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By Subba Reddy Borra, G. Jagadeeswar Reddy & E.Sreenivasa Reddy
Acharya Nagarjuna University, India

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SEISMICDATACOMPRESSIONUSINGWAVEATOMTRANSFORM

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Seismic Data Compression using Wave Atom Transform

Subba Reddy Borra [α], G. Jagadeeswar Reddy [σ] & E.Sreenivasa Reddy [ρ]

Abstract- Seismic data compression (SDC) is crucially, confronted in the oil Industry with large data volumes and Incomplete data measurements. In this research, we present a comprehensive method of exploiting wave packets to perform seismic data compression .Wave atoms are the modern addition to the collection of mathematical transforms for harmonic computational analysis. Wave atoms are variant of 2D wavelet packets that keep an isotropic aspect ratio. Wave atoms have a spiky frequency localization that cannot be attained using a filter bank based on wavelet packets and offer a significantly sparser expansion for oscillatory functions than wavelets ,curvelets and Gabor atoms .Wave atoms capture the coherence of patterns across and along oscillations where as curvelets capture coherence along oscillations only. Wave atoms precisely interpolate between Gabor atoms and (constant support) and directional wavelets (wavelength ∼ diameter) in the sense that the period of oscillations of each wave packet (wavelength) is related to the size of essential support by parabolic scaling law. Wave atom transform achieves the best result by some numerical examples.

Keywords: seismic data compression (SDC), curvelets, wavelets, wave atom.

I. Introduction

Modern seismic surveys with higher accuracy memorization that led to ever increasing amounts of seismic data [1and 2]. Management of these large datasets becomes important for transmission, storage processing and Interpretation. To make the storage more efficient and to reduce the broadcast and cost, many seismic data compression (SDC) algorithms have been developed. During the oil and gas exploration process, the main strategy used by the companies is the construction of sub surface images, which are used both to identify the reservoirs and also to plan the hydrocarbons distillation .The construction of those images begins with seismic survey that produces a huge amount of seismic data. Then, obtained data is transmitted to the processing center generate the subsurface image.

A typical seismic survey can produce hundreds of terabytes of data. Compression algorithms are subsequently desirable to make the storage more effective, and to reduce time and costs related to network and satellite broadcast. Multi-resolution methods are genuinely associated to image processing, biological, computer Vision and systematic computing. The curvelet transform is a multiscale directional transform that permits almost best non-adaptive sparse representation of objects with edges. It has generated enhancing importance in the community of applied mathematics and signal processing over the years. A review on the curvelet transform includes its history beginning from wavelets, its logical relationship to other multi resolution multidirectional methods like contourlets and shearlets, its basic theory and discrete algorithm. Further, we agree recent applications in video/image processing, seismic exploration, fluid mechanics, imitation of partial different equations, and compressed sensing [3].

For seismic data compression(SDC) ,the most important consideration is how to represent seismic signals efficiently ,that is to say ,using few coefficients to faith fully represent the signals ,and therefore preserve the useful information after maximally possible compression .It is easy to comprehend that compression effectiveness is used for different expansion bases. Many orthogonal transforms have been used for data compression .Discrete Fourier Transform (DCT) was the first generation orthogonal transform used in Data compression. Haar Transform use of rectangular basis functions .Slant Transform is an attempt to match basis vectors to the areas stable luminance slope. It has better decor relation efficiency .Discrete cosine Transform is one of the extensive families of sinusoidal transforms. The mainly efficient transform for decor relating input data is the Karhunen loeve Transform also known as Hotelling transform and Eigenvector transform [4].

Curvelets as a multi-scale, anisotropic multi-dimensional transform were introduced, very quickly to be used for seismic data processing and migration using a mapping migration method .Curvelets can build the local slopes information into the representation of the seismic data, and which was proved to be effective in the sparse decomposition of seismic data.

For example, wavelet [5 and 6] based compression algorithm can represent seismic data using only a fraction of the original data size. In this paper, Wave atom transform presents its advantage

Author α : Research Scholar, Department of Computer Science and Engineering Jntuh, Hyderabad, Telangana, India.
Author σ : Principal, Narayana Engineering College, Nellore, AP, India. e-mail: jagsuni@yahoo.com
Author ρ: Principal, University College of Engineering, Acharya Nagarjuna University, AP, India. e-mail: esreddy67@gmail.com

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over wavelets, curve lets[7] for conventional image compression .Their features are well suited to seismic data properties and have led to better results in terms of signal –to –noise ratio. Wave atoms come from the property that they also provide an optimally sparse representation of wave propagators, a mathematical effect of autonomous interest, with applications to fast numerical solvers for wave equations.

II. Image Compression – Transforms

a) *Wavelets*

During the last decade the appearance of many transforms called Geometric wavelets have paying attention of researchers working on image analysis. These novel transforms propose a new representation comfortable than the traditional wavelets multi-scale representation .We are responsive that for a particular type of images ,we can do better by choosing for this kind of specific images, a more suitable tool than classical wavelets[8,9 and10].

The orthogonal transforms have been broadly studied and used in image analysis and processing. To defeat the limitations of Fourier analysis many extra orthogonal transforms have been developed .The most important criteria to be fulfilled by the basis functions are localization in equally space and spatially frequency and orthogonality. Various efficient and sophisticated wavelet-based schemes have been developed. In Image compression, the use of orthogonal transform is dual. Primary, it décorrelates the image components and allows to identify the redundancy .Subsequent, it offers a high level of compression of the energy in the spatial frequency domain .These two properties permit to select the most related components of the signal in order to accomplish competent compression. Many orthogonal transforms possess these three characteristics and have been used for data compression.

Wavelets are much modified to isotropic structure; they are not modified for anisotropic structure. This transform cannot effectively represent textures and exceptional details in images for lacking of directionality. 2D wavelet transforms produce high energy coefficients along the contours[11 and 12]. To overcome this limitation, a few solutions have been proposed . A first solution consists in using directional filter banks tuned at fixed scales, orientations and positions. Another solution is exploit an adaptive directional filtering based on a numerical model. So, two important approaches fixed and adaptive have been developed. Figure. 1. shows difficulties of wavelet transform to represent regularity of a contour compared to new multi-scale transformed where geometric anisotropy and rotations are taken into description.

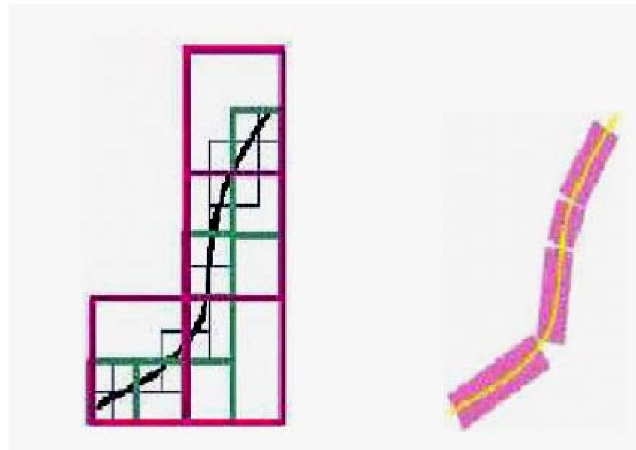

Figure 1 : Comparison between wavelet and adapted transform

b) *Ridgelets and Curvelets*

Ridgelet transform [13 and 14] have been developed to analyze objects whose significant information is concentrated approximately linear discontinuities such as lines. Ridgelet coefficients are obtained by a One Dimensional wavelet transform of all projections of the image resulting from Radon Transform .Ridgelet transform is that wavelet analysis on One Dimensional slices of the Radon Transform, where the angle is fixed.

Continuous Ridgelet Transform is defined as

$$Rf(a,\theta,b) = \iint f(x_{1,}x_2)\psi_{a,\theta,b}(x_1,x_2)dx_1dx_2 \quad (1)$$

Where $\psi_{a,\theta,b} = a^{-1/2}\psi((x_1 * \cos(\theta) + x_2 * \sin(\theta) - b)/2)$ is a One Dimensional Wavelet.

Ridgelets are expressed through Radon Transform as:

$$Rf(a,\theta,b) = \int Rf(r,\theta)a^{-1/2}\psi(t-b)/a\ dt \quad (2)$$

Where R f is Radon transform defined by

$$Rf(t,\theta) = \int f(x_1,x_2)\delta(-x_1\sin\theta + x_2\cos\theta - t)dx_1dx_2 \quad (3)$$

A curvelet is defined as function $x = f(x_1,x_2)$ at the scale 2^{-j}, orientation θ_l and position $x_k^{(j,l)} = R_{\theta,l}^{-1}(k_1 2^{-j}, k_2 2^{-j/2})$ *by:*

$$c(j,l,k) = \langle f, \theta_j, l, k \rangle = \int_{R2} f(x)\varphi_{i,l,k}(x)dX \quad (4)$$

Curve let computation steps:

Step 1: Decomposition into sub bands
Step 2: Partitioning
Step: Ridgelet analysis(Radon Transform + Wavelet transform 1D)
Block size can change from a sub band to another one; the following algorithm will be applied

Step 1: Apply a wavelet transform (J sub bands).

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Step 2: Initialize the block size: $B_{min} = B_j$.

Step 3: For j=1, -----, J do

Step 4: Partition the sub bands W_j in blocks B_j .

Step 5: if (J modulo 2=1) then $B_{j+1} = 2B_j$ otherwise $B_{j+1} = B_j$

Step 6: Apply Ridgelet transform to each block.

Figure. 2. Shows the curve let tiling in space and frequency domains

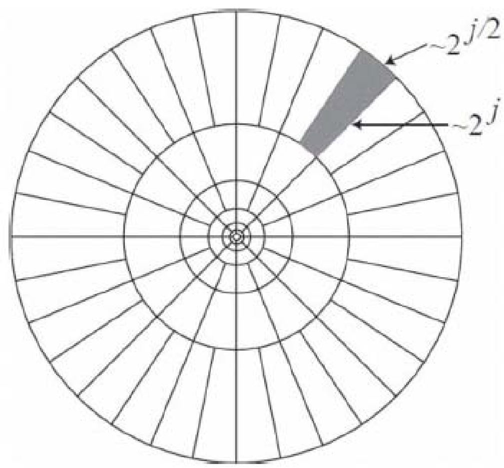

Figure 2 : Curvelet tiling in space and frequency domains.

c) Wave atoms

In the standard wavelet transform, only the estimate is decomposed, when, we pass from phase to another. While in the wavelet packets, the decomposition could be pursued into the other sets, which is not optimal .The optimality is linked to the greatest energy of decomposition. The notion is then to fetch for the way yielding to the maximum energy through the different sub bands.

Wave atom [15] is a novel member in the family of oriented, multiscale transforms for image processing and also numerical analysis. For the sake of completeness, we remember here some fundamentals notations following

$$\hat{f}(\omega)= \int e^{-ix\omega} f(x)dx \qquad (5)$$

$$f(x)=\frac{1}{(2\pi)^2} \int e^{ix\omega}\, \hat{f}(\omega)d\omega \qquad (6)$$

Wave atoms are noted as, with subscript. The indexes are integer -valued related to a point in the phase-space defined as follows. $x_\mu= 2^{-j}n, \omega_\mu = \pi 2^j m$ $C_1 2^j \le \max_{i=1,2}|m_i| \le C_2 2^j$, they suggest two parameters are enough to index a lot of known wave packet architectures. The index indicates whether the decomposition is multi scale (α=1) or not (α=0); and β indicates whether basis elements are localized and poorly directional (β=1) or, on the opposite side extended and fully directional (β=0)[16,17 and18].

We think that the description in terms of α and β will clarify the connections between various transforms of modern harmonic analysis. Wavelets correspond to α=β=1, for ridge lets α=1, β=0[19 and 20], Gabor transform α=β=0 and curvelets correspond to α=1,β=1/2. Wave atoms are defined for α=β=1/2. Figure. 3. Illustrates this classification

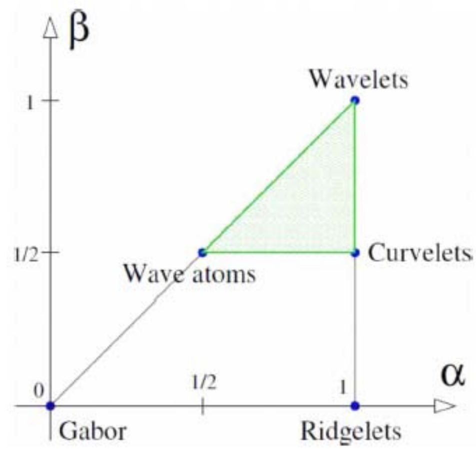

Figure 3 : (α β) diagram

In order to introduce the wave atom, let us first consider the 1D case .In practice, wave atoms are constructed from tensor products of adequately chosen 1D wavelet packets. A one-dimensional family of real - valued wave packets $\psi^j_{m,n}(x), j \ge 0, m \ge 0, n \in Z$, centered in frequency around $\pm\omega_{j,m} = \pm\pi 2^j m$, with $C_1 2^j \le \max_{i=1,2}|m_i| \le C_2 2^j$ and centered in space around $x_{j,n} = 2^{-j}n.$, is constructed. The one dimensional version of the parabolic scaling inform that the support of $\psi^j_{m,n}(\omega)$ be of length O (2^{2j}), while $\omega_{j,m} = O(2^{2j})$. The desired corresponding tiling of frequency is illustrated at Figure. 4. Filter bank-based wavelet packets is considered as a potential definition of an orthonormal basis satisfying these localization properties. The wavelet packet tree, defining the partitioning of the frequency axis in 1D, depth j when the frequency is 2^{2j} , as shown in Figure. 4.

Figure. 4.Presents the wavelet packet tree corresponding to wave atoms. The bottom graph depicts Villemoes wavelet packets [20 and 21] on the positive frequency axis. The dot below the axis indicates a frequency where a change of scale occurs .The labels "LH" and "RH" indicates that left-handed and right-handed window respectively

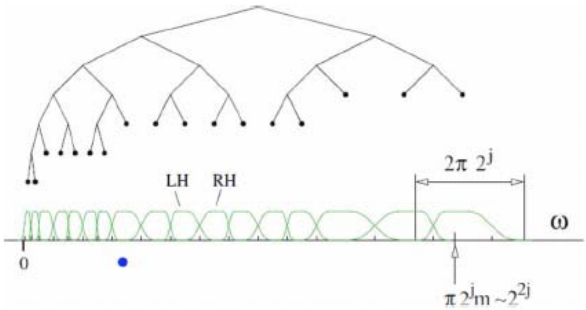

Figure 4 : Wavelet packet tree corresponding to wave atoms

In 2D domain the construction presented above can be modified to certain applications in image processing or numerical analysis: The orthobasis variant. [22,23 and24]. A two-dimensional orthonormal basis function in frequency plane with four bumps is formed by individually taking products of 1D wave packets .Mathematical formulation and implementations for 1D case are detailed in the earlier section.2D wave atoms are indexed by μ=(j,m,n), where m=(m_1,m_2) and n=(n_1,n_2). creation is not a simple tensor product since there is only one scale subscript j .This is similar to the non-standard or multi-resolution analysis wavelet bases where the point is to enforce same scale in both directions in order to retain an isotropic aspect ratio.

$$\varphi_{\mu}^{+}(x_1, x_2) = \psi_{m1}^{j}(x_1 - 2^{-j} n_1)\ \psi_{m2}^{j}(x_2 - 2^{-j} n_2). \quad (7)$$

The Fourier transform of (7) is separable and its dual orthonormal basis is defined by Hilbert transformed [25] wavelet packets in (9)

$$\hat{\varphi}_{\mu}^{+}(\omega_1, \omega_2) = \hat{\psi}_{m1}^{j}(\omega_1) e^{-i2^{-j} n_1 \omega_1}\ \hat{\psi}_{m2}^{j}(\omega_2) e^{-i2^{-j} n_2 \omega_2} \quad (8)$$

$$\varphi_{\mu}^{-}(x_1, x_2) = H\psi_{m1}^{j}(x_1 - 2^{-j} n_1)\ H\psi_{m2}^{j}(x_2 - 2^{-j} n_2). \quad (9)$$

Combination of (8) and (9) provides basis functions with two bumps in the frequency plane, symmetric with respect to the origin and thus directional wave packets oscillating in a single direction are generated.

$$\varphi_{\mu}^{(1)} = \frac{\varphi_{\mu}^{+} + \varphi_{\mu}^{-}}{2},\ \varphi_{\mu}^{(2)} = \frac{\varphi_{\mu}^{+} - \varphi_{\mu}^{-}}{2} \quad (10)$$

Together form the wave atom frame and are jointly denoted by $\varphi\mu$. Wave atom algorithm is based on the apparent generalization and its complexity is O (N^2 LogN).

In practice, one may want to work with the original orthonormal basis $\varphi_{\mu}^{+}(x)$ instead of tight frame. Since $\varphi_{\mu}^{+}(x) = \varphi_{\mu}^{1}(x) + \varphi_{\mu}^{+2}(x)$ each basis function $\varphi_{\mu}^{+}(x)$ oscillates in two distinct directions, instead of one. This is called the orthobasis variant.

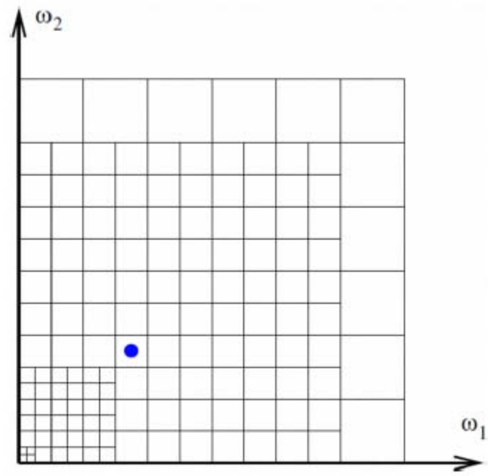

Figure 5 : Wave atom tiling of the frequency plane

Figure. 5. Represents the wave atom tiling frequency plane. The size of the squares doubles when the scale j increases by one .At a given scale j, squares are indexed by m1, m2 opening from zero near the axis.

In practice, the algorithm for wave atoms [26, 27, 28 and 29] is based on the obvious generalization of the 1D wrapping strategy to two -dimensions -except for slight complication. The admissible tiling's of the frequency plane at scale j are restricted by

$$\max_{i=1,2} |m_i| = 4n_j + 1 \quad (11)$$

For some integer n_j depends on j. we check that this property holds with $n_0 = 0, n_1 = 1$ and $n_2 = 2.$ The rationale for this restriction is that a window needs to be right-handed in both directions near a scale doubling ,and that this parity needs to match with the rest of the lattice .The rule is that $\hat{\varphi}_{m,+}^{j}$ is right -handed for m odd and left-handed for m even, so for instance $\hat{\varphi}_2^2(\omega_1)\ \hat{\varphi}_2^2(\omega_2)$ would not be admissible window near a scale doubling, where as $\psi_3^2(x_1)\ \psi_3^2(x_2)$ is admissible (by a dot in Figure. 5.).

III. Results and Discussion

This section demonstrates some numerical examples to explain the properties and potential of the wave atom frame and its ortho basis variation.

Now we illustrate the potential of the wave atoms with example. In the example, we consider the compression properties, i.e the decay rate of the coefficients of images under the wave atom bases. Besides the wave atom orthobasis and the wave atom frame, we include other two bases for comparison: the daubechies db5 wavelet, and a wavelet packet that uses db5 filter and shares the same wavelet packet tree with our wave atom or thobasis.

The quality of reconstructed image is usually specified in terms of peak signal to noise ratio (PSNR).

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The PSNR values were calculated using the following expression:

$$psnr = 20\log 10 \frac{M_1 \times M_2 \times \max(f(i,j))}{\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}[f(i,j) - f'(i,j)]^2} dB \quad (12)$$

Here M1 and M2 are the size of the image. f (i,j) is the Original image, f′(i,j) is the decompressed image.

Table 1 : PSNR of wavelet, curvelet and wave atom

S.no.	No. of coefficients used for decompression	PSNR of decompressed image in dB		
		wavelet	*curvelet*	*waveatom*
1	5536	38.6992	38.0497	42.9066
2	6536	39.2739	38.5499	43.5110
3	7536	39.8192	39.0153	44.0314
4	8536	40.3407	39.4428	44.4903
5	9536	40.8406	39.8336	44.9026

Table 2 : Compression Ratio comparison of wavelet, curvelet and wave atom

S.no.	No. of coefficients used for decompression	Compression ratio		
		wavelet	*curvelet*	*waveatom*
1	5536	47	342	94
2	6536	43	311	86
3	7536	39	285	78
4	8536	36	262	72
5	9536	33	242	67

Table 3 : Execution time comparison of wavelet, curvelet and wave atom

S.no.	No. of coefficients used for decompression	Execution time in seconds		
		wavelet	*curvelet*	*waveatom*
1	5536	0.484	4.902	0.929
2	6536	0.491	8.334	3.260
3	7536	0.756	9.612	3.384
4	8536	0.178	2.907	1.413
5	9536	0.272	3.174	0.930

From Table 1, we note that PSNR of waveatom Decompressed image is high for any no of coefficients used for reconstruction. From Table 2, it is observed that, curvelet representation has more redundant data compared to waveatoms and wavelets. Table 3 shows that, execution time required is less in case of wavelets compared to waveatoms and curvelets. Hence waveatom is the best alternative of the other two techniques.

Figure. 6, 7, 8 and 9 show input image ,wavelet reconstruction, curvelet reconstruction and wave atom reconstruction respectively and Figure . 10 and 11 show graphical representation of PSNR vs. No. of coefficients used for reconstruction and PSNR vs. compression ratio respectively for the three considered compression techniques. It is observed from the below figures, that waveatom compression technique outperforms than wavelet and curvelet techniques.

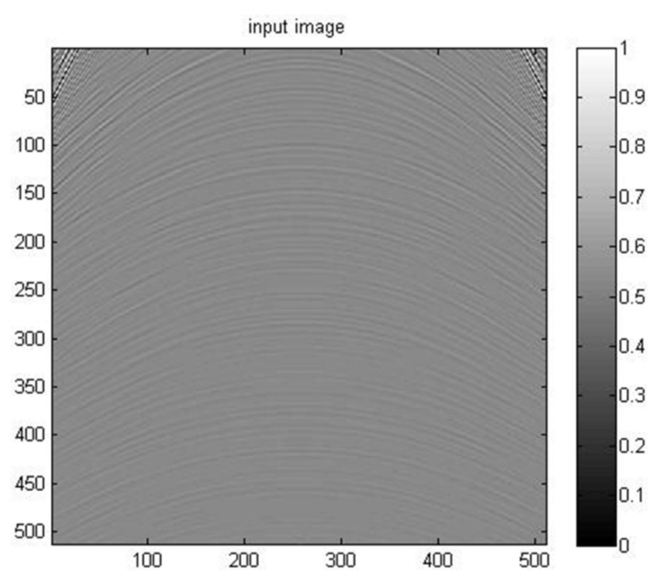

Figure 6 : Input Image

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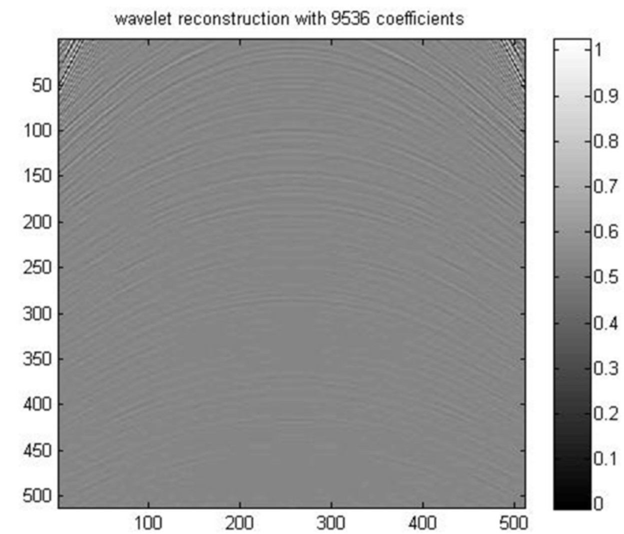

Figure 7 : Wavelet reconstruction

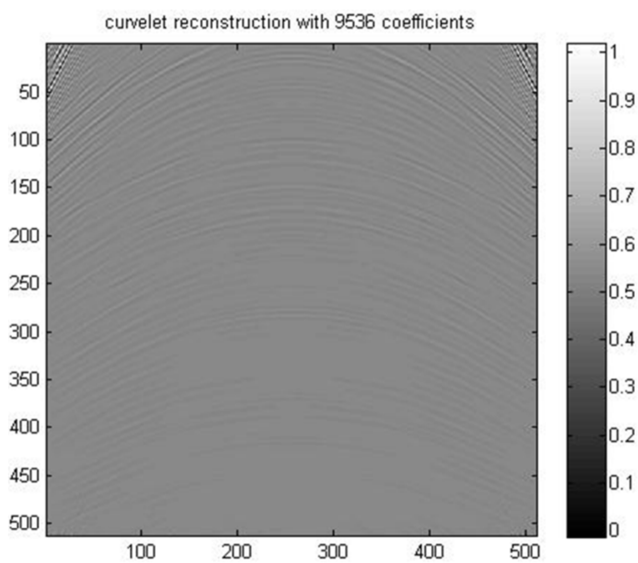

Figure 8 : Curvelet reconstruction

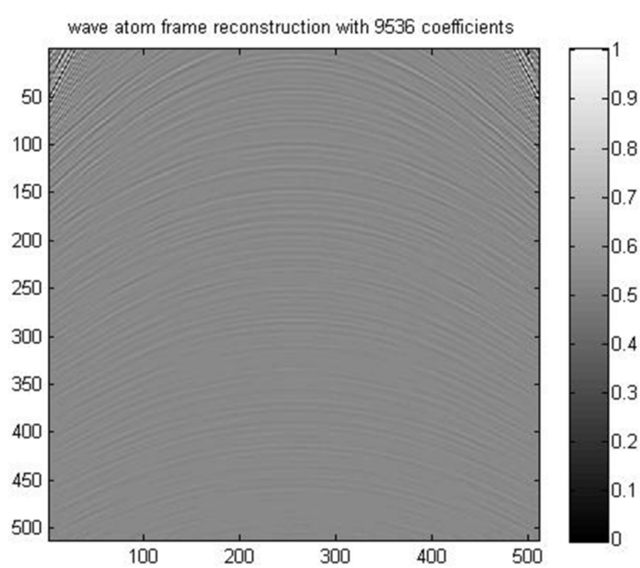

Figure 9 : Wave atom reconstruction

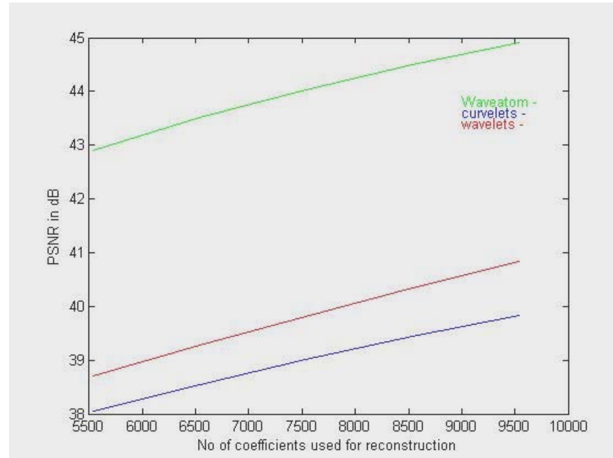

Figure 10 : PSNR vs. No. of coefficients used for reconstruction

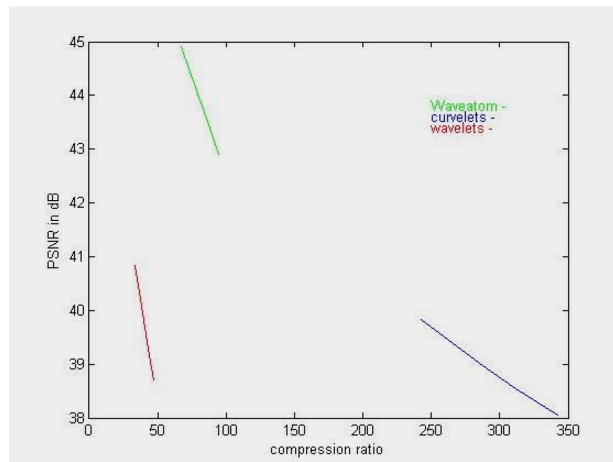

Figure 11 : PSNR vs. Compression Ratio

IV. Conclusions

We have shown that for a seismic data images, we can find a transform that is more appropriate than Curvelets and wavelets. Using Wave atom transform we obtained better PSNR and Compression Ratio than other transforms.

References Références Referencias

1. R.C.Gonzalez and R.E.Woods, "Digital Image Processing".
2. Geng, Y., R.Wu , and J. Gao, in Dreamlet Transform applied to Seismic compression and its effects on migration, pp. 3640-3644,2009.
3. Douma, H., and M.V. de Hoop, leading order Seismic imaging using Curvelets: Geophysics, 72,pp. 231-248,2007.
4. R.J .Clarke, Transform Coding of images, Academic Press, London, 1985.
5. Raghuveer M.Rao and Ajit S.Bopardikar, "Wavelet Transforms, Introduction to Theory and Applications".

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6. Shapiro, J. Embedded image coding using zerotrees of wavelet coefficients. IEEE Transactions on Signal Processing December 1993; 41(12):3445-3462.
7. E.J.Candès and D.L.Donoho, "Curvelets," [Online] Available:http://www.stat.stanford.edu/~donoho/Reports/1999 /curvelets.pdf, 1999.
8. D. S. Taubman, M. W. Marcellin, JPEG 2000: Image Compression Fundamentals, Standards, and Practice, New York: Kluwer International Series in Engineering and Computer Science, Nov.2001.
9. MPEG-4: Coding of moving pictures and audio, ISO/IEC 14496, 1999.
10. Rao, K.R. and P. Yip, Discrete Cosine Transform – Algorithms, Advantages and Applications, New York: Academic Press, 1990.
11. D. Salomon, Data compression, the complete reference, Fourth edition, Sprnger, 2007.
12. F.Friedrich H. Fhr, L. Demaret, "Beyond wavelets: New image representation paradigms," Survey article in document and image compression, M.Barni and F.Bartolini (eds), pp. 179-206, May 2006.
13. E .Candes, D.Donoho, "Ridgelets: A key to higher-dimensional intermittency?" Philosophical transactions Royal Society, Mathematical, physical and engineering sciences, vol. 357, no.1760, pp.2495, 1999.
14. E.Candes, D.Donoho, Curvelets – A surprisingly effective nonadaptive representation for objects with edges, curves and surfaces , Curves and Surfaces, Vanderbilt University Press, Nashville, TN, 1999.
15. L.Demanet and L. Ying, "Wave Atoms and Sparsity of Oscillatory Patterns ", Appl. Comput. Harmon. Anal., vol. 23(3) pp.368-387, 2007
16. S. Mallat, A Wavelet Tour of Signal Processing. Second edition. Academic Press, Orlando-San Diego, 1999.
17. J. P. Antoine, R. Murenzi, "Two –dimensional directional wavelets and the scale-angle representation ". Sig.Process, 52, 259-281, 1996.
18. Selesnick, R. G. Baraniuk, N.G. Kingsbury, "The duel-tree complex wavelet transform ", IEEE Sig.Proc.MAg. 22(6).pp, 123-151, 2005
19. M.N .Do and M.Vetterli ,"The contourlet Transform : An Efficient Directional Multiresolution Image Representation ",IEEE Trans. Image Processing, vol.14(12), pp.2091-2106,2005
20. L.Villemoes, "Wavelet Packets with Uniform Time-Frequency Localization", in Comptes Rendus Math, vol. 335(10), pp.793-796,2002
21. A.K .Jain, P.M. Farrelle, V.R.Algazi, Image data compression, in: M.P.Ekstrom (Ed), Digital Image Processing Techniques, Academic Press, New York, 1984, pp.171-226
22. Candès, E. J., L. Demanet, D. L. Donoho, and L. Ying, 2006a, Fast discrete curvelet transforms: Multiscale Modeling and Simulation, 5,861–899.
23. Ali N.Akansu,"Wavelets and Filter Banks", IEEE Circuit and Devices, pp .14-18, November 1994
24. Demanet, L., 2006,"Curvelets, Wave atoms and wave equations,"Ph.D .Thesis, California Institute of Technology
25. Pat Yip, the Transform and Data Compression Handbook", CRC Press, sept. 2000.
26. L. Demanet and L.Ying, "Scattering in Flatland: Efficient Representation via Wave Atoms ", in Foundation of Comput. Math, 2008
27. Patrick Le Callett, Florent Autrusseau, "Subjective quality assessment IRCCyN/IVC database" ,2005
28. D.M. Chandler and S.S. Hemami, "VSNR: A Wavelet–based visual signal to noise ratio for natural images," IEEE Trans. Image Process,16(9), 2284-2298,2007.
29. http://foulard.ece.cornell.edu/dmc27/vsnr/vsnr.html.

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