Image Super Resolution based on RF Interpolation

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Abstract - *This paper presents image super resolution procedure which scales-up the lower resolution image into higher resolution image. First, investigated the analytical properties of an image by constructing the RF(Rational fractal) interpolation model. The RF interpolation model has various values of scaling factors and shape parameters, So that the model has ability to describe image features better than the current interpolation models. RF interpolation model is combination of the better schemes of fractal interpolation and rational interpolation. Second, Developed an image super resolution algorithm based on the proposed model. The low resolution image is divided into texture and non texture regions, and then according to the characteristics of the local structure the image is interpolated. Critical step in the algorithm is nothing but the calculation of scaling factor in texture region. Based on the local fractal analysis we present a a method for calculating the scaling factor in texture region. Proposed algorithm achieves great performance with fine tuned details and sharp edges.*

Key Words: Super resolution, Image, fractal interpolation, rational interpolation.

1.INTRODUCTION

Reconstruction of higher resolution image from the input of a lower resolution image is the main purpose of image super resolution. Super resolution is the widely used method of image processing for academics and industrial applications. Consumer electronics, video surveillance, criminal investigation, medical image processing etc are the important areas, which utilize image super resolution. Setting up higher resolution image sensors are too much expensive and some functionalities demands higher resolution images for the image processing or some surveillance. In those case image super-resolution helps with low expense or relatively inexpensive. So that existing low resolution image becomes useful for higher resolution image requirements.

1.1 Super resolution

Combination of low resolution images sequence of a scene can be utilized to generate a high resolution image or image sequence is the basic idea of image super resolution. Thus it attempts to reconstruct the original scene image with higher image resolution. In general the low resolution image is resampling of high resolution image. There are two main categories of existing super resolution methods - Learning based method and interpolation based method.

Learning based super resolution based on the learning from training set of high resolution and low resolution image pairs. There are two categories of learning based method. First category depends on the external dictionary created from the set of external training images, and the second category replaces the external training set with low resolution image itself.

Interpolation based methods calculates the pixels in the Higher Resolution grid by employing their neighbors. The most widely used methods in practice for interpolation are bi-linear and bi-cubic interpolation. Isotropic is the kernel function used in the above method. Thus zigzagging artifacts at the edges and blurring details in textures are producing on the above interpolation methods. So that edge-directed interpolation methods are proposed recently for compensating the above mentioned issues. The above method compensate image edge artifacts but those are often generates noise or distortion in the image. In image interpolation the rational function are the ideal kernel functions has been applied. By using rational function interpolation produces the better visual results in the reconstructed images. But the ration interpolation function is not much good at preserving textural details.

2. RELATED WORKS

Learning based image super resolution is a High resolution image is generated from a single Low resolution image by using training pairs. Patch-based method methods, sparse representation approaches, regression-based method are the commonly used methods. Furthermore, state-of-the-art quality performance provided by anchored neighbourhood regression and simple functions. For fast super resolution an adjusted anchored neighbourhood regression method was proposed by combining the best qualities of ANR and SF. Numerous researchers are widely used deep learning technology in recent years. A deep leaning approach, super resolution convolution neural network(SRCNN) was proposed for directly learned and end-to-end mapping between Low resolution and High resolution images. Learning based methods perform well for some images, which are works based on the external datasets, but those have considerable drawback, they are fixed and are thus not adapted to the input image. Patch based Super Resolution method results irregularities along the edges, when the external datasets does not match with the content of the images. Learning based methods produce High Resolution images by executing similarity redundancy information with same scales and across different scales. In the learning based approach, which does not adapted to the input image, for each low resolution patch, similar self-examples where found, and direct mapping of each Low resolution image into its High resolution image by employing necessary linear function. However, in learning method thus not adapted to the input image, Low resolution - High resolution patch pairs were found by searching on the down-scaled image patches. A self-similarity-driven Super Resolution algorithm, which improves the visual effect pretty well, which was proposed to expand the internal patch search with geometric variations. The above algorithms tends to produce sharp edges instead of fine details, if the Low Resolution image does not contain sufficient amount of repetitive patterns. By considering the interpolation based method and learning based method for super resolution, studies developed an image interpolation which has non local auto regressive modeling. This method helps to increase the visual effect well but it tends to degrade the texture features and image details in the reconstructed High resolution image, when higher magnification ratios are performed.

3. EXISTING METHODS

For texture classification, description and segmentation fractal is the efficient tool widely applied. Multifractal spectrum proposed for analysis in wavelet pyramids of texture images. By combining information from spatial and frequency domains, presented a textural descriptor. Dynamic fractal analysis based dynamic texture classification was proposed. Multifractal characterization based High Resolution optical image segmentation was proposed. A method for edge detection was presented based on fractal dimension-invariant filtering. By using local fractal analysis and boundary consistency analysis a depth up-sampling algorithm was proposed. A limited literature is available on applying fractal analysis in image Super Resolution. A special type of orthogonal fractal coding method has been proposed for image Super Resolution algorithm, which can produce pleasing details, but sharper edges recovery becomes failed. Texture enhancement algorithm can effectively enhance image details, which uses local fractal analysis for improving single image Super Resolution performance. This algorithm does not follow the local fractal property and cannot provide satisfactory results in stochastic texture region. The above methods characterize texture feature by using fractal dimension primarily. Fractal dimension cannot accurately calculate the textural details but can describe the roughness of the texture. For describing the image details accurately, there is a necessary to construct a fractal function and apply related properties.

4. PROPOSED METHOD

The proposed approach is constructed a RF(Rational fractal) interpolation model. Rational fractal interpolation function is more accurate in approximation function in compared with other polynomial interpolation kernel functions. Image edge structures are preserved well with this approach. When using rational fractal function interpolation the reconstructed image have fine textural details and structural information and fractal function is an efficient model for describing image texture. The fractal analysis method is applied in image interpolation, which is the novel single-image Super Resolution algorithm proposed. Fig-1 illustrated the proposed algorithm. First divide the image features into texture region and non-texture region. Second execute rational fractal interpolation function in the texture region and rational interpolation model in the non-texture region. At last High resolution image obtained by pixel mapping.
There are some advantages by applying the rational fractal interpolation function model in image Super Resolution reconstruction, are as follows. Compared with other interpolation methods it can recover the best pleasing image details. Because of this approach can achieve competitive performance by only using low resolution image patch, there is no need to depend on the source of training patches like learning based methods.

Following steps show the proposed method.
1. Investigate the analytical properties such as error analysis, stability analysis, fractal dimension and quasi-locality by constructing rational fractal interpolation model.
2. Proposed single-image super resolution method by applying the fractal analysis method in the interpolation model. Textural details, image details and spatial characteristics information of the image is recovered accurately by applying the above method.
3. There are two aspects for extension, First is local characteristics of the image is considered. Second is relationship consideration on scaling factor and fractal dimension. Then accurately calculate the scaling factor using this method.

4.1 Algorithm basics

Spatial characteristics of information of the image is described by fractal texture. Approximation of sinc function characterized by rational function, which is correspond to ideal filtering. Construct a rational fractal interpolation model based on the above described general characteristics of images and relevant theoretical analysis provided. Proven that algorithm can control interpolation error and better in approximation effect by analyzing error analysis results. Its proven that the model has strong image interpolation adaptability by doing stability analysis. The model is good for explaining the local features of image, in according to the quasi-locality property. The image texture complexity defined by fractal dimensions. So that the model possess strong correlation with the scaling factors. Fractal dimension are calculated by the provided method. The proposed model has greater practicality and flexibility than the older models, as per the above model description.

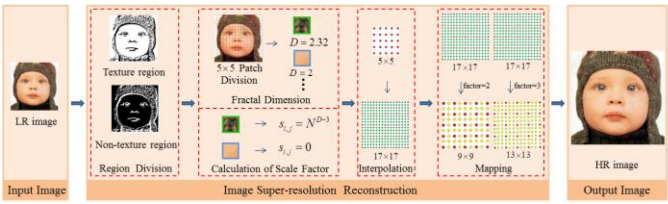


Fig - 1 Algorithm basic idea

4.2 Function for RF (Rational fractal) interpolation

Fractal interpolation functions are generated by continuous functions such as iterated function systems. The following Iterated function system are corresponding to fractal interpolation functions.

$\phi_i(x) = a_i x + b_i,$

$\varphi_j(y) = c_j y + d_j,$

$F_{i,j}(x, y, z) = s_{i,j} z + q_{i,j}(x, y),$ -----------------------------(1)

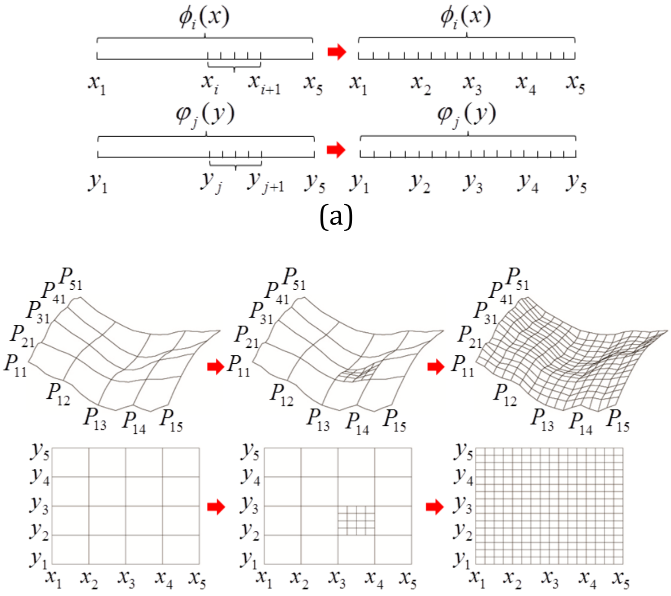
Where $|S_{i,j}| < 1$ and $S_{i,j}$ - Vertical scaling factors, $q_{i,j}(x,y)$ - continuous function

Proposed a method for constructing bi-variate rational Fractal Interpolation Function based on the previous work on bi-variate rational interpolation. Representing the $q_{i,j}$ continuous function in (1) as a fractal perturbation of bi-variate rational interpolation function $P_{i,j}(\phi_i(x), \varphi_j(y))$, which is derived from the perturbation of base functions $B_{i,j}(x,y)$.

$q_{i,j}(x,y) = P_{i,j}(\phi_i(x), \varphi_j(y)) - s_{i,j}B_{i,j}(x,y)$

Thus the bi-variate rational Fractal Interpolation Function $\Phi(x, y)$, derived from the iterated function system (1)

$\Phi(\phi_i(x), \varphi_j(y)) = s_{i,j}\Phi(x, y) + P_{i,j}(\phi_i(x), \varphi_j(y))$
$- s_{i,j}B_{i,j}(x, y)$ ------------------------------- 2)



(a)

(b)

Fig - 2 Iteration system illustrations

$\Phi(x, y)$ can be rewritten as follows only if suitable mild conditions satisfied by shape parameters.

$\Phi(\phi_i(x), \varphi_j(y)) = s_{i,j}\Phi(x, y) + AEB,$

A - 4 dimensional row vector
B - 4 dimensional column vector
E - constant matrix of order 4

Using 5x5 grid, interpreted the iterative process of the system $\{(x_i, y_j, f_{i,j}) : i, j = 1, 2, \cdots, 5\}$. Contractive homeomorphisms $\phi_i(x)$ and $\varphi_j(y)$ on each i, j (i,j=1,2,3,4), map intervals $[x_1, x_5]$ and $[y_1, y_5]$ to sub-intervals $[x_i, x_{i+1}]$ and $[y_j, y_{j+1}]$. As shown in Fig-2(a) 5 points are derived on $[x_i, x_{i+1}]$ and $[y_j, y_{j+1}]$ respectively. On each sub region $[x_i, x_{i+1}] \times [y_j, y_{j+1}]$, 5 x 5 interpolation points provided. Using iterative scheme 5 x 5 points on the interpolation surface are acquired. So that after first iteration 17 x 17 points were obtained on the region $[x_1, x_5] \times [y_1, y_5]$ and obtained corresponding interpolation region as well.

4.3 Interpolation of single image

4.3.1 Division of image regions: Different structural characteristics are present in different regions in a single digital image. Using single model it is difficult for interpolation of image to achieve better quality. The proposed interpolation model can be used to handle different image regions, because it has different forms of expression. The key step of the interpolation algorithm is regional division. Regional division results tightly coupled with the image interpolation quality.
Proposed Super Resolution algorithm is able to play an important role in rational fractal interpolation function because the main objective is nothing but detect more

detailed textures, not like image texture detection methods such as canny operators and sobel. For regional division, introduced isoline method that is detect the image textural and structural information. Chosen an image of suitable size to conduct an experiment for the texture detection. A 5 x 5 patch of the given Low resolution image as shown in Fig-4, is treated as unit for detecting the texture roughness because it becomes noise sensitivity if choosing a patch is too small. Similarly if size of the image patch is too large then the texture regions be considered as non-texture regions.

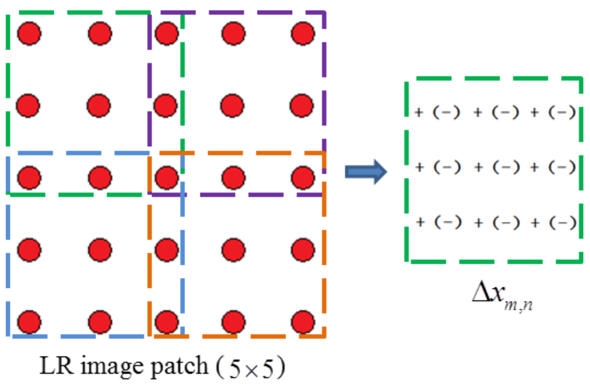


Fig - 3 Detection of texture

The most intuitive expression of various structures in generic natural images is pixel value and it denotes the attributes of image itself. So that difference in pixel values helps to detect the textural details. Texture region is nothing but the region detected includes an isopleth, Otherwise it is a non-texture region. The main procedure for the texture details detection is as follows. First divide the each low resolution image path (5 x 5) into 4 sub-blocks of 3 x 3 size. Second, first sub-block used for the example, for Low resolution patch $f_{m,n}$, m, n = 1, 2, · · · , 5,

$$\lambda = \frac{\sum_{m=1}^{5}\sum_{n=1}^{5} f_{m,n}}{5 \times 5},$$

Where,
$f_{m,n}$ - pixel value at the point (m, n)
λ - Average value of all pixels

Let $\Delta x_{m,n} = f_{m,n} - \lambda$, m, n = 1, 2, 3;

The texture region and non-texture region is calculated using the following formula.

1. non − texture region, if $\Delta x_{m,n} \geq 0$ or $\Delta x_{m,n} \leq 0$, ∀m, n,
2. texture region, otherwise.

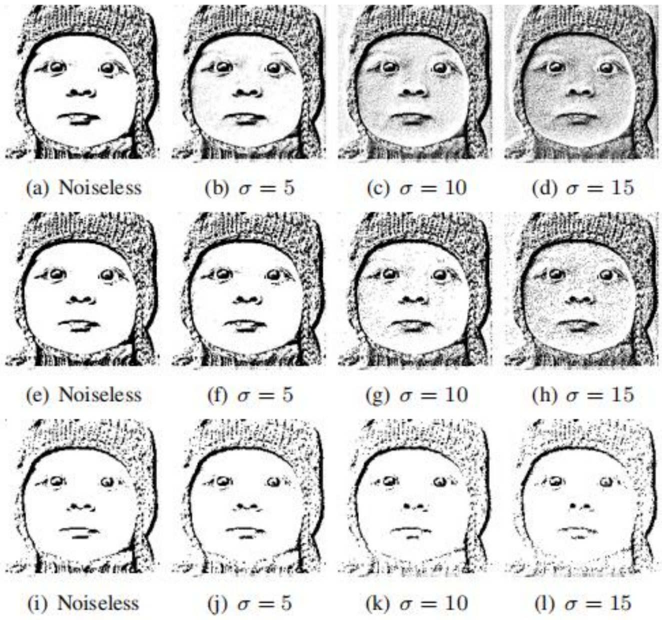


Fig-4 Results of texture detection in noisy images: (a)-(d) 3 x 3 patch, (e)-(h) 5 x 5 patch and (i)-(l) 7 x 7 patch.

The non-texture is detected by considering the 5 x 5 Low resolution image patch doesn't include an isopleth. Otherwise detected as texture region.

4.3.2 Calculation of scaling factor: The complexity of texture reflects in scaling factor for image processing. In the rational fractal interpolation function, the scaling factor plays an important role. So that the value of scaling factor is tightly with the quality of interpolation. Quality of the interpolation improves along with the accuracy of the scaling factor improves. In traditional fractal interpolation methods, the same scaling factor is using for the interpolation of image patch, which ignores the image local variations. Based on the local features of the image, presented a method for calculating the scaling factors. There are two steps for calculating scaling factor. First obtained the initial values of scaling factors for each low resolution image patch. Second, according to the texture information of image, obtained further scaling factors.
Concrete steps for calculating the scaling factor are as follows as shown in Fig-5 Presented an efficient method for calculating the scaling factor of the image patch with the help of local fractal dimension, based on the proposed bi-variate fractal interpolation function, which has a good capacity of quasi-locality on the parameters in the rational iterated function system. If consider each low resolution image patch uses the same scaling factor then the following formula is used for calculating the initial scaling factor $S_{initial.}$

$S_{initial} = N^{D-3}$ ---(3)
In the case of low resolution image patches with complex geometric structures, it is not suitable to use the same

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scaling factor. Consider the sub-block 1 ($f_{m,n}$ m,n = 1,2,3)following equation used for the texture region.

$$Aver = \frac{f_{1,1} + f_{1,2} \ldots + f_{3,3}}{9}$$

$$Sum = |f_{1,1} - aver| + | f_{1,3} - aver| + |f_{3,1} - aver| + |f_{3,3} - aver|$$

$S_{1,1} = S_{initial} \times |f_{1,1} - aver| / sum$
$S_{1,2} = S_{initial} \times |f_{1,3} - aver| / sum$
$S_{2,1} = S_{initial} \times |f_{3,1} - aver| / sum$
$S_{2,2} = S_{initial} \times |f_{3,3} - aver| / sum$

If the sub-block is a non-texture region then,

$S_{1,1}=S_{1,2}=S_{2,1}=S_{2,2}=0$

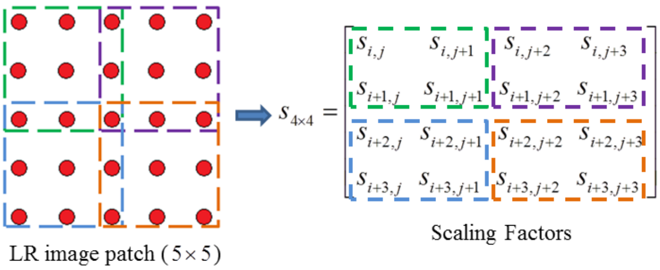

Fig - 5 Scaling factors of local image patch

4.3.3 Algorithm of interpolation: The texture and non-texture region is separately addressed by the different forms of expression present in the interpolation model. Ration fractal interpolation is used for the texture region and rational interpolation is used for the non-texture region. The low resolution input image is divided into 5 x 5 patches.

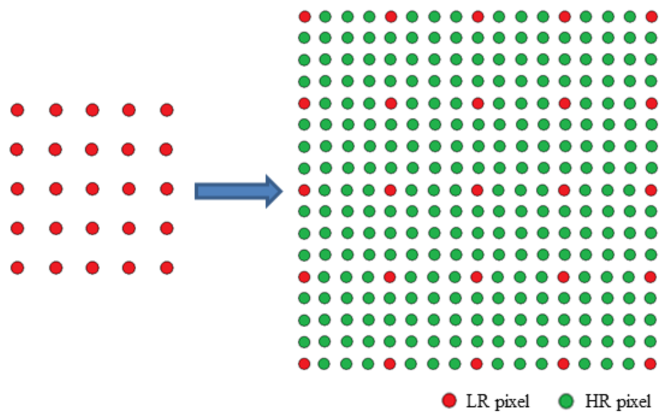

Fig - 6 RF(Rational fractal) interpolation model

To construct the interpolation surface a 5 x 5 vector control grid is used. Rational fractal interpolation is used to compute every point's intensity in image, which is magnified. A 17 x 17 patch can be obtained from the 5 x 5 image patch by using the proposed model, as shown in the Fig - 6. High Resolution image represented by green dots and Low resolution image represented by red dots. As shown in the Fig - 7 the interpolation is extended to the entire image by traversing each patch in low resolution image in the order of raster-scan, which is left to right and from top to bottom.

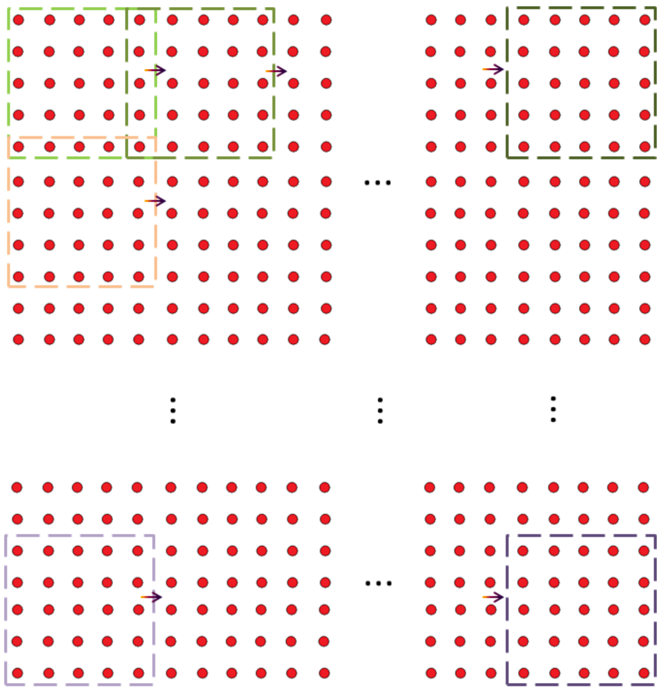

Fig - 7 Image interpolation process

4.4 Pixel mapping

With increasing the number of iteration, large number of pixels are obtained as the rational fractal interpolation function is an iterative function system. So that more detailed information can be captured. Via pixel mapping, image can be amplified. The image can be magnified with three scale factors such as x2 , x3 and x4 on after the first iteration. A 17 x 17 patch can be obtained from the 5 x 5 image by using the proposed model. So that the image up scaling factor of 4 can be directly obtained by using the ration fractal interpolation model. Using pixel mapping two different scale factor (2 and 3) magnification is obtained on the low resolution image.

Following equation for the pixel mapping as shown in the Fig - 8.

$$g_{x,y+1} = \sum_{t=j}^{j+4} \frac{f_{i,t}}{\sum_{t=j}^{j+4} f_{i,t}} \times f_{i,t}, g_{x+1,y} = \sum_{s=i}^{i+4} \frac{f_{s,j}}{\sum_{s=i}^{i+4} f_{s,j}} \times f_{s,j},$$

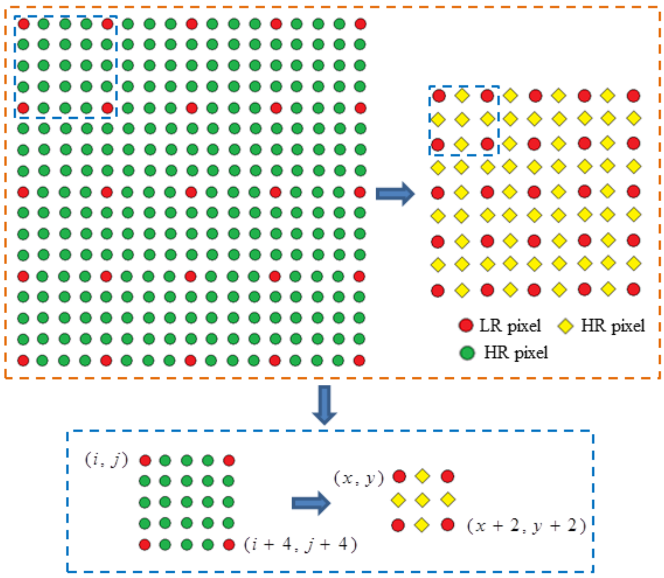

Fig - 8 (x 2) pixel mapping process

$g_{i+1,j+1}$ is obtained from the following equations:

$varHor = var(f_{i+2,j+1}, f_{i+2,j+2}, f_{i+2,j+3})$,
$varVer = var(f_{i+1,j+2}, f_{i+2,j+2}, f_{i+3,j+2})$,
$var45 = var(f_{i+1,j+3}, f_{i+2,j+2}, f_{i+3,j+1})$,
$var135 = var(f_{i+1,j+1}, f_{i+2,j+2}, f_{i+3,j+3})$,
$varMin = min(varHor, varVer, var45, var135)$,

Where,
var() - Variance of the function
Min() - minimal function

5. CONCLUSIONS

In this paper, presented rational fractal interpolation based image super resolution algorithm. For detecting the texture isoline method is used on each low resolution image patch, detailed texture information can be obtained and low resolution image is divided into texture region and non-texture region. The influence of the shape parameter is minor but the major role played by scaling factor in interpolation model. By using image local structure features, scaling factor is accurately calculated based on the relationship between scaling factor and fractal dimension. In the texture region rational fractal interpolation used and in the non-texture region rational interpolation used. Traversing across the entire low resolution image by extending the interpolation of low resolution image patch. By selecting a suitable mapping, final High resolution image is obtained by the pixel mapping. The proposed algorithm generates High quality super resolution image with sharper edges and rich in texture information.

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