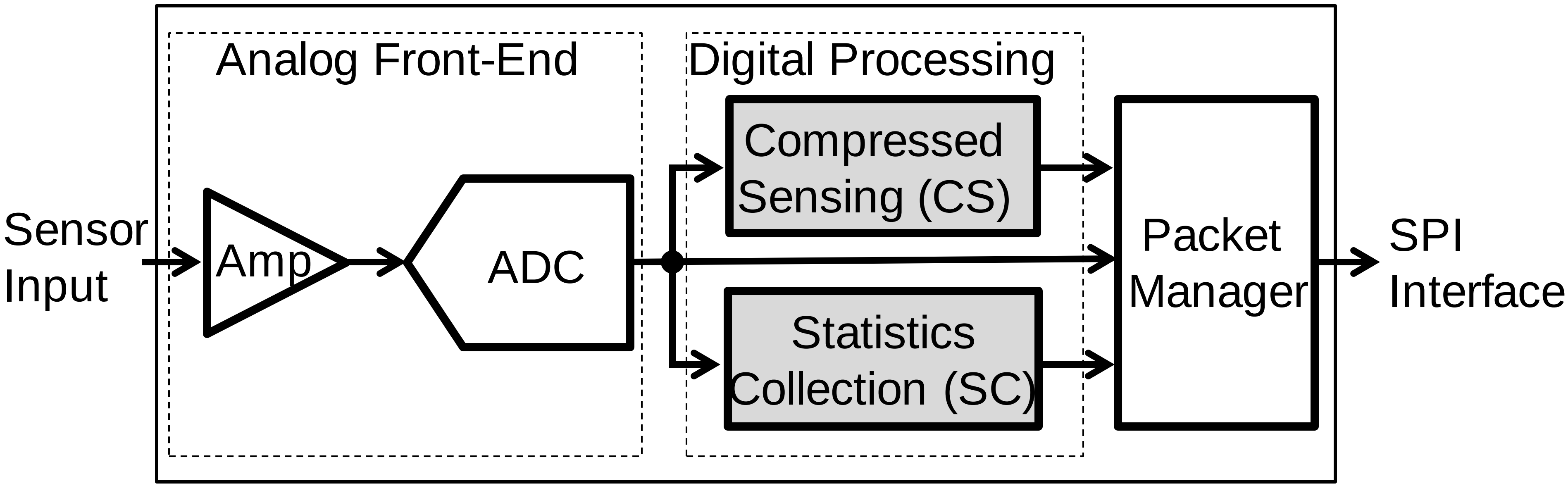


Construct W based on statistics of input data

Block Diagram of SoC

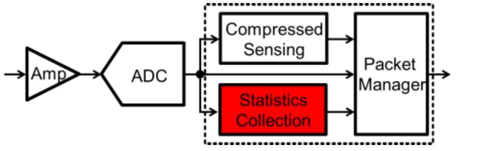


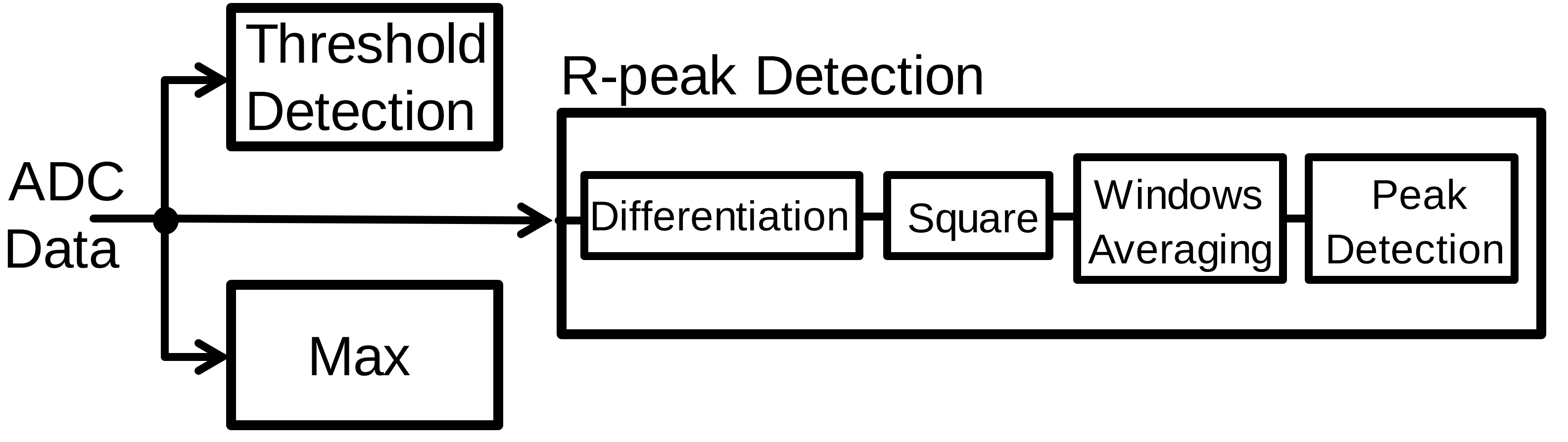
Analog Front-End:

- Variable Gain, Variable BW Amplifier
- 2-step Incremental ADC [1]

[1] C.H. Chen, et al., " A 11 µW 250 Hz BW two-step incremental ADC with 100 dB DR and 91 dB SNDR for integrated sensor interfaces," CICC 2014.

Statistics Collection

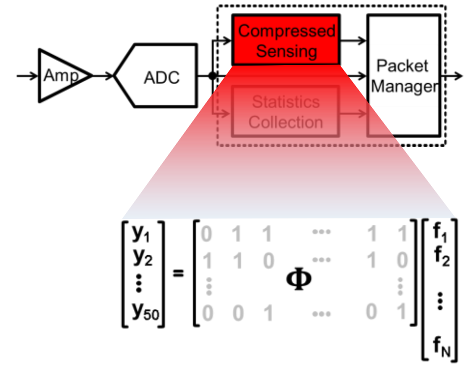


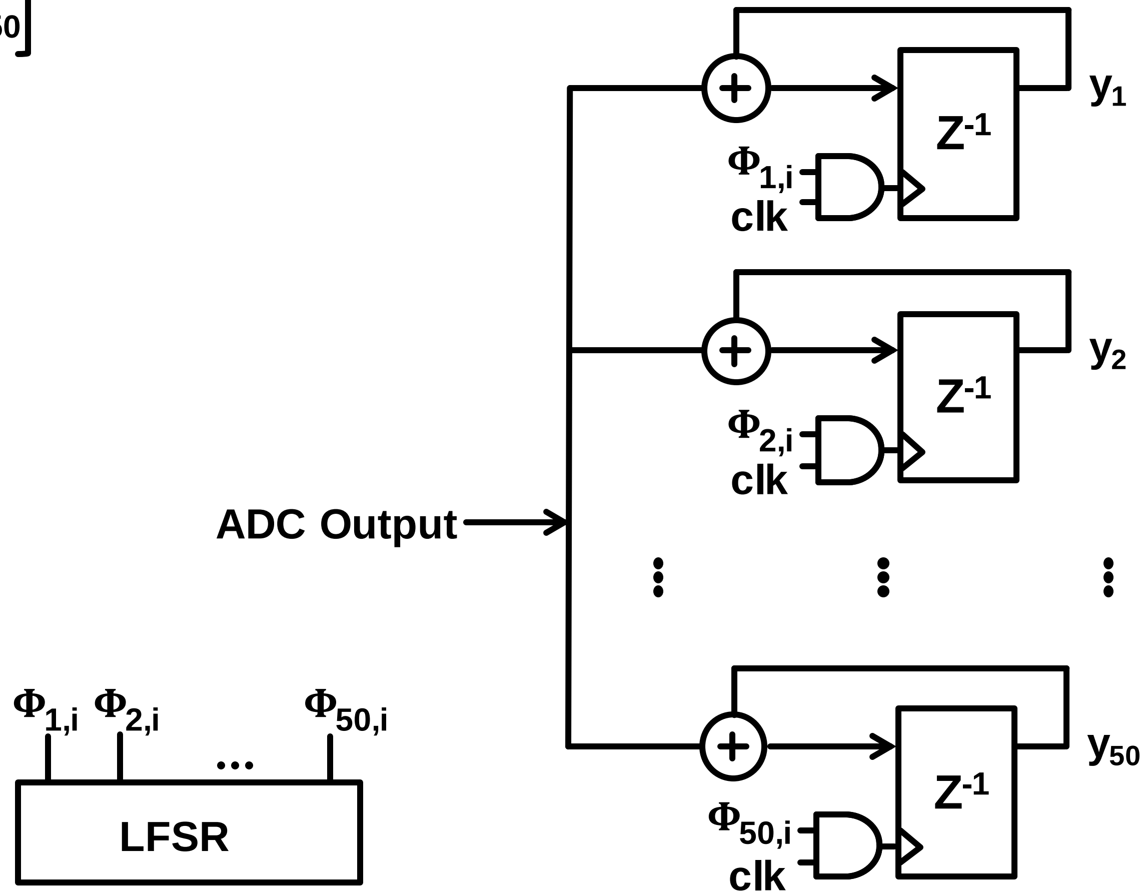


- All Statistics: 20% Data Overhead
- R-peak: 8% Data Overhead
- Threshold: 8% Data Overhead

CS Implementation

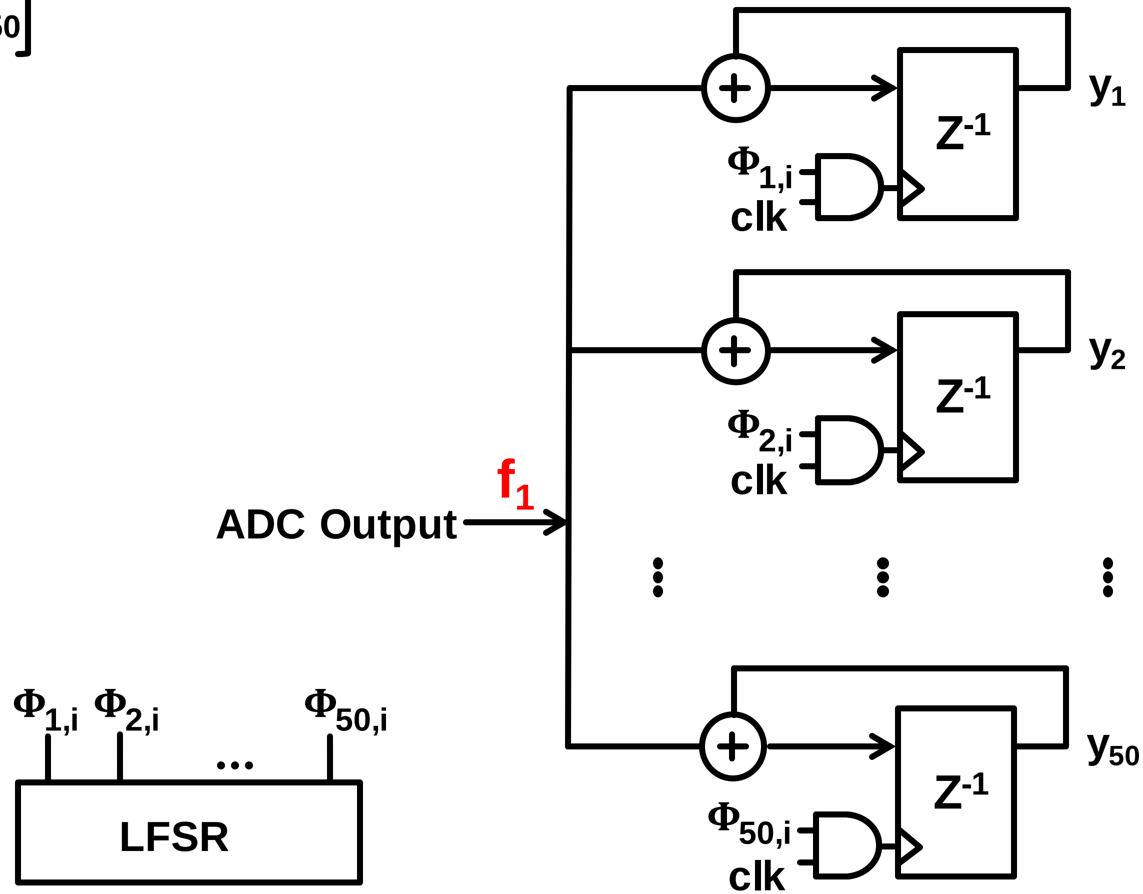
$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{50} \end{bmatrix} = f_1\ \Phi_1 + f_2\ \Phi_2 + \cdots + f_N\ \Phi_N$$

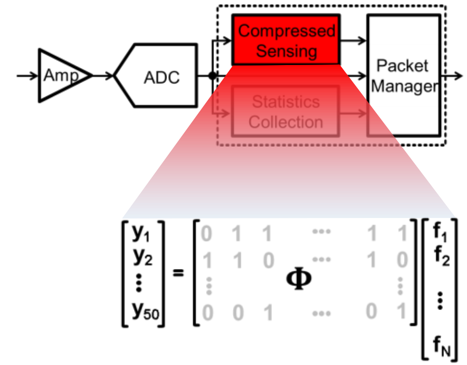




CS Implementation

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{50} \end{bmatrix} = \color{red}{f_1}\color{black}{\ \Phi_1 + f_2\ \Phi_2 + \cdots + f_N\ \Phi_N}$$





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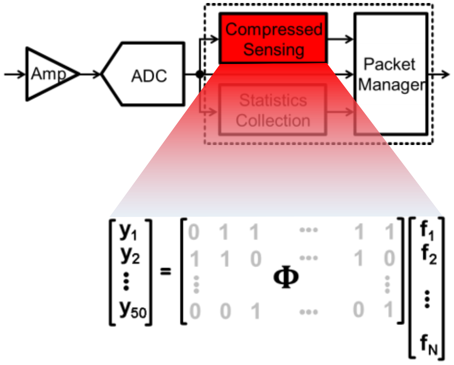

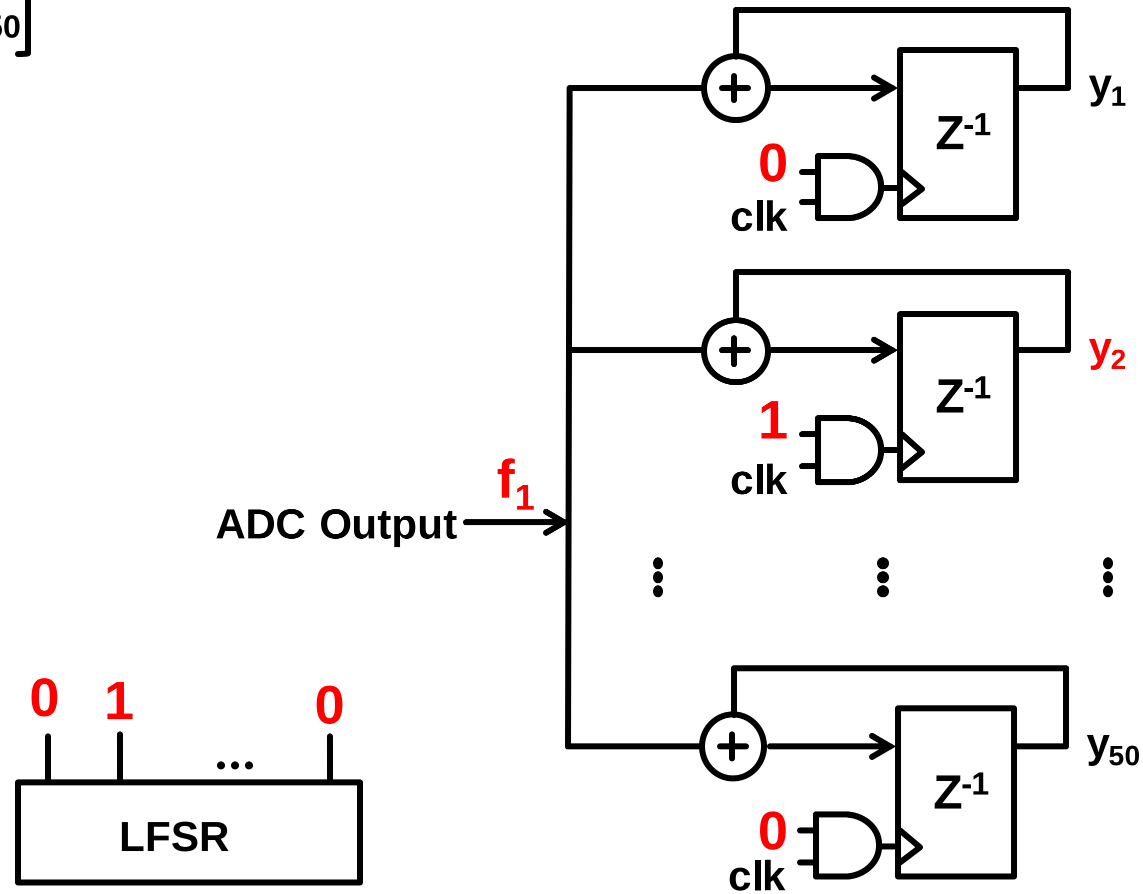

CS Implementation

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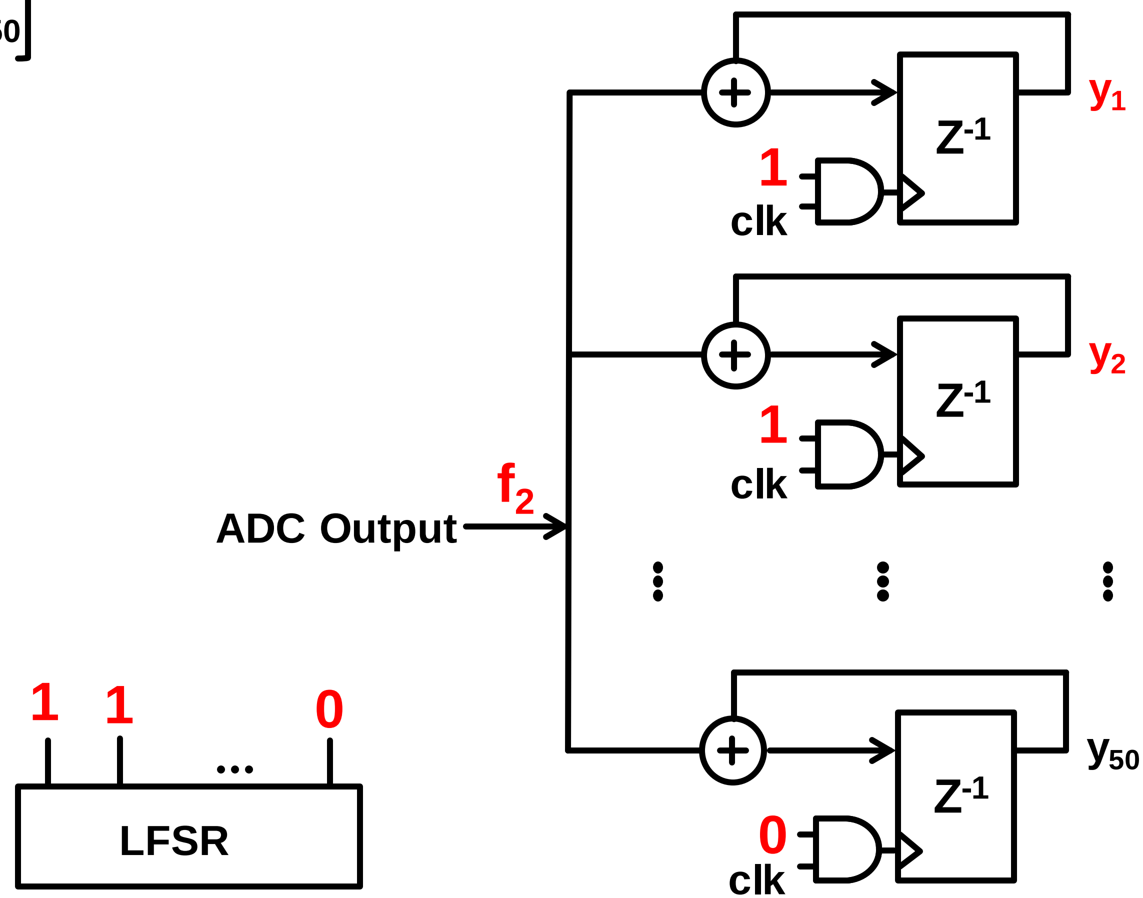

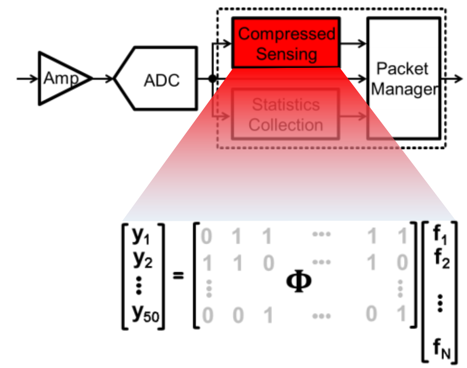

CS Implementation

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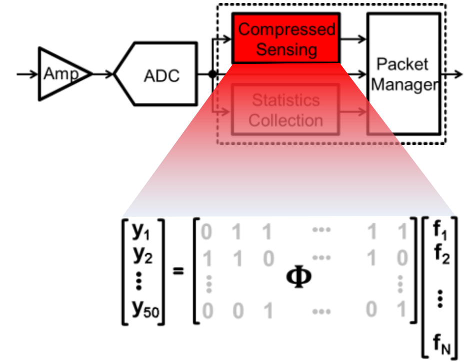
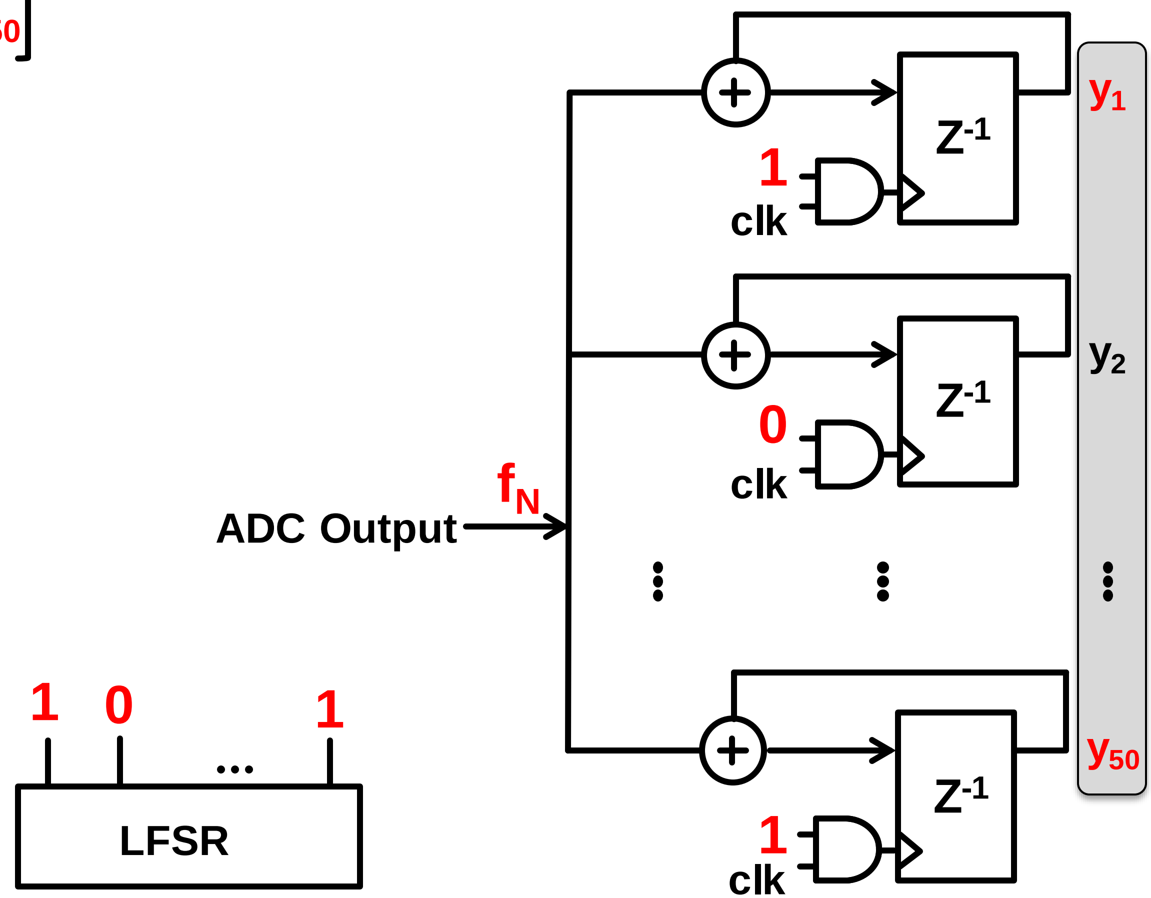
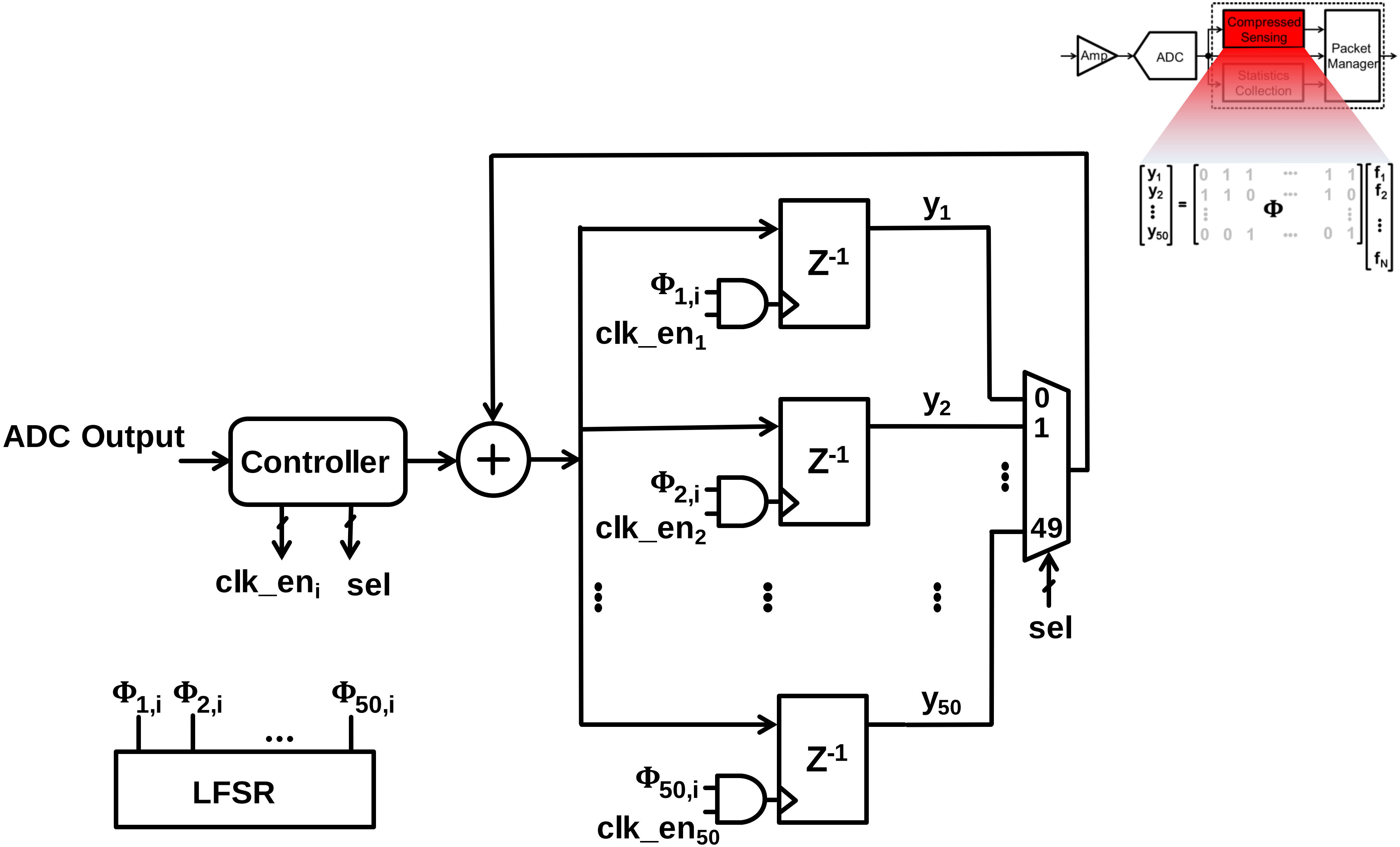
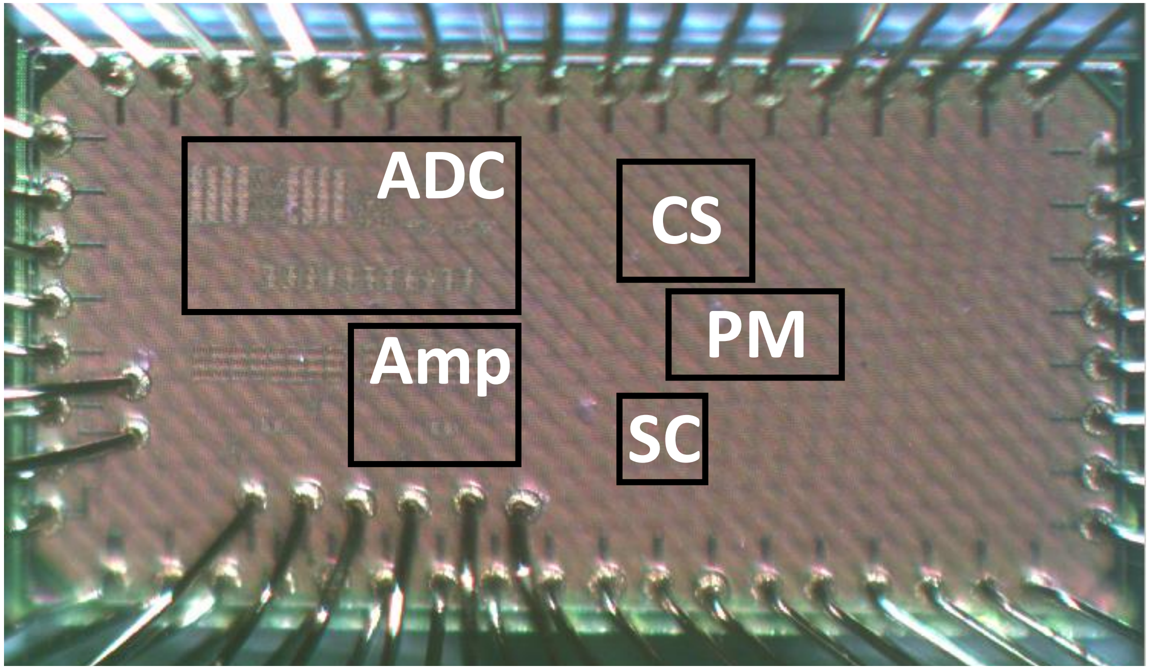




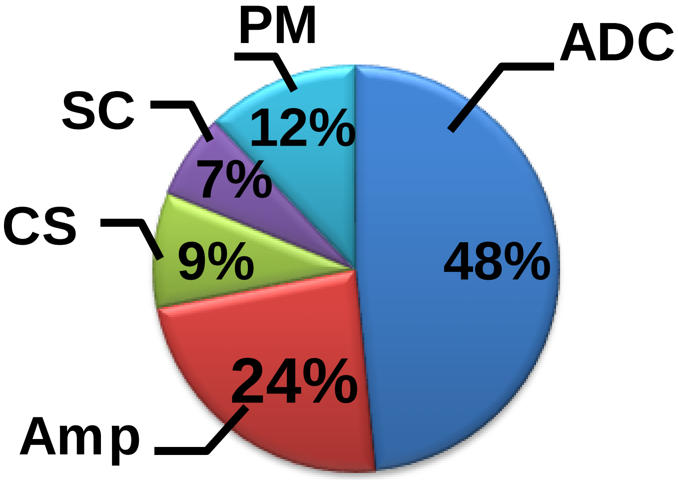
CS Implementation



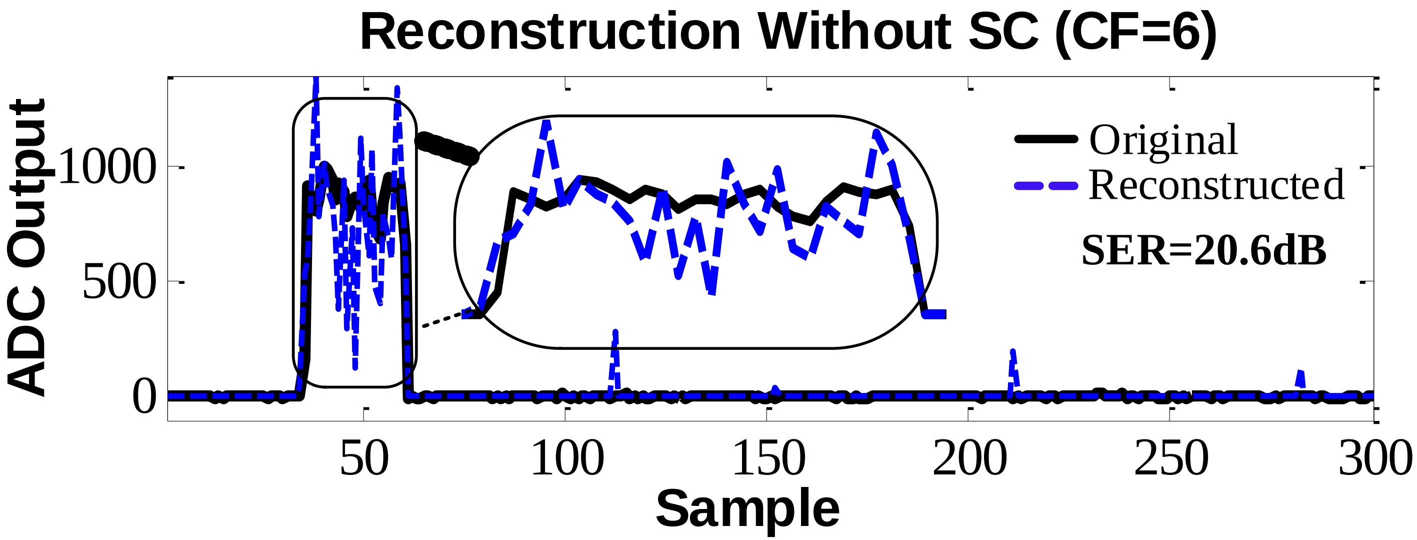
Die Photo

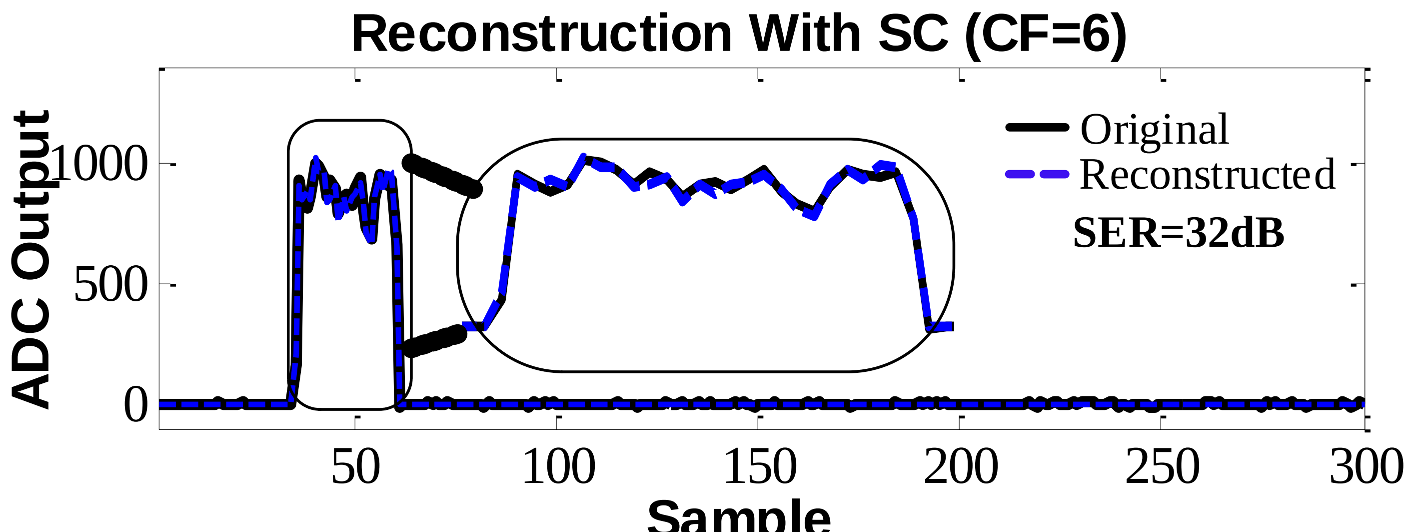


Area Breakdown

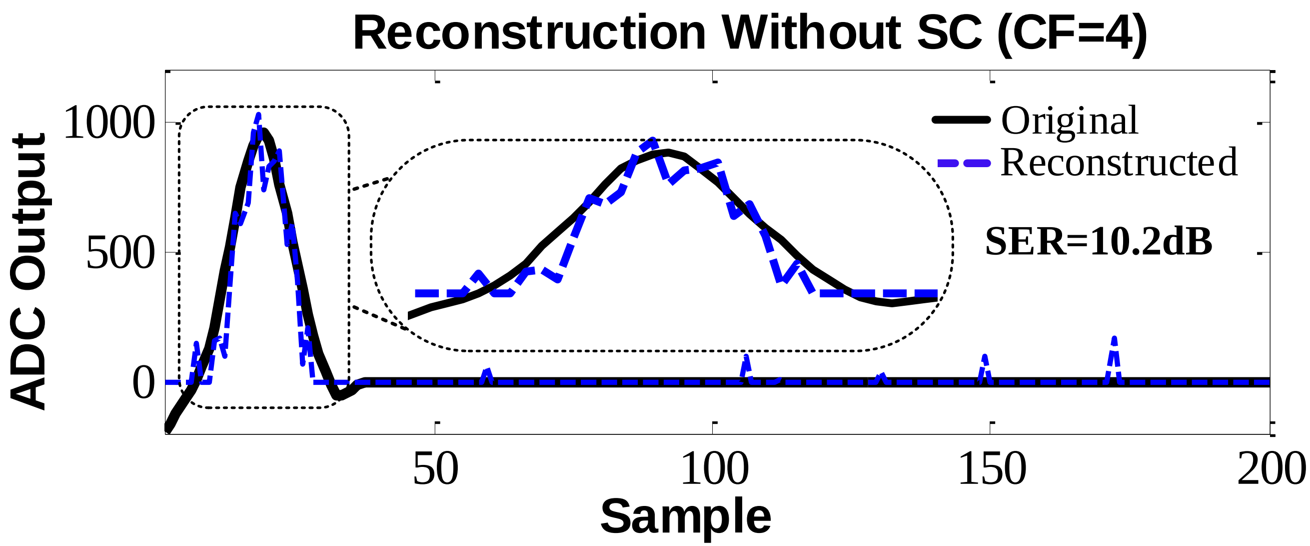


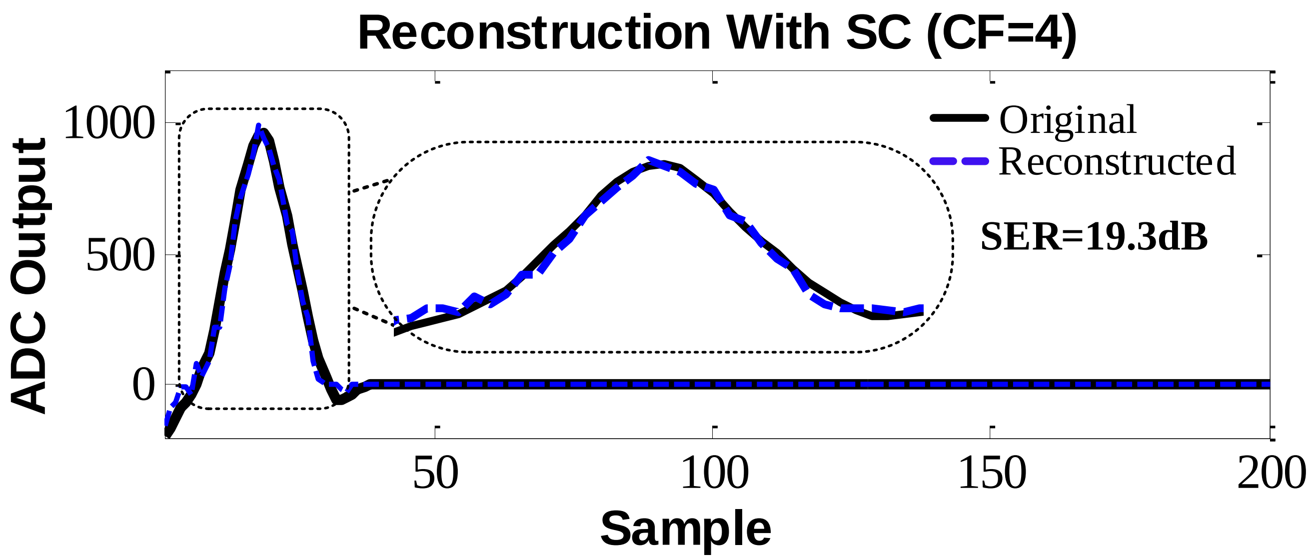
Measurement Results: Pulse Input



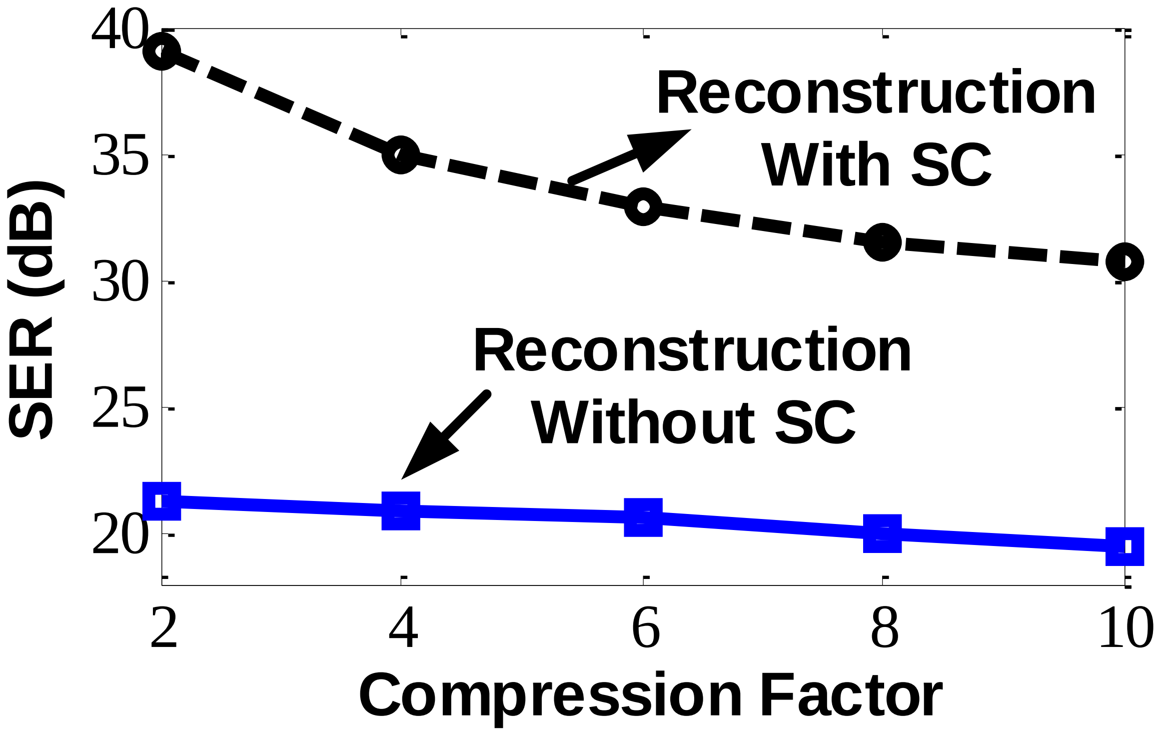


Measurement Results: ECG Input





SER vs. Compression Factors



Performance Summary

	Previous CS Sensor-on-Chip		This Work
	[Chen, CICC 2010]	**[Gangopadhyay, JSSC 2014]**	
Amp	No	No	Yes (10µW)
ADC	SAR 5-bits ENOB	SAR 6.5-bits ENOB	Incremental 15-bits ENOB (10.7µW)
CS Power	2.5µW @ 100 kHz	28nW @ 2kHz	0.7 µW-Dyn @ 96kHz
SC Power	No	No	0.4 µW-Dyn[1] @ 96kHz
Technology	90 nm CMOS	0.13 µm CMOS	65nm CMOS

- SC power overhead is 9%.

[1]12.6 µW Static

Conclusions

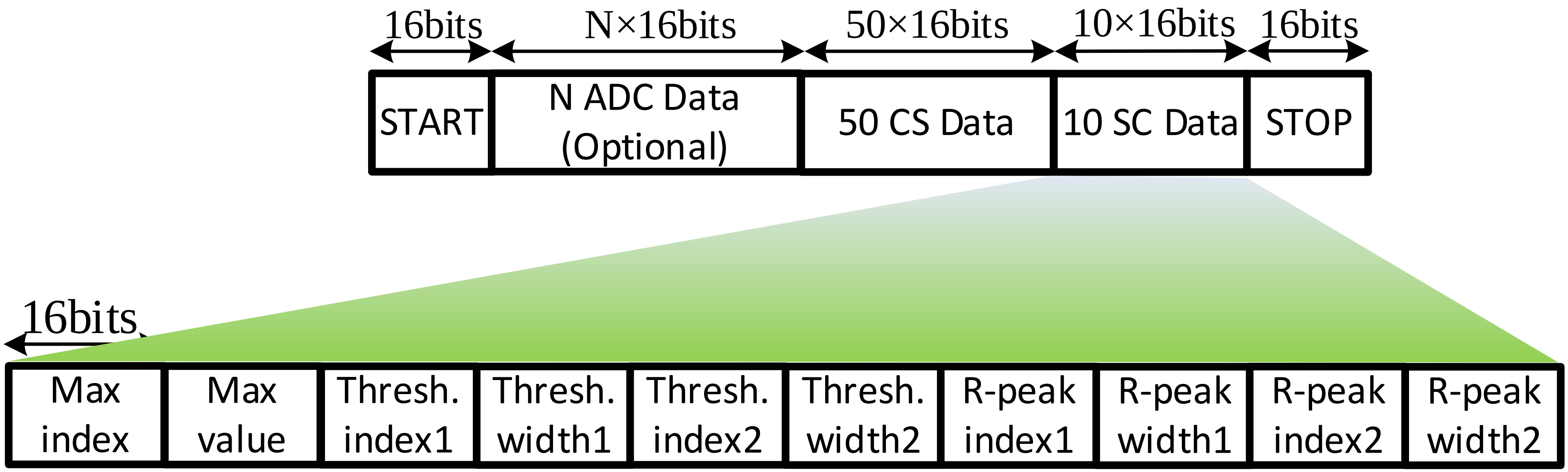
- An intelligent CS SoC presented.
- Signal statistics used to substantially increase SER.

Acknowledgement

- This project was supported in part by grants from the Center for Design of Analog-Digital Interface Circuits (CDADIC) and USDA.

Thank you

Back up Slide: Data Format



Back up Slide: LFSR

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{50} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1 & \cdots & 1 & 1 \\ 1 & 1 & 0 & \cdots & 1 & 0 \\ \vdots & & & \Phi & & \vdots \\ 0 & 0 & 1 & \cdots & 0 & 1 \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}$$