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Image Preservation using Wavelet Based On Kronecker Mask, Birge - Massart And Parity Strategy

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Abstract: Image carries more information about the ideas than text. Growth of social media, images has become the universal language because it is more interactive. Images are used in different fields like medical, multimedia, industries etc. When using the images, we need to find effective storage and transmission methods to reduce storage size and transmission time. Lossless and lossy are two ways to compress the image to reduce the storage and transmission time. The proposed method implements the concept of lossless image compression using the method of Kronecker delta notation, wavelet based on Birge-Massart strategy and parity strategy. This paper presents that enhancing the image by applying the Kronecker delta notation as the mask and applying the wavelet based on Birge-Massart strategy, finally applying the parity threshold to compress the image. The proposed method is compared the compression ratio (CR) with the existing lossless compression methods such as Birge – Massart without the enhanced method and Unimodal method. This proposed algorithm is very simple and more efficient to reduce the storage capacity and maintain the quality of an image than the existing lossless compression techniques. The experimental result shows that the Birge-Massart strategy combined with Kronecker mask and parity threshold produces the best CR than the simple Birge- Massart(without enhancement and threshold) strategy. This efficient method is proved by without loss of information of an original image with low MSE, high PSNR and high CR. An experimental result shows that the proposed algorithm achieved maximum CR of 146% on medical images and maximum CR of 19.2% on standard images than the existing methods.

Keywords : *Birge-Massart, Kronecker Mask, Lossless Image Compression, Parity strategy, Threshold, Unimodal, Wavelet*.

I. INTRODUCTION

The quasi-lossless and improved quasi-lossless fractal coding algorithms are found to outperform standard fractal coding thereby proving the possibility of using fractal-based image compression algorithms for medical image compression. The proposed algorithm allows significant reduction of encoding time and also improvement in the compression ratio[1]. Hybrid algorithms have been implemented based on Daubechies wavelet, global thresholding and Huffman encoding for medical image compression. Performance of the hybrid algorithm works well than the previous compression methods [2]. A Medical image compression using adaptive sub band threshold algorithm focused to detect the more influenced coefficients in an image based on threshold. This threshold and arithmetic coding gives better subjective quality than JPEG and SPIHT coding [3]. Threshold predicting wavelet based algorithm enhanced the medical image compression by segmenting the image area in to region of background and region of interest [4]. Different image compression formats like true color images and gray scale images, lossy compression format JPEG produces high compression ratio (CR). In lossless compression, the compression formats TIFF and PNG have given good result [5]. Volumetric medical image compression by wavelets which are accomplished with the Integer wavelet filters. Scaling and Truncations keeps the integer precision is small and transforms unitary [6].

Compared different techniques like Global Histogram Equalization (GHE), Local Histogram Equalization (LHE), BPDHE and AHE for enhance the MRI images [7]. Finding the smallest circle containing the iris based on median filter produces the better result than the wavelet based transform and median-filter approach which is more robust to find better radius [8]. RLE and Huffman encoding techniques which are suited for JPEG based image compression. SPIHT encoding method has suited for JPEG 2000 based image compression [9]. Adaptive multi-wavelet Transform (AMWT) outperforms the other well-known transform technique. This AMWT is derived from the adaptive lifting scheme [10].To maximize the CR, ROI is compressed using lossless compression and other areas of the image are compressed using lossy wavelet compression technique [11]. Different threshold processes applied for speckle reduction and finding the occurrence of the coefficients in an image [12]. Speckled image has been filtered first, then compressed using JPEG2000 encoder. This method performs well in signal to noise ratio and visual quality [13]. Compressed the medical image with the help of filtering and SPIHT algorithm and proved that compression ratio and image quality [14]. In medical images, universal threshold and Weiner threshold have used to de-noise the image. Soft and hard threshold used for shrink the wavelet coefficient of medical image [15]. Normal filters are suitable only when the noise level of an image is low, if the noise level is high, combination of filters are required to de-noise the image [16]. Neighbourhood pixel filtering Algorithm (NPFA) with sub band thresholding works well than all other filtering techniques [17].

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In medical image Baye's threshold removes the noise in better way and also maintains all the information of an image. Baye's threshold has used to perform well than the soft and hard threshold [18]. In medical compression Adaptive median filter produces the high quality image with high PSNR in both compression and decompression process [19]. The low-pass filters usually employ moving window operator which affects one pixel of the image at a time, changing its value by some function of a local region (window) of pixels. The operator moves over the image to affect all the pixels in the image [20].

In the comparative study of Birge-Massart strategy and Unimodal threshold for image compression using wavelet transform in which the Birge-Massart Threshold based on level dependent threshold to produce good compression ratio. The Unimodal threshold based global thresholding to produce high PSNR of an image [21]. The comparative study of 2-d wavelet coders for image compression, wavelet transforms like Cohe-Daubechies-feauveau-5/3 and Cohen-Daubechies –Feauveau-9/7 have used with different encoding schemes like SPIHT, SPECK, BISK and TARP. Cohen-Daubechies –Feauveau-9/7 yields better compression over other methods [22].

This paper presents the new lossless image compression technique using Kronecker filtering, DWT based on Birge-Massart and Parity strategy. Various test images such as standard, MRI, CT scan, Radiology images have been tested by applying the proposed method. Performances of the proposed algorithm are evaluated in terms of peak-signal-to-noise ratio (PSNR) and compression ratio (CR) of an image. Experimental result shows that the performance of the proposed method works out well than the other compression methods.

The rest of the paper has explained as follows. Section 2 describes the related work of the proposed method. Section 3 has explains overview and the implementation of proposed algorithm. Experimental results with test sample images are discussed in Section 4. Finally conclusion is presented in section 5 of the paper.

II. RELATED WORK

A medical image compression is very much important for analysing and to diagnose diseases. In medical field many of the images need to send from one place to another place. During the transmission of an image, storage and transmission play an important role. Compression methods are used to reduce the storage and increase the transmission speed effectively. Lossy image compression, decompressed image lost some of the information and produces high compression ratio. In Lossless compression the reconstructed image is 'exact' replica of original image [20].

In image acquisition, some common problem occurs such as unknown noise and poor contrast. These problems must be reduced by pre-processing step in image processing model. This step is very important in medical image processing to preserve all the information of an image [19]. This pre-processing manipulation performed directly on the pixel of an image. This manipulation is called as spatial domain. De-noise is the process to eliminate the noise such as unwanted signal and some additive information occurred during the image acquisition. The de-noising process is done by spatial filtering. Spatial filtering performs two types of operations such as smoothing and sharpening. Both the operations are performed on the neighbourhood of every pixel of an image [20]. Spatial filter consists of the neighbourhood of the pixel and also apply the predefined operation on that pixels also referred as spatial mask, kernel, template or window. Filtering creates a new pixel with coordinates are derived from the neighbourhood of the centre pixel, and that new pixel value is the resultant pixel value .The centre pixel value is replaced by the new pixel value. The resultant enhanced image as the centre of the filter is visited the every pixel in the image. Let $f1(x, y)$ be the image and $f2(x, y)$ be the image after applying threshold. Intensity values of the image $f1(x, y)$ can be grouped in to two dominant groups, such as object pixels and background pixels. To extract the object pixels from the background pixels by using the threshold value T is shown in equation (1).Every pixel (x, y) in $f1(x, y)$ compared with T value, which is $f1(x, y) > T$ is called the object pixel. If $f1(x, y) \leq T$ the pixel is called the background pixel. This process is segment the image in to two groups.

$$f2(x, y) = \begin{cases} 1 & \text{if } f1(x, y) > T \\ 0 & \text{if } f1(x, y) \leq T \end{cases} \quad (1)$$

If T is a constant over an entire image, then the process is referred as global threshold. If T varies over an image then the process is called as binary threshold. Wavelet is a multi-resolution process. It has been convert the image in to different sub band images with the help of filter bank. When increasing the decomposition level of wavelet, the compression ratio would be increased.

III. PROPOSED METHOD

This proposed method works out well with any type of images. The whole compression process is divided in to two processes. The first process is encoding process, this process would generate the compressed image and the second process is decoding process. This process would generate reconstructed image from compressed image. The fig.1 shows an overview of the proposed method.

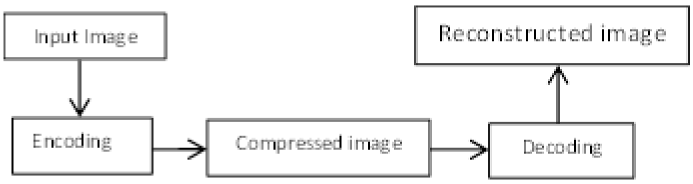

Fig. 1. Image Compression Process Model.

The fig. 2a shows the encoding process and 2b shows the decoding process of the proposed method. The proposed algorithm shows the step by step procedure for the proposed compression method .This proposed algorithm was implemented using Matlab 2009a.

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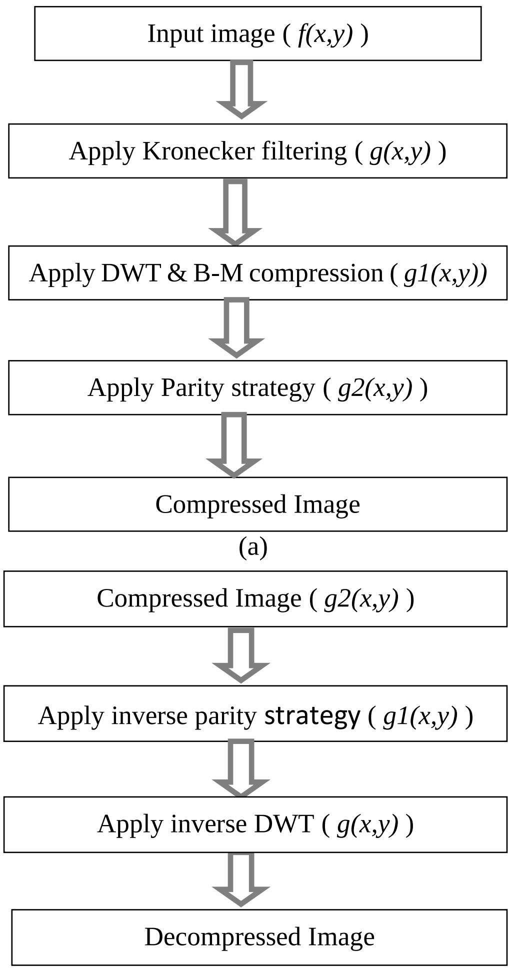


(b)

Fig. 2. Proposed Method. a. Encoding Process, b. Decoding Process.

A. Proposed Algorithm

1. Read an Image from user input.
2. Apply the Kronecker mask to pre-process the image.
3. Do the dot multiplication from top left corner of the image coefficient matrix A1 with mask λ, move to right hand side direction.
   for i=1:size(A1,1)-2
   for j=1:size(A1,2)-2
   x1(i, j)=sum (sum (F1 . A1 (i : i+2, j : j+2)))*
   end
   end
4. Apply Discrete wavelet transform
5. Decompose the image up to the fourth level.
6. Compress the image using the given wavelet family based on Birge - Massart strategy.
7. $K_j = \frac{m}{(J+j-2)^\wedge\alpha}$
   J –Decomposition level
   m- Length of the coarsest value.
   α value is 1.5.
8. Check every coefficient value with Threshold value
   q (i, j) = x1(i, j) / 2;
   r (i, j) = mod(x1 (i, j), 2);
   If r (i, j) < 1
   X2(i, j) = 50;
   else
   X2(i, j) = 255;
   end
9. The resultant matrix will be the compressed image.
10. Apply the inverse threshold logic.
11. Apply the inverse discrete wavelet transform.
12. The resultant matrix will be the reconstructed image from compressed image.
13. Calculate MSE, PSNR, CR and elapsed time.
14. Display the original image, compressed image and decompressed image with PSNR and CR value.

B. Kronecker Filtering

This proposed method uses the Kronecker mask [25] as the linear spatial filter to enhance the image. This Kronecker mask is a weighted grid of 3x3 sub pixels. The Kronecker Delta $\delta_{i,j}$ is a function of the two arguments i and j. If i and j are the same value (i.e. i=j) then the function $\delta_{i,j}$ is equal to 1.Otherwise the Kronecker Delta is equal to zero. Formally this is written:

$$\delta_{i,j} = \begin{cases} 1, & i=j \\ 0, & i \neq j \end{cases}$$

Let $\delta_{i,j}$ is divided by β. β is an adjusting factor of proposed mask to enhance the image. When β is 2 the proposed mask works well and produce visualized image. If β value is increased then the enhanced image looks darken. If β value is decreased then the enhanced image looks brighter. To find the enhanced image by the equation (2) shown in below.

$$s = T(r) \tag{2}$$

Let s is an enhanced image and *r* is an input image and *T* is the Kronecker mask as the smoothing filter mask. The filter manipulation on the image is shown in equation (3) is given below.

$$g(x, y) = \omega(-1, -1)\, f(x-1, y-1) + \omega(-1, 0)\, f(x-1, y) + \omega(0, 0)\, f(x, y) + \omega(1, 1)\, f(x+1, y+1) \tag{3}$$

where ω(0, 0) is the centre coefficient of the mask. The mask size is *m* x *n*, where *m = 2a*+1 and *n = 2b*+ 1, where a, b are the any scalar value so the size of mask (*m* x *n)* is always in odd size [20]. Before manipulate the filtering, padding the rows of image with *(m-2)* row of zeros and column with *(n-2)* column of zeros. M x N is the size of an image. The linear Kronecker filtering image has been calculated by the equation (4) is given below.

$$g(x,y) = \sum_{m=-a}^{a} \sum_{n=-b}^{b} \omega(m,n)\, f(x+m, y+n) \tag{4}$$

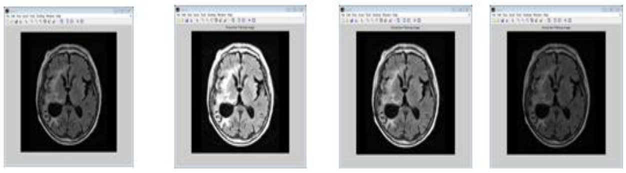
where *a* is the row of the mask and *b* is the column of the mask and *m* and *n* are the variable. Kronecker mask is 3 x 3 grid size, Hence *a* starts from -1 to 1 and *b* starts from -1 to 1. Each pixel in *ω* visits every pixel in *f(x, y)*.

The kronecker mask is given in figure 3, where $\lambda = \frac{1}{\beta}$.

λ	0	0
0	λ	0
0	0	λ

Fig. 3. Kronecker mask (3x3)

The fig. 4 shows the images after Kronecker filtering for different β value in a mask.

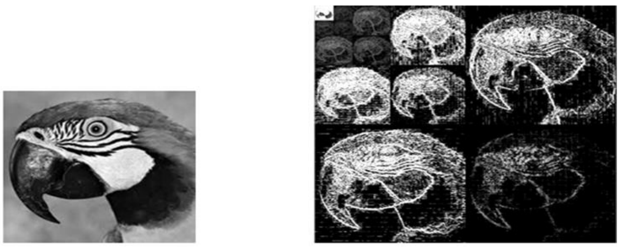


a b c c

Fig. 4. MRI image after Kronecker filtering for different β value in a mask. a. Original image, b. More brighter image when *β<2 (* λ =.75), c. Pererfect image when *β=2 (* λ = .5), d. More darken image when β>2 (λ = .25).

C. Discrete Wavelet Transform

Filtered image g(x, y) has been feed to the input of the wavelet transform. Discrete wavelet transform down sampled the image g(x, y) into two different sub bands image such as low frequency band image and high frequency band image [23-24]. Again the low frequency sub band has been down sampled. This down sampling process has been continued until the process reached the desired level. This proposed method decomposed the image in to four levels and produced sixteen samples which are shown in fig. 5.



a b

Fig. 5. Image decomposition, a. Original image, b. Fourth level decomposition of an image.

The approximation coefficients have been compressed based on Birge-Massart strategy, which is the hierarchical threshold, has been denoted in equation (6).

$$g1(x,y) = \frac{m}{(J + j - 2)^\wedge \alpha} \tag{6}$$

where *J* be a Decomposition level, *j* be the coordinate value, *m* be the Length of the coarsest value and *α* denote the compression process. If *α* value is 1.5 that indicates compression process. If *α* value is 3 that indicate de-noising process. Each level of wavelet decomposition coefficient was filtered by a varied threshold based on equation (6). The output image would be *g1(x, y)*.

D. Parity Threshold

The proposed method uses the parity strategy for threshold process. Let *g1(x, y)* be the output image from the DWT process which is an input for the threshold. At any point *(x, y)* of an image *g1(x, y)* is compared with the threshold T value. In this parity strategy

Let $T = g1(x, y) \bmod \beta$

(7)

$$T = \begin{cases} 0 & if \;\; g1(x,y) \; is \; even \\ 1 & if \;\; g1(x,y) \; is \; odd \end{cases} \tag{8}$$

Threshold T value calculated by the equation (7). T value should be either 0 or 1 defined in equation (8). Using this T value the image is segmented. In this parity strategy minimum value is 50 that indicate the *(x, y)* is the even parity pixel and maximum value is 255, denotes that *(x, y)* is the odd parity pixel. The min and max value will be selected based on the threshold which perfectly segments image into background and foreground objects. This parity strategy segments the image *g1(x, y)* in to min value group and max value group. In the proposed method T varies depends on the odd or even value of the intensity of the pixel *(x, y)*. The value of *g1(x, y)* depends on the T value that given in equation (9).

$$g2(x,y) = \begin{cases} min & if \;\; T = 0 \\ max & if \;\; T = 1 \end{cases} \tag{9}$$

T value depends on the value of the pixel *(x, y)* in an image *g1(x, y)*, so T is called as variable threshold. The output of the parity threshold produces an image in a compressed manner. The compressed image will be reduced in size compared with original image. Decoding is the inverse process of encoding.

IV. EXPERIMENTAL RESULTS

Different field of images like MRI, CT and standard test images have been tested and compressed by the new proposed compression method. The performance of the proposed compression method evaluated by the parameters such as Peak-signal-noise ratio (PSNR), Compression Ratio (CR) defined as in (12) and (14) respectively [21].

$$PSNR = 20 \log_{10}\left(\frac{Max.pixelvalue}{\sqrt{MSE}}\right) \tag{12}$$

$$MSE = \frac{1}{MN}\sum_{0}^{M-1}\sum_{0}^{N-1} \| f(i,j) - g(i,j) \|^2 \tag{13}$$

Where M, N is the dimension of the image *g(i, j)* denotes the pixel value in the reconstructed image and *f(i, j)* is the pixel value in the original image. The MSE value calculated using the formula is given in equation (13). If the MSE value is lower means the error is less. MSE and PSNR are inversely proportional to each other. Compression ratio is defined as the ratio between the size of the original image and compressed image [21, 22] is shown below the equation (14).

$$CR = \frac{Original\ Image}{Compressed\ Image} \tag{14}$$

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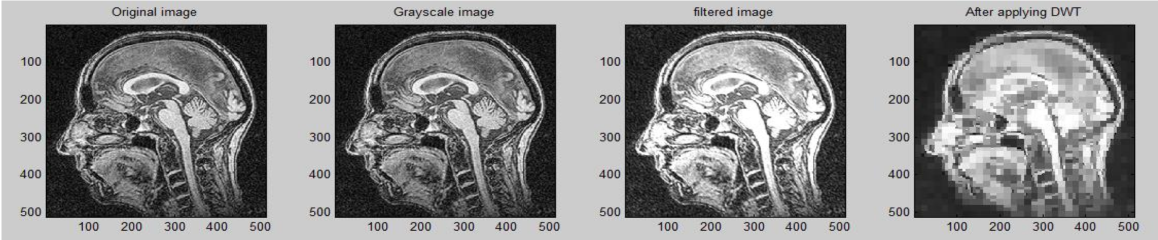
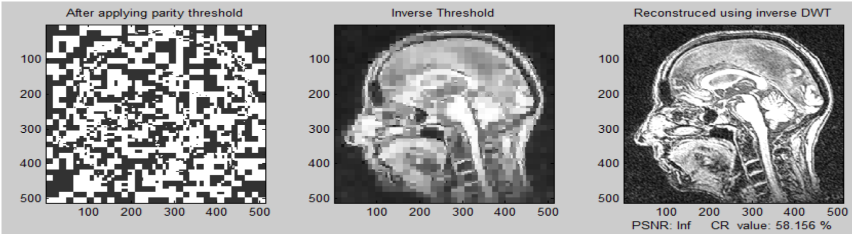
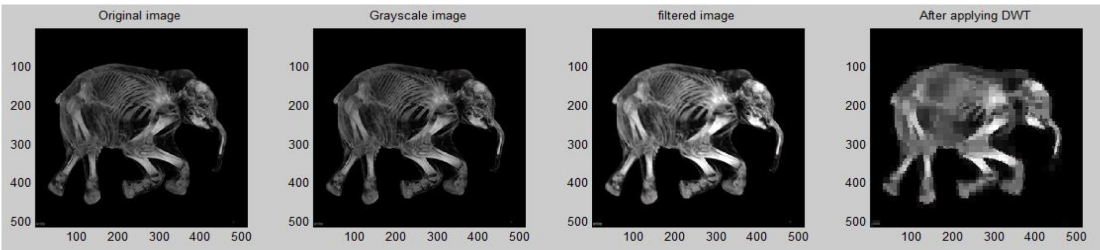


a

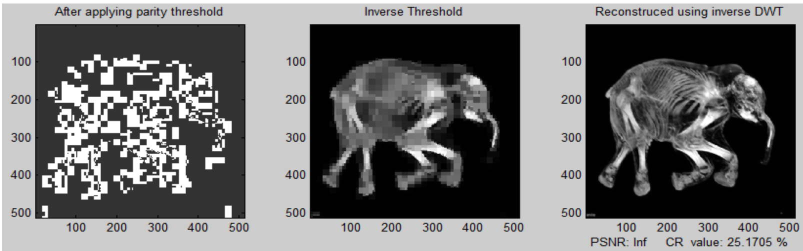


b

Fig. 6. The proposed method on MRI sample brain Image. a. Encoding process, b. Decoding process.

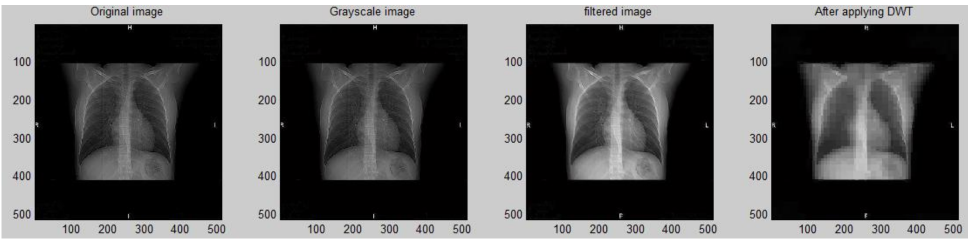


a

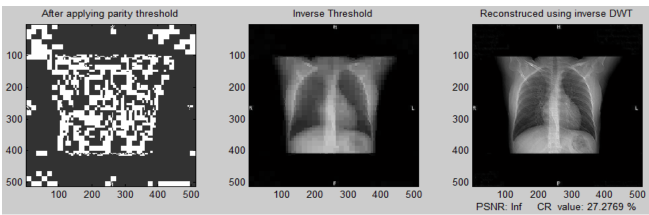


b

Fig. 7. The proposed method on the CT scan sample Mammoth image. a. Encoding process, b. Decoding process.



a



b

Fig. 8. The proposed method on the Radiology sample image. a. Encoding process, b. Decoding process.

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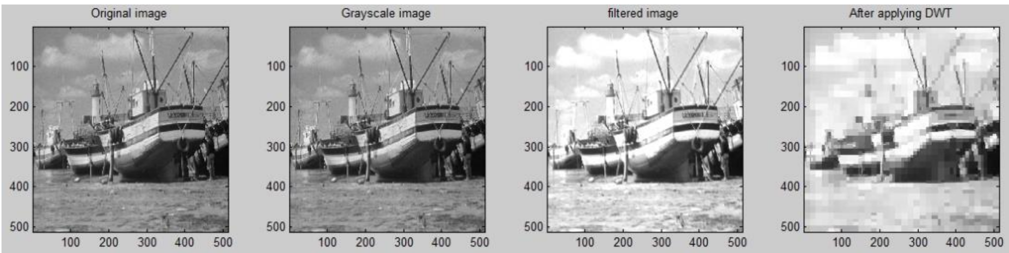
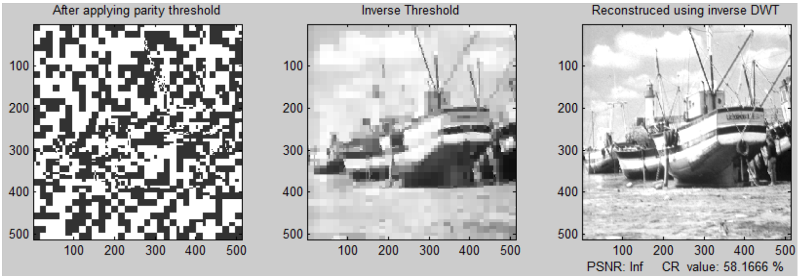


a



b

Fig. 9. The proposed method on the sample Standard image boat. a. Encoding process, b. Decoding process.

The proposed method is implemented on different set of standard test images by enhancing the image by Kronecker mask and compress the image by using Birge-Mssart and parity threshold. The proposed compression method was evaluated by various parameters such as MSE, PSNR and CR.

The proposed method performed well on all the test images and produced better quality images as in the original image without loss of information, which has been shown in the above figures. The proposed technique is applied on many images in different modalities that were tabulated in different tables below.

The proposed compression method produces the reconstructed image which is same as the original image. Thus the image is preserving completely without loss. The proposed compression method is suitable for MRI images. The Experimental result shows that the proposed method on Hand MRI image produces 77.48% more compression ratio than the existing Birge-Massart and Unimodal strategy compression methods.

The proposed method on all MRI images have been produced an average of 39.54% more compression ratio than the existing methods. The proposed method outperforms well on MRI images compared with existing wavelet methods based on Birge-Massart and Unimodal thresholding shown in Table I.

Table I Performance comparison between the proposed method and existing wavelet methods on MRI images

MRI images (512x512)	**Birge-Massar t CR**	**Unimodal(Rosin) CR**	**Proposed Method CR**	**(Proposed method-max.existing metod) / min. CR value**	**% of CR increase from existing method**
Brain1	31.07	27.76	**46.48**	(46.48-31.07)/31.07	**49.59**
Skeleton	52.99	50.92	**57.36**	(57.36-52.99)/52.99	**8.24**
Brain	56.75	56.46	**58.15**	(58.15-56.75)/56.75	**2.46**
Foot	17.83	8.1	**27.87**	(27.87-17.83)/17.83	**56.30**
Hand	10.26	6.75	**18.21**	(18.21-10.26)/10.26	**77.48**
Neck bone	23.65	15.95	**33.86**	(33.86-23.65)/23.65	**43.17**

The proposed method outperforms well on CT scan images compared with existing wavelet methods based on Birge-Massart and Unimodal threshold shown in Table II.

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Table II Performance comparison between the proposed method and existing wavelet methods on CT images.

CT Scan imaes (512x512)	Birge-Massart CR	Unimodal(Rosin) CR	Proposed method CR	(Proposed method-max.existing metod) / min. CR value	% of CR increase from existing method
Heart	15.44	15.59	**26.08**	(26.08-15.44)/15.44	**68.91**
Mammoth	11.27	8.03	**25.17**	(25.17-11.27)/11.27	**123.33**
Abdomen	24.64	13.70	**40.33**	(40.33-24.64)/24.64	**63.67**
Head bone	27.62	22.09	**45.31**	(45.31-27.62)/27.62	**64.04**
Brain	40.63	36.67	**46.80**	(46.80-40.63)/40.63	**15.18**

The proposed compression method produces the reconstructed image which is same as the original image. Thus the proposed compression method is suitable for CT scan images. The Experimental result shows that the proposed method on Mammoth CT scan image produces 123.33% more compression ratio than the existing Birge-Massart and Unimodal threshold compression methods. The proposed method on all CT scan images have been produced an average of 67.02% more compression ratio than the existing methods.

The proposed method outperforms on radiology images compared with existing wavelet methods based on Birge-Massart and unimodal threshold shown in Table III.

Table III Performance comparison between the proposed method and existing wavelet methods on Radiology images

Radiology images (512x512)	Birge-Massart CR	Unimodal(Rosin) CR	Proposed Method CR	(Proposed method-max.existing metod) / min. CR value	% of CR increase from existing method
Malarbones	17.78	10.21	**33.94**	(33.94-17.78)/17.78	**90.88**
Radiology	14.50	7.81	**27.27**	(27.27-14.50)/14.50	**88.06**
Teeth	41.71	31.24	**54.42**	(54.42-41.71)/41.71	**30.47**
Heart	10.30	6.03	**23.56**	(23.56-10.30)/10.30	**128.73**
Vascular	7.60	2.43	**18.70**	(18.70-7.60)/7.60	**146.05**
Thorax	22.08	13.46	**36.37**	(36.37-22.08)/22.08	**64.71**

Thus the proposed compression method is suitable for Radiology images. The Experimental result shows that the proposed method on vascular radiology image produces 146.05% more compression ratio than the existing Birge-Massart and Unimodal strategy compression methods. The proposed method on all Radiology images have been produced an average of 91.48% more compression ratio than the existing methods.

The proposed method outperforms on Standard images compared with existing wavelet methods based on Birge-Massart and Unimodal threshold shown in Table IV.

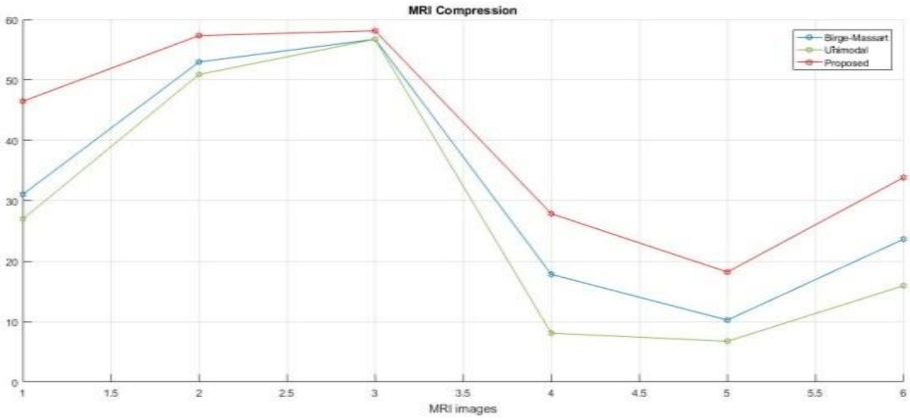
Table IV Performance comparison between the proposed method and existing wavelet methods on Standard images.

Standard images (512x512)	Birge-Massart CR	Unimodal(rosin) CR	Proposed Method CR	(Proposed method-max.existing metod) / min. CR value	% of CR increase from existing method
Lena	51.39	51.52	**54.69**	(54.69-51.52)/51.52	**6.15**
Pepper	51.19	51.52	**54.46**	(54.46-51.52)/51.52	**5.7**
Parrot	50.05	48.65	**51.9**	(51.9-50.05)/50.05	**3.6**
Cameraman	41.75	38.32	**49.8**	(49.8-41.75)/41.75	**19.28**

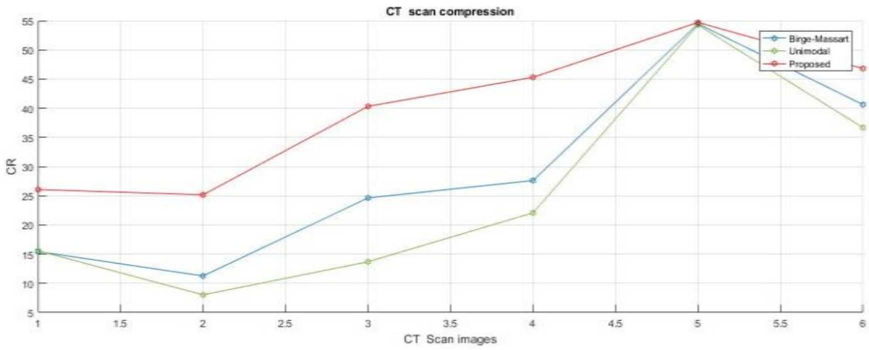
The proposed compression method produces the reconstructed image which is same as the original image. Thus the proposed compression method is suitable for Standard images. The Experimental result shows that the proposed method on cameraman standard test image produces 19.28% more compression ratio than the existing Birge-Massart and Unimodal strategy compression methods. The proposed method on all standard test images have been produced an average of 8.6% more compression ratio than the existing methods.

The experimental results of the proposed method's CR value have been shown on Table I, Table II, Table III and Table IV. The proposed method produced the high compression ratio and high(∞) PSNR value and low MSE value compared with wavelet compression based on Birge-Massart strategy and Unimodal (Rosin) thresholding with decomposition level is 4 and haar wavelet family [21]. High PSNR value denotes the proposed compression method is the lossless compression method; it would produce the high quality image with pre-processing steps of the proposed algorithm

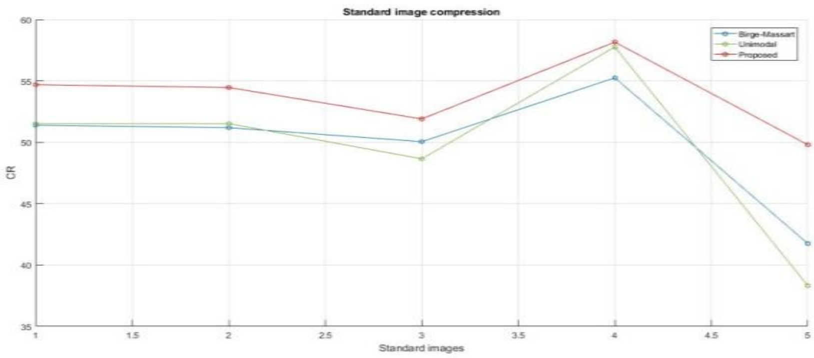
Graphical representation of the compression ratio comparison between Birge-Massart, Unimodal and proposed method is shown in fig. 10. The X- axis represents images and Y-axis represents compression ratio.



a



b



c

Fig. 10. Performance of proposed method on different types of images is compared with existing compression Methods. a. CR comparison between proposed and existing compression on different MRI images. b. CR comparison between proposed and existing compression on different CT scan images, c. CR comparison between proposed and existing compression on different Standard images.

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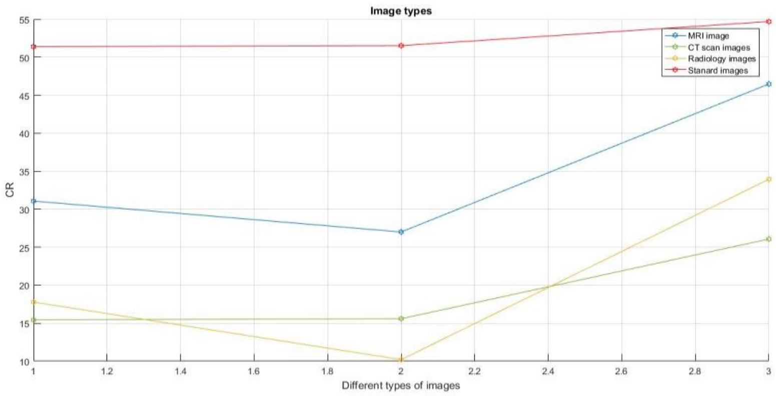

Fig. 11. Compression Ratio of different types of images using proposed method.

The proposed compression method has applied on different types of images is shown in fig. 11. We observed that the compression ratio of the MRI images have been higher than the CT scan, Radiology and standard test images.

V. CONCLUSION

The proposed compression method based on Kronecker mask ,Birge-Massart strategy and parity strategy implemented on MRI, CT scan, Radiology and standard images. The performance is evaluated by testing images of various modalities. Experimental results have denoted that the proposed method yields significant superior quality image with high compression ratio than the existing wavelet compression methods such as Birge-Massart and Unimodal threshold with decomposition level 4 and Haar wavelet family.

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