Wavelet Coding Design for Image Data Compression

Othman Khalifa
Electrical and Computer Department, International Islamic University, Malaysia

Abstract: *In this paper, image compression algorithms using scalar and vector quantisation are proposed. An analysis of wavelet coefficients encoding is explained. Wavelet capability of energy compaction is shown. Also, wavelet vector quantisation and multiresolution codebook generation is discussed. General description of the proposed image compression algorithm with its feature is presented. In addition, simulation results and comparison with other coders is shown.*

Key words: *Image compression, wavelet, scalar quantisation, vector quantization.*

Received January 21, 2004; accepted May 25, 2004

1. Introduction

Wavelet image coding has been an exciting and fertile area of research in the image processing community in recent years particularly in relation to image compression. It does not only provide a good compression result, but it is also suitable for progressive transmissions and provides a multi resolution capability. However, applying the wavelet transform on images for compression alone does not reduce the amount of data to be compressed, since it may remove some of the redundancy and decorrelate the neighbour pixels. A common way to reduce the number of bits required for compression is to quantise the resulting coefficients from the transformation. The introduction of wavelets in the mid eighties has raised significant applications, which is the wavelet based image compression. These compression systems, preceded by a wavelet transform with further quantization of the wavelet coefficients followed by an entropy coder have proven to be a successful application in the field of image and video compression. In 1993, Shapiro introduced a new quantisation scheme called Embedded Zerotree Wavelet (EZW), where progressiveness was achieved without overhead information. This scheme is particularly well suited for important applications e. g., client/server transmission where the client can choose the actual compression ratio as well as compression of images with a special target rate. The refinement of this algorithm is Set Partitioning in Hierarchical Trees algorithm (SPIHT) by Said and Pearlman [16]. However, since the underlying model, the zerotrees are algorithmically complex to handle, other authors introduced run-length based quantization schemes. Villasenor *et al* [20] algorithm allows faster execution times but suffer from inferior quality of the reconstructed images (measured in PSNR). Lewis and Knowles [13] suggested a new algorithm which uses the non-linear spatial correlation inherent in a transformed image to compress it at below its entropy. It is the extension of the following authors [19, 21].

2. Wavelet Coefficients Encoding

The wavelet transform decomposes the input image into low-frequency coefficients or coarse band and a number of high frequency bands or detail signals according to the level of decomposition. These results can be considered as low-pass and high-pass versions of the original image. The low band pass has a flat distribution and its approximation of the distribution of luminance and chrominance values are similar to those of the original image as shown in Figure 1 for one level multiresolution. The high band coefficients have probability distribution that is similar to laplacian characters with mean zero as shown in Figure 2. Moreover, the wavelet transform generates coefficients that are much less correlated than the original images and are easier to code. Also, it can be observed that all the same corresponding position bands look like scaled versions of each other, vertical to vertical lower of higher band and horizontal to horizontal and the same diagonal to diagonal. However, it is noted that the bulk energy in the high bands is concentrated more or less in the vicinity of areas that correspond to edge activity in the original image. This recommends that areas, which contain most of the information, must be encoded more precisely than the rest. Therefore, for image compression proposes a wavelet transform must be combined with another technique for coefficient coding. In fact the compression of wavelet coefficients is based on the assumption that details at high resolution are less visible to human eye and therefore can be reconstructed with low processing.

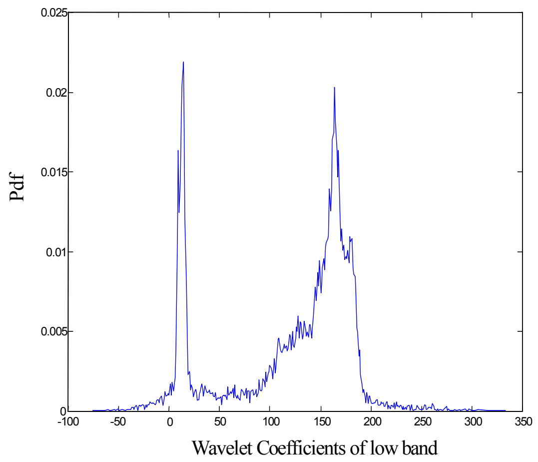


Figure 1. Low band wavelet coefficient for one level decomposition.

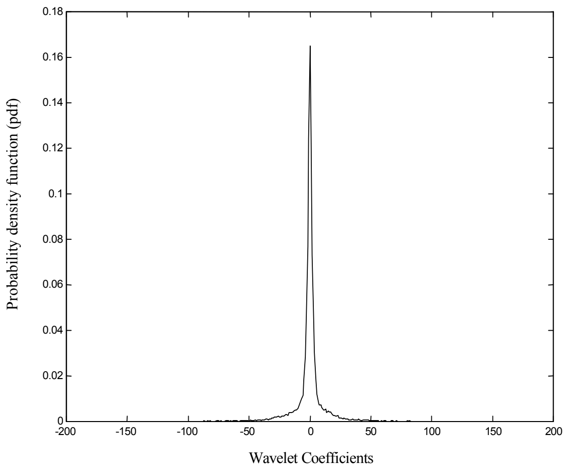


Figure 2. Vertical band distribution of test image cameraman in first level wavelet decomposition.

A two dimensional n-stage wavelet transform can be represented as in Figure 3, where L_i, V_i, H_i, and D_i (i = 1,…….l) are, respectively, the low band, vertical, horizontal and diagonal bands generated after three-stage transformation. Figure 4 shows a 3-stage wavelet transform of cameraman test image.

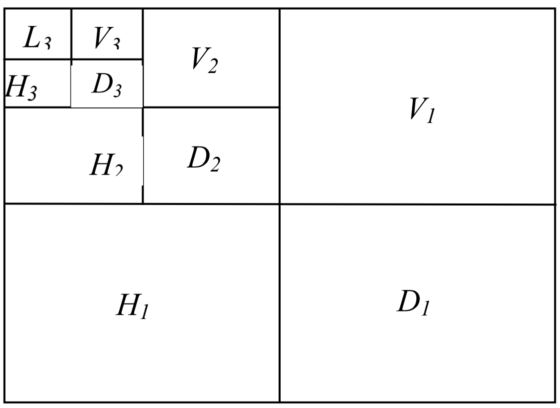


Figure 3. Wavelet multiresolution image decomposition (3-levels).

The image coding schemes assumes that the gray value of image to be coded is already present in a digital form (8 bit/pixel). In general, the depth of the splitting tree ranges from 3 to 5 levels, the reason is that if a low pass subband contains frequency components that are all equally important in subjective visual quality, then further decomposition is not efficient. The decomposition into subbands is assumed to correspond to important and less important information that is used by the Human Visual System (HVS). This means that some of the subbands have to be transmitted more accurately than others.

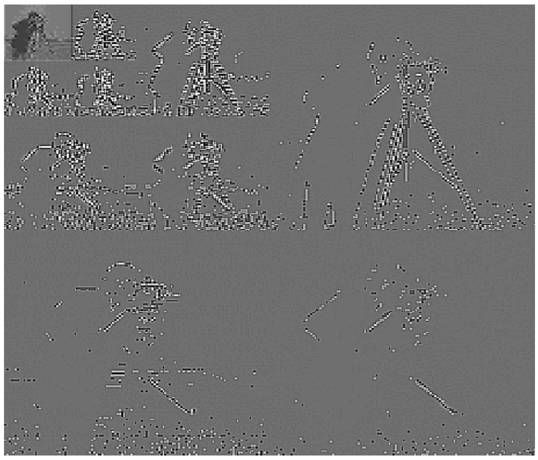


Figure 4. Wavelet transform for cameraman test image three-levels.

Wavelet Transform combined with Scalar Quantisation (SQ) and Vector Quantisation (VQ) have led to numerous schemes for image data compression [2, 4, 5, 6, 9, 13] using a multiresolution and pyramid algorithm [10, 12, 14, 15] the wavelet transform organises the coefficients to enable effective SQ and VQ encoding. Both approaches have their own advantages and disadvantages. It is known that the high frequency coefficients can be modelled fairly. Scalar quantisation takes advantage of this fact for the design of their quantisation table. On the other hand, it is known that sharp edges are characterised by frequency components of all resolution. Hence, there will be some residual correlation between coefficients of different scales. Vector quantisation exploits the correlation among coefficients of different scales.

A summary of PSNR performances of some of the methods described is presented in Table 1 for grey level test image Lena size 256x256 and 512x512. In [1], the low frequency band is scalar quantised and coded by PCM, while the remaining bands are coded using VQ. The codebook is designed separately for each orientation. Since the bands in each orientation have strong structural characteristics (either horizontal, vertical or diagonal details), this is a one possibility of VQ when applied to wavelet transform coding. The work described in [13] uses zerotrees in wavelet image compression. It is based on the information given in previously encoded coefficients, which enables the decoding to take place without the need for any overhead. The disadvantage of this method is to decide whether coefficients in a higher frequency band are significant or not based on the information in the lower frequency bands. This could lead to a wrong decision about the existence of a zerotree root and therefore, to the loss of significant image detail [16, 19] combine the zerotree with successive approximation scalar quantisation. The wavelet coefficients are refined in several passes, the most important information being transmitted first. It has the ability to perform the optimal bit allocation among the bands. Moreover, in each pass, it guarantees that a certain level of distortion will not be exceeded by each wavelet coefficient. These two methods provide the best results published to date. A generalization of these methods can be found in [21], where optimal sub tree of coefficients are found through a global bit allocation procedure.

Table 1. PSNR and bit rate for various wavelet compression schemes for test image 'Lena' size 256x256 and 512x512.

Method	Lena Size 256x256		Lena Size 512x512	
	Bitrate (bpp)	PSNR (dB)	Bitrate (bpp)	PSNR (dB)
[Antonini *et al*,1992] Filter-1 Filter-2 Filter-3	 0.80 0.78 0.80	 31.82 32.10 31.46	--	--
[Lewis and Knowles, 1992]	0.43	33.18	--	--
[Shapiro, 1993]	--	--	0.125 0.250 0.50	30.23 33.17 36.28
[Huh *et al*, 1994]	--	--	0.30 0.40	31.50 32.30
[Said & Pearlman, 1994]	--	--	0.25 0.50	33.69 36.84
[Efstratiadis *et al*, 96]	0.40	30.5	--	--
[Averbuch *et al* 1996] (Daub16) (Beylkin18)	--	--	0.128 0.128	33.10 33.41
[Xiong *et al*, 1997]	--	--	0.20 0.50	33.32 37.36

3. Wavelet Scalar Quantisation

This technique compares the input data or image value element by element with decision levels of the quantiser. An index is then transmitted to the receiver indicating which quantisation interval is appropriate and the receiver reconstructs an approximation to the corresponding level. One of the succeeded wavelets was using scalar quantisation to date and the first persons who used this idea successfully are Gharvi and Tabatabi. They have taken the 2 level wavelet transform, the lowest resolution is coded using Differential Pulse Code Modulation (DPCM) and a non uniform scalar quantiser followed by variable length coding. The other bands are coded by PCM with uniform quantiser followed by run length coding. The Federal Bureau of Investigation's (FBI) standard fingerprint images compression [3, 7] has adopted a Wavelet-Scalar Quantisation (WSQ) which uses bit allocation scheme. Each subband has a different quantisation step that is determined by the energy of the subband.

WSQ by Aware [7] provides a high performance software implementation of the FBI WSQ digital fingerprint compression algorithm. Where the compression range about 2:1 as a minimum and 50:1 as a maximum. The Embedded Zero tree Wavelet algorithm EZW [19] of Shapiro is an iterative WSQ algorithm that uses a fixed threshold at each iteration to determine which coefficients across subbands are to be quantised and encoded. The threshold is set to be the bit size of the uniform scalar quantisation that is used to quantise the coefficients. The threshold and quantisation steps are refined by one half at each iteration and the algorithm results in an embedded code. In this matter, we suggest another technique that associates a wavelet transform and scalar quantisation using bit allocation map according to their scale and the measures of the energy distribution, where the number of quantisation steps are doubled when cascading one more level of filtering. A mask was used with the size of input image. The bit plane is assigned according to the required image rate compression using the energy distribution. This mask is scanned on the wavelet coefficients resulting from the wavelet transformation. Then the entropy coding is used to the resulting data. These streams are stored or sent to the receiver with a side information or deader describe the mask specifications. There are several advantages of this scheme, since quantisation error variance can be separately controlled in each band by careful allocation of bit rate.

3.1. Energy Distribution

A noted characteristic of wavelet transform is its capability to place a large percentage of total signal energy in the low band subimage (band 3-1, in Figure 5). Also, from the behaviour of this transform that most of the coefficients in every band lie in a narrow range around the origin, and the higher levels contain smaller coefficients and variances. Table 2 shows the energy performance of several subbands from test image 'Lena' using Daubeche's 6-tap in the case of three level multiresolution. Also, it is noticed that the subimages 1-4, 2-4, 3-4 have the lowest energy. Therefore, it is proposed that they should be quantised using different bits, the subimage with higher energy should be quantised using large bits, whereas the subimage with lower energy may be quantised with less number of bits. From Figure 5, the subimage numbers 3-4, 2-4, 1-4 contain less information or energy than subimages 3-2, 3-3, 2-2, 2-3, 1-2, 1-3 respectively. Therefore, this implies that it could double the number of quantisation steps when cascaded more than one level of filtering as shown in

Figure 6. If subimages 1-2, 1-3 have to be assigned 8-level of quantisation steps (coded using 3-bits), subimage 2-2, 2-3 assign 16-level (coded using 4-bits). On the other hand the subimages 3-4, 2-4, 1-4 may be assigned three times fewer, which is 2-level or one-bit. Figure 7 shows the performance of the proposal quantisation on test images 'Cameraman'. Figure 8 shows the wavelet coefficients distribution before quantisation. Figure 9 shows the scalar quantisation of wavelet coefficients at four level multiresolution. To implement this bit allocation, a mask used with proper size and depending on the number of bits assigned to quantise each block, this can be set according to the maximum and minimum values in each block. Then the code is mapped to a bit streams. A header containing the maximum and minimum values of each block is also added to the bit stream.

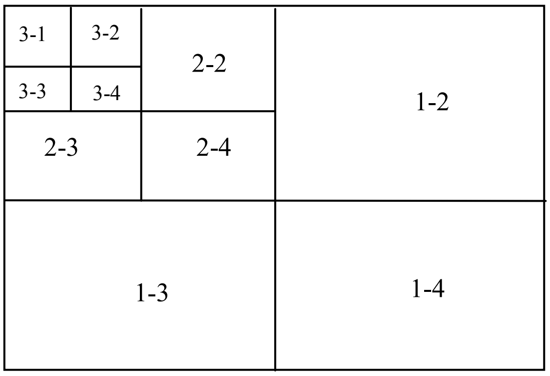


Figure 5. Wavelet multiresolution image decomposition (3-levels).

Table 2. Energy distribution of some test images.

Level No.	Subimage Number	Energy		
		Lena	Camera	Boat
1	1-2	5.36 %	6.76 %	6.23 %
1	1-3	8.44 %	8.35 %	6.97 %
1	1-4	4.11 %	3.88	2.80 %
2	2-2	3.40 %	3.84 %	4.47 %
2	2-3	6.47 %	5.01 %	4.30 %
2	2-4	2.80 %	2.25 %	1.98 %
3	3-1	60.17%	63.10%	66.45%
3	3-2	2.31 %	2.43 %	3.23 %
3	3-3	5.04 %	2.99 %	2.35 %
3	3-4	1.89 %	1.39 %	1.23 %

In case of decoding, the bit stream converted back to integers. The intervals were recreated using the maximum and minimum values for each block that saved in the header. Each integer was mapped to its corresponding interval based on the code and assigned the centre value of the interval according to quantiser map. Then the entire image is taken through the inverse of wavelet transform used. Table 3 shows the performance result of the proposed technique.

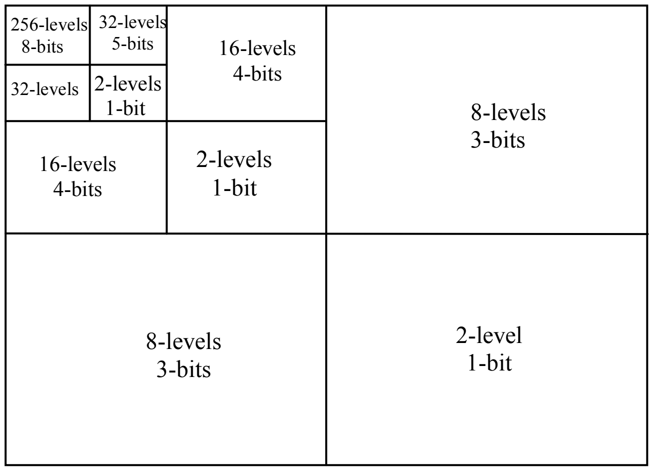


Figure 6. Wavelet multiresolution bit allocation scheme.

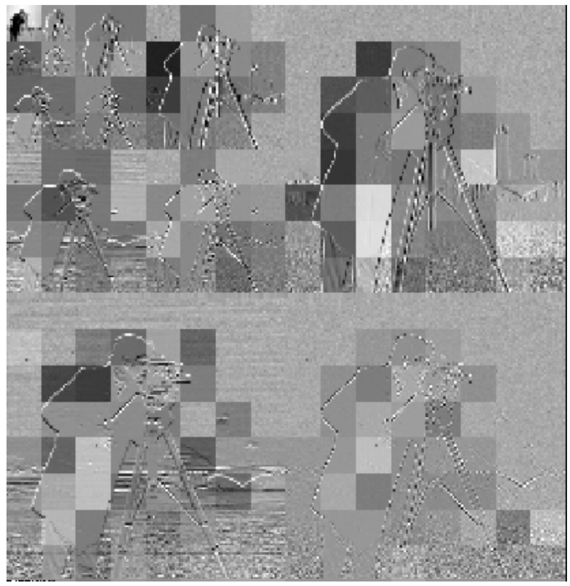


Figure 7. Wavelet coefficient scalar quantisation.

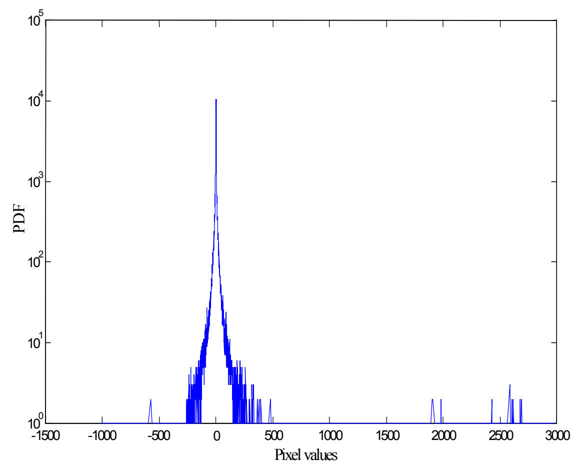


Figure 8. Wavelet coefficients distribution for camera test image with four levels multiresolution.

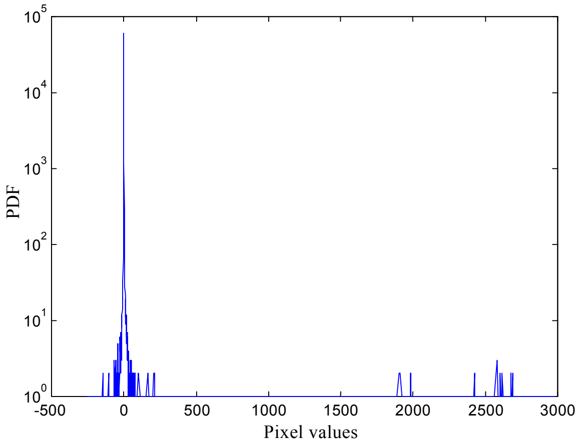


Figure 9. Scalar quantisation of wavelet coefficients of camera test image with four level multiresolutions.

Table 3. PSNR verse average bit rate for some of test images.

Lena		Camera		Boat	
PSNR (dB)	**Rate (bpp)**	**PSNR (dB)**	**Rate (bpp)**	**PSNR (dB)**	**Rate (bpp)**
37.15	6.0	35	6.0	37	6.0
35.87	4.0	33	4.0	36.53	4.0
29.17	3.0	27.35	3.0	28.81	3.0
27.95	1.96	26	1.96	27.73	1.96
20.53	1.0	19	1.0	20.10	1.0
19.05	0.5	17	0.5	19.5	0.5

4. Wavelet Vector Quantisation

Vector Quantisation (VQ) is a generalisation of scalar quantisation that enables us to exploit the similarity among bands of wavelet multiresolution. The principle involves encoding a sequence of samples (vector) rather than encoding each pixel individually. According to Shannon's distortion theory [17, 18], better results are always obtained when vectors rather than scalars are encoded.

4.1. Multiresolution Codebook Generation

The decomposition of an image into several resolution levels and different edge directions produce subimages whose statistical characteristics are much easier to compress than the original image. Codebooks are typically generated by training a set of images that are representative of the images to be encoded. Obviously, to compress any particular image, the optimal codebook would be structured using the image itself as a training image. This kind of codebook is called a local codebook and usually results in good performance during code procedures, because most of the coded image features are represented in the codebook vectors. This type of codebooks has two main disadvantages. Firstly, it is not possible to perform in real time since it is computationally intensive during the generation the local codebook for every image to be encoded. Secondly, the local codebook must be transmitted to the decoder or receiver as overhead information, which increases the bit rate and time transmission.

A global codebook could be generated using a training of several images that can overcome the drawbacks mentioned of a local codebook. As a wavelet decomposes an image into several resolution levels, it enables the generation of a codebook containing two-dimensional vectors for each resolution level according to subbands (vertical, horizontal and diagonal). This could be advantageous even as it exhibits lower distortion than a codebook obtained for an entire image in the original domain. Also, it could reduce quantisation errors and preserve better edges. In addition, the search for the best match vector is speeded up. This results in the quality of encoded image and the performance implementation being superior. Each of these codebooks is generated using the modified LBG algorithm. The various subcodebooks are constructed, forming a general codebook called a multiresolution codebook. The low frequency subimage is quantised using a scalar quantiser or DPCM and transmitted as wavelet coefficient subimage.

4.2. General Description of the Compression Algorithm

A block diagram of the algorithm is shown in Figure 10. The algorithm is initialised by the wavelet transform decomposition which is used to decompose an image into desired resolution level usually between 3 to 5 levels using Daubechies wavelet. The low subimage encoded separately. Since this subimage affects the reconstructed image quality the most, it is highly correlated which can be exploited to predict pixel values. It contains most of the image energy, representing mainly image texture information. DPCM is the best technique to be used for encoding this subimage and a large number of bits are assigned to it. The remaining subimages are the high frequency bands that might be divided into vectors with various sizes. They are coded by vector quantisation using a multiresolution codebook which is a combination of different band codebooks for various resolutions which are generated by the modified LBG using partial search partial distortion [8]. The other step in the proposed scheme is the entropy coding compression a lossless stage which could use Huffman or arithmetic coding.

5. Simulation Results

Experiments are performed on standard 256x256 greyscale Lena, Cameraman, Boat and Goldhill images to test the proposed algorithms at several bit rates.

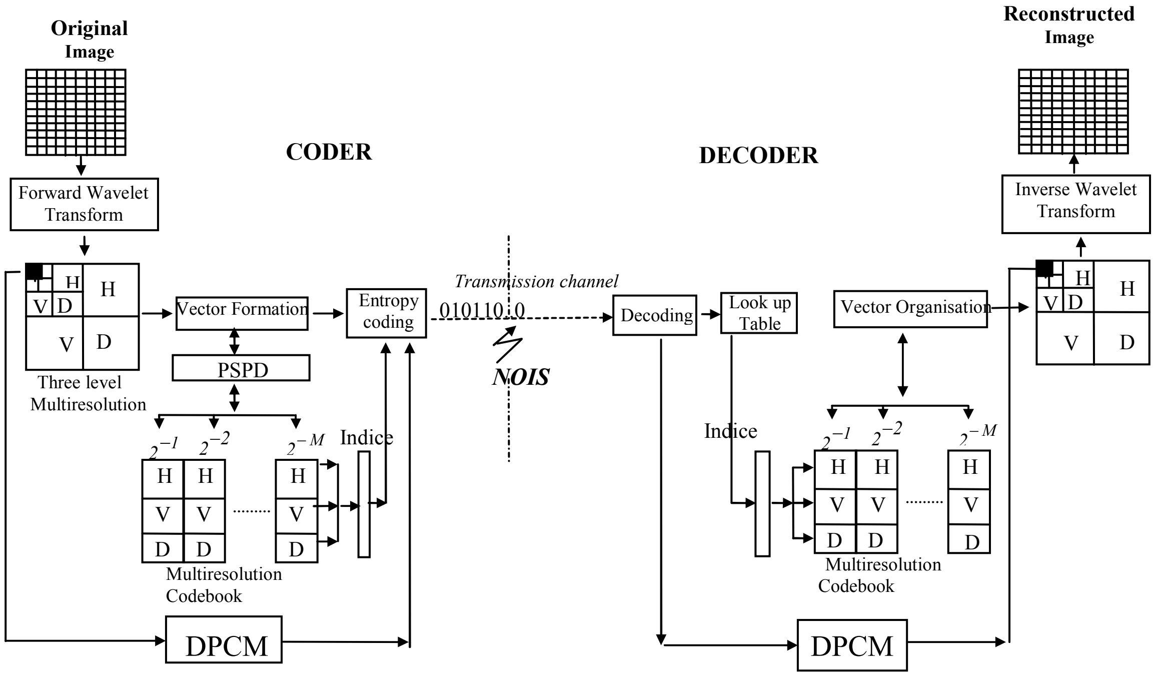


Figure 10. Block diagram of wavelet coder scheme.

The Daubechies filters are used in the experiments with 4-level wavelet decomposition. The lowest band is coded separately from the remaining bands. The results of this algorithm on the above test images are presented. All the images have a mixture of large smooth regions and long oscillatory patterns. In order to evaluate the performance of the algorithm, it is compared to the direct VQ and the standard JPEG. The performance of the algorithm is reported in Figures (11, 12, 13). Figure 11 shows the PSNR versus compression ratio for the test images using this algorithm. Figure 12 shows reconstructed 'Lena' test image with different compression ratios and PSNR in decibel. As it may be seen, no blocking effect can be noticed and the image quality is acceptable. Also, Figure 13 shows Cameraman test image with different compression ratio. The images out side the training has less PSNR approximately by 1-1.5 dB.

6. Comparison with other Coders

The measure criterion for comparison was PSNR, which can be calculated directly from the original and reconstructed data. Figures (14, 15) show a comparison of JPEG and the proposed wavelet codec for the test image Lena and cameraman with a size 256x256. The visual quality of the two system's coder for reconstruction 'Lena' as shown in Figures (12, 13, 16, 17). In terms of statistical error, wavelet codec gives higher signal to noise ratio in two of the examples, Lena and Cameraman. Although all images contained noise introduced by the digitisation process, the wavelet codec effectively removed this noise whilst JPEG spent valuable bits sending this data. The results of direct VQ are also included in Figures (18, 19, 20) as a comparison where the VQ component is performed on 4x4 blocks. As a conclusion, it provides a very efficient implementation in terms of execution time, quality and compression ratio. To summarise, the proposed wavelet codec performed well when compared with the industrial standard JPEG algorithm and much better than vector quantisation technique. These results show that the algorithm provides a highly competitive solution to the problem of image data compression.

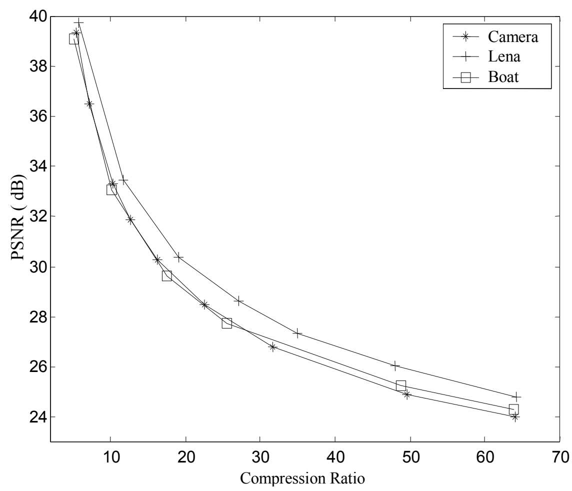


Figure 11. Compression ratio vs. PSNR of the proposed algorithm upon some of the test images.

a) Original test image. b) Compression ratio 16:1 PSNR = 32.50.

c) Compression ratio 35:1 PSNR = 27.34. d) Compression ratio 64:1 PSNR = 24.77.

Figure 12. Simulation results using wavelet transform.

a) Original test image. b) Compression ratio 12:1 PSNR = 32.85.

c) Compression ratio 31.6:1 PSNR = 26.78. d) Compression ratio 64.25:1 PSNR = 23.99.

Figure 13. Simulation results using wavelet transform.

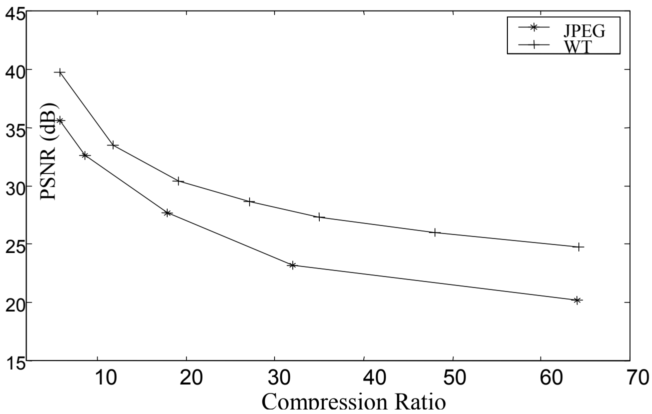


Figure 14. PSNR comparison between JPEG and proposed wavelet technique for Lena test image.

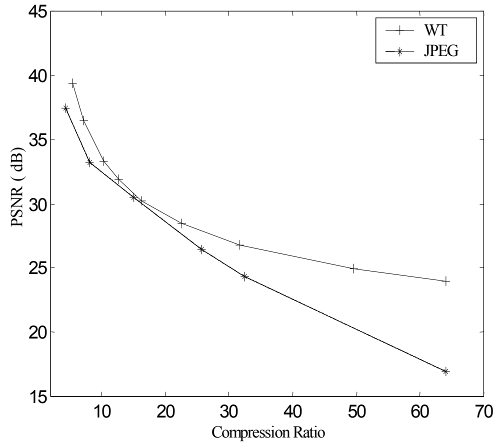


Figure 15. PSNR comparison between JPEG and proposed wavelet technique for Cameraman test image.

a) Original test image. b) Compression rate 8:1 PSNR = 37.82 dB.

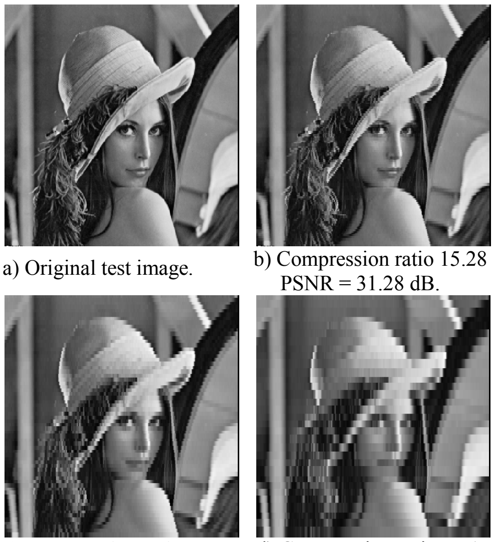
c) Compression rate 32:1 PSNR = 30.81 dB. d) Compression rate 64:1 PSNR = 21.93 dB.

Figure 16. Simulation results using standard JPEG.

a) Original test image. b) Compression ratio 8:1 PSNR = 33.19 dB.

c) Compression ratio 32:1 PSNR = 24.3 dB. d) Compression ratio 64:1 PSNR = 16.9 dB.

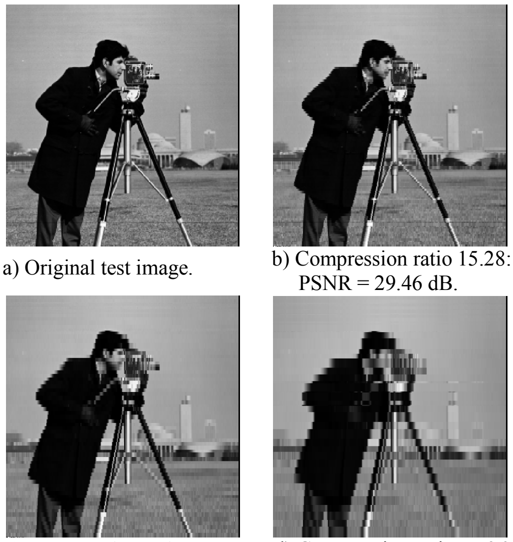
Figure 17. Simulation results using standard JPEG.



a) Original test image. b) Compression ratio 15.28 PSNR = 31.28 dB.

c) Compression ratio 29.25 PSNR = 27.27 dB. d) Compression ratio 55:1 PSNR = 24.04 dB.

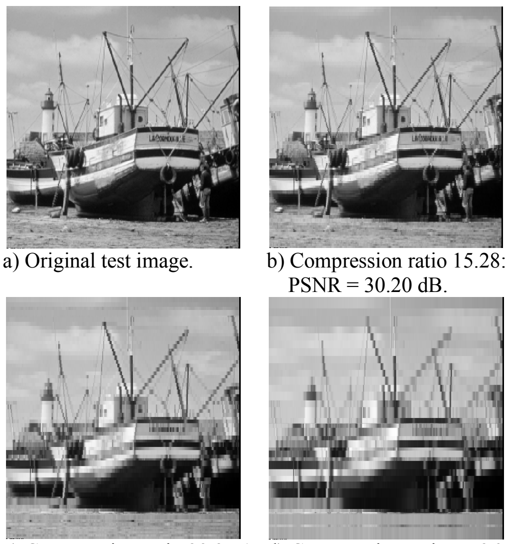
Figure 18. Simulation results using vector quantization.



a) Original test image. b) Compression ratio 15.28:1 PSNR = 29.46 dB.

c) Compression ratio 29.25:1 PSNR = 25.78. d) Compression ratio 55.36:1 PSNR = 22.62 dB.

Figure 19. Simulation results using vector quantisation.



a) Original test image. b) Compression ratio 15.28:1 PSNR = 30.20 dB.

c) Compression ratio 29.25:1 PSNR = 26.15 dB. d) Compression ratio 55.36:1 PSNR = 23.68 dB.

Figure 20. Simulation results using vector quantization.

References

[1] Antonini M., Barlaud M., and Daubechies I., "Image Coding Using Wavelet Transform," *IEEE Transactions on Image Processing*, vol. 1, no. 2, pp. 205-220, 1992.

[2] Averbuch A., Laza D., and Israeli M., "Image Compression Using Wavelet Transform and Multiresolution Decomposition," *IEEE Transactions on Image Processing*, vol. 5, no. 1, pp. 4-15, 1996.

[3] Bradley J., Brislawn C., and Hopper T., "The FBI Wavelet/Scalar Quantization Standard for Gray-Scale Fingerprint Image Compression," Technical Report LA-UR-93-1659, Los Alamos Nat'l Lab, Los Alamos, 1993.

[4] Da Silva E. A. B., "Wavelet Transforms for Image Coding," *PhD Thesis*, Electronic Systems Engineering, University of Essex, 1995.

[5] Daubechies I., "The Wavelet Transform, Time-Frequency Localization and Signal Analysis," *IEEE Transaction on Information Theory*, vol. 36, no. 5, pp. 961-1004, September 1990.

[6] Gray R. M., "Vector Quantization," *IEEE ASSP Magazine*, pp. 4-28, April 1984.

[7] Hopper T. and Preston F., "Compression of Gray-Scale Fingerprint Images," *in Proceedings of the Data Compression Conference (DCC'92),* Snowbird, Utah, pp.309-318, March 1992.

[8] Huang C. M., Stiles G. O., and Harris R. N., "Fast Full Search Equivalent Encoding Algorithm for Image Compression Using Vector Quantization," *IEEE Transactions on Image Processing*, vol. 1, no. 3, pp. 413-416, July 1992.

[9] Jain A. J., "Image Data Compression: A Review," *IEEE Proceedings*, vol. 69, pp. 349-389, March 1991.

[10] Khalifa O. O. and Dlay S. S., "Medical Image Lossless Compression for Transmission of Cross-Limited Bandwidth Channels," *SPIE, Medical Imaging*, San Diego, USA, pp. 342-346, February 1999.

[11] Khalifa O. O. and Dlay S. S., "Wavelets for Image Data Compression Using Bit Allocation with Scalar Quantization," *ISIE'97*, Guimaraes, Portugal, pp. 77-81, July 1997.

[12] Khalifa O. O. and Dlay S. S., "Wavelets Image Data Compression," *in Proceedings of the IEEE International Symposium on Industrial Electronics*, South Africa, pp. 407-410, July 1998.

[13] Lewis A. S. and Knowless G., "Image Compression Using 2-D Wavelet Transform," *IEEE Transactions on Image Processing*, vol. 1, no. 2, pp. 244-250, April 1992.

[14] Mallat S. G., "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation," *IEEE Transactions on Pattern*

Analysis and Machine Intelligence, vol. 11, no. 7, pp. 674-693, July 1989.
[15] Mallat S. G., "Multifrequency Channel Decompositions of Images and Wavelet Models," *IEEE Transactions Acoustics, Speech, and Signal Processing*, vol. 37, no. 12, pp. 2091-2110, December 1989.
[16] Said A. and Pearlman W. A., "A New Fast and Efficient Image Coder Based on Set Partitioning in Hierarchical Trees," *IEEE Transactions on Circuits and System for Video Technical*, vol. 6, pp. 243-250, June 1996.
[17] Shannon C. E., "A Mathematical Theory of Communication," *Bell System Technical Journal*, vol. 27, no. 3, pp. 379-423, and vol. 27, no. 4, pp. 623-656, July 1948.
[18] Shannon C. E., "Coding Theorems for a Discrete Source with a Fidelity Criterion," *in IRE National Convention Record*, New York, USA, vol. 7, part. 4, pp. 142-163, March 1959.
[19] Shapiro J. M., "An Embedded Hierachical Image Coder Using Zerotrees of Wavelet Coefficients," *IEEE Proceedings*, pp.214-223, 1993.
[20] Villasenor J. D., Belzer B., and Liao J., "Wavelet Filter Evaluation for Image Compression," *IEEE Transactions on Image Processing*, August 1995.
[21] Xiong Z., Ramchandran K., and Orchard M. T., "Space-Frequency Quantization for Wavelet Image Coding," *IEEE Transactions on Image Processing*, vol. 6, no. 5, pp. 677-693, 1997.

Othman Khalifa received his Bachelor degree in electronic engineering from the Garyounis University, Libya in 1986. He obtained his Master degree in electronics science engineering and PhD in digital image processing from Newcastle University, UK in 1996 and 2000, respectively. He worked in industry for eight years. Currently, he is an assistant professor at the Department of Electrical and Computer Engineering, International Islamic University, Malaysia. His areas of research interests are communications, information theory and coding, digital image/video processing, coding and compression, wavelets, fractal, and pattern recognition. He is a member of IEEE, IEEE Computer Society and Image Processing and Communication Society