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# Hardware Modeling of Motion Free Super Resolution

**Vidya K V[1], P. S. Shilpashree[2]**

[1]Department of Electronics and Communication, Siddaganga Institute of Technology, Tumkur, India

[2]Assistant Professor, Department of ECE, Siddaganga Institute of Technology, Tumkur, India

**Abstract:** ***The high resolution (HR) images have applications in a ample variety of areas such as robotics, industrial inspection, remote sensing, image transmission, medical imaging and surveillance because it offers additional details that are important for analysis. Super-resolution (SR) techniques can be used to increase the resolution from several degraded low resolution (LR) images. Unlike other SR imaging methods, for the motion-free SR case sub-pixel registration of given LR observations are not required. HR image is obtained from a set of down sampled observations blurred to dissimilar extents. In this work , SR reconstruction from LR images is implemented using Iterative Back Propagation (IBP) algorithm where High resolution image is estimated by back projecting the variation between simulated LR images through imaging blur and the observed LR images and the process is recurring iteratively till the error is minimized. Results are compared in terms of speed using MATLAB and XILINX simulation tools.***

**Keywords:** Super-resolution, image restoration, iterative back projection, low resolution, high resolution

## 1. Introduction

The term spatial resolution is the smallest discernible or measurable detail in a visual presentation and is measured in pixels per inch. LR images has the pixel density within an image small, hence it offers less details, where as HR images has the pixel density within an image large, thus offering more details. Since 1970s, charge-coupled device (CCD) and CMOS image sensors are used widely to capture digital images. These sensors are fitting for most imaging applications, but the existing resolution level and consumer price will not suit the future demand. Hence there is need for the resolution improvement [1]. Possible ways are, to reduce pixel size, increase chip size and to use SR methods. Reducing the pixel size leads to increase in the number of pixels per unit area but as the pixel size decreases, the amount of light available also decreases. Hence it generates shot noise that degrades the image quality severely. Consequently to reduce the pixel size without the agony of shot noise, limitation exists on the pixel size reduction, and the optimally limited pixel size is estimated at about 50 $\mu m^2$ [2].

In the second approach chip size is increased which leads to an increase in capacitance [3]. But it is difficult to speed up a charge transfer rate as capacitance increases; hence this approach is not effective. Accordingly in many viable applications regarding HR imaging, the high cost for high precision optics and image sensors is also an important concern.

Hence SR methods can be used which is based on the idea that a multiple LR images can be merged to get an HR image. SR techniques increase the spatial resolution by fusing information from several LR degraded images. At least, two non identical LR images are required to construct an HR image [4].

HR images are enviable in most of the computer vision applications such as remote sensing, medical imaging, robot vision, industrial inspection or video enhancement etc. Since HR images leads to a better analysis in the form of lesser misclassications, better fault detection, etc [5]. Hence the vital aim of SR is to generate a HR image from LR images.

The relative motion is assumed as part of the model in typical super-resolution. Yet, quality of the reconstructed super-resolved image is altered by the errors in registration. Super-resolution reconstruction can also be achieved with super-resolution techniques which will not involve any sub-pixel shifts of the camera i.e. when there is no relative motion between the camera and the scene. Super-resolution is possible even without motion, termed as motionless or motion-free super-resolution and an brief analysis of it is given by Elad and Feuer [6]. They demonstrated that SR image can be obtained from several LR observations which are obtained with different degrees of defocusing. In motion-free case the aim of super-resolution is to un-wrap the effects of blurring and aliasing by making use of the unique information's present in the given set of observations.

The SR restoration idea was first presented by Tsay and Huang [7]. They demonstrated the ability to reconstruct single image with improved resolution from several down sampled noise-free versions of observations, based on the spatial aliasing effect in frequency domain approach. Ur and Gross suggested spatial domain approach based on Papoulis and Yen generalized sampling theorems [8]. A SR restoration algorithm based on a minimum mean squared error (MMSE) approach was proposed by Srinivas and Srinath for the multiple image restoration problem and interpolation of the restored images into one [7].

A different approach based on the iterative back projection (IBP) method toward the SR restoration problem was suggested by Peleg *et al.* [9]. In this method an initial guess of the output image is made, and the temporary result is projected to the measurements (simulating them), and the temporary guess is updated according to this simulation error. In this paper IBP method has been used for SR image reconstruction from four low resolution images with varying blur parameters keeping noise constant.

This paper is organized as follows: in section 2, a motion free super resolution model is given. This section also gives a short description of LR image formation. In section 3, SR reconstruction using IBP method is described. In section 4, the SR reconstruction is evaluated through experimental results. Hardware modeling of motion-free super-resolution is discussed in section 5 along with simulation results. Conclusion will be finally discussed in section 6.

## 2. Motion-Free Super Resolution

Motion-free super resolution is the process of generating a HR image from a set of defocused, noisy and down sampled observations blurred to different extents. Even though relative motion between camera and scene is not considered in motion-free case, blur is assumed to be present because it is considered that blurring is inherent during the formation of an image due to the low resolution of the point spread function (PSF) of the capturing device which leads to loss of high frequency detail. Since it is assumed that blur is already present in the low resolution observations blur is used as cue. The relative blur between the observations are known when different images of a scene are captured using different camera parameter (focus, aperture, etc.,) settings [10].

### A. Observation Model

Many low-resolution observations are needed for the restoration of super-resolved image, at least; two low-resolution images are required for reconstruction [11]. In this paper, by considering decimated, blurred and noisy versions of an ideal high resolution image which are used to generate a super-resolved image the task of registration is avoided. In Motion-free case images are obtained with different blur parameters without considering any spatial shifts. To relate high and low resolution intensities the model is given as: A high-resolution image is blurred to different extents, blurred image is decimated and finally zero mean independent and identically distributed (i.i.d.) Gaussian noise is added to form low-resolution images. Fig. 1 gives an illustration of the model as explained [12]

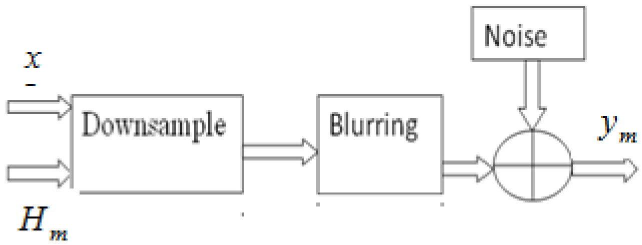


**Figure 1:** Low resolution image formation from high resolution image

Equation 1 gives the observation model that relate LR observations to HR image [13], where, $\underline{x}$ represents the HR image, which when down sampled, blurred and after incorporating the noise vector [14], forms LR observation $x_l$.

$$x_l = H_m D \underline{x}_H + n_m, \qquad m = 1, \ldots, p \tag{1}$$

Equation 1 can be expressed in matrix vector form as:

$$\begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_m \end{pmatrix} = \begin{pmatrix} DH_1 \\ DH_2 \\ \cdot \\ \cdot \\ \cdot \\ DH_m \end{pmatrix} \underline{x}_H + \begin{pmatrix} n_1 \\ n_2 \\ \cdot \\ \cdot \\ \cdot \\ n_m \end{pmatrix} \tag{2}$$

Where:

$\underline{x}$ is the original HR image

D is the decimation matrix of size $M_1 M_2 \times q^2 M_1 M_2$

H is the blur parameter of size $M_1 M_2 X M_1 M_2$

$n_m$ is the noise parameter $M_1 M_2 X 1$

p is the number of low resolution observations

The model indicates a collection of low resolution images, each of which differs from the others in the blur matrix. For SR reconstruction from the LR images as obtained from equation 1, IBP algorithm can be used.

## 3. Iterative Back Projection Algorithm

The HR image can be reconstructed back from the observed LR images using IBP method. In this approach error obtained as the difference between simulated LR images via imaging blur and the observed LR images is back projected. This process is repeated iteratively until the energy of the error is minimized. The matrices $H_m$, D implementation is simply the image blurring and decimation which models the image formation process [15].

### A. Mathematical Formulation

SR can be solved using explicit iterative methods and represented as a large sparse linear optimization problem. For practical reasons in the gradient based iterative methods it is assumed the noise is uncorrelated and has uniform variance. In this case, the maximum likelihood solution is found by minimizing the functional:

$$E(\underline{x}_H) = \frac{1}{2} \| \underline{x}_L - A \underline{x}_H \|^2 \tag{3}$$

Where $A$ is $DH_n$. Taking the derivative of E with respect to $\underline{x}_H$ and setting the gradient to zero:

$$\nabla E = 0 \Rightarrow A^T \left( A \underline{x}_H - \underline{x}_L \right) = 0 \tag{4}$$

$$\Longleftrightarrow \sum_{n=1}^{K} H_n^T D^T \left( DH_n \underline{x}_H - \underline{x}_L^{(n)} \right) = 0 \tag{5}$$

The matrices $H_n$, D model the image formation process and their implementation is simply the image, blurring and respectively

$$\underline{x}_H\{m+1\} = \underline{x}_H\{m\} + \sum_{n=1}^{K} H_m^T D^T (x_L^{(n)} - DH_m \underline{x}_H\{m\}) \tag{6}$$

Equation 6 is an IBP equation and $x_H\{m\}$ is the HR image of the current iteration. In happening iterations the obtained

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HR image is used as the original image and the error is back propagated.

## 4. Results and Discussion

In this section, experimental results are provided to demonstrate the performance of IBP algorithm by obtaining SR image from the observed LR images. All operations were implemented in the image domain only on synthetic images.

Case1: Ideal situation

In this experiment single high quality image of size $256 \times 256$ pixels is used [Fig. 2(a)], from which the four low resolution noisy images of size $128 \times 128$ pixels are generated. Each of the LR images were blurred with different blur parameters 0.05, 0.06, 0.07, 0.08 which then down sampled by a factor 2 and Gaussian noise of zero mean and 0.0001 variance were added. Fig. 2(b) shows one such degraded LR image. The image quality is not improved by using bilinear interpolation as shown in the Fig. 2(c). Fig. 2(d) shows the SR image obtained using the IBP algorithm which gives the good quality image and is very closely resembles the original HR image.


**Figure 2:** (a) Original HR image, (b) LR image, (c) Bilinearly interpolated image, (d) SR image using IBP

Case 2: High blur

The experiment is repeated by choosing negligible amount of white Gaussian noise with zero mean and variance of 0.0001 was added to each LR images. Fig. 3(a) shows the LR image and Fig. 3(b) shows the reconstructed image for blur parameters 0.1, 0.2, 0.3, 0.4. The blur parameters were increased to 0.5, 0.6, 0.7, 0.8 and the result with medium blur (Fig. 3(a)) is much better compared with high blur (Fig. 3(b)).


**Figure 3:** Results of IBP under high blur. Super-resolved image with noise=0.0001 (a) with blur 0.1, 0.2, 0.3, 0.4, and (b) with blur 0.5, 0.6, 0.7, 0.8.

Case 3: High noise

In this experiment, reconstruction is implemented by considering the same image with Gaussian blur of standard deviation of 0.05, 0.06, 0.07, and 0.08. White Gaussian noise of zero mean and variance of 0.1 was added to the LR images. Artifacts can be seen in the reconstructed super-resolved image as shown in Fig. 4(a). Fig. 4(b) shows the reconstructed super-resolved image where in the noise is increased to 0.2 which has more artifacts compared to fig. 4(a).

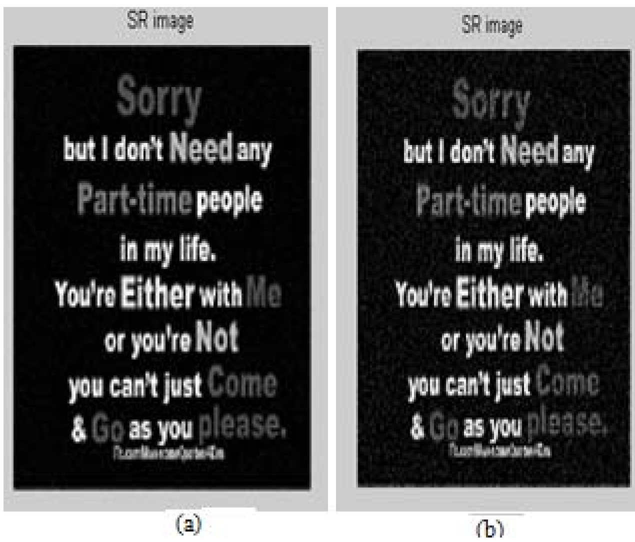


**Figure 4:** Results of IBP under high noise. Super-resolved image with blur 0.05, 0.066, 0.07, 0.08, (a) with noise=0.1 and (b) with noise=0.2.

**Table 1**: Comparisons of MSE and ISNR for various cases

| | *Ideal Case* | *High* | *High Noise* |
|---|---|---|---|
| MSE | 5.4326 | 16.734 | 68.456 |
| ISNR | 70.684 | 66.267 | 27.378 |

For the experiment; we used mean square error (mse) per pixel and improvement in signal-to-noise ratio (ISNR) as performance measures,
Where,

$$mse = \frac{1}{N_1 N_2} \| X - \hat{X} \| \tag{7}$$

$$ISNR = 10 \log_{10} \frac{\| X - X^{(0)} \|}{\| X - \hat{X} \|} \tag{8}$$

In the above equation, $X$ is the original image, $N_1 \times N_2$ is the size of original image, $X^{(0)}$ is the initial estimate of the super resolved image which is obtained by averaging the bilinear up-sampled aligned images, and $\hat{X}$ is the super resolved image. The mean square error plot is as shown in Fig. 5 which indicates the decrease in the error and improve mental signal to noise ratio (ISNR) is as shown in Fig. 6 for an ideal case, both of which shows the improve in performance of algorithm.

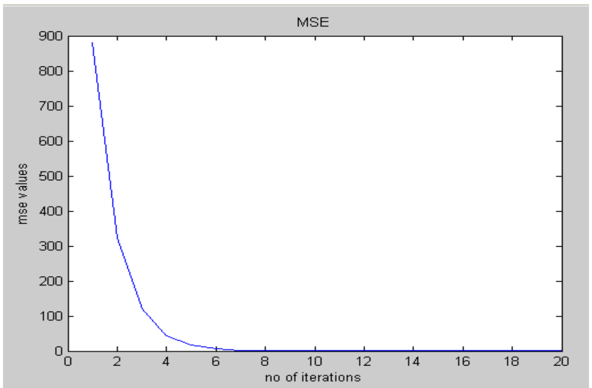


**Figure 5:** Plot of mse

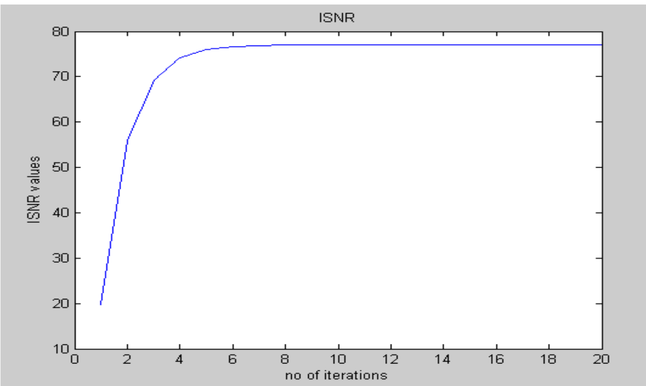


**Figure 6:** Plot of ISNR

## 5. Hardware Modelling Of Motion-Free Super-Resolution

The IBP method was implemented in XILINX (ISE Design Suite) tool. XILINX ISE provides an Integrated Software Environment is a software tool. For synthesis and analysis of HDL designs, enabling the developer to synthesize ("compile") their designs, perform timing analysis, examine RTL diagrams, simulate a design's reaction to different stimuli, and configure the target device with the programmer.

The LR images are imported from the MATLAB as the input to verilog coding in XILINX and the IBP process is carried for 20 iterations. The results of MATLAB which were also carried out for 20 iterations are compared with the simulation results obtained using XILINX as shown in Fig. 7 from which it is evident that both the images are similar. But in XILINX the simulations are obtained in pixels which have to be converted back to image. In table2 a comparison for mse and timing analysis for MATLAB and XILINX are compared from which it can be observed that simulations using XILINX tool is much faster compared to MATLAB.

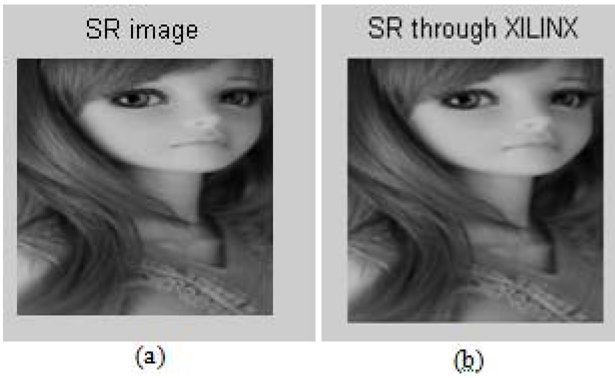


**Figure 7:** Results of IBP using (a) MATLAB (b) XILINX

**Table 2:** Comparisons of MSE and Timings for XILINX and MATLAB tools

| | *MSE* | *Timing Report* |
|---|---|---|
| MATLAB | 5.4326 | 4.8077seconds |
| XILINX | 5.286 | 8.23ms |

## 6. Conclusion

This paper addresses the problem of generating super resolution using IBP scheme from low resolution images which are degraded by different parameters such as down sample, blur and noise. The IBP method in this paper tackles the SR problem in spatial domain. It is observed that IBP gives the good results compared with the bilinear interpolation since IBP improves the quality of an image compared to bilinear interpolation. The statistical parameters like ISNR and mse are analyzed. The performance evaluation results show a promising improvement in ISNR for an ideal case whereas IBP is sensitive to noise. The simulations using XILINX performed better in terms of speed as compared to MATLAB which is evident from the timing report of the tools.

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## Author Profile

**Vidya K V** received the B.E. Degree in Electronics and Communication from Channabasaveshwara Institute of Technology, Gubbi, Karnataka, India. Perceiving M-Tech in Signal Processing at Siddaganga Institute of Technology, Tumkur, Karnataka, India.

**P S Shilpashree** received B.E. Degree in Electronics & Communication from Channabasaveshwara Institute of Technology, Gubbi, Karnataka, India and the M-Tech in Signal Processing at Siddaganga Institute of Technology, Tumkur, Karnataka, India. She is currently working as a Assistant Professor at Siddaganga Institute of Technology, Tumkur, India.