Medical Image Compression Algorithm Using Edge-Aware Adaptive Block Partitioning

Lecturer Hind J. Serteep[1]

hind_2018@uomustansiriyah.edu.iq

Abstract: As the world witnesses a major advance in medical staff diagnosis depending on medical images, including MRI and CT scans, it requires having compression approaches that balance between preserving essential medical information and reducing medical image data size. Such approaches that depend on local variance for the adaptive block partitioning mechanism , which is distinct form the classic method, like JPEG , in how usually experience blocking artifacts and loss of fine details. Instead of utilizing explicit edge detection, the algorithm uses both integer wavelet transform (IWT) and adaptive bit allocation to differentiate between smooth non-structural areas and structural regions containing vital edges. The algorithm shows superiority through applying the proposed algorithm on several medical images by achieving a Structural Similarity Index (SSIM) consistently exceeding 0.996 and an average Peak Signal-to-Noise Ratio (PSNR) of 48.01Db, which overcomes the performance of the JPEG standard in structural fidelity with the accomplishment of as equiponderant compression ratio (averaging 1.58) . The proposed algorithm is ideal for clinical application where accurate reconstruction in crucial, keeping diagnostically important structures and preserving tissue outlines.

Keywords: Medical image compression, Edge -Aware processing, integer wavelet transform, adaptive block partitioning, Diagnostic fidelity, lossy compression.

1. Introduction

Over the Last two decades, research in the medical field show longer life expectancy, decreased in hospital stays periods, less hospital admissions, exploratory surgery declines and decreases in mortality as a result of using medical image exam in diagnostics [1]. The rapid development of high-resolution image technology, especially in medical application and others like multimedia and remote sensing. This has led to produce massive data volumes and creating serious challenges in storage, transmission, and real time processing [2]. To deal with such important challenges, the idea of file compression (image, video) came about, which it known as a technology that lets people make image file smaller while still keeping a good amount of quality [3].

There are several advantages of file compression techniques, where the file size decreases, which makes them simpler to deal with and less costly to store. And regarding file transfer across networks or buses, it is very important to make file movement swift, preventing memory congestion or possibly leading to buffer overflow, and that is achieved by reducing file size as much as possible [4]. In addition to that, compression techniques maximize bandwidth use. Customers consider that extremely important to guarantee image-rich material access without consuming huge amounts of data in places with limited or expensive bandwidth, like an autonomous car driving system [5].

In the field of medical diagnosis and examination, where huge data are generated by ultrasound or computed tomography (CT) images and magnetic resonance imaging (MRI) that must be reviewed and analyzed by the medical staff, it is very important. To have an effective compression technique that can handle, store, and transmit this amount of data, where any small detail is very important and a faulty compressed image can cause a bad diagnosis [6].

Therefore, image compression is considered a crucial field of investigation in digital image processing. Researchers and computer scientists keep developing image compression techniques for image fidelity and

[1] Lecturer, department of computer science , Collage of education , AL- Mustansiriyah University, Baghdad , Iraq

file size reduction and focusing on essential needs of compression techniques which are critical visual information and compression efficiency [7].

In order to decrease data size, traditional compression algorithms like JPEG and JPEG2000 depend on duplication reduction techniques and frequency conversion, taking into consideration that the medical images are characterized by a highly diagnostic nature, which creates significant challenges when compressing these kinds of images. Creating an absence of fine details, which are essential to diagnosis, which are caused by losing high-frequency content [8]. Furthermore, when using techniques like DCT-based JPEG Compression artifacts occur that result in blocking artifacts and distortion in fine details and edges. These artifacts are unacceptable in the sequence of medical diagnosis. where it is possible to understand these artifacts as real elements in the image [9].

Additionally, current research reveals that conventional algorithms do not distinguish between necessary and unnecessary areas and are unable to locate sections that contain valuable information from those that do not, and that sometimes lead to excessive compression of sensitive diagnosis sections and loss of clinically valuable information, causing an increase in incorrect diagnosis or loss of essential date for medical staff image analysis software [10].

The most essential features in the medical diagnosis that depend on images are the edges. Which shows the actual borders between various body tissues according to unexpected shifts in pixel values [11] and pathological abnormalities, such as aberrant tissue and tumors. Which the medical staff depend on to make the precise clinical assessment. On the other side, the medical staff could have lower diagnostic accuracy and treatment results detrimental due to loss of tissue contours or substantial details because of a drop in edge representation as a result of failure to maintain edge information after compression [12].

Most current compression techniques do not properly include explicit procedures for keeping important edge information in medical images in spite of superiority in both conventional and sophisticated image compression algorithms, such as waveforms and deep learning. Probability of lost edge resolution after decompression as a result of the fact that the traditional methods do not differentiate between high importance and less diagnostically relevant edge areas. But they only concentrate on lowering high-frequency traces, especially at high compression ratios [13].

The research gap reveals the need to create an image compression technique that balances the retention of diagnostic information and compression ratio, considering computational efficiency and the ability to apply it on different image types. In order to close the gap between the practical clinical application and theoretical performance, the need arose to integrate critical structure analysis and edge information compression techniques [14].

The contribution of this paper can be summarized by integrating edge-aware structural analysis with a medical image compression technique to maintain diagnostically important structures and achieve a high compression ratio, Also the technique is characterized by lower computing complexity to facilitate implementation in medical systems.

The rest of this paper is ordered as follows: Section II describes a review of some related works, and Section III presents the key elements of the suggested compression technique; Section IV shows the experimental setup and results and comparative analysis; Section V A discussion of the results obtained.

2- Related Works

Many studies have appeared in the last years, concentrating on maintaining high edge and structural detail during the process of image compression techniques by utilizing deep learning techniques and transformational methods in order to keep important information and minimize distortion caused by data compression.

2.1 Edge-aware and post-processing for JPEG image

This research offered by Mishra et al. (2025) showed a technique that enhances image quality at low bitrates using edge-aware processing both before and after JPEG compression. This technique minimizes edge distortion by leveraging edge information using a novel loss function, which is not addressed by the traditional MSE standard. Additionally, it enhances detail in post-processing by making use of super-resolution networks, which makes the reconstructed images better than the standard methods. [15]

2.2 Edge - Preserving Image Smoothing Based on local structure Reconstruction.

Long et al (2025) demonstrate a method for improving images that maintains edges by rebuilding the local structure of the image through a preparation improvement framework, as preparation processes depend on the balance between maintaining sharp structures and noise removal in the image compression procedure, where small-scale edges are lost during conventional compression procedures [16].

2.3 Improved Median Edge Detection (iMED) for Loss Less Image Compression.

Amin et al. (2023) give a procedure for compressing images (a Lossless procedure) that achieves improvement in the structural accuracy of compressed images, which utilize an enhanced edge detection algorithm (iMED). This procedure obtains enhancement in fine details, and the results have good quality indicators like PSNR and SSIM by focusing on combining both lossless compression methods with edge detection approaches. [17]

2.4 Hybrid Deep Learning Architecture for Scalable high Quality Image compression.

A new study by AL-Khafije et al (2025) proposed a hybrid approach for Image compression established on deep learning that integrates several transformations, like stationary wavelet transform, with stacked denoising auto on coders and texture-based feature extraction. This approach gives minimal feature loss with a notable advancement in high-quality image compression by tightly partitioning and reconstructing the image into multiple layers, even if it does not concentrate on edges. [18]

3. The Proposed Methodology

This section explains the outline of the suggested image compression methodology that attempts to have efficient compression and keep edge information undistorted. Unlike the conventional methods, the proposed method distinguishes between structural and non-structural regions by exploiting edge-aware processing. Where the conventional methods do not take care about of it, pixel blocks that have strong edges require a large number of bits for proper representation, as they show greater local variability and a wider range of pixel values. Smooth regions on the other hand, have little local variation and high redundancy.

The compression method has a behavior of implicit edge awareness depending on adaptive bit allocation, where each block's count determined by counting the number of distiches locally revalued symbols. Blocks that have edges display higher local variability, as they contain a larger set of unique values and high bit requirements.

These block need less aggressively compression compared to smooth regions, which need fewer bits and high aggressive compression, and by this approach the edge information is automatically kept without explicit edge detection,

The compression algorithm is classified as Lossy method rather than lossless one, as the algorithm use approximation and adaptive processing techniques in the compression phase, which leads to losing some information during encoding.

3.1 The compression algorithm.

By examining local spatial activity inside the medical image, the proposed algorithm dynamically distributes computational resources. The fundamental logic uses local variance as a sensitive signal for structural complexity rather than uniform compression. A high Variance ($\sigma_k^2 > Ta$) indicates the existence of tissue boundaries or key diagnostic edges. In order to maintain fine features, the algorithm initiates an adaptive partitioning mechanism, dividing high-activity regions into smaller block (BS).In contrast, to optimize redundancy reduction; larger blocks (BL) are used to depict smooth areas. High structural fidelity (SSIM) and effective compression ratios are successfully balanced by this selective technique, which guarantees that the subsequent integer Wavelet Transform (IWT) and Huffman encoding are applied to data with optimum spatial resolution.

To guarantee precise reconstruction and complete decoder synchronization, the following crucial decoding data must put in the header (Image dimensions, Block parameters, Activity Threshold, Portion map, Huffman dictionary, transform type). The header contains the necessary data for reconstructing the image, like Huffman dictionaries and block map. In small images this overhead, take larger relative proportion of the bitstream causing a reduction in the actual compression ratio. To overcome the large overhead the suggested algorithm using a compact binary block-map to keep acceptable efficiency across all the image scales , the following steps illustrate the compression algorithm.

Input: Original Image I , Block sizes B_L , B_s , Activity Threshold T_a
Output: Compressed Bitstresm C

1. Preprocessing: $I_{pad} \leftarrow$ Padding (I) to multiple of 8.
2. Initial Partitioning: Divide I_{pad} into non-overlapping blocks B_K of size B_L
3. Adaptive Decision loop:
For each block B_K do:
- $\sigma_k^2 \leftarrow$ Compute local Variance (B_k)
- If $\sigma_k^2 > Ta$ then:
- $B_{eff} \leftarrow B_{s,i}$
- Else :
- $Beff \leftarrow B_k$
- Endif
4. Transformation & Encoding
- Apply 2D- IWT to $Beff$: $C_{coeff} = W.B_{eff}.W^T$
- Vectorize and apply Huffman Coding based on global probability $P(X_i)$.
5. Return $C=\{H , b'\}$ (Header and Bitstream).

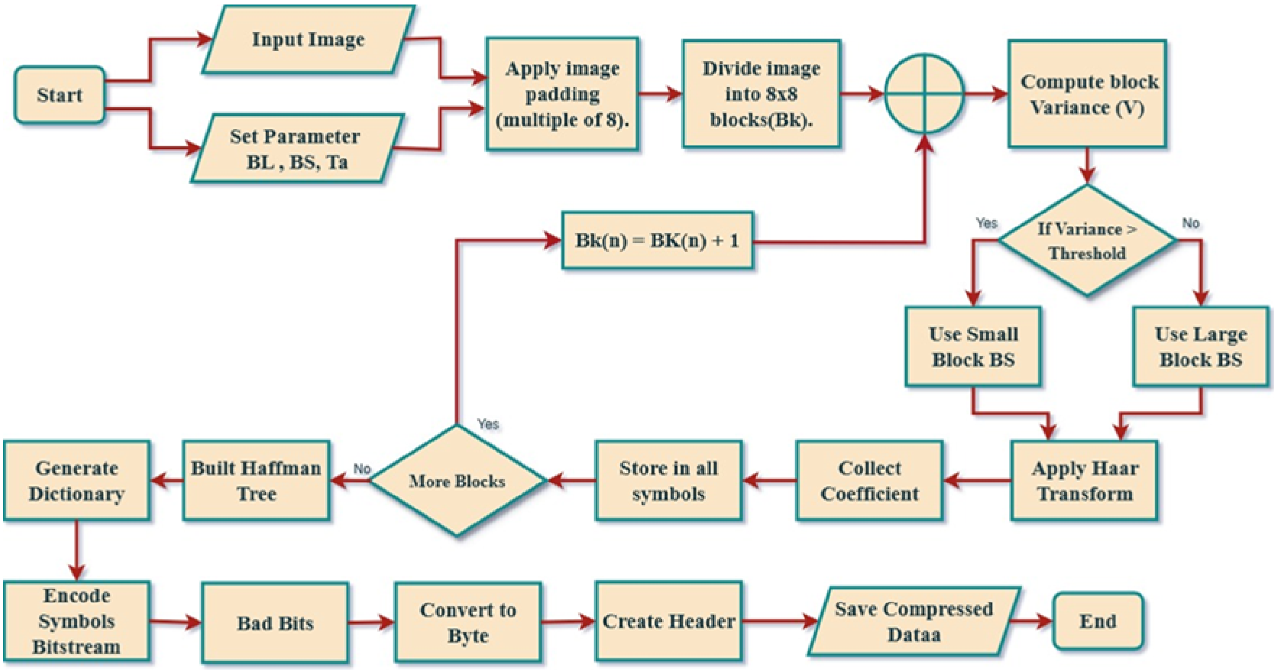

Figure 1:- The flowchart of the compression algorithm

3.2 The decompression algorithm.

Now the following steps illustrate the decompression algorithm: -

> Input: Compressed data stream *C* , Global Huffman dictionary *D*.
> Output: Reconstructed Image *I'*
>
> 1. Bitstream Unpacking: Separate Header *H* and Bitstream *b'*.
>   - Convert byte stream to binary sequence and remove padding bits.
> 2. Entropy Decoding: Reconstruct the invers Haffman dictionary D^{-1}
>   - Decode the bitstream to recover the wavelet coefficient sequence *S*.
> 3. Structural Reassembly:
>   For each block index *k* do :
>   - Retrieve block size (B_L or B_S) form the stored activity map.
>   - Reshape the decoded vector into the 2D coefficient matrix *Ck* (LL, LH, HL,HH bands)
> 4. Inverse transformation : Apply inverse interger wavelet transform (IWT) to each block.
>
> $$I'_i = W^T . C_K . W \quad ....(1)$$
>
> Where I'_i :the i reconstructed block
> W : transform matrix
> W^T : transpose matrix
> C: Coefficient Matrix consist of four Sub bands [LL , LH, HL, HH]
>
> 5. Final Synthesis: Place reconstructed block into their original spatial coordinates *(x,y)*.
>   - Remove padding to restore original dimensions M x N.
> 6. Return *I'* (Final Reconstructed Image)

The decompress algorithm prepare as deterministic inverse process, this phase synchronizes with the adaptive decisions made by the encoder. The Bitstream Unpacking (Step1) where the header metadata supplies the crucial "Blueprints" needed for precise synchronization , such us the activity map and image dimensions. The structural Reassembly (Step3) is the reconstruction's major strength; the decoder accurately determines which regions were divided into smaller blocks (BS) and which remained as large blocks (BL) by using the activity map that was recorded. This guarantees that matrices the precisely fit the initial multi-resolution arrangement are subjected to the Inverse Integer Wavelet Transform (IWT). Additionally, the accumulation of rounding errors during the transition from the wavelet domain bck to the spatial domain is avoided by using reversible integer transforms. By eliminating the padding during encoding, the last strp guarantees clinical validity and produces a rebuilt image (I') that preserves the precise spatial resolution and diagnostic contours of the original medical data.

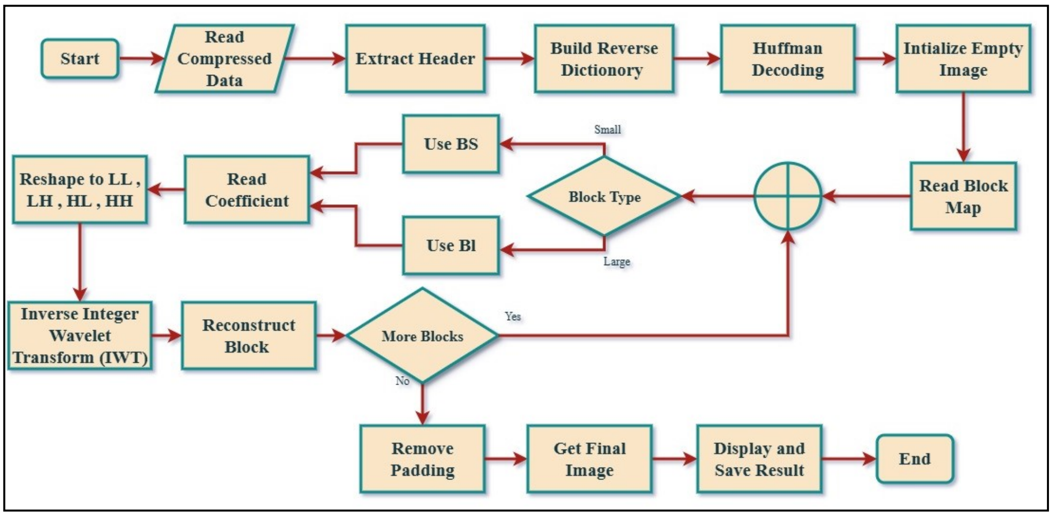

Figure 2: The flowchart of the decompression algorithm

To calculate the evaluation metrics such as MSR, PSNR and SSIM, It is required to have both the original and the reconstructed image, for this purpose only the reconstructed image is required during the decompression stage.

4-Results

Efficiency and image reconstruction quality were utilized to evaluate the performance of the proposed edge adaptive Lossy Image compression algorithm, which has been assessed in this section using standard metrics like compression ratio (CR), bit per pixel (bpp), mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM).

The Mean Squared Error (MSE) is considered the most popular and simplest quality metric used by researchers, which gives an indication about distortion quantity by a process on an image, where it relies on calculating the average squared difference between the original and reconstructed image [19],The Peak Signal-To-Noise ratio (measured in dB) is a metric utilized to evaluate the image or video quality after processing by comparison between the original and the reconstructed image which represents the maximum signal power to the errors. results from a process, The SSIM structural Similarity Index Measure unlike the PSNR which depends on numerical error, the SSIM calculation depends on structural similarity between two images, the original and the reconstructed image, the SSIM focuses on Luminance, structure and contrast [20], they above metrics can be calculate by the following equations(2) , (3) and (4).

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{n}[I(i,j) - I'(i,j)]^2 \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where :M,N image high and width
I (i , j) : Original Image pixel
I (i , j) :Reconstruction Image Pixel

$$PSNR = 10\ log_{10}\frac{MAXi^2}{MSE}\ \ldots\ldots\ldots\ldots\ldots(3)$$

Where: MAXi is the maximum possible pixel value.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)}\ldots\ldots\ldots(4)$$

Where x : original image , Y reconstructed image
µx , µy : the mean intensity of image x and image y
σx , σy : The variance of image x and image y
σxy : covariance between image x and image y
C, C: Small constants to avoid division b zero.

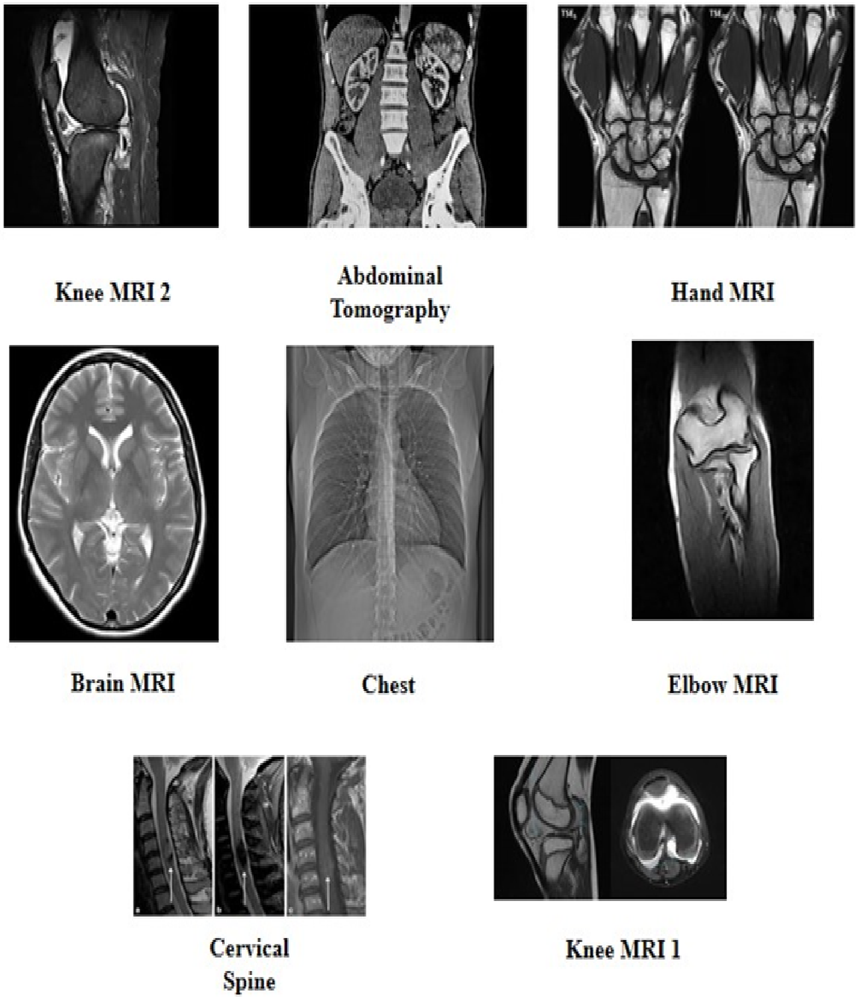

Figure 3: A Set of medical image used in test of the suggested Algorithm

Table #1: evaluation metric result of the proposed compression algorithm

Image name	Original size (Byte)	compressed size (Byte)	C.R	bpp	MSE	PSNR	SSIM
Chest	356580	246628	1.454	5.502	1.456733	46.497	0.995865
Knee MRI 1	50232	35068	1.432	5.585	0.99359	48.159	0.997646
Abdominal Tomography	5032	33474	1.503	5.3213	0.883259	48.67	0.999013
Cervical Spine	50286	42369	1.187	6.7405	1.459969	46.487	0.997824
Brain MRI	362916	189978	1.91	4.1878	0.833162	48.924	0.996196
Elbow MRI	70200	43596	1.61	4.9682	1.144217	47.546	0.992454
Knee MRI 2	50274	22663	2.218	3.6063	0.593189	50.399	0.997782
Hand MRI	198880	147558	1.348	5.9356	1.178349	47.418	0.997489
Average			1.58275	5.2308375	1.0678085	48.0125	0.9967836

The number show in table #1 above that the proposed algorithm achieved balanced performance between preserving image quality and compressing data, where the compression ratio (CR) value scale between 2.21 and 1.34, which gives indication that the compression algorithm noticeably decreases data and keep the essential Information of the image.

Regarding image quality, the PSNR record a value scale between 46 db and 50 db, which is considered a high value and gives minimal distortion resulting from the compression process, This indicates how well the Algorithm reduce distortion between the original and reconstruction image.

As for the SSIM metric, the result table display values that are extremely close to one (0.966 to 0.998) as the algorithm succeeded in keeping the structural information to high degree, which is extremely efficient in medical images where any small details great significance.

In spite of the results conforming the proposed algorithm being classified as Lossy one, the visual quality of the reconstructed image has negligible degradation. Thus, the algorithm gives a balanced performance between compression and perceptual quality with implicit edge-aware, where an explicit detection is not required for efficiently preserving high-frequency regions, for that the suggested algorithm is appropriate in cases where image quality and structural fidelity regardless of compression efficiency.

The benefit of the difference image is the reconstructed image assessment and to recognizing any diversion that can be difficult to notice by direct visual comparison, which can be calculated by the absolute pixel-wise difference between the original and reconstructed image, figure 4 below show samples of test, reconstructed and difference images. Where the minimal or no difference between pixels is represented by the darker area and vice versa the brighter area indicate a greater mismatch between corresponding pixels.

The difference images in figure 4 show that all of them are characterized by low intensity difference patterns, which enhances that the proposed algorithm keeps the original image's structural and overall characteristics with great accuracy.

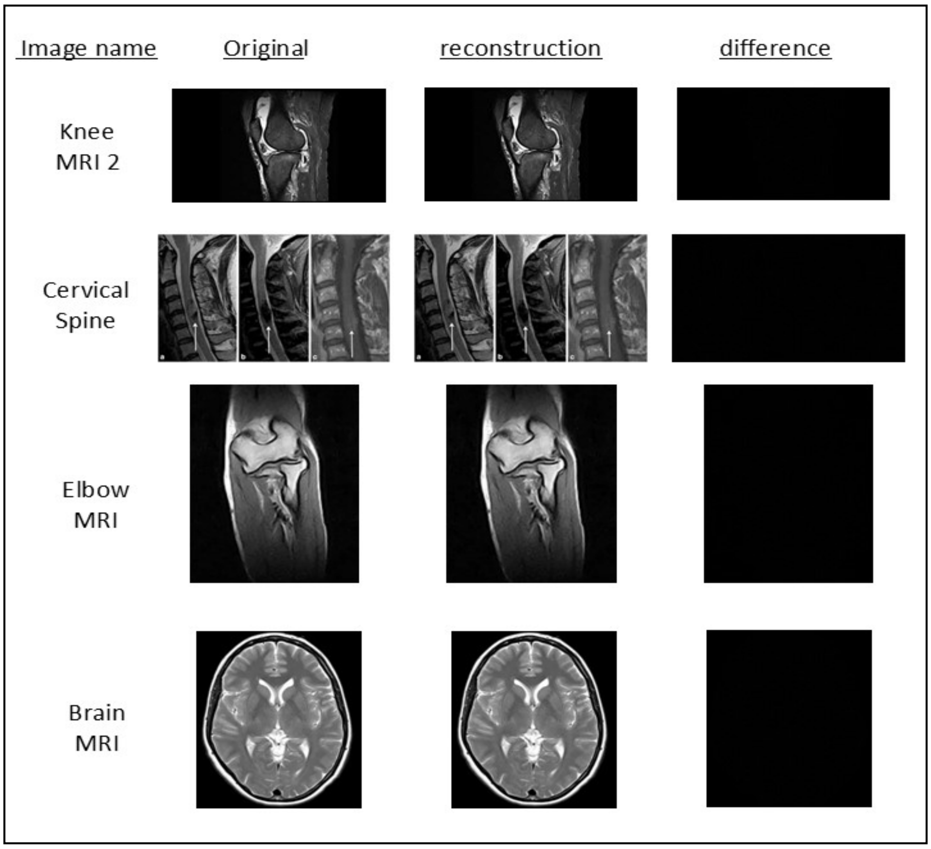

Figure 4: samples of test images with their reconstructed and difference images

4.1 compare with JPEG standard

Another assessment was applied to the proposed algorithm by comparing its performance with another compression approach. (JPEG standard) using three different quality factors (Q=30, 50 and 70.) which represent low, median and hard compression action by JPEG, the assessment utilized the same evaluation metrics that were used to evaluate the proposed algorithm. Which are the MSE, PSNR, SSIM, and C.R (shown in tables 2, 3 and 4 below) , the assessment takes into account the Reconstruction quality, Structural information and the Compression ratio.

Table #2 the evaluation metric of JPEG compression algorithm at Q=30

Image	MSE	PSNR	SSIM	CR
Chest	0.000180015	37.44692	0.931161318	4.560489527
Knee MRI 1	0.00067352	31.71649	0.935788175	3.097158379
Abdominal Tomography	0.001541034	28.12188	0.925662674	3.114520378
Cervical Spine	0.000822267	30.84987	0.9358256	2.914765742
Brain MRI	0.000210512	36.76723	0.935167793	2.028332404
knee MRI 2	0.000527276	32.77962	0.9540436	1.267601683
Hand MRE	0.000550197	32.59481	0.937542986	2.778388645
Elbow MRI	0.000226826	36.44307	0.943506515	3.798241758
Average	0.000591456	33.33999	0.937337333	2.944937315

Table #3 the evaluation metric of JPEG compression algorithm at Q=50

Image	MSE	PSNR	SSIM	CR
Chest	0.000108064	39.6632	0.955039274	3.398788709
Knee MRI 1	0.000422023	33.74664	0.957452001	2.542974781
Abdominal Tomography	0.000923878	30.34385	0.955345123	2.447096067
Cervical Spine	0.000434608	33.61902	0.965281113	2.415553543
Brain MRI	0.000117629	39.29484	0.948595747	1.382445737
knee MRI 2	0.000317849	34.97779	0.971303801	1.068574131
Hand MRE	0.000334894	34.75092	0.963321867	2.173352099
Elbow MRI	0.000135629	38.67648	0.966312024	2.965339739
Average	0.000349322	35.63409	0.960331369	2.299265601

Table #4 the evaluation metric of JPEG compression algorithm at Q=70

Image	MSE	PSNR	SSIM	CR
Chest	6.55736E-05	41.83271	0.970957837	2.555748326
Knee MRI 1	0.000102977	39.87259	0.989671898	1.850561798
Abdominal Tomography	0.000186621	37.29038	0.93822274	1.87989898
Cervical Spine	0.000107751	39.6758	0.990917325	1.8437014
Brain MRI	4.63558E-05	43.33896	0.993222077	1.209163148
knee MRI 2	8.64901E-05	40.63033	0.935907586	0.809421458
Hand MRE	0.000194761	37.10497	0.976535743	1.654021244

Elbow MRI	7.45407E-05	41.27607	0.980609712	2.280849941
Average	0.000108134	40.12773	0.972005615	1.760420787

4.1.1 Reconstruction quality

The Reconstruction image by the decompression process of the suggested algorithm introduced significantly less distortion which it exceeded the performance of the JPEG where the proposed Algorithm has an approximate average PSNR of 48.13 dB, while the values getting from JPEG at higher quality setting are PSNR = 40.13 at Q=70.

4.1.2 Structural information.

The proposed Algorithm shows better behavior in maintaining the reconstructed image structural information, through the values of the structural Similarity index (SSIM) are closed to unity (approximately 0.9968) in a consistent manner Compared to JPEG where the average SSIM value is equal to 0.9720 at Q=70.

4.1.3 Compression ratio.

Despite the fact that the proposed algorithm have a superiority in the reconstruction quality and structural information, trying to keep the visual fidelity as high as possible, studying compression efficiency shows that JPEG provides a higher compression ratio at the expanse of image quality (e.g. C.R=2.94 at Q = 30). The proposed algorithm, in the other hand, maintains a lower compression ratio (approximately 1,58).

4.2 compare with JPEG2000 standard

Another phase of comparison is made between the suggested algorithm and the JPEG2000 standard through the study of the same evaluation metrics (MSE, PSNR, SSIM and CR). The made at compression ratio equal to (2.5) which is reasonable in medical diagnostics as it represent a balance between image quality and data reduction.

Table #5 the evaluation metric of JPEG2000 compression algorithm at CR=2.5

Image	CR	MSE	PSNR	SSIM
Chest	2.5	2.16031E-05	46.6548	0.98771
Knee MRI 1	2.5	5.16802E-05	42.8668	0.98799
Abdominal Tomography	2.5	3.96249E-05	44.0203	0.9927
Cervical Spine	2.5	0.000162565	37.8897	0.97153
Brain MRI 1	2.5	4.20683E-05	43.7604	0.98734
knee 2 MRI	2.5	4.22314E-08	73.7436	0.99998
Hand MRE 1	2.5	9.26719E-05	40.3305	0.95033
Elbow_MRI_Cases2	2.5	8.58726E-06	50.6615	0.99518

The comparative metrics (MSE , PSNR and SSIM) at CR=2.5 are shown in table 5 above , It show that the JPEG 2000 is a robust wavelet-based standard and it start to show noticeable structural degradation as CR=2.5 with SSIM values falling to as low as 0.9503 in some cases like " Hand MRE1" .

The comparison between the proposed method and the JPEG 2000 standard depending on three viewpoints.

4.2.1. Stability of structural quality:

The proposes method achieve a stable and very high average SSIM value of 0.9967 at average compression ratio of 1.58, Conversely , the JPEG2000 show a significant decrease in SSIM value , especially in high-detail image.

4.2.2Adaptive Partitioning:

The suggested method avoid the uniformity compression of all parts of the image, unlike the JPEG2000 standard but it partitions high-activity edge regions in to small block (Bs) for more precise Compression utilized an implicit edge-aware mechanism that ensured more aggressive compression was applied to smooth areas, and vital diagnostic features were preserved.

4.2.3 Digital superiority: The proposed method achieve a better balance between size and quality (SSIM = 0.9977 at CR = 2.21 in Knee MRI 2) which it consider a strong result in contrast to the breakdown that could happen to the JPEG and JPEG2000 as the compression ration increases beyond their optimal range.

4.3 Validation via Standardized Public Dataset.

An additional evaluation phase was carried out on public DICOM database medical images for addressing the statistical significance of the suggested algorithm, The evaluation metrics numbers were illustrated in table #6 below of 10 sample images Chest CT Image (Axial Thoracic CT Slice) are shown in figure 5 below form the dataset, which shows that the SSIM average value is 0.997 and the PSNR of 52.94 dB, giving indication that the algorithm introduces high-fidelity reconstruction. Besides, the algorithm's structural integrity behavior shows remarkably stability at an average compression ratio of 2.809. As the mentioned results demonstrate, the algorithm performance (Edge-Aware adaptive block partitioning) is flexible, robust, and generalizable across standardized medical imaging archives, which meets the demand of digital medical communication instead of being limited to particular samples.

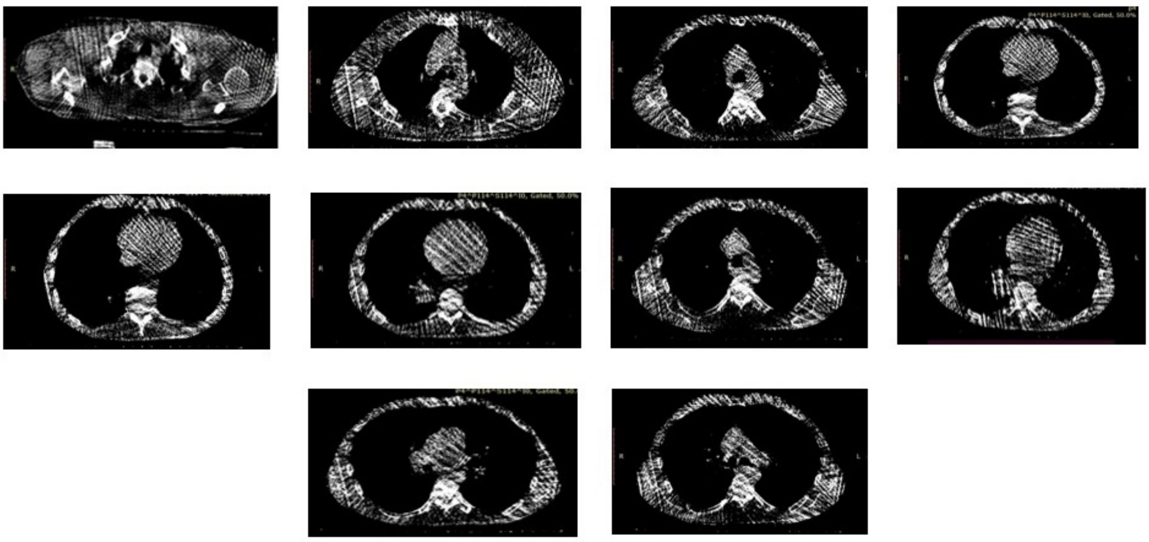

Figure 5: samples of test images form DICOM dataset

Table #6 the evaluation metric of the proposed algorithm on DICOM dataset

#	Image name	CR	BPP	MSE	PSNR	SSIM
1	IMG-0001-0001	3.02	2.648	0.2908	53.5	0.99997
2	IMG-0002-0001	2.84	2.814	0.31919	53.09	0.99971
3	IMG-0003-0001	2.95	2.711	0.30818	53.24	0.99971
4	IMG-0004-0001	2.96	2.701	0.30196	53.33	0.99969
5	IMG-0005-0001	2.94	2.721	0.3036	53.31	0.9997
6	IMG-0006-0001	2.97	2.696	0.30293	53.32	0.9997
7	IMG-0007-0001	2.85	2.806	0.32401	53.03	0.9997
8	IMG-0008-0001	2.95	2.712	0.30821	53.24	0.99971
9	IMG-0009-0001	2.43	3.3	0.40343	52.07	0.99968
#	IMG-0010-0001	2.18	3.666	0.47755	51.34	0.99965
	Average	2.81	2.877	0.33399	52.95	0.99972

4.4 Statistical Significance Analysis

Another validation of the effectiveness regarding the suggested algorithm with JPEG and JPEG2000, The assessment was built on paired-t tests for statistical significance of improvement in PSNR and SSIM compared with both JPEG AND JPEG2000 through all the tested medical images.

4.4.1 Comparison with JPEG

The obtained p-values were ($p=0.0212$:SSIM and $p=3.72*10^{-5}$:PSNR), revealing that the null hypothesis was rejected since both values were below the threshold of 0.05. These numbers confirm statistically significant superiority over JPEG in both reconstruction fidelity and structural similarity preservation

4.4.2 Comparison with JPEG2000

The statistical analysis yields that ($p=0.0711$:SSIM and $p=0.1064$:PSNR) , The numbers confirm that the null hypothesis could not be rejected since both p-values above the threshold of 0.05, which indicates there is no statistically significant between the suggested algorithm and the JPEG2000 standard.

4.5 Trade-off Between CR and Diagnostic Fidelity

When the medical staff deals with the medical image, the focus in the first stage is on diagnostic fidelity, and then care is taken in the second stage about the image compression ratio requirement .The compression ratio achieved in this study is (1.58) which is considered as acceptable ratio clinically that keeps subtle pathological marks and high-frequency edge details. In spite of the aggressive compression improving storage capacity but that leads to compromised medical data and distortion, causing incorrect medical diagnostics. As the suggested algorithm produces a balance between data reduction and clinical reliability by maintaining the SSIM value of 0.996,it ensures no damage of critical tissue outlines and diagnostic structures.

5-Discussion

The fundamental trade-off between data reduction and preservation of critical diagnostic information in medical imaging is successfully achieved by the proposed algorithm, beside of maintaining high structural fidelity as demonstrated by the SSIM values, which it exceeds 0.996 in a continuous manner, In the medical field where the tiny edges and tissue represent the pathological anomalies considered as a very important performance.

The suggested compression algorithm activity lies in using an implicit edge-awareness mechanism, which, depending on using local variance as a spatial activity indicator, enables the algorithm to identify more resources (smaller blocks) more easily in more complex areas like edges, which makes the algorithm deal with smooth areas with aggressive compression and removes the requirement of explicit detection filters, which are computationally costly.

The essential regulator between the image fidelity and compression efficiency is the activity threshold (Ta), there is a direct proportion between its value and the compression ratio , leading to an increase in the smooth regions that are classified in the larger blocks (BL) and on the other hand a threshold with a lower value leads to the creation of smaller blocks (BS) in the high-activity areas. At the selected (Ta) value of (20) the ideal balance was achieved the perceiving diagnostic features and acceptable data reduction.

The examination of the “difference image” in figure 4 above shows that the error in the reconstructed images is visually negligible and does affect diagnostic medical information. However, the algorithm is classified as lossy, beside the compressed images are small enough for safe transformation through medical networks, avoiding faulty diagnoses.

A comparison is made between the proposed algorithm and the JPEG standard. It is noticeable the suggested approach clearly outperforms the JPEG in terms of reconstruction quality, medically preserving the anatomical features as indicated by the SSIM average achieved value of 0.99677, In other hand the average SSIM value of the JPEG at Q=70 reaches 0.9720. It gives the impression that the suggested algorithm has a better behavior than traditional frequency-based transforms.

For evaluating the noise and distortion in the reconstructed image, it is clear that the high PSNR (average of 48.01 dB) was achieved by the proposed algorithm, which exceeds what is obtain by the JPEG standard in the best scenario (average PSNR=40.13 dB at Q=70). This fact indicates that the blocking artifacts can be minimized by utilizing the combination of both integer wavelet transform and adaptive block partitioning.

The results obtained from the tables above is that the suggested algorithm has a comparable performance to JPEG2000 while exceeding the performance of the conventional JPEG , Focus attention on its effectiveness on medical image compression application as a reliable solution.

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خوارزمية ضغط الصور الطبية باستخدام تقسيم الكتل التكيفي الواعي للحواف

الباحث هند جمعه سرتيب[1]

hind_2018@uomustansiriyah.edu.iq

المستخلص: مع التطور الكبير الذي يشهده العالم في تشخيص الكوادر الطبية بالاعتماد على الصور الطبية، بما في ذلك صور الرنين المغناطيسي والتصوير المقطعي المحوسب، تبرز الحاجة إلى أساليب ضغط تُوازن بين الحفاظ على المعلومات الطبية الأساسية وتقليل حجم بيانات الصور الطبية. تعتمد هذه الأساليب على التباين المحلي لآلية تقسيم الكتل التكيفي، وهو ما يختلف عن الأساليب التقليدية، مثلJPEG ، في أنها عادةً ما تُعاني من تشوهات في الصورة وفقدان التفاصيل الدقيقة. بدلاً من استخدام الكشف الصريح عن الحواف، تستخدم الخوارزمية كلاً من تحويل المويجات الصحيحة(IWT) وتخصيص البتات التكيفي للتمييز بين المناطق غير الهيكلية الملساء والمناطق الهيكلية التي تحتوي على حواف حيوية. أظهرت الخوارزمية تفوقًا ملحوظًا عند تطبيقها على العديد من الصور الطبية، حيث حققت مؤشر تشابه هيكلي (SSIM) يتجاوز باستمرار 0.996، ونسبة إشارة إلى ضوضاء قصوى (PSNR)متوسطة تبلغ 48.01 ديسيبل، متفوقةً بذلك على معيار JPEG في دقة البنية، مع تحقيق نسبة ضغط مماثلة (بمتوسط 1.58). تُعدّ الخوارزمية المقترحة مثالية للتطبيقات السريرية التي تتطلب إعادة بناء دقيقة، مع الحفاظ على البنى التشخيصية المهمة وحدود الأنسجة.

الكلمات المفتاحية: ضغط الصور الطبية، معالجة مُدركة للحواف، تحويل المويجات العددية، تقسيم الكتل التكيفي، دقة التشخيص، الضغط مع فقدان البيانات.

[1] مدرس في قسم علوم الحاسبات -الجامعة المستنصرية-كلية التربية – بغداد - العراق