

Sampling in image representation and compression

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Overview

- Problem statement
- Image representation concepts
- Image compression basics
- Sparsity is the key, l_0 -minimization, OMP
- Image compression revisited
- Imagery metrics
- Solving our problem: compressed sensing and *deterministic sampling masks*
- Solving our problem: results

Problem statement



9/24/13

Sampling in image representation
and compression

2

Problem statement



9/24/13

Sampling in image representation
and compression

3

Problem statement

JPEG, JPEG 2000

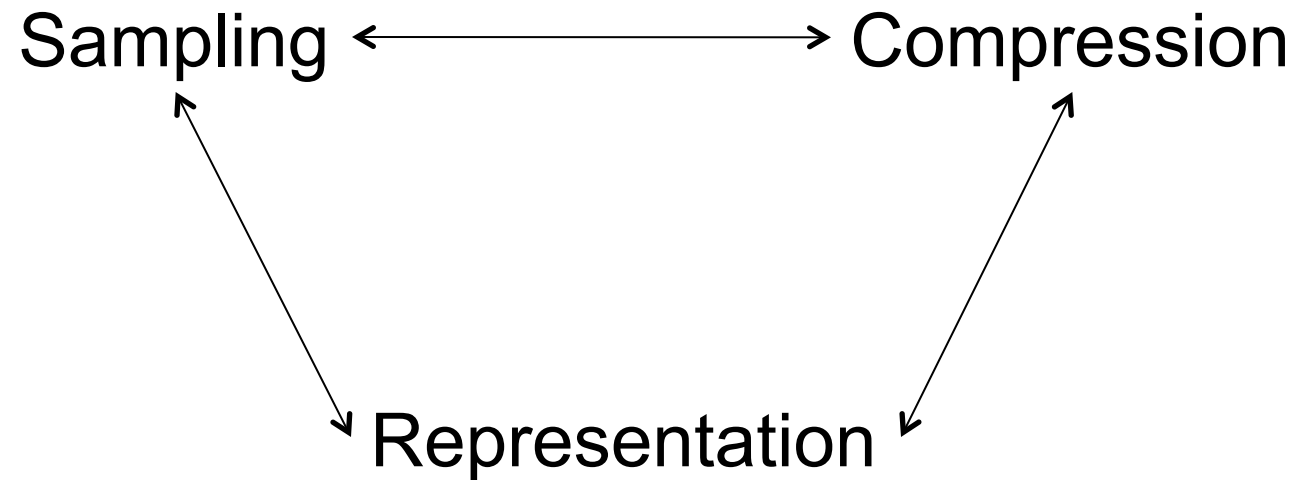


Image representation concepts

Image representation concepts

$$I[n_1, n_2]$$

$$0 \leq n_1 < N_1, 0 \leq n_2 < N_2$$

Image representation concepts

$$I[n_1, n_2] = \text{pixel}$$

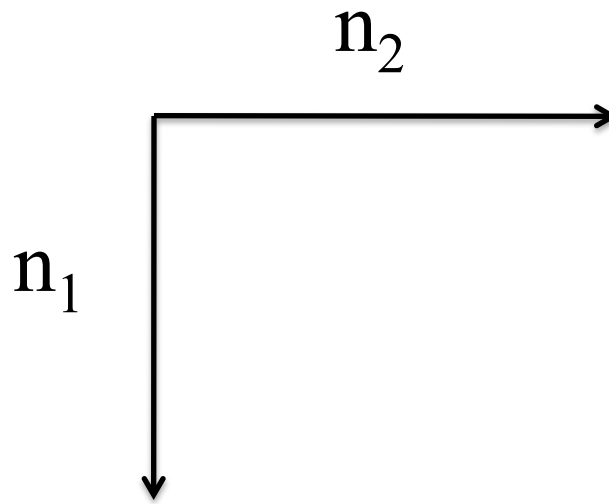


Image representation concepts

$I[n_1, n_2] \sim$ intensity, brightness
at $[n_1, n_2]$

$I[n_1, n_2] \in \{0, \dots, 2^B - 1\}$, or

$I[n_1, n_2] \in \{-2^{B-1}, \dots, 2^{B-1} - 1\}$, where

$I[n_1, n_2] = \text{round}(2^B I'[n_1, n_2])$ and

$I'[n_1, n_2] \in [0, 1)$ or $[-1/2, 1/2)$

Image representation concepts

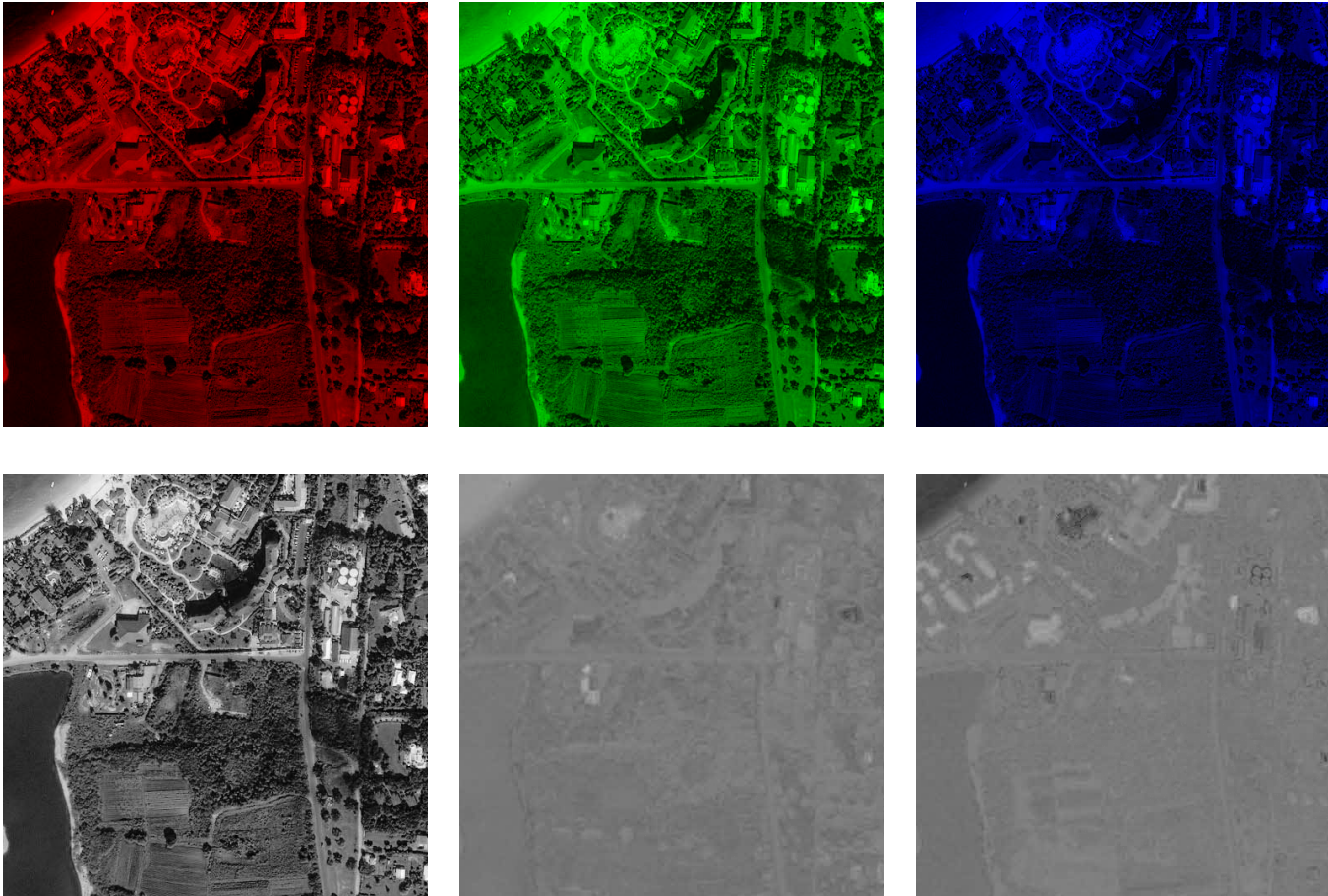


Image compression

$$512 \times 512 \times 8 \times 3 = 6,291,456 \text{ bits}$$

Image compression

JPEG, JPEG 2000

Image compression

1) Partitioning of the image I in sub-images

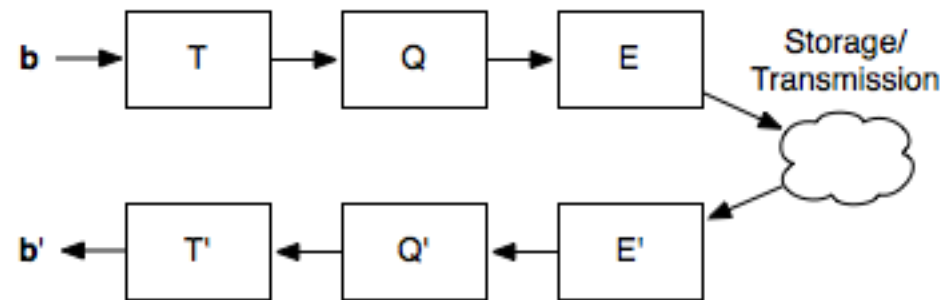
Image compression

- 1) Partitioning of the image I in sub-images
- 2) Transform sub-images to exploit correlations within them

Image compression

- 1) Partitioning of the image I in sub-images
- 2) Transform sub-images to exploit correlations within them
- 3) Quantize and encode

Image compression



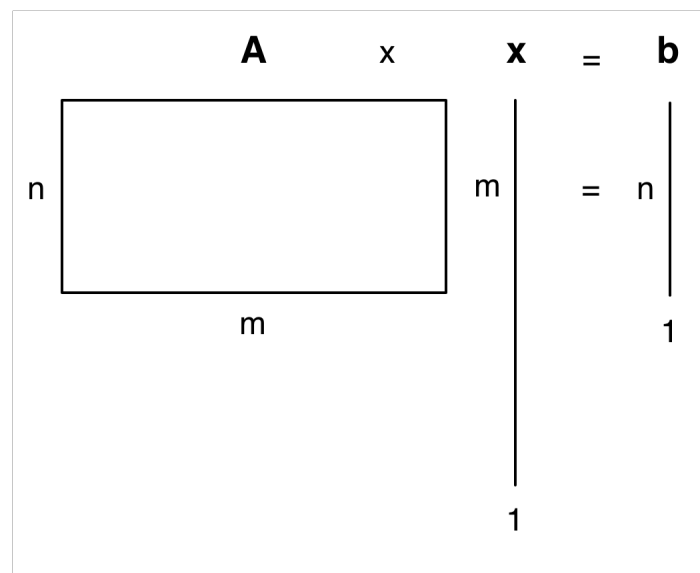
Sparsity is the key

Cn u rd ths?

VS

Can you read this?

Sparsity is the key



Sparsity

The l_0 “norm”:

$$\|\mathbf{x}\|_0 = \# \{k : x_k \neq 0\}$$

l_0 -minimization ~ sparse solution

$$(P_0): \min_{\mathbf{x}} \|\mathbf{x}\|_0 \text{ subject to } \|\mathbf{Ax} - \mathbf{b}\|_2 = 0$$

l_0 -minimization ~ sparse solution

$$(P_0^\varepsilon): \min_{\mathbf{x}} \|\mathbf{x}\|_0 \text{ subject to } \|\mathbf{Ax} - \mathbf{b}\|_2 < \varepsilon$$

l_0 -minimization \sim sparse solution

$$(P_0^\varepsilon): \min_{\mathbf{x}} \|\mathbf{x}\|_0 \text{ subject to } \|\mathbf{Ax} - \mathbf{b}\|_2 < \varepsilon$$

Solving (P_0^ε) is NP-hard!
Is there any hope?

Finding sparse solutions:OMP

Orthogonal Matching Pursuit algorithm:

Task: Approximate the solution of (P_0) : $\min_{\mathbf{x}} \|\mathbf{x}\|_0$ subject to $\mathbf{Ax} = \mathbf{b}$.

Parameters: We are given the matrix \mathbf{A} , the vector \mathbf{b} , and the threshold ϵ_0 .

Initialization: Initialize $k = 0$, and set

- The initial solution $\mathbf{x}^0 = \mathbf{0}$.
- The initial residual $\mathbf{r}^0 = \mathbf{b} - \mathbf{Ax}^0 = \mathbf{b}$.
- The initial solution support $\mathcal{S}^0 = \text{Support}\{\mathbf{x}^0\} = \emptyset$.

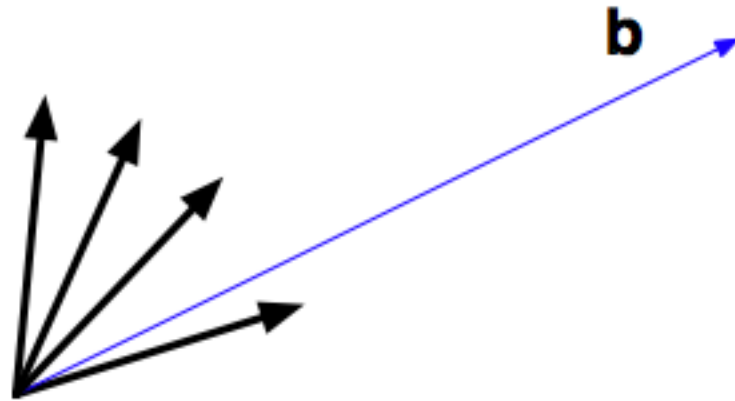
Main Iteration: Increment k by 1 and perform the following steps:

- **Sweep:** Compute the errors $\epsilon(j) = \min_{z_j} \|z_j \mathbf{a}_j - \mathbf{r}^{k-1}\|_2^2$ for all j using the optimal choice $z_j^* = \mathbf{a}_j^T \mathbf{r}^{k-1} / \|\mathbf{a}_j\|_2^2$.
- **Update Support:** Find a minimizer j_0 of $\epsilon(j)$: $\forall j \notin \mathcal{S}^{k-1}, \epsilon(j_0) \leq \epsilon(j)$, and update $\mathcal{S}^k = \mathcal{S}^{k-1} \cup \{j_0\}$.
- **Update Provisional Solution:** Compute \mathbf{x}^k , the minimizer of $\|\mathbf{Ax} - \mathbf{b}\|_2^2$ subject to $\text{Support}\{\mathbf{x}\} = \mathcal{S}^k$.
- **Update Residual:** Compute $\mathbf{r}^k = \mathbf{b} - \mathbf{Ax}^k$.
- **Stopping Rule:** If $\|\mathbf{r}^k\|_2 < \epsilon_0$, stop. Otherwise, apply another iteration.

Output: The proposed solution is \mathbf{x}^k obtained after k iterations.

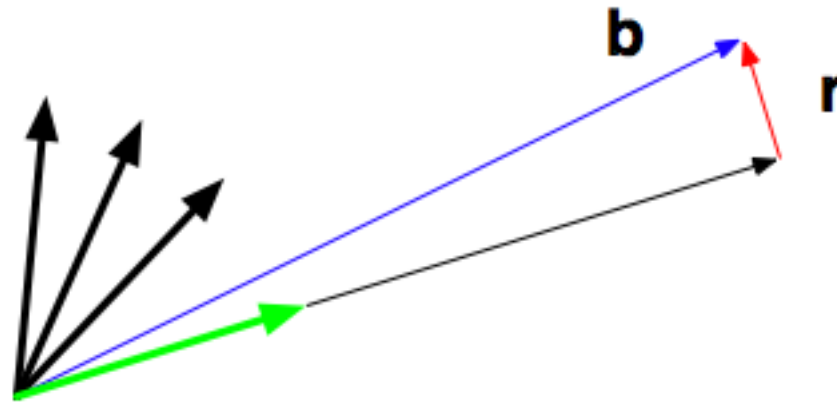
Finding sparse solutions:OMP

Orthogonal Matching Pursuit algorithm:



Finding sparse solutions:OMP

Orthogonal Matching Pursuit algorithm:



Finding sparse solutions:OMP

Orthogonal Matching Pursuit algorithm:

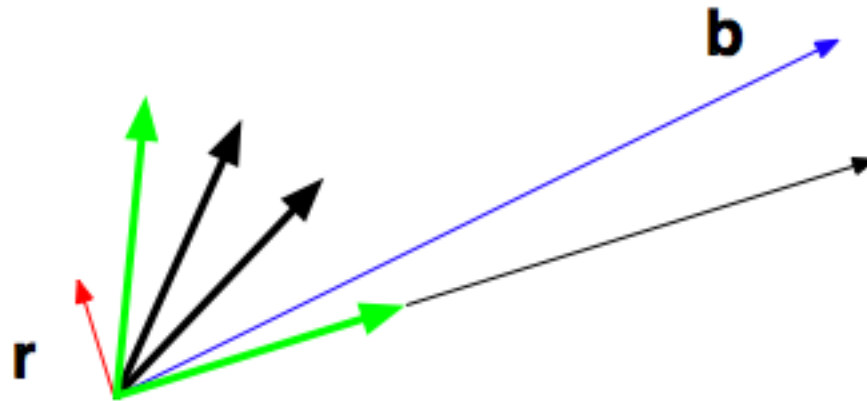
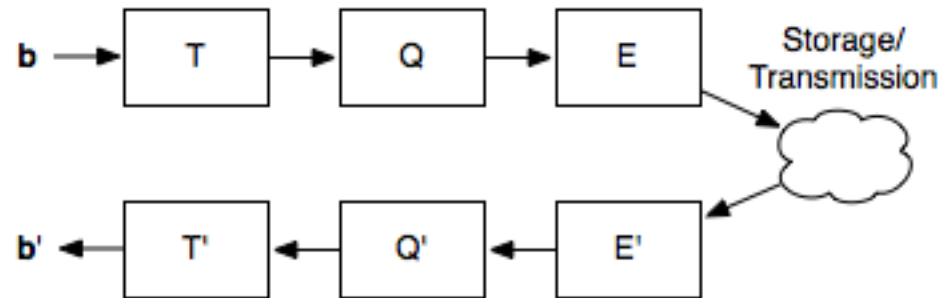
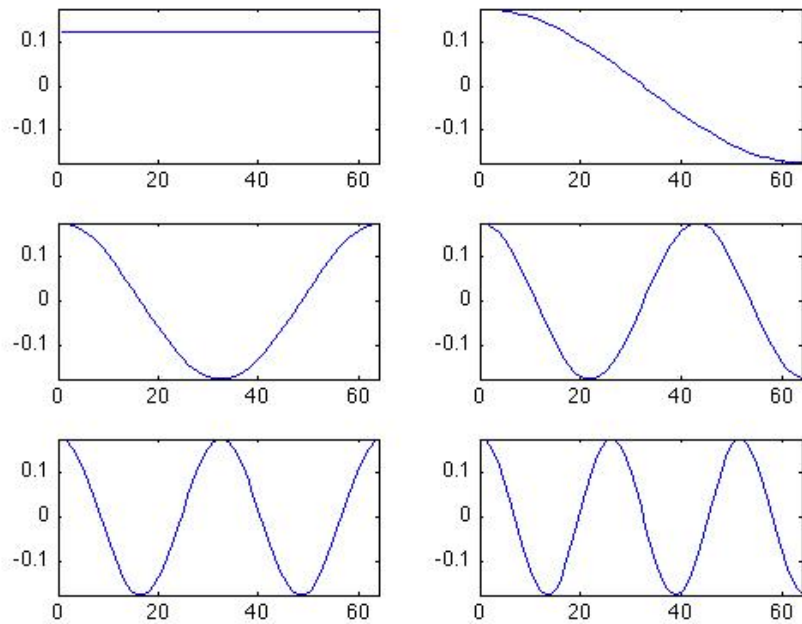


Image compression

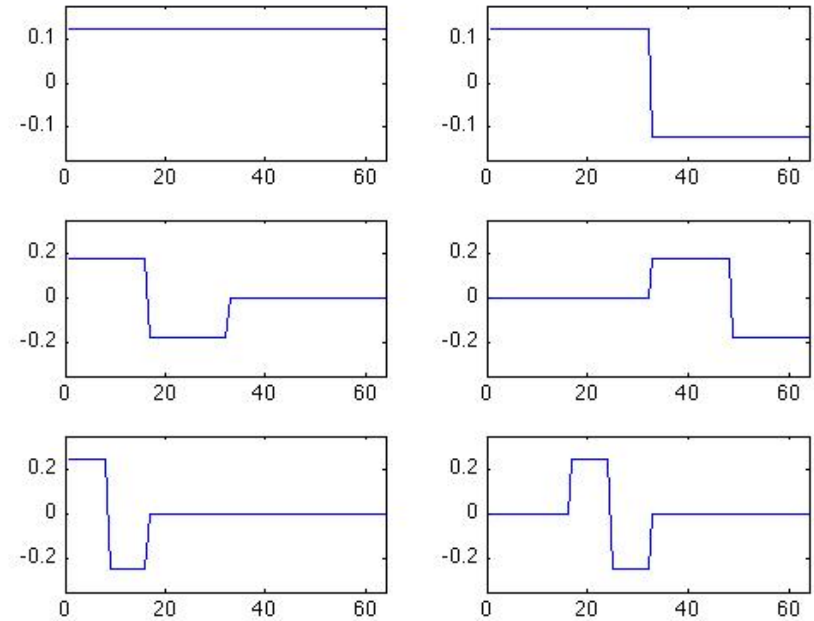


$$\mathbf{T} = \mathbf{T}_\varepsilon = \text{OMP}(\mathbf{A}, \cdot, \varepsilon), \quad \mathbf{T}' = \mathbf{A}$$

We need a matrix **A**

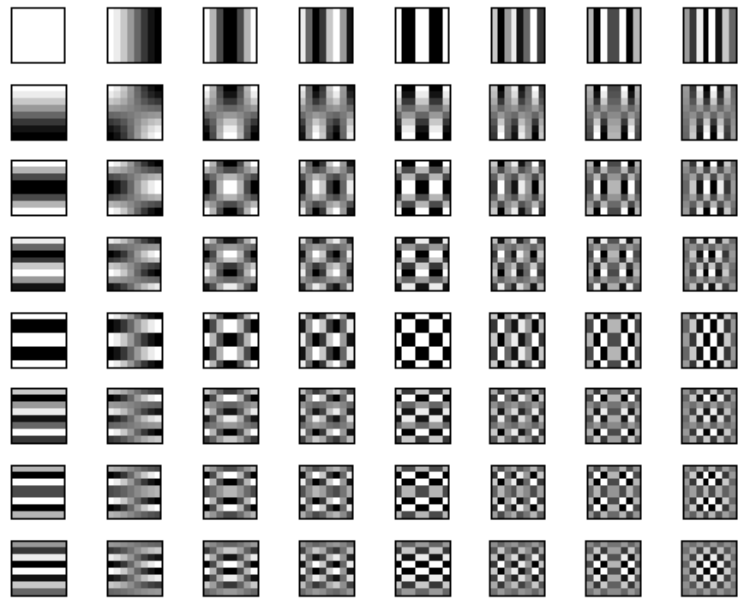


DCT

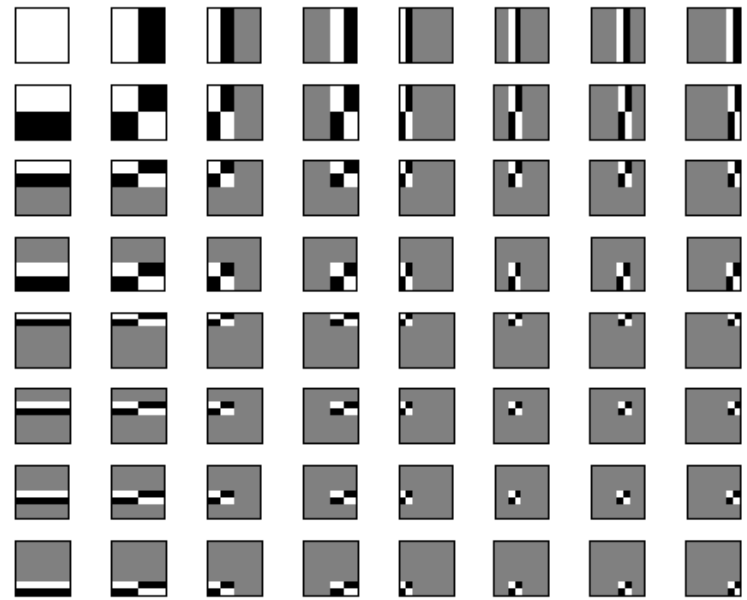


Haar

We need a matrix A

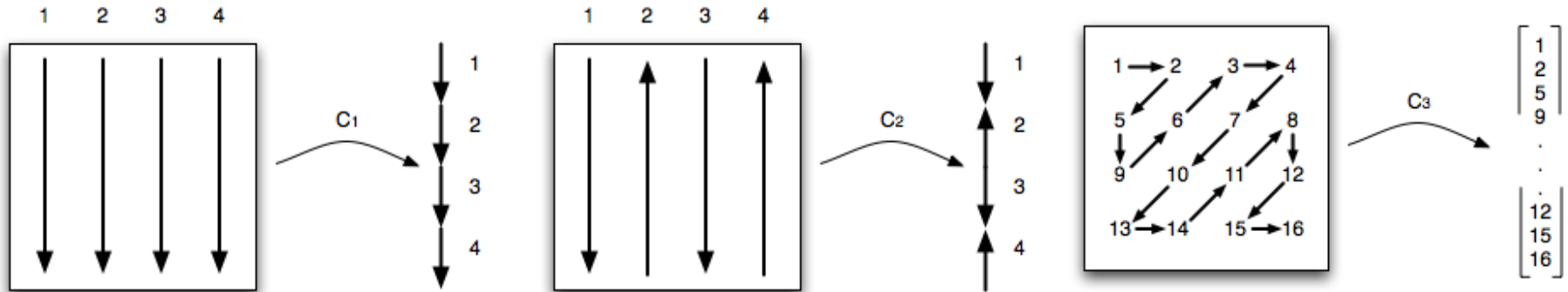


2D - DCT

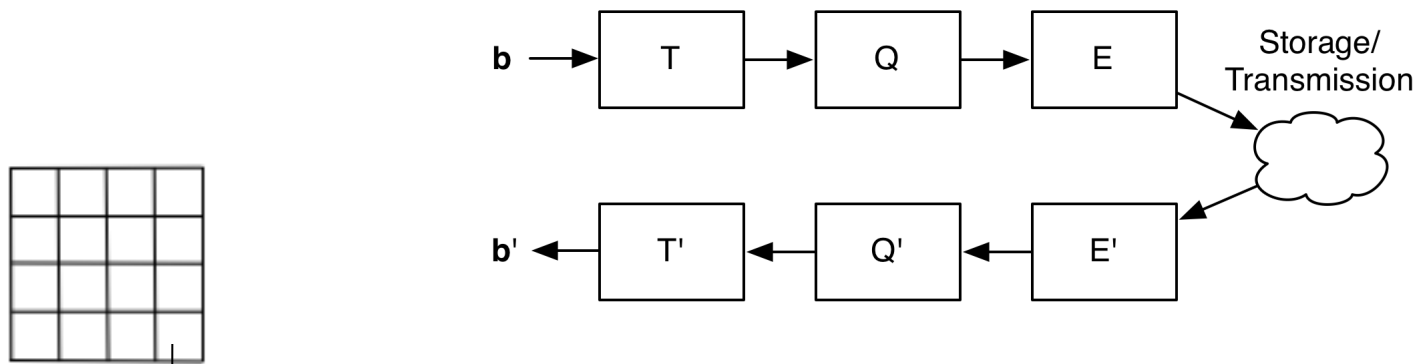


2D - Haar

We need a matrix **A**



Compressing a test image



$$c_3(\square) = \mathbf{b}$$

$$\mathbf{x}_0 = \mathbf{T}_\varepsilon \mathbf{b} = \text{OMP}(\mathbf{A}, \mathbf{b}, \varepsilon)$$

$$\square = c_3^{-1}(\mathbf{b}')$$

$$\mathbf{b}' = \mathbf{T}' \mathbf{x}_0 = \mathbf{A} \mathbf{x}_0$$

Compressing a test image

$$\square \sim \boxtimes ? \quad \| \mathbf{b} - \mathbf{b}' \|_2 < \varepsilon$$

But what does that mean visually?
How many bits were used?

Imagery metrics

Peak Signal-to-Noise Ratio (PSNR), measured in dB:

$$\text{PSNR}(\mathbf{X}, \mathbf{Y}) = 20 \log_{10}(\text{MAX}_B / \sqrt{\text{MSE}}),$$

with $\text{MAX}_B = 2^B - 1$, and $\text{MSE} = \sum_{i,j} [\mathbf{X}(i,j) - \mathbf{Y}(i,j)]^2 / nm$.
In our case, $n = m = 512$, and $B = 8$, i.e. $\text{MAX}_B = 255$.

Imagery metrics

Structural Similarity (SSIM), and Mean Structural Similarity(MSSIM) indices:

$$\text{SSIM}(\mathbf{x}, \mathbf{y}) = \frac{(2 \mu_x \mu_y + C_1) (2 \sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1) (\sigma_x^2 + \sigma_y^2 + C_2)}$$

$$\text{MSSIM}(\mathbf{X}, \mathbf{Y}) = \frac{1}{M} \sum_{j=1}^M \text{SSIM}(\mathbf{x}_j, \mathbf{y}_j)$$

Imagery metrics

The normalized sparse bit-rate is

$$\text{nsbr}(I, \mathbf{A}, \varepsilon) = \sum \|\mathbf{x}_j\|_0 / N_1 N_2,$$

where image I is of size N_1 by N_2 .

Imagery metrics: test images



Barbara



Boat

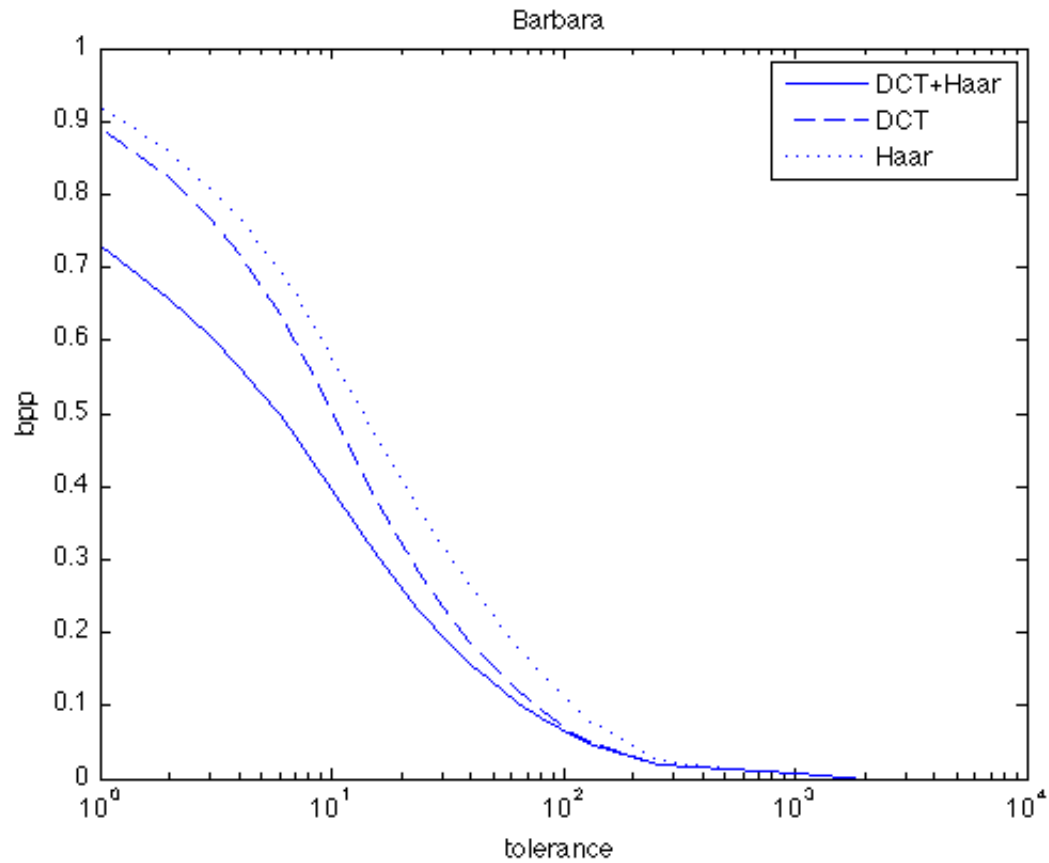


Elaine

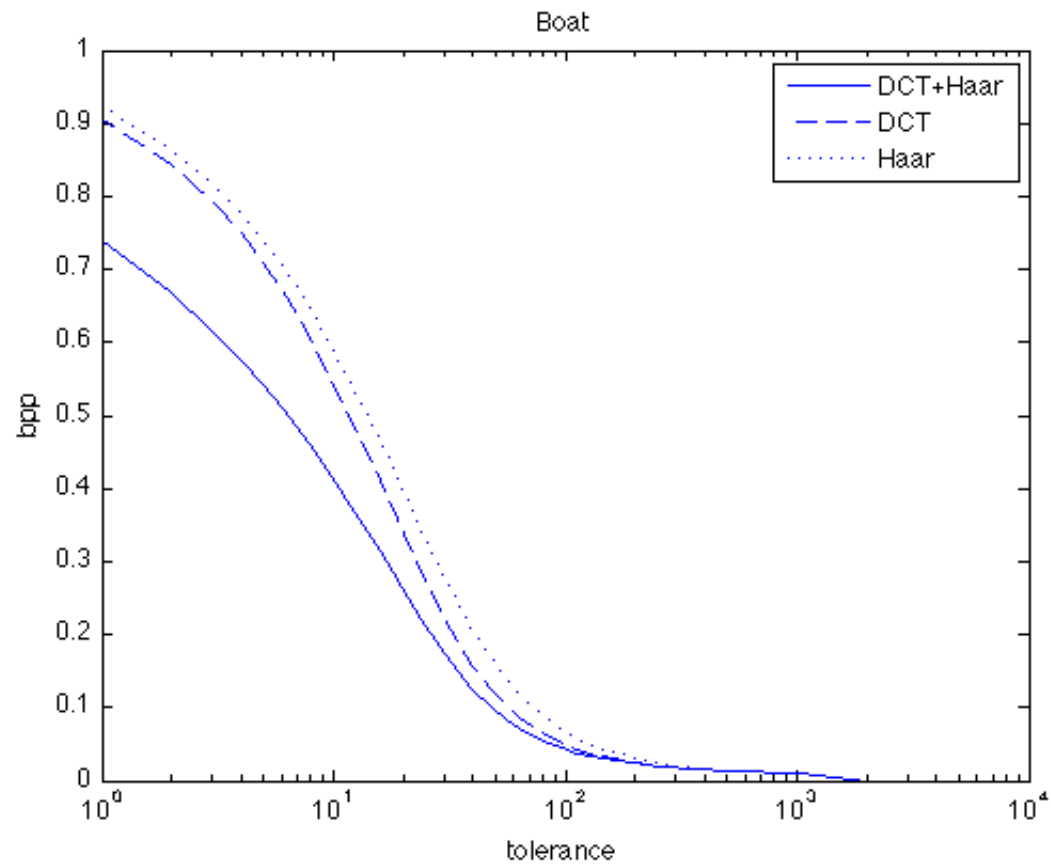


Stream

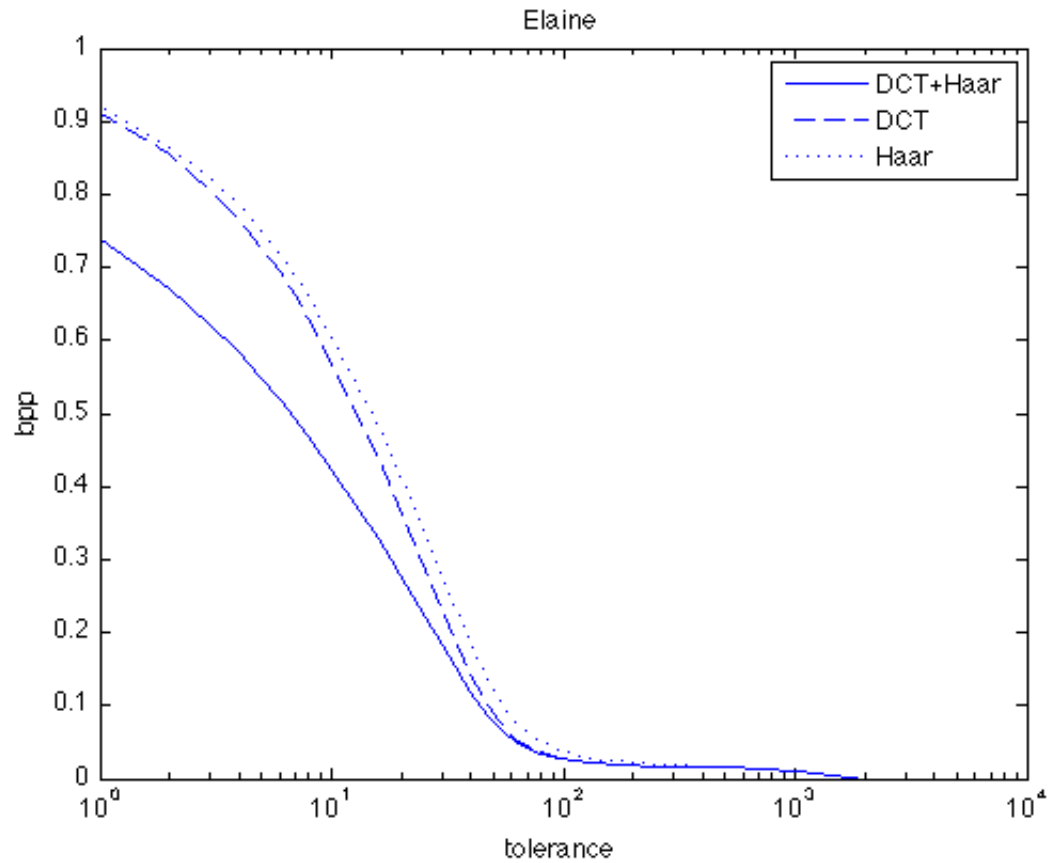
Imagery metrics: bpp vs ϵ



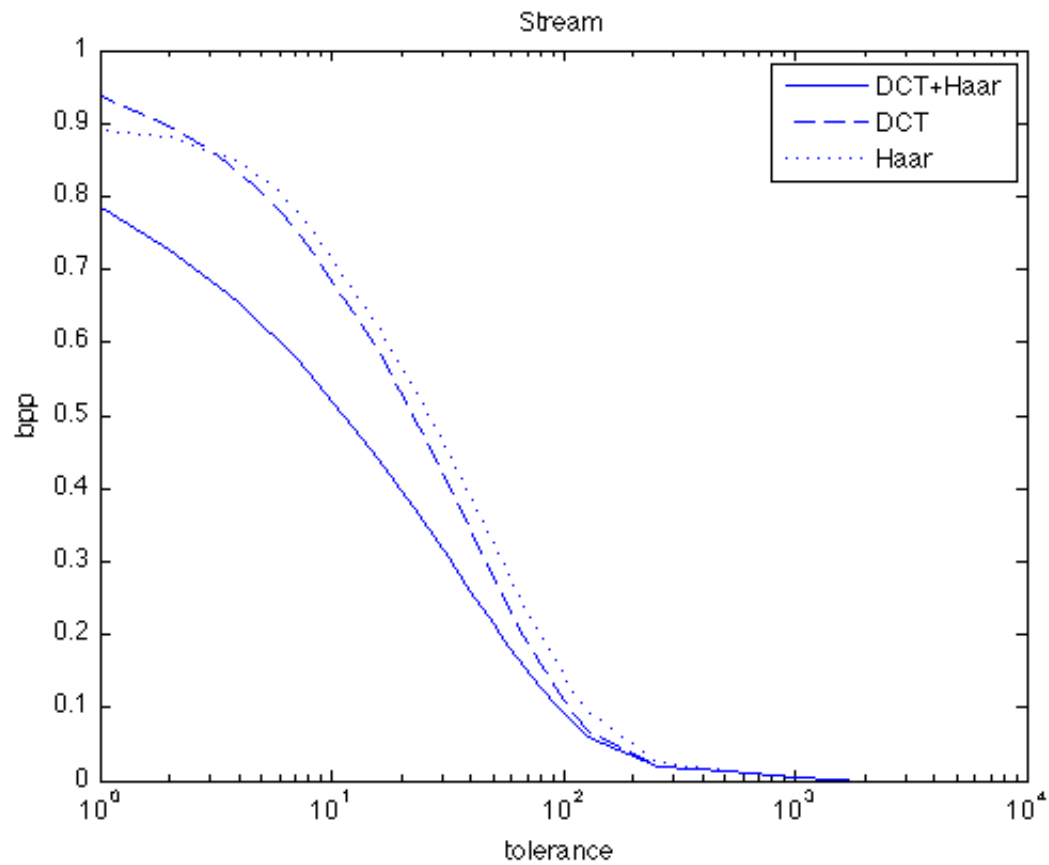
Imagery metrics: bpp vs ϵ



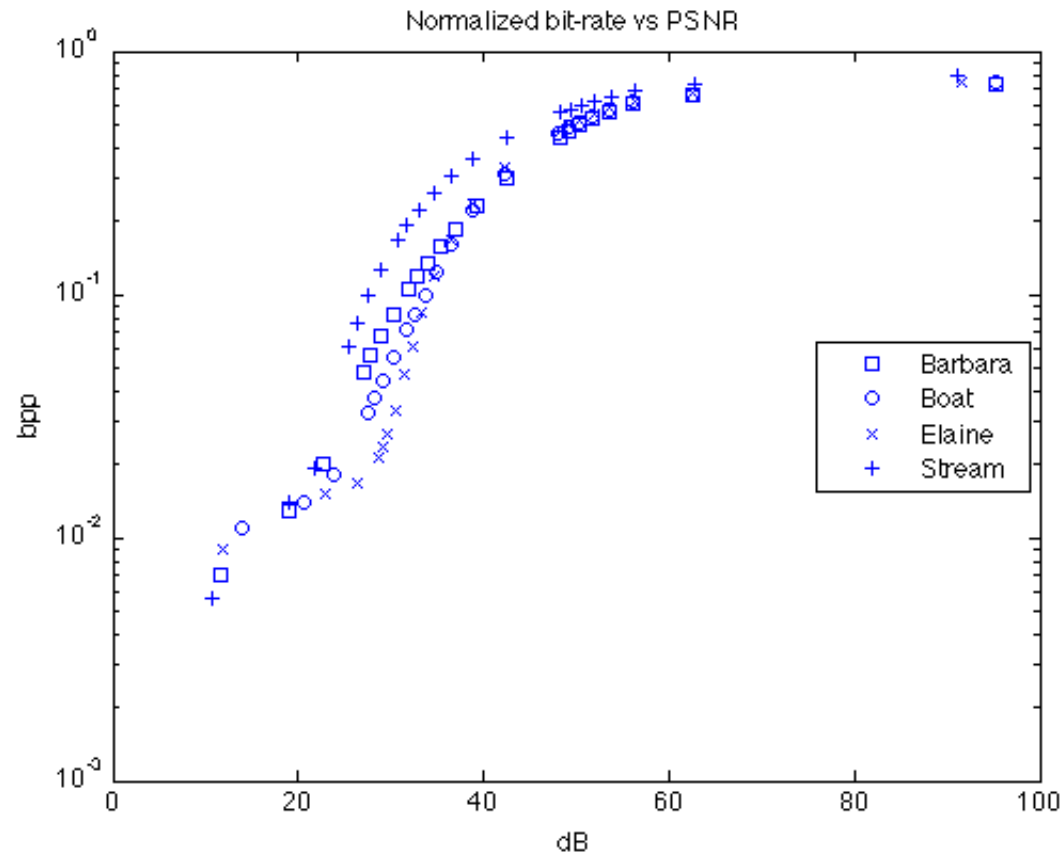
Imagery metrics: bpp vs ϵ



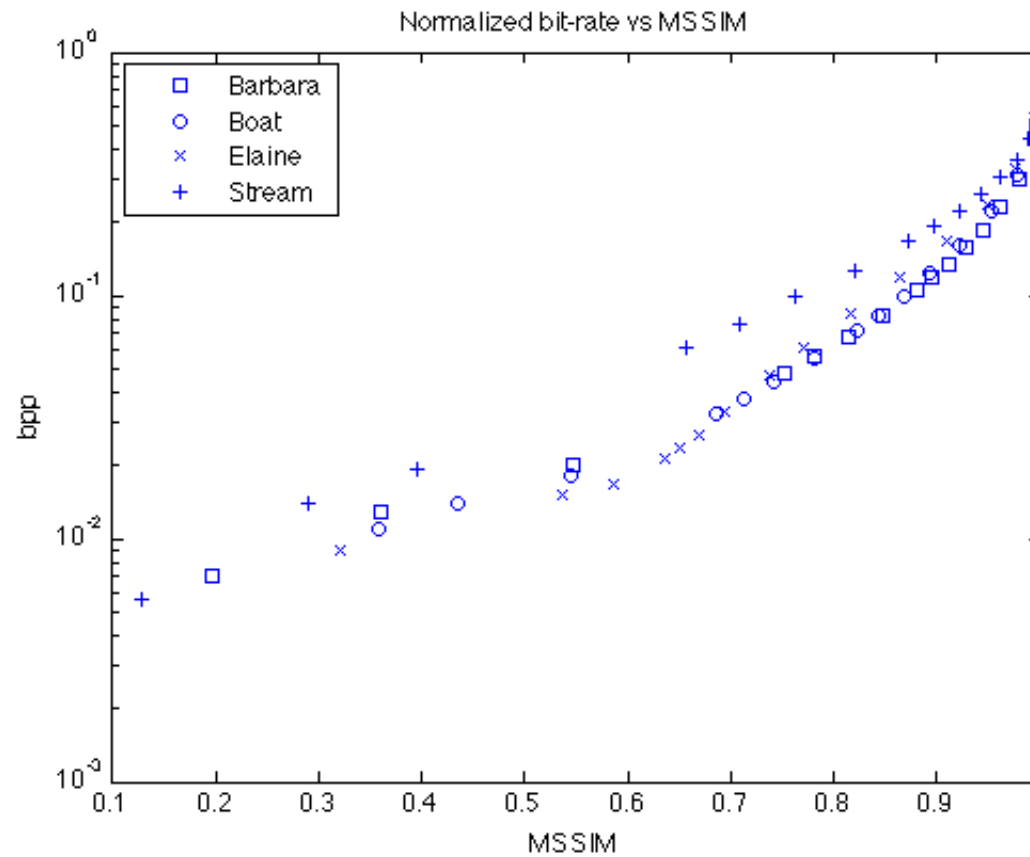
Imagery metrics: bpp vs ϵ



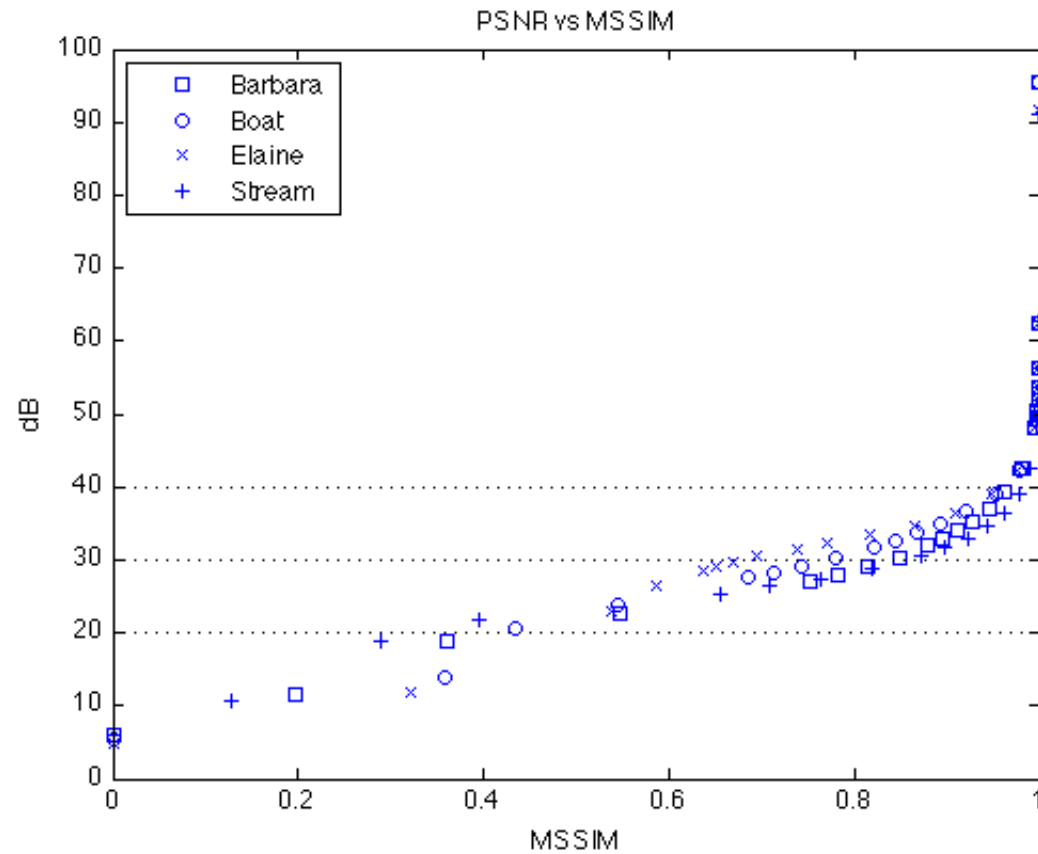
Imagery metrics: bpp vs PSNR



Imagery metrics: bpp vs MSSIM



Imagery metrics: PSNR vs MSSIM



Compression results



Original



Compressed



SSIM

$$\varepsilon = 32, c = 4$$

$$\text{PSNR} = 36.5220 \text{ dB}, \text{MSSIM} = 0.9104, \text{nsbr} = 0.1609 \text{ bpp}$$

Back to our original problem



$k = 40$ (62.5%)



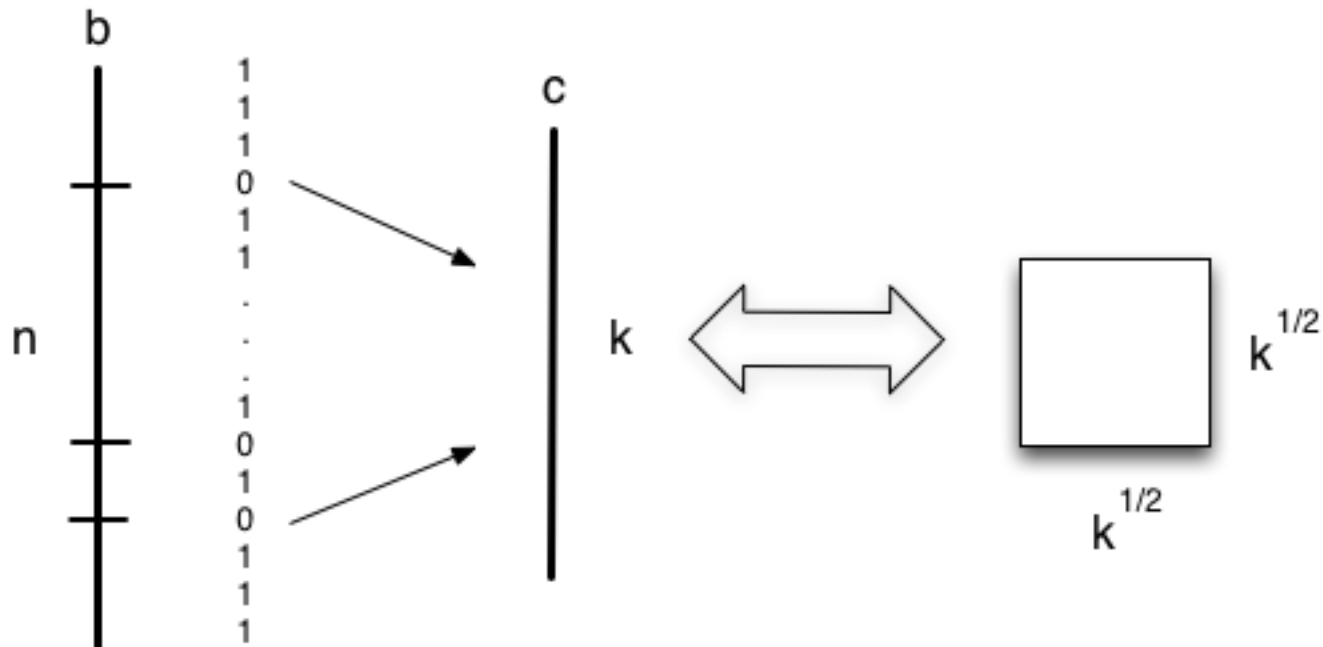
$k = 32$ (50%)

Compressed sensing and sampling

$$\min_{\mathbf{x}} \|\mathbf{x}\|_0 \text{ subject to } \|\mathbf{PA} \mathbf{x} - \mathbf{c}\|_2 < \varepsilon$$

\mathbf{P} in $\mathbb{R}^{k \times n}$, \mathbf{A} in $\mathbb{R}^{n \times m}$, and \mathbf{c} in \mathbb{R}^k

Deterministic sampling masks



$$\varepsilon = c \sqrt{k}, c = 4$$

Deterministic sampling masks

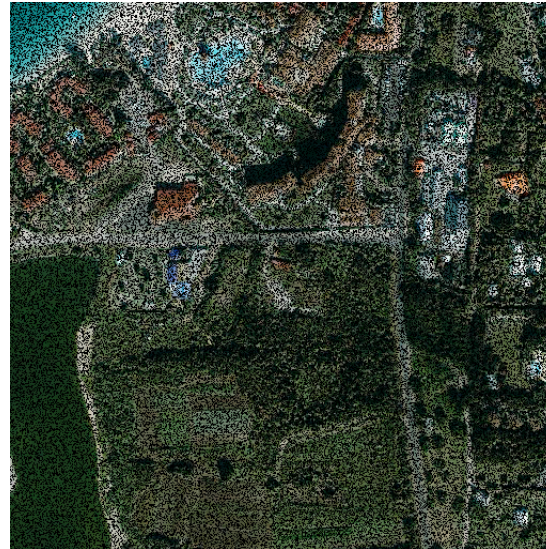
$$\|\mathbf{A}' \mathbf{x}' - \mathbf{c}\|_2 < \varepsilon, \text{ with } \mathbf{x}' = \text{OMP}(\mathbf{A}', \mathbf{c}, \varepsilon), \text{ and } \mathbf{x}' \text{ in } \mathbb{R}^m$$

Deterministic sampling masks

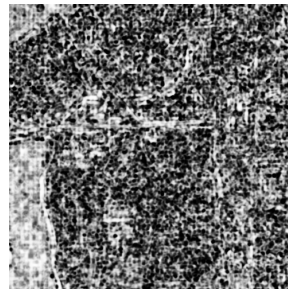
$\|\mathbf{A}' \mathbf{x}' - \mathbf{c}\|_2 < \varepsilon$, with $\mathbf{x}' = \text{OMP}(\mathbf{A}', \mathbf{c}, \varepsilon)$, and \mathbf{x}' in \mathbb{R}^m

$$\boxed{\mathbf{x}} = \mathbf{C}_3^{-1}(\mathbf{A} \mathbf{x}')$$

Results



$k = 40, c = 4$



Luminance SSIM

$k = 40, c = 4$

Results

PSNR = 21.1575



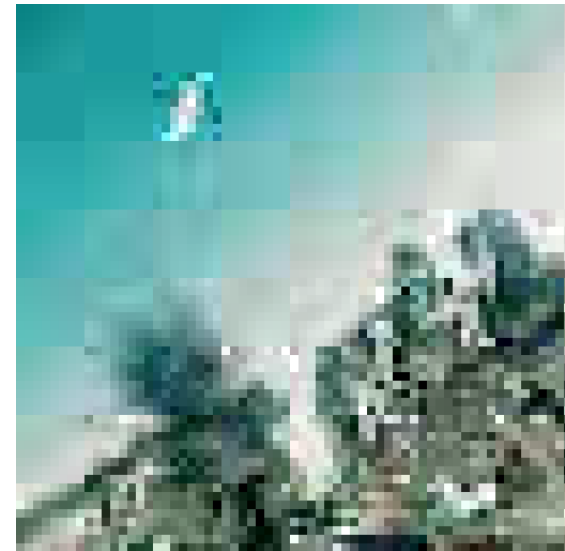
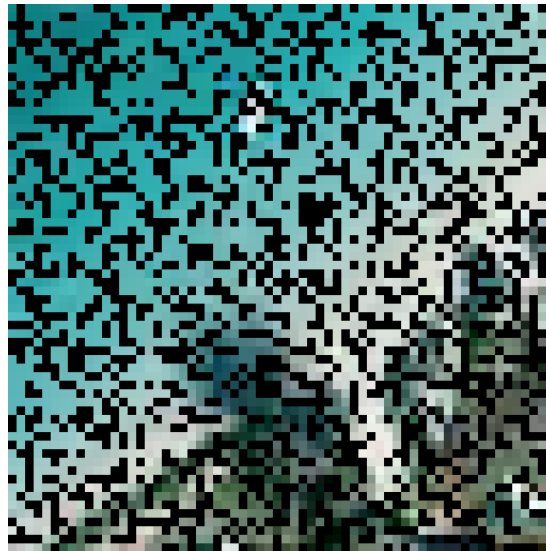
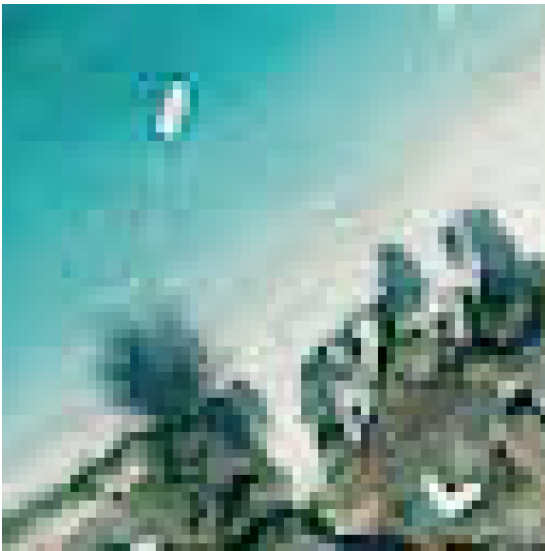
PSNR = 39.7019



PSNR = 39.4193



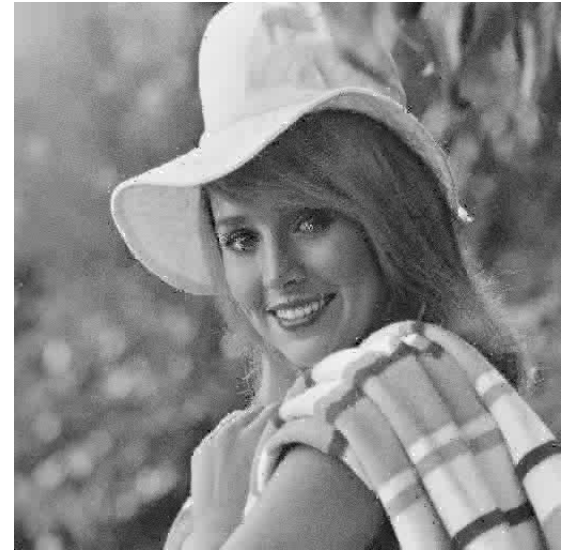
Results



$k = 40, c = 4$

Deterministic sampling masks
~ Inpainting?

Results



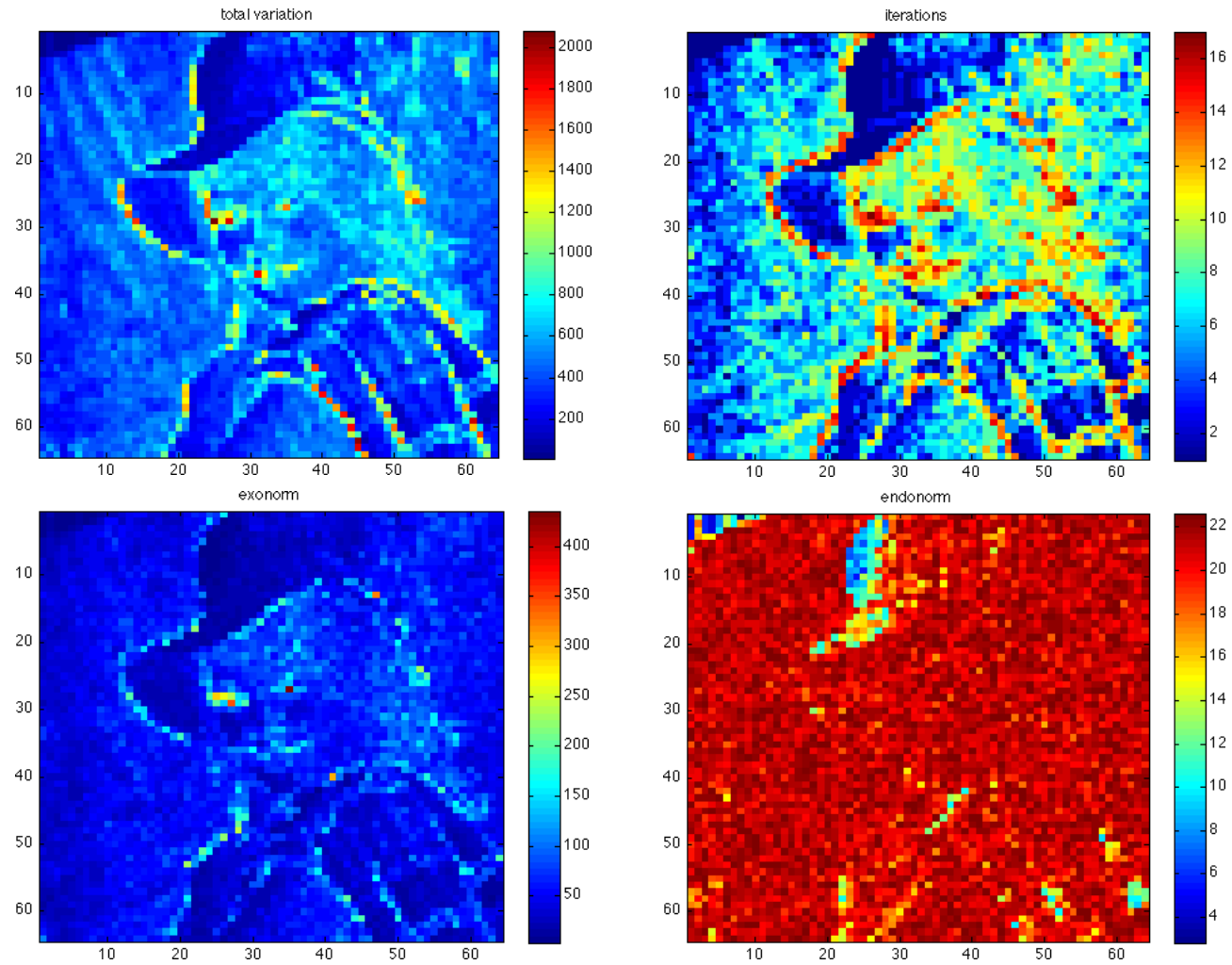
$k = 32, c = 4$



PSNR = 29.8081 dB
MSSIM = 0.7461

Results

$k = 32, c = 4$



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Sampling in image representation
and compression

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Thank you!

References

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<https://ece.uwaterloo.ca/~z70wang/research/ssim/index.html>