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COMPARATIVE STUDY OF ITERATIVE BACK PROJECTION AND DISCRETE ALGEBRAIC RECONSTRUCTION TECHNIQUE FOR RECONSTRUCTION OF LOW RESOLUTION IMAGES

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Abstract

This paper presents a comparison between Iterative Back Projection (IBP) and Discrete Algebraic Reconstruction Technique (DART). In this experiment, images were acquired using a digital camera of 5Mega Pixel (MP). A total of 50 images were used. The Images were degraded by introducing noise, blur and shift in angle. DART and IBP were used to reconstruct the degraded images which were converted to grey scale. The techniques were evaluated using Peak Signal to Noise Ratio and Mean Square Error. The average Peak Signal to Noise Ratio (PSNR) gotten for IBP is 82.425 and the average Mean Square Error (MSE) gotten for IBP is 0.00077 while the average PSNR obtained for DART is 71.7025 and the MSE obtained is 0.00479. The experimental results suggest that IBP performs better than DART in reconstructing low resolution images.

1.0 INTRODUCTION

Image processing is a method employed to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it [1]. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually image processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. Image processing can be done using analog or digital methods. Analog methods can be used for hard copies like printouts or photographs while digital processing technique helps in the manipulation of digital images by using computers [1]. Digital image processing is used to extract useful information from a given image of low quality. High resolution (HR) means that the pixel density within an image is high, and therefore an HR image can offer more details that may be critical in various applications like medical images which are very helpful for doctors to make correct diagnosis [2]. The field of image processing has grown considerably during the last few decades with improvements in size, speed and cost effectiveness of the digital computers. Since high-resolution images and videos are important in many applications such as astronomy, military monitor, medical diagnosis and remote sensing, super resolution (SR) reconstruction has a great significance in obtaining images with more detailed information [3].Super-resolution image reconstruction is a promising technique of digital imaging which attempts to reconstruct HR images by fusing the partial information contained within a number of under sampled low-resolution (LR) images of that scene during the image reconstruction process [4]. Super-resolution image reconstruction involves up-sampling of under-sampled images thereby filtering out distortions such as noise and blur. In comparison to various image enhancement techniques, super-resolution image reconstruction technique not only improves the quality of under-sampled, low-resolution images by increasing their spatial resolution but also attempts to filter out distortions [4]. Different techniques are available for the reconstruction of low resolution images but for the purpose of this experiment, IBP and DART are considered because they both achieve a resolved image in an iterative manner. Discrete Algebraic Reconstruction Technique (DART) stems from discrete tomography (DT), which is concerned with the problem of recovering images from their projections, where the images are assumed to consist of a small number (2 to 5) of gray values only [5]. If the set of gray levels is known or estimated in advance, this prior knowledge can be exploited by the DT reconstruction algorithm.

Iterative Back Projection (IBP) based reconstruction is an inversion problem using the gradient descent method to find a solution. Since inverse problems are ill-posed problems, they need regularization or optimization of the solution [6]. The IBP technique is an ill-conditioned linear algebraic problem which resembles an undetermined system with never unique solution, hence can be solved using multi-objective optimization algorithms [7].

1.1 Iterative Back PROJECTION (IBP)

IBP technique was first proposed by Irani *and* Peleg [8], it can attain the High Resolution image interpolation and de-blurring simultaneously, while its motto is that the reconstructed HR image from the degraded Low Resolution image should produce the same observed LR image if passing it through the same blurring and down-sampling process. The IBP technique can minimize the reconstruction error by iteratively back-projecting the reconstruction error into the reconstructed image. IBP is a classical SR method with low computational complexity that can be applied in real time applications [9]. Figure 1 shows a pictorial representation of IBP which shows that with the help of an estimate of the reconstructed HR image and a model of the imaging process, a set of simulated LR images can be generated. Each simulated LR image is compared with the actual version and then the error can be used for correcting the estimated image. This method uses multiple simulated LR image of similar scene to find corresponding HR image [10].

This technique is very easy to understand but SR reconstruction is not unique due to ill posed nature of inverse problem. It should be noted that the selection of back-projection matrix affects the resolution. The original back-projection method is suffering from chessboard effect or ringing effect, especially at edges [11].

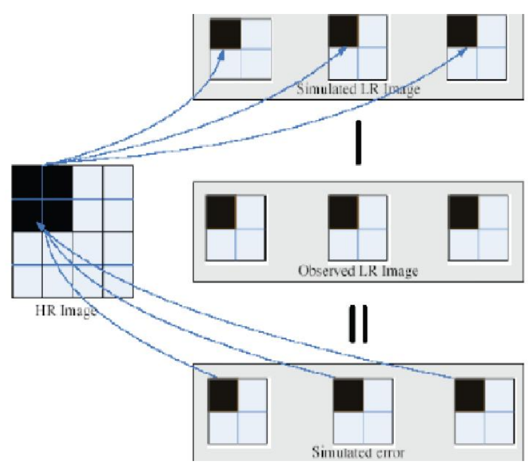

Fig. 1. A representation of IBP.

2.0 Discrete Algebraic Reconstruction Technique (DART)

Discrete algebraic reconstruction stems from discrete tomography (DT), which is concerned with the problem of recovering images from their projections, where the images are assumed to consist of a small number (2 to 5) of gray values only [5]. Potential benefits of DT are an increase of the reconstruction quality and a reduction of the required number of projection images. The DT reconstruction problem, however, is generally under determined and the number of possible solutions can be substantial. To guide the reconstruction process toward an optimal as well as intuitive solution, the DART algorithm was proposed [5]. The basic algorithm of DART according to [12]:

Compute a start reconstruction x^0 using ARM;
$t := 0$;
While (stop criterion is met) do
begin
$t := t + 1$;
Compute the segmented image $s^t = r(x^{t-1})$;
Compute the set B^t of boundary and I^t of non-boundary pixels of s^t;
Compute the image y^t from x^{t-1} and s^t, setting
$y_i^t := s_i^t$ if $i \in I^t$ and $y_i^t := x_i^{t-1}$ otherwise;
Using y as the start solution, compute the ARM reconstruction x^t,
while keeping the pixels in I^t fixed;
Apply a smoothing operation to the pixels that are in B^t;
End

Expressively, in each DART iteration, non-boundary pixels are assigned a given gray level in the prior known set of gray levels [12]. B as the boundary of the object in the thresholded image, which is defined as the set of all pixels that are adjacent to at least one pixel having a different gray level and I which denotes the remaining set of pixels such that all pixels in I are assigned their thresholded value. Then, idea of DART is to exclude the pixels in I from the regular Algebraic Reconstruction Method (ARM) iterations and, hence, only update the boundary pixels [12].

That is, several ARM iterations are performed on the pixels in B only. In this way, the number of variables in the linear equation system is significantly reduced, while the number of equations remains the same. In each iteration, the boundary pixels are allowed to vary independently, which may result in large local variations of the pixel values. To regularize the reconstruction algorithm, the boundary pixels are locally smoothed after applying ARM iteration on B. Subsequently, the resulting image is again put in threshold, a new set of boundary pixels B is determined, and the next ARM iteration is run on the pixels in B. These steps are iterated until a certain convergence criterion is met [13].

3.0 RELATED WORKS

High resolution (HR) images are very useful in different areas of life and are very applicable in areas like security, health o mention a few. Various researchers have explored the area of super resolution over the years using various methods.

Lin [14] developed an iterative back projection super resolution algorithm for low resolution image up-sampling. A super resolution (SR) algorithm based on an iterative back project interpolation was proposed to obtain more reliable information in the edge area. For evaluation of the performance, the PSNR and the SSIM criteria of the proposed algorithm were compared with those of other methods. The experimental results of 28.743 dB in average PSNR and the 0.9165 in average SSIM show the superiority of the method. Furthermore, the computational complexity of the algorithm is reduced while maintaining similar image quality. However, it is computationally complex while Fagbola [15] developed a pose illumination invariant feature extraction technique for low resolution video feeds. IBP-MAP was developed using edge and non-edge details in Maximum A Posterior (MAP) priors. Resulting reconstruction error was estimated, minimized and back-projected by Iterative Back Projection (IBP). LDA-LBP-GWT was developed by fusing the facial features of Linear Discriminant Analysis (LDA), Local Binary Pattern (LBP) and Gabor

Wavelet Transform (GWT) into a Single Feature Set (SFS). The SFS was optimized using particle swarm algorithm. The developed IBP-MAP technique produced PSNR of 33.77dB, ISNR of 11.82dB and NI of 34.00 and the developed LDA-LBP-GWT produced FA of 725, RA of 63.75%, RT of 103.65s and FR of 0.

Patel [16] addressed the problem of recovering a super resolved image from a single low resolution input. The technique is based on combining IBP method with the edge preserving Infinite Symmetrical Exponential Filter (ISEF). The method is applied on different type of images including face images, natural images and medical images; the performance was compared with a number of other algorithms, bilinear interpolation and nearest neighbor interpolation. The method showed marginal superiority to the existing method in terms of visual quality and PSNR. However, it is not reliable and efficient for highly degraded images when implemented in practice.

Zefreh *et al*. [5] developed a discrete algebraic reconstruction technique: a new approach for super resolution reconstruction of license plates. The researchers used DART to reconstruct a high resolution license plate from a set of low resolution camera images. The simulation and result shows that DART algorithm combines the efficiency of iterative algebraic methods from continuous tomography with the power of discrete algebraic reconstruction algorithm to compute an accurate HR image from a small number of LR images. However, one major drawback of DART is that it is less optimal.

Gompel *et al*. [13] developed a discrete tomography approach for super resolution micro-CT images: application to bone. The authors up-sampled the reconstruction grid combined with DART algorithm in which the scanned objects are assumed to be composed of homogeneous materials. Their results show that the method generates reconstructions with significantly more details compared to conventional reconstruction algorithms. However, the method still suffers from optimality because the method used is not highly optimal for super resolution reconstruction.

4.0 METHODOLOGY

The images used for this experiment were acquired using a digital camera of 5mega pixel (mp). A total of 50 images were used in the cause of this experiment. Images were acquired in (Joint Photographic Expert Group) JPEG formats. The images are kept in a file which was imported into the system one after the other as needed. Before the images are reconstructed, they are converted into grey scale. An example of the image used is presented in Figure 2.

Figure 2: A typical image used

The initial HR image was degraded by introducing blurring, warping and down-sampling to generate observed LR image using equation 1 [17];

$$y_k = AH_kC(S_k)x + n_k = B_k(s_k)x + n_k \qquad (1)$$

Noise was introduced to the degraded image by using equation 2 [18];

$$s_k = (\theta_k, c_k, d_k)^t \qquad (2)$$

where θ_k is the rotation angle, c_k and d_k are the horizontal and vertical translations of the kth HR image with respect to the reference image x, the effects of down-sampling, blurring and warping can be combined into a single $N \times PN$ system matrix B_k.

The performance metrics that will be used for the evaluation of the techniques are Peak Signal to

Noise Ratio (PSNR) and Mean Square Error (MSE).

MSE is defined as:

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\left\| f(i,j) - g(i.j)\right\|^{2} \quad (3)$$

Where m and n are the numbers of row and column in the input images respectively while g represents the matrix data of the degraded image and f is the matrix data of the original image.

PSNR is defined as:

$$PSNR = 10 \log_{10}\left(\frac{MAX}{MSE}\right) \quad (4)$$

where MAX is the maximum signal in the input image data type.

5.0 RESULTS AND DISCUSSION

The average of the evaluation results of SRR methods obtained from the 50 images presented in Table I. To evaluate the techniques used, Mean Square Error and Peak Signal to Noise ratio were used. The lower the mean square error, the better the technique. IBP produced an average PSNR of 83.801Db followed by DART which produced an average of 74.833Db. IBP produced an average MSE of 0.0009368 and DART produced an average of 0.001056. It is evident that IBP performs better than DART because the reconstruction error of IBP is lesser than that of DART. From the results, it is evident that IBP performs better than DART in PSNR and the error gotten is significantly low than that of DART which implies that IBP produces a better visual quality output than DART.

TABLE I. : AVERAGE OF PERFORMANCE EVALUATIONRESULTS OF THE SRR METHODS

SRR Methods	Performance Metrics	
	PSNR	*MSE*
IBP	83.801	0.0009368
DART	74.833	0.001056

6.0 CONCLUSION

Reconstructing images are very useful in various fields like medicine because HR images provide more details which are useful in these fields. This paper presented a comparative study of IBP and DART super resolution techniques to enhance low resolution images.

Further research can be done in the development of super resolution techniques by combining two or more techniques so that the strength of one will compensate for the weakness of another in order to get a more visual quality output image.

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