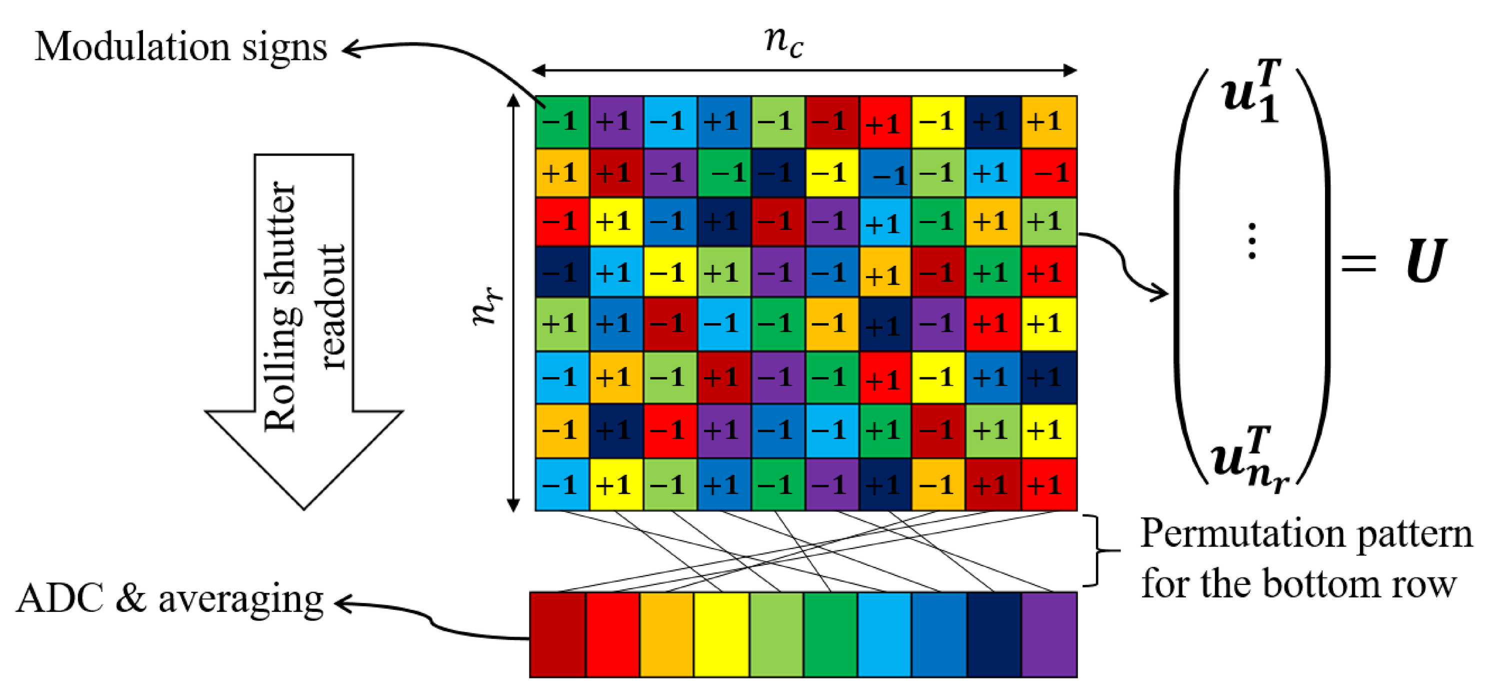
CONTACT: Wissam BENJILALI | Wissam.benjilali@cea.fr

HARDWARE-FRIENDLY COMPRESSIVE IMAGING BASED ON RANDOM MODULATIONS & PERMUTATIONS FOR IMAGE ACQUISITION AND CLASSIFICATION

Insights

- New Compressive Sensing (CS) scheme.
- Same theoretical performance as a randomly generated matrix.
- Compatible with CMOS Image Sensors applications:
  - ➔ **Low silicon footprint.**
  - ➔ **Low ADC clock cycles.**
  - ➔ **Low memory needs for inference tasks.**
- Outperforms state-of-the-art compressive imaging CMOS implementations.

Proposed CS model



Apply a random modulation ± 1, per-row random permutation, averaging by column to extract a compressed vector.

$$\Phi = \frac{1}{\sqrt{s}}\left(\left(P^{(1)}M^{(1)}\right)^\top, \dots, \left(P^{(s)}M^{(s)}\right)^\top\right)^\top \in \mathbb{R}^{s n_c \times n_r n_c}$$

➔ $P^{(i)} = \left(p_1^{(i)}, \dots, p_{n_r}^{(i)}\right) \in \{0,1\}^{n_c \times n_r n_c}$, with $p_j^{(i)} \in \{0,1\}^{n_c \times n_c}$ is a random permutation matrix applied to the j^{th} row of U.

➔ $M^{(i)} = diag\left(\varphi_1^{(i)}, \dots, \varphi_{n_r}^{(i)}\right)$, with $\varphi_j^{(i)} \in \{\pm 1\}^{n_c}$ Rademacher modulation vector applied to the j^{th} row of U.

➔ Tuned compression ratios through multiple snapshots s $(1 \le s \le n_c)$.

Analytical analysis

RIP (Restricted Isometry Property)

A matrix Φ satisfies the Restricted Isometry Property (RIP) of order $2k$ if there exists a $\delta_{2k} \in (0,1)$ such that:

$$(1-\delta_{2k})\|u-v\|_2^2 \le \|\Phi u - \Phi v\|_2^2 \le (1+\delta_{2k})\|u-v\|_2^2$$

holds for any $2k$-sparse vectors u and u in $\mathbb{R}^{n_r n_c}$.

Lemma

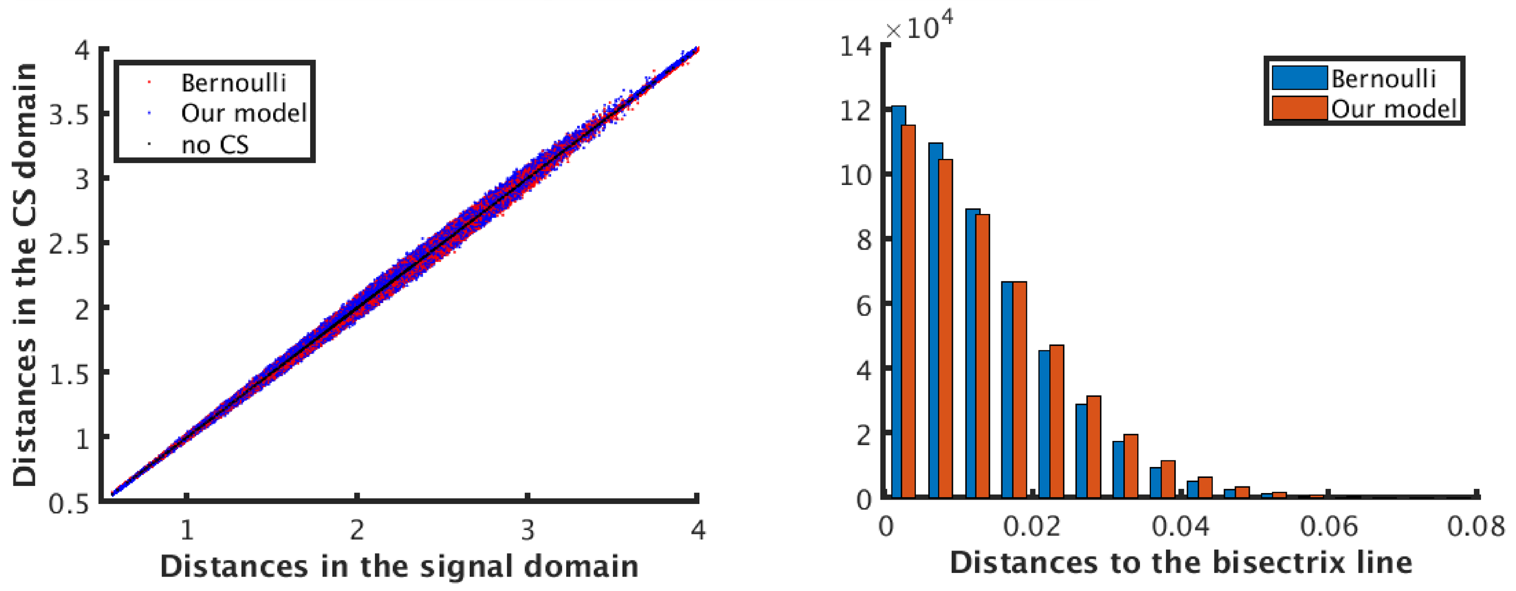
Let Φ the proposed CS matrix, For any k-sparse vector u,

$$\mathbb{E}\left(\|\Phi u\|_2^2\right) = \|u\|_2^2$$

➔ By expectation, the proposed CS matrix respects the RIP.

➔ The lemma can be extended to $\mathbb{E}\left(\|\Phi\Psi u\|_2^2\right) = \|\Psi u\|_2^2 = \|u\|_2^2$ by Parseval's identity if Ψ is an orthonormal basis.

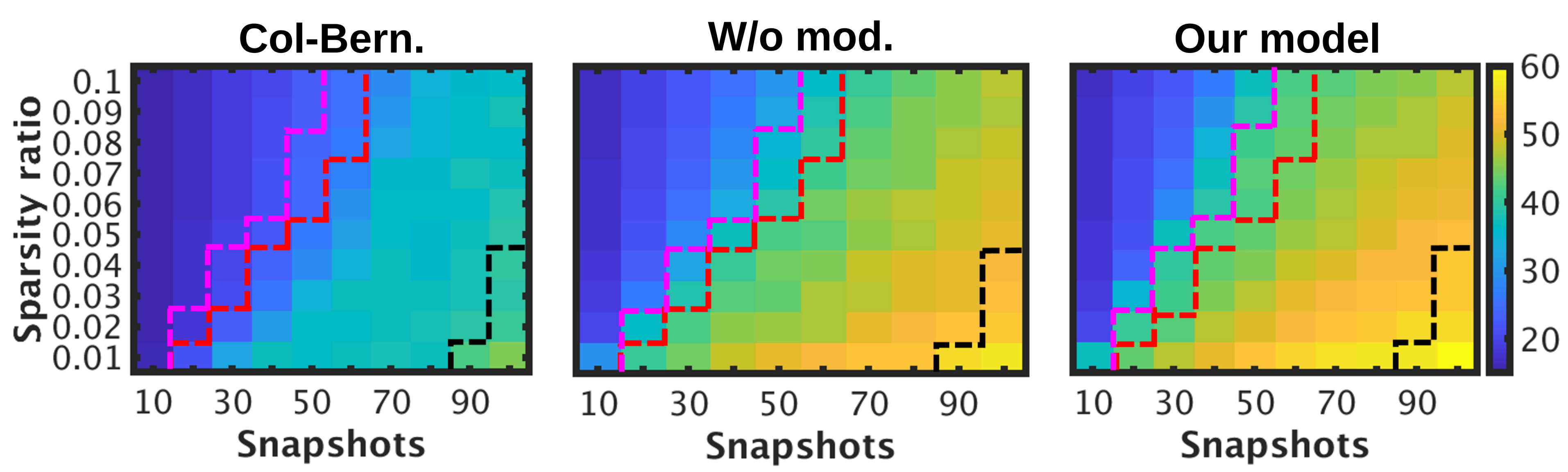
Concentration of pairwise distances



(left) Concentration of pairwise distances of our model and a Bernoulli distribution around the pairwise distances in the signal domain (bisector axis) for $N = 1024$, $k = 10$ and $M = 128$. **(right)** Histogram of distances to the bisector axis.

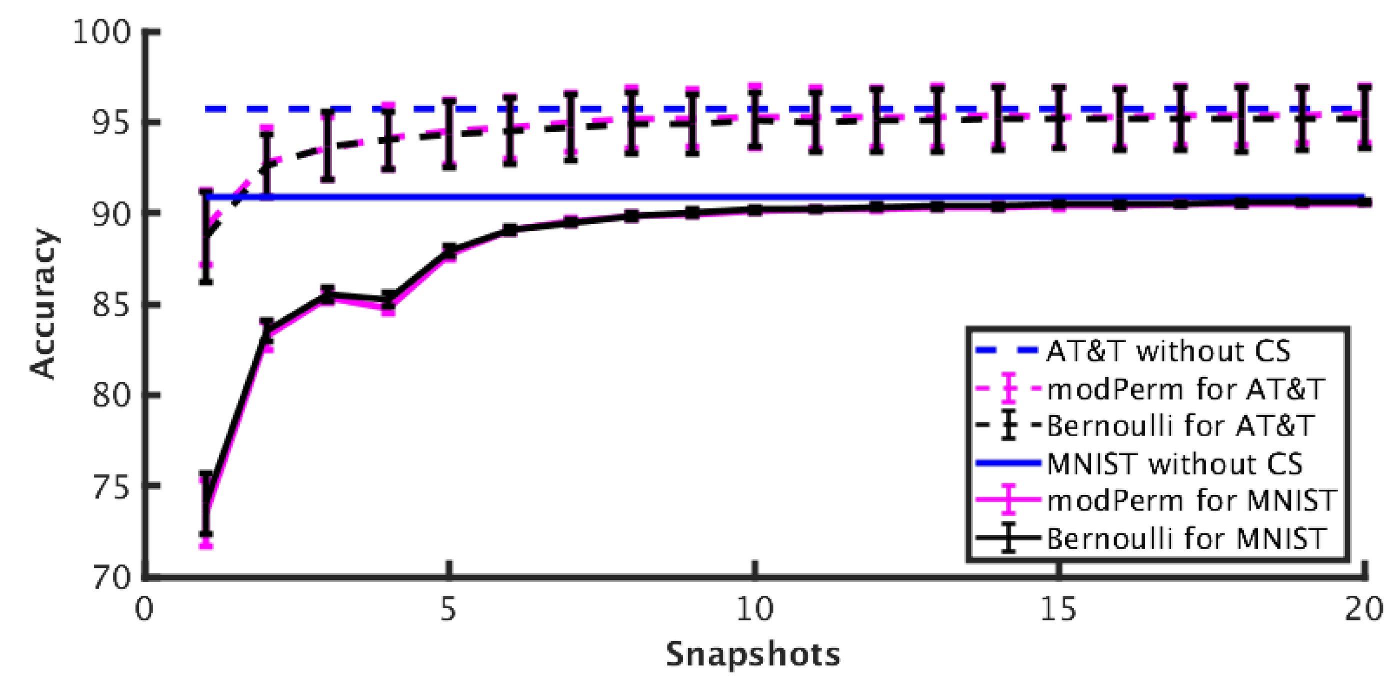
Experimental results

- Recovery of sparse 128×128 images.
  - ➔ Thresholded in the Db-6 wavelet domain and back projected.
  - ➔ (black line) transitions to a success reconstruction above $40\ dB$ for per-column Bernoulli.
  - ➔ (red line) transitions to a success reconstruction for our model without permutations.
  - ➔ (magenta line) transitions to a success reconstruction for our model.



- Recovery of cameraman under a dictionary of wavelets regularization operator $\left(\sum_{i=1}^{3}\|\Psi_i\Delta_v u\|_1 + \|\Psi_i\Delta_h u\|_1\right)$.

- Inference for two object recognition tasks.



- Possible hardware implementations.