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A Novel Image Compression Based on Lifting Wavelet Transform and Modified SPIHT

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Abstract-In this paper, a new approach of images coding by Shapiro algorithm (Embedded Zerotree Wavelet algorithm or EZW) is proposed. In this approach, the old Shapiro algorithm for image coding is modified. The new modified EZW (MEZW), distributes entropy differently and also optimizes the coding. This new version can produce good results that are a significantly improve the PSNR and compression ratio, without affecting the computing time. These results are also comparable with those obtained using the SPIHT and SPECK algorithms. The EZW, Spiht or Speck algorithms are based on the Wavelet transform. The principle of wavelet transform is to decompose hierarchically the input image into a series of successively lower resolution reference images and detail images which contain the information needed to be reconstructed back to the next higher resolution level. The sub-band images resulting from wavelet transform are not of equal significance. Some sub-bands contain more information than others (example the baseband sub band).

Keywords –SPIHT, EZW.PSNR, SPECK

I. Introduction

Since image has a very large information size, the image data size poses a problem when an image is stored or transmitted. Compression (encoding) of an image reduces the data size by removing the redundancy of the image or manipulating the values on levels that such manipulations are hard to visually recognize. Conventionally, as one of still image encoding methods, JPEG (Joint Picture Experts Groups) internationally recommended by the ISO and ITU-T is known. In JPEG, several kinds of encoding schemes are specified in correspondence with images to be encoded and applications. However, in its basic scheme except for a reversible process, an image is segmented into 8×8 blocks, the blocks undergo the discrete cosine transform (DCT) , and transform coefficients are appropriately quantized and are then encoded. In this scheme, since the DCT is done in units of blocks, so-called block distortion is produced, i.e. block boundaries are visible when transform coefficients are coarsely quantized and encoded. On the other hand, recently, encoding schemes based on the wavelet transform have been extensively studied, and various encoding schemes using this transform have been proposed. Since the wavelet transform does not use block division, it does not suffer any block distortion and image quality a high compression ratio is superior to that of JPEG[1].

Image compression - An image is essentially a 2-D signal processed by the human visual system. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. When we speak about image compression, there are generally two different solutions, the lossless compression and the lossy compression. Lossy compression methods most often rely on transforming spatial image domain into a domain that reveals image components according to their relevance, making it possible to employ coding methods that take advantage of data redundancy in order to suppress it.
A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS). Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. Since we will focus only on still image compression, we will not worry about temporal redundancy [2]. For still image compression, the `Joint Photographic Experts Group' or JPEG standard [4] has been established by ISO (International Standards Organization) and IEC (International Electro-Technical Commission). The performance of these coders generally degrades at low bit-rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) scheme. More recently, the wavelet transform has emerged as a

cutting edge technology, within the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. The following fig. 1 shows the existing image compression model[2]. JPEG has a big compressing ratio, reducing the quality of the image, it is ideal for big images and photographs. The performance of these coders generally degrades at low bit-rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) scheme [3]. This is improved by using wavelet decomposition, but it faces ringing artifacts. the wavelet decomposition structure. In wavelet decomposition; the approximate component of image is further decomposed. From the point of view of compression, where we want as many small values as possible, the standard wavelet transform may not produce the best result, since it is limited to wavelet bases (the plural of basis) that increase by a power of two with each step. These techniques suffer from blurring artifacts and ringing artifacts.

B. Compression from DCT to Wavelets

For still image compression, the `Joint Photographic Experts Group' or JPEG standard [4] has been established by ISO (International Standards Organization) and IEC (International Electro-Technical Commission). The performance of these coders generally degrades at low bit-rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) scheme. More recently, the wavelet transform has emerged as a cutting edge technology, within the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. Blocking artifacts [3] are the result of the independent processing of each block in block-based signal processing. Staircase noise is one form of blocking artifact, which appears when a block includes image edges; the edge is degraded such that the block bands looks like the edge. Grid noise is other form of artifact where slight change of image intensity along the block boundary becomes noticeable in areas with slowly varying intensity with position. Despite of its general success, the wavelet transform often fails to accurately capture high frequency information, especially at lower bit rates where such information is lost in quantization noise.

Among wavelet based technologies, SPIHT [7] is mostly used because of excellent rate-distortion performance. However, it does not entirely provide desired features of progressive transmission spatial scalability and optimal visual quality and does not consider human visual system (HVS) properties. Also a larger amount of memory is required to maintain three lists, namely list of insignificant pixels, list of significant pixels and list of insignificant sets that are used for storing the coordinates of wavelet coefficients and tree sets in the coding and decoding process. A great number of operations to manipulate the memory are also required in the codec scheme which greatly reduces the speed of coding procedure.

C. Wavelet based image coding techniques

Wavelet based image coding techniques [3] provide substantial improvements in picture quality at higher compression ratios. Wavelet based image compression schemes include embedded zerotree wavelets (EZW) [8], Set partitioning in Hierarchical Trees (SPIHT) [7], Set partitioning embedded block (SPECK), and embedded block coding with optimized truncation (EBCOT). The main idea in using transformation is to compact the energy of signals in much less samples than in time domain, so we can discard small transform coefficients. Wavelet transform has a good location property in time and frequency domain and is exactly in the direction of transform compression idea. The discrete wavelet transform (DWT) refers to wavelet transforms for which the wavelets are discretely sampled. A transform which localizes a function both in space and scaling and has some desirable properties compared to the Fourier transform. The transform is based on a wavelet matrix, which can be computed more quickly than the analogous Fourier matrix. Most notably, the discrete wavelet transform is used for signal coding, where the properties of the transform are exploited to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. The discrete wavelet transform has a huge number of applications in Science, Engineering, Mathematics and Computer Science.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. The basic idea of the wavelet transform is to represent any arbitrary signal ‘X’ as a superposition of a set of such wavelets or basis functions. These basis functions are obtained from a single photo type wavelet called the mother wavelet by dilation (scaling) and translation (shifts). The discrete wavelet transform for two dimensional signal can be defined as follows.

$$w(a_1, a_2, b_1, b_2) = \frac{1}{\sqrt{a}} \psi\left(\frac{X-b1}{a_1}, \frac{Y-b2}{a_2}\right)$$

Where, $a = a_1 a_2$

The indexes $w(a_1, a_2, b_1, b_2)$ are called wavelet coefficients of signal X and a_1, a_2 are dilation & b_1, b_2 are translation, ψ is the transforming function, which is known as mother wavelet. Low frequencies are examined with low temporal resolution while high frequencies with more temporal resolution. A wavelet transform combines both low pass and high pass filtering in spectral decomposition of signals.

In case of discrete wavelet, the image is decomposed into a discrete set of wavelet coefficients using an orthogonal set of basis functions. These sets are divided into four parts such as approximation, horizontal details, vertical details and diagonal details. Further decomposition of approximation is takes place, we get again four components shown in Figure 3.

II. METHODOLOGY

Lifting [6][10][13] was originally developed to adjust wavelet transforms to complex geometries and irregular sampling leading to so-called second generation wavelets [4]. It can also be seen as an alternate implementation of classical, first generation wavelet transforms. The main feature of lifting is that it provides an entirely spatial-domain interpretation of the transform, as opposed to the more traditional frequency-domain based constructions. The local spatial interpretation enables us to adapt the transform not only to the underlying geometry but also to the data, thereby introducing nonlinearities while retaining control of the transform's multi-scale properties. A time series is simply a sample of a signal or a record of something, like temperature, water level or data. Wavelets allow a time series to be viewed in multiple resolutions. Each resolution reflects a different frequency. The wavelet technique takes averages and differences of a signal, breaking the signal down into spectrum.

All the wavelet algorithms, on time series a power of two values (e.g., 64, 128, 256...). Each step of the wavelet transform produces two sets of values: a set of averages and a set of differences (the differences are referred to as wavelet coefficients). Each step produces a set of averages and coefficients that is half the size of the input data. For example, if the time series contains 256 elements, the first step will produce 128 averages and128 coefficients. The averages then become the input for the next step (e.g., 128 averages resulting in a new set of 64 averages and 64 coefficients). This continues until one average and one coefficient (e.g.2^0) is calculated.

The average and difference of the time series is made across a window of values. Most wavelet algorithms calculate each new average and difference by shifting this window over the input data. For example, if the input time series contains 256 values, the window will be shifted by two elements, 128 times, in calculating the averages and differences. The next step of the calculation uses the previous set of averages, also shifting the window by two elements. This has the effect of averaging across a four element window. Logically, the window increases by a factor of two each time. Wavelet compression is a form of data compression well suited for image compression (sometimes also video compression and audio compression). The goal is to store image data in as little space as possible in a file. A certain loss of quality is accepted (lossy compression). Using a wavelet transform, the wavelet compression methods are better at representing transients, such as percussion sounds in audio, or high-frequency components in two-dimensional images, for example an image of stars on a night sky. This means that the transient elements of a data Signal can be represented by a smaller amount of information than would be the case if some other transform, such as the more widespread discrete cosine transform, had been used. First a wavelet transform is applied. This produces as many coefficients as there are pixels in the image (i.e.: there is no compression yet since it is only a transform). These coefficients can then be compressed more easily because the information is statistically concentrated in just a few coefficients. This principle is called transform coding. After that, the coefficients are quantized and the quantized values are entropy encoded and/or run length encoded.

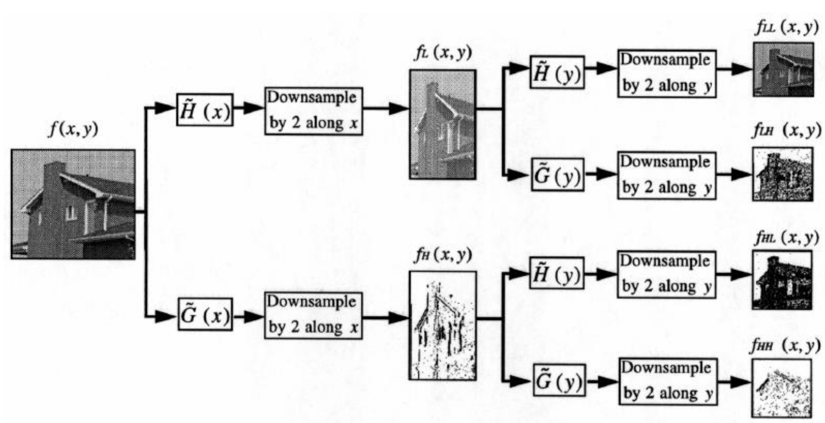

Fig 1a: Wavelet decomposition of an Image

III. Lifting Wavelet Transform

The wavelet transforn presents several properties:
* Residual correlation too small for any practical us
* Different distribution on different sub bands
* Stationary assumption quite unrealistic
* Most coefficients are zero after quantization
* Distribution somehow replicated on resolution hierarchy
* Variable quantization needs to be addressed (bit allocation)

The Discrete Wavelet Transform (DWT) can be implemented as a filter bank. This filter bank decomposes the original image into horizontal (HL High Low), vertical (LH : Low High), diagonal (HH High High), and baseband (LL : Low Low) sub ands, each being one-fourth the size of the original image. Then, the baseband can again be decomposed into four other sub-bands and so on [3,4]. This method favors hardware realization, can carry on the fast original position operation, does not need external storage space, computation complexity is lower and easy to reversible transformation, the wavelet coefficient obtained is the same as with which is obtained by using traditional wavelet transformation. The main advantage of the lifting wavelet transform is that it is efficient for implementation. The calculation in each step of the transform can be done completely in place. For the Daub 9/7 biorthogonal wavelet [14], the lifting scheme only requires 14 floating point arithmetic operations, including 8 additions and 6 multiplications per data point for every decomposition level, whereas in case of the standard filter bank scheme, there are 23 arithmetic operations required per data point for every decomposition level [4]. Therefore, the total computational cost of the lifting scheme is 60.87% of that in the standard filter bank implementation, which greatly improves the speed of the wavelet transform

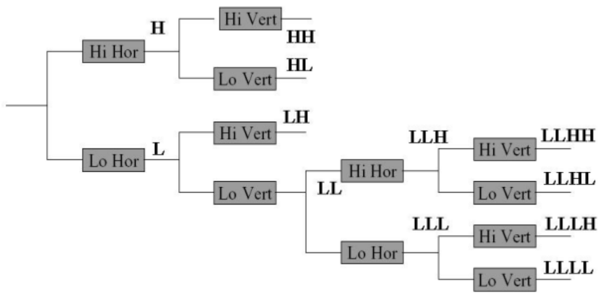

Figure 1 : multiresolution decomposition by filters bank

Where:

HiHor is One-dimensional digital High-pass Filter with Finite Impulse Response (FIR) applied at rows of image.
HiVer is One-dimensional digital High-pass Filter (FIR) applied at columns of image.
LoHor is One-dimensional digital Low-pass Filter (FIR) applied at rows of image.
LoVer is One-dimensional digital Low-pass Filter (FIR) applied at columns of image.
Hi and **Lo** are two mirror's digital filters (FIR).

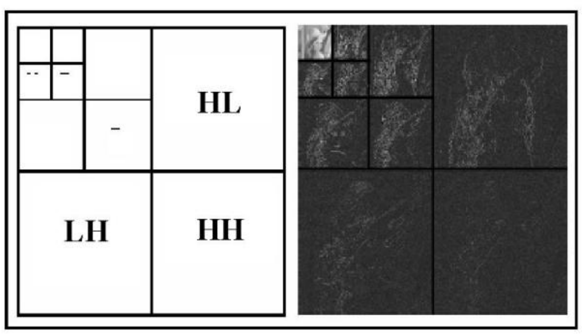

Figure 2: Example of Pyramid structure

This pyramid representation obtained by multiresolution decomposition, It has several properties, which are as follows:

- Hierarchical decomposition
- Can exploit structures on several scales
- Progressive transmission
- Good energy compaction
- Preliminary classification for entropy coding

IV Shapiro's EZW Algorithm

One of the most efficient algorithms of image compression, based on wavelets, is the Embedded Zerotrees of Wavelets (EZW) [1,9,10,1 1]. The Embedded Zerotree Wavelet (EZW) algorithm has, essentially, two proprieties and it uses, generally, four features.

Its two proprieties are:

- **-**Producing a fully embedded bit stream

- Providing competitive compression performance

The four features used by this algorithm are

- Discrete wavelet transform or DWT,
- Zerotree coding of wavelet coefficients
- Successive –Approximation quantization
- Arithmetic Coding

Initially, the discrete wavelet transform (DWT)(figure3), is applied to the image, and then the threshold To is determined so that so that: TO = 21g2(Cmax) where
Cmax is the largest wavelet coefficient.
Then, a sequence of Decreasing Thresholds is applied:
TO, T1, . . . , TN-], with Ti = Ti- 12 and I coefficients < 2 T,. For each threshold, perform two passes: Dominant Pass followed by Subordinate Pass:

a)-Dominant list contains D:

The coordinates of those coefficients that have not
yet been found to be significant in the same relative order as the initial scan (figure 4).

b) Subordinate list contains S:

The magnitudes of those coefficients that have been
found to be significant.
Note, that a wavelet coefficient is said to be insignificant if its absolute value is less than a given threshold T.

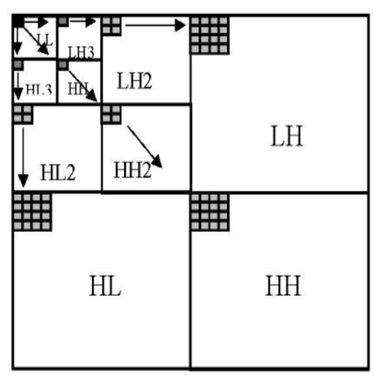

Figure 3: Parent-child dependencies of subbands

Figure 4 Scanning order of the subbands for encoding significance map:

- The parents must be scanned before children.
- All positions in a given subband are scanned before the scan moves to the next subband.

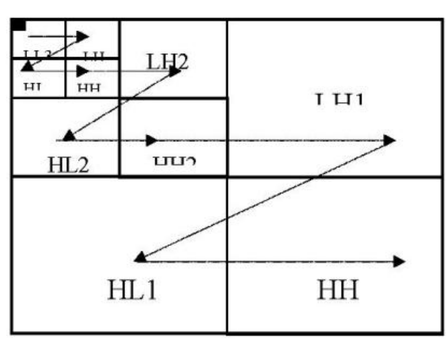

Figure 4 Scanning order of the subbands for encoding a significance map:

V. Proposed Algorithm (Modified EZW)

In Shapiro's EZW algorithm, the dominant list D is composed of four symbols {P, N, Z, and T}. hence, during a subordinate pass, each one is coded in two bits; these symbols are coded arithmetically before transmission.

In MEZW algorithm, the dominant list D is composed of six symbols (P, N, Z, T, Pt and Zt). Indeed, if all the descendants are judged insignificant, the coefficients are coded using the symbols Pt for positive coefficients and Nt for negative coefficients. Indeed, if a coefficient is tested and found to be significant, its descendants must also be tested. If at least one descendant is significant, then the coefficients are coded according to the doing rules of the Shapiro's algorithm, which is the case for the coefficients.

However, if all the descendants are judged insignificant, the coefficients are coded according to our MEZW algorithm's coding rules, using the symbols Pt for positive coefficients and Nt for negative coefficients:

- If the significant coefficient is in the root of the matrix (pyramidal structure: representing the parent and its descendants), then a symbol P, symbols "PTTT' (or "NTTT') in EZW algorithm.
- If the significant coefficient is not in the root of the matrix, P, (or Ne), in MEZW algorithm, represents five symbols "PTTTT' (or "NTTTT') in EZW algorithm,

VI. Results

Fig. 5 The original image

Fig. 6 The compressed image

$$\text{MSE} = \frac{1}{512 \text{x} 512} \sum_{x=1}^{x=512} \sum_{y=1}^{y=512} [p(x,y) - p'(x,y)]^2$$

$$\text{RMSE} = \sqrt{\text{MSE}}$$

$$\text{PSNR} = 20\log10(255/\text{RMSE})$$

Fig .7 Lena image after 3-level of transform

VII. CONCLUSION

In this paper, a new approach of image coding, based on EZW algorithm, is proposed. This algorithm is able to improve the performance of the EZW algorithm because:

1) using six significance symbols instead of four better optimizes the entropy and,

2) the binary regrouping of these symbols on 9 bits better optimizes the coding.

The proposed algorithm is able to accomplish this without increasing computation time. In addition, this algorithm performed comparably with the SPIHT and SPECK algorithms, which could be very interesting for the field of hierarchical coding.

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