Image Compression Techniques Based on Quantization and Statistical Coding

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Abstract **—Due to technical advancements that do not impact the range of picture operations, the availability of powerful image alteration software, or image management, the availability of images in a broad variety of applications has grown. The need for more storage space and more bandwidth for communications still outstrips what is currently available, even if storage and transmission technologies have advanced significantly. Consequently, picture compression is a useful method. We prioritize reducing file size without compromising picture quality or information when we compress images. The study provides an overview of the most popular lossy and lossless image compression methods, as well as their advantages, disadvantages, and potential future research directions. By comparing several compression methods, we can better pick the one that best suits our needs by highlighting its best features. We provide some broad guidelines for selecting the best picture compression algorithm in light of the review's findings. In addition, a comprehensive tabular analysis comparing the approaches' efficacy in picture compression is provided to showcase the assessment and performance of this research.**

I. INTRODUCTION

To conserve transmission and storage, image compression reduces or eliminates redundancy in picture representation. The compression techniques are often categorized as either lossless or lossy based on the quality of the reconstructed picture [1]. Lossless compression ensures that the reconstructed picture will function well in lieu of the original. Generally speaking, this kind of compression has a lower compression ratio than lossy compression. Techniques for lossless compression include entropy coding, LZW, and RLE[2]. In order to increase the compression ratio or reduce the size of the data, some nonessential information is eliminated in lossy compression. Therefore, the rebuilt picture is warped, but at a price. Lossy compression is implemented via the use of JPEG, SPIHT, and fractal compression algorithms[3][4]. Lossy and lossless compression methods both reduce picture size by eliminating image duplication using many core methodologies outlined below. (1) Reduce pixel correlation: The correlation between a pixel and its neighboring pixels might be quite significant[5] . Researchers may use variable length coding theory and statistical characteristics to reduce storage requirements by minimizing pixel correlation. (2) Quantization: Quantization reduces the amount of storage needed by assigning greater values to a smaller set of discrete values. Furthermore, quantization is a process that results in permanent distortion and loss of information. (3) Entropy coding: is a technique used to decrease the size of a picture for the purpose of storing [6][7]. Entropy coding assigns code words to symbols based on their likelihood. To reduce duplication, conventional picture encoding systems such as JPEG, HEVC intra-frame encoding, and JPEG2000 use a predefined manual transform, such as DCT or DWT. Subsequently, the process of entropy coding and quantization is carried out in order to get a compressed bit stream [8].

The wavelets and fractals schemes are the other techniques for picture compression. There isn't much of an Internet presence for these methods. However, both lossless or lossy systems give assurance since, for certain types of pictures, they offer a greater compression ratio than the GIF or JPEG models. The PNG format is another innovative method that takes the place of the GIF format [9]. The Firefly algorithm has been used for several sorts of noisy images. When dealing with program and text files, it is crucial that compression be lossless. This is because a specific mistake may have a severe impact on the meaning of a text file or cause a program to fail to execute. Due to this reason, visual pictures have the potential to be compressed to a greater extent compared to programs or text files[10].

II. IMAGE COMPRESSION TECHNIQUES

Based on our criteria, image compression algorithms may be divided into two main types. lossless compression and lossy compression. In this section, these two techniques are explained in detail

2.1 Lossy Compression Techniques

Lossy Compression refers to a method of data compression that involves sacrificing a certain amount of data or information. In some applications, it is acceptable to have a

DOI:http://doi.org/10.24086/cocos2024/paper.1567

certain degree of information loss, often in the form of a few bits. Lossy compression techniques may be used in such cases. To achieve real-time image rendering in video conferencing, even with a significant number of dropped frames. The loss of information may manifest as a reduction in color depth or visual details. The method of lossy compression involves identifying and permanently discarding 'redundant' pixel information. Lossy compression algorithms are unsuitable for text-based data since they must preserve all of its data. Lossy data compression is used in formats such as MP3, JPEG, MPEG, and 3GP[11][12].

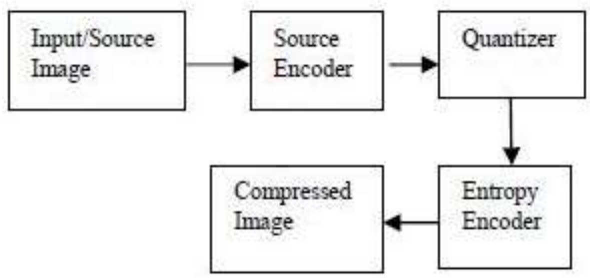

Figure1: Lossy Compression

2.1.1 Discrete Cosine Transform (DCT)

DCT is a commonly used method for compressing images and audio. It is a lossy compression technique. Illustration: JPEG Images. Discrete Cosine Transforms (DCTs) are used to transform data into the aggregate of a sequence of cosine waves vibrating at various frequencies. The Discrete Cosine Transform (DCT) is closely related to the Fourier Transform, although it specifically utilizes cosine functions and real coefficients. In contrast, the Fourier Transform use both sine and cosine functions as well as complex values. Cosine functions are more efficient for compression since they need fewer functions to approximate a signal. Both the Fourier transform and the Discrete Cosine Transform (DCT) are mathematical operations that translate data from the spatial domain to the frequency domain. They also have corresponding inverse functions that convert the data back to the spatial domain[13].

2.1.2 Discrete Wavelet Transform (DWT)

The DWT is a mathematical technique that decomposes a picture into a combination of wavelet functions, or wavelets, which have varying positions and scales. The discrete wavelet transform is often done using a hierarchical filter structure. This is applied to image blocks that are created by the pre-processor. The two-dimensional discrete wavelet transform (DWT) results in the breakdown of approximation coefficients at level j into four components: the approximation at level j+1, as well as the details in three different orientations (horizontal, vertical, and diagonal)[14].

2.1.3 The Fractal Compression

The fractal compression method is based on comparing picture portions to one another. It is possible to recreate the encoded picture by transforming these geometric forms, or fragments, into "fractal codes" using algorithms. There is no longer any link between picture resolution and fractal coding. There will be no quality loss or pixel-based compression artifacts when the picture is resized to suit any screen size[15].

2.1.4 Vector Quantization

Lossy compression is achieved via the use of Vector Quantization. The LBG-VQ algorithm is a certain kind of fixed-to-fixed length algorithm. The idea behind it is to divide a big dataset (vectors) into smaller datasets with about the same amount of neighboring points. Hence, "Block Quantization" and "Pattern matching Quantization" are other names for VQ. The process involves reducing a high-dimensional vector space to a discrete subspace with a smaller range of values. Data compression occurs because a smaller space vector needs less storage space. Errors in the compressed data are inversely related to density because of vector quantization's density matching characteristic. Codebooks often do the change. Vector quantization has several practical uses, including picture and speech reduction, voice recognition, and many more[16].

2.2 Lossless compression

Lossless compression reduces the size of a file without any damage or loss to the file or reduction in quality. In this data is compressed without any loss of data (bits). When it is decompressed the original data or bits are retrieved. It is applied where original bits are necessary. Mostly, it is applicable on text document files and spreadsheet, etc where the data or information is very important. The advantage of lossless compression is that it maintains quality of the data and on contrary it does not reduce too much size of the file[11][17].

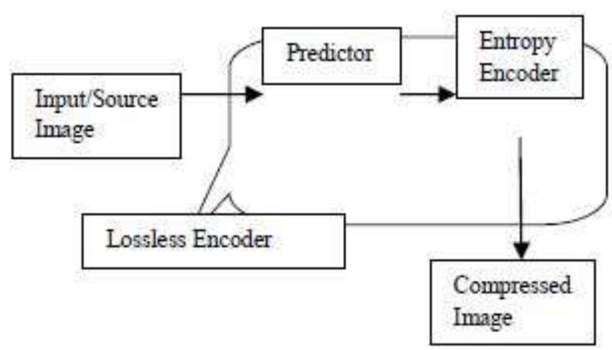

Figure2: Lossless Compression

2.2.1 The Huffman coding

The Huffman coding technique is a widely used method for generating prefix-free codes. It is the method used to eliminate unnecessary repetition in coding. It is a code that converts input symbols of a set length into code words of variable length. Dr. David A. Huffman introduced Huffman coding in 1952.The codes formed using this technique are referred to as Huffman codes. Huffman coding is a kind of statistical coding that minimizes the amount of bits needed to represent a sequence of symbols. This technique enables symbols to have variable lengths. This approach assigns shorter code words to symbols with greater probabilities of occurrence and longer code words to symbols with lower probabilities of occurrence[18].

DOI:http://doi.org/10.24086/cocos2024/paper.1567

2.2.2 Run Length Encoding (RLE)

RLE is a basic method of compressing images where consecutive data values are replaced by a single value and its count, instead of storing the original consecutive values. It is used for sequential data and is beneficial for repeating data. This approach involves replacing consecutive occurrences of the same symbol (pixel), which are referred to as runs. The Run length code for a grayscale picture is denoted by a sequence { Vi , Ri }, where Vi represents the intensity of a pixel and Ri indicates the number of consecutive pixels with the same intensity Vi, as seen in the figure. This technique is particularly beneficial for datasets that consist of several consecutive occurrences, such as basic visual representations like icons, line drawings, and animations. Files with few runs may not benefit from this feature, since it has the potential to significantly inflate the file size. Run-length encoding is a method of lossless picture compression.[19]

2.2.3 Entropy encoding

Entropy encoding is a kind of lossless compression that uses a small number of bits to represent often recurring patterns and a larger number of bits to represent rarely occurring patterns in order to compress digital material. Huffman coding is an entropy coding technique that uses an entropy coder to compress data without any loss. It does this by encoding symbols with a variable number of bits, with the number of bits being inversely related to the probability of the symbols. Huffman coding is a phrase used to describe compression methods or strategies that rely on the probability distribution of source symbols. Entropy encoding serves as the fundamental basis for Huffman coding, Arithmetic coding, and Shannon-Fano coding[20].

2.2.4 Arithmetic coding

Arithmetic coding is a technique of encoding data in a way that reduces redundancy and is often used in lossless compression. Typically, a sequence of characters is encoded using a predetermined amount of bits for each character, such as in the ASCII code. When a string is encoded using arithmetic encoding, often used characters are assigned smaller bit representations, while less frequently appearing characters are assigned larger bit representations. This leads to a reduction in the overall number of bits required. Arithmetic coding distinguishes itself from other methods of entropy encoding, such Huffman coding, by encoding the whole message as a single number instead of breaking it down into individual symbols and assigning codes to each symbol[21].

2.2.5 LZW Coding

The LZW algorithm is a lossless data compression method that was developed by Abraham Lempel, Jacob Ziv, and Terry Welch. Welch released it in 1984 as an enhanced version of the LZ78 algorithm, which was first published by Lempel and Ziv in 1978. LZW is a coding technique that relies on a dictionary. Dictionary-based code may be either static or dynamic. In static dictionary coding, the dictionary remains unchanged throughout the encoding and decoding procedures. Dynamic dictionary coding involves updating the dictionary in real-time. The technique is straightforward to implement and has the potential for achieving a very high throughput in hardware implementations. The technique in question is the one used by the popular UNIX file compression application called compress. It is also used in the GIF picture format. LZW compression emerged as the first and widely used global technique for compressing images on computers. An extensive English text file may generally be compressed using the LZW algorithm to around 50% of its initial size[22].

III. LITERATURE REVIEW

Tahar et al have used an improved EZW model to achieve superior compression performance in terms of bit rate and PSNR for both lossless and lossy image compression, respectively. To reduce the number of scans and eliminate duplicate symbols in the existing EZW system, the selected approach utilizes an innovative and efficient symbol map. Furthermore, the implemented methodology was designed to provide a scalable picture coding by effectively using the interdependence of color planes. The simulation findings demonstrate that the selected scheme outperforms both the classic EZW and other upgraded models in terms of subjective and objective principles across different compression strategies[23]. A innovative near-lossless technique in WCE for effective energy picture compression was presented by **Turcza and Mariusz**[24]. Using the Bayer CFA, the modeled compressor operates directly on data obtained from the CMOS image sensor. When compared to more traditional models, the exploited compressor achieves lower bit-rate error and better picture quality upon using the provided approach. The compression rate was 3.9 when compared to the typical WCE pictures, and the PSNR was 46.5 dB, indicating that higher image quality had been achieved. Lastly, it was shown that using a variety of data sets, the proposed approach improves the overall accuracy of the chosen technique. To generate the optimal picture waveform's bits-budget, **Ferda et al.**[25] have devised a technique based on "**the Tchebichef psychovisual"** threshold. This bits-budget was designed for picture compression in order to recover the majority of quantization tables. The results of the experiment showed that the constructed model can more effectively create the visual aspects of the final picture. Reduced artifact effects and pixel distortion are produced by the visual picture quality. As a result, a set of bits-budgets provides exceptional improvement in picture quality at shorter bit lengths. Ultimately, the chosen methodology was evaluated, and encouraging research outcomes were obtained when compared to the conventional frameworks. A novel method for calculating the affine constraints of fractal encoding has been introduced by **Swalpa et al**.[26] in an effort to reduce the computational complexity of the process. A simple but accurate scaling constraint estimate was found that satisfies all the properties required to achieve convergence. It allows to substitute the expensive process with a simple two-integer distribution. In addition, a modified HV block partition scheme was used, along with a number of cutting-edge approaches to improve the encoding time and decoded superiority over their conventional models. The results of the analysis shown that, in a shorter amount of time, the chosen approach achieves higher performance,

DOI:http://doi.org/10.24086/cocos2024/paper.1567

matching the standard fractal dependent picture compression models.

Pang et al. conducted a study on the QDCT, which demonstrated superior efficiency compared to its conventional equivalents in terms of complexity. Furthermore, the used QDCT was employed to develop and identify a quantum picture compression technique. The proposed compression model conducts a search to identify the most significant evaluated Discrete Cosine Transform (DCT) coefficients, as obtained using Grover's method. Hence, the newly proposed model has the capability to calculate the Discrete Cosine Transform (DCT) coefficients simultaneously by using two predictions. The evaluation of the chosen scheme also demonstrates that the implemented scheme outperformed the other traditional approaches. Therefore, the effectiveness of the suggested method compared to conventional strategies has been confirmed[27]. In order to achieve efficient transmission**, Devadoss et al. (2019)** investigated a medical picture compression system using hybrid fractal and Huffman encoding that combines block BWT–MTF. This constraint is addressed by the proposed compression strategy, which uses lossy compression for the other portion of the file and region-based compression for the critical features. Based on time consumption, space savings, CR, and PSNR, the compression strategy was evaluated. The quantitative results show that the proposed method works better for MRI and ultrasound pictures than conventional methods based on PSNR[28].To achieve both objectives at the same time, **Alex et al. (2021)** have created unified network topologies based on 3D reconstruction and RNN-based picture compression. These joint models use picture compression suitable for the 3D reconstruction requirement. The integration of compression and 3D reconstruction tasks into a single framework is done for two reasons. It has provided the 3 NN topologies for 3D reconstruction and joint picture compression, taking into account run time, decompression, 3D reconstruction quality, and image. The suggested models extremely efficiently and at almost no extra expense significantly increase the compression rates with plausible 3D reconstruction[29]. In their study, **Chong et al. (2021)** examined an EMHM technique that effectively reduces the number of GSNPP while maintaining picture quality. Following the merging of histograms, the entropy of the image decreased, and the entropy reduction was further enhanced by the use of the EMHM technique. According to Shannon's first premise, the source signal entropy yielded the smallest average code word length, making it beneficial for entropy encoding to reduce picture entropy. The EMHM shown the ability to decrease the code length of entropy coding, namely arithmetic coding and Huffman, by more than 20% while maintaining excellent objective quality and subjective visual quality[30].

Zixi et al. (2021) have developed a very sophisticated MSRIC technique that exhibits significant depth. A deep picture compression model with a multi-stage representation was provided. A distinctive multi-stage network architecture was specifically developed for this project. In order to do this, separate probability models were generated for each input image in a batch, corresponding to each output channel. Furthermore, a Discrete Conditional Finite Point Machine (DCFPM) was used to enhance the precision of the entropy estimation. Experimental findings indicate that the recommended technique leads to superior perceptual outcomes over a wider range of data rates. Furthermore, ablation experiments were conducted to assess the aforementioned technologies[31]. In order to optimize the reconstruction quality of SVD and compression ratio-based image compression techniques, **Shuai et al. (2021)** designed SVSR[32], a novel lossy image compression model that retains the sparse representation data. After examining its characteristics, the singular vector was treated as a signal and sparsely expressed via sparse sampling. The recommended method's compression ratio was around 70% higher than the traditional SVD method's. The assessment on several image data sets and the experimental results with various image compression algorithms clearly show the advantages of the chosen SVSR methodology in terms of compression ratio and reconstruction quality. An image compression technique for wireless capsule endoscopy has been presented by **Malathkar et al. (2021).** The suggested method featured corner clipping, uniform quantization, Golomb Rice coding, sub sampling, and differential pulse code modulation. Due to the special characteristics of endoscopic images, a YUV color space was simplified and produced very good results. After a number of quantization and subsampling techniques were assessed for performance, the recommended compression strategy produced an 89.3% compression ratio and a PSNR of 45.1. The proposed method performed better in terms of CR and PSNR than other previously reported methods[33]. A novel picture encryption process has been created by **Xu et al. (2021)** using a compression sensing approach in conjunction with a fractional-order chaotic system. As a result of the fractional-order chaotic model, the dynamical characteristics were first studied. In order to create and execute the hardware circuit, the DSP was used. Secondly, the block feedback diffusion mechanism was used to this encryption technology. All of the cypher block's parts were decided by the plain-text block and its front. Keep in mind that this method ran the scrambling calculation and the diffusion operation in parallel. It seems that the method can encrypt digital images, according to the simulation findings. An additional finding of the security investigation was the encryption algorithm's supposed effectiveness and security[34].

Table1: summary of the related work

Ref.	Years	Technique	Limitation	Contribute
[23]	2017	EZW	The selection of the filter bank must be done with more precision.	Better PSNR and lower bit rate
[24]	2017	WCE	Design and manufacturing complexities	PSNR and compression rate enhancements
[25]	2017	Tchebichef psychovisual	The difficulty of achieving the best results	Optimized bits allocation and Minimized artifact effects
[26]	2018	HV Block partition	Need to give fractal coding	Shorter time and Simpler

DOI:http://doi.org/10.24086/cocos2024/paper.1567

		system	greater attention	distribution of two numbers
[27]	2019	QDCT	Requires reflection to varying extents	Highly skilled and calculate the DCT coefficients
[28]	2019	BWCA	No improvements were made to the ROI encoding in order to decrease the time consumption.	Higher PSNR, Lower MSE, and Decreased CR
[29]	2021	RNN	Require enhancement of achievable compression rates by maximizing the overlap between adjacent picture views.	Reduced runtime and compression rates
[30]	2021	EMHM	Three observers couldn't tell the distinction between the original picture and the EMHM output image.	reduce code length, decreased GSNPP number, and lowered entropy
[31]	2021	MSRIC	It looked at a number of effective network frameworks to reduce the parameter volume.	Enhanced precision, Optimal compression effectiveness, and Superior subjective quality
[32]	2021	SVSR	Require enhancement of the reconstruction picture matrix and refinement of the singular value selection approach	Reduced PSNR, better reconstruction quality, and a higher compression ratio
[33]	2021	DPCM	Filtration was not feasible in WCE.	High compression ratio, low computational cost, good PSNR, and no additional memory.
[34]	2021	DWT	The issue of channel resource occupation cannot be fully resolved.	Maximal UACI score, improved MSSIM, and increased PSNR

IV. CONCLUSION

The significance of picture quality has grown in the contemporary era. However, in order to store and transmit such high-resolution pictures, more memory and bandwidth are required. That is, in order to address the issue of memory storage. The literature, however, has offered a plethora of learnt picture compression models. There is, nevertheless, a continued need for an improved compression and decompression method in this area. There has been a lot of study done in this field, but there is still room for new approaches and more efficient algorithms in the ones that are already out there, especially considering the growing need for low bit rate compression techniques. Various compression strategies have been discussed in this study. Complete data security. Data compression techniques are the primary subject of this article. Based on the review, it seems that this field will keep academics interested for the foreseeable future.

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DOI:http://doi.org/10.24086/cocos2024/paper.1567