Region based lossless compression for digital images using entropy coding

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ABSTRACT

Image compression is a method for reducing video and image storage space. Moreover, enhancing the performance of the transmission and storage processes is important. The region-based coding technique is important for compressing and sending medical images. In the medical field, lossless compression can help telemedicine applications achieve high efficiency. It affects image quality and takes a long time to encode. As a result, this study proposes region-based lossless compression for digital images using entropy coding. The best performance is achieved by segmenting these areas. In this case, an integer wavelet transform (IWT) is utilized after the ROI of the image was manually generated. The IWT compression method is helpful for reversibly reconstructing the original image to the required quality. For enhancing the quality of compression, entropy coding is utilized. By passing images of varying sizes and formats, various quantitative metrics can be determined. The simulation results demonstrate that the region based lossless compression technique utilizing range blocks and iterations resulted in reduced encoding time and improved quality.

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1. INTRODUCTION

Transmission bandwidth and storage spaces have been challenged by the increase in the number of digital images on the Internet and on personal devices. Since smart phones and imaging devices are so widely available, the sudden increasing in popularity of digital cameras requires focusing on efficiently managing, organizing, and storing a large number of images [1]. Additionally, they must be compressed in order to be used in some applications. For storage and memory, uncompressed images need a lot of memory and bandwidth. Image compression becomes an important tool for addressing this issue as a result. Image compression is essential for both image data transport and storage [2]. The main goal of image compression is to represent an image in the smallest number of bits without losing the information included in the original images [3].

The most of images contains characteristics of having neighboring pixels that are correlated and consequently include redundant data. The most crucial objective is to identify the image representation that is least correlated [4]. The image is compressed and its size is decreased by removing redundant bits through the use of compression algorithms [5]. Redundancy reduction and irrelevancy reduction are two fundamental components of compression. Maintaining the reconstructed image's visual quality and resolution while protecting it is similar to the original image, it must describe an image by eliminating spectral and spatial redundancy as much as necessary. The compressed data are applied to an inverse procedure known as decompression (decoding) in order to produce the reconstructed image [6]. The lossy and lossless compressions are the two types of image compression techniques [7]. When an image is compressed utilizing a lossy compression, all redundant data is removed completely, hence the reconstruction images has a reduction in comparison to the original. Since, lossy techniques can achieve far higher compression capabilities. Visually lossless viewing indicates that there is no visible loss [8]. Multimedia information including audio, video, and still images are most frequently compressed using lossy compression, particularly in applications including streaming media where a small fidelity reduction is accepted in order to obtain a substantial decrease in bit rate. This approach is not advisable for many applications, because using low bit rates allows the introduction of compression artifacts.

Lossless compression protects information; for artificial images like technical drawings, comics, or icons, as well as high-value content like medical images or archival image scans, the reconstructed image is an identical copy of the original [9]. Numerous lossless compression methods are avialable, including the area, run length, lempel-ziv-welch (LZW) encoding, Huffman encoding [10]. Using a medical picture compression approach based on ROI coding, an image is first split into a ROI and a background (BG) [11]. While the BG typically utilizes a lot of lossy compression, the ROI typically uses lossless or nearly lossless compression.

Low-bitrate image compression has been considered to be a difficult area of study due to the undisciplinarity of the transmission channel and the compatibility of display scalability across devices that have various resolutions. Even yet, it would be unacceptable to have visual compression artifacts caused by a small number of bits each pixel [12]. A sampling-based method of image compression has been presented for low bit rate coding. In this method, an image is down sampled prior to compression to reduce spatial redundancies among neighboring pixels and make the compression codec-friendly. Whenever displayed on screens with low resolution, such as those shown in mobile devices, lower resolution might provide flexibility. However, information loss during simple sampling may also effects image quality. Therefore, extensive algorithms for improving compressed image quality have been proposed. These algorithms can be divided into three main categories: deep learning approaches, dictionary learning, and iteration-based algorithms.

A new method for lossless image compression with embedded encoding is aim of this analysis. Floating point coefficients are generally produced by the wavelet transform (WT). While utilizing finite precision quantization and arithmetic leads to a lossy method, these coefficients are used frequently to rebuild the original image. To overcome this disadvantage, integer WT (IWT) was recently introduced. The following is the structure of the remainder of the analysis: literature review is included in section 2, section 3 provides a detailed description of region-based lossless compression; in section 4, the experiment results are shown; in section 5, the conclusion and summary are presented.

2. LITERATURE SURVEY

Zhao *et al.* [13] provides a novel technique for image de-blocking that reduces blocking artifacts and produces higher-quality images by utilizing quantization constraint (QC) prior and structural sparse representation (SSR) prior. In the framework of maximum, a posteriori, the optimization problem of image de-blocking is presented. While QC is expressly included to enable a more robust and accurate estimating, in order to successfully enforce the nonlocal self-similarity and inherent local sparsity of natural images, the SSR prior is used. Using an adaptively modified parameter value, the optimization problem is addressed with a new split Bregman iteration-based technique, which improves the practicality of the algorithm in its entirety. Experiments show that the described image-deblocking algorithms, which combines SSR and QC, works better in terms of peak signal-to-noise ratio and visual perception than current state-of-the-art techniques.

Juliet *et al.* [14] presented a ripplet-based method for compressing medical images. The technique's primary coefficients are encoded using the set partitioning in hierarchical trees (SPIHT) algorithm, single points on any shape curve are characterized using an anisotropic ripplet transformation. The interpretation and analysis of magnetic resonance imaging (MRI) images depends important on an automatic and accurate classification system.

Rothe *et al.* [15] using the image super-resolution, the novel artifact reduction methodology that performs well is described by the adjusted anchored neighborhood regression (A+) method. Impressive results have been obtained with a recently developed learned semi-local gaussian processes-based solution (SLGP). The improvement is less significant when used with better compression algorithms including JPEG 2000. Large storage reductions are possible with lossy image compression, but the compressed images possess reduced image fidelity. There is a lot of research that aims to restore by removing compression artifacts. When compared to state-of-the-art techniques like SLGP, they obtain orders of magnitude faster performances while double the relative gains in peak signal-to-noise ratio (PSNR).

Loganathan and Kumaraswamy [16] suggested investigating into various compression methods depending on region of interest (ROI). The paper proposes a novel adaptive active contour method that without edges to mark the ROI. Lossless compression is used to compress the specific ROI area, while lossy wavelet compression is used to compress the other parts of the image. Using a number of MRI images, the suggested method produced an overall compression ratio of 69-81% while maintaining the ROI's originality.

Liu *et al.* [17] this research proposes a fast fractal-based MRI image compression technique. To make the fractal compression-based image sequence operating, a two-dimensional (2D) image sequence needs to be created from three-dimensional (3D) MRI images. According to the experimental findings, there is a ten or more increase in PSNR and a two-to-three-fold increase in compression speed. It suggests that the suggested approach works well and resolves the contradiction between high quality MRI images and a high compression ratio.

Artuğer and Özkaynak [18] a suggested technique for compressing images is fractal. JPEG compression performs well for small-sized images but poorly for large-sized images. An image's processing time increases along with the image's size, accuracy, and compression ratio decreasing. The fractal compression technique, however, eliminates these issues. Matlab is used for developing the programs, and the results are evaluated. It is found that the fractal compression approach works better as the image sizes get larger.

Amirpour *et al.* [19] in this paper, a random access-oriented light field image encoding technique is proposed. The suggested technique divides 15×15 view images into 25 separate 3×3 view images, which are referred to as macro view images (MVI). Using a hierarchical reference structure, the center view image compresses the view images that are nearest to it to encode MVIs. Using the center of at most three MVIs and the most central view image as reference images, the disparity estimation process encodes the central view of each MVI. Furthermore, by using parallel computation, the suggested method can improve the encoding/decoding time complexity. HEVC tile partitioning is utilized to minimize memory footprint in the event that a ROI is required.

Parikh *et al.* [20] focuses compression efficiency in comparison to JPEG 2000 and discusses the usage of HEVC for medical image compression that is diagnostically acceptable. According to the results of experiments, comparing HEVC to JPEG 2000, compression efficiency can be increased by approximately 54%. Concurrently, a novel technique is proposed for lowering the HEVC encoding's computational cost for medical images. The results indicate that a significant increase in file size can be achieved while reducing the HEVC intra-encoding complexity by more than 55%.

Sun *et al.* [21] provided a CNN-based technique that divided image patches into a closed class of blur kernel types to remove non-uniform motion blur. A Markov random field model used the local classification outputs as input to estimate the dense non-uniform motion blur field across the entire image.

Mesra *et al.* [22] the purpose of the compression technique is to lessen data redundancy. In this work, a reversible low contrast mapping (RLCM) transformation is used in a different manner to embed specific datum bits into other datum in image data. The data is encoded by the algorithm in a cyclic -like manner. The suggested approach uses Huffman coding, which is different from RLCM. This study investigates the suggested technique using image data that is accessible to the public. The proposed method has a higher compression ratio than Huffman coding for all test images. Bhavani and Thanushkodi [23] evaluated the well various fractal coding techniques compressed MRI data, such as improved quasi-lossless fractal coding, fractal coding standards, and fractal coding. This led to the development of a new quasi-lossless fractal compression technique that successfully preserved important image features. The algorithm's encoding time was reduced and compression performance was improved using a machine learning technique.

Xinpeng [24] presents an novel scheme for lossy compression of an encrypted image that has an accessible compression ratio. To encrypt an original image, a pseudorandom permutation is used, and through eliminating the orthogonal transform's coefficients of extremely fine and rough information, the encrypted data are efficiently compressed. Once the compressed data is received, with the use of spatial correlation in a natural image, a receiver can iteratively update the coefficient values to reconstruct the key elements of the original image. In this way, the quality of the reconstructed image better with a smoother original image and a higher compression ratio.

Wu *et al.* [25] in order to further reduce the size of a group of joint photographic experts' group (JPEG) coded linked images without losing any information, provide an innovative lossless compression technique. In the feature, spatial, and frequency domains, the proposed approach jointly eliminates inter- and intra-image redundancy. They initially minimize the global prediction cost in the feature domain for each collection in order to arrange the images into a pseudo-video. Next, we introduce a hybrid disparity compensation technique that enhances the utilization of both local and global image correlations in the spatial domain. The suggested lossless compression technique is effective, as shown by the experimental results. Our technique achieves more than 31% on average bit savings when compared to the JPEG coded image collections.

3. REGION BASED LOSSLESS COMPRESSION

The block diagram of region based lossless compression for digital images using entropy coding is represented in below Figure 1. Using entropy coding on a number of images, the proposed approach aims to improve image compression. The image splits up into various blocks. Both encoding and decoding make use of entropy coding. It is utilized to a compressed image to enhance compression performance and reduce the encoding process. The input image is converted to a gray image despite its color. Recognize the image's dimensions; if they are not squares, modify them to the nearest square sizes.

Quantization is the method of estimating the continuous set of values in the image data using the finite nearest set of allowed values. The output of the quantizer is always one of a limited number of levels, while the input is the original data. To reduce encoding time, a good quantizer represents the original signal with the least amount of loss or distortion. To achieve better overall compression, a lossless entropy encoder further compresses the quantized data. For every quantized value, it generates an output code stream that is smaller than the input code stream by using a model to calculate the probabilities. Domain size, location, domain number and domain class information are computed as domain data. The classification of domains is carried through a method that considers the brightness values of the domains.

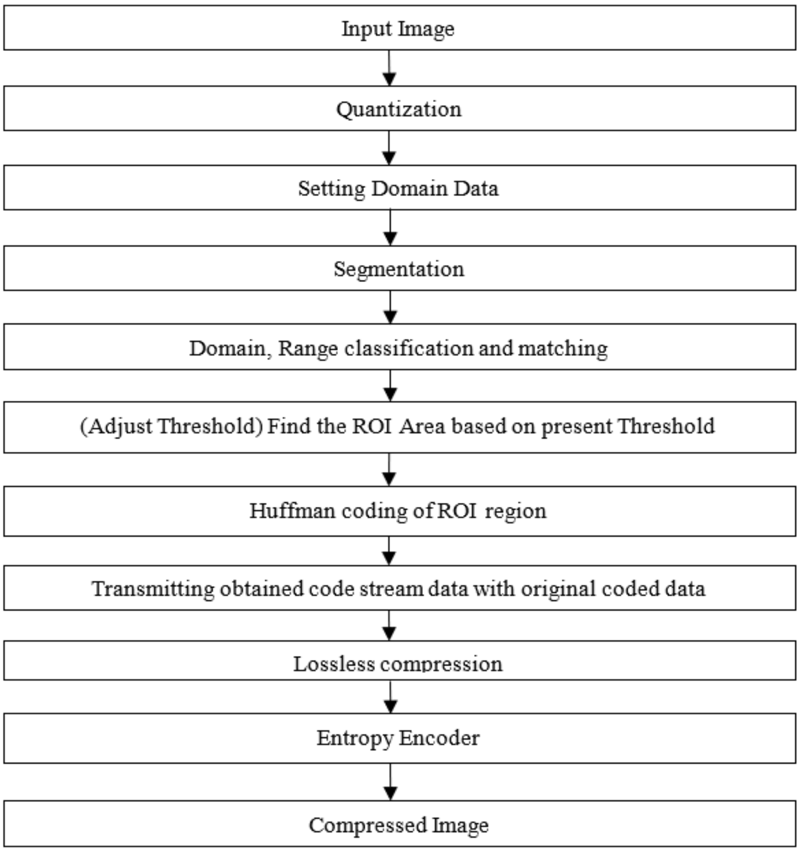

Figure 1. Block diagram of region based lossless compression

There are several components that make up a digital image, often known to as blocks, by the process of image segmentation. The primary objective of segmentation is to transform an image's representation into a meaningful component that can be used for analysis. It was also utilized for object and image boundaries localization. The basic concept behind image segmentation is to assign a label to each pixel in an image so that pixels that share the same label have different visual properties. To put it simply, image segmentation involves assigning labels to each pixel in an image so that pixels that share the same label have similar visual properties. The pixel neighbors of the initial "seed points" are analyzed in region growing segmentation to determine if they added to the area. The algorithm for data clustering is a lot similar to this process.

Every ranging block's ability to matching its domains blocks and the performance of the reconstructed image are both significantly impacted by the size of the domains blocking collections. In order to get the optimal domain-range matching, ranging blocks are first categorized utilizing the same categorization scheme as domains. The domains and ranges that can be compared must all to the same class, and the threshold is determined by computing the difference in error between them. More segmentation of the image has been performed. Calculation of a transformation is done if this error value exceeds the defined threshold.

Using the segmentation algorithm, the background of ROI was reduced to zero. Following that, the ROI portion of each image is identified. An automated procedure is used to identify the ROI for the compression. An ROI-mask is created so that the image's foreground is completely covered for the purpose of ROI detection. An ROI-mask can be effectively produced using morphological operations. This indicates that the value "1" can be found in the image's foreground while the value "0" can be found in the image's background. After that, the image and the mask are logically ANDed to separate the ROI part from the non-ROI portion.

For bit stream compression and reducing coding redundancy, the most used lossless method is Huffman coding. For source symbols with various probabilities, it offers a effective source coding algorithm. The statistical characteristics of the characters in the source streaming are used by Huffman coding to produce equivalent codes for such symbols. Through compares to symbol coding with lower probabilities, greater probability symbol codes are smaller. The frequency with which an essential requirement is the development of a particular data item (pixels or small blocks of pixels in images). An authorized code book contains the codes. Every image or collection of images has its own code book.

For medical images, lossless compression is offered by the IWT. For the provided signals or pixels, traditional WT usually provides the floating-point coefficients. Integer coefficients are produced by it. Therefore, its computational complexity is lower than that of other WTs. A method of lossless data compression is entropy encoding. One of the primary methods of entropy coding is used to assign a unique prefix code to each different symbol in the input. These entropy encoders then compress the information into words by replacing a corresponding variable-length prefix code for each fixed-length input symbol. Since the length of each code word is roughly proportional to the logarithm of the probability, the most frequent symbols are represented by the smallest coding. In this case, the image is effectively compressed with Huffman coding.

4. EXPERIMENTAL RESULT ANALYSIS

Using a number of performance parameters, they evaluate the region based lossless compression model's performance in this section. On the color to gray-scale level of image data, experiments have been carried successfully. Different performance metrics are used to compare the results. The experiment was conducted using the 300 images in this data set. The data set contains X-ray images of the spinal cord, lungs, skull, and other parts. The images are about 512×512 pixels in size. Applying the threshold segmentation technique divides the backgrounds of the input images. After separating the ROI parts of the images from the rest of the image, the ROI parts of the images could then be compressed. In order to obtain the original image, the compression algorithm's reverse part is then utilized. There are a number of metrics for objectively evaluating images perceptual quality. They utilize the MSE, PSNR, SSIM, and encoding time parameters.

Mean square error (MSE): the difference between the compressed and original images is examined using the MSE as shown in (1). Between PSNR and MSE, there is an inverse relationship: a lower value indicates less error.

$$MSE(i_1, i_2) = \frac{1}{NM} \sum_{x=1}^{M} \sum_{y=1}^{N} \left[i_1(x,y) - i_2(x,y)\right]^2 \qquad (1)$$

The original image is represented by i_1 (x,y), the reconstructed image by i_2 (x,y), and the image's dimensions are M and N.

Peak signal-to-noise ratio (PSNR): PSNR is used to evaluate the lossy image reconstruction performed. A representation's fidelity is determined by the ratio of the maximum power of the signal to the power of corrupting noise as shown in (2). Between the original and compressed images and this ratio is frequently used to measure quality. An image that has been compressed or reconstructed will have a higher PSNR, enhancing image quality.

$$PSNR = 10.log_{10}\left(\frac{B^2}{MSE}\right) \quad (2)$$

where, B is the signal with the greatest amplitude:

Encoding time (ET): for such purposes of storage or transmission, the use of a specific format is used to encode a sequence of characters.

Structural similarity index (SSIM): the SSIM is a perceptual measure that looks at how data compression or processing or data transmission losses affect image quality as shown in (3). Since it uses two images from the same image capture, it is a complete reference metric.

$$SSIM(i_1, i_2) = \frac{(2\mu_1\mu_2+C_1)(2\sigma_{12}+C_2)}{(\mu_1^2+\mu_2^2+C_1)(\sigma_1^2+\sigma_2^2+C_2)} \quad (3)$$

The luminances of the two images are compared using the local means $\mu_{1,2}$ for image 1 and image 2. The contrast is compared using the standard deviations σ_2 respectively. The co-variance, σ_{12}, is used to compare the structure. Depending on the dynamic range, c_1 and c_2 remain constants. A better object reconstruction for this metric indicates a higher SSIM value.

Comparative analysis of image compression using quadtree decomposition (IC-QD) and described region based lossless compression using entropy coding (RBLC-EC) is represented in below Table 1 in terms of performance parameters.

Table 1. Comparative analysis of performance parameters

Parameters	IC-QD	RBLC-EC
MSE	38	27
PSNR	28.3	36.4
ET (sec)	21	15
SSIM	0.7	0.9

In Figure 2 shows the comparative graphical representation of MSE, PSNR, and ET parameters for IC-QD model and described RBLC-EC. It states that, MSE and ET values of RBLC-EC model are less compared to IC-QD model, at the same time PSNR value of RBLC-EC model is high compared to IC-QD model which clearly explains the efficiency of described RBLC-EC model. Figure 3 shows the graphical representation of SSIM value for described RBLC-EC model and IC-QD model. The SSIM value of RBLC-EC model is high compared to IC-QD model. Therefore, reconstructed image is exactly same as original image. From results it is clear that the performance of region based lossless compression using entropy coding is better than other models in terms of high PSNR, low MSE, high SSIM, and less encoding time. The quality of the recovered image has also marginally improved.

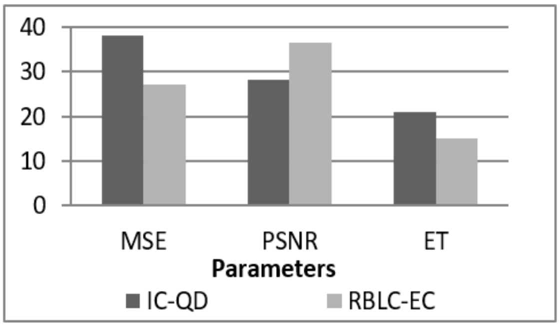

Figure 2. Comparative analysis

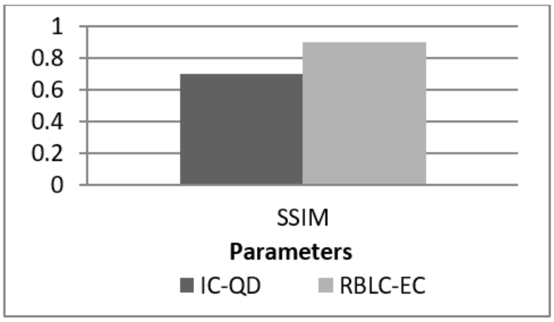

Figure 3. Comparative analysis in terms of SSIM

5. CONCLUSION

This analysis describes region based lossless compression for digital images utilizing entropy coding. When medical images are properly compressed, less data is transferred. After that, compressed data is sent and stored. Not only does it save storage space, but it also makes transmission faster and more effective. For medical image applications, IWT is recommended due to its perfect reconstruction and low computational complexity. The recovered image's quality can be improved with the help of entropy coding. There are a number of metrics for objectively evaluating images perceptual quality. They use MSE, PSNR, encoding time, and SSIM parameters. The performance of region based lossless compression using entropy coding is better than other models in terms of high PSNR, low MSE, and high SSIM and less encoding time. Therefore, the recovered image's quality is improved. Further improvement in PSNR value for the entropy coding can be achieved by considering the different dimensions of the range blocks. The encoding time can further be reduced by parallelizing the process.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mangalapalli Vamsikrishna		✓	✓		✓	✓		✓	✓	✓			✓	
Oggi Sudhakar	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		
Bhagya Prasad Bugge	✓			✓		✓			✓	✓			✓	
Asileti Suneel Kumar		✓	✓		✓		✓		✓		✓	✓		
Blessy Thankachan	✓		✓			✓		✓		✓			✓	
K.B.V.S.R. Subrahmanyam		✓		✓	✓		✓		✓		✓			
Natha Deepthi		✓	✓		✓		✓	✓		✓		✓		
Praveen Mande	✓		✓	✓		✓		✓		✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

- The data that support the findings of this study are openly available in [I. Benyahia, et. al.,] at http://10.11591/ijece.v8i4.pp2139-2147.org/[10.11591/ijece.v8i4.pp2139-2147], [12].
- The data that support the findings of this study will be available in [IEEE] [DOI: 10.1109/ACCESS.2023.3312265] following a [6 month] embargo from the date of publication to allow for the commercialization of research findings.
- The data that support the findings of this study are openly available in [H. Mesra, et. al.,] at http://10.11591/ijece.v6i6.pp2836-2845.org/[10.11591/ijece.v6i6.pp2836-2845], [22].

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