





# **COMPRESSION BASED ON COMPRESSIVE SENSING**

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# CONTENTS

## 1. WHAT?

- ❑ Introduction to Compressed Sensing (CS)



## 2. HOW?

- ❑ Theory behind CS



## 3. FOR WHAT PURPOSE?

- ❑ CS applications



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## 1. WHAT?

- Introduction to Compressed Sensing (CS)



## 2. HOW?

- Theory behind CS

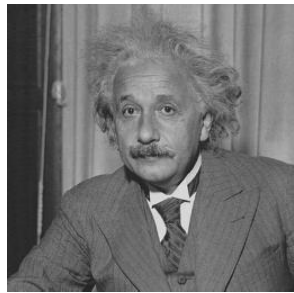


## 3. FOR WHAT PURPOSE?

- CS applications



# Shannon/Nyquist theorem



Sample

$N$

Compress

$N \gg K$

Transform + Quantized + Encoded

Transmit

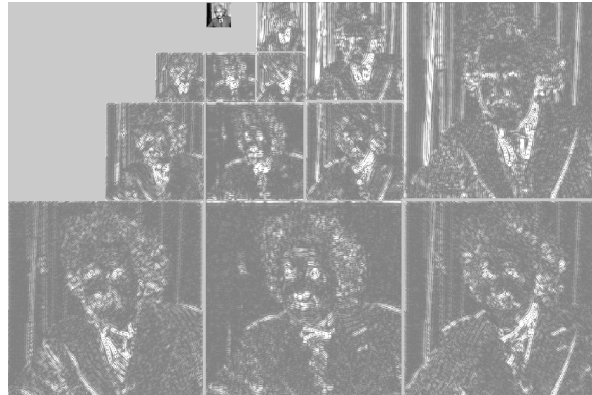
Receive

Decompress

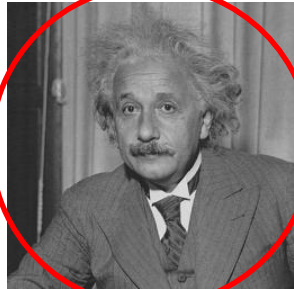
$N$

$K$

Receive

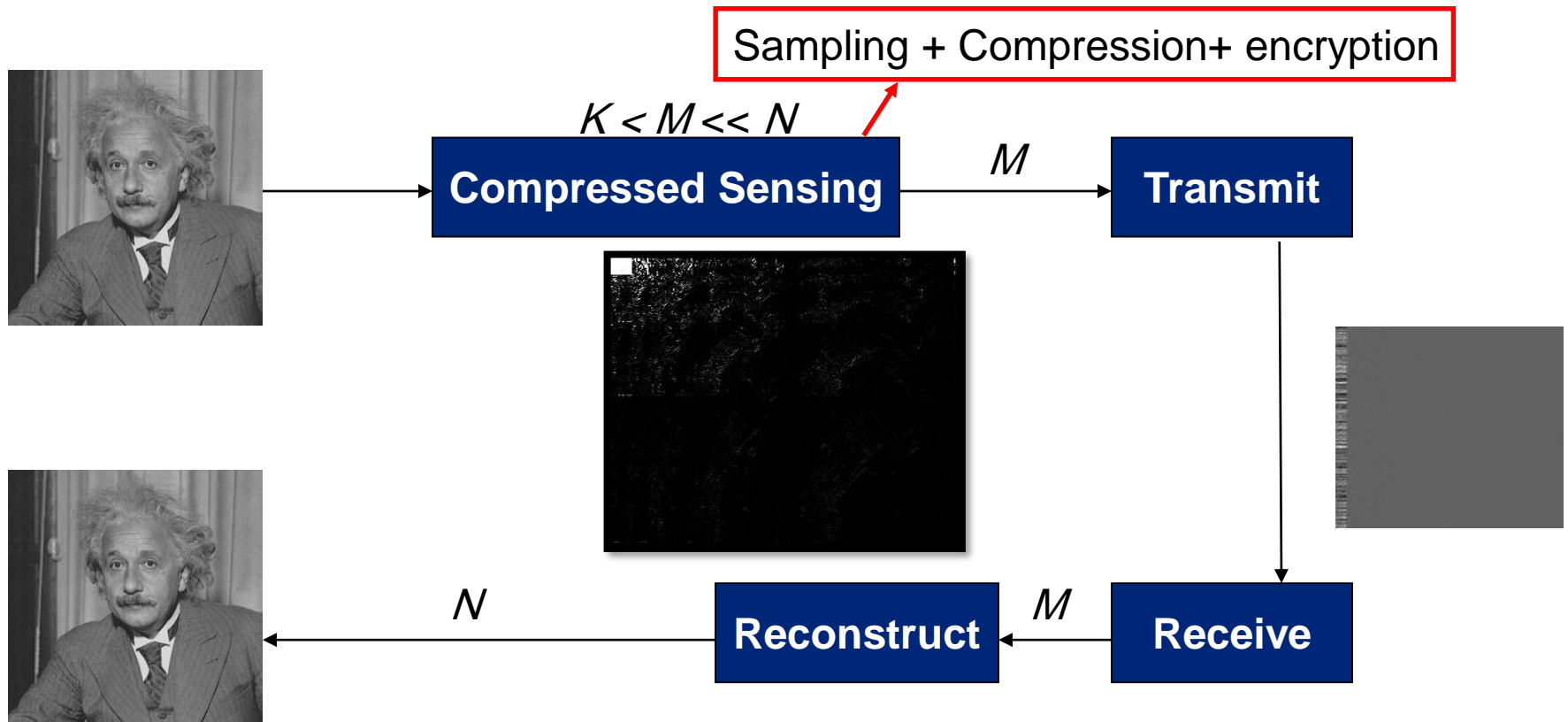


so many samples  
 $F_s \geq 2F_{max}$



Natural signals (sparse/compressible)  
→ no significant perceptual loss

# Compressed Sensing (CS)



- **COMPRESSIVE SENSING:-** is new method to capture and represent sparse/compressible signals at the rate well below Nyquist's rate.

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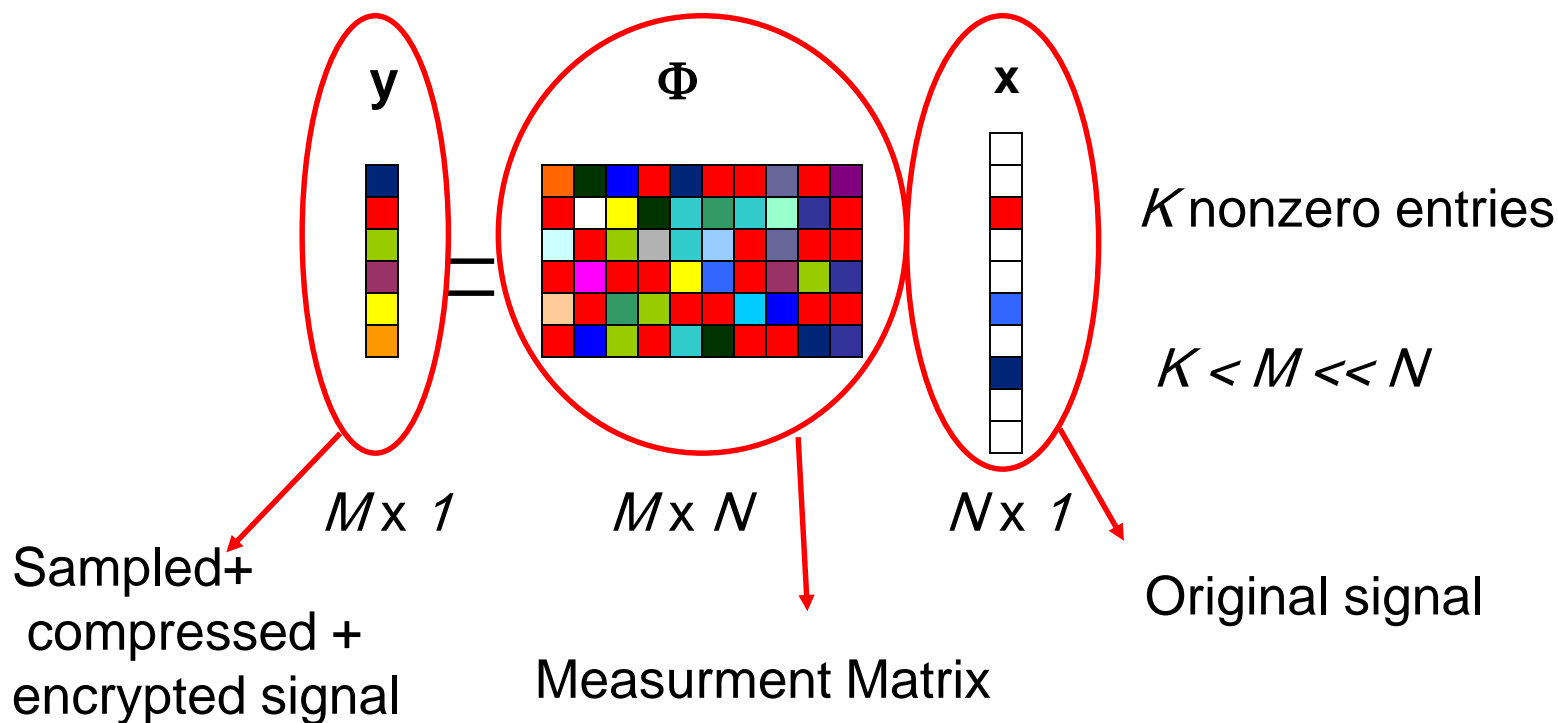
- CS applications



# CS consists of two parts:-

## 1- SAMPLING (ENCODING)

- When the signal is sparse/compressible, we can directly acquire a condensed representation with no/little information loss



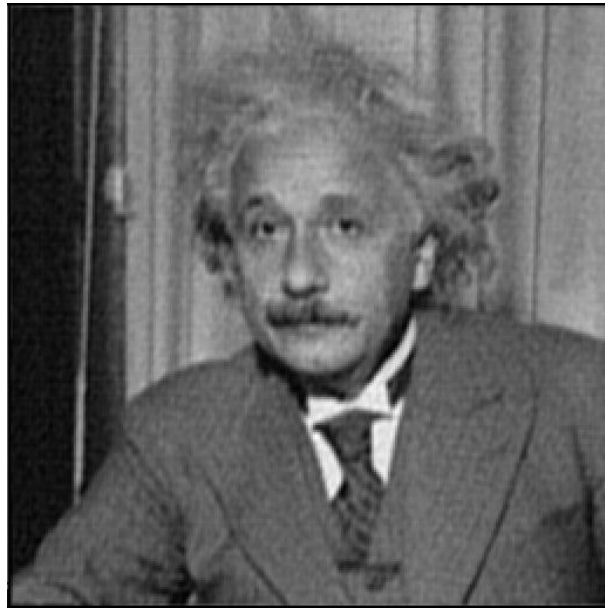


# Sparseness: less is more

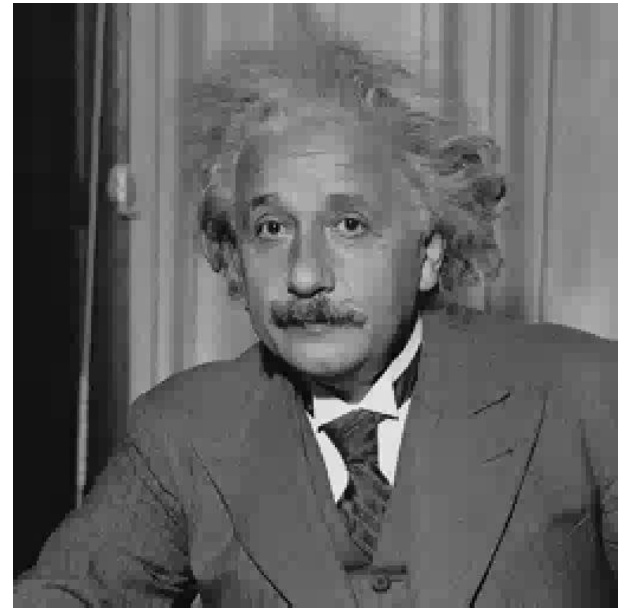
- Pixels: not sparse 😞
- A new domain can increase sparseness 😊



Taking 10% of pixels



10% Fourier coeffs.

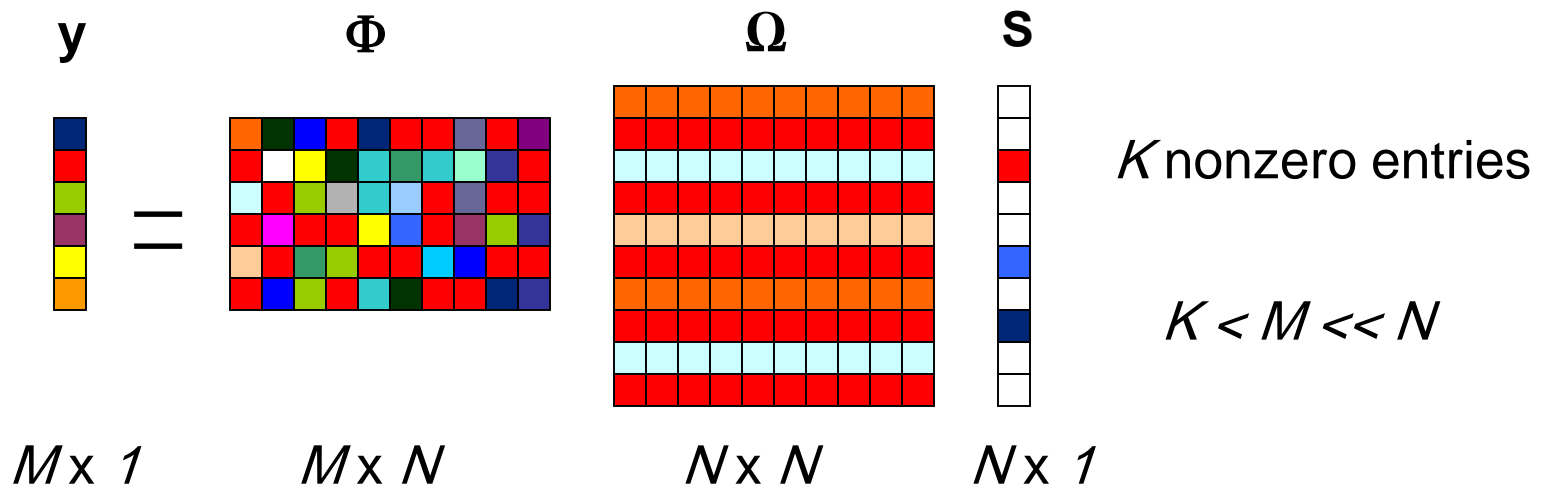


10% *Wavelet* coeffs.

# Universality

- Random measurements can be used if signal is sparse/compressible in any basis

$$Y = \Phi X = \Phi \Omega S = \Theta S$$



$\Theta =$  Compressive sensing Matrix

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## 2- RECOVERY (DENCODING)

- Minimization of  $L_1$ -norm
  - Greedy techniques
  - Iterative thresholding
  - Total-variation minimization
  - ...
-

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# How It Works



## **1) Undersample**

A camera or other device captures only a small, randomly chosen fraction of the pixels that normally comprise a particular image.

This saves time and space.

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# How It Works



## **2) Fill in the dots**

An algorithm called  $l_1$  minimization starts by arbitrarily picking one of the effectively infinite number of ways to fill in all the missing pixels.

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# How It Works



## **3) Add shapes**

The algorithm then begins to modify the picture in stages by laying colored shapes over the randomly selected image. The goal is to seek sparsity, a measure of image simplicity.

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# How It Works



## **4) Add smaller shapes**

The algorithm inserts the smallest number of shapes, of the simplest kind, that match the original pixels. If it sees four adjacent green pixels, it may add a green rectangle there.

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# How It Works



## **5) Achieve clarity**

Iteration after iteration, the algorithm adds smaller and smaller shapes, always seeking sparsity. Eventually it creates an image that will almost certainly be a near-perfect facsimile of a hi-res one.

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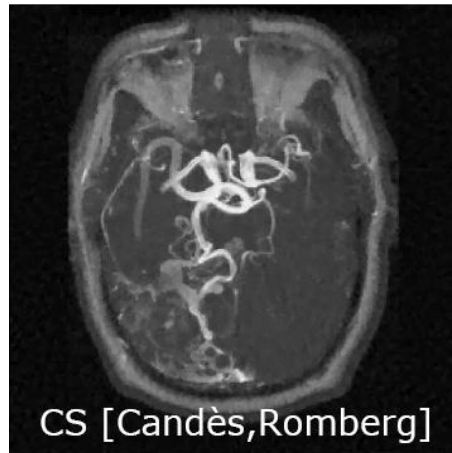
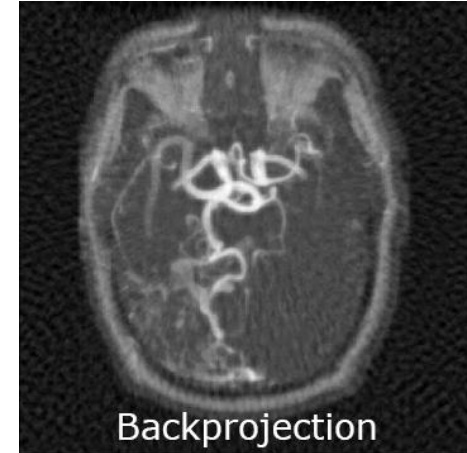
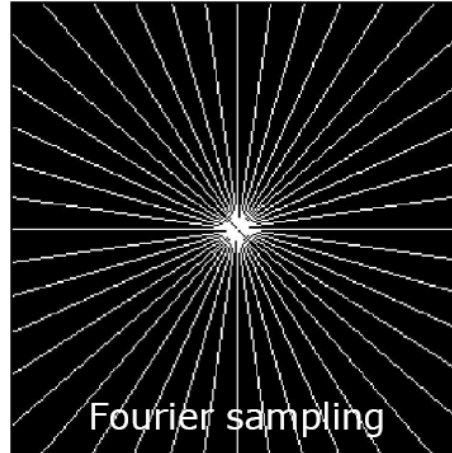
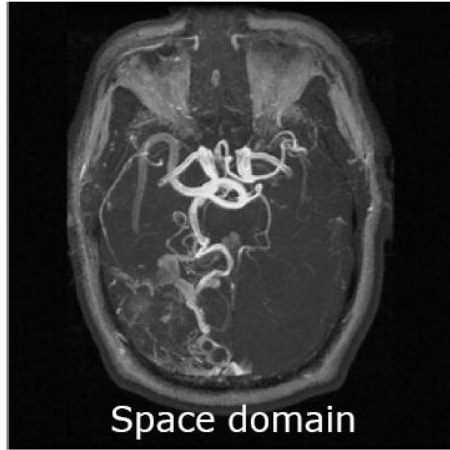


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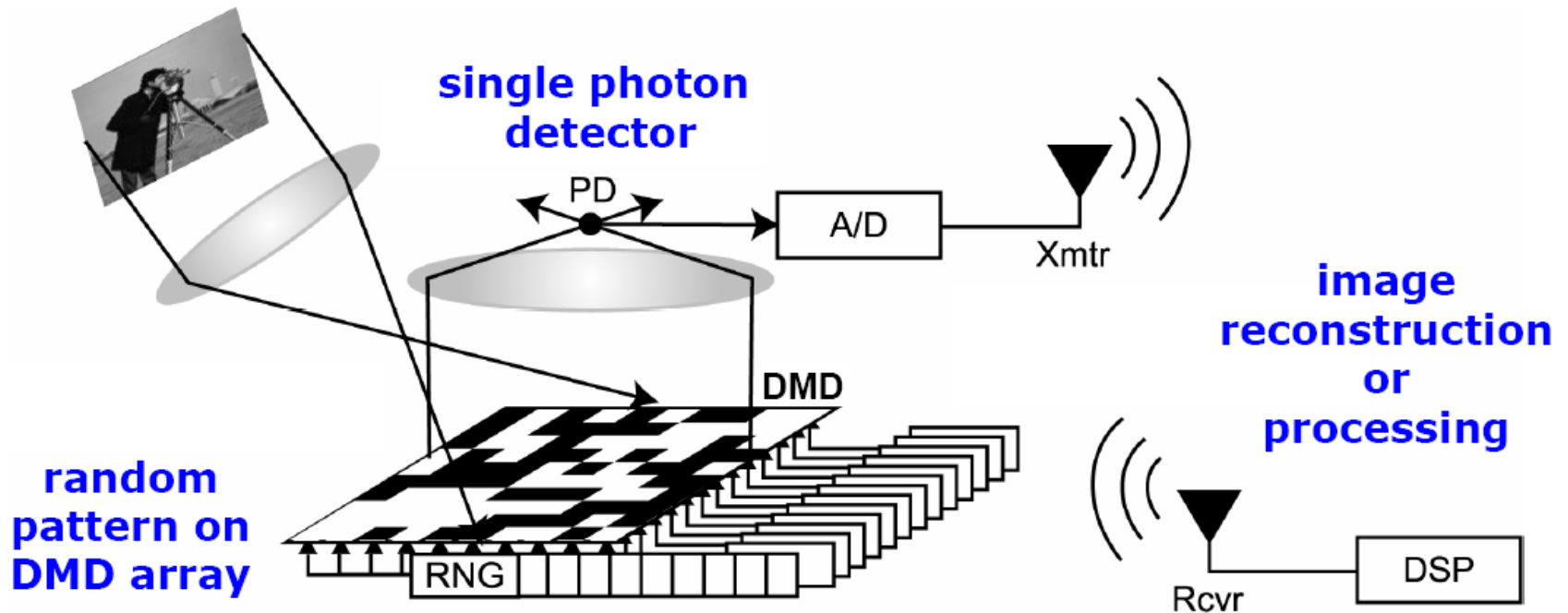
# Some CS applications

- Data compression
  - Compressive imaging
  - Detection, classification, estimation, learning...
  - Medical imaging
  - Analog-to-information conversion
  - Geophysical data analysis
  - Hyperspectral imaging
  - Compressive radar
  - Astronomy
  - Communications
  - Surface metrology
  - Spectrum analysis
  - ...
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# Magnetic resonance imaging



# Rice Single-Pixel CS Camera



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# Conclusions

- CS is a new technique for acquiring/ sensing and compressing Data simultaneously
  - Sparseness + Incoherence + random sampling allows perfect reconstruction under some conditions
  - A wide range of applications are possible
  - Big research effort now on recovery techniques
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*Thank you*

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