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Research Article

Image Reconstruction in Compressive Sensing Using The Level 4 Daubechies 4 (db4) Discrete Wavelet Transform And SP, CoSaMP and ALISTA Algorithm

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Abstract

This work proposes an efficient image reconstruction method based on compressive sensing (CS), combining the level-4 Daubechies 4 (db4) discrete wavelet transform with three iterative reconstruction algorithms: Subspace Pursuit (SP), Compressive Sampling Matched Pursuit (CoSaMP), and Analytic Learned Iterative Shrinkage Thresholding Algorithm (ALISTA). The approach follows four key steps: (1) decomposing the original image via the db4 wavelet transform to obtain a sparse representation, (2) performing compressed sampling using a random measurement matrix, (3) reconstructing the sparse signal from the reduced measurements using one of the three optimization algorithms, and (4) recovering the final image through the inverse wavelet transform. Experimental evaluation uses the standard Lena image (200 × 200 pixels) and compares the performance of the three algorithms according to two criteria: reconstruction quality (measured by SSIM) and computational cost (reconstruction time in minutes), across sampling rates ranging from 10% to 60%. Results show that all three methods achieve very similar SSIM scores (up to >0.96 at 60%), indicating high structural fidelity regardless of the algorithm chosen. However, ALISTA stands out significantly for its temporal efficiency, particularly at low sampling rates (<0.1 minute at 10%), while CoSaMP exhibits high and unstable computation times (peaking at ~35 minutes at 40%). SP offers a stable, nearly linear increase in runtime but remains consistently slower than ALISTA. These results demonstrate that ALISTA provides the best trade-off between quality and speed. Thus, this study validates the value of coupling the db4 wavelet basis with modern, learned optimization algorithms for practical CS applications in image processing, where computational efficiency is as critical as reconstruction accuracy.

Keywords

Compressive Sensing, Daubechies, CoSaMP, SP, ALISTA, Wavelet Transform

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1. Introduction

Image reconstruction from a reduced number of measurements is a major challenge in numerous fields such as medical imaging, remote sensing, and embedded systems. Compressive sensing (CS) provides a solution to this problem by exploiting the sparsity of signals in appropriate bases, such as wavelets [1]. This work proposes an image reconstruction method based on the level-4 Daubechies 4 (db4) discrete wavelet transform, combined with three iterative reconstruction algorithms: Subspace Pursuit (SP), Compressive Sampling Matched Pursuit (CoSaMP), and Analytic Learned Iterative Shrinkage Thresholding Algorithm (ALISTA). The aim is to evaluate their performance in terms of reconstruction quality measured by the Structural Similarity Index (SSIM) and computational cost, across sampling rates ranging from 10% to 60%. By comparing these algorithms under identical experimental conditions using the standard Lena image, this study seeks to identify the most efficient approach for practical CS applications where both fidelity and speed are critical [2].

2. Principle of Compressive Sensing Applied to an Image

2.1. Discrete Wavelet Transform Phase

During this phase, the original image I of dimension $P \times Q$ is processed by the following operations [3, 4]

$for\ j \leftarrow 1\ to\ 4$

$$I^{(j)} \leftarrow \left(\downarrow_{2,col}\left(\left(\downarrow_{2,row}\left(I^{(j-1)} *_{row} h\right)\right) *_{col} h\right)\right)$$

$$cH_j \leftarrow \left(\downarrow_{2,col}\left(\left(\downarrow_{2,row}\left(I^{(j-1)} *_{row} h\right)\right) *_{col} g\right)\right)$$

$$cV_j \leftarrow \left(\downarrow_{2,col}\left(\left(\downarrow_{2,row}\left(I^{(j-1)} *_{row} g\right)\right) *_{col} h\right)\right)$$

$$cD_j \leftarrow \left(\downarrow_{2,col}\left(\left(\downarrow_{2,row}\left(I^{(j-1)} *_{row} g\right)\right) *_{col} g\right)\right)$$

$endFor$

$$C \leftarrow \begin{bmatrix} vec\left(I^{(4)}\right), vec(cH_4), vec(cV_4), vec(cD_4), vec(cH_3), \\ vec(cV_3), vec(cD_3), \dots, vec(cD_1) \end{bmatrix}^T$$

$$S \leftarrow \begin{bmatrix} size\left(I^{(4)}\right), size(cH_4), size(cH_3), size(cH_2), \\ size(cH_1), size(I) \end{bmatrix}^T$$

Where:

1) $I^{(j)}$ is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing the image approximation at level j
2) $I^{(0)} = I$
3) h is an 8×1 vector representing the coefficients of the Daubechies 4 wavelet and is defined by the following formula:

$$h = \begin{bmatrix} -0.23040 \\ 0.71480 \\ -0.63090 \\ -0.0280 \\ 0.1870 \\ 0.03080 \\ -0.03290 \\ -0.0106 \end{bmatrix} \quad (1)$$

4) g is an 8×1 vector defined by the following formula:

$$g = \begin{bmatrix} g_0 \\ \vdots \\ g_7 \end{bmatrix} \quad (2)$$

Where:

1) $g_k = (-1)^{k+1} h_{7-k}$
2) $h_7 = 0.23040$
3) $k \in \{0, 1, \dots, 7\}$
4) cH_j is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing horizontal detail coefficients at level j
5) cV_j is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing vertical detail coefficients at level j
6) cD_j is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing the diagonal detail coefficients at level j
7) C is a column vector concatenating all the coefficients
8) S is a 5×2 matrix representing the details of subbands
9) $*_{row}$ denotes the convolution product along the rows
10) $*_{col}$ denotes the convolution product along the columns
11) $\downarrow_{2,row}$ denotes the horizontal sub-sampling operation
12) $\downarrow_{2,col}$ denotes the vertical sub-sampling operation
13) $vec(\,)$ denotes the column-wise vectorization operator
14) $size(\,)$ returns the dimensions of the matrix

2.2. Acquisition or Measurement Phase

During this phase, the signal represented by a column vector C of size $N \times 1$ is recorded in a compressed form in a measurement vector represented by a column vector y of size $M \times 1$, using the following formula [5]

$$y = AC \quad (3)$$

Where:

A is a rectangular matrix of size $M \times N$, known as the measurement matrix $(M < N)$

2.3. Reconstruction Phase

During this phase, the goal is to find the vector C that satisfies Equation (3). Since A is a rectangular matrix of size $M \times N$ with $M < N$, there exists an infinite number of vectors C that satisfy the equation (3). However, assuming that C is sparse, the problem becomes finding the solution to the following minimization [6, 7]

$$\hat{C} = arg\ min\|C\|_1 \text{ subject to } y = AC \quad (4)$$

2.4. Inverse Discrete Wavelet Transform Phase

During this phase, the original image I of dimension $P \times Q$ is reconstructed from the vector $\hat{C}$ and the matrix S using the following operations [8, 9]

$for\ j \leftarrow 4\ to\ 1$

$$I^{(j-1)} \leftarrow (\uparrow_{2,col}\left(\left(\uparrow_{2,row}\left(I^{(j)} *_{col} h\right)\right) *_{col} h\right))$$

$$+(\uparrow_{2,col}\left(\left(\uparrow_{2,row}\left(cH_j *_{col} g\right)\right) *_{col} h\right))$$

$$+(\uparrow_{2,col}\left(\left(\uparrow_{2,row}\left(cV_j *_{col} h\right)\right) *_{col} g\right))$$

$$+(\uparrow_{2,col}\left(\left(\uparrow_{2,row}\left(cD_j *_{col} g\right)\right) *_{col} g\right))$$

$endFor$

$$I_{rec} \leftarrow I^{(0)}$$

Where:
1) $I^{(j)}$ is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing the image approximation at level j
2) h is an 8×1 vector representing the coefficients of the Daubechies 4 wavelet and is defined by the formula (1)
3) g is an 8×1 vector defined by the formula (2)
4) cH_j is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing horizontal detail coefficients at level j
5) cV_j is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing vertical detail coefficients at level j
6) cD_j is a matrix of approximately $\frac{P}{2^j} \times \frac{Q}{2^j}$ dimensions representing the diagonal detail coefficients at level j
7) $\hat{C}$ is a column vector concatenating all the coefficients
8) S is a 5×2 matrix representing the details of subbands
9) $*_{row}$ denotes the convolution product along the rows
10) $*_{col}$ denotes the convolution product along the columns
11) $\uparrow_{2,row}$ denotes the horizontal over-sampling operation
12) $\uparrow_{2,col}$ denotes the vertical over-sampling operation
13) I_{rec} denotes the reconstructed image.

3. Metric for Evaluating Reconstruction Quality

3.1. Mean Squared Error (MSE)

The following provides its definition [10, 11]

$$MSE = \frac{1}{P \times Q} \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} \left(I_{ij} - \hat{I}_{ij}\right)^2 \quad (5)$$

Where:
1) MSE denotes the Mean Squared Error
2) P denotes the number of rows of the image
3) Q denotes the number of colomuns of the image
4) I_{ij} denotes the pixel value at position (i, j) in the original image
5) $\hat{I}_{ij}$ denotes the pixel value at position (i, j) in the reconstructed image

3.2. Peak Signal-to-Noise Ratio (PSNR)

The following provides its definition [12, 13]

$$PSNR = 10\ log_{10}\left(\frac{65025}{MSE}\right) \quad (6)$$

Where:
1) $PSNR$ denotes the Peak Signal-to-Noise Ratio
2) MSE denotes the Mean Squared Error

3.3. Structural Similarity Index (SSIM)

The following provides its definition [14, 15]

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x{}^2 + \mu_y{}^2 + C_1)(\sigma_x{}^2 + \sigma_y{}^2 + C_2)} \quad (7)$$

Where:
1) $SSIM$ denotes the Structural Similarity Index
2) μ_x denotes the mean intensity value of image x
3) μ_y denotes the mean intensity value of image y
4) σ_x denotes the variance of image x
5) σ_y denotes the variance of image y
6) σ_{xy} denotes the covariance between x and y
7) $C_1 = (K_1 L)^2$
8) $C_2 = (K_2 L)^2$
9) L denotes the dynamic range of pixel values
10) $K_1 = 0.01$
11) $K_2 = 0.03$

4. Comparison of the Original and Reconstructed Images

In this section, the following points are specified:

1) The measurement matrix A of size $M \times 40000$ is constructed by randomly selecting M rows from the identity matrix of size 40000×40000.
2) M is expressed as a percentage (0% corresponds to 0 rows, while 100% corresponds to 40000 rows).
3) The resolution of Equation (4) is carried out using the CoSaMP, SP and ALISTA algorithm
4) The Mean Squared Error (MSE) is computed using Equation (5)
5) The Peak Signal-to-Noise Ratio (PSNR) is computed using Equation (6)
6) The Structural Similarity Index (SSIM) is computed using Equation (7)
7) Processed image: Lena excerpted from the original publication: A. K. Jain, Fundamentals of Digital Image Processing, Prentice-Hall, 1989, p. 400. Original source: photograph from Playboy magazine, November 1972. Used here for non-commercial educational and research purposes.

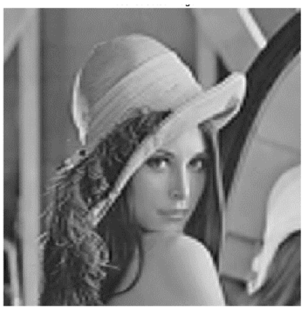
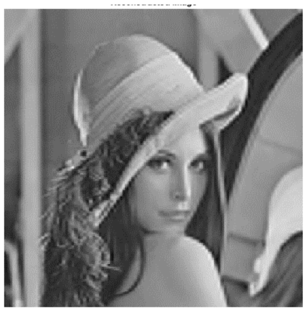
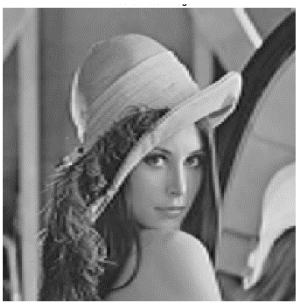
Figure 1. *Processed image.*

1) Image size: 200×200 pixels
2) Programming environment: MATLAB 2023
3) Hardware specifications: CPU: Intel(R) Core i7-9750H, GPU: NVIDIA GetForce RTX 2060, RAM: 16Go

Table 1 presents the images reconstructed by the CoSaMP, SP, and ALISTA algorithms for sampling rates ranging from 10% to 60%.

Table 1. *Images reconstructed.*

M (%)	**CosAmp**	**SP**	**ALISTA**
10	 SSIM: 0.7841 Time (min): 1.55	 SSIM: 0.7841 Time (min): 0.68	 SSIM: 0.7841 Time (min): 0.053
20	 SSIM: 0.8748 Time (min): 5.51	 SSIM: 0.8748 Time (min): 2.49	 SSIM: 0.8746 Time (min): 0.095

M (%)	CosAmp	SP	ALISTA
30	 SSIM: 0.9412 Time (min): 21.6	 SSIM: 0.9412 Time (min): 3.30	 SSIM: 0.9409 Time (min): 0.9184
40	 SSIM: 0.9469 Time (min): 35	 SSIM: 0.9469 Time (min): 4.89	 SSIM: 0.9467 Time (min): 3.01
50	 SSIM: 0.9525 Time (min): 20.45	 SSIM: 0.9525 Time (min): 6.53	 SSIM: 0.9523 Time (min): 5.29
60	 SSIM: 0.9622 Time (min): 27.75	 SSIM: 0.9622 Time (min): 8	 SSIM: 0.9621 Time (min): 8.11

The results obtained are summarized in Table 2.

Table 2. *Summary of the results.*

M(%)	SSIM			Reconstruction Time		
	CoSaMP	**SP**	**ALISTA**	**CoSaMP**	**SP**	**ALISTA**
10%	0.78415	0.78415	0.78412	1.55	0.68149	0.053
20%	0.87482	0.87482	0.8746	5.51	2.49	0.095
30%	0.9412	0.9412	0.9409	21.6	3.30	0.9184
40%	0.9469	0.9469	0.9467	35	4.89	3.01
50%	0.9525	0.9525	0.9523	20.45	6.53	5.29
60%	0.9622	0.9622	0.9621	27.75	8	8.11

5. Conclusion

This work introduces an effective compressed sensing technique for image reconstruction. It leverages the Daubechies 4 (db4) discrete wavelet transform to achieve a sparse representation of images and recovers them from a reduced set of measurements using the CoSaMP, SP, and ALISTA algorithms. The approach was evaluated based on reconstruction accuracy and computational efficiency under different subsampling ratios. Figures 2 and 3 below summarize the obtained results.

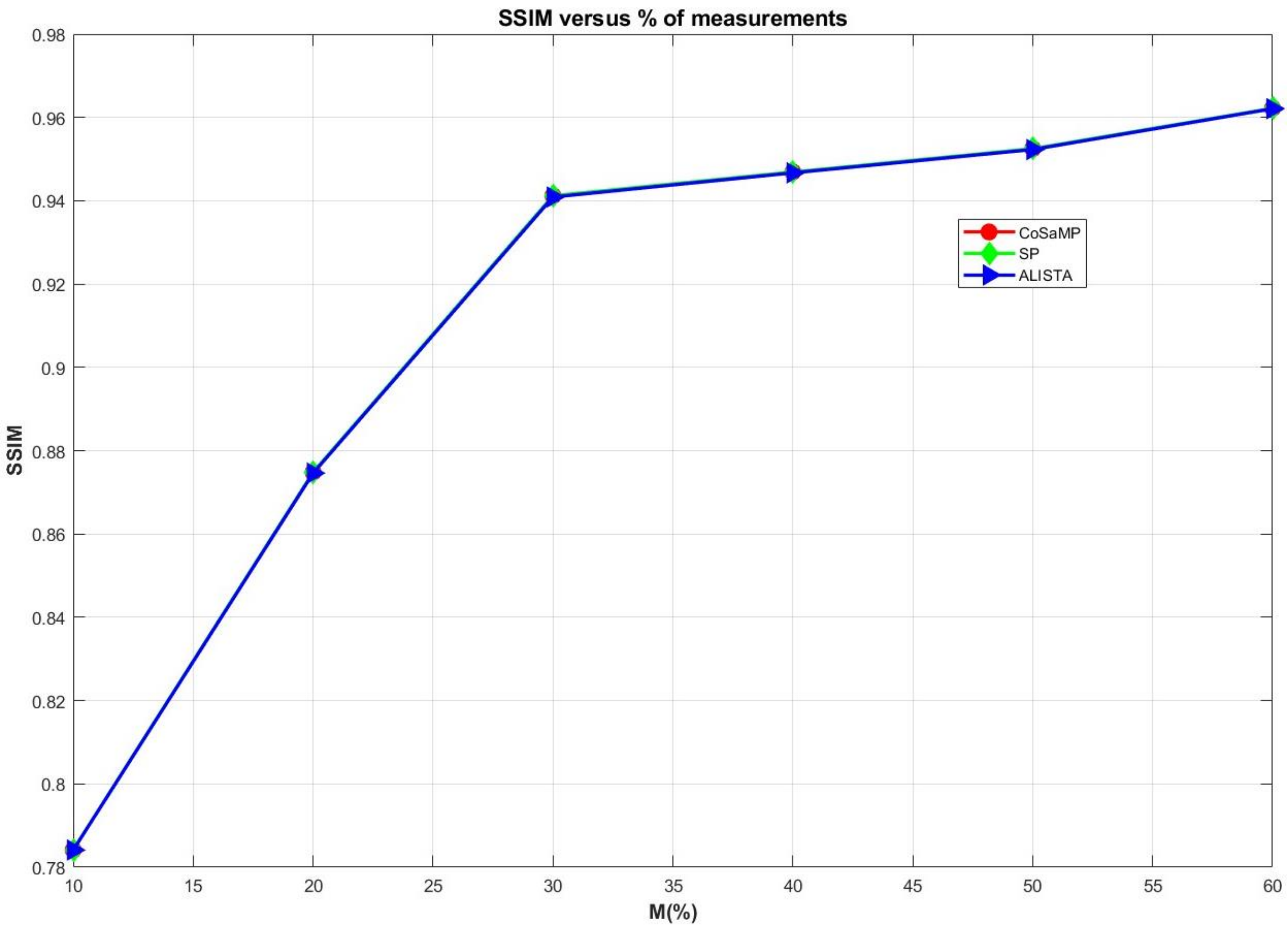


Figure 2. *SSIM vs% of measurements.*

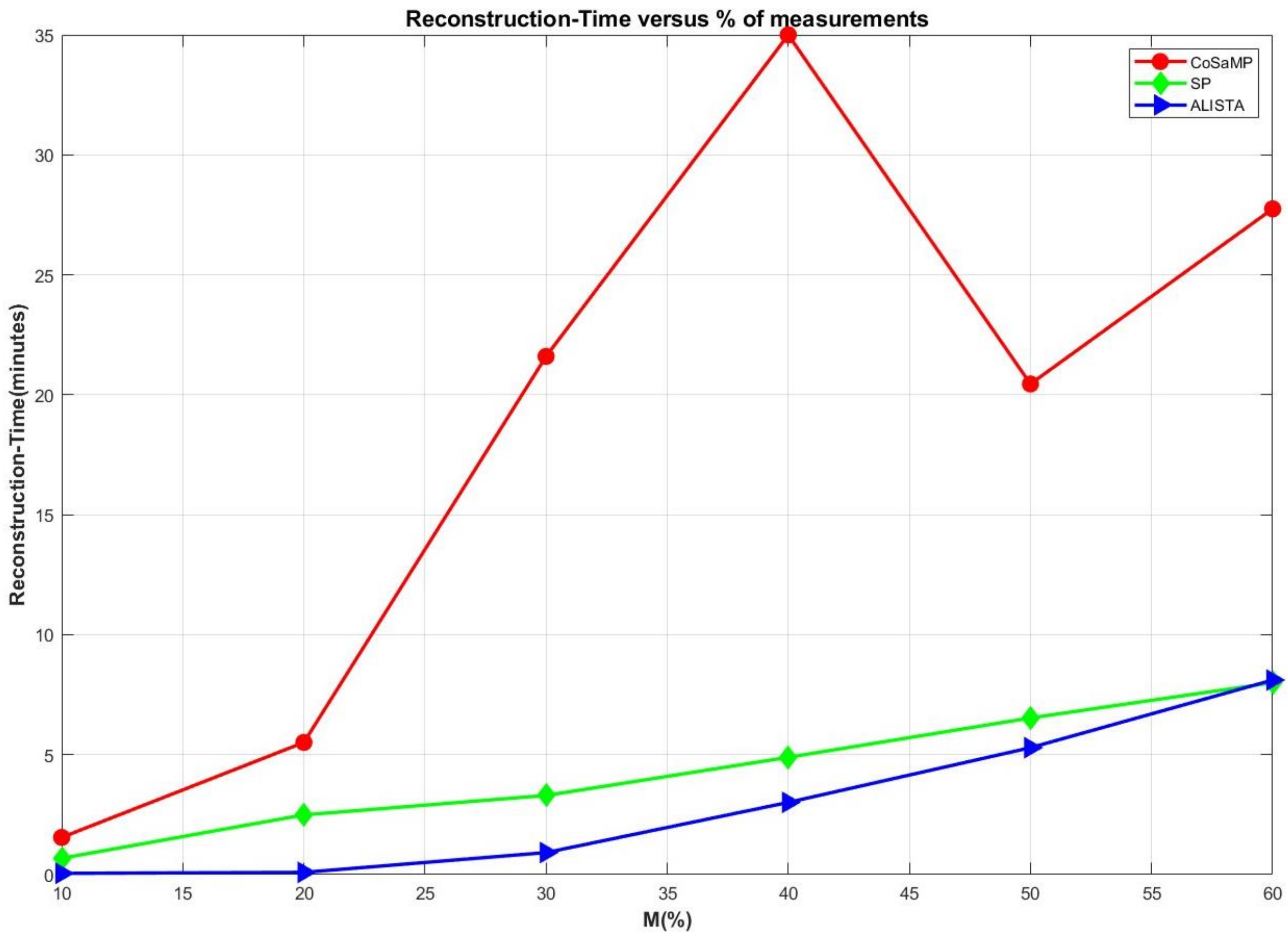


Figure 3. *Reconstruction time vs% of measurements.*

Figure 2 shows the evolution of SSIM as a function of the sampling rate for the CoSaMP, SP, and ALISTA algorithms. Overall, reconstruction quality improves as the percentage of measurements increases, which aligns with the principles of compressive sensing. The three methods exhibit nearly identical performance across the entire range, with curves that are visually indistinguishable suggesting structural fidelity is robustly maintained regardless of the algorithm chosen. At low sampling rates (10–20%), ALISTA and SP slightly outperform CoSaMP, though the differences are marginal (within 0.005 SSIM). All three algorithms converge to near-perfect reconstruction quality (SSIM > 0.96) at 60% sampling. These results indicate that while algorithmic design varies, their perceptual reconstruction outcomes are remarkably consistent, with no single method offering a clear structural advantage under these experimental conditions.

Figure 3 compares the reconstruction time (in minutes) of the three algorithms as a function of the sampling rate. ALISTA demonstrates exceptional computational efficiency: its runtime remains consistently low (under 8 minutes), increasing smoothly from less than 1 minute at 10% to approximately 8 minutes at 60%. SP follows a stable, nearly linear trend, rising gradually from 1 to 8 minutes over the same range. In contrast, CoSaMP exhibits erratic and significantly higher computational cost, peaking sharply at 40% (≈35 minutes) before dropping unexpectedly at 50% (≈20 minutes) and rising again at 60% (≈28 minutes). This non-monotonic behavior suggests CoSaMP's convergence is highly sensitive to measurement density, potentially due to increased iteration counts. These observations underscore that ALISTA not only matches the reconstruction quality of its competitors but also provides superior speed and predictability making it particularly suitable for real-time or resource-constrained applications.

A promising direction for simultaneously improving both the efficiency and sparsity of image representation in compressive sensing would be to replace the conventional DWT used in this work with the Lifting Wavelet Transform (LWT). Unlike the DWT, the LWT enables an in-place implementation without explicit convolution, significantly reducing both memory complexity and computational cost which could further amplify the runtime advantages already demonstrated by ALISTA.

Abbreviations

ALISTA	Analytic Learned Iterative Shrinkage Thresholding Algorithm

CoSaMP	Compressive Sampling Matched Pursuit
CS	Compressive Sensing
LWT	Lifting Wavelet Transform
MSE	Mean Squared Error
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index
SP	Subspace Pursuit

Author Contributions

Sarobidy Nomenjanahary Razafitsalama Fin Luc: Investigation, Methodology

Marie Emile Randrianandrasana: Supervision, Validation

Hariniony Bienvenu Rakotonirina: Conceptualization, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Writing – original draft, Writing – review & editing

Data Availability Statement

The datasets and code used for reconstruction are available upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Research Field

Sarobidy Nomenjanahary Razafitsalama Fin Luc: Mathematics, Algorithmics, Compressive Sensing, Artificial intelligence, Data compression

Marie Emile Randrianandrasana: Telecommunication, Signal processing, Compressive Sensing, Radar, Electromagnetic wave

Hariniony Bienvenu Rakotonirina: Telecommunication, Signal processing, Compressive Sensing, Artificial intelligence, High Amplifier Power Nonlinearity