EFFECTIVE IMAGE RECONSTRUCTION USING VARIOUS COMPRESSED SENSING TECHNIQUES

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ABSTRACT

Using methods of Compressive Sensing (CS), it is now possible to reconstruct signals and images efficiently in highly resource-limited scenarios by exploiting the sparsity of signals in specific domains, such as Wavelet or Fourier. In contrast, traditional techniques rely on the Nyquist-Shannon Sampling Theorem, in which it is determined that the sampling frequency must always be greater than twice the highest frequency in the signal, thereby requiring redundant data acquisition and high computational costs. But CS reduces the measurements needed and, thus, is better suited for applications like Medical Imaging, Autonomous Vehicles, and Surveillance Systems where data acquisition and transmission may be constrained.Flexible Compressive Sensing (FCS) designs the reconstruction procedure with adaptation of the Sensing Matrix and Reconstruction Algorithms according to the specific characteristics of an image. Adaptive flexibility in FCS achieves better performance across various classes of images and has gained much support from multiple key techniques, particularly through: Dynamically Adaptive Sensing Matrix Design that adjusts the sensing matrix based on the characteristics of the image, thus optimizing the sampling but after some level of knowledge of the image has been priorly attained. In Total Variation Minimization, edges are preserved, while noise is reduced in smoother areas of image. This would be useful in applications such as medical imaging but is computationally expensive and sensitive to regularization parameters. In Dictionary Learning, an overcomplete dictionary construction allows sparse representation of images in terms of its elements, making it relevant when the goal would be high versatility in different classes of images but it is very dependent on data used for training. Deep Learning uses neural networks for compressive sensing image reconstruction. Even though highly effective, this method requires big datasets and computational resources. The appropriate method is selected depending on characteristics of an image, availability of resources, and specific reconstruction objectives. Each algorithm has its tradeoff between performance and computational complexity. This research project's primary objective is to study Effective Image Reconstruction using Compressive Sensing with a particular emphasis on Discrete Transforms and Deep Learning.

1. INTRODUCTION

The Nyquist-Shannon Sampling theorem states that in order to accurately reconstruct a signal without any distortion, the sampling frequency needs to be greater than twice the highest frequency present in the signal. To reduce the inherent redundancies in the gathered samples, a compression process is applied, which requires substantial computational resources. This reliance on extensive computation poses a considerable challenge given the limitations of current technology.

The motivation for Image Reconstruction arises from the need to efficiently reconstruct images with reduced measurements, making it feasible in scenarios where data acquisition, transmission and storage resources are limited.

A potential solution to this issue is **Compressive Sensing**, which enables the reconstruction of signals from a significantly smaller number of measurements, making it ideal for situations with limited data resources. Natural images can often be represented sparsely in specific domains, such as Wavelet and Fourier. Compressive sensing takes advantage of this sparsity to effectively reconstruct images from fewer measurements. It involves gathering data from multiple sources to form a comprehensive representation of the environment. By utilizing various sensors, a broader spectrum of information is captured, allowing for a more complete understanding, as each sensor provides distinct insights. This approach is especially crucial in fields such as Medical Imaging, Autonomous Vehicles, and Surveillance Systems.

2. MOTIVATION AND LITERATURE SURVEY

Flexible Compressed Sensing (FCS) is a method that adapts the sensing matrix to the specific features of an image instead of relying on a fixed transform. This approach enables modifications to both the sensing matrix and reconstruction algorithms based on the unique attributes of the image. Such flexibility can enhance performance across different class of images. Various techniques can facilitate this, like Adaptive Sensing Matrix Design, Total Variation Minimization, Dictionary Learning, Deep Learning Models and many more.

A small description of each along with Pros and Cons are as under:

Adaptive Sensing Matrix Design involves the dynamic adjustment of the Sensing Matrix dynamically according to the characteristics of the image captured.

- **Advantages:** This approach can optimize the sampling strategy for particular images and improve reconstruction by concentrating on key features.
- **Disadvantages:** It necessitates prior knowledge of the images, which restricts its applicability.

Total Variation Minimization is based on the premise that natural images exhibit sparse gradients, which allows for the measurement of an image's rate of change. By minimizing total variation, this method helps maintain edges while reducing noise in smoother areas of the image.

- **Advantages:** It effectively preserves edges, making it particularly valuable for applications where sharp transitions are essential like Medical Imaging.
- **Disadvantages:** The selection of the regularization parameter is crucial, and solving the optimization problem can be computationally demanding.

Dictionary Learning entails creating an overcomplete dictionary of basis elements that allows images to be represented as sparse linear combinations of them.

- **Advantages:** This method is adaptable to a wide range of image classes and is more resilient to noise.
- **Disadvantages:** The quality of dictionary is highly dependent on training data and careful selection of regularization parameters.

Deep Learning utilizes deep neural networks such as Convolution Neural Networks (CNN) and Residual Networks to learn the relationships between compressed measurements and reconstructed images.

- **Advantages:** This approach can adapt to complex relationships between input and output mapping and yield high reconstruction quality.
- **Disadvantages:** It demands substantial computational resources and large datasets, which can sometimes result in challenges related to interpretability.

Determining which of the above methods is appropriate depends on several factors, including the unique characteristics of the image, available resources, and the ultimate goals of the reconstruction process. Additionally, solving the optimization problem can be computationally intensive, and the selection of the computational algorithm can significantly affect overall efficiency.

3. IMPLEMENTATIONS

1.Flexible Compressed Sensing Transformation

With the help of a Python code, we processed an image using the **Discrete Fourier Transform (DFT)**, manipulates its frequency components, and reconstructs the image with the **Inverse DFT (IDFT)**. The steps are as follows:

1. **DFT**: The image is converted to grayscale, and the DFT is computed using cv2.dft, producing complex coefficients.
2. **Frequency Manipulation**: The zero-frequency component is shifted to the center by using the function np.fft.fftshift. The magnitude and phase are extracted from the complex coefficients.
3. **Normalization**: The magnitude is normalized to sum to 1, preserving energy, and the Fourier coefficients are reconstructed using the normalized magnitude and original phase.
4. **Inverse DFT**: The IDFT (cv2.idft) converts the modified frequency representation back to the spatial domain.
5. **PSNR Calculation**: **PSNR** is computed to evaluate the reconstruction quality

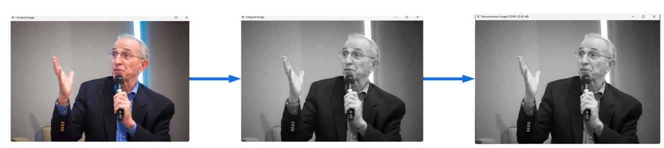
The PSNR is calculated as follows:

$$MSE = \left(\frac{1}{N}\right) * \Sigma\left(I_i - \widehat{I_i}\right)^2$$

$$PSNR = 20log_{10}\left(\frac{31}{\sqrt{MSE}}\right)$$

where 31 represents the maximum pixel value in an **5-bit grayscale image** (ranging from 0 to 31), hence it is used as a reference for the maximum signal strength while calculating the signal-to-noise ratio.

The results obtained are as shown in the screenshots below:



a. Original Image b. Gray-scaled Image c. Reconstructed Image

Fig. 1. Flexible Compressed Sensing Transformation Results

In the modified code, the image is processed as a color image instead of grayscale. The original image is split into its three color channels (Blue, Green, and Red) using cv2.split(). Each channel is individually processed using the Fourier Transform and Inverse Fourier Transform (cv2.dft and cv2.idft). The magnitude is normalized for each channel separately before reconstructing the channels back into a color image. The PSNR is then calculated for the entire color image using the reconstructed image. The color image is displayed and the size is tripled as compared to reconstructed grayscale image due to 3 separate channels.

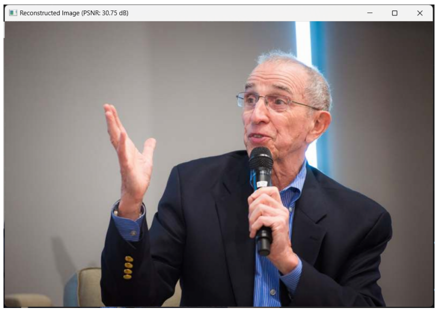


Fig. 2. Flexible Compressed Sensing Transformation (Color Image) Results

2. Compressed Sensing with Discrete Cosine Transform

1. With help of python code, we perform **image compression and reconstruction** using **Compressed Sensing (CS)** with the **Discrete Cosine Transform (DCT)** as the sparse transform.
2. The image is divided into **non-overlapping blocks**, and a fraction of pixels from each block is **randomly sampled** to simulate compressed sensing.
3. A **measurement matrix** is created by combining the DCT basis with the randomly sampled pixels.
4. **Lasso regression** is used to recover the sparse DCT coefficients from the measurements, promoting sparsity using a regularization parameter.
5. The image is reconstructed by applying the inverse DCT to the recovered coefficients for each block.
6. The **Peak Signal-to-Noise Ratio (PSNR)** is calculated to evaluate the quality of the reconstruction.

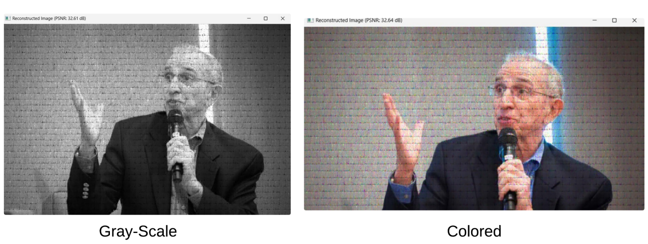


Fig. 3. Compressed Sensing with Discrete Cosine Transform Results

The key changes in the colored version of code compared to the previous grayscale version are:
1. **Color Channel Handling**: The image is processed in three color channels (Red, Green, and Blue) separately.
2. **Block Processing Loop**: A loop is added to iterate over each color channel and apply the same compressed sensing process to each channel independently.
3. **Reconstruction**: Each color channel is reconstructed separately and then combined to form the final color image.
4. **PSNR Calculation**: PSNR is computed for color images, considering all three channels together.
5. **Final Image Processing**: After reconstruction, the image is scaled back to [0, 255] and displayed in color format.

3. Deep Learning Based Approach

The steps followed are:
1. **Image Loading and Preprocessing**: The image is loaded, converted to grayscale using color.rgb2gray(), resized to 720x720, and prepared by adding channel and batch dimensions.
2. **Random Pixel Masking**: A function mask_random_pixels() is defined to mask a fraction (30%) of the image pixels, simulating missing data for reconstruction.
3. **Autoencoder Architecture**: A convolutional autoencoder is built with an encoder (Conv2D + MaxPooling2D) and decoder (Conv2D + UpSampling2D) layers to reconstruct the image.
4. **Training**: The autoencoder is trained on the masked image with the original image as the target.
5. **Reconstruction**: The trained model predicts the reconstructed image from the masked input.
6. **Evaluation**: MSE and PSNR are calculated to evaluate reconstruction quality.
7. **Visualization**: The original, masked, and reconstructed images are displayed, along with MSE and PSNR metrics.

Fig. 4. Deep Learning Based Approach Results

Method	Flexible Compressed Sensing Transformation	Compressed Sensing with DCT	Deep Learning-Based Approach
Domain	Frequency domain (DFT/IDFT)	Sparse domain (DCT + CS)	Learned features from the data (neural networks)
Reconstruction Quality	Moderate (depends on frequency manipulation)	High, especially with suitable sparsity	Very high (state-of-the-art for image tasks)
Computational Complexity	Low to moderate	Moderate to high	High (training neural networks is computationally expensive)
Artifacts	Potential artifacts in frequency-domain manipulation	Possible blurring/artifacts with low sampling rates	Low artifacts if trained properly, high-quality results
Training Requirements	No training required	No training required (but needs tuning of regularization)	Requires large labeled datasets and training time
Flexibility	Low flexibility (fixed transformation)	Moderate flexibility (fixed sampling, but sparse)	High flexibility (can handle a wide range of image types and missing data scenarios)

Table 1. Comparison of Image Reconstruction Methods

4. CONCLUSION

In this report, we have explored various methods for image reconstruction in the context of compressed sensing. The Nyquist-Shannon sampling theorem highlights the inherent challenge in accurately reconstructing signals from a large number of samples, which can be computationally intensive. To address this, the field of compressive sensing has emerged as a promising approach, enabling the reconstruction of signals from a significantly smaller number of measurements.

Ultimately, the choice of reconstruction method depends on factors such as the specific characteristics of the image, the available computational resources, and the desired trade-offs between reconstruction quality, computational complexity, and flexibility. As the field of compressed sensing continues to evolve, further advancements in these techniques and their applications are likely to emerge, offering promising solutions for efficient image reconstruction in resource-constrained scenarios.

5. REFERENCES

[1] M. Hema, R. Gurunadha, J. V. Suman and M. Mallam, ”Effective Image Reconstruction Using Various Compressed Sensing Techniques,” 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE), Shivamogga, India, 2024, pp. 1-6, doi: 10.1109/AMATHE61652.2024.10582191.