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An Analysis of the Effectiveness of Different Image Compression Methods

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Abstract:

Image compression presents compelling solutions across various domains, including image analysis, biomedical image processing, and wireless systems, emerging as a pivotal application in today's digital landscape. Its significance is particularly pronounced in the efficient transmission and storage of large data images in diverse applications such as big data and medical fields. Amidst these applications, Dynamic Magnetic Resonance Imaging (MRI) has garnered increasing attention due to its exclusive soft tissue contrast and diagnostic capabilities using magnetic and radio waves, avoiding X-ray radiations and producing detailed 3D anatomical images. This survey delves into the realm of image compression, specifically focusing on dynamic MRI images. The goal is to provide a comprehensive overview of different image compression schemes, aiming to design an efficient compression system tailored for dynamic MRI images. The paper explores various compression schemes, ranging from standalone implementations to hybrids incorporating two or more algorithms. Additionally, the author presents a comparative analysis of these surveyed compression schemes, paving the way for future research endeavors in the domain of image compression for dynamic MRI images.

Keywords **—Dynamic MRI, Image Compression, Compression Ratio, Redundancy, PSNR, SSIMetc.**

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I. INTRODUCTION

Magnetic Resonance Imaging (MRI) combines the advantages of non-invasiveness, providing superior flexible tissue contrast, and a non-exposing nature, eliminating high ionizing radiation. In contemporary medical research, MRI has evolved into a crucial area of study, facilitating computer-aided diagnosis and routine clinical procedures. These scans offer essential information about tissue structure, including size, shape, and localization, making the medical domain a preferred choice for researchers. Medical imaging, including MRI, plays a pivotal role in obtaining images of internal organs, bones, and tissues for research and analysis within the medical field. Such images contribute to the study of organ functions and are employed in radiology to visualize internal structures and functionalities. Unlike traditional 2D X-ray imaging, MRI provides 3D images of the internal organisms of the human body, aiding doctors in disease analysis and treatment.

Dynamic Magnetic Resonance Imaging (MRI) has been widely used in the past few decades to extract functional information related to peripheral vascular organisms. Multiphase MRI scans, coupled with intravenous injection of a contrast agent, are employed for clinical practices. Researchers have explored the utility of dynamic contrast enhancement (DCE) MRI for various diagnosis schemes, particularly in the case of salivary gland tumors. Several techniques, such as arterial spin labeling (ASL) MRI and Blood Oxygen Level-Dependent (BOLD) MRI, are frequently used to measure perfusion and energy consumption. However, these techniques have limitations, as they fail to provide information on volume functions or vessel permeability.

As medical imaging technology rapidly advances, the field of biomedical image processing undergoes significant transformation. While various imaging modalities are employed using diverse devices, MRI stands out as the dominant tool for visualizing internal organisms, facilitating precise measurements of human organ anatomy, and presenting superior contrast among soft tissues. Despite its advantages, MRI images pose challenges in terms of storage space, speed, and bandwidth, and cannot be efficiently compressed using common compression techniques

II. VARIOUS METHODS FOR IMAGE COMPRESSION

Image compression involves the reduction of data or information needed to represent a digital image efficiently. This methodology aims to provide an optimized and compact representation of digital images, reducing the requirements for image transmission and storage. Compression schemes are broadly classified into two categories based on the reconstructed data: lossy and lossless compressions. In lossy compression, the reconstructed image may exhibit degradation compared to the original, as redundant data is entirely discarded to achieve high compressibility. On the other hand, lossless compression ensures that the reconstructed image is identical to the original, but it is limited in compressibility, offering less significant compression.

Predictive coding-based compression techniques involve predicting future values for transmitted data, coding the differences to achieve compression. This spatial domain approach is straightforward to implement. Alternatively, transformation-based compression techniques enhance data compressibility by using various transforms, albeit at the cost of increased complexity and computations.This section explores various research endeavors in the domain of image compression over the past decade. A novel compression technique utilizing reference points coding and threshold values computation is introduced in [8], aiming to achieve both lossy and lossless compression with adjustable compression ratios.

Another study [9] employs the Integer Multi-Wavelet Transform (IMWT) for lossless image compression, enhancing performance through magnitude set coding. The research achieves a bit rate of 2.1 bpp using Magnitude Set-Variable Length Integer Representation (MS-VLI) with Run Length Encoding (RLE) and 3.1 bpp without RLE.

A hybrid technique for image compression is proposed in [10], combining embedded Wavelet-based coding with Huffman encoding. This study compares bit rates and PSNR values for various wavelet families, demonstrating efficiency in image quality and compression ratio compared to existing compression schemes.

In [11], a novel compression scheme with encryption is presented, using the Set Partitioning in Hierarchical Trees (SPIHT) scheme for compression and stream cipher technique for encryption, enhancing security and compression rates. A Hybrid Image Compression (HIC) scheme combining Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) is introduced in [12], demonstrating improved compression ratios, bit rates, and PSNR values.Histogram-based approaches for spatial compression are explored, subdividing the original image into clusters based on histogram thresholds, with threshold values calculated using Shannon's entropy theorem [13].

The Discrete Anamorphic Stretch Transform (DAST) [14] reshapes input images before uniform sampling, offering higher image space-bandwidth compression. This non-iterative scheme can be combined with other compression methods for further improvements. A fast zonal DCT-based technique [15] conserves energy in wireless image sensor networks using cardiac-based DCT and zonal DCT. The technique reduces energy consumption but may result in lower image quality.Wavelet compression based on entropy values [16] employs DWT and selectively compresses sub-bands based on entropy, saving energy compared to fully compressed schemes.

A cost-effective iterative threshold-based scheme [17] is proposed for brain tumor segmentation and isolation in MRI images. The scheme combines enhanced differential pulse code modulation transform (EDPCMT) with Huffman coding, reducing storage space and bandwidth efficiently. Several other efficient schemes, such as image inpainting [18], Side Match Vector Quantization (SMVQ) [19], low complexity arithmetic encoding [20], DCT SVD and RLE-based hybrid compression [21], and binary discrete cosine and Hartley transforms-based compression [22], have been proposed and proven effective in different aspects.

III. PERFORMANCE ANALYSIS PARAMETERS

The performance parameters play a crucial role in validating the efficiency and effectiveness of the implemented image compression algorithm. The choice of these parameters is contingent on the precision and nature of the compression schemes. In this section, we will explore different types of performance parameters that can be employed to justify the efficiency of the implemented compression technique. These parameters are as follows:

A. Compression Ratio (CR)-

The compression ratio is defined as shown in equation (1). This is generally used in order to measure the capability of data compression. Here, comparison of size of compressed image is performed with respect to the original image. As compression ratio increases, superiority of compression technique enhances.

$$CR = \frac{\text{Size of Uncompressed Image}}{\text{Size of Compressed Image}} \qquad (1)$$

B. Mean Square Error (MSE)

Mean Square Error (MSE) is defined as the cumulative squared error between the input image and the compressed image. It is calculated as shown in equation (2).

$$MSE = \frac{1}{M*N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\|I_o(x,y) - I_1(x,y)\|^2 \qquad (2)$$

In the context where M and N denote the number of rows (height) and columns (width) of an image, with M x N representing the image size and M*N as the total number of pixels, let M*N. I0(x, y) and I1(x,y)represent the pixel values for the initial uncompressed image and the final compressed image, respectively. If the mean square error is zero, it indicates that both the input uncompressed image and the compressed image are perfectly similar or identical.

C. Root Mean Square Error (RMSE)

The evaluation of Root Mean Square Error (RMSE) is demonstrated by equation (3). This metric is commonly employed to gauge disparities between sample and population data. In essence, RMSE serves as a representation of the sample standard deviation of the discrepancies between the original uncompressed input image and the resulting compressed output image. The RMSE parameter is generally considered a superior measure of accuracy. However, its limitation lies in its applicability solely to comparing forecasting errors among different models designed for a specific type of variable, rather than across various types of variables, owing to its dependence on scale.

$$RMSE=\sqrt{MSE} \qquad (3)$$

D. Peak Signal to Noise Ratio (PSNR)

This metric is employed to assess the impact of noise on signal quality. It is defined as the ratio of the maximum possible power of the signal to the power of interfering noise that affects signal representation quality. Typically expressed in logarithmic or decibel (dB) scale, PSNR is utilized to quantify variations in quality between the original input image and the final output image. Higher PSNR values correlate with superior output image quality. The calculation for PSNR can be expressed using equation (4) or (5) for any given image.

$$PSNR = 10\log_{10}\frac{(I_{max})^2}{MSE} \qquad (4)$$

Where, Imax = 255 i.e. the maximum pixel value for any image. Hence equation (4) can be rewritten as –

$$PSNR = 10\log_{10}\frac{(255)^2}{MSE} = 20\log_{10}\frac{255}{RMSE} \qquad (5)$$

E. Weighted Signal to Noise Ratio (WSNR)

This performance metric utilizes a frequency domain transform function called the Contrast Sensitivity Function (CSF). The CSF is applied to filter out spatially irrelevant or inappropriate frequencies based on the human vision system. The computation of WSNR allows for the assessment of the effects of image dimensions, printing resolutions, screening or visual distance, as well as ambient lighting and visualization. Like other parameters, WSNR is typically expressed on a logarithmic or decibel (dB) scale.

To compute WSNR, the process begins with the evaluation of an error image, obtained by taking the differences between the original input image and the resulting noisy image. Subsequently, this error image is weighted using a linear and spatially invariant approximation of the human visual system's frequency response, as given by the CSF transformation. In the final step, the weighted signal to noise ratio parameter is calculated as illustrated in equation (6).

$$WSNR = 10\log_{10}\frac{\sum_{xy}|I(x,y)CSF\ (x,y)|^2}{\sum_{xy}|\omega(x,y)CSF\ (x,y)|^2} \quad (6)$$

F. **Structural Similarity Index Measure (SSIM)**

The structural similarity measure serves as a crucial image quality parameter for assessing the output of compressed images. This metric involves evaluating two distinct signal vectors in the x and y dimensions, aiming to quantify the similarities between input and output images. Referred to as a full reference metric, SSIM allows the measurement of image quality based on an initial uncompressed or noise-free image as the reference image. This parameter is introduced to enhance traditional performance metrics like MSE and PSNR, addressing their inconsistencies concerning the human visual system. The fundamental concept behind SSIM revolves around inter-pixel dependencies within close spatial proximities or neighborhoods. These dependencies reveal significant information about the structure of objects from a visual standpoint. The calculation of this parameter is typically expressed using equation (7).

$$SSIM = \frac{(2\mu_1\mu_2 + C_1)(2\sigma_{12} + C_2)}{(\mu_1^2 + \mu_2^2 + C_1)(\sigma_1^2 + \sigma_2^2 + C_2)} \quad 7)$$

G. Quality Index (QI)

Quality Index (QI) parameter is also defined very similar to SSIM. This can be calculated as shown in equation (8)

$$QI = \frac{(4\sigma_{12}\mu_1\mu_2)}{(\mu_1^2 + \mu_2^2)(\sigma_1^2 + \sigma_2^2)} \quad (8)$$

In addition to the parameter discussed above few other parameters such as computational complexity, coding efficiency, power, entropy or randomness, bit rate, storage space, bandwidth, execution time etc.

IV. COMPARATIVE ANALYSIS

Table-I provides a comparative analysis of the compression schemes discussed and surveyed in this paper. The table presents various compression techniques along with their respective pros and cons, organized in chronological order. The choice of a specific compression scheme is contingent on the selection of performance parameters, including MSE, RMSE, PSNR, WSNR, CR, SSIM, QI, entropy, among others.

TABLE 1

COMPARISON OF DIFFERENT COMPRESSION SCHEMES

Compression Technique	Advantages	Disadvantages
Yi-Fei Tan et. al.[8]	Good CR Applicable for both lossy andlossless compression techniquesGoodPSNR	Extra calculation ofthreshold increasescomplexityOptimalthreshold criterion limits thequality
K. Rajakumar et.al. [9]	Good CR Optimized bit rates in case ofboth with and without RunLengthEncoding	IncreasedcomplexityCalculation of subbandsincreasesthe codingoverhead
C. Rengarajaswamyet. al.[11]	BetterCR Better security due toencryption Very compact output bit streamwith largebit variability	High complexityPSNRisnotgoodSingle bit error ofSPIHT More executiontime
Sujoy Paul et. al.[13]	Better PSNRBetter SSIMBetter CRLessMSE	ModeratedExecution timeModerated EntropyIncreased coding Complexity
Mohammad H.Asghari et. al.[14]	Very less MSESuperiorPSNR Less execution timeSuperiorSSIM	Increased codingcomplexity LessCR
B. Heyne et. al.[15]	Low computational	Low CRLowPSNR High MSELowSSIM

	complexityHighenergycompaction Lowprocessingpower	
A. Mittal et. al.[16]	HighCR Lowprocessingpower	High computational complexity Moderated PSNR Moderated SSIM Large memory Requirements
Yi-Fei Tan et. al.[8]	Good CR Applicable for both lossy andlossless compression techniquesGoodPSNR	Extra calculation ofthreshold increasescomplexityOptimalthreshold criterion limits thequality
K. Rajakumar et.al. [9]	Good CR Optimized bit rates in case ofboth with and without RunLengthEncoding	IncreasedcomplexityCalculation of subbandsincreasesthe codingoverhead
C. Rengarajaswamyet. al.[11]	BetterCR Better security due toencryption Very compact output bit streamwith largebit variability	High complexityPSNRisnotgoodSingle bit error ofSPIHT More executiontime
Sujoy Paul et. al.[13]	Better PSNR Better SSIM,Better CRLessMSE	ModeratedExecution timeModerated EntropyIncreased coding Complexity
Mohammad H.Asghari et. al.[14]	Very less MSESuperiorPSNR Less execution timeSuperiorSSIM	Increased codingcomplexity LessCR
B. Heyne et. al.[15]	Low computational complexityHighenergycompaction, Lowprocessingpower	Low CRLowPSNR High MSELowSSIM
A. Mittal et. al.[16]	HighCR, Lowprocessingpower	High computational complexity Moderated PSNR Moderated SSIM Large memory requirements

VII. CONCLUSION

This paper provides an extensive and up-to-date survey of various image compression schemes, with a particular emphasis on addressing the challenging issue of reconstructed image quality. This challenge is particularly pronounced in the context of biomedical images, such as CT and MRI images. Additionally, the paper underscores the equal significance of compression ratio and memory requirements in the development of efficient compression techniques. For the compression of dynamic MRI images, different performance metrics have been thoroughly discussed in their respective sections. Section 4 includes a summarized table that encompasses various compression techniques, highlighting their advantages and drawbacks. While achieving enhanced values of metrics such as PSNR, SSIM, and compression ratio (CR), certain issues like increased complexity, overhead, coding complexity, and cost are also acknowledged.

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