A New Compressive Imaging Camera Architecture using Optical-Domain Compression

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Joint work with
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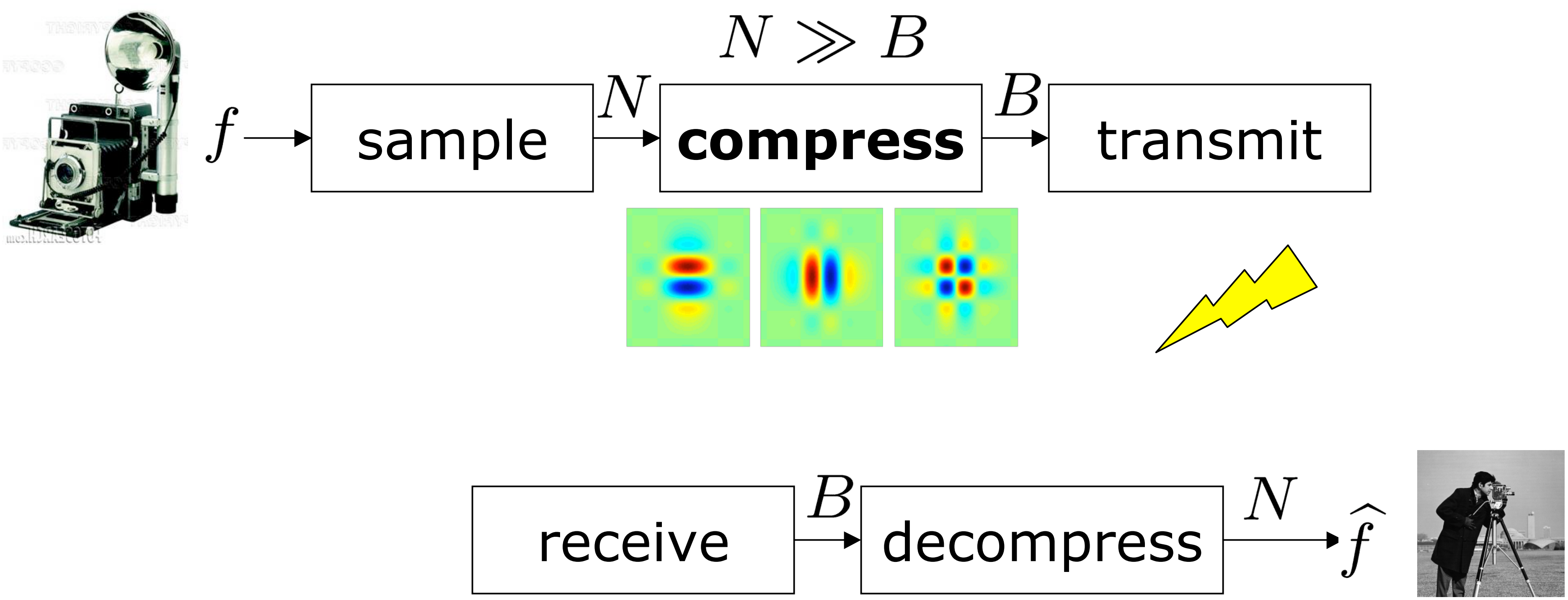
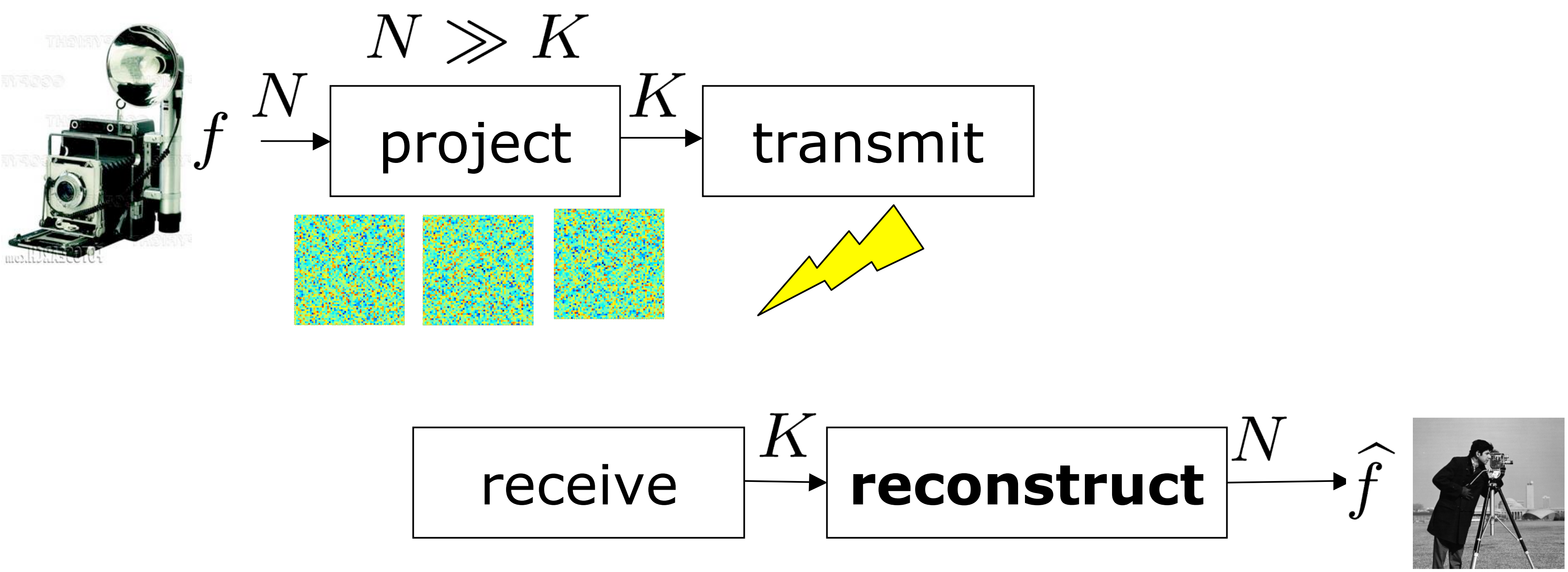
DSP Sensing

- The typical sensing/compression setup
  - compress = transform, sort coefficients, encode
  - most computation at *sensor* (asymmetrical)
  - *lots of work* to throw away >80% of the coefficients



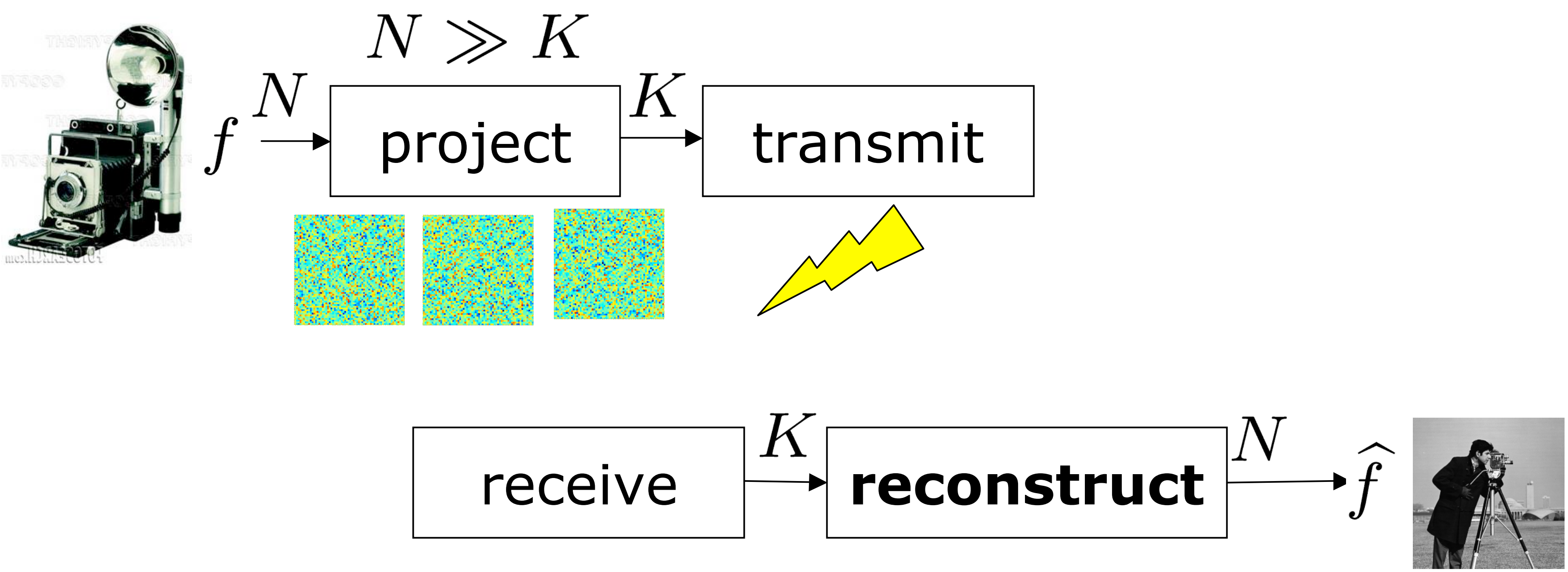
Compressive Sensing (CS)

- Measure projections onto *incoherent* basis/frame
  - random "white noise" is *universally incoherent*
- Reconstruct via nonlinear techniques
- Mild overmeasuring: $K \geq cB, \quad c \approx 3$
- Highly asymmetrical (most computation at *receiver*)

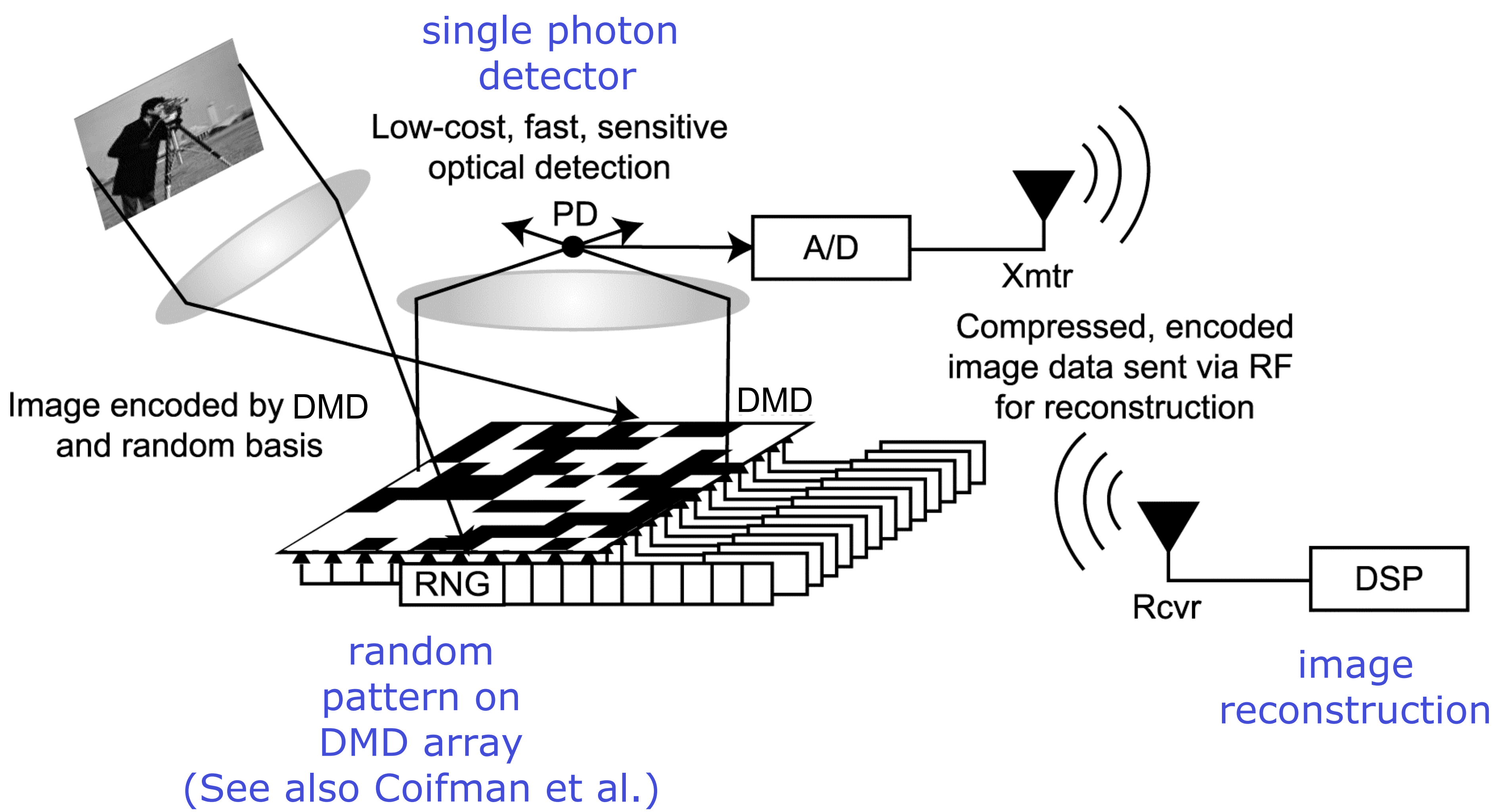


Compressive Imaging (CI)

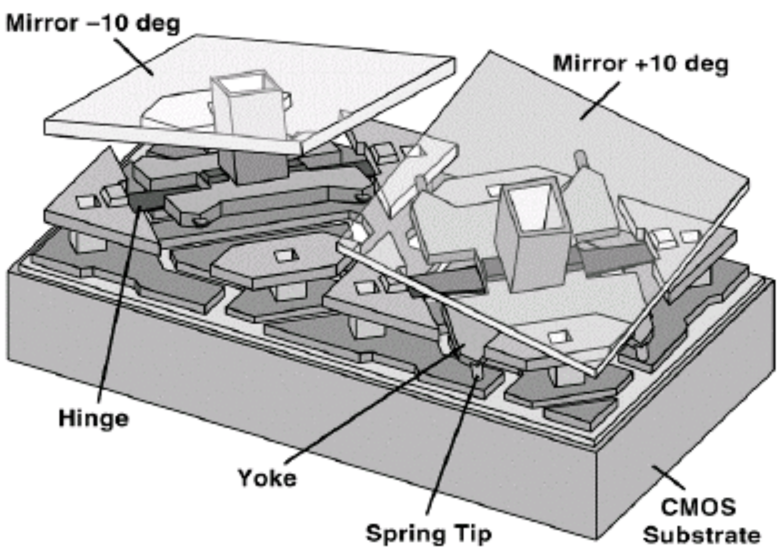
- Measure projections onto *incoherent* basis/frame
  - random "white noise" is *universally incoherent*
- Reconstruct via nonlinear techniques
- Mild overmeasuring: $K \geq cB, \quad c \approx 3$
- Highly asymmetrical (most computation at *receiver*)



Rice CI Camera



TI Digital Micromirror Device (DMD)



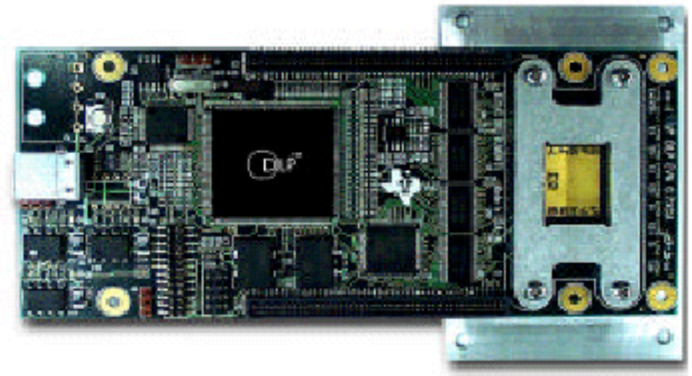
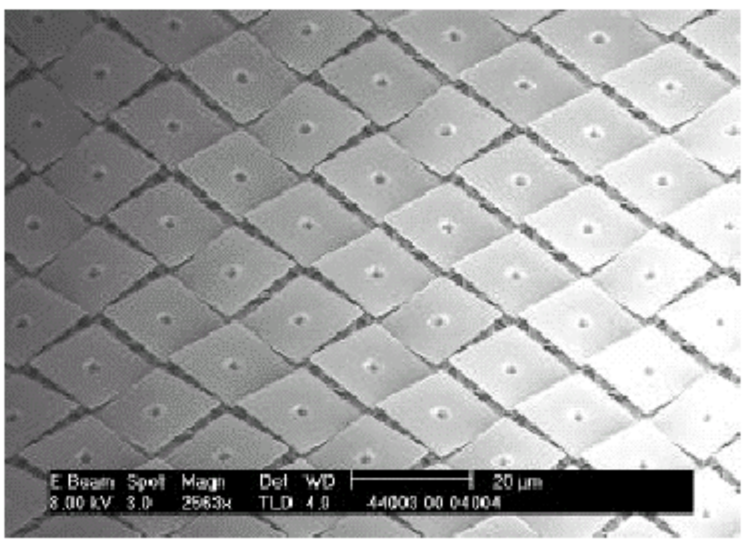


Figure 15: DMD Discovery™ Controller Board with DMD.



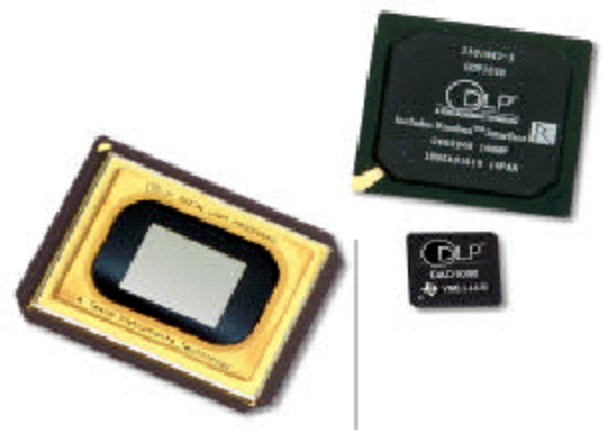
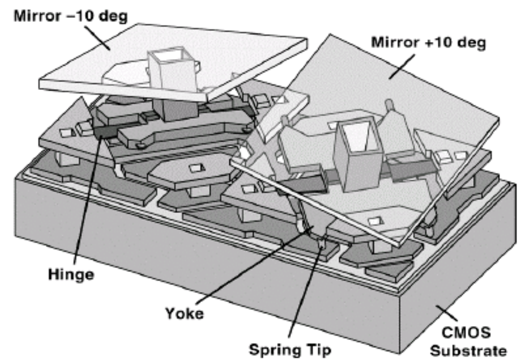


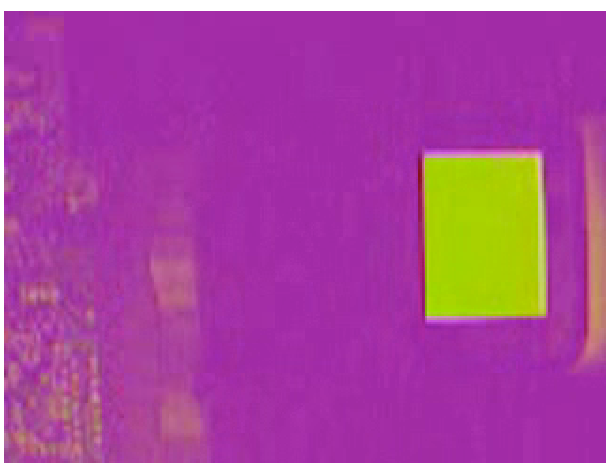
Figure 16. Discovery 1000 chipset with 0.7 XGA DDR DMD, digital controller, and analog mirror reset driver

Optical Projections

- Binary patterns are loaded into mirror array:
  - light reflected towards the lens/photodiode (1)
  - light reflected elsewhere (0)
  - pixel-wise products summed by lens

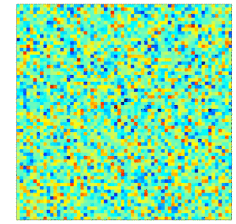


Lower resolution

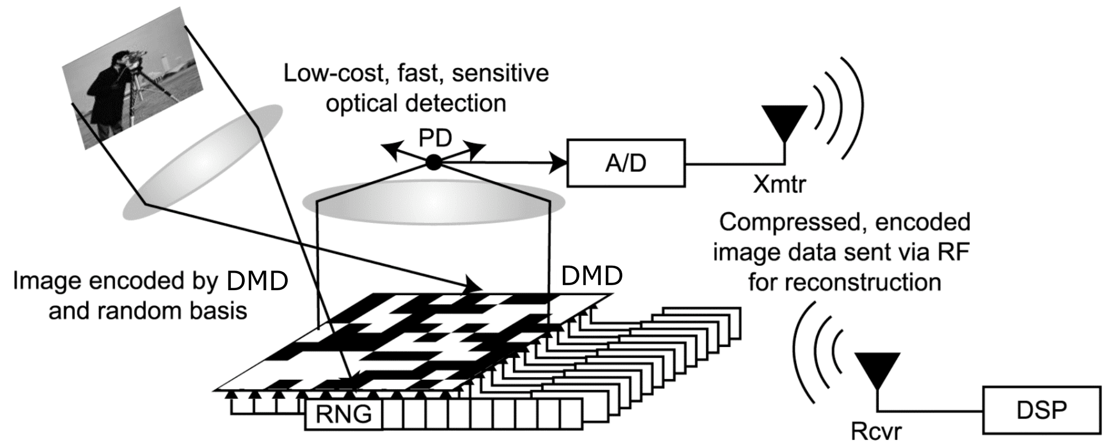


Higher resolution

Random Projections

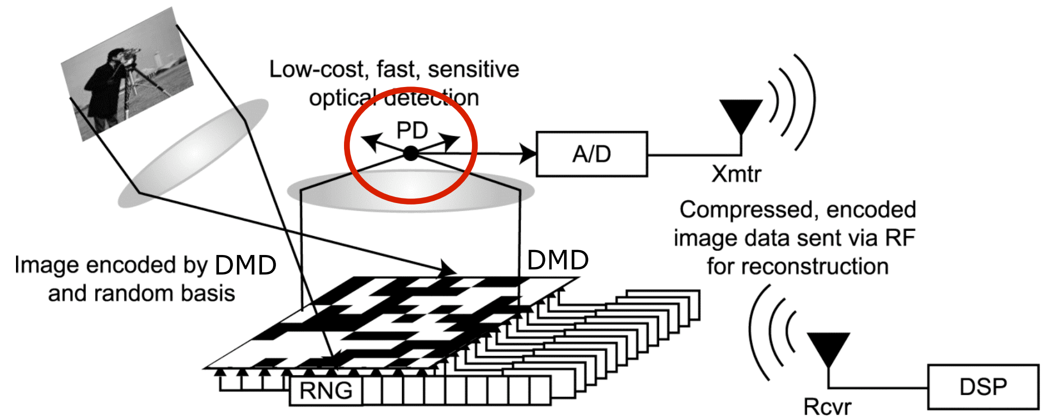


- Universal / agnostic representation
- Future proof
- Encrypted
- Simple coding
  - no position information
  - uniform quantization



- Robust
  - to quantization error [Candes, Romberg, Tao; Haupt, Nowak]
  - loss of measurements degrades reconstruction gracefully

CI Camera



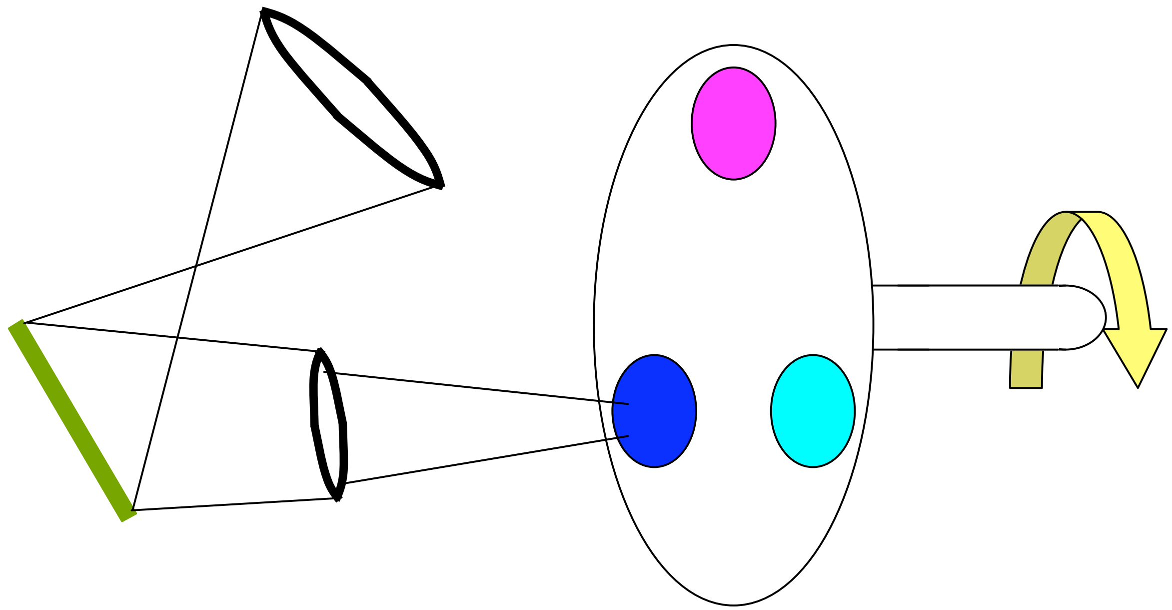
Single Sensor Camera

Potential for:

- new modalities beyond what can be sensed by CCD or CMOS imagers
- high-performance (speed, noise, bandwidth, …)
- low cost
- low power

Other CI approaches: D. Brady (Duke), R. Coifman (Yale)

Multispectral Imaging



Broadband

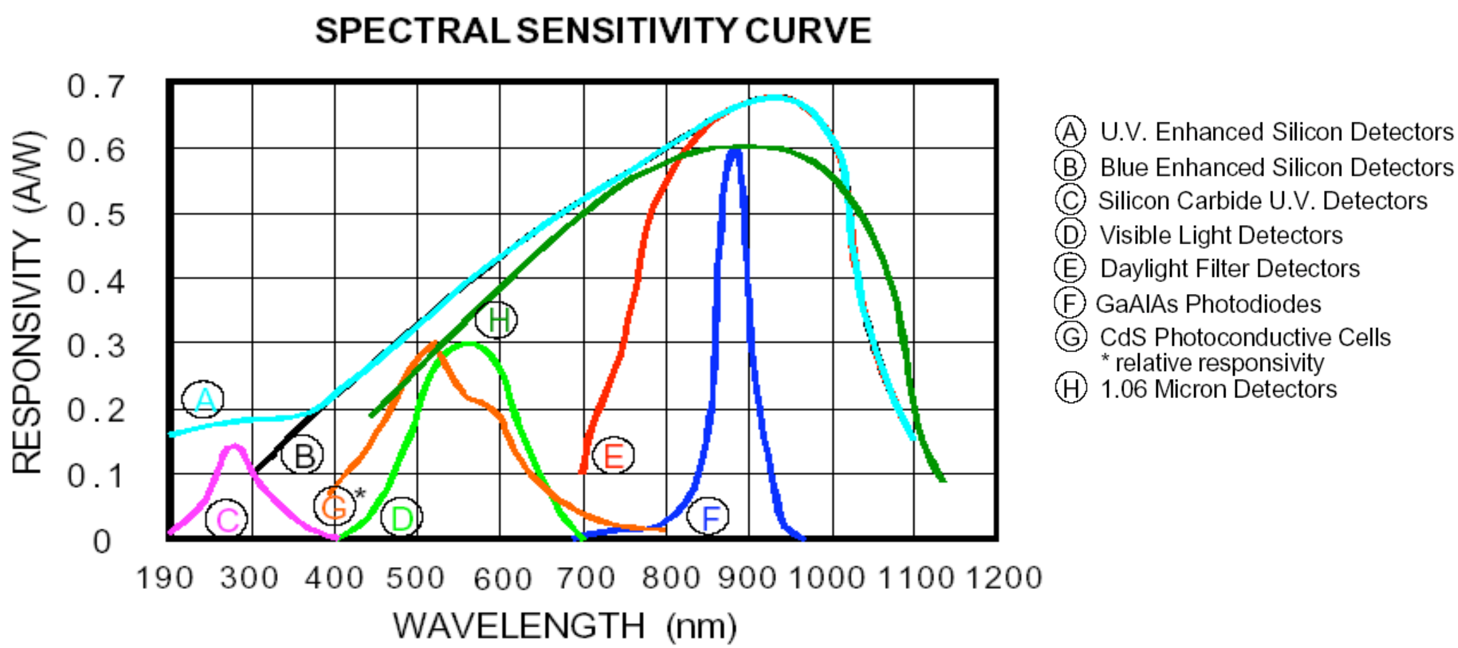
vs.

Narrow-Region

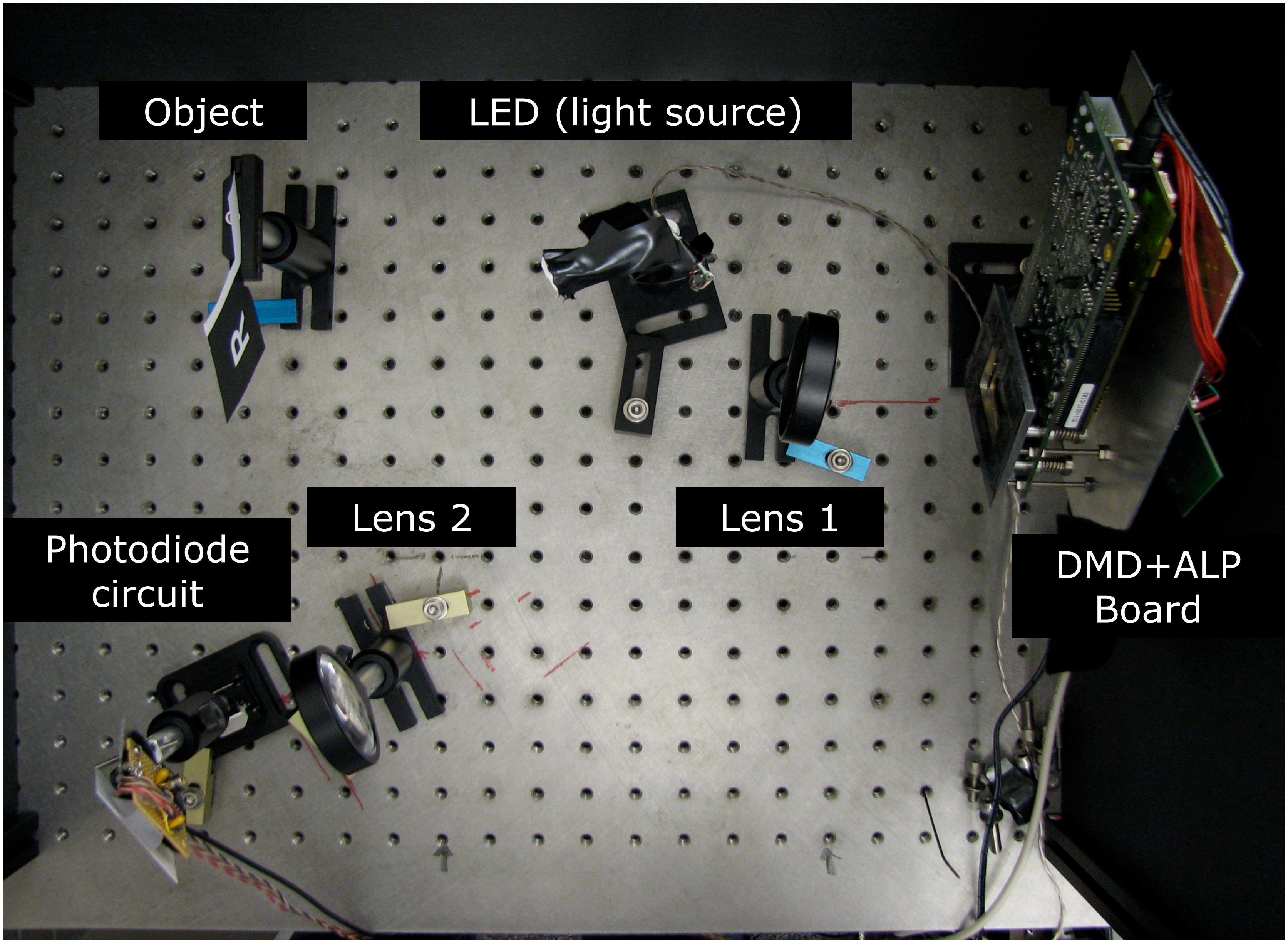
Near-IR

or

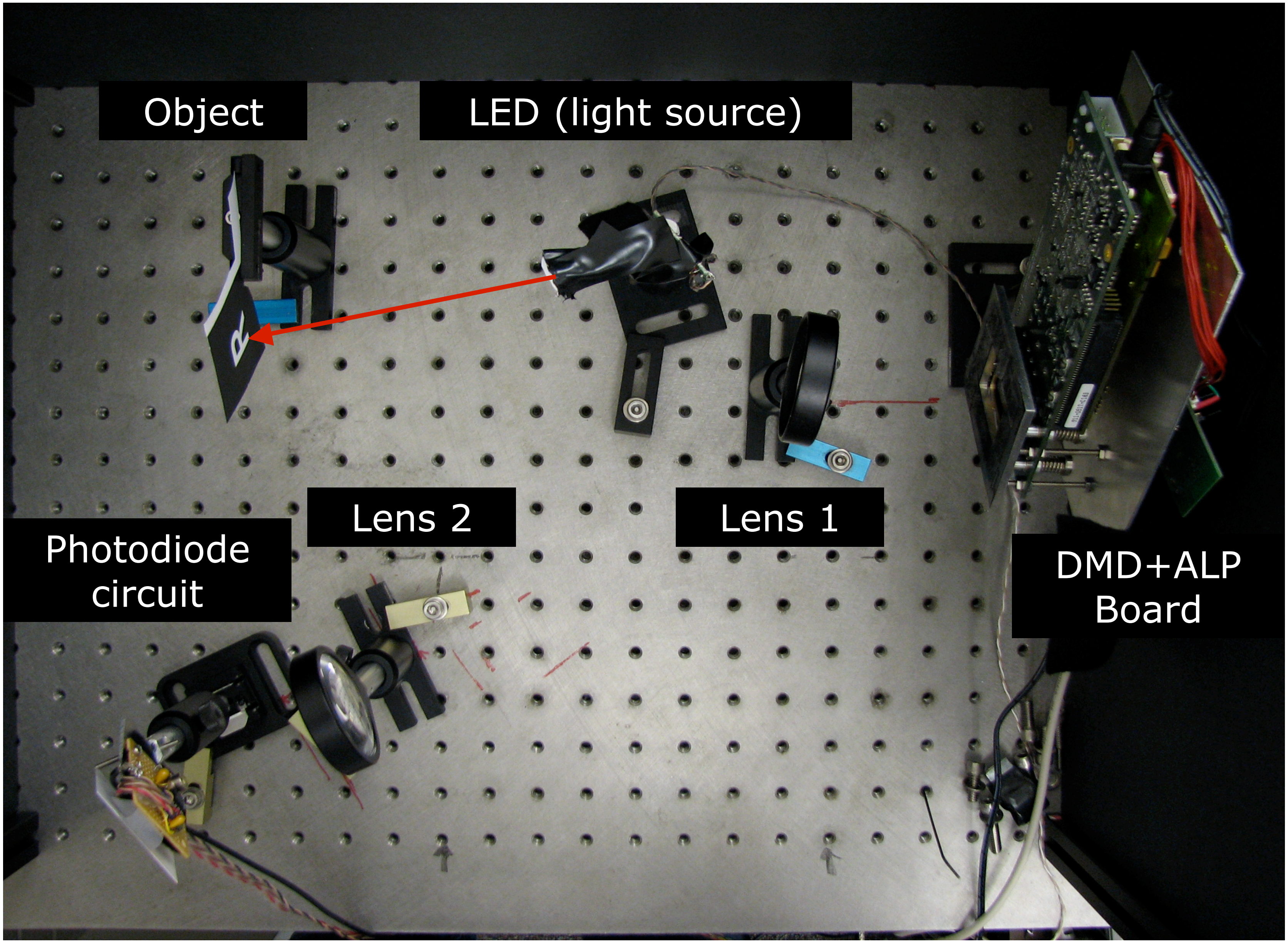
UV



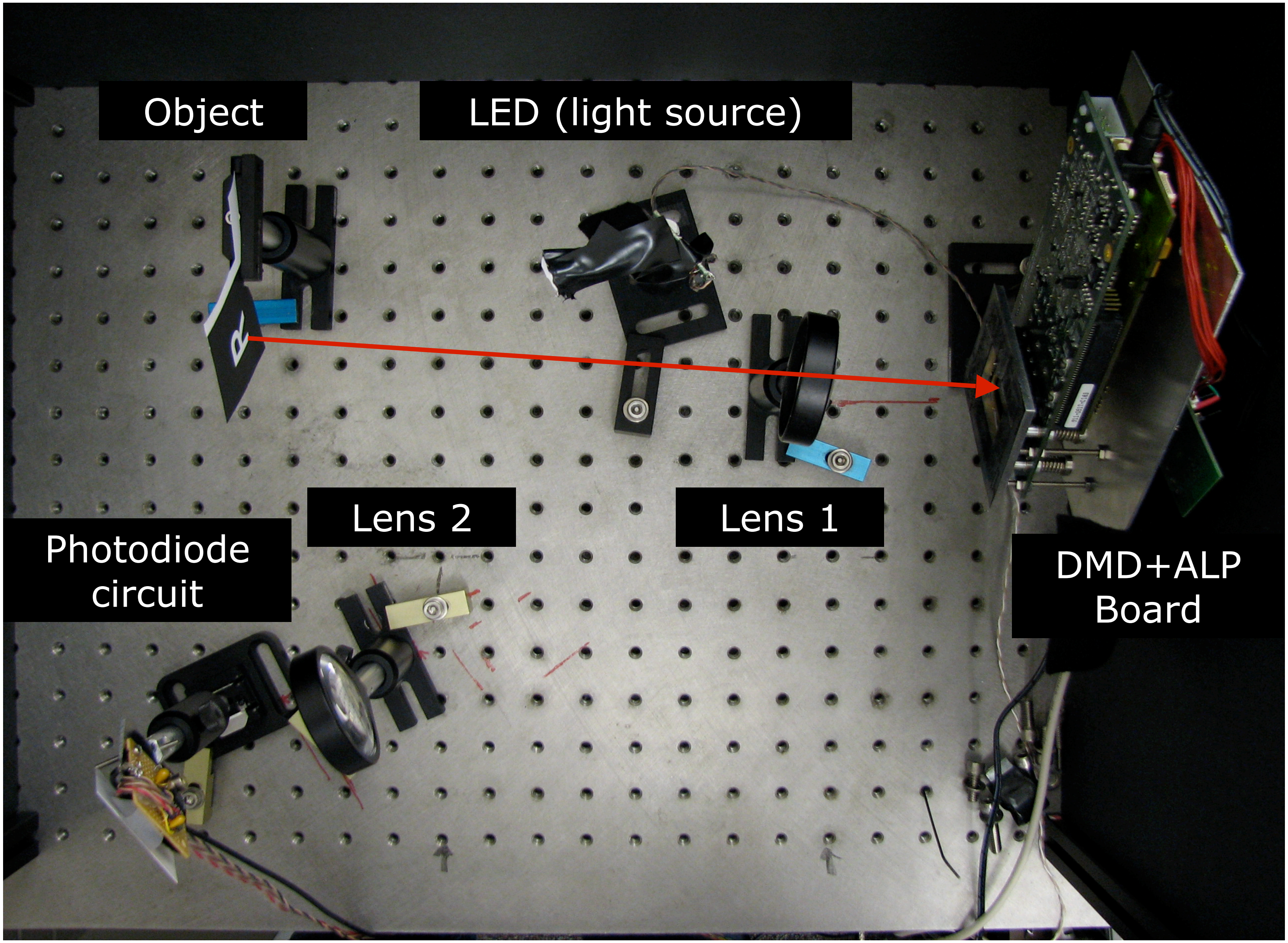
Rice CI Camera



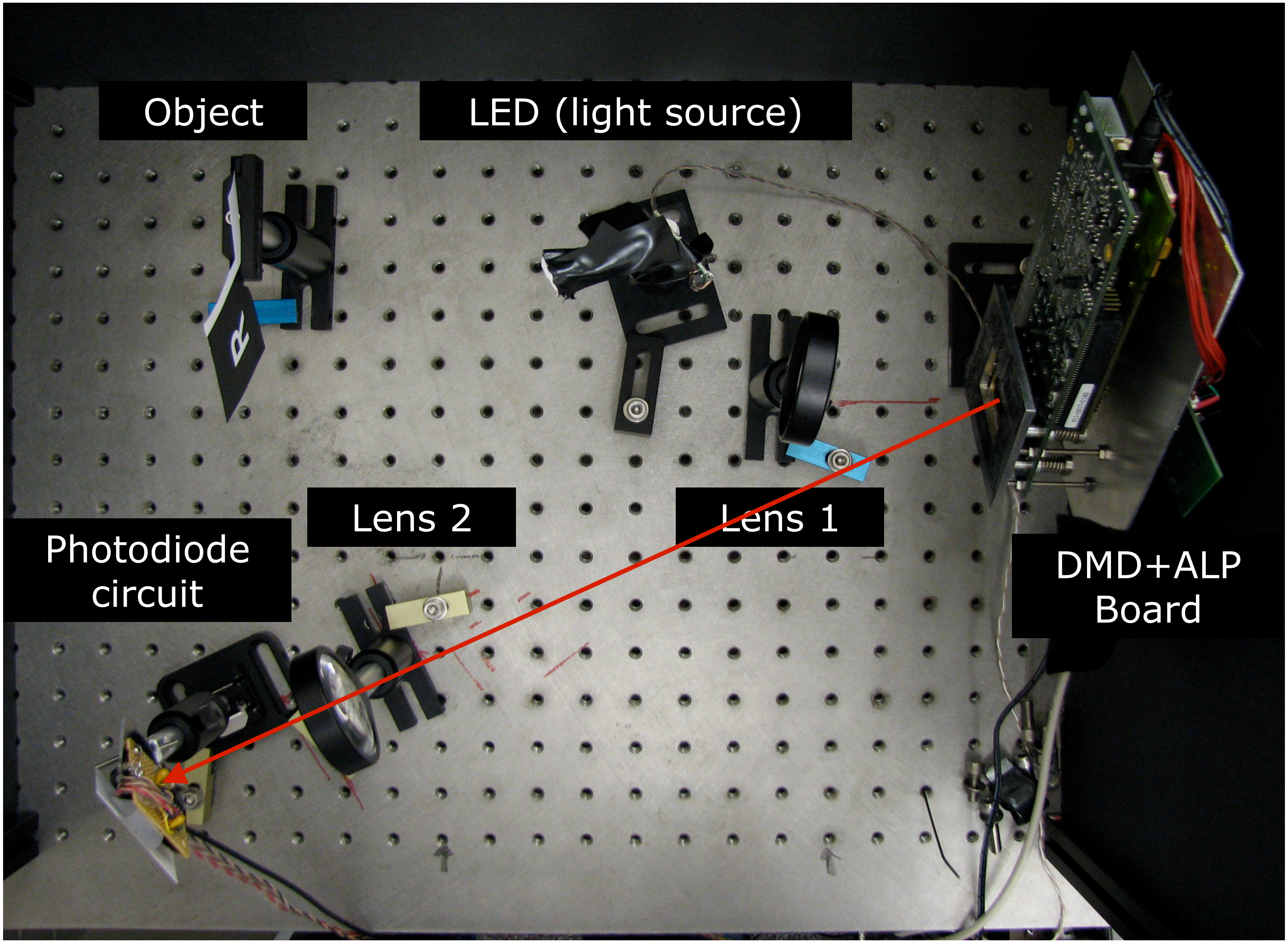
Rice CI Camera



Rice CI Camera



Rice CI Camera



(Pseudo) Random Projections

- Pseudorandom number generator outputs measurement basis vectors
- Mersenne Twister [Matsumoto/Nishimura, 1997]
  - Binary sequence (0/1)
  - Period 2^{19937}-1
  - Two generators: encoder and decoder



…

Image Acquisition

ideal 64x64 image
(4096 pixels)

400
wavelets

675
wavelets

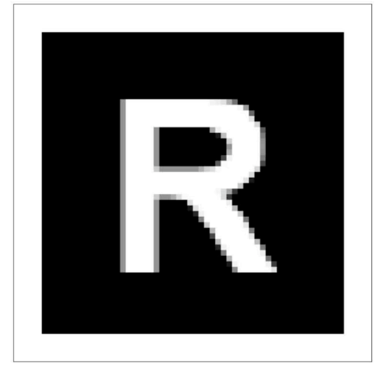
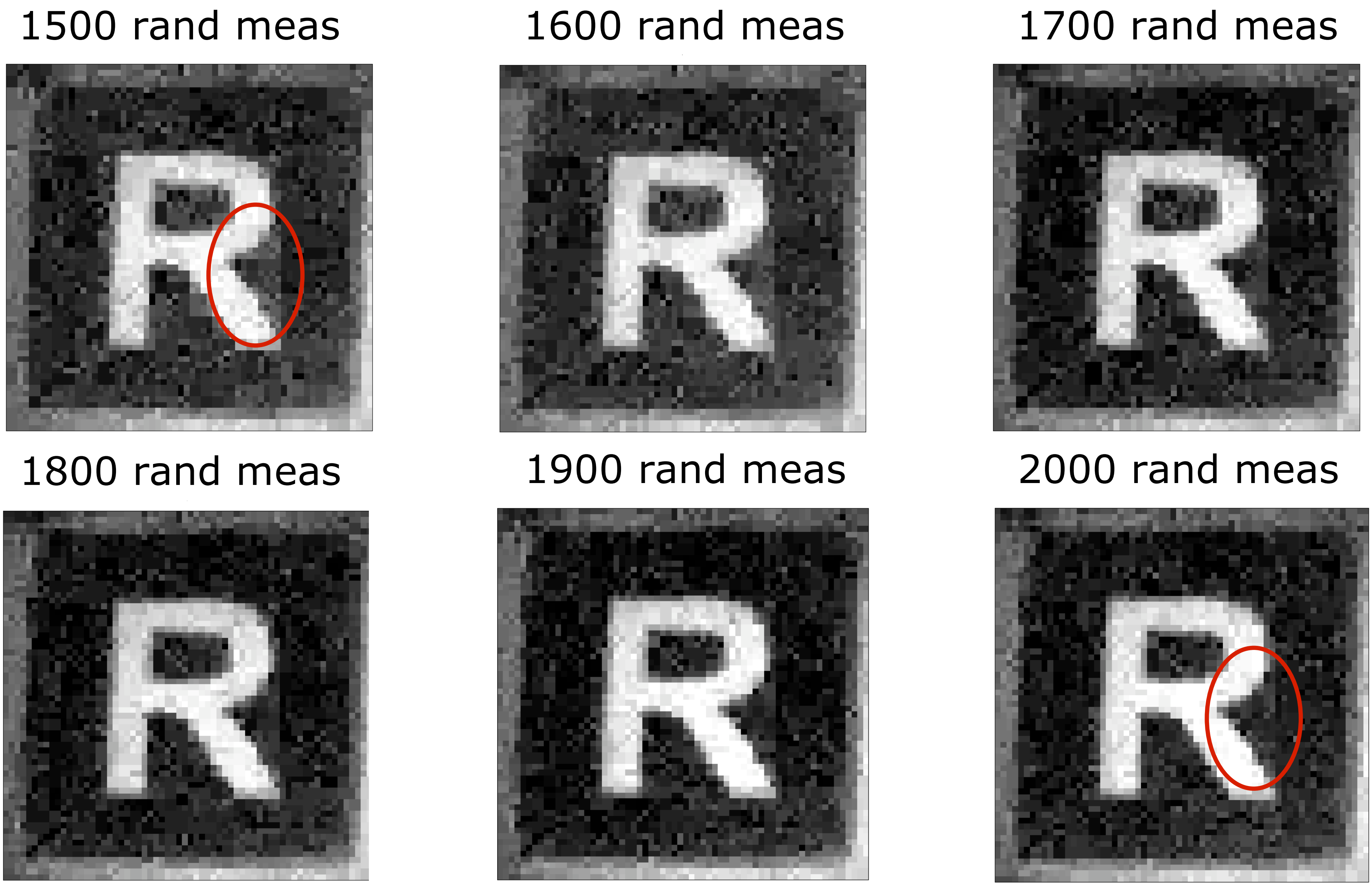


image on
DMD array

1600
random meas.

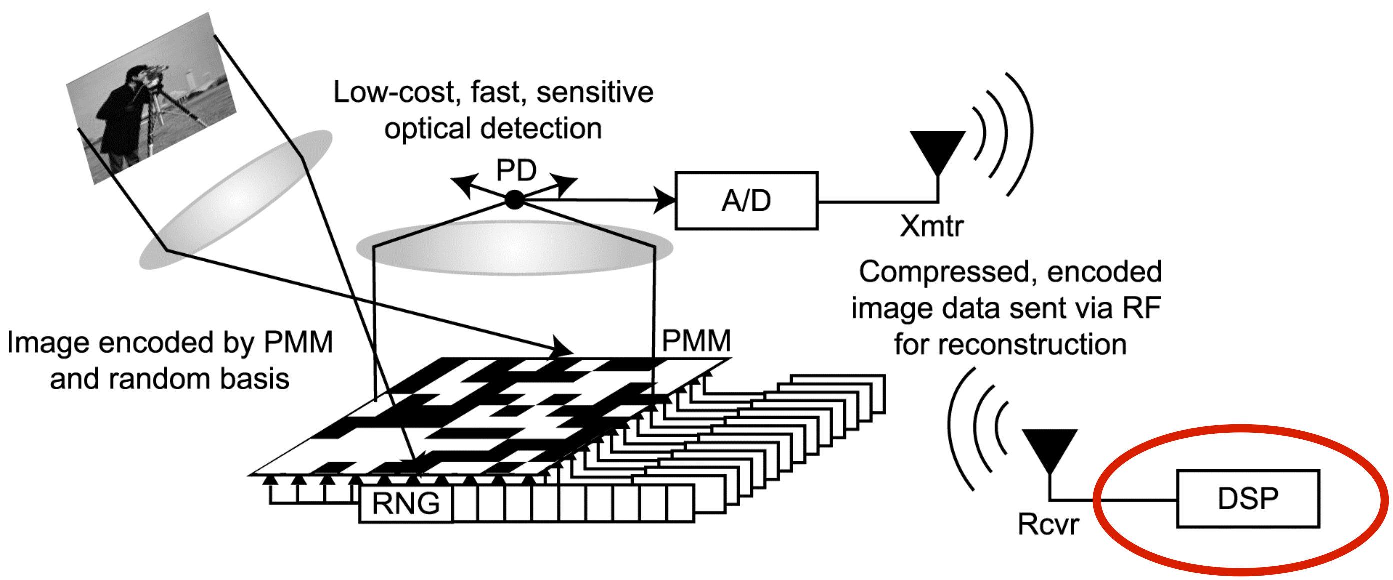
2700
random meas.

Progressivity



CI Challenges

- Reconstruction remains *computationally challenging*
  - N > few thousand impractical for many applications
  - DSP challenges: new reconstruction algorithms, ...



- Ensuring robustness to noise and quantization errors

Addressing the CI Challenges

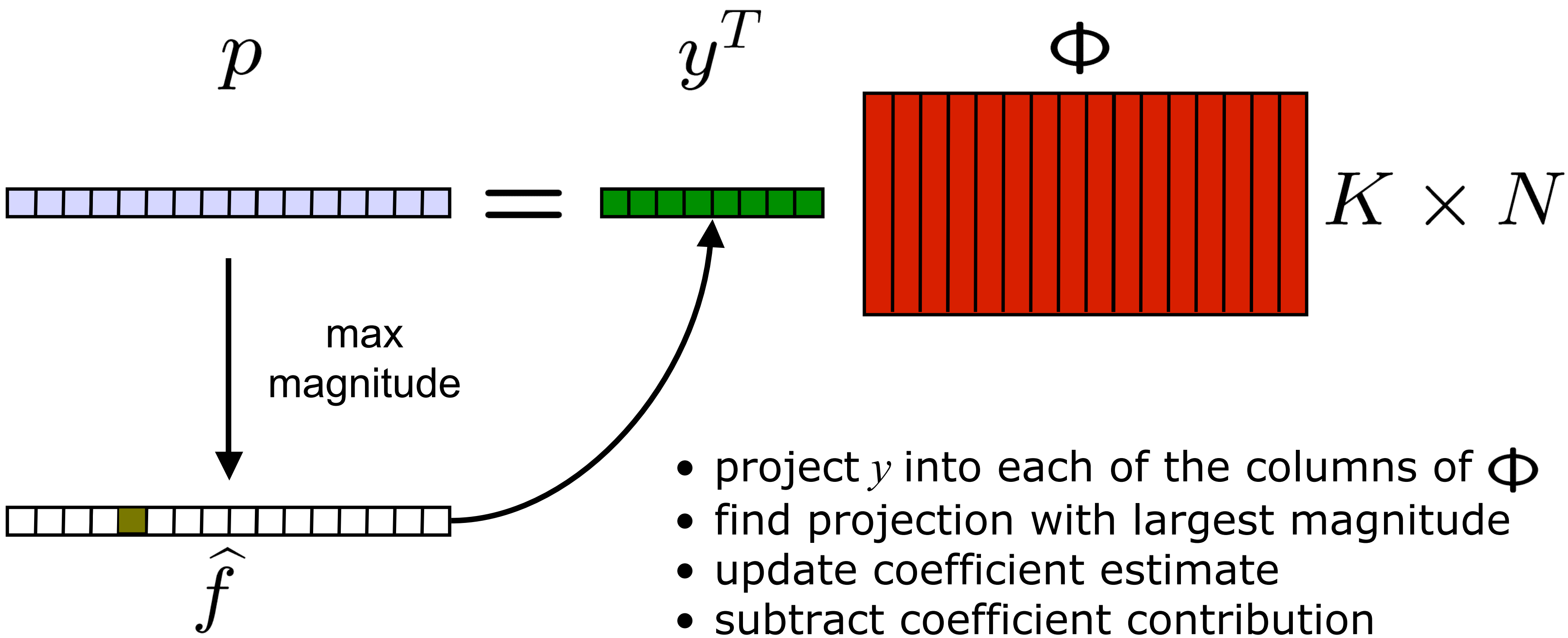
Fast, robust algorithms for signal reconstruction

- going beyond Basis Pursuit
- greedy algorithms for sparse signal approximation
  - Matching Pursuit: iterative, greedy algorithm
  - lower computational complexity
  - much faster in practice
- extend greedy algorithms
  - exploit *model* for signal structure
    - going beyond sparsity
    - improves speed *and* robustness

See also [J. Tropp and A. Gilbert, 2005]

Matching Pursuit

Goal: find sparse $\widehat{f}$ s.t. $y = \Phi \widehat{f}$



- project y into each of the columns of Φ
- find projection with largest magnitude
- update coefficient estimate
- subtract coefficient contribution
- repeat

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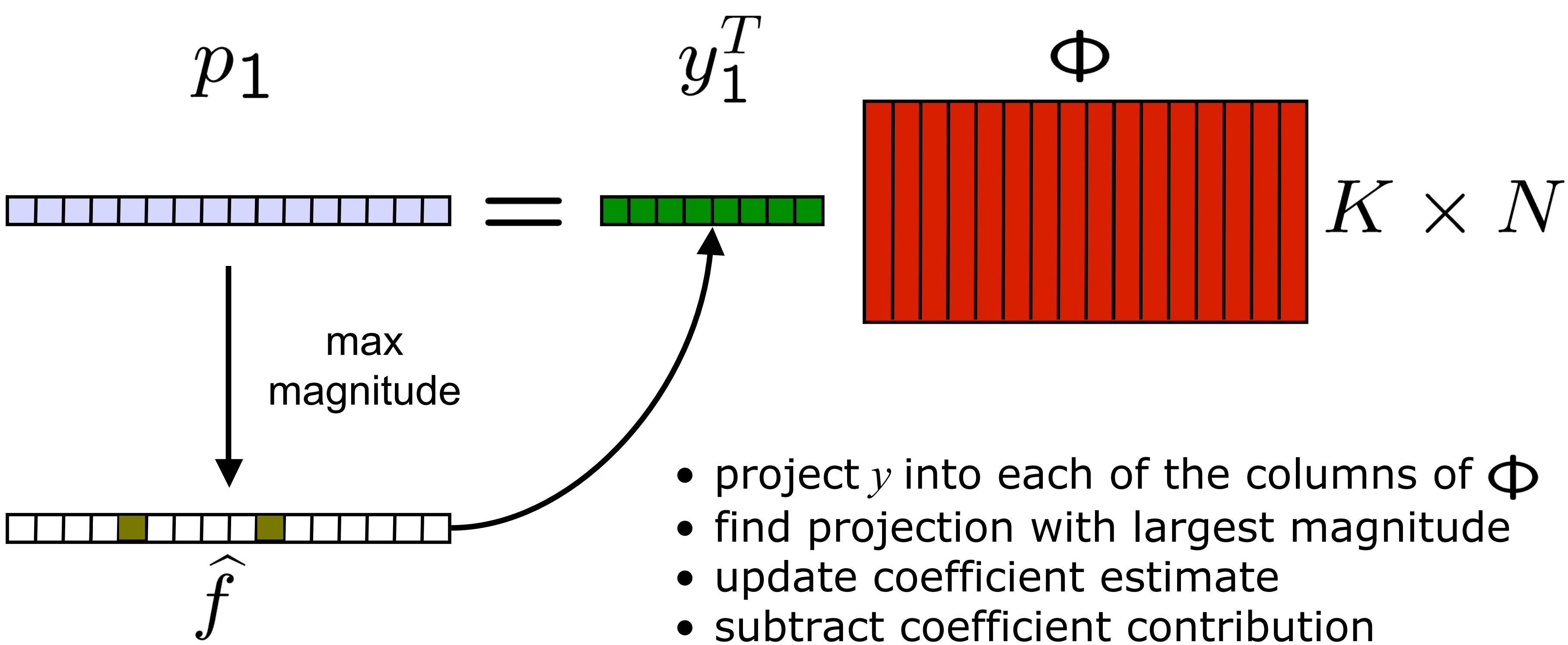

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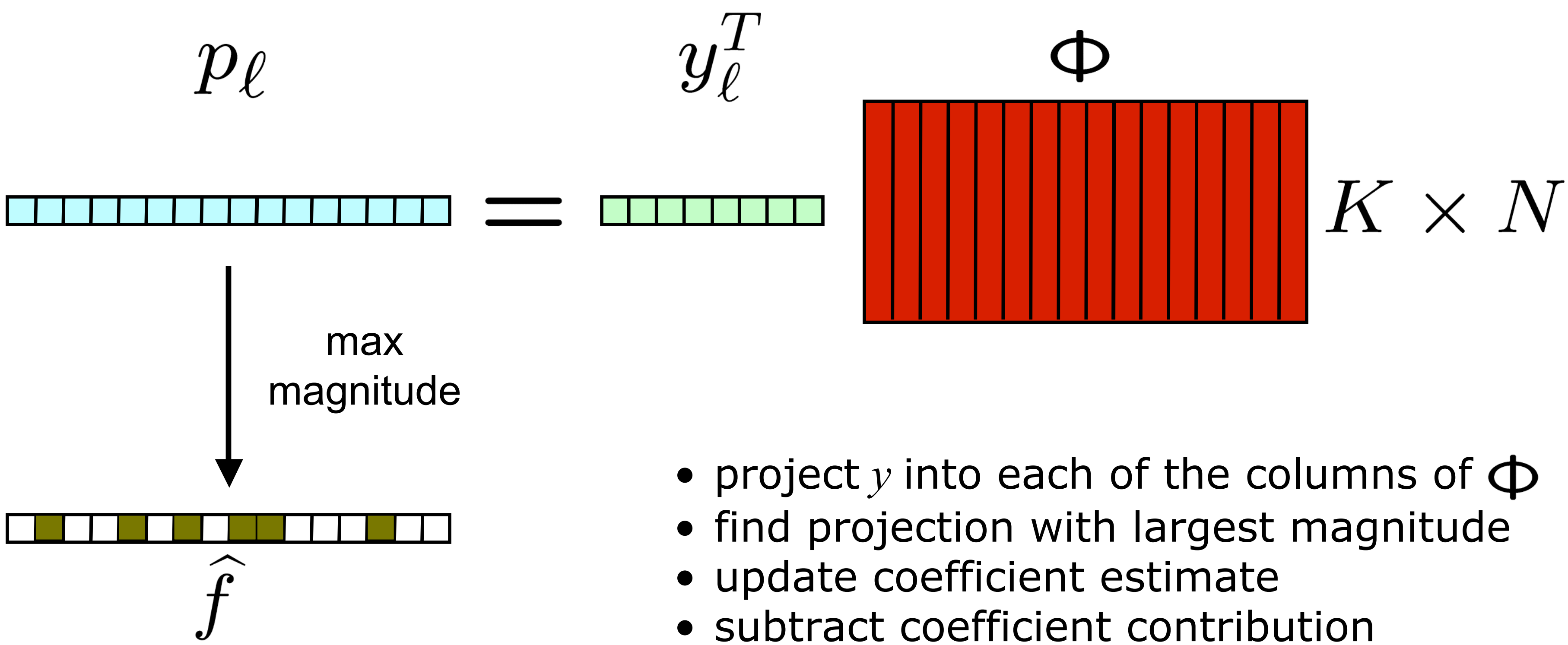


- project y into each of the columns of Φ
- find projection with largest magnitude
- update coefficient estimate
- subtract coefficient contribution
- repeat until $\|y_\ell\| \leq \epsilon \|y\|$

Matching Pursuit

Goal: find sparse $\widehat{f}$ s.t. $y = \Phi \widehat{f}$

Advantages:

- Low computational complexity: $O(BN \cdot \#\mathrm{Iter})$

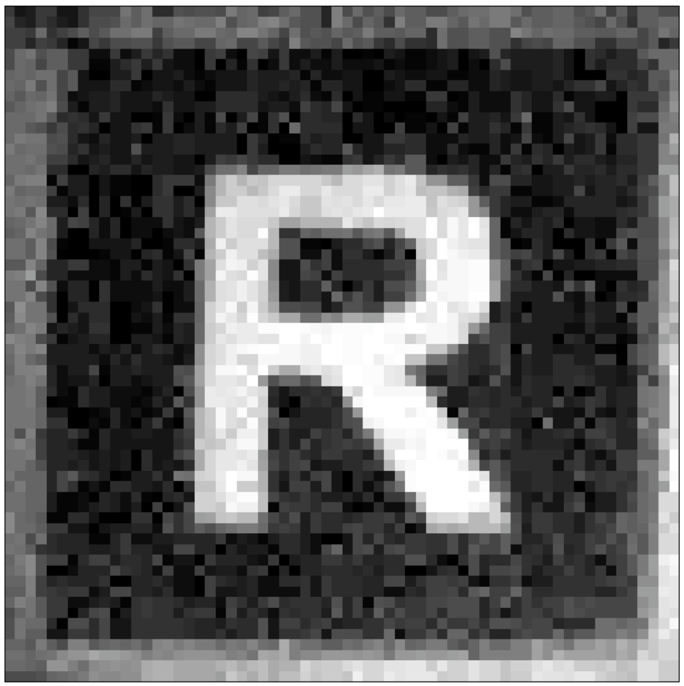
Disadvantages:

- Must project to all dictionary vectors every iteration
- May revisit previously selected coefficients
- Unbounded number of iterations needed for convergence
- Orthogonal Matching Pursuit (OMP) solves last two problems

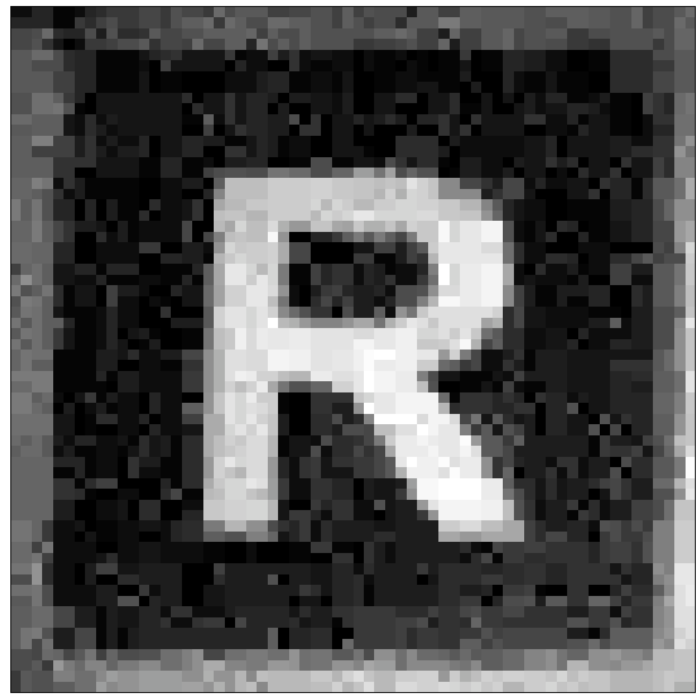
Matching Pursuits vs. Basis Pursuit

2000 random measurements

Basis Pursuit



Matching Pursuit
13X faster



Limitations

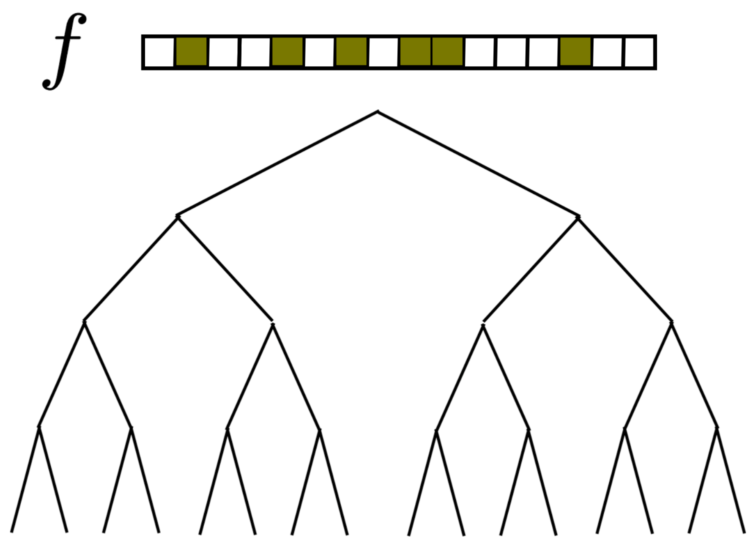
- Basis Pursuit and Greedy Algorithms exploit *sparsity*
  - each B-sparse coefficient vector is equally "good"

- We often expect *more* than just sparsity
  - how do the sparse coefficients behave?

- Idea: incorporate this model into reconstruction algorithms
  - even faster reconstruction
  - robustness to noise

Wavelets: more than just sparsity

- Wavelet transform sports a *tree structure*
- Piecewise smooth signal "rule of thumb"
  - small/large values tumble down the tree
  - wavelet coefficients decay monotonically along branches of wavelet tree



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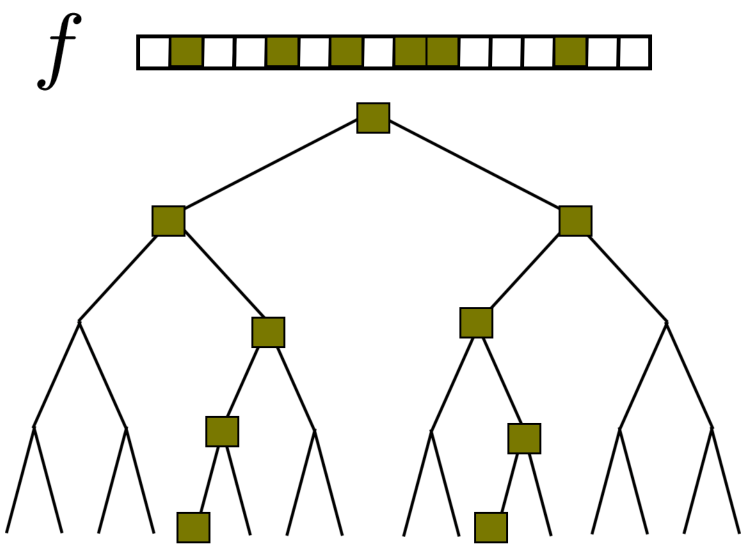
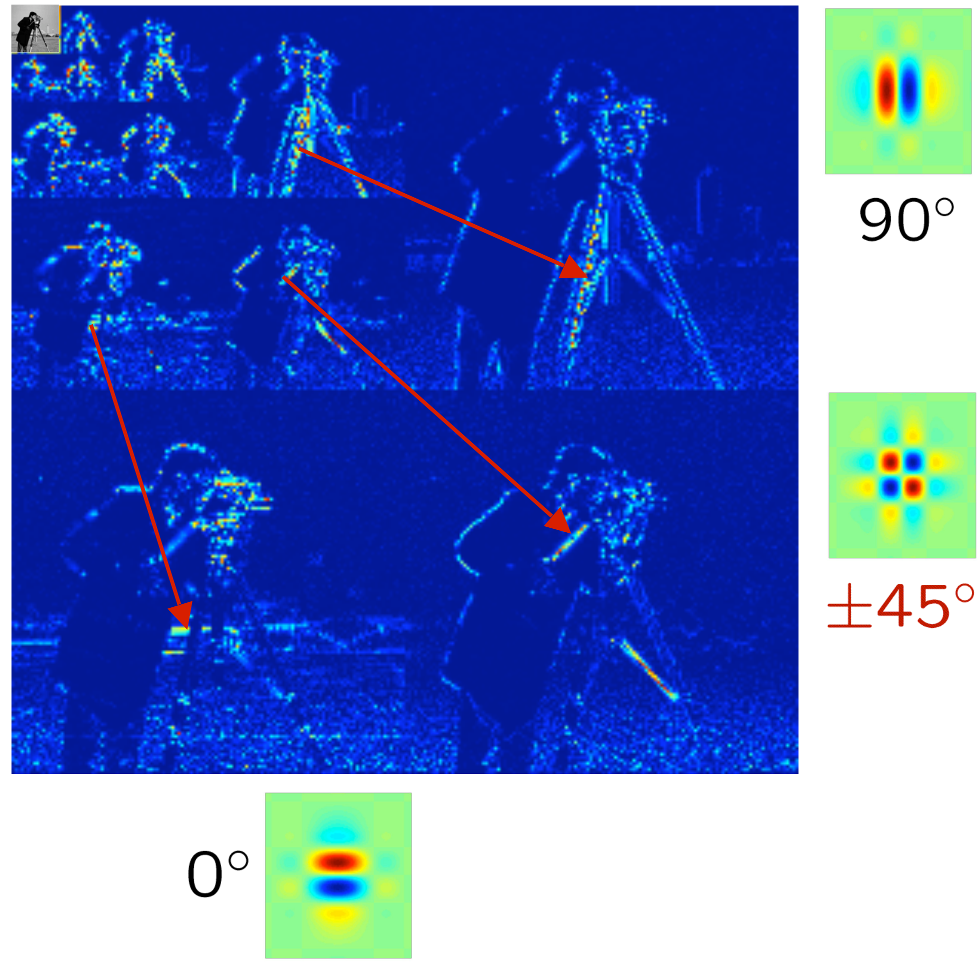


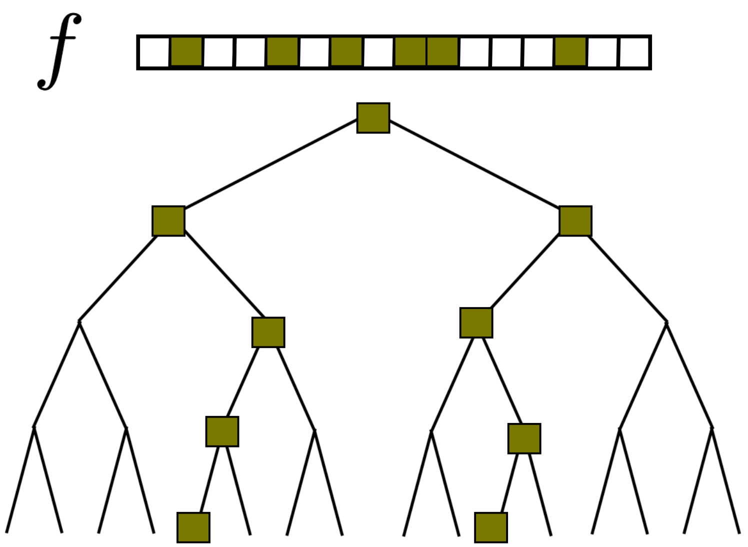
Image and Wavelet Transform



$$f = \sum_i \alpha_i \psi_i$$

Wavelets: more than just sparsity

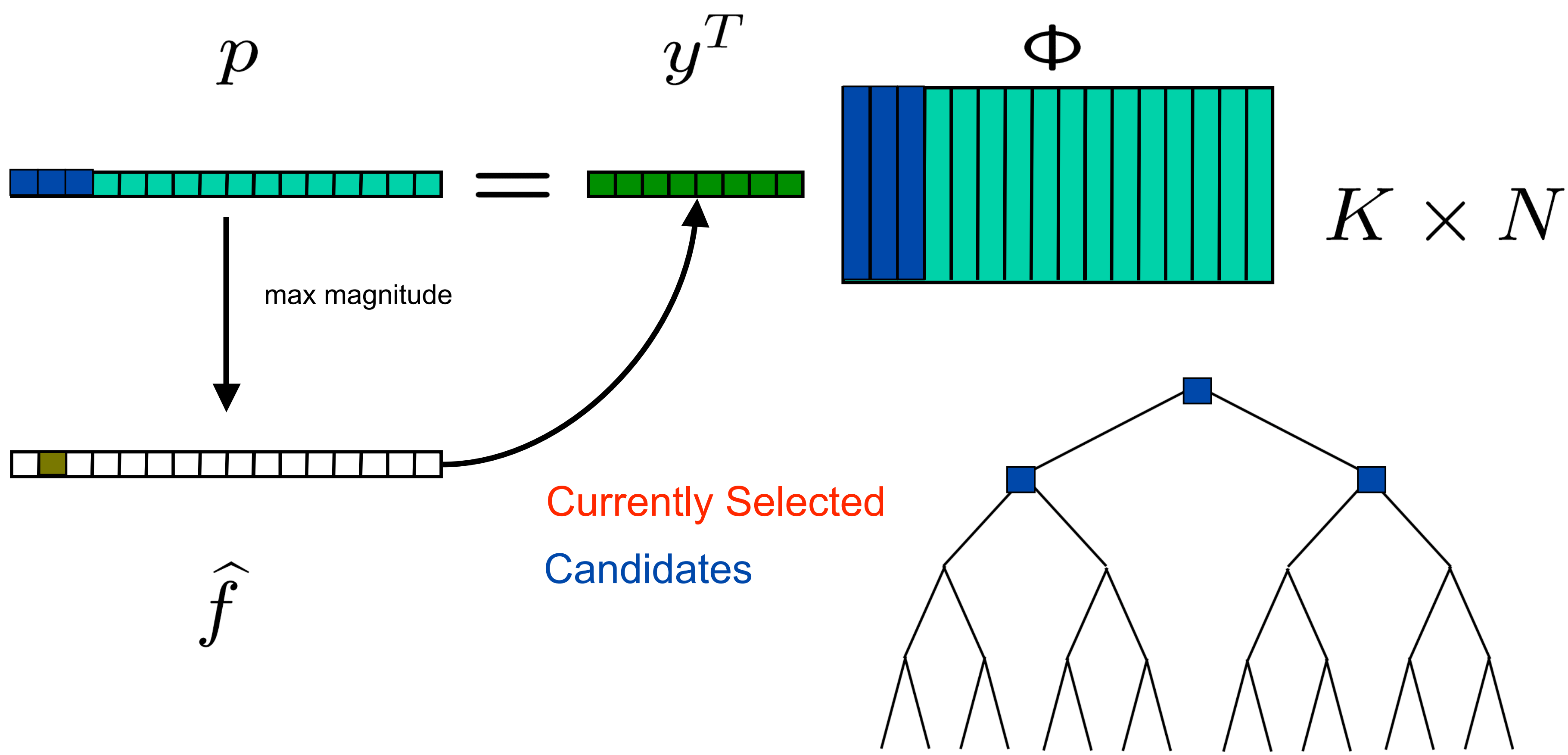
- Wavelet transform sports a *tree structure*
- Piecewise smooth signal "rule of thumb"
  - small/large values tumble down the tree
  - wavelet coefficients decay monotonically along branches of wavelet tree
- **Exploit this structure for**
  - **fast reconstruction**
  - **noise regularization**



- Tree MP/OMP: top-down greedy algorithm using branch info
- Fast: MP/OMP search drops from $O(B^2N)$ to $O(B^3)$

Tree Matching Pursuit

Goal: find sparse $\widehat{f}$ s.t. $y = \Phi \widehat{f}$



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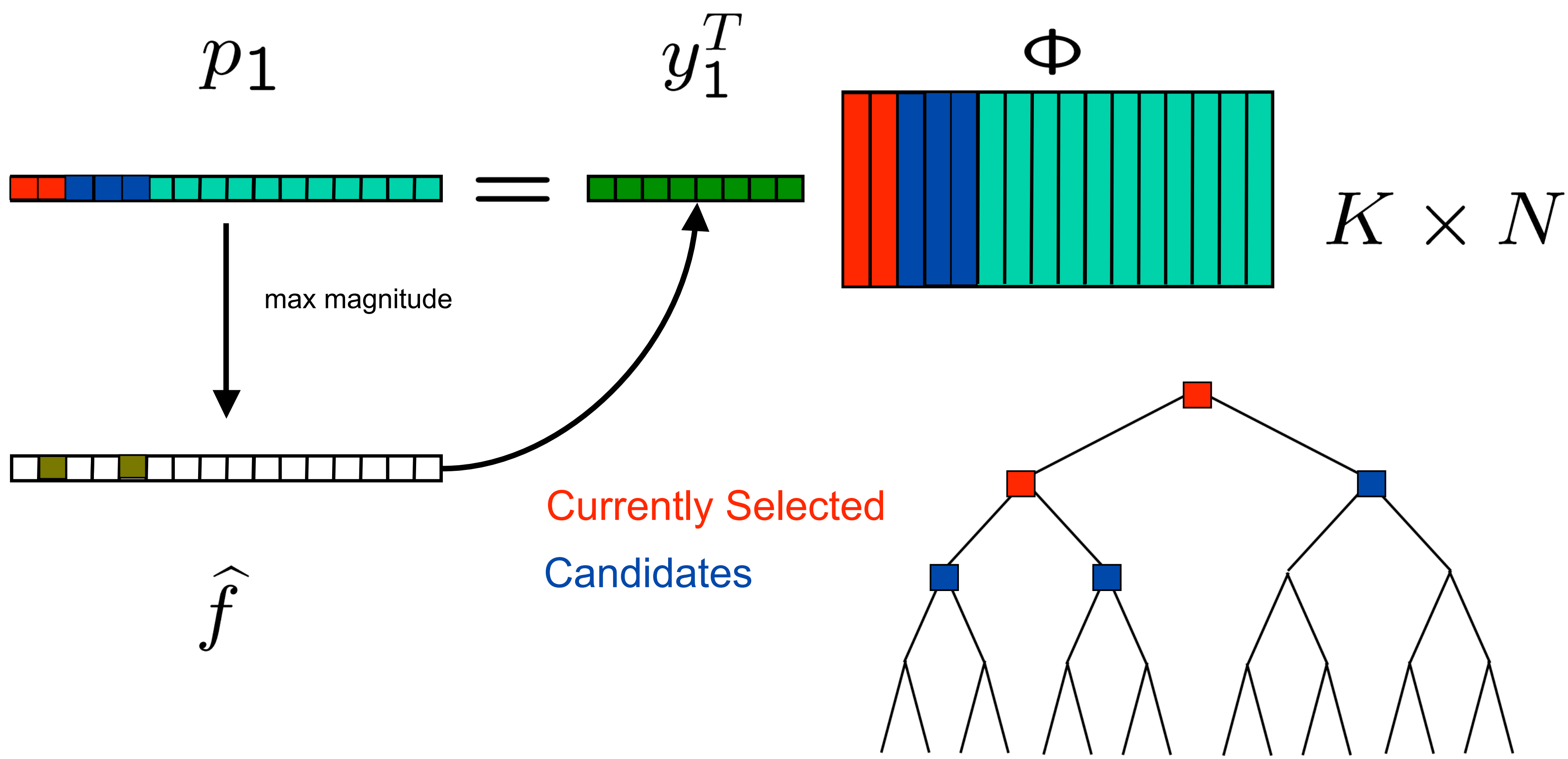

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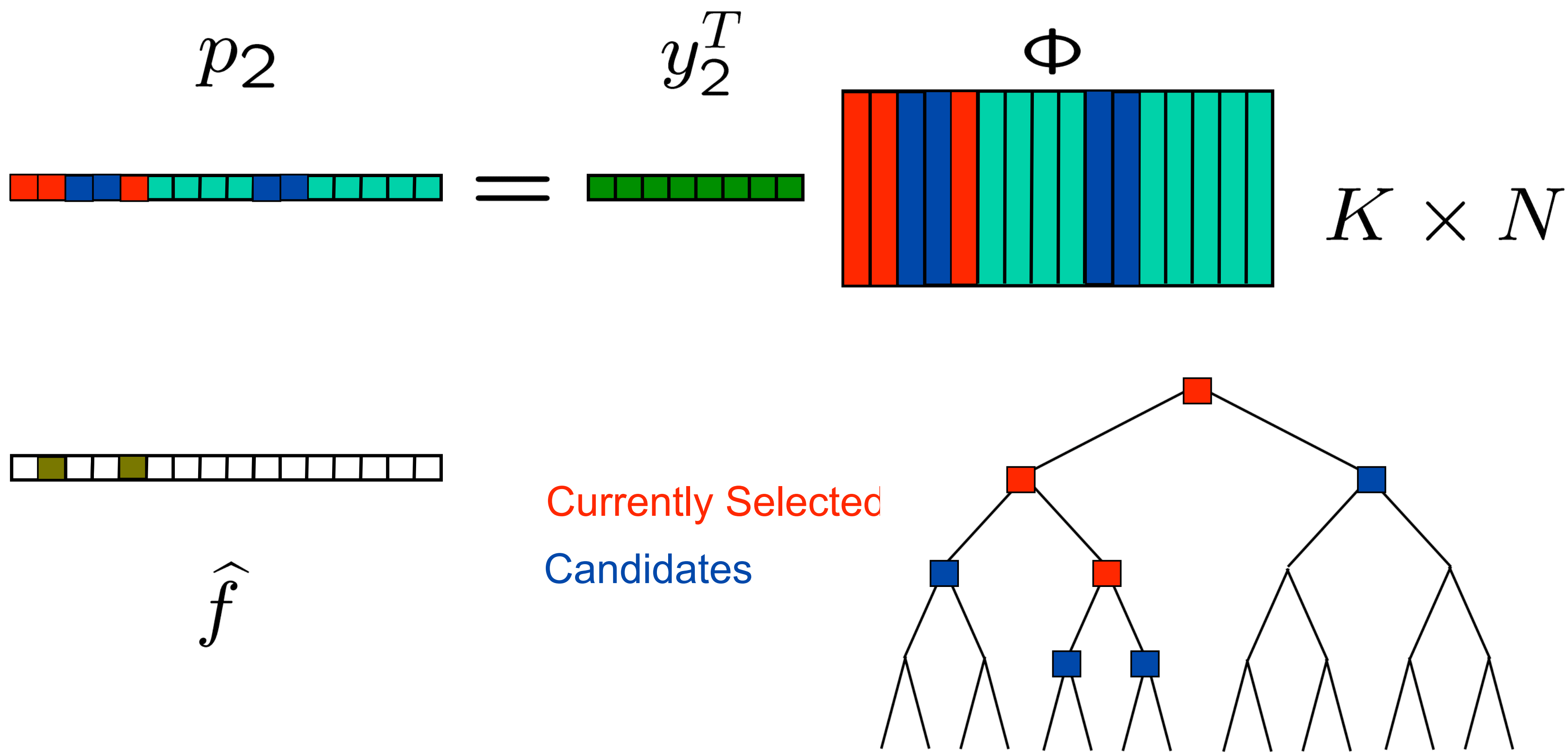


Tree Matching Pursuit

Goal: find sparse $\widehat{f}$ s.t. $y = \Phi \widehat{f}$

Advantages:

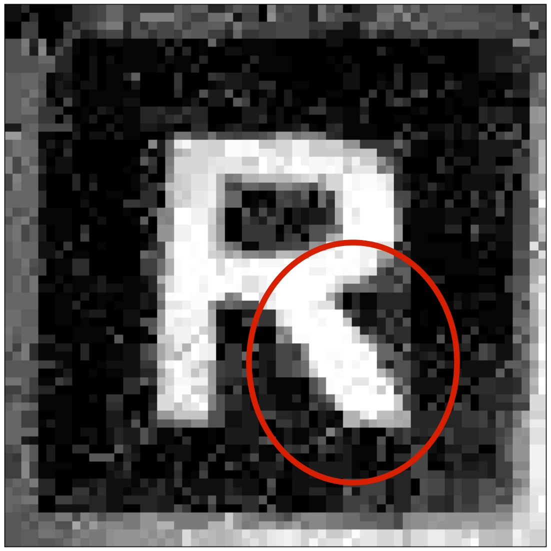
- Lower computational complexity: $O(B^3)$
- Search only in coefficient subset

Challenges:

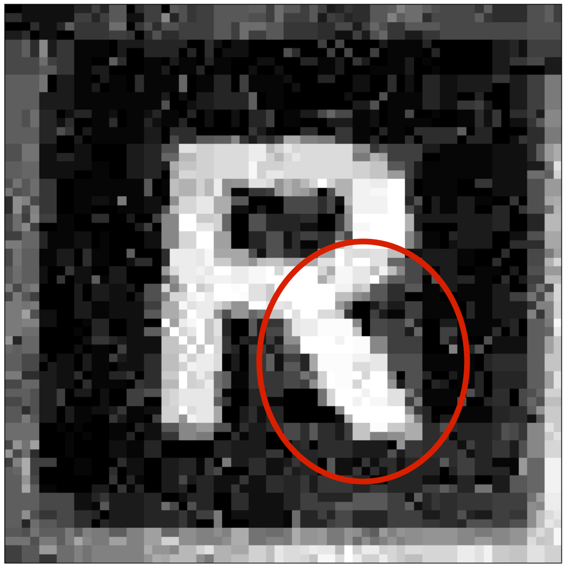
- TMP has unbounded number of iterations for convergence; solved by using Tree Orthogonal Matching Pursuit (up to K iterations)
- Success depends on tree structure

Tree Greedy Pursuit

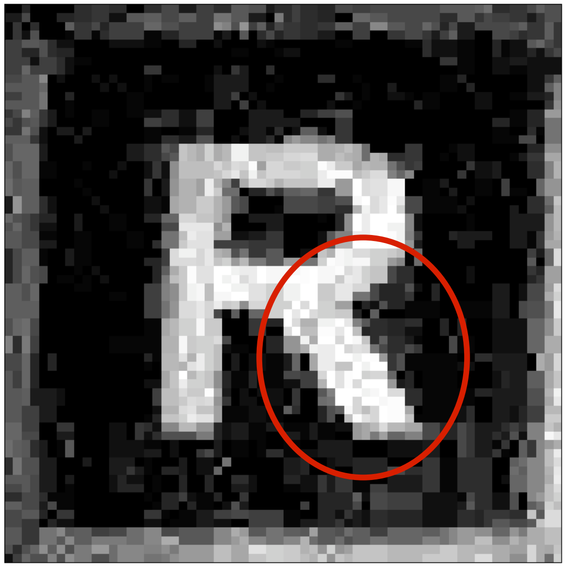
BP - 1500 rand meas



MP - 4M inner prod.

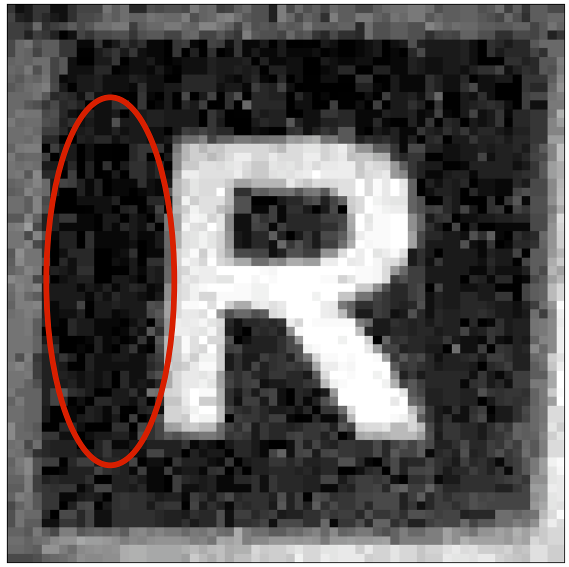


TMP - 2M inner prod.

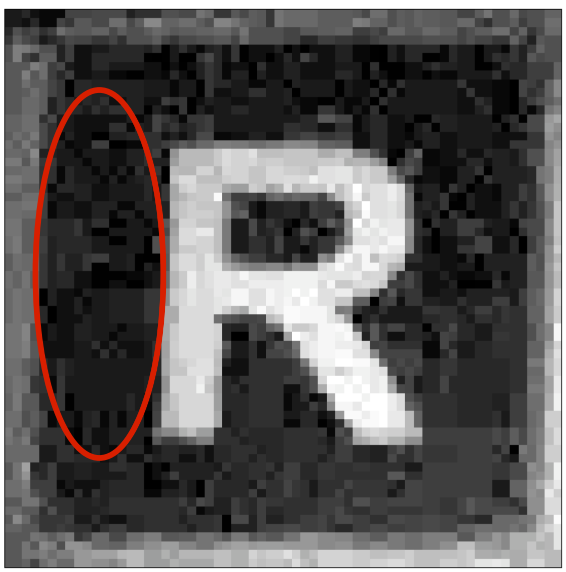


Denoising via wavelet thresholding

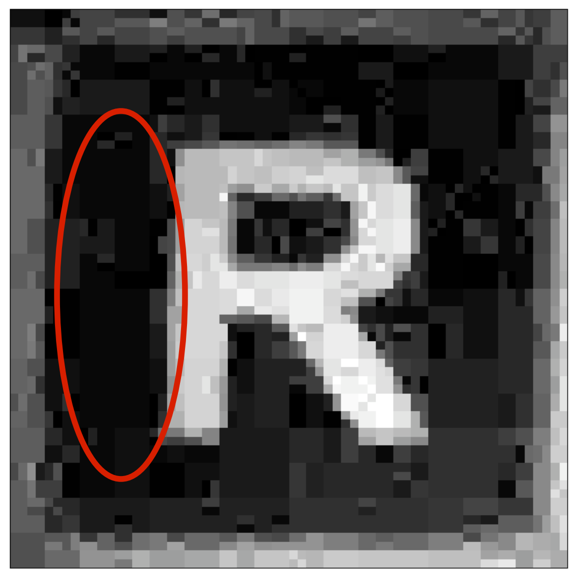
BP - 2000 rand meas



TMP - $\epsilon = 10^{-3}$



TMP - $\epsilon = 2 \times 10^{-3}$



Conclusions

- Compressive imaging
  - a new imaging framework based on compressive sensing
  - exploit a priori image sparsity information
  - based on new uncertainty principles

- Proof of concept: CI camera
  - single sensor element
  - universal, simple, robust image coding
  - progressive

- Current work
  - measurement and reconstruction using transforms
  - video acquisition
  - camera networks

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