

Image Coding Using EZT Based on Contourlet Transformation

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ABSTRACT

Due to the fact that most of the application on EZT algorithm were applied on wavelet transformation. In the last ten years, the contourlet transformation shows that its efficiency is higher than the wavelet transformation due to its ability to deal with multidirections instead of the vertical and horizontal directions which are covered by the wavelet transformation.

In this paper, the contourlet coefficient is adopted as inputs to the EZT (which normally are a wavelet coefficient). Arranging the contourlet coefficient to be studied as input to EZT, the result of adopting modified contourlet coefficient was studied on two parameters (the file size and threshold value) and tested by evaluating two factors (correlation and MSE).

Comparing the result which we get it with the wavelet technique shows that the contourlet gives a result closer, to the original one depending on the correlation factor plus the PSNR factor. So, the proposed technique can be achieved.

Keywords : Coding, LZB, Image processing, Image transformation, Contourlet transformation, image compression.

ترميز الصور باستخدام EZT معتمدا على التحويلات الكنتورية

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المخلص

استنادا إلى حقيقة كون اغلب التطبيقات على خوارزمية EZT طبقت من خلال تحويل الموجة، ولكن مع التطور الحاصل خلال العشرة سنين الأخيرة أظهرت التحويلات الكنتورية كفاءة أعلى من تحويل الموجة وذلك لقابليتها على التعامل باتجاهات متعددة بدلا من الاتجاه العمودي والأفقي المعتمدة في التحويل الموجي.

في هذا البحث تم اعتماد معاملات التحويلات الكنتورية كإدخالات EZT (والتي تكون عادة معاملات تحويل الموجة)، حيث تم ترتيب معاملات التحويلات الكنتورية لتتوافق كإدخالات إلى EZT. تم دراسة نتائج اعتماد معاملات التحويلات الكنتورية المحورة من خلال عاملين (حجم الملف وقيمة حد العتبة) واختبرت من خلال حساب معاملات كل من (معامل الارتباط ومعامل مربع الخطأ).

مقارنة النتائج التي تم الحصول عليها مع تقنيات تحويل الموجة أظهرت إن الكنتورليت يعطي نتائج أكثر قربا من صورة الأصل وذلك بالاعتماد على عامل التقارب وعامل ال PSNR. عليه يمكن توظيف التقنية المقترحة كأسلوب جديد لتقنية ترميز الصورة.

الكلمات المفتاحية : ترميز LZB، معالجة الصور، تحويلات الصور، التحويلات الكنتورية، كبس الصور.

1. Introduction

Wavelet transform transforms a signal from the time domain to the joint time-scale domain. This means that the wavelet coefficients are of two-dimensions. If we want to compress the transformed signal, we have to code not only the coefficient values, but also their position in time. When the signal is an image, then the position in time is better expressed as the position in space. After wavelet transforming an image we can represent it by using trees because of the sub sampling that is performed in the transform. A coefficient in a low subband can be thought of as having four descendants in the next higher subband illustrated in Figure (1). Each of The four

descendants also has four descendants in the next higher subband and we see a quad-tree emerge: every root has four leaves [1].

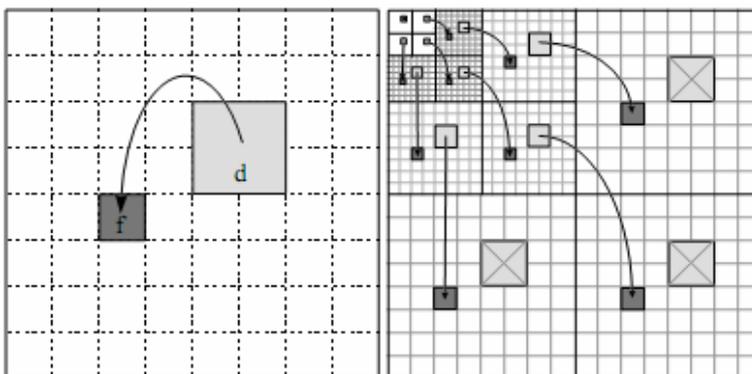


Figure (1). The Relation between Wavelet Coefficients in Subbands as Quad-Tree

The discrete wavelet transform of an image provides a set of wavelet coefficients which represent the image at multiple scales. The wavelet representation can be seen as a multilevel pyramid tree-structure with the coarsest scale coefficients at the top and the finest scale coefficients at the bottom of the pyramid. Typically, coefficients at different levels of the pyramid are assumed to be independent and they are quantized according to the signal statistics of the corresponding pyramid level [2].

The Definition Of The Zerotree: Is a quad-tree of which all nodes are equal to or smaller than the root. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeroes shown in Figure (2). To clutter this definition, we have to add that the root has to be smaller than the threshold against which the wavelet coefficients are currently being measured [1].

Zerotree based on the observation that wavelet coefficients decrease with scale. It assumes that there will be a very high probability that all the coefficients in a quad tree will be smaller than a certain threshold if the root is smaller than this threshold [1].

As an extension zerotree wavelet coding schemes exploit the correlation between different pyramid levels by setting entire insignificant subtrees to zero, so their coefficients do not have to be transmitted. For high coding efficiency, a careful selection of these zerotrees is crucial. A quantization of the wavelet coefficients followed by a zerotree encoding of the remaining indices does not lead to optimal coding performance [2].

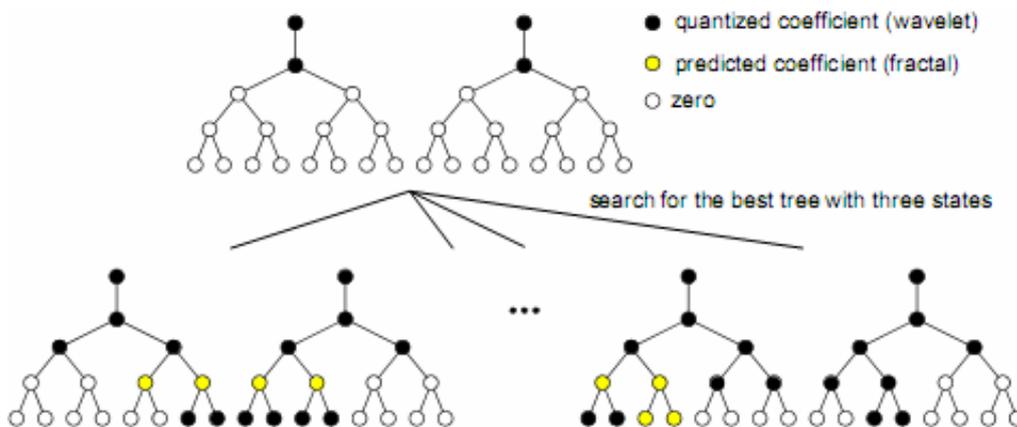


Figure (2). A search for the best three-valued zerotree has to be performed to achieve best coding efficiency (here shown with a binary tree). Two possible trees are shown.

2-Principles of EZW

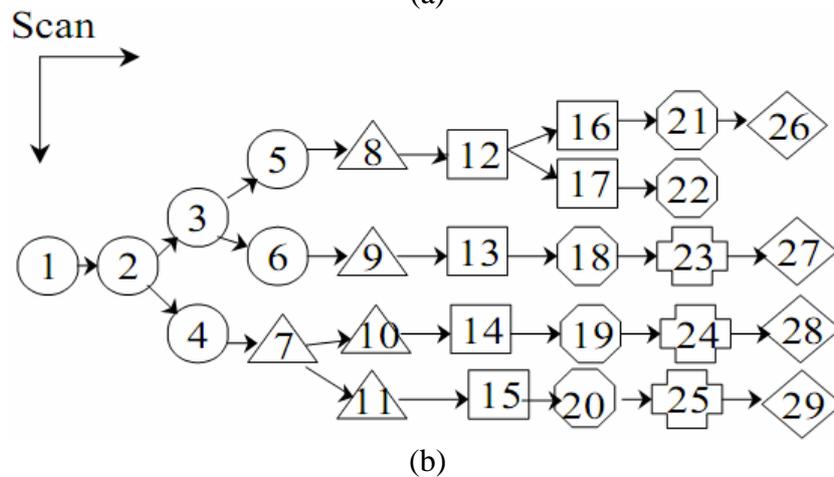
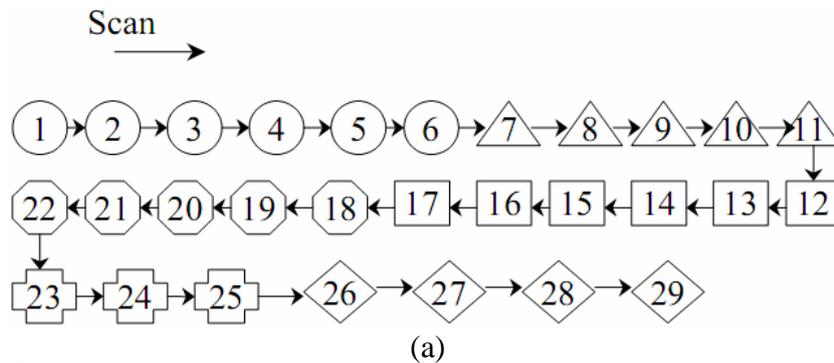
The main reason to utilize this storage method is that the coefficients close to the root have a larger absolute value. Therefore, coefficients closer to the leaves of the tree are less significant and can be sometimes represented by a single symbol to greatly reduce the data size.

The EZW encoder is based on two important observations:

1. Natural images in general have a low pass spectrum.
2. Large wavelet coefficients are more important than smaller wavelet coefficients.

To add more details to the encoded image, the above process is repeated until all the wavelet coefficients have been encoded completely or another criterion has been satisfied [3].

The first step of doing zero-tree scanning is to determine the tree structure of coefficients, i.e., the relationship of ancestors and descendants. Chain-tree, shown in Figure 3(a), is the straightforward idea to build a tree from low frequency bands to high frequency bands. To search a better tree structure, we consider the harmonics of audio signal. According to the characteristics of most instruments, except for the lowest frequencies, if one coefficient is assumed insignificant, there is a relatively high probability that the coefficients in its harmonics are also insignificant. Therefore, the harmonic full-tree is set up illustrated in Figure 3(b), where all descendants are harmonics of ancestors. However, we observe that the energy of wavelet packets coefficients concentrates in lower, but not the lowest bands. To make ZTR generated more easily, we separate the full-tree into four sub-trees and let high-energy band be the root of the sub-tree. Figure 3(c) shows the harmonic sub-trees.



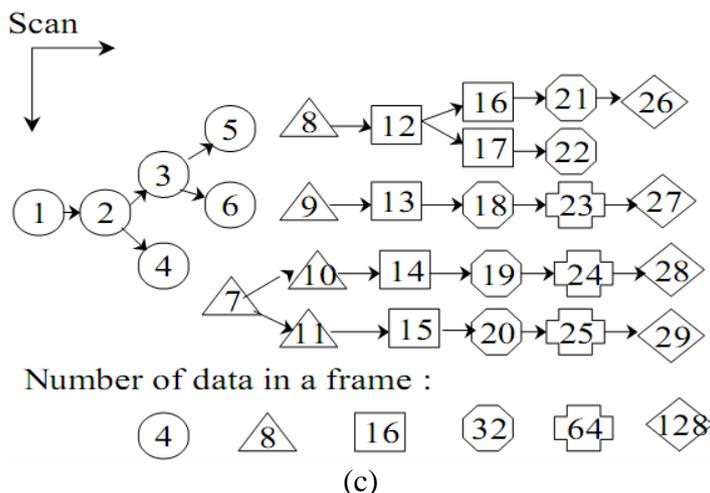


Figure (3). Three coefficient tree structures and scanning orders. (a) Chain-tree structure, (b) Harmonic full-tree structure, (c) Harmonic sub-tree structure.

To cooperate with the psychoacoustic model, we make a modification in the significance decision rule of EZWP. As we mentioned in last section, each subband has a minimum masking threshold. The wavelet packets coefficient C is significant only when it is larger than both threshold T and masking M_i value M_i . The flow chart illustrated in Figure (4).

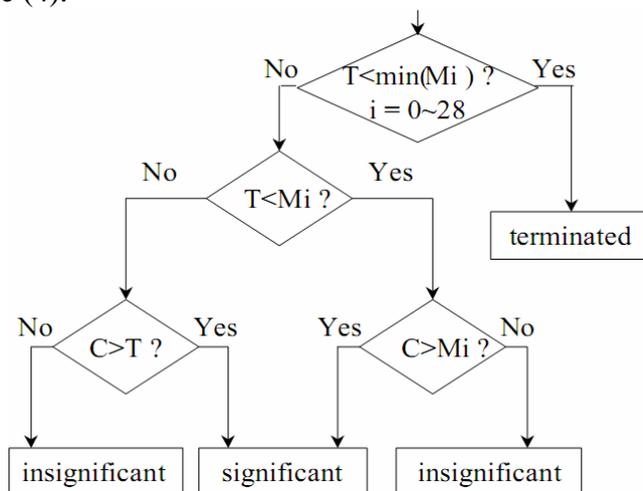


Figure (4). Flow chart of masking combined significance decision rule

Consequently, depending on the relation between T and M_i , the four symbols of zero-tree algorithm are determined as the two cases illustrated in Figure (5) [4].

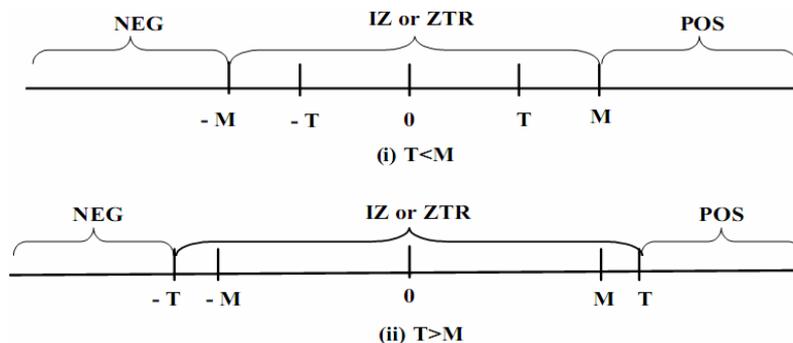


Figure (5). Two cases in symbol encoding

Shapiro's EZW algorithm which was normally used for high compression [5]. Then, two major modification have been done to produce the following algorithms:-

- the SPIHT (Set partitioning in Hierarchical Trees) [6],
- the SPECK (Set Partitioning Embedded Block) [7].

These algorithms have common properties that rely on embedded coding which create an embedded binary flow.

Said, A. Pesrlman, W.A. with their paper at 1993, used compression which was performed by four symbols different from the one used by Shapiro [8].

3- Contourlet Transform

Studying and exploiting the special properties of natural images has been one of the most important tasks in image processing. One key distinguishing feature of natural images is that they have intrinsic geometrical structures, for example, along object boundaries. Recently, Do and Vetterli proposed the contourlet transform as a directional multiresolution image representation that can efficiently capture and represent smooth object boundaries in natural images. The contourlet transform is constructed as a combination of the Laplacian Pyramid and the Directional Filter Banks (DFB) [9].

3-1. Laplacian Pyramid (LP)

One way to obtain a multiscale decomposition is to use the Laplacian Pyramid (LP) [10]. The LP decomposition at each level generates a down sampled lowpass version of the original and the difference between the original and the prediction, resulting in a bandpass image shown in Figure (6) depicts this decomposition process, where H and G are called (lowpass) analysis and synthesis filters, respectively, and M is the sampling matrix. The process can be iterated on the coarse (sampled down) signal (Low frequencies). Note that in multidimensional filter banks, sampling is

represented by sampling matrices; for example, down sampling $x[n]$ by M yields $x_d[n] = x[Mn]$, where M is an integer matrix [11].

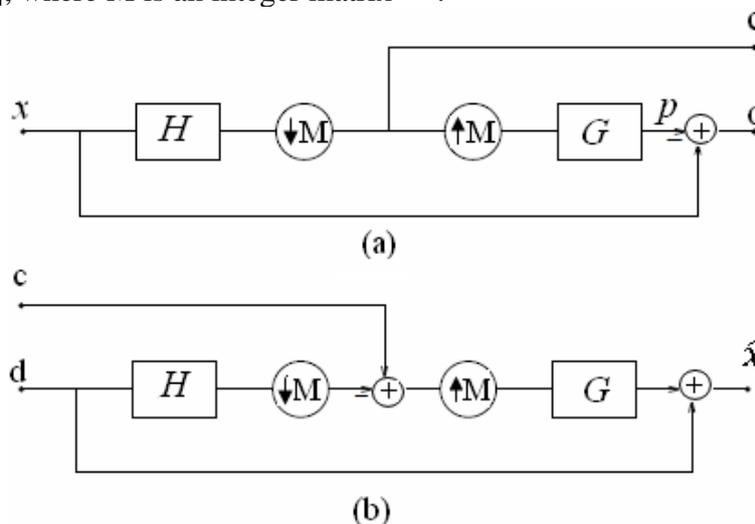


Figure (6). Laplacian Pyramid. (a) One level of decomposition. The outputs are a coarse approximation $a[n]$ and a difference $b[n]$ between the original signal and the prediction. (b) The new reconstruction scheme for the Laplacian Pyramid.

3-2. Directional Filter Bank (DFB)

Bamberger and Smith constructed a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. The DFB is efficiently implemented via an 1-level binary tree decomposition that leads to 2^l sub bands with wedge-shaped frequency partitioning illustrated in Figure (7). The original construction of the DFB involves modulating the input image and using quincunx filter banks with diamond-shaped filters [12].

To obtain the desired frequency partition, a complicated tree expanding rule has to be followed for finer directional sub bands. A proposed new construction for the DFB that avoids modulating the input image and has a simpler rule for expanding the decomposition tree. His simplified DFB is intuitively constructed from two building blocks. The first building block is a two-channel quincunx filter bank with fan filters which is clearly seen in Figure (8) that divides a 2-D spectrum into two directions: horizontal and vertical [13].

The second building block of the DFB is a *shearing* operator, which amounts to just reordering of image samples. Figure 9 shows an application of a shearing operator where a -45° direction edge becomes a vertical edge. By adding a pair of shearing operator and its inverse (“ unshearing ”) before and after respectively, a two channel filter bank in Figure 8, obtain a different directional frequency partition while maintaining perfect reconstruction. Thus, the key in the DFB is to use an appropriate combination of shearing operators together with two-direction partition of quincunx filter banks at each node in a binary tree-structured filter bank, to obtain the desired 2-D spectrum division as shown in Figure 7 [13].

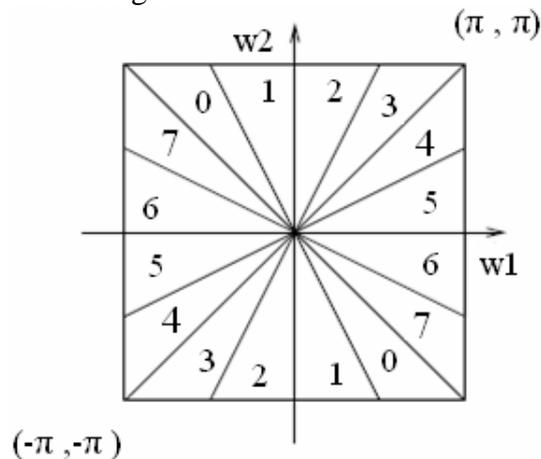


Figure (7). Directional filter bank. Frequency partitioning where $l = 3$ and there are $2^3 = 8$ real wedge-shaped frequency bands. Sub-bands 0–3 correspond to the *mostly horizontal* directions, while sub bands 4–7 correspond to the *mostly vertical* directions.

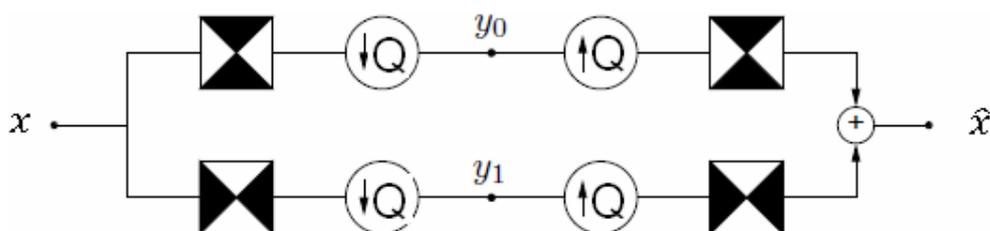


Figure (8). Two-dimensional spectrum partition using quincunx filter banks with fan filters. The black regions represent the ideal frequency supports of each filter. Q is a quincunx sampling matrix.



Figure (9). Example of shearing operation that is used like a rotation operation for DFB decomposition. (a) The “cameraman” image. (b) The “cameraman” image after a shearing operation

2. Multiscale & Directional Decomposition: The Discrete Contourlet Ransform

Combining the Laplacian pyramid and the directional filter bank, Since the directional filter bank (DFB) was designed to capture the high frequency (representing directionality) of the input image, the low frequency content is poorly handled. In fact, with the frequency partition shown in Figure 10, low frequency would “leak” into several directional sub bands, hence the DFB alone does not provide a sparse representation for images. This fact provides another reason to combine the DFB with a multiscale decomposition, where low frequencies of the input image are removed before applying the DFB. Figure (10) shows a multiscale and directional decomposition by using a combination of a Laplacian pyramid (LP) and a directional filter bank (DFB). Bandpass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double iterated filter bank structure, named *contourlet filter bank*, which decomposes images into directional sub bands at multiple scales [11].

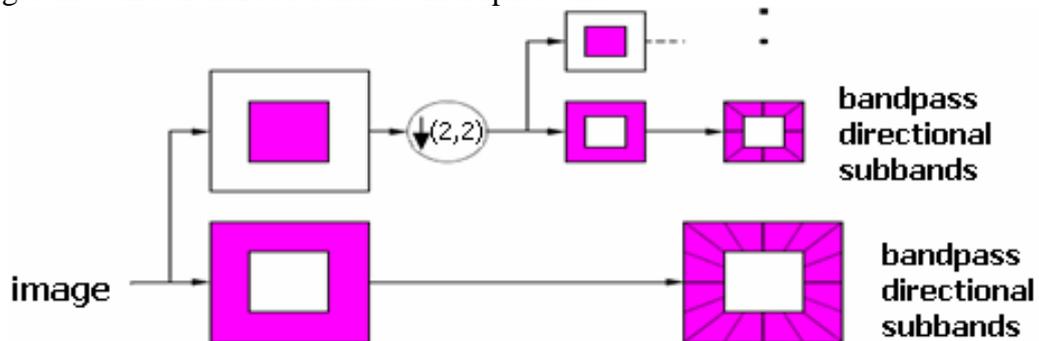


Figure (10). The contourlet filter bank: first, a multiscale decomposition into octave bands by the Laplacian pyramid is computed, and then a directional filter bank is applied to each band pass channel.

3. Multiresolution Analysis

As for the wavelet filter bank, the iterated PDFB can be associated with a continuous domain system, which we call contourlet. This connection will be made precise by studying the embedded grids of approximation as in the multi resolution analysis for wavelets. The new elements are multiple directions and the combination with multiscale [14].(as in figure 11)

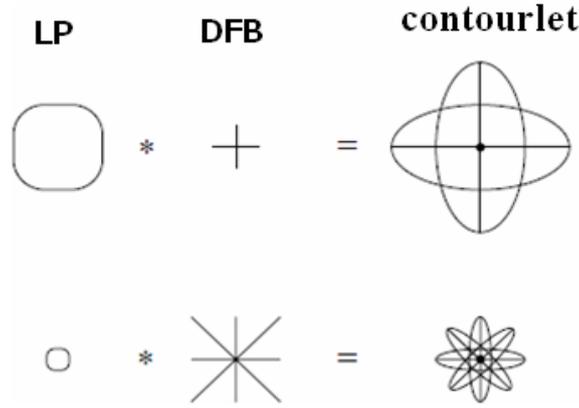


Figure (11). Illustration of the contourlet basis images that satisfies the curve scaling relation. From the upper line to the lower line, the scale is reduced by four while the number of directions is doubled.

5-1. Multiscale

Suppose that the LP in the PDFB uses orthogonal filters and down sampling by two is taken in each dimension. Under certain conditions, the low pass filter G in the LP uniquely defines an orthogonal scaling function $\phi^{(0)} \in L^2(\mathbb{R}^2)$ via the two-scale equation, Denote

$$\phi(t) = 2 \sum_{n \in \mathbb{Z}^2} g[n] \phi(2t - n)$$

$$\phi_{j,n} = 2^{-j} \phi\left(\frac{t - 2^j n}{2^j}\right), \quad j \in \mathbb{Z}, n \in \mathbb{Z}^2$$

Then, the family $\{\phi_{j,n}\}_n \in \mathbb{Z}^2$ is an orthonormal basis of V_j for all $j \in \mathbb{Z}$. the sequence of nested subspaces $\{V_j\}_{j \in \mathbb{Z}}$ satisfies the following invariance properties:

In other words, V_j is a subspace defined on a uniform grid with intervals

Shift invariance: $f(t) \in V_j \Leftrightarrow f(t - 2^j k) \in V_j, \quad \forall j \in \mathbb{Z}, k \in \mathbb{Z}^2$

Scale invariance: $f(t) \in V_j \Leftrightarrow f(2^{-1}t) \in V_{j+1}, \quad \forall j \in \mathbb{Z}$.

$2^j \times 2^j$, which characterize the image approximation at the resolution 2^j .

The different image in the LP carries the details necessary to increase the resolution of an image approximation. Let W_j be the orthogonal complement of V_j in V_{j-1} (also see Figure 12) [14].

$$V_{j-1} = V_j \oplus W_j$$

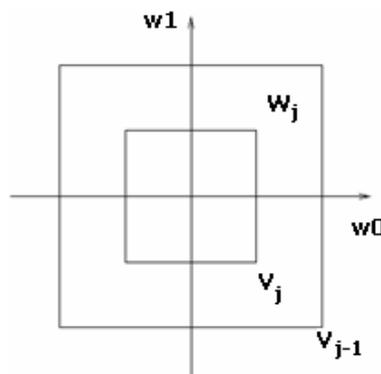


Figure (12). Multiscale subspaces generated by the Laplacian pyramid.

The LP can be considered as an oversampled filter bank where each poly phase component of the difference signal comes from a separate filter bank channel like the coarse signal . Let $F_i(z)$, $0 \leq i \leq 3$ be the synthesis filters for these poly phase components. Note that $F_i(z)$ are of high pass filters. As in the wavelet filter bank, we associate with each of these filters a continuous function $\psi^{(i)}(t)$ where

$$\psi^{(i)}(t) = 2 \sum_{n \in \mathbb{Z}^2} f_i[n] \phi(2t - n).$$

5-2. Multiscale and Multidirection

Figure 13 illustrates the detailed directional subspaces $W^{(l)}_{j,k}$ in the frequency domain. The indexes j , k , and n specify the scale, direction, and location, respectively. Note that the number of DFB decomposition levels l can be different at different scales j , and in that case will be denoted by l_j [11].

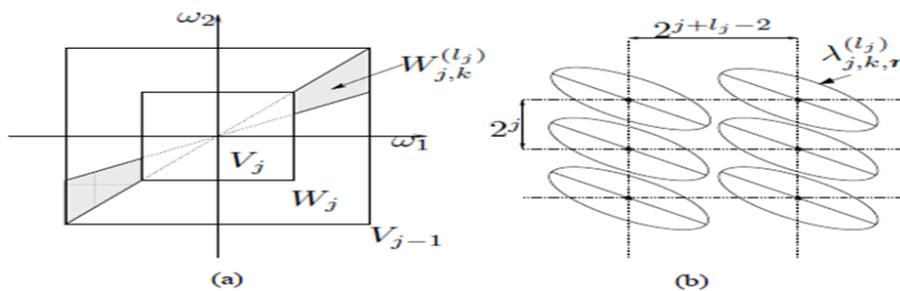


Figure. (13). (a) Contourlet subspaces. (a) Multiscale and multidirection subspaces generated by the contourlet transform which is illustrated on a 2-D spectrum decomposition.(b) Sampling grid and approximate support of contourlet functions for a “mostly horizontal” subspace $W^{(l_j)}_{j,k}$. For “mostly vertical” subspaces, the grid is transposed.

Figure (14) shows an example of Contourlet transform of the “Peppers” image. The image is decomposed into two pyramidal levels, which are then decomposed into four and eight directional subbands.

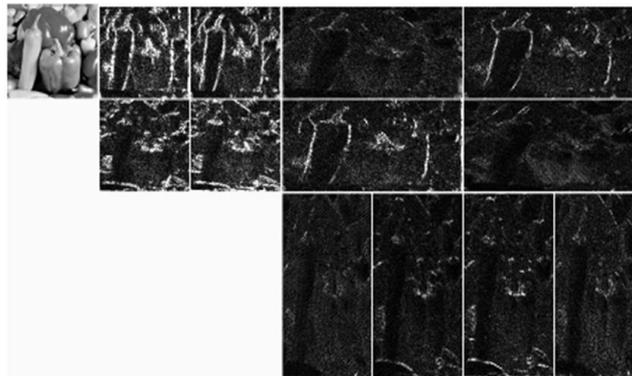


Figure (14). the result contourlet transform decomposed into two pyramidal levels.

6. EZT Algorithm

The following steps represent all the principle of EZW

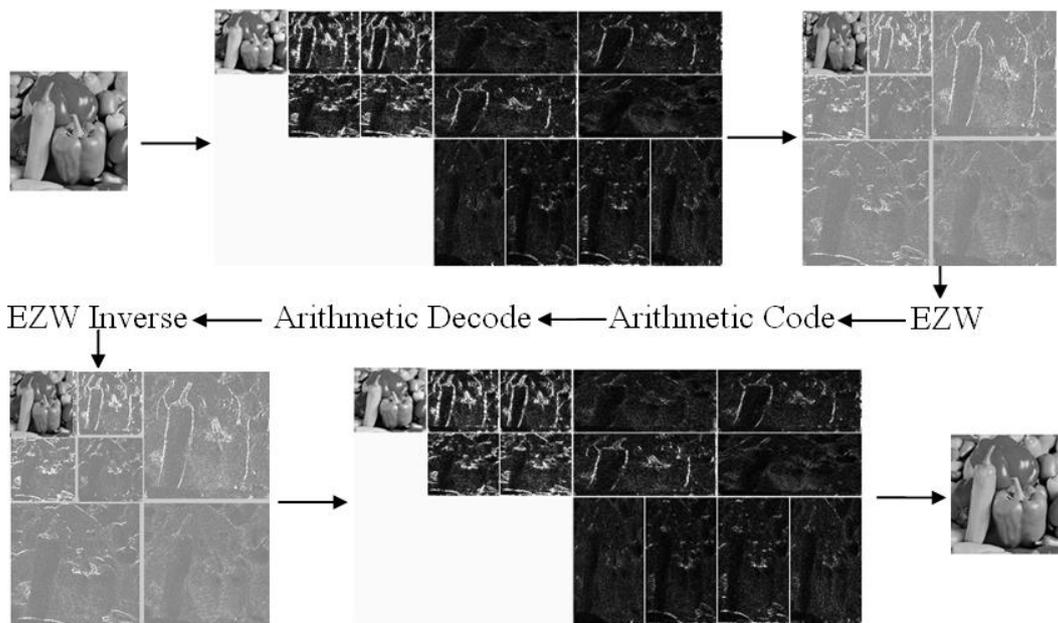
- First step: The DWT of the entire 2-D image will be computed by FWT
- Second step: Progressively EZW encodes the coefficients by decreasing the threshold
- All the coefficients are scanned in a special order

- If the coefficient is a zero tree root, it will be encoded as ZTR. All its descendants don't need to be encoded – they will be reconstructed as zero at this threshold level
- If the coefficient itself is insignificant but one of its descendants is significant, it is encoded as IZ (isolated zero).
- If the coefficient is significant then it is encoded as POS (positive) or NEG (negative) depending on its sign.
- Third step: Arithmetic coding is used to entropy code of the symbols^[15].

7. Proposed Algorithm

- 1- Read the input image.
- 2- Decomposition the input image by nonsampled contourlet transform (NSCT).
- 3- Rearrange the coefficient of contourlet transform in the same form as the coefficient of the wavelet transform.
- 4- Progressively EZW encodes the coefficients by decreasing the threshold
All the coefficients are scanned in a special order
 - If the coefficient is a zero tree root, it will be encoded as ZTR. All its descendants don't need to be encoded – they will be reconstructed as zero at this threshold level.
 - If the coefficient itself is insignificant but one of its descendants is significant, it is encoded as IZ (isolated zero).
 - If the coefficient is significant, then it is encoded as POS (positive) or NEG (negative) depending on its sign.
- 5- Arithmetic coding is used to entropy code the symbols.
- 6- Arithmetic decoding is used.
- 7- Applied EZW decoding.
- 8- Rearrangement in reverse direction of the coefficient of the previous step will be the same form of the contourlet transform.
- 9- Applied contourlet inverse.

8. Applied Example



9. Results and Discussion:-

Applied the proposed algorithm on original image lena.bmp having size 256 x 256 with different values of threshold. In table (1) the proposed algorithm shows that it is stable with varying threshold values which can be clearly seen from evaluating the correlation and MSE factors. Something illustrated in Figure (15).

Table (1). correlation and MSE factors related to threshold

Threshold	EZC			EZW		
	correlation	MSE	PSNR	correlation	MSE	PSNR
5	0.9610	508.988878	24.72	0.9804	108.0640	27.79
10	0.9607	500.978918	24.72	0.9806	107.1545	27.83
15	0.9607	500.978918	24.72	0.9806	107.1545	27.83
20	0.9556	525.743975	22.69	0.9797	111.7561	27.65
25	0.9556	525.743975	22.69	0.9797	111.7561	27.65
30	0.9556	525.743975	22.69	0.9797	111.7561	27.65
35	0.9362	716.475081	19.27	0.9715	155.6583	26.21
40	0.9363	716.475081	19.27	0.9715	155.6583	26.21
45	0.9362	716.475081	19.27	0.9715	155.6583	26.21
50	0.9362	716.475081	19.27	0.9715	155.6583	26.21
55	0.9362	716.475081	19.27	0.9715	155.6583	26.21
60	0.9362	716.475081	19.27	0.9715	155.6583	26.21

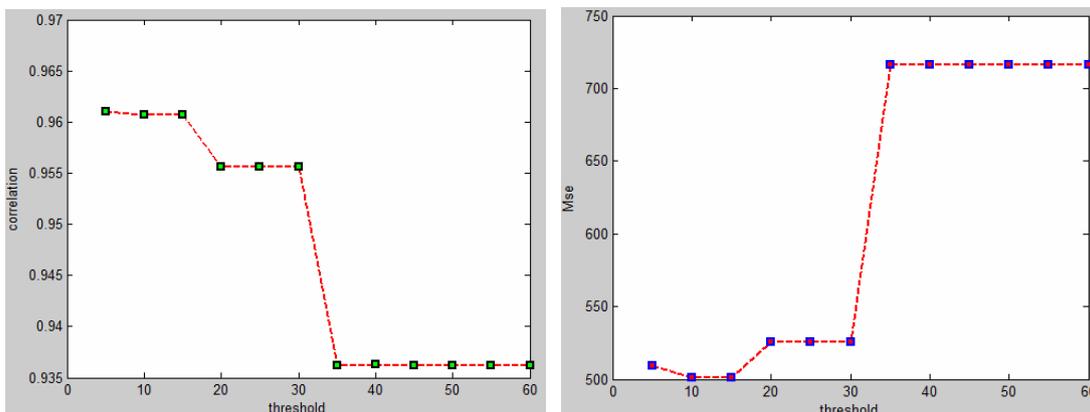


Figure (15). correlation and MSE factors related to threshold

Effect of the threshold value and the image size studied on known image LENA256.bmp, the difference between the original and retrieved one based on different size of the image and different value of the threshold value can be seen in the appendix.

Also, the algorithm stability was tested on different size of files and figure(16) can show its stability when the sizes were changed.

Table (2). different factors verses variable image size

File size	Threshold	Correlation	MSE
128	5	0.9273	378.799476
256	5	0.9610	508.988878
512	5	0.9881	65.231760

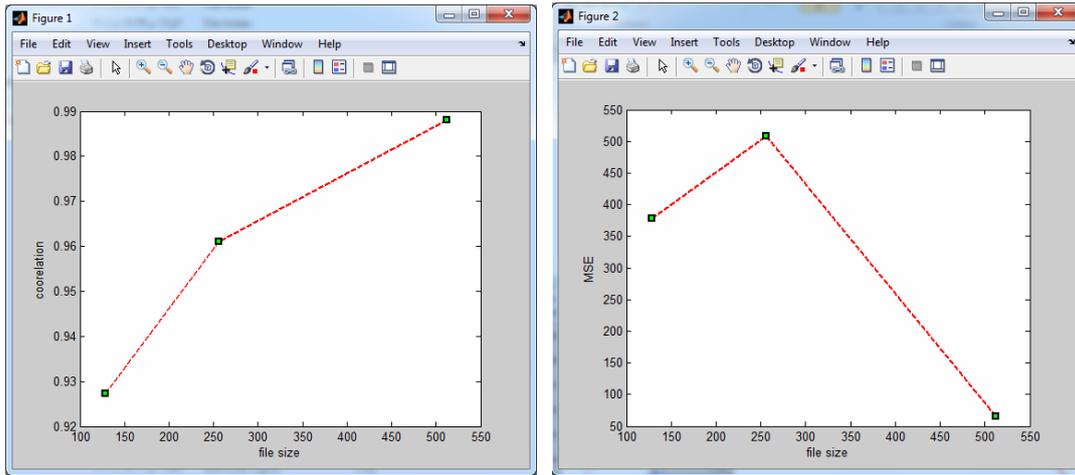


Figure (16). correlation and MSEQ verses variable image size

10. Conclusion

The proposed technique is a little bit slower than the technique based on the wavelet transform but the accuracy is higher because it deals with multidirectional, so it works with several numbers of filters. Also, this technique it seems to be a little bit more complicated due to its deep details.

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Appendix (A)



Figure (A-1). original and retrieved image with different value of threshold



Figure(A-2). original and retrieved image threshold 5 with any file size