A Novel Feature Transform Based on Iterative Back Projection and Linear Regression for Super Resolution

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Abstract- *In this paper, Super resolution of an image is obtained by Iterative Back Projection and linear regressions. Multiple low resolution images are combined to create a high resolution image. Interpolation based super resolution, example based super resolution and multi image super resolution techniques are different super resolution approaches. These methods are used to achieve a best approximation of image information. In this paper, gradient based feature transform and regression process is used to improve an image quality. Principle Component Analysis and patch extraction is used for better resolution of an image. The performance of this method, which IS), improves quality (PSNR) and it is better than any other state-of-the-art method.*

Keywords- Iterative back projection, Gradient, PCA compression, Regression.

I. INTRODUCTION

The main purpose of an image super resolution is improving quality of low resolution image. Image resolution is used to show the detail an image holds. Resolutions depend on different pixel density is Low-Resolution (LR): Pixel density within an image is small, offering fewer details. High-Resolution (HR): Pixel density within an image is larger, offering more details. Super resolution (SR): Obtaining a HR image from one or multiple LR images.In example based image super resolution, low resolution and high resolution images correspondence are measured from a set of training image set. In multi image super resolution, several images from same scenery are selected. Each image will have different information about the same scenery. Patch redundancy in same scale is used to model multi image super resolution problem. Patch redundancy in same scale is used to model example based super resolution problem.

II. LITERATURE REVIEW

In this paper, fast and efficient regression-based super resolution is performed by using Iterative Back Projection algorithm and some techniques used to improve the resolution performance.

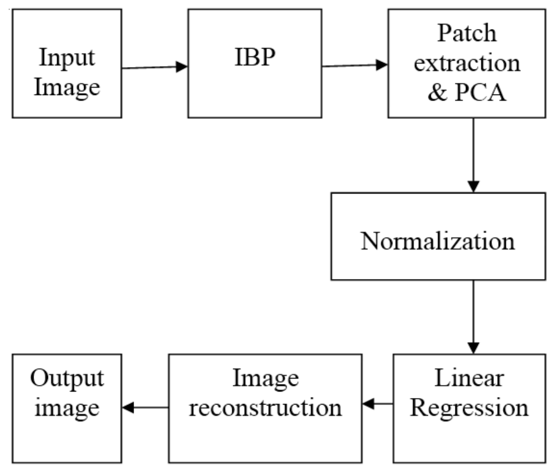

Figure 1. Block diagram of image super resolution

A. Input Image

Consider Low resolution image as an input image. It contains less details of an image that to be processed. From this low resolution image, number of low resolution images is simulated by changing the resolution property of an image.

B. Iterative Back Projection

The HR image is estimated by back projecting the difference between simulated LR images and the observed LR images.

$$X^{(1)} = X^{(0)} + X_e - X_H^{(0)}$$

Where,

$X^{(0)}$ - Initial interpolated image

X_e - Error correction

$X_H^{(0)}$ - Estimated image

Estimated HR image after n iterations,

$$X^{(n+1)} = X^{(n)} + X_e^{(n)} - X_H^{(n)}$$

C. Patch extraction & PCA compression

Patches are corresponding to corner or edge in the image. Patch match algorithm quickly finds correspondences between small square regions or patches of an image. The goal of the algorithm is to find the patch correspondence by defining a nearest-neighbor field. The algorithm can be used in various applications such as object removal from images, reshuffling or moving contents of images, or retargeting or changing aspect ratios of images. Patch becomes useful instead of working with the whole image. This will be useful for focusing small area of an image. Local patches often experience much less distortion than global images and therefore it becomes easier to define the similarity between two local patches. In patch extraction, image feature is extracted by using linear filter. PCA compression technique is used for dimension reduction of an image.

In PCA compression, the following steps are performed. Difference between image and mean of the image is taken for corrected image.

Image corrected by mean=Image - mean of image Covariance matrix is found by multiplying corrected image mean with transpose of corrected image mean.

covImage = Image corrected by mean × (Transpose of Image corrected by the mean)

Eigen vector and Eigen values are obtained for corresponding covariance matrix values.

vc = (av1, av2…..avn)

Final compression data is obtained by multiplying the transpose of eigen vector with transpose of difference between image and mean.

D. Normalisation

Normalisation is used to change the range of pixel intensity values. Normalization is also known as contrast stretching or histogram stretching. The linear normalization of a grayscale image is performed according to the formula

$$I_N = (I - Min)\frac{newMax - newMin}{Max - Min} + newMin$$

Where,

Min – Minimum value of image pixel

Max – Maximum value of image pixel

E. Linear Regression

Regression analysis is used to understand which among the independent variables are matched to the dependent variable and it is used to explore the forms of these relationships. Many techniques for processing regression analysis.

F. Image reconstruction

In image reconstruction, patches are overlapped and reconstructs the high resolution image to super resolution one. There are a number of different algorithms used to perform super-resolution reconstruction. These algorithms include non-uniform interpolation, frequency domain, deterministic and stochastic regularization, and projection onto convex sets, hybrid techniques, optical flow, and other approaches. Output super resolution image contains more details of an image and it has good quality.

III. RESULTS AND DISCUSSIONS

The original input image is low resolution image which contains very less details of an image. From low resolution image high resolution image is obtained by upscale the image using iterative back projection algorithm. Under some compression and regression process, the super resolute image is obtained as an output Take Low Resolution image.

Figure 2.

The above figure 2 shows an input low resolution image.

Figure 3.

The above figure shows some estimated low resolution images by changing its resolution. From low resolution image, some low resolution images are estimated. These images can be obtained by adjusting the resolution values of an input image.

Figure 4.

The above figure shows the high resolution image by iterative back projection. Iterative back projection is performed by using bicubic interpolation and gradient descent process. It produces high resolution image from low resolution image.

Figure 5.

The above figure shows gradient filtering of high resolution image. Gradient filtering is applied to interpolated image. An image gradient is a intensity directional change or colour in an image. Image gradients are used to extract information from images.

Figure 6.

The above figure shows the PCA compression output. Principle component analysis is obtained by using covariance matrix and Eigen vectors. PCA is used for image colour reduction. PCA takes best of eigenvectors properties for selected object orientation determination. PCA is defined as an orthogonal linear transformation in which the data is transformed into a new coordinate system such that the greatest variance comes to lie on the first coordinate called the first principal component then the second greatest variance on the second coordinate and so on.

Figure 7.

The above figure shows a super resolution image as an output image. It has more information of image compared to low resolution image. It has high quality of an image.

IV. CONCLUSION

The performance of super resolution is evaluated by calculating Peak Signal to Noise Ratio. The performance of proposed method is compared with the previous state of art methods. From the performance comparision table, this method has high PSNR value compared than other methods.

Table 1. Performance Comparision

Method	Scale	PSNR
Bicubic	2	32.79
CNN	2	33.49
SR	2	**35.01**

V. CONCLUSION

Super resolution algorithm developed in this paper is used to improve the peak signal to noise ratio and to properly recover the image details. The performance of proposed super resolution method is better compared with the previous state of art methods.

VI. ACKNOWLEDGEMENT

I would like to thank my guide Y.R.Packia Dhas, Associate Professor, Department of ECE, PET Engineering College.

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