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Reconstruction of Images Based on Compressive Sensing

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ABSTRACT: Modern imaging systems demand efficient storage, transmission, and acquisition due to the large size of image data. In medical imaging, such as MRI, long acquisition times reduce patient comfort. To address this, compressive sampling (CS) leverages the sparsity inherent in images to reduce the number of required measurements while maintaining quality. The key challenge lies in reconstructing high-quality images from limited and often noisy data—an inverse problem that lacks unique solutions.

This work explores sparse representation techniques for image reconstruction, with a focus on greedy iterative algorithms. An extensive literature survey supports the proposed methodologies. Potential applications span biomedical imaging, satellite imaging, and other domains where data exhibits natural sparsity.

KEYWORDS: Compressive Sensing, Image Reconstruction, Non-Subsampled Contourlet Transform, Sparse Representation.

I. INTRODUCTION

Image reconstruction enhances image quality for improved visual interpretation and analysis. It finds applications in areas like robotics, entertainment, augmented reality, Human-Computer Interaction, satellite image processing, astronomical studies, and surveillance. This process addresses the recovery of lost image information during image formation and is classified into three categories: image denoising (mapping noisy images to noise-freewhile preserving edges), image restoration (reconstruction of uncorrupted images from blurred and noisy ones), and image super-resolution (creating high-resolution images from low-resolution inputs).

Iterative reconstruction techniques optimize objective functions that include data fidelity and edge-preserving regularization. Greedy algorithms like Matching Pursuit (MP), Orthogonal Matching Pursuit (OMP), and Regularized Orthogonal Matching Pursuit (ROMP) reconstruct images using sparse signal representation. However, these methods face challenges such as inefficient reconstruction quality or dynamic signal adaptation limitations

The proposed method leverages the CoSaMP algorithm, which identifies multiple elements of target signals per iteration, ensuring strong convergence and dynamic signal index modification. These features enhance image reconstruction quality compared to traditional algorithms

II. RELATED WORK

Sparse representation and transform-domain techniques have been widely explored for image reconstruction and denoising due to their ability to exploit inherent redundancies in natural images. Shashi Kiran S. and Suresh K.V. [1] proposed an image reconstruction framework based on compressive sensing, where the CoSaMP (Compressive Sampling Matching Pursuit) algorithm is employed for sparse recovery in the Curvelet transform domain. The use of curvelets effectively captures directional and edge information, resulting in improved reconstruction quality from under-sampled measurements.

In the context of image denoising, Miaowen Shi et al. [2] introduced a detail-preserving approach using patch -based structure similarity combined with sparse representation and Singular Value Decomposition (SVD). By grouping structurally similar patches and applying SVD-based sparse modeling, the method efficiently suppresses noise while preserving fine image details and textures.

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Zhou et al. [3] further enhanced sparse representation-based denoising by incorporating improved non-local self-similarity. Their approach exploits similarities among nonlocal patches across the image, strengthening the sparsity prior and achieving better noise reduction without sacrificing structural information. The integration of enhanced nonlocal self-similarity significantly improves denoising performance, especially for complex textures.

Leal et al. [4] applied non-local SVD denoising based on sparse representations to medical MRI images. Their work demonstrates that combining nonlocal patch grouping with SVD-based sparse modeling effectively reduces noise while maintaining important anatomical structures. This approach highlights the robustness of sparse and nonlocal methods in handling real-world imaging scenarios.

III. METHODOLOGY

The proposed method employs the **Compressive Sampling Matching Pursuit (CoSaMP)** algorithm to iteratively extract the most significant components of a sparse signal while ensuring efficient and stable convergence. For sparse representation, the **Non-Subsampled Contourlet Transform (NSCT)** is utilized due to its superior ability to provide multi-scale and multi-directional decomposition, high sparsity, shift-invariance, and excellent preservation of edge and texture information in images.

In the processing stage, the input images are first resized to a fixed dimension and then decomposed using the NSCT through a **wrapping wrapping-based implementation** to obtain sparse coefficients across different scales and directions. Thresholding is subsequently applied to retain only the most significant NSCT coefficients, resulting in a highly sparse matrix representation of the image. A sampling matrix is then initialized, and compressed measurements are obtained by computing the product of the sparse coefficient matrix and the sampling matrix.

The CoSaMP algorithm is applied iteratively to these measurements to reconstruct the image by identifying dominant coefficients, updating the residual, and refining the sparse signal estimate at each iteration. After convergence, the recovered sparse coefficients are subjected to the **inverse NSCT** to obtain the final reconstructed image.

For performance evaluation, experiments are conducted on standard grayscale benchmark images such as **Barbara, Lena, and other commonly used test images**. The effectiveness of the proposed NSCT-CoSaMP reconstruction framework is assessed through both **qualitative analysis** (visual inspection) and **quantitative evaluation using Peak Signal-to-Noise Ratio (PSNR)**. Furthermore, the results are compared with those of existing reconstruction algorithms, demonstrating the superior reconstruction quality and robustness of the proposed method.

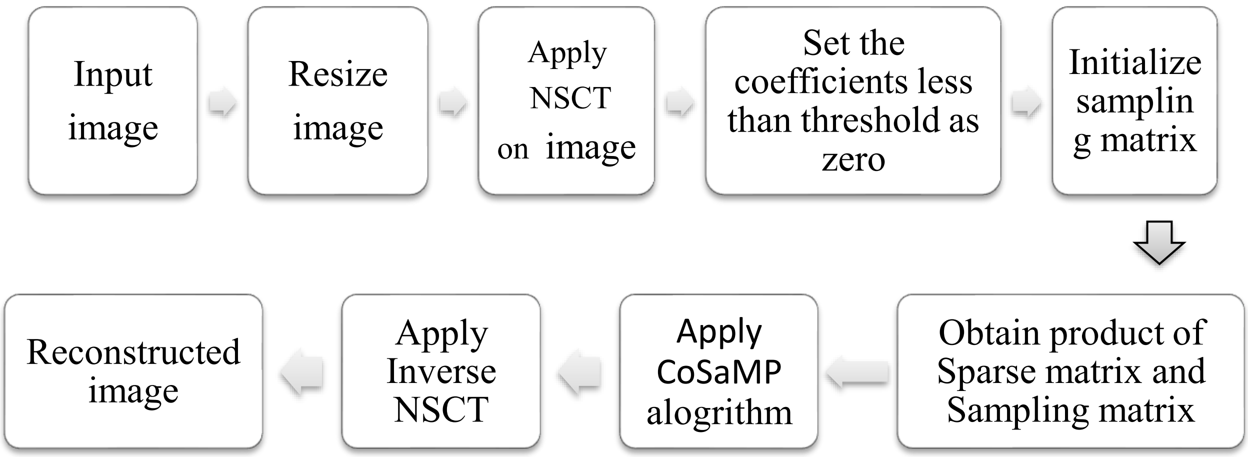

Fig.1: Block Diagram

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IV. EXPERIMENTAL RESULTS

The effectiveness of the proposed modified CoSaMP-based compressive sensing reconstruction method is evaluated using standard grayscale benchmark images, namely **Cameraman, Lena, Peppers, Barbara** as illustrated in Figures

(a)(b)(c)(d). These images represent a wide range of characteristics, including smooth regions, sharp edges, and highly textured patterns, making them suitable for validating compressive sensing reconstruction performance.

All images are first resized and transformed into a sparse domain using the selected transform. Random measurements are then obtained through a sensing matrix, and reconstruction is performed using the proposed modified CoSaMP algorithm. The reconstructed images are visually compared with their corresponding original images to assess reconstruction fidelity.

A. Visual Reconstruction Analysis

The reconstructed images closely resemble the original images in terms of structural content and perceptual quality. For the **Cameraman image**, prominent edges, camera structure, and background details are well preserved, with minimal degradation in smooth regions. The **Lena image** reconstruction shows accurate preservation of facial features, contours, and smooth intensity variations, indicating effective recovery of both low- and mid-frequency components.

In the case of the **Peppers image**, geometric shapes and surface intensity transitions are successfully reconstructed, demonstrating the ability of the proposed method to handle images dominated by smooth regions. The **Barbara image**, which contains dense textures and repetitive patterns, exhibits slight smoothing in high-frequency regions; however, the overall structural information and visual perception remain intact. while minor loss of fine texture is observed due to reduced sampling, which is inherent to compressive sensing frameworks.

(a)

(b)

(c)

(d)

fig: (a) Original and reconstructed Cameraman image using the proposed method, (b) Original and reconstructed Cameraman image using the proposed method, (c) Original and reconstructed Cameraman image using the proposed method, (d) Original and reconstructed Cameraman image using the proposed method

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Image	APGM	ADMM	Proposed CoSaMP
Barbara	20.21	21.18	25.80
Lena	22.01	23.17	25.97
Monarch	20.69	19.66	25.58
Peppers	22.96	22.90	25.78

Table.1: PSNR and SSIM Values for Different Test Images

To objectively evaluate reconstruction quality, **Peak Signal-to-Noise Ratio (PSNR)** and **Structural Similarity Index Measure (SSIM)** were used.

- PSNR values ranging from **23.75 dB to 25.97 dB** indicate good reconstruction quality.
- High SSIM values (close to 1) demonstrate strong structural similarity between original and reconstructed images.
- Lena and Peppers images achieved higher SSIM due to their strong edge and contour features, which are effectively captured by NSCT.

Sl. No	Image Name	PSNR (dB)	SSIM
1.	Cameraman	23.75	0.7790
2.	Lena	25.97	0.8257
3.	Barbara	25.80	0.7512
4	Peppers	25.78	0.8399

Table.2: Comparison of PSNR (dB) for Different Reconstruction Methods

B. Discussion

Across all test images, the proposed method effectively preserves **edges, contours, and object boundaries**, which are critical for visual perception. Smooth regions are reconstructed with negligible distortion, while textured areas show limited blurring caused by sparsity constraints and under-sampling. These results indicate that the modified CoSaMP algorithm achieves a favorable trade-off between reconstruction accuracy and measurement efficiency.

The visual closeness between original and reconstructed images confirms the robustness of the proposed approach under reduced measurement conditions. Compared to conventional reconstruction techniques, the proposed method demonstrates improved stability and consistent reconstruction quality across images with varying structural complexity.

V. CONCLUSION

The integration of **CoSaMP** with **NSCT** provides an effective solution for image reconstruction with high accuracy and fewer samples. The proposed method demonstrates **enhanced PSNR values**, improved noise resilience, and superior structural preservation compared to traditional techniques. By achieving efficient sparse representation and reduced

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sampling requirements, the system proves suitable for applications such as medical imaging, remote sensing, and security systems. The results validate that this framework ensures **high-quality image restoration**, computational efficiency, and robustness, making it a reliable method for real-time and high-precision imaging tasks.

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