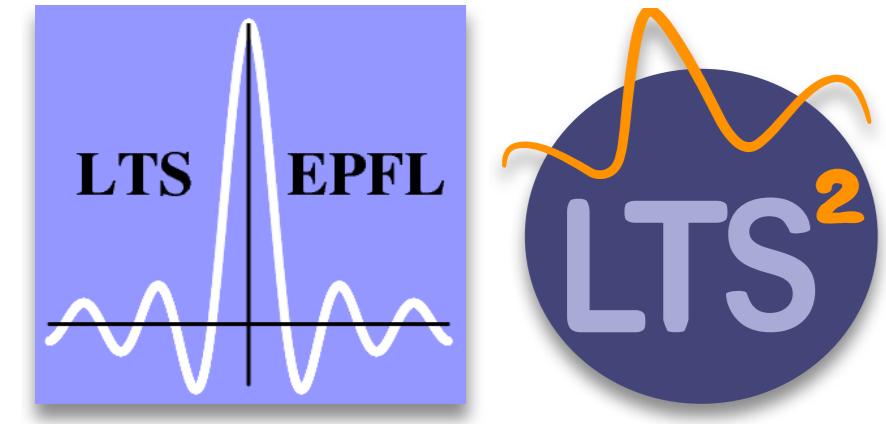


CMOS COMPRESSED IMAGING BY RANDOM CONVOLUTION

L. Jacques^{1,3}, P. Vandergheynst¹, A. Bibet², V. Majidzadeh², A. Schmid², Y. Leblebici²

¹ Signal Processing Laboratory. ² Microelectronic Systems Laboratory (LSM). Swiss Federal Institute of Technology (EPFL), Lausanne, Switzerland.

³ Communications and Remote Sensing Laboratory (TELE), Université catholique de Louvain (UCL), Belgium. (research supported by the Belgian FNRS-FRS)



OBJECTIVES:

- * CMOS Imager with Compressed Sensing coding
- * Simple (light) and fast compressed encoding + “fast” decoding
⇒ Random Convolutions [1] performed on the focal plane
- * Reduced power consumption (*wrt* pixel scanning)
- * Almost “Isometric” compression (since *random projection*)

I. COMPRESSED SENSING (briefly) [2]

Image: $x = \Psi\alpha \in \mathbb{R}^N$

Sparsity basis: $\Psi \in \mathbb{R}^{N \times N}$ (e.g. Canonical, Wavelet, DCT, ...)

A priori: $\alpha \in \mathbb{R}^N$ is K -sparse (or *compressible*),
or x must have a “sparse” gradient.

Sensing model: $y = \Phi x = \Phi \Psi \alpha \in \mathbb{R}^m$, $m < N$
 $\Phi \in \mathbb{R}^{m \times N}$ is the *Sensing* matrix

Reconstruction:

- * Not linear (on high CPU device)
- * Requirements: $\Theta = \Phi\Psi$ must be a **RIP** matrix !
- * If Φ is a Gaussian Random matrix,

$$m \geq O(K \log N / K)$$

* If $\Phi = \mathcal{S} \mathcal{F}^T H \mathcal{F} = \mathcal{S} \circ (h * \cdot)$, with $H = \mathcal{F} h$

\swarrow Random selection \searrow Fourier

$$m \geq O(K \log N / K) \quad \text{and} \quad m \geq O(\log^3 N / \delta)$$

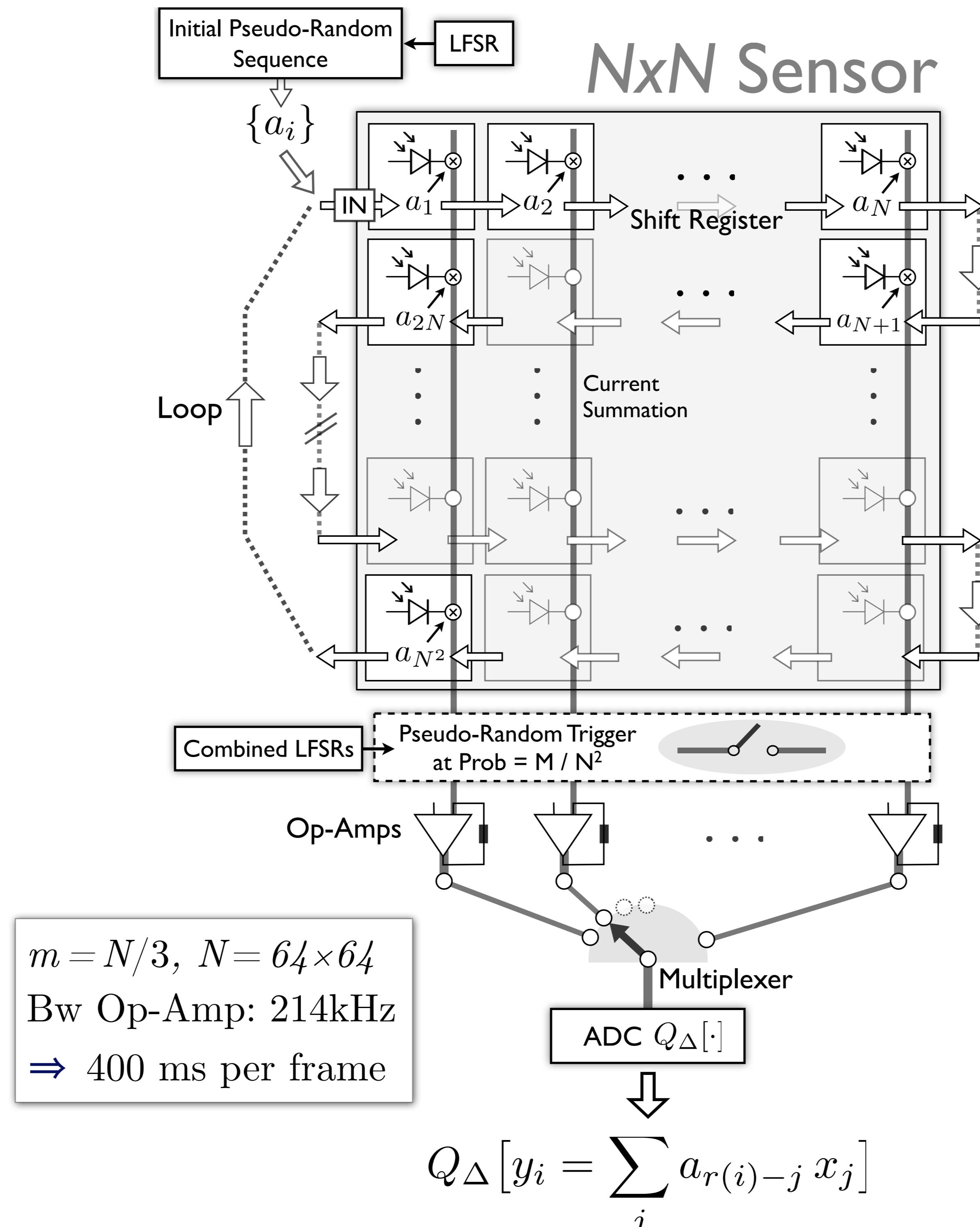
⇒ *Random Convolution* [1] ⇒ *but fast coding and faster decoding!*

* Decoding: *Basis Pursuit DeNoise* (BPDN) or *TV* variant

$$\arg \min_x \Sigma(x, \alpha) \quad \text{s.t.} \quad \|\Theta\alpha - y\|_2 \leq \epsilon$$

with $\Sigma(x, \alpha) = \|\alpha\|_1$ or $\|x\|_{TV}$

II. DESCRIPTION OF THE IMAGER



- * Compressed Sensing Coding ⇔ Analog Signal Processing
- * Idea: 1-bit *Shift Register* in the focal plane contains h
- * Convolution by h obtained by:
 - * current flipping by 1-bit SR $h_i = \pm 1$ (pseudorandom)
 - * shifting SR between measurement ⇔ pushing bits (box [IN])
 - * summing currents ⇔ *Kirchoff* law (in wires)
 - * (pseudo) randomness ⇔ convenient use of LFSRs
- * Current practical choices: (CMOS chip to be manufactured)
 - * 64×64 CMOS Passive Pixel Sensors (PPS, 200µA), 30µm×30µm
 - * 1-bit flip-flop SR, Op-Amp with bandwidth 214kHz
 - * Sums are multiplexed (column by column) to reduce currents

References:

- [1] J. Romberg, “Compressive Sampling via Random Convolution”. IEEE Int. Workshop CAMPSAP 2007, pp. 137-140.
[2] E. Candès, J. Romberg, Found. Comp. Math., 2006, 6, 227-254.
[3] M. Duarte, M. Davenport, D. Takbar, J. Laska, T. Sun, K. Kelly, R. Baraniuk, IEEE Sig. Proc. Mag., 2008, 25, pp. 83-91.
[4] R. Robucci, L. Chiu, J. Gray, J. Romberg, P. Hasler & D. Anderson, IEEE ICASSP, 2008, pp. 5125-5128.
[5] L. Jacques, D.K. Hammond, M. J. Fadili. “Dequantizing Compressed Sensing”, submitted to IEEE Trans. Inf. Theory (2009)
[6] M. Jenkner, M. Tartagni, A. Hierlemann, R. Thewes, C. Res, I. AG & G. Munich. “Cell-based CMOS sensor and actuator arrays Solid-State Circuits”, IEEE Journal of, 2004, 39, pp. 2431-2437.

III. PREVIOUS WORKS

- * One-pixel Camera of Rice University [3]
- * Digital Micromirror Device (random pattern) + 1 photosensor
⇒ Analog random sensing in the optical domain
- * But extra non-linearities due to DMD, optics, ...
- * CMOS Analog Imager of Georgia Tech [4]
 - * General implementation (Transform coding, noiselet, DCT ...)
 - * Larger architecture and larger onboard memory

III. CODING/DECODING SIMULATION

- * 256×256 images + thermal noise + 11-bits quantization of y
- * $y = \Phi x + n$, $n_i \sim_{iid} N(0, \sigma)$, $\sigma^2 = \sigma_{th}^2 + \sigma_{ADC}^2 + \frac{\Delta^2}{12}$ ($\sigma \simeq \|y\|_\infty / 100$)
- * Reconstruction with BPDN-TV, $\epsilon \simeq \sigma \sqrt{m}$ (by proximal methods)



Original Image (Lausanne)



$m = N/3$, PSNR = 27.3 dB

IV. POSSIBLE EXTENSIONS

- * Using Basis Pursuit *DeQuantizers* BPDQ [5] for $Q_{\Delta}[\cdot]$
- * $\arg \min_x \Sigma(x, \alpha) \quad \text{s.t.} \quad \|\Theta\alpha - y\|_p \leq \epsilon$, with $p \geq 2$
- * Adapting the sensor to a grid of biocompatible electrodes [6]
⇒ totally equivalent compressed coding

