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Comparative analysis of image coding methods A State-of-the-Art Survey

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Abstract

The need for image/video storage and transmission is growing dramatically in the current era of multimedia for purposes such as imaging, online meetings, and video streaming, etc. As a result of technological advancements, there has been a steady increase in communication channel network capacity. As a result of new advanced technology and increased capacity of existing ones, bandwidth requirement is increasing exponentially.Many of the current initiatives in the field of data compression are described by it. The objective of these endeavors is to propose new methods for encoding information sources like audio, images, and video in a manner that reduces the number of bits needed to represent the source content without noticeably compromising the quality. There is a necessity of the new methods that works by reducing the source data without significantly limiting the quality of the source. This

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is the main intension of these works. In the recent, there has been a significant increase in image compression research, which corresponds with a noteworthy rise in the generation of digital data in the form of images. The objective is to preserve the vital information contained in an image while representing it in the fewest possible bits. The three major types of information that images provide are irrelevant, redundant, and useful. Within the field of image information, there is a kind of data called deterministic redundant information that can be recovered with no loss by utilizing other data that is contained in the image. On the other hand, data that is excessively detailed and goes beyond the limits of perceptual significance is categorized as irrelevant data. Conversely, the part of the material that is neither redundant nor superfluous is the valuable information. The human visual system's limitations and capabilities provide the basis for how the ordinary person interprets decompressed images. This survey provides a comprehensive overview of current lossless and lossy image coding techniques. The methods are divided into many groups, and a taxonomy of techniques is shown. The different compression techniques are compared in this study. The compression algorithm performance evaluation parameters are presented. The main issues that were discovered during the current research are then reviewed, and potential directions for the future are presented.

Keywords: Compression, digital image, network capacity, Internet, Storage, redundancy, Human visual system.

1. Introduction

Nowadays, computers are used in an increasing number of contemporary activities worldwide. Due to bandwidth and storage space limitations, as well as it takes a lot of time and money, delivering a big volume of data over the Internet or another communication channel is the most difficult challenge to address [1]. Typically, a standard film camera records at 24 frames per second. Nevertheless, 120, 240, or 300 frames per second are supported by modern video standards. A video consists of static framesor images sent once every second, while a color image consists three color panels red, green and blue. Consider the scenario of sending or archiving a three-hour, 1200x1200, 50-frame color movie file. With each pixel encoded in 8 bits, it would require approximately (1200x1200x3x8x50x10800) bits, totaling 17,797,851.5625 Megabits, equivalent to 2172.5893 Gigabytes of storage. This presents a significant challenge in terms of both storage capacity and the feasibility of transmitting it over a computer or communication channel, including the Internet. It's important to note that a color image consists of red, green, and blue color channels, resulting in a total of 10,800 seconds. Moreover, the issues of transmission medium and latency pose additional significant challenges when it comes to transporting such large volumes of data. In order to transfer the video file across a medium capable of transmitting 50 Megabits per second, it will take about (17,797,851.5625 Megabits)/50 = 355,957.03125 s = 98.8769 h. Several factors make compression required. It is essential to represent images with minimum number of bits as possible while keeping their quality, and it enables the incredibly quick transmission of enormous amounts of data over the Internet or other communication channel [2,3].Figure 1 depicts the overall flow diagram of an image compression technique.

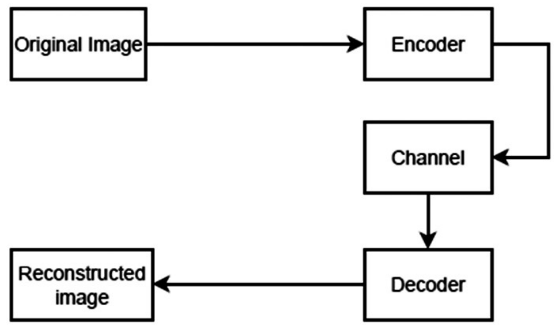

Figure 1. Image compression model flow diagram

There are several methods for compressing photos, with the optimum method having a greater compression ratio, shorter average code length, and shorter encoding and decoding times. Image coding methods are widely utilised in broadcast television, satellite images, magnetic resonance imaging (MRI), computer communication, radar-based military communication, teleconferencing, and medical imaging. Some applications, such as medical imaging, radar, and teleconferencing, require high-quality visual data while others do not. Lossy and Lossless methods are used to categorise compression, as depicted in figure 2.

While the lossy technique [4] recovers almost all data, it concurrently eliminates category information, particularly redundant data. The lossless approach [5] accurately recovers all data from encoded data. Several applications use lossless data compression. Lossless coding is commonly used for applications such as medical imaging, bitonal imaging, fax transmissions, the ZIP file format, Internet telephony, and streaming video files. A lossy technique is suitable for audio and video files because it is unlikely that the majority of consumers will notice any data loss. Lossy compression is commonly used to compress JPEG image files, which are regularly used for pictures and other complex, non-transparent still images on the web. There various methods which are offering lossless compression, some of the most prominently used coding techniques are Run-Length Encoding (RLE),Predictive coding, Area image coding, Entropy coding methods like Arithmetic coding, Huffman coding, and LZW[6].

Lossy compression aims to reduce the number of bits representing an image signal while allowing for the loss of some information, or to achieve the maximum possible fidelity given a specific transmission or storage bit rate capability. When a considerable reduction in bit rate is needed but a tiny (and potentially imperceptible) loss of fidelity is acceptable, lossy algorithms are ideally suited for natural images such as photographs. Transform-based coding methods- Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Color quantization, Chroma subsampling, and Fractal compression [7] are prominent lossy compression techniques.

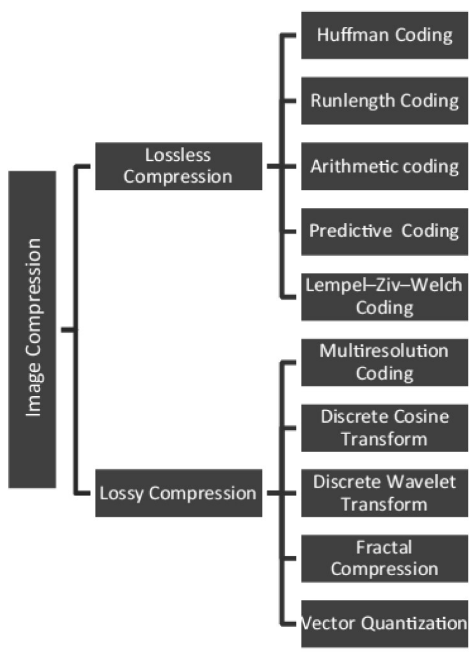

Figure 2. Categorization of image coding Techniques

Eliminating unnecessary data is essential to the compression process. In computer the digital images are represented in the form of 2D matrices of pixel intensity values. Redundant and unnecessary data are the main basis for compression techniques.

There are commonly two types of redundancy: statistical redundancy and psychovisual redundancy [8]. Coding redundancy and Inter-pixel redundancy are the two types in statistical redundancy. Spatial and temporal are the two types in Inter-pixel redundancy. The way different pixels are connected inside an image makes use of spatial or inter-pixel redundancy. To take use of temporal redundancy, the relationship between consecutive frames in a series of images is also utilized. To describe the image using the fewest number of bits possible, image compression techniques make use of both temporal and spatial redundancy. In digital image compression, there are three basic data redundancies: coding redundancy, inter-pixel redundancy and psychovisual redundancy.

1. Coding redundancy:

The representation of information is connected with redundant coding. Using codes to express the information Coding redundancy is the phrase used to characterise an image's grey levels when an excessive number of code symbols are employed to represent each grey level.

2. Inter-pixel Spatial Redundancy:

Correlation between adjacent pixels in an image produces redundancy between pixels. Hence, pixels close to one another are not statistically independent. Not all values of grey are equally probable. Due to their close proximity, the value of each pixel may be deduced from the values of its neighbours. Each individual pixel conveys a limited quantity of info. Image is depicted by exploiting the differences between the neighbouring pixels, hence decreasing interpixel redundancy.

3. Inter-pixel Temporal Redundancy:

The term "interpixel temporal redundancy" describes the statistical relationship between individual pixels in successive video frames. Temporal redundancy is also known as interframe redundancy. Using motion compensated predictive coding allows for the exploitation of temporal redundancy. Effective video compression is achieved by eliminating a substantial amount of redundancy.

4. Psychovisual Redundancy:

Human vision does not include a quantitative study of each pixel or brightness value, hence there are psychovisual redundancies. Because certain unnecessary material is not required for normal visual processing, and its removal from authentic visual information is possible.

The paper is organized as follows: introduction to image coding is covered in section 1. Brief description about research on compression algorithms covered in section 2. Section 3 covers the background concepts for lossless and lossy compression techniques. Section 4 discusses the issues and research directions in picture compression. Section 5 finishes with recommendations and a discussion.

2. RELATED WORKS

Poonlap Lamsrichan et al.[9] suggested image compression model for color images using block truncation coding method. For effective encoding of the four RVs in the 4-level BTC after color transformation a new technique is proposed and applied to the Y component. Using the 2-level BTC the chromatic components are quantized and encoded. In each block the information related number of levels is easily passed to the encoder and decoder with a simple adjustment technique is proposed. The compression ratio is controlled and adjusted by the bitmap of variable length. Without approximating the RVs, the proposed model is attaining 1 to 2 dB more PSNR than the other encoding methods based on BTC.

François Mentzer In order to develop an improved generative lossy compression system, George and his colleagues, as detailed in their research [10], have thoroughly investigated the combination of generative adversarial networks with learning compression approaches. They explore generator and discriminator topologies, training techniques, perceptual losses, and normalizing layers in particular. This approach differs from previous research in that it can be used to high-resolution photos, can operate over a wide range of bitrates, and produces visually appealing reconstructions that are also quite similar to the actual input data. Researchers bridge the theoretical and practical gaps in rate-distortion perception by a statistical comparison of the suggested method with multiple perceptual indicators and a user survey. The analysis reveals that the new strategy is superior to older ones, although employing more than twice the bitrate.

Guo Lu, Xingtong Ge et al. [11] proposed a new neural processing model, which is developed using existing conventional non-differential codecs, for preprocessing tasks before coding by the encoder to preserve the valuable supportive information for the coding process and removing the unrelated information for improving the bitrate in storing for image analysis tasks by the practical applications. In addition to do cooperatively the image analysis tasks along with the downstream machine vision methods, they proposed by the proxy network based model using conventional non-differential codecs. In this work bit rate is balanced in between subsequent operations by 20% of improvement.

Fan Zhang, Zhichao Xu et al.[12] suggested a new lossy model based on DWT,SSIM and residual networks. The network is trained using the similarity loss resulted from DWT and SSIM. The proposed network can discover how to conserve edges more effectively, because DWT coefficients can revealing edge information in an image. The suggested network can preserves the edges better by learning. The proposed model gives better performance with the competing methods in terms of PSNR and SSIM measures, specifically at less compression ratios while maintaining sharp edges accurately.

A unique color coding technique is proposed by H. H. Cheng [13] by implementing AMBTC. In this the visual quality is also evaluated using entropy. Finally it is observed that the proposed method minimizes the data around 82% with reference to results. The compression is evaluated by comparing other methods like JPEG, BTC and JPEG-LS, further it is observed that there is a significant superiority in the proposed method.

Heggere Rangaswamaiah Latha and Alagarswamy Ramaprasath et al. [14] proposed novel hybrid framework for image coding based on the wavelets, encryption and decryption schemes. Wavelets are used for compressing the images, later by using confusion and diffusion schemes the encryption and decryption is performed. The proposed model is attaining better performance in terms of performance evaluation metrics such as MSE, PSNR, SSIM, entropy, histogram, and autocorrelation comparing with similar methods.

According to what Emiel Hoogeboom and others have written in their work [15], lossless compression techniques use a statistical model to lower the expected size of the data representation without sacrificing the integrity of the data. Desirable optimization is achieved by implementing likelihood operation in flow-based models. There exist a reconstruction issues in conventional methods due to quantization. In case of proposed work, integrated and sophisticated model is implemented based on IDF. It is a flow-based model which generates discrete data. In case of IDF a flexible layer is provided to handle pieces of information generated by IDF. Compared to the most recent methods the proposed method providing better compression on different neural network approaches.

Uma Maheswari et al. [16] implemented an effective and efficient tetrolet transform to employ high compression rate with preservation of important information in medical image compression. The outcome of this approach produces high quality and low noise images.

C. A. Chen et al. [17] presented low memory and low complexity based color filter array (CFA) method using VLSI. The analysis of proposed work shows 81% of superiority with respect to JPEG-LS in encoding procedure. This work carried out for endoscopy images with respect to JPEG-LS compression ratio is increased by 17.15% and gate count is decreased by 28%.

According to Jooyoung Lee Seunghyun et al. [18], the development of contemporary communication technologies is rapidly increasing the demand for image data compression. In this technique compression ratio is boosted by combining transform and spatial coding techniques such as BTC and WHT. The efficiency of this method described as overall, the available evidence demonstrates that the recommended technique yields superior results. By dividing the input image and altering the arrangement of surrounding reference pixels, the processing dependence of the conventional algorithm is abolished. The parallel implementation considerably enhances visual quality and reduces processing time by 6–7 times, according to experimental findings.

Mishra et al. [19] investigated on several cutting edge technologies most of the technologies are belongs to deep learning architectures and lossy image compression. To provide a clearer and more comprehensive explanation, we have categorised all algorithms into several classes. The review is comprised of the contributions made by researchers in response to these challenges. There have been several discoveries made by the researchers, as well as explicit instructions for future researchers. The majority of compression-related studies assessed were published during the past four years and employ a variety of methods. The review has been summed up by providing image compression researchers with a new perspective.

Mu Li Wangmeng et al. [20] proposed multispectral image based coding, which reduces the space and time required to transmit the information over network. In this work extended BTC algorithm is implemented, which reduces the bits required to store the information. The parameters like MSE, SNR, PSNR are evaluated along with compression ratio.

3. BACKGROUND THEORY

In the last two decades, a variety of compression algorithms have been developed to address the severe problems associated with digital images. There are two main categories into which the compression techniques can be divided: lossy compression and lossless compression [21][22].

3.1 Lossy Compression techniques

As depicted in figure 3, the majority of lossy compressors are three-step algorithms, each of which satisfies the aforementioned three categories of redundancy. The initial transformation eliminates inter-pixel redundancy and effectively groups data. To eliminate redundancy caused by psychovisual data and to represent the dense information using the minimum number of bits, quantizer is utilized. The quantized bits are then efficiently encoded in order to take advantage of the redundancy and achieve extra compression.

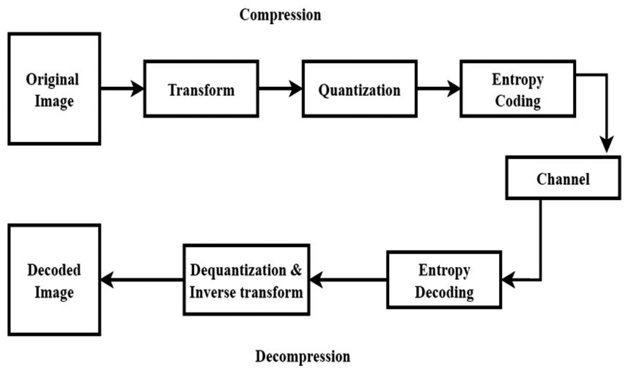

Figure 3. Lossy image compression model

1. Quantization

It is a process of mapping technique relates to many to one i.e many values are replaced with a single value. Further this mapping is divided into two types scalar and vector. In case of scalar one to one mapping is proposed, but in vector quantization code book is represented for a set of values. In the case of decoding from the code book index is considered. In the case of vector quantization code book need to be generated for a specific set of data with respect to this there is a distortion in compression. To overcome this problem variable base vector quantization is proposed.

2. Transform Coding

In this method encoding and quantization mechanisms are implemented. Generally this kind of method used for lossy compression. Depending on the application utilization of transformation id differed.

3. Block Transform Coding

In this coding method, the entire image is partitioned into small blocks by exploiting the correlation between pixels. Each block is quantized and coded independently. It is used in JPEG image compression, in this image is partitioned into 8x8 pixel blocks, DCT, Huffman or arithmetic coding are used. At extremely high compression ratios, blocking (or tiling) artefacts become visible with this method.

3.2 Lossless compression techniques

Lossless compressors [23] are commonly two-step algorithms, as depicted in figure 4. In the first stage, the original image is converted into a new format that decreases interpixel redundancy. An entropy encoder eliminates superfluous coding in the second stage. The lossless decompressor is the ideal counterpart to the lossless compressor.

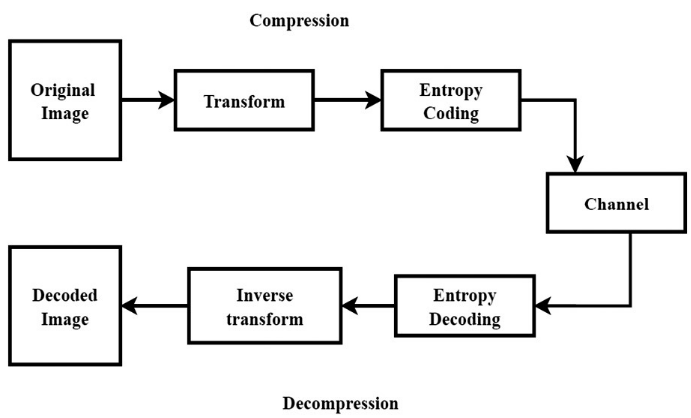

Figure 4. **Lossless image compression model**

1. Run-length coding

It is a simplest mechanism to implement in lossless compression. In this method number of runs for a particular value considered as a pair (L,V) here L indicates the number of runs, and V indicates the value of the given runs. This method is successful on bilevel image processing. When long runs are repeated for same value then only it provides good compression ratio.

2. Lossless predictive coding

Finding the difference between the predicted pixel value and the current pixel value is how Lossless Predictive Coding determines a new pixel value. This is done by comparing the current pixel to the predicted pixel value.To put it another way, this is the difference between the actual value of a pixel and its anticipated value is what is meant to be understood as the "new information" on that pixel.The strategy of lossless predictive coding is to only extract and code the new data from each pixel, hence removing the inter-pixel redundancies of closely spaced pixels.

DPCM is a technique for lossless image compression based on predictive coding (differential pulse code modulation).This is the foundation upon which lossless JPEG compression is built.

By segmenting the image into chunks and computing prediction estimates separately for each chunk, adaptive prediction, a type of lossless predictive coding, delivers strong prediction performance. This method is used to reduce the amount of data that must be stored in order to store prediction coefficients. Furthermore, it can be integrated with other techniques to create a high-performance hybrid system.

3. Multi-resolution coding

The HINT (hierarchical interpolation) technique for multi-resolution coding operates through subsampling. Initially starts with low resolution image and generates successively higher-resolution images by interpolating pixel values. Both the original low-resolution image and the differences between these interpolated values and the real ones are saved. Compression is achieved because both the error values and the low-resolution image can be stored using fewer bits compared to the original image.

Additionally, Burt and Adelson devised the Laplacian Pyramid, which is another multi-resolution picture reduction technique. This technique entails downsampling, which divides the number of pixels at each level in half and produces consecutive lower-resolution copies of the original image. The discrepancies among succeeding resolutions and the least resolution image are used to rebuild the original input image. Nevertheless, this technique reduces the possibility of obtaining high compression ratios by increasing the amount of data values more than four third of the size of original image. Smaller images with different resolutions are generated when using multiresolution coding.

In general, multiresolution techniques reduce the entropy of the image. The hierarchical tree structures created by these techniques can be leveraged to achieve greater compression in some cases.

3.3 Parameters to evaluate performance of the compression methods

When evaluating the assessment of an image coding system, the file size of the encoded representation and how well it creates the decoded image from its encoded representation should be the primary considerations. There are two types of coding algorithms: lossy compression and lossless compression [24]. Assessing the overall performance of such an algorithm is challenging due to its reliance on irrelevant and redundant image pixels to determine compression behaviour [25].

1. Compression Time (CT)

It quantifies the duration of the compression and decompression processes. When compression and decompression times are acceptable, it is assumed that the applicable algorithm is suitable in terms of the time factor. For this factor, the capability of the hardware components varies between machines. The temporal complexity of a compression algorithm influences compression time as well. Using an optimum method, compression and decompression times can be reduced to a minimum even with limited hardware resources. In the context of image processing, compression and decompression times must be determined to estimate how long the algorithm will execute..

2. Compression Ratio (CR)

One of the most popular and so essential metrics is the compression ratio. The compression ratio measures how much smaller an encoded version of a picture is compared to the original.

$$Compression\ ratio = \frac{size\ of\ compressed\ image}{size\ of\ original\ image} \quad (1)$$

3. Compression Factor (CF)

It is the reverse of the compression ratio, this is the ratio between the original image's size and the compressed image's size.

$$Compression\ factor = \frac{size\ of\ original\ image}{size\ of\ the\ compressed\ image} \quad (2)$$

4. Mean Squared Error (MSE)

A lossy image compression algorithm discards some of the pixel intensity data when compressing an image. There are a number of pixels that are distinguishable from their counterparts in the original image. MSE is an error metric that is utilised in the process of comparing the uncompressed and original versions of an image. Estimates of the cumulative squared error are made for every pixel in the original image and the corresponding pixel in the decompressed image. The formula for calculating the MSE is repressed as follows:

$$MSE = \frac{1}{MXN} \sum_{y=1}^{M} \sum_{x=1}^{N} [I(x,y) - I'(x,y)]^2 \quad (3)$$

Here, *I(x,y)* denotes the pixel intensity value in the original image *I`(x,y)* pixel intensity value in the corresponding decoded image, and *M, N* represent the resolution of the image

5. Peak Signal to Noise Ratio (PSNR)

The peak signal-to-noise ratio in short PSNR serves as a metric to gauge the relationship between the highest achievable intensity value (signal power) in an image and the level of introduced noise, influencing the image's quality when represented in logarithmic decibels. When assessing the original and decompressed versions of an image, a lower PSNR value signifies more noticeable numerical disparities, while a high PSNR value signifies image quality is high. The PSNR is defined as follows:

$$PSNR(dB) = 20X\log_{10}\left(\frac{I_{Max}}{\sqrt{MSE}}\right) \tag{4}$$

Where, I_{Max} is the maximum intensity value in the image.

6. Structural Similarity Index Measure (SSIM)

One often used perceptual metric to evaluate the loss in image quality is the Structural Similarity Index (SSIM). SSIM requires two images from the same scene or capture, just like PSNR calculation does. SSIM assesses the degree of similarity between the original and decompressed images, as opposed to just quantifying visual similarity, like PSNR does. The SSIM formula, derived from three comparison measurements between samples x and y, is presented in the following equations

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

$$c_3 = \frac{c_2}{2}$$

Equations 5, 6, and 7 can then be weighted and combined to calculate the SSIM. Once the SSIM index hits 1, the original and decompressed images are identical. SSIM index result is a decimal value between -1 and 1. When an image compression process is lossy, the SSIM value is not 1, but it must be very close to 1 in order to be acceptable.

$$SSIM(p,q) = [l(p,q)^{\alpha} X c(p,q)^{\beta} X s(p,q)^{\gamma} \quad (5)$$

Here, *l(p,q), s(p,q), c(p,q),* denotes the luminance, structure and contrast and *α, β, γ* denotes the weights.

7. Compression Gain:

The gain attained in the compression is calculated with the following formula.

$$Compression\ Gain = 100 \times \log_e \frac{Original\ image\ size}{Compressed\ image\ size} \quad (6)$$

8. Saving Percentage:

It is also used to represent the space set aside in representing the image.

$$Saving\ percentage = \frac{Original\ size - Compressed\ size}{Original\ size}\ \% \quad (7)$$

9. Bits per pixel:

It is used to represent the number of bits used to represent a pixel with respect to the reference image is evaluated by

$$Bits\ per\ pixel = \frac{size\ of\ compressed\ image}{Total\ number\ of\ pixels} \quad (8)$$

10. Entropy:

Visual quality is represented in terms of information gained from fusion and is evaluated as

$$H(X) = -\sum_{i=1}^{n} p_i \log_2 p_i \quad (9)$$

It is an important parameter in the evaluation of compression schemes, especially in lossy compression schemes.

4. CHALLENGES AND RESEARCH DIRECTIONS

Important research needs in the area of image compression includes the elimination of correlated information from the image and the production of compressed images with lower PSNR and lower blocking arti-facts. There are a large number of successful and popular applications in both the consumer and business markets, making the area of image processing quite diverse and gorgeous. To further push the boundaries of imaging technology, however, there are still many technological obstacles to overcome. The ability to successfully read and comprehend this enormous and complicated amount of visual data is one of two major trends, along with the constant improvement in image and video content quality and realism. This is by no means a comprehensive list; it just touches on a few of the many fascinating subjects that are out there, such as medical imaging, forensics, computational imaging, and information security. Significant progress in these fields is anticipated as a result of the convergence of image processing, artificial intelligence, computer vision, optics and many more. Therefore, in order to encourage these innovations moving forward, multidisciplinary collaborations including individuals from both academia and industry are essential.

5. CONCLUSION

Image compression research has been greatly impacted by recent developments in picture technology. Over the past few decades, as imaging technology has advanced, the study of image compression has become important. With the growth of mage technology, more data must be carried, necessitating an increase in bandwidth. So, in order to lower the required bandwidth, the image should be compressed prior to transmission. It is necessary to compress the image, the original image may be reconstructed from the compressed image. The article explores different lossy and lossless picture compression algorithms. Image compression dramatically reduces the cost of both transmission and storage. Each approach for image compression has its own unique applications, and new ones are always being developed to achieve higher compression ratios. No information is lost during the compression or decompression of an image with lossless compression. On the basis of multiple technologies, it is concluded that compression ratio, PSNR, MSE, and bits per pixel can be used to evaluate the quality of an image compression technology.

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