

Research Article

Image Reconstruction in Compressive Sensing Using Reverse Biorthogonal 6.8 (rbio6.8) and Lifting Wavelet Transforms with SP, CoSaMP, and ALISTA Algorithms

Sarobidy Nomenjanahary Razafitsalama Fin Luc¹ ,
Marie Emile Randrianandrasana² ,
Hariony Bienvenu Rakotonirina^{2,*} 

¹Department of Signal, Doctoral School of Engineering and Innovation Sciences and Techniques, Antananarivo, Madagascar

²Department of Telecommunication, High School Polytechnic of Antsirabe, Antsirabe, Madagascar

Abstract

This paper proposes an efficient image reconstruction for compressive sensing (CS) that combines the Lifting Wavelet Transform (LWT) using Reverse Biorthogonal 6.8 (rbio6.8) wavelets with three reconstruction algorithms: Subspace Pursuit (SP), Compressive Sampling Matching Pursuit (CoSaMP), and the Analytic Learned Iterative Shrinkage Thresholding Algorithm (ALISTA). Unlike the conventional Discrete Wavelet Transform (DWT) which relies on computationally intensive convolution operations the LWT provides a faster sparse representation while preserving the sparsity crucial for CS. The proposed approach leverages a key insight: among the four subbands produced by the LWT namely the approximation (CA) and the detail coefficients (LH, HL, HH) only the latter three are inherently sparse. Therefore, compressive sensing is applied exclusively to these detail subbands, while the CA subband is left uncompressed to retain essential low-frequency information. Experiments were conducted on both a natural test image (Lena) and a medical MRI scan, across image resolutions ranging from 200×200 to 512×512 pixels and sampling rates from 10% to 80%. Performance was assessed using the Structural Similarity Index (SSIM) and reconstruction time. Results consistently demonstrate that ALISTA significantly outperforms SP and CoSaMP in both reconstruction fidelity and computational efficiency. At an 80% sampling rate, ALISTA achieves SSIM values of 0.99314 for Lena and 0.97688 for the MRI image, compared to approximately 0.97402 and 0.93577, respectively, for the other two methods. Furthermore, ALISTA maintains remarkably low reconstruction times under 4 seconds even for 512×512-pixel images. These findings confirm that the ALISTA + LWT/rbio6.8 combination offers the best trade-off between image quality and speed, exhibiting robustness across different image types and scales.

Keywords

Compressive Sensing, Reverse Biorthogonal, ALISTA, Wavelet Transform

*Corresponding author: dao.rakotonirina@gmail.com (Hariony Bienvenu Rakotonirina)

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1. Introduction

Reconstructing images from a limited number of measurements remains a significant challenge in critical domains such as data compression, medical imaging, remote sensing, and embedded vision systems applications where real-time processing and stringent hardware constraints place high demands on computational efficiency. Compressive Sensing (CS) offers a powerful tool to tackle this problem by leveraging the inherent sparsity of signals in appropriate transform domains, particularly wavelet bases [1]. Traditionally, the Discrete Wavelet Transform (DWT) has been employed to achieve such sparse representations; however, its standard implementation using convolutional filter banks entails high computational complexity and latency, which severely limits its suitability for fast reconstruction scenarios. To address these drawbacks, this work employs the Lifting Wavelet Transform (LWT) a reformulation of the DWT that enables a faster computation while preserving the sparsity characteristics crucial for CS. We propose an image reconstruction method based on a level-1 LWT using Reverse Biorthogonal 6.8 (rbio6.8) wavelets, integrated with three iterative reconstruction algorithms: Subspace Pursuit (SP), Compressive Sampling Matched Pursuit (CoSaMP), and the Analytic Learned Iterative Shrinkage Thresholding Algorithm (ALISTA). Our goal is to evaluate and compare their performance in terms of reconstruction quality measured by the Structural Similarity Index (SSIM) and computational efficiency across sampling rates from 10% to 80%. Using both the standard Lena test image and a Magnetic Resonance Imaging (MRI) scan under consistent experimental conditions, this study seeks to identify the most effective algorithmic combination for practical compressive sensing applications, where both reconstruction speed and fidelity are simultaneously paramount [2].

2. Principle of Compressive Sensing Applied to an Image

2.1. Lifting Wavelet Transform Phase

The Lifting Wavelet Transform (LWT) is an efficient reformulation of the Discrete Wavelet Transform (DWT), designed to reduce computational complexity while preserving the sparsity properties essential for sparse signal representation.

The Lifting Wavelet Transform (LWT) is based on a three-step decomposition process:

- 1) *Split*: The input signal is divided into two subsequences typically even and odd indexed samples.
- 2) *Predict*: Odd samples are predicted from the even ones using a prediction operator, the difference between the prediction and the actual odd samples yields the detail coefficients (high-frequency components).

- 3) *Update*: The even samples are updated using the detail coefficients to produce the approximation coefficients (low-frequency components), while preserving certain global properties of the original signal (such as its average).

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

Initialization

$$M \leftarrow \text{number of rows of } I$$

$$N \leftarrow \text{number of columns of } I$$

$$p \leftarrow [0.2735, 0.2735, -0.2865, -0.2865, \\ 0.0998, -0.3438, -0.3438, 0.0998]$$

$$u \leftarrow [-2.6590, 0.9972, 3.8778, -3.2687, \\ -0.5486, 2.9418]$$

Horizontal decomposition (row by row)

For each row $i = 0$ to -1 :

Splitting

$$s[k] \leftarrow I[i, 2k] \quad \forall k = 0, \dots, K_s - 1$$

where $K_s \leftarrow \lfloor N/2 \rfloor$

$$d[k] \leftarrow I[i, 2k + 1] \quad \forall k = 0, \dots, K_d - 1$$

where $K_d \leftarrow \lfloor N/2 \rfloor$

Symmetric padding of s

$$\tilde{s} \leftarrow \text{sym_pad}(s, \text{left} = 4, \text{right} = 4)$$

Predict step

$$\text{pred}[k] \leftarrow \sum_{m=0}^7 p[m] \cdot \tilde{s}[k + m - 3] \quad \forall k = 0, \dots, K_d - 1$$

$$d[k] \leftarrow d[k] - \text{pred}[k]$$

Symmetric padding of d

$$\tilde{d} \leftarrow \text{sym_pad}(d, \text{left} = 4, \text{right} = 4)$$

Update step

$$\text{updt}[k] \leftarrow \sum_{m=0}^7 u[m] \cdot \tilde{d}[k + m - 3] \quad \forall k = 0, \dots, K_d - 1$$

$$s[k] \leftarrow s[k] + \text{updt}[k]$$

Horizontal recombination

$$H[i, 0: K_s - 1] \leftarrow s$$

$$H[i, K_s:K_s + K_d - 1] \leftarrow d$$

Vertical decomposition (column by column of H)

Temporarily transpose: H^T

For each column $j = 0$ to $(K_s + K_d) - 1$:

Splitting

$$s[k] \leftarrow H^T[2k, j] \quad \forall k = 0, \dots, L_s - 1$$

where $L_s \leftarrow \lfloor M/2 \rfloor$

$$d[k] \leftarrow H^T[2k + 1, j] \quad \forall k = 0, \dots, L_d - 1$$

where $L_d \leftarrow \lfloor M/2 \rfloor$

Symmetric padding of $s \rightarrow \tilde{s}$

Predict

$$pred[k] \leftarrow (p * \tilde{s})[k + 3]$$

$$d[k] \leftarrow d[k] - pred[k]$$

Symmetric padding of $d \rightarrow \tilde{d}$

Update

$$updt[k] \leftarrow (u * \tilde{d})[k + 3]$$

$$s[k] \leftarrow s[k] + updt[k]$$

Vertical recombination

$$V^T[0:L_s - 1, j] \leftarrow s$$

$$V^T[L_s:L_s + L_d - 1, j] \leftarrow d$$

Re-transpose: $T \leftarrow V$

Subband extraction

$$cA \leftarrow T[0:L_s - 1, 0:K_s - 1]$$

$$lh \leftarrow T[0:L_s - 1, K_s:K_s + K_d - 1]$$

$$hl \leftarrow T[L_s:L_s + L_d - 1, 0:K_s - 1]$$

$$hh \leftarrow T[L_s:L_s + L_s - 1, K_s:K_s + K_s - 1]$$

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].

$$y = AC \quad (1)$$

Where:

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

measurement matrix ($M < N$)

$$C = lh, hl, hh$$

2.3. Reconstruction Phase

During this phase, the goal is to find the vector C that satisfies Equation (1). 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].

$$\hat{C} = \arg \min \|C\|_0 \text{ subject to } y = AC \quad (2)$$

2.4. Inverse Lifting Wavelet Transform Phase

The principle of the inverse Lifting Wavelet Transform (inverse LWT) is to reconstruct the original signal from the approximation and detail coefficients by applying the LWT steps in reverse order and with inverse operations:

- 1) *Undo Update*: The approximation coefficients are used to recover the original even-indexed samples by reversing the update operation.
- 2) *Undo Predict*: The detail coefficients are added back to the reconstructed even samples to retrieve the original odd-indexed samples, thereby inverting the predict operation.
- 3) *Merge*: The even and odd samples are interleaved to fully reconstruct the original signal.

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].

Initialization

$$L_s \leftarrow \text{number of rows of } cA$$

$$K_s \leftarrow \text{number of columns of } cA$$

$$L_d \leftarrow \text{number of rows of } hl$$

$$K_d \leftarrow \text{number of columns of } lh$$

$$T \leftarrow \begin{bmatrix} cA & lh \\ hl & hh \end{bmatrix}$$

$$p \leftarrow [0.2735, 0.2735, -0.2865, -0.2865,$$

$$0.0998, -0.3438, -0.3438, 0.0998]$$

$$u \leftarrow [-2.6590, 0.9972, 3.8778, -3.2687, \\ -0.5486, 2.9418]$$

- 1) Vertical reconstruction (column by column of T)

Temporarily transpose: T^T

For each column $j = 0$ to $(K_s + K_d) - 1$:

Split subbands

$$s[k] \leftarrow T^T[k, j] \forall k = 0, \dots, L_s - 1$$

$$d[k] \leftarrow T^T[L_s + k, j] \forall k = 0, \dots, L_d - 1$$

Symmetric padding of d

$$\tilde{d} \leftarrow \text{sym_pad}(d, \text{left} = 4, \text{right} = 4)$$

Undo Update step

$$\text{updt}[k] \leftarrow \sum_{m=0}^7 u[m] \cdot \tilde{d}[k + m - 3] \forall k = 0, \dots, L_s - 1$$

$$s[k] \leftarrow s[k] - \text{updt}[k]$$

Symmetric padding of s

$$\tilde{s} \leftarrow \text{sym_pad}(s, \text{left} = 4, \text{right} = 4)$$

Undo Predict step

$$\text{pred}[k] \leftarrow \sum_{m=0}^7 p[m] \cdot \tilde{s}[k + m - 3] \forall k = 0, \dots, L_d - 1$$

$$d[k] \leftarrow d[k] + \text{pred}[k]$$

Merge (interleave) to reconstruct column

Initialize $\text{col_rec} \in \mathbb{R}^{L_s+L_d}$

$$\text{col_rec}[2k] \leftarrow s[k] \forall k = 0, \dots, L_s - 1$$

$$\text{col_rec}[2k + 1] \leftarrow d[k] \forall k = 0, \dots, L_d - 1$$

$$V^T[0:L_s + L_d - 1, j] \leftarrow \text{col_rec}$$

Re-transpose: $H_{rec} \leftarrow V$

2) Horizontal reconstruction (row by row of H_{rec})

For each row $i = 0$ to $(L_s + L_d) - 1$:

Split subbands

$$s[k] \leftarrow H_{rec}[i, k] \forall k = 0, \dots, K_s - 1$$

$$d[k] \leftarrow H_{rec}[i, K_s + k] \forall k = 0, \dots, K_d - 1$$

Symmetric padding of d

$$\tilde{d} \leftarrow \text{sym_pad}(s, \text{left} = 4, \text{right} = 4)$$

Undo Update step

$$\text{updt}[k] \leftarrow \sum_{m=0}^7 u[m] \cdot \tilde{d}[k + m - 3] \forall k = 0, \dots, K_s - 1$$

$$s[k] \leftarrow s[k] - \text{updt}[k]$$

Symmetric padding of s

$$\tilde{s} \leftarrow \text{sym_pad}(s, \text{left} = 4, \text{right} = 4)$$

Undo Predict step

$$\text{pred}[k] \leftarrow \sum_{m=0}^7 p[m] \cdot \tilde{s}[k + m - 3] \forall k = 0, \dots, K_d - 1$$

$$d[k] \leftarrow d[k] + \text{pred}[k]$$

Merge (interleave) to reconstruct row

Initialize $\text{row_rec} \in \mathbb{R}^{K_s+K_d}$

$$\text{row_rec}[2k] \leftarrow s[k] \forall k = 0, \dots, K_s - 1$$

$$\text{row_rec}[2k + 1] \leftarrow d[k] \forall k = 0, \dots, K_d - 1$$

$$\hat{I}[0:L_s + L_d - 1, j] \leftarrow \text{row_rec}$$

3. Metric for Evaluating Reconstruction Quality

3.1. Mean Squared Error (MSE)

The following provides its definition [10, 11].

$$MSE = \frac{1}{P \times Q} \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} (I_{ij} - \hat{I}_{ij})^2 \quad (3)$$

Where:

MSE denotes the Mean Squared Error

P denotes the number of rows of the image

Q denotes the number of columns of the image

I_{ij} denotes the pixel value at position (i, j) in the original image

$\hat{I}_{ij}$ 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].

$$PSNR = 10 \log_{10} \left(\frac{65025}{MSE} \right) \quad (4)$$

Where:

$PSNR$ denotes the Peak Signal-to-Noise Ratio

MSE denotes the Mean Squared Error

3.3. Structural Similarity Index (SSIM)

The following provides its definition [14, 15].

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (5)$$

Where:

$SSIM$ denotes the Structural Similarity Index

μ_x denotes the mean intensity value of image x

μ_y denotes the mean intensity value of image y
 σ_x denotes the variance of image x
 σ_y denotes the variance of image y
 σ_{xy} denotes the covariance between x and y

$$C_1 = (K_1 L)^2$$

$$C_2 = (K_2 L)^2$$

L denotes the dynamic range of pixel values

$$K_1 = 0.01$$

$$K_2 = 0.03$$

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 . It is a Gaussian measurement matrix. We selected it for its excellent statistical properties (RIP ou Restricted Isometry Property, incoherence), which are essential in compressive sensing.
- 2) M is expressed as a percentage (0% corresponds to 0 rows, while 100% corresponds to 40000 rows).
- 3) The resolution of Equation (2) is carried out using the Subspace Pursuit (SP) algorithm

- 4) The Mean Squared Error (MSE) is computed using Equation (3)
- 5) The Peak Signal-to-Noise Ratio (PSNR) is computed using Equation (4)
- 6) The Structural Similarity Index (SSIM) is computed using Equation (5)
- 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 (Lena).

We also processed a free medical MRI image available on iStockphoto.com, which offers royalty-free visual content. This image is available at this link

<https://www.istockphoto.com/fr/photo/cerveau-gm182682597-12321941?searchscope=image%2Cfilm>

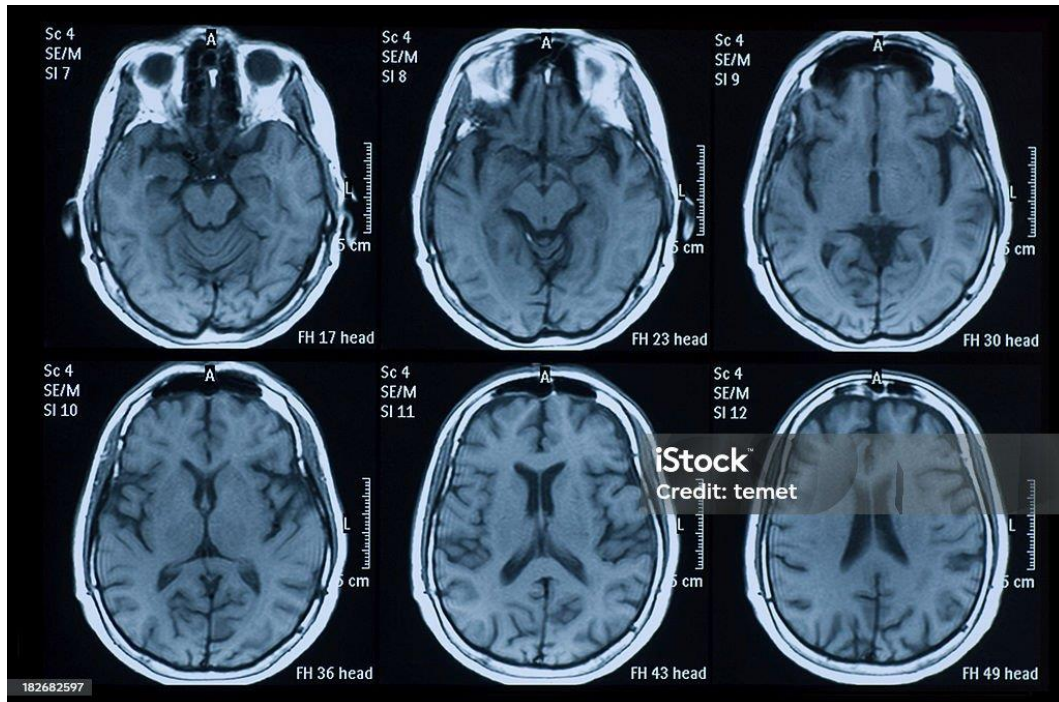


Figure 2. Processed image (MRI).

Image size: 200×200 pixels, 256×256pixels, 300×300pixels, 400×400pixels and 512×512pixels

Programming environment: MATLAB 2023

Hardware specifications: CPU: Intel(R) Core i7-9750H, GPU: NVIDIA GeForce RTX 2060, RAM: 16Go

There are two experimental scenarios:

Scenario 1: Performance evaluation of the proposed algorithms across different sampling rates and on two distinct images. The performance metrics are the Structural Similarity Index (SSIM) and image reconstruction time. Note that the image size was fixed at 200 × 200 pixels.

Scenario 2: Performance evaluation of the proposed algorithms on images of varying sizes (256 × 256, 300 × 300, 400 × 400, and 512 × 512 pixels), with the sampling rate fixed at 30%. This value was chosen to assess whether our algorithms can still successfully reconstruct the image even from a relatively small number of measurements. The experiment is again conducted on two different images, using SSIM and reconstruction time as performance criteria.

Table 1 presents the images reconstructed by the CoSaMP, SP, and ALISTA algorithms for sampling rates ranging from 10% to 80%.

Table 1. Images reconstructed for lena image (scenario 1).

M(%)	CoSaMP	SP	ALISTA
10	 SSIM=0.93999 Time(minute)=0.022624	 SSIM=0.93999 Time(minute)=0.015875	 SSIM=0.93999 Time(minute)=0.010961
20	 SSIM=0.94459 Time(minute)=0.033174	 SSIM=0.94459 Time(minute)=0.052732	 SSIM=0.94494 Time(minute)=0.018556
30	 SSIM=0.95601 Time(minute)=0.10559	 SSIM=0.95601 Time(minute)=0.090777	 SSIM=0.95791 Time(minute)=0.027402
40	 SSIM=0.96378 Time(minute)=0.34576	 SSIM=0.96378 Time(minute)=0.13808	 SSIM=0.96946 Time(minute)=0.033003

M(%)	CoSaMP	SP	ALISTA
50	 SSIM=0.96753 Time(minute)=0.32891	 SSIM=0.96753 Time(minute)=0.067427	 SSIM=0.97675 Time(minute)=0.039898
60	 SSIM=0.96949 Time(minute)=0.13119	 SSIM=0.96949 Time(minute)=0.07656	 SSIM=0.98172 Time(minute)=0.041073
70	 SSIM=0.97077 Time(minute)=0.14758	 SSIM=0.97077 Time(minute)=0.089394	 SSIM=0.98581 Time(minute)=0.052128
80	 SSIM=0.97402 Time(minute)=0.17383	 SSIM=0.97402 Time(minute)=0.10299	 SSIM=0.99314 Time(minute)=0.056272

The results obtained are summarized in [Table 2](#).

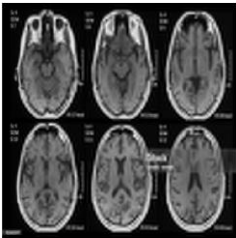
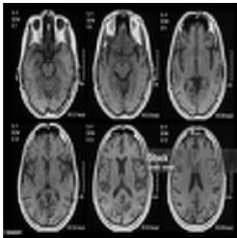
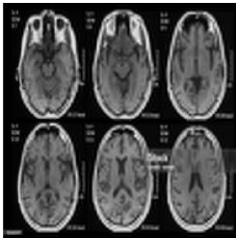
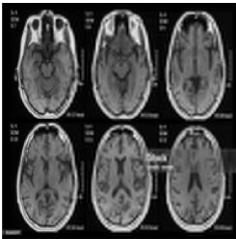
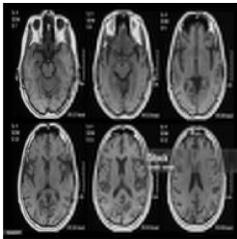
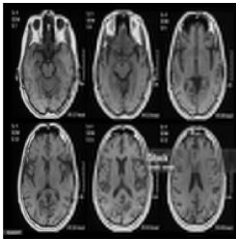
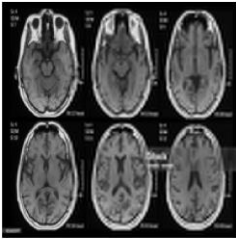
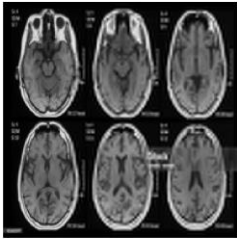
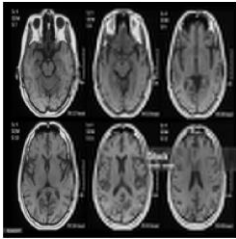
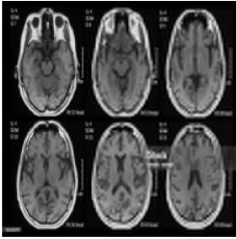
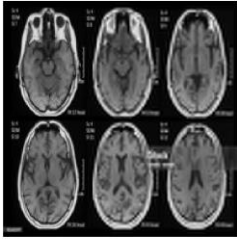
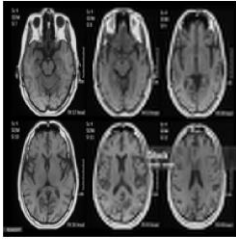
Table 2. Summary of the results for Lena image(scenario 1).

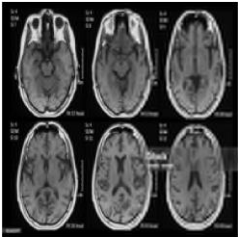
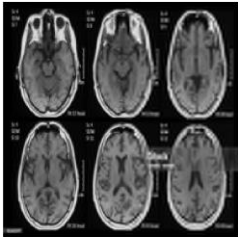
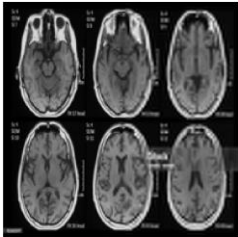
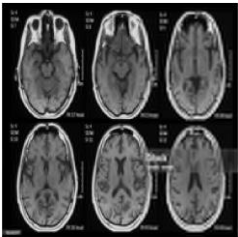
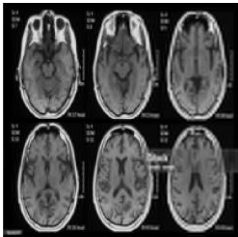
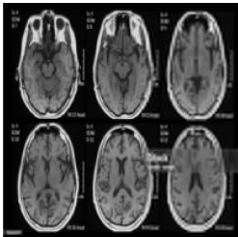
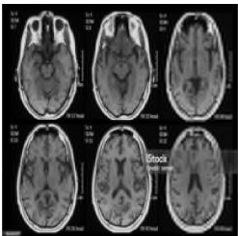
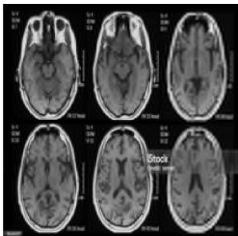
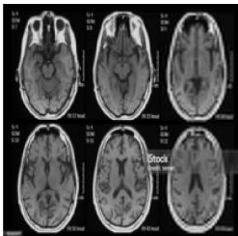
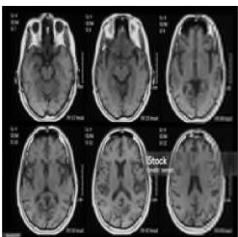
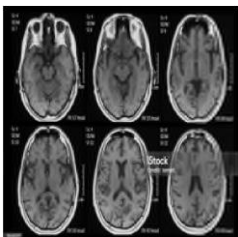
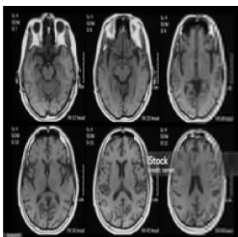
M(%)	SSIM			Reconstruction Time (minute)		
	CoSaMP	SP	ALISTA	CoSaMP	SP	ALISTA
10%	0.93999	0.93999	0.93999	0.022624	0.015875	0.010961
20%	0.94459	0.94459	0.94494	0.033174	0.052732	0.018556
30%	0.95601	0.95601	0.95791	0.10559	0.090777	0.027402
40%	0.96378	0.96378	0.96946	0.34576	0.13808	0.033003
50%	0.96753	0.96753	0.97675	0.32891	0.067427	0.039898

$M(\%)$	SSIM			Reconstruction Time (minute)		
	CoSaMP	SP	ALISTA	CoSaMP	SP	ALISTA
60%	0.96949	0.96949	0.98172	0.13119	0.07656	0.041073
70%	0.97077	0.97077	0.98581	0.14758	0.089394	0.052128
80%	0.97402	0.97402	0.99314	0.17383	0.10299	0.056272

Table 3 presents the images reconstructed by the CoSaMP, SP, and ALISTA algorithms for sampling rates ranging from 10% to 80% for MRI image.

Table 3. Images reconstructed for MRI Image (scenario 1).

$M(\%)$	CoSaMP	SP	ALISTA
10	 SSIM=0.88717 Time(minute)=0.010667	 SSIM=0.88717 Time(minute)=0.011889	 SSIM=0.88717 Time(minute)=0.003718
20	 SSIM=0.89801 Time(minute)=0.013981	 SSIM=0.89801 Time(minute)=0.013268	 SSIM=0.89876 Time(minute)=0.0036091
30	 SSIM=0.9058 Time(minute)=0.016224	 SSIM=0.9058 Time(minute)=0.01476	 SSIM=0.90984 Time(minute)=0.0038079
40	 SSIM=0.91403 Time(minute)=0.017787	 SSIM=0.91403 Time(minute)=0.016395	 SSIM=0.92278 Time(minute)=0.003729

M(%)	CoSaMP	SP	ALISTA
50	 SSIM=0.9219 Time(minute)=0.019835	 SSIM=0.9219 Time(minute)=0.019875	 SSIM=0.93824 Time(minute)=0.0038261
60	 SSIM=0.92485 Time(minute)=0.020832	 SSIM=0.92485 Time(minute)=0.020855	 SSIM=0.94909 Time(minute)=0.0036811
70	 SSIM=0.93143 Time(minute)=0.024139	 SSIM=0.93143 Time(minute)=0.020519	 SSIM=0.96349 Time(minute)=0.0035767
80	 SSIM=0.93577 Time(minute)=0.027414	 SSIM=0.93577 Time(minute)=0.023844	 SSIM=0.97688 Time(minute)=0.0036968

The results obtained are summarized in [Table 4](#).

Table 4. Summary of the results for MRI Image (scenario 1).

M(%)	SSIM			Reconstruction Time (minute)		
	CoSaMP	SP	ALISTA	CoSaMP	SP	ALISTA
10%	0.88717	0.88717	0.88717	0.010667	0.011889	0.003718
20%	0.89801	0.89801	0.89876	0.013981	0.013268	0.0036091
30%	0.9058	0.9058	0.90984	0.016224	0.01476	0.0038079
40%	0.91403	0.91403	0.92278	0.017787	0.016395	0.0033729

$M(\%)$	SSIM			Reconstruction Time (minute)		
	CoSaMP	SP	ALISTA	CoSaMP	SP	ALISTA
50%	0.9219	0.9219	0.93824	0.019835	0.019875	0.0038261
60%	0.92485	0.92485	0.94909	0.020832	0.020855	0.0036811
70%	0.93143	0.93143	0.96349	0.024139	0.020519	0.0035767
80%	0.93577	0.93577	0.97688	0.027414	0.023844	0.0036968

In order to interpret the results, we decided to present these values in the form of curves (Figures 3 and 4).

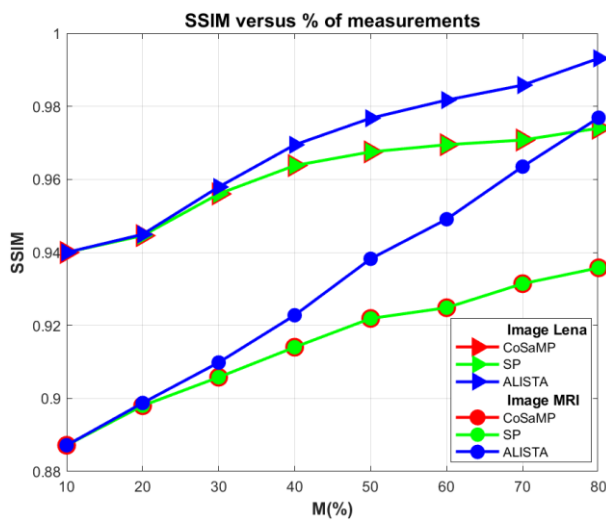


Figure 3. SSIM vs% of measurements.

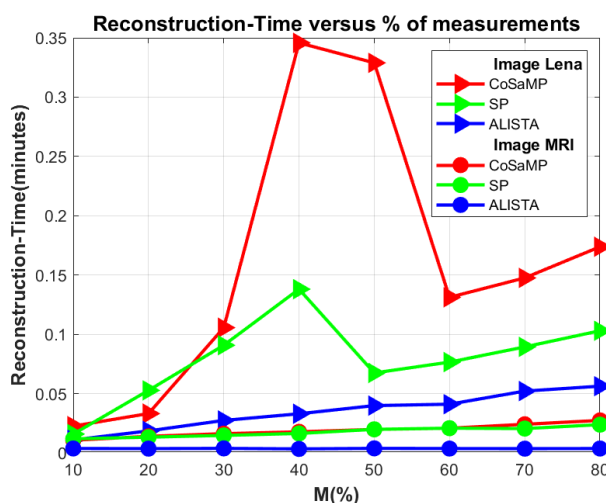


Figure 4. Reconstruction time vs% of measurements.

Figure 3 compares the performance of three image reconstruction algorithms in terms of image quality, measured by SSIM. Results are presented for two types of images. For all algorithms and all images, SSIM increases with the percentage of measurements which is logical: the more information available, the better the reconstruction. It is also evident that ALISTA is the most performant algorithm across both image types (0.97 for MRI image and 0.99 for Lena). Indeed, unlike CoSaMP and SP, which are greedy algorithms, ALISTA is based on learning approach; it learns optimal parameters from training data, enabling it to adapt to the specific characteristics of images, which explains its superior performance.

Figure 4 shows the reconstruction time (in minutes) as a function of the percentage of measurements used for three algorithms CoSaMP, SP, and ALISTA applied to two types of images: Lena (natural) and MRI (medical). It can be observed that ALISTA exhibits an extremely low and nearly constant reconstruction time less than 0.05 minutes (i.e., 3 seconds) regardless of the measurement rate or image type, making it the most efficient algorithm in terms of speed. In contrast, CoSaMP and SP show significantly higher reconstruction times that strongly depend on the number of measurements. This difference stems from the fundamentally distinct nature of these algorithms: ALISTA is based on a learning-based approach, whereas CoSaMP and SP are iterative greedy algorithms that require iterative selection and update steps whose convergence may vary depending on measurement density and image structure. Thus, ALISTA offers a dual advantage: high reconstruction quality (as previously demonstrated) and minimal computational cost, making it particularly well-suited for real-time or embedded applications where speed is critical.

For the second scenario, Tables 5 and 6 show the evaluation of the algorithms across different image sizes.

Table 5. Summary of the results for Lena Image (scenario 2).

Image size	SSIM			Reconstruction Time (minute)		
	CoSaMP	SP	ALISTA	CoSaMP	SP	ALISTA
256×256px	0.95623	0.95623	0.96027	0.029358	0.028787	0.0067035
300×300px	0.95559	0.95559	0.96137	0.04745	0.043778	0.010955
400×400px	0.95743	0.95743	0.96598	0.10937	0.12368	0.029126
512×512px	0.96	0.96	0.97	0.26509	0.24939	0.070043

Table 6. Summary of the results for Lena Image (scenario 2).

Image size	SSIM			Reconstruction Time (minute)		
	CoSaMP	SP	ALISTA	CoSaMP	SP	ALISTA
256×256px	0.91787	0.91787	0.9244	0.034533	0.028321	0.0066681
300×300px	0.93078	0.93078	0.93801	0.052192	0.045931	0.011032
400×400px	0.94162	0.94162	0.9501	0.11257	0.11058	0.033382
512×512px	0.95323	0.95323	0.9609	0.25178	0.27266	0.071477

In order to interpret the results, we decided to present these values in the form of curves (Figures 5 and 6).

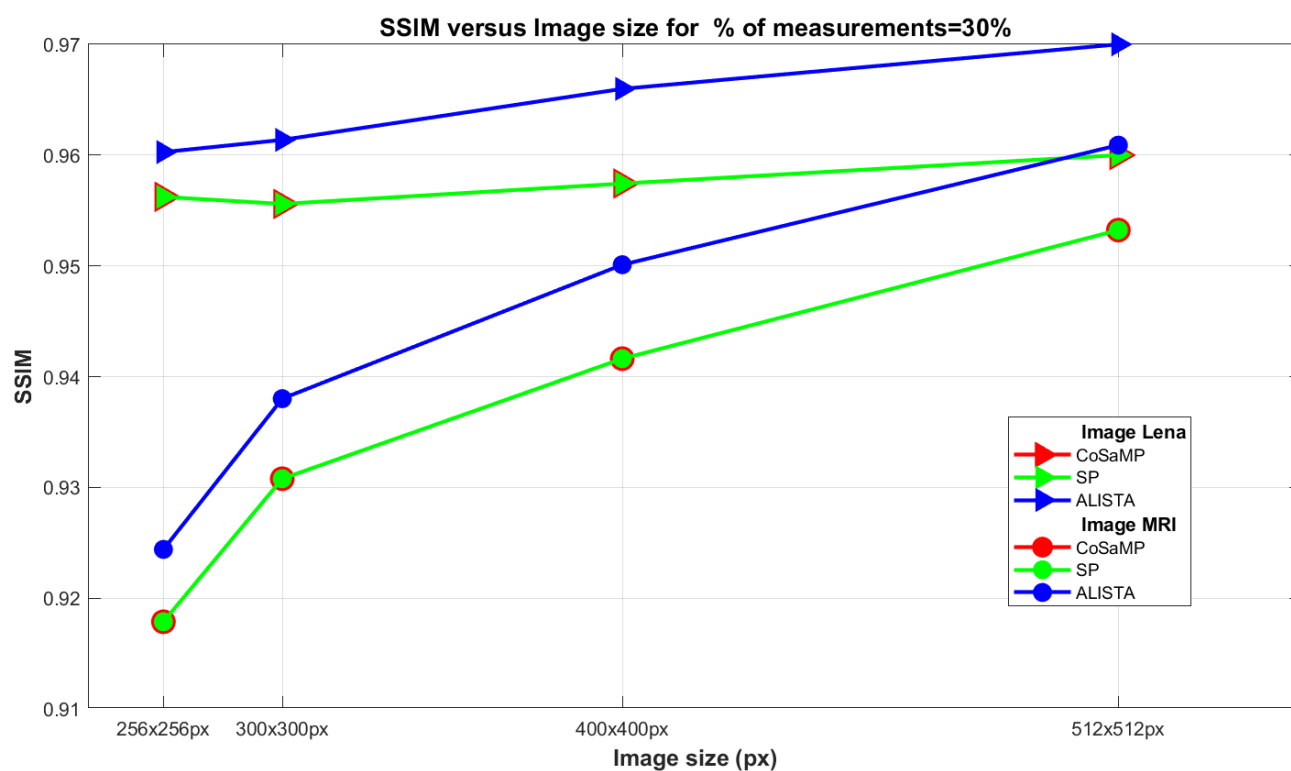
**Figure 5.** SSIM vs Image size for % of measurements=30%.

Figure 5 illustrates the reconstruction quality (SSIM) as a function of image size (in pixels), for a fixed measurement rate of 30%. It can be observed that, for all algorithms and all image types, SSIM increases with image size. Indeed, algorithms benefit from the greater structural richness and higher resolution offered by larger images. ALISTA clearly outperforms the other two algorithms across different resolutions and image types, achieving an SSIM > 0.97 for Lena and $>$

0.96 for MRI at 512×512 px. In contrast, CoSaMP and SP exhibit lower performance and are more sensitive to image content. Unlike classical greedy algorithms such as CoSaMP and SP, which rely heavily on iterative optimization, ALISTA uses predefined parameters (weight matrices and thresholds) learned from diverse image datasets, enabling robust reconstruction even on large-scale images.

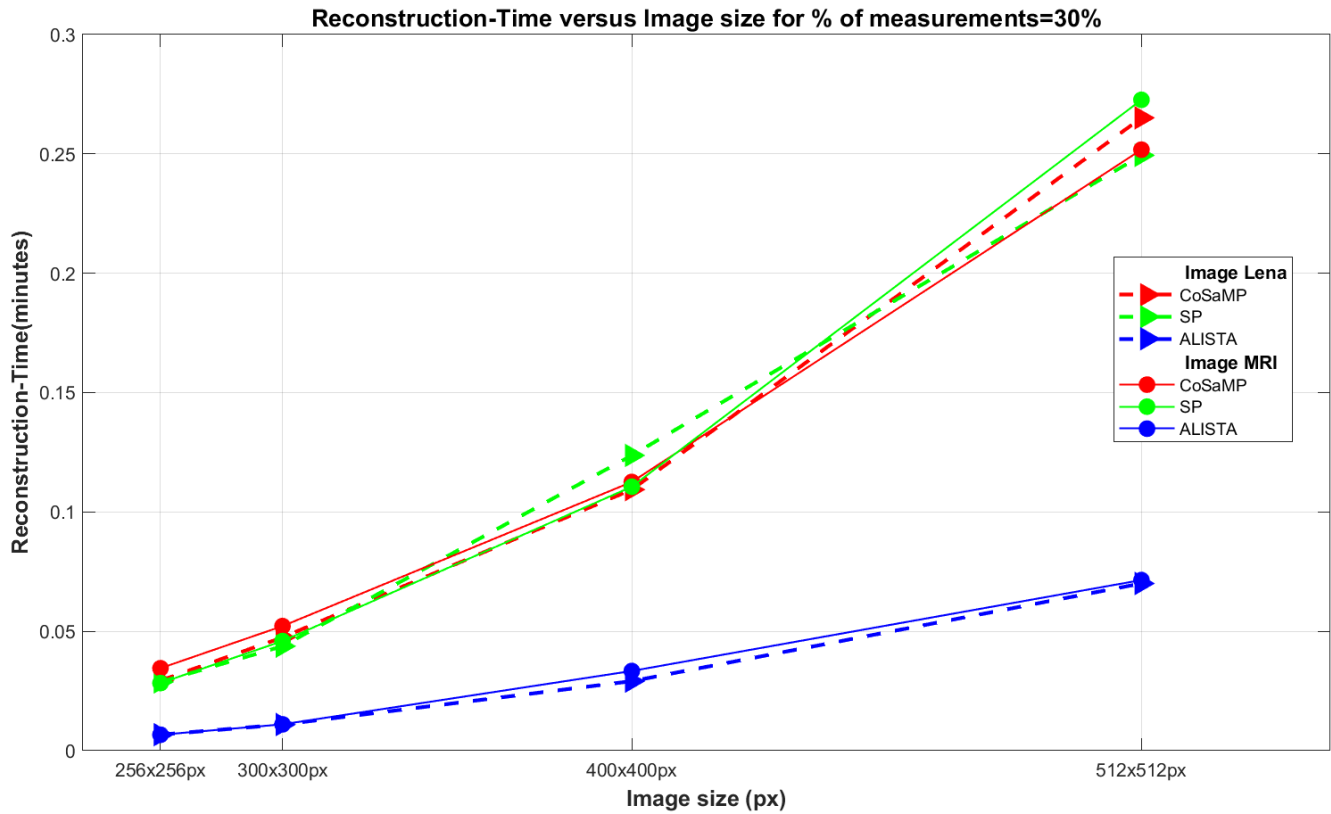


Figure 6. Reconstruction-Time vs Image size for % of measurements=30%.

Figure 6 shows the reconstruction time (in minutes) as a function of image size (in pixels), for a fixed measurement rate of 30%. It can be observed that ALISTA exhibits an extremely low and nearly linear reconstruction time, remaining below 0.08 minute (5 seconds) even for a 512×512 px image, confirming its very high computational efficiency. In contrast, CoSaMP and SP show significantly higher reconstruction times that increase sharply with resolution, reaching nearly 0.27 minute (16 seconds). ALISTA is faster than CoSaMP and SP primarily because it relies on a deterministic and non-iterative architecture. Unlike CoSaMP and SP which are iterative greedy algorithms requiring, at each iteration, costly operations such as selecting the most correlated atoms, solving a least-squares problem over the estimated support, and updating the solution, ALISTA executes a fixed and predefined number of steps, where the weight matrices and thresholds are learned once and for all on a training dataset. Moreover, the reconstruction time for

both Lena and MRI images is nearly identical for ALISTA, indicating that this algorithm is insensitive to image type and size.

5. Originality and Our Contribution to the Research

In compressive sensing, when processing images, the conventional Discrete Wavelet Transform (DWT) is typically used to obtain a sparse representation. However, this transform is computationally slow due to its convolution operations. In this paper, we propose a novel approach based on the Lifting Wavelet Transform (LWT) to address this limitation. Moreover, the originality and our key contribution lie in the methodology adopted for compressive sensing. Specifically, the LWT of an image yields four components:

- 1) CA: A reduced and blurred version of the original image
- 2) LH: Vertical details
- 3) HL: Horizontal details
- 4) HH: Diagonal details

According to our studies, the LH, HL, and HH components are inherently sparse matrices, unlike the CA component. This observation led us to apply compressive sensing only to these three detail components while leaving the CA component untouched. We therefore evaluated the performance of this proposed approach using various reconstruction algorithms. In this article, we use the Lifting Wavelet Transform (LWT) with the Reverse Biorthogonal 6.8 (rbio6.8) wavelets.

6. Conclusion

This study demonstrates the effectiveness of a compressive sensing (CS) that combines the Lifting Wavelet Transform (LWT) using Reverse Biorthogonal 6.8 (rbio6.8) wavelets with three reconstruction algorithms: Subspace Pursuit (SP), Compressive Sampling Matching Pursuit (CoSaMP), and Analytic Learned ISTA (ALISTA). Experimental results, obtained on both standard (Lena) and medical (MRI) images, clearly show that ALISTA significantly outperforms SP and CoSaMP in both reconstruction quality (measured by SSIM) and computational efficiency. At an 80% sampling rate, ALISTA achieves an SSIM of 0.99314, compared to 0.97402 for the other two methods, while requiring less than 4 seconds for reconstruction versus over 20 seconds in certain cases for CoSaMP. Moreover, ALISTA maintains stable and fast performance even at low sampling rates (10%) and for image resolutions up to 512×512 pixels, highlighting its robustness and adaptability. This superiority stems from its learning-based approach, where thresholds and weight matrices are pre-learned, thereby avoiding the computationally expensive iterative loops characteristic of classical greedy methods. Finally, using LWT instead of the conventional Discrete Wavelet Transform (DWT) not only reduces algorithmic complexity but also effectively preserves the sparsity of wavelet coefficients. The combination of ALISTA with the LWT/rbio6.8 transform is highly promising for real-time applications such as telemedicine, embedded vision, or remote sensing, where both high accuracy and minimal latency are critical.

While this study leverages the Reverse Biorthogonal 6.8 (rbio6.8) within the Lifting Wavelet Transform (LWT) framework for efficient sparse representation, further enhancements could be achieved by incorporating adaptive or learned wavelet-like transforms, such as those implemented via neural networks and jointly optimized with the reconstruction algorithm. In addition, replacing the random Gaussian or subsampled identity measurement matrices with structured sensing operators, like partial Fourier or Hadamard matrices, could reduce hardware complexity and accelerate

data acquisition.

Abbreviations

ALISTA	Analytic Learned Iterative Shrinkage Thresholding Algorithm
CoSaMP	Compressive Sampling Matched Pursuit
DWT	Discrete Wavelet Transform
LWT	Lifting Wavelet Transform
MRI	Magnetic Resonance Imaging
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, Supervision, Writing – original draft, Writing – review & editing

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