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A Review on Recent Developments in Image Compression Techniques

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Abstract

In recent times, the digital image compression has indeed been the subject of a great deal of study. As a consequence, new and improved image compression technologies are always being developed. Using digital pictures efficiently requires the use of specialized strategies to limit the number of bits necessary for their display. In the field of the Digital Image Processing, it really has led to an immediate increase. We don't only focus on lowering the size of a picture, but we also focus on doing thus without sacrificing the quality or content of the image. Images may be compressed using lossy or lossless approaches. The study highlights the merits and downsides of both types of compression. A better understanding of the advantages and disadvantages of different compression methods may be gained through this investigation. Here, an overview of several picture compression algorithms is provided so that researchers may gain an idea of the efficient methods to be applied.

Keywords: Image Compression, Lossyand Lossless Compression

1. INTRODUCTION

As information technology advances, our everyday lives are increasingly filled with multimodal information like text, pictures, and audio, which presents significant storage as well as communication issues. So the data compression is extensively employed with in transmission, storage, as well as transfer

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of digital information [1]. The number of photographs created is much more than the no. of other sorts of data. It's fortunate that photos include a lot of the redundant information, like geographical temporal redundancy, redundancy and the visual redundancy, among others. Furthermore, the human eye isn't affected by differences in picture quality or color contrast. There has been an increase in interest in picture compression as a result of such developments.

It is the process of compressing digital photographs by using data compression. Image data must be reduced in redundancy so that it may be stored or transmitted more efficiently. The storage as well as the transmission bandwidth needed to store and transmit the uncompressed multimedia data (graphics, music, as well as video) is enormous [2][3]. No matter how quickly storage density, the processor speed as well as the digital communication system performance improve, demand for the data storage space as well as the bandwidth continues to exceed the capabilities of currently available technology. Since the recent proliferation of the data-intensive multimedia-based online applications, compression of the signals and pictures has become an essential part of both storage and transmission technologies.

2. LITERATURE REVIEW

An image compression as well as the classification system employing multi-task learning has been presented for the visual Internet of Things (IoT) applications [4]. Generative Adversarial Networks (GANs) are discussed in detail, including the encoder, the generator, the discriminator, quantizer, and classifier to do picture compression as well as the classification at same time. Compression as well as classification is made possible by quantized latent representation, which is at the heart of the proposed architecture. With the perceptual quality, GANs are able to accomplish the low-bitrate compression as well as minimize data.

Also, several sequences forecast model was tested for lossless compression of 3D medical pictures (16-bit depth) using various input configurations including sampling strategies [5]. Authors want to figure out how to get the suggested Long Short-Term Memory model (LSTM) for achieving the high compression ratio as well as quick encoding-decoding speeds. Datasets obtained from several hospitals, representing various body segments as well as the scanning modalities, were used for experimental assessment (CT including MRI). When compared to earlier approaches, the new ology enables for simple parallelization, resulting in a decoder speedup of up to 37 per second. The trained models surpass well-known lossless approaches by between 17% and 12% when it comes to compressing 3D medical pictures without losing quality. For the lossless compression of the volumetric medical imaging, this will be the first work which focuses on the voxel-wise predictions.

The Entropy Minimization Histogram Mergence (EMHM) has been developed as a method to minimize the amount of the Gray Scales with Nonzero Pixel Populations (GSNPP) without sacrificing picture quality [6]. Paper demonstrated theoretically that now the entropy of such a picture is lowered following histogram merging, and that this reduction is maximized using EMHM. Since the Shannon's first theorem states that the minimal the average code word length per source symbol is equal to entropy of source signal, the reduction in picture entropy is beneficial for an entropy encoding. Experimental evidence shows shown EMHM is capable of a 20% reduction in overall code length whereas still maintaining excellent picture quality when used with entropy coding methods like Shannon, Huffman, and the arithmetic coding. Another benefit of utilizing EMHM to preprocess photos is that it may increase performance of several traditional lossy image compression algorithms, including such Joint Photographic Expert Group 200 (JPEG2000), Better Portable Graphics (BPG), as well as other members of such Joint Photographic Expert Group (JPEG).

A new hybrid picture compression and encryption approach is presented in this paper, allowing compression within the encryption domain [7]. Permutation as well as the substitution is used to encrypt the data, which is grounded on Chaos theory. The shuffled picture is first compressed losslessly, and afterwards compressed bit stream is reassembled into 8-bit parts for the replacement step. Medical picture compression as well as encryption may benefit from the suggested method's lossless nature. Proposed methods have been tested and indicate that they are able to meet security requirements while maintaining compression efficiency of the lossless algorithms. Entropy encoder performance may be improved by using the data-to-symbol mapping approach using no. theory to the represent contiguous pixels as a single block of values. For Uncompressed Color Image Database (UCID) dataset, compression savings increased from 5.76% to 15.45 % when using this approach.

Compressed pictures are often used in computer vision applications. JPEG2000 and other well-known the image compression standards are commonly utilized [8]. The problem, though, is that they don't take into consideration the exact end-goal. Author presented unified network topologies for both picture compression as well as the 3D reconstruction grounded on previous work on the Recurrent Neural Network (RNN) based image compression. The picture compression provided by such the joint models is specifically designed for the job of 3D reconstruction. As comparison to the JPEG2000 compression, suggested models result in better 3D reconstruction performance. A wider variety of the compression rates may now be used to rebuild 3D models. The results also demonstrate that this could be done very rapidly and nearly at no extra cost in order to gain compression on the top of computation currently necessary to do 3D reconstruction work.

When using compression approach based on the Singular Value Decomposition (SVD), it is recommended that more than the half of smaller singular values as well as accompanying singular vectors be omitted SVD [9]. Despite the fact that such deleted regions include some noise as well as the fuzzy elements, they also provide valuable information for picture reconstruction. Singular Vector Sparse Reconstruction (SVSR) is a revolutionary lossy image compression approach that retains sparse representation data of the additional singular vectors to improve the compression ratio as well as the reconstruction quality of the SVD-based image compression. The singular vector is treated as a signal as well as expressed sparsely using sparse sampling depending on the examination of singular vector's features. As a result, the suggested approach has the compression ratio that really is around 70% more than the typical SVD method. Proposed SVSR technique outperforms other image compression algorithms in terms of compression ratio as well as the reconstruction quality when tested on a variety of picture datasets.

Generative Adversarial Block Truncation Coding (GABTC) is the compression models with many variances have been presented [10]. Multi-layered Deep Neural Networks (DNNs) using Generative Adversarial (GA) neural models are used to build GABTC. The use of both the GA models as well as the Block Truncation Coding (BTC) concepts dramatically improves block building and restoration. Varieties of E-Learning pictures (Color and Grey Scale) as well as the compression quality assessments are used in this study to evaluate overall the model complexity as well as the efficiency.

Here, Author developed a novel approach of compressing Remote Sensing Images (RSIs) that is influenced by standard compression methods and uses the Symmetrical Lattice Generating Adversarial Network (SLGAN) [11]. Numerous symmetrical encoder-decoder lattices are being used to develop a generator that first generates deep representative codes of pictures as well as then decodes them, as shown in the figure. Discriminators are built for every encoded as well as the decoded lattice pair to undertake adversarial learning. The cooperative learning approach is suggested to provide training jointly pairs of the symmetric lattices within generator whenever the multiple discriminators are employed for all lattices. An Enhanced Laplacian of Gaussian (ELoG) loss is used to train SLGAN to improve edges, the contours, and the textures within decomposed RSIs. SLGAN outperforms other current state-of-the-art algorithms in experiments using panchromatic pictures from GF2 satellite.

The Sparse Flow Adversarial Model (SFAM) is a new way for compressing data that has been presented [12]. For robust compression, it leverages an advanced the generative framework that learns an efficient and reversible mapping across picture distributions. The sparse adversarial map is also incorporated into SFAM to limit the SFAM to create more sparse features for optimal compression purposes. In order to demonstrate the method's efficacy and resilience, several tests are carried out on various datasets. SFAM, on the other hand, requires just a single training set and performs well on three separate datasets, demonstrating the resilience of the algorithm as described.

3. TYPES OF IMAGES

Images may take up a lot of space in Random Access Memory (RAM) as well as storage when they're in their raw form. Streaming a picture across the network may use a lot of bandwidth if indeed the image isn't compressed properly. The followed are the most common types of images:

1. **JPG:** JPG is best suited for the continuous tone pictures that include a large number of colors, such as photos [6]. JPG reduces the amount of data stored in photographs by removing the types of details that the human eye is unlikely to detect. It saves data in the form of 24-bit color images. JPG has a configurable compression level. Even at great magnification, the human eye is unable

to perceive any difference between the original and the compressed picture. More than about 20 compression factors are generally acceptable.

2. **Tagged Image File Format (TIFF):** The picture file format which can be used for both lossless and lossy compression is TIFF. For the 24-bit as well as 48-bit totals, it typically stores 8 or even16 bits per color (red, green, blue). The file also contains information about the methodology used to save the images. A lossless picture storage format, TIFF is the almost solely employed for this purpose. There are no online images that employ TIFF files. TIFF files are large and, more crucially, are not visible in the majority of web browsers.
3. **JPEG:** A good approach to save the 24-bit photographic pictures, which are often used in the imaging as well as the multimedia applications, is to utilize the JPEG. A 24-bit JPEG picture on the Video Graphics Array (VGA) display looks better than an 8-bit (256 color) JPEG image on the same device and is at its best whenever shown on 24-bit display hardware (that is now the quite inexpensive). Color or even the gray-scale continuous-tone pictures of real-world objects, such as photos, video stills, or any sophisticated graphics resembling natural scenes, may be compressed using JPEG. It is unreasonable to think that JPEG would effectively compress animations, the ray tracing, line drawing, and other types of vector graphics such as black-and-white texts. Furthermore, while JPEG is already being used to the compress motion video, the standard does not provide any specific provisions for this use.
4. **Graphics Interchange Format (GIF):** Useful for the pictures with fewer than 28 colors, gray scale graphics, including black as well as white text is the GIF. GIFs may only be used on pictures with the 8-bits per pixel or even less, that implies 256 or even less colors are supported. Most color pictures have a pixel count of 24 bits. The picture must first be converted from the 24 bits to the 8 bits before it can be stored in GIF format. GIF seems to be the lossless file format for images. As a result, only pictures with 256 colors or less may be considered "lossless" in the context of GIF. GIF might lose 99.998% of the colors in a beautiful, true-color picture. Since each picture may only have 256 colors, it is not suited for photographing photos.
5. **(Portable Network Graphics) PNG:** Images may be compressed without sacrificing quality by using the PNG file format. PNG files may often compress images by 10% points – 30% points more than GIF files. When the picture gets compressed, it enables for trade-off between the file size as well as image quality. More colors and lower files are also advantages of this method. Partial transparency is also supported in PNG. For example, fades as well as the antialiasing for such text might benefit from the partial transparency.
6. **BMP:** Windows' Bitmap also represented as (BMP) file type is used to store graphical files. BMP files are often huge since they are uncompressed, but their simplicity, widespread usage, and compatibility with Windows programs make them a worthwhile trade-off.

7. **RAW:** When it comes to the digital cameras, RAW consists of a variety of raw picture formats (output). For the full-size processed photos from same cameras, this format often uses lossless or almost lossless compression, resulting in substantially reduced file sizes than TIFF. Unlike TIFF files, raw images do not follow any standards and are four times larger. The drawback is that every other manufacturer's RAW format is distinct, necessitating the use of such proprietary software in order to examine the photographs.

4. PRINCIPLE OF IMAGE COMPRESSION

The nearby pixels throughout most photographs are correlated, which means that now the information they carry is redundant. The first step is to identify a less connected visual representation. Redundancy and relevance reduction constitute two of the most important aspects of compression. In order to reduce redundancy, signal source (image or even video) must be cleaned up. Reducing the signal's irrelevance eliminates sections of signal that would not be detected by signal receiver, such as the Human Visual System (HVS). There are three main forms of redundancy:

A. Coding Redundancy: An information or sequence of events may be represented by a set of the symbols (texts, numerals, bits, etc.) known as a code. Using a series of code symbols, known as the code word, every item of the information or event is encoded. Every code word's length is determined by the no. of the symbols it contains. Most of the 2-D intensity arrays utilize 8-bit codes, which include more bits than the necessary to express the intensities in such arrays' data.

B. Spatial Redundancy and Temporal Redundancy: Most of the 2-D intensity arrays include spatially linked pixels; therefore, information is redundantly represented in correlated pixels' representations. Temporally connected pixels in the video sequence also share information.

C. Psycho-visual Redundancy: It is indeed a redundancy comparable to the different sensitivity of individual eyes to everyone picture inputs. As a result, it may be sufficient to exclude some less important information from our visual processing.

Compressing a picture typically involves the following steps:

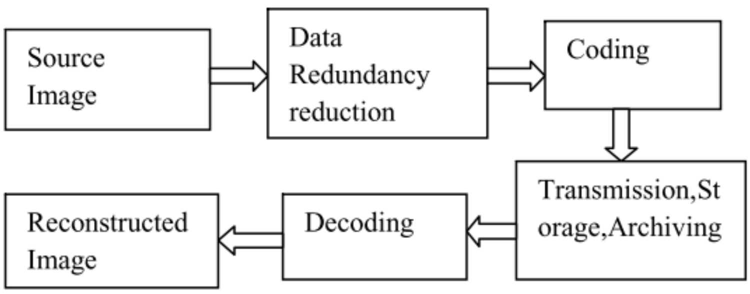

Figure 30 Steps of Image Compression [13]

- To get a desired result, it is necessary to provide the target image's Rate (number of bits available) as well as Distortion (permissible mistake).
- Classifying the picture data according to its significance
- As little distortion as possible is achieved by dividing all available bit budget throughout such classes.
- Use bit allocation data generated in step3 to quantize every class independently.
- Use the entropy coder to encode every class independently and save the results to a file. Reconstruct the picture from compressed data is generally a quicker process than compressing it. It's a lengthy process.
- An entropy decoder may be used to read inside quantized data from file into memory. (Step 5 is reversed).
- Reduce the data's precision by de-quantizing it. (Step 4 is reversed).
- Create a new picture. (Step 2 is reversed)

5. IMAGE COMPRESSION TECHNIQUES

Various compression techniques have indeed been developed during last 2 decades in order to meet the primary issues of digital image. It's possible to divide such compression techniques into two basic categories: the Lossy Compression as well as the Lossless Compression [13] [14].

1. **Lossy Compression methods**

Most lossy compressors (Fig 2) comprise 3-step algorithms, all based on the three forms of redundancy described above. The first step is a transformation that removes the redundant information between pixels in order to effectively group data. It is then quantized to remove any the psycho-visual redundancy so that the information may be represented with as little bits as possible. Quantized bits are therefore the resourcefully encoded in order to benefit from either coding redundancy or reduce the file size further.

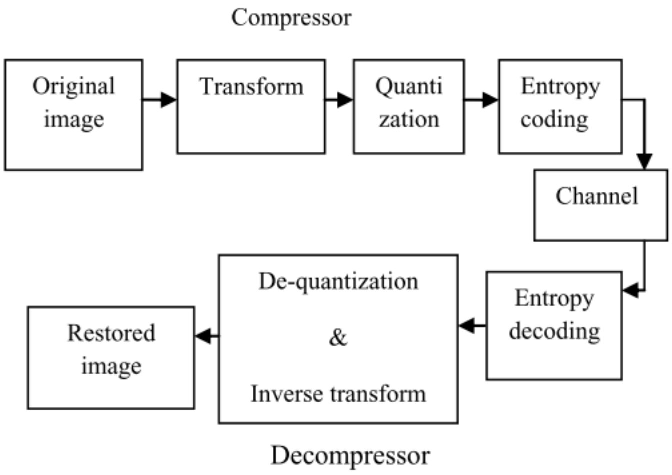

Figure 31 Lossy image compression [15]

It is the mapping from a collection of the values to a single value which is called quantization. Quantization may be divided into two basic categories: scalar as well as vector. On every value, Scalar Quantization (SQ) applies a different to one mapping. Utilizing a few proximity dimensions, Vector Quantization (VQ) substitutes each input pixel block with index of the vector inside the codebook. When a decoder gets an index, it goes to codebook to find the corresponding vector.

Photos and other natural pictures may benefit from lossy compression algorithms since they can be used to reduce the bit rate while still maintaining a high level of fidelity.

Transform coding: Lossy picture compression is often achieved via the use of transform coding. This technique uses a reversible as well as linear transformation to turn the original picture into a collection of transform coefficients. After that, coefficients being quantized as well as sequentially coded inside the domain of transformation. In a variety of contexts, transforms are employed. Distinct Karhunen-Loeve Transform (KLT) depending just on Hoteling transform is perhaps the most beneficial for its own information-packing capabilities but is typically not practical because it is difficult to figure out. Additionally, the Distributed Fourier Transform (DFT) and the Discrete Cosine Transform (DCT) are quite accurate in their estimation of KLT's energy-packing efficiencies. Since DFT coefficients require almost twice as much storage space as DCT coefficients, DCT is the most common practical transform system being used today.

DCT: For picture and audio compression, the DCT is a popular choice of algorithm. Consider JPEG images. Digital Signal Processing (DSP) is used to transform data into the sequence of the cosine waves with varying frequencies. While Fourier Transforms employ complex numbers as well as sine including cosine functions, DCT use just real coefficients as well as Cosine functions. Because fewer functions are required to the approximate a signal using Cosine functions, they are far more effective for the signal compression. In both the Fourier as well as the DCT, data is transformed from a spatial to the frequency domain and then back again.

Discrete Wavelet Transform (DWT) In the DWT, each picture is represented as the sum of a number of wavelet functions, each with a distinct location as well as the scale, referred as the wavelets. The hierarchical filter structure is often used to construct discrete wavelet transform. The pre-processor generates picture blocks to which this filter is applied. The approximations at level j+1 as well as the details in 3 dimensions are decomposed into four components using two-dimensional DWT (horizontal or vertical or even diagonal).

The Fractal Compression (FC) It is based on the notion that some sections of a picture resemble the other parts of the very same image inside the FC process. Its geometric forms that are transformed into "fractal codes" using fractal algorithms that are then utilized to decode the encoded picture. When a picture is transformed into the fractal code, it loses its connection to a certain resolution; it is now resolution-agnostic. Pixel-based compression introduces artifacts and reduces sharpness when resizing a picture to fit a smaller screen.

2. Lossless Compression Methods

Figure 3 shows a typical lossless compressor method. The first step is to convert the original picture to a format that reduces the amount of duplication between pixels. Using an entropy encoder, we remove coding redundancy inside the second phase. When a lossless compressor is used, lossless decompressor performs an exact opposite function.

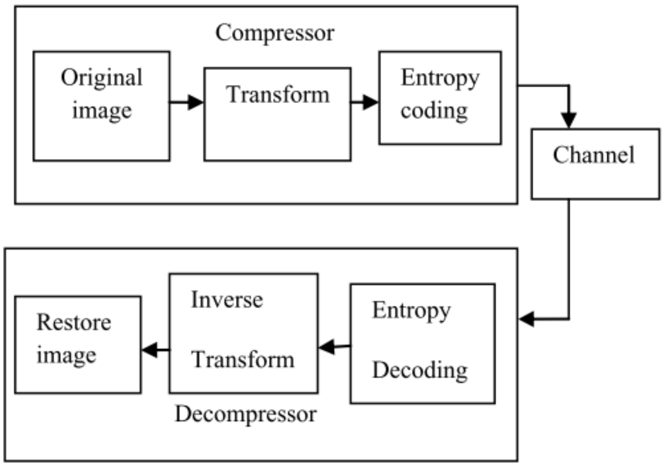

Figure 32 Lossless image compression [15]

When data is replaced by the (length, value) pairs, "value" is indeed the repeating value as well as "length" is indeed the repetition count. Since a lengthy run of such a value inside a gray-scale picture is rare, this strategy works exceptionally well when compressing bi-level images. The gray-scale picture may be broken down into the bit planes as well as compressed one bit plane at a time. One type of the run length coding includes effective run-length coding.

Lossless predictive coding: Every pixel's value may be predicted using the values of the neighboring pixels, which is called lossless predictive coding. A prediction error rather than the actual pixel value is stored in each pixel. Less storage space is needed to retain minor mistakes since they're so little in comparison to real value.

Differential Pulse Code Modulation (DPCM): It is possible to compress lossless images using DPCM that uses predictive coding. The Lossless JPEG compression is built on top of it. The adaptive prediction is indeed a modification just on lossless predictive coding which separates the picture into the blocks as well as calculates equal prediction coefficients for each block individually to achieve excellent prediction performance. It may also be used in conjunction with another scheme to create a more efficient coding method.

Hierarchical INTerpolation (HINT): It is a subsampling-based coding technique that allows for many resolutions to be encoded simultaneously. With a low-resolution picture, it starts by interpolating pixel values to produce higher resolutions. The initial low-resolution picture and the errors between the interpolation values as well as the true values are saved. The low-resolution picture as well as error values may both be recorded with fewer bits than that of the real image, therefore compression is possible.

Laplacian Pyramid: One of the picture compression methods created by Burt as well as Adelson is the Laplacian Pyramid. In order to achieve a two-fold reduction in pixel count at each scale, it down samples the original picture and creates successively lower quality versions of the original. A complete picture reconstruction is possible by storing and using the changes between successive resolution versions, as well as the lowest resolution image. However, since the quantity of the data values is indeed improved just 4/3 of the real picture size, it cannot achieve a higher compression ratio.

6. RECENT DEVELOPMENTS IN IMAGE COMPRESSION TECHNIQUES

Arithmetic Encoding: The lossless encoding method known as "Arithmetic Encoding" compresses data by representing it as discrete intervals on a number line ranging from 0 to 1. Essentially, it separates the 0-1 range into the smaller intervals, each corresponding to a different probability for each of the message's symbols to appear. The first symbol then picks an interval that is subdivided into the smaller intervals by a second symbol in the chain. Such intervals may be selected using a next input symbol. With each symbol, the specified range narrows, allowing any no. in the final range to constitute a message. Increasing the accuracy of the input code by one bit increases output code precision by one bit. In terms of symbol coding, AC is by far most efficient way. IBM created the Q-Coder, a variant on the arithmetic coding, in the late year 1980s.

Entropy: The smallest dataset required to transmit a given quantity of information is called entropy of dataset. Entropy coding methods include Huffman coding, Lempel-Ziv (LZ) coding, as well as the arithmetic coding. Entropy Coding employs a technique known as the redundancy to reduce file size. Repetitive characters are written down, and rather than reusing them at every pixel, the locations of such pixels are noted as well as they are all marked as having the same sign. So-called the non-lossy coding prevents data loss.

Lempel–Ziv–Welch (LZW) Coding: Repetitive substrings are replaced in the input data by references to previous occurrences of strings using LZW Coding LZ77 as well as LZ78 are two methods of dictionary-based compression. With a sliding window, LZ77 finds previously encountered substrings as well as uses the (position or even length) pair to refer back to the original. Substrings are replaced using index within dictionary that is dynamically constructed from the input file. Grounded on such concepts, LZW is indeed a technique for compressing data.

Huffman coding: The Huffman coding is indeed a data compression technique that uses entropy encoding. For example, Huffman Coding uses a variable length code, wherein the short code words are given to more often occurring values as well as the longer code words being assigned to the less commonly occurring values. If you compare the Huffman algorithm to others, it produces the fewest redundant codes. Compression systems including, MPEG2, JPEG, H.263 or H.264 have all employed Huffman coding to great success.

Quarter-tree decomposition: It is possible to decompose a picture using Quarter-tree decomposition technique, although the compression ratio isn't really particularly high. However, extracting the interactive function that is so crucial towards the quality of such reconstruction is challenging, and large calculations are also required. Fractal coding as well as the Quarter-tree decomposition both use image decomposition as their foundation.

It's easy and quick to figure out how to use the Quarter-tree decomposition picture compression technique. In addition, it works with images that are based on the data in the picture. Rectangle Segmentation and Sparse Matrix Storage (RSSMS**)** compression technique, that considers neighboring pixel spots meeting the consistency criteria to be one picture block, this problem may be remedied in one step. As an added benefit, the picture block may be rectangular rather than square, which is constrained by 2n. This allows for a smaller file size while maintaining a higher compression ratio. Combining the storage technique of the sparse matrix with image compression may increase the compression ratio even more. Images that have been compressed using another means may still benefit from correlating them. However, the compression ratio is limited, particularly for intricate photos.

7. EVALUATION OF COMPRESSED IMAGE

The quality of a picture may be assessed using a variety of metrics, including Peak Signal to Noise Ratio (PSNR) as well as Mean Squared Error (MSE). This section focuses on a variety of factors. The MSE measures the sum of the squared differences between the original and compressed images.

$$\mathrm{MSE} = \frac{1}{\mathrm{MN}}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j) - y(i,j))^2$$

The image's maximum error as compared to its compressed counterpart is used to calculate the PSNR:

$$PSNR(dB) = 10log_{10}\left(\frac{255^2}{\text{MSE}}\right)$$

In this case, i(x, y) represents the real picture, z(x, y) represents the estimated version (that is really a decompressed image), whereas M, N represent images' dimensions. To put it simply, a lower MSE indicates a lower level of error, which in turn results in a higher PSNR number.

8. LOSSY vs. LOSSLESS COMPRESSION

Using lossy techniques may reduce the size of the compressed file while still matching the application's requirements, which makes them preferable to lossless ones in certain situations.

Compression of sound, pictures, and videos is often done using lossy techniques. When it comes to compressing files, lossy video codecs are virtually always superior to their audio as well as still-image counterparts in almost every case. At 10:1 audio compression, the quality is unaffected; at 300:1 video compression, the quality is noticeably reduced. Similar to compressed music, lossy-compressed still photos may be reduced to a tenth of their original size while maintaining the same image quality.

User acquisition of lossy compressed files (e.g. to save download time) may result in a file that is substantially different from the true at a bit level, but that is unrecognizable to a person's senses for most practical uses. For instance, the fact that perhaps the human eye could only see certain light frequencies is taken into account in several ways. To understand how sound may be drastically compressed without affecting its perceived quality; psycho-acoustic model is used to explain how this occurs. Compression artifacts are defects that may be seen or heard as a result of lossy compression.

Statistical redundancy is often used in the lossless compression methods to replicate sender's data more succinctly but still perfectly. Because almost all the real-world data contains statistical redundancy, the lossless compression is possible. Because the letter 'z' is less prevalent than the letter 'e' in English literature, it is less likely to follow letter 'q' than just the letter e.

It's possible to compress data using the lossy data compression if you're okay with some quality being sacrificed. It's possible that, for instance, a viewer of an image or a television show would not realize if some of the most important aspects of the scene are missing. Likewise, a listener may mistakenly believe that two audio recordings are the same despite the fact that one lacks information that the other has. It is possible to reduce the size of a photo, video or audio file using the lossy data compression methods.

When it comes to data compression, lossless techniques preserve the original data, whereas lossy methods sacrifice some data to achieve a greater level of compression. A few files will never be able to be compressed using the lossless data compression techniques, and this is true for all algorithms that attempt to compress data that has no identifiable pattern. When trying to the compress data which has previously been compressed or data which has been encrypted, even an expansion is almost always the consequence.

It's also possible that the lossy data compression would get to the point wherein compressing again doesn't work, but some really lossy technique, such as one that constantly eliminates the final byte of each and every file, would always compress file until it's empty.

9. CONCLUSION

Compression of images has been an increasingly popular and important area of study in recent years. In the last several years, a number of academics have come up with a variety of methods for compressing images. Here, the most common compression methods and quality assessment factors are discussed. As a result, we can say that compression may be achieved via the employment of two distinct sorts of methods. It is possible to get a high compression ratio using lossless techniques, but the quality might not be as good as with lossy methods. If you use lossy compression methods, you may get a higher compression ratio although at the expense of picture quality.

The image compression is indeed a trade-off between the compression ratio as well as the peak signal to the noise ratio, however better and more efficient compression-decompression algorithms are still needed in the industry. Research in this field has been significant, but new ways as well as the more efficient algorithms may be developed to meet ever-increasing demand for the low-bit rate compression methods. According to the analysis, this area will continue to pique the attention of scientists for some time to come.

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