International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume No. 2, Issue No. 8, pp : 783-788 1 Aug. 2013

A Review on Wavelet-Based Image Compression Techniques

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Abstract - The world creates and feeds on huge chunks of storage space containing multimedia. Most part of this belongs to images. As technology is constantly growing, the sizes and the pixel density of these images are getting enhanced. Hence, efficient techniques are required to maintain their size and reusability. For example, in the field of medicine, highly detailed images requires storage of large quantities of digitized clinical data. Due to the bandwidth and storage limitations, these medical images must be compressed before transmission and storage. Diagnosis is effective only when compression techniques preserve all the relevant and important image information needed. Hence, image compression comes into the spotlight. The objective of compression is to reduce irrelevance and redundancy of the image data in order to be able to store or transmit data in an efficient form. There are basically two types of image compression: lossless and lossy. Lossless coding does not permit high compression ratios whereas lossy coding can achieve high compression ratio. Among the existing lossy compression schemes, transform coding is one of the most effective strategies. In the vicinity of this paper, the various coding techniques with their description and highlights of their merits and demerits are discussed. This can provide an insight to users on comparing and considering all the techniques and to choose the one based on requirement in hand.

Keywords - EZW, SPIHT, SPECK, WDR, ASWDR, EBCOTS

1. INTRODUCTION

In many different fields, digitized images are replacing conventional analog images as photograph or x-rays. The volume of data required to describe such images greatly slows down transmission and makes storage prohibitively costly.

The information contained in images must, therefore, be compressed by extracting only visible elements, which are then encoded. Thus the quantity of data involved is reduced substantially. The fundamental goal of image compression is to reduce the bit rate for transmission or storage while maintaining an acceptable fidelity or image quality.

Uncompressed multimedia (graphics, audio, video) data requires considerable storage capacity and transmission bandwidth despite rapid progress in mass storage density, processor speeds and digital communication system performance. The demand for data storage capacity and data transmission bandwidth continues to outstrip the capabilities of available technologies. The recent growth of data intensive multimedia-based web applications have not only the need for more efficient ways to encode signals and images but have made compression of such signals central to storage and communication technology. Table 1 shows Multimedia data types and uncompressed storage space, transmission bandwidth and transmission time required.

The above information clearly illustrates the need for sufficient storage space, large transmission bandwidth and long transmission time for image, audio and video data. At the present state of technology, the only solution is to compress multimedia data before its storage and transmission, and decompress it at the receiver for playback. For example for a compression Ratio of 32:1, the space, bandwidth and the transmission time requirements can be reduced by a factor of 32, with acceptable quality.

Multimedia Data	**Size/Duration**	**Bits/Pixel(bpp) or Bits/Sample(bps)**	**Uncompressed Size(b-bytes)**	**Transmission Bandwidth (b-bits)**	**Transmission Time (28.8k Modem)**
Page of text	11”x 8.5”	Varying Resolution	4-8 KB	32-64 Kb/page	1.1-2.2 Secs
Telephone quality speech	10 s	8 bps	80 KB	64Kb/sec	22.2 Secs
Grayscale image	512x512	8 bpp	262 KB	2.1 Mb/image	1Min13 Secs
Color image	512x512	24bpp	786 KB	6.29 Mb/image	3Min39Secs
Medical image	2048x2048	12bpp	5.16 MB	41.3 Mb/image	23Min54 Secs

Table 1 Multimedia Data

1.1 Principal Behind Compression

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). In general, three types of redundancy can be identified:-

- Spatial Redundancy or correlation between neighboring pixel values.
- Spectral Redundancy or correlation between different color planes or spectral bands.
- Temporal Redundancy or correlation between adjacent frames in a sequence of images (in video applications).

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.

1.2 Advantages of Compression

• It provides a potential cost savings associated with sending less data over switched telephone network.
• Where cost of call is really usually based upon its duration.
• It not only reduces storage requirements but also overall execution time.

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• It also reduces the probability of transmission errors since fewer bits are transferred.
• It also provides a level of security against illicit monitoring.

1.3 Types of Compression

Categorizing it broadly, there are two types of compression techniques -
1. Lossless compression
2. Lossy compression

1.3.1 Lossless compression - In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. However lossless compression can only a achieve a modest amount of compression.
Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art, or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts.

1.3.2 Lossy Compression - An image reconstructed following lossy compression contains degradation relative to the original. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression. Under normal viewing conditions, no visible loss is perceived (visually lossless).

Lossy methods are especially suitable for natural images such as photographs in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. Lossy image compression is used in digital cameras, to increase storage capacities with minimal degradation of picture quality. Similarly, DVDs use the lossy MPEG-2 Video codec for video compression.

2. Image Coding

A typical lossy image compression system is shown in Figure 1. It consists of three closely connected components namely (a) Source Encoder (b) Quantizer, and (c) Entropy Encoder. Compression is accomplished by applying a linear transform to de-correlate the image data quantizing the resulting transform coefficients, and entropy coding the quantized values.

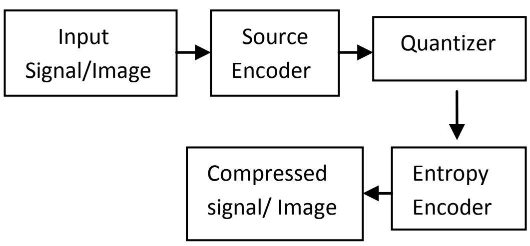

Figure 1 Lossy Image Coder

2.1 Source Encoder (Linear Transformer)

Over the years, a variety of linear transforms have been developed which include Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT)[1], Discrete Wavelet Transform (DWT)[3] and many more, each with its own advantages and disadvantages.

2.2 Quantizer

A quantizer simply reduces the number of bits needed to store the transformed coefficients by reducing the precision of those values. Since this is a many-to-one mapping, it is a lossy process and is the main source of compression in an encoder. Quantization[4] can be performed on each individual coefficient, which is known as Scalar Quantization (SQ). Quantization can also be performed on a group of coefficients together, and this is known as Vector Quantization (VQ). Both uniform and non-uniform quantizers can be used depending on the problem at hand.

2.3 Entropy Encoder

An entropy encoder further compresses the quantized values losslessly to give better overall compression. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than the input stream. The most commonly used entropy encoders are the Huffman encoder and the arithmetic encoder, although for applications requiring fast execution, simple run-length encoding (RLE) has proven very effective.

3. Wavelets and Image Compression

One of the most successful applications of wavelet methods is transform-based image compression (also called coding). The overlapping nature of the wavelet transform alleviates blocking artifacts, while the multi-resolution character of the wavelet decomposition leads to superior energy compaction and perceptual quality of the decompressed image. Furthermore, the multi-resolution transform domain means that wavelet compression methods degrade much more gracefully than block-DCT methods as the compression ratio increases. Since a wavelet basis consists of functions with both short support (for high frequencies) and long support (for low frequencies), large smooth areas of an image may be represented with very few bits, and detail added where it is needed .

Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. Over the past few years, a variety of powerful and sophisticated wavelet-based schemes for image compression have been developed and implemented. Because of the many advantages, wavelet based compression algorithms are the suitable candidates for the new JPEG-2000 standard.
Such a coder operates by transforming the data to remove redundancy, then quantizing the transform coefficients (a lossy step), and finally entropy coding the quantizer output. The loss of information is introduced by the quantization stage which intentionally rejects less relevant parts of the image information. Because of their superior energy compaction properties and correspondence with the human visual system, wavelet compression methods have produced superior objective and subjective results.

3.1 Wavelet Based Image Coding Schemes

Over the past few years, a variety of novel and sophisticated wavelet-based image coding schemes have been developed. These include Embedded Zero tree Wavelet (EZW), Set-Partitioning in Hierarchical Trees (SPIHT) , Set Partitioned Embedded block coder (SPECK) , Wavelet Difference Reduction (WDR), Adaptively Scanned Wavelet Difference Reduction (ASWDR) , Space –Frequency Quantization (SFQ), Compression with Reversible Embedded Wavelet (CREW), Embedded Predictive Wavelet Image Coder (EPWIC), Embedded Block Coding with Optimized Truncation (EBCOT) , and Stack- Run (SR).

3.1.1 Embedded Zero Tree Wavelet(EZW)

An EZW[5],[11] encoder is an encoder specially designed to use with *wavelet transforms*. The EZW encoder was originally designed to operate on images (2D-signals) but it can also be used on other dimensional signals.

The EZW encoder is based on *progressive encoding* to compress an image into a bit stream with increasing accuracy. This means that when more bits are added to the stream, the decoded image will contain more detail.
Progressive encoding is also known as embedded encoding, which explains the E in EZW.
The EZW encoder is based on two important observations:-

1. Natural images in general have a low pass spectrum. When an image is wavelet transformed the energy in the sub bands decreases as the scale decreases (low scale means high resolution), so the wavelet coefficients will, on average, be smaller in the higher sub bands than in the lower sub bands. This shows that progressive encoding is a very natural choice for compressing wavelet transformed images, since the higher sub bands only add detail
2. Large wavelet coefficients are more important than small wavelet coefficients.

For every pass a threshold is chosen against which all the wavelet coefficients are measured. If a wavelet coefficient is larger than the threshold it is encoded and removed from the image, if it is smaller it is left for the next pass. When all the wavelet coefficients have been visited the threshold is lowered and the image is scanned again to add more detail to the already encoded image.This process is repeated until all the wavelet coefficients have been encoded completely or another criterion has been satisfied (maximum bit rate for instance).
A zerotree is a quad-tree of which all nodes are equal to or smaller than the root. The root has to be smaller than the threshold against which the wavelet coefficients are currently being measured. The EZW encoder exploits the zerotree based on the observation that wavelet coefficients decrease with scale. The zerotree is based on the hypothesis that if a wavelet coefficient at a coarse scale is insignificant with respect to a given threshold t_0, then all wavelet coefficients of the same orientation in the same spatial location at a finer scales are likely to be insignificant with respect to t_0. The idea is to define a tree of zero symbols which starts at a root which is also zero and labeled as end-of-block. The EZW algorithm encodes the tree structure so obtained.
To arrive at a perfect reconstruction, the process is repeated after lowering the threshold, until the threshold has become smaller than the smallest coefficient to be transmitted. Similarly, the decoder can also stop decoding at any point resulting in the image that would have been produced at the rate of the truncated bit stream.

3.1.2 Set Partitioning In Hierarchical Trees (SPIHT)

The SPIHT[2] coder is a highly refined version of the EZW algorithm and is a powerful image compression algorithm that produces an embedded bit stream from which the best reconstructed images in the *mean square error* sense can be extracted at various bit rates. Some of the best results—highest PSNR values for given compression ratios — for a wide variety of images have been obtained with SPIHT.

SPIHT is a wavelet-based image compression coder. It first converts the image into its wavelet transform and then transmits information about the wavelet coefficients. The decoder uses the received signal to reconstruct the wavelet and performs an inverse transform to recover the image.
SPIHT is a method of coding and decoding the wavelet transform of an image. By coding and transmitting information about the wavelet coefficients, it is possible for a decoder to perform an inverse transformation on the wavelet and reconstruct the original image. The entire wavelet transform does not need to be transmitted in order to recover the image. Instead, as the decoder receives more information about the original wavelet transform, the inverse-transformation will yield a better quality reconstruction (i.e. higher peak signal to noise ratio) of the original image. SPIHT divides the wavelet into *Spatial Orientation Trees*.
Fig. 2 shows how the spatial orientation tree is defined in a pyramid constructed with recursive four-band splitting. Each node of the tree corresponds to a pixel, and is identified by the pixel coordinate. Its direct descendants (offspring) correspond to the pixels of the same spatial orientation in the next finer level of the pyramid. The tree is defined in such a way that each node has either no offspring or four off-springs, which always form a group of 2X2 adjacent pixels. The pixels in the highest level of the pyramid are the tree roots and are also grouped in 2X2 adjacent pixels. However, their offspring branching is different, and in each group one of them (indicated by the star in Fig) has no descendants. Parts of the spatial orientation trees are used as the partitioning subsets in the sorting.

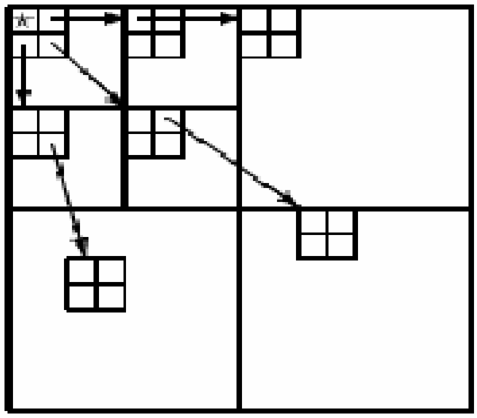

Figure 2 Parent - Offspring Dependencies In Spatial Orientation Tree

SPIHT codes a wavelet by transmitting information about the significance of a pixel. By stating whether or not a pixel is above some threshold, information about that pixel's value is implied. Furthermore, SPIHT transmits information stating whether a pixel or any of its descendants are above a threshold. If the statement proves false, then all of its descendants are known to be below that threshold level and they do not need to be considered during the rest of the current pass. At the end of each pass the threshold is divided by two and the algorithm continues. By proceeding in this manner, information about the most significant bits of the wavelet coefficients will always precede information on lower order significant bits, which is referred to as bit plane ordering. Within each bit plane data is transmitted in three lists: the list of insignificant pixels (LIP), the list of insignificant sets (LIS) and the list of significant pixels (LSP).

3.1.3 Set Partitioned Embedded Block Coder (SPECK)

The image coding scheme the SPECK[8] does not use trees which span,it makes use of sets in the form of blocks. The main idea is to exploit the clustering of energy in frequency and space in hierarchical structures of transformed images.
The SPECK algorithm makes use of rectangular regions of image. These regions or sets, henceforth referred to as sets of type *S*, can be of varying dimensions. The dimension of a set *S* depends on the dimension of the original image and the subband level of the pyramidal structure at which the set lies.
During the course of the algorithm, sets of various sizes will be formed, depending on the characteristics of pixels in the original set. A set of size 1 consists of just one pixel. The other type of sets used in the SPECK algorithm is referred to as sets of type *I*. These sets are obtained by chopping off a small square region from the top left portion of a larger square region. Figure 3 shows A typical set I and partitioning of set S and set I. Two linked lists: LIS - List of Insignificant Sets, and LSP- List of Significant Pixels are maintained. The former contains sets of type *S* of varying sizes which have not yet been found significant against a threshold *n* while the later obviously contains those pixels which have tested significant against *n*. Two types of set partitioning are used in SPECK. They are quad tree partitioning and octave band partitioning.

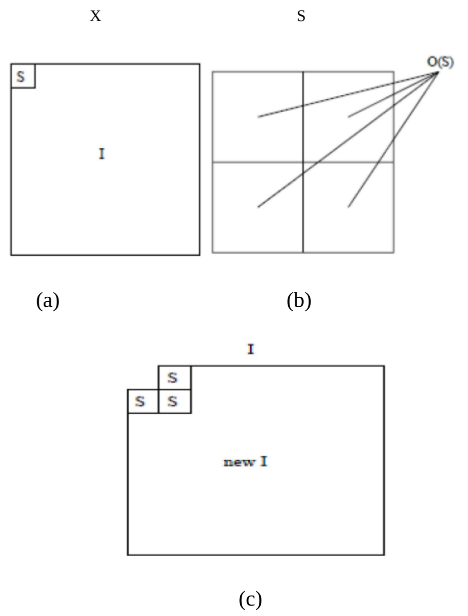

Figure 3 (a) Partitioning of Image X into sets S & I (b) Partitioning of set S (c) Partitioning of set I

If a set *I* is significant against some threshold *n*, it is more likely that the pixels that cause *I* to be significant lie in the top left regions of *I*. These regions are decomposed into sets of type *S*, and are put next in line for processing. In this way, regions that are likely to contain significant pixels are grouped into relatively smaller sets and processed first, while regions that are likely to contain insignificant pixels are grouped into a large set. The decoder uses the same mechanism as the encoder. It receives significance test results from the coded bit stream and builds up the same list structure during the execution of the algorithm. Hence, it is able to follow the same execution paths for the significance tests of the different sets, and reconstructs the image progressively as the algorithm proceeds. It can be seen that SPECK gives higher compression ratios. This shows advantage of processing sets in the form of blocks rather than in the form of spatial orientation trees.

3.1.4 Embedded Block Coding With Optimized Truncation (EBCOT)

The EBCOT[10] algorithm uses a wavelet transform to generate the subband coefficients which are then quantized and coded. The original image is represented in terms of a collection of subbands, which may be organized into increasing resolution levels. The lowest resolution level consists of the single LL subband. Each successive resolution level contains the additional subbands, which are required to reconstruct the image with twice the horizontal and vertical resolution.

The EBCOT algorithm is related in various degrees to much earlier work on scalable image compression.

A key advantage of scalable compression is that the target bit-rate or reconstruction resolution need not be known at the time of compression. Another advantage of practical significance is that the image need not be compressed multiple times in order to achieve a target bit-rate. EBCOT partitions each subband into relatively small blocks of samples and generates a separate highly scalable bit-stream to represent each so called code-block. The algorithm exhibits state-of-the-art compression performance while producing a bit-stream with an unprecedented feature set, including resolution and SNR scalability together with a random access property. The algorithm has modest complexity and is extremely well suited to applications involving remote browsing of large compressed images.

3.1.5 Wavelet Difference Reduction (WDR)

One of the defects of SPIHT is that it only implicitly locates the position of significant coefficients. This makes it difficult to perform operations which depend on the position of significant transform values, such as region selection on compressed data. Region selection, also known as region of interest (ROI), means a portion of a compressed image that requires increased resolution. This can occur, for, example, with a portion of a low resolution medical image that has been sent at a low bpp rate in order to arrive quickly.

Such compressed data operations are possible with the WDR algorithm of Tian and Wells[6],[7]. The term difference reduction refers to the way in which WDR encodes the locations of significant wavelet transform values.

Although WDR will not produce higher PSNR values than SPIHT, it can produce perceptually superior images, especially at high compression rates.

The features of WDR algorithm are as follows: Low complexity, Region of interest, Embeddedness and Progressive SNR.

The only difference between WDR and bit-plane encoding is the significant pass. In WDR, the output from the significance pass consists of the signs of significant values along with sequences of bits which concisely describe the precise locations of significant values.

3.1.6 Adaptively Scanned Wavelet Difference Reduction (ASWDR)

ASWDR[9] algorithm modifies the scanning order used by WDR in order to achieve better performance. ASWDR adapts the scanning order so as to predict locations of new significant values. If a prediction is correct, then the output specifying that location will just be the sign of the new significant value- the reduced binary expansion of the number of steps will be empty. Therefore, a good prediction scheme will significantly reduce the coding output of WDR. The prediction method used by ASWDR is: if w (m) is significant for threshold T, then the values of the children of m are predicted to be significant for half threshold T/2. For many natural images, this prediction method is reasonably good.

High compression ratio images are used in reconnaissance and in medical applications, where fast transmission and ROI are employed, as well as multi-resolution detection.

4. DISCUSSIONS

The performance of various coding techniques and the demerits of the same are tabulated in Table 2.

Each technique can be well suited with different images based upon the user requirements. The latest techniques such as EBCOT, ASWDR are performing better than its predecessors such as EZW, WDR.

TYPE	FEATURES	DEMERITS
EZW	➢ Employs progressive and embedded transmission ➢ Uses predefined scanning order ➢ Uses zero tree concept ➢ Tree coded with single symbol ➢ Good results without prestored tables, codebooks, training	➢ Transmission of coefficient position is missing ➢ No real compression ➢ Followed by arithmetic encoder

SPIHT	➢ Widely used-high PSNR values for given CRs for variety of images ➢ Employs spatial orientation tree structure ➢ Quad-tree or hierarchical trees set-partitioned ➢ Keeps track of state of sets of indices by means of 3 lists: LSP,LIS.LIP ➢ Employs progressive and embedded transmission ➢ Superior to JPEG in perceptual image quality and PSNR	➢ More memory requirements due to 3 lists ➢ Only implicitly locates position of significant coefficient ➢ Suits variety of natural images ➢ Transmitted information is formed of single bits ➢ Perceptual quality not optimal
SPECK	➢ Does not use trees ➢ Uses blocks-rectangular regions ➢ Exploits clustering of energy in frequency and space ➢ Employs quad tree and octave band partitioning ➢ Employs progressive and embedded transmission ➢ Low conceptual complexity ➢ Better PSNR then SPIHT ➢ Low memory requirements due to 2 lists	
EBCOT	➢ Supports packet decompositions also ➢ Block based scheme ➢ Bit stream composed of a collection of quality layers ➢ Modest complexity ➢ Superior rendition of textures ➢ SNR scalability can be obtained ➢ Less ringing around edges ➢ Preserves edges lost by SPIHT	➢ As layers increases, performance decreases ➢ Suits applications involving remote browsing of large compressed images
WDR	➢ Uses ROI concept ➢ Introduced by Tian and Wells ➢ Encodes the location of significant wavelet transform values ➢ No searching through quad trees as in SPIHT algorithm ➢ Better perceptual image quality than SPIHT	➢ PSNR not higher than SPIHT
ASWDR	➢ Modified scanning order compared to ➢ WDR ➢ Prediction of locations of new significant values ➢ Dynamically adapts to the locations of edge details ➢ Encodes more significant values than WDR ➢ Perceptual image quality better than SPIHT and slightly better than WDR ➢ PSNR better than SPIHT and WDR ➢ Slightly higher edge correlation values than WDR ➢ Preserves more of the fine details ➢ Suits high CR images like in reconnaissance and medical images	

Table 2 Performance & Demerits Of Various Coding Techniques

5. CONCLUSION

There are many image coding schemes in use and function, and the most widely used ones of them were describe above. Each one of them has its own area of usage and related application. There are many challenges in developing new techniques such as image coding based on models of human perception, scalability, robustness, error resilience. Despite all this moving forwards, new algorithms and schemes shall continue being designed due to the increasing user demand. There are many aspects that shall be kept in mind, the most important ones being judicial usage of storage space and bandwidth. New schemes have a great potential which shall decrease redundancy to a great extent keeping the storage size as minimum as possible. A user shall have greater choice and flexibility, and even more customization options due to rapid development in this field.

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