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Development to Improve the Image Quality by Super Resolution Representation of Low Resolved Image.

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Abstract:- Image compression remains a pure research objective in image processing from the evaluation of imaging applications. Various image compression algorithms were suggested in past with the objective of higher compression or better accuracy or both with regard to achieving compression for better accuracy. Where lossy schemes were proposed for compression architecture with high data rate, they compromise with obtained error limit. System where accuracy is prime factor lossy compression schemes cannot be used and demands for a lossless compression scheme.

Various compression schemes were proposed in past for the achievement of data compression in lossless manner for both colored and gray scale images. In case of a practical image compression the image is captured from the camera and passed to the coding architecture before storage. The image information saved, are pixels represented in lower resolution so as to acquire lower memory dimension. When retrieving the image data this information's are to be regenerated on to higher resolution for accurate representation.

Presentation of the colored pixel information in higher resolution generated from a lower resolution provides a lower visual quality. In this paper we focus on the development of an approach to improve the image quality by super resolution representation of low resolved image. To valuate the work we develop it on Matlab tool and test on various images.

Keywords:- air pixel, Matlab

I. 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.

II. PROBLEM STATEMENT

Where various compression algorithms were developed for the compression of image in lossy or lossless very few approaches were made to compress the data retaining the quality nature of the image in real time cameras. The representation of the color image coefficient and its compression as well as it representation is the major problem in today's current image capturing and compression in camera technology. The issue of higher resolution image capturing for clarity and storage at lower resolution for compression is transforming the image where the pixel values lost it's originality and resulting poorer regeneration.

Objectives:

In this paper main focus is towards the development of an image representation for loseless compression and reproduction at higher level representation using a super resolution algorithm. The concept of super resolution approach over real time camera information contained from color sensor in color image capturing cameras is the main objective of this project work. The development of such an algorithm is focused with minimum computational complexity and better visual quality representation with good compressed representation.

Literature Review:

In recent years, there has been a vivid interest in compression of "electronic" or digital image data. In particular, image compression is considered very useful in multimedia applications and in distributed information systems that operate in network environments. Especially, lossless compression is very useful for medical images, where loss of information is forbidden. Our main interest belongs to the lossless case, where image do not reduce any information in compressed representation.

However, the vast majority research and development in image compression area is focused on lossy compression. It is agreed upon of fact that by allowing a small amount of distortion in the reconstructed picture one can obtain much better compression than is possible for lossless coding. From information theory it is known principle about tradeoff between the compression performance and the amount of distortion in the restored picture. Such tradeoff was formalized in rate-distortion theory of Shannon. In such case lossless compression can only provide moderate compression performance. To achieve better compression rather to code the data in image coding algorithms such as entropy coding or lifting coding scheme, a approach of image representation for lower the pixel representation without transforming the image coefficient were focused in recent years. The concept of image representation has recent come up in the area of image representation in super resolution approach presented in [1]. From the development of this algorithm various approaches were made for the compressed image storage and higher resolution representation were made. In such an approach in [2] P. Vandewalle, S. Süsstrunk, M. Vetterli in their paper presented and approach of representing image in higher resolution for better visual quality for aliased images. In [3] they presented a method of presenting image in higher resolution with double resolution representation. In [4] the image representation with super resolution for video sequencing was proposed by Z. Jiang, T.T. Wong and H. Bao. Though various approaches were made towards the representation of image in lower resolution such approach is yet not been focused on merging the image representation with digital color cameras. Digital cameras were used to capture high resolution images to maintain the visual quality of images, but this higher resolution image may require large memory to store these pixel. A lower resolution representation of these pixel may reduce the memory requirement but may loose the image information. In this work we focus on the image compression approach by reducing the image representation approach at lower resolution and reproducing it in higher resolution is developed for camera sensor data.

III. EXPERIMENTAL WORK

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

$$MSE = \frac{1}{(n)(m)} \sum_{i=1}^{n} \sum_{j=1}^{m} [Xij - Xij'] \qquad \text{……………..} \qquad (1.1)$$

Where, n×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 (2552/MSE)………… (1.2)

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,

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

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.1.1.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.1.2.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.1.3.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 tabulated below.

Name of the image	PSNR by proposed method	PSNR by conventional method	NCC by proposed method	NCC by conventional method
Lena.bmp	48.97	20db-40db	.867	Around 0.75
Barbara.bmp	52.38	20db-40db	.91	Around 0.75
Skoda.jpg	51.33	20db-40db	0.8974	Around 0.75

[**Table.1.1**.Comparison of PSNR and NCC using super resolution approach and by a conventional method.]

These are the results of our image compression method 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.

Simulation results:

Figure 1.4: Original image jpeg image of (256X256) image resolution, 24 bit depth, RGB colored

Figure 1.5: RGB project image coefficient in there respective color plane

Figure1.6: compressed low resolution image

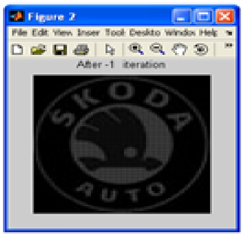

Figure1.7 Output image after1st iteration.

Figure1.7 (b) Output image after 2nd iteration

Figure1.7(c) Output image after 3rd iteration

Figure1.7 (d) Output image after 4th iteration

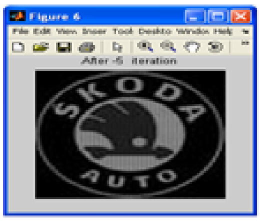

Figure 1.7 (e) Output image after 5th iteration

Figure1.7 (f) Output image after 6th iteration

Figure.6.7 (g) Output image after 7th iteration

Figure1.7 (h) Output image after 8thiteration

Figure6.7 (i) Output image after 9th iteration

Figure1.7 (j) Output image Output image after 10th iteration

Figure1.7 (k) Output image after 11th iteration

The above figure shows the implemented system result obtained after each intermediate iteration. It could be observed that the image projected from lower resolution to higher resolution get clearer and clearer with every iteration and for about 11 iteration the image is completely observed to be recovered with no visual quality reduction. A low resolved image with 40 X 40 image resolutions is transformed to 320 x 320 resolution. A similar evaluation was also carried out for other images and their computed NCC and PSNR value is presented in previous sections.

IV. CONCLUSION

This paper is 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 was 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 color image compression is developed with minimum complexity and higher accuracy.

This work 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.

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