



Medical Image Compression using Hybrid Technique of Wavelet Transformation and Seed Selective Predictive Method

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ABSTRACT

In this paper, a hybrid coding system of lossless and lossy base is introduced for compressing medical images, where the selected seed predictive coding of approximation subband, and the detail subbands of hierarchical scheme of wavelet transform exploited, respectively. The test results indicate that the suggested method can lead to promising performance using various thresholding values and extended scheme.

Key Words: Image compression, selected seed, wavelet transform of thresholding base and hierarchical model

1. Introduction

In electronic medical recording, images such as *X-rays*, *MRI's* (Magnetic Resonance Imaging), *CT's* (Computer tomography) and *US's* (Ultrasound), are digitized and stored as a matrix of binary digits in computer memory. The number of medical images stored in digital form has increased significantly in recent years. Attention is, therefore, focused on reducing the storage required for archiving and transmitting digital images, through compressing the data [1].

Digital image is generally represented as a sequence of numbers, corresponding to the designated intensities of an array of certain rows and columns, to resemble the width and height respectively of the real image. Each cell of this array is called a *pixel* or sometimes *pel*, short for picture element. Each pixel's value (intensity) constitutes a piece of information from the image (i.e., as in a story, where each word has a meaning, here the meaning comes from a specified intensity value) and is represented by a finite number of bits (more precisely, data bits). These are determined by the image's nature, in terms of the maximum number of colours that can be displayed. For example, for a binary image with 2 colours, 1 bit per pixel; for a gray scale image with 256 colours, 8 bits per pixel. We represent the intensity of the pixel at location x,y by $I(x,y)$, of an assumed square image of size $N \times N$ [2].

Image compression is primarily employed to minimize the number of bits required for storing and transmitting an image [1]. In other words, a compression system generally represents the essential form of information processing used to manipulate significant information properly, while losing insignificant information, which is called the redundancy [2]. Generally, Image compression

techniques fall into two categories: namely *lossless* and *lossy* depending on the redundancy type exploited, where lossless also called information preserving or error free techniques, in which the image compressed without losing information that rearrange or reorder the image content, and are based on the utilization of statistical redundancy of alone of low compression ratio, such as Huffman coding, Arithmetic coding and Lempel-Ziv algorithm, while lossy which remove content from the image, which degrades the compressed image quality, and are based on the utilization of psycho-visual redundancy, either solely or combined with statistical redundancy, of high compression ratio such as vector quantization, fractal, transform coding and JPEG [3].

Lossless image coding, due to its unique attributes and applications in medical and satellite photographs, has attracted lots of attentions since its inception. However, because of the local similarity or correlation (statistical dependency) of image pixels in natural images, seldom can a lossless coding scheme achieve a compression ratio of more than 4:1 [1,2]. In conventional lossless coders, the predictive coders used widely due to its simplicity, symmetry of encoder and decoder and flexibility of use are the most significant advantages of this technique. Simply, it is based on utilizing the image directly within the spatial domain, by modelling the correlation or statistical dependency embedded between neighbouring pixels, where each pixel's value can be predicted or estimated from nearby or neighbouring pixels. The difference between the actual pixel value and the predicted pixel value is referred to as the residual or prediction error that is encoded, because of the reduced image information compared to the original image, so the idea is to store and transmit the prediction model coefficients and the residual, which should be easier and more efficient to compress. On the other hand that characterized by lower compression ratio, where the performance is quite strongly affected by the modelling formula and image details or characteristics [2].

This paper is concerned with improving the performance of lossless coding technique to provide high compression ratio, while retaining high quality images (minimum degradation) using a *hybrid* selected seed predictive coding of wavelet transform of multi resolution base to exploit the medical image redundancy effectively. The rest of paper organized as follows, section 2 contains comprehensive clarification of the proposed system; the results for the proposed system and the conclusions, is given in sections 3 and 4, respectively.

2. Proposed System

The proposed technique incorporated both the wavelet transform of multi resolution coefficients base along with the selected seed predictive coding, by using the following steps, the layout of the suggested system is illustrated in figure (1).

Step 1: Load the input uncompressed image I of size $N \times N$ that corresponds to high resolution image.

Step 2: Perform wavelet transform that decompose I image into four quadrants of *approximation* and *detail* sub bands (I_{LL} , I_{LH} , I_{HL} and I_{HH}) respectively, each of size $(N/2 \times N/2)$, where each sub bands (approximation and details) compressed differently. In other words that the I_{LL} , I_{LH} , I_{HL} and I_{HH} sub band partitions indicate the approximation image (average image) and the images with horizontal edges, vertical edges and diagonal edges respectively.

Step 3: Apply the predictive coding of selective seed values techniques on the approximation sub band (I_{LL}) (i.e., highly correlated) that explained in the following sub steps:

1- Partition the I_{LL} sub band into non overlapping blocks of fixed size $n \times n$, the seed values of the first row and first column of each block is utilized corresponding to the left and bottom seed values.

2- Create the predicted image using the seed values, where the left bottom pixels predicted based on the horizontal and vertical differences according to equations below (1-6), for more details see [4].

$$\text{HorizontalX Predcurr} = \text{Xvalue} - \text{Left} \quad (1)$$

$$\text{VerticalX Predcurr} = \text{Xvalue} - \text{Bottom} \quad (2)$$

$$\text{X Predcurr} = \begin{cases} \text{HorizontalX Predcurr} & (\text{HorizontalX Predcurr} \leq \text{VerticalX Predcurr}) \\ \text{VerticalX Predcurr} & \end{cases} \quad (3)$$

$$\text{HorizontalLeftBottomPredcurr} = \text{LeftBottom} - \text{Bottom} \quad (4)$$

$$\text{VerticalLeftBottomPredcurr} = \text{LeftBottom} - \text{Left} \quad (5)$$

$$\text{LeftBottomPredcurr} = \begin{cases} \text{HorizontalLeftBottomPredcurr} & (\text{HorizontalLeftBottomPredcurr} \leq \text{VerticalLeftBottomPredcurr}) \\ \text{VerticalLeftBottomPredcurr} & \end{cases} \quad (6)$$

The predicted image depends on the lowest difference values of either horizontal or vertical difference values of the current pixel value or the left bottom value [4]. In other words, the predicted image created by computing the horizontal and vertical differences using the current pixel and the left bottom pixel, the lowest difference is adopted.

3- Find the residual (residue) as the difference can be computed as a difference between the original image I_{LL} and the predicted one and encode the information of seed and residual values using the Huffman coding technique.

Step 4: Since the details sub bands coefficients (I_{LH} , I_{HL} and I_{HH}) are very small (i.e., less correlated) they can be set to zero without significantly changing the image [5], but here we restricted to medical images where keeping all the image information is prioritised as much as possible, the following sub steps are applied [6]:

1- Select a threshold value of each quadrant choose according to the sub band importance, that known as *quantile* threshold, where the threshold preserve a certain percentage of the total coefficients of each quadrant.

The technique simply starts by entering the *percentage* of the detail sub bands coefficients that want to preserved, that computed such as:

$$\text{NoCoffKeep} = \frac{(100 - \text{PerCoeff})}{100} \quad (7)$$

The threshold values selected by *sorting* the coefficient in ascending form then compute the threshold according to equation below, in other words the threshold value selected according to it's importance that determined by percentage of preserved coefficients and the dimension of the quadrants:

$$\text{SelThre} = \text{SortQuadrant}(\text{NoCoffKeep} \times \text{QuadrantDimension}) \quad (8)$$

2- Traverse the thresholded wavelet data's sub band matrix line by line and copy the *nonzero* values to compressed quadrants that coded efficiently using the Huffman techniques.

To reconstruct the decompressed image all the above mentioned steps are reversed, where the decoder exploits the information received from the encoder to reconstruct the lossless approximation sub band image (I_{LL}), by first utilizing the seed values to build a predicted sub band image, and then adding the residual to the prediction, such that:

$$I_{LL}(i, j) = \text{Re } s(i, j) + I_{LL}^{\sim}(i, j) \quad (9)$$

The lossless approximation sub band image (I_{LL}) and the detailed sub bands coded information (I_{LH} , I_{HL} and I_{HH}) used in the inverse wavelet transform to reconstruct the compressed (decoded) image.

Finally, we have to mention that the previously discussed method corresponding to first level multiresolution scheme, that can be extended into several levels representing a hierarchical model base, that based on implementing the wavelet transform more than once, by exploring the approximation sub band of the preceding layer. Namely, the approximation subband (i.e., LL quadrants) of the resulting image is input of the next iteration (level), here three levels (iterations) will be sufficed (used).

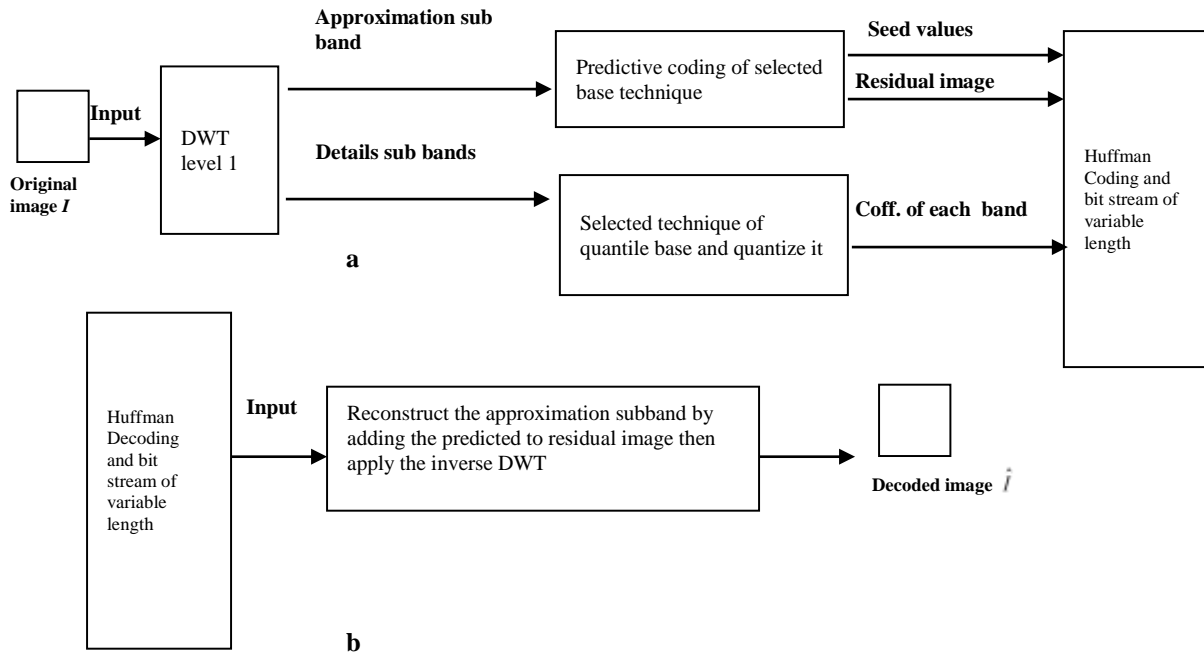


Figure1 : The Proposed System (a) Encoder & (b) Decoder.

3. Experimental Results

For testing the proposed system performance; it is applied on two *MRI* medical images (see figure 2 for an over view), all the images are gray of 256 gray levels (8 bits/pixel) but with different sizes. The tests have been performed using different block sizes $\{2 \times 2\}$, of three wavelet base decomposition (i.e., three hierarchical levels scheme).



Fig. (2): Medical Tested Images

The suggested techniques preserved all the information of approximation subband (i.e., lossless base), while losing the insignificant information of the detail sub bands that implicitly affected by the threshold value (i.e., lossy base), so the compression ratio, which is

the ratio of the original image size to the compressed size is computed, along with the Peak -Signal-to Noise- Ratio (*PSNR*) between the original image I and the decoded image \hat{I} was utilized as a fidelity or degradation measure.

$$PSNR(dB) = 10 \log_{10} \left[\frac{(\text{maximum gray scale of image})^2}{MSE} \right] \dots \dots \dots (10)$$

$$MSE = \frac{1}{N \times N} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} [\hat{I}(x, y) - I(x, y)]^2 \dots \dots \dots (11)$$

The results are shown in tables (1 & 2) summarizes the compression ratio, *PSNR* of three levels representations of the two tested images. Certainly a higher compression ratio corresponds to higher degradation of the image (i.e., high distortion levels). Inversely, low compression ratios mean high quality, where there is a trade-off between the desired compression ratio and the desired quality.

It is clear that the threshold values of the detail sub bands affected by the entered percentage of the coefficients and the dimension of the level(s) used that directly relates to the technique performance in terms of compression ratio and quality.

There are a number of highlight issues need to be mentioned according the above results:

- 1- Obviously, as the preserved coefficients of the detail sub bands increase the quality improve with less compression ratio (i.e., small threshold leads to more significant coefficients of nonzero value).
- 2- By extended into hierarchal scheme more compression ratio achieved with less quality.
- 3- Finally, the results affected by the image details or characteristics, since the approximation base compressed using the spatial based technique.



Table 1: The performance of the proposed system on the first medical image using various threshold values and three multiresolution bases.

Enter Percentage of Coeff.			Layer ₁					Layer ₂					Layer ₃				
LH	HL	HH	LH Tr ₁	HL Th ₁	HH Th ₁	CR	PSNR	LH Tr ₂	HL Th ₂	HH Th ₂	CR	PSNR	LH Tr ₃	HL Th ₃	HH Th ₃	CR	PSNR
20	10	10	22	20	9	19.3265	41.1710	150	110	76	28.9982	36.1044	1020	597	415	35.4824	31.7872
20	30	30	22	6	3	15.2587	43.6042	150	34	24	19.0956	38.6810	1020	174	142	21.2022	44.9868
40	60	60	7	1	0	11.2740	53.3264	34	6	4	12.3049	49.7917	218	36	20	12.8881	46.0893
50	20	20	4	10	5	14.6843	48.6037	18	56	42	18.0540	43.5917	116	331	241	19.8654	39.8724
50	40	40	4	4	2	12.6787	54.2366	18	19	14	14.3530	50.7217	116	108	82	15.2516	47.5403
60	50	50	2	2	1	11.4794	60.0038	10	12	8	12.5404	56.0536	57	68	41	13.1361	53.2730
80	40	40	0	4	2	11.8875	56.2434	0	19	14	13.0706	52.6043	2	108	82	13.7307	49.5274
80	60	60	0	1	0	10.3581	70.1837	0	6	4	10.9482	65.6508	2	36	20	11.3286	62.1342

Table 2: The performance of the proposed system on the second medical image using various threshold values and three multiresolution bases.

Enter Percentage of Coeff.			Layer ₁					Layer ₂					Layer ₃				
LH	HL	HH	LH Tr ₁	HL Th ₁	HH Th ₁	CR	PSNR	LH Tr ₂	HL Th ₂	HH Th ₂	CR	PSNR	LH Tr ₃	HL Th ₃	HH Th ₃	CR	PSNR
20	10	10	27	48	20	18.8376	34.6586	147	229	138	29.5074	30.5400	706	1094	700	36.3685	27.6564
20	30	30	27	18	8	14.2253	39.1246	147	82	51	18.0689	34.9152	706	409	265	20.0049	32.0135
40	60	60	11	3	2	10.7630	49.2669	60	15	11	11.9178	45.0851	283	94	57	12.4735	41.9950
50	20	20	7	27	12	13.9054	39.7922	35	131	78	17.3789	35.8417	186	626	414	19.0956	32.8952
50	40	40	7	12	6	11.6508	46.7402	35	53	91	13.3014	43.1858	186	267	177	14.0877	40.1236
60	50	50	3	7	4	10.7208	52.6800	16	33	22	11.8446	49.0726	103	176	110	12.3887	45.7517
80	40	40	0	12	6	11.2508	47.5225	0	53	32	12.6689	44.0034	0	276	177	13.3420	41.0218
80	60	60	0	3	2	10.1717	61.6563	0	15	11	11.0237	58.1190	0	99	127	11.4453	54.2649



4. Conclusions

From the test results of the proposed system, the following remarks are stimulated:

- 1- The incorporation between the lossless and lossy bases improves the compression ratio and preserved quality of medical image.
- 2- The utilization of the approximation sub band (*LL*) losslessly, preserved the image quality as much as possible, since that sub band contains low variation part of the image data that significantly increase the efficiency of the compression ratio.
- 3- The proposed technique improves the performance of the medical image compression that affected by the entered percentage preserved of the detail subband, the threshold and the levels.

5. References

1. Jian, W. 2001. Lossless Medical Image Compression. Ph.D. thesis, University of Wollongong.
2. Ghadah, Al-k. 2012. Intra and Inter Frame Compression for Video Streaming. Ph.D. thesis, Exeter University, UK.
3. Ghadah, Al-K. 2013. Image Compression based on Quadtree and Polynomial. International Journal of Computer Applications, 76(3), 31-37.
4. Ghadah, Al-K. and Haider, Al-M. 2016. Lossless Image Compression using Adaptive Predictive Coding of Selected Seed Values. International Journal of Computer Applications, 4(141), 26-29.
5. Mohammed, M. and Ghadah, Al-K. 2013. Applied Minimized Matrix Size Algorithm on the Transformed Images by DCT and DWT used for Image Compression. International Journal of Computer Applications, 70(15), 33-40.
6. Strang, G. 1994. Wavelets. American Scientist, 82, 250-255.