Image Compression Using 3-D Two-Level Techniques

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ABSTRUCT

In this paper three techniques for image compression are implemented. The proposed techniques consist of three dimension (3-D) two level discrete wavelet transform (DWT), 3-D two level discrete multi-wavelet transform (DMWT) and 3-D two level hybrid (wavelet-multi-wavelet transform) technique. Daubechies and Haar are used in discrete wavelet transform and Critically Sampled preprocessing is used in discrete multi-wavelet transform. The aim is to maintain to increase the compression ratio (CR) with respect to increase the level of the transformation in case of 3-D transformation, so, the compression ratio is measured for each level. To get a good compression, the image data properties, were measured, such as, image entropy (He), percent root-mean-square difference (PRD %), energy retained (Er) and Peak Signal to Noise Ratio (PSNR).

Based on testing results, a comparison between the three techniques is presented. CR in the three techniques is the same and has the largest value in the 2nd level of 3-D. The hybrid technique has the highest PSNR values in the 1st and 2nd level of 3-D and has the lowest values of (PRD %). so, the 3-D 2-level hybrid is the best technique for image compression.

KEYWORD: Image compression, 3-D two level wavelet transform, 3-D two level multi-wavelet transform, 3-D two level hybrid technique, Image data properties.

ضغط الصورة باستخدام تقنيات ثنائية المستوى لثلاثي الابعاد

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الخلاصة

تم في هذا البحث بناء ثلاث تقنيات لضغط الصورة. التقنيات المقترحة تتضمن اسلوب التحويل الثنائي المستوى –الثلاثي الابعاد للمويجة وقد تم هذا باستعمال (Daubechies) و (Haar) واسلوب التحويل الثنائي المستوى –الثلاثي الابعاد للمويجة المتعددة وتم هذا باستعمال نوع (Critically Sampled preprocessing) والتقنية الاخرى استخدام الاسلوب الهجين(تحويل المويجة – المويجة المتعددة) الثنائي المستوى – الثلاثي الابعاد. الهدف هنا هو الحفاظ على زيادة نسبة الضغط بالصورة مع زيادة مستوى التحويل في حالة التحويل الثلاثي الابعاد لذلك تم هنا قياس نسبة الضغط بالصورة لكل مستوى من مستويات التحويل. ايضا تم قياس خواص بيانات الصورة وذلك للحصول على ضغط جيد للصورة ومن هذه الخواص مقياس الطاقة المتاحة (entropy) ، النسبة المئوية للجذر التربيعي لمتوسط مربع الفرق بين الصورة الاصلية والصورة المرجعة (قيمة الخطأ) نسبة الى متوسط مربع الصورة الاصلية (percent root-mean-square difference) ، ذروة الاشارة نسبة الى التشويه و التشويش فيها (Peak Signal to Noise Ratio) ، والحفاظ على الطاقة(energy retained).

اعتمادا على نتائج الاختبار تم مقارنة التقنيات الثلاث وتبين أن تقنية الاسلوب الهجين للمستويين الاول والثاني الثلاثي الابعاد اعطى اعلى قيم لذروة الاشارة نسبة الى التشويه و التشويش فيها واقل قيم للنسبة المئوية للجذر التربيعي لمتوسط مربع الفرق بين الصورة الاصلية والصورة المرجعة نسبة الى متوسط مربع الصورة الاصلية. أما بالنسبة لنسبة الضغط فانها

متساوية للتقنيات الثلاث واعلى قيمة لها في المستوى الثاني لثلاثي الابعاد. لذلك فان الاسلوب الهجين الثنائي المستوى – الثلاثي الابعاد هو افضل تقنية لضغط الصورة.

كلمات رئيسية: ضغط الصورة، اسلوب التحويل الثنائي المستوى –الثلاثي الابعاد للمويجة، اسلوب التحويل الثنائي المستوى –الثلاثي الابعاد للمويجة المتعددة، اسلوب الهجين الثنائي المستوى – الثلاثي الابعاد، خواص بيانات الصورة.

INTRODUCTION

Image compression algorithms aim is to remove redundancy in data in a way which makes image reconstruction possible. This basically means that image compression algorithms try to exploit redundancies in the data; they recognize which data needs to be kept in order to reconstruct the original image and therefore which data can be 'thrown away'. By removing the redundant data, the image can be represented in a smaller number of bits, and hence can be compressed [Karen Lees, 2002],

Related Works

Talib M. Jawad Abbas presented two techniques for comparison. The first technique was the hybrid technique, which used Multi-walidlet. This technique is a combination of 2-dimentional Discrete Multi-wavelet Transform (DMWT) and Walidlet Transform, which converts the speech signal from (1-D) into two dimensional (2-D) forms. Next, the 2-D Multi-walidlet transform is applied to each 2-D signal. The second technique used 3D-(DMWT) on multi-walidelet coefficients matrices using GHM four multi-filters and using an over-sampled schema of preprocessing [Talib M. Jawad Abbas, 2008].

A method for image compression is described, in the wavelet transform technique the coefficients below a certain threshold are removed so a global threshold is used to improve the wavelet compression technique. The aim is to maintain the retained energy and to increase the compression ratio with respect to other global thresholds commonly used [Macarena Boix, 2010].

In order to develop an efficient compression scheme and to obtain better quality and higher compression ratio using multi-wavelet transform and embedded coding of multi-wavelet coefficients through set partitioning in hierarchical trees algorithm (SPIHT) is used [Muna F. Al-Sammaraie, 2011]. Different wavelets are used to carry out the transform of test image and the results analyzed according to the values of peak signal to noise ratio obtained and the computation time taken for decomposition and reconstruction [P.M.K. Prasad, 2012].

COMPRESSION USING WAVELET TRANSFORM:

Wavelet analysis can be used to divide the information of an image into approximation and detail sub signals. The approximation sub signal shows the general trend of pixel values, and three detail sub signals show the vertical, horizontal and diagonal details or fast changes in the image [P.M.K. Prasad, 2012].

Discrete wavelet transform employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high filters, respectively. The first level decomposition mathematical expressions are [Tara Othman, 2006]:

$$y_{high}[k] = \sum_n x[n].g[2k-n] \qquad (1)$$

$$y_{low}[k] = \sum_n x[n].h[2k-n] \qquad (2)$$

In the decomposition level one, the image will be divided into 4 sub-bands, called LL, LH, HL, and HH. The LL sub-band is a low-resolution residue that has low frequency components, which are often referred to as the average image, LH provides vertical detailed images, HL provides detailed images in the horizontal direction, finally, the HH sub-band image gives details on the diagonal, while the LL sub-band is divided again at the time of decomposition at a higher level i.e. LL sub-band can be further decomposed into four sub-bands labeled as LL2, LH2, HL2, and HH2 as shown in Fig. (1).

The process is repeated in accordance with the desired level. In this research, a 2- level decomposition is considered.

In the discrete wavelet transform (DWT), there are properties for precise reconstruction. This nature gives a sense that in fact no information is lost after the transformed image is set to its original form. But there are missing information on image data compression with wavelet transform that occurs during quantization. Information loss due to compression should be minimized to keep the quality of the compression.

A good quality compression is generally achieved in the process of memory consolidation, which generates a small reduction, and vice versa. The quality of an image is subjective and relative, depending on the observation of the user [P.M.K. Prasad, 2012].

COMPRESSION USING MULTI-WAVELET TRANSFORMS:

Multi-wavelet possess more than one scaling function offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. Multi-wavelets can achieve better level of performance than scalar wavelets with similar computational complexity. In the case of nonlinear approximation with multi-wavelet basis, the multi-wavelet coefficients are effectively “reordered” according to how significant they are in reducing the approximation error [S. Esakkirajan, 2008].

The multi scaling function and the multi-wavelet function will satisfy matrix dilation as in the following equations [Muna F. Al-Sammaraie, 2011]:

$$\emptyset(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} H_k \emptyset(2t-k) \tag{3}$$

$$\varphi(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} G_k \varphi(2t-k) \tag{4}$$

The multi-wavelet used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. Since, multiple iteration over the low - pass data is desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together. The multi-wavelet decomposition sub-bands are shown in Fig. (2). for multi-wavelets the L and H have subscripts denoting the channel which the data corresponds. For example, the sub-band labeled L1H2 corresponds to data from the second channel high pass filter in the horizontal direction and the first channel low pass filter in the vertical direction. This shows how a single level of decomposition is done. In practice, more than one decomposition performed on the image. Successive iterations are performed on the low pass coefficients from the previous stage to further reduce the number of low pass coefficients. Since the low pass coefficients contain most of the original signal energy, this iteration process yields better image compression [P.V.N.Reddy, 2011].

IMAGE DATA PROPERTIES:

In order to make meaningful comparison of different image compression techniques, it is necessary to know the properties of the image. One property is the image entropy; a less details picture will have low entropy. For example a very low frequency, highly correlated image will be compressed well by many different techniques; one way of calculating entropy is suggested by:

$$H_e = -\sum_{k=0}^{G-1} P(k)\, \mathrm{Log}_2[P(k)] \tag{5}$$

where G is the image grey-levels and the probability of grey-level k is p(k). The entropy also can be calculated using:

$$H_e = \text{Image Entropy}(I(x,y)) \qquad (6)$$

where $I(x,y)$ is the original image [Karen Lees, 2002].

The most common criterion to measure reconstructed image quality is the Percent Root-mean-square Difference (PRD%).

Let $X[n]$ and $X'[n]$ be the original and reconstructed signals, respectively, N is the length of the window over which the metrics are calculated, and $e[n] = X[n] - X'[n]$ the coding noise [Carlos Bazán-Prieto, 2012]. PRD parameter as quality measurement, can mask the real performance of an algorithm since it depends on the mean value of the original signal [Manuel Blanco, 2005], it is given by:

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1} e^2[n]}{\sum_{n=0}^{N-1} x^2[n]}} \times 100 \qquad (7)$$

The PRD describes the error in terms of percentage of image energy which is useful to assess the impact of the error on the image. [Carlos Bazán-Prieto, 2012]:

There are two things that can be used as benchmarks of compression quality, the Peak Signal to Noise Ratio (PSNR) and compression ratio (CR). PSNR is one of the parameters that can be used to quantify image quality. PSNR parameter is often used as a benchmark level of similarity between reconstructed images with the original image. A larger PSNR produces better image quality. PSNR equation is illustrated below [P.M.K. Prasad, 2012]:

$$PSNR = 20\log_{10}\frac{255}{\sqrt{MSE}} \qquad (8)$$

where

$$MSE = \frac{1}{mn}\sum_{y=1}^{m}\sum_{x=1}^{n}\left(I(x,y) - I'(x,y)\right)^2 \qquad (9)$$

where $I'(x,y)$ is the reconstructed image, m and n are the dimensions of the image.

Compression ratio is the ratio of number of bits required to represent the data before compression to the number of bits required to represent data after compression. Increase of compression ratio causes more effective compression technique employed and vice versa [Nagamani .K, 2012].

To reach this goal, compression methods introduce certain, sometimes undesirable, effects such as the increase of computational complexity, processing delays, and coding noise or distortion. In order to quantify the effect of distortion, two objective metrics are used: PRD and Root Mean Square Error (RMSE) [Carlos Bazán-Prieto, 2012].

To analyze the efficiency of the compressor, one can use as a parameter, the energy retained:

$$E_r = \frac{\|I_c(x,y)\|^2}{\|I(x,y)\|^2} \times 100 \qquad (10)$$

where $I_c(x,y)$ represents the compressed image [Macarena Boix, 2010].

THE PROPOSED TECHNIQUES BLOCK DIAGRAM:

The proposed technique consists of three techniques applied to the image after image preprocessing step, these techniques are:

1. Three dimension (3-D) two-level discrete wavelet transform.
2. 3-D two-level discrete multi-wavelet transform.
3. 3-D two-level hybrid (wavelet- multi-wavelet transform) technique.

The transformation algorithm is applied in *x*, *y* direction then applied in the *z*-direction [Talib M. Jawad Abbas, 2008], i.e., a 2-D transform (1st and 2nd level) is applied in *x*, y direction then 1-D transform (1st and 2nd level) is applied in the *z*- direction.

Fig. (3) shows the block diagram of 3-D two-level wavelet image compression, Fig. (4) shows the block diagram of 3-D two-level multi-wavelet image compression and Fig. (5) shows the block diagram of proposed 3-D two-level hybrid technique

In this research, the parameters, PRD, PSNR and CR are calculated for all proposed techniques, i.e., for each first and second level in 3-D wavelet, multi-wavelet and hybrid techniques.

IMAGE PREPROCESSING:

The first step is to deal with the image using some of image processing techniques in order to prepare it to the next step. So the following steps must be followed:

1. Input the color or grey image of any size or format.
2. Convert the image to a grey-scale form (if it is color). By using matlab functions, one can reconstruct the color image.
3. Resize the image into a nearest square and to power of two in order to apply DWT or DMWT, i.e., the conditions of DWT or DMWT.
4. Some of images are resized to be of size (256*256) which is the nearest square and power of two to their original sizes, some of them are resized to be of size (512*512) while the other are resized to be of size (1024*1024).

COMPUTATION OF THE PROPOSED TECHNIQUE ALGORITHM:

A: 3-D Two-Level Wavelet Transform:

The following steps illustrate the computation of 3-D two-level wavelet transform:

1. For a general NxNxM, 3-D array, where N*N is the dimension of the image and M=4=no. of matrices, i.e.4 input images, apply a single level discrete 2-D wavelet transform using Daubechies wavelet transform for all matrices.

2. Apply a 2^{nd} level 2-D DWT using Daubechies wavelet transform for each low – low sub-band of each matrix.

3. Apply a single level 1-D Haar DWT to each low-low sub band (those produced from **step 2**) in the z-direction. This can be done as follows:

a. Construct a vector (v) containing four elements (this number as the number of the matrices), v (1, 1) = [a_{11} b_{11} c_{11} d_{11}], where a_{11}, b_{11}, c_{11} and d_{11} are the first elements in each matrix.

b. Construct a second vector containing four elements, v (1, 2) = [a_{12} b_{12} c_{12} d_{12}], where a_{12}, b_{12}, c_{12} and d_{12} are the elements in the position first raw and second column in each matrix.

c. The same procedure continue till reach to the vector numbered (N/4*N/4), where (N/4*N/4) is equal to the size of the low-low sub-band that produced from **step 2**.

d. Apply a single level 1-D Haar DWT to each vector.

4. Apply a 2^{nd} level 1-D Haar DWT to the approximation coefficients vector of each vector that produced from **step 3**.

5. Finally, Take only the approximation coefficients vector that produced from **step 4.**

B: 3-D Two - Level Multi-wavelet Transform:

The following steps illustrate the computation of 3-D two-level multi-wavelet transform:

1. For a general NxNxM, 3-D array, where N*N is the dimension of the image and M=4=no. of matrices, i.e.4 input images, apply a single level critically sampled preprocessing 2-D DMWT for all matrices.

2. Apply a 2^{nd} level critically sampled preprocessing 2-D DMWT for each low–low sub-band of each matrix.

3. Apply a single level 1-D DMWT to each low-low sub-band (those produced from **step 2**) in the z-direction. This can be done as follows:

a. Construct a vector (u) containing four elements (this number as the number of the matrices), u(1,1) = [e_{11} f_{11} g_{11} h_{11}], where e_{11}, f_{11}, g_{11} and h_{11} are the first elements in each matrix.

b. Construct a second vector which contain four elements, u (1, 2) = [e_{12} f_{12} g_{12} h_{12}], where e_{12}, f_{12}, g_{12} and h_{12} are the elements in the position first raw and second column in each matrix.

c. The same procedure continue till reach to the vector numbered (N/4*N/4), where (N/4*N/4) is equal to the size of the low-low sub-band that produced from **step 2**.

d. Apply a single level 1-D critically sampled preprocessing DMWT to each vector.

4. Apply a second level 1-D critically sampled preprocessing DMWT to the low sub-band that produced from **step 3**.

5. Finally, Take only the low sub-band that produced from **step 4.**

C: 3-D Two - Level Hybrid Technique:

The following steps illustrate the computation of 3-D two-level wavelet-multi-wavelet transform:

1. For a general NxNxM, 3-D array, where N*N is the dimension of the image and M=4=no. of matrices, i.e.4 input images, apply a single level discrete 2-D wavelet transform using Daubechies wavelet transform for all matrices.

2. Apply a 2nd level 2-D DWT using Daubechies wavelet transform for each low – low sub-band of each matrix.

3. Apply a single level 1-D DMWT to each low-low sub-band (those produced from **step 2**) in the z-direction. This can be done as follows:

a. Construct a vector (w) containing four elements (this number as the number of the matrices), w(1,1)=[q_{11} r_{11} s_{11} t_{11}], where q_{11}, r_{11}, s_{11} and t_{11} are the first elements in each matrix.

b. Construct a second vector which contain four elements, w (1, 2) = [q_{12} r_{12} s_{12} t_{12}], where q_{12}, r_{12}, s_{12} and t_{12} are the elements in the position first raw and second column in each matrix.

c. The same procedure continue till reach to the vector numbered (N/4*N/4), where (N/4*N/4) is equal to the size of the low-low sub-band that produced from **step 2**.

d. Apply a single level 1-D critically sampled preprocessing DMWT to each vector.

4. Apply a second level 1-D critically sampled preprocessing DMWT to the low sub-band that produced from **step 3**.

5. Finally, Take only the low sub-band that produced from **step 4.**

An example test is applied to a standard image, “Lena”, of size 1024*1024 pixels. Figures 6, 7 and 8 illustrate the results of applying the proposed techniques on “Lena” image.

TESTING AND EVALUATION OF RESULTS:

There are five tables show the results measured for the proposed system when applied on the data base images. The bold values are the best results.

For a comparison between 3-D one and two level wavelet transform, Haar, Db3, Db5, and Coiflet, the energy retained (Er), entropy (He), percent root-mean-square difference (PRD%) and peak signal to noise ratio (PSNR) from eq.’s 10, 6, 7 and 8 are measured and the results are shown as tabulated in table 1. Energy retained in the 2nd level of Db5 and Coiflet1 is better than that in the 1st level, but the entropy is good in the 2nd level for Db3, Db5, Coiflet1 and Haar (which is the best one) than that in the 1st level. Db5 is the best one in measuring PRD% (PRD% = 38.2121) and PSNR (PSNR=31.5256) which are the lowest and highest values, respectively. It can be conclude that, Haar and Db5 are compressed better than Db3 and Coifle1.

In table 2, measurements of PRD% and PSNR for 2-D and 3-D one and two level wavelet transform for samples of (14) images, The PRD% in 3-D is half that of 2-D, that’s means that, when using 3-D, the error in terms of percentage of image energy is reduced to half of its value of 2-D. In the other side, the PSNR in 3-D is greater than that in 2-D. In 3-D, the second level PRD% and PSNR is better than that in first level, it can be conclude that,
the image is compressed better when using 3-D tow level.

Table 3 and 4, show 2-D and 3-D critical DMWT and hybrid results, in 3-D, the PRD% is quarter that of 2-D and the PSNR is greater than that of 2-D, also whenever the decomposition Levels increases the PSNR values are also increasing .

Table 5 shows a comparison between the proposed 3-D two-level techniques, 3-D and 2-D one and two level techniques according to the values of PRD%, PSNR and CR. As shown from the results, in 2-D the results of wavelet and hybrid are the same for PRD%, PSNR and CR because the hybrid is 2-D wavelet in x and y direction and 1-D multi-wavelet in z-direction. in 3-D, CR values are 32:1 and 64:1 in the 1st and 2nd level respectively for wavelet, multi-wavelet and hybrid, while in the 2-D CR values are 4:1 and 16:1, also, PRD% in 3-D is less half the value in 2-D in 1st and 2nd level in wavelet and quarter that of 2-D in multi-wavelet and hybrid, hybrid technique has a largest values of PSNR (35.2721) in the 1st Level and (40.6906) in the 2ndLevel in 3-D.

CONCLUSIONS:

The techniques presented in this paper produce some of the best-reported results to date for a 3-D two-level discrete wavelet transform (DWT), discrete multi-wavelet transform (DMWT) and hybrid technique-based image compression and comparison between them.

It is obvious from the results that any wavelet giving good results for decomposition will produce good results for advanced techniques being used for image compression.

Based on testing results, it can be concluded that the hybrid technique has the highest PSNR value in the 1st and 2nd level of 3-D and has the lowest values of (PRD %). CR in the three techniques is the same and has the largest value in the 2nd level of 3-D. So, when the image is compressed to a high CR, then it is increasing the speed of computation and decreasing the wasting time, so, one can use it in authentication, recognition, using as a feature, etc...Therefore, the 3-D 2-level hybrid is the best technique for image compression.

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LIST OF ABBREVIATIONS:

1-D:	One dimension
2-D:	Two dimension
3-D:	Three dimension
DMWT:	Discrete multi-wavelet transform
DWT:	Discrete wavelet transform
CR:	Compression ratio
He:	Entropy
PRD:	Percent root-mean-square difference
MSE:	mean square error
Er :	Energy retained
SPIHT:	Set Partitioning In Hierarchical Trees
GHM	Geronimo, Hardian, Masopute

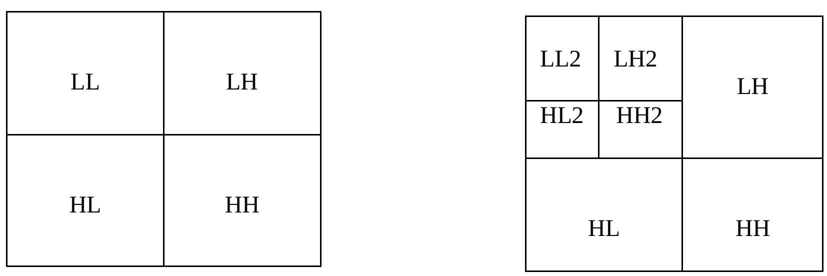


Fig. 1: One and two level wavelet decomposition

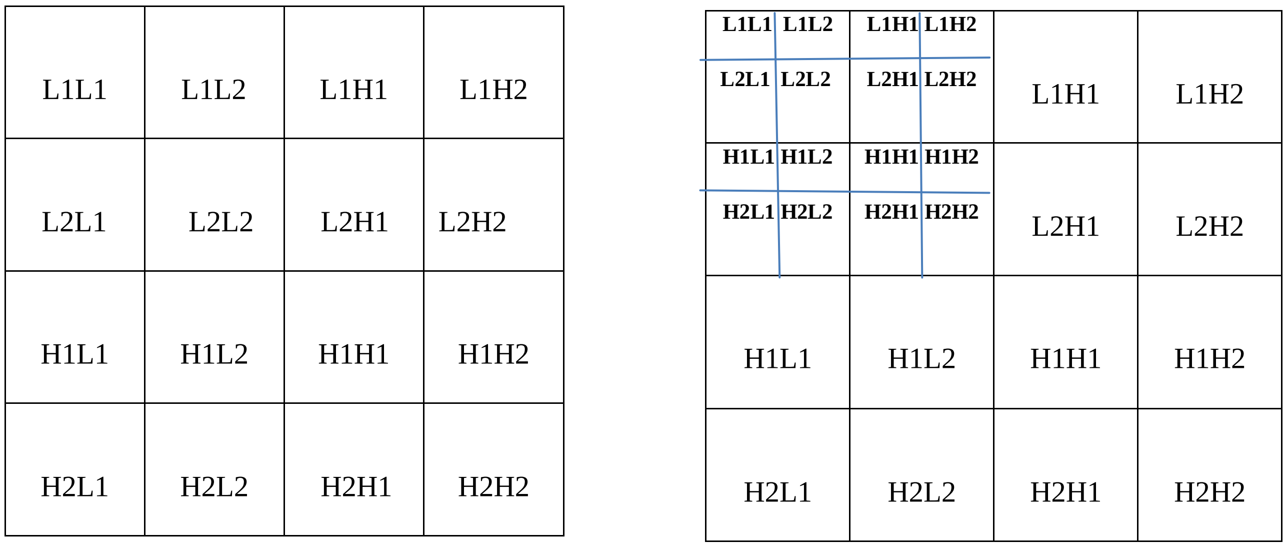


Fig. 2: One and two level multi-wavelet decomposition

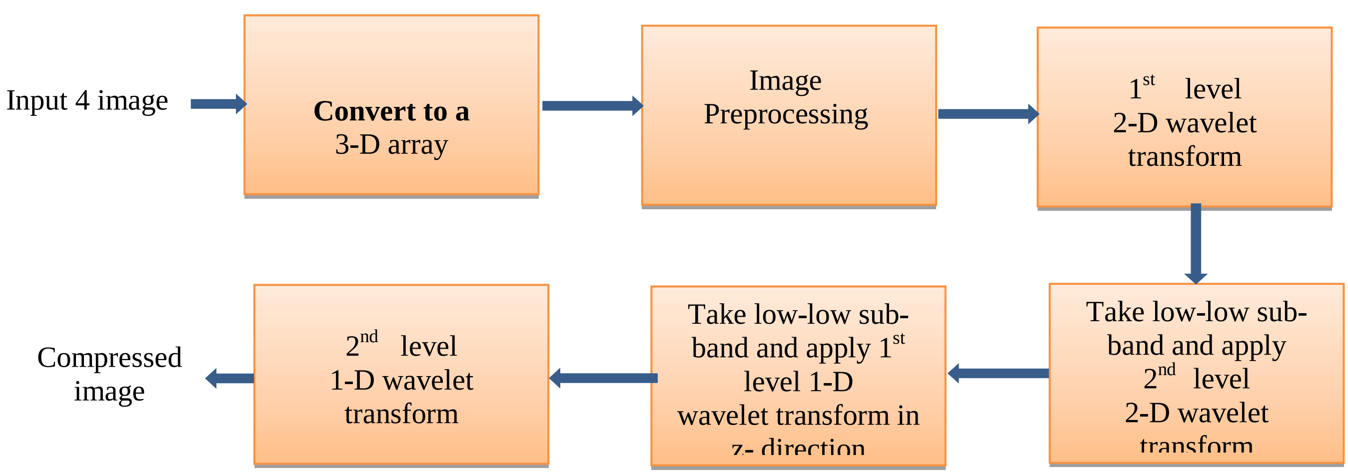


Fig. 3: Block diagram of 3-D two-level wavelet image compression

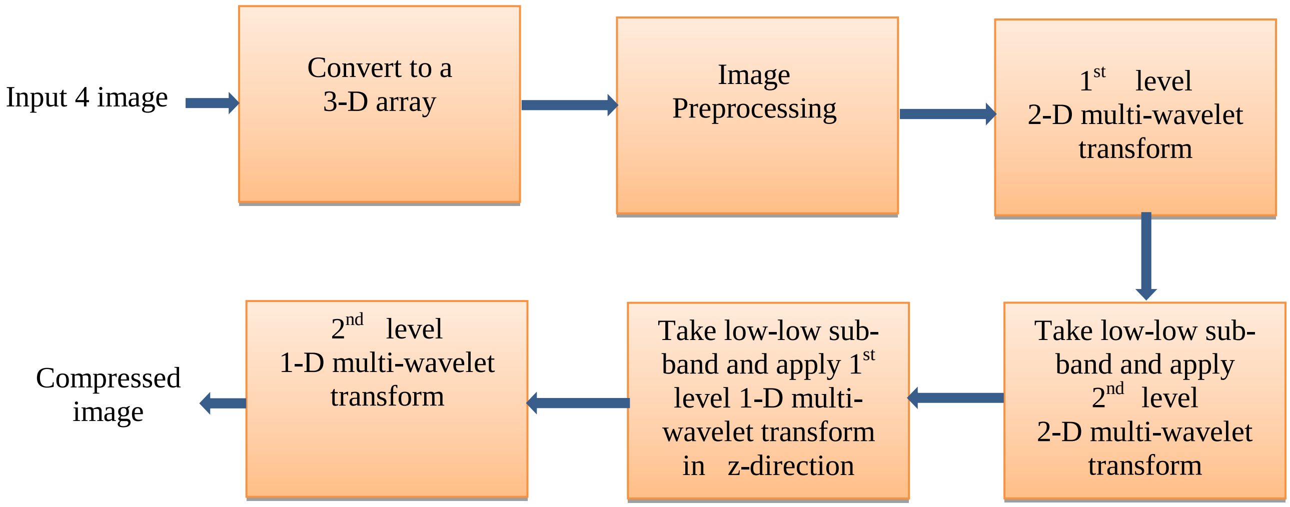


Fig. 4: Block diagram of 3-D two-level multi-wavelet image compression

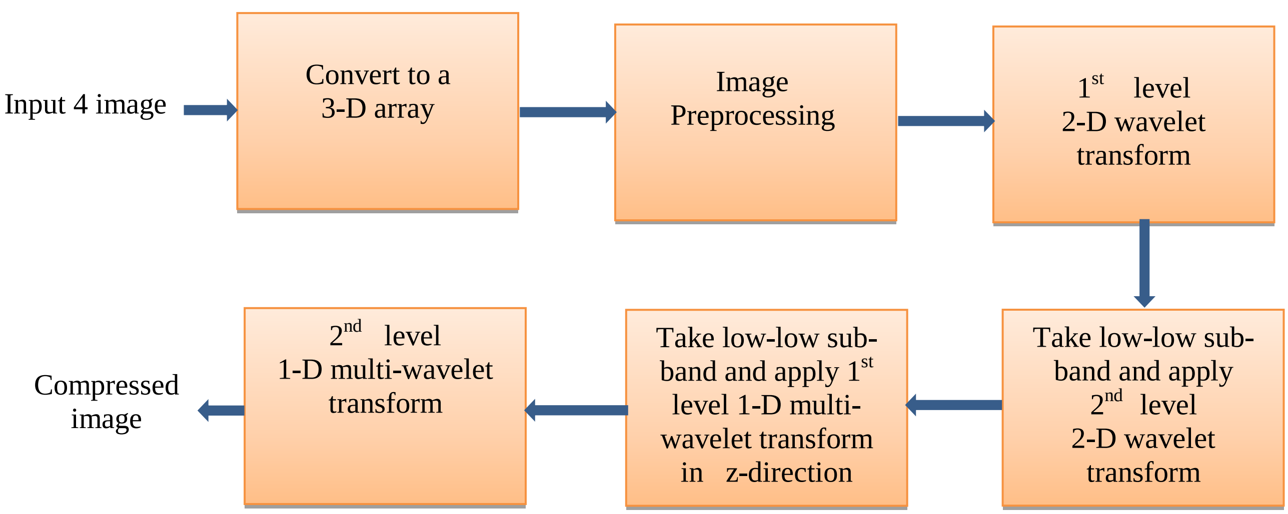


Fig. 5: Block diagram of the proposed 3-D two-level hybrid technique

Original image

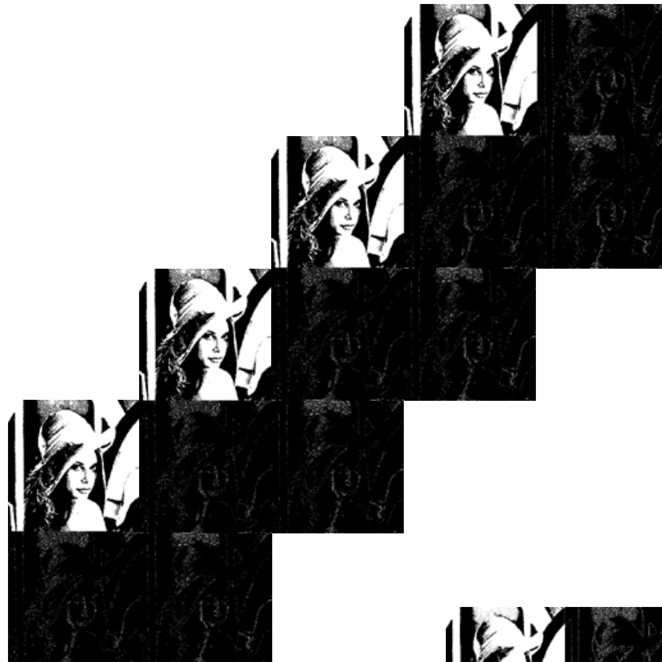


Image after 1st level 2-D wavelet transform

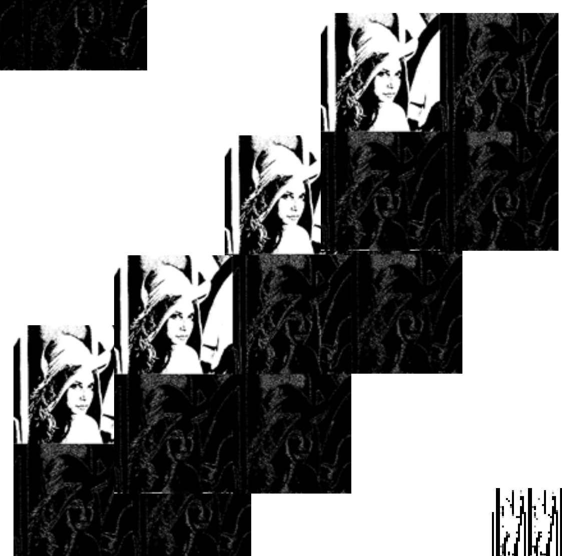


Image after 2nd level 2-D wavelet transform

Image after 3-D 2-level wavelet transform

Fig. 6: 3-D 2- level wavelet transform

Original image

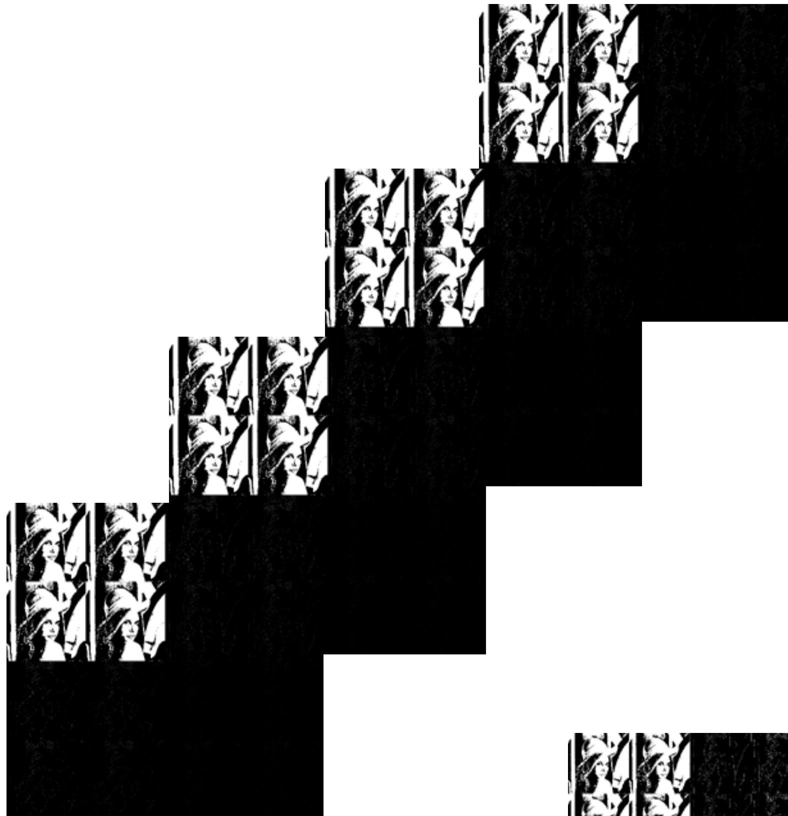


Image after 1st level 2-D multi-wavelet transform

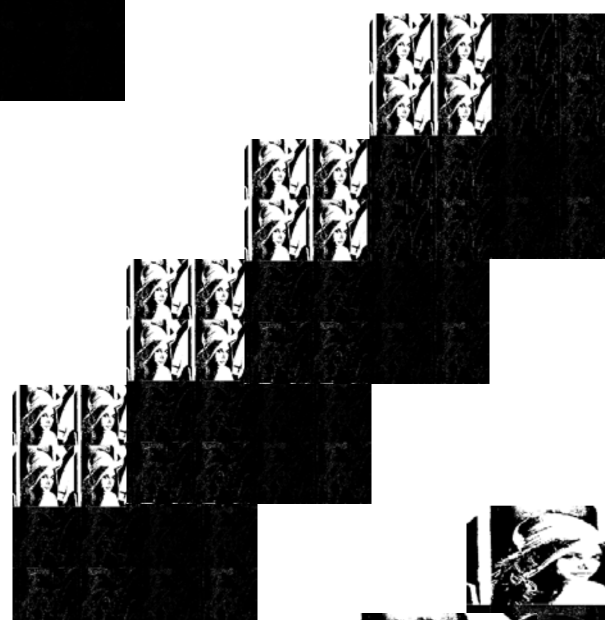


Image after 2nd level 2-D multi-wavelet transform

Image after 1st level 1-D multi-wavelet transform

Image after 2nd level 1-D multi-wavelet transform

Image after 3-D 2- level multi-wavelet transform

Fig.7: 3-D 2- level multi-wavelet transform

Original image

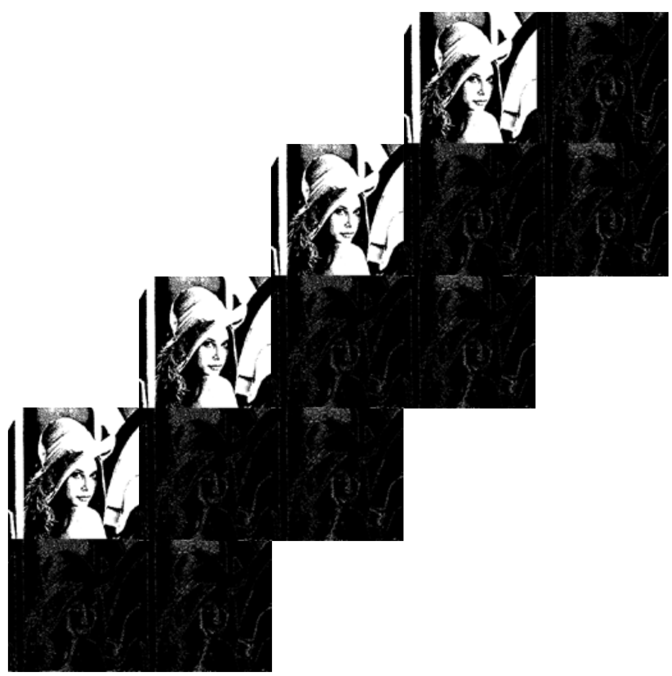


Image after 1st level 2-D wavelet transform

Image after 2nd level 2-D wavelet transform

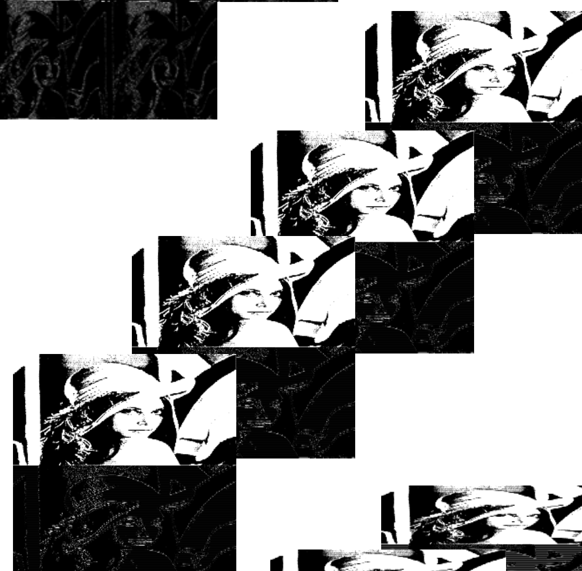


Image after 1st level 1-D multi-wavelet transform

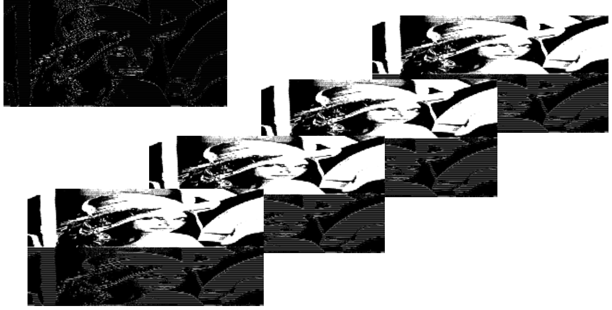


Image after 2nd level 1-D multi-wavelet transform

Image after 3-D 2- level hybrid technique

Fig. 8: 3-D 2- level hybrid technique

Table 1: 3-D Wavelet transform

3-D wavelet transform	Haar		Db3		Db5		Coiflet1	
	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level
Er	**99.9578**	99.8707	**100.002**	99.9897	100.0564	100.1867	99.9753	**99.9874**
En	1.0879	**0.9080**	1.1331	**1.0471**	1.1633	**1.1443**	1.0603	**1.0036**
PRD%	41.4125	**41.4030**	**39.8878**	40.4483	39.3609	**38.2121**	**40.0527**	40.8571
PSNR	30.5364	**30.5714**	**30.8640**	30.8321	30.981	**31.5256**	**30.8291**	30.7300

Table 2: PRD% and PSNR for wavelet transform

Wavelet transform	2-D wavelet transform		3-D wavelet transform		2-D wavelet transform		3-D wavelet transform	
	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level
	PRD%	PRD%	PRD%	PRD%	PSNR	PSNR	PSNR	PSNR
Image1	99.9906	99.9729	41.3898	**41.3086**	29.3574	26.3478	30.9957	**31.0102**
Image2	100.0001	99.9982	**41.4170**	41.4211	27.2455	24.2354	**28.8816**	28.8814
Image3	99.9997	100.0001	41.4246	**41.4167**	22.7343	19.7240	**24.3685**	24.3683
Image4	100.0010	100.0050	**41.4219**	41.4319	25.9887	22.9781	**27.6240**	27.6224
Image5	100.0098	100.0191	41.4330	**41.4316**	26.8338	23.8223	28.4661	**28.4663**
Image6	99.9996	99.9985	41.4215	**41.4087**	30.7860	27.7758	32.4207	**32.4227**
Image7	100.0464	100.0121	41.4425	**41.3157**	34.8994	31.8972	36.5336	**36.5346**
Image8	100.0072	100.0151	41.3917	**41.3423**	27.8306	24.8201	29.4711	**29.4767**
Image9	100.0683	100.1911	**41.4273**	41.5572	31.1759	28.1606	**32.8273**	32.8062
Image10	99.9242	99.7350	**41.3840**	41.5758	36.8591	33.8816	**38.5224**	38.4658
Image11	99.9889	99.9975	**41.3996**	41.4156	31.7132	28.7029	**33.3540**	33.3486
Image12	100.0033	100.0043	41.4159	**41.4158**	27.1797	24.1692	28.8158	**28.8176**
Image13	99.9905	99.9278	41.4550	**41.3583**	38.0153	35.0095	39.6446	**39.6701**
Image14	100.0000	100.0006	41.4091	**41.3621**	35.4521	32.4418	37.0899	**37.1009**

Table 3: PRD% and PSNR for critical multi-wavelet transform

Critical multi-wavelet transform	2-D multi-wavelet		3-D multi-wavelet		2-D multi-wavelet		3-D multi-wavelet	
	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level
	PRD%	PRD%	PRD%	PRD%	PSNR	PSNR	PSNR	PSNR
Image1	100.0161	100.0712	**28.7822**	30.7654	29.3552	26.3381	34.1453	**39.5178**
Image2	99.9873	99.9752	**28.5843**	30.2937	27.2466	24.2381	32.1046	**37.5340**
Image3	99.9932	100.0426	**28.6053**	30.4233	23.7349	29.7205	27.5830	**32.9834**
Image4	100.0619	100.0865	**28.6006**	30.2948	25.9834	22.9683	30.8344	**36.2728**
Image5	100.0029	100.0138	**28.5816**	30.3118	26.8344	23.8230	31.6916	**37.1135**
Image6	99.9990	99.9544	**28.5092**	30.1489	30.7861	27.7797	35.6675	**41.1047**
Image7	99.9302	99.8310	**28.0404**	29.9174	34.9095	31.9157	39.9389	**45.2079**
Image8	99.0109	99.9537	**28.7686**	30.6766	27.8303	24.8251	32.6330	**38.0277**
Image9	99.1084	100.0712	**28.7854**	30.4758	31.1724	28.1668	35.9802	**41.4620**
Image10	100.5874	99.3157	**29.6639**	31.2546	36.8016	33.7125	41.3269	**46.9136**
Image11	99.9985	99.2686	**28.9320**	30.7105	31.7124	28.5929	36.4080	**41.8685**
Image12	100.8408	99.9715	**28.5796**	30.3084	27.1073	24.1357	32.0035	**37.4289**
Image13	99.5162	99.5109	**28.5047**	31.0393	38.0566	35.0655	42.9431	**48.1322**
Image14	100.0046	100.0237	**28.4475**	30.1683	35.4517	32.4396	40.3497	**45.7566**

Table 4: Hybrid technique

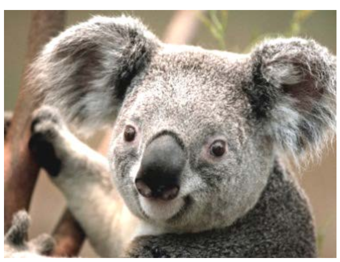
Hybrid technique	2-D multi-wavelet		3-D multi-wavelet		2-D multi-wavelet		3-D multi-wavelet	
	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level	1st Level	2nd Level
	PRD%	PRD%	PRD%	PRD%	PSNR	PSNR	PSNR	PSNR
Image1	99.9906	99.9729	**28.7947**	30.7630	29.3574	26.3478	34.1473	**39.5286**
Image2	100.0001	99.9982	28.5648	**27.2455**	30.2824	24.2354	32.1085	**37.5328**
Image3	99.9997	100.0001	**28.6128**	30.4313	22.7343	19.7240	27.5824	**32.9832**
Image4	100.0010	100.0050	**28.5853**	30.2768	25.9887	22.9781	30.8457	**36.2836**
Image5	100.0098	100.0191	**28.5985**	30.3223	26.8338	23.8223	31.6861	**37.1110**
Image6	99.9996	99.9985	**28.5035**	30.1603	30.7860	27.7758	35.6672	**41.0985**
Image7	100.0464	100.0121	**27.7841**	29.5763	34.8994	31.8972	40.0066	**45.2617**
Image8	100.0072	100.0151	**28.7231**	30.6488	27.8306	24.8201	32.6447	**38.0319**
Image9	100.0683	100.1911	**28.6583**	30.3581	31.1759	28.1606	36.0280	**41.4989**
Image10	99.9242	99.7350	**29.5543**	31.3428	36.8591	33.8816	41.4466	**46.9716**
Image11	99.9889	99.9975	**28.9327**	30.7174	31.7132	28.7029	36.4661	**41.9254**
Image12	100.0033	100.0043	**28.5789**	30.2839	27.1797	24.1692	32.0383	**37.4706**
Image13	99.9905	99.9278	**28.8425**	30.7758	35.0095	38.0153	42.7955	**48.2112**
Image14	100.0000	100.0006	**28.4585**	30.1674	35.4521	32.4418	40.3475	**45.7599**

Table 5: Comparison between three proposed techniques

Algor-ithm	2-D						3-D					
	1st Level			2nd Level			1st Level			2nd Level		
	PRD%	PSNR	CR	PRD%	PSNR	CR	PRD%	PSNR	CR	PRD%	PSNR	CR
Wavelet	100.0021	30.4360	4:1	99.9912	27.6408	16:1	41.4166	32.0725	32:1	41.4115	32.0708	**64:1**
Multi-wavelet	**99.9326**	**30.4987**	**4:1**	**99.8634**	**28.1228**	16:1	28.6703	35.2578	32:1	30.4847	40.6659	**64:1**
Hybrid	100.0021	30.4360	4:1	99.9912	27.6408	16:1	**28.6565**	**35.2721**	**32:1**	**30.2192**	**40.6906**	**64:1**

Samples of Images from Data-Base:


1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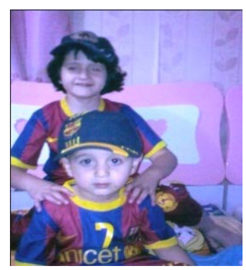
3



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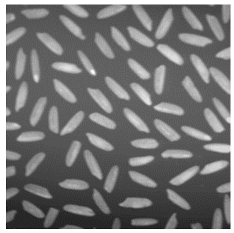
12



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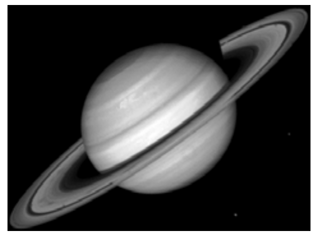

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