Compression Analysis of Hybrid Model Based on Scalable WDR Method and CNN for ROI-based Medical Image Transmission

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***Abstract*—The image compression techniques are the fast-growing methods and have developed on large scale. Among them, wavelet-based compression methods are most promising and efficient techniques widely used in the field of medical image processing and transmission. The compression techniques are treated as lossy or lossless models and these can be applied on the medical images considering different situations. The medical image parts are separated into two regions. The central part of the image is treated as core region called region of interest (ROI) and others are treated as non-ROI. ROI based coding techniques are considered as most important in the medical field for efficient transmission of clinical data. The proposed method focuses on these concepts. The ROI parts considered are either smooth or textured regions. These are extracted using a segmentation method called singular value decomposition (SVD) method. An efficient run length coding method called wavelet difference reduction method (WDR) with region growing approach is used to code the extracted ROI part after applying 5/3 based integer wavelet transform. The remaining parts called non-ROI part or background artifacts are coded using Convolution Neural etwork (CNN) method. The proposed method is also restructured as layered structure to achieve adaptive scalable property and named as scalable WDR-CNN (SWDR-CNN) method. The proposed SWDR-CNN method has been evaluated using rate distortion metrics such as Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM). The coding gains in terms of PSNR values of SWDR-CNN method has been analysed and compared to popular scalable algorithm like S-SPIHT. The SWDR-CNN method has achieved better coding gain from 0.2 dB to 6 dB in terms of PSNR values. Hence, it is proved that proposed model can be used to code the ROI of images and has applications in the field of medical image data coding and transmission.**

Keywords*—Medical image segmentation; compression; region of interest; wavelet difference reduction; convolutional neural network; singular value decomposition

I. Introduction

Design and development of efficient image processing methods is a subject of intense research for the last several decades. The demand of properly designed algorithm is much more in image coding [1] and transmission scenario. Advanced development in the networking technologies [2] with high processing power and transmission capacity, make it possible to implement modern signal processing [3] techniques in data computing scenarios. Hence, new technologies are developed, combining more than one method called hybrid model [4] to address specific user requirements. Moreover, tremendous growth of the Internet and data sharing facilities, the developed hybrid model addresses the situations to achieve better computing capabilities in different network access bandwidths.

The image coding algorithms are developed and widely accepted with multiresolution features which are based on the JPEG2000 image compression standard. For Human Visual Systems, multi-resolution based coding algorithms are developed by using [5] wavelet transform. Thus, wavelet transform is used as supportive framework for decomposing images with different time-scale resolution form. The data analysis in wavelet domain has significant impact on the medical image computing scenario like in disease diagnosis and visualization. Due to the powerful multiscale/multiresolution representation of data in wavelet domain, many wavelet-based coding algorithm are developed for magnetic resonance Imaging (MRI) technologies.

Considering the inter scale/intra scale properties of wavelet transform, different approaches were developed in the late 1990s and 2000s. Among them, Shapiro's [6] Embedded Zero-tree Wavelet (EZW) coding scheme, Set Partitioning in Hierarchical Trees (SPIHT) [7] introduced by Said and Pearlman are most important. Due to the spatial orientation tree (SOT) based algorithm, the computational complexity of these algorithms remained very high. Hence, alternate methods that avoid the heavy use of SOTs, without sacrificing the desired properties of embedded coding, progressive transmission and scalability were also required to be developed.

Considering the time complexity, a new method called Wavelet Difference Reduction (WDR) method [9, 10] was developed by Tian and Well. The spatial orientation tree-based data structure was precluded in this method, but preserves the embedded principles, lossless bit plane coding and set partitioning concepts. The wavelet coefficients are linearly arranged using a fixed scan path by mapping the 2-D transform coefficients to 1-D index array which are present in the multiresolution pyramidal structure of wavelet transform. The WDR performs the run between two neighbouring significant coefficients and takes the difference between their indices and then these indices are coded efficiently. The WDR also maintains the simplicity while keeping the coding performance advantages of spatial orientation tree-based methods like EZW and SPIHT. Further, WDR methods were improved by incorporating many other desired features [24, 25] like coding regions of interest, scalability [26, 27, 28], object-based shape coding etc. Among them, Adaptive Scanned WDR (ASWDR) of Walker and Nguan [11] considers one level of parent-child relationship, embedded progressive coding method developed by Wilhelm Berghorn [22, 23] with context conditioning and Context Modelling with ASWDR method (CMWDR) developed by Yuan and Mandal [12] considered much better method with coding gain than standard SPIHT algorithm even if the absence of entropy coding.

Significant development of coding methods is progressed to incorporate scalability concepts to decode the data by different resolution capacity devices on particular bit rate. David Taubman proposed a method called EBCOT, originally based on JPEG2000 standard [31] which supports SNR scalability. These types of algorithms are suitable for applications like remote browsing of large compressed images. The scalable image transmission is possible by using the layered approach and Hwang and Chine [43] proposed a medical image compression and transmission called Layered SPIHT. In LSPIHT, the bit streams are generated from different layers of subbands. According to time scale property of wavelet sub-bands, subbands are arranged on the basis of the priority and the bit streams are produced progressively with scalable property. Astri Handayani [44] proposed a medical image transfer method considering the ROI over heterogenous network, where good image quality and data compactness are both of crucial concern. The method follows wavelet-based coding techniques with layered approach as used in JPEG2000.

In ROI based image compression scenario, the new technique called object coding was developed by using shape adaptive wavelet transform, proposed [18] by Shipeng Li in 2000. In 2005, Ping Xu [19] and Shanan Zhu proposed a method for arbitrary shaped ROI coding based on integer wavelet transform. Using this arbitrary shaped adaptive wavelet transform, Danyali [8] proposed the flexible scalable object coding using SPIHT method. Mehrotra, Srikanth and Ramakrishanan [30] proposed their coding method for MR images using shape adaptive integer wavelet transforms.

Generally, the medical images are coded using lossless image compression techniques and that can be done using integer wavelet transform. Many of the methods with progressive transmission facility have poor rate distortion performance in low bit rates. In medical images, the central portion of the image is considered as most important part. These central parts are either smooth or textured regions and can be extracted using some segmentation techniques. These segments are coded with maximum priority in lossless manner. The background can be repeatedly coded with lossy/lossless algorithm. In this paper, the objects are identified as ROI using singular value decomposition method and are coded using scalable WDR method [13, 14, 15, 16, 17]. The scalable WDR method is a layered architecture of wavelet different reduction method with embedded region growing method (WDR-SRG). The lossless coding is performed by using arbitrary shaped integer wavelet transform and SWDR. The remaining parts are coded using lossy coding techniques. Here, we use convolution neural network (CNN) model to code non-ROI area of the image. In 2020, Chung K. J. et al. proposed [34] a cross-domain cascade of U-nets that was the W-net compression technique and operated over the discrete cosine transform (DCT). In 2020, Guo P. et al. [41] had introduced the CNN-based compression technique. The model focuses on retina optical coherence tomography (OCT) images. The model was trained and tested on OCT images with pathological details.

Here, the paper presents a hybrid model which includes SVD based image segmentation and DWT based object coding. The layered region-growing approach [15] based WDR method is used in DWT Coding algorithm. Also, CNN-based medical image compression [35] technique with minimum information loss is used for non-ROI. The coding performance of proposed model is analysed in terms of PSNR values and SSIM [41] metric. The analysis shows that the coding gain is much better in terms of PSNR values from 0.2 dB to 6 dB in various bit rates than the traditional coding schemes like SPIHT and its scalable version.

II. Segmentation Using SVD Method

Segmentation is a process to identify important portion of an image as per the user requirements. Most probably, the central portion of the medical images is considered as ROI which consists of important information. Hence, ROI part should be extracted for lossless data coding and can be done very efficiently by using the SVD method. SVD method [15] is based on eigen value and eigen vector analysis and it is observed that a small Eigen values in the non-ROI part will be generated. Therefore, applying some optimum threshold value on Eigen value, we can extract the ROI part of the image. The eigen value analysis applied on image to get textured region is explained below.

Consider the image, *I (x, y).* Before starting the SVD analysis, windowing method is applied on the image *I (x, y)* and collected fixed sized windows which are used for labelling content feature. The textured regions are identified in terms of corners and edges. These can be easily separated by doing the gradient calculation. Let L_i is the linearly arranged signal values in window '*w*'. ∇L_i is the gradient in *w*.

$$\nabla L(i) = \left(L_x(i), L_y(i)\right)^T \tag{1}$$

where $L_x(i) = \partial L/\partial x$ and $L_y(i) = \partial L/\partial y$

The autocorrelation matrix is calculated as follows:

$$C = \begin{bmatrix} \sum L^2{}_x(i) & \sum L_x(i)L_y(i) \\ \sum L_x(i)L_y(i) & \sum L^2{}_y(i) \end{bmatrix} \tag{2}$$

The generated 2x2 matrix C is as symmetric autocorrelation matrix and eigen value analysis is applied on this matrix. After analysis, we can write symmetric matrix C as,

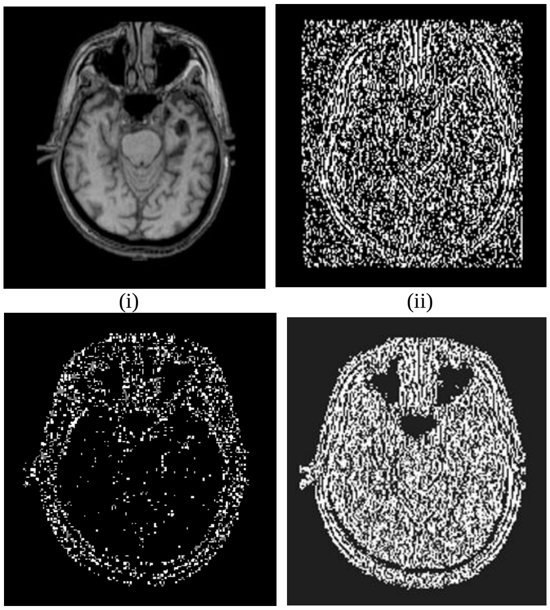
$$C = \mathrm{UDU}^T \tag{3}$$

where, U is the ortho-normal column vector and D is the diagonal matrix. The diagonal matrix consists of two eigen values. The matrix values satisfy the following condition such that $diag(e_1, e_2)$, $e_1 \geq e_2$, where $e_i$are the eigen values of the autocorrelation matrix C. Considering the values of e's, the segmentation can be done according to the following conditions.

1) Let the window w contains a smooth region, then corresponding eigen values e_1 and e_2 are small.

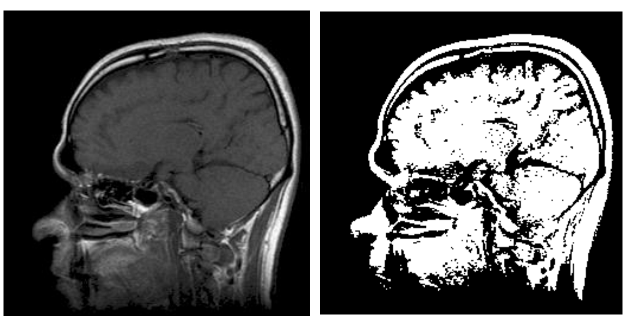
2) Let the window w contains edges or corners, then first eigen value e_1 is of principal component and the second eigen value e_2 is of extremely small magnitude.

3) Let the content in window w consists of textures and patterns, then eigen value e_2 is significant one.



(i) (ii) (iii) (iv)

Fig. 1. Segmentation using SVD (i) Original MRI image (512x512) (ii) binary representation (iii) identified ROI (T = 1000 for eigen value) (iv) identified ROI (T = 10 for eigen value).



(i) (ii)

Fig. 2. Segmentation using SVD (i) Original MRI image (256x256) (ii) identified ROI.

The texture extraction is done by applying threshold value on eigen values (e_1,e_2) satisfying the above three conditions. Segmentation using SVD analysis of *MRI* medical image is shown in Fig. 1 and Fig. 2. The eigen values are calculated on each block with window size 2x2. The obtained eigen values are from 0 to a value of power of 10. A threshold value *T* can be applied to remove negligible correlation of values and it may be in noise part or smooth region of the image. The obtained eigen values from 100 window blocks are shown in the Fig. 3.

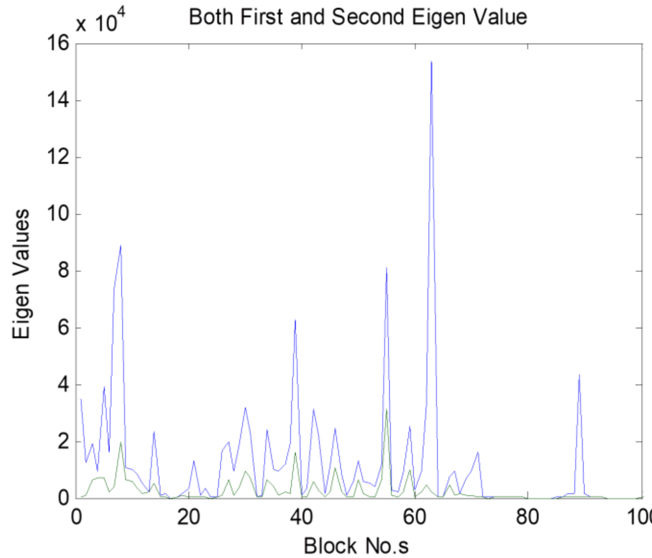


Fig. 3. Eigen values of first 100 blocks (window - 2x2).

III. Layered Scalable WDR Method with Selected Region Growing Approach (SWDR-SRG)

The ROI based coding is important in many applications in telemedicine so that important medical data needs to be coded without loss. The balance between coding of ROI and BG of the medical images is maintained by using object coding. Moreover, Integer Wavelet Transform is used to improve the quality of the reconstructed ROI. The Shape Adaptive DWT is used in object coding and also maintains spatial correlation between the actual data and its transformed data. Moreover, it keeps count of the coefficients obtained from SA-DWT [18, 19] is same to the count of pixels in the region.

The shape adaptive DWT [20, 29, 30] is done based on the procedure as follows. The process begins by identifying arbitrary shaped objects using a segmentation method. The first segment of the object is applied by length adaptive 1-D DWT with proper subsampling. The calculated wavelet coefficients are categorized into low pass and high pass bands. After the completion of row wise operation, each column of the low pass and high pass objects are applied by the same operations. The same operation is repeatedly applied on object in low pass band to get desired level of wavelet decomposition. Thus, 2D SA-DWT provides multi-resolution pyramid of arbitrary shaped objects. The subband structure of arbitrary shaped object is shown in the Fig. 4.

The segmentation process is carried out as a preprocessing in image compression model. The main aim is not only object identification, but classifying spatially connected homogeneous pixels present in a small region with similar gray levels. In this situation, region growing approach is better for ROI based image coding. The Selected Region Growing starts with a seed pixel and connected with four neighbouring pixels with similar features. The process progresses until last seed pixel reaches and terminated when condition fails. Here, the SRG process is done on the transform values which are present in the wavelet domain. The significant coefficients are identified in the extracted region. WDR method is used here to perform SRG operation. Index coding with differential coding method is used in WDR method where it codes the index positions of significant transform values very efficiently. The 2D wavelet transform coefficients are linearly arranged in increasing order of the index positions using a predefined scan path [21]. The general structure of algorithm WDR-Selected Region Growing (WDR-SRG) [15] is depicted below:

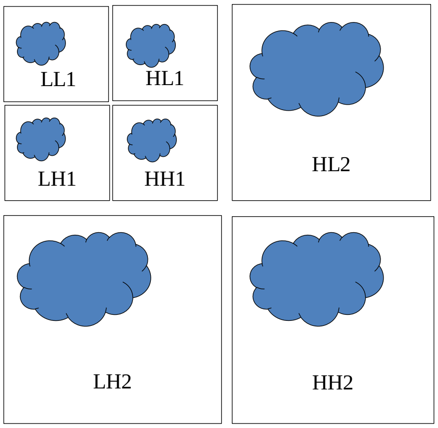


Fig. 4. Subband structure of objects using shape adaptive DWT.

A. *Wavelet Difference Reduction with Selected Region Growing (WDR-SRG)*

Algorithm starts with two-dimensional shape adaptive DWT which is applied on the arbitrary shaped objects. The decomposition of the medical ROI is done using a 5/3-tap wavelet filter with symmetric extension. Wavelet coefficient at pixel location (i, j) is represented as w_{ij} . The iterative operation is progressed within the limit of a threshold value and initialised as, $t_{n-1} = 2^{n+1}$ and $t_n = t_{n-1}/2$, where $n = \left\lfloor log_2 \left(\max_{(i,j)\in I} |w_{ij}| \right) \right\rfloor$. The algorithm is progressed through sorting pass and refinement pass. These are narrated as below.

1) Sorting pass: The sorting pass uses different data structures or lists to store the positions of coefficients which are collected during the process. The collection of coefficients during region growing process is stored in the list R, significant coefficients are stored in the list C and its neighbouring pixels are stored in the list N. The parent child connection pixels are stored in the list P. The list T is used to store temporary set of significant coefficients. Also, the list I is used to store set of remaining insignificant coefficients.
The significant coefficients are identified by using $\sigma(w, t_n)$ such as,

$$\sigma(w, t_n) = \begin{cases} 1 & : \quad |w| \geq t_n \\ 0 & : \quad |w| < t_n \end{cases} \tag{4}$$

The sign of coefficient '*w*' is identified by using function $Sign(w)$ such as,

$$Sign(w) = \begin{cases} + & : \quad w \geq 0 \\ - & : \quad w < 0 \end{cases} \tag{5}$$

The $cluster(w_{ij}, t_n)$function is to collect the neighbouring coefficients of the significant coefficients. The sorting pass procedure is depicted below:

If I $\neq \varphi$ {

If $\sigma(w_{ij}, t_{n-1}) = 0${

If $\sigma(w_{ij}, t_n)$ =1{

Coding (w_{ij});

$R = cluster(w_{ij}, t_n)$;

Do {

If $R \neq \varphi$ {

If$\sigma(R(w_{ij}), t_n)$=1{

Coding (w_{ij})
$R = cluster(w_{ij}, t_n)$}}

} While *(End (R)! =True);*}}}

The encoding process is done by differential coding using a function Coding (w_{ij}). The function procedure is depicted below:

Function Coding (w_{ij})
{

Binary representation of value obtained as distance between two significant coefficients avoiding MSB '1'. The sign information generated using the function$Sign(w_{ij})$. Append w_{ij} into temporary list *T*.

}

The next step of sorting pass is progressed only after the updation of list and that is depicted in the Index updating pass as shown below:

If $T \neq \varphi${

$N = cluster(w_{ij}, t_n) \quad ; \quad \forall (i, j) \in T$

$P = child(w_{ij}, t_n) \quad ; \quad \forall (i, j) \in T$

List of insignificant coefficients, *I* is reset after removing these coefficients}

I = *R* + *N* + *P* + *I*.

2) Refinement pass: After the sorting pass, the collected significant coefficients are coded as bit plane coding manner using the refinement pass as shown below:

If C $\neq \varphi$ {

If C$(\sigma(w_{ij}, t_{n-1}) = 1)${

Add nth MSB of C(w_{ij}).}}

C=*C*+*T*.

T=ϕ

Next iteration starts after the threshold update process. i.e.,$t_{n-1} = t_n$, $t_n = t_n/2$. The encoding procedure generates four symbols like +, -, 1 and 0. The entropy coding like arithmetic coding is avoided by replacing the symbols by using two bits like 11 for +, 10 for -, 01 for 1 and 00 for 0.

B. Scalable Wavelet Difference Reduction Method

The developed coding scheme WDR-SRG is quite useful in the field of communication over heterogeneous networks if it supports the concepts of adaptive scalability. For that, wavelet difference reduction method with selected region growing (WDR-SRG) is applied on ROI after the SA-DWT. Thus, the base algorithm is restructured in layered manner so that the algorithm can generate different scalable images. Hence, we renamed the method as scalable WDR (SWDR) [13, 14, 16] method. Thus, the coding procedure is following the adaptive scalable concepts. The coding procedure is depicted in Fig. 5. The scalable image generation from the layered bit stream is depicted in Fig. 6.

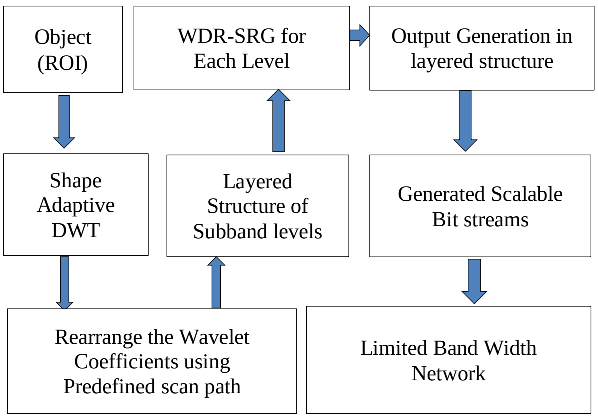


Fig. 5. Scalable WDR model (SWDR).

C. Algorithm: ROI coding using Scalable Wavelet Difference Reduction Method

Step 1: The MRI Medical Image is inputted in the procedure, *I (x, y)*

Step 2: The SVD is applied on MRI medical image to identify the ROI

- $I(x, y) \rightarrow O(x, y) + N(x, y)$
- Input Image = Object Image + Noise
- Input Image = ROI + nonROI

Step 3: The ROI is treated as object and applied SA-DWT

- $O(x, y) \rightarrow SA(x, y)$

Step 4: The Layered Structure of Scalable WDR is applied.

- $SA(x, y) \rightarrow SWDR(x, y)$

Step 5: The bit stream is generated for transmission

- $SWDR(x, y) \rightarrow E(Binary)$

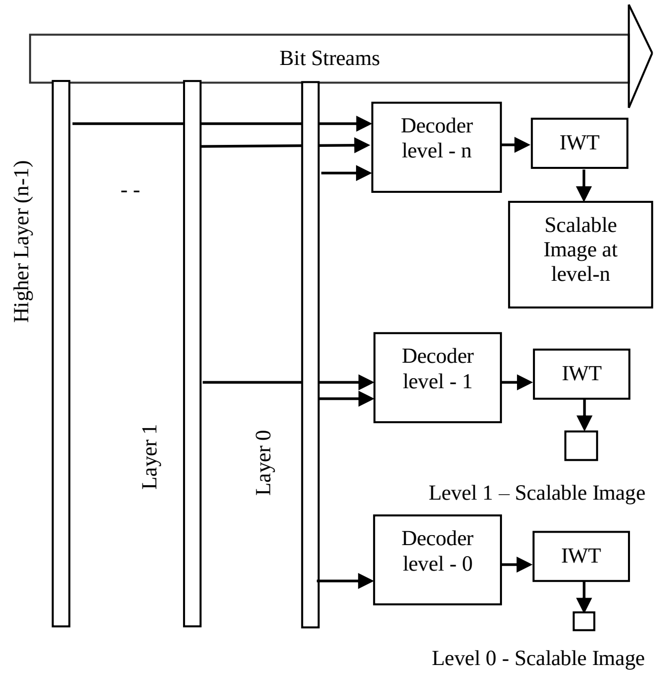


Fig. 6. Scalable image generation (layered architecture).

IV. NON-ROI CODING USING CNN MODEL

During the image compression process, the artifacts are identified with several features. These artifacts may be suppressed efficiently by using CNN model. In this field, many of the scientists [32, 33, 34] have developed efficient CNN models which can be used in data coding situations. Fully convolutional model is also used to obtain a compact representation of an image. The general idea of CNN model is shown in Fig. 7. The image features are identified and represent as parameters to train the data how it can be represented in compact form. Here, a series of convolutional layers are fixed in such a way that features of [35, 36, 37] images are captured. Thus, structural configuration of an image is maintained as well. The model shown in Fig. 7 describes the CNN Forward as a well-designed network [38, 39, 40] which is used to represent the image in identified properties. Thus, CNN forward is used to compress in such a way that original data can be reproduced by reconstruction network. The model consists of three convolutional layers in which the second layer followed by batch normalization layer. After the operation of first convolutional layer, the image size is reduced by half. The data in the form of grid is used in Convolutional Neural Networks. In CNNs, each kernel produces in a new convoluted layer. These layers are also called activation maps. In CNN model, the convolution operation is used such that a kernel or a mask moves over an image and a convoluted representation of output is generated [40, 41]. The identified dependencies in an image are captured by CNN.

CNN Model [45] with different layers is used to perform convolution operation on matrix data. The image is inputted as matrix with two dimensional or three-dimensional form. The other matrix called filter matrix or kernel matrix is inputted with features like height, width and dimension. Let inputted image is I (x, y), then filter matrix is F (h, w, d), where h is height, w is width and d is dimension. After convolution operation, generated output matrix is C (x-h, y-w) for gray scale image. The basic architecture of CNN is shown in Fig. 8.

A. Algorithm: Non-ROI Coding using CNN Model

Step 1. Input nonROI image ← N (x, y)

Step 2. Read N (x, y) and transform to CNN forward

Step 3. ReLU based Two-dimensional convolution with Layer 1 and Layer 2
Optimum Value ← Padding and striding is used in Max pooling two-dimensional layer 1

Step 4. ReLU based Two-dimensional convolution with Layer 3 and Layer 4
Optimum Value ← Padding and striding is used in Max pooling two-dimensional layer 2

Step 5. ReLU based Two-dimensional convolution with Layer 5

Step 6. NE(Binary) ← Compressed nonROI MRI medical image

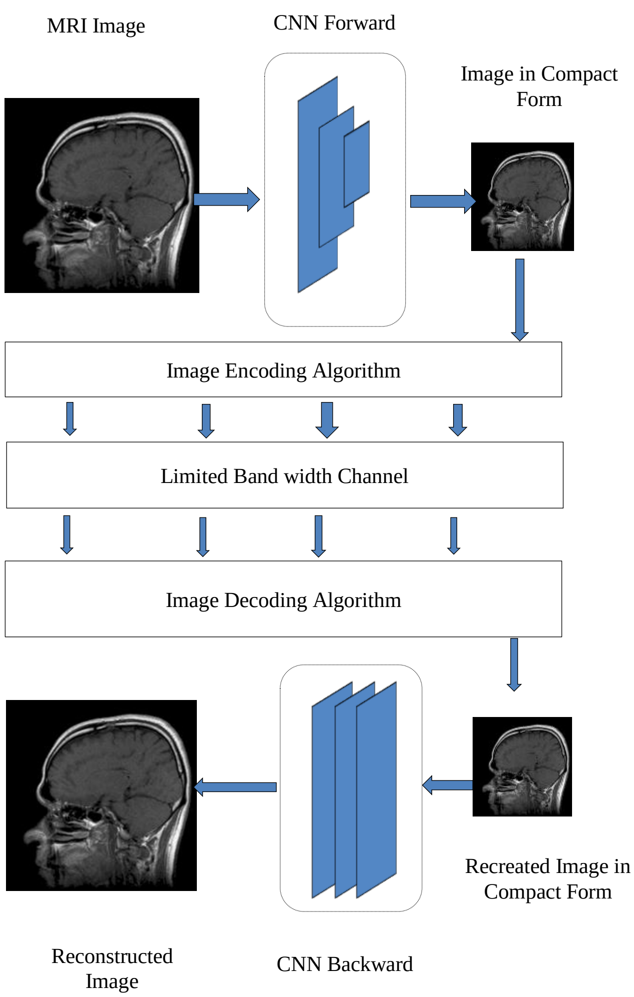


Fig. 7. CNN model for image compression.

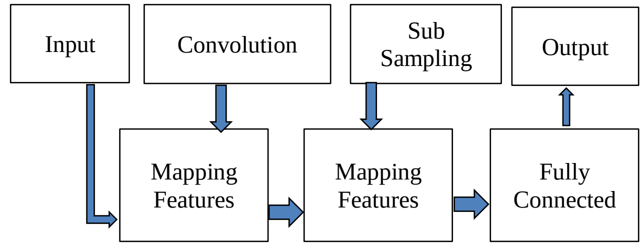


Fig. 8. Basic architecture of convolutional neural network.

The CNN model consists of three layers: convolution layers, pooling layers or subsampling, and fully connected layers. The model uses specific filters for image compression and decompression. The filter helps to represent the image in definite manner so that it removes the unnecessary features. The size of Kernel can be adjusted to increase the performance of data coding which is used in convolution operation at every point. The padding process is applied on all sides of image matrix to reduce the loss of data. The pooling layer is one layer used to reduce the feature map's dimension. But it is possible to recall necessary information. The optimum value is taken as maximum value which is done by Max pooling operation. Famous method called ReLU (Rectified Linear Unit) [32, 36, 37, 38] activation function is used in CNN for a non-linear operation. This method activates neurons in which the gradient provides all times the optimum value.

V. Proposed Method: Hybrid Scheme with Scalable WDR and CNN

The paper proposes a hybrid scheme with two coding techniques, one for the ROI and another for unimportant parts nonROI of the medical image. ROI parts are identified as object and coded using DWT based coding method (suitable for lossless image compression). The remaining nonROI parts called BG part is coded using CNN (useful for lossy image compression scheme). Medical image is inputted and SVD analysis is done for object identification. The shape adaptive DWT is applied on arbitrary shaped object and Scalable WDR is used to perform the lossless coding. The remaining BG part is coded using a lossy compression with CNN model. The outline of proposed method is shown in Fig. 9.

VI. Experimental Results

This paper presents the compression analysis of a new fast hybrid method SWDR-CNN for medical image transmission. The MRI medical images are used for the simulation and analysis. The proposed scheme SWDR-CNN model is analysed in terms of the basic parameters like PSNR and SSIM. The hybrid model is useful for both lossy and lossless image coding. The quality of images at any bit rates is calculated as the peak signal to noise ratio (PSNR). It is defined as,

$$PSNR = 10\,log_{10}\left(\frac{max^2}{MSE}\right) \quad dB \tag{6}$$

where, MSE is mean squared error obtained by comparing the inputted image and the recreated image; ***max*** is the extreme value of a pixel inside the image.

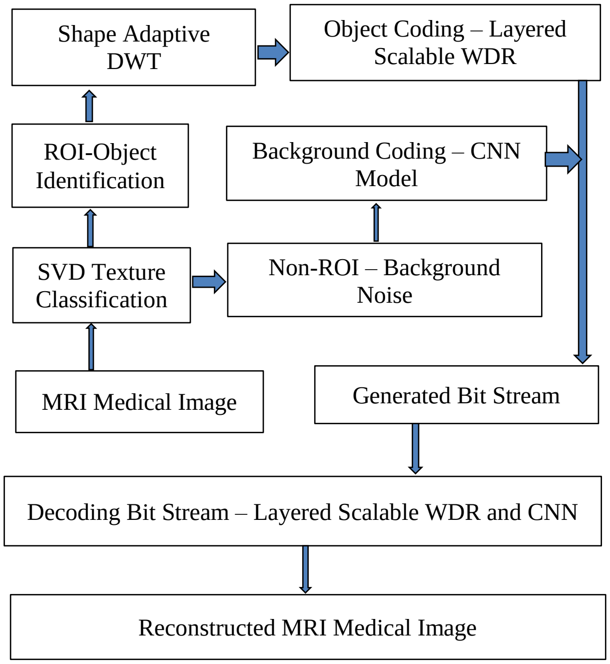


Fig. 9. Proposed compression method – SWDR-CNN.

Structural similarity index (SSIM) [42] is also used to analyse the performance used as rate distortion metric and can be defined in following equations. The SSIM between signals x and y is calculated as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \quad (7)$$

where μ_x is mean of x, μ_y is mean of y, ${\sigma^2}_x$ is variance of x, ${\sigma^2}_y$ is variance of y and σ_{xy} is the covariance of x and y, C_1 and C_2 are constants, i.e., $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$ where L is the dynamic range of the pixel values, and K_1 and K_2 are two constants. The overall quality value called the average of the quality map or the *Mean SSIM* (*MSSIM*) index is defined as,

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j) \quad (8)$$

where X is reference image and Y is the distorted image. x_j and y_j are the image contents at the j^{th} local window and M is the number of local windows of the image.

The rate distortion metric PSNR is calculated and coding gain of SWDR-CNN method is compared with the traditional methods like SPIHT and CMWDR without any entropy coding. Coding results for MRI test image with size 256x256 are shown in Table I and Fig. 10. Reconstructed images with size 256x256 are shown in Fig. 11. Coding results for MRI test image with size 512x512 are shown in Table II and Fig. 12. Reconstructed images with size 512x512 are shown in Fig. 13. The wavelet transform with 6-level is done for 512x512 images and 5-level is done for 256x256 images.

TABLE I. PSNR OF MRI IMAGE (256X256)

Bits per pixel	SPIHT	CMWDR	SWDR-CNN
0.125	26.9010	27.0121	27.1157
0.25	29.8901	30.0574	30.2246
0.5	33.1537	33.4325	33.6975
1.0	37.9891	38.1208	38.2972

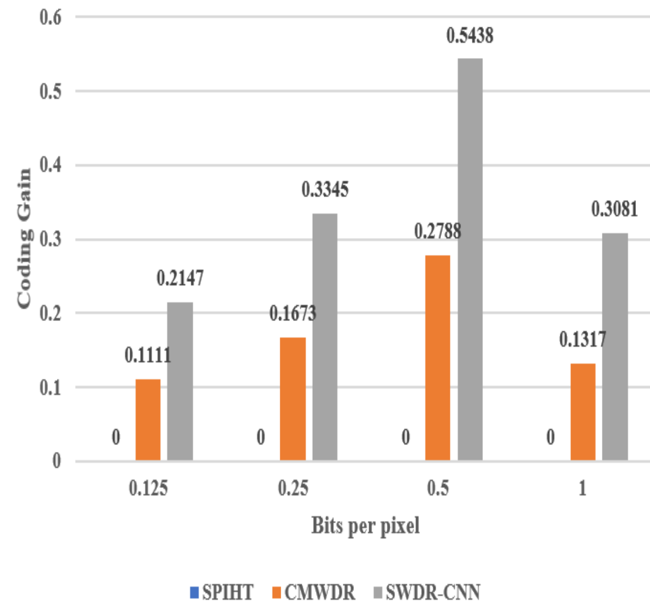
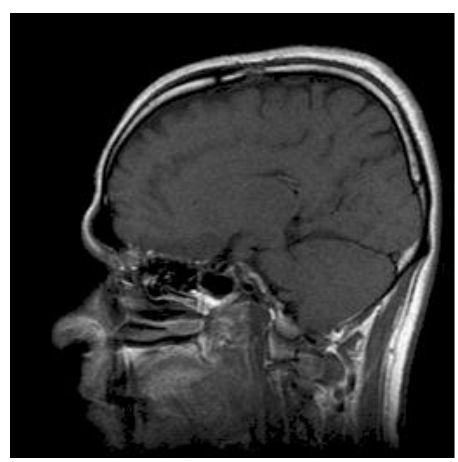


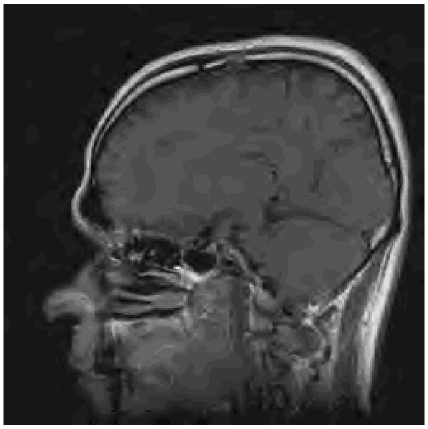
Fig. 10. Coding Gain (in dB) MRI Image (256x256).

TABLE II. PSNR OF MRI IMAGE (512X512)

Bit rate	SPIHT	CMWDR	SWDR-CNN
0.125	33.9175	34.1120	34.6784
0.25	38.1521	38.2831	38.9485
0.5	43.1421	43.5563	43.9025
1.0	49.1461	49.1145	49.5936



(i)



(ii)

Fig. 11. Image reconstruction (bpp = 0.25). (i) original image (256x256) (ii)SWDR-CNN

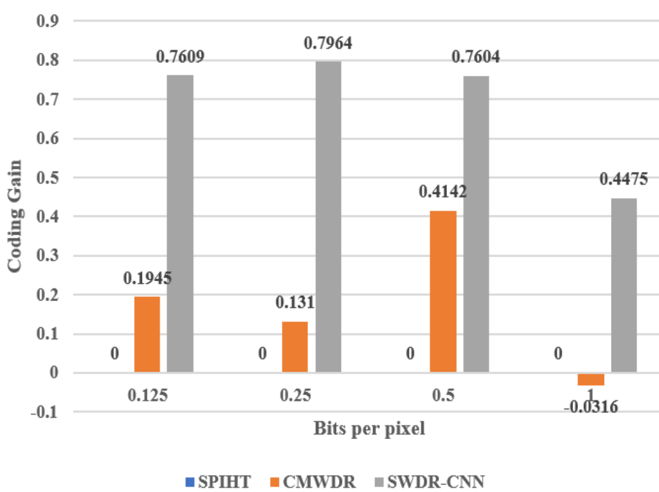


Fig. 12. Coding gain in dB of MRI image (512x512).

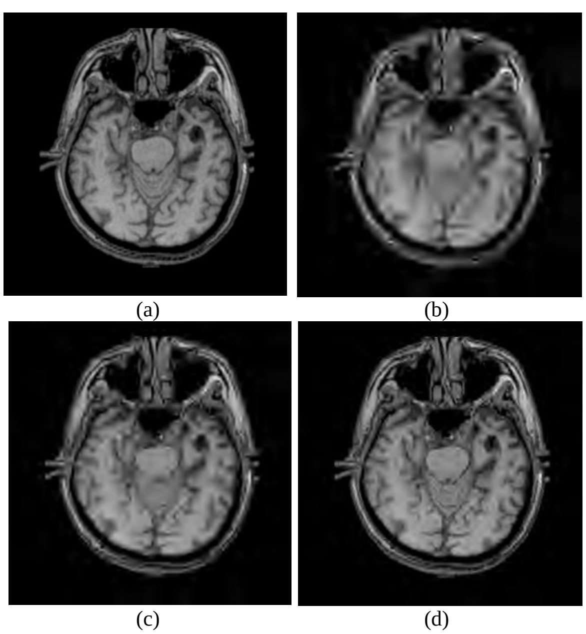


Fig. 13. Image reconstruction using SWDR-CNN Model at different bit rate (a) original image (512x512 - scale 40%) (b) 0.015625 (c) 0.03125 (d) 0.0625.

Structural Similarity Index (SSIM) of MRI image is shown in Table III. The proposed method is also simulated by incorporating with the scalability concept. Here, the comparison of the proposed model SWDR-CNN is done with layered form SPIHT method. Simulation results obtained are given in Table IV. For MRI with Full resolution, the coding is from 0.3 dB to 0.7 dB for different bpp. During the analysis, we identified one important point is that the coding gain in PSNR values (in dB) tremendously changes when the resolution scale decreases. At level 2 resolution 256 x 256, the coding gain is from 0.80 dB to 5.50 dB compared to SPIHT and from 0.7 dB to 1.5 dB compared to its scalable version at different bpp.

MATLAB tool in Windows OS is used to implement all the algorithm modules. The convolution-based DWT is developed using Bi-orthogonal 5/3 tap filter coefficients.

TABLE III. STRUCTURAL SIMILARITY INDEX VALUE OF MRI IMAGE (512x512)

Test Image	Bit rate (bpp)	Image Size (512x512)	
		SPIHT	SWDR-CNN
MRI	0.125	0.91672	0.91946
	0.25	0.95834	0.96079
	0.5	0.98360	0.98604
	0.75	0.99225	0.99297
	1	0.99605	0.99648

TABLE IV. PSNR VALUES IN DIFFERENT SCALABLE RESOLUTIONS

Level 1 - Full Resolution (512x512)				
Methods	Bits Per Pixel			
	0.125	0.25	0.5	1.0
SPIHT	-	-	-	-
Scalable SPIHT	31.11	35.79	40.31	47.05
SWDR-CNN	31.83	36.39	40.89	47.35
Level 2 - Half Resolution (256x256)				
Methods	Bits Per Pixel			
	0.0625	0.125	0.25	0.5
SPIHT	27.47	31.15	36.39	43.23
Scalable SPIHT	27.71	31.09	38.91	47.34
SWDR-CNN	28.49	32.05	39.52	48.71

VII. CONCLUSION

The paper presents a hybrid scheme based on wavelet based scalable encoder with convolution neural network for image transmission. The scheme has high encoding performance with scalability property and can be used in medical image transmission field. The paper focused on efficient transmission of important parts present in medical images where quality is effectively preserved. It is required to review large images which are often required in the field of medical image computing. Moreover, data transfer is required over limited bandwidth channel in very low bit rate. Hence, object coding is essential for data transfer and here a modified

WDR called SWDR is used. These are implemented by using the arbitrary shaped DWT. Thus, new method has interesting perceptions for numerous medical data computing and transmitting applications. The medical data is classified into ROI and non-ROI with the help of SVD method. ROI parts are compressed using the SWDR and non-ROI parts are compressed using CNN model. The Shape Adaptive DWT in association with scalable WDR method is used as lossless compression technique and it is applied on an ROI portion of medical image data. Then, CNN model is applied on non-ROI as lossy coding scheme which is used to reduce the losses using weight and learning rate. After analysis, the projected method is good one with better coding speed with 12% gain than that of traditional methods. Moreover, better coding gain is obtained in terms of PSNR value from 0.2 dB to 6 dB in all situations. Thus, proposed coding scheme called SWDR-CNN model have better results than the existing coding models.

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