EIGHT ADJACENT REGRESSION BASED IMAGE INTERPOLATION FOR HR IMAGES

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Abstract: **with bitmap graphics, as the size of an image is enlarged, the pixels that form the image become increasingly visible, making the image appear "soft" if pixels are averaged, or jagged if not. Image interpolation methods however, often suffer from high computational costs and unnatural texture interpolation. Image interpolation, which is based on an autoregressive model, has achieved significant improvements compared with the traditional algorithm with respect to image reconstruction, including a better peak signal-to-noise ratio (PSNR) and improved subjective visual quality of the reconstructed image. However, the time-consuming computation involved has become a bottleneck in those autoregressive algorithms. The main purpose of this work is to provide recursive algorithms for the computation of the Newton interpolation polynomial of a given two-variable function.**

Keywords: **Newton bivariate interpolation Terms—Image interpolation, autoregressive model, parallel optimization**

I-INTRODUCTION

Image interpolation becomes pre-processing step in order to other image processing tasks like image registrations, image rotation. Image registration needs interpolation to accurately register image at sub-pixel level. Interpolation techniques are mainly divided in two categories:

- Non-adaptive techniques
- Adaptive techniques

Non-adaptive interpolation techniques are based on direct manipulation on pixels instead for considering any statistical feature or content for an image. These are kernel based interpolation techniques where unknown pixel values are found by convolving with kernel. Hence they follow same pattern for calculation in order to all pixels. Moreover most for them are easy to perform and have less calculation cost. Various non-adaptive techniques are nearest neighbor, bilinear, bicubic, etc.
Adaptive techniques consider image feature like intensity value, edge information, texture, etc. Non-adaptive interpolation techniques have problems for blurring edges or artifacts around edges and only store low frequency components for original image. in order to better visual quality, image must have to preserve high frequency components and this job can be possible with adaptive interpolation techniques. Various adaptive techniques exists in order to image interpolation NEDI, DDT, ICBI, etc.
The interpolation is a method for enhancing image resolution means enhancing pixel data, here need to guess new value between available pixels problem is that guessing what should be value for new pixel which will be produce a smooth and sharp highly resolute image. available procedure for image interpolation are good enough however only problem is that this methods are using linear interpolation means pixels that they develops between two pixels is computed as per mean value between two continuous pixels.

II-METHODOLOGY

Conventional bilinear interpolation (2 pixels), cubic convolution interpolation (4 pixels), cubic spline interpolation (4 adjacent pixels), these classical algorithms can lead to interpolation artifacts such as blurring, ringing, jaggies, and zippering.
To preserve edge structures in interpolation, Li and Orchard proposed to estimate the covariance of HR images from the covariance of LR images, and to then interpolate the missing pixels based on the estimated covariance.
Zhang and Wu present SAI (soft-decision adaptive interpolation) which use 2-D autoregressive model, But the core of autoregressive models was a time-cost approach, which makes it difficult to meet the requirements of real-time reconstruction in actual production.
SAI image modal can be presented as

$$X(i,j) = \sum_{(m.n)\in W} \alpha(m,n) X(i+m, j+n) + v_{i,j} \qquad \dots (1)$$

$\alpha(m,n)$ is the autoregressive coefficient Li and Orchard SAI modal use gauss siedel regression modal to compute $\alpha(m,n)$
Jiaji Wu et al [1] use following method to compute nine unknown pixels y1 to y9 form, sixteen know pixels using following auto-regression modal:-
A is a 16x4 matrix for the sub image as shown in below figure developed for diagonal four 8-connected neighbours.
B is 16x4 matrix for the sub image as shown in below developed for vertical four of 4-connected neighbours.

$$a = (A^T A)^{-1} A^T x)$$
$$b = (B^T B)^{-1} B^T x)$$

To compute 9 unknown pixels of y=[y1,y2….y9]
$y = (C^T C)^{-1} C^T D x$

Where

$$C = \begin{bmatrix} I9 \\ H \end{bmatrix}$$

Let a non interpolated image is P_{ij} having size of NxM, where i=1,2,3,4…………N and j=1,2,3,4………..M

Histogram equalization

Position (k)	0	1	2	3	4	………	255
Pixel intensity (P_k)	0's in Pij	1's in Pij	2's in Pij	3's in Pij	4's in Pij	……… …	255's in Pij
Count	C_0	C_1	C_2	C_3	C_4	……… …	C_{255}
Probability $Pb = \frac{NxM}{C_k}$	$\frac{NxM}{C_0}$	$\frac{NxM}{C_1}$	$\frac{NxM}{C_2}$	$\frac{NxM}{C_3}$	$\frac{NxM}{C_4}$		$\frac{NxM}{C_{255}}$
Cumulative Probability $CPb_l = \sum_{r=0}^{l-1} Pb_r$	$\frac{NxM}{C_0}$	$\frac{NxM}{C_0} + \frac{NxM}{C_1}$	$\frac{NxM}{C_0} + \frac{NxM}{C_1} + \frac{NxM}{C_2}$	$\frac{NxM}{C_0} + \frac{NxM}{C_1} + \frac{NxM}{C_2} + \frac{NxM}{C_3}$	$\frac{NxM}{C_0} + \frac{NxM}{C_1} + \frac{NxM}{C_2} + \frac{NxM}{C_3} + \frac{NxM}{C_4}$	……… ………	$\frac{NxM}{C_0} + \frac{NxM}{C_1} + \frac{NxM}{C_2} + \frac{NxM}{C_3} \dots \dots \frac{NxM}{C_{255}}$
$DR_k = CPb_k * 255$	$CPb_0 * 255$	$CPb_1 * 255$	$CPb_2 * 255_2$	$CPb_3 * 255$	$CPb_4 * 255$	……… …..	$CPb_{255} * 255$
$R_k = fix\|DR_k\|$	$R_0 = fix\|DR_0\|$	$R_1 = fix\|DR_1\|$	$R_2 = fix\|DR_2\|$	$R_3 = fix\|DR_3\|$	$R_4 = fix\|DR_4\|$	……… …..	$R_{255} = fix\|DR_{255}$

R_{ij} is Histogram Equalized image can be obtain form P_{ij} by

$K's\ pixel\ intensity\ of\ P_k = R_k \quad where\ k = 0,1,2, \dots \dots 255$

HSV stretching $T_{ij} = RGB2HSV(R_{ij})$

let R,G and B are the pixels of red, green and blue frames of R_{ij}

$$H=\begin{cases} Undefine & if\ MAX = Min \\ 60X\frac{G-B}{MAX-MIN} + 0 & if\ MAX = R\ and\ G \geq B \\ 60X\frac{G-B}{MAX-MIN} + 360 & if\ MAX = R\ and\ G < B \\ 60X\frac{B-R}{MAX-MIN} + 120 & if\ MAX = G \\ 60X\frac{R-G}{MAX-MIN} + 240 & if\ MAX = B \end{cases}$$

$$S=\begin{cases} 0 & if\ MAX = 0 \\ 1 - \frac{MIN}{MAX} & otherwise \end{cases}$$

V=MAX

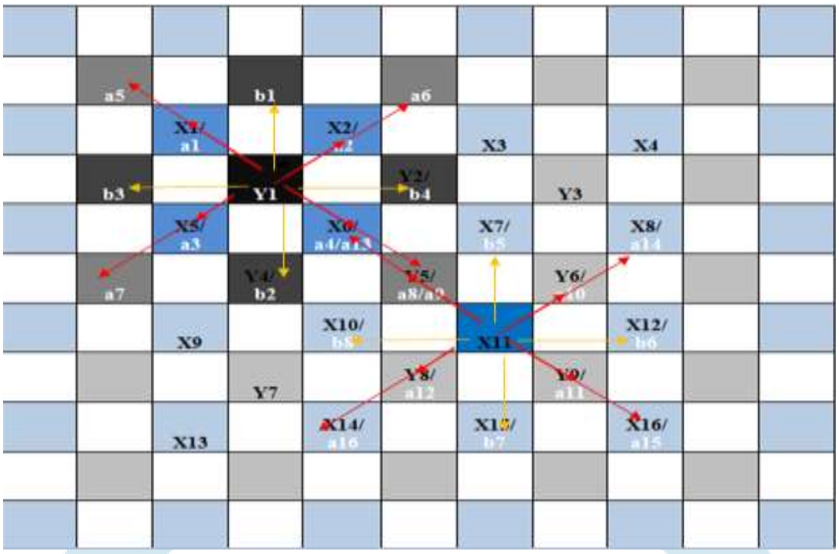

Figure 1 Image interpolation neighbours

$$\{X_{ij}\}_{6x6} = \{T_{ij}\}\ for\ i = (e{:}\,e+5)\ , j = (f{:}\,f+5) \qquad where\ e = 1{:}\,6{:}\,N\ and\ f = 1{:}\,6{:}\,M$$

A is a 16x4 matrix isolated from the sub image of X_{ij} for diagonal four 8-connected neighbours.
B is 16x4 matrix isolated for the sub image for vertical four of 4-connected neighbours.

$$a = (A^T A)^{-1} A^T x)$$
$$b = (B^T B)^{-1} B^T x)$$

To compute 9 unknown pixels of y=[y1,y2….y9]

$y = (C^T C)^{-1} C^T Dx$

Where

$$x = [x1, x2 \ldots . x16]^T$$
$$C = \begin{bmatrix} I9 \\ H \end{bmatrix}$$

And

H=	a1	a2	0	a3	a4	0	0	0	0
	0	a1	a2	0	a3	a4	0	0	0
	0	0	0	a1	a2	0	a3	a4	0
	0	0	0	0	a1	a2	0	a3	a4
	0	-b1λ	0	-b3λ	1	-b4λ	0	-b2λ	0

And

$$\lambda = \sum_{i=0}^{3} \left\{ \left[\frac{\sum_{i=1}^{3} a_i}{8} + \frac{\sum_{i=1}^{3} b_i}{8} \right] - a_i \Big/ 4 \right\}$$

And

By putting value of D, H, λ , C and x the values of unknown pixels y can be computed from equation above and obtain full sub image will be of 11x11 the same process will continue for the next sub-image of 6x6 and generate a new sub image of 11x11

C	1	0	0	0	0	0	0	0	0
	0	1	0	0	0	0	0	0	0
	0	0	1	0	0	0	0	0	0
	0	0	0	1	0	0	0	0	0
	0	0	0	0	1	0	0	0	0
	0	0	0	0	0	1	0	0	0
	0	0	0	0	0	0	1	0	0
	0	0	0	0	0	0	0	1	0
	0	0	0	0	0	0	0	0	1
	a1	a2	0	a3	a4	0	0	0	0
	0	a1	a2	0	a3	a4	0	0	0
	0	0	0	a1	a2	0	a3	a4	0
	0	0	0	0	a1	a2	0	a3	a4
	0	-b1λ	0	-b3λ	1	-b4λ	0	-b2λ	0

D	a1	a2	0	0	a3	a4	0	0	0	0	0	0	0	0
	0	a1	a2	0	0	a3	a4	0	0	0	0	0	0	0
	0	0	a1	a2	0	0	a3	a4	0	0	0	0	0	0
	0	0	0	a1	a2	0	0	a3	a4	0	0	0	0	0
	0	0	0	0	a1	a2	0	0	a3	a4	0	0	0	0
	0	0	0	0	0	a1	a2	0	0	a3	a4	0	0	0
	0	0	0	0	0	0	a1	a2	0	0	a3	a4	0	0
	0	0	0	0	0	0	0	a1	a2	0	0	a3	a4	0
	0	0	0	0	0	0	0	0	a1	a2	0	0	a3	a4
	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 2 below shows flow for proposed interpolation technique it is been seen that available methods for interpolation does not concerns about original image quality if original image is not good than its interpolated image will also be not good. So proposed work is concerning about it and first enhancing original image quality than performing interpolation, Proposed block diagram is shown above, flow for proposed algorithm as follow:-

Step 1: capture or choose any image in any YUY or RGB format, image should be a low resolution image which we require to interpolation.

Step 2: perform histogram equalization in order to equalized distribution for colour quality; histogram equalization is a popular procedure in order to performing equalised

Step 3: perform HSV (Hue, Saturation amd Value) stretching is in order to enhancing quality for image, MAX is maximal value in R, G, B for all pixels in image, and MIN is minimal one.

$$H=\begin{cases} Undefine & if\ MAX = Min \\ 60X\frac{G-B}{MAX-MIN}+0 & if\ MAX = R\ and\ G \geq B \\ 60X\frac{G-B}{MAX-MIN}+360 & if\ MAX = R\ and\ G < B \\ 60X\frac{B-R}{MAX-MIN}+120 & if\ MAX = G \\ 60X\frac{R-G}{MAX-MIN}+240 & if\ MAX = B \end{cases}$$

$$S=\begin{cases} 0 & if\ MAX = 0 \\ 1-\frac{MIN}{MAX} & otherwise \end{cases}$$

V=MAX

Step 5: Perform Proposed interpolation as explain above it will produce a horizontally interpolated image.

Step 6: Perform image filtering in order to having a good final image

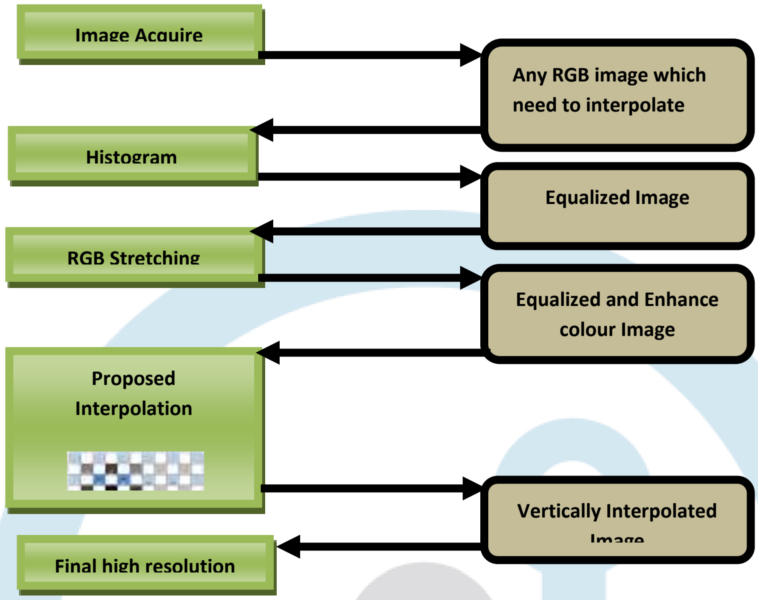

Figure 2: flow for Proposed Interpolation technique

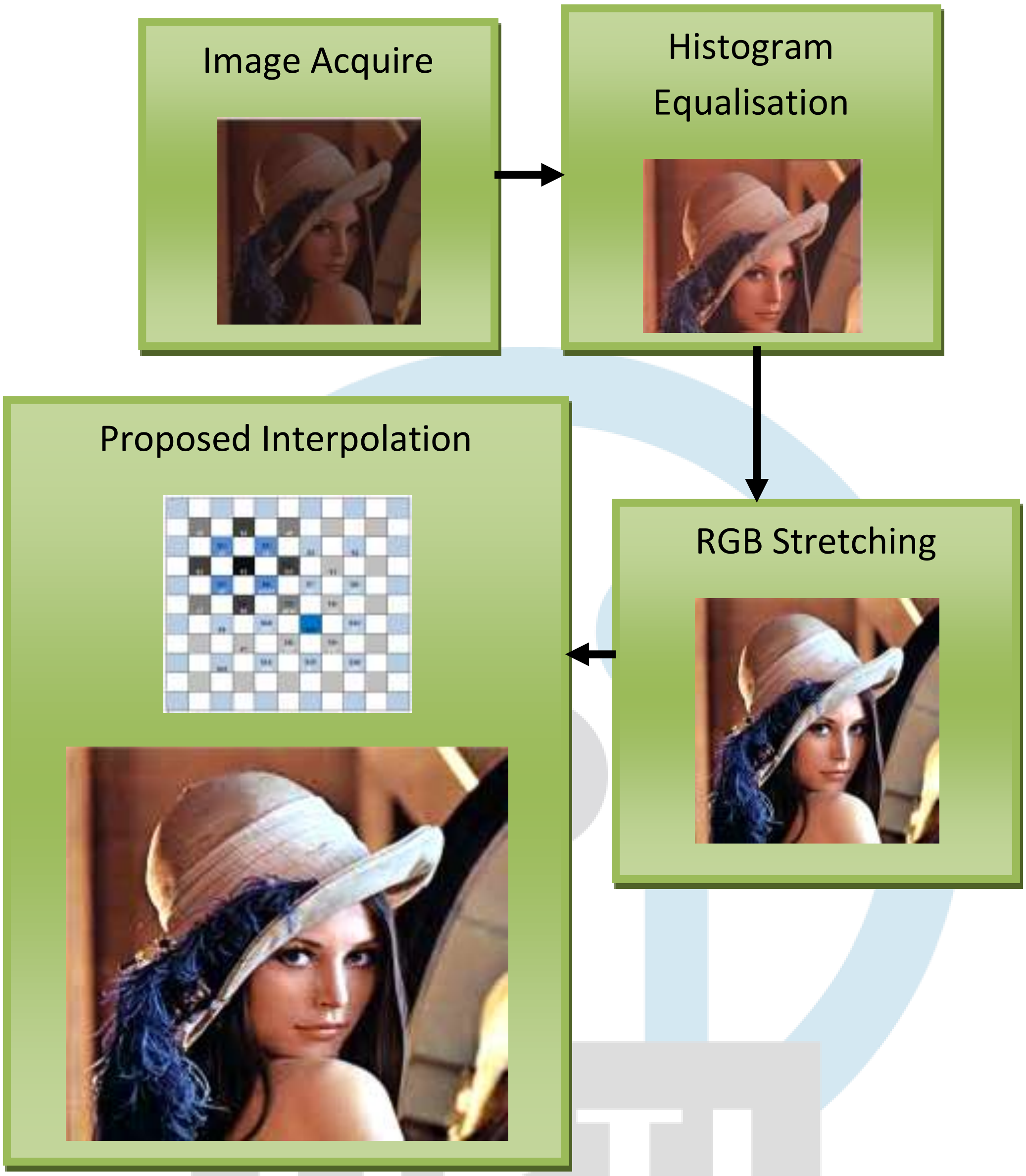

Figure 3 Proposed method flow

III-RESULTS

Mean Squared Error (MSE) Definition: mean squared error MSE for an estimator is one from many types to quantify & difference between values used by an estimator & actual values for quantity being estimated. MSE measures averages for squares for errors.MSE should be less in order to better performance.

let D is data, C is cipher, len is length for data, MSE: Mean Square Error , SNR: Signal to Noise ratio

$$MSE=\frac{(D-C)^2}{len}$$

Peak Signal-to-noise ratio (**PSNR**) **Definition:** PSNR is a measurement that compares level for a required signal to level for background noise. It is defined as ratio for actual signal power to noise power, often expressed in decibels. SR should be high in order to better performance for design system

$$PSNR = 20log_{10}\frac{256^2}{MSE}$$

propose work has done simulation for the target MATLAB standard images of Lena, Barbara, Cameraman and peppers, this images taken for the test of proposed work because the exact same images were taken by the base works [1] to [10].

Table 1 Observe results of the test images

Image name	Before Interpolation		After interpolation	
	Size	Pixels	Size	Pixels
Lena	8 Kb	225x225	372 Kb	2022x2022
Barbara	100 Kb	512x512	1.92 Mb	4605x4605
Peppers	12 Kb	225x225	348 Kb	2022x2022
Cameraman	8 Kb	204x204	260 Kb	1833x1833

from table 1 above it can be observe that the size of the all test images increases and also the number of pixels increases using proposed method hence interpolation has been done as was expected now it has to be observe that new develop images are having same information as it was in its original or not, for that we need to measure MSE and PSNR between original and interpolated image.

Table 2 PSNR and MSE results of the test images

Image name	PSNR	MSE
Lena	38.9498	0.7395884
Barbara	41.69	0.5394
Peppers	43.8010	0.4230886
Cameraman	34.16	0.6238

table 2 above shows the observe PSNR and MSE for all test images it can be seen that the average PSNR is approximately 40 db which signifies that the very less amount of changes between original and interpolated.

Table 3 show the comparative results between propose work and Jiaji Wu [1], Tudor Barbu [2], Shuyuan Zhu [3], Delibasis [4], Kazu Mishiba [5] and Lei Shu[8] works for the test images of Lena, Barbara, Peppers and Cameraman, the comparison parameter is PSNR.

Table 3 PSNR comparison for test images

Image name	**Proposed work PSNR**	**Jiaji Wu [1]**	**Tudor Barbu [2]**	**Shuyuan Zhu [3]**	**Delibasis [4]**	**Kazu Mishiba [5]**	**Lei Shu [8]**
Lena	38.9498	32.96		34.84	31.62	35.46	35.1025
Barbara	41.69			22.22		25.66	
Peppers	43.8010		31.27				
Cameraman	34.16			26.14	27.50		

from the table 3 and figure 7 it can be clearly observe that the proposed work PSNR is better than available work for all test images, it is because of proposed new interpolation method which is been discussed earlier.

IV-CONCLUSION

As interpolation is technique which is used in order to improving and modification for image, video or any other data, so many interpolation techniques are been developed in area, basically interpolation was application for signal processing now it has versatile uses. Proposed work is new idea for doing interpolation which includes a mathematical procedure developed in order to finding approximation here we have used that procedure in order to finding empty pixel value or pixel which is to be interpolated. procedure is using eight beside pixels to computer one unknown pixel. Proposed work is a new concept for using approximation procedure in order to image interpolation, many old and latest methods are available and all for it using various signal processing methods like nearest neighbour, linear interpolation, bicubic etc. few methods uses sinc function and various standard windows (harr, keiser, barlett etc.) however all for this methods were computing new pixel with either 1pixel or 2 pixel or 4 pixel however our procedure is computing new pixel with 8 pixels and so new pixels generated in proposed work is much accurate than other methods.

Proposed work has achieve better results than available work and we can conclude that after implementation for our defined approach for interpolation we will have very good and better quality for image as desired modification in it. One can also conclude that time taken in order to method not higher than existing work and proposed work has achieve better SNR and MSE then existing work. Inage Interpolation can be used for enhancing image quality. Proposed work has explored limits for Interpolation practice & theory. Improvement for image interpolation system using approximation approach is providing a good quality image. A *approximation* has been used to system during interpolation and in near future few other approximation procedure can be implemented. Or may possible to develop new approximation procedure proposed procedure is using one 2 dimension interpolation row wise an column wise in near future it can be in frame for image.

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