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LOSSY COMPRESSION IN REMOTE SENSING

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ABSTRACT

Remote sensing has become a crucial tool for studying the earth's natural resources and environment. However, handling the vast amounts of data generated by remote sensing sensors is a significant challenge. Lossy image compression has emerged as a solution by producing compressed images with some data loss while maintaining image quality. This paper explores the different techniques and algorithms used for lossy image compression in the remote sensing domain, with a focus on multichannel remote sensing for quality control of images. The paper also discusses various image classifications and their applications, such as mapping crops and forest areas. The research aims to provide insights into the potential of lossy compression for remote sensing applications. The paper also presents a literature survey of studies that have investigated the effect of lossy compression on the classification of remote sensing imagery, with recommendations for further research.

Keywords- Remote Sensing, Mapping, Lossy Compression, Monitoring, Image Classification

1. INTRODUCTION

Remote sensing has become an increasingly important tool for studying our planet's natural resources and environment. One of the key challenges in remote sensing is handling the vast amounts of data generated by sensors. Lossy image compression solves this problem by producing compressed images with some data loss while maintaining image quality. This paper explores the different techniques and algorithms used for image processing in the remote sensing domain, focusing on multichannel remote sensing for quality control of images. Additionally, the paper identifies different image classifications and their applications, such as mapping crops and forest areas. Through this research, we aim to provide insights into the potential of lossy compression for remote sensing applications.

2. LITERATURE SURVEY

[1] The study aimed to investigate the effect of lossy compression using JPEG 2000 on the classification of very high-resolution WorldView-2 imagery. The study compared the classification results of the object-based classification methods, namely k-nearest neighbour and support vector machine. The results indicated that the support vector machine method can be used with compression ratios of up to 30:1 without any loss of accuracy. On the other hand, the best result produced by the k-nearest neighbour method was obtained with the highest compression ratio of 100:1, but the outcome was unreliable. The study found that the support vector machine method provides better classification results than the k-nearest neighbour method and is recommended for further research. Before compression and classification, the images were prepared adequately. The panchromatic and multispectral images were orthorectified in the ENVI program using RPC coefficients. The high spatial resolution of the panchromatic images and the high spectral resolution of multispectral images were preserved by combining them into a pan-sharpened image using the Gram-Schmidt method. The use of a smaller image size facilitated faster processing and manual classification of the area, which was used later to verify the accuracy of the automatic object-based classification. The study focused on the classification of a selected region that included agricultural land, forests, and urban areas.

[2] Compressing single images and sequences of images is an essential component of remote sensing imaging. The primary purpose of remote sensing imaging is to identify targets, monitor major events, analyze geological and climate changes, and predict natural disasters. However, satellite imaging systems must collect scenes in various bands of the electromagnetic spectrum, which requires significant data bandwidth to facilitate transmission. Additionally, since the satellite is not always in contact with the ground station, the sensor's image data cannot be transmitted until the satellite revisits a specific point and establishes contact with the ground station. This implies that the longer the satellite takes to revisit, the more data volume will be generated, resulting in the communication system handling a vast amount of data when the satellite revisits the ground station. The communication system must also possess a strong downlink margin to allow missed traffic. Upon arrival on the ground, the data must be calibrated, processed, and stored, presenting the challenge of storing vast data volumes. Therefore, compressing satellite images on board is a crucial step before transmission. To accomplish this, we describe the single image compression architecture in detail and use our CNN-based method to replace the inter-frame encoding module.

[3] Automated data collection is a common practice, where information is primarily processed by algorithms. However, data compressors are developed to preserve perceptual fidelity instead of just the information needed for downstream

tasks. We trained a universal image compressor using these objectives, which resulted in significant rate savings compared to JPEG on 8 datasets without compromising downstream classification performance. The existing lossy compressors cannot meet this challenge since they aim to reconstruct data for human perception, which often includes unnecessary perceptual information. In contrast, our goal is to identify the bit rate required to achieve optimal performance on prediction tasks. We face the challenge of ensuring good performance on any future task of interest, which may not be entirely known at the time of compression, or too large to enumerate. We overcome this challenge by focusing on sets of tasks that remain invariant under user-defined transformations, such as translation, brightness, and cropping. This approach helps to identify the bit rate required to perform well on all invariant tasks and compress the worst-case labels. We achieve rate savings by discarding information from those transformations. Additionally, we provide two unsupervised neural compressors to target the optimal rates.

[4] To compress digital images, it is necessary to achieve a high compression ratio while minimizing distortions that could significantly reduce classification accuracy. The speed of compression is also an important factor, as well as the privacy of compressed data. The DAC algorithm uses a lossy image compression approach that involves preprocessing, discrete transform, quantization, and encoding. This process is illustrated in Figure 1 for full-color digital images. In this study, we use the AC algorithm to compress bitstreams obtained from quantised DAT-coefficients, with various methods available to transform data into a bitstream, such as the special bit planes bypass shown in document number 1. Classification accuracy depends on several factors, including the classifier used, its parameters, methodology of training, image properties, and compression parameters. While the classifier type, its parameters, and the methodology of training are fixed, we analyze two images of different complexity to explore the impact of compression parameters. The first image has sufficient overlap of feature distributions with other classes, and probability density functions for this class are narrow. The second image has large homogeneous areas, which can result in misclassifications due to distortions caused by lossy compression, particularly mean shifting.

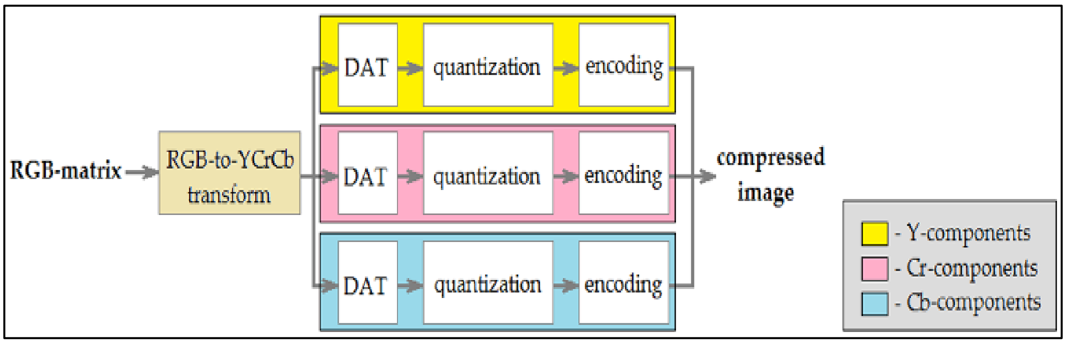

Fig. 1 Discrete atomic compression of full-color digital images

[5] Lossless compression techniques can achieve a compression ratio (CR) of up to 4.5, but only for hyperspectral images when spatial and spectral data redundancies are maximized. If a higher CR is desired, such as one greater than 3.7, lossy compression methods must be used instead.

[6] Compression of remote sensing data is fundamental because of the massive amount of data captured, and the limited downlink capacity of the satellite. To fit the mission's bitrate requirements, lossy compression is often utilised. In the last six years, machine learning (ML) has revolutionised lossy compression for natural images, outperforming traditional methods such as JPEG, JPEG 2000, and intraframe HEVC. The current state-of-the-art approach for lossy image compression based on ML is end-to-end optimized transform coding.

[7] To evaluate the impact of top climatic variables and compression on the classification results of forest and crop areas, different scenarios were analyzed. The scenarios considered include scenario R with only radiometric variables for forest areas, and scenario RTC with topoclimatic variables and NDVI. For crop areas, scenario R included only radiometric variables, whereas scenario RHN also had humidity and NDVI variables. In both scenarios, JPG and J2K compression techniques were analyzed. It is essential to note that the same compression ratio may produce different quality outcomes depending on the image type. The radiometric corrections and the presence of a small number of clouds in the original images may display areas without data (NODATA). However, not all compression/decompression programs can recognize these NODATA values, and it is necessary to remove them from the images before compression to avoid errors in the generated images. As the compression ratio (CR) decreases, the classified area tends to increase in scenario R and RHN, which could be due to a beneficial homogenization of the images when compressed. However, in scenario RTC, the classified area decreases, indicating that compression affects top climatic variables more heavily, possibly because they are more continuous. The global accuracy increases initially as the CR decreases. However, it decreases for JPG at low CR, particularly in scenario R - JPG. In scenario RTC - JPG or RHV - JPG, accuracy also

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decreases but to a lesser degree. While the J2K format is better than JPG for forests, it is not as effective for crops. The classification obtained from J2K compressed images has less "salt and pepper effect". Therefore, the J2K approach is much more effective for both forest and crop areas.

3. METHODOLOGY

A. Classification of Lossy Compression.

In this context, we will explore some of the techniques that can be employed to reduce file sizes. the same it is hugely needed to make the files smaller in size, this can be achieved by compressing the files. Here we are looking at such techniques to reduce the file size. The techniques that adapt these are the compression techniques.

Lossy compression [8] is a type of data compression method used in information technology. It involves using inexact approximations and partial data discarding to represent the content. The main purpose of these techniques is to reduce the size of data for storing, handling, and transmitting content. The different versions of the photo of the cat on this page show how higher degrees of approximation create coarser images as more details are removed. Lossy compression is different from lossless data compression, which does not degrade the data. Lossy compression can reduce data size much more than lossless techniques.

Lossy compression formats are prone to generation loss, which means that repeatedly compressing and decompressing a file will cause it to lose quality over time. There are two types of lossy compression schemes. In lossy transform codecs, the picture or sound samples are taken, divided into small segments, transformed into a new basis space, and then quantized. The resulting quantized values are entropy-coded. In lossy predictive codecs, the current sound sample or image frame is predicted by using the previously decoded data and/or subsequent decoded data. The error between the predicted data and the real data, along with any additional information needed to reproduce the prediction, is then quantized and coded.

1) Transform Coding: Transform coding[11] is a method of compressing data, used for natural data such as audio signals or photographic images. The transformation itself is usually lossless, meaning that it can be perfectly reversed. However, it is used to enable better quantization, which results in a lower-quality copy of the original input. In transform coding, information is selected to discard based on knowledge of the application, which reduces its bandwidth. The remaining information can then be compressed using a variety of methods. When the output is decoded, it may not be identical to the original input, but it is expected to be close enough for the application's purpose.

Transform coding techniques operate on reversible linear transform coefficients of the image (ex. DCT, DFT, Walsh etc.).

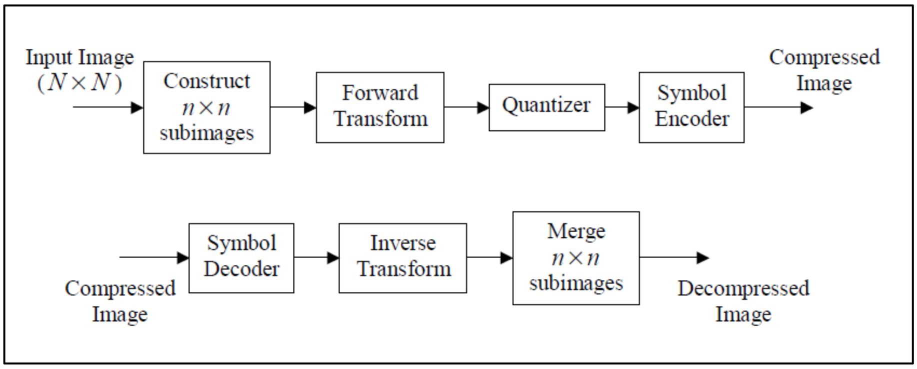

Fig. 1 Block diagram of Transform Coding

2) Input N × N image is subdivided into sub-images of size n × n. n × n sub-images are converted into transform arrays. This tends to decorrelate pixel values and pack as much information as possible in the smallest number of coefficients. The quantizer selectively eliminates or coarsely quantizes the coefficients with the least information. The symbol encoder uses a variable-length code to encode the quantized coefficients. Any of the above steps can be adapted to each sub-image (adaptive transform coding), based on local image information, or fixed for all sub-images. DCT is by far the most popular choice and is used in the JPEG (Joint Photographic Experts Group) image standard. Predictive Coding: Linear predictive coding (LPC) is a popular technique used in audio signal processing and speech processing to represent the spectral envelope of a digital speech signal in a compressed form. This method utilizes the information derived from a linear predictive model to encode good-quality speech at a low bit rate, making it the most widely used method in speech coding and synthesis. LPC is a powerful speech analysis technique that provides a useful way to compress speech signals while maintaining their quality.

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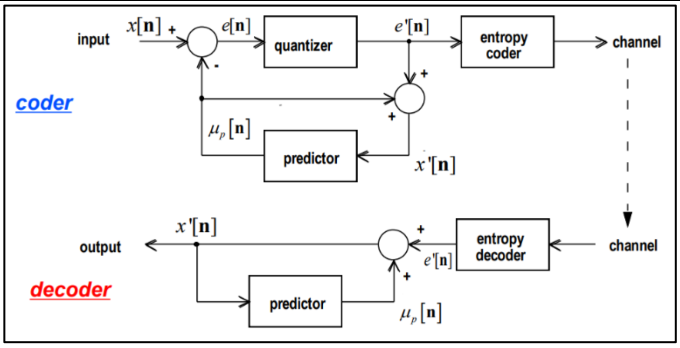

Fig. 3 Block diagram of Predictive Coding

B. Algorithms used in Lossy Compression.

Quantization is the process of mapping input from a large set, like an analogue signal, to numerical output values in a smaller, usually finite set. There are three different forms of quantization: uniform, non-uniform, and vector.

Uniform scalar quantization subdivides the domain of the input into output values at regular intervals, with exceptions at the two outer extremes. Non-uniform quantization, on the other hand, outputs values that are not at equally spaced intervals. The midpoint of each interval and the length of each interval are referred to as the step size. Finally, vector quantization has high decoding complexity and output values can be distributed irregularly, not in a grid fashion, as in the scalar quantization case, because an output value represents a vector and not a scalar value.

Transform coding is the second step in Lossy Compression. It is the process of creating a quantized group of blocks containing all pixels in a frame of consecutive samples from a source input and converting it into vectors. The goal of transform coding is to decompose or transform the input signal into something easier to handle.

There is a good chance that there will be substantial correlations among neighboring samples. To put it in other words, adjacent pixels are usually similar, and therefore, a compressor will remove some samples to reduce file size. The range of pixels that can be removed without degrading quality irreparably is calculated by considering the most salient ones in a block.

For example, if Y is the result of a linear transform T of the input vector X in such a way that the components of Y are much less correlated, then Y can be coded more efficiently than X. If most information is accurately described by the first few components of a transformed vector Y, then the remaining components can be coarsely quantized, or even set to zero, with little signal distortion. As correlation decreases between blocks and subsequent samples, the efficiency of the data signal encode increases. Spatial frequency is one of the most important factors of transform coding because it defines how an image, and the pixels within it, change throughout playback concerning previous and future pixel blocks.

The graphs depict two variations of Lossy Compression - Spatial Frequency Comparison charts. Spatial frequency indicates how many times pixel values change across an image block. It is important to note that the human eye is less sensitive to higher spatial frequency components associated with an image than to lower spatial frequency components.

If amplitude falls below a predefined threshold, it will not be detected by the average human eye. A signal with high spatial frequency can be quantized more coarsely and therefore maintain quality at lower data rates than a signal with low spatial frequency, which will need more data to provide the user with high perceived quality. One of the other factors is the Discrete Cosine Transform (DCT), which implements the measure of motion by tracking how much image content changes corresponding to the number of cycles of the cosine in a block. The DCT is part of the encoding algorithm and converts pixel values in an image block to frequency values, which can be transmitted with lower amounts of data. DCT is lossless, apart from rounding errors, and spatial frequency components are called coefficients. The DCT splits the signal into a DC-direct current component and an AC-alternating current component. With the IDCT or Inverse Discrete Cosine Transform, the original signal is reconstructed and can be decoded and played back.

3) Discrete Cosine Transform: The Discrete Cosine Transform (DCT)[9] is used to express a finite sequence of data points using a sum of cosine functions that oscillate at different frequencies. It was first proposed by Nasir Ahmed in 1972 and is widely used in signal processing and data compression. DCT is an essential technique in digital media such as digital images (JPEG and HEIF), digital video (MPEG and H.26x), and digital audio (Dolby Digital, MP3, and AAC). It is also used in digital television (SDTV, HDTV, and VOD), digital radio (AAC+ and DAB+), and speech coding (AAC-LD, Siren, and Opus). DCT is also useful for various other applications in science and engineering, such as digital signal processing, telecommunication devices, reducing network bandwidth usage, and spectral methods for solving partial differential equations.

Given a two-dimensional N × N image f (m, n), its discrete cosine transform (DCT) C(u, v) is defined as:

$$C(u,v) = \alpha(u)\alpha(v)\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} f(m,n)\cos\left[\frac{(2m+1)u\pi}{2N}\right]\cos\left[\frac{(2n+1)v\pi}{2N}\right],$$

$u, v = 0,1,\ldots,N-1$, where

$$\alpha(u) = \begin{cases} 1/\sqrt{N}, & u = 0 \\ \sqrt{2/N}, & u = 1,2,\ldots,N-1 \end{cases}$$

Similarly, the inverse discrete cosine transform (IDCT) is given by:

$$f(m,n) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v)C(u,v)\cos\left[\frac{(2m+1)u\pi}{2N}\right]\cos\left[\frac{(2n+1)v\pi}{2N}\right],$$

$m, n = 0,1,\ldots,N-1.$

The DCT is Separable (can perform 2-D transform in terms of 1-D transform). Symmetric (the operations on the variables m, n are identical) Forward and inverse transforms are identical

The DCT is the most popular transform for image compression algorithms like JPEG (still images), MPEG (motion pictures)

4) Discrete Wavelet Transform: [10] Wavelets are frequently utilized to eliminate noise from two-dimensional signals, such as images. In this example, we will provide three steps to remove undesired white Gaussian noise from the noisy image. Matlab was used to import and filter the image. The first step is to select a wavelet type and a level of decomposition. In this case, biorthogonal 3.5 wavelets were utilized with a level of 10. Biorthogonal wavelets are commonly used in image processing to detect and filter out white Gaussian noise, due to their high contrast of neighboring pixel intensity values. Using these wavelets, a wavelet transformation is performed on the two-dimensional image. After decomposing the image file, the next step is to determine threshold values for each level from 1 to N. The Birgé-Massart strategy is a typical method for selecting these thresholds. Using this process, individual thresholds are created for N = 10 levels. The majority of the actual filtering of the signal involves applying these thresholds. The final step is to reconstruct the image from the modified levels. This is accomplished using an inverse wavelet transform. The resulting image, with white Gaussian noise removed, is shown below the original image. When filtering any form of data, it is critical to quantify the signal-to-noise ratio of the result.
5) JPEG Lossy compression algorithm: It consists of three successive stages, as shown below, DCT Transformation -> Coeff Quantization ->Lossless Compression. Both DCT Transformation and the final compression of the quantized data are lossless procedures (negligible precision may be lost during DCT Transformation due to minor round-offs). So the Coeff Quantization is the driving force behind JPEG's overall "lossyness". Coefficient Quantization: Quantization is the process of reducing the number of bits needed to store an integer value by reducing the precision of the integer. Given a matrix of DCT coefficients, we can generally reduce the precision of the coefficients more and more as we move away from the DC coefficient. This is because the farther away we are from the DC coefficient, the less the element contributes to the graphical image, and therefore, the less we care about maintaining rigorous precision in its value.

Let's represent the DCT coefficients as DCT(i,j) and the quantization matrix as Quantum(i,j). The quantized value QuantizedValue(i,j) is given as: Quantized Value(i,j) = DCT(i,j) /Quantum(i,j) Rounded to the nearest integer. At this point, one might wonder how the values in the quantization matrix are selected. An enormous number of schemes could be used to define these values, and the two most common experimental approaches for testing the effectiveness of such schemes are as follows:

Measure the mathematical error found between an input image and its output image after it has been decompressed, trying to determine an acceptable level of error. Simply "eyeball it". Although judging the effect of decompression on the human eye is purely subjective, it may, in some cases, be more credible than mathematical differences in error levels. Lossless Compression of Quantized Values: The final step of the JPEG image compression process is to compress the quantized DCT values.

This can be done by following three procedures: Convert the DC coefficient to a relative value. Reorder the DCT block in a zig-zag sequence. Entropy Encoding. The final output that results from JPEG compression can be mathematically reversed and decompressed to produce an image that, to a computer, lacks defining data, but to a human eye, appears identical to the original image.

[12]JPEG makes use of the discrete cosine transform (DCT) for 8x8 contiguous sub-blocks of the image. The transform matrix C = c(k, n) is defined as:

$$c(k,n)=\begin{cases}\frac{1}{\sqrt{8}}, & k=0,\ 0\le n\le 7\\ \frac{1}{2}\cos\frac{\pi(2n+1)k}{16}, & 1\le k\le 7,\ 0\le n\le 7.\end{cases}$$

Most of the energy is packed into the first few transform coefficients. Varying levels of compression can be achieved by using variable quantization of these coefficients. Other compression algorithms, such as improved quantization of the DCT and wavelet transform compression, are much superior both visually and in terms of mean square error, but are not yet image processing standards like JPEG.

6) JPEG2000 Lossy compression algorithm: JPEG200 consists of four basic steps in the algorithm as shown below: **Preprocessing-> Transformation -> Quantization ->Encoding.** JPEG2000 uses a new coding method called Embedded Block Coding with Optimized Truncation.

The more recent JPEG2000 standard uses wavelet transforms instead of DCT. Preprocessing: The preprocessing step we use here is centering of the grayscale intensity values. Transformation: We use Discrete Wavelet Transformation (DWT) instead of DCT. If we perform lossy compression, we use the DWT with the CDF97 filter. Quantization: For lossy compression, it employs a quantization scheme similar to that used by JPEG on the 8 x 8 blocks. For two iterations, the DWT creates seven blocks and each of these blocks is quantized separately. Values in each block are either moved closer to zero or converted to zero and then converted to an integer via the floor function. Encoding: For the final step in the compression standard, we use Embedded Block Coding with Optimized Truncation. For lossy compression, EBCOT allows us to use only 84,504 bits as opposed to the original size of 160*240*8 = 307,200 bits. The compression rate is about 2.2bpp. If we compress the same image using JPEG, we need 103,944 bits for a compression rate of 2.7bpp.

7) Image Data Compression (IDC) designed by the Consultative Committee for Space Data Systems, known as "CCSDS-IDC": In the last few years, CCSDS has defined several techniques for data compression. The IDC recommendation is one of its lossy compression algorithms for satellite images. The compression technique described in this recommended standard can produce both lossy and lossless compression. We used the CCSDS-IDC lossy compression technique to achieve a high compression ratio. The compressor in CCSDS-IDC consists of two functional parts, a DWT module that performs decorrelation, and a Bit-Plane Encoder (BPE), which encodes the décor-related data. In the first part, the DWT is applied, and the Cohen-Daubechies-Feauveau 9/7 biorthogonal filter is employed in the lossy compression. In the second part, the BPE processes the wavelet coefficients in groups of 64 coefficients referred to as blocks before encoding them into rearranged blocks with a size of 8×8.

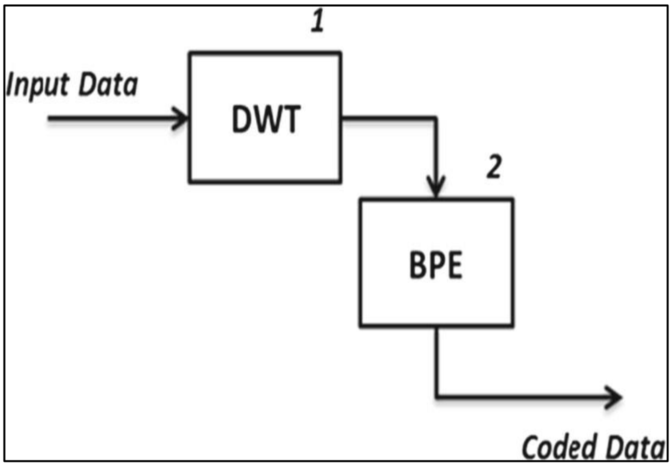

Fig. 4 Image Data Compression

4. APPLICATIONS

With the current and future availability of increasing number of remote sensing instruments, the problem of storage and transmission of large volumes of data has become a significant concern. For example, the high-resolution hanging Spectrometer will acquire data at a 30-meter resolution in 192 spectral bands. This translates to a data rate of 280 Mbps! The Spaceborne Imaging Radar --C (SIR-C) will generate data at the rate of 45Mbps per channel with four high data rate channels. To accommodate this explosion of data, there is a critical need for data compression. One can view the utility of data compression in two different ways. If the rate at which data is being generated exceeds the transmission resources, one can use data compression to reduce the amount of data to fit the available capacity. Or given some fixed capacity, data compression permits the gathering of more information than could otherwise be accommodated.

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A. Satellite Image Transmission:

Describe the challenges associated with transmitting large volumes of satellite imagery data from space to ground stations. Highlight the role of lossy compression in facilitating efficient data transmission, emphasizing the balance between compression ratios and maintaining essential information for accurate analysis. Discuss specific satellite missions or scenarios where lossy compression has been successfully employed for timely data delivery.

B. Data Archiving:

Discuss the significance of long-term data archiving in remote sensing for historical and trend analysis. Elaborate on how lossy compression contributes to more efficient storage, reducing the space requirements for large datasets while preserving critical information. Provide examples of remote sensing archives or databases that utilize lossy compression for managing extensive collections of imagery.

C. Web-based data sharing:

Explore the growing demand for web-based platforms for remote sensing data sharing and collaboration. Examine the role of lossy compression in facilitating quick and responsive web interfaces for users to access and interact with compressed imagery. Discuss considerations for balancing compression levels to ensure accessibility and usability in web-based applications.

D. Real-time Applications:

Investigate the requirements of real-time applications in remote sensing, such as live video streaming from drones or other aerial platforms. Showcase how lossy compression is essential for achieving low latency in transmitting high-quality imagery for real-time monitoring and decision-making.

Providing examples of real-world applications where lossy compression is crucial for maintaining real-time responsiveness.

A. Environmental Monitoring:

Explore the challenges of continuous environmental monitoring and the need for efficient data management. Discuss how lossy compression supports environmental studies by enabling the compression of extensive datasets collected over time, facilitating analysis and trend identification. Provide examples of environmental monitoring programs that leverage lossy compression for data efficiency.

B. Disaster Response and Management:

Explain the urgency of accessing high-resolution imagery in the aftermath of natural disasters. Showcase how lossy compression contributes to rapid data transmission and analysis, aiding disaster response and management efforts. Discuss case studies or instances where lossy compression played a crucial role in disaster response.

C. Resource Exploration:

Examine the role of remote sensing in resource exploration, including geological and geophysical data acquisition. Elaborate on how lossy compression facilitates the storage and transmission of large datasets in resource exploration applications.

Providing examples of resource exploration projects benefiting from the use of lossy compression.

A. Urban Planning:

Discuss the complexities of urban planning and the reliance on high-resolution satellite imagery for detailed analysis. Elaborate on how lossy compression supports the storage and analysis of large urban datasets, making it feasible for planners to handle extensive imagery efficiently. Provide examples of urban planning initiatives that have successfully employed lossy compression for data management.

B. Scientific Research:

Explore the diverse applications of remote sensing in scientific research, such as climate studies and biodiversity monitoring. Explain how lossy compression aids scientists in managing and analyzing large and diverse datasets efficiently. Provide specific examples or research projects where lossy compression has been integral to the success of scientific studies.

5. CONCLUSION

In conclusion, lossy image compression has proven to be an effective solution for handling the vast amounts of data generated by remote sensing sensors while maintaining image quality. The paper explored various techniques and algorithms used for lossy compression in the remote sensing domain, with a focus on multichannel remote sensing for quality control of images. Additionally, the research identified various image classifications and their applications, such as mapping crops and forest areas. The literature survey presented in the paper highlighted several studies that have investigated the effect of lossy compression on the classification of remote sensing imagery. Based on the findings, it is recommended that further research be conducted on the use of support vector machine methods for remote sensing classification. Overall, this research provides valuable insights into the potential of lossy compression for remote sensing applications, which could lead to new and innovative ways of utilizing remote sensing data.

6. REFERENCES

[1] Marsetic, A., Z. Kokalj, and K. Ostir. "THE EFFECT OF LOSSY IMAGE COMPRESSION ON OBJECT BASED IMAGE CLASSIFICATION–WORLDVIEW-2 CASE STUDY." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 38 (2012): 187-192.

[2] Ma, Xianghe. "High-resolution image compression algorithms in remote sensing imaging." Displays (2023): 102462.

[3] Dubois, Yann, et al. "Lossy compression for lossless prediction." Advances in Neural Information Processing Systems 34 (2021): 14014-14028.

[4] Makarichev, Victor, et al. "Discrete atomic transform-based lossy compression of three-channel remote sensing images with quality control." Remote Sensing 14.1 (2021): 125.

[5] Zemliachenko, Alexander N., et al. "Lossy compression of noisy remote sensing images with prediction of optimal operation point existence and parameters." Journal of Applied Remote Sensing 9.1 (2015): 095066-095066.

[6] I Verdú, Sebastià Mijares, et al. "Reduced-complexity multi-rate remote sensing data compression with neural networks." IEEE Geoscience and Remote Sensing Letters (2023).

[7] Zabala, Alaitz, et al. "Effects of JPEG and JPEG2000 lossy compression on remote sensing image classification for mapping crops and forest areas." 2006 IEEE International Symposium on Geoscience and Remote Sensing. IEEE, 2006.

[8] Wikipedia contributors. "Lossy compression." Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 11 Dec. 2023. Web. 16 Dec. 2023.

[9] Wikipedia contributors. "Discrete cosine transform." Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 11 Dec. 2023. Web. 16 Dec. 2023.

[10] Wikipedia contributors. "Discrete wavelet transform." Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 20 Nov. 2023. Web. 16 Dec. 2023.

[11] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 4th ed. Prentice Hall.

[12] Paola, Justin D., and Robert A. Schowengerdt. "The effect of lossy image compression on image classification." 1995 International Geoscience and Remote Sensing Symposium, IGARSS'95. Quantitative Remote Sensing for Science and Applications. Vol. 1. IEEE, 1995.