EE123
Digital Signal Processing

Lecture 23
Compressed Sensing

RADIOS

- https://inst.eecs.berkeley.edu/~ee123/sp15/radio.html

Compressive Sampling

Anything

0 T

Q: What is the rate you need to sample at?

A: At least Nyquist!

Compressive Sampling

Something

0 T

Q: What is the rate you need to sample at?

A: Maybe less than Nyquist....

Image Compression

Images are compressible
  Standard approach: First collect, then compress

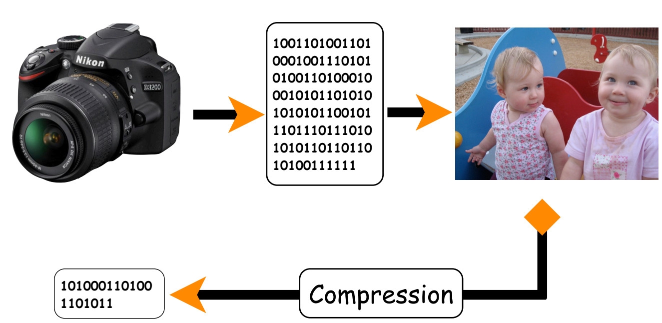
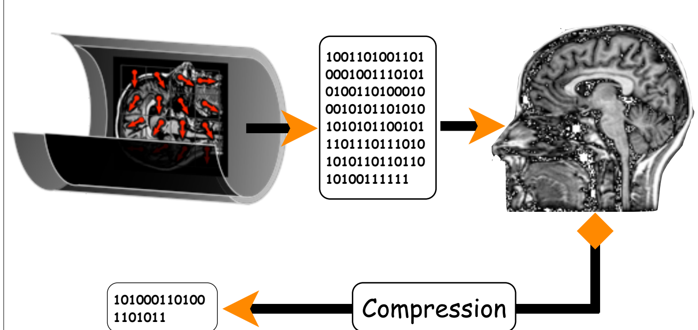


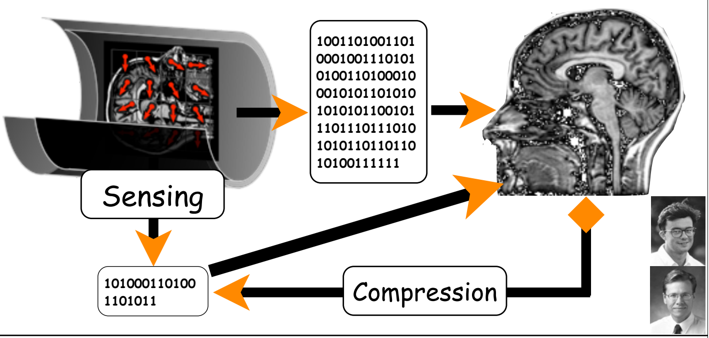
Image Compression

Medical images are compressible
  Standard approach: First collect, then compress



Medical images are compressible

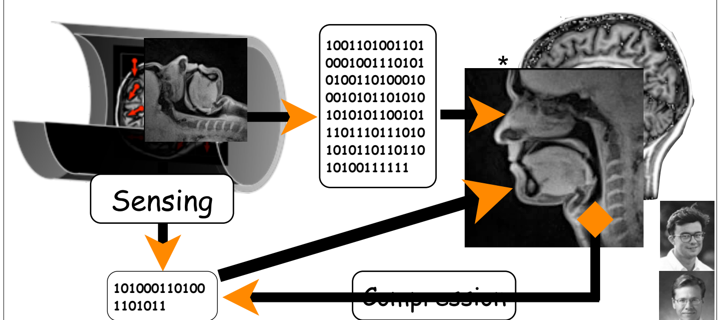
Standard approach: First collect, then compress



Compressed Sensing

Medical images are compressible

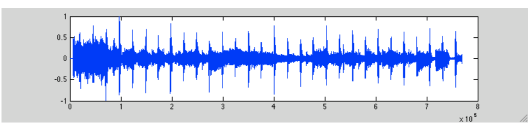
Standard approach: First collect, then compress



*Courtesy, M. Uecker, J Frahm Max Planck

M. Lustig, EECS UC Berkeley

Example I: Audio



Raw audio: 44.1Khz, 16bit, stereo = 1378 Kbit/sec

MP3: 44.1Khz, 16bit, stereo = 128 Kbit/sec

10.76 fold!

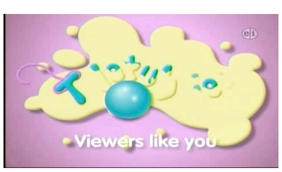
Example II: Images

Raw image (RGB): 24 bit/pixel

JPEG : 1280x960, normal = 1.09 bit/pixel

22 fold!

Example III: Videos



Raw Video: (480x360)p x 24b/p x 24fps + 44.1Khz x 16b x 2 = 98,578 Kb/s

MPEG4 : 1300 Kb/s

75 fold!

Compression

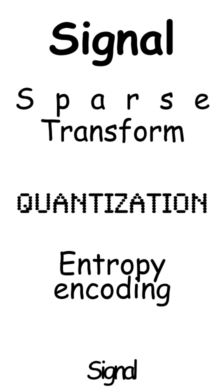
Almost all compression algorithm use transform coding

mp3: DCT

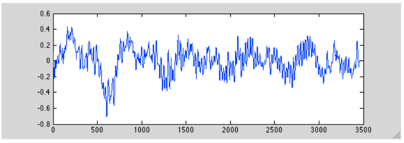
JPEG: DCT

JPEG2000: Wavelet

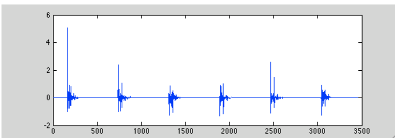
MPEG: DCT & time-difference



Sparse Transform



DCT



Signal

Sparse Transform

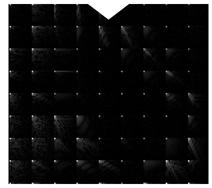
QUANTIZATION

Entropy encoding

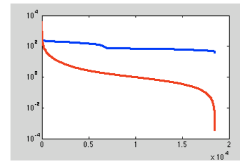
Signal

Sparse Transform

DCT



sorted coefficients



Signal

Sparse Transform

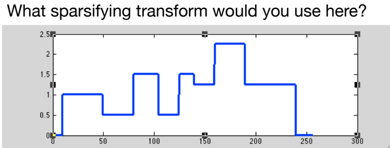
QUANTIZATION

Entropy encoding

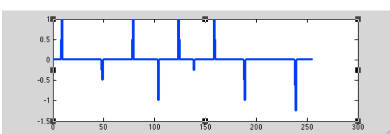
Signal

Sparse Transform

What sparsifying transform would you use here?



Difference



Signal

Sparse Transform

QUANTIZATION

Entropy encoding

Signal

Sparsity & Compressibility

Sparsity and Noise

sparse

not sparse

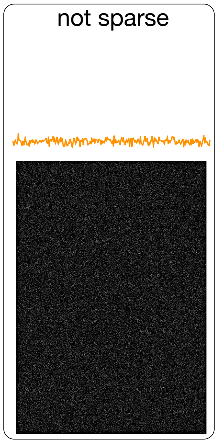
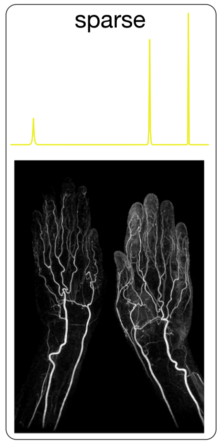
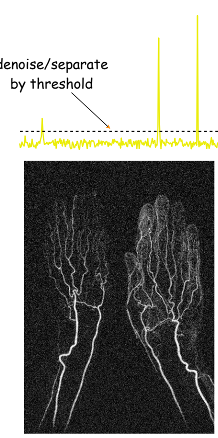


*image courtesy of J. Trzasko

Sparsity and Noise

sparse





not sparse

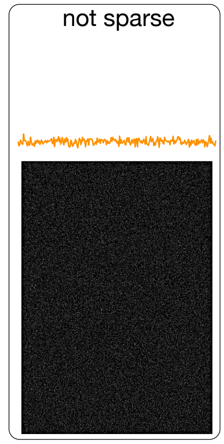
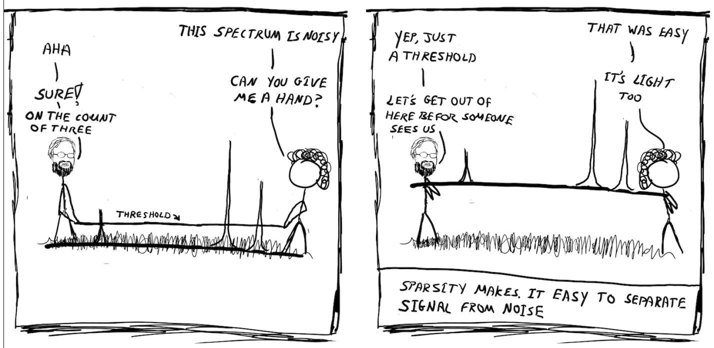


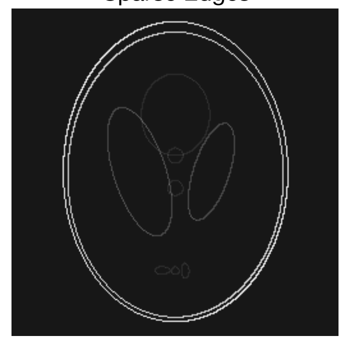
*image courtesy of J. Trzasko



Transform Sparsity

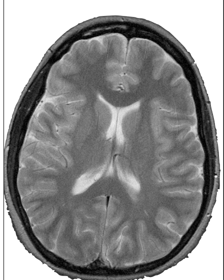
not sparse

Sparse Edges



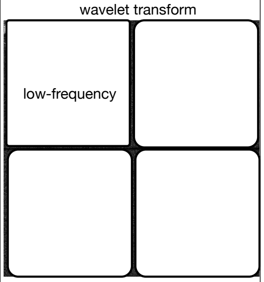
Transform Sparsity and Denoising

not sparse



sparse

wavelet transform

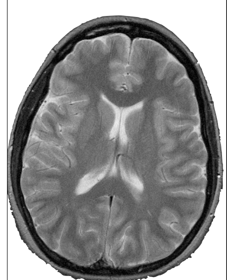


denoised

DL Donoho, I Johnstone Biometrika 1994;81(3):425-55

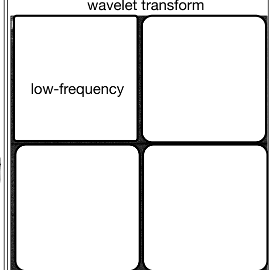
Transform Sparsity and Denoising

not sparse

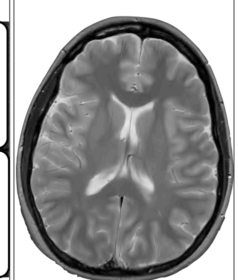


sparse

wavelet transform



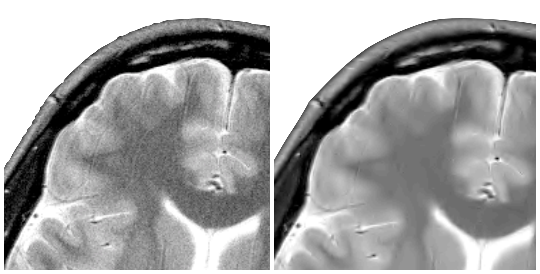
denoised



DL Donoho, I Johnstone Biometrika 1994;81(3):425-55

Transform Sparsity and Denoising

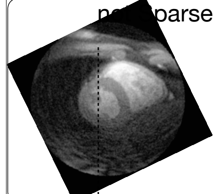
wavelet denoising



DL Donoho, I Johnstone Biometrika 1994;81(3):425-55

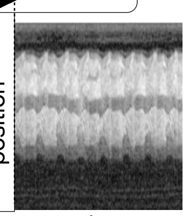
More Sparse Transforms

not sparse



*Video courtesy of Juan Santos, Heart Vista

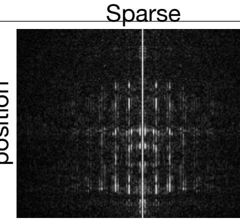
position



time

Sparse

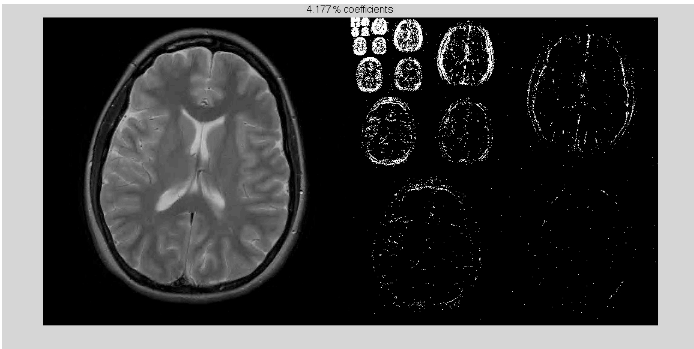
position



temporal frequency

Sparsity and Compression

- Only need to store non-zeros



From Samples to Measurements

- Shanon-Nyquist sampling
  - Worst case for ANY bandlimited data
- Compressive sampling (CS)

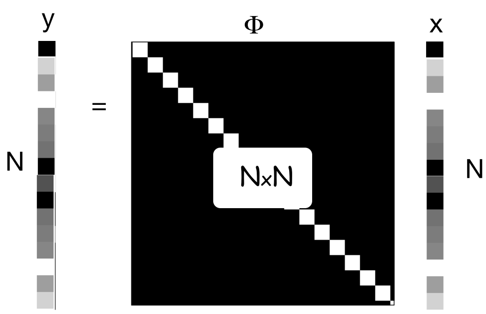
  "Sparse signals statistics can be recovered from a small number of non-adaptive linear measurements"

  - Integrated sensing, compression and processing.
  - Based on concepts of incoherency between signal and measurements

Traditional Sensing

Desktop scanner/ digital camera sensing

- $x \in \Re^N$ is a signal
- Make N linear measurements

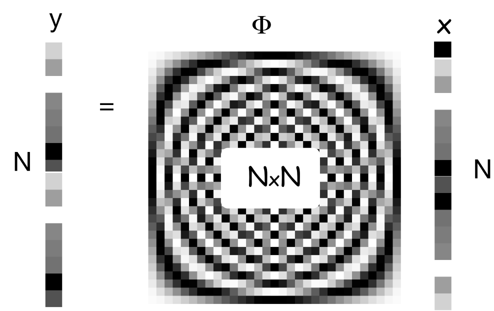


sensing matrix

Traditional Sensing

MRI Fourier Imaging

- $x \in \Re^N$ is a signal
- Make N linear measurements

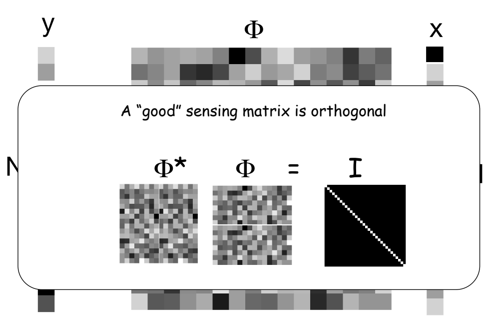


sensing matrix

Traditional Sensing

Arbitrary sensing

- $x \in \Re^N$ is a signal
- Make N linear measurements

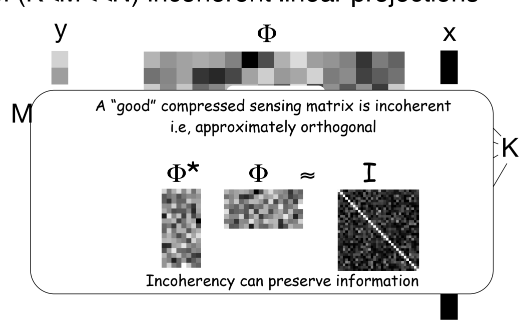


sensing matrix

Compressed Sensing

(Candes, Romber, Tao 2006; Donoho 2006)

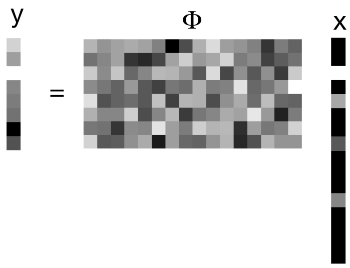
- $x \in \Re^N$ is a K-sparse signal (K<<N)
- Make M (K<M<<N) incoherent linear projections



CS recovery

$\left.\begin{array}{l}\bullet\ \text{Given } y = \Phi x \\ \quad \text{find } x\end{array}\right\}$ Under-determined

- But there's hope, x is sparse!



CS recovery

$\left.\begin{array}{l}\bullet\ \text{Given } y = \Phi x \\ \quad \text{find } x\end{array}\right\}$ Under-determined

- But there's hope, x is sparse!

CS recovery

$\left.\begin{array}{l}\bullet\ \text{Given } y = \Phi x \\ \quad \text{find } x\end{array}\right\}$ Under-determined

- But there's hope, x is sparse!

minimize $\|x\|_2$

s.t. $y = \Phi x$

WRONG!

CS recovery

$\left.\begin{array}{l}\bullet\ \text{Given } y = \Phi x \\ \quad \text{find } x\end{array}\right\}$ Under-determined

- But there's hope, x is sparse!

minimize $\|x\|_0$

s.t. $y = \Phi x$

HARD!

CS recovery

$\left.\begin{array}{l}\bullet\ \text{Given } y = \Phi x \\ \quad \text{find } x\end{array}\right\}$ Under-determined

- But there's hope, x is sparse!

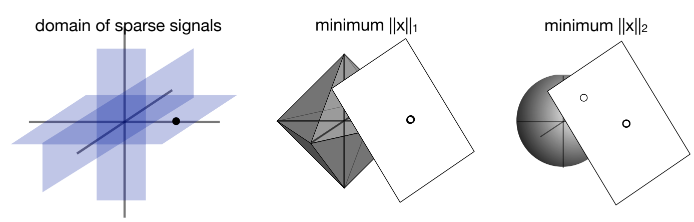
minimize $\|x\|_1$

s.t. $y = \Phi x$

need $M \approx K \log(N) << N$

Solved by linear-programming

Geometric Interpretation



$$\begin{bmatrix}0\\3\\0\end{bmatrix}\begin{bmatrix}0\\0\\1\end{bmatrix}\begin{bmatrix}1\\0\\0\end{bmatrix} \qquad \begin{bmatrix}a_1 & a_2 & a_3\end{bmatrix}\begin{bmatrix}x_1\\x_2\\x_3\end{bmatrix} = [y_1]$$