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Image Compression Based on DWT Using EZW/SPIHT Encoders

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Abstract— **this paper reviews recent research on image compression techniques utilizing the Embedded Zero-Tree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPIHT) algorithms. The study addresses the question of which algorithm, EZW or SPIHT, provides superior compression performance for various image types. The research method involves a comprehensive analysis of published research papers that employed these algorithms for image compression. The findings indicate that SPIHT generally outperforms EZW in terms of compression ratio, computational efficiency, and image quality, making it a more versatile and effective choice for various image compression applications.**

Index Terms—**Image Compression, EZW, SPIHT, DWT, Wavelet Transform, Compression Ratio, PNSR.**

I. INTRODUCTION

Image compression plays a pivotal role in modern digital communication and storage. It aims to reduce the amount of data required to represent an image without compromising its visual quality. This reduction in data size allows for faster transmission, efficient storage, and reduced bandwidth consumption. Image compression algorithms can be broadly classified as lossless and lossy. Lossless algorithms guarantee perfect reconstruction of the original image, while lossy algorithms introduce some level of information loss to achieve higher compression ratios.

This paper focuses on two prominent lossy image compression algorithms: Embedded Zero-Tree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPIHT). Both algorithms leverage the Discrete Wavelet Transform (DWT) to exploit the inherent redundancy in image data. The DWT decomposes an image into multiple frequency bands, allowing for efficient compression by selectively representing and discarding less important information.

This paper reviews two prominent lossy image compression algorithms: Embedded Zero-Tree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPIHT). Both algorithms leverage the Discrete Wavelet Transform (DWT) to exploit image redundancy. The paper explains the principles of DWT, EZW, and SPIHT, highlighting their key components and advantages. It then analyzes previous research comparing their performance in terms of compression ratio, image quality, and computational efficiency. The paper concludes that SPIHT generally outperforms EZW, offering higher compression ratios, faster processing, and better image quality.

II. METHODOLOGY

This research paper adopts a systematic literature review approach to analyze and compare the performance of two prominent lossy image compression algorithms: Embedded Zero-Tree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPIHT). The review focuses on identifying the strengths and weaknesses of each algorithm, particularly in terms of compression ratio, computational efficiency, and image quality.
The methodology involves the following steps:

1. Literature Search: A comprehensive search was conducted using relevant keywords such as "image compression," "EZW," "SPIHT," "DWT," and "wavelet transform" in reputable academic databases like IEEE Xplore, ScienceDirect, and Google Scholar.
2. Selection Criteria: The search results were filtered based on the following criteria:
   - Relevance: Papers focusing on the comparative analysis of EZW and SPIHT for image compression.
   - Quality: Studies published in peer-reviewed journals or reputable conferences.
   - Recency: Research published within the last 10 years to ensure the inclusion of recent advancements.
3. Data Extraction: Relevant information was extracted from the selected papers, including:
   - Image types: The types of images used in the studies (e.g., grayscale, color, hyperspectral).
   - Compression performance: Compression ratios, Peak Signal-to-Noise Ratio (PSNR),

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  and Mean Square Error (MSE) achieved by each algorithm.
  - Computational efficiency: Execution time or computational complexity of the algorithms.
  - Implementation details: Wavelet filters, compression parameters, and any modifications made to the original algorithms.
4. Data Analysis: The extracted data was analyzed to identify trends and patterns in the performance of EZW and SPIHT across different image types and compression scenarios.
5. Synthesis: The findings were synthesized to provide a comprehensive overview of the comparative advantages and disadvantages of EZW and SPIHT, highlighting their strengths and limitations in various image compression applications.

This systematic approach ensures a comprehensive and objective analysis of the research literature on EZW and SPIHT, providing a valuable basis for understanding the current state of the art in image compression using these algorithms.

III. IMAGE COMPRESSION

Image compression is a crucial technique for efficiently representing and storing image data. Its primary goal is to minimize the number of bits needed to represent an image, thereby reducing storage space and transmission time. This is achieved by eliminating data redundancy, which exists in images due to the correlation between adjacent pixels.

There are three main types of redundancy in images:

- Inter-pixel redundancy: Adjacent pixels often share similar values, leading to redundant information.
- psychovisual redundancy: The human eye is less sensitive to certain details, allowing for selective removal of information without noticeable degradation.
- Coding redundancy: Inefficient encoding methods can introduce redundancy.

Image compression techniques aim to remove these redundancies, resulting in smaller file sizes without significant loss of visual quality. There are two primary categories of image compression:

- Lossless compression: This technique preserves all the original image data, ensuring perfect reconstruction. However, it typically achieves lower compression ratios.
- Lossy compression: This technique removes some image data, resulting in a smaller file size but potentially sacrificing some visual quality. This approach is often preferred for applications where image quality is less critical, such as online image sharing or video streaming.

Overall, image compression is a vital field that significantly impacts the efficiency of storing, transmitting, and displaying digital images. Researchers continue to develop new algorithms and techniques to improve compression ratios, maintain image quality, and adapt to the ever-evolving demands of digital media [2].

IV. IMAGE COMPRESSION BASED ON DISCRETE WAVELET TRANSFORM (DWT)

Image has information as low and high frequency [1], and wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components [7]. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale [7]. In DWT, the most important information of an image is found in low frequency range and the least information is found gradually in the high frequency range [1]. The DWT with filters divides the image into four sub-bands LL, HL, LH, and HH as in Figure 1.

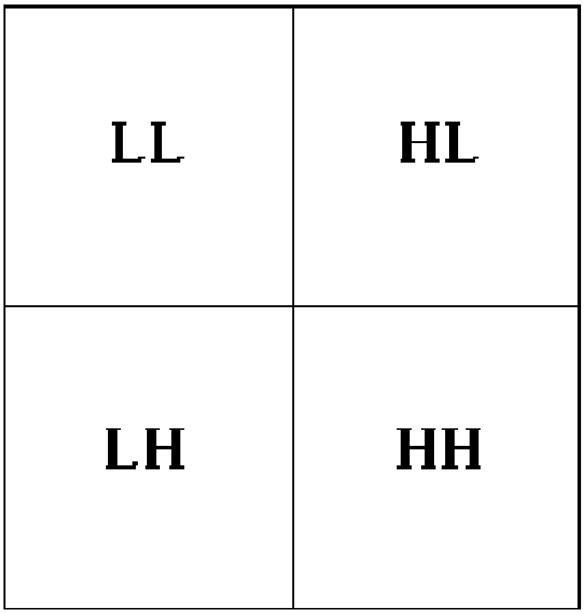

Fig. 1 shows the sub-bands in wavelet transform.

DWT is used in image compression for different reasons. First, DWT is good at image coding because of its data reproduction capabilities [6]. Natural image in general has a low pass spectrum. After DWT is applied on an image, the energy in sub-bands decreases as the scale decreases, so wavelet coefficients will be smaller in the higher sub-bands than in the lower sub-bands [5]. That means, the higher sub-bands only will add just details [5]. Large wavelet coefficients are low frequency (approximations) and small wavelet coefficients are high frequency (details). Second, DWT can analyze signals simultaneously in both time and frequency. Fourier transform cannot do that. As a result, because of these properties, DWT is used in many applications.

V. EMBEDDED ZERO TREE WAVELET ENCODING(EZW)

EZW is a lossy algorithm for image compression. E stands for embedded which means progressive encoding. Progressive encoding means that the more bits to the bits stream, the more detail is added to the compressed image in an accurate way. W stands for wavelet transform because DWT is used in this algorithm to take advantage of its properties. Z stands for zero tree. Zero tree is a data structure used in EZW. It is a quad-tree. The coefficients in the wavelet transform have a parent-child relation, so it is obvious to use a tree to represent them.

A. *The Wavelet Coefficients in EZW*

After DWT, the large coefficient numbers are found in lower sub-bands, and the smaller coefficients number are found in higher sub-bands. In addition, the large coefficients are important than the smaller, because large coefficients represent the low frequency and the smaller coefficients represent the high frequency (information of image).
Every coefficient in sub-bands can be represented as four coefficients from the same sub-bands (in the same spatial position) but in different resolutions (scale). That means coefficients can be represented in a hierarchical way, here comes the zero tree as a data structure being used. Figure 2 illustrates the relationship between coefficients and decompression level.

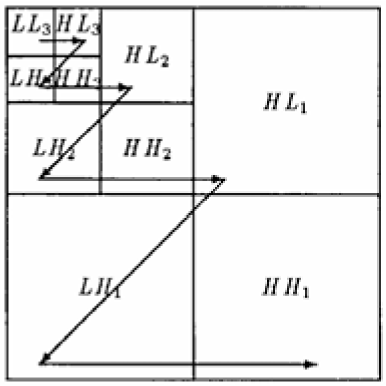

Fig. 2 illustrates the relationship between coefficients and decompression level.

B. *The Significance Map Encoding*

The significance map takes place by using the threshold. If the coefficient is bigger than the threshold, it is significant. If not, it is insignificant.
A coefficient X is

|x| < T insignificant.

|x| >= T significant.

Where T is the given threshold.

The coefficients in a tree have four passes

1- Positive significance.

2- Negative significant.

3- Isolated tree, if the root of the tree is zero, but one of its descents is significant.

4- Zero tree root, if the root is zero, and all its descents are zero's.

Figure 3 shows a flow diagram for significance map encoding and the coefficients.

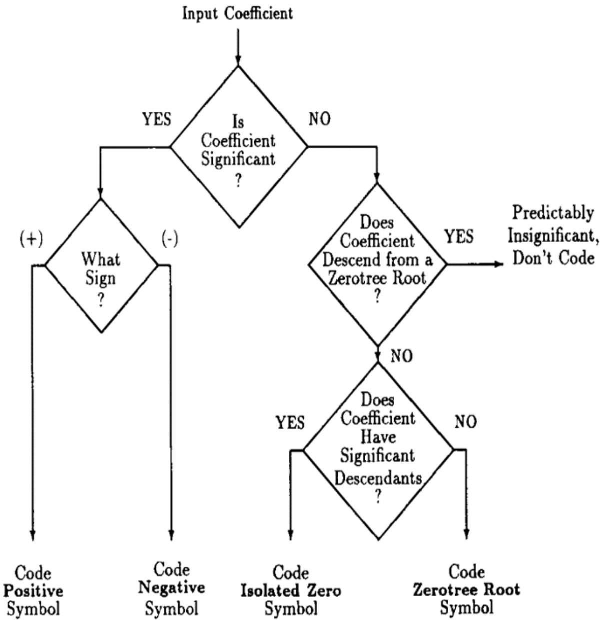

Fig. 3 shows the significant map encoding.

C. *Successive Approximation*

The EZW algorithm uses a successive approximation strategy to refine the representation of the image as more bits are added to the bitstream. This process involves iteratively updating the significance map and encoding the most significant bits of the coefficients [1].

D. *Basic EZW block diagram*

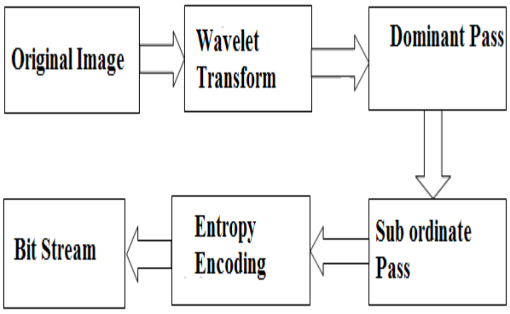

Fig. 4 shows a basic EZW block diagram

VI. SET PARTITION IN HIERARCHICAL TREE(SPIHT)

SPIHT is an advanced algorithm from the EZW algorithm; SPIHT will produce higher compression and improve efficiency than EZW[2].

SPIHT divides the wavelet into spatial orientation trees (SOT). Each node in the tree corresponds to an individual pixel [8]. The offspring of a pixel are the four pixels in the same spatial location of the same sub-band of at the next finer scale of the wavelet. Every pixel is part of a 2x2 block with its adjacent pixels [8].

SPIHT codes a wavelet by transmitting information about the significance of a pixel [8]. By stating whether or not a pixel is above some threshold [8]. SPIHT transmits information stating whether a pixel or any of its descendants are above a threshold [8]. 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 [8]. 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 bit, which is referred to as bit plane ordering [8]. 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 lists (LSP) [8].

SPIHT properties include:

1) High Image Quality: SPIHT typically produces high-quality compressed images with a high peak signal-to-noise ratio (PNSR).
2) Fast Coding and Decoding: The algorithm is designed for efficient encoding and decoding, making it suitable for real-time applications.
3) Fully Progressive Bitstream: SPIHT generates a progressive bitstream, allowing for gradual reconstruction of the image as more bits are received.
4) Lossless Compression: SPIHT can be used for lossless compression by encoding all the wavelet coefficients.
5) Error Protection: The algorithm can be combined with error protection techniques to improve its robustness.
6) Bit Rate Control: SPIHT allows for precise bit rate control, enabling the user to specify the desired level of compression.

VII. SYSTEM PERFORMANCE MEASURE

These methods are used to measure the compression performance.

A) *Compression Ratio (CR)*

CR is used to measure the decrease in data representation size produced by a compression algorithm. Equation (1) illustrates the relationship between uncompressed file size and compressed file size.

$$CR = \frac{uncompressed\ file\ size}{compressed\ file\ size} \qquad (1)$$

B) *Mean Square Error (MSE)*

MSE is used to measure of image compression algorithm. The error function Er is compute as a difference between the original (input G(x,y)) and the reconstructed (output G'(x,y)) image as shown in equation (2).Equation (3) shows how to compute the MSE.

$$ER = G(x,y) - G'(x,y) \qquad (2)$$

$$MSE = \frac{1}{W \times H} \sum_{x=0}^{w-1} \sum_{y=0}^{h-1} ER^2 \qquad (3)$$

Where W, H is the width and height of the image individually.

C) *Peak Signal to Noise Ratio (PNSR)*

PNSR is one of the most important tools for the estimate of the compressed image. The PNSR is measured in decibels (DB), and defined in equation (4).

$$\text{PNSR}(db) = \log_{10}\left[\frac{(R-1)^{\wedge}2}{MSE}\right] \qquad (4)$$

Where R is the intensity level number of the image.

VIII. RESULTS AND DISCUSSIONS

I summarize four papers in different applications and their results. Some compression techniques are used to exploit the redundancy and provide a rate distortion and transmission bandwidth problem with bit redundancy[1]. In [1], researchers have modified the EZW encoding to provide an excellent bit rate with low encoding complexity, and they also exploit the bit redundancy at different spatial position and increase the bandwidth efficiency with higher PNSR and compression ratio (CR)[1]. As a result, memory can be saved and the coding efficiency can be improved by modified EZW encoding[1]. In [2], image compression can be divided by using two algorithms. The proposed compression algorithm that combined dual image compression techniques (DICT) takes advantage of the excellent

paper	Image	Type image	Wavelet filter	Method	PNSR(db)	CR	Computa tion time in seconds
[3]	Botswana	hyperspectral	Bior 4.4	Hybrid transform with EZW	57.17	_	365
[3]	Botswana	hyperspectra	Bior 4.4	Hybrid transform with SPIHT	57.17	_	118
[2]	friends	Color image	(Bior 4.4+Haar)	Dual combined(SPIHT+EZW)	28.09	6.23	__
[4]	Lena	Gray image	__	EZW-SC	38.71	_	_
[1]	Lena	Gray image	___	EZW	33.05	__	___

Table1 shows comparison between images from different papers

features for each algorithm. The compression approaches are SPIHT and EZW based on Bior 4.4 and Haar wavelet methods. As a result, the DICT the image compression. efficiency between 8 to 24% [2].in [3], they propose a hyperspectral image compression technique using a hybrid transform. They use the integer Karhuen-Loeve transform that is applied to remove the correlation among contiguous highly correlated spectral bands using clustering and tiling, then the 2D integer discrete wavelet transform is applied over the spatial data[3]. For the wavelet coefficients, they use either EZW or SPIHT. They find out that SPIHT has the better performance than EZW.in[4], the researchers in this paper try to reduce the zero-tree symbol number and to save bits by analyzing only the significant sub-bands. As a result, they present an algorithm namely EZW-SC concept which helps to predicate insignificant sub-bands in the first passes, as well as an improved significant map representing nine symbols[4]. Then, EWZ-SC is used for color and grayscale images.

In Table 1, I show the comparison between the four papers with their performance if it is presented in the original paper.

In table1, Botswana is a hyperspectra image is compressed one with SPIHT and one with EZW. According to the table, the SPIHT is way better in computation time. In addition, for Lena images is used in different papers. Each paper is used their technique for compression. From the first glace, the table shows the technique in paper [4] is better than in paper[1] because PNSR is higher. Yet, I cannot tell because the size is missing.

CONCLUSION

This review of recent research on image compression using EZW and SPIHT algorithms demonstrates that SPIHT generally outperforms EZW in terms of compression efficiency, computational speed, and image quality. SPIHT's ability to handle different image types and its flexibility in achieving both lossy and lossless compression make it a highly valuable algorithm for various applications.

Future research directions could focus on:

- Developing hybrid compression algorithms that combine the strengths of EZW and SPIHT.
- Exploring the use of deep learning techniques to enhance the performance of image compression algorithms.
- Investigating the application of these algorithms to specific image types, such as medical images or remote sensing data.

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