A Survey of Image Compression Methods

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ABSTRACT
The research in the field of image compression is driven by the ever increasing bandwidth requirements for transmission of images in computer, mobile and internet environments. In this context, the survey summarizes the major image compression methods spanning across lossy and lossless image compression techniques and explains how the JPEG and JPEG2000 image compression techniques are distinct from each other. Further, the paper concludes that still research possibilities exist in this field to explore efficient image compression.

General Terms
Image compression, Huffman coding, low bit rate transmission.

Keywords
JPEG, JPEG2000, wavelet, image compression, etc.

1. INTRODUCTION
Image compression as a specialized discipline of electronic engineering has been gaining considerable attention on account of its applicability to various fields. Compressed image transmission economizes bandwidth and therefore, ensures cost effectiveness during transmission. The application areas for such compressions today range from mobile, TV and broadcasting of high definition TV up to very high quality applications such as professional digital video recording or digital cinema/large-screen digital imagery and so on. This has led to enhanced interest in developing tools and algorithms for very low bit rate image coding [1]. An image is a two dimensional (2-D) signal processed by the human visual system. The signals representing images are usually in analog form. They are converted to digital form for processing, storage and transmission. An image is a two dimensional array of pixels. Different types of images are used to form the significant part of data, is particular critical in the fields such as remote sensing, biomedical and large-screen digital imagery etc. The ever increasing bandwidth requirements image compression continues to be a critical focus of research discipline [2].

2. IMAGE COMPRESSION
Image compression is applied to reduce the amount of data required to represent a digital image. The amount of data associated with visual information is so large that its storage would require enormous capacity. It is a process by which a compact representation of an image storage or transmission is possible. Compression is achieved by the removal of three basic data redundancies, which are coding, interpixel and psychovisual redundancies. Image compression is broadly classified into lossless and lossy image compression.

2.1 Lossless Compression Techniques
The feature of the lossless compression technique is that the original image can be perfectly recovered from the compressed image. It is also known as entropy coding since it use decomposition techniques to eliminate or minimize redundancy [2]. Lossless compression is mainly used for applications like medical imaging, where the quality of image is important. The following are the methods that fall under lossless compression: Run length encoding, Huffman encoding, LZW coding and Area coding.

2.1.1 Run length encoding
Run length encoding is an image compression method that works by counting the number of adjacent pixels with the same gray-level value. This count, called the run length, is then coded and stored. The number of bits used for the coding depends on the number of pixels in a row: If the row has2^n pixels, then the required number of bits is n. A 256x256 image requires 8 bits, since $2^8 = 256$.

2.1.2 Huffman encoding
Huffman coding can generate a code that is as close as possible to the minimum bound, the entropy. This method results in variable length coding. For complex images, Huffman code alone will reduce the file size by 10 to 50%. By removing irrelevant information first, file size reduction is possible.

2.1.3 LZW coding
LZW (Lempel- Ziv – Welch) coding can be static or dynamic, which is a dictionary based coding. In static dictionary coding, dictionary is fixed during the encoding and decoding processes. On the other hand in dynamic dictionary coding, the dictionary is updated on fly. The computer industry is widely using LZW. It is also implemented as compress command on UNIX.

2.1.4 Area coding
Area coding is an enhanced form of run length coding, which reflects the two dimensional character of images. It is a significant advancement over the other lossless methods. It does not make much of a meaning to interpret the coding of an image as a sequential stream, as it is in fact an array of

sequences building up a two dimensional object. The idea behind this is to find the rectangular regions with the same characteristics. These rectangular regions are coded in a descriptive form as an element with two points and a certain structure. Area coding is highly effective and it can give high compression ratio but the limitation being non-linear in nature, which prevents the implementation in hardware.

2.2 Lossy Compression Techniques

Lossy compression technique provides higher compression ratio than lossless compression. In this method, the compression ratio is high; the decompressed image is not exactly identical to the original image, but close to it. Different types of lossy compression techniques are widely used, characterized by the quality of the reconstructed images and its adequacy for applications. The quantization process applied in lossy compression technique results in loss of information. After quantization, entropy coding is done like lossless compression. The decoding is a reverse process. The entropy decoding is applied to compressed data to get the quantized data. Dequantization is applied to it & finally the inverse transformation is performed to get the reconstructed image. The methods that fall under lossy compression technique are listed below:

2.2.1 Vector Quantization

As part of vector quantization technique a dictionary of fixed-size vectors is developed and its index in the dictionary is used as the encoding of the original image vector. Normally entropy coding is used. It exploits linear and non-linear dependence that exists among the components of a vector. Vector quantization is superior even when the components of the random vector are statistically independent of each other.

2.2.2 Fractal Coding

Firstly, the image is decomposed into segments by using standard image processing techniques such as edge detection, colour separation and spectrum and texture analysis. Then each segment is looked up in a library of fractals. The Fractal coding library actually contains codes called iterated function system (IFS) codes, which are compact sets of numbers. Using a systematic procedure, A set of codes for a given image are determined using a systematic procedure; accordingly when the IFS codes are applied to a suitable set of image blocks yield an image that is a very close approximation of the original. This scheme is highly effective for compressing images that have good regularity and self-similarity.

2.2.3 Block truncation coding

The principle applied here is that the image is divided into non overlapping blocks of pixels. The mean of the pixel values in the block (threshold) and reconstruction values are determined for each block. Then a bitmap of the block is created by replacing all pixels whose values are greater than or equal (less than) to the threshold by zero or one. Then for each segment (group of 1s and 0s) in the bitmap, the reconstruction value is determined. This is the average of the values of the corresponding pixels in the original block.

2.2.4 Sub band coding

In the sub band coding, the image is analyzed and find the components containing frequencies in different bands, the sub bands. Then the quantization and coding are performed for each subbands. The main advantage of this coding is that quantization and coding for each subband can be designed separately.

2.2.5 Transformation Coding

Here a block of data is unitarily transformed so that a large fraction of its total energy is packed in relatively few transform coefficients, which are quantized independently. Transforms such as DFT (Discrete Fourier Transform) and DCT (Discrete Cosine Transform) are used to change the pixels in the original image into transform coefficients. These coefficients have several properties like energy compaction property that results in most of the energy of the original data being concentrated in only a few of the significant transform coefficients; those few significant coefficients are selected and the remaining are discarded. The selected coefficients are considered for further quantization and entropy encoding. DCT coding has been the most common approach to transform coding, which is also adopted in JPEG.

3. JPEG

JPEG (Joint Picture Expert Group) standard is one of the most popular and comprehensive still frame compression standards. The ever expanding multimedia and internet applications necessitated further expansion in technologies in the field of still image compression. JPEG standard defines three different coding systems, such as loss baseline coding system based on DCT, an extended coding system for greater compression, higher precision, or progressive reconstruction of applications and lossless independent coding system for reversible compression [3].

In the sequential or the baseline system, the input and output data precision is limited to 8 bits, whereas the quantized DCT values are restricted to 11 bits. The steps involved are: computation of DCT, quantization and variable length code. Thus, the image is compressed and decompressed in a block-based roster fashion from top to bottom. As each 8 X 8 block or sub image is faced, its 64 pixels are level-shifted by subtracting the quantity 2K -1. Thereafter, the transform of the block is computed, quantized as per the quantized optimization equation and recorded, using zigzag pattern to form a 1-D sequence of quantized coefficients [2].

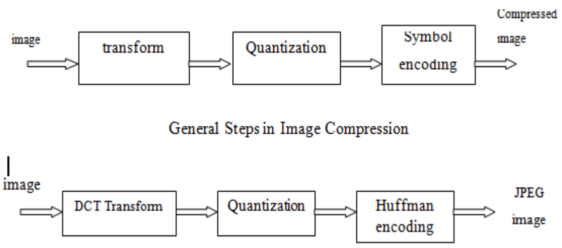

Fig 1: Process flow of JPEG Image compression

The image is first divided into 8 by 8 blocks of pixels. For the description of the process, let us take that the colour of each pixel as represented by a three-dimensional vector (R,G,B*)* consisting of its red, green, and blue components. A significant amount of correlation exists between these components. Therefore, a colour space transform can be used to produce a new vector whose components represent luminance, *Y,* and blue and red chrominance, C_b and C_r. Thus, the three quantities are typically less correlated than the components (R, G, B). Further, the human eye is more sensitive to luminance than chrominance, which can support us to neglect larger changes in the chrominance without affecting image perception[4]. Since this transformation is invertible, we will be able to recover the *(*R,G,B) vector from the (Y, C_b, C_r) vector.

3.1 The Discrete Cosine Transform

Over an 8 by 8 block, the changes in the components of the (Y, C_b, C_r) vector are rather mild. Instead of recording the individual values of the components, the average values and how much each pixel differs from this average value can be recorded. In many cases, the differences from the average to be rather small and hence safely ignored. This is the essence of the Discrete Cosine Transform (DCT). When first focus on one of the three components in one row in the block and imagine that the eight values are represented by f_0, f_1, ..., f_7. These values in a block can be represented in a way so that the variations become more apparent. For this reason, the values as given by a function f_x, where x runs from 0 to 7, and write this function as a linear combination of cosine functions

$$f_x = \frac{1}{2}\sum_{w=0}^{7} C_w F_w \cos\left[\frac{\pi(2x+1)w}{16}\right].$$

Here, the function f_x is being represented as a linear combination of cosine functions of varying frequencies with coefficients F_w. One can observe more variations with higher frequencies. Therefore, if the values f_x change relatively slowly, the coefficients F_w for larger frequencies should be relatively small. Thus, one could choose not to record those coefficients in an effort to reduce the file size of the image. The following equation is used to derive DCT:-

$$F_w = \frac{1}{2}C_w \sum_{x=0}^{7} f_x \cos\left[\frac{\pi(2x+1)w}{16}\right].$$

The equation makes clear that the DCT is invertible. For example, begin with f_x and record the values F_w. At the time of reconstruction of the image, the coefficients F_w is available and the f_x can be recomputed. The DCT coefficients may be efficiently computed through a Fast Discrete Cosine Transform, in the same spirit that the Fast Fourier Transform efficiently computes the Discrete Fourier Transform.

3.2 Quantization

Since the coefficients $F_{w,u}$, are real numbers, they can be stored as integers. This means that the coefficients need to be rounded; which would facilitate greater compression. Instead of rounding the coefficients $F_{w,u}$, it would be desirable to first divide by a *quantizing factor* and then record round($F_{w,u}$ / $Q_{w,u}$). This procedure permits to emphasize certain frequencies over others. More specifically, the human eye is not particularly sensitive to rapid variations in the image. This means we may deemphasize the higher frequencies, without significantly affecting the visual quality of the image, by choosing a larger quantizing factor for higher frequencies [4]. The JPEG algorithm uses extremely efficient means to encode sequences like this (Huffman coding). Reconstructing the image from the information is rather straight forward. The quantization matrices are stored in the file so that approximate values of the DCT coefficients may be recomputed. From here, the (Y, C_b, C_r) vector is found through the Inverse Discrete Cosine Transform. Then the (R, G, B) vector is recovered by inverting the colour space transform. In a recent study [5] showed that an iterative algorithm not only results in a compressed bit steam completely compatible with existing JPEG and MPEG decoders, but is also computationally efficient. Furthermore, when tested over standard test images, it achieves the best JPEG image compression result, to the extent that its own JPEG compression performance even exceeds the quoted PSNR results of some state of the art wavelet based image coders such as Shapiro's embedded zero tree wavelet algorithm at the common bit rate under comparison. Both the graph based algorithm and the iterative algorithm can be applied to application areas such as web image acceleration, digital camera image compression, MPEG frame optimization and transcoding.

3.3 JPEG Applications

JPEG has been widely used in many areas. For example, digital photography, medical imaging, wireless imaging, document imaging, pre-press, remote sensing and GIS (Geographical Information System), cultural heritage, scientific and industrial fields, digital cinema, image archives and databases, printing and scanning, surveillance, facsimile etc

4. JPEG 2000

Though JPEG has been a very successful method, the extensive use of digital imageries in the day to day life has necessitated the need for high performance image compression. Through the application of JPEG, it is observed that, the JPEG algorithm's use of the DCT leads to discontinuities at the boundaries of the 8 by 8 blocks in the sense that, the colour of a pixel on the edge of a block can be influenced by that of a pixel anywhere in the block, but not by an adjacent pixel in another block. This leads to *blocking artifacts* with the quality parameter and explains why JPEG is not an ideal format for storing line art. In some instances, it is desirable to also recover the image at lower resolutions, allowing, for instance, the image to be displayed at progressively higher resolutions while the full image is being downloaded. Thus, JPEG2000 encompasses not only new compression algorithms, but also flexible compression architectures and formats. Further, the standard intends to compliment and not to replace the current JPEG standards. It addresses areas where current standards have limitations in producing the best quality or performance. JPEG2000 provides low bit rate operation (below 0.25 bits/pixel) with subjective image quality performance superior to existing standards, without sacrificing performance at higher bitrates. The key differentiator is that the JPEG 2000 uses a wavelet transform in place of the DCT. Thus, we shall briefly explain the wavelet transform, which is the integral part of JPEG 2000 standard.

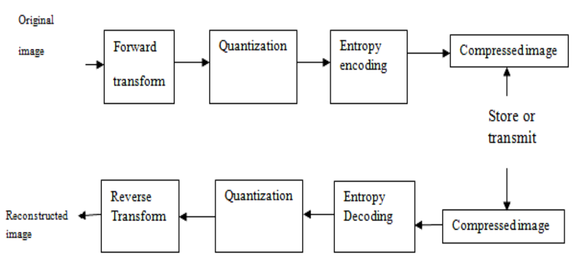

Fig 2: Block Diagram of JPEG-2000 image compression

Though the diagram looks like the one for the conventional JPEG, there are radical differences in all of the processes of each block of the diagram. The JPEG 2000 image compression processes can be split into three parts, they are preprocessing, the core processing, and the bit-stream formation, although there exists high interrelation between them[6]. In the preprocessing part the image tiling, the dc-level shifting and the component transformations are covered.

The core processing part consists of the discrete transform, the quantization and the entropy coding processes. The areas such as the precincts, code blocks, layers, and packets are included in the bit-stream formation, which is the final part.

4.1 Preprocessing

4.1.1 Image Tiling

Tiling referred as the partition of the source image into rectangular non-overlapping blocks (tiles). These blocks are compressed independently, as though they are entirely different images [7],[6]. The operations such as component mixing, wavelet transform, quantization and entropy coding are performed independently on the image tiles. Tiling reduces memory requirements, and since they are also reconstructed independently, they can be used for decoding specific parts of the image instead of the whole image.

Other than those at the boundary of the image, all tiles have exactly the same dimensions. Arbitrary tile sizes are allowed, upto and including the entire image (i.e., the whole image is regarded as one tile). Components with different subsampling factors are tiled with respect to a high-resolution grid, which ensures spatial consistency on the resulting tile components. The process of tiling can affect the image quality. Smaller tiles create more tiling artifacts compared to larger tiles. That means larger tiles perform visually better than smaller tiles. Image degradation is more severe in the case of low bit rate than the case of high bit rate. From the studies undertaken earlier, it was observed that, at 0.125 b/p there is a quality difference of more than 4.5 dB between no-tiling and tiling at 64 × 64, while at 0.5 b/p this difference is reduced to approximately 1.5 dB [7].

4.1.2 DC Level Shifting

This is done by subtracting the same quantity 2P-1, where P is the component's precision. DC level shifting is performed on samples of components that are unsigned.It converts an unsigned representation to a two's complement representation, or vice versa. If colour transformation is used, dc level shifting is performed prior to the computation of the forward component transform. At the decoder side, inverse dc level shifting is performed on reconstructed samples by adding to them the bias 2P-1 after the computation of the inverse component transform.

4.1.3 Component Transformations

JPEG2000 supports multiple- component images. Different components need not have the same bit depths nor need to all be signed or unsigned. For lossless systems, the only requirement is that the bit depth of each output image component must be identical to the bit depth of the corresponding input image component. Component transformations improve compression and allow for visually relevant quantization. The standard supports two different component transformations, one irreversible component transformation (ICT) that can be used for lossy coding and one reversible component transformation (RCT) that may be used for lossless or lossy coding, and all this in addition to encoding without colour transformation.

Since the RCT may be used for lossless or lossy coding, it may only be used with the 5/3 reversible wavelet transform. The RCT is a decorrelating transformation, which is applied to the three first components of an image. Three goals are achieved by this transformation, namely, colour decorrelation for efficient compression, reasonable colour space with respect to the human visual system for quantization, and ability of having lossless compression, i.e., exact reconstruction with finite integer precision. For the RGB components, the RCT can be seen as an approximation of a YUV transformation. All three of the components shall have the same sampling parameters and the same bit depth. There shall be at least three components if this transform is used. The forward and inverse RCT is performed.

4.2 Core processing – Wavelet Transform

Wavelet transform is used for the analysis of the tile components into different decomposition levels. These decomposition levels contain a number of subbands, which consist of coefficients that describe the horizontal and vertical spatial frequency characteristics of the original tile component. The pre-requisites of the wavelet's history begin in 1910, when Alfred Haar, a German mathematician, developed the now called *Haar function* and associated *Haar matrix* [8]. It is a special kind of matrix: by 2 operations (*translation* – compressing - and *dilation* - shifting) on a "mother vector", the matrix is constructed, all vectors being automatically perpendicular to each other, due to the special "mother" vector. With this scheme, it was possible to create orthogonal matrices of any size, all vectors being based on one first vector [9] , [10]. In the following, much research has been done to overcome and understand the limitations of the FT [9]. One main field of interest was to break up a complicated phenomenon into many simple pieces [11].

In the 30's, these were *Littlewood- Paley techniques*, further developed in the 50's and 60's and leading to applications of the *Calderon-Zygmund theory*. In the 70's, atomic decompositions like in *Hardy space theory* were widely used. G. Weiss and R. Coifman provided much research on these atomic decompositions [12]. In 1980, A. Grossmann and J. Morlet broadly defined wavelets in the context of quantum physics. Little later, J. Strömberg discovered the first orthogonal wavelets. Later in the 80's, Y. Meyer and other independent groups realized discrete calculations of the Littlewood-Paley techniques, followed by the understanding, that this could be effectively a substitute for Fourier techniques. It was Grossmann and Morlet who first suggested the name "wavelets" instead of "Littlewood-Paley theory" [11]. Later development in the 80's and 90's is marked by research of S. Mallat (introducing multiresolution analysis), Y. Meyer (constructing the first non-trivial wavelets) and I. Daubechies (creating compactly supported wavelets of fixed regularity).

4.2.1 Constant Q Filter Bank Analysis

The problem of equal spaced frequency bands with the FT has led to a variety of *constant Q* filter bank analysis transforms. They have been used in audio research since the late 1970s [13]. Examples are the *auditory transform* and the *bounded-Q frequency transform*. Also the wavelet transform can be classified as a constant Q technique. Q can be seen as the quotient of width of a band to its center frequency (also referred to as Äf / f with f=frequency). So with increasing frequency, the bandwidth becomes greater in constant Q analysis. The analysis bands are thin for low frequencies and wide for high frequencies. The FT transform, though, could be classified as a constant bandwidth transform. The length of the analysis window is also proportional to the frequency being analyzed: long windows are used to analyze low frequencies, short windows for high frequencies [13] Constant Q analysis trades off time versus frequency resolution "inside" the transform: temporal uncertainty but high frequency resolution in lower octaves (narrow analysis bands) and high temporal resolution with low frequency resolution in higher octaves. As short transients tend to contain high-frequency components, the constant Q scheme allows good time localization of events. The ear has a similar frequency response as a constant Q response, especially above 500Hz: the human auditory system performs a kind of filter bank analysis with frequency-dependent width of bands. These bands are called *critical bands* [13]. Constant Q analysis can be performed by applying several low pass (and optionally high pass) filters successively to a signal, or by applying several band pass filters to the same signal. Other approaches exist, e.g. based on FFT algorithms to exploit the high development status of FFT algorithms. While constant Q filter banks typically are less efficient in calculation, they do not need to do as many calculations: e.g. in order to analyze 4 octaves with resolution of half notes (12 half notes per octave), a constant Q analysis needs 48 bands (each one covering a half note frequency bandwidth), while Fourier analysis needs e.g. 200 bands [13].

4.2.2 Perfect Reconstruction

Under certain conditions, a filter bank is reversible, so that the original input can be retrieved from the bands. Reconstruction is very useful; the filter bank becomes a forward transform/inverse transform pair.For reconstruction, *upsampling* (*expanding*) must be done in order to undo the decimation. This is done by inserting a zero after each sample. Additionally, 2 resynthesis filters F0 and F1 are needed to smooth out the zeros, reversing the analysis low pass and high pass filters. The resulting samples are obtained by adding the outputs of the resynthesis filters. The diagram given below shows a 2-channel filter bank, analysis followed by resynthesize:

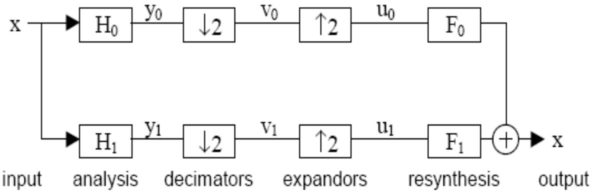

Fig 3: Block diagram of 2 – Channel filter bank, analysis followed by re-synthesis.

There are many aspects in order to fulfil the perfect reconstruction property for a filter bank. A selection is presented in the following.

4.2.3 The Discrete Wavelet Transform

The discrete wavelet transform (DWT) is calculated analogously to the CWT. Here is presented the dyadic DWT, which is scaled in powers of 2, resulting in the following discrete transform [10].

$$\psi_{j,k} = 2^{j/2}\psi(2^j t - k) \qquad b_{j,k} = \int f(t)\psi_{j,k}(t)dt$$

Equation : Forward DWT

The *bj,k* coefficients are the wavelet coefficients, analogous to the *F(a,s)* coefficients. The discrete inverse transform is straightly adding the translated, dilated wavelets, weighted by the coefficients.

$$f(t) = \sum_{j,k} b_{j,k}\psi_{j,k}(t)$$

Equation : inverse DWT

4.3 Bit-Stream Formation

4.3.1 Precincts and code blocks

After quantization, each subband is divided into rectangular blocks, i.e., nonoverlapping rectangles. Three spatially consistent rectangles (one from each subband at each resolution level) comprise a packet partition location or precinct. Each precinct is further divided into nonoverlapping rectangles, called code blocks, which form the input to the entropy coder. The size of the code block is typically 64x 64 and no less than 32 x 32.

4.3.2 Packets and Layers

For each code block, a separate bit stream is generated. No information from other blocks is utilized during the generation of the bit stream for a particular block. Rate distortion optimization is used to allocate truncation points to each code block. The bit stream has the property that it can be truncated to a variety of discrete lengths, and the distortion incurred, when reconstructing from each of these truncated subsets, is estimated and denoted by the mean squared error. During the encoding process, the lengths and the distortions are computed and temporarily stored with the compressed bit stream itself. The compressed bit streams from each code block in a precinct comprise the body of a packet. A collection of packets, one from each precinct of each resolution level, comprises the layer. A packet could be interpreted as one quality increment for one resolution level at one spatial location, since precincts correspond roughly to spatial locations. Similarly, a layer could be interpreted as one quality increment for the entire full resolution.

5. JPEG and JPEG 2000 Comparison

Having explained the major image compression standards such as JPEG and JPEG 2000, it would be also desirable to explain the major differences between JPEG and JPEG 2000. The lossy baseline JPEG is the very well known and popular standard for compression of still images. In the JPEG the source image is divided into 8 X 8 blocks and each block is transformed by using DCT. The data compression is achieved by variable length coding. The quantization step size for each of the 64 DCT coefficients is specified in a quantization table, which remains the same for all blocks in the image. In JPEG the degree of comparison is determined by a quantization scale factor [6].The DC coefficients of all blocks are coded separately using a predictive scheme. Therefore, the block based segmentation of the source image is a fundamental limitation of the DCT-based compression system. This degradation is known as “blocking effect” it depends on compression ratio and image content.The performance of the block-based DCT scheme degrades at high compression ratio. On the other hand, DWT offers adaptive spatial frequency resolution, that is, better spatial resolution at high frequencies and better frequency resolution at low frequencies. This can provide better image quality than DCT, especially at higher compression ratio [14].

JPEG 2000 is based on DWT, which is applied on image tiles. DWT tiles are decomposed into different decomposition (resolution) levels. After transformation, all transform coefficients are quantized. Scalar quantization is used in Part I of the standard. Arithmetic coding is employed in the last part of the encoding process. Any image quality or size can be decompressed from the resulting code-stream, upto and including those selected at encode time. Thus, JPEG 2000 supports progression in four dimensions, that is, quality, resolution, spatial location and component.Apart from supporting resolution and spatial location, JPEG 2000 supports images with upto 16384 components. Generally images with more than four components are from scientific instruments.

6. CONCLUSION

Though extensive research have been taking place in this area, keeping in view the everincreasing need for low bit rate compression methods, scope exists for new methods as well as evolving more efficient algorithms in the existing methods. The review makes clear that, the field will continue to interest researchers in the days to come.

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