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Wavelet Based Image Compression Algorithms – A Study

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Abstract

Image compression is a process which helps us to minimize the utilization of storage space by compressing the image effectively which in turn it increases the data transmission rate. Image compression can be divided into lossy and lossless compression. Wavelet transform provide extensive improvement in picture quality at privileged compression ratio. EZW algorithm is based on liberal encoding to wrapping an image into a bit stream with accumulative precision. SPIHT is a very proficient image compression algorithm that is depends on the idea of coding groups of wavelet coefficients as zero trees. EBCOT algorithm exhibits state-of-the-art compression presentation while manufacturing a bit-stream with a rich superiority set. In this paper, we are going to make a study on merits and demerits of various compression algorithms such as Wavelet based compression algorithms EZW, SPIHT, EBCOT.

Keywords

Image Compression, Lossy, Lossless, Compression algorithms, EZW, SPIHT, EBCOT.

1. Introduction

Compression is a process of coding that will reduce the total number of bits needed to represent certain information effectively. Image is a 2-D signal processed by human visual system [1]. The image single are usually in an analog form, but these analog signals are converted to digital form for processing, storing and transmission of images using computer applications. Image data plays a vital role in many applications such as biomedical, Remote sensing, Military, Industrial inspection/quality control, morphology, criminology/forensics, etc. [2].

Image Compression is the art and science of decreasing the amount of information required to signify the image. It is the most successful and useful technology in the field of digital image processing [1].The reduction in image representation size allows more images to be stowed in a given quantity of disk or recollection space. It also reduces the moment in time requisite for images to be sent over the Internet or downloaded from Web pages. There are several different methods in which image files can be compressed.

Two fundamental mechanism of compression are redundancy and irrelevancy decline. Redundancy reduction aims at removing replication from the signal source (image/video) [1]. Irrelevancy decrease omits parts of the pointer that will not be noticed by the indicator receiver. In common, three forms of redundancy can be recognized.[4]

- Coding redundancy is present when fewer than optimal code words are used.
- Interpixel redundancy outcomes from relationships connecting the pixels of an image.
- Psychovisual redundancy is due to record that is without being seen by the human visual system.

Image Compression system [1] is composed of two distinct functional components such as: an encoder and decoder.

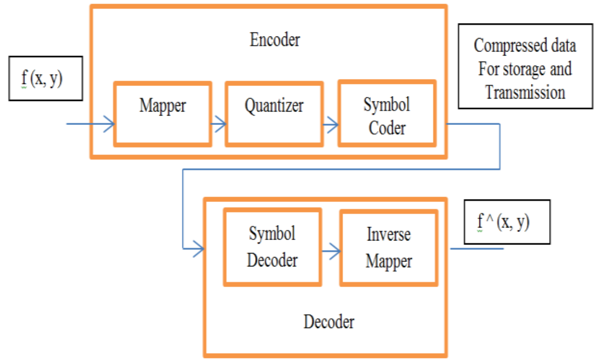

Figure 1: Functional Block Diagram of General Image Compression Systems

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In the encoding process, the mapper transforms the image f(x,y) to reduce the spatial and temporal redundancy. This operation is reversible and it may or may not reduce the amount data required to reduce the image. The quantizer reduces the accuracy of the mapper output in accordance with the pre-established fidelity criterion. The symbol encoder generates a fixed or variable – length code to form a compressed data for storage and transmission (Fig 1.1). The decoder contains two components such as symbol decoder and inverse mapper, which perform, in reverse order to recover the original image from the compressed data.

Classification of Compression Techniques
In the image compression techniques mainly it have four compression techniques they are: Lossy compression, Lossless Compression, Predictive coding, Transform coding.[4]

Lossy Compression
In this compression there is loss of information and the original image is not recovered exactly. This is irreversible. Most lossy data compression formats suffer from generation loss: repeatedly compressing and decompressing the file cause it to progressively loss quality. Lossy compression techniques includes following schemes: Transformation coding, Vector quantization, Fractal coding, Block Truncation coding, and Subbands coding [1].

Lossless Compression
The goal of lossless image compression is to represent an image signed with the smallest possible number of bits without loss of any information, thereby speeding up transmission and minimizing storage requirement. This reproduces the original image without any quality loss. This is irreversible [2]. Following techniques are included in lossless compression: Run length encoding, Huffman encoding, LZW coding, and Area coding.

Predictive coding
In this information already sent or obtainable is used to forecast future values, and the variation is hinted. Since this is prepared in the image or spatial area, it is relatively simple to realize and is readily adapted to local image individuality. Differential Pulse Code Modulation (DPCM) [2] is one picky paradigm of predictive coding.

Transform coding
In transform coding, first transforms the image from its spatial area representation to a different type of depiction using some well-known renovate and then codes the changed values [1]. This method provides larger data compression compared to analytical methods, although at the outlay of greater computation.

2. Wavelet Based Compression Technique

Wavelets are mathematical functions that scratch up data into altered occurrence components, and then study each section with a pledge matched to its scale [13]. Wavelets were developed autonomously in the arenas of mathematics, quantum physics, electrical engineering, Image processing and so on. Wavelets are functions defined over a limited interval and having a standard value of nil. The basic idea of the wavelet transform is to signify any arbitrary function (t) as a superposition of a rest of such wavelets or basis functions. These origin functions or infant wavelets are obtained from a single archetype wavelet called the mother wavelet, by dilations or else contractions and translations [5]. The DWT of a controlled length signal x(n) having N components, for example, is uttered by an N x N matrix [7]. Wavelet transform has become an important method for image compression. Using a wavelet transform, the wavelet compression methods are satisfactory for representing transients, such as percussion sounds in audio, or high-frequency gears in two-dimensional images. Wavelet-coding schemes are particularly suitable for applications where scalability and tolerable humiliation are important. Recently the JPEG group has released its fresh image coding standard, JPEG-2000, which has been based upon DWT [1].

Wavelet transform [2] provide substantial improvement in picture quality at higher compression ratio. It also known as discrete wavelet transforms (DWT). This transform organize the image information into a uninterrupted wave, typically with many peaks and dips and centers it on zero. The Discrete Wavelet Transform of a limited extent signal x(n) having N components, is uttered by an N x N matrix.

The DWT [3] provides sufficient information for the analysis and synthesis of a signal, but is advantageously; much more efficient. Discrete

Wavelet analysis is computed using the concept of filter banks. Filters of different cut-off frequencies analyse the signal at different scales. Resolution is changed by the filtering [8]; the scale is transformed by up sampling and down sampling. If a signal is put through two filters: High-pass filter, high frequency information is kept, low frequency information is lost. Low pass filter, low frequency information is kept, high frequency information is lost. Then the signal is effectively decomposed into two parts, a detailed part (high frequency), and an approximation part (low frequency). The filtering is done for each column of the transitional data. The resulting two-dimensional collection of coefficients contains four bands (sub bands)[3] of data, each labelled as LL (low-low)**:** low sub bands for row and column filtering, HL(high-low)**:** high sub bands for row filtering and low sub bands for column filtering, LH (low-high)**:** low sub bands for row filtering and highsubbands for columns filtering and HH (high-high)**:** high sub bands for row and column filtering [10].

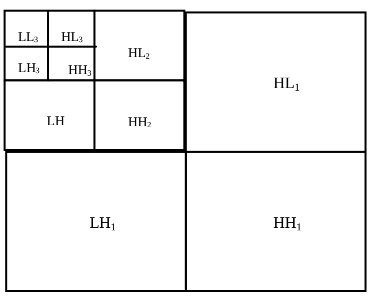

Figure 2: Subband Decomposition

Each level of DWT decomposes is iterative. The entire coefficient is discarded except the LL coefficient that is transformed into the second level. The coefficient is then passed through a constant scaling factor to achieve the desired compression ratio. Over the past few years, a mixture of story and complicated wavelet-based image coding schemes has been urbanized. These embrace Embedded Zero tree Wavelet [2.1], Set-Partitioning in Hierarchical Trees [2.2], Set Partitioned Embedded bloCK coder [2.3], Embedded Block Coding with Optimized Truncation [2.4].

Embedded Zero Tree Wavelet (EZW)

The embedded zero tree wavelet (EZW) [9] steadily produces compression results that are good with practically all known compression algorithms on regular test images. The EZW have four concepts: A distinct wavelet transform or hierarchical sub band disintegration, Prediction in the lack of significant information across scales by taking advantage of the self-similarity natural in images, Entropy-coded successive-ballpark figure quantization, Universal lossless data compression which is reached via adaptive arithmetic coding.

A discrete wavelet transforms [7] which provide a solid multi resolution representation of the image, The Zero trees coding which provides a compact multi resolution depiction of implication maps, which are binary maps representative the positions of the significant coefficients. Zero tree allow the successful prediction of insignificant coefficients cross scales to be efficiently represented as part of exponentially growing trees.

Successive Approximation which delivers a squashed multiprecision representation of the major coefficients and facilitates the embedding algorithm, The prioritization protocol whereby the ordering of significance is dogged, in order, by the precision, magnitude, scale, and spatial position of the wavelet Coefficients [12], Adaptive multilevel arithmetic coding which provides a fast and efficient method for entropy coding strings of symbols, and requires no training or pre stored table, The algorithm runs sequentially and stops whenever a target bit rate or a target misrepresentation is met. A target bit rate can be met exactly, and an operational rate vs. distortion function (RDF) can be computed point by- point. These are the various features of EZW [9]. The discrete wavelet transform used in EZW is identical to a hierarchical sub band system, where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. To improve the compression of significance maps of wavelet coefficients, a new data structure called a zero tree [1].

A wavelet coefficient x is said to be irrelevant with esteem to an agreed threshold T if 1x1 <T. The coefficient at the coarse scale is called the blood relation, and all coefficients corresponding to the similar spatial spot at the next better scale of similar orientation are called children. For a given parent, the set of all coefficients at all improved scales of similar orientation corresponding to the similar location are called descendants [11]. Similarly, for a given child, the set of coefficients at all coarser scales of parallel Orientation consistent to the same location are called ancestors. Given a threshold level T to establish

whether or not a coefficient is significant, a coefficient x is said to be an ingredient of a zero tree for threshold T if itself and all of its descendent are insignificant with respect to T. A component of a zero tree for threshold T is a Zero tree root if it is not the descendant of a before found zero tree root for threshold T [15].

EZW Algorithm

Sequence of Decreasing Thresholds: To, T1, . . , T_{N-1}
with T_i= T_i-1/2 and |coefficients| < 2 T_0
Maintain Two Separate Lists:
Step 1: Coordinates Dominant List.
Step 2: Magnitudes of coefficients Subordinate List.
For each threshold, perform two passes: Dominant Pass then Subordinate Pass
Dominant Pass (Significance Map Pass)
Step 1: Coeff's on Dominant List are compared to T_i.
Step 2: The resulting significance map is zero-tree coded and sent.
Step 3: Zerotree Root (ZTR) • Positive Significant (POS)
Step 4: Isolated Zero (IZ) • Negative Significant (NEG)
– For each coeff that has now turn into significant (POS or NEG)
Subordinate Pass (Significance Coefficient Refinement Pass)
Step 1: Provide next lower signif. bit on the extent of each coeff on Subord List
– Halve the quantizer cells to get the next finer quantizer
– If magnitude of coeff is in upper half of old cell, provide "1"
– If magnitude of coeff is in lower half of old cell, provide "0"
Step 2: Entropy code sequence of modification bits using an adaptive AC
Now repeat with next lower threshold
Step 3: Stop when total bit budget is exhausted
Step 4: Encoded stream is an implanted stream

SPIHT Coding

An image coding method called Set Partitioning in Hierarchical Trees (SPIHT) [6], offers high performance and low complexity image compression. It also creates an embedded bit stream with very fast execution. In EZW coding, have a lot of zero tree root symbols are transmitted. But, the SPIHT coding algorithm uses a dividing of trees in a manner that have a tendency to keep insignificant coefficients together in bigger subsets [13]. These partitioning results provide a significance map training that is additional efficient than EZW coding. SPIHT coding is based on three thoughts [14]:
1) Partial ordering of the transmuted image elements by magnitude, with broadcast of order by a subset partitioning algorithm that is duplicated at the decoder,
2) Ordered bit plane broadcast of refinement bits, and
3) Exploitation of the self-similarity of the wavelet transformed image across different scales.
The SPIHT coding algorithms have two permits, viz., (1) sorting pass, (2) refinement exceed. SPIHT is a wavelet based image compression coder. It first changes the image into its wavelet transform and then transmits data about the wavelet coefficients. The decoder uses the expected signal to rebuild the wavelet and performs an opposite transform to recover the image. SPIHT features [14]:

- Best image quality with a higher PSNR and not for color image
- Speediest coding and decoding
- A fully progressive bit stream
- It Can be used for lossless compression
- May be joint with error protection
- Capacity to code for accurate bit rate or PSNR

SPIHT Algorithm

O(i,j): set of coordinates of all offspring of node (i,j); children only
D(i,j): set of coordinates of all descendants of node (i,j); children, grandchildren, great-grand, etc.
H (i,j): set of all tree roots (nodes in the highest pyramid level); parents
L (i,j): D(i,j) – O(i,j) (all descendents except the offspring); grandchildren, great-grand, etc.
Initialization
n = [log2 (max |coeff|)]
LIP = All elements in H
LSP = Empty
LIS = D's of Roots
Significance Map Encoding ("Sorting Pass")
Process LIP
for each coeff (i,j) in LIP
Output S_n(i,j)
If S_n(i,j)=1
Output sign of coeff(i,j): 0/1 = -/+
Move (i,j) to the LSP
Endif
End loop over LIP

Process LIS
for each set (i,j) in LIS
if type D

Send $S_n(D(i,j))$
If $S_n(D(i,j))=1$
for each (k,l)∈ O(i,j)
output$S_n(k,l)$
if$S_n(k,l)=1$, then add (k,l) to the LSP and output sign of coeff: 0/1 = -/+
if$S_n(k,l)=0$, then add (k,l) to the end of the LIP
endfor
endif
else (type L)
Send $S_n(L(i,j))$
If $S_n(L(i,j))=1$
add each (k,l) ∈ O(i,j) to the end of the LIS as an entry of type D
remove (i,j) from the LIS
end if on type
End loop over LIS
Refinement Pass
Process LSP
for each element (i,j) in LSP – except those just added above
Output the nth most significant bit of coeff
End loop over LSP
Update
Decrement n by 1
Go to Significance Map Encoding Step
Adaptive Arithmetic Code (Optional)

Set Partitioned Embedded bloCK coder (SPECK)

The SPECK image coding is different from EZW and SPIHT because does not use it does not use trees which span, and develop the similarity, across different sub bands; rather, it makes use of sets in the structure of blocks [1]. The main idea is to exploit the clustering of energy in frequency and space in hierarchical constructions of transformed images. The SPECK algorithm [2] can be said to fit in to the class of scalar quantized significance enquiry schemes. It has its stocks mainly in the ideas developed in the SPIHT, and few block coding image coding algorithms.

SPECK Algorithm

Initialization
Partition image transform X into two sets: S = root & I= X – S.
Output n = floor ($\log_2$ (max $|C_{i,j}|$)).
¥(i,j) € X
Add S to LIS & set LSP = Φ.
First sorting pass
Process S(S)
Process I ( )
Sort LIS in increasing order of set size C.
Further sorting passes
For each set S € LIS
Process S(S)
Refinement pass
For each (i,j) € LSP, except those included in the last
Sorting pass, output the nth MSB of $|C_{i,j}|$.
Quantization step
Decrement n by 1, and go to next sorting stage

Embedded Block Coding with Optimized Truncation (EBCOT)

The EBCOT algorithm [10] procedures a wavelet transform to generate the subband coefficients are quantized and coded. Although the normal dyadic wavelet decomposition is typical, other "packet" decompositions are also supported and occasionally preferable. EBCOT algorithm also generates scalable packed in bit-streams. A key pro of scalable compression is that the goal bit-rate or reconstruction pledge need not be identified at the time of compression.

Another benefit of realistic implication is that the image need not be flattened various times in order to achieve a target bit-rate, as is common with the offered JPEG compression ordinary [15]. EBCOT partitions each subband into relatively minor blocks of samples and produces a separate highly scalable bit-stream to illustrate each so called code-block. The algorithm exhibits state-of-the-art compression performance while creating a bit-stream with an unparalleled feature set, containing resolution and SNR scalability together with random access possessions. The algorithm has modest complexity and is extremely well-matched to applications involving remote browsing of bulky compressed images. The original image is represented in terms of a collection of subbands, which may be organized into increasing resolution levels [16]. 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 double the horizontal and vertical resolution.

EBCOT Algorithm

Step 1: Calculate u using $u=(w_1-\alpha\sigma_{max})/m + n/2$
Step 2: Find m smallest samples from set X that are larger than Y_{u-1} and execute Mann- Whitney test;
Step 3: If hypothesis H_0 is rejected, then set u= u- 1 and go to step 2, otherwise, go to step 4;

Step 4: Begin the pixel-by-pixel repetition in backward manner. The initial test set consists of m smallest samples from set X that are larger than Y_u.

3. Discussions

The performance of various wavelet based image compression algorithms and the demerits of the same are tabulated in Table 1.Each algorithm can be well suited with different images based upon the user necessities. The latest techniques such as EBCOT are performing better than its predecessors such as EZW, SPIHT [11][9][5][16].

Table1: Comparison of Wavelet Based Compression Algorithms

TYPE	QUALITIES	DRAWBACKS
EZW	• Employs progressive and embedded transmission • Uses predefined scanning order • Uses zero tree concept • Tree coded with single symbol • Good results without restored tables, training, codebooks	• 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 supplies 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

4. Conclusion

This paper presents various types of image compression algorithms. In this image compression algorithms there are EZW, SPIHT and EBCOT image compression algorithms are used. Comparing the performance of compression algorithm is difficult unless identical data sets and performance measures are used. EBCOT algorithms are obtained well for certain compression techniques, while generating a bit-stream with a rich eminence set, including determination and SNR scalability together with a random access possession. EZW and SPHIT algorithms perform well for certain classes of data and poorly for others. EBCOT algorithms compare better solution than EZW and SPIHT algorithms.

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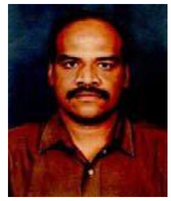

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