Adaptive Frequency Domain Block Processing for Color Image Compression

Pinki Gour[1], Prof. Khushboo Verma[2]

[1]MTech. Scholar, [2]Research Guide

Department of Computer Science and Engg, Bansal Institute of Science and Technology, Bhopal

Abstract - With the advancement of internet and communication system multimedia data like image has become most trending object among people. The extensive demand of the development of transmission and accessing of multimedia data through the telecommunication network and Internet is increased. The Image compression has turned out to be basic for effective transmission and storage of images. With the utilization of digital cameras, requirements for storage, control, and exchange of digital images, has developed violently. These image files can be very large and can possess a great deal of memory. Image data include a critical part of the multimedia data and they involve the significant portion of the communication transfer speed for multimedia data communication. Therefore improvement of productive methods for image compression has turned out to be quite necessary. A fundamental property of image formation for most images is that the neighboring pixels are much correlated and subsequently contain highly redundant information. The basic objective of image compression is to discover a less correlated pixel representation of an image. As recently, the requirement for efficient image compression frameworks can be seen. In the rapidly growing field of Internet applications, not only still images but also small image sequences are used to enhance the design of private and commercial web pages. In this work an adaptive frequency domain block processing for color image compression has proposed and examined based on its PSNR performance in MATLAB image processing environment.

Keywords - Image Processing, Block Processing, Data Compression, Color Image Compression, PSNR, Lossi and Lossless. compression.

I. INTRODUCTION

In today's modern era, multimedia technology has tremendous impact on human lives. Image is one of the most important 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 on-line. Due to the internet, the huge information trans- missions 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 technology continues at the rapid rate. The means for reducing the storage requirement of image is still needed in most of the situations. And hence it is highly desirable that the image be processed, so that efficient storage, representation and transmission of the image can be worked out. The processes involve one of the important tasks - Image Compression. Methods for digital image compression have been the subject of research over the past three decades.

Meeting bandwidth requirements and maintaining acceptable image quality simultaneously are a challenge. Continuous rate scalable applications can prove valuable in scenarios where the channel is unable to provide a constant bandwidth to the application. The goal of image compression is to obtain a representation that minimizes bit rate with respect to some distortion constraint. Typical compression techniques achieve bit rate reduction by exploiting correlation between pixel intensities. The performance of any image compression scheme depends upon its ability to capture characteristic features from the image, such as sharp edges and fine textures, while reducing the number of parameters used for its modeling. Image compression is one of the most important and successful applications of the wavelet transform. Wavelets are mathematical functions that provide good quality compression at very high compression ratios, because of their ability to decompose signals into different scales or resolutions. The standard methods of image compression come in numerous ranges. Most of the well-established compression schemes use the bi-variate Discrete Wavelet Transform (DWT) on wavelet-based image coding. At high compression rates, wavelet-based methods provide much better image quality in comparison with the JPEG (Joint Photogrphic Experts Group) standard, which relies on the discrete cosine transform (DCT). The good results obtained from DWT are due to multi- resolution analysis, which essentially brings out information about the statistical structure of the image data. The current most popular methods rely on removing high frequency components of the image by storing only the low frequency components (e.g., DCT based algorithms). This method is used on JPEG (still images), MPEG (motion video images), H.261 (Video Telephony on ISDN lines), and H.263(Video Telephony on PSTN lines) compression algorithms.

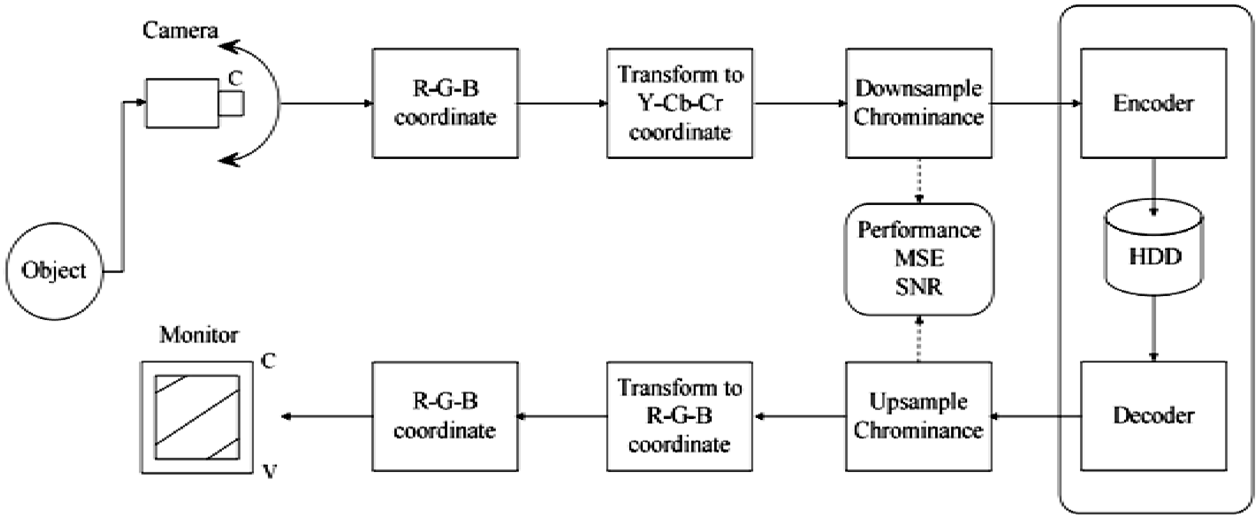

Fig. 1.1 General Image Storage systems.

Image compression coding is to store the image into bit-stream as compact as possible and to display the decoded image in the monitor as exact as possible. Now consider an encoder and a decoder as shown in Fig. 1.2. When the encoder receives the original image file, the image file will be converted into a series of binary data, which is called the bit-stream. The decoder then receives the encoded bit-stream and decodes it to form the decoded image. If the total data quantity of the bit-stream is less than the total data quantity of the original image, then this is called image compression. The full compression flow is as shown in Fig. 1.2.

Fig. 1.2 The basic flow of image compression.

II. SYSTEM MODEL

Number of bits required to represent the information in an image can be minimized by removing the redundancy present in it. There are three types of redundancies: (i)spatial redundancy, which is due to the correlation or dependence between neighbouring pixel values; (ii) spectral redundancy, which is due to the correlation between different color planes or spectral bands; (iii) temporal redundancy, which is present because of correlation between different frames in images. Image compression research aims to reduce the number of bits required to represent an image by removing the spatial and spectral redundancies as much as possible.

Data redundancy is of central issue in digital image compression. If n1 and n2 denote the number of information carrying units in original and compressed image respectively, then the compression ratio CR can be defined as

$$CR = n1/n2$$

And relative data redundancy RD of the original image can be defined as

$$RD = 1 - 1/CR$$

Three possibilities arise here:

(1) If n1=n2,then CR=1 and hence RD=0 which implies that original image do not contain any redundancy between the pixels.

(2) If n1>>n1,then CR→∞ and hence RD>1 which implies considerable amount of redundancy in the original image.

(3) If n1<<n2,then CR>0 and hence RD→-∞ which indicates that the compressed image contains more data than original image.

JPEG stands for the Joint Photographic Experts Group, a standards committee that had its origins within the International Standard Organization (ISO).JPEG provides a compression method that is capable of compressing continuous-tone image data with a pixel depth of 6 to 24 bits with reasonable speed and efficiency.JPEG may be adjusted to produce very small, compressed images that are of relatively poor quality in appearance but still suitable for many applications. Conversely, JPEG is capable of producing very high-quality compressed images that are still far smaller than the original uncompressed data.

JPEG is primarily a lossy method of compression.JPEG was designed specifically to discard information that the human eye cannot easily see. Slight changes in color are not perceived well by the human eye, while slight changes in intensity (light and dark) are. Therefore JPEG's lossy encoding tends to be more frugal with the gray-scale part of an image and to be more frivolous with the color. DCT separates images into parts of different frequencies where less important frequencies are discarded through quantization and important frequencies are used to retrieve the image during decompression. Compared to other input dependent transforms, DCT has many advantages: (1) It has been implemented in single integrated circuit; (2) It has the ability to pack most information in fewest coefficients; (3) It minimizes the block like appearance called blocking artifact that results when boundaries between sub-images become visible.

III. PROPOSED METHODOLOGY

The primary goal is to design a image compression framework suitable for image processing, storage and transmission, and in addition giving satisfactory computational complexity appropriate to functional execution. The essential guideline of compression is to decrease the number of bits expected to represent to a digital image. In a computer an image is represented as an array of numbers, integers to be more specific, that is called a digital image. The image array is normally two dimensional (2D), If it is gray scale or black and white and three dimensional (3D) in the event that it is color image. Digital image compression algorithms exploit the redundancy in an image with the goal that it very well may be represented to utilizing a smaller number of bits while as yet keeping up worthy visual quality.

In the array each number represents an intensity value at a particular location in the image and is called as a picture element or pixel. Pixel values are typically positive whole numbers and can run between 0 to 255. This implies every pixel of a BW image occupies 1byte in a computer memory.

On the other hand, a color image has a triplet of values for each pixel one each for the red, green and blue primary colors. Hence, it will need 3 bytes of storage space for each pixel. To reduce the size of image and to achieve an efficient PSNR an adaptive frequency domain block processing for color image compression algorithm has been proposed in this work. Fig. 3.1 shows the block representation of proposed approach in MATLAB image processing environment.

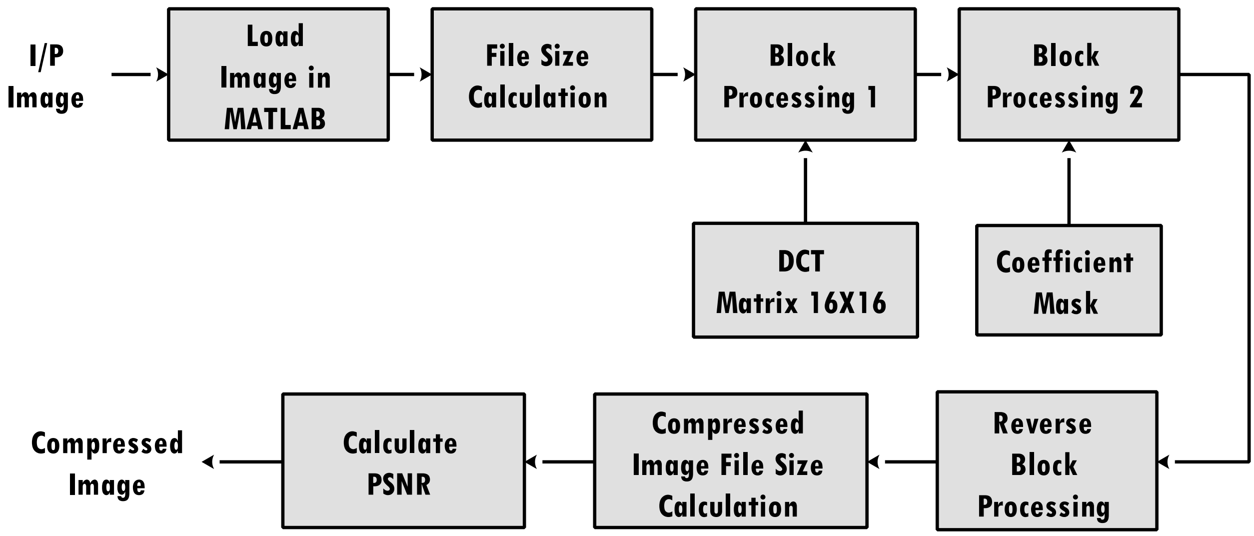

Fig.3.1 Block Diagram of Proposed Methodology.

For energy-efficient image compression and communication in wireless networks. adaptive frequency domain block processing is a lossy compression with very low complexity. This algorithm operates on blocks of 16x16 pixels in which each block is encoded freely, based on three phases: uniform scalar quantization, self-adaptive pixel removal, and variable-length coding. In this technique, the self-adaptive pixel removal part is more important.

This method removes that pixel which induces the smallest block distortion between original and decompressed image and its place is inserted into the LSBs of the three remaining pixels. Finally, the spatial correlation among the remaining pixels is saved, so as to search the missing pixels at the decoder side.

Fig. 3.2 shows the flow chart of proposed algorithm in MATLAB tool. First select a color image for compression and load it into MATLAB to start compression algorithm. Define a transfer domain mask coefficient Matrix. There are different layers of color RGB image if number of layers is less than three convert images into double format apply block coding using 16X16 DCT matrix. Define mask matrix of 16X16 and block process on previous stage o/p. Now reduce DCT operation to get output image and compare number of layers again. If layers are more than three save compressed image and calculate size of file in KB with compression ratio and PSNR. End process exit from MATLAB.

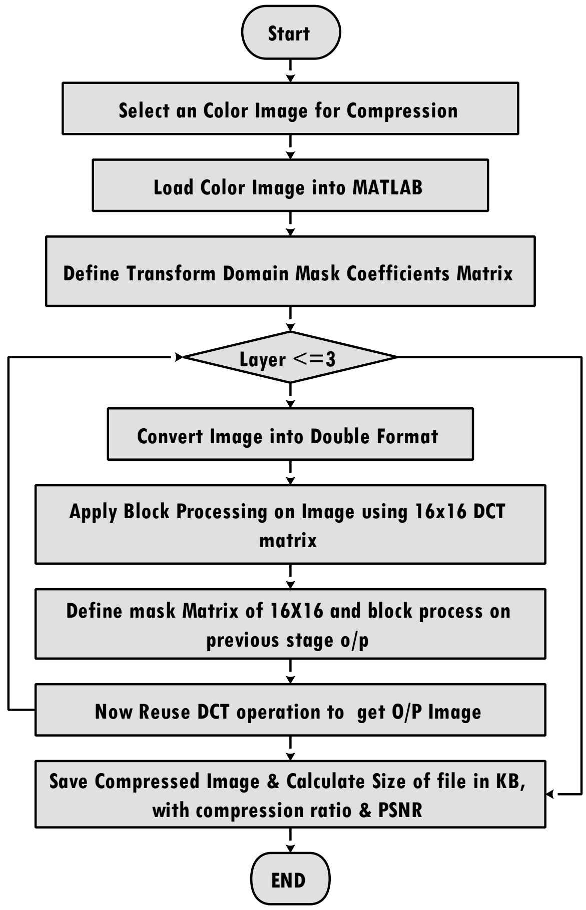

Fig.3.2 Execution Flow Chart of Proposed Methodology

IV. EXPERIMENTAL RESULTS

In this work prominence were given on the amount of compression used and how good the reconstructed image is similar to the original. Examination was done based on the measure of distortion, which was determined utilizing imperative distortion measures: mean square error (MSE), peak signal-to-noise ratio (PSNR) measured in decibels (dB) and compression ratio (CR) measures were used as performance indicators. Image having same PSNR value may have different perceptual quality. The quality of reconstructed images can be evaluated in terms of objective measure and subjective measure. In objective evaluation, statistical properties are considered whereas, in subjective evaluation, viewers see and investigate image directly to determine the image quality. A decent compression algorithm would reproduce the image with low MSE and high PSNR.

a. Mean Square Error (MSE)

The MSE is the cumulative squared error between the compressed and the original image. A lower value of MSE means lesser error, and it has the inverse relation with PSNR. Mean square error is a criterion for an estimator: the choice is the one that minimizes the sum of squared errors due to bias and due to variance. In general, it is the average of the square of the difference between the desired response and the actual system output.

$$MSE = \frac{1}{m \times n} \sum_{y=1}^{m} \sum_{x=1}^{n} [I(x,y) - I^{'}(x,y)]^2$$

Where, I(x, y) is the original image and I'(x, y) is the reconstructed image and m, n are the dimensions of the image. Lower the value of MSE, the lower the error and better picture quality.

b. Peak Signal to Noise Ratio (PSNR)

PSNR is a measure of the peak error. Many signals have very wide dynamic range, because of that reason PSNR is usually expressed in terms of the logarithmic decibel scale in (dB). Normally, a higher value of PSNR is good because it means that the ratio of signal to noise is higher. Here, a signal represents original image and noise represents the error in reconstruction. The PSNR is defined as:

$$PSNR = 10log_{10}\left(\frac{{MAX_1}^2}{MSE}\right) = 20log_{10}\left(\frac{MAX_1}{\sqrt{MSE}}\right)$$

PSNR is computed by measuring the pixel difference between the original image and compressed image.

The performance of the proposed image compression algorithms. The proposed algorithms are applied on several types of images: House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse such that the performance of proposed algorithm can be verified for various applications. These benchmark images are the standard image generally used for the image processing applications as shown in Fig. 4.1. A Compression Images: Red Layer, Green Layer, Blue Layer and Color Image of House Respectively are shown in Fig. 4.2.

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

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

The performance analysis of proposed work based in PSNR in dB is shown in Table 1 and graphical representation is shown in 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.

Table 1: Performance of PSNR(dB) for Proposed Methodology

Images	***CSDDS-Based Method***				***Proposed (Our)***			
	R	***G***	***B***	***Overall***	***R***	***G***	***B***	***Overall***
House	37.74	35.96	37.62	37.03	56.19	57.20	55.76	56.38
Plants	38.18	42.16	36.40	38.31	50.40	49.81	52.88	51.03
Hat	47.33	43.81	41.29	43.49	50.19	51.87	51.85	51.30
Yacht	41.53	41.96	39.74	40.97	48.33	49.51	48.95	48.93
Cablecar	40.73	39.04	39.12	39.56	47.32	48.27	48.05	47.88
Cornfield	40.49	39.34	36.37	38.37	46.67	47.36	47.09	47.04
Lena	38.16	41.26	38.07	38.93	48.74	49.87	49.84	49.48
Airplane	39.78	37.61	40.11	39.02	53.13	53.33	52.58	53.01
Peppers	35.20	35.17	34.82	35.06	54.64	56.81	54.44	55.29
Bikes	48.58	47.85	46.28	47.46	48.09	48.69	48.58	48.45
Coast	49.28	52.20	47.40	49.21	51.34	51.45	51.15	51.31
Backyard	43.95	47.71	45.17	45.34	45.72	46.61	46.93	46.42
Boat	50.62	53.68	52.20	51.99	44.96	46.24	46.26	45.82
Statue	48.08	51.90	47.36	48.35	48.35	48.98	48.73	48.68
Lighthouse	49.09	51.91	49.24	49.90	50.09	50.82	50.65	50.52
Average	43.25	44.10	42.08	42.89	**49.61**	**50.45**	**50.25**	**50.10**

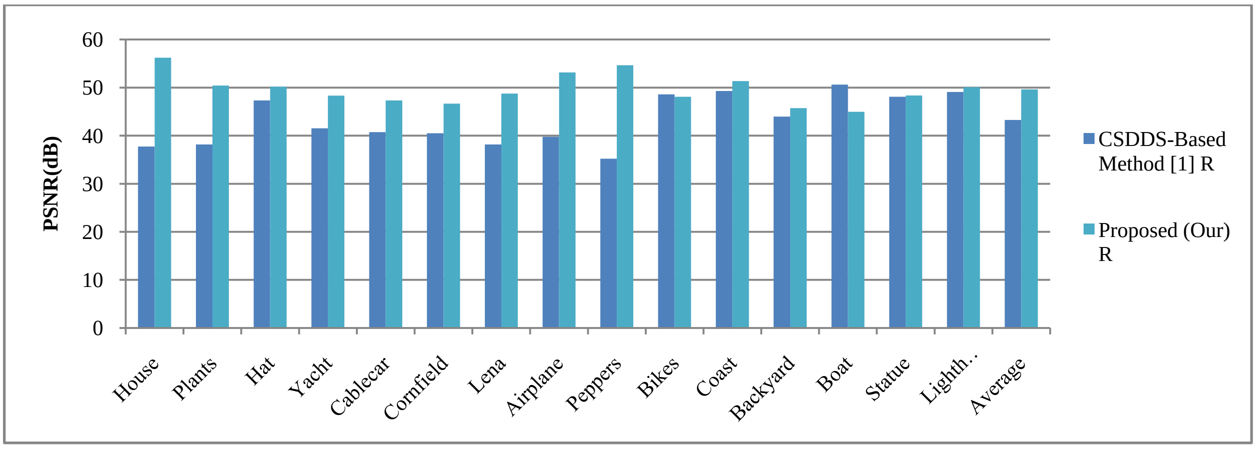

Fig.4.3 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of RED Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

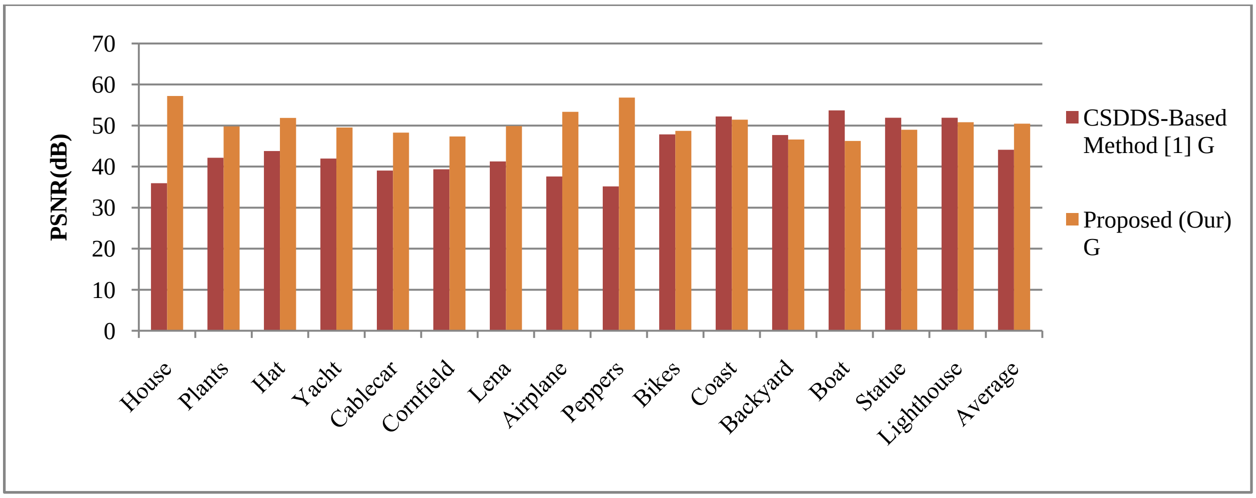

Fig.4.4 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of GREEN Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

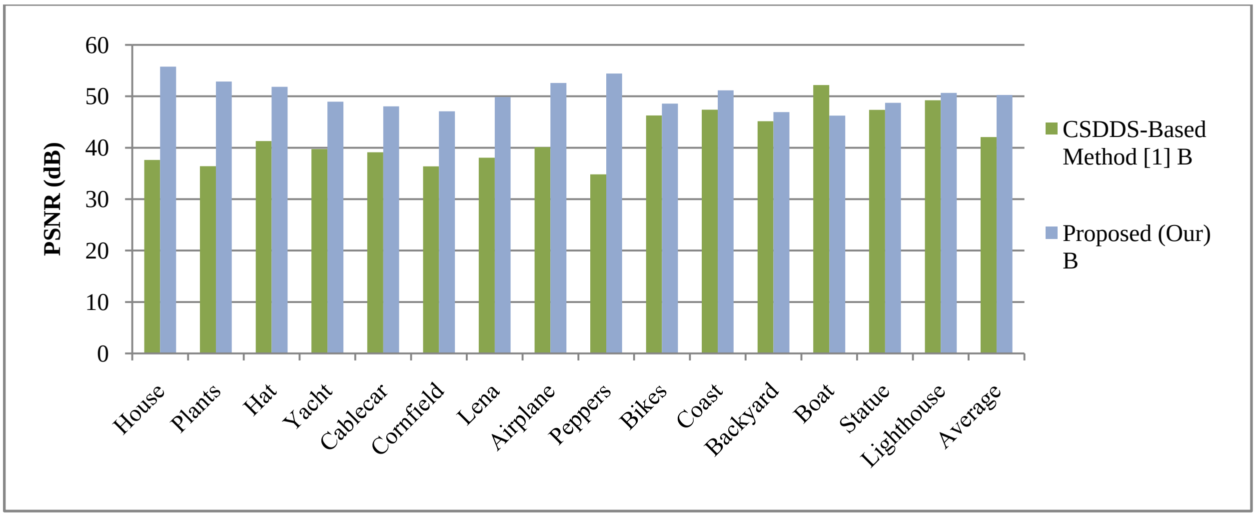

Fig.4.5 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of BLUE Layer for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

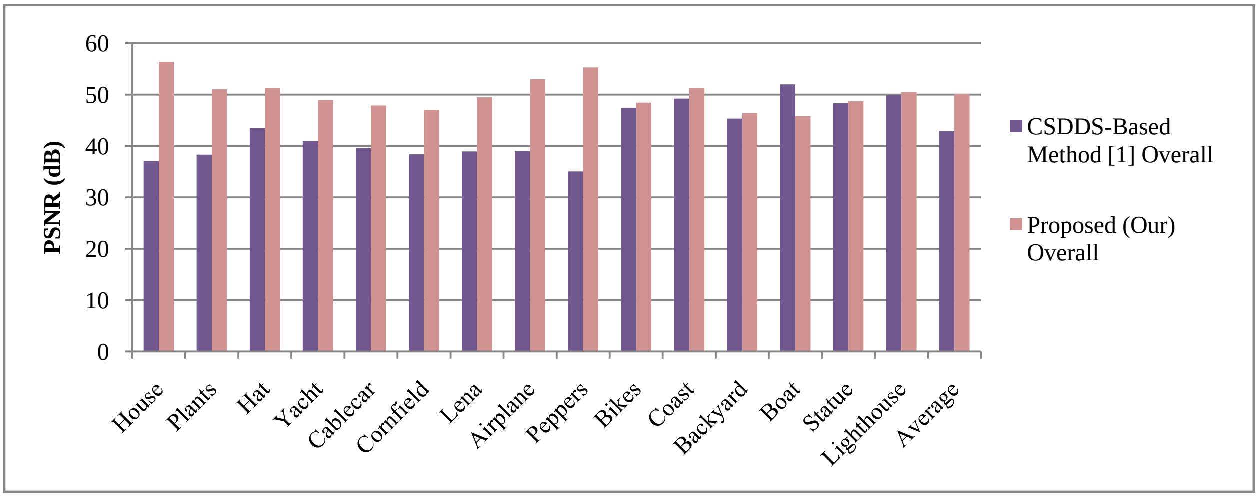

Fig.4.6 Peak Signal to Noise Ratio Comparison of Previous [1] and Proposed (our) Method of Overall RGB Image for House, Plants, Hat, Yacht, Cablecar, Cornfield, Lena, Airplane, Peppers, Bikes, Coast, Backyard, Boat, Statue and Lighthouse Images Respectively.

Fig.4.4 shows 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 shows 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.

Fig.4.6 shows 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.

V. CONCLUSION AND FUTURE SCOPE

In this research work an adaptive frequency domain block processing for color image compression algorithm has proposed. The analysis of proposed Image compression technique for different images is done based on parameters, mean square error (MSE) and peak signal to noise ratio (PSNR). DCT based standard JPEG images utilizes blocks of image, yet there are still correlation exits crosswise over blocks. Block boundaries are discernible in some cases. Blocking artifacts can be seen at low bit rates. The result in this examination provides a strong foundation for future work for the hardware design. All of the analysis presented in this research work involved exhaustive simulations. The algorithm can be realized in hardware implementation as a future work. It can also be a good option for the image processor of the wireless capsule endoscopic system. The research work has been analyzed for high compression ratio

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