AN EFFICIENT SUPER RESOLUTION TECHNIQUE FOR LOSS LESS COMPRESSED BAYER COLOUR FILTER ARRAY IMAGES

K.Chiranjeevi[1] U.V. Ratna Kumari[2]
Prabhakar.Telagarapu[3]

[2]Department. of .ECE,University College of Engineering, J.N.T.U.Kakinada, AP, India.
[1,3]Department. of .ECE, GMR Institute of Technology, Rajam, Srikakulam District,AP, India.

Abstract

In digital cameras, Bayer color filter array(CFA) images are captured and demosaicing is carried out before compression. Recently, it was found that compression-first schemes outperform the conventional demosaicing-first schemes in terms of output image quality. An efficient prediction-based lossless compression and super-resolution schemes are proposed in this paper. Compressed image is coded with rice code. The proposed compression and super resolution schemes can achieve a better compression and high image quality than conventional lossless CFA image coding schemes.

Keywords: Bayer color filter array(CFA), demosaicing, lossless compression, image coding schemes

1. Introduction

Data compression is the process of converting data files into smaller files for efficiency of storage and transmission. As one of the enabling technologies of the multimedia revolution, data compression is a key to rapid progress being made in information technology. It would not be practical to put images, audio, and video alone on websites without compression. Now let us elucidate the concept of image compression and the necessity of it. Many people might have heard of JPEG (Joint Photographic Experts Group) and MPEG (Moving Pictures Experts Group), which are standards for representing images and video. Data compression algorithms are used in those standards to reduce the number of bits required to represent an image or a video sequence. Compression is the process of representing information in a compact form. Data compression treats information in digital form that is, as binary numbers represented by bytes of data with very large data sets. Fox example, a single small 4″ × 4″ size color picture, scanned at 300 dots per inch (dpi) with 24 bits/pixel of true color, will produce a file containing more than 4 megabytes of data. At least three floppy disks are required to store such a picture. This picture requires more than one minute for transmission by a typical transmission line (64k bit/second ISDN). That is why large image files remain a major bottleneck in a distributed environment. Although increasing the bandwidth is a possible solution, the relatively high cost makes this less attractive. Therefore, compression is a necessary and essential method for creating image files with manageable and transmittable sizes. In order to be useful, a compression algorithm has a corresponding decompression algorithm that, given the compressed file, reproduces the original file. There have been many types of compression algorithms developed. These algorithms fall into two broad types, lossless algorithms and lossy algorithms. A lossless algorithm reproduces the original exactly. A lossy algorithm, as its name implies, loses some data. Data loss may be unacceptable in many applications. For example, text compression must be lossless because a very small difference can result in statements with totally different meanings. There are also many situations where loss may be either unnoticeable or acceptable. In image compression, for example, the exact reconstructed value of each sample of the image is not necessary. Depending on the quality required of the reconstructed image, varying amounts of loss of information can be accepted.

2. Implementation Approach

In this chapter, we have developed the algorithms and the corresponding Flow Charts for various intermediate functions which help in obtaining the super resolution image from a low resolution image. We have also developed a Matlab coding for these intermediate functions to estimates the shift and rotation angles, and is used for obtaining the demosaicked image, Pg algorithm, which is developed for obtaining the output image after obtaining the P-G Algorithm which is used for obtaining the final super resolution output image from a low resolution image. For the implementation of the proposed approach a mat lab implementation were made and the performances were evaluated. The system architecture used for the implementation is as shown in Fig 2.1.

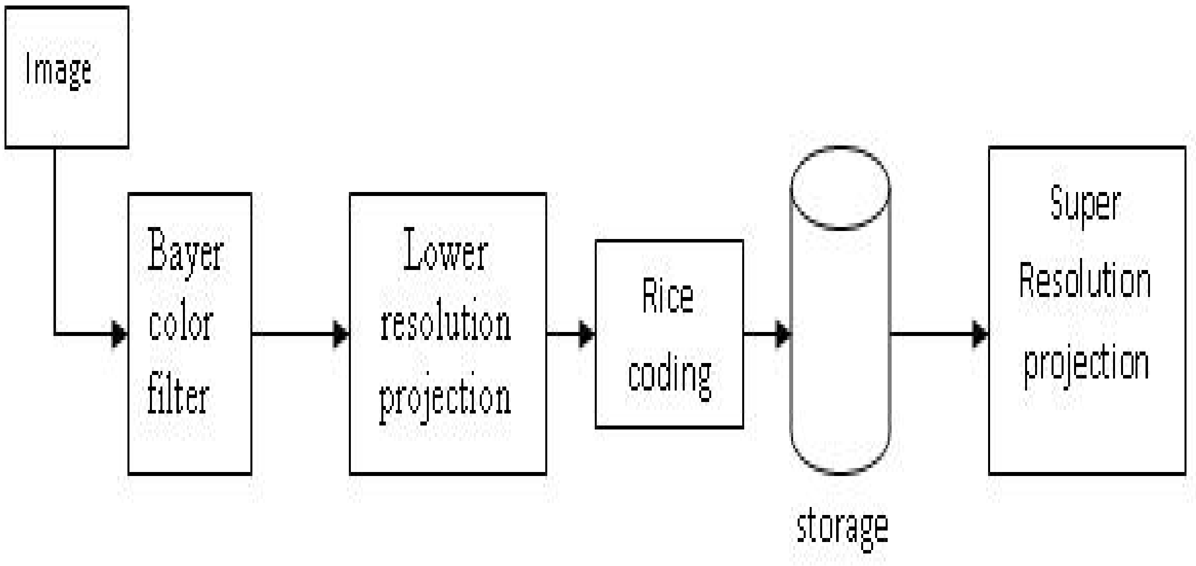

Figure 2.1 System block diagram

The implementation approach for the compression of image data for lossless image compression saved in lower resolution and are retrieved with super resolution.

The operation algorithm for estimating the shift and rotation angles is as given below .

i)Evaluate the length of input data.

ii)Define the size of the central aliasing free part for given data.

iii)Read the input image data.

iv)Calculate the Fourier Transform (FFT) of the reference image.

v)Calculate the Fourier Transform (FFT) of the registered image.

vi)Calculate the average pixel value of reference image.

vii)Calculate the normalized FFT value for each pixel.

viii)Compute the beginning and ending Coefficient locations (x,y) to extract the central frequency region.

ix)Extract the (x,y) pixel values from this obtained location.

The corresponding Flow Chart for estimating the shift and rotation angles is given below.

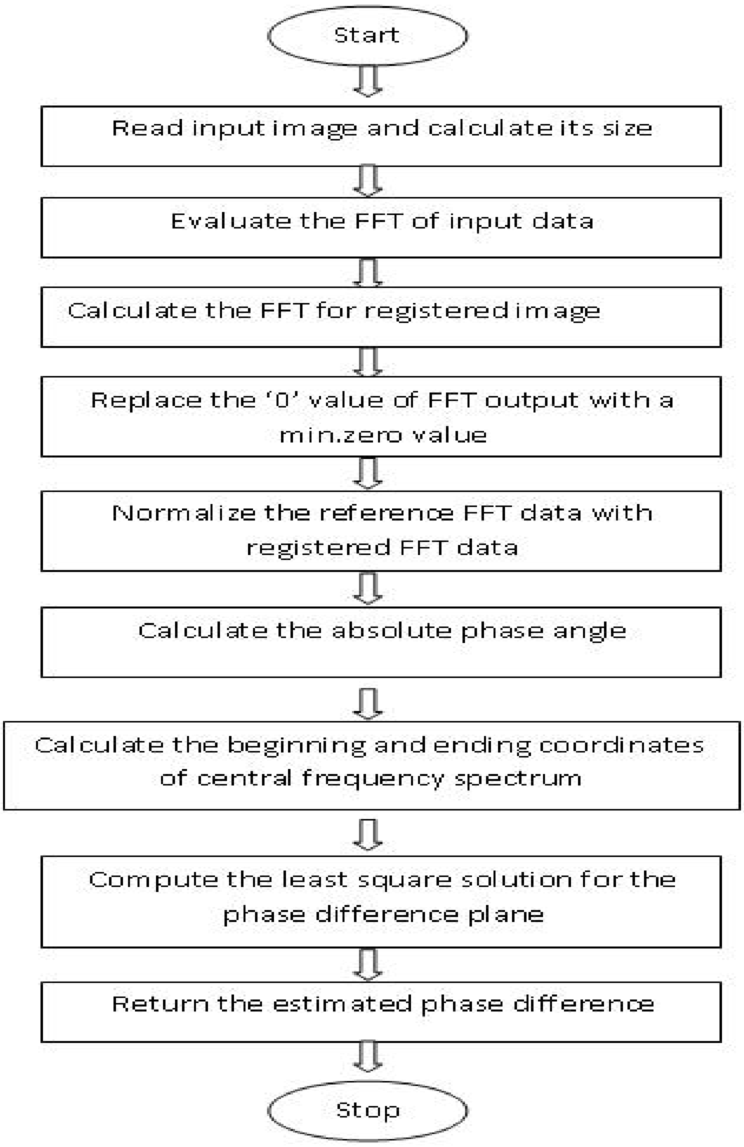

Fig 2.2 operational flow chart for estimation algorithm

The algorithm for obtaining the demosaicked image is described below.

i)Read input data and compute the dimension of the image

ii)Initialize the x and y value for rows and column.

iii)Compute the shifting of x and z plane over y-plane.

iv)For the computed phase shift variation, rotate the pixel coordinates and increment the pixel location.

v)Repeat the shifting operation of pixel coordinates until the image coefficients reaches the last comparison.

The Flow Chart for obtaining the demosaicked image is described below.

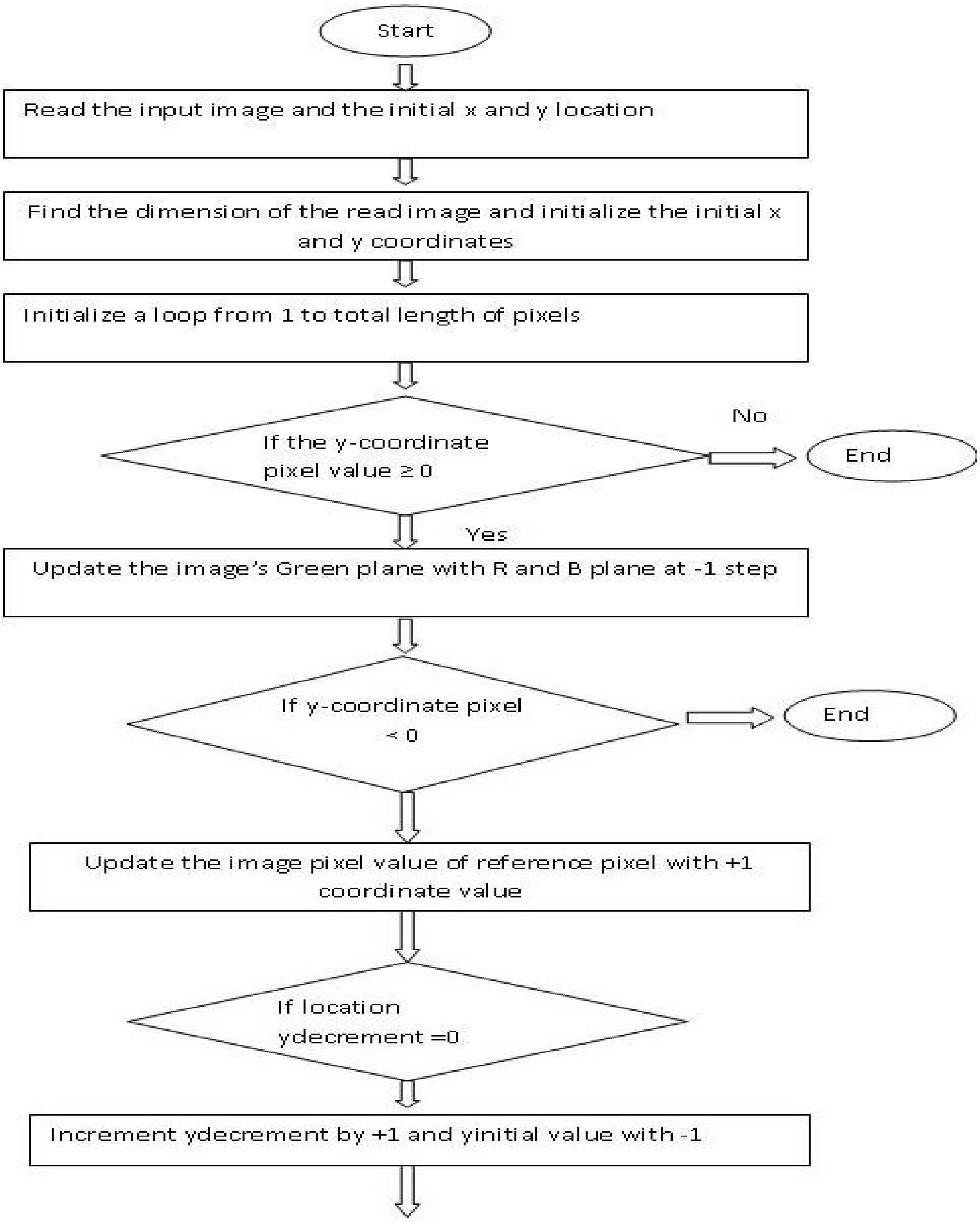

Fig.3: PG Algorithm

This function develops PG-algorithm for the projection of the given image into higher resolution. The data is projected onto a grid plane and regenerated using grid alignment of the pixels to generate super-resolution image. This algorithm takes the known values of the pixels and estimates the unknown pixel coefficients by interpolation and projects these values onto high resolution grid.

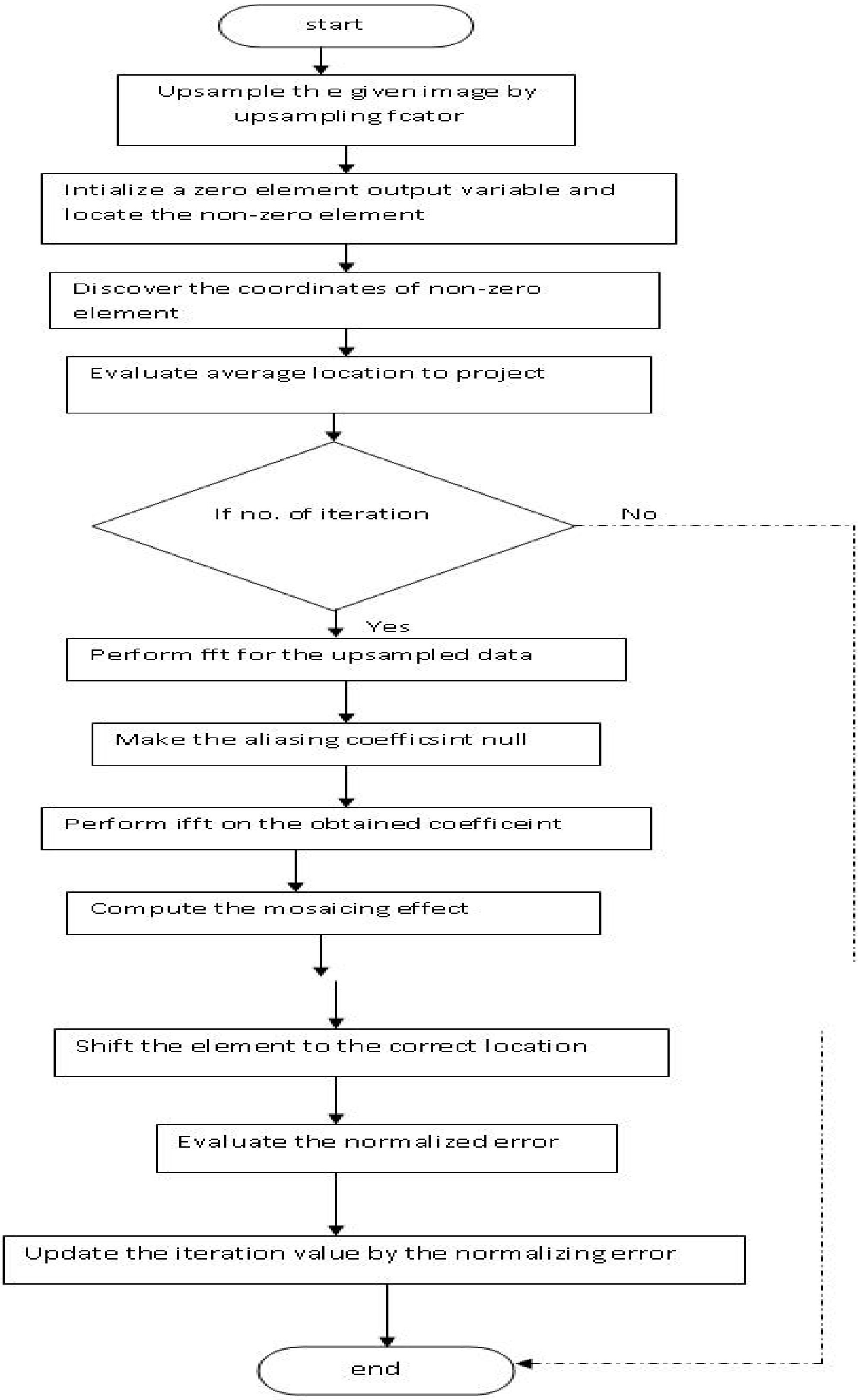

Figure 4: operational flow chart for the implemented PG algorithm

we have developed the algorithms and the corresponding Flow Charts for various intermediate functions which help in obtaining the super resolution image from a low resolution image. We have developed a Matlab coding for these intermediate functions and super resolution technique.

3. Results

This section describes the experimental setup and the results obtained by using the above algorithm on bunch of images. The PSNR could have been calculated, but all we care about is how the HR looks visually. It was pretty clear from the results that SR had an edge over any conventional method, so calculation of PSNR or MSE or Normalized Cross Correlation(NCC) would show that the performance of this project is satisfactory when compared to the conventional methods. Quantitatively, we are presenting here the application of our project to three sets of pre- existing images. Experiments are performed on various captured images to verify the proposed method. These images are represented by 8 bits/pixel with a lower resolution. An often-used global objective quality measure is the mean square error (MSE) defined as

$$MSE = \frac{1}{(n)(m)}\sum_{i=1}^{n}\sum_{j=1}^{m}[Xij - Xij']$$ …(3.1)

Where, $n \times m$ is the number of total pixels. X_{ij} and X'_{ij} are the pixel values in the original and reconstructed image respectively. The peak to peak signal to noise ratio (*PSNR* in dB) is calculated as

PSNR = 10 log (255^2/MSE)……………….. (3.2)

Where usable grey level values range from 0 to 255.The other metric used to test the quality of the reconstructed image is Normalized Cross Correlation (*NCC*). It is defined as,

$$NCC = \frac{\sum_i\sum_j\left(X_{ij}-\bar{X}\right)\left(X'_{ij}-\bar{X'}\right)}{\sqrt{\left[\sum_i\sum_j\left(X_{ij}-\bar{X}\right)^2\right]\left[\sum_i\sum_j\left(X'_{ij}-\bar{X'}\right)^2\right]}}$$ -(3.3)

where, X indicates the mean of the original image and X' indicates the mean of the reconstructed image. For quantitative results, we have considered three pre-existing images lena.bmp, barbara.bmp and skoda.jpg. For the considered images , the PSNR and NCC values obtained are,

a) lena.bmp (8bit/pixel, gray scale, 67x71 size)

Figure.5 .lena.bmp

The obtained PSNR = 48.97 and the NCC obtained is 0.867

b) For ‘Barbara.bmp’ (8 bit/pixel, colored, 63x76 size)

Figure.6. Barbara.bmp

The obtained PSNR = 52.38 and the NCC obtained is 0.91

c) For the colored image ‘skoda.jpg’ 24bit/pixel , of size 64x64

Figure.7..skoda.jpg.

The obtained PSNR = 51.33 and the NCC obtained is 0.8947.

Generally the PSNR of a conventional algorithm or method ranges between 20Db and 40 Db. But, using super resolution method, we produced a PSNR greater than the conventional methods of image compression. The following are the results produced when we apply our method of image compression to the image skoda.jpg. We can clearly observe the quality of the content of the original input image and output image with high resolution.

These results are quantitatively. In qualitative treatment, we carry two sets of experiments i.e on Synthetic images and real images.

1. Synthetic images – In this experiment, one high-res image was taken, it was randomly shifted to create 4 images. These images were then down-sampled (without low-pass filtering).
The four down-sampled images were fed in the algorithm.
Three different experiments were performed to test not only the common case but also boundary cases.
Common case includes when the various low-res images have some redundant and some non-redundant information among them.
Boundary cases involve low-res images that either have only redundant or no redundant information among them.

2. Real images – Four images were taken with the camera and SR algorithm was applied to create one HR image.

Figure 8: Original image

jpeg image of (256X256) image resolution, 24 bit depth, RGB colored

These are the results of our image compression method

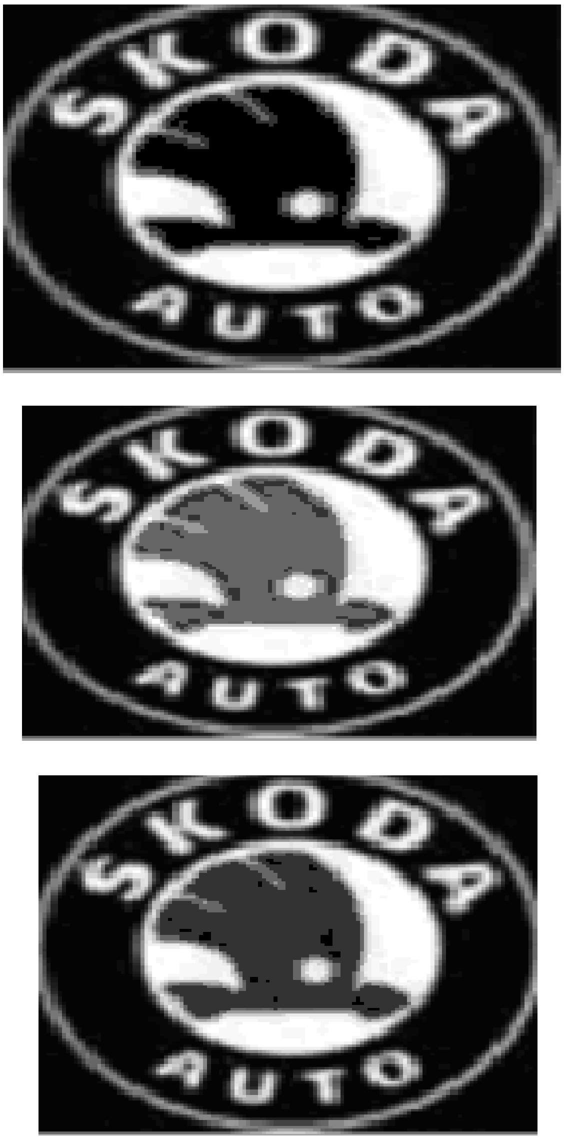

Figure.9: RGB project image coefficient in there respective color plane

Fig.10:Compressed low resolution image

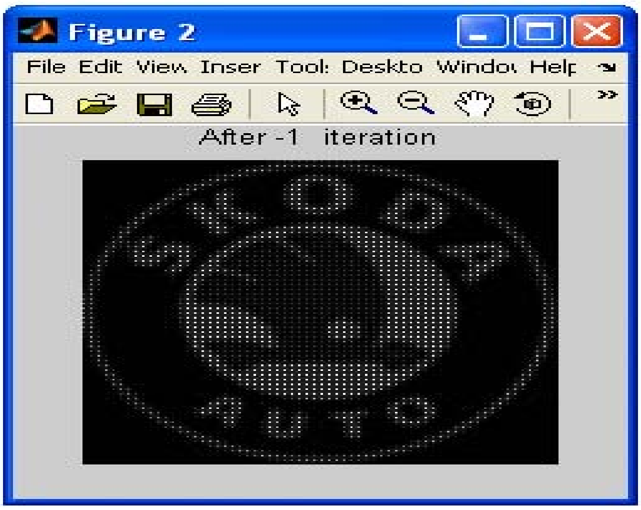

Fig.11:Output image after1st iteration.

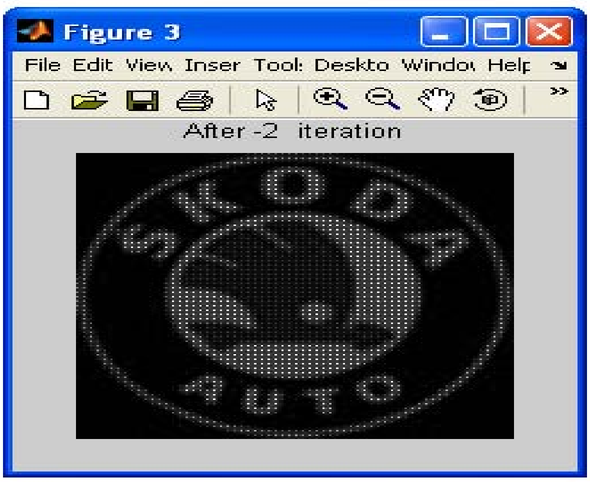

Fig.12:Output image after 2nd iteration

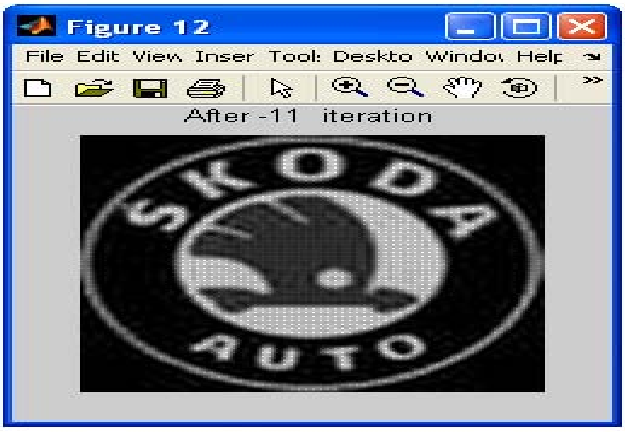

Fig.13:Output image after 3rd iteration

Fig.14:after 11th iteration

7. Conclusion

This paper was focused for the realization of a higher visual quality image representation with high compression and representation for color image cameras. The color image capturing devices are often used to capture high-resolution data and require very high memory space for the storage. The issue of storing these high-resolution data in lower storage space was focused in this work. For the implementation of this application a higher resolution image was taken and is passed through Bayer filter arrays for color projections. These projections are then compressed using lower resolution representation and the conventional rice coding. It is observed that the low-resolution data were compressed up to 3 times from the original dimension with good visual quality. For the implementation of the super resolution projection the image is processed with mosaicing effect, registration, and a PG algorithm was developed for the image projection in higher resolution. The qualitative analysis were performed on various images and the obtained PSNR and NCC values were observed to be satisfactorily. From all the observation made it could be concluded that a high visual quality compression algorithm for colour image compression is developed with minimum complexity and higher accuracy. This paper doesn't focus on the external effects on the captured image. The work could further be extended with various noise effects on the captured image with various image filtration techniques for obtaining further image quality improvement. The work could also be tested for other image application such as astronomical applications, medical application etc. where visual quality is a prime importance.

References

[1] S.M.Park, M.K.Park, M.G.Kang, Super-Resolution Image Construction: A Technical Overview, IEEE signal processing magazine 2003

[2] P. Vandewalle, S. Süsstrunk, M. Vetterli, Superresolution images reconstructed from aliased images, Proc. SPIE/IS&T Visual Communications and Image Processing Conference, July 2003, Vol. 5150, p. 1398-1405, Lugano, Switzerland.

[3] P. Vandewalle, S. Süsstrunk and M. Vetterli, Double resolution from a set of aliased images, accepted to Proc. IS&T/SPIE Electronic Imaging 2004: Sensors and Camera Systems for Scientific, Industrial, and Digital Photography Applications V, January 2004, Vol. 5301.

[4] Z. Jiang, T.T. Wong and H. Bao. Practical Super-Resolution from Dynamic Video Sequences. In Proceedings of IEEE Computer Vision and Pattern Recognition 2003 (CVPR 2003), Vol.2. Pages 549~554, Madison, Wisconsin, USA, June 16~22, 2003.

[5] Papoulis, A New Algorithm in Spectral Analysis and Band-Limited Extrapolation, IEEE Transactions on Circuits and Systems 22(9), pp. 735-742, 1975

[6] R.W. Gerchberg, Super-resolution through error energy reduction, Optica Acta 21(9), pp. 709-720, 1974

[7] K. Hirakawa and T.W. Parks, “Adaptive homogeneity-directed demosaicing algorithm,” IEEE Trans. Image Processing, vol. 14, no. 3, pp. 360–369, March 2005.

[8] S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, “Advances and challenges in super-resolution,” IEEE Trans. Image Processing, vol. 15, no. 1, pp. 141–159, January 2006.

[9] S. C. Park, M. K. Park, and M. G. Kang, “Super-resolution image reconstruction, “A technical overview,” IEEE Signal Processing Magazine, vol. 20, no. 3, pp. 21–36, May 2003.

[10] R. Y. Tsai and T. S. Huang, Multiframe Image Restoration and Registration, In: Advances in Computer Vision and Image Processing, ed. T.S.Huang. Greenwich, CT, JAI Press, 1984.

[11] S. P. Kim, N. K. Bose, and H. M. Valenzuela, “Recursive reconstruction of high resolution image from noisy undersampled multiframes,” IEEE Trans. Acoust. Speech Sign. Proc., vol. 38, pp. 1013–1027, June 1990.

[12] S.H. Rhee and M.G. Kang, “Discrete cosine transform based regularized highresolution image reconstruction algorithm,” Optical Engineering, vol. 38, no. 8, pp. 1348–1356, April 1999.

[13] M. Irani and S. Peleg, “Improving resolution by image registration,” CVGIP: Graphical Models and Image Processing, vol. 53, pp. 231–239, May 1991.

[14] B. C. Tom and A. K. Katsaggelos, “Reconstruction of a high resolution image by simultaneous registration, restoration, and interpolation of low-resolution images,” in Proc. IEEE Int. Conf. Image Processing, October 1995, vol. 2, pp. 539–542.

[15] H. Stark and P. Oskoui, “High-resolution image recovery from image-plane arrays, using convex projections,” J. of the Optical Society of America, vol. 6, no. 11, pp. 1715–1726, 1989.

K.Chiranjeevi received B.E Electronics and Communication Engineering from J.N.T.U. Anantapur, and M.Tech Instrumentation and Control from JNTU Kakinada, He is working as Asst. Professor in GMR Institute of Technology. His research interests are in Signal Processing and Image Processing.

T.Prabhakar received M.Tech degree from Jawarlal Nehru Technological University Kakinada, Andhra Pradesh, India. B.Tech degree in Electronics and Communication Engineering from SIR C.R.Reddy College of Engineering, Eluru, Andhra Pradesh, India. He is presently working as Senior. Assistant Professor in the Department. of Electronics and Communication Engineering at GMR Institute of Technology. Prior to join in this Institute he worked as a Service Engineer in Machine Diagnostics and Deployed to work at National Remote Sensing agency, Department. of. Space, Hyderabad for 1 year 1 month and Trainee Programmer in Indo Tech Computers, for 8 months in Hyderabad. Having Total experience is 12 years out of which 10 years in Teaching (GMRIT) and 2 Years in Industry. His research interests are Communication, Signal Processing and Image Processing. He has published 9 technical papers in various International journals and conferences. He is a life member of ISTE Since 2002.