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Comparative Analysis of Greedy Iterative Algorithms for Compressed Sensing MRI Reconstruction

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Abstract: Thisstudypresentsacomparativeanalysisoffivesparserecoveryalgorithms—Orthogonal Matching Pursuit(OMP), Basis Pursuit (BP), IterativeHardThresholding(IHT),CompressiveSamplingMatchingPursuit(CoSaMP),andSubspacePursuit(SP)—toaccelerate Mag- neticResonanceImaging(MRI)viaCompressedSensing(CS).Employingapatch-basedframework withaDiscrete Cosine Transform(DCT) dictionaryandaGaussiansensingmatrix, performance was evaluatedusing PSNR,SSIM, MSE, and executiontime.ResultsdemonstratethatCoSaMPachievesthehighestreconstructionquality(27.25dBPSNR),followedcloselybySPand OMP,whileBPoffersthefastestexecution atthecostofaccuracy.Thisresearchhighlightsthecriticaltrade-offsbetweenre construction qualityand computationalefficiency,providinga 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 superiorsoft-tissuecontrast. However,oneofitsprimarylimitationsistheinherentlylongacquisitiontimerequiredtosamplethe fullk-spacedata.Thisprolongedscanningdurationnotonlyreducessystemefficiencybutalsoincreasespatientdiscomfortand susceptibility to motion artifacts.

Compressedsensing(CS)offersapromisingsolutiontothischallengebyenablingaccurateimagereconstructionfromsignifi-cantlyfewer measurements thanthoserequiredbyconventionalNyquistsampling. ThekeyprincipleunderlyingCSisthatmany naturalsignals, includingmedicalimages, exhibitsparsityorcompressibilityinanappropriatetransformdomain.Byleveraging 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 SubspacePursuit(SP)iterativelyselectbasiselementsthatbestapproximatethesignal,offeringabalancebetweencomputational efficiencyandreconstructionaccuracy. Optimization-basedmethods,suchasBasisPursuit(BP),formulatetheproblemasanℓ_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, conver- gence 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 mea- surements if it admits a sparse representation in an appropriate transform domain.

In medical imaging, particularly MRI, this assumptionholdswellbecauseanatomical structure sexhi bitredundancyandcanbecompactlyrepresentedusingtransformssuch 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:

$$y=\Phi x \tag{1}$$

where$x\in\mathbb{R}^N$istheoriginalsignal(imagepatch),$y\in\mathbb{R}^M$representsthecompressedmeasurementswith$M\ll N$,andΦ isthe sensing matrix.
Sincenaturalimagesarenotinherentlysparseinthespatialdomain,theyaretransformedintoasparsedomainusingadictionary D,suchthat:

$$x=D\alpha \tag{2}$$

whereα isavectorofsparsecoefficients.Substitutingintothemeasurementmodel:

$$y=\Phi D\alpha \tag{3}$$

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

$$\min_{\alpha} \|\alpha\|_0 \quad \text{subjectto} \; y=\Phi D\alpha \tag{4}$$

However, solving the ℓ_0-norm problem is computationally intractable.Therefore, practical algorithms approximate this problem using greedy strategies, convex relaxation, or iterative thresholding methods.
InMRIapplications,CSenablesreducedsamplingin$k$-space,significantlydecreasingacquisitiontimewhilemaintainingim- age quality [4].In this work, instead of operating directly in the k-space, a patch-based image-domain CS approach is adopted. Eachimage isdividedinto smallnon-overlapping patches(8×8), allowinglocalizedsparsity exploitationand reducingcompu- tational complexity.
ADCT-baseddictionaryisusedduetoitsstrongenergy compaction property, whichconcentratesmostofthesignalinformation intoafewcoefficients. CompressedmeasurementsarethenobtainedusinganormalizedGaussiansensingmatrix,whichsatisfies the incoherence requirement essential for accurate reconstruction [2].
Therecoveryofthesparsecoefficientsisperformedusingdifferentalgorithmicapproaches.Greedyalgorithmsiterativelybuild 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

Thetheoryofcompressedsensingwasformallyintroducedby Donoho[1],whodemonstratedthatsparsesignalscanberecovered from far fewer samples than required by traditional sampling theory.This work was further strengthened by Cande`s, Romberg, andTao[2],whoestablishedthetheoreticalguaranteesforexactrecoveryundercertainconditionssuchastheRestrictedIsometry Property (RIP). These foundational works laid the groundwork for applying CS in practical domains.
Cande`sandWakinprovidedacomprehensiveoverviewofcompressivesamplingandhighlighteditsapplicabilityacrosssignal processing fields,includingimagingsystems. InthecontextofMRI,Lustigetal.[4]pioneeredtheapplicationofCStoaccelerate MRI acquisition, demonstrating that high-quality reconstruction is achievable from undersampled k-space data.
EarlyreconstructiontechniquesprimarilyreliedonconvexoptimizationapproachessuchasBasisPursuit,introducedbyChen et al., which formulates sparse recovery as an ℓ_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], offersacomputationallyefficientapproachbyiterativelyselectingthedictionaryatommostcorrelatedwiththeresidual 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 ac- curacy.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.

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IV. PROPOSED METHODOLOGY

The proposed system implements a compressed sensing-based MRI reconstruction framework that combines sparse representation, randomizedsampling,anditerativerecoveryalgorithms.Theobjectiveistoreconstructhigh-qualityimagesfromundersampled measurements while analyzing the trade-offs between reconstruction accuracy and computational complexity.

A. *Preprocessing and Patch Formation*

TheinputMRIimages,providedinDICOMformat,arefirstconvertedtograyscaleandnormalizedtoensureconsistentintensity scaling. Each image is resized to a fixed resolution of 128 ×128 to maintain uniformity across experiments.
Theimageisthendividedintonon-overlapping8×8patches,resultinginsmallerblocksthatcanbeprocessedindependently.
Thispatch-basedapproachimprovessparsityrepresentationandreducescomputationalcomplexitybylocalizingthereconstruc-tionprocess.

Table1:ComparisonwithRelatedWorks

Ref	Method	Focus	KeyContribu-tion	Limitation
[1]	Donoho (2006)	CSTheory	Introduced sparsity-basedrecovery	Theoretical only
[2]	Cande`set al.(2006)	RIPThe-ory	Recoveryguar-antees	Not application-specific
[3]	Cande`s &Wakin(2008)	CSFrame-work	Practical CS overview	No algorithm comparison
[4]	Lustiget al.(2007)	CS-MRI	FirstCS-MRI implementation	Optimization-heavy
[5]	Chenetal. (2001)	BP	$\ell_1$minimiza-tion	Highcomplex-ity
[6]	Troppet al.(2007)	OMP	Efficientgreedy method	Slowerforhigh sparsity
[7]	Needellet al.(2009)	CoSaMP	Multi-atomse-lection	Moderatecom-plexity
[8]	Daietal. (2009)	SP	Improvedsup-portrefinement	Parametersen-sitive
[9]	Blumensath (2009)	IHT	Simpleiterative method	Loweraccuracy
[10]	Foucart (2011)	HTP	Improvedcon-vergence	Nothardware-tested
This Work	Multi-algorithm	MRI	Unifiedcom-parison + hardwareview	Patch-based limitation

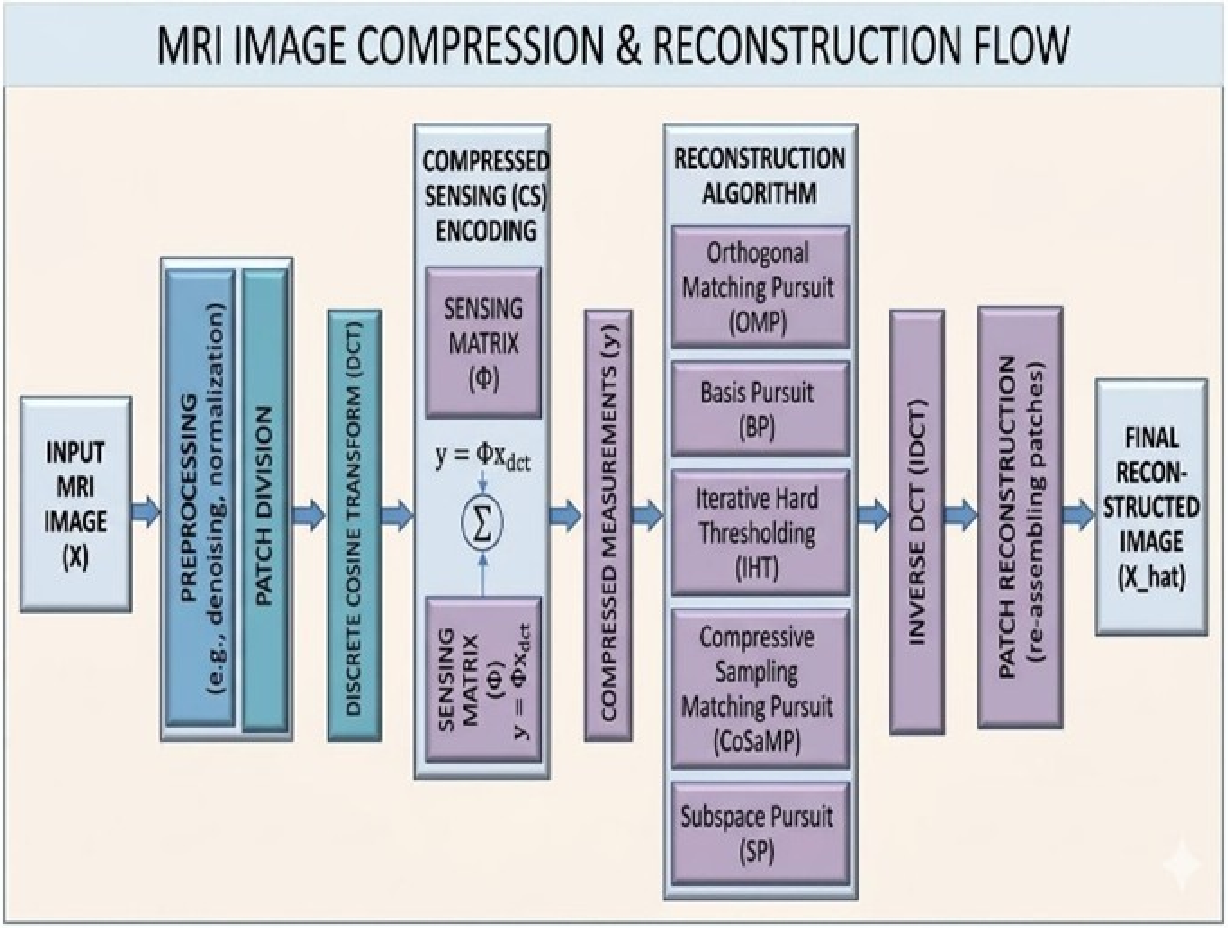

Figure1:FlowchartofProposedSystem

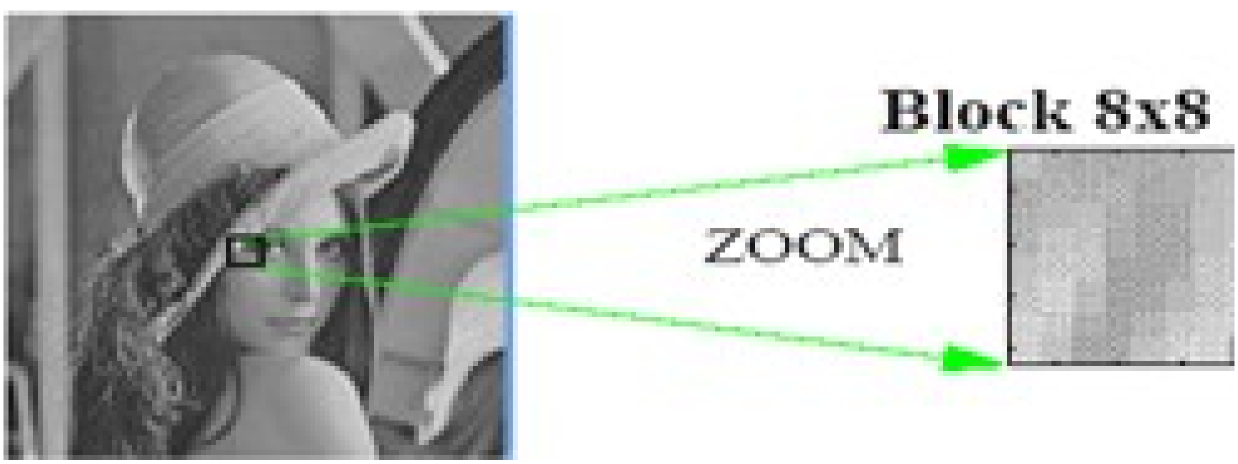

Figure2:Patch-baseddivisioninto8×8 blocks

B. SparseRepresentationusingDCT

Each image patch is transformed into a sparse domain using a two-dimensional Discrete Cosine Transform (DCT) dictionary. TheDCTischosenduetoitsstrongenergycompactionproperty,wheremostofthesignalinformationisconcentratedinasmall number of coefficients.

ThedictionaryisconstructedusingtheKroneckerproductof1DDCTbases:

$$D=\mathrm{kron}(D_1,D_1) \quad (5)$$

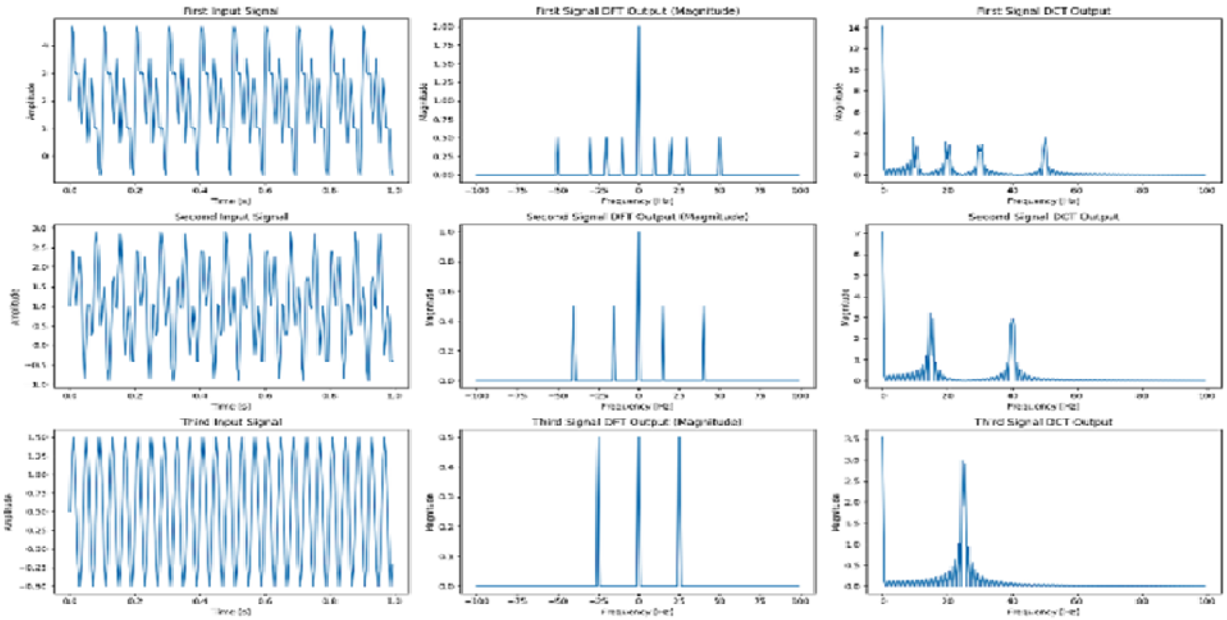

Figure3:DCTdomainrepresentationofimagepatch

C. MeasurementAcquisition

CompressedmeasurementsareobtainedusingarandomGaussiansensingmatrix:

$y=\Phi x$ 6)

whereΦ $\in \mathrm{R}^{M\times N}$with$M$=48and$N$=64.Thecolumnsofthesensingmatrixarenormalizedtoensurestabilityandsatisfy incoherenceconditionsrequiredforcompressedsensing.

D. MathematicalModel

Thecompletecompressedsensingmodelisexpressedas:

$x=D\alpha,$ $y=\Phi D\alpha$ (7)

where:

- x:originalsignal(patch)
- D:sparsifyingdictionary
- α:sparsecoefficients
- y:compressedmeasurements

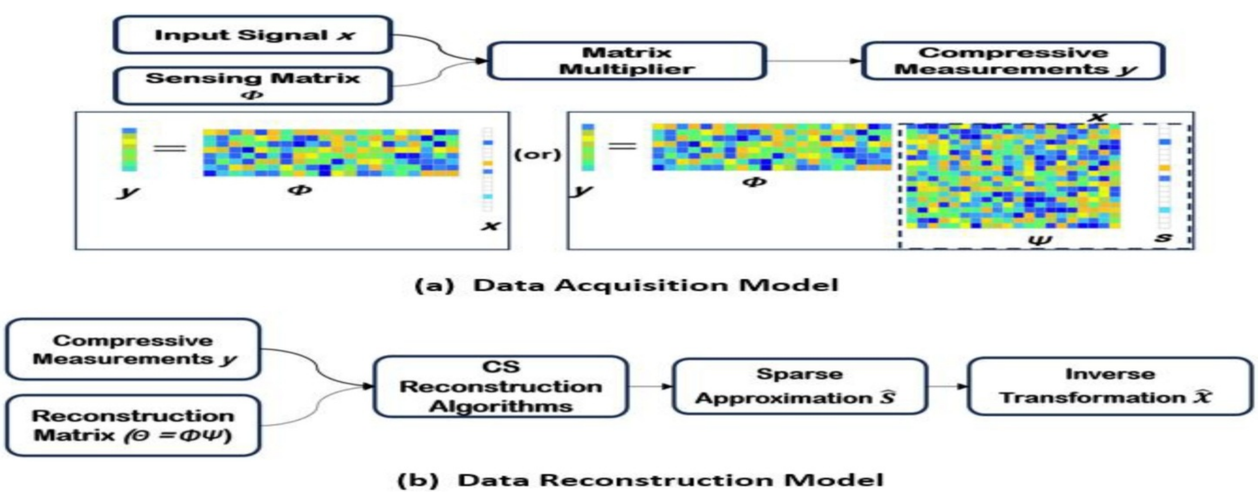

Figure4:CompressedSensingConceptDiagram

E. Reconstruction Algorithms

Thereconstruction stageinvolves estimating the sparsecoefficientvector αfromcompressed measurementsusingfivealgorithms:

- OMP(Fixed-point):Iterativelyselectsatomsbasedoncorrelation;suitableforhardwareimplementation.
- BP(ISTA):Solvesℓ1optimizationproblem;producesstablebutdensesolutions.
- IHT:Usesgradientdescentwithhardthresholding;computationallysimple.
- CoSaMP:Selectsmultipleatomsperiteration;improvesconvergenceandaccuracy.
- SP:Refinessupportsetiteratively;balancesaccuracyandspeed.

F. Parameter Configuration

Thesystemisevaluatedundercontrolledparametersettings:

- Patchsize:8×8
- Signaldimension:N=64
- Measurements:M=48
- Sparsitylevel:K=10
- Iterations:ISTA=50,IHT=50,CoSaMP/SP=3–10

Theseparametersarealsovariedsystematicallytoanalyzeperformancetrends.

G. Performance Metrics

Thereconstructionperformanceisevaluatedusingthefollowingmetrics:

- PSNR(PeakSignal-to-NoiseRatio)–measuresreconstructionquality.
- SSIM(StructuralSimilarityIndex)–evaluatesperceptualsimilarity.
- MSE(MeanSquaredError)–quantifiespixel-wiseerror.
- ReconstructionError–measuresdeviationfromgroundtruth.
- ExecutionTime–assessescomputationalefficiency.

Thesemetricsprovideacomprehensiveunderstandingofalgorithmperformanceacrossaccuracyandcomplexitydimensions.

V. RESULTS AND DISCUSSION

TheperformanceoftheproposedMRIreconstructionframeworkisevaluatedthroughqualitativeandquantitativeanalyses.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 ×128 and processed using the 8 ×8 patch-based framework described in the methodology.Unless otherwise specified, the default configuration used for comparativeanalysiswas$M$=48measurementsandasparsitylevelof$K$=10.

B. QualitativeAnalysis

The visual quality of the reconstructed MRI images varies significantly across the implemented algorithms.Greedy algorithms, specificallyCoSaMP,SP,andOMP,demonstratesuperiorperformanceinpreservingstructuraledgesandfinedetails.Conversely,BP(ISTA) producessmootherresultsduetoits$\ell_1$minimizationapproach,whichoftenleadstolesssparsecoefficientestimations in patch-based domains. IHT provides a balanced but slightly lower detail resolution.

C. QuantitativeComparison

The performance metrics for all five algorithms at the standard configuration (M= 48,K= 10) are detailed in Table 2. CoSaMP achievesthehighestPSNR(27.25dB),followedbyOMP(26.32dB)andSP(26.11dB).WhileBP(ISTA)offersthefastest execution time (0.057 s), it records the lowest PSNR and SSIM, highlighting the trade-off between speed and accuracy.

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Table2:DetailedPerformanceComparisonat$M$=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

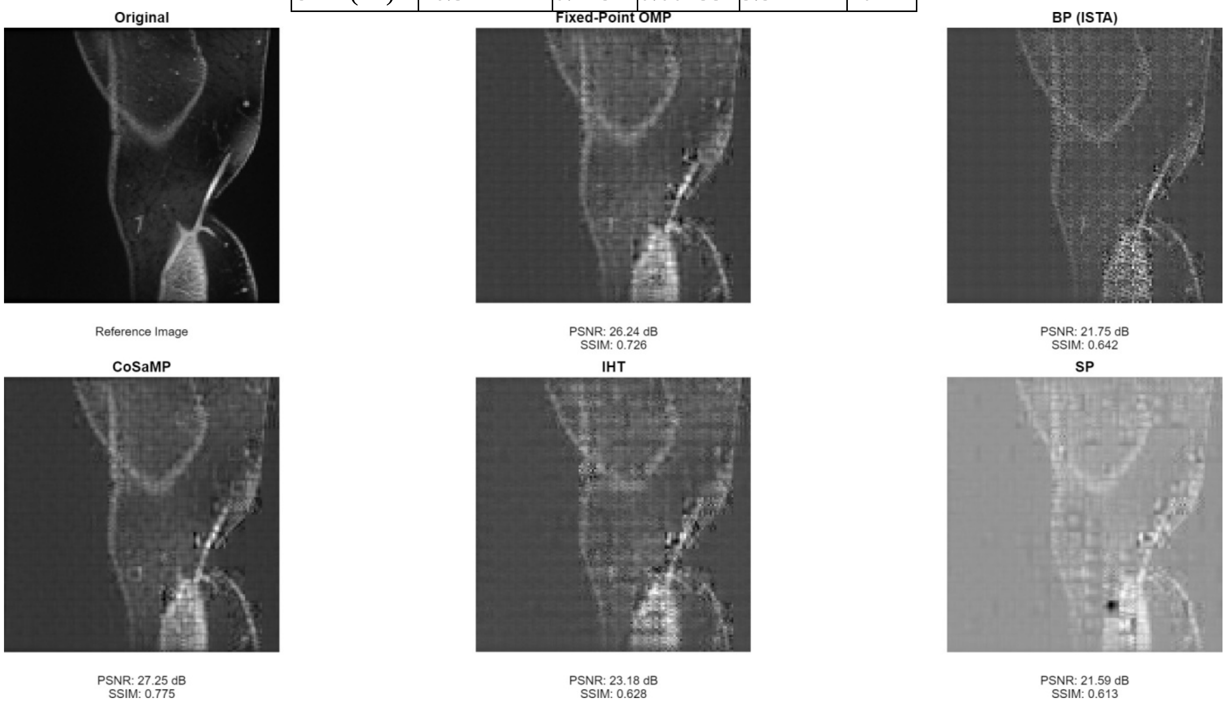

Figure5:QualitativecomparisonofreconstructedMRIimages(OriginalvsOMP,BP,IHT,CoSaMP,SP)

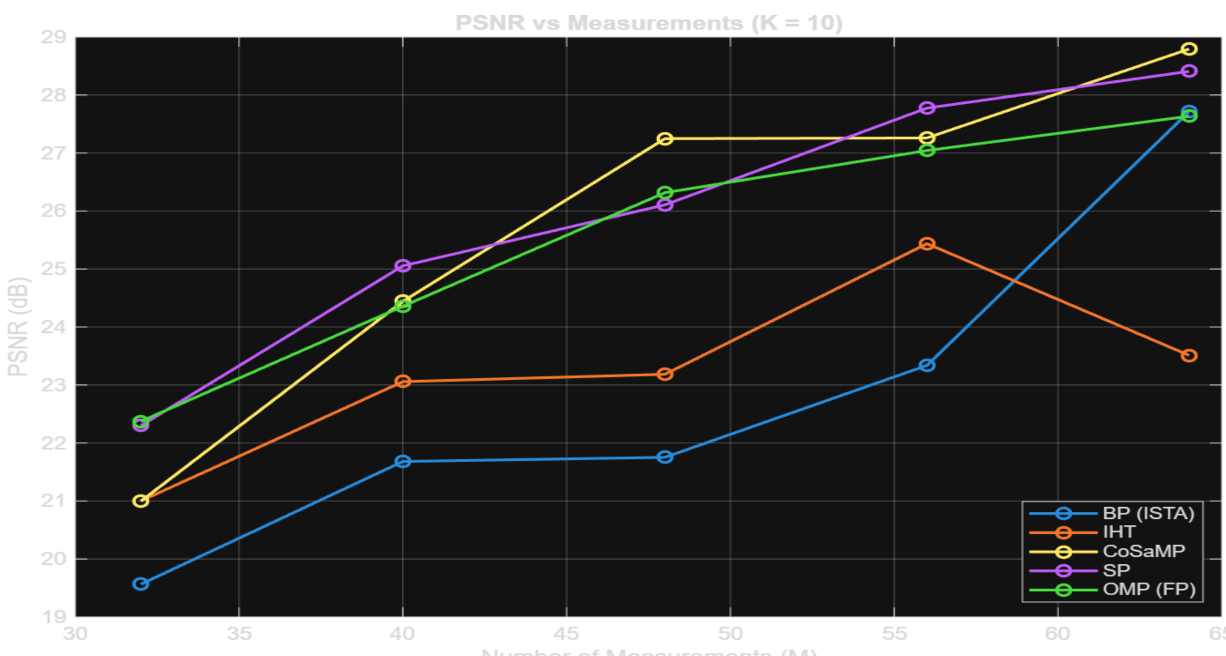

Figure6:Effectofmeasurementcount(M)onPSNR

D. EffectofMeasurementCount(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. EffectofSparsityLevel(K)

The relationship between sparsity level $K$and PSNR was studied at a fixed measurement count M=48.The results indicate thatgreedyalgorithmslikeCoSaMPandSPbenefitsignificantlyfromanincreaseintheassumedsparsitylevel,reachingoptimal reconstruction points more effectively than iterative thresholding or optimization-based methods.

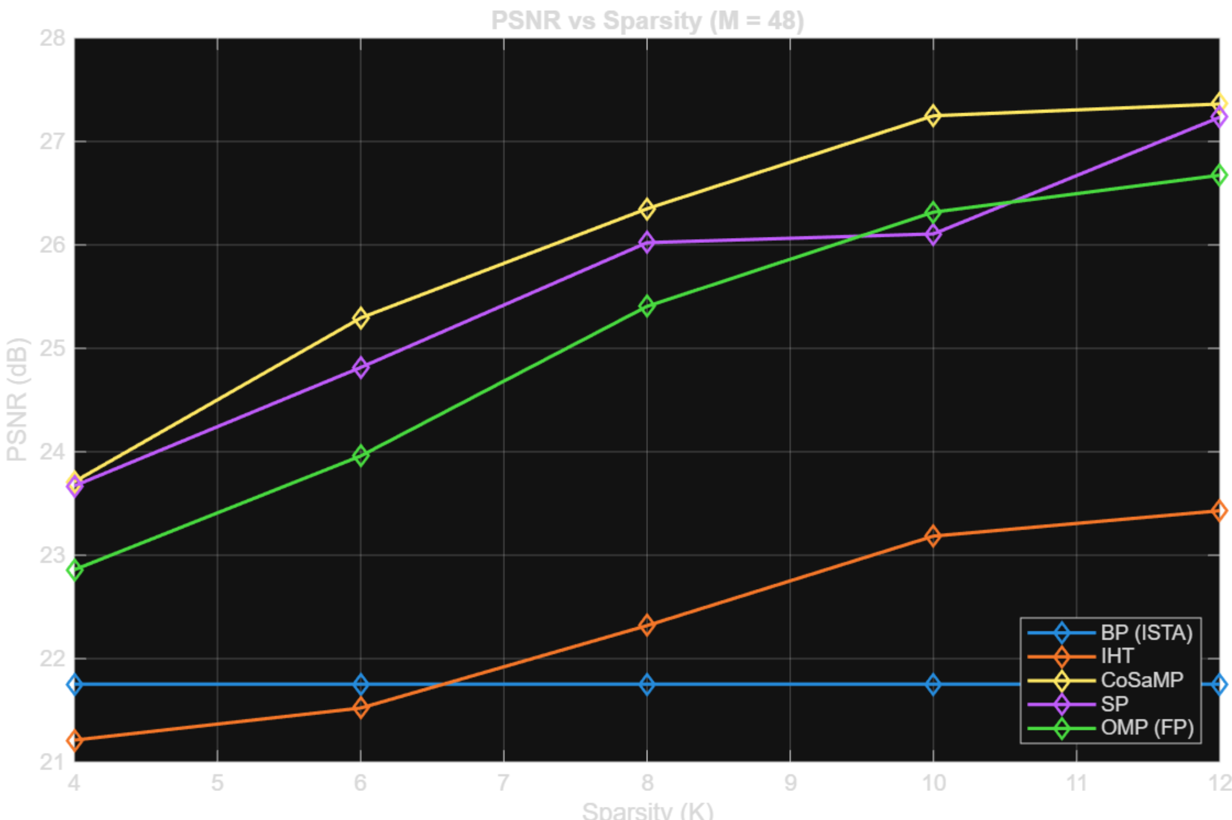

Figure7:PSNRvariationacrossdifferentsparsitylevels(K)

F. ComputationalComplexityAnalysis

Executiontimewasmeasuredagainstvaryingsparsitylevelstoassessreal-timeviability. OMPexhibitsthehighestcomputational overhead, particularly as Kincreases, 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 be-tweenreconstructionfidelity,convergencebehavior,andcomputationaloverhead.Thesefindingsprovideatechnicalroadmapfor 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 perfor-mance is attributed to its multi-atom selection strategy; unlike single-atom methods, CoSaMP identifies and refines a larger portion ofthesignalsupportineachiteration.Thisresultsinfasterconvergencetoalowererrorfloor, makingithighlyeffectiveforthe localized sparsity found in patch-based MRI reconstruction.

SubspacePursuit(SP)performscompetitivelywithCoSaMP,offeringastrongbalancebetweenaccuracy(26.11dBPSNR)andexecutionspeed(0.140s) .SinceSPutilizesasimilarsupportrefinementmechanismbutwithamorestreamlinedpruningstep,

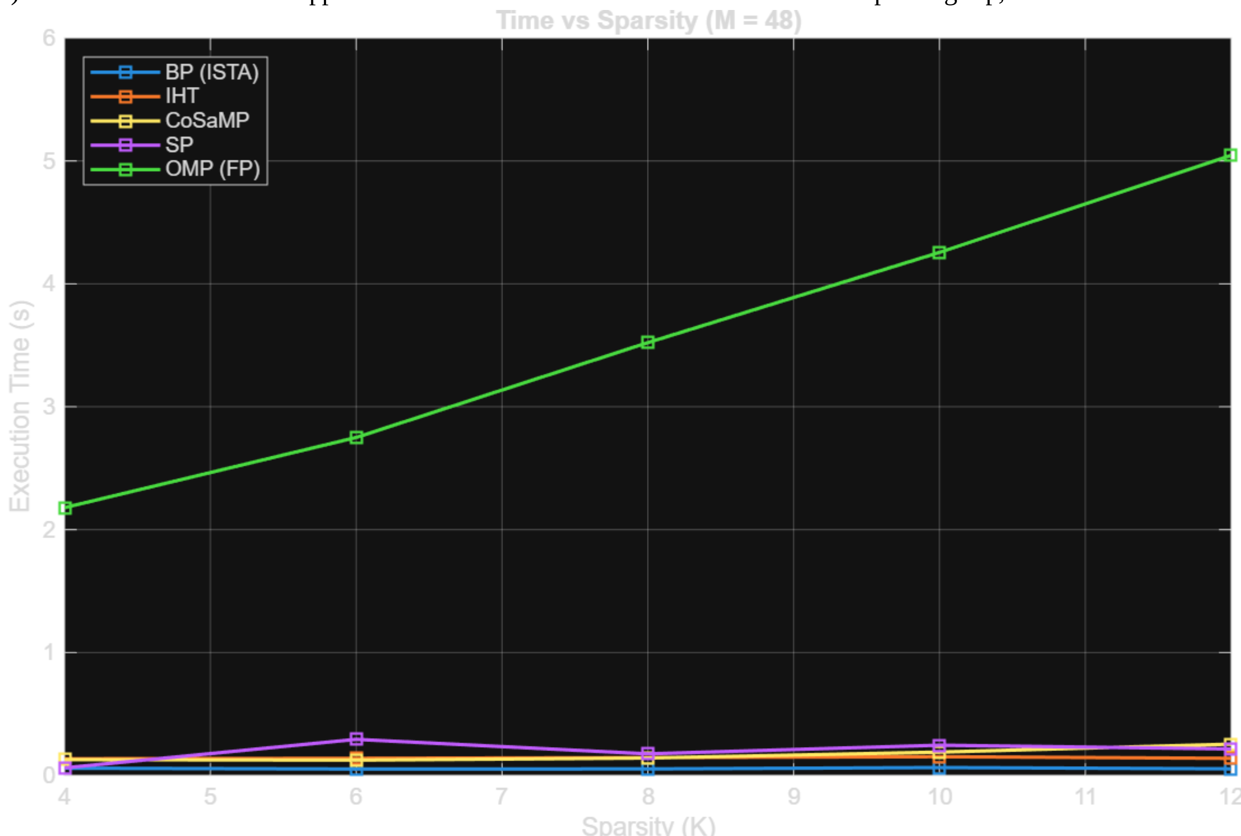

Figure8:Executiontimeanalysisrelativetosparsitylevel(*K*)

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

B. ComputationalComplexityandConstraints

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 makesasoftware-onlyimplementationofOMPlesssuitableforreal-timeimaging;however,itsstructurediterativelogicremains highly favorable forhardware-orientedaccelerationonplatformslikeFPGAs,whereparallelprocessingcanmitigateitssequential 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:

- MaximumFidelity:CoSaMPispreferredduetoitssuperiorstructuralpreservation.
- BalancedReal-timeProcessing:SPoffersthebesttrade-offbetweenPSNRandlatency.
- HardwareRealization:OMP(Fixed-point)isidealforhardware-leveloptimization.
- High-SpeedScreening: BP(ISTA)issuitableforrapid,low-resolutionpreviews.

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

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VII. CONCLUSION AND FUTURE SCOPE

This study presented a comprehensive comparative analysis of five sparse recovery algorithms—Orthogonal Matching Pursuit (OMP),BasisPursuit(BP)usingISTA,IterativeHardThresholding(IHT),CompressiveSamplingMatchingPursuit(CoSaMP), and Subspace Pursuit (SP)—within a unified compressed sensing framework for MRI reconstruction.

TheexperimentalevaluationdemonstratesthatCoSaMPachievesthehighestreconstructionaccuracy,consistentlyoutperform- ing 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 competitivereconstructionquality,itsiterativenatureincurssignificantlyhigherexecutiontime,suggestinganeedfordedicated 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 thecritical trade-off betweenimage fidelity andcomputational latency.For clinicalscenarios requiring high-quality reconstruction, CoSaMP is preferred, whereas SP is more suitable when computational throughput is equally prioritized.

Futureworkcanextendthisframeworkinseveralpromisingdirections:

- 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.
- AdvancedSparsity: Incorporatingadaptiveorlearneddictionaries,suchasK-SVD,tofurtherenhancetherepresentation of complex anatomical structures.
- DeepLearningIntegration: Combiningthephysics-basedCSframeworkwithDeepLearning(e.g., ResidualU-Nets)to improve performance in highly undersampled and noisy scenarios.
- Real-worldValidation: Evaluatingthesystemonactual*k*-spaceundersampledMRIdatafromclinicalscannerstovalidate its practical applicability under varied noise conditions.

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