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Evolutionary Standards in Image Compression along with Comparative Analysis of their performance

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Abstract- **Image compression has developed as full fledged field from past many years because of rapidly growing entertainment market and unparalleled increase in the use of internet services for storage transmission and processing of multimedia data. Data compression techniques are primarily divided into two categories, lossless and lossy. The lossy technique is most widely accepted because it allows high compression rates with tolerable distortion. This paper presented a review of all the image compression standards for lossy image compression that has been established since beginning to more recent along with their comparative performance analysis which helps us to know the reason for this evolutionary change. Also it gives information about the new advancements introduced to a particular standard in order to improve its performance. This paper will help a lot to those who want to know about all image compression standards from the beginning, starting as a layman. Image Compression is important field as images form a considerable portion of today's data dealt by machines and humans.**

Keywords: **Compressive Sensing, Contourlet Transform, Slepian Wolf Coding (SW), Wavelet Transform (WT) .**

1. INTRODUCTION

Image Compression being one of the subfields of the Data Compression inherits all the basic features of the parent field with added advantage of being to a certain degree tolerant to the distortion due to peculiar characteristics of human vision system. The human eye is sensitive to low frequency signal and less sensitive to high frequency information and Human Visual System (HVS) can easily distinguish the changes in edge information of the image but cannot detect the gray error of the edges.

The benefits of image compression include less required storage space, quicker sending and receiving of images and less time lost on image viewing and loading. A good example to illustrate this is the health industry, where the constant scanning and/or storage of medical images and documents take place. Depending on the type of compression applied, images can be compressed to save storage space, or to send to multiple physicians for examination.

Most of the current standards used in image compression are based on the common concept of Transform Coding. In Transform Coding, the full N samples of image is acquired by using the Nyquist criterion and then Transform coefficients [Si] are computed for all the N samples via $S=\Psi^T x$. The K largest coefficients are computed and (N-K) smallest coefficients are discarded. The K values and their locations of largest coefficients are encoded. But this sample and compress framework suffer from many inefficiencies like the number of initial samples taken are very large so more computation time involved in its compression and the increased overhead of sending the location information of largest coefficients. So, this lead to the incoming of Compressive Sensing standard for image compression which is in use today in some particular areas.

In the following section basic theory of different image compression standards from the very beginning has been discussed. In Section 3, performance of these standards has been compared with the help of images and in the last Section 4, the paper has been concluded.

2. IMAGE COMPRESSION STANDARDS

2.1 Embedded Zero Tree Wavelet (EZW) algorithms

The conventional embedded zero tree wavelet (EZW) algorithm takes advantage of the hierarchical relationship among sub-band coefficients of the pyramidal wavelet decomposition [1]. It was designed with the purpose that image coding applications should involve the use of DWT. The most effective property of this algorithm was to allow the bits in the bit stream to be arranged in 'order of performance' so that the encoding process can be stopped at any point once the target has been achieved.

In EZW, the temporal orientation tree is achieved by iterating the relation between every coefficient at any scale to two other coefficients at immediate lower scale. The set of coefficients and its descendents are called zero tree. In the encoding process, the whole set of coefficients of a zero tree can be referenced by its root, which is the first coefficient of the temporal orientation tree at the lower scale. Also, a coefficient is called significant if its magnitude is greater than a given threshold value Ɛ. Therefore, depending on the magnitude of a coefficient related to Ɛ, i.e., its significance, it can be encoded as a symbol of a reduced alphabet to obtain a significance map. The EZW algorithm takes into account the hierarchy of the DWT coefficients among different sub-bands to efficiently encode the significance map and use an alphabet of four symbols: {POS, NEG, IZ, ZTR} .Symbols {POS} and {NEG} indicate the sign of a significant coefficient. A non-significant coefficient is encoded with the symbol {ZTR} if it is the root of a zero tree

Where all its coefficients are non-significant. Conversely, a non-significant coefficient is encoded as an isolate zero with the symbol {IZ}. The cocept of EZW has been depicted diagrammatically in the Figure (1) below:

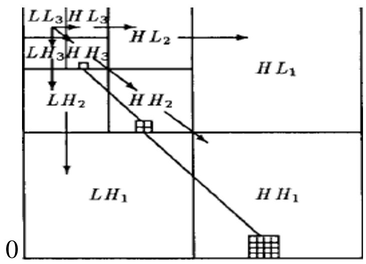

Figure 1 Diagram depicting formation of sub-bands in the case of EZW standard of image compression.

2.2 SPIHT algorithm

Set Partitioning in Hierarchical Trees SPIHT was introduced by Said and Pearlman [2] as an extension of work by Shapiro on EZW coding [1]. So, it is basically based on the foundation of EZW. In EZW-based coding, a tree is partitioned once it is found to be significant; SPIHT assumes that the significant test result of any tree is very likely to be from its direct descendants. Therefore, if a set is found to be significant, only its direct descendants are encoded and a significance test will be performed on its non-direct descendants. The set is kept non partitioned until one of its nondirect descendants is found to be significant.

The SPIHT algorithm produces an embedded and progressive bit-stream of ones and zeros based upon certain set portioning rules and transmits information in decreasing order of significance using binary thresholds. It effectively use the similarity between major coefficients with different scale sub-bands and also give full consideration to the correlation of the same scale wavelet coefficients by introducing the special orientation tree to map the effective value and collect invalid value in the subset as many as possible, then represent with a unit symbol, hence it can save encoding bit-stream in order to achieve compression.

SPIHT starts with taking wavelet transform like HAAR to transform the image. Thereafter parent-child relationships are established as following: Every coefficient in a coarse resolution level except the ones in *LL* band of the coarsest level and the ones in the finest level acts as parent to a block of 2 × 2 coefficients in next finer resolution level as shown in Figure (2).

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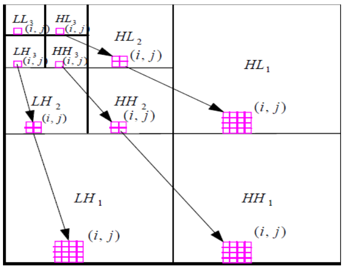

Figure 2 Diagram depicting formation of sub-bands in the case of SPIHT standard of image compression USING Parent-child-offspring relationship

Here in the Figure (2) each layer is divided into four sub-bands. The lowest sub-band is divided into four (2*2) factor groups.

The following set of coordinates is used to represent SPIHT:

1. *O(i,j)*: set of coordinates of all offspring of node *(i,j)*.
2. *D(i,j)*: set of coordinates of all descendants of the node *(i,j)*.
3. *H*: set of coordinates of all spatial orientation tree roots.
4. *L(i,j)*: *D(i,j) - O(i,j)*.

The set partitioning rules used are as follows:

1. The initial partition is formed with the sets {*(i,j)*} and *D(i,j)*, for all *(i,j)* 2 *H*.
2. If *D(i,j)* is significant, then it is partitioned into *L(i,j)* plus four single-element sets with *(k,l)* 2 *O(i,j)*.
3. If *L(i,j)* is significant then it is partitioned into the four sets *D(k,l)*, with *(k,l)* 2 *O(i,j)*.

SPIHT pays more attention to preserve image edge information so it is used widely to encode high frequency sub-band. Using SPIHT a hybrid image compression algorithm was developed with its combination with fractal image coding. This algorithm was based on human visual system [3] and helped to raise the coding efficiency and reconstructed image quality, reduces the image encoding time.

2.3 JPEG algorithm

Joint Photography Experts Group (JPEG) standard applies to Black White and color photos, fax and print pictures [4]. It has two basic Compression algorithms, the first one was based on space linear prediction techniques, namely, lossless compression algorithm of differential pulse code modulation, the second was lossy compression algorithms based on DCT, and further run length coding and entropy coding. The JPEG coding has been diagrammatically depicted below in Figure (3):

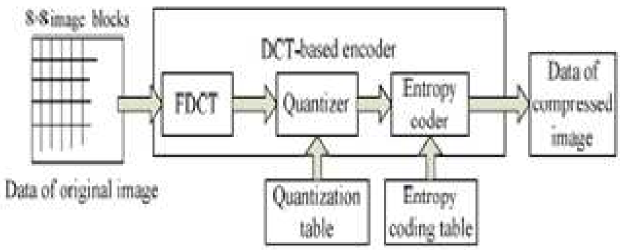

Figure 3 JPEG coding block diagram

JPEG use YCrCb color model for encoding where Y represents visibility and Cr, Cb represents hue. To obtain higher compression ratio more detailed quantization could be used only to the Y component.JPEG encode separate for each frame, its smallest processing unit is 8*8 image block. The box of 8*8 points then passes through a 2-D DCT transform:

$$F_c(u,v)=\frac{2}{\sqrt{MN}}c(u)c(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)\cos[\frac{\pi}{2N}2(x+1)u]\cos[\frac{\pi}{2M}2(y+1)v] \quad (1)$$

$$c(x)=\begin{cases}1/\sqrt{2} & x=0\\ 1 & x=1,2,\ldots,N-1\end{cases}, \quad M=N=8. \quad (2)$$

After this quantization coefficients are obtained by dividing every coefficient of image after DCT with their respective quantization step size according to the quantization table.

$$\tilde{F}(u,v)=INT[\frac{F(u,v)}{S(u,v)}\pm 0.5] \quad (3)$$

S (u,v) represents quantization table. The frequency response (i.e. detection of change in frequency) of human visual system decreased with increasing spatial frequency (i.e. as frequency of image increases to high, the eyes frequency change detection power decreases) and it goes much faster to two chrominance component than brightness component so JPEG recommend quantization table coefficient of brightness and chroma component. After this step, the coefficient was divided into direct current (DC) or alternating current (AC).

In JPEG after DCT transform, majority of 8*8 box's coefficient become 0, the more consecutive 0's the higher the coding efficiency is, so it adapts Z-scan approach i.e. zigzag scan approach . The entropy coding of JPEG basic system uses Huffman code which has highest average compression ratio.

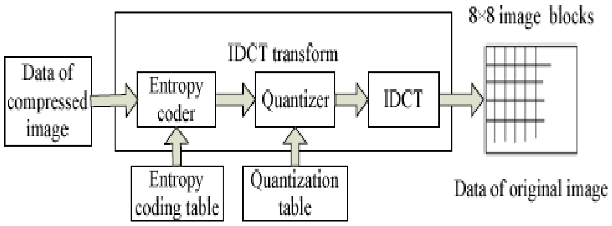

Figure 4 JPEG decode block diagram

Decoding data goes to continuous energy range after inverse quantization and is depicted with the help of diagram in Figure (4):

$$\hat{F}(u,v)=\tilde{F}(u,v)S(u,v) \quad (4)$$

After IDCT transformation (M=N=8, C(x) the same as above), it reverts to 8×8 pixel blocks, combining all this pixel blocks it goes to the reconstructed image of JPEG decompression.

$$f(x,y)=\frac{2}{\sqrt{MN}}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}c(u)c(v)F_c(u,c)\cos[\frac{\pi}{2N}(2x+1)u]\cos[\frac{\pi}{2M}(2(y+1)v)] \quad (5)$$

To JPEG scheme, the concept of compressive sensing in combination with noiselet information has been introduced in recent years [5] in order to reduce the encoder computation time and recover the original image by minimizing the total variation (TV) via SOCP under an equality constraint, i.e $Ax^*=y$.

2.4 JPEG -2000 algorithm

JPEG2000 codec is designed to compress images [6]. It is intended to replace its highly successful predecessor JPEG in many applications. Besides providing state-of-the-art compression performance, it offers a number of functionalities that address the requirements of emerging imaging applications, like progressive transmission by quality, resolution, component, or spatial locality. Lossy and lossless compression, random (spatial) access to the bit-stream, region of interest coding by progression, compressed domain processing are other features provided by this scheme. The basic block diagram of JPEG-2000 has been drawn below:

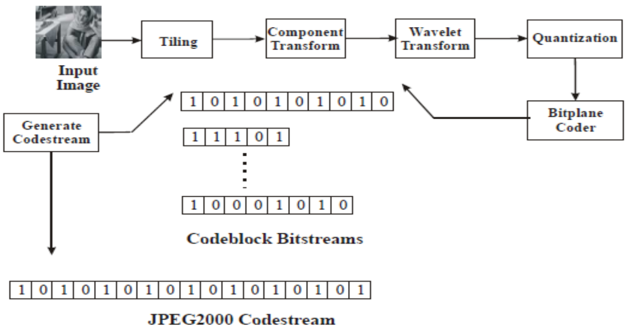

Figure 5 JPEG-2000 encoder

The first step in JPEG2000 compression is to divide the image into non-overlapping rectangular tiles. The tile size can be selected at compression time, and the entire image can be compressed as a single tile. Each tile component is transformed using a wavelet transform and quantized. The quantization indices in each wavelet sub-band are divided into rectangular code blocks. The quantization indices within each code block are compressed using a bit-plane coder. The individual code block bit-streams are then grouped together to form the JPEG2000 code stream.

2.5 Compressive Sensing algorithm

Compressive sensing (CS) provides a mathematical framework for exploiting the inherently sparse nature of the commonly encountered signals and has been the subject of scientific research in recent years. Compressive sensing is all about data compression during the image acquisition so as to avoid the large data set to arrive at the first step. It is based on the concept that small collections of non-adaptive linear projections of a sparse signal contain enough information for its effective reconstruction using some optimization procedure [7].

To understand the concept of compressive sensing finite length, real valued, one - dimensional, discrete time signal x has been considered. Ψ is basically dictionary of every element of x i.e. x(1),x(2),….x(N) has its basic definition in Ψ .

$$x=\sum_{i=1}^{N} Si\Psi i \qquad \text{or} \qquad x=s\,\Psi \tag{6}$$

'Si' is sparse signal matrix with K nonzero coefficients. The signal x is K sparse if K of the Si coefficients in eqn. (6) are nonzero and (N-K) are zero and (K<<N). Signal x is compressible if it has a few large coefficients and many small coefficients. Now general linear measurement is done that computes M<N inner products between x and a collection of vectors $\Phi_{j=1}^{M}$ as in

$$y_j=\langle x * \Phi j\rangle \tag{7}$$

Then measurements y_j are arranged in an (M*1) vector y, so y is a column vector that is acquired by the sensor with elements M such that M<<N. Φ is mostly taken as the i.i.d Gaussian random noise. The Gaussian measurement matrix satisfies two significant and useful properties of incoherence and RIP (Restricted Isometry Property).

$\boldsymbol{l_1}$ minimization norm is used for reconstruction because (i) Sparse signals have small $\boldsymbol{l_1}$ norms related to their energy. (ii) It is convex, which makes optimization problem tractable.

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$$\hat{s} = \text{argmin} \, \|s'\|_1 \quad \text{such that } \Theta s' = y. \tag{8}$$

The location of the important transform coefficients can be determined and their value can be reconstructed from equation 4.

Compressive Sensing (CS) provides robust image compression which is not provided by any of its precedence image compression standards, so it is best suited to be applied in noisy environments as in [8]. Recently CS has been combined with Vector Quantization (VQ) and Arithmetic Coding (AC) to solve the problem of limited computational source and transmission bandwidth in case of remote sensing systems as in [9]. Radio Astronomy makes use of the CS as the observations of the sky using interferometers are inherently under-sampled in angular frequency as in [10].

3. Results

EZW was very initial technique which is rarely or not in use today as it performance was not sufficient. So , in the results the performance comparison of previous widely accepted standards with the upcoming standard i.e. CS has been mentioned. First performance analysis of EZW and SPIHT with CS has been presented with the help of images shown in Figure (6). The results compare the performance of EZW, SPIHT and CS algorithms [1, 2, 11].

(a) (b) (c) (d)

Figure 6 (a) Original image (b) image reconstructed using EZW (c) image reconstructed using SPIHT (d) image reconstructed using CS.

From the above images it is clear image (d) recovered with CS has better visual quality and less distorted as compared to image (c) recovered using SPIHT at (0.04bpp). Moreover, CS provides parallel processing of (128*128) blocks formed as a result of which the computation time at the encoder is greatly reduced. The image (a) recovered using EZW at (0.04bpp) is greatly distorted so this technique is not used now for image compression.

When CS is used in combination with VQ and AC for remote sensing systems, the results can be evaluated using MATLAB. Here, to show the performance of this algorithm a man's image of size 1024x1024 pixels has been taken. This image is segmented into blocks of size 128 x128 and then CS framework has been applied at both the transmitting and receiving side. The results that are obtained are then compared with DCT based JPEG in which image is segmented into blocks of size 8 x8 pixels. However, PSNR of JPEG recovered image is slightly higher but the computation time in CS scheme at the encoder has 110x reduction in latency on the transmit side as compared to JPEG. Moreover, the reconstruction quality of reconstructed image obtained by CS technique is better than that of JPEG as shown in Figure (7). The results compare the performance of CS with JPEG algorithm [9].

(a) (b) (c)

Figure 7 Original image and Comparison between CS and JPEG reconstructed images at the 0.47 and 0.5 bpp respectively.

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4.Conclusion

Compression is basically the process of encoding information using fewer bits than an unencoded representation would use, through use of specific encoding scheme. One of the most popular compressing techniques is Transform coding which relies on making a signal compressible in some domain by applying some transform on the signal. Such compressibility is attained due to the segregation of most of the information in large coefficients of the transformed signal which can be encoded by storing only their values and locations effectively. This process is the basis behind many Compression schemes like JPEG, JPEG2000, MPEG and MP3 standards.

From above results it can be concluded that CS has potential to replace or stand among the other image compression standard widely in use (JPEG, SPIHT and JPEG-2000). Also it provides the additional advantage of robust image compression which is very important as most of the signals /images are practically sent over noisy channel. Wavelet based CS techniques prove better than DCT based JPEG or DCT based CS as the parallel computing can't be performed on the image transformed by using DCT due to the introduction of block artifacts in the reconstructed image But the main limitation of CS is that it can be effectively applied for the compression of high frequency information and the significant amount of attention that has been given to the theoretical aspects of compressive sensing, the practical image compression is still dominated by JPEG and JPEG-2000.

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