International Journal of Modern Trends in Engineering and Research
www.ijmter.com
e-ISSN No.:2349-9745, Date: 2-4 July, 2015

Lifting based wavelet transform along with SPIHT algorithm used for Image compression

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Abstract— In the coming of era the digitized image is an important challenge to deal with the storage and transmission requirements of enormous data, including medical images. Compression is one of the indispensable techniques to solve this problem. In this paper, we propose an algorithm for medical image compression based on lifting base wavelet transform coupled with SPIHT (Set Partition in Hierarchical Trees) coding algorithm, of which we applied the lifting structure to improve the drawbacks of conventional wavelet transform. We compared the results with various wavelet based compression algorithm. Experimental results show that the proposed algorithm is superior to traditional methods for all tested images at low bit rate. Our algorithm provides better PSNR, Quality factor and MSSIM values for medical images only at low bit rate. Compressed image can be represent in various format such as GIF, JPG, BMP and PNG

Keywords- Compression, wavelet, Lifting scheme, SPIHT, Entropy coding.

I. INTRODUCTION

As uncompressed Image requires considerable storage capacity and transmission bandwidth, Image compression is one of the most important and successful applications of the wavelet transform to reduce the space required for storage and transmission. As long as medical field is concern Medical data sets are the important assets for the diagnosis. Therefore, repository for medical images requires huge storage capacities. Over the past ten years, the discrete wavelet transform was used for Image compressions and achieve a great success in the field of Image compression, but have had come across the limitation for the multi-scale representations of multi dimensional signals.

Lifting base wavelet transform along with SPIHT algorithm plays the important role to overcome the problem of Image compression for multi scale representations of multi dimensional signals. In order to improve the Image compression, we compare the PSNR, MSSIM and quality factor of Image compression results with the existing techniques. Along with this we are going to analyze effect of Image resizing on bit rate. Analyzing the various Image formats to observe Image compression ratio in respective format and at what bit rate the Image compression is being achieved.

II. WAVELET TRANSFORM

The wavelet Lifting Scheme is a method for decomposing wavelet transforms into a set of stages. Lifting scheme algorithms have the advantage that they do not require temporary arrays in the calculations steps and have less computation.

A. Spliting
In this stage the input signal is divided in to two disjoint sets, the odd (X[2n+1]) and the even samples (X[2n]).

B. Lifting
In this module, the prediction operation P is used to estimate X0(n) from Xe (n) and results in an error signal d(n). Then we update d(n) by applying it to the update operation U, and the resulting signal is combined with Xe(n) to S(n) estimate, which represents the smooth part of the original signal.

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 Ke to produce the wavelet sub-band XL1. Similarly in the odd-index part the error signal d(n) is multiplied by K0 to obtain the wavelet sub band XH1. The output result is XL1 and XH1 by using the lifting-based WT are the same as those of using the convolution approach for the same input. For lifting implementation, the CDF 9/7 wavelet filter pair can be factorized into a sequence of primal and dual lifting. The most efficient factorization of the poly phase matrix for the 9/7.

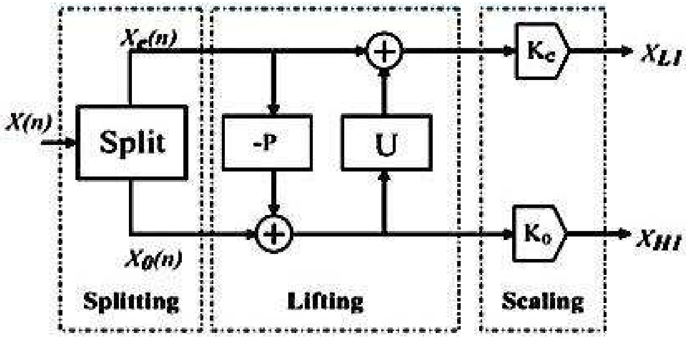

Figure 1. The lifting-based Wavelet Transform.

III. SPIHT CODING SCHEME

SPIHT (Set Partition in Hierarchical Trees) is one of the most advanced schemes, even outperforming the state-of-the art JPEG 2000 in some situations. The basic principle is the same; a progressive coding is applied, processing the image respectively to a lowering threshold. The difference is in the concept of zero trees (spatial orientation trees in SPIHT). There is a coefficient at the highest level of the transform in a particular subband which considered insignificant against a particular threshold; it is very probable that its descendants in lower levels will be insignificant too. Therefore we can code quite a large group of coefficients with one symbol. A spatial orientation tree is defined in a pyramid constructed with recursive four subbands splitting. According to this relationship, the SPIHT algorithm saves many bits that specify insignificant coefficients.
The flowchart of SPIHT is presented in Fig.3 as a First step the original image is decomposed into subbands. Then the method finds the maximum iteration number. Second, the method puts the DWT coefficients into a sorting pass that finds the significance coefficients in all coefficients and encodes

the sign of these significance coefficients. Third, the significance coefficients that can be found in the sorting pass are put into the refinement pass that uses two bits to exact the reconstruct value for approaching to real value. The first, second and third steps are iterative, and then iteration decreases the threshold (Tn) and the reconstructive value (Rn – Rn-1 /2). As a fourth step, the encoding bits access entropy coding and then transmit or store the bit. The result is in the form of a bit stream. All of the wavelet-based-image encoding algorithms improve the compression rate and the visual quality, but the wavelet-transform computation is a serious disadvantage of those algorithms.

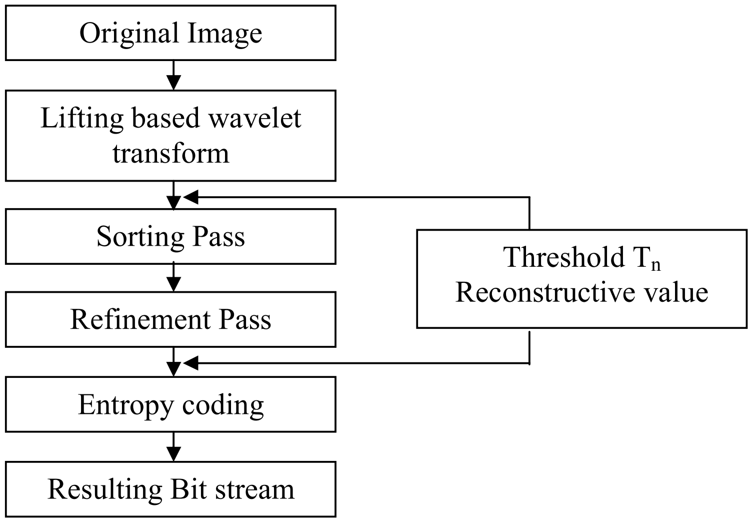

Figure 2. Flow chart of SPIHT coding scheme

III. PERFORMANCE OF IMAGE COMPRESSION SCHEME

The Peak Signal to Noise Ratio (PSNR) is the most commonly used as a measure of quality of reconstruction in image compression. The PSNR are formulating as:

$$PSNR = 10\log_{10}\left(\frac{Dynamics\ of\ \text{image}}{MSE}\right)$$

Mean Square Error (MSE) which requires two M N grayscale images. Usually an image is encoded on 8 bits. It is represented by 256 gray levels. Finally the quality measurement can provide a spatial map of the local image quality, which provides more information on the image quality degradation. For application, we require a single overall measurement formula as:

$$MSSIM(I, I_d) = \frac{1}{M}\sum_{i=1}^{M} SSIM(I_{i,j})$$

Where I and I_d are respectively the reference and degraded images, I and I_d are the contents of images at the ith local window. M is the total number of local windows in image. The MSSIM values exhibit greater consistency with the visual quality.

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V. RESULT AND DISCUSSION

We are interested in lossy compression methods based on 2D wavelet transforms because their properties are interesting. Indeed, the 2D wavelets transform combines good spatial and frequency locations. As work on medical image, the spatial location and frequency are important

We applied the proposed algorithm on test image of Lina (Fig.3) of size 512×512 encoded by 8 bpp. Fig.4 illustrates the compressed image quality for different bit-rate values (number of bits per pixel). To show the performance of the proposed method, we make a comparison between these different types of transform. For each application we calculate the PSNR and MSSIM. The results obtained are given and in Table 1. By comparing the different values of PSNR and MSSIM, we show clearly the effectiveness of our algorithm in terms of compressed image quality for low bit rate. This study was subsequently generalized to a set of medical images of the GE Medical Systems database. The Fig.4 presents the results obtained after application of our algorithm on various images. We note that our algorithm is adapted for the various medical image compressions.

Figure 3. Input Image

Figure 4. Compressed Image

Table 1. PSNR and MSSIM values for various Images

Sr.No.	Type of Image	Input size of Image	Size of compressed image	Entropy	Bit rate	PSNR	MSSIM	Quality factor
1	lena.tif	512	128	7.4456	30.1767	18.49	0.9956	0.2691
2	transeverse1.jpg	256	64	6.1353	101.5853	17.03588	0.9891	0.42706
3	transeverse2.jpg	256	64	6.0179	115.0404	16.8936	0.9897	0.42158
4	transeverse3.jpg	256	64	5.88	222.9188	16.86	0.9902	0.41202
5	transverse.4.jpg	256	64	5.88	152.79	16.59	0.9902	0.39506
6	transeverse5.jpg	256	64	5.7117	41.24716	16.7	0.9894	0.40582
7	transeverse6.jpg	256	64	5.6042	239.4078	16.77	0.9894	0.4118

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