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Procedia Computer Science 54 (2015) 838 – 848

Procedia
Computer Science

Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015)

Hierarchical Lossless Image Compression for Telemedicine Applications

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Abstract

The main aim of hierarchical lossless image compression is to improve accuracy, reduce the bit rate and improve the compression efficiency for the storage and transmission of the medical images while maintain an acceptable image quality for diagnosis purpose. The cost and limitation in bandwidth of wireless channels has made compression is necessity in today's era. In medical images, the contextual region is an area which contains an important information and must be transmitted without distortion. In this paper the selected region of the image is encoded with Adaptive Multiwavelet Transform (AMWT) using Multi Dimensional Layered Zero Coding (MLZC). Experimental results shows that Peak Signal to Noise Ratio (PSNR), Correlation Coefficient (CC), Mean Structural Similarity Index (MSSIM) performance is high and Root Mean Square Error (RMSE), Mean Absolute Error (MAE) values are low, and moderate Compression Ratio (CR) at high Bits Per Pixel (BPP) when compared to the integer wavelet and multiwavelet transform.

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Peer-review under responsibility of organizing committee of the Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015)

Keywords: AMWT; Contextual region; Hierarchical image coding; MLZC; Multiwavelet.

1. Introduction

Medical images play an important role in telemedicine applications like teleradiology, telepathology, telecardiology etc. In telemedicine applications medical images like MRI, CT scan, Positron Emission Tomography (PET) are used in detecting the diseases and injuries. In medical diagnosis image acquisition, storage, transmission plays a critical role.

In the process of image acquisition, medical images may be corrupted by image capturing equipment and some environmental issues. These degraded medical images will influence on the diagnosis of the patient¹. In medical image processing removal of noise from corrupted images is a challenging issue. Over the past decades several filtering techniques were developed for enhancing the images²⁻⁵. For noise removal of medical images a Spatial Adaptive Mask Filter (SAMF) is used. For telemedicine applications, medical images must be stored prior to transmission. For this purpose an efficient compression algorithm is required. Image compression algorithms reduces the memory requirement and bandwidth of wireless channels. But traditional compression algorithms for progressive

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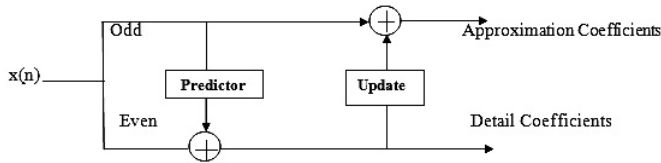


Fig. 1. Convolution based lifting structure.

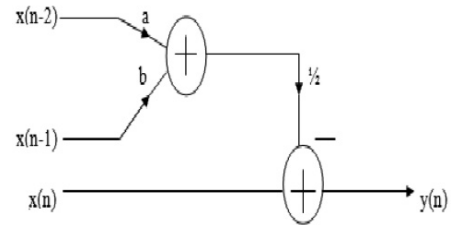


Fig. 2. Adaptive predictor scheme.

data compression for medical conferencing are not fast enough to process vast amount of data⁶. In general a medical image consists of foreground and background parts. Foreground contains medical information and most of the cases the background doesn't contain any clinical information and it is not useful for diagnosis. Hence most of the researchers transmitted and decoded the foreground part using lossless compression techniques and background can be transmitted and decoded using a lossy compression technique^{7,8}. But traditional compression techniques suffer from low PSNR, compression ratio, poor reconstructed quality and high MSE. Hence, in this paper, we propose contextual based medical image coding. In the contextual based medical image coding selected regions of medical image to be coded with selective compression ratio and higher quality as compared to the non selected regions of medical image. The non selected regions are to be coded with high compression ratio. By using morphological operations select the Region of Interest (ROI) in the medical image. In the proposed contextual based medical image coding the contextual part of medical image is transmitted using adaptive multiwavelet transform and contextual MLZC⁹ with high priority and low compression ratio and background of the image is rejected completely.

2. Adaptive MultiWavelet Transform (AMWT)

The traditional medical image compression method suffers from high Mean Square Error (MSE), low PSNR and poor reconstructed image quality¹⁰⁻¹². Lossless image coding is not possible with traditional multiwavelet transform because they cannot map integer to integer valued coefficients. Hence the adaptive multiwavelet transform can be designed with adaptive lifting steps. The conventional convolution based lifting structure is as shown in Fig. 1.

Due to the convolution operation the computational complexity was increased. In¹³ the designed prediction filter performs an averaging operation on the right and left neighboring samples in column or row on 2D images and also processed the samples horizontally and vertically. This method reduces the prediction error signal energy. To reduce the computational complexity, bpp the multiwavelet transform modified via adaptive lifting scheme. In the proposed adaptive lifting scheme the predictor can be modified and maintain the fixed update filter. In adaptive predictor the current pixel value is predicted from the previous two samples by computing the following equation.

$$y(n) = x(n) - [a * x(n - 2) + b * x(n - 1)] * \frac{1}{2} \tag{1}$$

where $x(n)$ & $y(n)$ are the coefficients before and after the lifting $x(n - 1)$ & $x(n - 2)$ are the two previous samples, a & b are lifting parameter.

The proposed adaptive predictor is as shown in Fig. 2.

The adaptive multiwavelet transform was designed with adaptive lifting implementation of multiwavelet transform based on multi scaling functions and multi wavelets. The proposed adaptive multiwavelet transform diagram is as shown in Fig. 3.

3. Spatial Adaptive Mask Filter (SAMF)

In medical image process, for accurate diagnosis, removal of noise is very important. In this paper for removing of noise in medical images SAMF is proposed. The SAMF filter is the modified version of the adaptive median filter¹⁴.

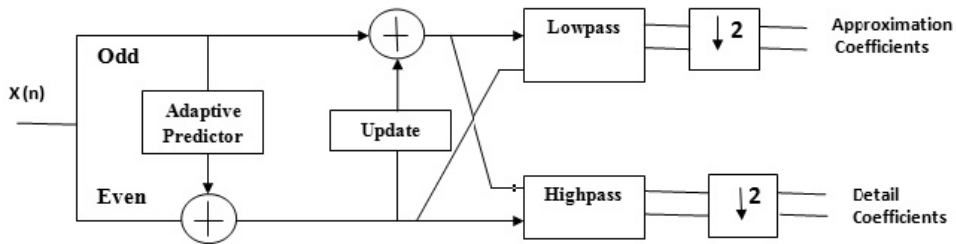


Fig. 3. Forward multiwavelet transform using adaptive lifting scheme.

The main advantage of the proposed filter is it reduces the noise while preserving the edges and enhances the quality of medical images. The proposed modified filter works as explained below.

1. Calculate the mean of horizontal pixels and vertical pixels marked as H and V in 90° neighbours of 5×5 window.
2. Calculate the median of diagonal pixels marked as D in 45° neighbours of 5×5 window.
3. Calculate median of H, V, D and center pixel.

$$S_{med} = \text{median}(H, V, D, C)$$

4. Calculate the minimum and maximum gray level value in rectangular region S_{XY} marked as S_{min} and S_{max} .
5. Consider the gray level at coordinates (x,y) marked as G_{xy} .
6. Maximum allowed size of S_{xy} marked as R_{max} .
7. Level 1: $B1 = S_{med} - S_{min}$

$$B2 = S_{med} - S_{max}$$

If $B1 > 0$ AND $B2 < 0$, GO to LEVEL 2

Else increase the window size

If window size $\leq R_{max}$ repeat level 1

Else output G_{xy} .

$$\text{Level 2: } C1 = G_{xy} - S_{min}$$

$$C2 = G_{xy} - S_{max}$$

If $C1 > 0$ AND $C2 < 0$ output G_{xy} ,

Else output S_{med} .

4. Contextual Multidimensional Layered Zero Coding (CMLZC)

In contextual coding methods the medical image is segmented using contextual (ROI) mask¹⁵. In CMLZC mask can be generated based on the content. The main advantage of CMLZC is to remove artifacts along region boundaries and also provide a fully embedded bitstream upto a lossless range of bitrates. In contextual coding each context is encoded independently based on priority. In this paper, we consider medically investigated part is a context and the background is a non context region. In the proposed method clinically important region is encoded by using CMLZC algorithm. Fig. 5(a), (b) and (c) shows the original ultrasound image, ROI and background (BG). The reconstructed image is shown in Fig. (d). After extracting ROI, the CMLZC algorithm is applied as shown in Fig and non ROI is encoded with low quality of the reconstructed image. In¹⁶ the MLZC is proposed. In MLZC the spatial and inter band relationships are exploited, the concepts of generalized neighborhood and significance state of a given coefficient are used. The CMLZC algorithm works explained below:

The encoder is based on two important observations:

- Medical images in general have a low pass spectrum. When a medical image is wavelet transform the energy in the sub bands decreases as the scale decreases (low scale means high resolution), so the wavelet coefficients will,

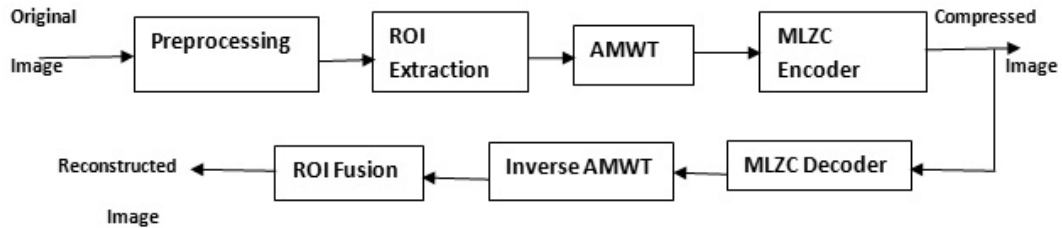


Fig. 4. Block diagram of proposed work.

on average, be smaller in the higher sub bands than in the lower sub bands. This shows that progressive encoding is a very natural choice for compressing wavelet transformed medical images, since the higher sub bands only add detail;

- Large wavelet coefficients are more important than small wavelet coefficients. These two observations are exploited by encoding the individual subbands.
- Apply whole quantizers set to each subband before switching to next level. For this purpose each subband is divided into square boxes having the width of 4.
- For each lattice v , calculate the maximum absolute value x_{\max} . Let $T_v = \lceil \log_2 \text{abs}(x_{\max}) \rceil$ be the threshold of v^{th} subband.
- Set the maximum of all thresholds as global threshold T_g .
- Scan the wavelet coefficients in each individual subband in zig zag manner.
- If $T_v < T$ the wavelet coefficient is, the lattice is insignificant. If $T_v \geq T$, the lattice is significant. If this lattice is first time significant, a '1' is stored. If the lattice is already significant, no information is sent to the decoder.
- If the lattice is significant, check for the significance of each coefficient in raster scan order. If coefficient is significant a '1' is assigned to significant list otherwise a '0' is assigned to sign list or '1' if it is negative significant.
- After all lattices are scanned, set $T_g = T_g - 1$. If $T_g \geq 0$ go to step 6, otherwise stop.
- The image reconstructed at $T_g = 0$ will be identical to the original image and hence results in lossless compression.

5. Proposed Work

The proposed work can be designed by adaptive multiwavelet transform followed by MLZC algorithm. Figure 4 shows the general block diagram of the proposed system.

1. For filtering purpose apply Spatial Adaptive Mask Filter (SAMF) to the given image.
2. Generate ROI mask based on context and process by segmentation method.
3. Based on priority adjustment first encode the contextual region and encode the background later.
4. Encoding of the ROI part i.e performed separately with CMLZC with high bits per pixel and low compression ratio.
5. Encoding of the background is performed with CMLZC with low bits per pixel and high compression ratio.
6. Merge the encoded background with encoded ROI get the compressed image

6. Evaluation Metrics

The image quality is inspected by objective evaluation. There are various evaluation metrics used for objective evaluation of medical images. The preferred metrics are Root Mean Squared Error (RMSE), Peak Signal to Noise Ratio (PSNR), Mean Absolute Error (MAE), Correlation Coefficient (CC), Mean Structural Similarity Index (MSSIM)

and Compression Ratio (CR)¹⁷⁻¹⁹. Higher PSNR, MSSIM, CC and lowest RMSE, MAE values provide high image quality²⁰⁻²². The metrics for comparison is given below (Table 4–6):

$$RMSE = \frac{1}{MN} \sqrt{\sum \sum (X_{ij} - Y_i)} \tag{2}$$

$$PSNR = \log_{10}(255^2/RMS) \tag{3}$$

$$MAE = \frac{1}{MN} \sum_i \sum_j |r_{ij} = x_{ij}| \tag{4}$$

$$CC = \frac{N^2 \sum X_{ij} Y_{ij} - \sum X_{ij} \sum Y_{ij}}{\sqrt{(N^2 \sum X_{ij}^2 - (\sum X_{ij}^2)) (N^2 \sum Y_{ij}^2 - (\sum Y_{ij}^2))}} \tag{5}$$

$$CR = \frac{\text{original image} - \text{compressed image}}{\text{original image}} \times 100 \tag{6}$$

$$SSIM = \frac{(2 \times x \times y \times c1)(2 \times \sigma_{xy} \times C2)}{(\sigma_x^2 + \sigma_y^2 + c2) \times ((x)^2 + (y)^2 + c1)} \tag{7}$$

$$MSSIM = \frac{1}{M} \sum_{j=1}^M SSIM_j \tag{8}$$

Table 1. Comparison on PSNR of proposed work with existing methods.

Bpp	IWT	MWT	AMWT	Proposed
0.1	14.20	20.40	27.85	29.99
0.2	18.98	23.21	30.84	32.08
0.3	21.88	26.26	32.53	33.49
0.4	24.03	27.64	33.91	34.69
0.5	25.45	28.87	35.12	36.16
0.6	26.48	29.83	36.51	37.37
0.7	28.48	30.61	37.88	38.91
0.8	29.39	31.52	39.21	40.07
0.9	30.04	32.01	40.77	41.70
1.0	30.92	32.74	42.15	43.25

Table 2. Comparison on RMSE of proposed work with existing methods.

Bpp	IWT	MWT	AMWT	Proposed
0.1	2780.6	593.14	106.57	65.16
0.2	820.86	310.53	53.57	40.24
0.3	421.35	153.74	36.30	29.07
0.4	256.91	111.90	26.42	22.08
0.5	185.16	84.30	19.98	15.70
0.6	146.23	67.58	14.50	11.90
0.7	92.16	56.45	10.58	8.34
0.8	74.80	45.77	7.79	6.39
0.9	64.35	40.97	5.45	4.39
1.0	52.50	34.59	3.96	3.07

Table 3. Comparison on CR of proposed work with existing methods.

Bpp	IWT	MWT	AMWT	Proposed
0.1	297.41	568.98	82.36	17.23
0.2	51.97	230.72	14.16	7.32
0.3	25.80	108.96	6.94	4.86
0.4	13.00	65.12	4.55	3.49
0.5	8.96	32.38	3.35	2.74
0.6	5.54	17.46	2.67	2.22
0.7	4.38	10.55	2.17	1.89
0.8	3.52	6.40	1.85	1.65
0.9	2.75	4.69	1.63	1.44
1.0	2.28	3.44	1.40	1.29

Table 4. Comparison on MAE of proposed work with existing methods.

Bpp	IWT	MWT	AMWT	Proposed
0.1	31.53	36.29	15.98	10.74
0.2	17.04	23.60	8.91	7.23
0.3	12.20	17.29	6.26	5.12
0.4	9.75	13.96	4.70	4.09
0.5	8.49	11.82	3.57	2.87
0.6	7.79	9.97	2.66	2.31
0.7	6.10	8.75	2.11	1.80
0.8	5.62	7.19	1.46	1.22
0.9	5.25	6.55	1.14	0.89
1.0	4.79	5.99	0.82	0.65

Table 5. Comparison on CC of proposed work with existing methods.

Bpp	IWT	MWT	AMWT	Proposed
0.1	0.47	0.18	0.85	0.92
0.2	0.79	0.65	0.94	0.95
0.3	0.87	0.78	0.96	0.97
0.4	0.91	0.85	0.97	0.97
0.5	0.93	0.89	0.97	0.97
0.6	0.94	0.92	0.97	0.98
0.7	0.96	0.93	0.98	0.98
0.8	0.96	0.95	0.98	0.98
0.9	0.96	0.95	0.98	0.98
1.0	0.97	0.96	0.98	0.98

Table 6. Comparison on MSSIM of proposed work with existing methods.

Bpp	IWT	MWT	AMWT	Proposed
0.1	0.44	0.41	0.58	0.70
0.2	0.59	0.48	0.77	0.82
0.3	0.69	0.57	0.86	0.89
0.4	0.74	0.62	0.91	0.93
0.5	0.79	0.67	0.94	0.96
0.6	0.81	0.73	0.96	0.97
0.7	0.86	0.78	0.98	0.98
0.8	0.88	0.84	0.98	0.99
0.9	0.89	0.86	0.99	0.99
1.0	0.90	0.88	0.99	0.99

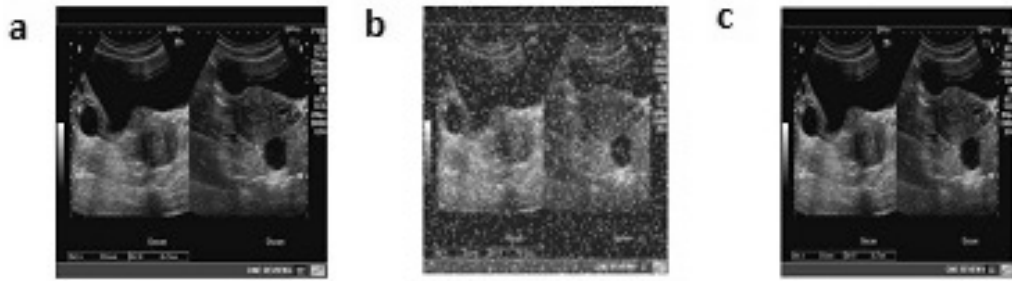


Fig. 5. (a) Original image; (b) Noisy image; (c) Denoised image using SAME.

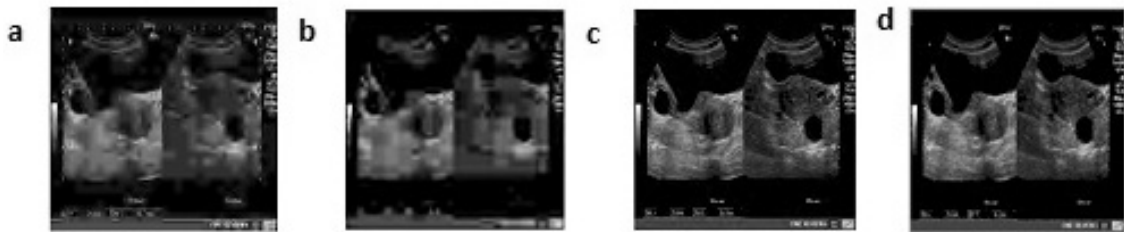


Fig. 6. Reconstructed images using (a) IWT; (b) MWT; (c) AMWT; (d) Proposed.

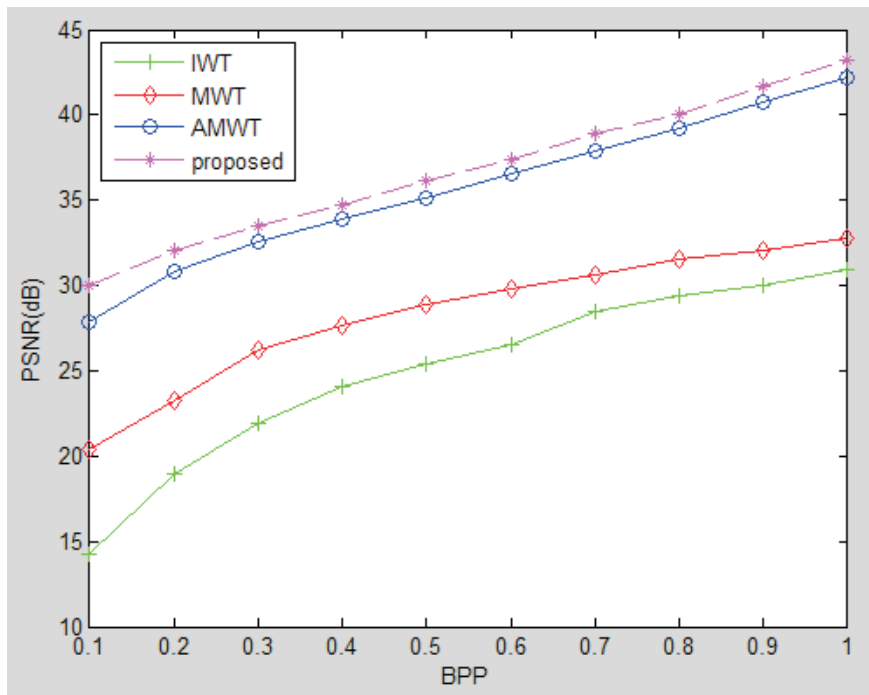


Fig. 7. Obtained PSNR observations for different data rate coding for IWT, MWT, AMWT and proposed work.

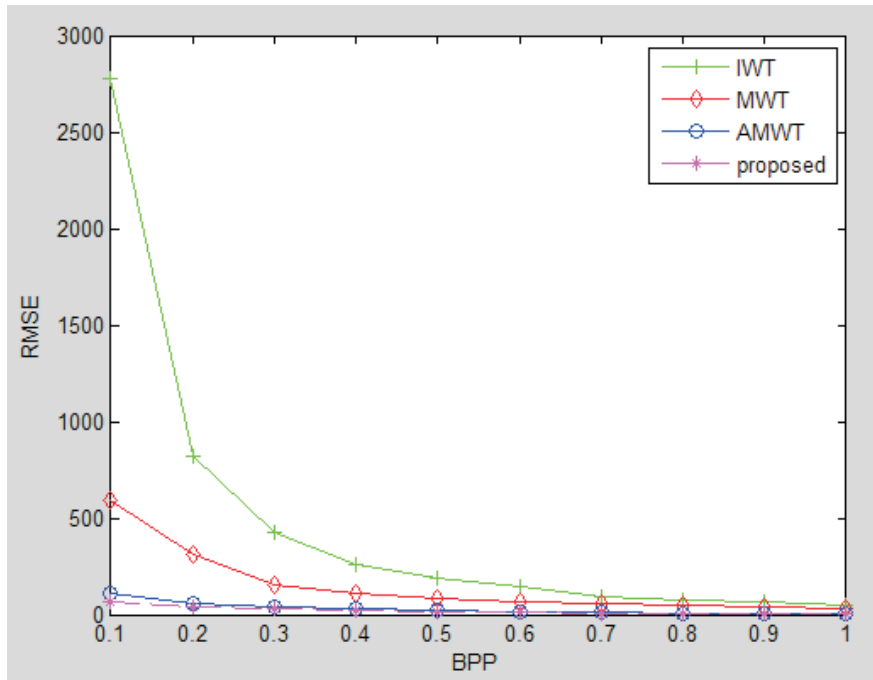


Fig. 8. Obtained RMSE observations for different data rate coding for IWT, MWT, AMWT and proposed work.

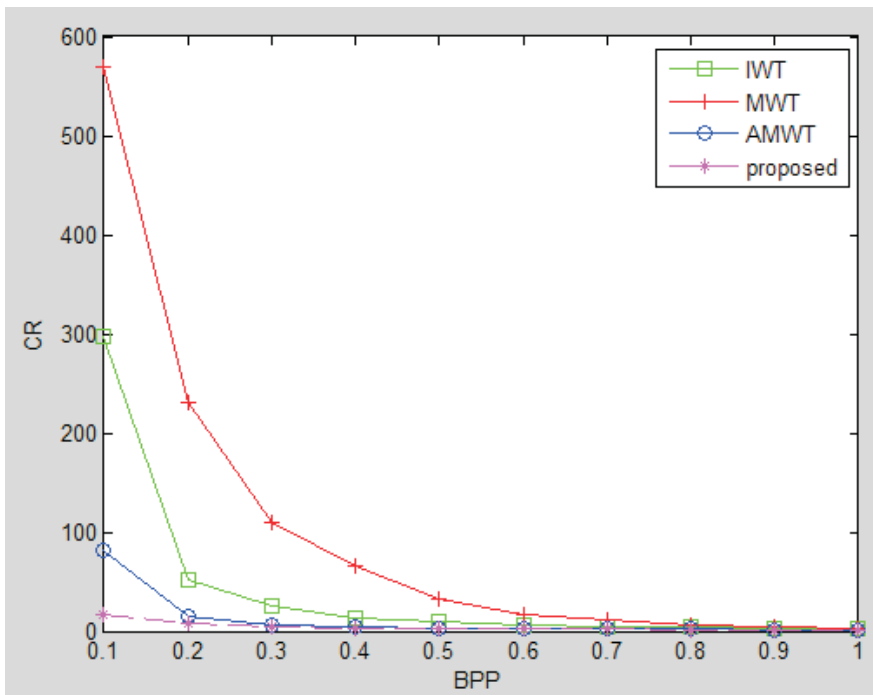


Fig. 9. Obtained CR observations for different data rate coding for IWT, MWT, AMWT and proposed work.

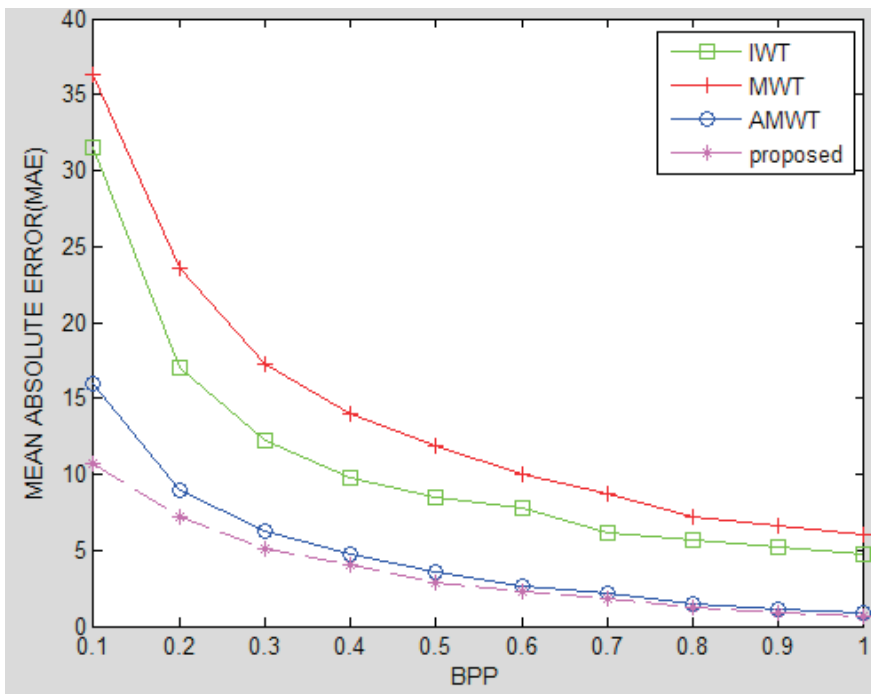


Fig. 10. Obtained MAE observations for different data rate coding for IWT, MWT, AMWT and proposed work.

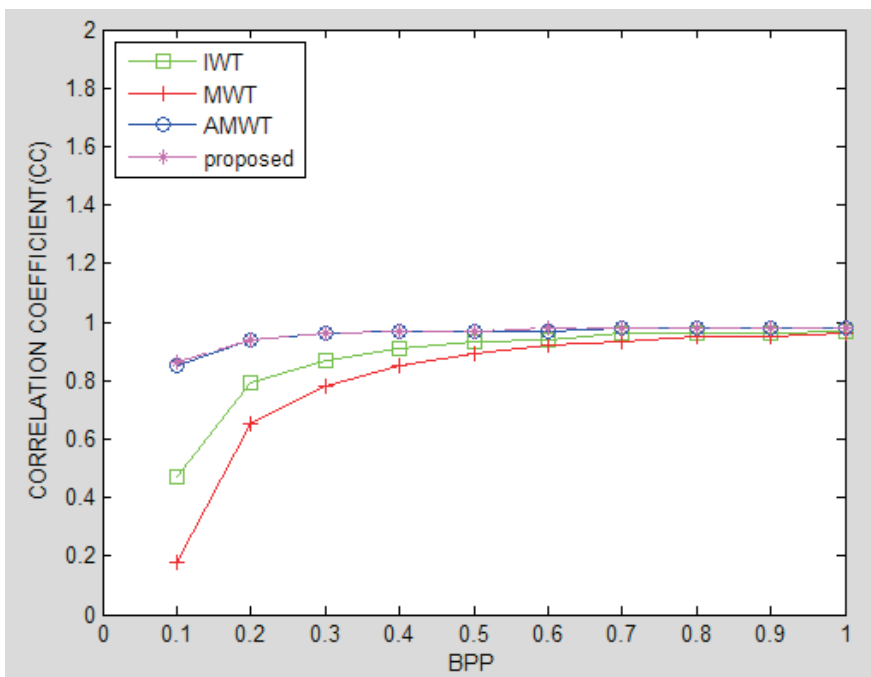


Fig. 11. Obtained CC observations for different data rate coding for IWT, MWT, AMWT and proposed work.

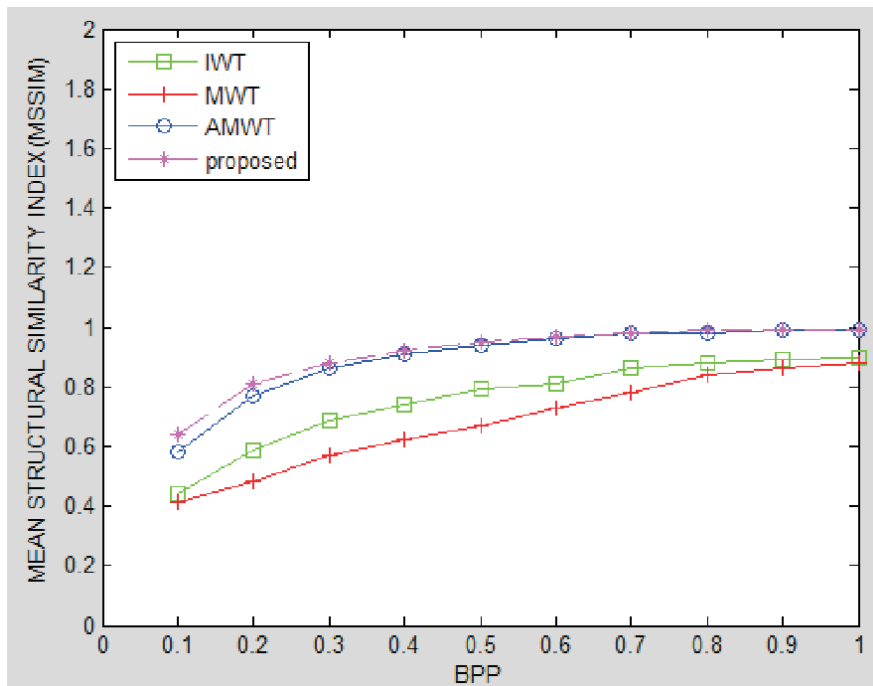


Fig. 12. Obtained MSSIM observations for different data rate coding for IWT, MWT, AMWT and proposed work.

7. Experimental Results

We compare the performance of our adaptive multiwavelet transform (AMWT) with integer wavelet transform (IWT) and Multiwavelet transform (MWT) in terms of bpp, PSNR, RMSE, CR, MAE, CC, MSSIM. We apply the above transforms on 8-bit ultrasound image. Table 1 gives the result of comparison of different transform techniques at different bpp in terms of PSNR. In Table 2 and 3 we compare the AMWT with existing transform techniques at different bpp in terms of MSE & CR. The figure shows the graphical results of different quality performance evaluation parameters. Figure 5(a), (b) & (c) shows the original, foreground and background images. Figure 6(a), (b) & (c) shows the original image, reconstructed images using IWT, MWT and AMWT at 0.5 bpp. The Fig. 7–Fig. 12 gives the comparative graphical results of different quality performance evaluation parameters.

8. Conclusion

In this paper, the AMWT filter coefficients were derived from the adaptive lifting scheme. In the adaptive lifting scheme the predictor was modified based on two previous values for calculating the current pixel. The proposed predictor reduces the computational complexity. Experimental results were obtained by applying the proposed method to an 8-bit ultrasound image. It is shown that the proposed AMWT outperforms the other well-known transform techniques. The experimental results show that the proposed method gives more PSNR, MSSIM, CC and lowest RMSE, MAE value at different bpp in the range of 0.1 to 1 and the images are transmitted with moderate CR in the high quality of reconstructed images.

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