



Medical Image Compression using Wavelet Quadrants of Polynomial Prediction Coding & Bit Plane Slicing

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Abstract--In this paper, a promising medical image compression is introduced, it is based on utilizing the wavelet sub bands according to correlation embedded using the linear polynomial approximation model and bit plane slicing. The test results showed elegant performance of lossless image compression techniques.

Keywords--Image Compression, Medical Image, Wavelet Transform.

I. INTRODUCTION

Medical image compression or simply referred as lossless image compression, characterized by preserving image quality; where the image can be reconstructed exactly as identical to the original with error free, but unfortunately there is a limitation of the compression performance achieved (i.e., small compression ratio from 2 to 10) due to on exploiting the statistical redundancy only (i.e. exploits coding redundancy and/or inter pixel redundancy). Reviews of various medical compression techniques can be found in [1-8].

In order to improve the performance of the medical compression system, either by utilizing the combination different techniques such as wavelet and prediction [9-11], or by exploring a technique that selects significant blocks and exclude others [12]. This paper introduced an effective combination techniques that uses the polynomial predictive coding of linear based with the bit plane slicing according to the correlation embedding between the wavelet quadrants. The rest of this paper is organized as follows; the proposed medical compression system with the experimental results given in sections 2 and 3 respectively.

II. THE PROPOSED SYSTEM

The steps below illustrate clearly the implementation of proposed system in details, the system layout shown in Figure(1):

Step 1: Load the original uncompressed gray image I of size $N \times N$.

Step 2: Apply the wavelet transform that characterized by simplicity and high compression ratio. The transform basically based on decompose input image I into four quadrants each of size $(N/2 \times N/2)$ that composed of approximation subband (LL) and detail sub bands (LH , HL and HH). In general the approximation sub band (LL) considered the most significantly important part, since contains all the image information, while the other sub bands or details sub bands considered to be less significant, since contains very small image information and they can be set to zero without significantly changing the image [13,14].

Step 3: Compute autocorrelation function between neighbouring pixels of approximation and detail image sub bands, such as:

$$LL_{xshif, yshif} = \frac{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((LL(x, y) - \mu_{LL}) \cdot ((LL(x + x_{shif}, y + y_{shif}) - \mu_{LL}))}{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((LL(x, y) - \mu_{LL})^2)} \quad (1)$$

$$LH_{xshif, yshif} = \frac{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((LH(x, y) - \mu_{LH}) \cdot ((LH(x + x_{shif}, y + y_{shif}) - \mu_{LH}))}{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((LH(x, y) - \mu_{LH})^2)} \quad (2)$$

$$HL_{xshif, yshif} = \frac{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((HL(x, y) - \mu_{HL}) \cdot ((HL(x + x_{shif}, y + y_{shif}) - \mu_{HL}))}{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((HL(x, y) - \mu_{HL})^2)} \quad (3)$$

$$HH_{xshif, yshif} = \frac{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((HH(x, y) - \mu_{HH}) \cdot ((HH(x + x_{shif}, y + y_{shif}) - \mu_{HH}))}{\sum_{x=0}^{(N/2)-1} \sum_{y=0}^{(N/2)-1} ((HH(x, y) - \mu_{HH})^2)} \quad (4)$$

Here m_{LL} , m_{LH} , m_{HL} and m_{HH} refers to the mean of the approximation and details sub bands, $LL(x+xxshift,y+yyshift)$, $LH(x+xxshift,y+yyshift)$, $HL(x+xxshift,y+yyshift)$ and $HH(x+xxshift,y+yyshift)$ the shifted images by $xshift$ and $yshift$ refers to the amount of shift in pixel(s) in both directions.

Step 4: Apply compression techniques depending on the correlation embedded between image quadrants, in other words apply polynomial prediction coding or bit plane slicing of the subband images, such that:

a) For highly correlated quadrant, namely the approximation subband (LL) the polynomial prediction of linear based model utilized to remove the correlation or spatial redundancy embedded between image pixel values, using the following steps:

1- Partition the approximation subband (LL) into nonoverlapping blocks of fixed size $n \times n$, and performs the polynomial representation according to equations (5,6 and 7) [15]:

$$a_0 = \frac{1}{n \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} LL(i, j) \dots \dots \dots (5)$$

$$a_1 = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} LL(i, j) \times (j - x_c)}{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (j - x_c)^2} \dots \dots \dots (6)$$

$$a_2 = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} LL(i, j) \times (i - y_c)}{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (i - y_c)^2} \dots \dots \dots (7)$$

Where $LL(i, j)$ is the approximation sub-band of original image of block of size $(n \times n)$ and

$$x_c = y_c = \frac{n-1}{2} \dots \dots \dots (8)$$

2- Create the predicted image \tilde{L}_L using the calculated coefficients above, such as:

$$\tilde{L}_L = a_0 + a_1(j - x_c) + a_2(i - y_c) \dots \dots (9)$$

3-Find the residual or residue between the original LL and predicted \tilde{L}_L approximated subband images

$$R(i, j) = LL(i, j) - \tilde{L}_L(i, j) \dots \dots \dots (10)$$

b) For less correlated quadrants or the detail sub bands (LH , HL and HH), the simple plane slicing techniques exploited, the following steps performed for each detail band:

1- Apply mapping process by converting the negative and positive values into positive values only either even or odd, using the mapping formula below.

$$Map_i = \begin{cases} 2Map_i & \text{if } Map_i \geq 0 \\ |2Map_i| - 1 & \text{else} \end{cases} \dots \dots \dots (1)$$

Where Map_i is the i^{th} value of the subband, where the negative values mapped to odd while the positive values mapped to even.

2- Convert each of the mapped detail sub bands into it's layers according to image intensity value, where the bit plane slicing separating it into eight layers, in general the Least Significant Layers ($LSLs$) arranged from layer₀ to layer₃, while the Most Significant Layers ($MSLs$) from layer₄ to layer₇.

3- Remove the low or small image contribution effects by discarding the Least Significant Layers ($LSLs$) and keeping only the Most Significant Layers ($MSLs$) of highly effect. Simply, now each subband needs or required only four layers.

Step 5: Use LZW symbol encoder of dictionary based to compress the residual, coefficients of approximated subband (i.e., LL) and the most significant layers ($MSLs$) of the mapped detail sub bands.

Step 6: Reconstruct the compressed image that identical to the original one I using the following steps:

a) Use the symbol decoder to reconstruct the compressed image information.

b) For the approximation subband, the residual along with the coefficients used to rebuild the LL quadrant:

$$LL(i, j) = R(i, j) + \tilde{L}_L(i, j) \dots \dots \dots (12)$$

c) For the detail sub bands, applied the following steps:

1- Use the Most Significant Layers ($MSLs$) of each subband, the four high order layers.

2- Perform the inverse mapping process, to map each value into equivalent representation, by applying the following:

$$InvMap_i = \begin{cases} Map_i / 2 & \text{if even} \\ (Map_i + 1) / 2 & \text{else} \end{cases} \dots \dots \dots (13)$$

Here, the values mapped again into negative and positive values.

d) Apply the inverse wavelet transform to reconstruct the compressed image.

III. EXPERIMENTS AND RESULTS

In general, to test the system performance, various medical image types adopted (see Figure 2 for an over view) where all the images are gray square of size 256×256 pixels with block sizes $\{4 \times 4$ and $8 \times 8\}$ using the only measure of goodness corresponding to compression ratio. Figure 3 shows the autocorrelation function of the wavelet transform sub bands of the tested images that presents clearly the spatial redundancy within the image quadrants of approximation and subband details. The results are shown in Table 1 that summarizes the size of the compressed information and the compression ratio against the utilized block sizes for the test images. The highly superior compression ratio achieved for a lossless medical system characterizes this techniques compared to other techniques based on the same concept [10,11,12,15,16], in which the compression ratio improved about three times or more on average. Also the result illustrates that the compression ratio vary according to image details or characteristics where for simple or low detail images like tummy and chest x-ray higher compression achieved compared to complex or highly detail images like brain, knee ct-scan and echo. Lastly, it is obvious that the compression ratio of the proposed system is affected by the block size of the approximation subband (i.e., LL), whereas the block size increase the compression ratio improves because less coefficient parameters required.

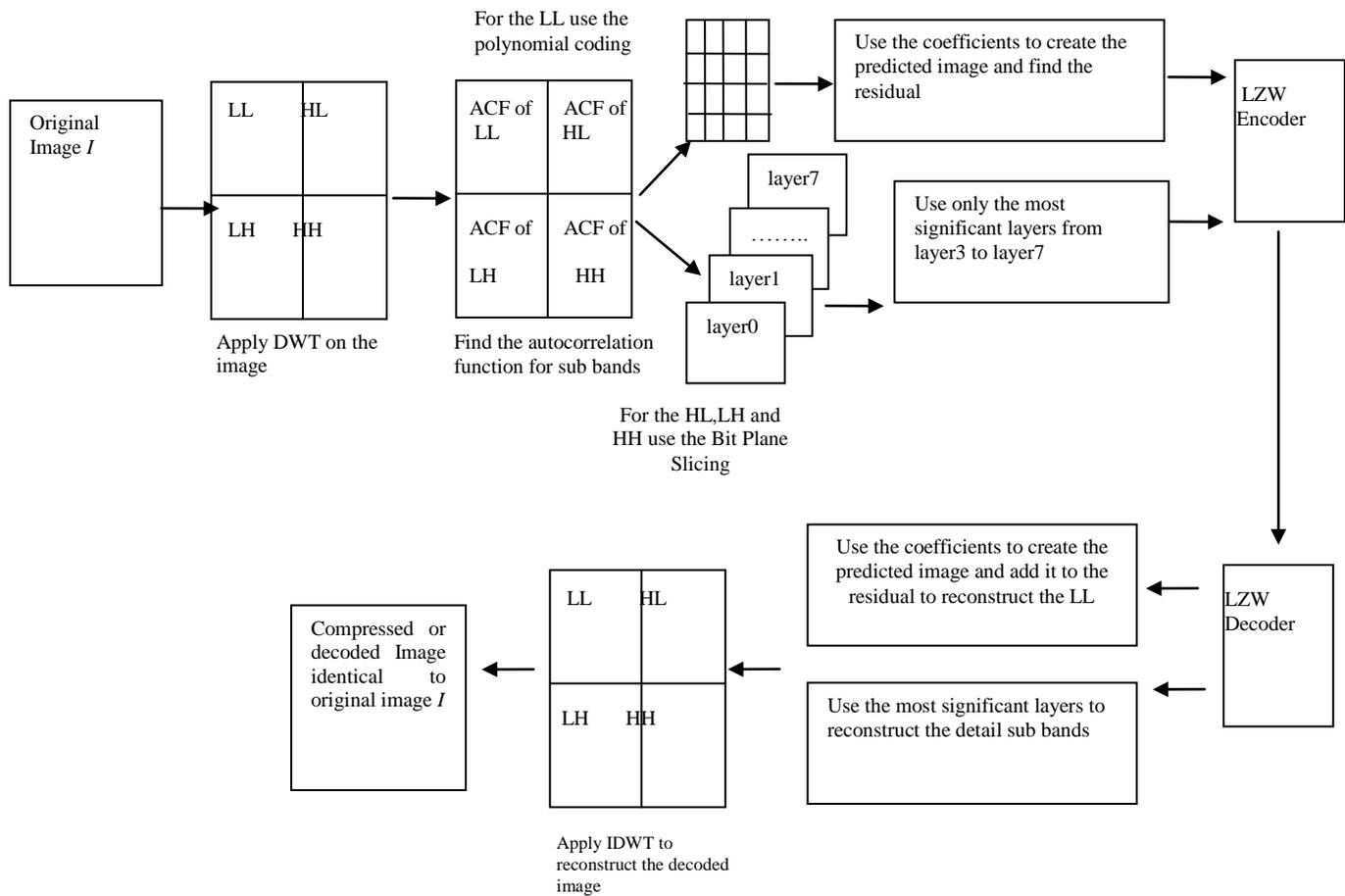


Fig. (1): Compression system structure.

TABLE 1: THE MEDICAL COMPRESSION PERFORMANCE FOR THE TESTED IMAGES

Tested Image	Size in bytes of Original image	Block Size 4		Block Size 8	
		Size in bytes compressed information	Comp. Ratio	Size in bytes compressed information	Comp. Ratio
Brain	65536	2508	26.1308	2136	30.6816
Echo	65536	2552	25.6803	1804	36.3282
Knee	65536	1942	33.7467	1586	41.3216
Tummy	65536	1782	36.7767	1636	40.0587
Xray-chest	65536	1772	36.9842	1260	52.0127

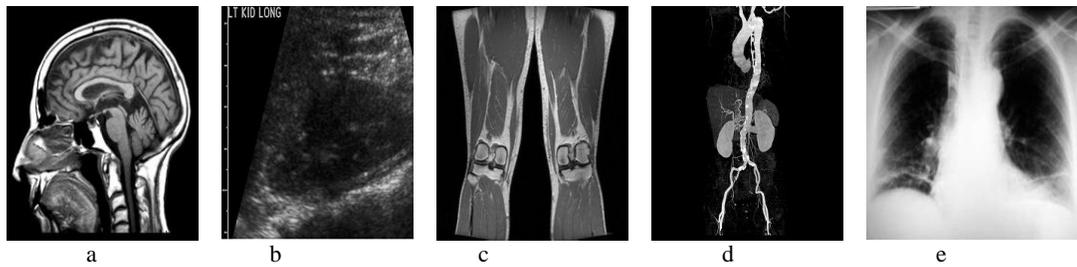


Fig. (2): Overview of the medical test images.

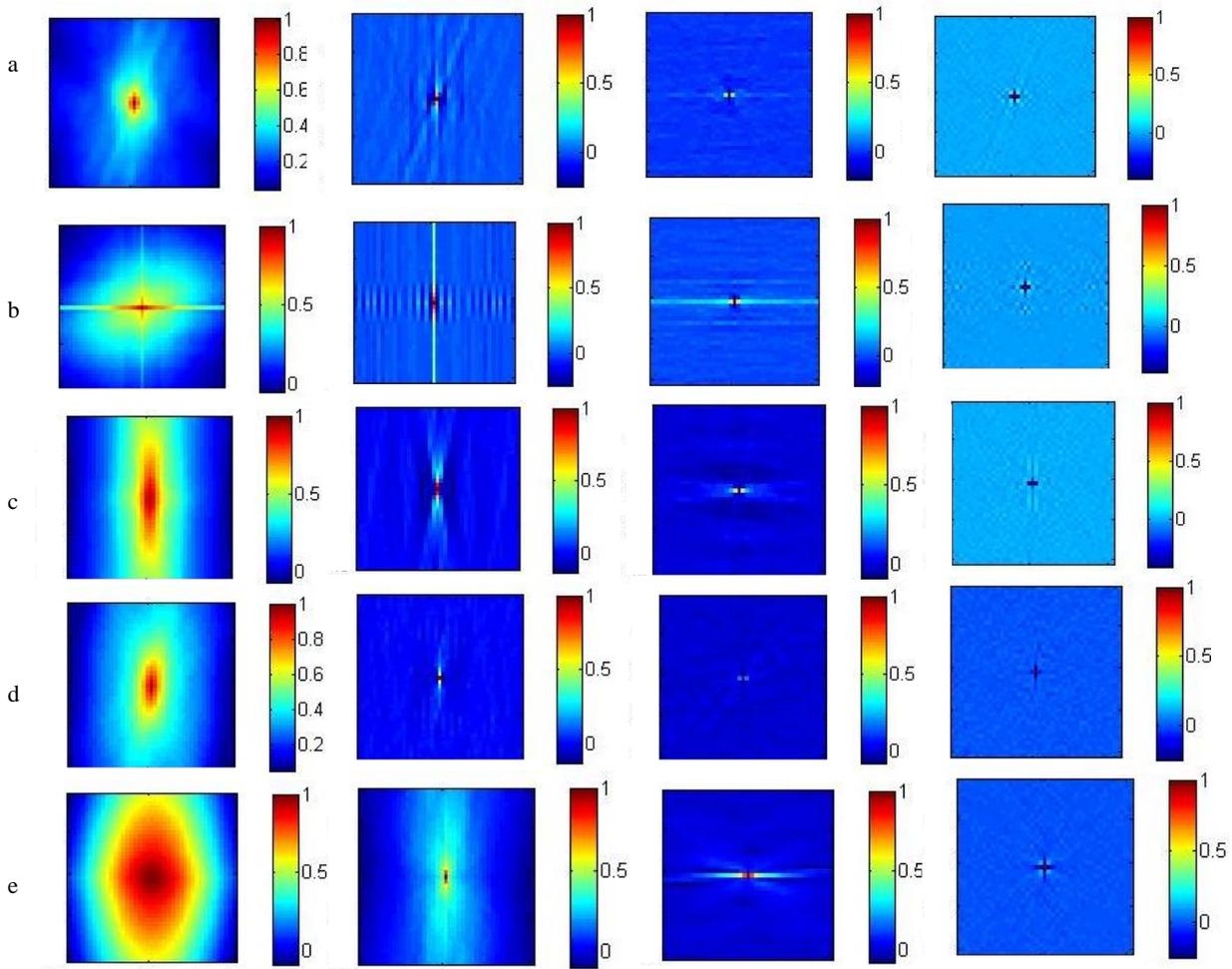


Fig. (3): The autocorrelation values of approximation and detail sub bands of the tested images.

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