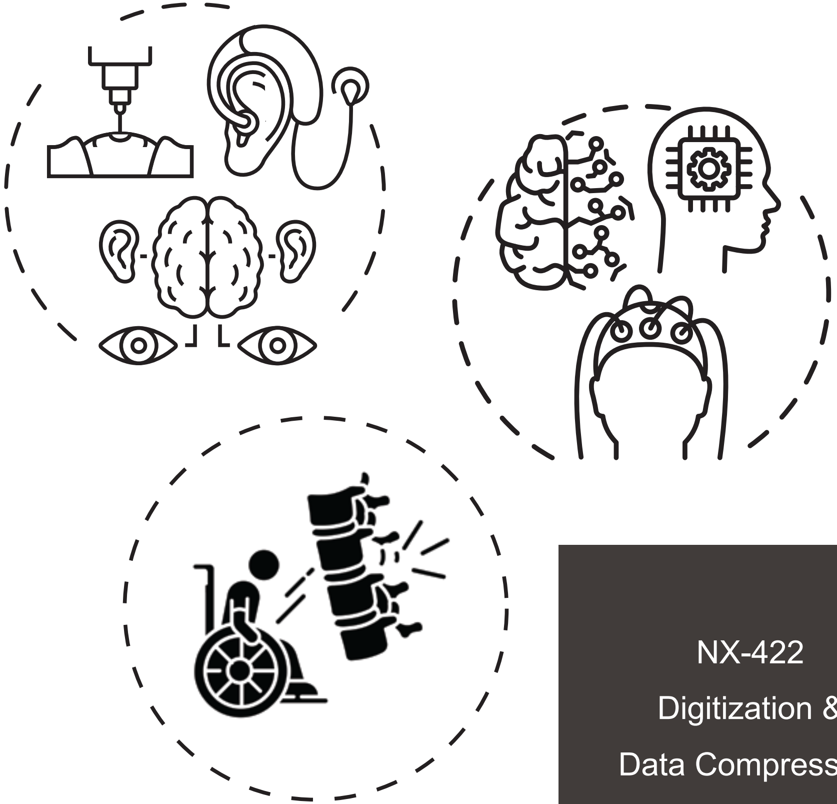


Neural Interfaces

NX-422

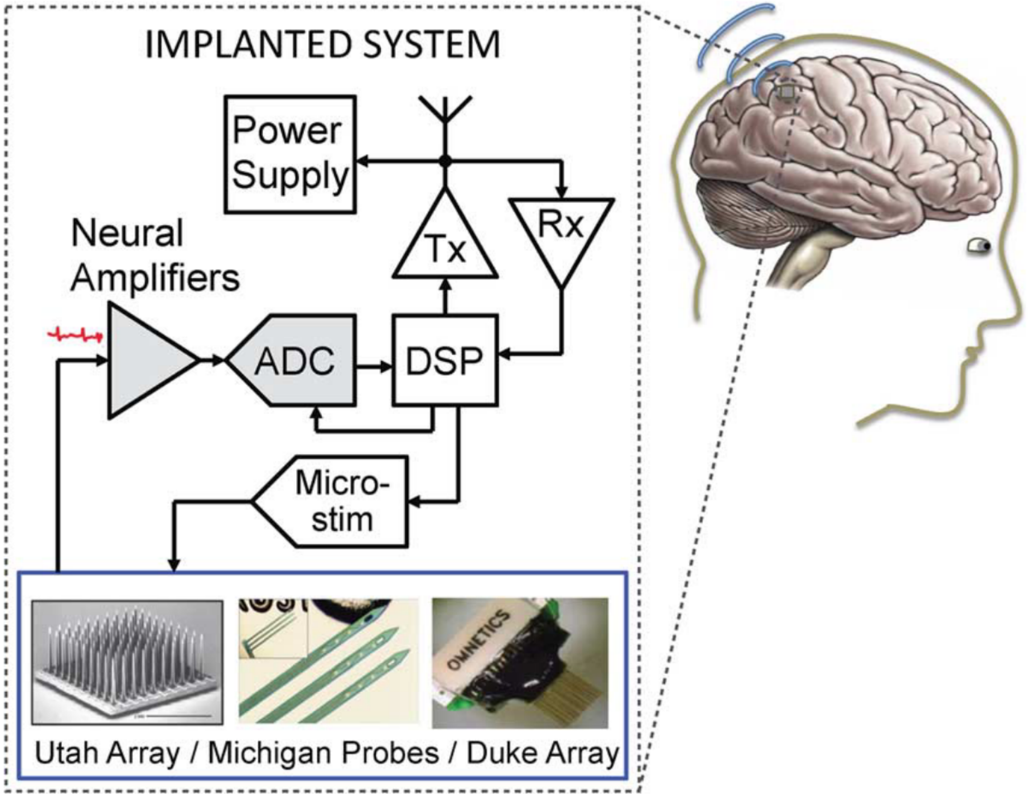
Digitization &

Data Compression

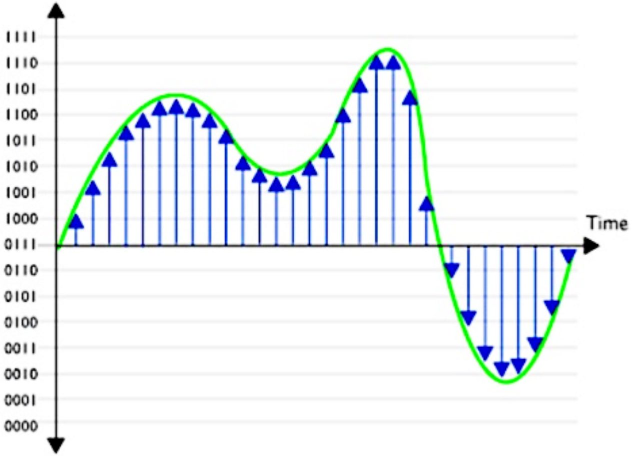
Mahsa Shoaran

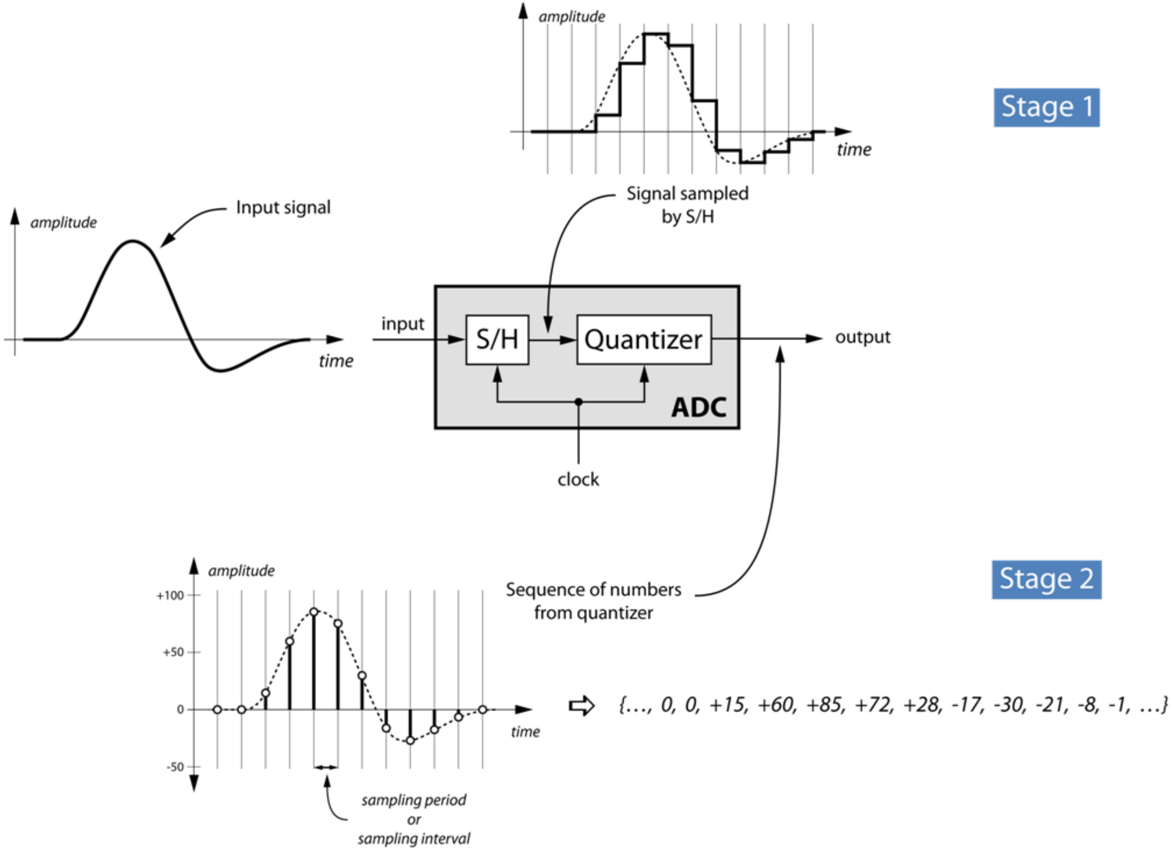
IEM and Neuro-X Institutes

Recap: Block Diagram of a Neural Interface: ADC

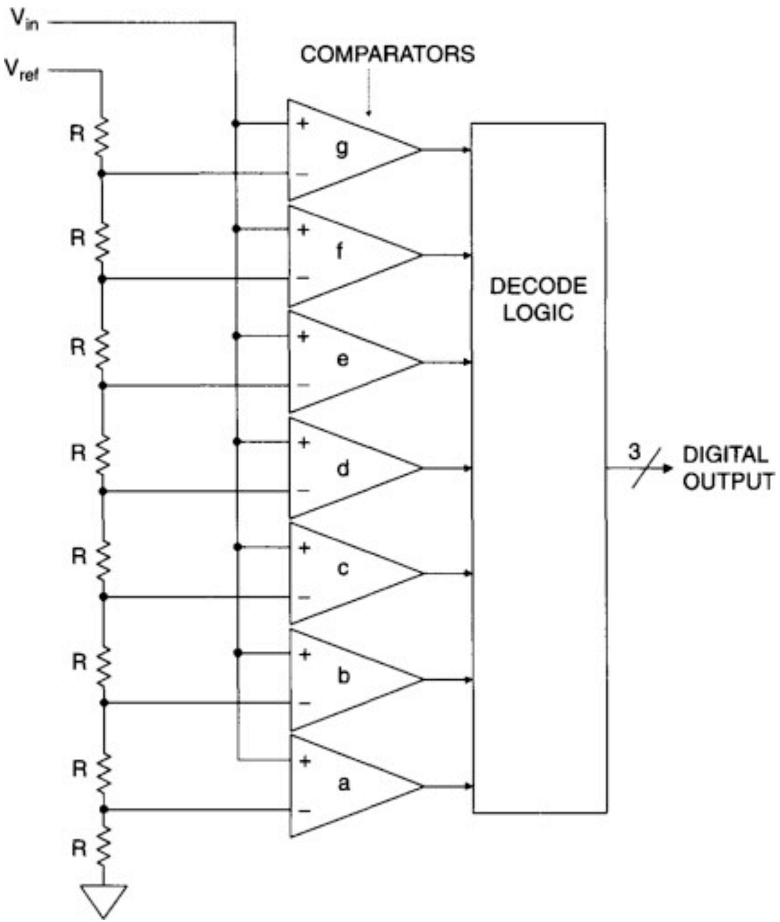


Recap: ADC Basics





Recap: 3-bit flash (parallel) ADC

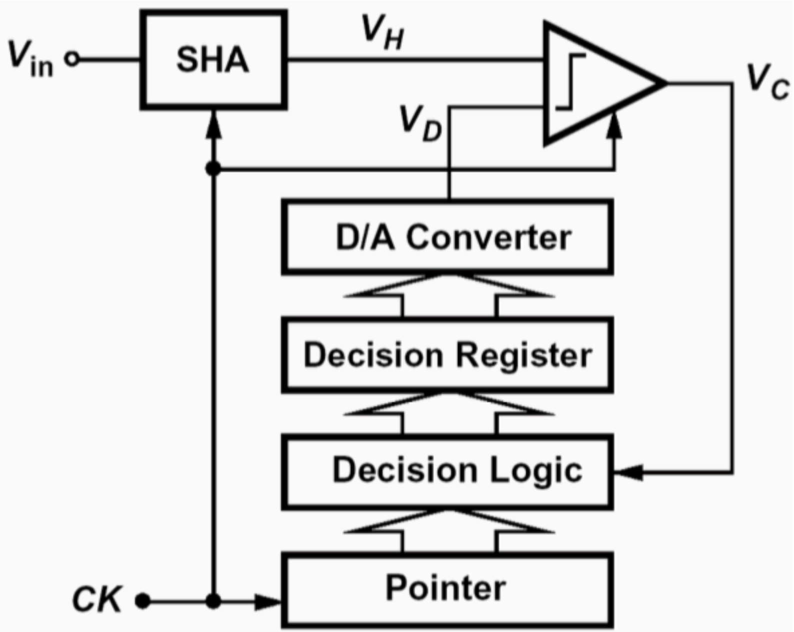


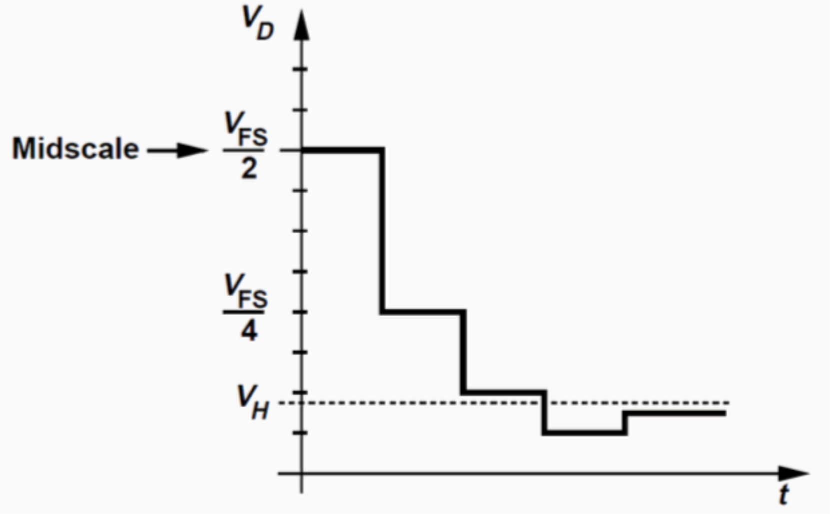
- An n-bit flash ADC uses 2^n-1 comparators, 2^n resistors and a decode logic.

- Pros: the fastest type of ADC.
- Cons: limited resolution, expensive, large power consumption and low accuracy

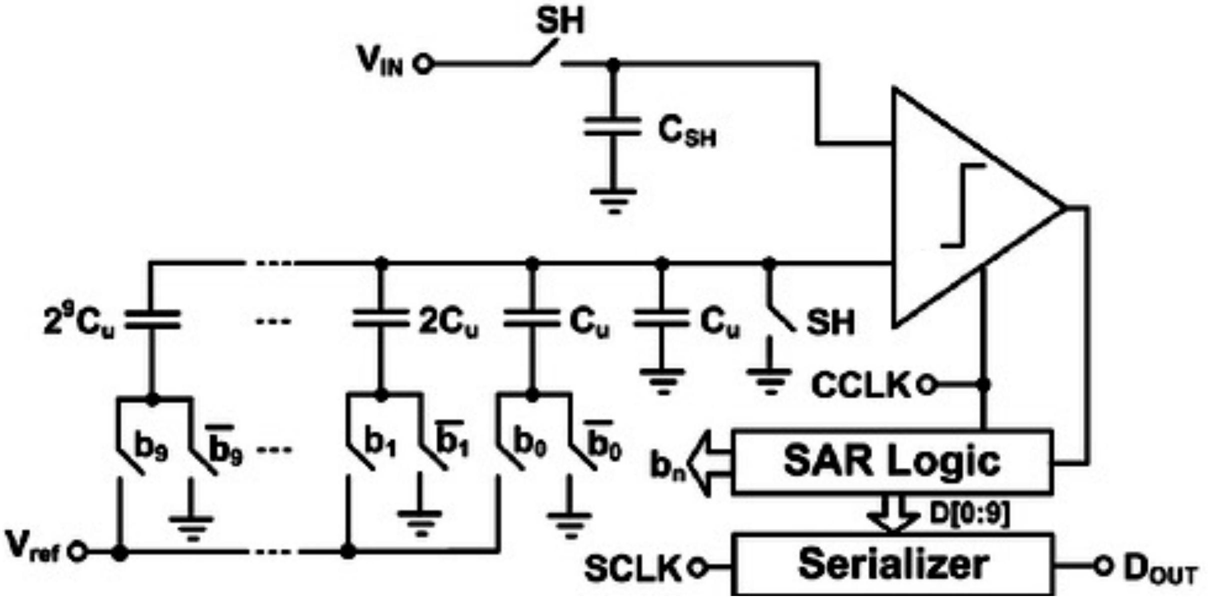
- Applications: Data acquisition, sampling oscilloscope and high-density disk drives.

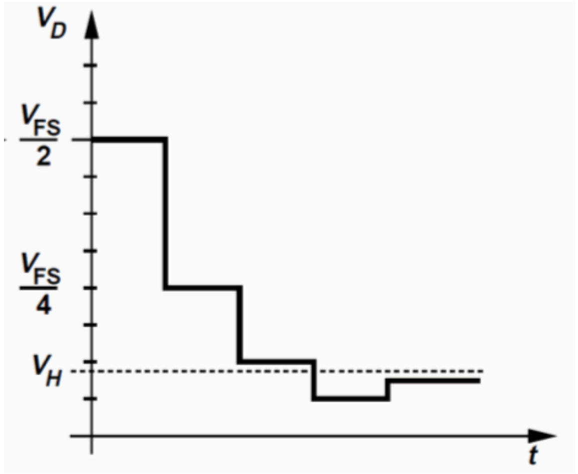
Recap: Successive-approximation-register (SAR) ADC





Successive-approximation-register (SAR) ADC

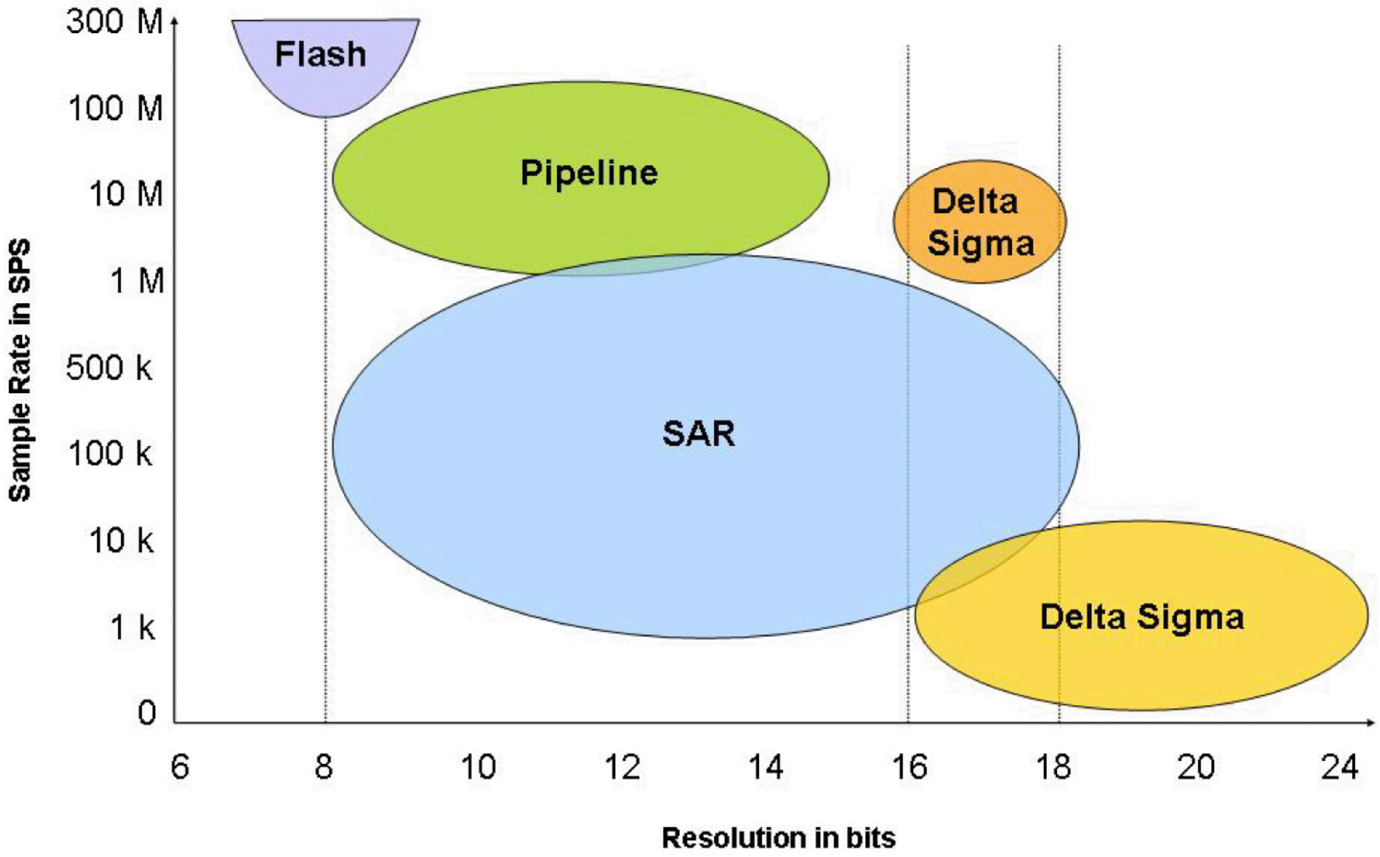




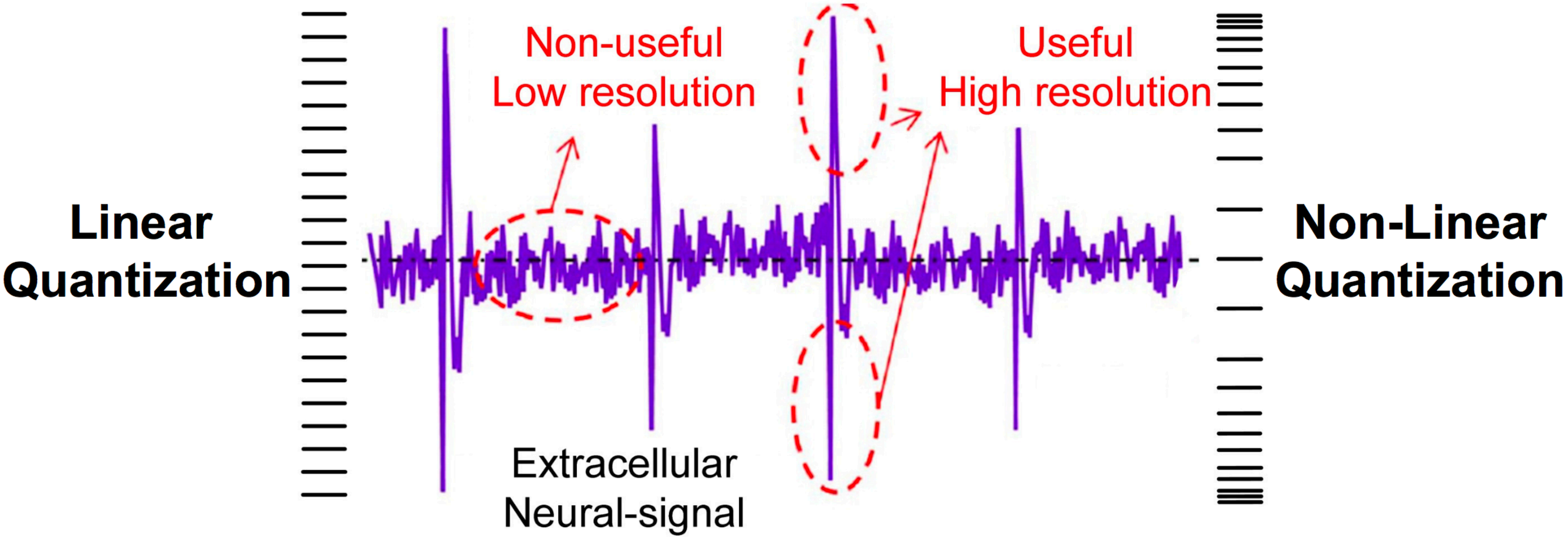
ADC Architectures

- Many different ADC architectures exist
  - Successive Approximation Register (SAR)
  - Flash
  - Pipeline
  - Delta-Sigma (ΔΣ)
  - …

Speed and Resolution of ADC Types



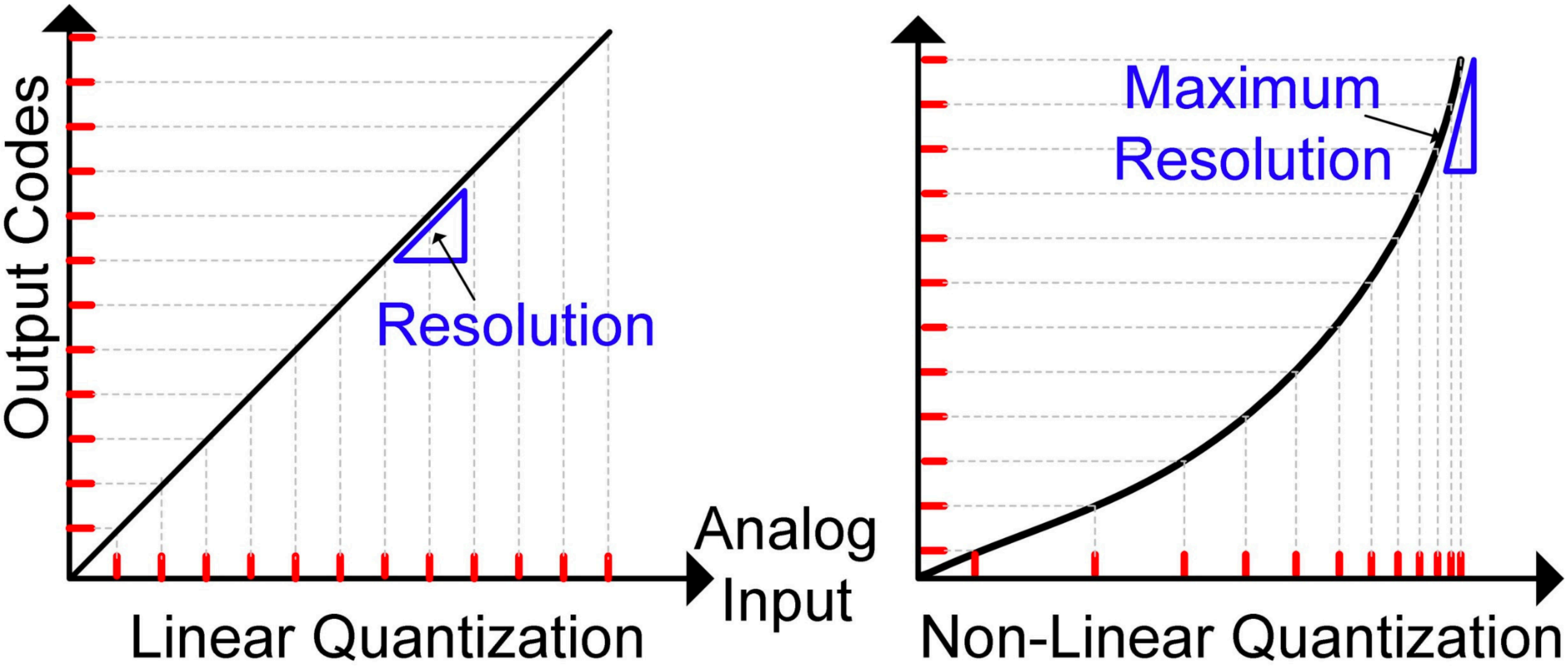
Optimized ADCs for Neuro Applications



- Complete re-construction not necessary
- Information not distributed uniformly

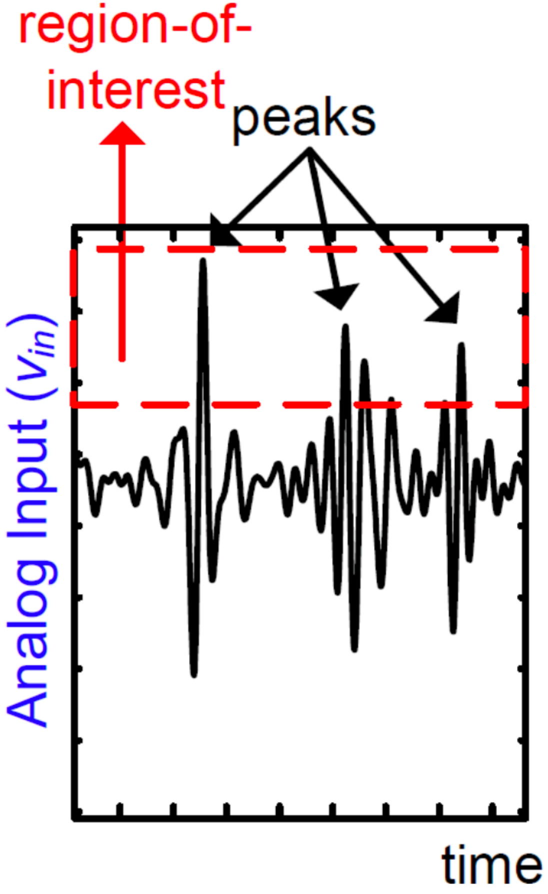
M. Judy, et al,, TBCAS’14

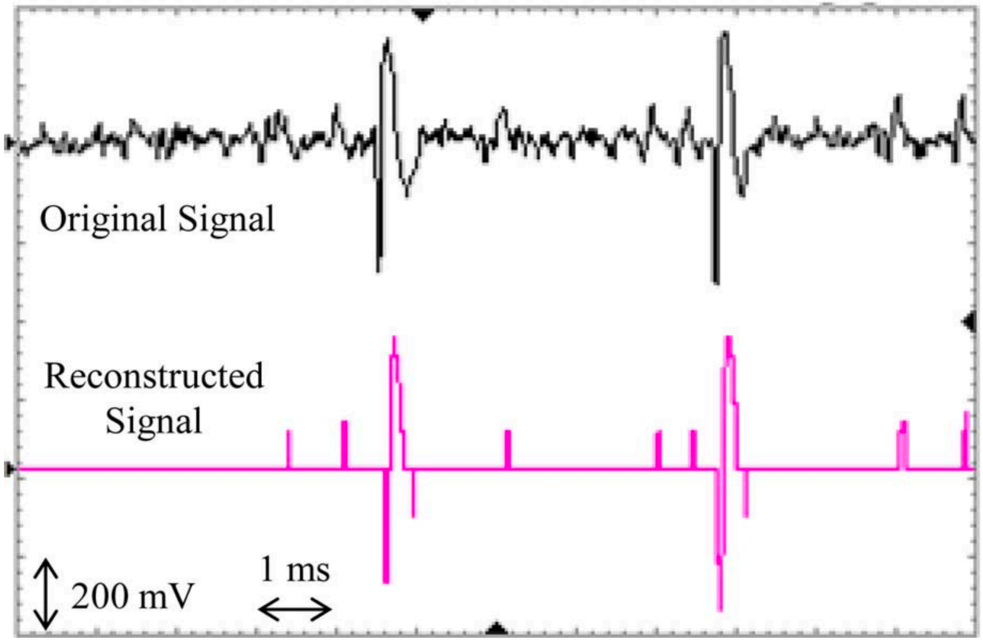
Optimized ADCs for Neuro Applications



- Higher resolution for identical number of output codes

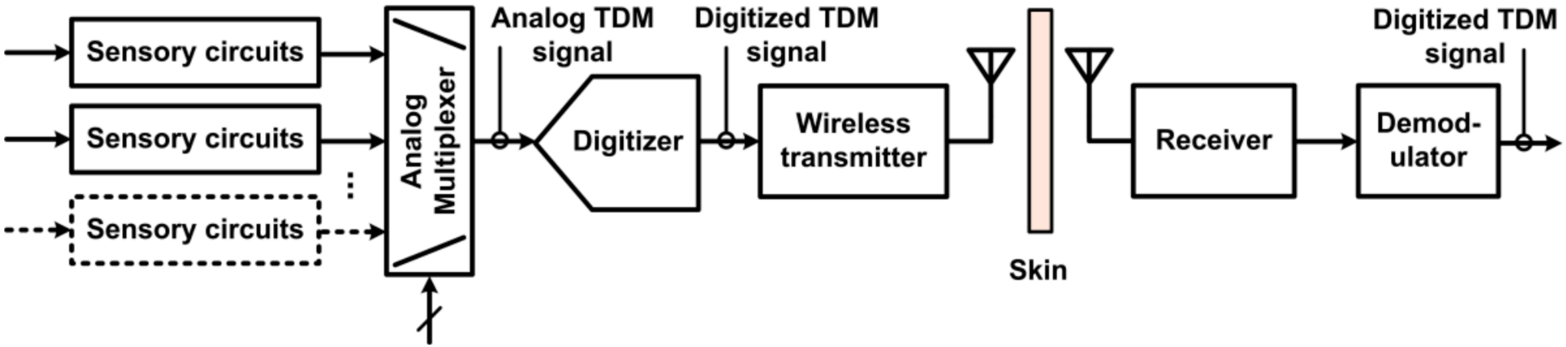
Optimized ADCs for Neuro Applications



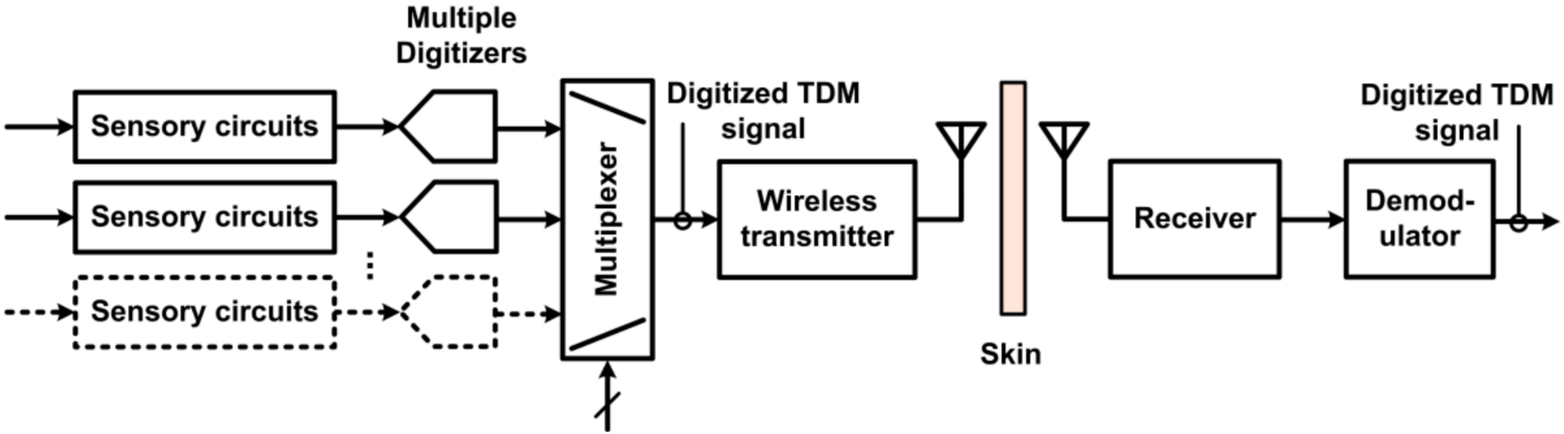


M. Judy, et al,, TBCAS'14

Multichannel Architectures



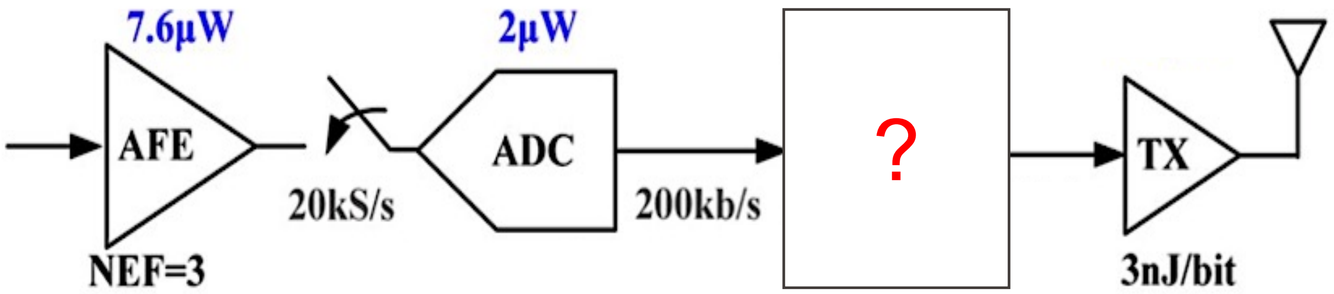
(a)



(b)

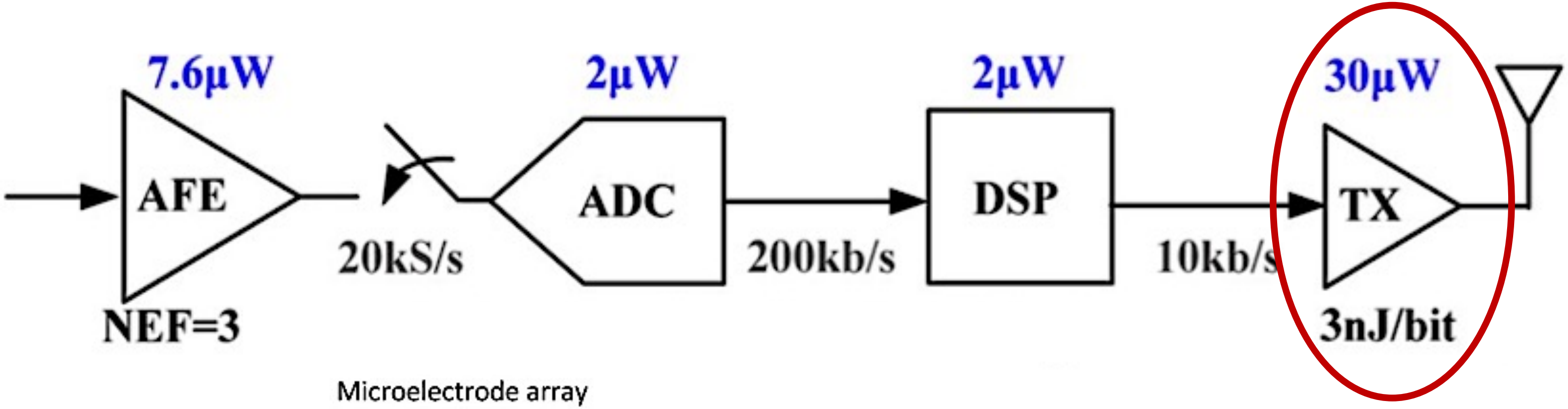
Neural Interface: ADC and Compression

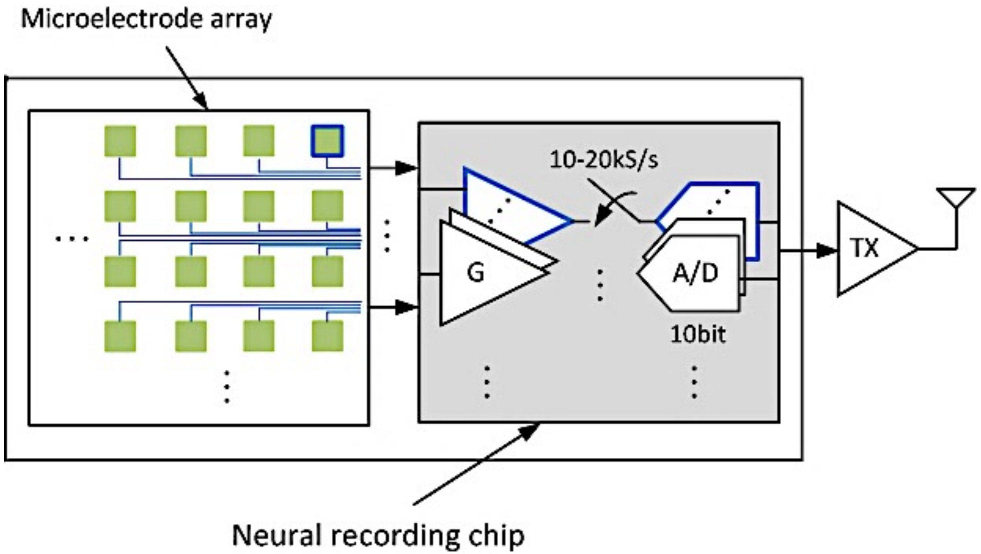
- The typical circuit blocks used in sensors for medical monitoring and their associated energy cost and power consumption



F. Chen et al, *JSSC'12*

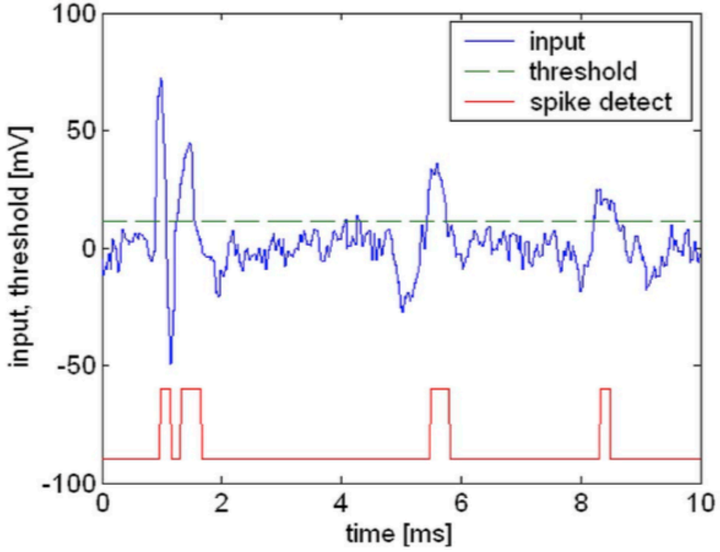
Data Compression

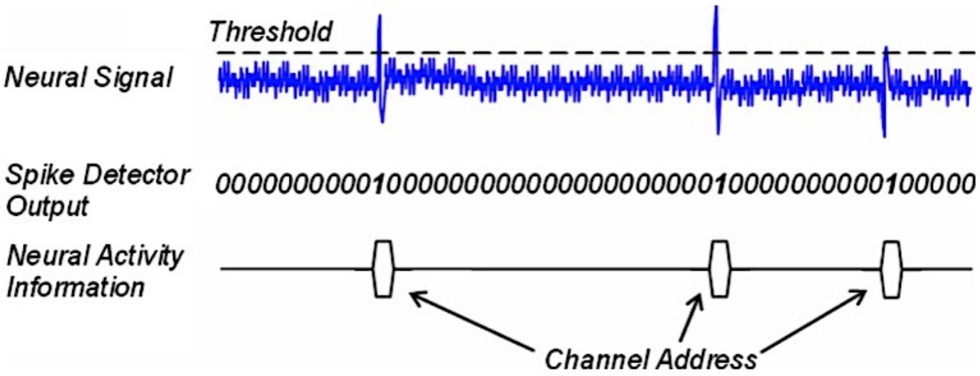




On-Chip Compression of Neural Signal

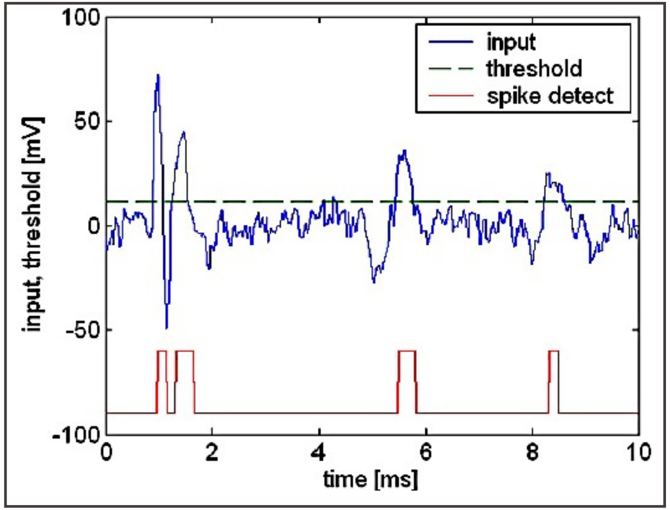
- Spike Detection





Compression of Neural Signal

- Spike Detection
  - High compression ratio (CR)
  - × Losing the raw waveform
  - × Unreliable in long-time



Compression of Neural Signal

- Compressive Sensing (CS):
  - CS relies on the signal of interest being sparse in some basis, Ψ.
  - Many biological signals of interest are sparse e.g. EEG, ECG, etc.

Digital Data Acquisition

Foundation: *Shannon/Nyquist sampling theorem*

"if you sample densely enough (at the Nyquist rate), you can perfectly reconstruct the original analog data"

Signal Type	Sampling Rate	Frequency of Events
Extracellular APs	30 kHz	10 – 150 /s
EMG	15 kHz	0 – 10 /s
EKG	250 Hz	0 – 4 /s
EEG, LFP	100 Hz	0 – 1 /s

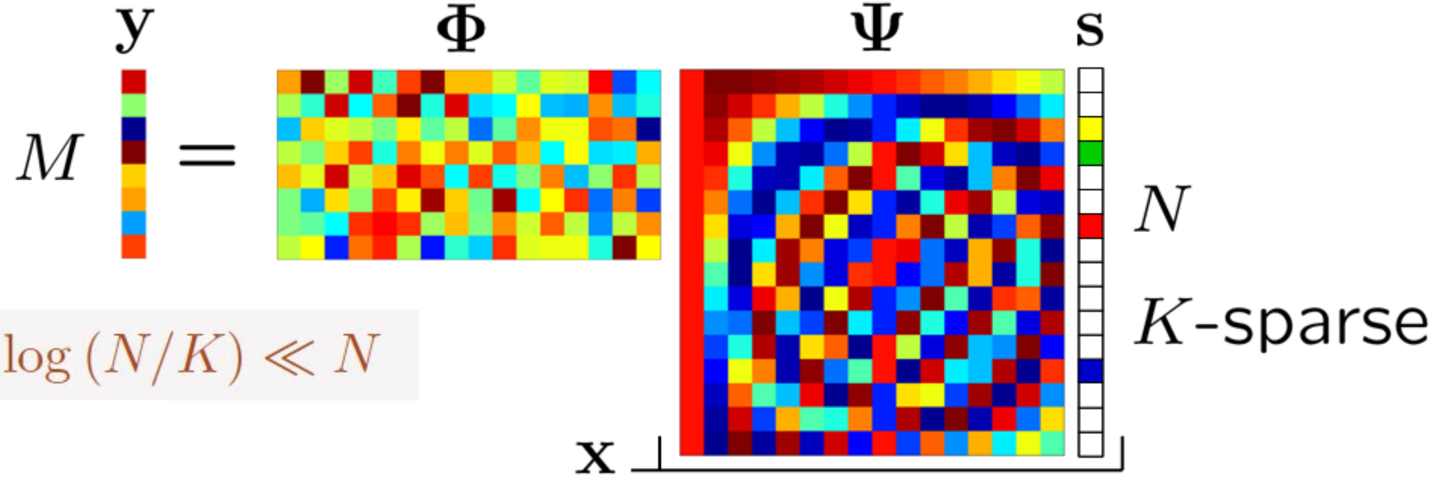
Data Reduction in Wireless Sensors

What we want:

- Compression: minimize data, but retain the information
- Low cost: must be less than transmission savings
- Generality: we don't want to customize every sensor design

Compressive Sensing

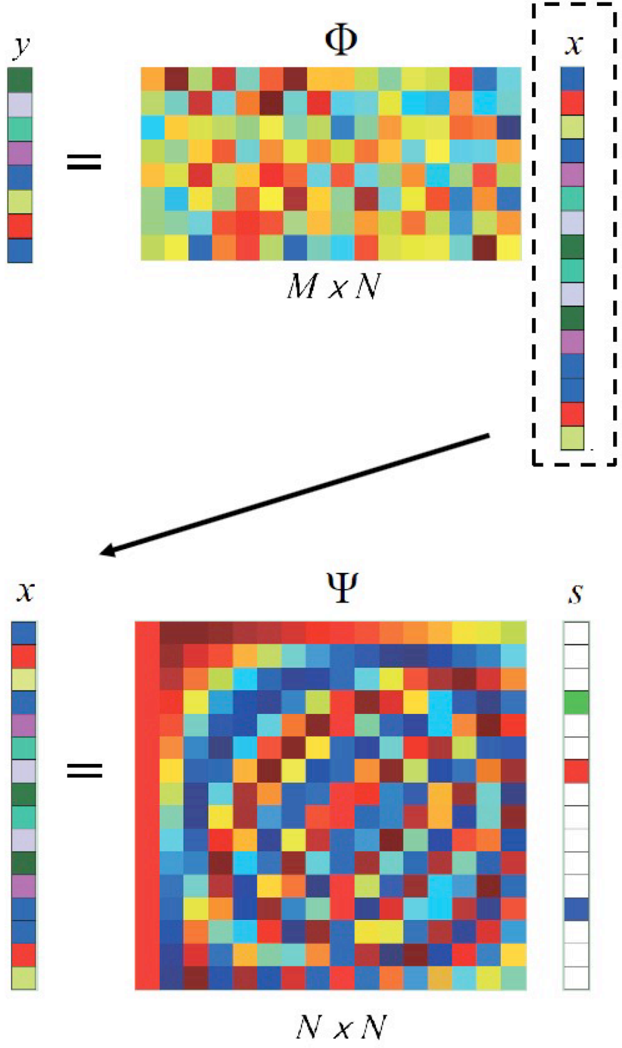
- In 2006, **Candès and Donoho** proved that given a signal's sparsity, it may be reconstructed with even fewer samples than the sampling theorem requires
- **Low cost, generality**



$$M \geq cK \log\left(N/K\right) \ll N$$

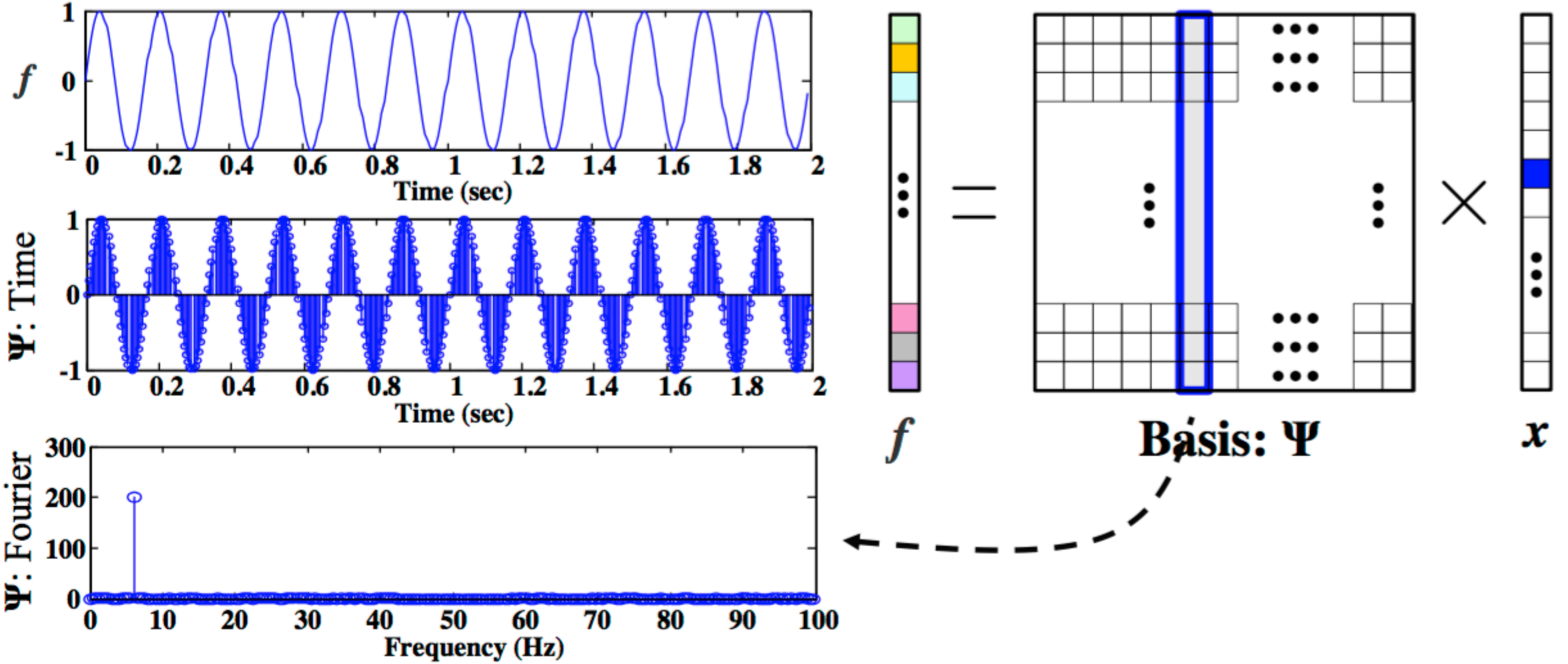
- Random matrix with Gaussian or Bernoulli entries (random 0, 1)
- Recovery: a convex minimization problem

Compressive Sensing

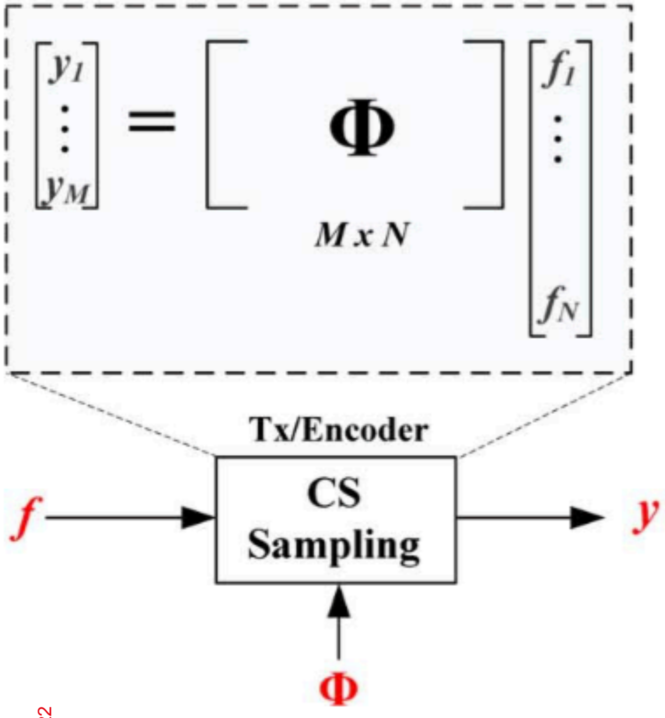


Compressive Sensing

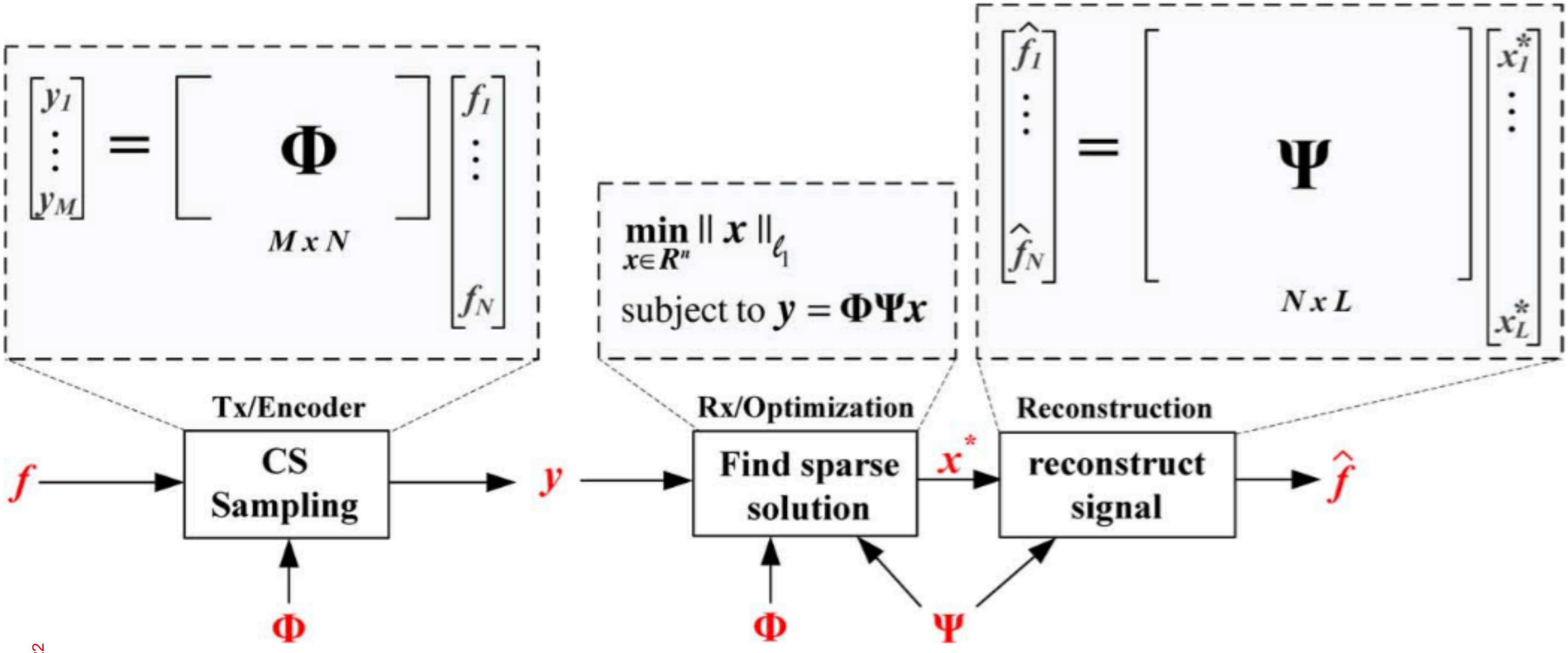
- Sinusoid example:



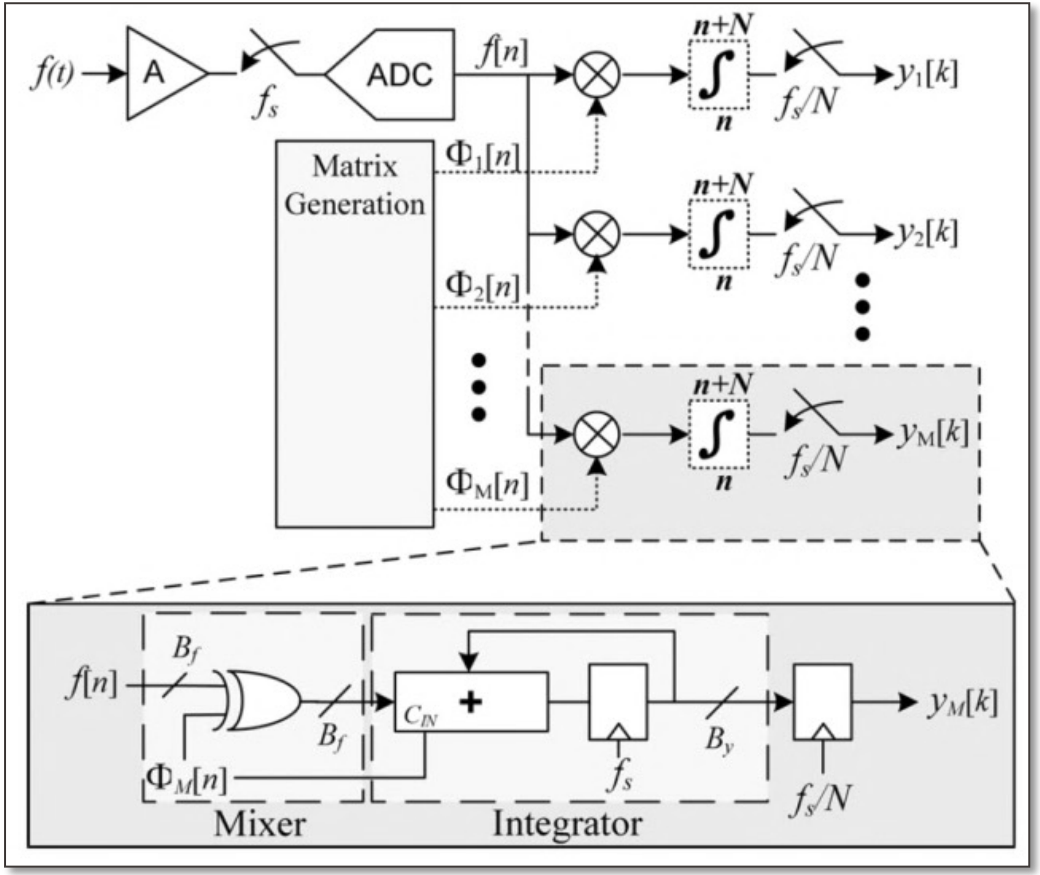
Compressive Sensing



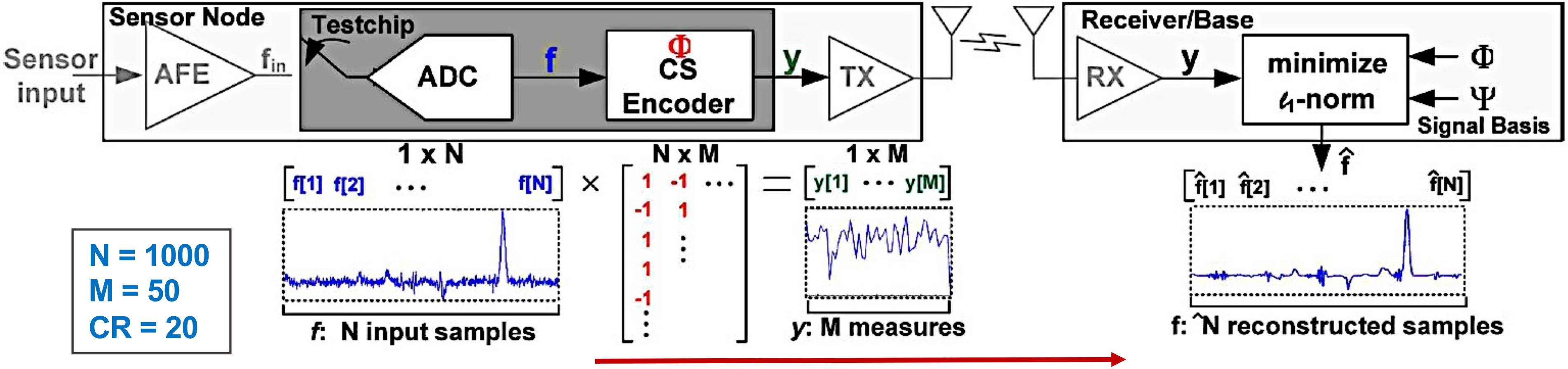
Compressive Sensing



Compressive Sensing Hardware: Digital



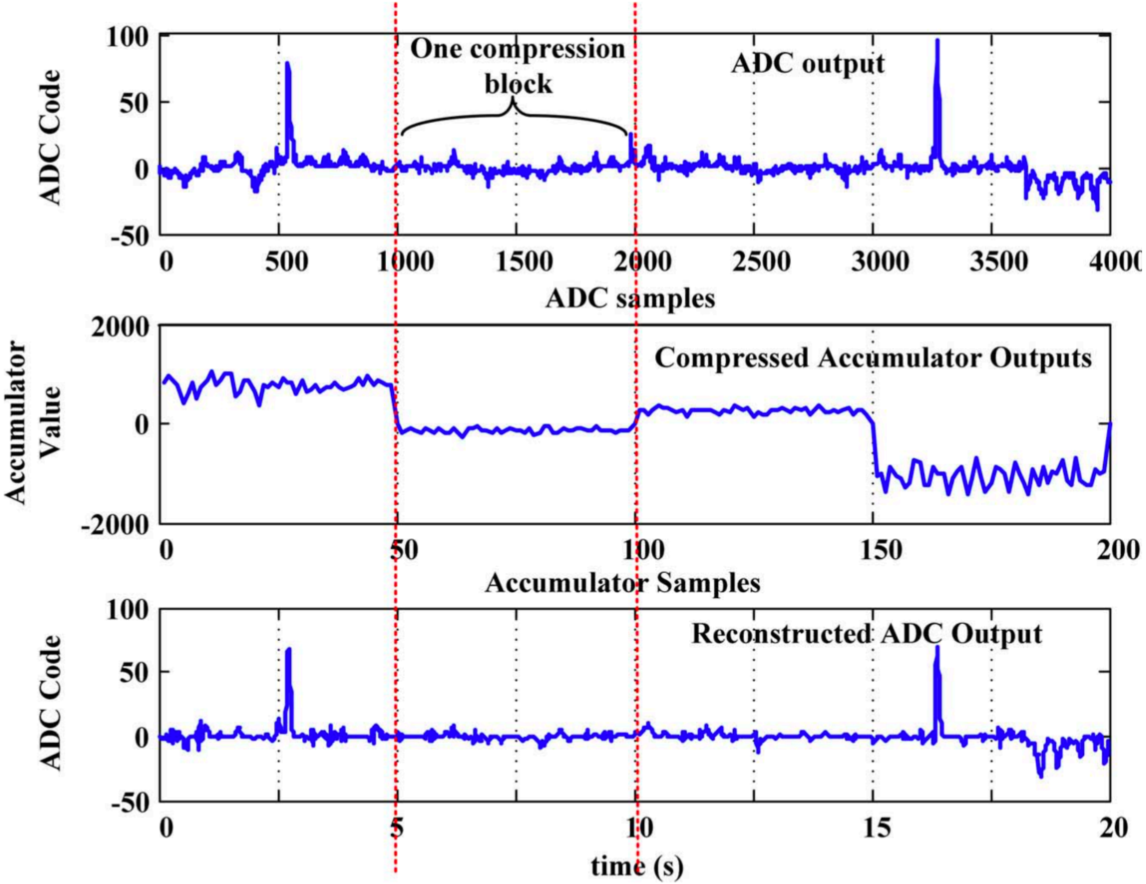
Compressive Sensing: Digital



N = 1000
M = 50
CR = 20

F. Chen, JSSC'12

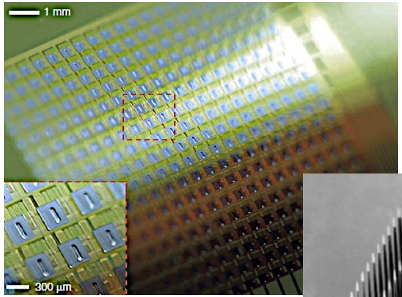
Compressive Sensing: Digital

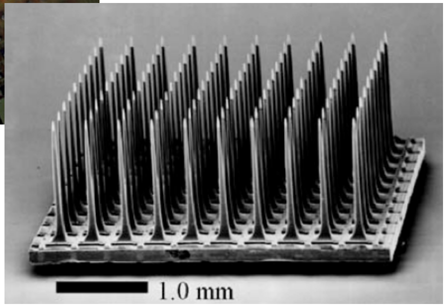


EPFL

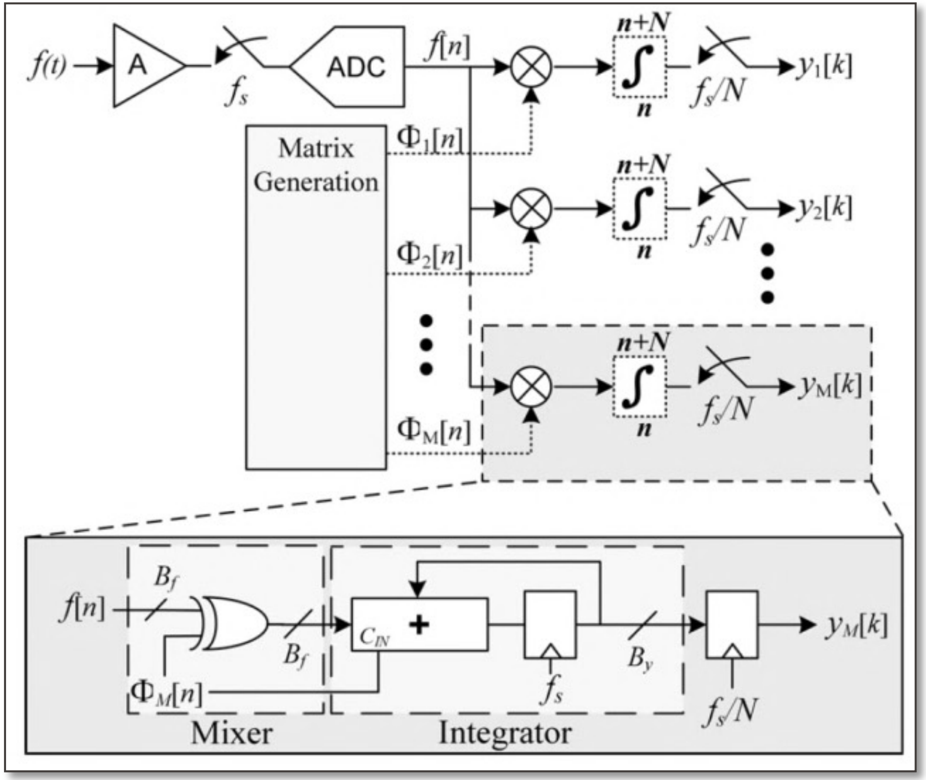
Compressive Sensing: Digital

- Significant data reduction
- × Power: **1.9μW**
- × Large area: **+0.1mm²/channel**
- Need for a more efficient approach





→ ?

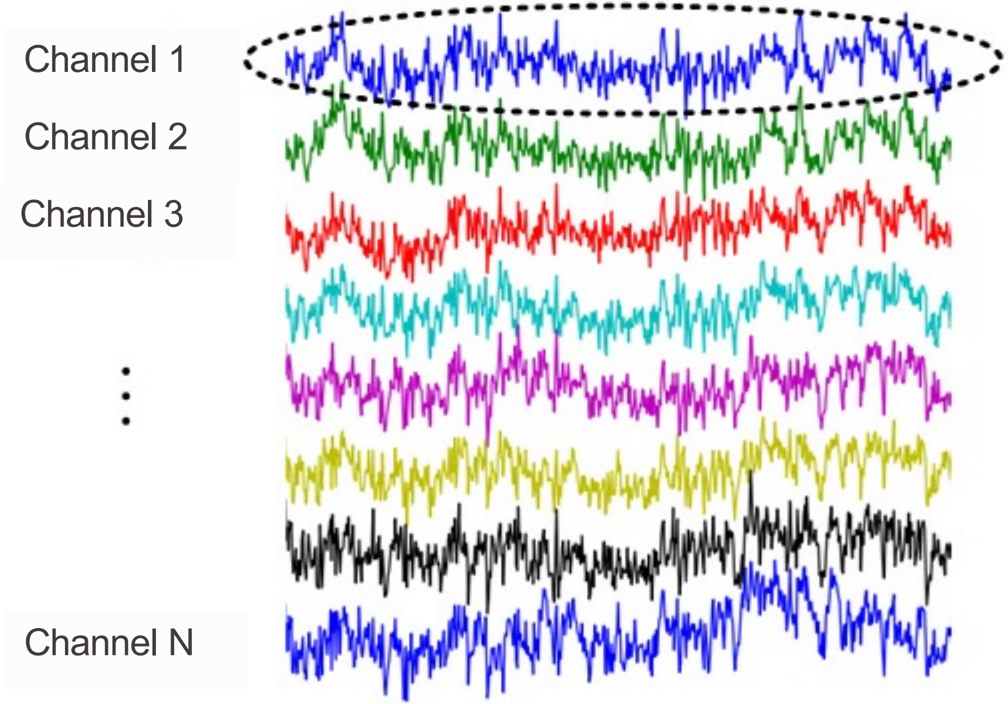


Single-Channel Compressive Sensing

$\mathbf{X} \in \mathbb{R}^{d \times N}$

$\boldsymbol{\Phi} \in \mathbb{R}^{m \times d}$

$x \in \mathbb{R}^{d}$



$y = \boldsymbol{\Phi} x$

CR = d/m

Spatial-Domain Compressive Sensing

$\mathbf{X} \in \mathbb{R}^{d \times N}$

$x \in \mathbb{R}^N$

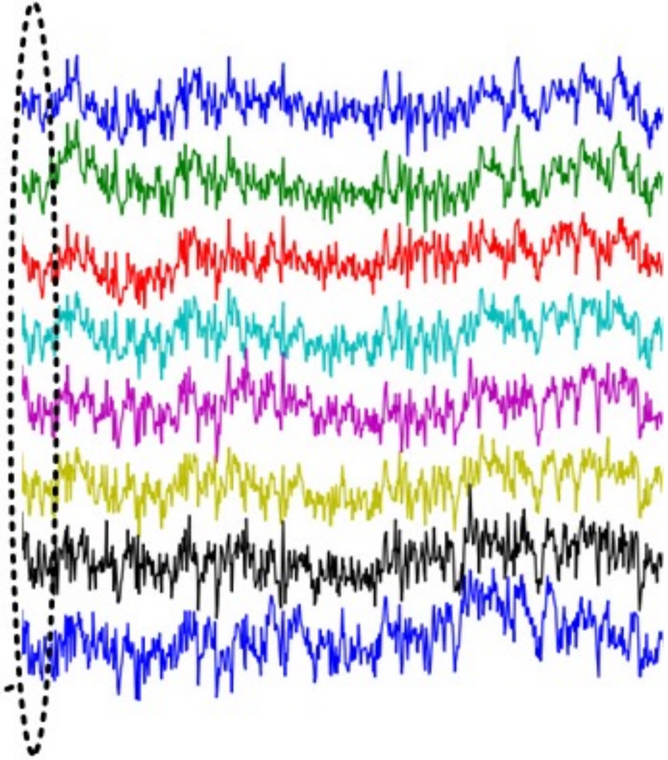
Channel 1

Channel 2

Channel 3

$\vdots$

Channel N



$$\mathbf{\Phi}_i = \begin{bmatrix} \phi_i^{1,1} & \cdots & \phi_i^{1,N} \\ \phi_i^{2,1} & \cdots & \phi_i^{2,N} \\ \vdots & \ddots & \vdots \\ \phi_i^{M,1} & \cdots & \phi_i^{M,N} \end{bmatrix}$$

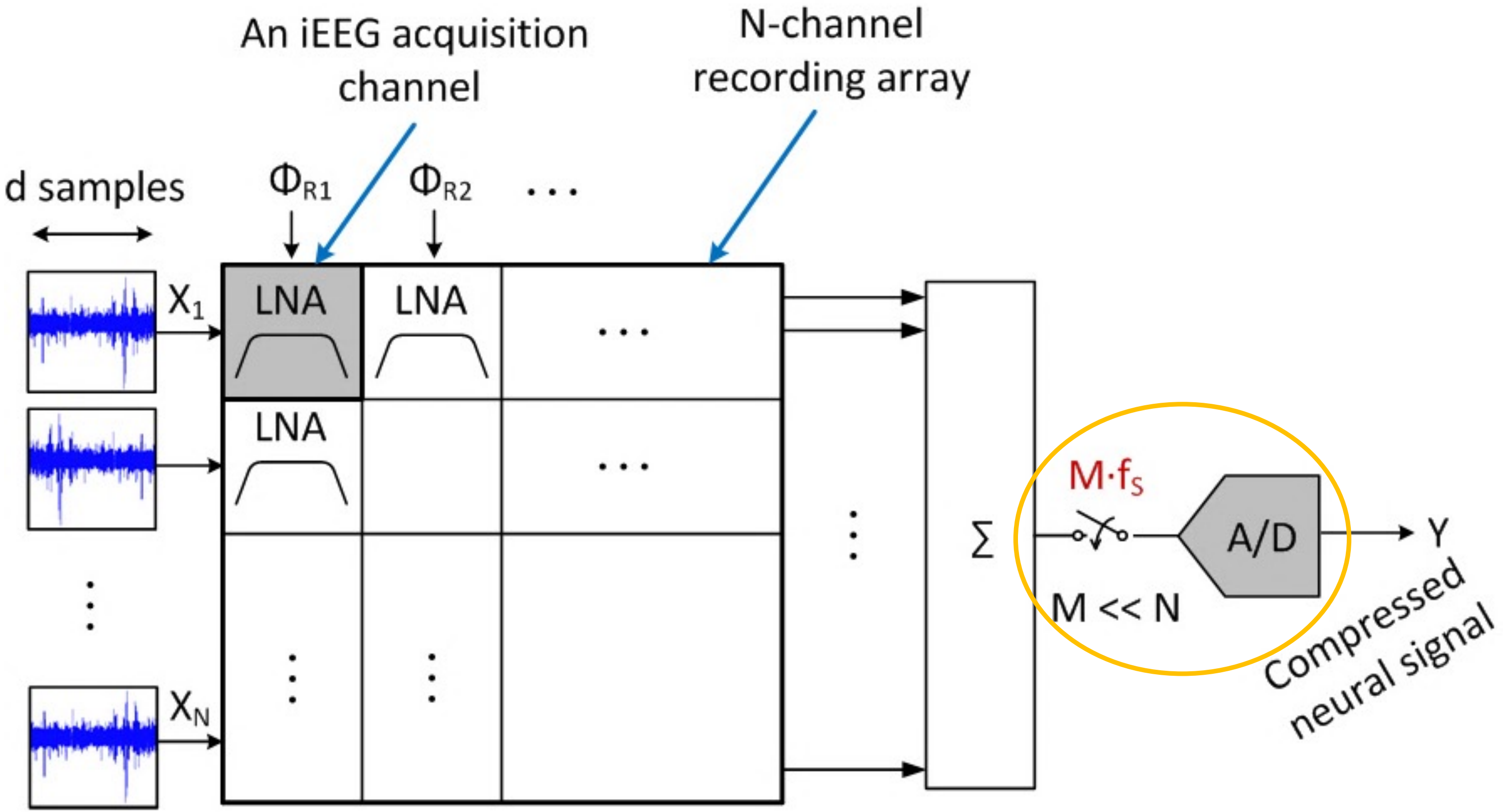
$y = \mathbf{\Phi}_i \, x$

CR = N/M

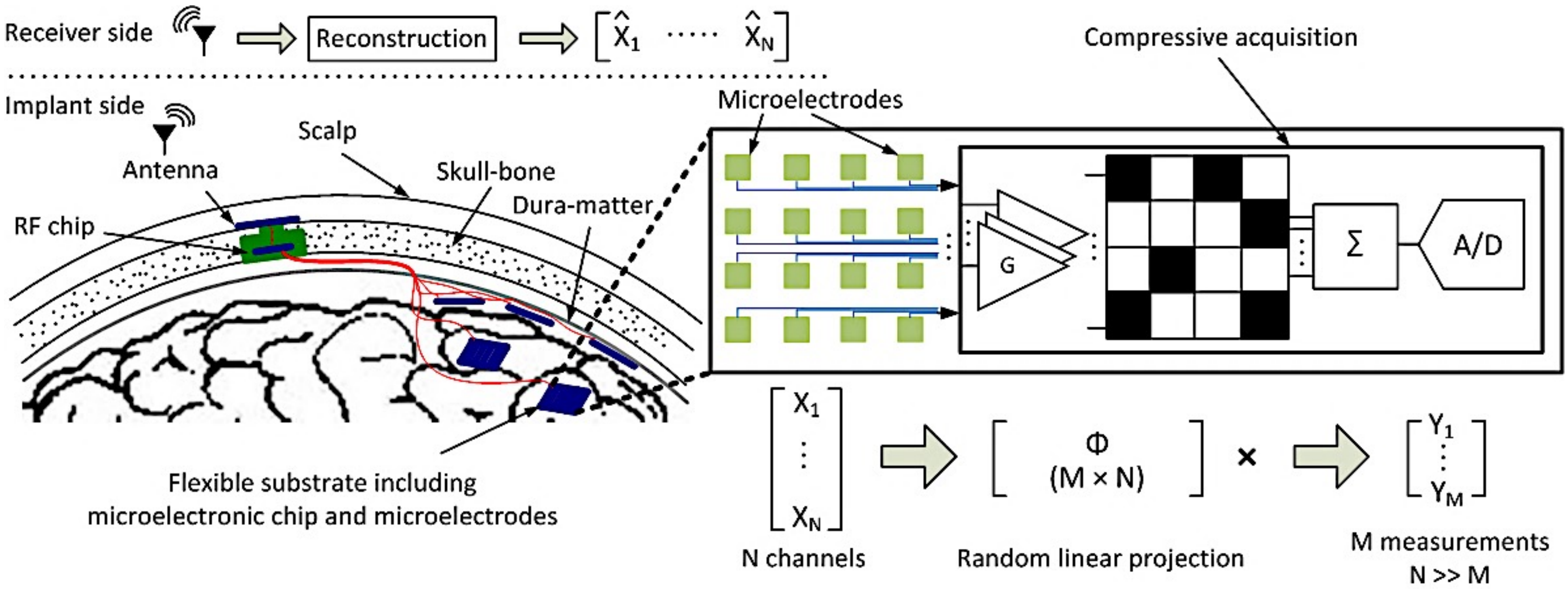
1 ≤ M < N

M. Shoaran, TBCAS’14

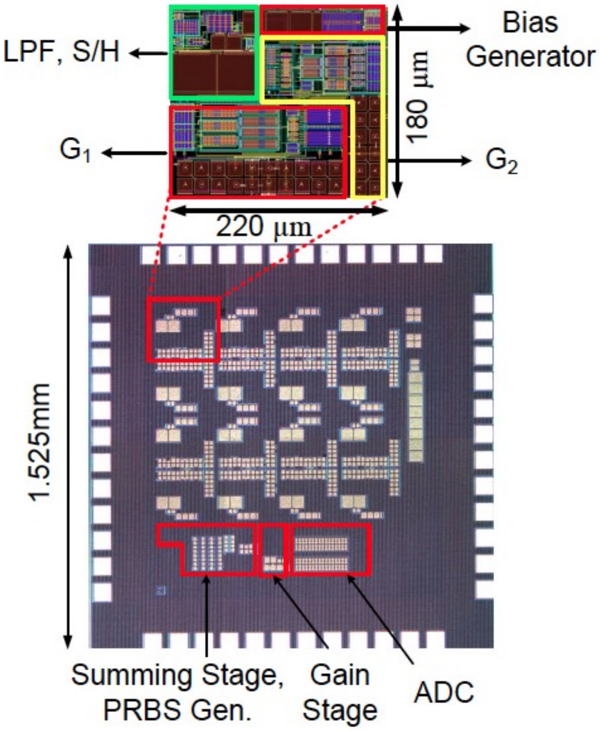
Spatial-Domain Compressive Sensing

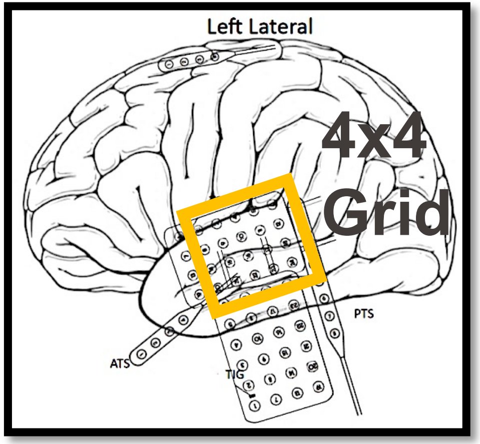


Spatial-Domain Compressive Sensing



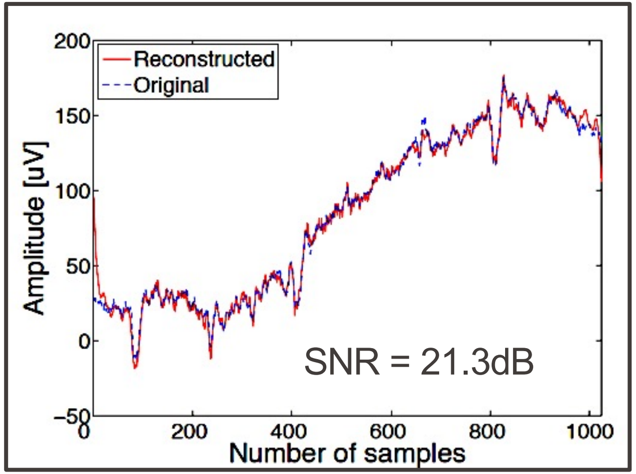
Measurements and Die Photo



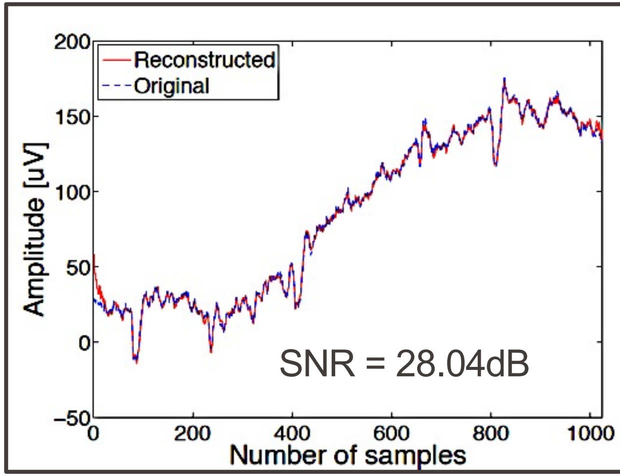


$$SNR = -20\log_{10}\|x-\hat{x}\|_2/\|x\|_2$$

ℓ_1 recovery



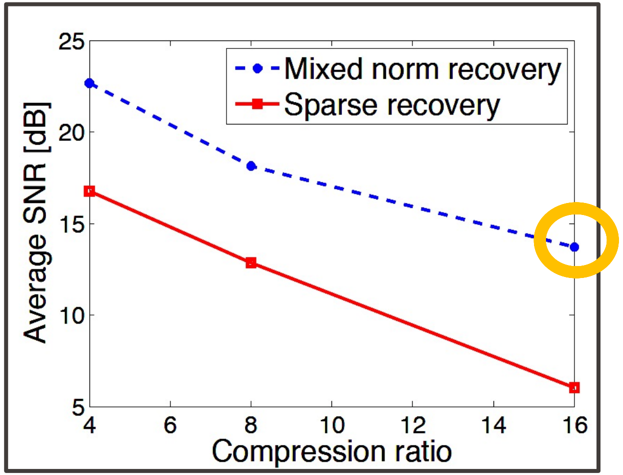
$\ell_{1,2}$ recovery



Spatial Compressive Sensing

Average SNR

- ✓ 16× increase in number of channels
- ✓ No increase in transmission power



Parameter	JSSC'12	TBCAS'12	JSSC'07	TCAS-I'09	This Work
Technology [μm CMOS]	0.09	0.13	0.5	0.5	0.18
Power supply [V]	0.6	1.2	3.3	-	1.2
Compression method	DCS	Spike det.	Spike det.	DWT	MCS
Number of channels	1	1	100	32	16
Compression area per channel [mm^2]	0.103	0.080	0.160	0.18	0.008
Compression power per channel [μW]	1.9	1.18	27	95	0.95
Sampling rate per channel [kS/s]	$\leq$20	90	15	25	4
Compression ratio	$\leq$10	125	150	$\leq$20	$\leq$16