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Optimization of Mathematical Morphology based Super-Resolution Image Reconstruction using Genetic Algorithm

Shimil Shijo
Post Graduation Student/Department of CSE
National Institute of Technology Calicut,
India

Dr.V K Govindan
Professor/Department of CSE
National Institute of Technology Calicut,
India

***Abstract*—Super-resolution technique generates images of high resolutions (HR) from image(s) with low resolutions. A single image super-resolution technique based on genetic algorithm is presented in this paper. Genetic algorithm permits the choice of best high resolution image for a given low resolution image through iterative selection process using a fitness function to minimize error. Locally adaptive edge detection technique using mathematical morphology is employed to preserve the boundary information.**

Index terms -Tomography, Reconstruction algorithms, Image resolution, Image enhancement

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I. Introduction

Resolution enhancement is one of the most popular terms in image processing. It gives more pleasing view to the human eye. Super resolution aims to obtain a high resolution image from observed low resolution (LR) image(s). Each input image differs from other by different parameters like sub-pixel shift, blur and noise. The redundant information from the LR image is utilized here. Super-resolution (SR) is considered as an *ill-posed* inverse problem in which original information is reconstructed from degraded images. Mathematically, super-resolution problem can be expressed as follows.

Given a set $\{Y_k\}_N^{k=1}$ of low-resolution images .

$$Y_k = D_k B_k G_k X + E_k , k = \{1..N\} \quad (1)$$

Where:

X : Original high resolution image
Y_k : k-th low resolution input image
D_k : Decimation operator(sampling rate) for the k-th image
B_k : Blur operator(Point Spread Function) of the k-th image
G_k : Geometric transformation operator for the k-th image
E_k : White Additive Noise

High resolution images are always desirable in the applications like satellite imaging, sports photographs, medical imaging, archeology study, microscopy, computer vision, remote sensing, surveillance systems, target detection and recognition. It is also applicable in high resolution videos, compression, astronomy etc. The need of zooming of images to analyze visual information also increases the demand of super-resolution.

We can improve resolution using complex image acquisition process or by increasing the chip size. These remedies are practically difficult because of the high cost. Resolution can also be improved by reducing the pixel size. But, this method degrades the image quality by creating shot noises. These difficulties lead to exploit image processing techniques. As the software level costs are low compared to the hardware methods it became popular within a short period.

SR algorithms can be categorized into two: Frequency domain and spatial domain techniques. The benefit of frequency domain approach is its simplicity and low computational overhead, though it is less flexible. Spatial domain methods provide highly flexible more efficient reconstructed images. Hence, most of the current research is focusing on this technique. The major methods for super-resolution are listed below.

Frequency-Domain SRR Methods:

- Restoration via Alias Removal
- Multichannel Sampling Theorem Methods
- Recursive Total Least Squares Methods
- Recursive Least Squares Methods

Spatial-Domain SRR Methods:

- Hybrid Methods
- Iterative Back-Projection Methods
- Interpolation of Nonuniformly-Spaced Samples
- Stochastic Methods
- Optimal and Adaptive Filtering Methods
- Set Theoretic Methods
- Algebraic Filtered Back-Projection Methods

II. Related Work

Super resolution is an active topic of research since for a decade. A number of publications are available in the literature. This Section briefly reviews some of the important work in this topic.

First contribution to the super-resolution research was from Tsai and Huang [1]. They introduced frequency domain approach for HR image reconstruction using aliasing in the LR images. It focuses on three concepts of Fourier transform: a)Shifting property, b)the continuous Fourier transform (CFT)- Discrete Fourier transform (DFT) relationship and c) the HR image is assumed to be band-limited. The advantages of Tsai-Huang approach is its theoretical simplicity and low computational complexity. It also reduces hardware complexity by enabling parallel implementation.

Projection onto Convex Sets Approach (POCS) was introduced by Stark and Oskoui[2]. It is one of the prominent approaches in Set Theoretic Method. This method can be used as an alternative to least squares or matrix inversion technique. It solves restoration and interpolation problem using registration parameters. In order to include sensor noise, Tekalp et al. [4] extended the POCS formulation. Later, the motion blur occurring during the aperture time of the camera was addressed by Patti et al.[5]. The advantage of POCS is its simplicity and powerful insertion of a-priori information.

Irani and Peleg [3] suggested iterative back-projection (IBP) approach which uses an iterative algorithm for SR reconstruction. The method is adopted from the back-projection approach used in Computer Aided Tomography (CAT). The advantage of IBP is its simplicity. Inclusion of priority constraints is not easily achieved in the IBP method.

A technical survey conducted by Sung Cheol Park et al.[6] explains the SR technology and provides an outline of main SR approaches and related issues. The article begins by illustrating the need of super resolution in this era. Then, it discusses the methods to improve resolution and the research in SR algorithms. An observation model to relate input LR image(s) and output HR image is formulated. The general SR reconstruction approach is discussed. The overview also focuses on colour SR algorithms. The authors also emphasize the role of SR algorithm in compression system.

Evolutionary approaches are also applicable in super-resolution. Felix Totir et al. [8] proposed evolutionary computation technique that is useful to solve optimization problems. Genetic algorithms [7] are suitable for the situation like insufficient information and noise. Since both the pixel values of image and genomes are represented as integers, genetic algorithm gives better performance in comparison with the conventional method. It simplifies computational complexity by avoiding complex mathematical operations.

Super-resolution technology has significant role in medical imaging. By applying SR technology on medical imaging true isotropic 3D imaging can be obtained. Greenspan [9] gave an excellent review on SR techniques in medical imaging. Kouame and Ploquin [10] emphasized the power of SR technology in his paper. Based on the analysis of the point spread function [PSF], a new technique for achieving super-resolution is employed. Here, estimation of B-mode images is done by using parametric modelling. Sable and Gaikwad [11] designed an SR technique that includes pre-processing and post processing. The authors claim that it can improve the performance of adaptive iterative algorithm.

Example-based super-resolution method presented by Senda Shuji et al.[12] belongs to one of the latest SR technique called learning based approach. It enables the reconstruction of magnified SR images like license plates and human face. The advantage of learning based approach is that it requires very few LR images when compared to the conventional techniques. It is faster, more versatile and gains high magnification factor (MF).

Marco Bevilacqua [13] described an example based single image super-resolution technique. This algorithm uses negative neighbour embedding technique. This approach achieves high performance and low computational overhead; but it is often affected by ringing aircrafts.

Shi Chao et al. [14] employed a novel super-resolution technique using interpolation algorithm. The idea is based on weighted least square method. In this paper, resolution enhancement from a single-frame image is discussed. This method exploits more information for SR reconstruction compared to the conventional method. The visual impression and the objective evaluation index are superior to that of other conventional methods.

Venkatesh and Govindan[15] presented an improved resolution method using geometric image registration. The approach makes use of geometric registration, feature detection and contrast stretching. This algorithm gives better results and achieves good accuracy and reduced processing time. The drawback of this method is that the Hough transform misleads the results when objects happen to be aligned by chance and it requires lots of memory and computation for objects with many parameters.

Shimil and Govindan[16] suggested a single image super resolution technique which utilizes the benefits of both frequency and spatial domain approaches. Minimization of reconstruction error is done using Iterative Back-Projection method and Wiener filter is introduced to remove high frequency noise. Robert’s edge detector helps to preserve the boundary information.

Though there are many attempts to reconstruct super resolution images, and some of them report better performances, there is still further scope for improving the performance of reconstruction. The technique presented in this paper is an attempt for better super resolution reconstruction using Genetic Algorithm (GA), and making use of mathematical morphology for preserving edges.

III. THE METHODOLOGY

The approach employed here makes use of genetic algorithm for iterative reconstruction. The quality of reconstruction is enhanced by preserving edges employing mathematical morphology to detect them. These techniques are presented in the following subsections.

A. Edge Detection using Mathematical Morphology

In computer vision, the concept of Mathematical morphology, which is based on set theory is widely used for extracting the image components. The basic morphological operations– dilation, erosion, opening and closing along with the structuring element segregates the boundary information from the image. The structuring element (S) is a kernel with a particular shape which suppresses or discloses the features of an image. The shape can be chosen according to the nature of the image. Crisscross, diamond and disk shaped structural elements, shown in Fig. 1, are usually used for edge detection since they are symmetrical.

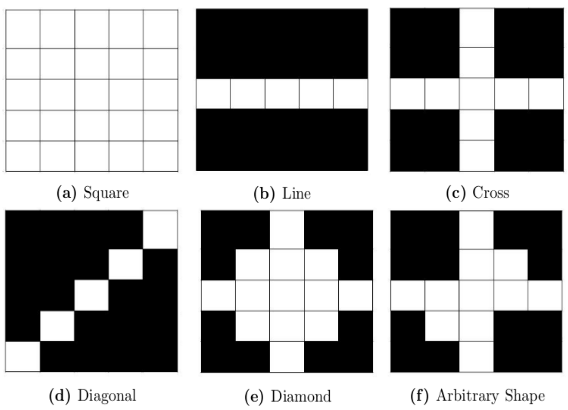

Figure 1: Different types of structuring elements

The basic operations are explained below.

1. Dilation(⊕)

Dilation operation gives the maximum value among the neighborhood pixels of the given pixel. Hence, it removes the darker information in the image and increases the number of brighter pixels. When the structuring element is swept over the image each pixel is replaced with the maximum value in that window.

$$A \oplus S = \max (A[m-j,n-k] \cup S[j,k]) \ , [j,k] \forall S \quad (2)$$

Where, A - Original Image, and S - Structuring Element

2 Erosion(ϴ)

Erosion operation which is the reverse of dilation replaces the pixel with its minimum neighborhood value; so, images become darker. It is defined as

$$A \ominus S = \min (A[m-j,n-k] \cap S[j,k]) \ , [j,k] \forall S \quad (3)$$

3 Morphological Opening and Closing

Opening *(open)*- an erosion followed by a dilation removes the brighter regions which is smaller in size than the structuring element. That is, it removes the smaller objects in the image.

$$A \circ S = (A \ominus S) \oplus S \quad (4)$$

Closing (close) is the reverse process of opening. That is, it removes the darker regions of the image by performing dilation followed by erosion in the regions which are smaller than the structuring element.

$$A \bullet S = (A \oplus S) \ominus S \quad (5)$$

Gradient image is calculated as follows.

$$\text{Gradient} = \text{Dilation} - \text{Erosion} \quad (6)$$

Edges can also be detected using a composition of opening and closing operations called Alternating Sequential Filter (ASF).

Edge detection method using mathematical morphology can produce better result than basic edge filtering operators like sobel, prewitt and canny edge detection algorithm. Analysis based on PSNR is given below in Fig.2

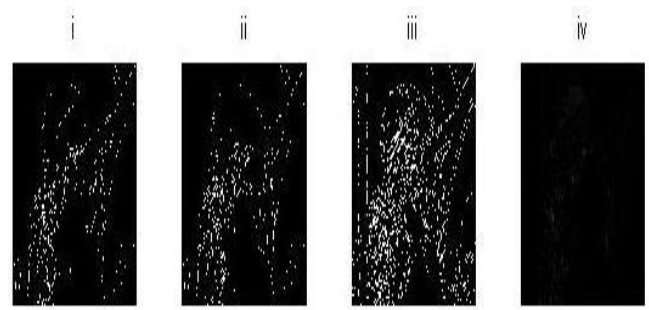

Figure 2: Different edge detection methods i) Sobel PSNR= 7.1278, ii) Prewitt-PSNR=7.1277, iii) Canny-PSNR=7.1313 , iv) Morphological edge detection-PSNR=7.2209

B. Optimization using Genetic Algorithm

Genetic algorithm is a subset of evolutionary algorithms which can be used to find out the solution for optimization problems. It generates a set of solutions using the techniques of natural evolution like selection, crossover and mutation. The set of solution is known as population. A series of computations are performed on each population and a new generation is created. Fitness function is used to optimize the solution. Here, in order to reduce reconstruction error, mean squared error (MSE) is taken as the fitness function. This error is added to the next population. This process is repeated until the error approaches to zero or pre-specified criteria is met.

IV. PROPOSED APPROACH : IMPLEMENTATION

A. Pre-Processing Stage

An image captured by camera is taken as the original high resolution image. Input LR image is obtained by blurring, downsampling and shifting of the original image. Using this input, a high resolution image is reconstructed which is almost same as that of the original HR image.

B. Method

Basic idea of the proposed method is adopted from [16] and [20].Input image (n x n) is upsampled using bicubic interpolation. The approach makes use of genetic algorithm to obtain the best high resolution image from a population using iterative optimization based on MSE as the fitness function. N number of population is initialized. Each population is an image of size 2n × 2n in row major order. Fitness value of each population is calculated separately and it is sorted in the increasing order of Mean Squared Error. Crossover operation is performed on the first few population and new offspring are generated. The parents along with the offspring are mutated randomly. Scalar fitness value is calculated again and the best N population with minimum MSE is chosen to the next generation. This process is repeated until the convergence criteria is met. The first population from the sorted array is taken as the intermediate HR image.

Morphological gradient based edge detection is performed on the error image. In order to get gradient image, Alternating Sequential Filtering(ASF) which is a composition of opening and closing operations is performed. Negative of the gradient image reveals the inner details. Object is differentiated from the background with the help of bottom-hat transformation. Smoothening of edges is done by averaging the image pixels and binary image is generated in the next stage. Components of the binary image is labelled and the number of pixels on each region is counted separately. Label with largest connected component is identified and the image background is removed. Interest points are detected with the help of Harris corner detector.

The edge, corner and error information is back-projected to the intermediate HR image and final HR image is formed.

The algorithm to perform the above described task is presented in the following:

C. Algorithm

Input : A single low–resolution (LR) image (n × n)
Output : High-resolution image(2n × 2n)

1. Read LR image ,I^l.
2. Upsample I^l using bicubic interpolation to get $I^h(t)$.
3. Perform Genetic Algorithm
   3.1 Initialize N population randomly.
   3.2 Calculate scalar fitness of each population as follows. t=1.
      3.2.1 Convert the population into image and downsample it by averaging to get $I^{ld}(t)$
      3.2.2 Reconstruct the error E(t);
      $$E(t) = I^l - I^{ld}(t) \tag{7}$$
      3.2.3 Upsample the error using bicubic interpolation
      3.2.4 Compute the mean square error,
      $$MSE = \sum \sum E(t) / (2n \times 2n) \tag{8}$$
      3.2.5 t = t + 1
   3.3 Selection : Select the first two population with minimum mean square error as parents
   3.4 Crossover : Perform single point order crossover and generate two new offsprings. Update the population
   3.5 Mutation : Mutate the population randomly
   3.6 Compute the fitness value of each population as in step 3.2
   3.7 Select the best 10 population with minimum MSE and update it as new generation
   3.8 Repeat from step 3.2 until the convergence criteria is met.
4. Select the best population with minimum MSE
5. Convert it into image (I^{HR}), downsample and calculate the error
$$E'(t) = I^{ld}(t) - I^{HR}(t) \tag{9}$$
6. Upsample the error using bicubic interpolation(E(t))
7. Detect edges using mathematical morphology: Perform the following operations on the upsampled error image(E(t)) using the structuring element S (Fig 3).
   i) Find the morphological gradient of input image :
   $$I^{grad}(t) = (((E(t) \bullet S) \circ S) \bullet S) - Erosion((((E(t) \bullet S) \circ S) \bullet S)) \tag{10}$$
   ii) Generate the negative image of the gradient image :
   $$I^{negative}(t) = \sim(I^{grad}(t)) \tag{11}$$
   iii) Use bottom-hat transformation to separate the image from background:
   $$I^{bottomhat}(t) = (I^{negative}(t) \bullet S) - E(t) \tag{12}$$
   iv) Compute the average of input image (AVG)
   v) Using AVG value convert it into binary image
   vi) Identify the largest connected region (CC).
   vii) Compute the difference between the smoothened image and largest connected region to get the edge image (I^{EDGE}).
8. Detect the corners of the edge image using Harris Corner Detection (I^{CORNER})
9. Back-project the error and edge information: High resolution image is updated using *Iterative back-projection*(IBP) method as follows:
$$SR\_image = E(t) + I^{HR} + I^{EDGE} + I^{CORNER} \tag{13}$$

The flowchart for the edge detection process using mathematical morphology is presented as in Fig.3.

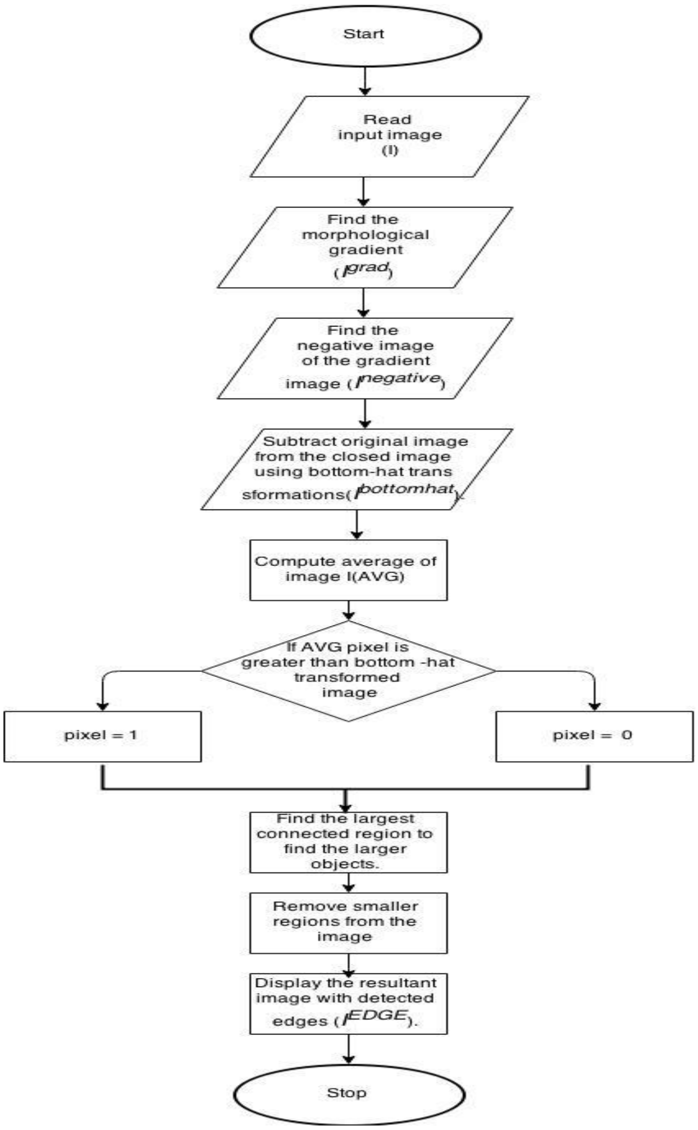

Figure 3 : Edge Detection Using Mathematical Morphology[19]

V. EXPERIMENTAL RESULTS AN DISCUSSION

The algorithm is implemented in MATLAB. A comparative study based on PSNR and SSIM (Structural Similarity) is performed between the proposed method and some of the existing methods. These two parameters (PSNR & SSIM) are computed for bilinear, bicubic [17], wavelet with zero-padding (WZP) interpolation, wavelet and spatial domain (WS) [16] approaches and the proposed approach. Experiment is conducted on five 512×512 standard test images. Quantitative evaluations are tabulated as in Tables I and II.

Tables I and II clearly demonstrate the superior performance of the proposed approach in terms of PSNR and SSIM for all of the cases of test images. Optimization of reconstruction error with the help of genetic algorithm makes the proposed method dominant over all other methods. Edge detection using mathematical morphology reduces the computation overhead compared to other edge detection methods and Harris corner detector helps to keep track of the interest points.

	BILINEAR	BICUBIC	WZP	[16]	PROPOSED METHOD
IMAGE 1	31.6220	33.2173	30.2551	32.7244	**34.1091**
IMAGE 2	20.0405	20.5100	19.9942	20.3134	**20.7057**
IMAGE 3	25.0757	25.4942	25.1826	25.0803	**25.6278**
IMAGE 4	26.2025	27.4839	25.3876	27.2803	**28.1942**
IMAGE 5	25.8165	26.9172	25.0925	26.5610	**27.4584**

TABLE I. PERFORMANCE COMPARISON OF THE PROPOSED APPROACH WITH DIFFERENT APPROACHES BASED ON PSNR.

	BILINEAR	BICUBIC	WZP	[16]	PROPOSED METHOD
IMAGE 1	0.8888	0.9118	0.8778	0.9229	**0.9310**
IMAGE 2	0.6244	0.6624	0.6422	0.6792	**0.6874**
IMAGE 3	0.7606	0.7937	0.7682	0.8103	**0.8192**
IMAGE 4	0.8259	0.8687	0.8110	0.8715	**0.8896**
IMAGE 5	0.7338	0.7746	0.7320	0.7860	**0.7983**

TABLE II. PERFORMANCE COMPARISON OF THE PROPOSED APPROACH WITH DIFFERENT APPROACHES BASED ON SSIM

VI. CONCLUSION AND FUTURE WORK

A single image super-resolution technique is proposed in this paper. It exploits the benefits of genetic algorithm in the optimization process. Edge preservation using mathematical morphology reduces the computational overhead. Experimental results demonstrate that the method proposed here can produce better quality images when compared to the results of other approaches, namely, Bilinear, Bicubic, WZP and [16] given in the literature.

Since the edge detection using mathematical morphology magnifies the reconstruction error, a better optimization algorithm can be used in order to achieve still better efficiency. Multiscale morphology for edge-preserving and Adaptively edge-guided IBP algorithm which adds local edge information adaptively can further increase the efficiency of the algorithm

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.Authors Profile

Shimil Shijo Received the **B.Tech.** degree in computer science and engineering from the Govt. Engineering College, Thrissur, Calicut University, Kerala, India, in 2012.Currently doing **M.Tech** in computer science and engineering in National Institute of Technology Calicut, India. Her research interest includes Image processing

Dr.V K Govindan Professor, retired from Department of Computer Science and Engineering at National Institute of Technology, Calicut.He has received bachelor's and master's degrees in electrical engineering from Regional Engineering College Calicut in the year 1975 and 1978,respectively.He has obtained PhD degree from IISc Banglore. His research areas include Image processing, pattern recognition, operating systems, and machine learning.