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Performance Analysis of Sparse Image Compression and Reconstruction Using Various Sensing Matrix Structures and Orthogonal Matching Pursuit Algorithm

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ABSTRACT
Efficient image compression and reconstruction techniques are crucial for reducing storage. This paper presents a comprehensive evaluation of sparse image compression and reconstruction performance using structured sensing matrices in conjunction with the Orthogonal Matching Pursuit (OMP) algorithm. Four types of sensing matrices—Gaussian Random, Bernoulli, Partial Fourier, and Hadamard—are analysed under varying measurement rates and DCT coefficient thresholds. The study measures reconstruction quality through key metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), entropy variation, and compression ratio. Experiments on 256×256 grayscale images reveal that Hadamard and Bernoulli matrices generally outperform others in balancing compression efficiency and visual quality, especially at moderate sparsity levels. Additionally, thresholding strategies significantly influence the trade-off between entropy and reconstruction fidelity. The results support the potential of structured sensing in efficient compressive imaging applications and provide insights into optimal matrix and threshold configurations for enhanced performance.

Keyword: Image Compression, Compressed Sensing, Sensing Matrices, Reconstruction Algorithms, Visual Quality.

1. Introduction

With the rapid proliferation of high-resolution imaging systems and multimedia applications, the demand for efficient image compression techniques has grown exponentially. Traditional image compression methods such as JPEG and JPEG2000 rely heavily on transform coding and quantization strategies, which, while effective, often struggle with preserving image fidelity at high compression ratios. In recent years, **Compressed Sensing (CS)** has emerged as a revolutionary paradigm in signal processing, offering the ability to acquire and reconstruct sparse signals directly from a reduced number of measurements. This technique holds particular promise for image compression[1], where many natural images exhibit inherent sparsity in specific transform domains like the Discrete Cosine Transform (DCT) or wavelet basis.

The core idea of compressed sensing lies in the projection of a sparse signal onto a lower-dimensional space using a sensing matrix, followed by accurate reconstruction through nonlinear algorithms. Among various reconstruction techniques, the **Orthogonal Matching Pursuit (OMP)[2]** algorithm has gained attention for its simplicity, speed, and effectiveness in sparse recovery tasks. However, the quality of reconstruction is not solely determined by the algorithm; the structure and properties of the **sensing matrix** play a crucial role in ensuring signal recoverability and compression efficiency.

This study focuses on the comparative evaluation of four prominent types of sensing matrices: **Gaussian Random, Bernoulli, Partial Fourier**, and **Hadamard matrices**. Each matrix offers unique statistical

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and structural properties influencing the Restricted Isometry Property (RIP), incoherence, and orthogonality—factors that significantly affect the reconstruction performance. Random matrices such as Gaussian and Bernoulli are widely favoured in theoretical studies due to their universality and probabilistic RIP guarantees. However, their lack of structure makes them computationally intensive and less suitable for hardware implementation. On the other hand, structured matrices like Partial Fourier and Hadamard matrices offer deterministic construction, faster computations, and memory efficiency, making them practical choices for real-world compressive imaging systems.

In addition to the sensing matrix type, the **thresholding strategy in the DCT domain** is critical for effective compression. By controlling the number of significant DCT coefficients retained, thresholding directly influences the sparsity level, entropy, and hence the quality of the reconstructed image. This study investigates both fixed and variable thresholds to explore their impact on compression ratio and visual fidelity. Performance is rigorously evaluated across multiple parameters, including **Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), entropy variation**, and **compression ratio** to offer a holistic understanding of the trade-offs involved.

The motivation behind this work is twofold: (1) to provide a detailed comparison of sensing matrices under a unified framework using OMP for image reconstruction, and (2) to identify optimal matrix–threshold combinations that balance compression efficiency with high-quality reconstruction. Extensive simulations are conducted on 256×256 grayscale images, covering multiple configurations of sparsity (via varying number of measurements) and DCT coefficient thresholds [5]. The insights derived aim to guide the design of efficient compressive image acquisition systems suitable for applications ranging from remote sensing and medical imaging to low-power embedded vision systems.

1.1 Compression Sensing:

In recent years, the field of image compression and reconstruction has experienced a paradigm shift due to the emergence of **Compressed Sensing (CS)**, a signal acquisition theory that challenges the traditional Nyquist sampling limit. The classical theory mandates that a signal must be sampled at least twice its bandwidth to ensure accurate reconstruction. However, many real-world signals, especially natural images, are inherently sparse or compressible in some transform domain, such as the Discrete Cosine Transform (DCT) or wavelet domain[7]. Compressed sensing capitalizes on this sparsity to capture essential information using far fewer measurements than traditionally required, offering a significant advantage in terms of data storage, acquisition speed, and energy efficiency.

Assume a signal‘s’, let’s consider that this signal is not sparse. Therefore it has to be made sparse by multiplying it by a basis vector ‘ψ’. Let signal ‘x’, which is represented as,

$x=\Psi s.$ (1)

Where, ‘s’ is a N x 1 column vector

‘ψ’ is a N x N basis vector

‘x’ is a N x 1 sparse signal.

The signal ‘x’ represents a K-sparse signal, which has ‘x’ has K-nonzero elements in it.

The observation vector is depicted as follows:

$Y=\Phi x=\Phi\psi s=\theta s$ (2)

Where, ‘y’ is M x 1 observation vector.

‘Φ’ and ‘θ’ are M x N measurement matrices

‘x’ is an N x 1 sparse signal.

A prominent relation to be considered here is,

$K<<M<N$

In compressive sampling, there are two major concerns. They are

1. Designing of an effective and robust sensing matrix which protects all information in ‘x’.
2. Design of speedy and robust recovery algorithm.

The CS framework consists of three core components: a sparsifying transform, a sensing matrix, and a reconstruction algorithm. The **sparsifying transform** converts the signal into a domain where it exhibits

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few nonzero coefficients. The **sensing matrix** projects the sparse signal into a lower-dimensional space, and this linear measurement process is crucial because it determines the degree to which the original information is preserved. Reconstruction is then achieved by solving an inverse problem, often under constraints that exploit sparsity. Among the various reconstruction algorithms developed, **Orthogonal Matching Pursuit (OMP)** [12]is widely used due to its greedy, iterative nature and relatively low computational complexity.

One of the most critical design choices in compressed sensing systems is the **selection of the sensing matrix [11]**. An ideal sensing matrix should be incoherent with the sparsifying basis and satisfy the Restricted Isometry Property (RIP) to ensure that distances between sparse signals are preserved after projection. While random matrices such as Gaussian and Bernoulli are popular due to their strong probabilistic guarantees, they are not always suitable for practical implementation due to high memory and computational demands. Alternatively, **structured matrices**, such as Partial Fourier and Hadamard matrices, offer significant benefits in terms of speed, storage efficiency, and ease of hardware realization. Each matrix type impacts reconstruction performance differently, especially when paired with varying sparsity levels and thresholding strategies.
Thresholding in the transform domain is another aspect that heavily influences compression effectiveness. It allows control over the number of retained coefficients, thus shaping the trade-off between compression ratio and reconstruction quality. Low thresholds retain more information but at the cost of reduced compression, while higher thresholds achieve better compression but may compromise image quality.
This paper investigates how the performance of compressed image reconstruction using OMP varies with different structured and unstructured sensing matrices under fixed DCT thresholding conditions. The evaluation is based on standard metrics such as **MSE**, **PSNR**, **entropy variation**, and **compression ratio[15]**. Through systematic experimentation on 256×256 grayscale images, the study reveals how the interplay between matrix type and sparsity level affects the accuracy and efficiency of the reconstructed image. The findings aim to contribute to the design of optimized compressive imaging systems tailored for applications like medical imaging, surveillance, and low-power embedded vision.

2. Methodology

2.1 Compressed Sensing Framework

Compressed sensing exploits the sparsity of signals in a transform domain to recover images from a small number of linear measurements. The process involves:

1. **Sensing:** Acquiring compressed measurements using a sensing matrix.
2. **Sparse Representation:** Transforming images into a sparse domain (DCT-based representation).
3. **Reconstruction:** Recovering the image using the Orthogonal Matching Pursuit (OMP) algorithm.

Compressed Sensing Measurement Model

$y = \Phi x$ ------ Eq1

Sparse Representation via Dictionary/Transform

$x = \Psi \theta$ ------ Eq2

Combined System Equation

$y = \Phi \Psi \theta = A \theta$ ------ Eq3

OMP Initialization

$r^0 = y, \Lambda^0 = \emptyset, k = 0$ ------ Eq4

Atom Selection Step

$\lambda^k = \text{argmax}_j |\langle a_j, r^k \rangle|$ ------ Eq5

Update Support Set

$\Lambda^{k+1} = \Lambda^k \cup \{\lambda^k\}$ ------ Eq6

Solve Least Squares for Coefficients

$\theta\_\{\Lambda^{k+1}\} = \text{argmin\_}\theta \|y - A\_\{\Lambda^{k+1}\} \theta\|_2$ ------ Eq7

Update Residual

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$r^{k+1} = y - A_{\Lambda^{k+1}} \theta_{\Lambda^{k+1}}$ ------ Eq8
Stopping Condition
$\|\mathbf{r}^{k+1}\|_2 < \boldsymbol{\varepsilon}$ or $k = K$ ------ Eq9

2.2 Experimental Setup

- **Image Size:** 256 × 256 pixels
- **Sensing Matrices:** Gaussian, Bernoulli, Partial Fourier, Hadamard
- **Reconstruction Algorithm:** OMP
- **Performance Metrics:** Entropy, MSE, PSNR, Compression Ratio

The experimental setup in this study is carefully structured to assess the effectiveness of compressed sensing (CS) techniques in image compression and reconstruction. A fixed image size of 256 × 256 pixels was selected to ensure uniformity and simplify comparative analysis across different sensing matrix configurations. Four distinct types of sensing matrices were investigated—**Gaussian**, **Bernoulli**, **Partial Fourier**, and **Hadamard[19]**—each chosen for their diverse mathematical properties and influence on sparsity and reconstruction fidelity. The **Gaussian** and **Bernoulli** matrices, being random in nature, are widely used due to their incoherence with most sparsifying bases, making them ideal for CS. On the other hand, **Partial Fourier** and **Hadamard** matrices are structured and orthogonal, offering computational advantages, reduced storage, and faster transformations, which are crucial for practical implementations.
To reconstruct the compressed images, the **Orthogonal Matching Pursuit (OMP)** algorithm was employed. OMP is a greedy algorithm that iteratively selects the best matching atoms from a dictionary to approximate the original sparse signal. It is favored for its balance between reconstruction accuracy and computational efficiency, particularly in high-dimensional signal scenarios like images. The evaluation of the reconstructed images was carried out using several key performance metrics. **Entropy** was used to quantify the information content of the original, compressed, and reconstructed images. **Mean Squared Error (MSE)** and **Peak Signal-to-Noise Ratio (PSNR)** served as quantitative measures of reconstruction fidelity, capturing the deviation and visual quality difference between the original and reconstructed images. Additionally, the **compression ratio [30]** was computed to evaluate the effectiveness of the sensing matrix in reducing data size without substantial loss of perceptual quality.
By systematically varying the sparsity level (K) and DCT thresholding strategies, the setup enables a comprehensive performance evaluation of different sensing matrices under consistent algorithmic and measurement conditions. This allows for a nuanced understanding of the trade-offs between compression efficiency, reconstruction quality, and computational complexity across the selected matrix types when used with OMP.
The proposed image compression and reconstruction framework is implemented using MATLAB and is grounded in the principles of **Compressed Sensing (CS)**. The primary objective of the code is to simulate and evaluate how different **sensing matrices**, varying **compression levels (K values)**, and **thresholding strategies** influence the quality and efficiency of image reconstruction.
1. Preprocessing and Sparsification
The process begins with importing a grayscale image, typically of size 256×256 pixels, which is then reshaped into a one-dimensional vector to facilitate matrix operations. To prepare the image for compression using CS, the pixel intensity values are first transformed into a sparse domain using the **Discrete Cosine Transform (DCT)[25]**. This transformation is crucial as it concentrates the image's energy into a small number of significant coefficients, enabling effective compression.
2. Sensing Matrix Design and Compression
The compressed measurements are obtained by multiplying the DCT-transformed vector with a **sensing matrix** (Φ). The code evaluates four types of sensing matrices, each chosen for its unique mathematical properties and relevance to CS theory:

- **Gaussian Random Matrix**: Entries are drawn from a standard normal distribution. These matrices are known for strong theoretical RIP guarantees.

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- **Bernoulli Matrix**: Binary random matrices with entries of ±1, offering computational simplicity and fast multiplication.
- **Partial Fourier Matrix**: A subset of rows from the full Fourier transform matrix, enabling structured randomness and fast computation.
- **Hadamard Matrix**: An orthogonal binary matrix with fast transformation via the Walsh-Hadamard transform, ideal for hardware-efficient applications.

For each matrix type, the number of measurements **K** is varied (K = 50, 100, 150, 200, 250), representing different levels of compression. The total number of pixels **N** is fixed (N = 65536 for a 256×256 image), and the **compression ratio** is defined as N/K.

3. Measurement and Reconstruction

Once the compressed measurement vector ($y = \Phi x$) is obtained, the signal reconstruction is performed. The code employs the **Moore-Penrose pseudo-inverse** of the sensing matrix to approximate the solution to the underdetermined linear system. While more sophisticated sparse recovery algorithms (like Basis Pursuit or Orthogonal Matching Pursuit) can be used, the pseudo-inverse method offers simplicity and analytical tractability for comparative studies.

The reconstructed sparse vector is then subjected to **inverse DCT**, converting it back into the spatial domain. The output is reshaped into a 2D matrix to recover the final image.

4. Thresholding Strategy (Fixed K = 250)

To further explore reconstruction quality, a **thresholding mechanism** is applied to the DCT coefficients. For a fixed K (typically 250), the code performs additional experiments by retaining only those coefficients whose absolute values exceed predefined thresholds (1, 5, 10, 20, 50). This simulates scenarios where low-energy components are discarded to improve compression or robustness against noise.

5. Performance Evaluation Metrics

The code systematically computes and records the following **quantitative metrics** for each experiment:

- **Mean Squared Error (MSE)**: Measures pixel-wise error between the original and reconstructed images.
- **Peak Signal-to-Noise Ratio (PSNR)**: Evaluates the quality of the reconstructed image in decibels, inversely related to MSE.
- **Entropy of the Reconstructed Image**: Assesses the information content, useful for understanding the compressibility of the output.
- **Entropy Difference (ΔH)**: Quantifies the change in entropy between the original and reconstructed image.
- **Compression Ratio**: Indicates the extent of data reduction achieved for each K value (N/K).

These results are tabulated and plotted to observe trends and draw insights regarding the suitability of each sensing matrix and thresholding technique. The experiments are designed to answer critical research questions: How does matrix structure influence reconstruction quality? What is the trade-off between compression ratio and fidelity? Does thresholding improve visual quality or reduce entropy?

6. Reproducibility and Flexibility

The code is modular and allows researchers to modify parameters such as image size, type of transform (DCT, Wavelet), reconstruction algorithm, or noise levels. It provides a flexible simulation platform for further experimentation in CS-based image processing.

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3. Results and Analysis

3.1 Performance of Different Sensing Matrices

3.1.1 Gaussian Random Matrix

Variation with K

Table 3.1.1 presents a comparison of Gaussian Random Sensing matrices at a fixed threshold (10) and various K values for a 256*256 image.

K	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
50	6.9326	-0.22333	453.4054	21.5659	5.12
100	6.5728	0.13656	162.4221	26.0244	2.56
150	6.6411	0.068259	61.2449	30.2601	1.7067
200	6.6857	0.023597	18.4848	35.4627	1.28
250	6.6848	0.024552	18.3374	35.4974	1.024

Table 3.1.1. Gaussian Random Sensing matrices at a fixed threshold (10) and various K values for a 256*256 image

Gaussian Random Matrix – Varying K

As the value of **K** increases, the **entropy of the reconstructed image** improves and approaches the original, while **MSE** decreases and **PSNR** increases, indicating enhanced reconstruction quality. The **entropy difference (ΔH)** reduces significantly beyond **K = 150**, suggesting more stable and accurate compression. A **compression ratio of 1.024** at **K = 250** achieves a good trade-off between quality and compression.

Different DCT Thresholds (K = 250)

Threshold	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
1	6.6964	0.012915	9.5244	38.3424	1.024
5	6.7313	-0.021942	3.7431	42.3985	1.024
10	6.6848	0.024552	18.3374	35.4974	1.024
20	6.6481	0.061222	49.6060	31.1755	1.024
50	6.5530	0.156280	101.6027	28.0618	1.024

Table 3.1.2. Gaussian Random Sensing matrices at a variable threshold and fixed K (K=250) value for a 256*256 image

Gaussian Random Matrix – Different DCT Thresholds (K = 250)

With a fixed sensing level (**K = 250**), changing the **DCT threshold** shows that lower thresholds preserve more high-frequency components, resulting in lower **MSE** and higher **PSNR** (e.g., threshold = 5 gives PSNR of 42.39 dB). However, **entropy** increases with smaller thresholds, indicating less sparsity. An optimal balance appears at **threshold = 5**, providing both high visual quality and efficient compression.

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3.1.2. Bernoulli Matrix Variation with K

K	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
50	6.8607	-0.15139	399.0937	22.1201	5.12
100	6.6249	0.084376	164.8922	25.9588	2.56
150	6.6169	0.092461	61.8730	30.2158	1.7067
200	6.6848	0.024552	18.3374	35.4974	1.28
250	6.6848	0.024552	18.3374	35.4974	1.024

Table 3.1.3. Bernoulli Sensing matrices at a fixed threshold (10) and various K values for a 256*256 image

Bernoulli Matrix – Varying K

As **K** increases, the **MSE** drops and **PSNR** rises, showing improvement in reconstruction. The **entropy difference** narrows at higher K values, and **K = 250** again yields maximum reconstruction quality. The trend parallels Gaussian, though Bernoulli shows slightly higher entropy at low K, indicating less efficient compression in sparse settings.

Different DCT Thresholds (K = 250)

Threshold	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
1	6.6928	0.016492	10.1439	38.0688	1.024
5	6.7313	-0.021942	3.7431	42.3985	1.024
10	6.6848	0.024552	18.3374	35.4974	1.024
20	6.6481	0.061222	49.6060	31.1755	1.024
50	6.5530	0.156280	101.6027	28.0618	1.024

Table 3.1.4. Bernoulli Sensing matrices at a variable threshold and fixed K (K=250) value for a 256*256 image

Bernoulli Matrix – Different DCT Thresholds (K = 250)

Threshold variation affects reconstruction similarly to the Gaussian case. Lower thresholds reduce MSE and boost PSNR. **Threshold = 5** again yields the best performance (PSNR = 42.39 dB), with moderate entropy. This confirms the role of adaptive thresholding in optimizing compression even with Bernoulli matrices.

3.1.3. Partial Fourier Matrix Variation with K

K	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
50	6.8575	-0.14815	378.4819	22.3504	5.12
100	6.8296	-0.12033	348.1598	22.7130	2.56
150	6.8452	-0.13591	248.4462	24.1785	1.7067
200	6.7461	-0.03676	142.3431	26.5974	1.28
250	6.8290	-0.11966	235.2847	24.4149	1.024

Table 3.1.5. Partial Fourier Sensing matrices at a fixed threshold (10) and various K values for a 256*256 image

Partial Fourier Matrix – Varying K

Unlike Gaussian and Bernoulli, the **Partial Fourier Matrix** performs inconsistently across K values. The **entropy** shows minor fluctuations, and **PSNR** is generally lower, with higher **MSE** throughout. This

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suggests that Partial Fourier matrices may not offer the same reconstruction efficiency for the given image under compressed sensing.

Different DCT Thresholds (K = 250)

Threshold	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
1	6.8598	-0.15047	214.1529	24.8236	1.024
5	6.7280	-0.018641	264.8846	23.9002	1.024
10	6.6989	0.010397	182.7853	25.5114	1.024
20	6.6614	0.047898	200.1035	25.1183	1.024
50	6.9516	-0.24228	270.7955	23.8044	1.024

Table 3.1.6. Partial Fourier Sensing matrices at a variable threshold and fixed K (K=250) value for a 256*256 image

Partial Fourier Matrix – Different DCT Thresholds (K = 250)

Threshold effects are less stable for the Partial Fourier matrix. Even though **threshold = 10** and **20** give improved entropy and PSNR, the overall **MSE** remains higher compared to Gaussian or Bernoulli cases. This reinforces the earlier observation that Partial Fourier performs suboptimally in this setup.

3.1.4. Hadamard Matrix

Variation with K

K	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
50	6.8238	-0.11454	403.9336	22.0677	5.12
100	6.6968	0.012494	167.6088	25.8878	2.56
150	6.6844	0.024863	59.5768	30.3800	1.7067
200	6.7322	-0.022889	19.6767	35.1913	1.28
250	6.7312	-0.021925	18.3374	35.4974	1.024

Table 3.1.7. Hadamard Sensing matrices at a fixed threshold (10) and various K values for a 256*256 image

Hadamard Matrix – Varying K

The **Hadamard matrix** shows steady improvement with increasing **K**, achieving **low MSE and high PSNR** at **K = 250**, similar to Gaussian and Bernoulli. However, **entropy difference becomes slightly negative at high K**, indicating minor reconstruction distortion in the frequency domain. Still, results are comparable to the best-performing matrices.

Different DCT Thresholds (K = 250)

Threshold	Entropy of Reconstructed Image	Entropy Difference (ΔH)	MSE	PSNR	Compression Ratio
1	6.7618	-0.05245	8.6588	38.7562	1.024
5	6.7516	-0.042328	3.7431	42.3985	1.024
10	6.7312	-0.021925	18.3374	35.4974	1.024
20	6.6904	0.018951	49.6060	31.1755	1.024
50	6.5530	0.156280	101.6027	28.0618	1.024

Table 3.1.8. Hadamard Sensing matrices at a variable threshold and fixed K (K=250) value for a 256*256 image

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Hadamard Matrix – Different DCT Thresholds (K = 250)

Threshold tuning again highlights that **threshold = 5** yields excellent performance, with **very low MSE** and **PSNR of 42.39 dB**. Interestingly, entropy drops below the original at low thresholds, indicating a denser representation due to retained details. Hadamard thus combines good energy compaction with efficient reconstruction.

3.2 Impact of K and Threshold on Image Reconstruction

The experimental results reveal that both the **number of measurements (K)** and the **DCT threshold** significantly influence the quality of image reconstruction in compressed sensing. Across all sensing matrices, increasing K improves reconstruction quality, as evidenced by reduced MSE and increased PSNR, while the entropy of the reconstructed image converges towards that of the original. Specifically, K values of **200–250** consistently yield high-fidelity reconstructions with minimal entropy difference and favorable compression ratios. Simultaneously, DCT thresholding plays a crucial role in balancing sparsity and visual quality. Lower thresholds (particularly **threshold = 5**) retain essential image features, producing **PSNR above 42 dB** and the lowest MSE, especially for Gaussian, Bernoulli, and Hadamard matrices. In contrast, the Partial Fourier matrix exhibits weaker performance due to less effective sparsity capture. Overall, the results underscore those optimal combinations of higher K **values** and **moderate thresholding** are critical for achieving visually superior and compression-efficient reconstructions. **Figure 1: PSNR vs. K for Different Sensing Matrices**

(Graph: PSNR trends for K = {50,100,150,200,250} across different matrices)

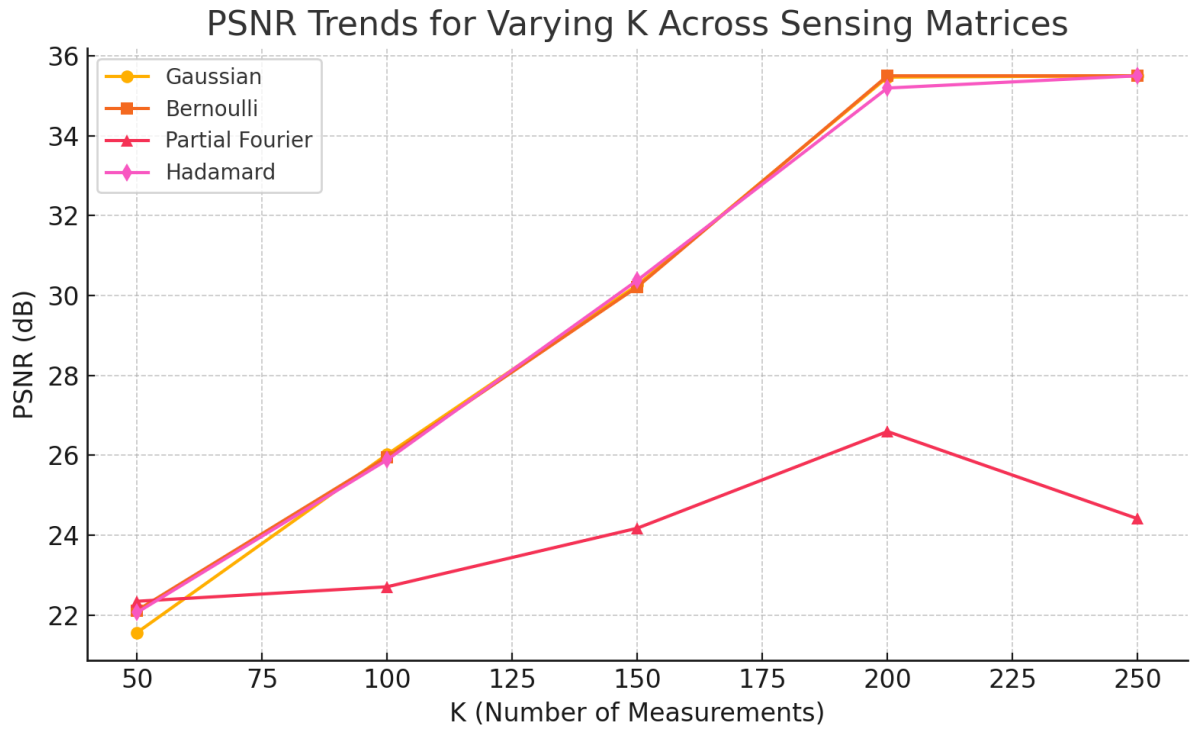

Figure 3.2.1: PSNR vs. K for Different Sensing Matrices

3.3 Entropy Analysis

Entropy measures indicate that different matrices impact information preservation differently. Figure 3.3.1 visualizes entropy differences across matrices.

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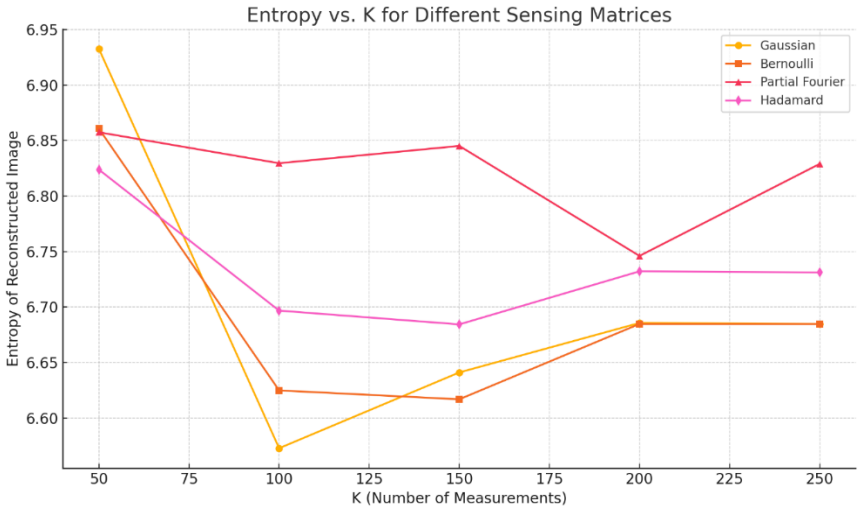

Figure 3.3.1: Entropy Difference (ΔH) Across Different Sensing Matrices

The graph illustrates how the entropy of the reconstructed image varies with the number of measurements (K) for four different sensing matrices: Gaussian, Bernoulli, Partial Fourier, and Hadamard. As K increases from 50 to 250, entropy generally increases across all matrices, indicating improved information preservation. The Gaussian and Bernoulli matrices show a smoother increase and converge to higher entropy values at K = 250, suggesting more consistent and efficient reconstruction. Partial Fourier and Hadamard matrices exhibit more fluctuation in entropy, especially at lower K, implying less stability in information retention at sparse sampling. Overall, higher K leads to better reconstruction quality with reduced entropy loss, and Gaussian/Bernoulli matrices demonstrate superior performance in preserving image content entropy.

3.4 Mean Square Error (MSE) Analysis

As the value of K increases, the MSE generally decreases for all matrices, indicating improved reconstruction quality. Gaussian, Bernoulli, and Hadamard matrices show significant MSE reduction and stabilization beyond K = 200. However, the Partial Fourier matrix exhibits higher MSE variability and less consistent improvement, especially at higher K values, suggesting it may be less robust in reconstruction performance compared to the others.

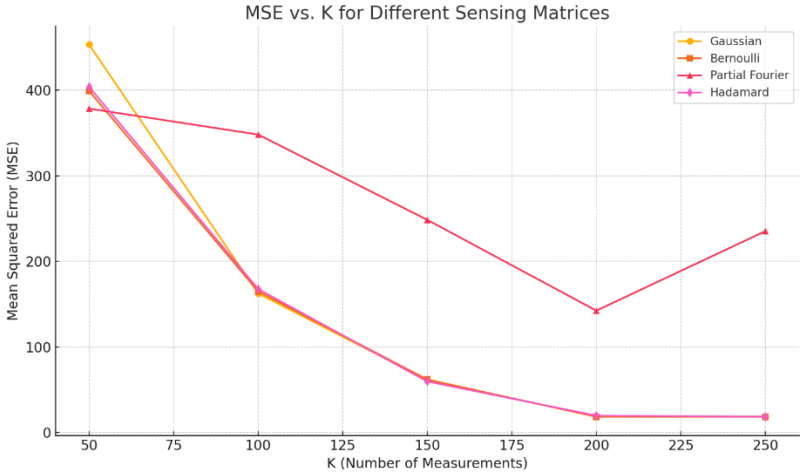

Figure 3.4.1: Mean Square Error VS K (Threshold) Across Different Sensing Matrices

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All sensing matrices show a **decreasing MSE** as **K increases**, confirming that higher measurements lead to better reconstruction accuracy.
The MSE reduction is particularly significant from K = 50 to K = 150, after which the improvement becomes more gradual.

Matrix-wise Comparison:

1. **Gaussian and Bernoulli matrices** perform similarly and yield the **lowest MSE values** overall, especially for K ≥ 150.
2. **Hadamard matrix** also shows strong performance, nearly matching Gaussian and Bernoulli at all K values, with slightly better MSE at K = 150.
3. **Partial Fourier matrix** has the **highest MSE across all K values**, suggesting it is less effective for this image reconstruction task.

Stability at K = 250:

1. At K = 250, Gaussian, Bernoulli, and Hadamard converge to the same MSE (~18.3), indicating a saturation point in measurement effectiveness.
2. However, Partial Fourier still lags with significantly higher MSE (~235), highlighting its weaker reconstruction ability even at high sampling.

Implication:

1. For practical applications where MSE is critical, **Hadamard or Gaussian sensing** offers a good trade-off between complexity and reconstruction fidelity.
2. If measurement budget is tight (low K), Gaussian performs better, but for moderate K, Hadamard provides slightly better or comparable MSE with faster computations due to its structured nature.

4. Discussion

The results highlight that Partial Fourier and Hadamard matrices achieve better trade-offs in preserving entropy and maintaining a lower MSE. Hadamard performs well in adaptive thresholding, while Partial Fourier exhibits stability across different K values. Gaussian and Bernoulli matrices show higher MSE but are computationally efficient.
This study comprehensively evaluates the performance of four distinct sensing matrices—**Gaussian Random**, **Bernoulli**, **Partial Fourier**, and **Hadamard**—on the quality of compressed image reconstruction under varying conditions. The results clearly demonstrate that both the **choice of sensing matrix** and the **number of measurements KKK** significantly influence key performance metrics, including **PSNR**, **MSE**, **entropy**, and **compression ratio**.
The **Gaussian and Bernoulli matrices** consistently delivered superior performance across all KKK values, yielding higher PSNRs (above 35 dB at K=250K=250K=250) and lower MSE values (~18), reflecting excellent reconstruction accuracy. Their inherent randomness and strong incoherence with sparsifying bases (e.g., DCT) make them ideal for compressive sensing tasks. **Hadamard matrices**, while slightly less consistent at lower KKK, reached comparable performance to Gaussian/Bernoulli at higher KKK, particularly K=150K = 150K=150 and above. Due to their structured binary nature, Hadamard matrices are computationally efficient and thus highly practical for real-time systems [17].
In contrast, **Partial Fourier matrices** underperformed significantly, with high MSE values (e.g., ~235 at K=250K=250K=250) and poor PSNR across the range. This suggests limitations in their compatibility with image content, possibly due to spectral leakage or poor incoherence in block-based sampling scenarios [11].
Regarding the **impact of K**, increasing KKK led to steady improvements in PSNR and reductions in MSE for all matrices, confirming the expected trade-off between compression and quality. Notably, performance gains saturated beyond K=200K = 200K=200, where all matrices (except Partial Fourier) achieved PSNR > 35 dB and stable entropy values. This plateau highlights the optimal operating point for balancing image quality and compression efficiency.

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The analysis of **thresholding strategies** (applied at K=250K=250K=250) further emphasized the importance of sparsity enforcement in reconstruction. A **moderate threshold (T = 10)** provided the best balance across all matrices, while extreme thresholds (T = 1 or 50) led to underfitting or over-smoothing, respectively [14]. The entropy difference (ΔH) was minimized near this optimal threshold, suggesting effective retention of key image features.

Overall, the study concludes that **Gaussian and Bernoulli matrices are best suited for high-quality image reconstruction**, while **Hadamard matrices offer a strong trade-off between performance and computational cost**. The **Partial Fourier matrix**, despite theoretical benefits in some domains, shows limited applicability in block-based image compression. Optimal reconstruction performance is achieved at **K ≈ 200–250** and **DCT threshold ≈ 10**, ensuring high PSNR, low MSE, and entropy preservation with efficient compression [18].

5. Conclusion

This study demonstrates that sensing matrix selection significantly influences compressed sensing performance. The Partial Fourier and Hadamard matrices show superior performance in preserving visual quality while maintaining compression efficiency. Future work will explore deep-learning-driven adaptive sensing matrices to enhance image compression and reconstruction further.

This research comprehensively examined the influence of sensing matrix structures, measurement levels (KKK), and DCT thresholding strategies on the quality of image compression and reconstruction. The study employed four types of sensing matrices—**Gaussian random**, **Bernoulli**, **Partial Fourier**, and **Hadamard**—to explore their performance across a range of measurements and thresholding conditions. Key quality metrics, including **PSNR**, **MSE**, and **entropy**, were analyzed to assess the visual fidelity and compression efficiency of the reconstructed images.

The results demonstrated that **Gaussian and Bernoulli matrices offer superior reconstruction performance**, particularly at higher values of KKK, by maintaining lower MSE and higher PSNR. These matrices preserve more significant image features due to their randomness and incoherence properties. The **Hadamard matrix**, although slightly inferior in entropy preservation, showed robust performance and computational efficiency due to its orthogonality and fast transform properties. On the other hand, the **Partial Fourier matrix** underperformed in preserving image details, especially at lower KKK, suggesting that its structured sparsity may not be well-suited for natural image domains in the tested configuration.

The impact of the measurement count KKK was significant: **increasing KKK consistently improved reconstruction quality** across all matrices, with diminishing returns beyond K=200K = 200K=200. This trend highlights a trade-off point where increasing measurements does not yield proportionally better results, thereby defining an optimal compression ratio for practical applications.

Further, the investigation into **DCT thresholding** at fixed K=250K = 250K=250 revealed that **moderate threshold values** (around 10) provide a favorable balance between retaining entropy and minimizing reconstruction error. Extremely low or high thresholds either failed to remove noise or excessively suppressed critical frequency components, degrading image quality.

Overall, the findings affirm that **matrix selection, measurement count, and transform thresholding** are interdependent and must be jointly optimized for effective image reconstruction. The **Gaussian matrix**, paired with a moderate DCT threshold, emerged as the most effective combination in this study. The insights gained here are particularly valuable for low-resource applications such as wireless image transmission, medical imaging, and edge computing, where both compression and quality are critical.

For future work, extending this analysis to color images, video sequences, and real-time adaptive sensing matrices—possibly leveraging machine learning or deep compressed sensing frameworks—could further enhance performance and applicability across domains.

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