

# 18-660: Numerical Methods for Engineering Design and Optimization

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## Outline

- **Project 2: Image Recovery**
  - ▼ Objective
  - ▼ Methods
  - ▼ Submission details

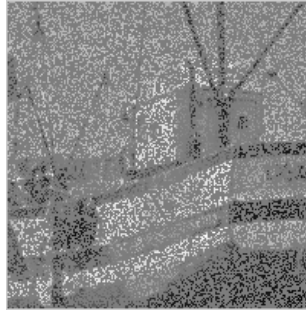
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## Objective

- Apply compressed sensing to recover a full image from a small number of sampled pixels



Original image



Sampled image



Recovered image

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## Application

- Corrupted image recovery



Corrupted image



Recovered image

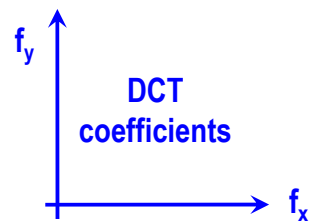
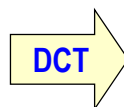
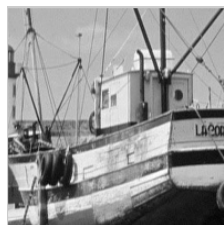
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## Outline

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## 2-D DCT Transform

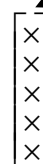
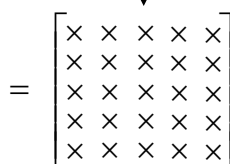
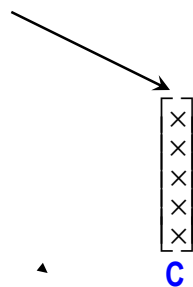


$$g(x, y) = \sum_{u=1}^P \sum_{v=1}^Q \alpha_u \cdot \beta_v \cdot \cos \frac{\pi(2x-1)(u-1)}{2 \cdot P} \cdot \cos \frac{\pi(2y-1)(v-1)}{2 \cdot Q} \cdot G(u, v)$$

Image pixel

Transformation

DCT coefficient



$$x, u \in \{1, 2, \dots, P\}$$

$$y, v \in \{1, 2, \dots, Q\}$$

$$\alpha_u = \begin{cases} \sqrt{1/P} & (u = 1) \\ \sqrt{2/P} & (2 \leq u \leq P) \end{cases}$$

$$\beta_v = \begin{cases} \sqrt{1/Q} & (v = 1) \\ \sqrt{2/Q} & (2 \leq v \leq Q) \end{cases}$$

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## Compute DCT Coefficients

$$\begin{bmatrix} \times \\ \times \\ \times \end{bmatrix}_B = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix}_T \cdot \begin{bmatrix} \times \\ \times \\ \times \\ \times \\ \times \end{bmatrix}_\alpha$$

- Transformation matrix  $T$  is known

- How to compute DCT coefficients?

- ▼ If the full image  $C$  is given:  $\alpha = T^{-1} \cdot C$
- ▼ If only a few samples of  $C$  (sampled vector  $B$ ) is given, *can we get an approximate solution of  $\alpha$ ?*

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## Compute DCT Coefficients

- Sampled image leads to an underdetermined linear system:

$$B = A \cdot \alpha$$

Under-determined linear system

$$\begin{bmatrix} \times \\ \times \\ \times \end{bmatrix}_B = \begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix}_A \cdot \begin{bmatrix} \times \\ \times \\ \times \\ \times \\ \times \end{bmatrix}_\alpha$$

- Compute DCT coefficients  $\alpha$  by *solving an underdetermined linear system*:  $B = A \cdot \alpha$

- Once DCT coefficients are computed, recover the full image by  $C = T \cdot \alpha$

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## Image Recovery

- Apply compressed sensing to determine approximate DCT coefficients from sampled pixels
- Apply inverse DCT transform to recover the full image

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## Compressed Sensing

$$\underbrace{\begin{bmatrix} \times \\ \times \\ \times \end{bmatrix}}_{\mathbf{B}} = \underbrace{\begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix}}_{\mathbf{A}} \cdot \underbrace{\begin{bmatrix} 0 \\ \times \\ \times \\ 0 \\ 0 \end{bmatrix}}_{\alpha \text{ (Sparse)}}$$

- Solve the underdetermined linear system:  $\mathbf{B} = \mathbf{A} \cdot \alpha$
- If  $\alpha$  is sparse:
  - ▼ Find the sparse solution  $\alpha$  by  $L_0$ -norm regularization

$$\begin{array}{ll} \min_{\alpha} & \|A\alpha - B\|_2^2 \\ \text{S.T.} & \|\alpha\|_0 \leq \lambda \end{array}$$

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## Implementation Issues

- $\alpha$  is expected to be sparse
- How to solve the optimization with  $L_0$ -norm regularization?
- How to determine  $\lambda$ ?

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## Construct Sparse DCT Coefficients



- DCT coefficients of a large image are often not sparse
- Solution: break a large image into small blocks
  - ▼ Each small block corresponds to few non-zero DCT coefficients
  - ▼ You can try different block size  $K$  in your own experiments
  - ▼ 8x8 block is suggested for the small test image
  - ▼ 16x16 block is suggested for the large test image

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## Solve $L_0$ -norm Regularization

### ■ Use Orthogonal Matching Pursuit (OMP) to solve:

$$\begin{aligned} \min_{\alpha} \quad & \|A\alpha - B\|_2^2 \\ \text{S.T.} \quad & \|\alpha\|_0 \leq \lambda \end{aligned}$$

- ▼ Step 1: Set  $F = B$ ,  $\Omega = \{ \}$  and  $p = 1$
- ▼ Step 2: Calculate inner product values  $\theta_i = \langle A_i, F \rangle$
- ▼ Step 3: Identify the index  $s$  for which  $|\theta_s|$  takes the largest value
- ▼ Step 4: Update  $\Omega$  by  $\Omega = \Omega \cup \{s\}$
- ▼ Step 5: Approximate  $F$  by the linear combination of  $\{A_i; i \in \Omega\}$

$$\min_{\alpha_i, i \in \Omega} \left\| \sum_{i \in \Omega} \alpha_i \cdot A_i - B \right\|_2^2$$

- ▼ Step 6: Update  $F$

$$F = B - \sum_{i \in \Omega} \alpha_i \cdot A_i$$

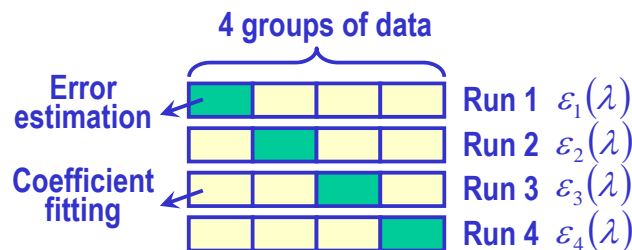
- ▼ Step 7: If  $p < \lambda$ ,  $p = p+1$  and go to Step 2. Otherwise, stop.  
 $\alpha_i = 0 \quad (i \notin \Omega)$

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## Determine $\lambda$ by Cross Validation

### ■ For each $\lambda$ in a given list

- ▼ Calculate DCT coefficients from the training set
- ▼ Estimate approximation "error" from the testing set
  - ❖ Use mean square error as a measurement of the "error"
- ▼ Example: 4-fold cross validation



$$Error(\lambda) = [\varepsilon_1(\lambda) + \varepsilon_2(\lambda) + \varepsilon_3(\lambda) + \varepsilon_4(\lambda)]/4$$

### ■ Select $\lambda$ with the minimum error

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## Cross Validation with Random Subsets

### ■ N-fold cross validation

- ▼ Distribute all data into N folds such that the numbers of samples in all folds are equal
- ▼ Take one fold as the test set at each iteration
- ▼ Training-and-test process is repeated for N times

### ■ Cross validation with random subsets

- ▼ At each iteration, randomly draw  $m$  samples to form the test set and use all other samples as the training set
  - ▼ Use  $m = \text{floor}(S/6)$  in this project, where  $S$  is the total number of samples
- ▼ Repeat the training-and-test process for M times
  - ▼ Use  $M = 20$  in this project

### ■ Apply cross validation with random subsets in this project

- ▼ When the data set is small, using this method with large M is more accurate than N-fold cross validation
- ▼ It is easy to implement if the data set cannot be divided equally into N folds

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## Median Filter

### ■ Median filtering is to replace each pixel in an image by the median of its neighborhood

### ■ Median filtering algorithm where filter size is $m \times n$ :

- ▼ Sort all pixel values in an  $m \times n$  block, centered at  $(x,y)$ , to find the median
- ▼ Replace the pixel value  $f(x,y)$  by the median

123	125	126	130	140
122	124	126	127	135
118	120	150	125	134
119	115	119	123	133
111	116	110	120	130

Neighbourhood values:

115, 119, 120, 123, 124,  
125, 126, 127, 150

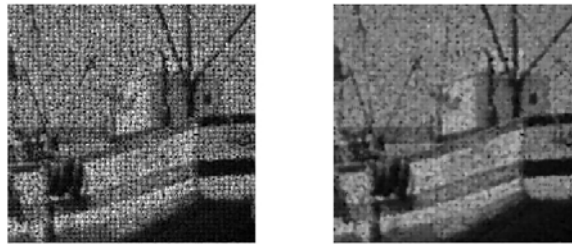
Median value: 124

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## Median Filter

- Apply median filter (MF) to improve the quality of recovered images
  - ▼ You can use MATLAB function `medfilt2`
  - ▼ Set filter size  $3 \times 3$
- Compare the error of the recovered image w/ MF and w/o MF



Recovered images ( $4 \times 4$  block)  
(Left: w/o median filter, Right: w/ median filter)

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## Summary of Image Recovery

- Read in an image
- Break image into blocks where block size is  $K \times K$
- For each block:
  - ▼ Randomly sample a few pixels where sample size is  $S$ 
    - ❖ *No repetition* for each pixel
  - ▼ Compute DCT coefficients from the samples
    - ❖ Use OMP algorithm
    - ❖  $\lambda$  is determined by cross validation using random subsets
  - ▼ Apply inverse DCT transform to recover the block
- Combine all recovered blocks into a full image
  - ▼ Apply median filter to improve image quality

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## Critical Functions

- The following three functions are critical for your implementation and grading:
  - ▼ Data sampling
  - ▼ OMP solver
  - ▼ Optimal  $\lambda$  selection via cross validation

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## Quality Measurement

- Mean square error between recovered image and original image is used to measure the quality of recovery
  - ▼ 
$$\frac{1}{W \times H} \sum_{\substack{1 \leq x \leq W \\ 1 \leq y \leq H}} [\hat{g}(x, y) - g(x, y)]^2$$
  - ▼  $W$  : image width  
 $H$  : image height
  - ▼  $\hat{g}(x, y)$  : pixels of recovered image  
 $g(x, y)$  : pixels of original image

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## Project Files

**All files for this project can be found from the distributed package**

- **A report template**
  - ▼ Proj2.doc
- **Two test images**
  - ▼ fishing\_boat.bmp
  - ▼ lena.bmp
- **Three MATLAB functions**
  - ▼ imgRead.m
  - ▼ imgShow.m
  - ▼ imgRecover.m

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## MATLAB Functions

### ■ **imgRead.m**

- ▼ Load test image: *e.g. `A = imgRead('lena.bmp')`*
- ▼ Input: input file name
- ▼ Output:  $H$ -by- $W$  matrix
  - ❖  $A(i,j)$ : image pixel at  $i$ -th row and  $j$ -th column
  - ❖  $W$ : image width
  - ❖  $H$ : image height

### ■ **imgShow.m**

- ▼ display image: *e.g. `imgShow(B);`*
- ▼ Input:  $H$ -by- $W$  matrix
  - ❖  $B(i,j)$ : image pixel at  $i$ -th row and  $j$ -th column
  - ❖  $W$ : image width
  - ❖  $H$ : image height

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## MATLAB Functions

### ■ **imgRecover.m**

- ▼ Should be implemented by you
- ▼ Syntax: `imgOut = imgRecover(imgIn, blkSize, numSample)`
- ▼ Input:
  - ❖ `imgIn`:  $H$ -by- $W$  input matrix
  - ❖ `blkSize`: block size, i.e.,  $K$  on Slide 12
  - ❖ `numSample`: number of samples per block, i.e.,  $S$  on Slide 15
- ▼ Output:  $H$ -by- $W$  matrix
  - ❖ Recovered image without median filtering

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## Project Submission

- You should zip the MATLAB code (.m) and figures (.fig) into a single file and submit it to the course web site
  - Your code must work on Linux cluster without any modification
  - Follow instructions specified in the WORD template
- You should also submit a **PDF** report (at most **4 pages** ) to the course web site
  - ▼ Follow instructions specified in the WORD template

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## Grading Criteria

- 75% for MATLAB code and results
- 25% for project report

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