

A Metaheuristic Approach for Tetrolet-Based Medical Image Compression

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ABSTRACT

Medical imaging plays a significant role in clinical practices. Storing and transferring the huge volume of images becomes complicated without an efficient image compression technique. This paper proposes a compression algorithm that uses a Haar-based wavelet transform called Tetrolet transform, which reduces the noise on the input images and decomposes with 4×4 blocks of equal squares called tetrominoes. It opts for a decomposing using optimal scheme for achieving the input image into a sparse representation which gives a much-detailed performance for texture and edge information better than wavelet transform. Set partitioning in hierarchical trees (SPIHT) is used for encoding the significant coefficients to achieve efficient image compression. It has been investigated with various metaheuristic algorithms. Experimental results prove that the proposed method outperforms the other transform-based compression in terms of PSNR, CR, and complexity. Also, the proposed method shows an improved result with another state of work.

KEYWORDS

Medical Image Compression, Metaheuristic Algorithm, SPIHT, Tetrolet Transform

1. INTRODUCTION

Over recent years, there has been a huge series of images that are getting generated in hospitals to diagnose various diseases. Doctors / Clinicians prefer to judge the illness of the patients through the images generated of internal organs. These Medical images are often generated using acquisition devices such as CT scan, MRI, X-Ray, Etc., Commonly these medical images are volumetric in size which requires high storage (Gonzalez et al., 2009). Speed and Bandwidth are the major setbacks as considered while transmitting the medical images (Smith-Bindman et al., 2008) for telemedicine. This problem can be overcome by compressing a medical image effectively. Digital image compression achieves the redundancy in an image that can be represented using a smaller number of bits to acquire an acceptable quality image. Compression deals with two variety of methods such as Lossy compression and Lossless compression. Generally, images used in a medical domain need to be compressed without losing the data (Khalaf, Abdulsahib, Kasmaei, et al., 2020) for better diagnosis, which directs an efficient lossless medical image compression algorithm.

Even a vast number of algorithms were already proposed for finding an efficient compression algorithm, still finding a lossless medical image compression algorithm is a challenging task. The

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performance of the lossless algorithm is measured using the ratio bit rate required for the original input image to its compressed image called compression ratio (CR). Bit rate is defined by an average number of bits essential to represent each pixel of the compressed image. Subjective and Objective quality measures are also considered over compression. Popular transforms such as Wavelet and JPEG based algorithm achieves a high compression ratio but failed to maintain the quality of the image. As the main drawback states that algorithms are irreversible, this paper proposes a compression method for medical images using a Haar wavelet-based transform called Tetrolet (Krommweh, 2010). This method decomposes the input medical images into blocks to find a sparsest tetrolet representation over the image and encodes with (SPIHT) Set partitioning hierarchical tree method (Dragotti et al., 2000).

The proposed method is analyzed by comparing its performances through different metrics with metaheuristic algorithms and also with transform-based compression methods (Saravanan et al., 2013), (Juliet et al., 2016) and (Uma Vetri Selvi & Nadarajan, 2017) with a dataset of medical images. Experimental results prove that the proposed method achieves a higher value with various performance metrics such as peak signal-noise ratio (PSNR), Compression Ratio (CR), and Computational time (CT) over other algorithms. This paper is arranged as follows: Section 2 deals with related works over the different compression transforms followed by Section 3 that describes the proposed method with Tetrolet transform and SPIHT encoder. Section 4 details the performance analysis of the proposed algorithm over other methods with various metrics. Section 5 deals with the Results and discussion of the compression algorithms and finally conclusions are given in section 6.

2. RELATED WORKS

To obtain an efficient algorithm for achieving a better visual quality medical image, there has been an enormous number of algorithms identified. It has been widely classified as lossy and lossless compression (Hussain et al., 2018). Transform based compression are popular which transforms the image from one domain (spatial/temporal) to a different type of representation. Then the values are coded to achieve good quality image data. To reduce the correlation between the pixels in an image is also an important factor when we analyze the transform-based coding such a DCT, DFT, and DWT. DCT (Gupta et al., 2014) declares quantization as an essential sector which deals with reducing the number of bits to store the transformed values. However, quantization makes the algorithm lossy. DFT (Hao & Shi, 2001) decomposes a complex signal into a weighted sum of zero frequency term. Wavelet-based compression, DWT (Wu, 2014) overcomes the blocking effect limitation in DCT. It generally works on the function that integrates to a zero waving over the x-axis and also results in better values over the other algorithms. Based on the wavelet transform, there are many other forms of transforms derived such as Haar wavelet (Harikrishnan et al., 2017) that isolate the image into segments, and the detail is achieved through averaging and differencing. Daubechies (Nagendran & Vasuki, 2019) proposed wavelet (dB1, dB4) which focused on dividing into constituents namely split, prediction, and update method. Bandelet (Yang et al., 2014), Contourlet (Uma Vetri Selvi & Nadarajan, 2017), Curvelet (Saravanan et al., 2013), Noislet (Wen et al., 2010), Wedgelet (Romberg et al., 2002), Chirplet (Mann & Haykin, 1995), Tetrolet (Krommweh, 2010), etc are also the other wavelet-based lets which are derived based on parameters of multiscale, Directionality, Geometric representations (Jacques et al., 2011).

For an efficient representation of geometric features over the images, these star-lets were originated. Ridgelets (Jacques et al., 2011) is a combination of a one-dimensional wavelet transform and a radon transform that focuses on the efficient representation of discontinuities over straight lines. Curvelet (Rupa et al., 2014; Saravanan et al., 2013) is identified to enable the efficient representation of two-dimensional singularities along arbitrarily shapes curves over the image. Contourlets (Uma Vetri Selvi & Nadarajan, 2017) are considered as a low redundancy discrete approximation of curvelets which are designed in a spatial domain to achieve the close to critical directional representation. Ripplet (Juliet et al., 2016) has been identified to achieve the directionality and scalability features

on the image. When it intersects with the curves in an image, the respective coefficients will occur a large magnitude and the coefficients will decay along the direction of singularities. All of these starlets are being proposed to improve the behavior of geometric image structures with more accuracy on directional sensitivity. Since over the medical image retaining the image quality with low noise and detailed decorrelation can be opted with the use of these wavelet-based transforms. Bandelet (Yang et al., 2014) is represented to maintain the geometrical structure over the image. It works to achieve the optimal (Khalaf & Sabbar, 2019) geometric flows to determine by a coarse and exhaustive search. Tetrolet (Krommweh, 2010), (Jain & Tyagi, 2015), (Zhang et al., 2016) haar based wavelet transform works on the principle of connecting the four identical square tiles. And it has been widely used for denoising over the image and its result achieves a strong efficiency for image approximation. Many researchers have proposed the hybrid combinations of transforms (Srivastava et al., 2009), (Karthikeyan & Thirumoorathi, 2016).

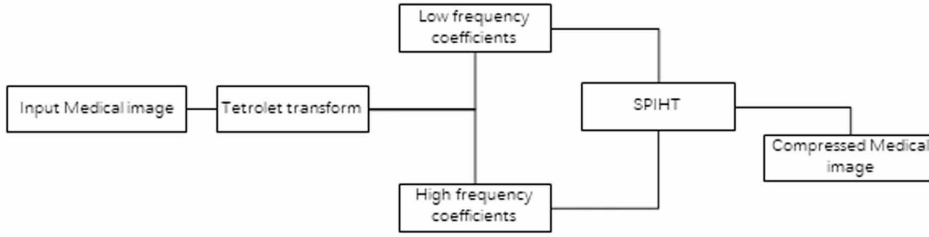
The encoding process is essential as it applies to reduce repeated bit patterns. For this reason, the enormous number of encoders is used with different transforms. To obtain a lossless process of compression, a lossless encoder/decoder to be used. Huffman encoder (Venugopal et al., 2016) is one such type, which generates a codebook to process, where its results depend on the size of the codebook. It requires to encode its input symbols and encoding complexity. Whereas arithmetic coder is much more complex than the Huffman coder as it doesn't even need a codebook. Other popular encoders include SVD Singular value decomposition (Thanki & Kothari, 2019) which decomposes the image into three matrices U, V, and S also called a low-rank approximation technique. SPIHT encoder (Xiang et al., 2014) tackles the bit assignment problem at its root. Its categories all coefficients in order to decrease the magnitude for making a perfect bit assignment and moreover it lifting structure improvise the drawbacks of the wavelet transform. From the survey, it has been identified that medical images occur with main problems due to degradations like noise and detail blurring. Denoising, which removes the noise as well as the other factors like sharp structures, textures, and edges. So, availing a transform that also preprocesses over the image can achieve a quality image that can be achieved through an edge preservative domain called tetrolet algorithm (UmaMaheswari & SrinivasaRaghavan, 2020) – a haar type wavelet transform. It reduces the noise over the image and also maintains the structure preservation through using shrinkage rule over the high-frequency coefficients but it has a drawback of not using an encoder. SPIHT finds it to be efficient as compared with the (EZW) Embedded Zero Tree wavelet coder (Ahire & Baviskar, 2015). SPIHT can be applied over lossy and lossless compression techniques and it generally outperforms as compares with other encoders. Modified algorithms (Khalaf et al., 2018) also results in an efficient outcome (Abdulsahib & Khalaf, 2018), (Salman et al., 2019), (Ogudo et al., 2019).

Metaheuristic algorithms including genetic algorithm, artificial bee colony optimization (K. M. Sagayam & Hemanth, 2018) (Khalaf, Abdulsahib, & Sabbar, 2020), particle swarm optimization (M. Sagayam et al., 2020), ant colony optimization (Li et al., 2008), etc., have been implemented with another transform-based coding for optimizing an image through the threshold and achieves a higher performance metrics in terms of Compression ratio and peak signal-noise ratio. Proposed method is motivated towards achieving a lossless image compression for different medical modality images with the denoising feature used avoid the artifacts.

3. PROPOSED METHOD

The Block diagram in **Figure 1** explains the process of the proposed method. Input medical uncompressed raw images are considered with the resolution of 256 X 256 – 8 bits in DICOM format collected from the Kaggle online database for CT images “<https://www.kaggle.com/kmader/siim-medical-images>” and MRI images from “<http://prostatemrimagesdatabase.com/Database/>”, which is allowed to process with the Tetrolet transform for preprocessing and decomposition. Tetrolet transform decomposes the images into 4 X 4 square blocks called tetromino partition (Naqvi, 2013). Tetrominoes

Figure 1. The block diagram of the proposed compression scheme



are shapes made of connecting four equal-sized squares that joint together with one square along an edge. Over the geometric shapes forms an orthonormal basis which leads to a decomposition of an image into a sparse representation. By applying the shrinkage method to the transform coefficients for obtaining the image approximation and to reconstruct the image with the encoder SPIHT. To obtain the efficiency of this combination of algorithm, there have been several performance metrics like Compression ratio (CR), Peak signal Noise ratio (PSNR), Mean square error (MSE)(Khalaf & Abdulsahib, 2019), Computational time (CT) which are explained in Section 4.

3.1 Tetrolet Transform

Tetrolet transform is a haar wavelet-based transform, also called a geometric adaptive transform, which has the tetromino support and the ability to find the directional over an image. For implementation, the input image is divided into blocks with 4 X 4 pixels. Computing the optimal partition of the block into five tetrominoes (O, I, T, S, L) shapes which are illustrated in **Figure 2**. Each 4 X 4 block has 16 indices which are rearranged in 22 different behaviors if rotation and reflections are avoided. A maximum of 117 different tilings of tetrominoes can be made by using the rotation and reflection. Over to 8 * 8 blocks instead of 4 * 4 blocks will obtain 1178 possibilities for reducing the computational complexity. 4 X 4 combinations are used to avoid a huge number of solutions. Finally, at the decomposition level, a coefficient matrix with the same size of the input image is obtained.

Tetrolet transform explains with terminologies and notations for better understanding. The input image is considered as $f=f(m,n)$ for two dimensional data. $I = \{(m,n):m,n=0,...,M-1\}$ denotes the index set of an image where $M=2^r$, then n -neighborhood of the index (m,n) may occur over the vertex or at the boundary is defined by

$$\tilde{n}(m,n) = \{(m-1,n), (m+1,n), (m,n-1), (m,n+1)\} \quad (1)$$

An Index at the vertex can have the maximum of two neighbors, whereas the index at the boundary can have a maximum of three neighbors. One dimensional indexing is formed using bijective mapping. And the input image is divided into partitions P as $I_0, I_1, \dots, I_r$ where $r \in \mathbb{N}$ and the collection of partitions represented as

$$I_p = \bigcup_{p=0}^r \quad (2)$$

Each I_p has four indices in which each index is at least connected to other neighbors over its boundary. Such collection is called tetrominoes which are illustrated in **Figure 2**. Five different

Figure 2. Shapes of Tetrominoes



tetrominoes are reflected and rotated to obtain many combinations of tetrominoes. In such a case from 4 * 4 blocks can bring 16 indices, if its image dimension (M) is even. So, it can fill within four tetrominoes as illustrated in **Figure 3**. 22 different combinations can be achieved in 4 X 4 block if the reflection and rotation are avoided. A total of 117 choices of tilings can occur with these 22 shapes by reflecting and rotating.

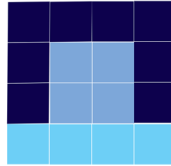
The haar wavelet transform is applied over each tiling of four tetrominoes which is denoted by $I_s^{(c)}$ where $s = 0,1,2,3$ and coverings $c = 1, \dots, 117$ results in low frequency and high frequency coefficients:

$$f^{r,(c)} = \left(f^{r,(c)}[s] \right)_{s=0}^3; w_l^{r,(c)} = \left(w_l^{r,(c)}[s] \right)_{s=0}^3 \quad (3)$$

Where $f^{r,(c)}$ represents the pixel average of the tetrominoes and $w_l^{r,(c)}$ represents the three high frequency coefficients for $l=1,2,3$. After the haar wavelet transformation matrix is generated, the optimum partition for the image geometry from any 117 possible tilings are obtained with the optimum decomposition coefficients of image. Therefore, low frequency and high frequency coefficients are arranged in 2 X 2 blocks of the highest correlation with haar partitioning. A local structure of image block is improved.

Thereafter the labeling process is achieved by comparing the square case. Over the 24 different possibilities, the four tetrominoes are labeled with numbering in the highest correlation with haar partition as shown in **Figure 4 a)**. Bad order as illustrated in **Figure 4 b)** can make the high computational complexity. Then the haar wavelet is dealt with the vector to estimate the approximation and tetralet coefficients.

Figure 3. Combination of tetrominoes with 4 * 4 pixel blocks



3.2 SPIHT Encoding

Over this transform-based compression algorithms, to improvise the performance in compression is by bringing the entropy coding. A huge number of encoding methods has been proposed to deed the dependency over the location and value of coefficients across different frequency level in an image. The efficient method as per the survey tends to fulfill the performance through low bit rate performance and scalability is achieved by the Set Partitioning Hierarchical Tree encoder (SPIHT). This encoder works based on the pyramid structure-based wavelet decomposition style of an image. It specializes in bringing progressive transmission on pixel accuracy. Its effectiveness is based on the iterative search over the pyramid tree for significant pixels and collecting the coefficients according to the significance test. The collective property of tetrolet transform with the coding coefficient using SPIHT brings out an efficient compression over a medical image.

3.3 Metaheuristic Algorithm

The experimental results achieved with the tetrolet transform are developed as a transform matrix, which is implemented to the machine learning algorithm to achieve a predictive result. Based on the survey with various machine learning algorithms as shown in **Table 2**, which shows the performance achieved with the existing approach.

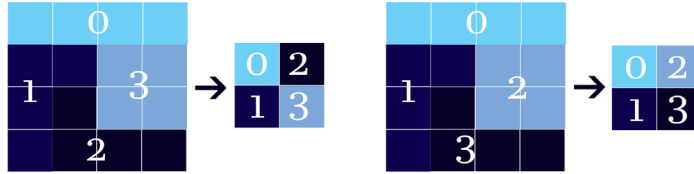
4. PERFORMANCE METRICS

The following section presents an experimental investigation of the behavior of proposed method of compression.

The main objective of compression method is to obtain the best visual quality with minimum bit utilization. Peak Signal Noise Ratio (PSNR) is a parameter used for assessing the quality of the compressed image. It is defined as

$$PSNR = 10 * \log_{10} \left(\frac{255^2}{\sqrt{MSE}} \right) \text{-----} \quad (1)$$

Figure 4. a) Bad order b) best order



Mean Square Error (MSE) in (1) represents the mean squared error of the image defined as

$$\text{MSE} = \frac{1}{N} \times \sum_i \sum_j \left(f(x, y) - F(x, y) \right)^2 \text{-----} \quad (2)$$

where N denotes the total number of pixels, $f(x, y)$ represents the pixel intensities of the original image and $F(x, y)$ represents the pixel intensities of the compressed image.

Table 1. Algorithm for image compression using Tetrolet transform and SPIHT encode

Step 1: Input the medical image $f(m, n)$ (256 X 256 – 8 bits)
Step 2: Input image is divided into 4 X 4 blocks
Step 3: Tetrolet transform (haar based wavelet) is applied considering the 117 solutions of tetrominoes segmentation to obtain the high frequency and low frequency coefficients
$f^{r,(c)} = \left(f^{r,(c)} [s] \right)_{s=0}^3; w_l^{r,(c)} = \left(w_l^{r,(c)} [s] \right)_{s=0}^3$
where $f^{r,(c)}$ represents the pixel average of the tetrominoes and $w_l^{r,(c)}$ represents the three high frequency coefficients for $l=1,2,3$
Step 4: High frequency and low frequency coefficients of each block are rearranged into 2 X 2 blocks.
$a^r = \left(a_{Q_{m,n}}^r \right)_{m,n=0}^{\frac{M}{4}-1}$ represents the low frequency coefficients
$W_l^r = \left(w_{lQ_{m,n}}^r \right)_{m,n=0}^{\frac{M}{4}-1}$ represents the high frequency coefficients
Step 5: Store the tetrolet coefficients (high frequency)
Step 6: apply step 2- 5 to the low frequency coefficients
Step 7: Encode the resulting coefficients with SPIHT encoder
Step 8: Resulting the output image quality in terms of PSNR, MSE, CR and CT.

Table 2. Performance analysis with existing metaheuristic algorithm with Lena image

Algorithm	PSNR	CR
Ant Colony Optimization (Li et al., 2008)	24.27	28:1
BAT algorithm + LBG (Karri & Jena, 2016)	31	high
Artificial Bee Colony (Hornig, 2011)	21.68	high
Cuckoo search (Chiranjeevi & Jena, 2018)	29	high

Similarly, Compression Ratio (CR) analyzes the performance of compressed image. It is defined as the ratio between the original image divided by the size of the compressed image as shown in Eq 3.

$$\text{Compression Ratio (CR)} = \frac{\text{Size of the Original Image}}{\text{Size of the compressed image}} \text{-----} \quad (3)$$

This compression ratio (CR) represents the picture quality. When the ratio is high it states that the quality of the compressed image will be low. Over this compression process, factors between the CR and picture quality plays an important role in achieving a lossless image.

Computational time (CT) is calculated based on the time taken for processing the algorithm with the input image to produce the resultant image. These all are considered here as a performance metrics which is tested for the proposed method and the results are discussed in section 5

5. RESULTS AND DISCUSSION

The performances are evaluated for the proposed method with a set of six medical images of size (256 X 256, 8 bits per pixel) with DICOM format and the quality of the compressed images has been measured in terms of Peak signal noise ratio (dB), Mean square error (MSE), Compression ratio and computational time. The effectiveness of the proposed method is evaluated on comparison with existing algorithms such as Curvelet (Saravanan et al., 2013), Contourlet (Uma Vetri Selvi & Nadarajan, 2017) and Ripplet transform (Juliet et al., 2016), all combined with SPIHT encoder.

Figure 5 illustrates the six set of sample medical images collected from the online image archive databases for performance evaluation. In Matlab, Image processing toolbox has been used for implementation and measuring the performance of the proposed method. The following subsections details the experimental results obtained from the evaluation.

Four set of results are obtained with the medical images in comparing the proposed method, Tetrole with SPIHT algorithm with the curvelet transform proved efficient in finding the edges and bringing the image representation accurate (Rupa et al., 2014) with the SPIHT encoder. Ripplet transform (Juliet et al., 2016) and Contourlet transform (Uma Vetri Selvi & Nadarajan, 2017) the findings are illustrated in the **Table 3** with **Figure 6**, **Figure 7** and **Figure 8** for the different performance metrics.

From the observation of implementing the different compression algorithms, it has been found that the proposed tetrole transform with SPIHT compression has achieved a higher value in PSNR, Compression ratio, and Computational time. In the future, the hybrid method with a metaheuristic approach will be proposed to improvise the result to achieve the best visually lossless compression image. Thus, it proves that it is an efficient medical image compression technique as compared with the other existing compression algorithms.

Figure 5. Input medical images considered for evaluation

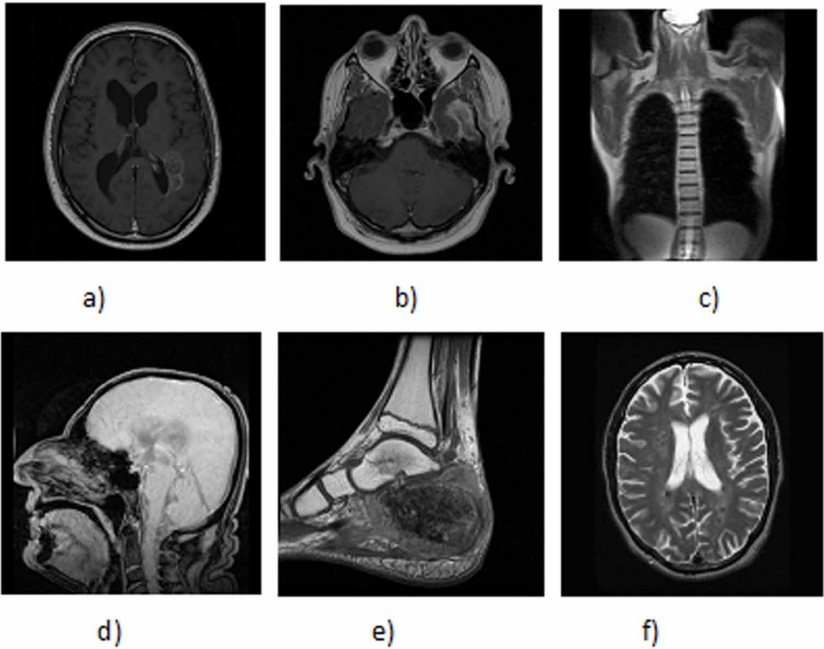


Table 3. Comparison of Proposed method with other two existing algorithms with different metrics

Sample Images	Compression methods	PSNR (dB)	MSE (dB)	CT (sec)	CR
Image 1 T2WI-axial-1 view of brain	Curvelet +SPIHT	31.14	3.9	0.79	6.3
	Contourlet +SPIHT	32.33	3.2	0.84	8.2
	Ripplet + SPIHT	34.21	2.46	0.69	9.74
	Proposed	34.31	2.41	0.44	11.51
Image 2 T2WI-axial-2 view of brain	Curvelet +SPIHT	30.21	3.74	0.63	5.2
	Contourlet +SPIHT	31.14	3.9	0.99	6.8
	Ripplet + SPIHT	32.85	3.37	0.51	12.35
	Proposed	32.65	3.53	0.45	16.5
Image 3 T1-weighted MRI lungs	Curvelet +SPIHT	30.6	4.9	0.61	5.1
	Contourlet +SPIHT	30.9	3.6	0.92	5.8
	Ripplet + SPIHT	31.4	4.7	0.59	5.43
	Proposed	33.31	3.04	0.55	7.43
Image 4 sagittal stir axial view of head	Curvelet +SPIHT	31.8	3.95	0.82	6.8
	Contourlet +SPIHT	34.8	2.8	0.67	9.24
	Ripplet + SPIHT	35.1	2.01	0.96	11.38
	Proposed	36.13	1.58	0.56	14.9
Image 5 Ankle MRI	Curvelet +SPIHT	30.1	4.2	0.58	5.01
	Contourlet +SPIHT	29.8	3.7	0.68	4.6
	Ripplet + SPIHT	31.17	4.96	0.47	7.32
	Proposed	30.93	5.25	0.44	10.03
Image 6 T2WI-axial-3 view of brain	Curvelet +SPIHT	30.82	4.43	0.65	6.9
	Contourlet +SPIHT	30.66	4.1	0.84	5.27
	Ripplet + SPIHT	31.34	4.7	0.56	7.87
	Proposed	32.8	5.38	0.5	11.61

Figure 6. Comparison of PSNR values (dB) obtained with test images using different compression algorithms

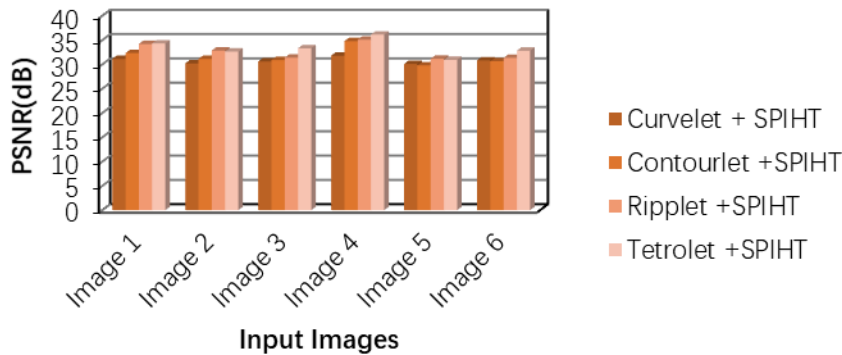


Figure 7. Comparison of CR values obtained with test images using different compression algorithms

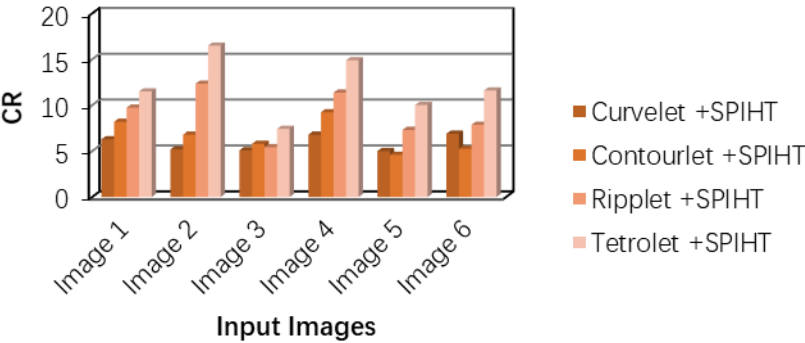
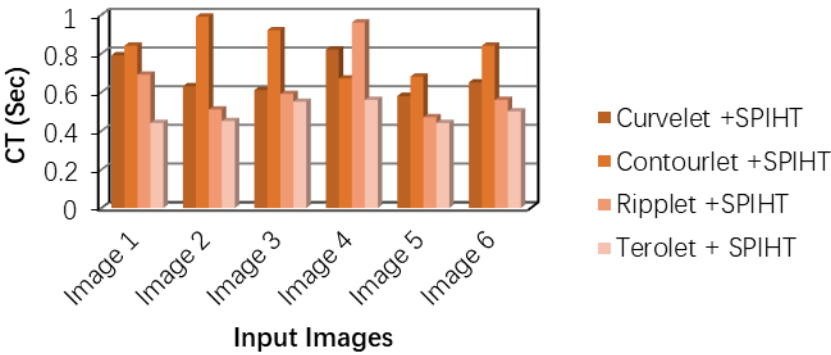


Figure 8. Comparison of CR values obtained with test images using different compression algorithms



6. CONCLUSION

In this paper, an efficient medical image compression technique is proposed which uses a tetrolet transform (haar based wavelet), a geometric adaptive transform. Tetrolet transform is unique in the way of achieving a denoising pattern with tetromino support which enables it to adapt to the directional features of an image. On comparing its efficiency with Curvelet, contourlet, and Ripplet transforms, the proposed method called tetrolet outperforms in terms of high PSNR and high compression ratio. The hybrid method with a metaheuristic approach achieves an even higher PSNR and compression ratio which states as an improved result. Moreover, the computational time is also less which proves that the low complexity. Thus, Tetrolet transforms with SPIHT encoder proves to its an efficient image compression algorithm for medical images.

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