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IMPROVED INTEGER WAVELET TRANSFORM (IIWT) BASED MEDICAL IMAGE COMPRESSION METHOD

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Abstract- Medical imaging is the technique used to get pictures of the human organs for analyzing and identifying diseases. The increasing pervasiveness of chronic diseases has led to the development of sophisticated medical imaging modalities and platform to facilitate accurate analysis and diagnosis. For the purpose of future reference and medical history, these images are saved and maintained for long period of time. However, storing poses an extreme challenge since there is limited memory to save these images. To solve such an issue, image compression method is adopted. Image compression enables for effective storage and broadcasting by lowering image size without compromising image quality. In this work, animate compression method by integrating Improved Integer Wavelet Transform and Discrete Cosine Transform (IIWTDCT) is proposed to compress medical images without losing diagnostic information and the quality of the image. In this method, raw medical images are passed to Hybrid Median Filter (HMF) to remove noisy data. After preprocessing, the images are decomposed using IIWT. An improved threshold technique is proposed to generate optimized detailed coefficients. DCT is applied to approximation coefficients and then quantized. Finally, the resultant values are Huffman encoded for transmission or storage. The reverse process of compression is performed to restore the image. The recommended method's performance has been shown and compared to the former method to prove its superiority. The results show that the proposed IIWTDCT can significantly reduce the size of the medical image that saves storage space and allows efficient transmission and at the same time retaining the salient diagnostic data.

Keywords: Improved Integer Wavelet Transform, Improved Threshold, Medical Imaging Modalities, Medical Image Compression and Quantization**.**

1. INTRODUCTION

In medical imaging, there are a wide range of approaches to make pictures of the human body. It can be used to analyze and diagnose diseases like identification of tumors. There are many different types of medical imaging techniques such as X-rays, Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Ultrasoun (US) [1]. A hospital with above mentioned imaging modalities generates a greater number of images per patient and these images requires 20 to 25 GB of memory per day [2]. The hospital memory space is limited, but it is required to save and retain each patient's medical history.

Telemedicine is one of the emerging applications of clinical medicine where patients' data is transferred over the communication network for perusal by an expert or physician. It allows physician to analyze, diagnose and treat patients at a distance via communication technology [3]. Telemedicine uses the Internet to transfer patients' medical records from one institution to another. Patients' medical records are kept in the hospital's archives for future reference. Transmission of medical images through network requires high bandwidth which increases the communication cost. Further to this, transmitting a greater number of medical data over the network encounters transmission issues especially in rural areas. To deal the aforementioned issues, medical image compression has been introduced.

Image compression aims to reduce the size of the medical image without degradation in the quality [4]. In theory, a lower Compression Ratio (CR) signifies a higher quality image recovered. Thus, developing a good compression method with high CR and good picture reconstruction is critical. Image compression is classified as lossy or lossless. In lossy method, high CR is obtained with loss of some data. On the other hand, the original and restored image are similar and CR is low [5]. Lossless method is chosen in medical image to retain the relevant information of the image. Telemedicine application require high CR to speed up transmission via different communication networks which can be reached by lossy compression. The major contributions this work is summarized as follows:

- A novel hybrid image compression method for telemedicine application is developed by combining

Improved Integer Wavelet Transform and Discrete Wavelet Transform (IIWTDCT)

- Hybrid Median Filter (HMF) is proposed to preserve salient information while mitigating the negative impact of noisy data.
- Improved threshold method is developed to select optimal detailed coefficients from all sub bands or images.
- The proposed IIWTDCT method's performance is validated using four various types of medical imaging, including X-ray, US, CT and MRI and compared to the current method to demonstrate its superiority.

2. RELATED WORKS

Many strategies, including hybrid methods, Discrete Wavelet Transform (DWT) based methods, and DCT based methods, have been developed in the field of medical image compression. Due to the advantages of greater CR and Peak Signal-to-Noise Ratio, hybrid approaches have been applied in medical image compression (PSNR). Kaur et al. [2] presented a hybrid method for compression which is based on context tree and fractal. Hosny et al. [3] suggested a method for image compression by combining Legendre moments and whale optimization algorithm. An adaptive sub band threshold-based image compression method to increase CR is developed by Vidhya [4]. Ali [5] combined DWT and DCT to reduce the size of medical images for efficient storage. Ammah and Owusu [6] analyzed the strength of DWT in compressing medical images for telemedicine applications. DWT and sub band coding is in medical image compression in order to ensure rapid transmission and adequate storage by Agarwal et al. [7]. Mofreh, et al. [8] designed a lossless compression method using DWT and Huffman technique. Setyaningsih and Harjoko [9] presented a detailed review of hybrid methods for image compression along with their merits and demerits. Kadam and Rathod [10] presented the improved CR and PSNR using a wavelet-based fractal quad tree and Huffman coding combination. A compression method which uses tetrolate transformations presented by Umamaheswari, et al. [11]. Agrwal, et al. [16] proposed a hybrid compression method by fusing IWT and DCT and proved that IWT based compression method provides better performance compared to DWT based method.

3. PROBLEM STATEMENT

Compression of medical images is one of the most important study topics in the field. It plays a pivotal in telemedicine for image transmission. Several methods have been reported in the literature. Each method has their own merits and demerits. Most of the methods have focused on reducing the size of the image for efficient transmission. According to Kadam, et al. [10] and Umamaheswari, et al. [11], the quality of medical images is affected by noise. During acquisition, medical images are vulnerable to noise. It's challenging to diagnose correctly if the visual quality has deteriorated. The resolution of medical images is a critical issue in medical image transmission. Image compression is used to address the aforementioned issue while also reducing memory usage. With the use of the Improved Integer Wavelet Transform-Discrete Cosine Transform, this work aims to design a robust picture compression approach for telemedicine applications (IIWTDCT). Furthermore, the suggested method's performance is evaluated using various wavelet filters in order to determine which one is best for robust compression and efficient transmission.

4. PROPOSED METHODOLOGY

The idea of this research is to create a medical image compression method that minimizes or reduces the number of bits necessary to represent the image for efficient storage and transmission. The suggested image downsizing method is depicted in Figure 1. As shown in Figure 1, the proposed method possesses five major process namely (i) Preprocessing (ii) Decomposition (iii) Forward DCT (iv) Detailed coefficient thresholding (vi) Quantization and Huffman encoding and (v) Decompression.

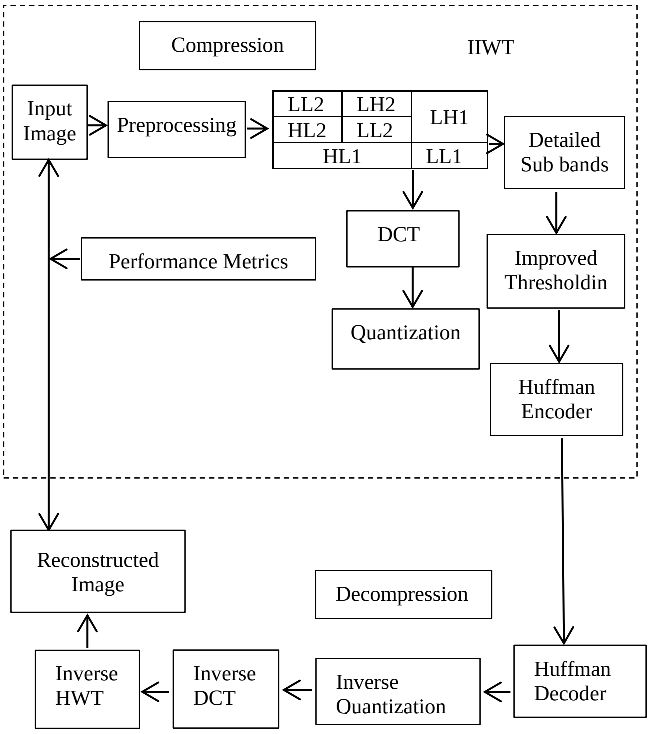


Figure 1. Overview of the proposed IIWTDCT method

4.1. Image Processing

Medical images are inherently affected by noises during acquisition. The quality of the medical images is reduced by various noises like salt and pepper and speckle noises. In this investigation, medical images are preprocessed using *HMF* to remove noisy data. Median filter is chosen due to its capability of edge preserving compared to mean and other filters. *HMF* is an improved version of median filter. Performance of *HMF* is better than *MF* in reducing noise and preserving boundaries and edges [12]. For example, consider the kernel $n \times n$ (3×3), shown in Equation (1), *HMF* replaces the pixel '*P*' from median values of three values, as given in Equation (2).

$$\begin{pmatrix} A_1 & B_1 & A_2 \\ B_2 & P & B_3 \\ A_3 & B_4 & A_4 \end{pmatrix} \tag{1}$$

$$HMF\left(P\right) = median\begin{cases} median(A_1, A_2, P, A_3, A_4) \\ median(B_1, B_2, P, B_3, B_4) \\ P \end{cases} \tag{2}$$

In this investigation, salt and pepper noise for MRI, CT and X-ray images and speckle noise for US images is considered to validate the denoising potential of the *HMF*. Kernel size of *HMF* is 3×3. Sample images before and after filtering is given in Figure 2. It can be observed that the proposed *HMF* filter efficiently preserves edges and curves while denoising.

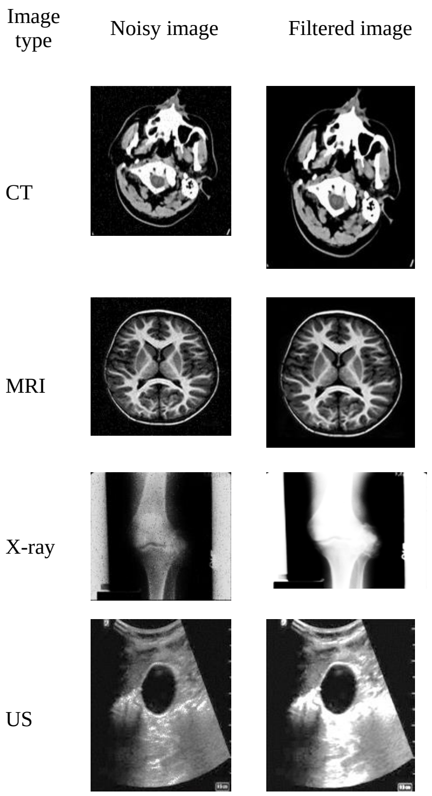


Figure 2. Sample images before and after preprocessing

4.2. Decomposition

Multiple stages of Integer Wavelet Transform (IWT) decomposition are applied to the preprocessed image. Multilevel decomposition displays frequency band information and highlights image details for subsequent processing. The inevitability wavelet transform (IWT) is a type of wavelet transform that supports inevitability. Unlike the DWT, the IWT is invertible with negligible computing overhead in finite precision arithmetic [13], [14]. As a result, these transforms are useful in picture compression. The main reason for selecting IWT over DWT is that IWT maps the integer data to another integer data whereas DWT transforms the floating points to integers by truncation which loses some data. If the input data is in integer form, the perfect reconstruction is possible without loss of data.

The strengths of IWT are: faster computation than DWT, IWT generates integer numbers which guarantee perfect reconstruction and low computational cost compared to DWT which operates on floating point numbers. Additionally, a rapid responding system with low computational cost is mandatory for telemedicine application. Thus, IWT is chosen. IWT decompose the preprocessed image into approximation and detailed coefficients. Five different wavelets are used and decomposition level is set to 2. Decomposition level is fixed by experimentation. Approximation coefficients are processed with DCT followed by quantization whereas detailed coefficients are subjected to thresholding to select optimal coefficients.

4.3. Discrete Cosine Transform (DCT)

The DCT algorithm uses a sum of cosine functions that oscillates at various frequencies to represent a finite series of data [15]. Smaller 8x8 blocks of the sub picture are processed using a 2D DCT for each block. There are two ways to express the two-dimensional DCT,

$$F\left(u,v\right) = \frac{2}{M} c\left(u\right) c(v) \sum_{x,y=0}^{N-1} f\left(x,y\right) \times \times\cos\left[\frac{(2x+1)\pi}{2M}\right]\cos\left[\frac{(2y+1)\pi}{2M}\right] \tag{3}$$

Inverse 2D DCT can be represented as,

$$f\left(i,j\right) = \frac{2}{M} c\left(u\right) c(v) \sum_{u,v=0}^{N-1} F\left(u,v\right) \times \times\cos\left[\frac{(2x+1)\pi}{2M}\right]\cos\left[\frac{(2y+1)\pi}{2M}\right] \tag{4}$$

4.4. Improved Sub Image Threshold

To achieve high CR, optimum number of salient coefficients is to be selected from detailed sub band. In this investigation an improved thresholding method is proposed to select the significant coefficients for all the sub-bands. If all sub bands are thresholder using common threshold, then there is a chance of losing the important information. Therefore, the proposed algorithm uses adaptive threshold for all sub bands. Mathematically, the proposed thresholding method can be represented as;

$$\overline{w(x,y)}_j = = \begin{cases} \left(w(x,y)_j\right)\left(w(x,y)_j - T_j \dfrac{T_j}{2\propto+1}\right) & \left|w(x,y)_j\right| \geq T_j \\ \dfrac{\left(w(x,y)_j\right)^{2\propto+1}}{(2\propto+1)T_j^{2\propto}} & \left|w(x,y)_j\right| < T_j \end{cases} \tag{5}$$

$$T = 0.3936 + 0.1829 \times \left(\frac{\log n_j}{\log 2}\right) \tag{6}$$

where, T is the threshold at jth scale, n is the size of image at jth scale, $w\left(x,y\right)$ and $\overline{w(x,y)}_j$ represents the original and thresholder coefficients, respectively. The detailed sub band coefficients are selected based on the condition which is given in Equation (5).

This condition is selected to choose the optimum number of detailed sub band coefficients to get better CR. This method is used because a single threshold cannot be used for all detailed sub bands as the information posed by each sub band differ. As far as medical data is concerned, it is necessary to extract the salient information in each of the sub bands. Examples of thresholder detailed sub bands are evinced in Figure 3.

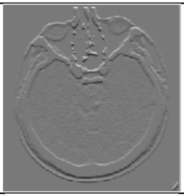
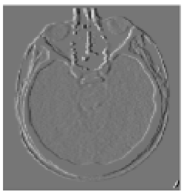
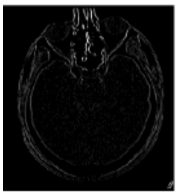
Sub bands	Before thresholding	After thresholding
Horizontal band		
Diagonal band		
Vertical band		

Figure 3. Outcome of improved thresholding

4.5. Quantization and Huffman Coding

Huffman encoding is used to minimize the bit size of quantized values. Using the compressed bits and their code, the receiver can successfully recover the original image and ensure correct decoding. The original image is reconstructed by reversing the image compression process. Data is decoded using a Huffman decoder and then quantized using a quantization decoder. After then, IDCT is used to analyze the data. An inverse IIWT is used to successfully extract the original image. The restored image is exactly the same size as the original. Listed below are the algorithmic processes that make up the suggested image compression method:

Procedure 1. Medical image compression based on IIWT

Input-Medical Images (CT, X-ray, MRI) Output-Decompressed Image
Step 1: Read medical image from database and compute dimensions Step2: For preprocessing, apply HMF to the input image Step 3: Apply IWT to the filtered image to get approximation coefficients and detailed coefficients Step 4: Segregate the approximation coefficients into 8×8 blocks Step 5: Apply DCT to the segmented blocks and then quantize the resulting values Step 6: Apply improved threshold method to all sub images or detailed coefficients to select optimal coefficients Step 7: Make use of the Huffman coding method in order to produce a stream of compressed bits. Step 8: Recover the image by performing reverse process of compression Step 9: Use statistical criteria to evaluate the recovered image's quality

5. DISCUSSION OF EXPERIMENT RESULTS

This section presents the statistical metrics used for evaluation and numerical outcomes obtained from the experimentation. The proposed image compression method is experimented with the MRI and CT images and the effectiveness is evaluated by computing the standard metrics. The proposed method is implemented on MATLAB 2019a platform executed in Intel core i5 processor with 3.7 GHz speed and 16 GB RAM.

5.1. Performance Indicators

The suggested image compression method's performance is assessed using the four-performance metrics listed in Table 1.

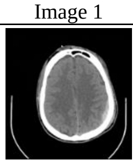
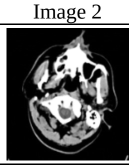
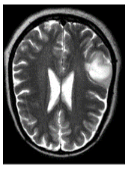
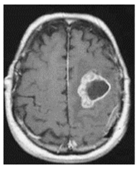
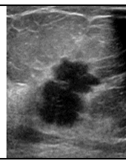
5.2. Performance Evaluation and Comparison

Experiments are conducted with CT, MRI, X-ray and US medical images, which is publicly available. Here, sample of medical images are shown in Table 2.

Table 1. Performance metrics

Metrics	Formula
Mean Square Error	$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[O(i,j) - R(i,j)\right]^2$
Peak Signal to noise Ratio	$PSNR = \log_{10}\left(255/MSE\right)$
Mean Structural Similarity index	$SSIM = \frac{(2\mu_x\mu_y + c_1) + (2\sigma_{xy} + c_2)}{(\mu_x^2\mu_y^2 + c_1)(\sigma_x^2\sigma_y^2 + c_2)}$ $MSSIM = \frac{1}{N}\sum_{i=1}^{N} SSIM_i$
Compression ratio	$CR = \frac{\text{Size of original image}}{\text{Size of compressed bit stream}}$

Table 2. Sample medical images used for analysis

Type	Image 1	Image 2	Image 3
CT			
MRI			
X ray			
US			

Primarily, the collected images are preprocessed using *HMF* in order to remove noise. Subsequently, the preprocessed images are decomposed using IIWT and then approximation coefficients are processed with DCT followed by quantization. Optimal detailed coefficients are selected using the proposed improved thresholding technique. Different wavelet filters are adopted to find out suitable one for efficient image compression. Table 3 shows the results of the suggested method for CT image compression utilizing various wavelet filters.

Table 3. Performance analysis using different wavelets (CT image)

Wavelet name	Haar	Db4	Symlet 3	Coiflets1	Biorthogonal
Reconstructed image					
MSE	0.0207	0.008	0.0097	0.0249	0.0216
PSNR (dB)	41.06	44.99	44.19	40.1	40.7
MSSIM	0.794	0.9577	0.9406	0.7928	0.7806
CR	7.01	7.94	6.75	5.42	6.36

Five wavelet filters namely Haar, Debauches (Db), Symlet, Coilflet and biorthogonal are considered. Based on the values of performance metric listed in Table 1, suitable wavelet is selected. If *PSNR*, CR, and *MSSIM* values are high, the compression method is efficient and vice versa. Thus, Db4 is chosen which poses higher value for *PSNR* of 44.99 dB, *MSSIM* of 0.9577 and CR of 7.94. After selection of wavelet, the proposed method is applied on 15 images each in CT, MR, X-ray and US. The quality measures such as *MSE*, *PSNR*, *MSSIM* and *CR* are computed after applying the proposed method and DWT [6] separately.

5.3. Result Analysis for MRI Images

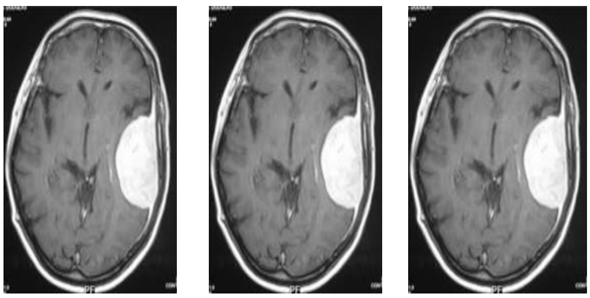
Tables 4(a) and (b) compare the outcomes of the proposed method with DWT method for 15 MRI images in terms of performance metrics. From the Table 4, as compared to the previous method used as a comparison, the new method appears to produce superior outcomes. In Tables 4(a) and (b), with respect to the obtained values of MSE, it is found that the DWT method possess average value of 0.0150 and the proposed IIWTDCT method resulted in yielding a value of 0.0071 showing its potential. In case of *PSNR*, the IIWTDCT method achieved higher *PSNR* value of 8.71 dB than that of DWT.IIWTDCT has mean *MSSIM* of 0.9607 compared to 0.8404 for DWT. This *MSSIM* proves that the IIWTDCT preserves more information compared to DWT. Further to this, the IIWTDCT method outperformed by possessing high *CR* of 7.1859. This is observed for other imaging modalities. Figures 4(a)-4(c) presents MRI image compressed using DWT and the IIWTDCT method.

Table 4. (a) Performance comparison of the proposed IIWTDCT with DWT for MRI images

MRI image No.	*MSE*		*PSNR* (dB)	
	DWT	IIWTDCT	DWT	IIWTDCT
1	0.0426	0.0057	37.77	46.52
2	0.0539	0.0056	36.75	46.60
3	0.0457	0.0051	37.47	46.98
4	0.0491	0.0074	37.15	45.37
5	0.0358	0.0056	38.53	46.58
6	0.0592	0.0075	36.34	45.33
7	0.0491	0.0059	37.15	46.36
8	0.0491	0.0088	37.16	44.64
9	0.0544	0.0058	36.71	46.43
10	0.0418	0.0055	37.85	46.69
11	0.0425	0.0058	37.79	46.40
12	0.0777	0.0186	35.16	41.38
13	0.0425	0.0055	37.78	46.67
14	0.0478	0.0067	37.27	45.79
15	0.0735	0.0076	35.40	45.27
Average	0.0510	0.0071	37.09	45.80

Table 4. (b) Performance comparison of the proposed IIWTDCT with DWT for MRI images

MRI image No.	*MSSIM*		*CR*	
	DWT	IIWTDCT	DWT	IIWTDCT
1	0.8465	0.9664	3.71	7.58
2	0.8605	0.9779	3.06	5.95
3	0.8820	0.9782	3.75	9.26
4	0.8365	0.9578	3.51	5.25
5	0.8583	0.9643	5.87	5.10
6	0.8077	0.9641	3.17	9.36
7	0.8235	0.9697	3.68	11.3
8	0.8273	0.9387	3.52	8.08
9	0.8224	0.9741	2.64	8.66
10	0.8989	0.9598	4.20	6.00
11	0.8245	0.9637	4.76	7.12
12	0.8421	0.8996	2.85	5.12
13	0.8503	0.9729	5.11	7.02
14	0.8200	0.9596	3.38	6.31
15	0.8064	0.9641	3.88	5.68
Average	0.8404	0.9607	3.81	7.19



(a) MRI Image (b) DWT (*PSNR*=37.15, *MSSIM*=0.8235) (c) IIWTDCT (*PSNR*=46.36, *MSSIM*=0.9697)

Figure 4. Sample reconstructed image after application of DWT and the IIWTDCT

5.2. Result analysis for CT images

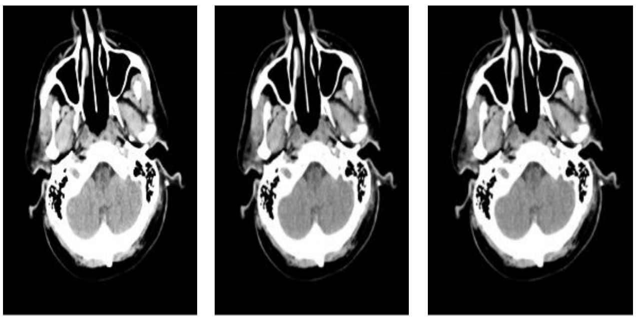
Tables 5(a) and (b) present the performance comparison of the IIWTDCT with DWT method for CT images. Analyzing the Table.6, the proposed IIWTDCT method provided outstanding performance by yielding lower mean *MSE* value of 0.091 and better mean *PSNR* value of 44.52 dB and better mean *CR* value of 7.56 and good *MSSIM* value of 0.9606 when compared to DWT method yields mean *MSE*, *PSNR*, *CR* and *MSSIM* values of 0.0557,36.67dB,4.82 and 0.8809 respectively. Table-5(a) and 5(b) also shows that the proposed IIWTDCT outperforms DWT in all compression metrics. Figure.5 (a)-(c) shows CT image and reconstructed image obtained using DWT and the IIWTDCT method.

Table 5. (a) Performance comparison of the proposed IIWTDCT with DWT for CT images

CT image No.	*MSE*		*PSNR* (dB)	
	DWT	IIWTDCT	DWT	IIWTDCT
1	0.0834	0.0100	34.85	44.08
2	0.0617	0.0101	36.16	44.01
3	0.0541	0.0100	36.73	44.07
4	0.0643	0.0110	35.99	43.64
5	0.0449	0.0073	37.54	45.41
6	0.0524	0.0083	36.87	44.88
7	0.0567	0.0089	36.53	44.55
8	0.0563	0.0095	36.56	44.30
9	0.0558	0.0105	36.60	43.84
10	0.0384	0.0066	38.22	45.84
11	0.0475	0.0081	37.30	44.99
12	0.0533	0.0090	36.79	44.52
13	0.0633	0.0108	36.05	43.74
14	0.0517	0.0086	36.93	44.70
15	0.0520	0.0077	36.91	45.22
Average	0.0557	0.0091	36.67	44.52

Table 5. (b) Performance comparison of the proposed IIWTDCT with DWT for CT images

CT image No.	*MSSIM*		*CR*	
	DWT	IIWTDCT	DWT	IIWTDCT
1	0.8442	0.9614	2.62	8.00
2	0.8974	0.9557	3.29	6.43
3	0.8619	0.9572	6.16	7.97
4	0.8671	0.9540	3.62	6.28
5	0.8279	0.9588	5.62	6.61
6	0.8520	0.9588	5.11	7.40
7	0.9367	0.9693	4.34	7.96
8	0.9317	0.9634	4.60	7.82
9	0.8642	0.9556	6.44	7.98
10	0.8933	0.9697	7.69	9.28
11	0.8936	0.9641	5.60	8.91
12	0.9016	0.9611	4.48	7.47
13	0.8927	0.9589	3.74	6.72
14	0.8305	0.9535	4.24	6.75
15	0.9183	0.9669	4.75	7.88
Average	0.8809	0.9606	4.82	7.56



(a) CT Image (b) DWT (*PSNR*=36.60, *MSSIM*=0.8642) (c) IIWTDCT *PSNR*=43.84, *MSSIM*=0.9556

Figure 5. Sample reconstructed image after application of DWT and the IIWTDCT

5.3. Result Analysis for X-Ray Images

Tables 6(a) and 6(b) show the compression ability of the proposed IIWTDCT approach utilizing X-ray pictures. It appears from the Table 7 that the proposed IIWTDCT yielded promising results when compared to DWT based compression method. DWT based compression method attained *MSE*, *PSNR*, *MSSIM* and *CC* values are 0.0414, 37.97 dB, 0.8079, 0.9668 and 8.34, respectively. The IIWT-DCT-H method achieved average *MSE*, *PSNR*, *MSSIM* and *CC* values are 0.0057, 46.61 dB, 0.9968 and 11.83, respectively. These values reveals that the IIWTDCT method has the potential to compress and decompress the medical images without loss of salient information as well as quality. Figures 6(a)-6(c) evinces X-ray image compressed using DWT and the IIWTDCT method.

Table 6. (a) Performance comparison of the proposed IIWTDCT with DWT for X-ray images

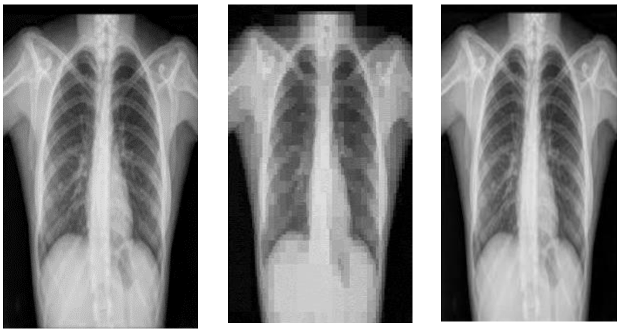
X-ray image No.	*MSE*		*PSNR* (dB)	
	DWT	IIWTDCT	DWT	IIWTDCT
1	0.0368	0.0080	38.40	45.06
2	0.0523	0.0059	36.88	46.34
3	0.0325	0.0054	38.95	46.73
4	0.0374	0.0055	38.34	46.69
5	0.0391	0.0054	38.14	46.77
6	0.0439	0.0073	37.64	45.41
7	0.0376	0.0046	38.31	47.40
8	0.0330	0.0046	38.88	47.42
9	0.0342	0.0031	38.72	49.14
10	0.0521	0.0050	36.89	47.06
11	0.0368	0.0080	38.40	45.05
12	0.0480	0.0055	37.25	46.70
13	0.0467	0.0041	37.37	47.94
14	0.0378	0.0065	38.29	45.95
15	0.0521	0.0071	36.89	45.57
Average	0.0414	0.0057	37.9574	46.6152

Table 6. (b) Performance comparison of the proposed IIWTDCT with DWT for X-ray images

X-ray image No.	*MSSIM*		*CR*	
	DWT	IIWTDCT	DWT	IIWTDCT
1	0.8732	0.9688	5.03	13.8
2	0.7651	0.9665	5.81	6.46
3	0.8075	0.9667	8.82	14.18
4	0.8513	0.9629	6.57	7.09
5	0.8503	0.9676	5.08	12.5
6	0.7651	0.9549	6.51	13.2
7	0.8311	0.9703	12.7	15.3
8	0.8172	0.9705	5.79	8.47
9	0.7911	0.9785	14.28	15.3
10	0.6829	0.9703	15.52	15.1
11	0.8732	0.9686	5.03	13.9
12	0.7909	0.9734	7.77	14.6
13	0.8200	0.9636	8.85	5.29
14	0.8284	0.9678	13.2	16.0
15	0.7716	0.9511	4.11	5.78
Average	0.8079	0.9668	8.34	11.8

5.4. Result Analysis for US Images

Performance of the IIWTDCT with DWT method for 15 US images is given in Table 7(a) and (b). Using all criteria, the IIWTDCT approach outperforms the DWT based compression method. The mean *MSE*, *PSNR*, *MSSIM*, and *CR* values for DWT and IIWTDCT compression methods are (0.0469 and 0.0066), (37.44 dB and 46 dB), (0.7585 and 0.9625), and (4.62 and 9.68), respectively. From the Table 9, it is evident that the IIWTDCT method can reduce the size of medical image as well as restore the image without loss of relevant information. Figures 7(a)-7(c) illustrates US image and reconstructed image obtained using DWT and the IIWTDCT method.



(a) X-ray image (b) DWT (*PSNR*=38.72, *MSSIM*=0.7911) (c) IIWTDCT (*PSNR*=49.14, *MSSIM*=0.9785)

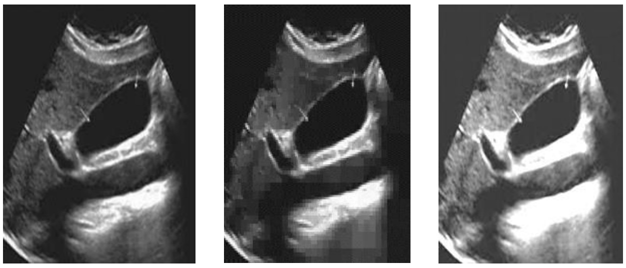
Figure-6 Sample reconstructed image after application of DWT and the IIWTDCT

Table 7. (a) Performance comparison of the proposed IIWTDCT with DWT for US images

US image No.	*MSE*		*PSNR* (dB)	
	DWT	Proposed	DWT	Proposed
1	0.0389	0.0052	38.17	46.94
2	0.0378	0.0047	38.29	47.30
3	0.0307	0.0046	39.19	47.44
4	0.0392	0.0051	38.13	47.00
5	0.0413	0.0056	37.91	46.56
6	0.0397	0.0054	38.08	46.72
7	0.0634	0.0075	36.05	45.30
8	0.0634	0.0056	36.05	46.60
9	0.0437	0.0085	37.66	44.78
10	0.0500	0.0073	37.08	45.45
11	0.0506	0.0068	37.02	45.71
12	0.0437	0.0072	37.66	45.46
13	0.0468	0.0085	37.37	44.76
14	0.0575	0.0089	36.47	44.55
15	0.0564	0.0073	36.55	45.44
Average	0.0469	0.0066	37.44	46.00

Table 7. (b) Performance comparison of the proposed IIWTDCT with DWT for US images

US image No.	*MSSIM*		*CR*	
	DWT	Proposed	DWT	Proposed
1	0.8142	0.9734	4.16	8.30
2	0.7357	0.9735	4.82	8.32
3	0.8199	0.9709	7.35	6.57
4	0.8204	0.9691	4.43	11.3
5	0.8272	0.9723	6.02	11.8
6	0.7987	0.9672	5.04	10.0
7	0.7788	0.9643	4.58	10.9
8	0.7788	0.9722	4.58	12.1
9	0.8093	0.9645	4.55	10.8
10	0.8089	0.9596	4.01	6.88
11	0.7611	0.9624	3.36	11.9
12	0.6647	0.9446	3.67	8.85
13	0.6501	0.9458	4.07	8.57
14	0.6705	0.9499	3.75	8.33
15	0.6390	0.9471	4.85	10.2
Average	0.7585	0.9625	4.62	9.68



(a) US image (b) DWT (PSNR=38.13, MSSIM=0.8204) (c) IIWTDCT (PSNR=47, MSSIM=0.9691)

Figure 7. Sample reconstructed image after application of DWT and the IIWTDCT

6. CONCLUSIONS

This paper presented a robust medical image compression method by fusing IIWT and DCT. Primarily, the medical images are preprocessed employing *HMF*. Secondly, IWT is adopted to decompose the preprocessed image into approximation and detailed coefficients. Thirdly, approximation coefficients are processed with DCT followed by quantization. Subsequently, detailed coefficients are selected using improved thresholding method. Then, the resultant values are encoded utilizing Huffman encoder. Decompression stage is performed by Huffman decoding, dequantization, inverse DCT and inverse IIWT. The proposed method is validated using different medical images such as MRI, CT, X-ray and US. Empirical findings demonstrated that the proposed method outperformed by yielding higher *PSNR*, *SSIM* and *CR* and lower *MSE* when compared to the former method taken for comparison. Future enhancement of the investigation, machine learning and nature inspired algorithms will be explored to further improve *PSNR* and *CR* values.

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