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PAPER

A State Table SPHIT Approach for Modified Curvelet-based Medical Image Compression

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ABSTRACT

Medical imaging plays a significant role in clinical practice. Storing and transferring a large volume of images can be complex and inefficient. This paper presents the development of a new compression technique that combines the fast discrete curvelet transform (FDCvT) with state table set partitioning in the hierarchical trees (STS) encoding scheme. The curvelet transform is an extension of the wavelet transform algorithm that represents data based on scale and position. Initially, the medical image was decomposed using the FDCvT algorithm. The FDCvT algorithm creates symmetrical values for the detail coefficients, and these coefficients are modified to improve the efficiency of the algorithm. The curvelet coefficients are then encoded using the STS and differential pulse-code modulation (DPCM). The greatest amount of energy is contained in the coarse coefficients, which are encoded using the DPCM method. The finest and modified detail coefficients are encoded using the STS method. A variety of medical modalities, including computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI), are used to verify the performance of the proposed technique. Various quality metrics, including peak signal-to-noise ratio (PSNR), compression ratio (CR), and structural similarity index (SSIM), are used to evaluate the compression results. Additionally, the computation time for the encoding (ET) and decoding (DT) processes is measured. The experimental results showed that the PET image obtained higher values of the PSNR and CR. The CT image provides high quality for the reconstructed image, with an SSIM value of 0.96 and the fastest ET of 0.13 seconds. The MRI image has the shortest DT, which is 0.23 seconds.

KEYWORDS

image compression, curvelet transform, medical imaging

1 INTRODUCTION

Image compression techniques have been a crucial topic in the image-processing community for almost 50 years. It has become a crucial subject and is booming due to its wide application in various fields, such as medicine, agriculture, and

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defense [1–6]. In the classical definition, image compression refers to reducing the size of an image without degrading its quality [2]. The smaller image size requires less storage space and directly increases the transmission bandwidth. However, a higher compression ratio typically impacts the quality of the reconstructed images. Thus, researchers emphasize the need for improved compression techniques.

On the other hand, medical image processing is significant due to its ability to provide clear visualization and quantitative analysis [7–8]. Information visualization of medical images is used to diagnose patients' diseases. One medical embodiment thus, carries a lot of data that has been generated by various medical tools such as computed tomography (CT) [9], positron emission tomography (PET) [10], ultrasound (US) [11], magnetic resonance imaging (MRI) [12], and X-rays [11]. The organization of the memory units has been affected by the vast amount of data that needs to be processed in the context of medical algorithms. The data and intermediate data must first be stored in a larger amount of space before being used for the subsequent operation. The majority of subfields in medical image processing also contribute to matrix transformation procedures [13–16].

Previously, wavelets and related multi-scale representations have been widely used in all areas of signal and image processing. The reason is that wavelets have good performance for piecewise smooth functions in one dimension [15]. However, wavelets suffer from limitations in representing the edges of an image. It requires a large number of coefficients to analyze the images. Hence, a new multi-scale transform known as the curvelet transform has been introduced to overcome the limitations of wavelets. The Curvelet offers optimal sparsity for curved images, objects, and wave propagators [17].

This paper proposes a technique for image compression using a modified fast discrete curvelet transform (FDCvT). The medical image was decomposed into several levels to obtain the curvelet coefficients. These coefficients are large and complex and indirectly affect the algorithmic computations. Hence, the main philosophy of this research is to modify the curvelet coefficients before they are employed in the encoding schemes. Practically, the curvelet coefficients have symmetrical properties, in which the duplicated coefficients can be deleted to reduce the complexity of the algorithm.

Additionally, the curvelet coefficients are further converted into a stream of integer values using two proposed encoding methods. The first encoding method uses the state table set partitioning in hierarchical trees (STS), which is an improved version of the set partitioning in hierarchical trees (SPIHT) algorithm. State tables are used instead of lists. The differential pulse code modulation (DPCM) encoding technique is used to encode the remaining curvelet coefficients. The compression results are evaluated using various quality metrics, such as peak signal-to-noise ratio (PSNR), compression ratio (CR), and structural similarity index (SSIM). Additionally, computation times for the encoding (ET) and decoding (DT) operations are also considered. Experimental results over a large number of medical images have shown an improvement in both PSNR and CR values. Additionally, it provides the highest SSIM at different bitrates and the shortest ET and DT to compute the proposed algorithm.

The remainder of the paper is organized as follows: Section 2 summarizes the related work. The mathematical background for the curvelet transform and SPIHT algorithm is described in Section 3. Section 4 describes the proposed compression method. The results and discussions are explained in Section 5. Finally, the conclusion and future directions for further research are discussed in Section 6.

2 RELATED WORKS

More than 50,000 patients are critically admitted to hospitals and medical facilities every year [18]. As a result, medical imaging files increase in size and require more storage space. Moreover, high-speed and efficient bandwidth transmission is necessary for the transfer of medical data between hospitals. Considering the current circumstances, medical image compression has become prevalent in the field of medical informatics. Image compression typically benefits by decreasing the amount of storage space required for archiving in hospitals, thereby reducing the overall storage cost [19–20]. In the following, an overview of medical image compression methods will be provided.

An approach for medical image compression based on the embedded zero-tree wavelet (EZW) coder is briefly described in [7]. The main objective of this paper is to investigate and explore the viability of the EZW wavelet coder for compressing therapeutic and medical images. The EZW algorithm applies a similar method to the discrete wavelet transform (DWT), where the image is decomposed into different levels using wavelet filters. Then, the generated unit cells are separated into a predominant pass and a subordinate pass. In the first pass, the initial threshold is assigned to half of the maximum coefficient of the pixel value. Additionally, a zig-zag method is used to scan the coefficients. The simulation results show that the performance of the proposed methodology is influenced by the type of medical modalities and the storage format utilized. This result was verified based on the recorded PSNR values.

Another issue in medical image compression is presented in [19]. A compression technique for medical images is proposed, utilizing wavelet-based sparsification and coding. The proposed compression technique is based on adaptive scan wavelet difference reduction (ASWDR). Moreover, the ASWDR technique employs index coding, binary representation, and adaptive coding. One of the advantages offered by the ASWDR coding technique is that the coefficients at all levels of the image decomposition are scanned systematically. Moreover, the ASWDR coding technique is efficient in preserving the detailed values of an image. The results of the proposed methodology show that a structure similarity of 97.5–99.5% is achieved, and the biorthogonal 6.8 wavelet (Bior6.8) is found to be the most suitable for the chosen medical image in terms of compression ratio.

Q. Min *et al.* [21] have proposed a lossless medical image compression technique based on anatomical information and deep neural networks. This work aims to enhance the compression of medical images by utilizing a combination of anatomical knowledge and deep neural network (DNN) technology. In this compression scheme, the segmentation process involves dividing the medical image into multiple regions based on its anatomy. By dividing the image into regions, the compression algorithm can treat each region differently and exploit the anatomical information to compress the data more effectively. The numerical results support the validity of the proposed technique as an effective solution for data compression. It provides 38% better results for CR parameters compared to JPEG-2000. However, the proposed compression scheme was only tested on the CT image. It is better to utilize multiple medical imaging modalities, such as MRI, PET, and X-ray, to validate the results.

A new method for lossless image compression, specifically designed for telemedicine images, is presented in [22]. The medical image was compressed using delta compression. The method converts an image into a binary row vector and identifies repetitive sequences of unique elements. The resulting reduced data is then encoded using entropy coding for further compression. The process is then reversed for decoding. In addition, the proposed technique was tested on various medical images, such as X-rays, CT scans, MRI scans, and US. Two evaluation parameters, the CR and bits per pixel (BPP), are calculated to measure the effectiveness of the proposed technique. Moreover, the experimental results were compared with previous and existing compression techniques such as JPEG-2000, DPCM, and lossless region of interest (ROI) compression. The proposed method has been shown to be more efficient than the JPEG-2000 method, and it produces an exact reconstruction of the original image. However, the details of the delimiter compression are not discussed in this work.

An evaluation of hybrid medical image compression for improved diagnosis was conducted [23] by H. A. Elsayed *et al.* This work primarily focuses on medical image compression using the non-decimated wavelet transform (NDWT) and a combination of lossy and lossless compression techniques. The issue raised in this is that most medical images contain a large volume of image data that is not fully utilized for further analysis. Therefore, the proposed methodology combines both lossy and lossless compression techniques to achieve superior results. The input image is resized to 8×8 and converted from RGB to grayscale. After the pre-processing, the image is subjected to two vector quantization algorithms, namely Linde, Buzo, and Gray (LBG) or K-means clustering techniques. Zigzag scanning is then used to transform the outcome into a vector. Continuously, the compressed image undergoes additional lossless compression using either run-length encoding (RLE), Huffman coding, or arithmetic coding. In summary, the sequences of NDWT, K-means clustering, zigzag scanning, and the RLE encoding algorithm yield improved results in terms of CR and PSNR. However, this work only uses a chest X-ray image to evaluate performance.

All the previous works discussed are summarized in Table 1. It has been established that by employing transform-based compression algorithms in lossy techniques, better results can be achieved. The most commonly used transform-based algorithm for this purpose is the wavelet transform. In addition, combining the lossy and lossless techniques makes it possible to achieve a balance between reducing file size and preserving quality, which is suitable for medical images. Another point of concern is the input data or medical images used for experimental analysis of performance. Only works in [7] and [22] utilized more than one medical image, while the remaining works only used US, CT, and X-ray images. Hypothetically, efficient results can be achieved by considering various input data when evaluating performance. Furthermore, the standard parameters used in analyzing compression performance include PSNR and CR. In image compression analysis, these parameters are commonly used. Hence, additional assessment parameters are needed to effectively analyze the data.

Table 1. Summary of the previous works

Refs.	Medical Image	Techniques	Performance Evaluations	
			PSNR	CR
[7]	MRI, US, X-ray	Lossy – EZW	✓	
[19]	US	Lossy – ASWDR	✓	✓
[21]	CT	Lossless – DNN	✓	✓
[22]	X-ray, CT, MRI, US	Lossless		✓
[23]	X-ray	Hybrid – lossy and lossless	✓	✓

3 MATHEMATICAL BACKGROUND

3.1 Curvelet transform

The curvelet transform is a high-dimensional wavelet transform used to analyze an image with various scales and directions. The multidimensional theory is enhanced by the multiresolution design of the curvelet transform. In the wavelet domain, the image is divided into approximation and detail subbands of various scales that are smaller than the scale of the original image. A third attribute of signal localization, in addition to size and space, distinguishes the curvelet from other signal processing techniques. Generally, there are two major revisions of the curvelet transform, known as the first and second generations of the curvelet transform. The first generation, also known as Curvelet-99, uses a complex procedure that includes ridgelet analysis. Initially, the image is divided into several sub-images using a series of disjoint clusters. Each cluster is further processed using the ridgelet transform. However, the performance of the first generation is too slow because the image boundaries are treated by periodization. Thus, the second generation is proposed to overcome the drawbacks of the first generation.

In the second generation of the curvelet transform, the ridgelet analysis step is discarded in order to reduce the complexity of the algorithm. In addition, it handles the image boundaries using mirror extension. Thus, making the second generation curvelet transform more efficient and faster. FDCvT utilizes the advantages of fast Fourier transform (FFT). The image and curvelet are divided into the Fourier domain at various scales and orientations. Then, a spatial domain convolution technique is applied between the curvelet and the image. Finally, the inverse FFT is used to calculate the curvelet coefficients.

On the other hand, there are two methods that can be used to compute the curvelet coefficients: the unequally spaced fast Fourier transform (USSFT) and the wrapping-based method. Theoretically, both methods produce the same output. However, the wrapping-based method is faster and more efficient in terms of computation time. Hence, in this work, the wrapping-based method was utilized in the proposed compression technique. Generally, there are three steps involved in using the wrapping-based method. First, a 2-D image is processed using the FFT algorithm to generate FFT coefficients. The FFT coefficients are then partitioned into a collection of digital tiles. At the final step, an additional four sub-steps are utilized for each digital tile, as follows:

1. Convert the tile to the origin;
2. Wrap the parallelogram shaped support of the tile around a rectangle centered at the origin;
3. Employ the inverse FFT algorithm to the wrapped support; and
4. Compute the curvelet array to the collection of curvelet coefficients.

Before decomposing the input image using the wrapping-based method, three parameters are calculated: the number of scales n_{scales}, the number of orientation ℓ_j, and the number of angular panels n_{quad}. For a 2-D image with a size of 128×128 pixels, it has five scales and eight orientations. At scale number two, there are four angular panels; at scales three and four, there are sixteen orientations with eight angular panels. The details of the calculations are described in Table 2, and the summarized values are recorded in Table 3.

Table 2. Parameter calculation

Parameters	Calculations
Number of scales (n_{scales})	$n_{scales} = floor(log_2(\min(m, n, p))) - 2$ $= floor(log_2(\min(128, 128))) - 2$ $= 5$ *where m, n, p are the size of image*
Number of orientation at scale 2, 3, …, $n_{scales-1}$ (ℓ_j)	$\ell_j = 8 \times 2^{ceil\left(\frac{n_{scales-i}}{2}\right)}$ where $i = n_{scales}, j = 2$ where $i = n_{scales-1}, j = 3$ where $i = 3, j = n_{scales-1}$ $\therefore \ell_2 = 8 \times 2^{ceil\left(\frac{n_5-5}{2}\right)} = 8$ $\therefore \ell_3 = 8 \times 2^{ceil\left(\frac{n_5-4}{2}\right)} = 16$ $\therefore \ell_4 = 8 \times 2^{ceil\left(\frac{n_5-3}{2}\right)} = 16$
Number of angular panels (n_{quad})	$n_{quad-j} = 4 \times 2^{ceil\left(\frac{n_{scales}-i}{2}\right)}$ where $i = n_{scales}, j = 2$ where $i = n_{scales-1}, j = 3$ where $i = 3, j = n_{scales-1}$ $\therefore n_2 = 4 \times 2^{ceil\left(\frac{2-2}{2}\right)} = 4$ $\therefore n_3 = 4 \times 2^{ceil\left(\frac{3-2}{2}\right)} = 8$ $\therefore n_4 = 4 \times 2^{ceil\left(\frac{4-2}{2}\right)} = 8$

Table 3. Curvelet decomposition summarization

Number of Scales	Number of Orientations	Number of Angular Panels
1	1	1
2	8	4
3	16	8
4	16	8
5	1	1

Figure 1 illustrates the five scales (S1 to S5) of the FDCvT decomposition. At scale one (S1), the lowest subband contains the greatest amount of energy and is referred to as the coarse subband. While the highest-frequency coefficients are represented by the outermost subband (S5) and are known as the finest. The remaining curvelet coefficients are used from scale two (S2) to scale four (S4). Furthermore, the curvelet coefficients are separated into four quadrants. A further division into angular panels is made for the curvelet coefficients at each quadrant.

Moreover, the curvelet oriented at an angle θ produces the same coefficients as the one oriented at an angle π+θ. In other words, the curvelet coefficients in the upper half (color wedges) and lower half (white wedges) are conjugate or symmetrical. Therefore, only half of the coefficients can represent an image instead of the actual coefficients. The first contribution of this research is based on modifying the curvelet coefficients by deleting the symmetrical coefficients (white wedges). Indirectly, reduce the dimensions and complexity of the architecture.

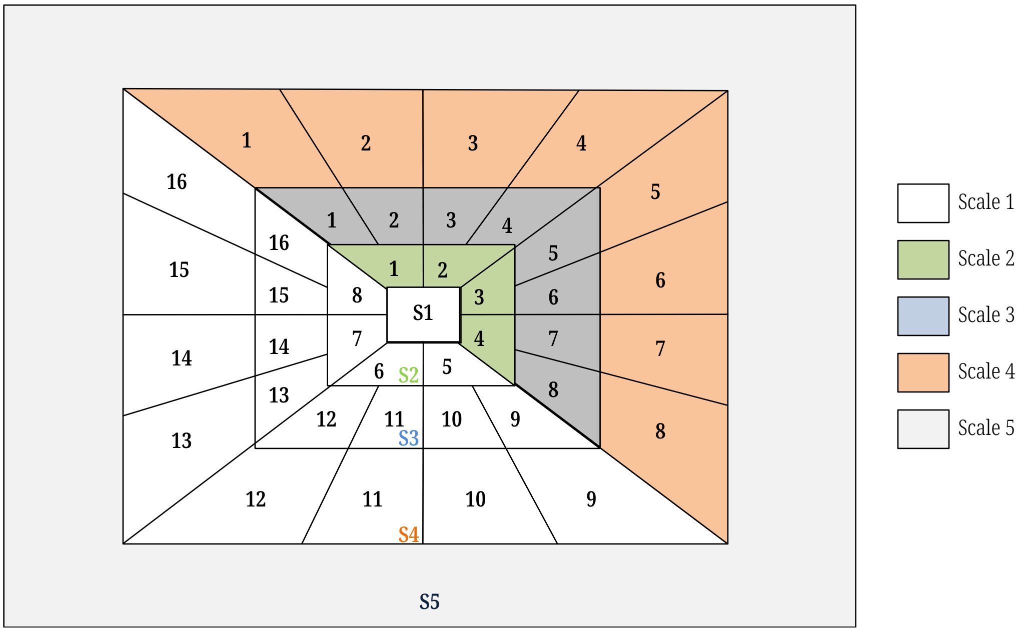

Fig. 1. Five-scales of curvelet decomposition

3.2 Set partitioning in hierarchical trees

Numerous encoding techniques have been developed to address the discrepancy between the position and value of coefficients at different frequency levels in an image. A high PSNR value and good image quality are provided by the set partitioning in hierarchical trees (SPHIT) encoding technique. The SPHIT encoder goes through three fundamental steps: initialization, sorting pass, and refinement pass. The refinement pass is based on a pyramid structure decomposition. As illustrated in Figure 2, there are three lists involved in the encoding and decoding process; the list of insignificant pixels (LIP), the list of insignificant sets (LIS), and the list of significant pixels (LSP). The initial value of the threshold is established during the initialization phase, and the local intensity probability (LIP) is initialized with a set that includes all the coefficients in the lowest sub-band.

Additionally, LSP is initially configured as an empty list, while LIS holds the coordinates of all tree roots. The iterative sorting pass follows, where members of LIP are handled first, and subsequently, members of LIS are handled. The final processing of LSP items occurs at the refining stage, and these lists are updated each time a node is examined. Moreover, the SPIHT technique is self-adaptive and offers a high PSNR value for image compression applications. The main drawback of SPIHT is that it uses three lists to store the addresses of coefficients during operations [24]. These dynamic lists may, in the worst-case scenario, need to store more addresses than there are total coefficients.

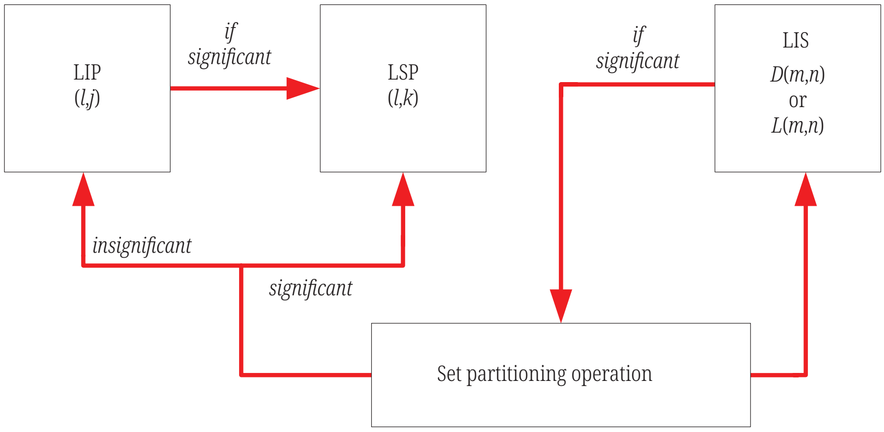

Fig. 2. The SPIHT algorithm

4 PROPOSED METHOD

To address the memory limitations of the SPIHT algorithm, the STS method makes use of a modified curvelet transform. Basically, the state table is used to store the state information for each coefficient. Based on their level of importance and their placement in the image, this state information is used to determine which coefficients should be encoded and transmitted first. The state-table-based strategy enables the algorithm to avoid unnecessary calculations and effectively track the state of each coefficient during the encoding process. The suggested method relies on a state-table approach that records the status of each block of coefficients. The spatial orientation of each coefficient block at different levels is exploited.

In contrast to the Morton scan order employed in wavelet transforms, the scan order for curvelet coefficients is often based on a spiral pattern that starts in the center of the image and spirals outwards. The STS algorithm essentially utilizes the following components:

1. ST_SB: state table for the significance of block
2. ST_SDB: state table for the significance of descendant block
3. LCB: list of child block
4. LPB: list of parent block

The significance of each coefficient block is recorded in the state table ST_SB. A node is considered "1" if at least one of its associated coefficients is determined to be significant or if any of its descendant nodes are determined to be significant. On the other hand, the state table ST_SDB is used to indicate whether a node contains any irrelevant data or not. A DPCM algorithm is used to encode the majority of energy coefficients. While the STS is used to encode the remaining coefficients. The image was split into chunks in STS, each consisting of two by two pixels. These blocks are considered nodes of the spatially oriented tree.

As illustrated in Figure 3, the proposed compression technique utilizes four stages. The symmetrical curvelet coefficients were removed at stage two in order to decrease the complexity of the algorithm. Then, at stage 3, the remaining coefficients were encoded using two different methods. The details and fine coefficients were encoded using STS, while the coarse coefficients were encoded using DPCM. All the encoded bitstreams are combined at the final stage, and the inverse processes are employed to reconstruct the compressed image. The proposed compression algorithm using the modified FDCvT is described in Algorithm 1 as follows:

Algorithm 1: Algorithm to Compress Medical Image Using Modified FDCvT

Input: *Medical image* $f(m, n)$ *with a size of* $512 \times 512 - 8bits$
Output: *Compressed medical image*

Apply FDCvT to the input image to obtain the approximation and details coefficients
if *the coefficients are symmetrical*
    Delete the half symmetry coefficients
else
    Remain the coefficients
if *the coefficients contain wedges*
    Encode using DPCM
else
    Encode using STS
Analyze the output image quality in terms of PSNR, CR, SSSIM, ET and DT
end

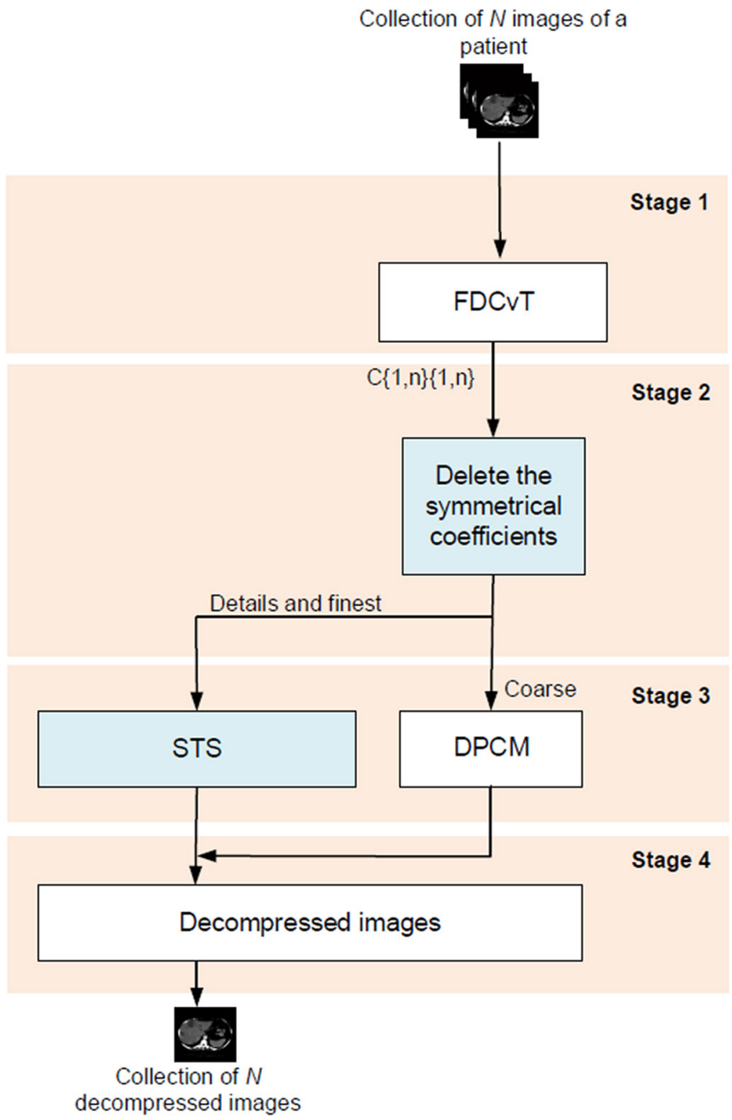

Fig. 3. Proposed compression technique

5 RESULTS AND DISCUSSIONS

The proposed method is implemented and tested on a set of three medical images: CT, MRI, and PET. Moreover, objective quantitative evaluation is used to analyze the proposed compression method. Finally, an effective comparison with the previous works has been efficiently conducted.

5.1 Experimental setup

The experiment used MATLAB R2022b on Windows 10 Pro (64-bit) with an Intel Core i5 processor and 8 GB of RAM. The proposed denoising techniques were implemented using a MATLAB live script to observe the simulation results. Moreover, this experiment uses the grayscale format and an image size of 512 × 512 for the medical image. A total of three medical images from different modalities were used as test data, including MRI, PET, and CT images. The medical images were retrieved from the National Library of Medicine's Lister Hill National Center for Biomedical Communications [18].

5.2 Performance evaluations

Different quality metrics, such as PSNR, CR, SSIM, and computational time for ET and DT processes, are evaluated to compile compression results. In addition, the effectiveness of the proposed method is evaluated in comparison with existing algorithms such as wavelet [25] and curvelet [26].

PSNR: Adequate parameters for measuring the quality difference between the original and compressed images. Higher PSNR indicates a better quality of the compressed or reconstructed image [27].

$$PSNR = 10log_{10}\left(\frac{255^2}{MSE}\right), \quad where \tag{1}$$

$$MSE = \frac{1}{M \times N}\left[\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(f(x,y) - F(x,y))^2\right] \tag{2}$$

CR: A measurement to quantify the size reduction produced by the image compression algorithm. Higher CR indicates more data reduction has been achieved [27].

$$CR = \frac{Uncompressed\ image\ size}{Compressed\ image\ size} \tag{3}$$

SSIM: An objective image quality metric used to measure the similarity between two images. A value closer to one indicates better image quality [28].

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{4}$$

Figure 4 illustrates the three sets of sample medical images that were collected from the online image archive database for performance evaluation. There are PET axial views of the abdomen, CT axial views of the pelvis, and MRI axial views of the brain. In MATLAB, the image processing toolbox was used to implement and evaluate the performance of the proposed method.

(a) (b) (c)

Fig. 4. Input medical images (a) PET, (b) CT, and (c) MRI

Each medical imaging technique produces different results, as indicated in Table 4. This is so because different machines with distinct properties are used to generate medical images. So, it is a valuable experiment to consider various medical modalities when analyzing the effectiveness of the suggested approaches. In order to adequately evaluate the results, two previous studies on the compression system are compared. The first work was proposed by P. Sreenivasulu and S. Varadarajan [25], and the second was presented by P. Chamberlin and S. Balasubramanian [27]. The previous works utilized a wavelet transform algorithm and the ROI method for image decomposition. Furthermore, the previous work in [25] used only MRI images, while the previous work in [27] used CT and MRI images. According to the table, the proposed compression technique provides better results in terms of PSNR and SSIM than the wavelet algorithm. In addition, eliminating the symmetry curvelet coefficients can reduce the execution time (ET) and data transfer (DT). Indirectly reduce the time required for image decomposition and reconstruction. On the other hand, previous works have not considered the time required to compute the algorithm.

Table 4. The results for image compression techniques on various medical images

Medical Images	Parameters	Proposed Technique	[25]	[27]
CT	PSNR (dB)	34.4	NA	33.5
	CR	4.3	NA	3.8
	SSIM	0.96	NA	NA
	ET (s)	0.13	NA	NA
	DT (s)	0.44	NA	NA
MRI	PSNR (dB)	34.5	31.0	34.1
	CR	4.1	3.9	4.4
	SSIM	0.95	NA	NA
	ET (s)	0.35	NA	NA
	DT (s)	0.23	NA	NA
PET	PSNR (dB)	37.8	NA	NA
	CR	6.1	NA	NA
	SSIM	0.93	NA	NA
	ET (s)	0.52	NA	NA
	DT (s)	1.73	NA	NA

The relationship between BPP, PSNR, and SSIM is investigated using different algorithms: DWT with STS encoder, FDCvT with STS encoder, and the proposed method (modified FDCvT with STS and DPCM). With a higher BPP value, more bits are used to represent each pixel, which leads to a larger file size and greater detail in the image. A maximum PSNR value is reached at the highest BPP, as shown in Figure 5, and the PSNR value increases as the BPP rises. On the other hand, the experimental results show that the maximum SSIM value occurs at the highest BPP, as depicted in Figure 6.

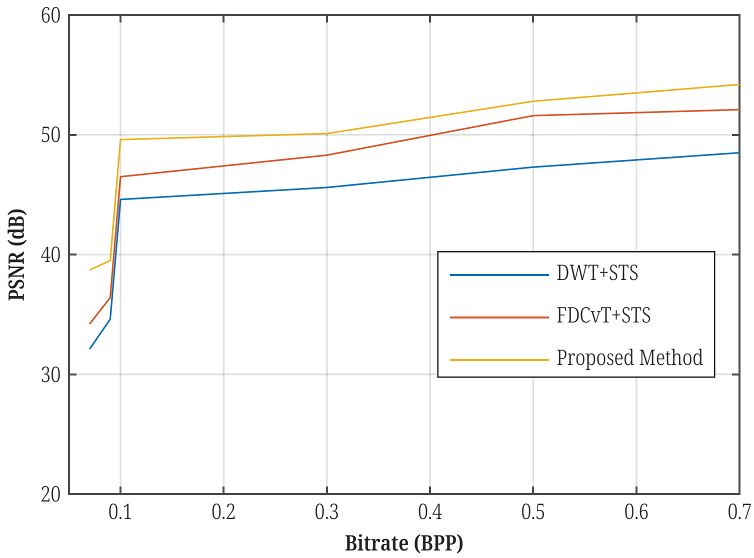

Fig. 5. The graph of PSNR vs. BPP for CT image

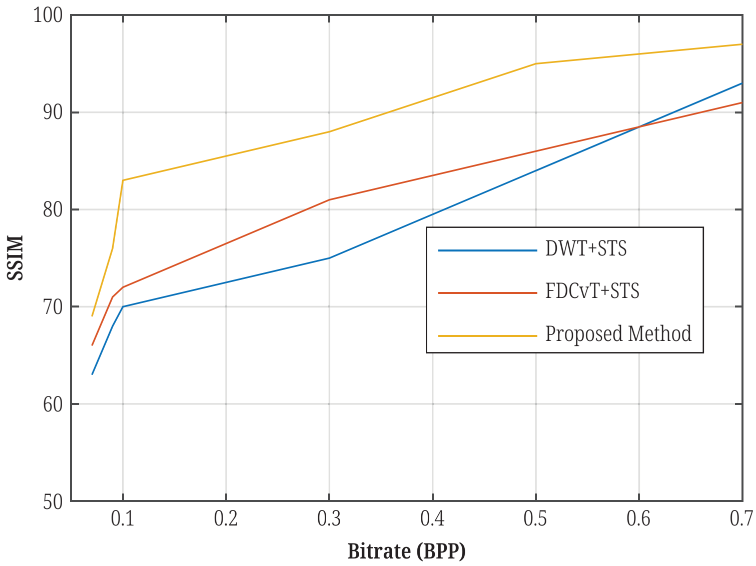

Fig. 6. The graph of SSIM vs. BPP for MRI image

6 CONCLUSION

This paper presents the implementation of FDCvT algorithms with the STS encoding scheme in compression systems. Efficient techniques for medical image compression systems using the curvelet transform and modified SPIHT have been proposed. The experiment results have revealed that modifying the curvelet transform algorithm indirectly increases the time taken for encoding and decoding. In addition, a comparative study also demonstrated that the proposed compression method yields superior results in terms of PSNR, SSIM, and CR. On the other hand, depending on the type of disease, each medical imaging modality is used to produce a specific kind of medical image. Therefore, the medical images used in this work as input (CT, MRI, and PET) are not from the same subject. Furthermore, the encoding methods used in developing the compression technique are limited to STS and DPCM. In the future, the proposed compression technique can be enhanced by combining different encoder methods, such as Huffman, to improve performance. Additionally, applying ROI extraction will improve algorithm computations and speed while preserving the diagnostic value.

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8 REFERENCES

[1] S. Saravanan and S. Juliet, "A methaheuristic approach for tetrolet-based medical image compression," *Journal of Cases on Information Technology*, vol. 24, no. 2, pp. 1–14, 2022. https://doi.org/10.4018/JCIT.20220401.oa3

[2] M. R. Lone and N. U. Hakeem, "FPGA implementation of a low-power and area-efficient state-table-based compression algorithm for DSLR cameras," *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 26, no. 6, pp. 2927–2942, 2018. https://doi.org/10.3906/elk-1804-208

[3] F. R. Lucas, M. M. Rodrigues, S. Cruz, and M. M. Faria, "Lossless compression of medical images using 3-D predictors," *IEEE Transactions on Medical Imaging*, vol. 36, no. 11, pp. 2250–2260, 2017. https://doi.org/10.1109/TMI.2017.2714640

[4] M. Limaye and A. Phaitane, "Implementing image compression using transform-based approach," in *International Conference on Computing Methodologies & Communication*, Erode, India, 2017, pp. 834–840. https://doi.org/10.1109/ICCMC.2017.8282582

[5] L. Inouri, S. Tighidet, M. Azni, A. Khireddine, and K. Harrar, "A fast and efficient approach for image compression using curvelet transform," *Sensing and Imaging*, vol. 19, no. 26, 2018. https://doi.org/10.1007/s11220-018-0212-0

[6] A. K. J. Saudagar, "Biomedical image compression techniques for clinical image processing," *International Journal of Online and Biomedical Engineering*, vol. 16, no. 12, pp. 133–154, 2020. https://doi.org/10.3991/ijoe.v16i12.17019

[7] A. Dhivakar, M. G. Ahamad, and D. Ravichandra, "Medical image compression using embedded zerotree wavelet (EZW) coder," in *International Conference System Modeling & Advancement in Research Trends (SMART)*, 2016. https://doi.org/10.1109/SYSMART.2016.7894482

[8] M. S. Sadi, M. Alotaibi, P. Saha, F. Y. Nishat, J. Tasnim, T. Alhmiedat, H. Almoamari, and Z. Bassfar, "COV-CTX: A deep learning approach to detect COVID-19 from lung CT and X-ray images," *International Journal of Online and Biomedical Engineering*, vol. 19, no. 9, pp. 47–65, 2023. https://doi.org/10.3991/ijoe.v19i09.38147

[9] K. Bryant, "Advances in computer tomography (3D) for demanding electronicsapplications," in *Pacific Microelectronics Symposium (Pan Pacific),* IEEE, 2018. https://doi.org/10.23919/PanPacific.2018.8318998

[10] C. Sachpekidis, H. Goldschmidt, and A. Dimitrakopoulou-Strauss, "Positron emission tomography (PET) radiopharmaceuticals in multiple myeloma," *Molecules*, vol. 25, no. 134, pp. 1–17, 2020. https://doi.org/10.3390/molecules25010134

[11] J. G. Proakis and D. G. Monalakis, *Digital Signal Processing: Principles, Algorithms and Applications*, 3rd Edition. New Jersey: Prentice-Hall International, 1996.

[12] R. H. Caverly, "RF aspects of high-field magnetic resonance imaging (HF-MRI): Recent advances," *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, vol. 3, no. 2, pp. 111–119, 2019. https://doi.org/10.1109/JERM.2018.2879396

[13] H. Y. Saad and M. Z. Abdullah, "Real-time implementation of fractal image compression in low cost FPGA," in *IEEE International Conference on Imaging Systems and Techniques (IST)*, 2016, pp. 13–18. https://doi.org/10.1109/IST.2016.7738190

[14] A. Bousselham, O. Bouattane, M. Youssfi, and A. Raihani, "Thermal effect analysis of brain tumor on simulated T1-weighted MRI images," in *International Conference on Intelligent Systems and Computer Vision (ISCV)*, 2018, pp. 1–6. https://doi.org/10.1109/ISACV.2018.8354083

[15] D. Ravichandran, R. Nimmatoori, and M. R. Dhivakar, "Performance of wavelet-based image compression on medical images for cloud computing," in *3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, 2016, pp. 297–302.

[16] N. H. Jaafar and A. Ahmad, "Algorithm development and hardware implementation for medical image compression system: A review," *Indonesian Journal of Electrical Engineering and Computer Sciences*, vol. 18, no. 3, p. 1331, 2020. https://doi.org/10.11591/ijeecs.v18.i3.pp1331-1341

[17] H. Al-Marzouqi and G. AlRegib, "Curvelet transform with learning-based tiling," *Signal Processing: Image Communication*, vol. 23, pp. 24–39, 2017. https://doi.org/10.1016/j.image.2017.01.009

[18] National Library of Medicine, Lister Hill National Center for Biomedical Communications, "Health facts 2020 references data for year 2019," Ministry of Health Malaysia, 2020.

[19] U. Patbhaje, R. Kumar, A. Kumar, and H. N. Lee, "A compression system of medical image using wavelet based sparsification and coding," in *4th International Conference on Signal Processing and Integrated Networks (SPIN)*, 2017. https://doi.org/10.1109/SPIN.2017.8049981

[20] H. T. Sadeeq, T. H. Hameed, A. S. Abdi, and A. N. Abdulfatah, "Image compression using neural networks: A review," *International Journal of Online and Biomedical Engineering*, vol. 17, no. 14, pp. 135–153, 2021. https://doi.org/10.3991/ijoe.v17i14.26059

[21] Q. Min, X. Wang, B. Huang, and Z. Zhou, "Lossless medical image compression based on anatomical information and deep neural networks," *Biomedical Signal Processing and Control*, vol. 74, pp. 1–10, 2022. https://doi.org/10.1016/j.bspc.2022.103499

[22] M. P. Reddy, B. V. R. Reddy, and C. S. Bindu, "The lossless medical image compression for telemedicine applications with delimiter," *Journal of Advance Research in Synamic & Control Systems*, vol. 10, no. 3, pp. 74–79, 2018.

[23] H. A. Elsayed, Q. E. Majeed, and M. M. E. Sherbiny, "Non-decimated wavelet transform and vector quantization for lossy medical images compression," *Journal of Computer Science*, vol. 19, no. 3, pp. 363–371, 2023. https://doi.org/10.3844/jcssp.2023.363.371

[24] M. R. Lone and N. Hakim, "A novel hardware-efficient spatial orientation tree-based image compression algorithm and its field programmable gate array implementation," *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 27, no. 5, pp. 3823–3836, 2019. https://doi.org/10.3906/elk-1903-14

[25] 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, 2018. https://doi.org/10.1515/jisys-2018-0180

[26] P. Lakshmi and R. S. Sabeenian, "Medical image compression using wrapping based fast discrete curvelet transformand arithmetic coding," *Circuits and Systems*, vol. 7, pp. 2059–2069, 2016. https://doi.org/10.4236/cs.2016.78179

[27] P. Chamberlin and S. Balasubramanian, "Near lossless medical image compression using block BWT–MTF and hybrid fractal compression techniques," *Cluster Computing*, vol. 22, no. 1, pp. 12929–S12937, 2019. https://doi.org/10.1007/s10586-018-1801-3

[28] U. Sara, M. Akter, and M. S. Uddin, "Image quality assessment through FSIM, SSIM, MSE and PSNR—A comparative study," *Journal of Computer and Communications*, vol. 7, no. 3, pp. 8–18, 2019. https://doi.org/10.4236/jcc.2019.73002

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