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A Survey on Various Image Compression Techniques

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***Abstract*:** **Image compression technique is widely used in multimedia applications such as image, video, audio data and medical field. Image compression aims to reduce the redundancy of an image data and reduce the storage space of an image. Different image compression techniques were proposed to achieve high compression ratios and high image qualities in low computation time. This document presents the review of various lossless and lossy compression techniques.**

***Index Terms*- lossless compression, lossy compression, discrete cosine transform, discrete wavelet transform, discrete anamorphic transform.**

I. INTRODUCTION

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems. Digital image processing allows the use of much more complex algorithms, and hence, can offer both more sophisticated performance at simple tasks, and the implementation of methods which would be impossible by analog means.

Image compression addresses the problem of reducing the amount of information required to represent a digital image. It is a process intended to yield a compact representation of an image, thereby reducing the image storage transmission requirements. Every image will have redundant data. Redundancy means the duplication of data in the image. Either it may be repeating pixel across the image or pattern, which is repeated more frequently in the image. The image compression occurs by taking benefit of redundant information of in the image. Reduction of redundancy provides helps to achieve a saving of storage space of an image. Image compression is achieved when one or more of these redundancies are reduced or eliminated. In image compression, three basic data redundancies can be identified and exploited. Compression is achieved by the removal of one or more of the three basic data redundancies.

This Paper is a survey of various methods of data compression. When the computer age came about in the 1940's, storage space became an issue. Data Compression was the answer to that problem. The Compression process takes an original data set and reduces its size by taking out unnecessary data [1]. In 1949 Claude Shannon and Robert Fano devised a systematic way to assign code word based on probabilities of blocks [2]. In 1951 David Huffman found an optical method for data compression. Early implements were typically done in hardware, with specific choices of code words being made as compromises between compression and error correction [2].almost all the compression were based on adaptive Huffman coding. There are two main types of compression, Lossy and Lossless [1]. There many methods of compression which deals with the data.

In this paper study about lossless compression techniques, Wavelet based image compression, DCT based compression and Discrete Anamorphic Stretch Transform (DAST) based compression techniques.

II. COMPRESSION TECHNIQUES

This section discusses about set of compression techniques used for various applications.

A. LOSSLESS COMPRESSION

As the name indicates the original image can be perfectly recovered using the lossless compression techniques. They are also known as entropy coding, noiseless compression etc. They will not introduce any noises to the image and they are using statistics or decomposition techniques to reduce the redundancy. Lossless Image compression is widely used in many applications where no information loss is allowed during compression [3] medical imaging, technical drawing etc. The following are some of the methods which are used for lossless compression.

a) Run Length Encoding

Run-length encoding (RLE) is a very simple form of image compression in which runs of data are stored as a single data value and count, rather than as the original run. It is used for sequential [4] data and it is helpful for repetitive data. In this technique replaces sequences of identical symbol (pixel), called runs. The Run length code for a gray scale image is represented by a sequence { Vi , Ri } where Vi is the intensity of pixel and Ri refers to the number of consecutive pixels with the intensity Vi. This is most useful on data that contains many such runs for example, simple graphic images such as icons, line drawings, and animations. It is not useful with files that don't have many runs as it could greatly increase the file size. Run-length encoding performs lossless image compression [5]. Run-length encoding is used in fax machines.

b) Entropy Encoding

Entropy encoding is another lossless compression technique. It works independent of the specific characteristics of medium. This method works as follows. It will create a unique prefix code and assign this code to unique symbol in the input. Entropy encoder works by compressing data by replacing the fixed length output with a prefix code word. This is of varying size after creating the prefix code. This will be similar to the negative logarithm of probability. There are many entropy coding methods. The most common techniques are Huffman coding and arithmetic coding.

c) Constant Area Encoding

This method is an enhanced form of run length encoding method. There is some significant advantage of using this technique over other lossless methods. In constant area coding special code words are used to identify large areas of contiguous 1's and 0's. Here the image is segmented in to blocks and then the segments are classified as blocks which only contains black or white pixels or blocks with mixed intensity. Another variant of constant area coding is to use an iterative approach in which the binary image is decomposed into successively smaller and smaller block. A hierarchical tree is built from these blocks. The section stops when the block reaches certain predefined size or when all pixels of the block have the same value. The nodes of this tree are then coded. For compressing white text a simpler approach is used. This is known as white block skipping. In this blocks containing solid white areas are coded to 0 and all other areas are coded to 1. They are followed by bit pattern.

d) Lempel–Ziv–Welch Coding

Lempel–Ziv–Welch (LZW) is a universal lossless data compression algorithm created by Abraham Lempel, Jacob Ziv, and Terry Welch. It was published by Welch in 1984 as an improved implementation of the LZ78 algorithm published by Lempel and Ziv in 1978. LZW is a dictionary based coding. Dictionary based coding can be static or dynamic. In static dictionary coding, dictionary is fixed during the encoding and decoding processes. In dynamic dictionary coding, the dictionary is updated on fly. LZW is widely used in computer industry and is implemented as compress command on UNIX. The methods of the first group try to find if the character sequence currently being compressed has already occurred earlier in the input data and then, instead of repeating it, output only a pointer to the earlier occurrence.

e) Huffman Encoding

In computer science and information theory, Huffman coding is an entropy encoding algorithm used for lossless data compression. It was developed by Huffman. Huffman coding [6] today is often used as a "back-end" to some other compression methods. The term refers to the use of a variable-length code table for encoding a source symbol where the variable-length code table has been derived in a particular way based on the estimated probability of occurrence for each possible value of the source symbol. The pixels in the image are treated as symbols. The symbols which occur more frequently are assigned a smaller number of bits, while the symbols that occur less frequently are assigned a relatively larger number of bits. Huffman code is a prefix code. This means that the (binary) code of any symbol is not the prefix of the code of any other symbol.

f) Arithmetic Coding

Arithmetic coding is a form of entropy encoding used in lossless data compression. Normally, a string of characters such as the words "hello there" is represented using a fixed number of bits per character, as in the ASCII code. When a string is converted to arithmetic encoding, frequently used characters will be stored with little bits and not-so-frequently occurring characters will be stored with more bits, resulting in fewer bits used in total.

Arithmetic coding differs from other forms of entropy encoding such as Huffman coding [7] in that rather than separating the input into component symbols and replacing each with a code, arithmetic coding encodes the entire message into a single number.

B. LOSSY COMPRESSION

Lossy compression as the name implies leads to loss of some information. The compressed image is similar to the original uncompressed image but not just like the previous as in the process of compression [8] some information concerning the image has been lost. They are typically suited to images. The most common example of lossy compression is JPEG. An algorithm that restores the presentation to be the same as the original image is known as lossy techniques. Reconstruction of the image is an approximation of the original image, therefore the need of measuring of the quality of the image for lossy compression technique. Lossy compression technique provides a higher compression ratio than lossless compression. Lossy methods are especially suitable for natural images such as photographs in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The Lossy compression that produces imperceptible differences may be called visually lossless [9]. The following methods are used in lossy compression.

a) Chrome Sub sampling

This technique basically used in video encoding for example jpeg encoding and etc. This takes advantage of the fact that the human eye perceives spatial changes of brightness more sharply than those of color, by averaging or dropping some of the chrominance information in the image. It works by taking advantage of the human visual system's lower acuity for color differences than for luminance.

b) Fractal Compression

It is one of the lossy compression technique used in digital images. As the name indicates it mainly based on the fractals. This approach is good for natural images and textures. The essential idea here is to decompose the image into segments by using standard image processing techniques such as color separation, edge detection, and spectrum and texture analysis. Then each segment is looked up in a library of fractals. The library actually contains codes called iterated function system codes, which are compact sets of numbers. Using a systematic procedure, a set of codes for a given image are determined, such that 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. Fractal compression is an asymmetrical process that takes large amount of time to compress and to decompress an image. This characteristic limits the usefulness of fractally compressed data to applications where image data is constantly decompressed but never recompressed. Fractal compression is highly suited for use in image databases and CD-ROM applications [10].

c) Vector Quantization

Vector quantization (VQ) is a classical quantization technique from signal processing which allows the modeling of probability density functions by the distribution of prototype vectors. It was originally used for image compression. It works by dividing a large set of points (vectors) into groups having approximately the same number of points closest to them. The density matching property of vector quantization is powerful, especially for identifying the density of large and high-dimensioned data. Since data points are represented by the index of their closest centroid, commonly occurring data have low error, and rare data high error. This is why VQ is suitable for lossy data compression. It can also be used for lossy data correction and density estimation.

d) Block Truncation Coding

The image is divided into non overlapping blocks of pixels. For each block, threshold and reconstruction values are determined. The threshold is usually the mean of the pixel values in the block. Then a bitmap of the block is derived by replacing all pixels whose values are greater than or equal (less than) to the threshold by a 1 (0). 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.

e) Transform Coding

It is a type of compression for natural data like photographic images. It will result a low quality output of original image. It is a core technique recommended by jpeg. In this coding scheme, transforms are used to change the pixels in the original image into frequency domain coefficients (called transform coefficients). These coefficients have several desirable properties. One is the 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. This is the basis of achieving the compression. Only those few significant coefficients are selected and the remaining are discarded. The selected coefficients are considered for further quantization and entropy encoding. Deferent type of Transform coding techniques are

(i) Discrete Cosine Transform (DCT): A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering. DCT helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain. The one-dimensional DCT is useful in processing one-dimensional signals such as speech waveforms. For analysis of two-dimensional (2D) signals such as images, we need a 2D version of the DCT. For an n x m matrix s, the 2D DCT is computed in a simple way: The 1D DCT is applied to each row of s and then to each column of the result. Since the 2D DCT can be computed by applying 1D transforms separately to the rows and columns, we say that the 2D DCT is separable in the two dimensions. As in the one-dimensional case, each element of the transform is the inner product of the input and a basis function, but in this case, the basis functions are n x m matrices. Each two-dimensional basis matrix is the outer product of two of the one-dimensional basis vectors.

The discrete cosine transform is closely related to the Discrete Fourier Transform (DFT). Both take a set of points from the spatial domain and transform them into an equivalent representation in the frequency domain. The difference is that while the DFT takes a discrete signal in one spatial dimension and transforms it into a set of points in one frequency dimension and the Discrete Cosine Transform (for an 8x8 block of values) takes a 64-point discrete signal, which can be thought of as a function of two spatial dimensions x and y, and turns them into 64 DCT coefficients which are in terms of the 64 unique orthogonal 2D spectrum. The DCT coefficient values are the relative amounts of the 64 spatial frequencies present in the original 64-point input. The element in the upper most left corresponding to zero frequency in both directions is the “DC coefficient” and the rest are called “AC coefficients.”

Because pixel values typically change vary slowly from point to point across an image, the FDCT processing step lays the foundation for achieving data compression by concentrating most of the signal in the lower spatial frequencies. For a typical 8x8 sample block from a typical source image, most of the spatial frequencies have zero or near-zero amplitude and need not be encoded. At the decoder the IDCT reverses this processing step. It takes the 64 DCT coefficients and reconstructs a 64-point output image signal by summing the basis signals. Mathematically, the DCT is one-to-one mapping for 64-point vectors between the image and the frequency domains.

The basic algorithm steps are

Step 1: Input the Image.

Step 2: The image firstly broken into 8x8 blocks of pixels.

Step 3: The Discrete Cosine Transform (DCT) is applied to each and every block; it reads pixels from left to right, and top to bottom.

Step 4: Each block is compressed using quantization table.

Step 5: The array of compressed blocks of image is occupy less memory space.

***Step 6*:** The image is reconstructed through decompression, a process that uses the Inverse Discrete Cosine Transform (IDCT) [11].

(ii) Discrete Wavelet Transform (DWT): A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. A wavelet is a mathematical function used to divide a given function or continuous-time signal into various scale components. Wavelet analysis has proved to be very important development in the search of more efficient methods of image compression [13]. Like most Lossy image coders, wavelet based image coders typically comprise three major components. Wavelet filter bank decomposes an image into wavelet coefficients, which are then thresholded and quantized if necessary, and finally an entropy encoder encodes these quantized coefficients into out bit stream.

Wavelet transform is a pair of filters. The way we compute the wavelet transform by recursively averaging and differentiating coefficients is called the filter bank [13], where one is a low pass filter and the other is a high pass filter. Each of the filters is down sampled by two and low frequencies signal of those two output signals can be further transformed. Similarly, this process can be repeated recursively several times, resulting in a tree structure called the decomposition tree. Wavelet transform can be used to analyze or decompose signals or images called decomposition [14][15]. The same components can be assembled back into the original signal without loss of information; this is called reconstruction or synthesis. The structure of Wavelet can be represented as a four channel perfect reconstruction of filter bank. Each filter is 2D with subscript indicating the type of filter (LPF or HPF) for separation of horizontal and vertical components. The resulting four-transform components consist of all possible combinations of high and low pass filtering in the two directions. By using these filters in one stage an image can be decomposed into four bands. There are three types of details of images for each resolution Diagonal (HH), Vertical (LH) and Horizontal (HL). The operations can be repeated on the low low (LL) i.e. on approximation band using the second identical filter bank [10]. The decomposition process can be iterated, with successive approximations being decomposed. However, in practice, more than one decomposition level is performed on the image data. Successive iterations are performed on the low pass coefficients (approximation) from the previous stage to further reduce the number of low pass coefficients. Since the low pass coefficients contain most of the original signal energy, this iteration process yields better energy compaction. The quality of compressed image depends on the number of decompositions. Compression of an image can be obtained by ignoring all coefficients less than the threshold value. If we use decomposition iteration, it will be more successful in resolving DWT coefficient because Human Visual System (HVS) is less sensitive to removal of smaller details. Decomposition iterations depend on the filter order. Higher order does not imply better image quality because of the length of the wavelet filter. This becomes a limiting factor for decomposition. Usually, three levels of decompositions are used in current wavelet based image compression [15].

(iii) Discrete Anamorphic Stretch Transform**:** DAST is a physics-inspired transformation that emulates diffraction of the image through a physical medium with specific nonlinear dispersive property. Also use the Stretched Modulation Distribution, it will provide the recipe for the image compression. By performing space-bandwidth compression, it reduces the data size required to represent the image for a given image quality. This diffraction based compression is achieved through a mathematical restructuring of the image and not through modification of the sampling process as in compressive sensing (CS) [10][11]. This technique does not need feature detection and is non-iterative**.** DAST is a nonlinear transform, both in terms of amplitude and in terms of the phase operation. DAST is related to the recently introduced method for analog time-bandwidth compression of one-dimensional temporal signals [12]-[14]. For rare cancer cell detection in blood, screening of millions of cells in a high speed flow stream is required. Such problems has fueled development of record throughput real-time instruments such as the time-stretch camera that allowed the detection of cancer cells in blood with sensitivity of one cell in a million [15] and the time-stretch spectrum analyzer enabling the discovery of Optical Rogue Waves [16].

DAST could be as a standalone algorithm or combined with existing digital compression techniques to enhance speed or quality or to improve the amount images can be compressed. The results have shown that AST can outperform standard JPEG image compression format, with dramatic improvement in terms of image quality and compression factor. DAST is operated on the original image followed by resampling (down-sampling) and secondary compression such as spatial or entropy encoding as well as other standard image compression algorithms. To recover the original image, the inverse operation is performed on the compressed image. For DAST operation, the original image is convolved with DAST Kernel, and then Nth power magnitude of the result is computed.

III. CONCLUSION

This paper provides a short survey on recent lossy image compression algorithms. There are different types of image compression techniques. These techniques are basically classified into Lossy compression techniques and lossless compression technique. Comparing the performance of compression technique is difficult unless identical data sets and performance measures are used. These techniques are good for various applications. But all methods of compression have some drawbacks also.

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