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International Journal For Research in  
Applied Science and Engineering Technology



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# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

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**Volume:** 14    **Issue:** IV    **Month of publication:** April 2026

**DOI:** <https://doi.org/10.22214/ijraset.2026.80720>

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# Comparative Analysis of Greedy Iterative Algorithms for Compressed Sensing MRI Reconstruction

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**Abstract:** This study presents a comparative analysis of five sparse recovery algorithms—Orthogonal Matching Pursuit (OMP), Basis Pursuit (BP), Iterative Hard Thresholding (IHT), Compressive Sampling Matching Pursuit (CoSaMP), and Subspace Pursuit (SP)—to accelerate Magnetic Resonance Imaging (MRI) via Compressed Sensing (CS). Employing a patch-based framework with a Discrete Cosine Transform (DCT) dictionary and a Gaussian sensing matrix, performance was evaluated using PSNR, SSIM, MSE, and execution time. Results demonstrate that CoSaMP achieves the highest reconstruction quality (27.25 dB PSNR), followed closely by SP and OMP, while BP offers the fastest execution at the cost of accuracy. This research highlights the critical trade-offs between reconstruction quality and computational efficiency, providing a guide for algorithm selection in real-time and hardware-oriented MRI systems.

**Keywords—** Compressed Sensing, Magnetic Resonance Imaging (MRI), Sparse Recovery Algorithms, CoSaMP, Patch-based Reconstruction, Image Quality, Computational Complexity.

## I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a widely used non-invasive imaging modality known for its high spatial resolution and superior soft-tissue contrast. However, one of its primary limitations is the inherently long acquisition time required to sample the full-k-space data. This prolonged scanning duration not only reduces system efficiency but also increases patient discomfort and susceptibility to motion artifacts.

Compressed sensing (CS) offers a promising solution to this challenge by enabling accurate image reconstruction from significantly fewer measurements than those required by conventional Nyquist sampling. The key principle underlying CS is that many natural signals, including medical images, exhibit sparsity or compressibility in an appropriate transform domain. By leveraging this property, CS reconstructs high-quality images from undersampled data, thereby reducing acquisition time.

The reconstruction of signals from incomplete measurements is fundamentally an ill-posed inverse problem. To address this, various sparse recovery algorithms have been developed, each employing a distinct strategy to estimate the underlying sparse representation. These methods can be broadly categorized into three classes: greedy algorithms, convex optimization-based approaches, and iterative thresholding techniques.

Greedy algorithms such as Orthogonal Matching Pursuit (OMP), Compressive Sampling Matching Pursuit (CoSaMP), and Subspace Pursuit (SP) iteratively select basis elements that best approximate the signal, offering a balance between computational efficiency and reconstruction accuracy. Optimization-based methods, such as Basis Pursuit (BP), formulate the problem as an  $\ell_1$ -norm minimization task often achieving high accuracy at the expense of increased computational complexity. Iterative methods like Iterative Hard Thresholding (IHT) provide a simpler alternative by combining gradient updates with sparsity enforcement.

This work presents a comprehensive comparative study of five widely used sparse recovery algorithms—OMP, BP (ISTA), IHT, CoSaMP, and SP—within a unified experimental framework. The evaluation focuses on reconstruction quality, convergence behavior, and computational efficiency under varying sparsity and measurement conditions. Additionally, the suitability of these algorithms for hardware implementation is examined, with particular emphasis on fixed-point realizations for real-time applications.

## II. BACKGROUND AND OVERVIEW

Compressed sensing (CS) is based on the principle that a signal can be accurately reconstructed from a limited number of measurements if it admits a sparse representation in an appropriate transform domain.

In medical imaging, particularly MRI, this assumption holds well because an anatomical structure is highly bit-redundant and can be compactly represented using transforms such as the Discrete Cosine Transform (DCT) or wavelets.

In the CS framework, the acquisition process is modeled as a linear projection of the original signal onto a lower-dimensional space:

$$y = \Phi x \quad (1)$$

where  $x \in \mathbb{R}^N$  is the original signal (image patch),  $y \in \mathbb{R}^M$  represents the compressed measurements with  $M \ll N$ , and  $\Phi$  is the sensing matrix.

Since natural images are not inherently sparse in the spatial domain, they are transformed into a sparse domain using a dictionary

$D$ , such that:

$$x = D\alpha \quad (2)$$

where  $\alpha$  is a vector of sparse coefficients. Substituting into the measurement model:

$$y = \Phi D\alpha \quad (3)$$

The reconstruction problem thus reduces to estimating the sparse vector  $\alpha$  from an underdetermined system. This is typically formulated as follows:

$$\min_{\alpha} \|\alpha\|_0 \quad \text{subject to } y = \Phi D\alpha \quad (4)$$

However, solving the  $\ell_0$ -norm problem is computationally intractable. Therefore, practical algorithms approximate this problem using greedy strategies, convex relaxation, or iterative thresholding methods.

In MRI applications, CS enables reduced sampling in  $k$ -space, significantly decreasing acquisition time while maintaining image quality [4]. In this work, instead of operating directly in the  $k$ -space, a patch-based image-domain CS approach is adopted. Each image is divided into small non-overlapping patches ( $8 \times 8$ ), allowing localized sparsity exploitation and reducing computational complexity.

ADCT-based dictionary is used due to its strong energy compaction property, which concentrates most of the signal information into a few coefficients. Compressed measurements are then obtained using a normalized Gaussian sensing matrix, which satisfies the incoherence requirement essential for accurate reconstruction [2].

The recovery of the sparse coefficients is performed using differential algorithmic approaches. Greedy algorithms iteratively build the support set, optimization-based methods solve relaxed convex problems, and iterative thresholding methods refine solutions through successive approximations. The comparative behavior of these approaches is the focus of this study.

### III. LITERATURE REVIEW

The theory of compressed sensing was formally introduced by Donoho [1], who demonstrated that sparse signals can be recovered from far fewer samples than required by traditional sampling theory. This work was further strengthened by Candes, Romberg, and Tao [2], who established the theoretical guarantees for exact recovery under certain conditions such as the Restricted Isometry Property (RIP). These foundational works laid the groundwork for applying CS in practical domains.

Candes and Wakin provided a comprehensive overview of compressive sampling and highlighted its applicability across signal processing fields, including imaging systems. In the context of MRI, Lustig et al. [4] pioneered the application of CS to accelerate MRI acquisition, demonstrating that high-quality reconstruction is achievable from undersampled  $k$ -space data.

Early reconstruction techniques primarily relied on convex optimization approaches such as Basis Pursuit, introduced by Chen et al., which formulates sparse recovery as an  $\ell_1$ -norm minimization problem. While these methods provide high reconstruction accuracy, their computational complexity limits their use in real-time applications.

To address this limitation, greedy algorithms were developed. Orthogonal Matching Pursuit (OMP), proposed by Tropp and Gilbert [6], offers a computationally efficient approach by iteratively selecting the dictionary atom most correlated with the residual signal. However, its single-atom selection strategy can limit reconstruction performance in highly undersampled scenarios.

Subsequent advancements led to the development of Compressive Sampling Matching Pursuit (CoSaMP) by Needell and Tropp [7], which improves upon OMP by selecting multiple atoms per iteration, thereby enhancing convergence speed and accuracy. Similarly, Subspace Pursuit (SP), introduced by Dai and Milenkovic [8], refines the support set iteratively, achieving a strong balance between computational efficiency and reconstruction quality.

Iterative thresholding methods have also gained attention due to their simplicity and scalability. Iterative Hard Thresholding (IHT), proposed by Blumensath and Davies [9], employs gradient-based updates followed by hard thresholding to enforce sparsity.

Variants of these methods have been further explored to improve convergence and robustness in large-scale problems.

#### IV. PROPOSED METHODOLOGY

The proposed system implements a compressed sensing-based MRI reconstruction framework that combines sparse representation, randomized sampling, and iterative recovery algorithms. The objective is to reconstruct high-quality images from undersampled measurements while analyzing the trade-offs between reconstruction accuracy and computational complexity.

##### A. Preprocessing and Patch Formation

The input MRI images, provided in DICOM format, are first converted to grayscale and normalized to ensure consistent intensity scaling. Each image is resized to a fixed resolution of  $128 \times 128$  to maintain uniformity across experiments.

The image is then divided into non-overlapping  $8 \times 8$  patches, resulting in smaller blocks that can be processed independently.

This patch-based approach improves sparsity representation and reduces computational complexity by localizing the reconstruction process.

Table 1: Comparison with Related Works

Ref	Method	Focus	Key Contribution	Limitation
[1]	Donoho (2006)	CS Theory	Introduced sparsity-based recovery	Theoretical only
[2]	Candès et al. (2006)	RIP Theory	Recovery guarantees	Not application-specific
[3]	Candès & Wakin (2008)	CS Framework	Practical CS overview	No algorithm comparison
[4]	Lustig et al. (2007)	CS-MRI	First CS-MRI implementation	Optimization-heavy
[5]	Chen et al. (2001)	BP	$\ell_1$ minimization	High complexity
[6]	Tropp et al. (2007)	OMP	Efficient greedy method	Slower for high sparsity
[7]	Needell et al. (2009)	CoSaMP	Multi-atom selection	Moderate complexity
[8]	Dai et al. (2009)	SP	Improved support refinement	Parameter sensitive
[9]	Blumensath (2009)	IHT	Simple iterative method	Lower accuracy
[10]	Foucart (2011)	HTP	Improved convergence	No hardware-tested
This Work	Multi-algorithm	MRI	Unified comparison + hardware review	Patch-based limitation

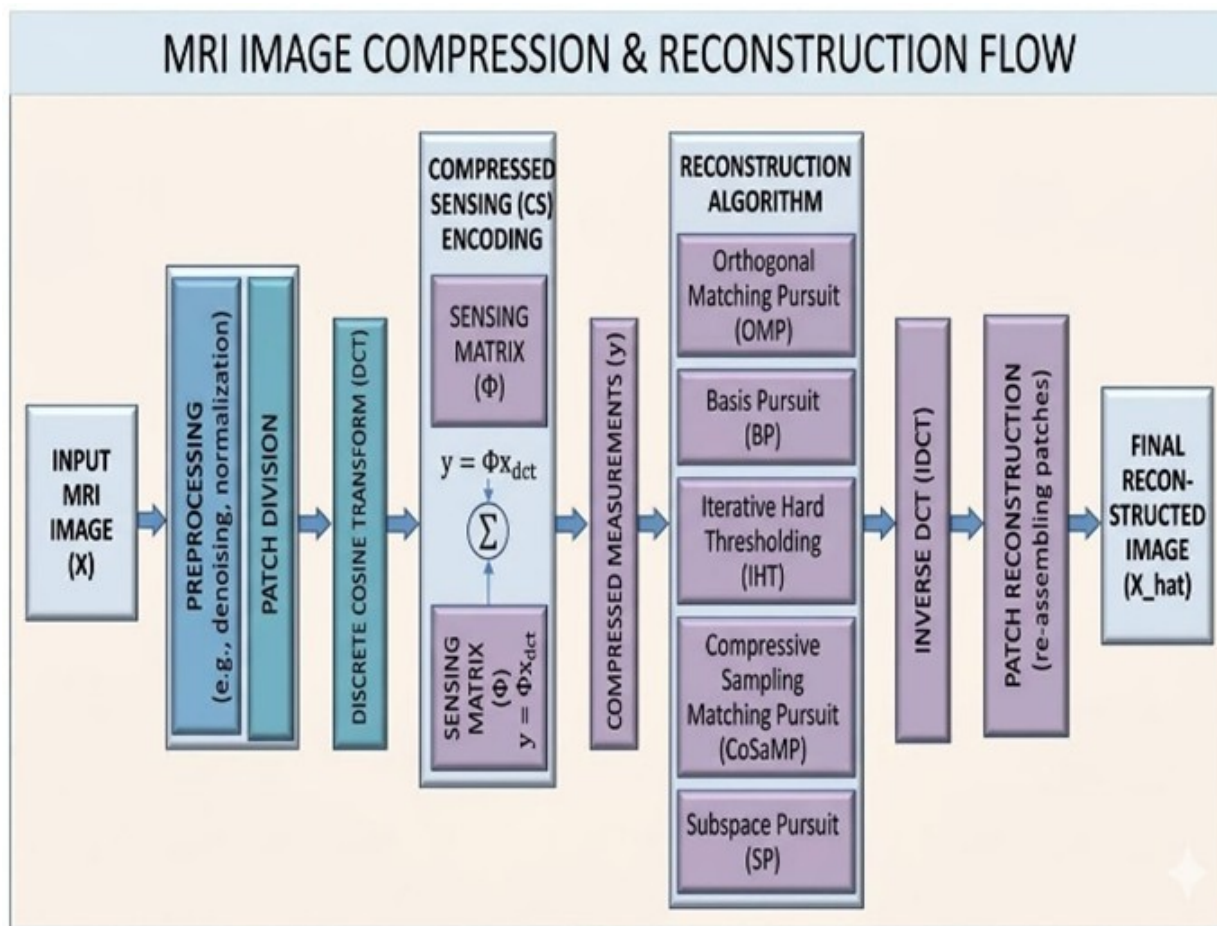


Figure1:FlowchartofProposedSystem

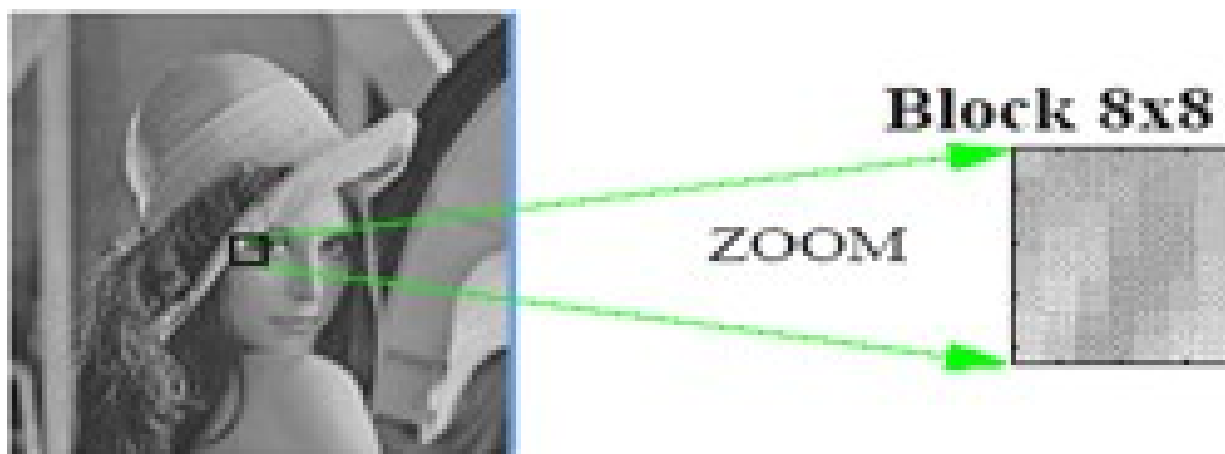


Figure2:Patch-baseddivisioninto8×8 blocks

### B. Sparse Representation using DCT

Each image patch is transformed into a sparse domain using a two-dimensional Discrete Cosine Transform (DCT) dictionary. The DCT is chosen due to its strong energy compaction property, where most of the signal information is concentrated in a small number of coefficients.

The dictionary is constructed using the Kronecker product of 1D DCT bases:

$$D = \text{kron}(D_1, D_1)$$

(5)

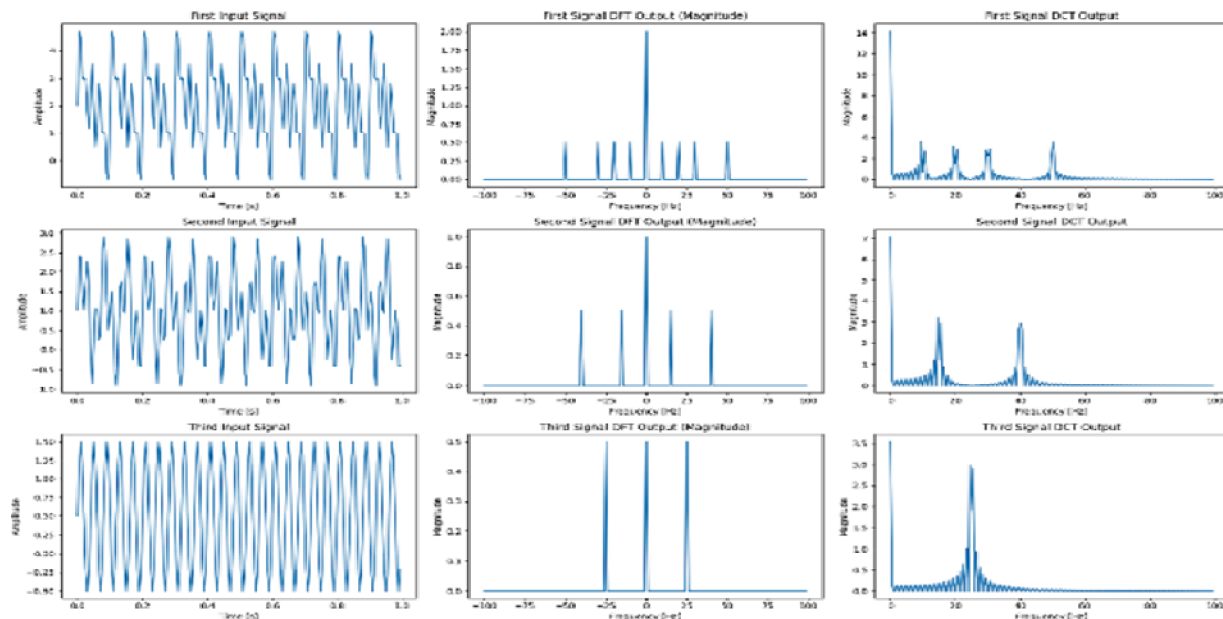


Figure3:DCTdomainrepresentationofimagepatch

C. Measurement Acquisition

Compressed measurements are obtained using a random Gaussian sensing matrix:

$$y = \Phi x \tag{6}$$

where  $\Phi \in \mathbb{R}^{M \times N}$  with  $M=48$  and  $N=64$ . The columns of this sensing matrix are normalized to ensure stability and satisfy incoherence conditions required for compressed sensing.

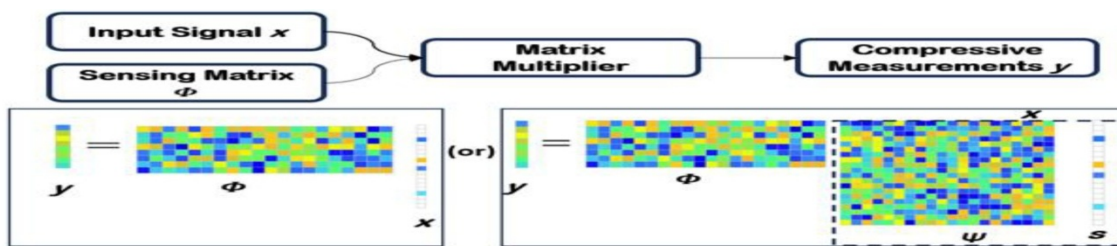
D. Mathematical Model

The complete compressed sensing model is expressed as:

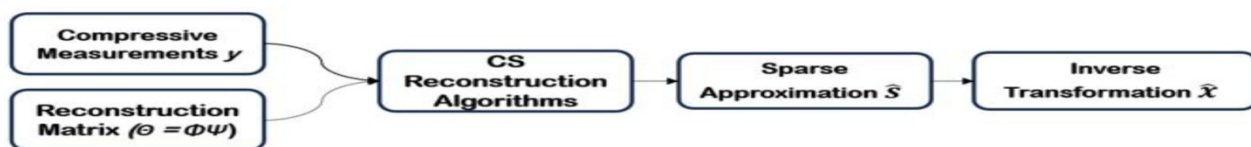
$$x = D\alpha, \tag{7} \quad y = \Phi D\alpha$$

where:

- $x$ : original signal (patch)
- $D$ : sparsifying dictionary
- $\alpha$ : sparse coefficients
- $y$ : compressed measurements



(a) Data Acquisition Model



(b) Data Reconstruction Model

Figure4:CompressedSensingConceptDiagram

### E. Reconstruction Algorithms

The reconstruction stage involves estimating the sparse coefficient vector  $a$  from compressed measurements using five algorithms:

- OMP (Fixed-point): Iteratively selects atoms based on correlation; suitable for hardware implementation.
- BP (ISTA): Solves  $\ell_1$  optimization problem; produces stable but dense solutions.
- IHT: Uses gradient descent with hard thresholding; computationally simple.
- CoSaMP: Selects multiple atoms per iteration; improves convergence and accuracy.
- SP: Refines support set iteratively; balances accuracy and speed.

### F. Parameter Configuration

The system is evaluated under controlled parameter settings:

- Patch size:  $8 \times 8$
- Signal dimension:  $N=64$
- Measurements:  $M=48$
- Sparsity level:  $K=10$
- Iterations: ISTA=50, IHT=50, CoSaMP/SP=3–10

These parameters are also varied systematically to analyze performance trends.

### G. Performance Metrics

The reconstruction performance is evaluated using the following metrics:

- PSNR (Peak Signal-to-Noise Ratio) – measures reconstruction quality.
- SSIM (Structural Similarity Index) – evaluates perceptual similarity.
- MSE (Mean Squared Error) – quantifies pixel-wise error.
- Reconstruction Error – measures deviation from ground truth.
- Execution Time – assesses computational efficiency.

These metrics provide a comprehensive understanding of algorithm performance across accuracy and complexity dimensions.

## V. RESULTS AND DISCUSSION

The performance of the proposed MRI reconstruction framework is evaluated through qualitative and quantitative analyses. The experiments were conducted in MATLAB on a system equipped with a Ryzen 7 7735HS processor, focusing on reconstruction accuracy and computational efficiency across five different recovery algorithms.

### A. Experimental Environment

The evaluation utilized a dataset of MRI images in DICOM format. Each image was resized to  $128 \times 128$  and processed using the  $8 \times 8$  patch-based framework described in the methodology. Unless otherwise specified, the default configuration used for comparative analysis was  $M=48$  measurements and a sparsity level of  $K=10$ .

### B. Qualitative Analysis

The visual quality of the reconstructed MRI images varies significantly across the implemented algorithms. Greedy algorithms, specifically CoSaMP, SP, and OMP, demonstrate superior performance in preserving structural edges and fine details. Conversely, BP (ISTA) produces smoother results due to its  $\ell_1$  minimization approach, which often leads to less sparse coefficient estimations in patch-based domains. IHT provides a balanced but slightly lower detail resolution.

### C. Quantitative Comparison

The performance metrics for all five algorithms at the standard configuration ( $M=48, K=10$ ) are detailed in Table 2. CoSaMP achieves the highest PSNR (27.25 dB), followed by OMP (26.32 dB) and SP (26.11 dB). While BP (ISTA) offers the fastest execution time (0.057 s), it records the lowest PSNR and SSIM, highlighting the trade-off between speed and accuracy.

Table2: Detailed Performance Comparison at  $M=48, K=10$

Algorithm	PSNR(dB)	SSIM	MSE	Time(s)	Iter
BP(ISTA)	21.75	0.642	0.00667	0.057	50
IHT	23.18	0.628	0.00480	0.204	50
CoSaMP	27.25	0.775	0.00188	0.197	3.94
SP	26.11	0.752	0.00245	0.140	3.54
OMP(FP)	26.32	0.725	0.00233	5.51	10

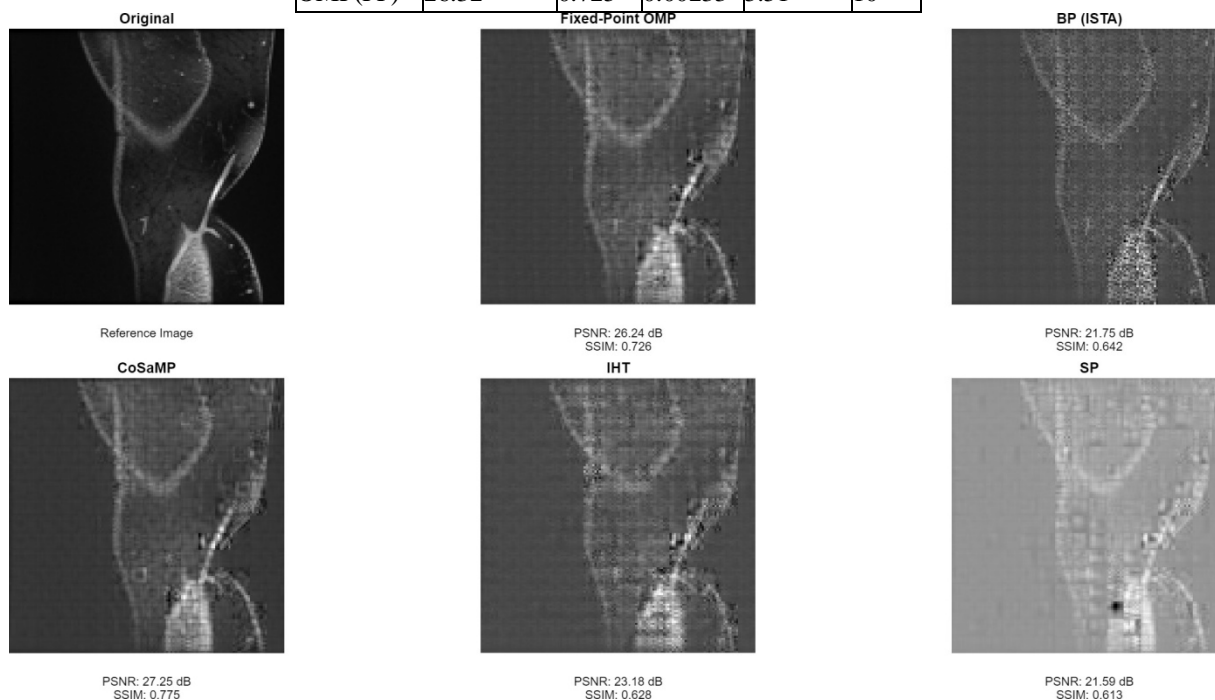


Figure 5: Qualitative comparison of reconstructed MRI images (Original vs OMP, BP, IHT, CoSaMP, SP)

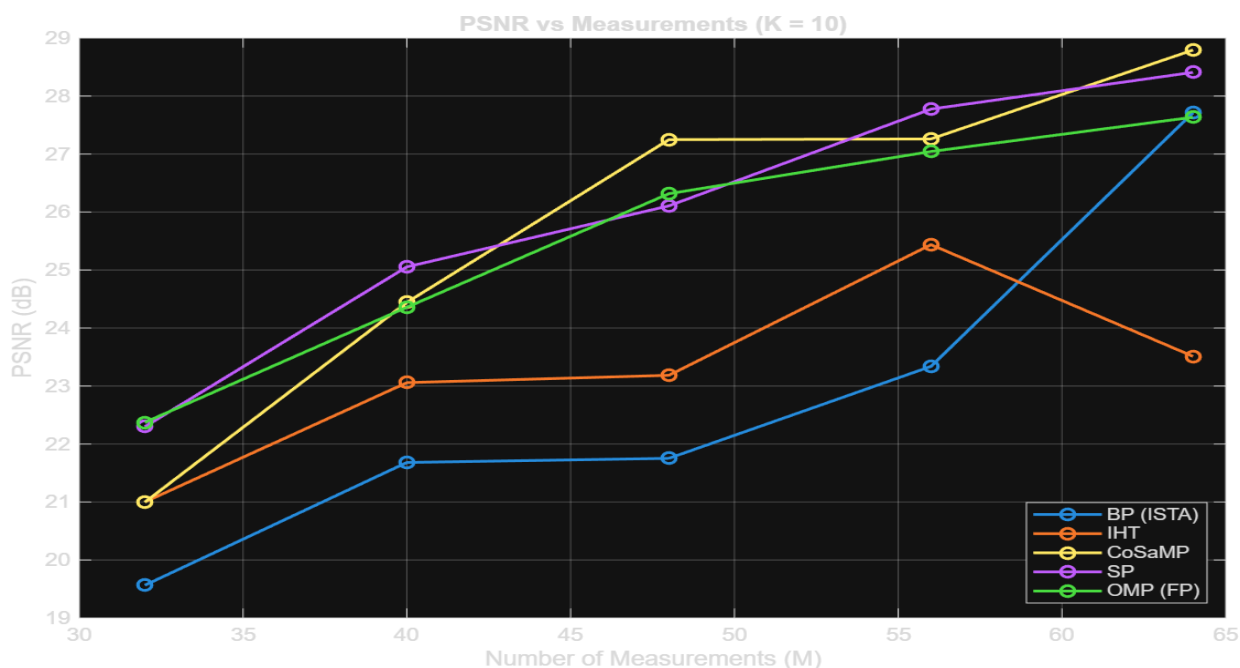


Figure 6: Effect of measurement count (M) on PSNR

**D. Effect of Measurement Count ( $M$ )**

The impact of varying measurements  $M$  on the Peak Signal-to-Noise Ratio (PSNR) was analyzed while maintaining a constant sparsity  $K=10$ . As  $M$  increases, the reconstruction quality improves for all algorithms, as the sensing matrix captures more information about the underlying signal. CoSaMP consistently outperforms other methods across the entire measurement range.

**E. Effect of Sparsity Level ( $K$ )**

The relationship between sparsity level  $K$  and PSNR was studied at a fixed measurement count  $M=48$ . The results indicate that greedy algorithms like CoSaMP and SP benefit significantly from an increase in the assumed sparsity level, reaching optimal reconstruction points more effectively than iterative thresholding or optimization-based methods.

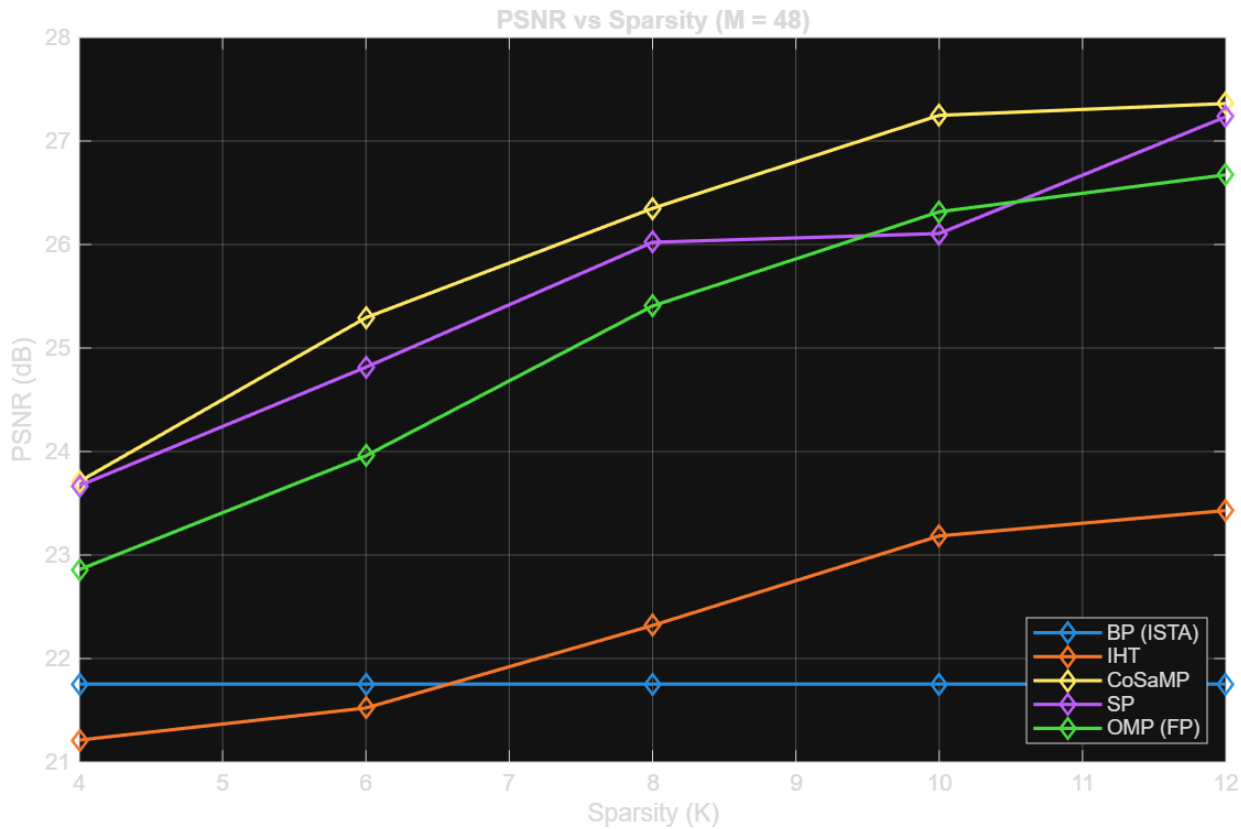


Figure 7: PSNR variation across different sparsity levels ( $K$ )

**F. Computational Complexity Analysis**

Execution time was measured against varying sparsity levels to assess real-time viability. OMP exhibits the highest computational overhead, particularly as  $K$  increases, due to its single-atom selection per iteration. In contrast, BP (ISTA) maintains a nearly constant and low execution time. CoSaMP and SP provide a robust middle ground, making them suitable for high-performance reconstruction tasks.

**VI. DISCUSSION**

The experimental results demonstrate that the choice of sparse recovery algorithm involves a multi-dimensional trade-off between reconstruction fidelity, convergence behavior, and computational overhead. These findings provide a technical roadmap for selecting recovery methods in practical MRI systems.

**A. Algorithmic Efficiency and Accuracy**

CoSaMP achieves the highest reconstruction quality among all evaluated methods, recording a PSNR of 27.25 dB. This performance is attributed to its multi-atom selection strategy; unlike single-atom methods, CoSaMP identifies and refines a larger portion of the signal support in each iteration. This results in faster convergence to a lower error floor, making it highly effective for the localized sparsity found in patch-based MRI reconstruction.

Subspace Pursuit (SP) performs competitively with CoSaMP, offering a strong balance between accuracy (26.11 dB PSNR) and execution speed (0.140s). Since SP utilizes a similar support refinement mechanism but with a more streamlined pruning step,

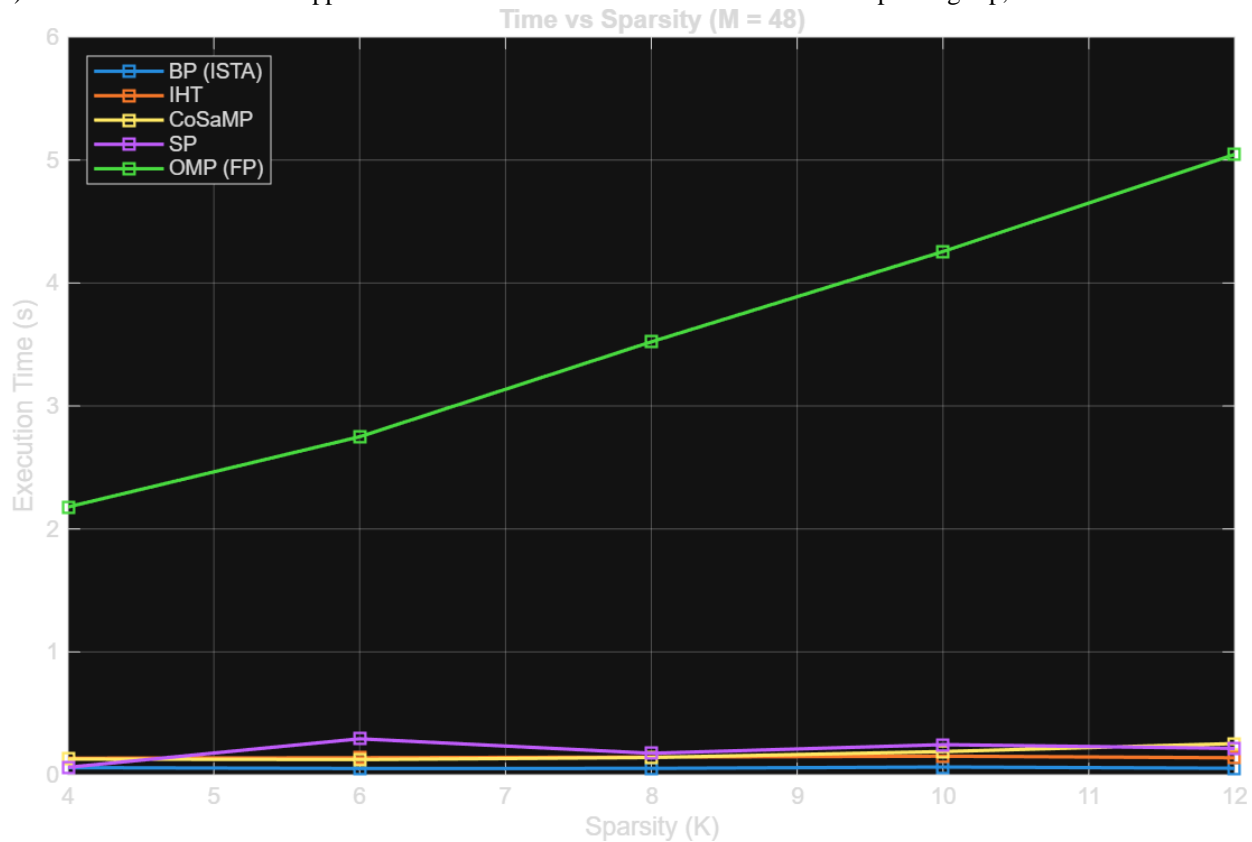


Figure 8: Execution time analysis relative to sparsity level (K)

it serves as an optimal candidate for systems where computational resources are moderately constrained but high fidelity is still required.

### B. Computational Complexity and Constraints

Orthogonal Matching Pursuit (OMP), while producing high-quality reconstructions comparable to SP, suffers from the highest execution time (5.51 s). Its sequential, greedy nature increases the computational load linearly with the sparsity level  $K$ . This makes a software-only implementation of OMP less suitable for real-time imaging; however, its structured iterative logic remains highly favorable for hardware-oriented acceleration on platforms like FPGAs, where parallel processing can mitigate its sequential bottlenecks.

In contrast, Basis Pursuit (BP) via ISTA provides the fastest execution (0.057 s). However, its tendency to produce dense coefficient vectors via  $\ell_1$  minimization reduces the overall sparsity efficiency, leading to the lowest PSNR (21.75 dB). This suggests that while BP is computationally light, it may not satisfy the stringent image quality requirements of medical diagnosis without significant refinement.

### C. Summary of Design Trade-offs

The analysis indicates that no single algorithm is universally optimal. The selection must be driven by specific application constraints as summarized below:

- **Maximum Fidelity:** CoSaMP is preferred due to its superior structural preservation.
- **Balanced Real-time Processing:** SP offers the best trade-off between PSNR and latency.
- **Hardware Realization:** OMP (Fixed-point) is ideal for hardware-level optimization.
- **High-Speed Screening:** BP (ISTA) is suitable for rapid, low-resolution previews.

These findings are particularly relevant for next-generation MRI systems, where integrating hardware-efficient greedy algorithms can significantly reduce the latency between measurement acquisition and clinical visualization.

## VII. CONCLUSION AND FUTURE SCOPE

This study presented a comprehensive comparative analysis of five sparse recovery algorithms—Orthogonal Matching Pursuit (OMP), Basis Pursuit (BP) using ISTA, Iterative Hard Thresholding (IHT), Compressive Sampling Matching Pursuit (CoSaMP), and Subspace Pursuit (SP)—within a unified compressed sensing framework for MRI reconstruction.

The experimental evaluation demonstrates that CoSaMP achieves the highest reconstruction accuracy, consistently outperforming other methods in terms of PSNR (27.25 dB) and SSIM (0.775). Subspace Pursuit (SP) provides a robust balance between accuracy and computational efficiency, making it a highly practical choice for real-time applications. While OMP produces competitive reconstruction quality, its iterative nature incurs significantly higher execution time, suggesting a need for dedicated hardware acceleration. Furthermore, optimization-based methods like BP offer high speed but fail to match the reconstruction fidelity of greedy algorithms in patch-based configurations.

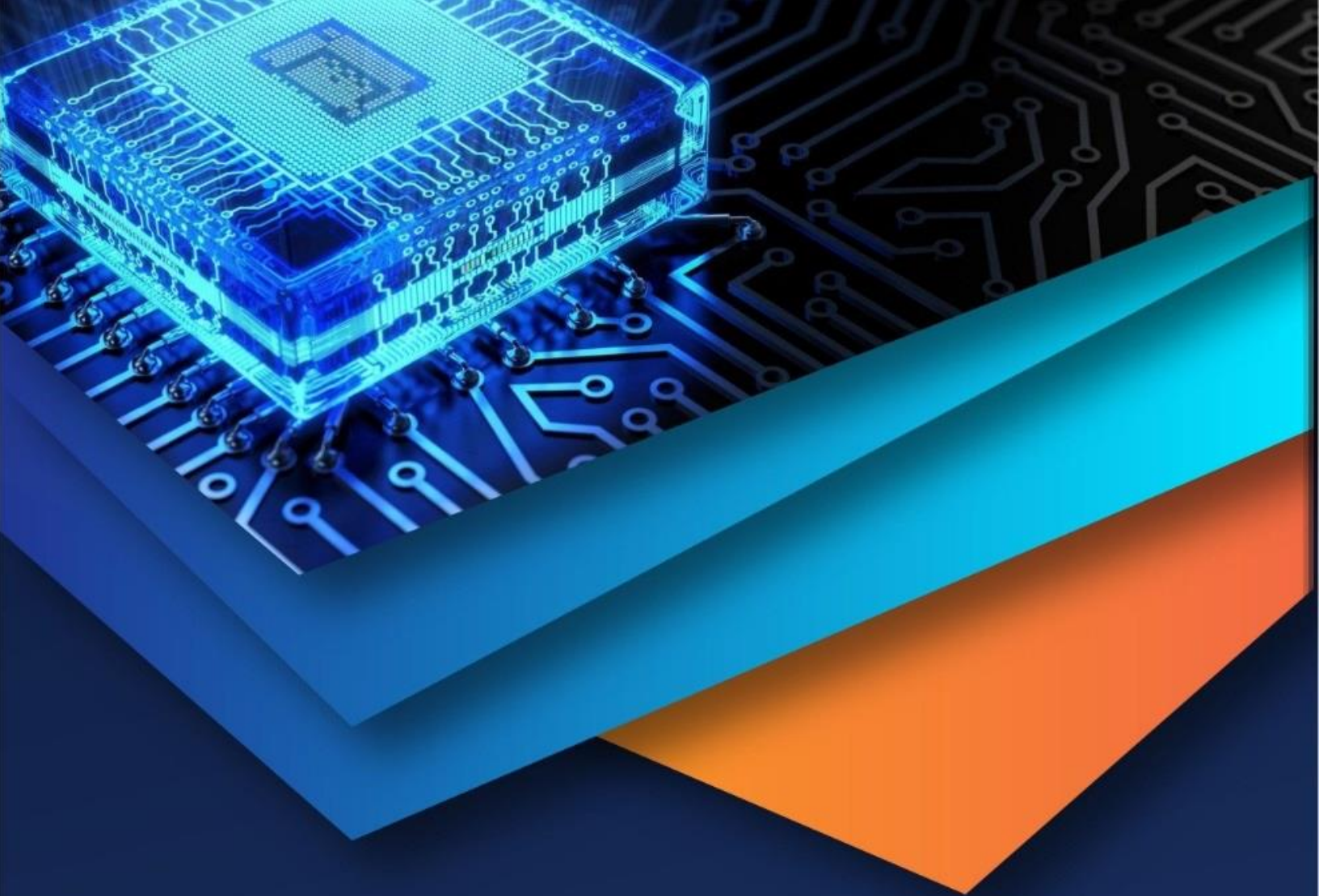
These results highlight that the selection of a reconstruction algorithm must be guided by application-specific requirements, particularly the critical trade-off between image fidelity and computational latency. For clinical scenarios requiring high-quality reconstruction, CoSaMP is preferred, whereas SP is more suitable when computational throughput is equally prioritized.

Future work can extend this framework in several promising directions:

- **Hardware Acceleration:** Implementing these algorithms on GPU or FPGA platforms (using HLS or Verilog) to achieve nanosecond-level execution speeds for real-time clinical deployment.
- **Advanced Sparsity:** Incorporating adaptive or learned dictionaries, such as K-SVD, to further enhance the representation of complex anatomical structures.
- **Deep Learning Integration:** Combining the physics-based CS framework with Deep Learning (e.g., Residual U-Nets) to improve performance in highly undersampled and noisy scenarios.
- **Real-world Validation:** Evaluating the system on actual  $k$ -space undersampled MRI data from clinical scanners to validate its practical applicability under varied noise conditions.

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