

Efficient Image Compression using Reverse Bi-Orthogonal Wavelet Filtering with Hard Thresholding

Divyani¹, Prof. Manish Rai²

¹Mtech. Scholar, ²Guide

Department of Computer Science and Engineering, RKDF College of Engineering, Bhopal

Abstract – In the present modern era, media innovation has huge effect on human lives. Image is a standout amongst the most significant media contributing to multimedia. Information transmission is the key means to acquire and give the knowledge or data related to a particular event. For example: video conferences, medical data transfer, business data transfer and so on, require much more image data to be transmitted and stored online. Due to the internet, the huge information transmissions take place. The processed data required much more storage, computer processor speed and much more bandwidth for transmission. While the advancement of the computer storage innovation proceeds at the fast rate. The means for reducing the storage requirement of image is still needed in most of the situations. And hence, thus it is exceptionally attractive that the image be processed, so that efficient storage, transmission and representation of the image can be worked out. Recently, the requirement for efficient image compression frameworks can be seen. Based on the existing schemes, an efficient image compression using reverse Bi-Orthogonal wavelet filtering with hard thresholding image compression algorithm is developed and analysis of performance has verified based on MATLAB simulation in this research work, to compress the images effectually maintaining the quality.

Keywords – Image Processing, Image Compression, Wavelet Filtering, Reverse Bi-Orthogonal Wavelet, Hard Thresholding.

I. INTRODUCTION

A digital image represents a two-dimensional array of samples, where each sample is called a pixel. Precision is determined by how many levels of intensity can be represented, and this is expressed as the number of bits per pixel (bpp). The value of bpp reflects different components of the colour systems used. For example, in greyscale images the values represent brightness or luminance

resolution and range from 1,2,4,8,12 or 16 bpp. For RGB colour images, the values represent the intensity of each colour space, and resolution is usually 24 bpp. An ideal image compression would remove redundant and irrelevant information before the coding process. Redundancy in images can be classified as statistical redundancy or psycho visual redundancy[1]. Statistical redundancy can be classified into three types[2] :

- Spatial, due to the correlation between neighboring pixels in an image;
- Spectral, from correlation between colour planes or spectral bands;
- Temporal, in terms of correlation between neighbouring frames in a sequence of images.

Irrelevant information or psycho-visual redundancy refer to the limitations of or variations in the human visual system (HVS) in responding to certain stimuli under certain viewing conditions. In image compression systems, different colour components are often compressed separately as different greyscale images, and they can be represented with different spatial resolutions. However, the implementation of composite methods can further exploit spectral redundancy and introduce rate scalable colour image coding. Image compression can be classified as lossless and lossy compression. The basic framework of both types of compression system is shown in Figure 1.1. Lossless compression is bit preserving compression, where the reconstructed image is numerically identical to the original image. This type of compression is important for applications such as medical and satellites imaging, where distortion or loss of information is unacceptable.

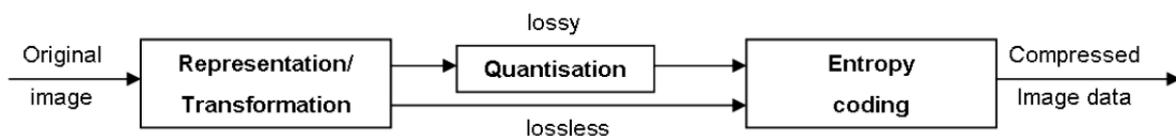


Fig.1.1 general image compression framework.

However, lossless compression can only achieve a modest degree of compression at ratios of around 2 ~ 5: 1 with a completely reversible process. Lossless algorithms usually compress the source to bit-rates close to its entropy. The quantisation process is removed in lossless compression so that the image can be recovered exactly. However, this work investigates efficient image compression using reverse bi-orthogonal wavelet filtering with hard thresholding.

II. SYSTEM MODEL

There are several ways wavelet transforms can decompose a signal into various subbands. These include uniform decomposition, octave-band decomposition, and adaptive or wavelet-packet decomposition. Out of these, wavelet-packet decomposition is the most widely used. This is a non-uniform band splitting method that decomposes the lower frequency part into narrower bands and the high-pass output at each level is left without any further decomposition. Fig. 2.1 shows the various subband images of a 3-level octave-band decomposed Lena using the popular biorthogonal wavelet.

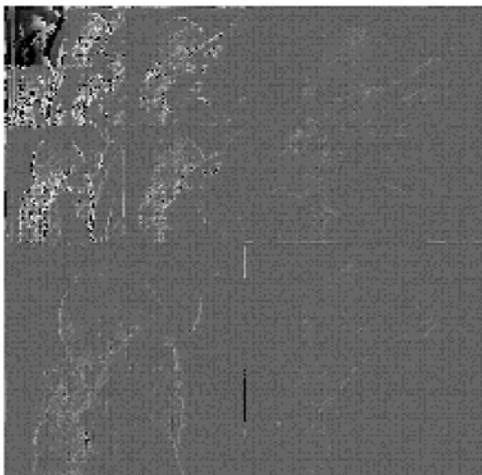


Fig.2.1 Three level decomposition of Lena image.

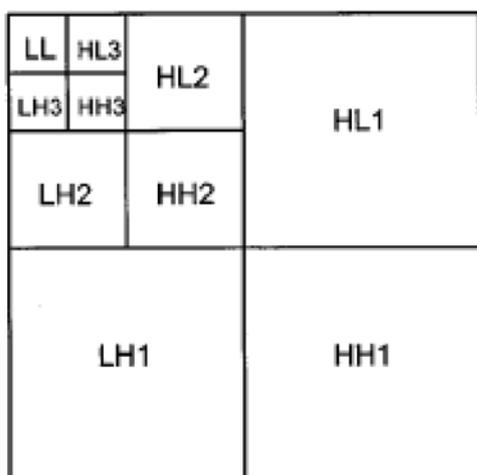


Fig.2.2 Spectral decomposition and ordering.

Most of the subband and wavelet coding schemes can also be described in terms of the general framework depicted as in Fig. 2.2. The main difference from the JPEG standard is the use of DWT rather than DCT. Also, the image need not be split into 8 x 8 disjoint blocks. Of course, many enhancements have been made to the standard quantization and encoding techniques to take advantage of how the wavelet transforms works on an image and the properties and statistics of transformed coefficients so generated.

III. PROPOSED METHODOLOGY

Image compression is a significant issue in digital image processing and finds broad applications in numerous fields. This is the basic operation performed frequently by any digital photography technique to capture an image. For longer use of the portable photography device it should consume less power so that battery life will be more. To improve the conventional methods of image compressions utilizing the DCT have just been accounted for and adequate literature works are accessible on this. The JPEG is a lossy compression plot, which utilizes the DCT as a tool and utilized predominantly in digital cameras for compression of images. In the ongoing past the interest for low power image compression is developing. Accordingly different research specialists are effectively drawn in to develop proficient strategies for image compression utilizing latest digital signal processing approach. The objective is to achieve a reasonable compression ratio as well as better quality of reproduction of image. Keeping these objectives in mind the research work in the present examination work has been undertaken. A framework of proposed reverse bi-orthogonal (rbior) wavelet filtering with hard thresholding 2.2 level based on thresholding image compression has shown in block representation Fig. 3.1. An input image is taken by the computer in MATLAB, wavelet transform is performed on the digital image and transform domain mask of coefficient matrix has defined, thresholding is done on the digital image, entropy coding is done on the image where necessary, in this manner the compression of image is done on the computer. At that point with the compressed image, reconstruction of wavelet transformed image is done, at that point inverse wavelet transform is performed on the image, in this way image is reconstructed. Fig.3.2 shows the algorithmic flow diagram of proposed compression system.

The wavelet hard thresholding is utilized can be characterized as decomposition of the data of image into wavelet coefficients, looking at the detailed coefficients having a given threshold esteem, and minimizing these coefficients near zero to remove the impact of noise in the data. At that point image is reconstructed from modified coefficients. This is otherwise called inverse discrete

wavelet transform. At the time of thresholding, a wavelet coefficient is contrasted with the given threshold and is set to zero if its magnitude is not exactly the threshold else, it is then retained or modified relying upon the thresholding rule. Thresholding recognizes coefficients because of noise

and the ones comprising of significant signal data. The determination of a threshold is a significant focal point. It assumes a significant job in the removal of noise in the images since de-noising most often creates smoothed images, by decreasing the sharpness of the image.

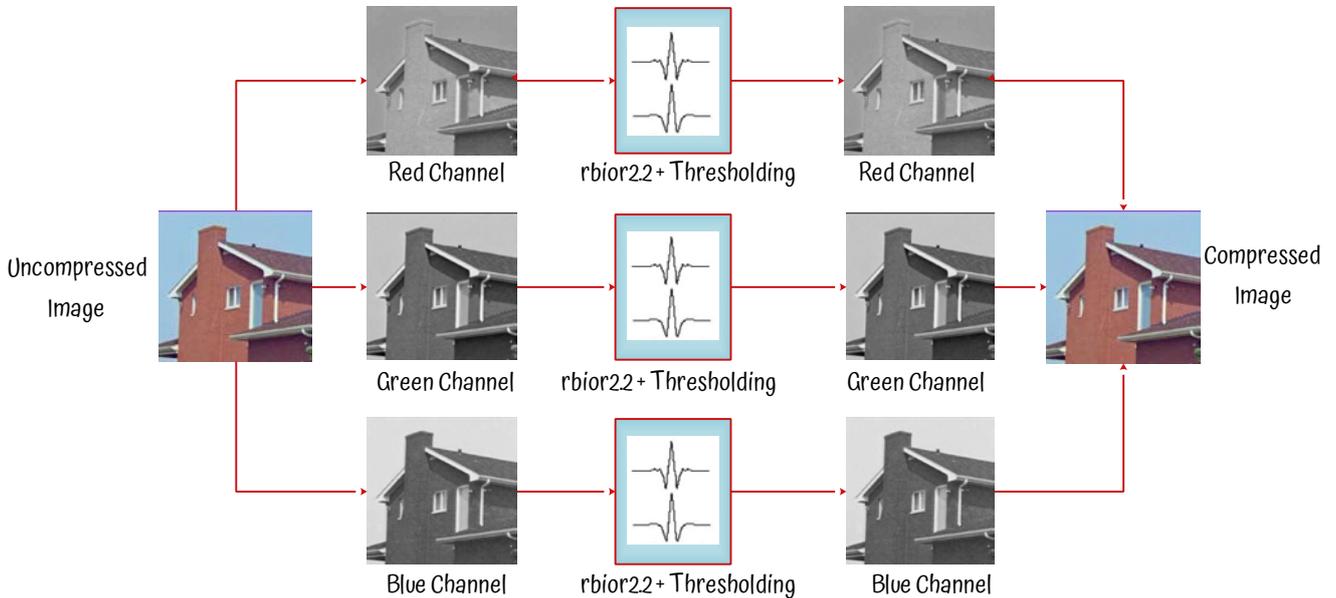


Fig.3.1 Framework of Proposed rbior2.2 Level Dependent Thresholding Image Compression.

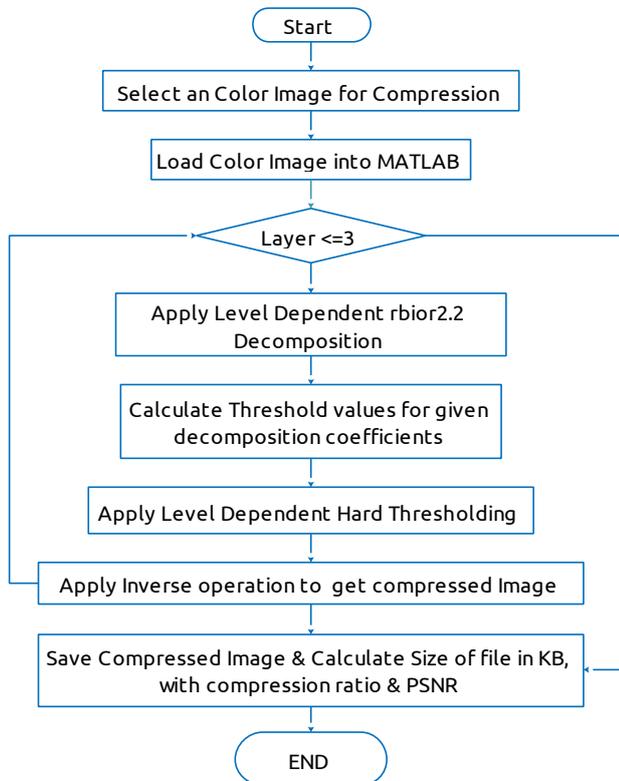


Fig.3.2 Algorithmic Flow Diagram of Proposed Compression System

As shown in Fig 3.2 algorithmic flow of proposed examination the step by step execution of proposed algorithm is as follows.

Step1: Start execution of proposed algorithm in MATLAB image processing environment.

Step2: Select a color image to be compressed using proposed algorithm in to MATLAB.

Step3: Check for the condition if layer are less than three then apply following steps and if the layers are more than three jump to step 8.

Step4: Apply level dependent reverse orthogonal wavelet decomposition (rbior22).

Step5: calculate Threshold values for given decomposition coefficients.

Step6: Apply inverse operation to get compressed image

Step7: Save compressed image & calculate size of file in KB, with compression ratio & PSNR.

Step8: End simulation with MATLAB.

IV. SIMULATION RESULTS

The implementation and simulation of the program is carried out in MATLAB with various subroutines that enable the wavelet transformation, image compression and threshold computation from the Wavelet Toolkit. The experimental analysis based on software simulation is performed on several types of gray scale and color images

in Wavelet Hard Thresholding. As seen from Table 1, House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue, Lighthouse images are used to examine the performance of

proposed scheme. Fig. 4.1 shows the Input Uncompressed Images of House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Respectively.



Fig. 4.1 Input Uncompressed Images House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Respectively.



(a) Airplane



(b) Hat

Fig.4.2 Compression Images: Red Layer, Green Layer, Blue Layer and Color Image of Plane and Hat Respectively.

Fig. 4.2 shows the compression images using proposed algorithm in Fig. 4.2 a input image of airplane and in Fig. 4.2 compression image of Hat given in both figure three separated layers are shown Red layer , Green Layer, Blue layer and color image correspondingly.

in table 1 where PSNR values of various images are compared layer wise with corresponding value of previous approach PSNR outcomes. From the observation of table it is clear that proposed work has better performance as compared to previous approach based on CSDDS.

The experimental outcomes of peak signal to noise ratio (PSNR) for Different color test image inputs are tabulated

Table 1: Signal to Noise Ratio (PSNR) for Different Experimental Outcomes of Peak Color Image Inputs

Images	CSDDS-Based Method				Proposed (Our)			
	R	G	B	Overall	R	G	B	Overall
House	37.74	35.96	37.62	37.03	56.14	57.15	55.69	56.33
Plants	38.18	42.16	36.40	38.31	50.36	49.78	52.87	51.01
Hat	47.33	43.81	41.29	43.49	50.17	51.84	51.84	51.28
Yacht	41.53	41.96	39.74	40.97	48.18	49.43	48.85	48.82
Cablecar	40.73	39.04	39.12	39.56	47.1	48.16	47.95	47.74
Cornfield	40.49	39.34	36.37	38.37	46.33	47.16	46.92	46.8
Lena	38.16	41.26	38.07	38.93	48.65	49.84	49.81	49.43
Airplane	39.78	37.61	40.11	39.02	52.96	53.13	52.44	52.84
Peppers	35.20	35.17	34.82	35.06	54.43	56.5	54.17	55.03
Bikes	48.58	47.85	46.28	47.46	48.65	49.49	49.35	49.16
Coast	49.28	52.20	47.40	49.21	51.22	51.29	51.03	51.18
Backyard	43.95	47.71	45.17	45.34	46.07	47.21	47.43	46.9
Boat	50.62	53.68	52.20	51.99	45.12	46.81	46.81	46.24
Statue	48.08	51.90	47.36	48.35	49.21	50.02	49.69	49.64
Lighthouse	49.09	51.91	49.24	49.90	51.48	52.62	52.26	52.12
Average	43.25	44.10	42.08	42.89	49.738	50.69	50.47	50.30

The graphical representation of Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of

RED Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively are shown in Fig. 4.3.

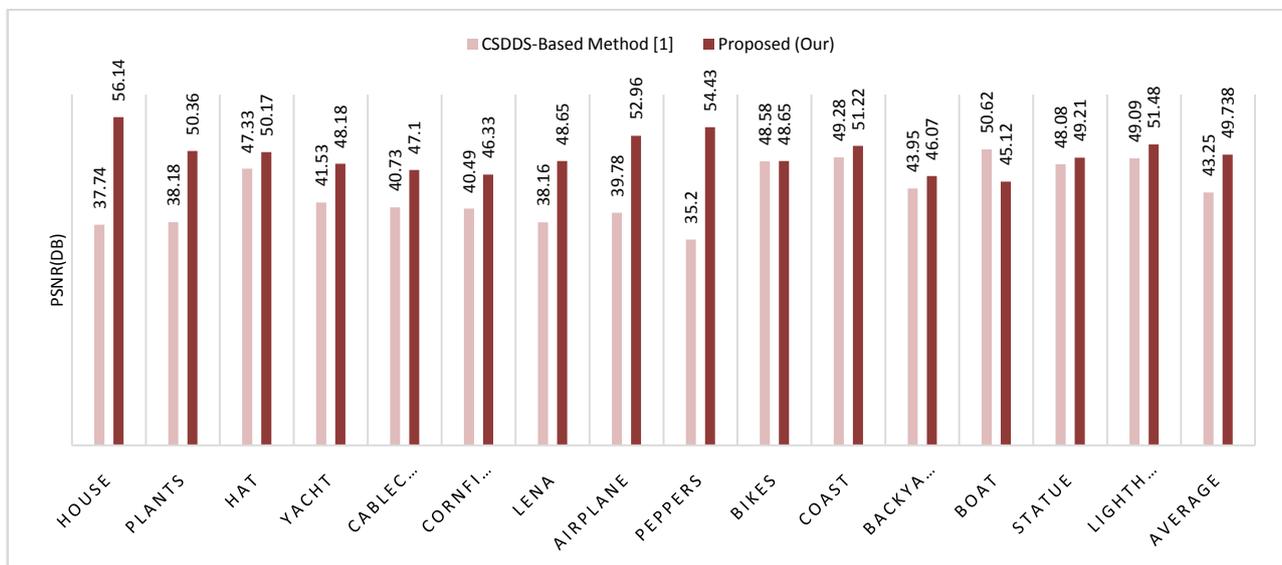


Fig.4.3 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of RED Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

Graphical representation of Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of GREEN Layer for House, Plants, Hat, Yacht, Cablecar,

Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively are shown in Fig. 4.4.

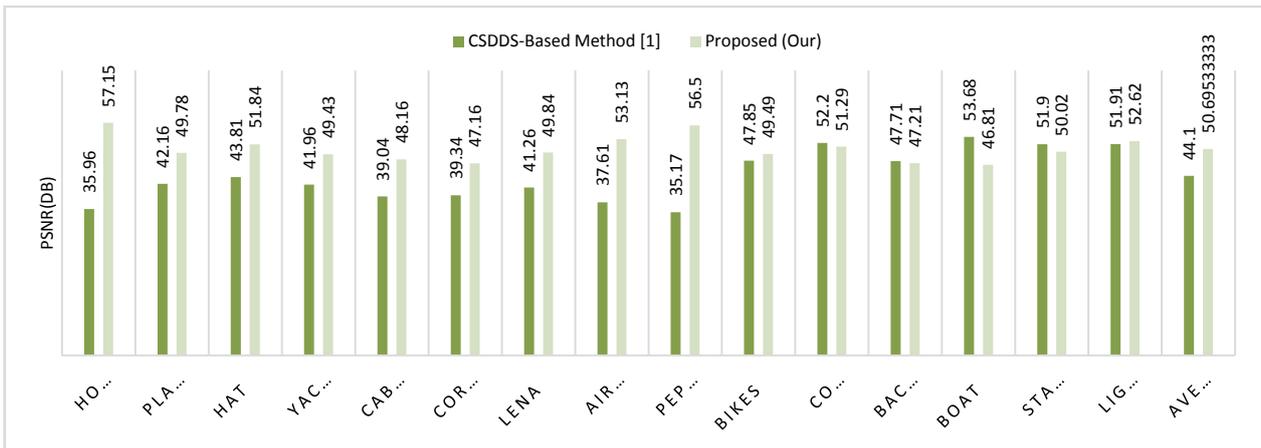


Fig.4.4 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of GREEN Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

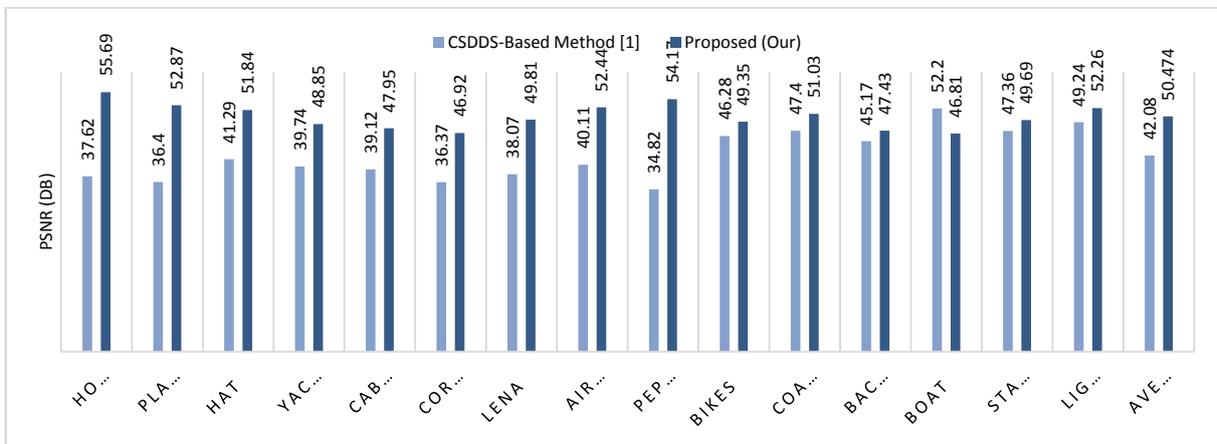


Fig.4.5 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of BLUE Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

Graphical representation of Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of BLUE Layer for House, Plants, Hat, Yacht, Cablecar,

Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively shown in Fig. 4.5

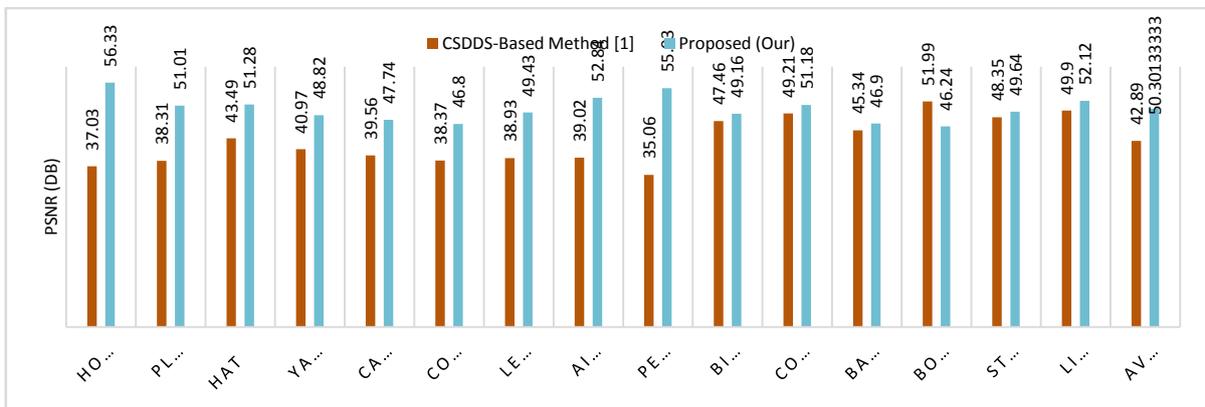


Fig.4.6 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of Overall RGB Image for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

Graphical representation of peak signal to noise ratio comparison of previous [1] and proposed (our) method of overall RGB image for House, Plants, Hat, Yacht,

Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively are shown in Fig. 4.6.

V. CONCLUSION AND FUTURE SCOPE

A strategy for digitally implementing the efficient image compression using reverse bi-orthogonal wavelet filtering with hard thresholding is presented. The resulting implementations have the exact reconstruction property and gives table reconstruction in MATLAB. The experimental results showed that proposed examination implemented in MATLAB image processing using hard thresholding consistently produces the highest PSNR. Although best results are obtained while compressing the sample images in terms of PSNR it is noticed in the result that highest PSNR is obtained for most of test images when compared to previous work images. The results clearly indicate that wavelet transform using thresholding techniques proves to be inferior in compression of images.

The work presented in this research work has also carried many new ideas for lossless compression of modern image types. Based on the ideas given in the proposed examination, it can also be concluded that challenges remain in the end of extended lossless image compression. Further investigation is likely to yield still improved compression and hence the end is still worthy of research.

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