Compression of IR Image Based on Wavelet Algorithm

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Summary
In the research field of infrared imaging techniques, there is an important and popular technique that has enormous data to be stored and transmitted. Various algorithms have been proposed to improve the performance of the compression scheme. In this paper we extended a traditional wavelet algorithm to an image compression with updated technology and then compare its performance with others based on normal parameters. It is well known that lifting based Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) wavelet transform is very efficient and effective in image compression which coupled with Set Partition in Hierarchical Trees (SPIHT) coding algorithm and entropy coding techniques. One of our contributions in this paper is to demonstrate the choice of decomposition level is playing a very important role in achieving superior wavelet compression performances. Image quality is assessed objectively by parameters of compression ratio, peak signal-to-noise ratio (PSNR), mean structural similarity index (MSSIM). It is also evaluated subjectively by using perceived image quality. It needs to be highlighted that comparative the compression ratio has been significantly improved by 88%, together with highest PSNR values and MSSIM is close to 1 and found the best decomposition level and required bit rate per pixel for infrared (IR) images with our algorithm

Keywords:
IR, PSNR, MSSIM, SPIHT, Entropy coding.

1. Introduction

Infrared (IR) light is electromagnetic radiation with a wavelength longer than that of visible light, measured from the normal edge of visible red light at 0.74 micrometers, and extending conventionally to 300 micrometers [1]. These wavelengths corresponding to frequency range of approximately 1 to 400THz, and include most of the thermal radiation emitted to objects near room temperature.
Infrared imaging has been used extensively for military and civilian purpose, in particular in dark conditions. Military applications include target acquisition, surveillance, and night vision, homing and tracking. On-military uses include thermal efficiency analysis, remote temperature sensing, short-ranged wireless communication, spectroscopy, and weather forecasting. As another example, infrared astronomy uses sensor-equipped telescopes to penetrate dusty regions of space, such as molecular clouds; detect objects such as planets, and to view highly red shifted objects from the early days of the universe.

The far infrared medical imaging technique, based on the principle of infrared radiation, mainly researches the temperature distribution of the human body or parts thereof. Its merit includes: non-invasive, radiation-free, economical, intuitionistic, and so on. It is widely being used in clinical diagnostics and scientific research and becoming a new biomedical functional imaging technique.
Data compression stands for compressing data or files containing data so that they can be stored in much less memory space that they had been stored in their original form. Data transmission or storage without compression has some impractical reasons: (1) the data handle by different digital environments is increasing at a rate now a day for image processing application; (2) the storing of digital data without compression would be tragedy; (3) the transmission is major concern in modern world because of more than 7500 Tera Bytes of data is being downloading and/or uploading in the Internet. Hence, it was more important to have compression in one form or other to storage or transmission. In this sense, modifying any image, frequency domain is normally assumed to be more convenient.
In this paper, we have tried to find out the best decomposition level of compressed for IR images and also increased different bit rate for the best level of decomposition in terms of mean square error (MSE), peak signal-to-noise ratio (PSNR), mean structural similarity index (MSSIM) and compression ratio (CR).
Wavelet transforms have received significant attentions in the field of signal processing in particular for image denoising and image compression. Recently, a new wavelet construction called *lifting scheme*, has been developed by Wim Sweldens and Ingrid Daubechies [2]. Even though it has other applications, such as the possibility of defining wavelet-like transform that maps integers to integers. This method has gained increasing interests in scientific community, due to its advantages such as reduced computational complexity by first factoring a classical wavelet filter into lifting steps.
In this paper we have used the technology called *lifting* based on CDF9/7 [3] to compress the test images by using Set Partition in Hierarchical Trees (SPIHT) algorithm [4, 5] with entropy coding. It has been investigated to enhance the image quality with different level of decomposition. For the best performance in the image compression, we

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have investigated the most common entropy coding techniques, such as Run-length encoding and Huffman coding. These compression methods are compared over the basis of *compression ratio* which is defined as follows:
Compression ratio is the define as

$$Compression\ Percentage = \frac{A}{B} \times 100$$

Or alternatively,

$$Compression\ Percentage = \frac{A-B}{A} \times 100$$

where A =Number of Bytes in the original data set
B = Number of Bytes in the compressed data set.
The average number of bits required to represent the data value for the single pixel of an image is referred as bits/pixels.
The compressed IR images obtained from the higher compression ratios, as well as the higher image quality by our new algorithm are demonstrated. It is the fact that the outcomes by our algorithm significantly improved on the mean square error (MSE), the peak signal to noise ratio (PSNR), the mean structural similarity index (MSSIM) and on the compression ratio.
This paper is structured as follows. Section 2 describes our proposed algorithm, including, wavelet logical transform, CDF 9/7 wavelet transform, SPIHT coding algorithm, and entropy coding. Section 3 shows image quality evaluation with our novel algorithm. Section 4 demonstrates the simulation results and our discussion about the novel algorithm. Finally in Section 5, a conclusion is presented.

2. Proposed Algorithm

The diagram of the trail process IR images compression and image decomposition can be seen in Figure.1. In this proposed dissertation work IR image compress using Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) with lifting structure and Set Partition in Hierarchical Trees (SPIHT) will be implemented. The dissertation work can be carried out in the following steps in our algorithm:
Step1. Read the IR image on the workspace of the MATLAB.
Step2. Convert the given color image into gray level image.
Step3. Perform CDF9/7 wavelet transform to the IR image: from the decomposition process the coefficients can be extracted.
Step4. Apply Set Partition in Hierarchical Trees (SPIHT) encoding combined with Huffman encoding and Run length encoding reduced the redundancy in the coefficient data.
Step.5 Set Partition in Hierarchical Trees (SPIHT) with Huffman encoded coefficients is saved the compressed bit streams instead of image.
Step.6 Apply decoding procedure, from the compressed bit stream data, using Set Partition in Hierarchical Trees (SPIHT) combined with Huffman decoding and Run length decoding, as well as inverse CDF 9/7 wavelet transform to reconstruct the images.
Step.7 Calculate compression ratio, MSE, PSNR and the overall image quality MSSIM.
Step.8 Display the results reconstruction 1, reconstruction 2, reconstruction 3, i.e., level 1, 2, 3, 4…20(as we considered) and comments on the quality of images with original image.
Step.9 The above procedure is repeated for consider different bit rate per pixels with a fixed level of decomposition and display the results and compressed images.
Step10. The same process is repeated for various IR images and compares its performance.

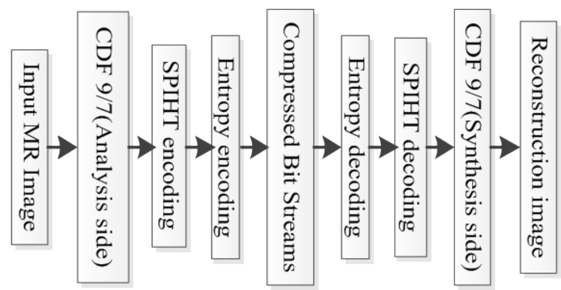

Figure.1 Proposed image compression block diagram.

1.1 Wavelet Transform Logical Support

The lifting scheme based a wavelet transform [6, 7] can be implemented as shown in Figure 2, by which it is obviously clear that our scheme can reduce the computational complexity. It also can be seen that only the decomposition part of wavelet transform (WT) is depicted in Figure 2, this is because the reconstruction process is just the reverse version of the one described in Figure.2. The lifting-based WT consists of three sections, namely splitting, lifting, and scaling modules. The WT itself can be treated as prediction-error decomposition. It can be found that the scheme provides a complete spatial interpretation of WT. In Figure 1, let X denote the input signal and X_{L1} and X_{H1} be the decompose output signals where they are obtained through the following three modules (A, B, and C) of lifting base inverse DWT, which can be described as below:
A. *Splitting*-In this module, the original signal X is divided into two disjoint parts, i.e., samples $X(2n+1)$ and $X(2n)$ that denotes all odd-indexed and even-indexed and odd-indexed samples of X , respectively [2].
B. *Lifting*-Lifting consist of three basic steps: Split, Predict, and Updating. A brief description of these three steps is given below [2, 6, and 7].

1. *Split* -In this stage the input signal is divided in to two disjoint sets, the odd ($X[2n+1]$) and the even samples ($X[2n]$). This splitting is also called the Lazy Wavelet transform [10].
2. *Predict*-In this stage the even samples are used to predict the odd coefficients. This predicted value, $P(X[2n])$, is subtracted from the odd coefficients to give error in the prediction.

$$d[n] = X[2n+1] + P(X[2n]) \quad (1)$$

Here $d[n]$s are also called the detailed coefficients.

3. *Update*-In this stage, the even coefficients are combined with $d[n]$s which are passed through an update function, U (.) to give

$$C[n] = X[2n] + U(d[n]) \quad (2)$$

C. *Scaling*-A normalization factor is applied to $d(n)$ and $s(n)$, respectively. In the even-indexed part $S(n)$ is multiplied by a normalization factor K_e to produce the wavelet sub band X_{L1}. Similarly in the odd-index part the error signal $d(n)$ is multiplied by K_0 to obtain the wavelet sub band X_{H1}.

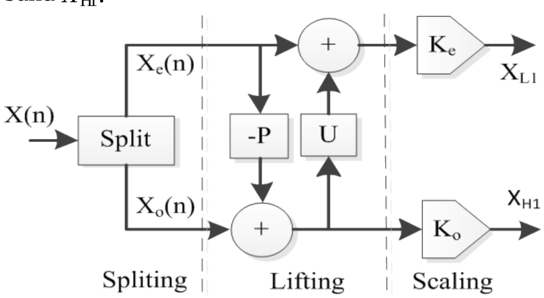

Figure.2: The lifting-based Wavelet Transform.

1.2 CDF 9/7 WAVELET TRANSFORM

The lifting scheme based on a wavelet transform can reduce the computational complexity. The Lifting scheme of the wavelet transform Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) [3] can go through of four steps as described in [6]: two prediction operators (‘a’ and ‘b’) and two update operators (‘c’ and ‘d’) as shown it Figure.3:

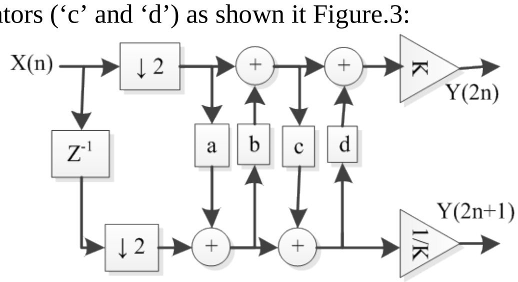

Figure.3: Lifting implementation of the analysis side of the CDF 9/7 filter bank.

For lifting implementation, Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) pair can be factorized into a sequence of primal and dual lifting. The most efficient factorization of the polyphase matrix for the 9/7 filter may be following [2] as follows:

$$P(Z) = \begin{bmatrix} 1 & a(1+Z^{-1}) \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ b(1+Z) & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & c(1+Z^{-1}) \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ d(1+Z) & 1 \end{bmatrix} \cdot \begin{bmatrix} K & 0 \\ 0 & 1/K \end{bmatrix} \quad (3)$$

where a, b, c, d and K are irrational values approximately equal to the following values that we also assumed to meet our case [2]:
$a \approx -1.58613432$, $b \approx -0.05298011854$, $c \approx 0.8829110762$ $d \approx 0.4435068522$, $K \approx 1.149604398$.Instead of using equation (3), the following equation (4) describes the four “lifting” steps and the two “scaling” steps with same parameter as follows:

$$L^0(n) = Y(2n), H^0(n) = Y(2n+1)$$
$$H^1(n) = , H^0(n) + (\mathrm{a} \times [, L^0(n) + , L^0(n+1)])$$
$$L^1(n) = , L^0(n) + (\mathrm{b} \times [H^1(n) + H^1(n-1)])$$
$$H^2(n) = H^1(n) + (\mathrm{c} \times [L^1(n) + L^1(n+1)]) \quad (4)$$
$$L^2(n) = L^1(n) + (\mathrm{d} \times [H^2(n) + H^2(n-1)])$$
$$\mathrm{H}(n) = \frac{H^2(n)}{\mathrm{K}}$$
$$L(n) = \mathrm{K} \times L^2(n)$$

where H and L represents the high and low frequency component of input signal or image respectively.
The synthesis side of the CDF9/7 filter bank simply inverts the scaling, and reverses the sequence of the lifting and update steps. Figure.4 shows the synthesis side of the filter bank using lifting structure to reconstruct of the signal or image.

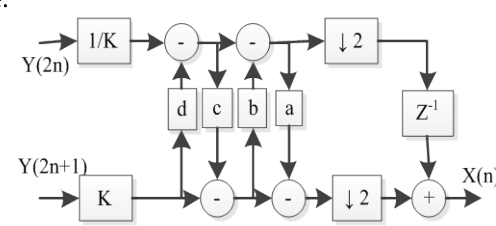

Figure.4: Lifting implementation of the synthesis side of the CDF 9/7 filter bank.

1.3 Set Partition In Hierarchical Trees (SPIHT)Coding Scheme

Set Partition in Hierarchical Trees (SPIHT) [4] is the wavelet based image compression method. It provides the highest image quality, progressive image transmission, fully embedded coded file, simple quantization algorithm, fast coding/decoding, completely adaptive, lossless compression, and exact bit rate coding and error protection.

SPIHT makes use of three lists – the List of Significant Pixels (LSP), List of Insignificant Pixels (LIP) and List of Insignificant Sets (LIS). These are coefficient location lists that contain their coordinates. After the initialization, the algorithm takes two stages for each level of threshold – the sorting pass (in which lists are organized) and the refinement pass (which does the actual progressive coding transmission). The result is in the form of a bit stream. It is capable of recovering the image perfectly (every single bit of it) by coding all bits of the transform. However, the wavelet transform yields perfect reconstruction only if its numbers are stored as infinite precision numbers.

1.4 Entropy Coding

For image compression technique, it is well known that three of the most common entropy encoding techniques would be the Huffman coding, Run length encoding (RLE), and arithmetic coding (AC). We shall concentrate on the Huffman and RLE methods for simplicity. Run-length encoding [8] is a form of data compression in which it encodes a run of bytes to the following 2-byte form: {byte, length}, with length representing the number of runs of a single byte. On the other hand, Huffman coding techniques collects unique symbols from the source images and calculates its probability value for each symbol and sorts the symbols based on its probability value. Further, from the lowest probability value symbol to the highest probability value symbol, two symbols combined at a time to form a binary tree. Moreover, allocates zero to the left node and one to the right node starting from the root of the tree. To obtained Huffman code for a particular symbol, all zero and one collected from the root to that particular node in the same order [9].

3. Image Quality Evaluation

Let x_i and y_i be the i^{th} pixel in the original image x and degraded image y, respectively. The MSE and PSNR between two images are given by

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i))^2 \quad (5)$$

$$PSNR = 10\ log_{10}\left(\frac{R^2}{MSE}\right) \quad (6)$$

Where *N* is the total number of pixels in the image and *R* is the maximum fluctuation of the input image data value. For 8 bit/pixel gray-scale images, *R*=255.

- *The structural similarity index (SSIM)*-We assess a new model to estimate the quality of medical images, specifically the ones compressed by CDF 9/7, based on the hypothesis that the human visual system (HVS) is highly adapted to extract structural information. The basic spatial domain SSIM algorithm [10] compares the brightness, contrast and structure between each pair of vectors, where the structural similarity index (SSIM) between two signals *x* and *y* extracted from the original and degraded images, respectively, the luminance, contrast and structural similarity between them are evaluated as

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

respectively. Here μ_x, $\sigma_x = \sqrt{\mu_x(x^2) - \mu_x^2}$ and $\sigma_{xy} = \mu_{xy} - \mu_x\mu_y$ represent the mean, standard deviation and cross–correlation evaluations, respectively. $C_1 = (K_1L)^2$, $C_2 = (K_2L)^2$, $C_3 = \frac{C_2}{2}$ (Setting $K_1 = 0.01, K_2 = 0.03$) are small constant that have been found for low luminance and contrast regions and stabilizing the performance when the denominators are close to zero. The SSIM index define as the product of three components which gives

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_x\sigma_y + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (7)$$

For application, we require a single overall measurement of the whole image quality that is given by the following formula

$$MSSIM\ (X,Y) = \frac{1}{M}\sum_{i=1}^{M} SSIM(x_i, y_i) \quad (8)$$

Where *X* and *Y* are respectively the reference and degraded images, $x_i\ and\ y_i$ are the contents of images at the i^{th} local window. *M* is the total number of local windows in image. The MSSIM (Mean Structural Similarity Index) values demonstrate greater reliability with the visual quality.

4. Results and discussion

We have applied algorithm to compress IR images. For this reason, we have chosen an infrared image size 500×500 encoded on 8 bits per pixel,(Figure.10 (a)). This image is taken from the database [12].The importance of our work lies in the possibility of reducing the rates for which the image quality remains acceptable. Estimates and judgments of the compressed image quality are given by the PSNR evaluation parameters and the MSSIM similarity Index.

From our investigating, we would highlight that the quality of compressed image depends on the number of decompositions level. The number of decompositions determines the resolution of the lowest level in wavelet domain. If we use larger number of decompositions, we will be more successful in resolving important DWT coefficients from less important coefficients. The HVS is less sensitive to removal of smaller details.

Fig. 9 shows comparison of reconstructed IR image for 1, 2, 3, 4, 5, 6, 7 and 8 decompositions. In this example, CDF9/7 combined with SPIHT and Huffman and Run length coding is used. It can be seen that image quality is better for a larger number of decompositions. On the other hand, a larger number of decompositions cause the loss of the coding algorithm efficiency. Therefore, adaptive decomposition is required to achieve balance between image quality and computational complexity. MSE, PSNR, MSSIM, CR tends to saturate for a larger number of decompositions [Fig. 6&7]. For each MSE, PSNR, MSSIM & compression ratio, these image characteristics represents the optimal number of decompositions. From these image characteristics we found best decomposition level for IR image compression. We have seen best decomposition level is 5 as shown bold font in Table.1 and also Figure. 9(b). This decomposition has shown the roll of significant for the IR image. It has highest value of PSNR, MSSIM which is close to 1 as reference of Wang at el. [10] and better compression ratio as compared to other decompositions level.

This five stage wavelet transform out is demonstrated at Figure.5 which gives the processing data unit for the next steps where SPIHT algorithm is used for data encoding.

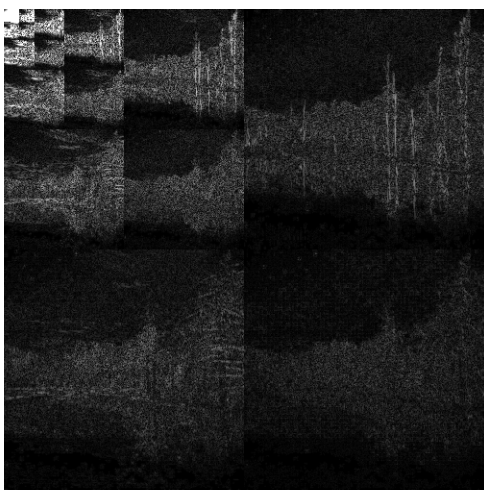

Figure.5: Five stages Wavelet decomposition.

TABLE.1 MSE, PSNR AND MSSIM and Compression ratio(CR) values of decompositions level for CDF9/7(Lifting based) + SPIHT + Huffman coding +Run length coding.

Levels of decomp.	MSE (Comp. image)	PSNR(dB) (Compressed. image)	MSSIM (Compressed Image)	CR(%)
1	0.0010	29.6130	0.8035	92.9141
2	2.1586e-04	36.3814	0.9504	88.7863
3	1.5254e-04	37.8892	0.9645	87.8149
4	1.4097e-04	38.2318	0.9718	87.5598
5	**1.3918e-04**	**38.2875**	**0.9728**	**87.5157**
6	0.0057	22.1796	0.4014	87.5084
7	0.0042	24.0240	0.5289	87.5060
8	0.0030	25.0247	0.6383	87.5065

TABLE.2 MSE, PSNR AND MSSIM and Compression ratio(CR) values for CDF9/7(Lifting based) + SPIHT + Huffman coding +Run length coding.

R (BPP)	MSE (Compressed image)	PSNR(dB) (Compressed image)	MSSIM (Compressed Image)	CR(%)
0.125	1.3918e-04	38.2875	0.9728	87.5157
0.25	2.7108e-05	45.3922	0.9884	75.0304
0.5	6.2329e-06	51.7762	0.9960	62.5363
0.75	1.4525e-06	58.1019	0.9989	50.0356
1	3.6034e-07	64.1560	0.9998	37.5331
1.5	8.5921e-08	70.3821	0.9999	25.0385
2	2.0139e-08	76.6828	1.0000	12.5373

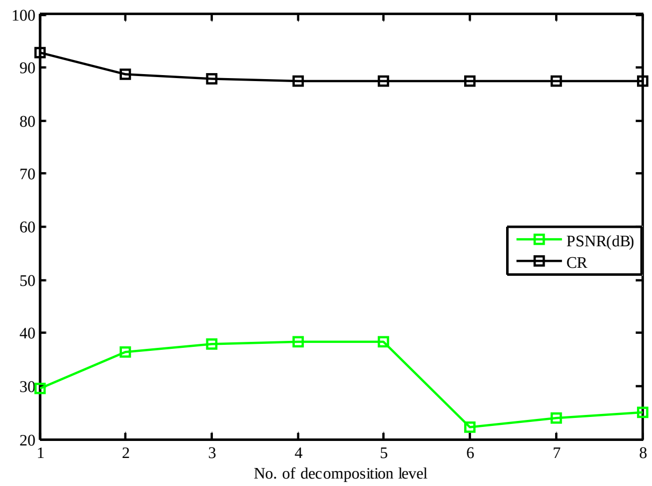

Figure.6 No. of decomposition levels verses PSNR and Compression ratio (CR) of IR image(CDF9/7 (Lifting scheme) combined with SPIHT coding and Huffman and Run length coding).

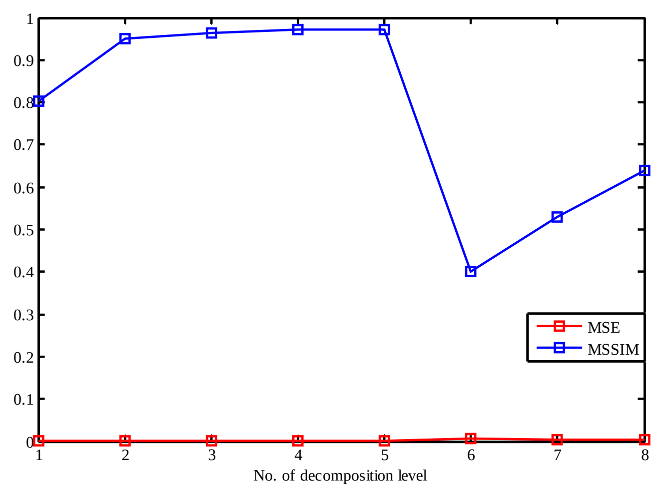

Figure.7 No. of decomposition levels verses MSE and MSSIM of IR image (CDF9/7 (Lifting scheme) combined with SPIHT coding and Huffman and Run length coding).

To show the performance of the proposed IR image compression method, we made a comparison in terms of image quality increased by the MSE, PSNR, MSSIM & Compression ratio (CR) curves represented in Figures.6, 7&8.

The bit rates per pixel (BPP) were in the range of 0.125 to 2 respectively, and were chosen no uniformly such that the resulting distribution of subjective quality scores was approximately uniform over the entire image. The MSE, PSNR and MSSIM and Compression ratio (CR) measurement results are given in the Table 2. Obliviously, MSE perform as very poorly in this case that's why PSNR values were enhanced by the increased the bits/pixel. The MSSIM values exhibit much better consistency with qualitative visual appearance.

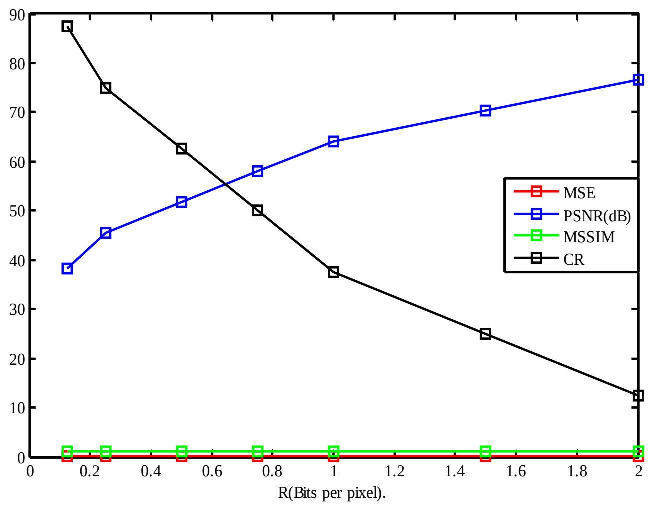

Figure.8 BPP verses MSE, PSNR, MSSIM, and Compression ratio (CR) of IR image(CDF9/7 (Lifting scheme) combined with SPIHT coding and Huffman and Run length coding).

By comparing the different values of MSE, Peak Signal to Noise Ratio(PSNR) and Mean Structural Similarity Index (MSSIM) & Compression ratio as per increased the bit rate, we displayed as in Figures.10.The effectiveness of our proposed method in terms of compressed image quality which shown good results. We have seen our compression technique with decomposition level 5 found good result compressed image quality and also achieve higher compression ratio for IR as shown in Table 2 &Figure. 10. It was good compression ratio 87.5157% for 0.125 bits/pixels but lowest PSNR value 38.2875dB but highest PSNR value 76.6828dB as shown the lowest compression ratio and MSSIM value is 1 which means the image quality is well for 2 bit/pixels. As expected bits/pixels was increased, the compression ratio enhanced from 13% to 88% approximately for bottom to top as shown in Table 2. The experiment shows that the higher data redundancy helps to achieve more compression. This experiment shows that CDF 9/7 couple with SPIHT, Huffman coding and Run length coding achieves more compression 87.5157 % for this proposed compression algorithm.

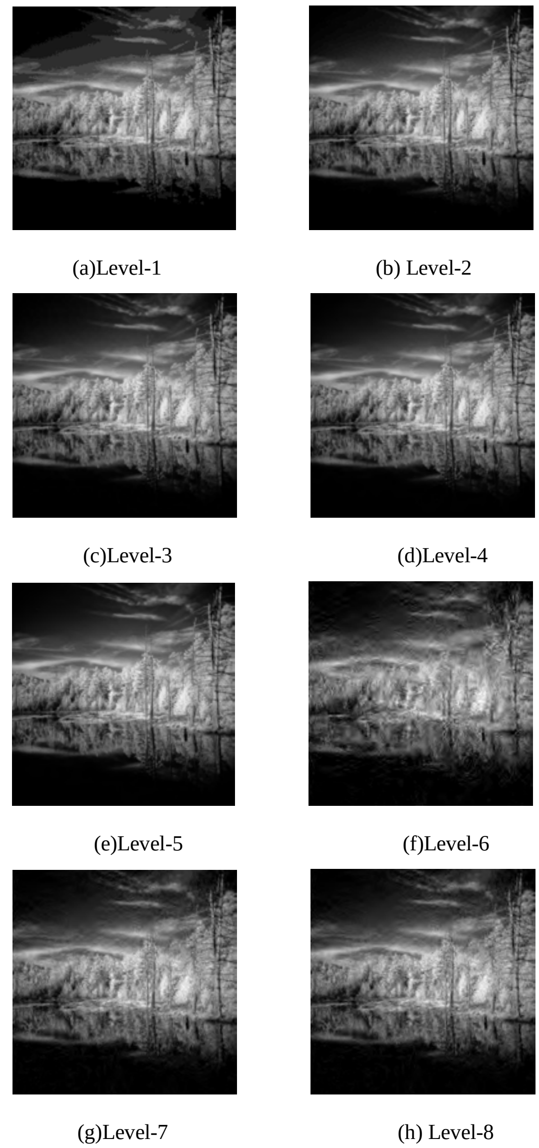

Figure.9 Compressing of IR image with CDF9/7 (Lifting scheme)and SPIHT combined with Huffman and Run length coding.(a) Original IR(500 × 500,8 bits/pixel, (b) decomposition level 1 (c) decomposition level 2 (d) decomposition level 3,(e) decomposition level 4, (f) decomposition level 5, (g) decomposition level 6, (h) decomposition level 6.

From the above results this technique performed well for gray IR image but poorly performed when compressing generic color IR images. This compression technique can save time in infrared (IR) image transmission and achieving process. So this simple and efficient compression technique can very useful in the field of infrared image processing and transmission.

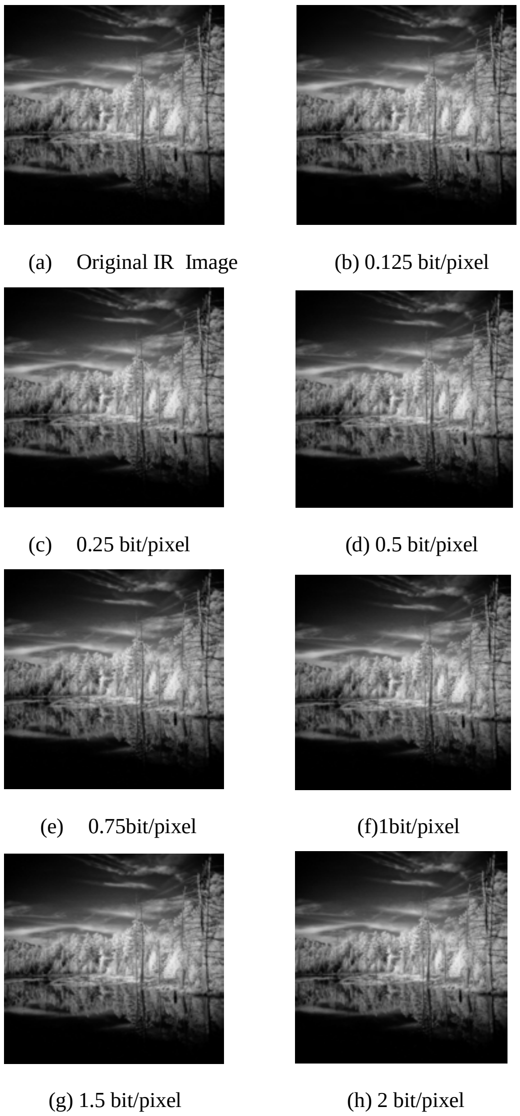

Figure.10 Compressing of IR image with CDF9/7 (Lifting scheme)and SPIHT combined with Huffman and Run length coding.(a) Original IR(500×500,8 bits/pixel, (b) 0.125 bit/pixel (c) 0.25 bit /pixel, (d) 0.5 bit/pixel,(e) 0.75 bit/pixel (f) 1 bit/pixel (g) 1.5 bit/pixel, (h)2 bit per pixel.

5. Conclusion

In this paper, IR images quality has been enhanced evidenced by Figures 6-10 under our novel algorithm following the compression steps in our compression technique. We used the lifting based on Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) with the SPIHT coding to have the more effective compression. Two entropy codes such as Huffman and Run Length coding were used after above technology to make further enhancement. In our proposed image compression algorithm it is noted that the compression is efficient and effective to both text and images. The proposed method provides better compression ratio approximately 88%, highest PSNR values and the performance of MSSIM measurements. It is achieving as overall correct recognition rate as 99.30 % values for IR images and this is more suitable for this category of images. Thus, we conclude that the results obtained are very satisfactory in terms of MSE, PSNR, MSSIM as well as compressed IR image quality. In perspective, we aim to apply this algorithm to compress all types of data not only to store but also for communication purpose with lower cost.

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