

# E9 222 Signal Processing in Practice

## Assignment 2

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### 1. Plot 1D DCT Basis Functions

#### (a) Construct the basis

**Ans:** A function `dct_matrix(N)` was implemented that constructs the  $N \times N$  orthonormal DCT-II matrix  $D$  with entries:

$$D_{k,n} = \phi_k[n] = \alpha_k \cos\left(\frac{\pi}{N} \left(n + \frac{1}{2}\right) k\right)$$

where  $\alpha_k = \sqrt{1/N}$  for  $k = 0$  and  $\alpha_k = \sqrt{2/N}$  for  $k = 1, 2, \dots, N - 1$ .

For  $N = 32$ , The orthonormality of the DCT matrix is verified by computing the Frobenius norm:

$$\|DD^\top - I\|_F = 1.8845 \times 10^{-14}$$

Ideally, it should be 0. But the small error is there due to the rounding off effect in machine and machines cannot be infinite precision.

#### (b) Visualize basis functions

**Ans:** Figure 1 shows the first eight DCT basis functions ( $k = 0, 1, \dots, 7$ ) for  $N = 32$ .

Observations:

- The  $k = 0$  basis function is a constant (DC component), representing the average value of the signal.
- As  $k$  increases, the basis functions oscillate with increasing frequency.
- The basis functions form a complete orthonormal set, enabling perfect reconstruction of any signal.

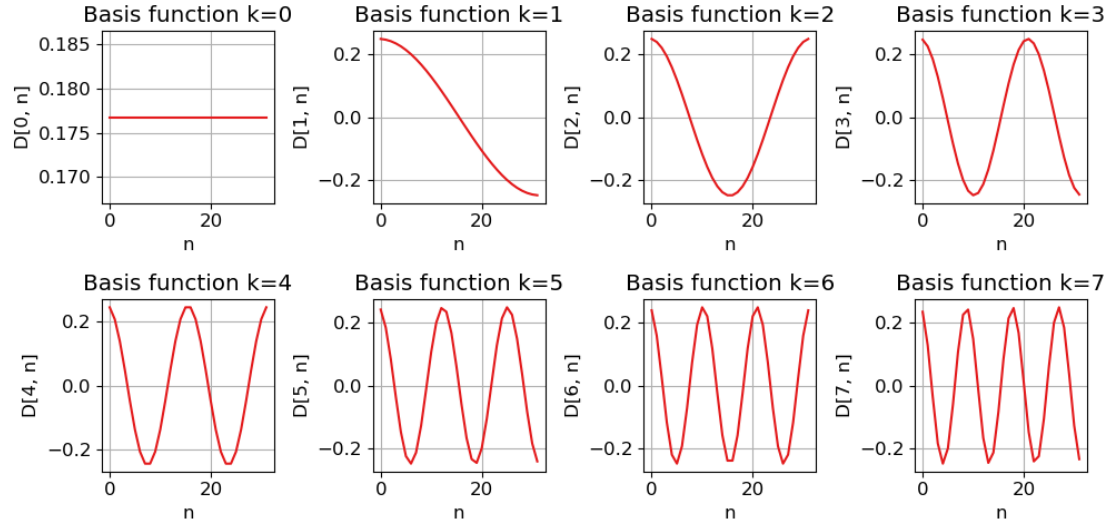


Figure 1: First eight 1D DCT-II basis functions ( $k = 0, 1, \dots, 7$ ) for  $N = 32$ .

## 2. Plot 2D DCT Basis Functions

### (a) Separable 2D basis

**Ans:** The 2D DCT basis functions are constructed using the separable property of the DCT. For indices  $(u, v)$ , the 2D basis pattern is defined as:

$$\Phi_{u,v}[m, n] = \phi_u[m] \cdot \phi_v[n], \quad m, n \in \{0, \dots, 7\}$$

A function `dct2d_basis(u, v, M, N)` was implemented that computes the outer product of two 1D basis vectors to generate the 2D basis image for any  $(u, v)$ .

### (b) Visualize the full $8 \times 8$ set

**Ans:** Figure 2 displays all 64 basis patterns  $\{\Phi_{u,v}\}$  arranged in an  $8 \times 8$  grid, where rows are indexed by  $u$  (vertical frequency) and columns by  $v$  (horizontal frequency).

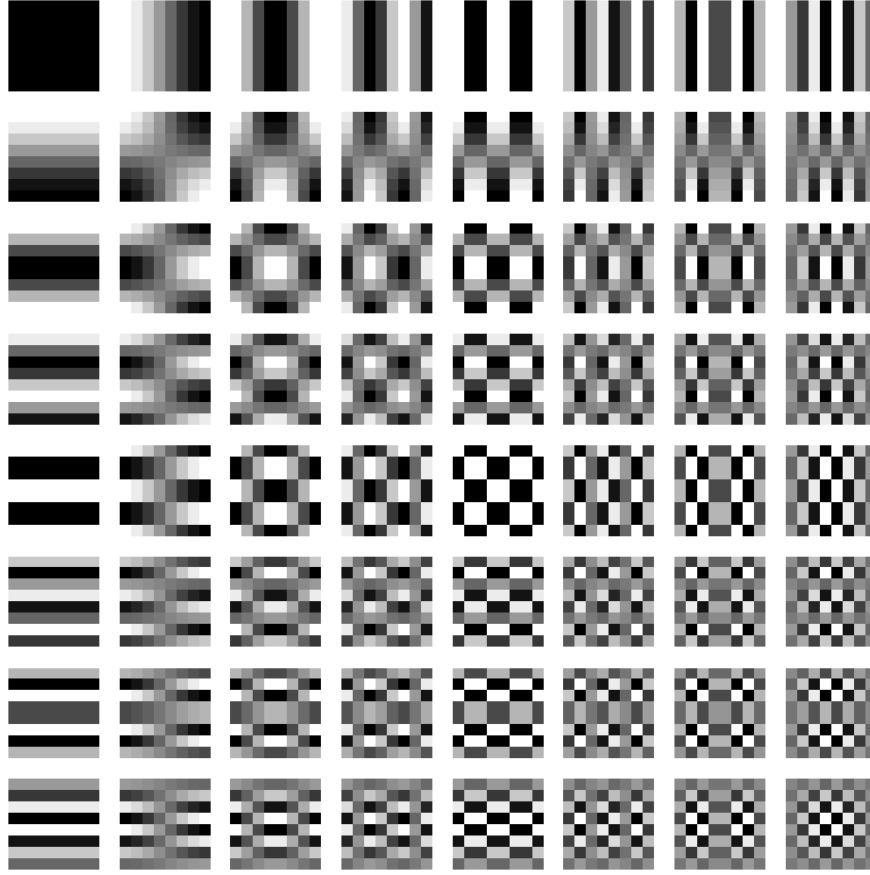


Figure 2: Complete set of 64 2D DCT basis patterns ( $8 \times 8$  grid) for  $M = N = 8$ .

(c) 2D DCT on image blocks

**Ans: (i) 2D DCT on an  $8 \times 8$  image block:**

The 2D DCT was applied to an  $8 \times 8$  grayscale image block by projecting onto the 2D basis functions. The DCT coefficients  $\hat{x}[u, v]$  are computed as:

$$\hat{x}[u, v] = \sum_{m=0}^7 \sum_{n=0}^7 x[m, n] \cdot \Phi_{u,v}[m, n]$$

**(ii) Perfect reconstruction:**

The image was reconstructed from its DCT coefficients using:

$$x[m, n] = \sum_{u=0}^7 \sum_{v=0}^7 \hat{x}[u, v] \cdot \Phi_{u,v}[m, n]$$

Figure 3 shows the original and reconstructed images, demonstrating perfect reconstruction.

**(iii) Energy distribution in DCT coefficients:**

Figure 4 shows the distribution of DCT coefficients for a typical image block. The energy is highly concentrated in the low-frequency coefficients (top-left corner), with the DC coefficient (0,0) containing the largest magnitude. Higher frequency coefficients (bottom-right) have significantly smaller values.

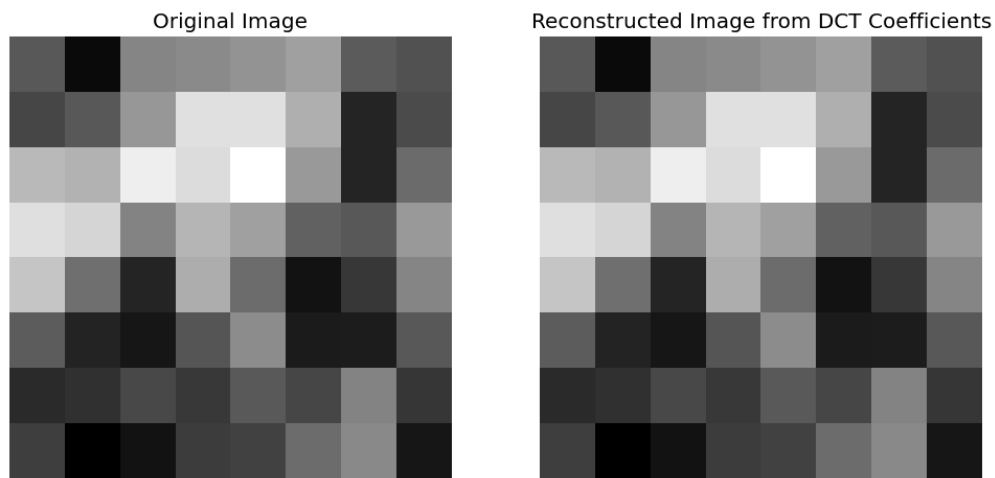


Figure 3: Original  $8 \times 8$  image block and its reconstruction from DCT coefficients.

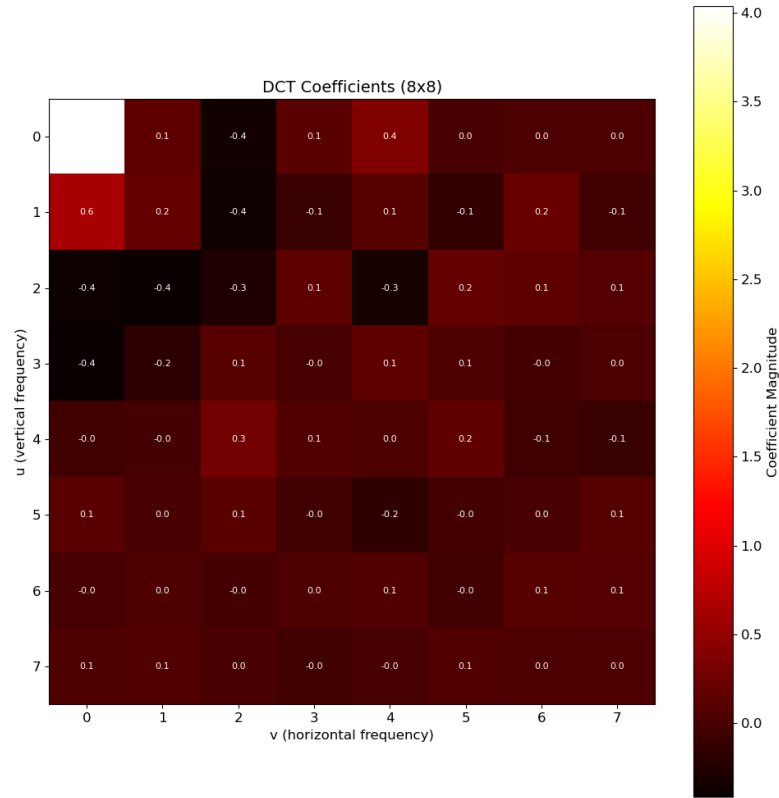


Figure 4: DCT coefficient magnitudes for an  $8 \times 8$  image block. Energy is concentrated in low-frequency components (top-left).

### 3. Implement JPEG-style Compression and Investigate Energy Compaction

#### (a) Block DCT and reconstruction (no quantization)

**Ans:** Block based DCT was implemented and error between reconstructed and original is calculated. It is approximately 0.

The maximum absolute reconstruction error without quantization was:

$$\max |x_{\text{original}} - x_{\text{reconstructed}}| = 5.329 \times 10^{-15}$$

This error is at machine precision, confirming perfect reconstruction when no quantization is applied.

#### (b) Quantization (JPEG idea)

**Ans:** JPEG-style was implemented quantization using a parametric quantization matrix:

$$Q[u, v] = 1 + s(u + v)$$

where  $s > 0$  is the compression strength parameter. The quantization process is:

$$\hat{x}_Q[u, v] = \text{round} \left( \frac{\hat{x}[u, v]}{Q[u, v]} \right), \quad \tilde{x}[u, v] = \hat{x}_Q[u, v] \cdot Q[u, v]$$

This quantization matrix applies stronger quantization to higher frequency components (larger  $u+v$ ), which aligns with the JPEG philosophy of preserving low-frequency information while aggressively quantizing high-frequency details that are less perceptually important.

#### (d) Quality vs compression study

**Ans:** Five compression strengths was tested:  $s \in \{0.01, 0.1, 1, 10, 100\}$ . Figures 5–9 show the reconstructed images at each compression level.



Figure 5: Compression with  $s = 0.01$ : Near-lossless reconstruction.

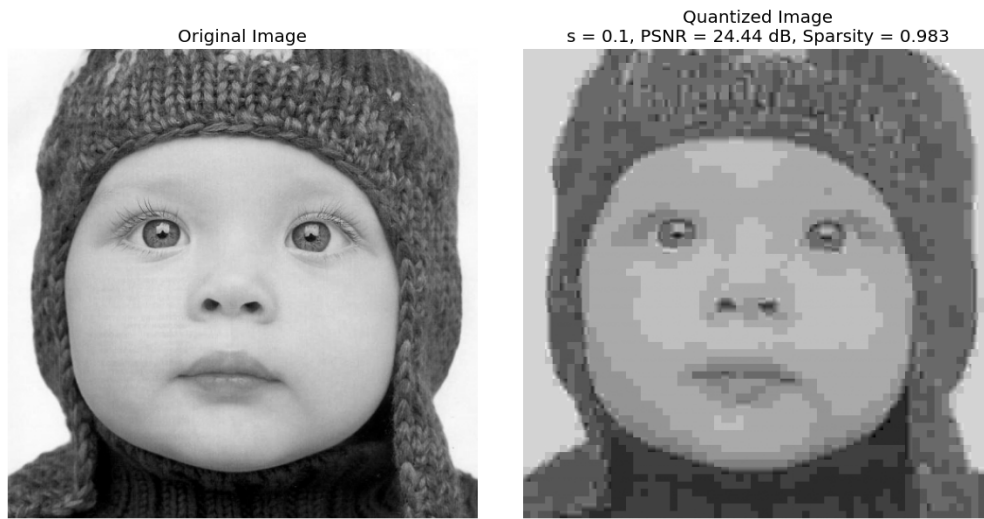


Figure 6: Compression with  $s = 0.1$ : High quality reconstruction.



Figure 7: Compression with  $s = 1$ : Moderate compression with some visible artifacts.

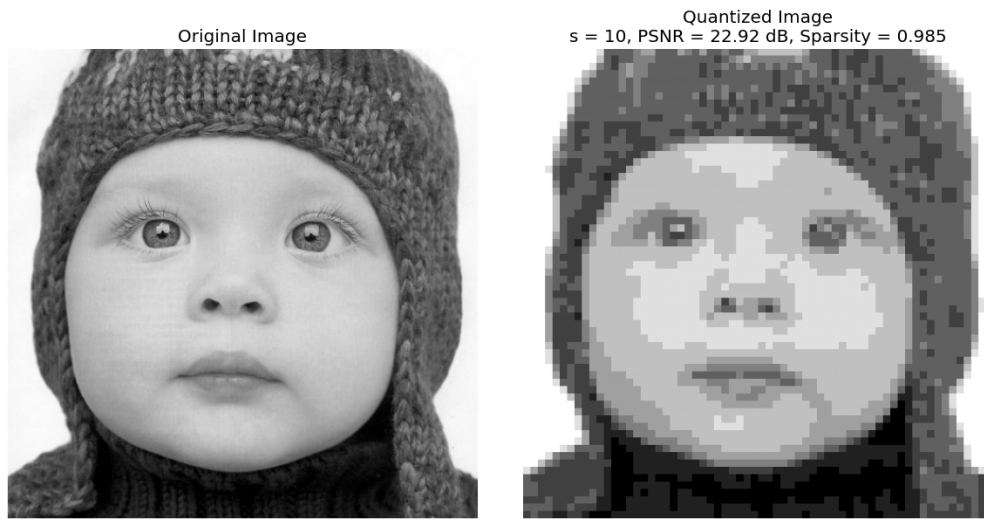


Figure 8: Compression with  $s = 10$ : High compression with noticeable blocking artifacts.



Figure 9: Compression with  $s = 100$ : Severe compression with significant quality degradation.



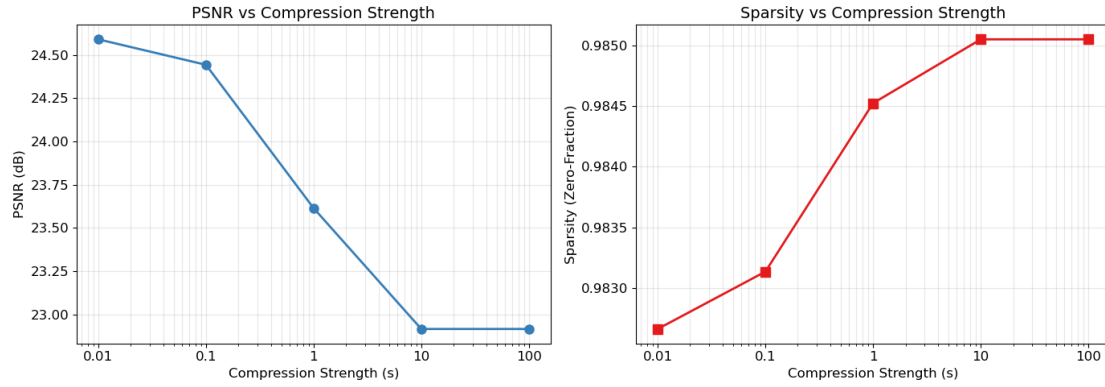


Figure 10: PSNR and Sparsity vs Compression Strength. Left: PSNR decreases as  $s$  increases. Right: Sparsity (zero-fraction) increases with  $s$ .

### (e) Energy compaction (core concept)

**Ans:** I computed the energy compaction for all  $8 \times 8$  blocks in the image:

$$E_{\text{total}} = \sum_{u,v} |\hat{x}[u,v]|^2, \quad E_K = \sum_{(u,v) \in S_K} |\hat{x}[u,v]|^2$$

where  $S_K$  contains the indices for a  $K \times K$  region.

**(a) Low-frequency energy fractions (top-left  $K \times K$ ):**

| <b>K</b> | $E_K/E_{\text{total}}$ |
|----------|------------------------|
| 1        | 0.9584                 |
| 2        | 0.9824                 |
| 3        | 0.9917                 |
| 4        | 0.9952                 |
| 5        | 0.9974                 |
| 6        | 0.9987                 |
| 7        | 0.9995                 |
| 8        | 1.0000                 |

Table 1: Energy fraction in top-left  $K \times K$  coefficients.

**(b) Interpretation:**

The energy accumulates extremely rapidly in the low-frequency coefficients:

- Just the DC coefficient ( $K = 1$ ) captures **95.84%** of the total energy.
- The top-left  $2 \times 2$  coefficients capture **98.24%** of the energy.

- By  $K = 4$ , we have **99.52%** of the total energy using only 25% of the coefficients.

This demonstrates the excellent **energy compaction** property of the DCT for natural images.

**(c) High-frequency comparison (bottom-right  $K \times K$ ):**

| <b>K</b> | $E_K/E_{\text{total}}$ |
|----------|------------------------|
| 1        | 0.0000                 |
| 2        | 0.0000                 |
| 3        | 0.0001                 |
| 4        | 0.0004                 |
| 5        | 0.0012                 |
| 6        | 0.0032                 |
| 7        | 0.0110                 |
| 8        | 1.0000                 |

Table 2: Energy fraction in bottom-right  $K \times K$  coefficients.

The high-frequency coefficients contain negligible energy. Even the bottom-right  $7 \times 7$  region (49 out of 64 coefficients, excluding only the DC and first row/column) contains only **1.1%** of the total energy. This stark contrast between low and high frequency energy distribution is why JPEG compression works so well—we can heavily quantize (or even discard) high-frequency coefficients with minimal perceptual impact.

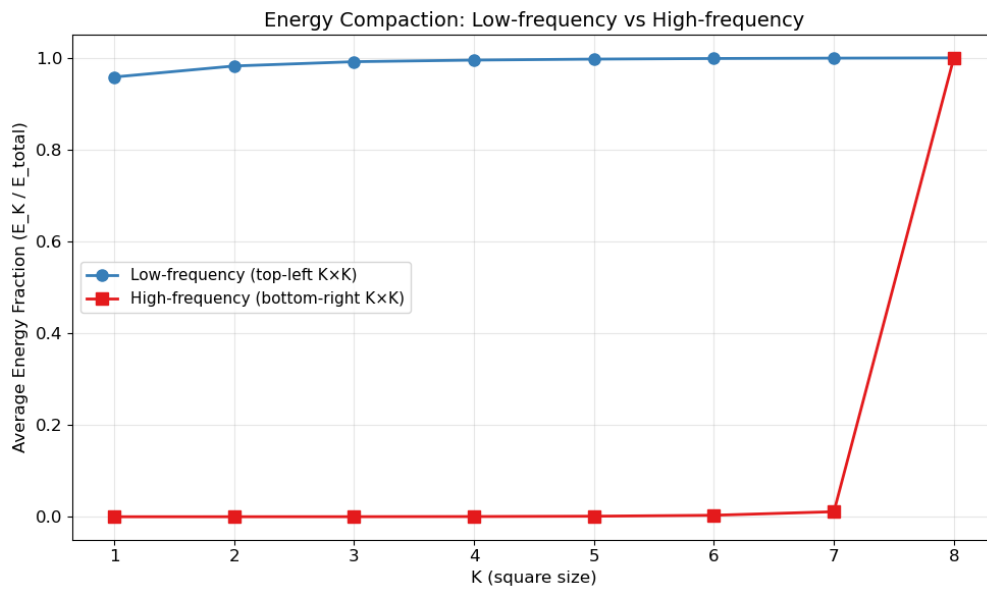


Figure 11: Energy compaction comparison: Low-frequency (top-left  $K \times K$ ) vs High-frequency (bottom-right  $K \times K$ ). The DCT exhibits excellent energy compaction, with most energy concentrated in low-frequency coefficients.