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Compression of Medical Images Using Wavelet Transform and Metaheuristic Algorithm for Telemedicine Applications

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ABSTRACT- Medical image compression becomes necessary to efficiently handle huge number of medical images for storage and transmission purposes. Wavelet transform is one of the popular techniques widely used for medical image compression. However, these methods have some limitations like discontinuity which occurs when reducing image size employing thresholding method. To overcome this, optimization method is considered with the available compression methods. In this paper, a method is proposed for efficient compression of medical images based on integer wavelet transform and modified grasshopper optimization algorithm. Medical images are pre-processed using hybrid median filter to discard noise and then decomposed using integer wavelet transform. The proposed method employed modified grasshopper optimization algorithm to select the optimal coefficients for efficient compression and decompression. Four different imaging techniques, particularly magnetic resonance imaging, computed tomography, ultrasound, and X-ray, were used in a series of tests. The suggested method's compressing performance is proven by comparing it to well-known approaches in terms of mean square error, peak signal to noise ratio, and mean structural similarity index at various compression ratios. The findings showed that the proposed approach provided effective compression with high decompression image quality.

Keywords: Integer Wavelet Transform, Modified Grasshopper Optimization Algorithm, Optimization and Telemedicine Applications.

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1. INTRODUCTION

Medical images play a significant role in identification, diagnosis and surgical planning of disorders. These images have large volume of relevant information that assist physicians or doctors in analysing more accurately and planning the diagnosis for patients. For the purposes of medical history and future reference of patients, medical images should be stored. Due to the advancements in imaging techniques, the amount of generation of medical images for both diagnosis and telemedicine applications has increased in recent years. However, because to a lack of memory and limited transmission bandwidth, hospitals find it difficult to store and transmit medical images. To rectify the aforementioned concerns, image compression is introduced. Image compression aims to minimize the size of medical images for efficient transmission and storage while keeping image quality for diagnostic purposes [3].

Several image compression techniques have been developed so far for compressing medical images [12]. However, most of the techniques able to yield good outputs at low Compression Ratio (CR) and memory and computation cost are yet to be a critical issue. Therefore, compressing medical images at high CR without losing important data is an extremely challenging task.
Recently, metaheuristic algorithms are integrated with image compression methods to enhance the CR and reduce storage space demand. Researches have used the metaheuristic algorithm as an optimization method for image compression [5] [6] [11]. Medical images are compressed, and certain critical details are lost, posing a risk during analysis and diagnosis. Thus, this paper presents a novel hybrid compression algorithm by integrating Integer Wavelet Transform (IWT) and metaheuristic algorithm. The major contribution of this paper are as follows:

• A new optimized image compression method is proposed by using Integer Wavelet Transform (IWT) and Modified Grasshopper Optimization Algorithm (MGOA), named as MGOA-IWT.
• Hybrid Median Filter (HMF) is proposed to suppress noisy data.
• The proposed algorithm, MGOA select the optimal coefficients for compression and decompression

• The new MGOA-IWT approach's performance is validated using four various types of medical imaging, including MRI, CT, X-ray, and US, and compared to the existing method to demonstrate its superiority.
• The compression ability of the MGOA-IWT is analysed by varying CR.

2. REVIEW OF PREVIOUS METHODS

Alkinami et al. [1] combined WT and Particle Swarm Optimization (PSO) for developing an efficient method for image compression scheme.
Hosny et al. [2] presented a compression method by using Legendre moments and whale optimization algorithm.
Sreenivasulu et al. [3] presented a method for image compression which is based on wavelet based modified region grouping algorithm.
Ammah et al. [5] used Daubechies WT and Huffman encoding for compressing biomedical images. However, WT based compression has some drawbacks like poor reconstruction due to floating points.
Medical image compression by applying harmony search algorithm was introduced by Haridoss et al. [4].
Region of Interest (ROI) based medical image compression by applying modified rider optimization algorithm was implemented by Sreenivasulu et al. [6].
Honsy et al. [7] proposed a Tchebichef moments and artificial bee colony algorithm-based picture compression approach.
Wu et al. [9] introduced image compression method using genetic algorithm and discrete WT.
A hybrid algorithm based on IWT and Particle Swarm Optimization (PSO) algorithm was invented by Vijayvargia et al. [11].
Bouetta et al. [12] used discrete WT and genetic algorithm for compressing images without loss of data.

3. PROPOSED MEDICAL IMAGE COMPRESSION METHOD

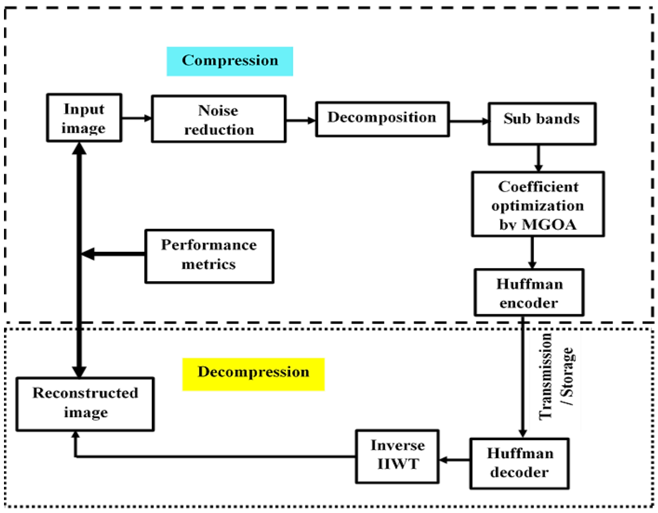

Figure 1: Framework of the proposed medical image compression method

The prime objective of this work is to integrate IWT and MGOA to reduce the size of medical images of different modalities for efficient storage and transmission. The complete processes involved in the proposed method is evinced in *figure -1*.

3.1. Noise Suppression

The Hybrid Median Filter (HMF) is used to eliminate noise from medical images in this study. Let a kernel with size of 3 X 3 shown in Figure. 2, HMF replaces the pixel ‘P’ from the median values of three values, as given in Equation (1),

$$\begin{bmatrix} A1 & B1 & A2 \\ B2 & P & B3 \\ A3 & B4 & A4 \end{bmatrix}$$

Figure 2: 3 X 3 Kernel

$$\mathrm{HMF(P)} = \mathrm{median}\begin{cases} \mathrm{median(A1, A2, P, A3, A4)} \\ \mathrm{median(B1, B2, P, B3, B4)} \\ \mathrm{P} \end{cases} \quad (1)$$

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 de-noising potential of the HMF. Kernel size of HMF is 3 X 3. Sample images before and after filtering is given in *figure-3*.

3.2. Decomposition

In this research work, IWT is adopted for decomposition. The IWT has three phases split, predict and update.
Split: Let the input signal x(n) is divided into even samples $X_e(n)$ and odd samples $X_o(n)$

$$X_e(n) = x(2n) \quad (2)$$
$$X_o(n) = x(2n+1) \quad (3)$$

Predict: Both X_e and X_o are obtained by dividing X. So, there exists a correlation between them. A Predictor P is applied on the $X_e(n)$ and then difference between $P[X_e(n)]$ and $X_o(n)$ turns out as the detail signal. Detail signal can be expressed as,

$$D(n) = X_o(n) - P[X_e(n)] \quad (4)$$

Update: An update operator U is applied on D(n) and then $X_e(n)$ is modified by U[D(n)] to get low frequency component, A.

$$A(n) = X_e(n) - U[D(n)] \quad (5)$$

3.3. Coefficient Optimization

GOA is a recent bio inspired algorithm developed by Saremi et al. [8] for solving optimization problems. According to Saremi et al. [8], the swarming behavior of grasshopper can be expressed as,

$$X_i = S_i + G_i + A_i \quad (6)$$

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Where, X is the Position of the i^{th} grasshopper, S, G and A are social interaction, gravity force and wind advection respectively. Social interaction, S can be defined as,

$$S_i = \sum_{j=1}^{N} s(d_{ij})\widehat{d_{ij}} \;, j \neq i \tag{7}$$

$$d_{ij} = |x_j - x_i| \tag{8}$$

$$\widehat{d_{ij}} = (x_j - x_i)/d_{ij} \tag{9}$$

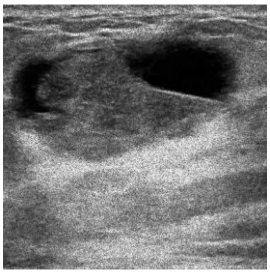
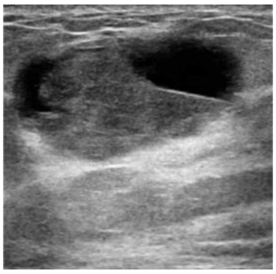
Image type	Noisy image	De-noised image
US		

Figure 3: Sample medical image before and after noise suppression

X_iWhere, dij is distance between i^{th} and j^{th} grasshopper and s is the Social force and s can be defined as,

$$s(r) = fe^{\left(-r/l\right)} - e^{-r} \tag{10}$$

Gravitational force, G can be computed using Equation (11),

$$G_i = -g\widehat{e_g} \tag{11}$$

Wind advection, A can be calculated using Equation (12),

$$A_i = u\widehat{e_w} \tag{12}$$

Where, f denotes intensity of attraction, l is attractive length scale, g is gravitational constant, $\widehat{e_g}$,u and $\widehat{e_w}$ are centre of earth, constant drift and wind direction . Substituting *Equation (7), Equation (11)* and *Equation (12)* in *Equation (6)*,

$$X_i = \sum_{j=1}^{N} s(|x_j - x_i|)\frac{x_j - x_i}{d_{ij}} - g\widehat{e_g} + u\widehat{e_w} \tag{13}$$

Equation (13) cannot be used to solve real time or complex problems, because grasshoppers achieve their comfort zone and do not cluster on a single location. Therefore, *Equation (13)* is modified by adding some parameters to solve complex problems. The modified version is given in *Equation (14)*.

$$X_i^d = w\left[\sum_{\substack{j=1\\ i\neq j}}^{N} w\frac{(ub_d - lb_d)}{2} s(x_j^d - x_i^d)\frac{x_j - x_i}{d_{ij}}\right] + \widehat{T_d} \tag{14}$$

$$w = wmax - l\frac{wmax - wmin}{L} \tag{15}$$

Where, ub_d is upper bound in the d^{th} dimension, lb_d is lower bound in the d^{th} dimension, $\widehat{T_d}$ is value of the dimension in the target, w is decreasing coefficient , ,l is current iteration, L is maximum number of iterations, wmax and wmin are maximum value and minimum value respectively.

As in *Equation (14)*, the value of w decreases linearly from 1 to minimum value to achieve best solution. But, this characteristic causes local optima problem. To address such an issue, w update equation proposed in this work and delineated in *Equation (16)*. The proposed update equation is adaptive with iteration and non-linear.

$$w = 1 - \frac{l}{L-(l-1)} \tag{16}$$

In this work, MGOA is adopted to select the optimal coefficients in order to enhance the quality of recovered image. Based on the CR, Optimal Number of Coefficients (ONC) are computed as represented in equation (17).

$$ONC = round\left(\left(1 - \frac{CR}{100}\right)\right) X\, m^2 \tag{17}$$

During first iteration, decomposed image is divided into m X m (8 X 8) sub block. *Equation (17)* is utilized for each submatrix to select optimal coefficients where maximization of PSNR as fitness function of the MGOA. The selected coefficients are encoded, compressed and then decompressed. The PSNR between the input and reconstructed image is computed. This process is repeated to a predefined iteration. The selected coefficients which gives higher PSNR is taken as optimized coefficients. Optimization workflow is given in the form of algorithmic steps in *Table. 1*.

4. RESULTS AND DISCUSSION

For validation, a collection of medical images from various modalities such as MRT, CT, US, and X-ray are acquired from a publically available source.

4.1 Image Quality Evaluation Metrics

To gauge the compression ability of the proposed method, four performance measuring metrics namely Mean Square Error (MSE), PSNR and Mean Structural Similarity Index (MSSIM) between the original (O) and recovered (R) images were computed. The higher values of these metrics, the better the compression obtained.

4.2 Performance Analysis and Comparison

The proposed medical image compression method has been implemented in MATLAB 2019a and validated with a large set of medical images of different imaging modalities. The medical images of four different imaging modalities, MRI, CT, US and X-ray were compressed using both standard GOA and MGOA for CRs varies from 40% to 90%. The compression efficiency of both GOA and MGOA was assessed in a quantitative form where the obtained values were reported in *Table 2* for MRI and CT images and *Table 3* for US and X-ray images. From observations, the proposed MGOA-IWT algorithm significantly improves compression when compared to the GOA-IWT compression algorithm in almost all the CRs.

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For MRI image and CR is 40%, GOA-IWT method achieved mean MSE, PSNR and MSSIM are 0.0730, 59.68dB and 0.8824 respectively. The proposed MGOA-IWT compression method attained mean MSE is 0.008, mean PSNR is 79.12 dB and mean MSSIM is 0.9988. The obtained values clearly showed that the proposed compression method produce better results than that of the conventional compression algorithm. *Figure 5* provides the graphical delineation of *Table 2*.

To further prove the performance, a comparison with the existing methods was done such as Harmony Search based Compression (HSA) method [9], PSO based method [10] and Whale Optimization Algorithm (WOA) based method [11]. *Figure 6* shows the comparison in terms of PSNR for MRI images at various CRs. It is inferred from the *figure 9* that the MGOA-IWT compression method achieved higher PSNR for almost all CRs which indicates that the decompressed image is closer to the original images in comparison with the existing methods taken for comparison. The overall analysis confirmed the superiority of the MGOA-IWT compression method.

Table 1. Pseudo code of the proposed optimization algorithm

```
Input: IWT coefficients
Output: reconstructed image
Fitness function: max (PSNR)
Initialize population, maximum number of iterations, Imax and iteration counter i.
Read input image
Noise suppression of input image
Decomposition of preprocessed image
Huffman encoding
Huffman decoding
Decompression of image
Evaluate fitness function
While (i<Imax)
        do
           Execute MGOA and search for solutions
           Evaluate the fitness function for current solution
           Select the ONCs
           Huffman encoding
           Huffman decoding
           Decompression of image
           Compute fitness function
      if current fitness > previous fitness, then
             best solution=current fitness
     else
   Search for new solution
     end if
     end while
```

Table 2. Performance comparison of the GOA and MGOA for MRI and CT images

IMAGE TYPE	METRICS	GOA-IWT						MGOA-IWT					
	CR (%)	40	50	60	70	80	85	40	50	60	70	80	85
MRI 1	MSE	0.0190	0.0828	0.4172	0.7224	0.9556	1.1792	0.0007	0.0009	0.0030	0.0048	0.0055	0.0070
	PSNR (dB)	65.346	58.951	51.927	49.543	48.328	47.415	79.680	78.493	73.360	71.318	70.727	69.680
	MSSIM	0.9756	0.8653	0.8551	0.7452	0.7165	0.7067	0.9989	0.9987	0.9981	0.9976	0.9969	0.9961
MRI 2	MSE	0.046	0.095	0.117	0.565	0.903	1.185	0.0006	0.0007	0.0015	0.0044	0.0063	0.0061
	PSNR (dB)	61.520	58.355	57.438	50.612	48.574	47.392	80.349	79.680	76.370	71.696	70.137	70.278
	MSSIM	0.9308	0.8554	0.8394	0.8094	0.7295	0.71643	0.9999	0.9989	0.9988	0.9980	0.9975	0.9964
MRI 3	MSE	0.0204	0.0720	0.0898	0.3325	0.6696	1.9467	0.0007	0.0008	0.0009	0.0024	0.0045	0.0082
	PSNR (dB)	65.044	59.555	58.600	52.913	49.873	45.238	79.749	79.323	78.400	74.275	71.578	68.972
	MSSIM	0.9734	0.8655	0.8589	0.8495	0.7371	0.7056	0.9990	0.9987	0.9984	0.9979	0.9970	0.9957
MRI 4	MSE	0.0288	0.0424	0.0902	0.5362	0.8827	0.9472	0.0005	0.0008	0.0019	0.0026	0.0053	0.0078
	PSNR (dB)	63.543	61.861	58.578	50.838	48.673	48.367	80.807	78.993	75.343	73.981	70.888	69.210
	MSSIM	0.957	0.9435	0.867	0.8123	0.7489	0.721	0.9999	0.9988	0.9986	0.9982	0.9997	0.9965
CT 1	MSE	0.0139	0.0455	0.5470	0.8941	0.1689	0.3593	0.0006	0.0007	0.0009	0.0036	0.0056	0.0081
	PSNR (dB)	66.703	61.554	50.751	48.617	55.855	52.576	80.497	79.498	78.493	72.568	70.649	69.046
	MSSIM	0.9821	0.9467	0.8222	0.7563	0.82	0.8136	0.9998	0.9988	0.9985	0.9981	0.9969	0.9962
CT 2	MSE	0.0142	0.0323	0.1162	0.7145	0.9881	1.2565	0.0005	0.0006	0.0011	0.0034	0.0061	0.0092
	PSNR (dB)	66.594	63.044	57.479	49.591	48.183	47.139	81.503	80.572	77.717	72.816	70.278	68.479
	MSSIM	0.9813	0.9616	0.8501	0.7980	0.7453	0.7220	0.9999	0.9988	0.9984	0.9972	0.9963	0.9958
CT 3	MSE	0.0143	0.0290	0.0502	0.0727	0.0901	0.3002	0.0008	0.0010	0.0018	0.0057	0.0085	0.0099
	PSNR (dB)	66.568	63.499	61.121	59.518	58.583	53.356	79.100	78.263	75.578	70.572	68.837	68.174
	MSSIM	0.9815	0.9722	0.9512	0.8962	0.8780	0.8419	0.9991	0.9985	0.9982	0.9964	0.9955	0.9949
CT 4	MSE	0.0142	0.0323	0.1162	0.7145	0.9881	1.2565	0.0007	0.0007	0.0020	0.0046	0.0082	0.0100
	PSNR (dB)	66.594	63.044	57.479	49.591	48.183	47.139	79.742	79.498	75.142	71.541	68.987	68.135
	MSSIM	0.9813	0.9616	0.8501	0.7980	0.7453	0.7220	0.9991	0.999	0.9981	0.997	0.9966	0.9948

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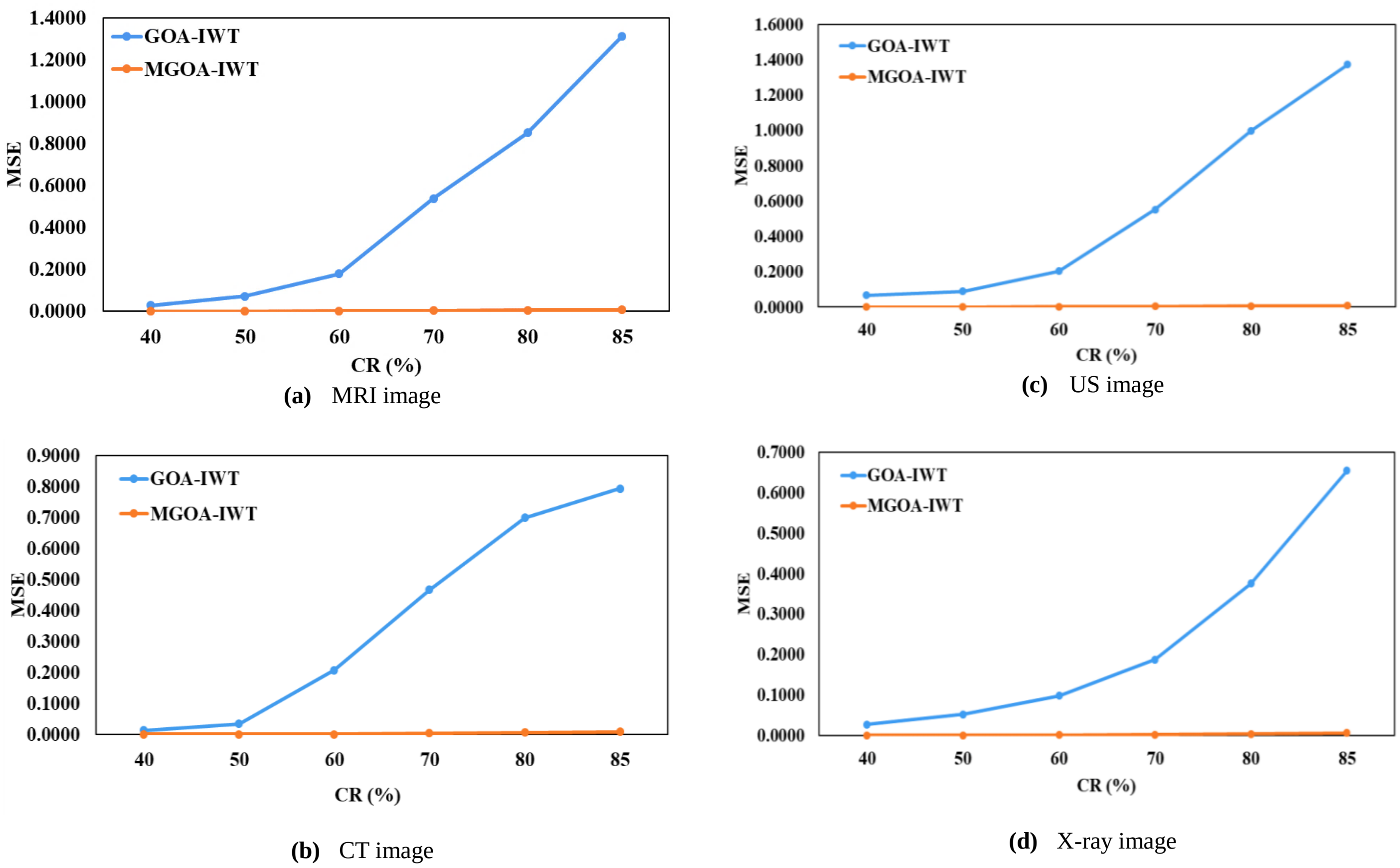
Table 3. Performance comparison of the GOA-IWT and MGOA-IWT for US and X-ray image

IMAGE TYPE	METRICS	GOA-IWT						MGOA-IWT					
	CR (%)	40	50	60	70	80	85	40	50	60	70	80	85
US 1	MSE	0.0795	0.0922	0.3099	0.6901	1.5032	1.7645	0.0007	0.0010	0.0044	0.0071	0.0082	0.0099
	PSNR (dB)	59.128	58.485	53.219	49.742	46.361	45.665	80.002	78.174	71.696	69.618	68.993	68.174
	MSSIM	0.8827	0.8779	0.8439	0.7979	0.7606	0.7472	0.9972	0.9984	0.9980	0.9963	0.9960	0.9951
US 2	MSE	0.0821	0.0954	0.1528	0.5571	0.9179	1.1981	0.0006	0.0008	0.0010	0.0013	0.0026	0.0057
	PSNR (dB)	58.986	58.336	56.289	50.671	48.503	47.346	80.727	78.993	78.150	76.991	73.964	70.595
	MSSIM	0.8884	0.8695	0.8658	0.8223	0.7678	0.7012	0.9988	0.9988	0.9981	0.9979	0.99728	0.9967
US 3	MSE	0.0515	0.0839	0.0938	0.2980	0.6188	0.9418	0.0005	0.0009	0.0027	0.0050	0.0065	0.0074
	PSNR (dB)	61.012	58.892	58.411	53.389	50.215	48.391	81.229	78.637	73.817	71.141	70.002	69.415
	MSSIM	0.9598	0.8625	0.8666	0.8491	0.8227	0.7606	0.9994	0.9989	0.9984	0.9973	0.997	0.9969
US 4	MSE	0.0552	0.0877	0.2542	0.6654	0.9512	1.5846	0.0004	0.0007	0.0010	0.0027	0.0059	0.0092
	PSNR (dB)	60.713	58.701	54.079	49.900	48.348	46.132	82.220	80.002	78.354	73.817	70.422	68.479
	MSSIM	0.9525	0.8608	0.8394	0.7821	0.7130	0.6858	0.9999	0.9987	0.9980	0.9976	0.9969	0.9958
X-RAY 1	MSE	0.0546	0.0993	0.1873	0.4530	0.6811	0.7827	0.0005	0.0007	0.0010	0.0037	0.0064	0.0075
	PSNR (dB)	60.757	58.162	55.406	51.569	49.799	49.195	80.888	79.680	78.131	72.449	70.069	69.380
	MSSIM	0.9618	0.8638	0.8460	0.8254	0.7903	0.7290	0.9985	0.9982	0.9980	0.9974	0.9971	0.9965
X-RAY 2	MSE	0.0200	0.0450	0.0750	0.0999	0.3516	0.7296	0.0003	0.0005	0.0011	0.0025	0.0050	0.0073
	PSNR (dB)	65.128	61.597	59.380	58.134	52.671	49.500	82.946	81.055	77.717	74.229	71.123	69.498
	MSSIM	0.9832	0.9582	0.8986	0.8538	0.8398	0.7621	0.9999	0.999	0.9984	0.9973	0.9965	0.9968
X-RAY 3	MSE	0.0143	0.0348	0.0653	0.0964	0.3343	0.5624	0.0002	0.0005	0.0007	0.0010	0.0036	0.0054
	PSNR (dB)	66.592	62.709	59.978	58.288	52.889	50.631	85.121	80.864	79.564	78.354	72.629	70.783
	MSSIM	0.9848	0.9751	0.8853	0.8654	0.8430	0.8124	0.9999	0.9987	0.9983	0.998	0.9974	0.997
X-RAY 4	MSE	0.0193	0.0311	0.0658	0.0988	0.1330	0.5408	0.0002	0.0003	0.0007	0.0009	0.0012	0.0044
	PSNR (dB)	65.265	63.201	59.950	58.182	56.894	50.801	84.707	82.851	79.618	78.446	77.501	71.696
	MSSIM	0.9771	0.9716	0.8936	0.8238	0.8134	0.8007	0.9999	0.9992	0.9983	0.9985	0.9972	0.997



(a) MRI image

(c) US image

(b) CT image

(d) X-ray image

Figure 5: MSE for the proposed and GOA-IWT compression methods

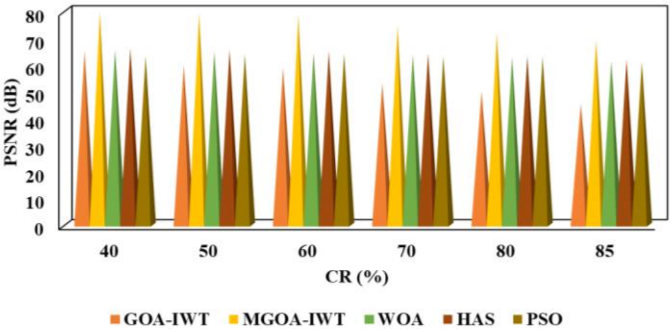


Figure 6: Performance comparison in terms of PSNR

5. CONCLUSION

This paper has presented a novel method for medical image compression using IWT and metaheuristic algorithm. Metaheuristic algorithm, MGOA successfully used with wavelet coefficients for compressing medical image. By applying MGOA as an optimized and extracting the best wavelet coefficients from each sub matrix, efficient compression was achieved. The medical images were pre-processed decomposed using IWT and then divided into m x m blocks. Different medical imaging, such as MRI, CT, US, and X-ray, were used to assess the suggested method's performance. The various evaluation metrics such as PSNR, MSE, MSSIM, CR and NCC were computed and compared with the former methods additionally, the visual quality of the reconstructed image was considered for comparison. Although, the medical image compression method introduced by IWT and MGOA achieved the highest reconstruction quality. In future, different metaheuristic algorithm will be used for further improving the quality of reconstructed image.

REFERENCES

[1] M.H. Alkinami, E.A. Zanaty and S.M. Ibrahim, "Medical image compression based on wavelet with particle swarm optimization", Computers, Materials and continua, vol. 67, no. 2, pp. 1577-1592, 2021.
[2] K.M. Hosny, A.M. Khalid and E.R. Mohamed, "Optimized medical image compression for telemedicine applications", In: Masmoudi M., Jarboui B., Siarry P. (eds) Artificial Intelligence and Data Mining in Healthcare. Springer, Cham, 2021.
[3] P. Sreenivasulu and S. Varadarajan, "An efficient lossless ROI image compression using wavelet-based modified region growing algorithm", Journal of Intelligent Systems, vol. 29, no. 1, pp. 1063-1078, 2020.
[4] R. Haridoss and S. Punniyakodi, "Compression and enhancement of medical images using opposition based harmony search algorithm", Journal of Information Processing Systems, vol. 15, no. 2, pp. 288-304, 2019.
[5] P.N.T. Ammah and E. Owusu, "Robust medical image compression based on wavelet transform and vector quantization", Informatics in Medicine Unlocked, vol. 15, 2019.
[6] P. Sreenivasulu, S.V. Rajan and S. Thenappan, "Medical image compression by optimal filter coefficients Aided Transforms using modified rider optimization algorithm", International Journal. Engg and Adv. Tech, vol. 9, no. 2, 2019.
[7] K.M. Honsy, A.M. Khalid and E.R. Mohamed, "Efficient compression of bio-signals by using Tchebichef moments and Artificial Bee Colony", Biocybernetics and Biomedical Engineering, vol. 38, no. 2, pp. 385-398, 2018.
[8] S. Saremi, S. Mirjalili and A. Lewis, "Grasshopper optimization algorithm: Theory and Application", Advances in Engineering Software, vol. 105, pp. 30-47, 2017.
[9] M.S. Wu, "Genetic algorithm based on discrete wavelet transformation for fractal image compression", Journal of Visual Communication and Image Representation, vol. 25, no. 8, pp. 1835-1841, 2014.
[10] M. Rehman, M. Sharif and M. Raza, "Image compression: A survey", Research Journal of Applied Sciences, Engineering and Technology, vol. 7, no. 4, pp. 656-672, 2014.
[11] G. Vijayvargiya, S. Silakari and R. Pandey, "A novel medical image compression technique based on structure reference selection using integer wavelet transform function and PSO algorithm", International Journal of Computer Applications, vol. 91, no. 11, pp. 9-13, 2014.
[12] A. Boucetta and K.E. Melkemi, "DWT based-approach for color image compression using genetic algorithm", In International conference on image and signal processing, pp. 476-484, 2012.