Super Resolution of Medical Images Using Integrated Approach of Deep Learning and Sparse Coding

Thesis submitted in partial fulfillment of the requirements for the award of degree

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Master of Engineering

In

Information Security

Submitted By

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "***Super Resolution of Medical Images using Integrated Approach of Deep Learning and Sparse Coding***", in partial fulfillment of the requirements for the award of degree of Master of Engineering in ***Computer Science and Engineering*** submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of ***Ms. Harkiran Kaur*** and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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ABSTRACT

Image Super-Resolution is the active field of image processing. Images and videos with high resolution are used in various fields like medicine, agriculture, pattern recognisation etc for better analysis. The need of enhancement of the resolution of image is motivated due to the advancement of the pictorial information used by humans for interpretations, for autoarchic machine applications and for the purpose of efficient storage and transmission. One of the major fields is medical imaging. As medical images are more sensitive to noise, so to enhance the intensity of the image is turn out to be a major area. The High resolution medical images can localize any disease or analyzes the body part more accurately. There are many applications for increasing the resolution of image but they are not very effective as they add physical artifacts such as noise and blur. There are various algorithms of image super resolution which uses dictionaries for reconstruction and these dictionaries have to train explicitly.

This thesis proposes a method to increase the resolution of a medical image. In this framework conventional sparse coding model has been extended with key concepts of deep learning. This framework doesnot require training of dictionaries explicitly. Firstly, a low resolution medical image is denoised to remove noise. As medical images are more sensitive to noise due to the acquisition devices. Then this denoised image is inputted to the network where features are extracted for each LR patch. Then LR patch is fed into a network.

This network is based on learned iterative shrinkage and thresholding algorithm (LISTA) whose layers strictly correspond to each step in the processing flow of sparse coding based image SR. This way sparse representation technique is effectively encoded in our network structure, and at the same time all the components of sparse coding can be trained jointly through back-propagation. In the next layer sparse code obtained is multiplied with dictionary to reconstructs HR patch and then the recovered patches are placed back to their respective positions in the HR image by the fixed layer which aligns pixels in overlapping patches. At last, a HR medical image is obtained as output.

The performance evaluation of the proposed method is based on Peek Signal to

Noise ratio (PSNR), Structure Similarity Index (SSIM) values. The PSNR and SSIM values of our proposed algorithm are better than the Bicubic interpolation, Sparse coding algorithm for both noiseless and noisy image etc. The average PSNR value of proposed method is more than that of sparse coding by 0.27 for noiseless image.

CONTENTS

LIST OF ABBREVIATIONS

SR	Super Resolution
LR	Low Resolution
HR	High Resolution
CAT	Computerized Axial Tomography
MRI	Magnetic Resonance Imaging
CPs	Control Points
PSF	Point Spread Function
PDE	Partial Differential Equation
ScSR	Sparse Coding Super Resolution
PSNR	Peak Signal-To-Noise Ratio
SSIM	Structured Similarity of Index
SAI	Soft Adaptive Interpolation
SVD	Singular Value Decomposition
GPU	Graphics Processing Unit
SRHE	Sub regions Histogram equalization
SWSR	Sparse Weighted Super Resolution
PCA	Principal Component Analysis
LISTA	Learned Iterative Shrinkage Threshold Algorithm
MSE	Mean Square Error

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CHAPTER 1
INTRODUCTION

1.1 Preamble:

Digital images are defined as an ordered 2-D array of small elements called pixels. The number of columns and rows of array represent image width and height respectively. A specific pixel can be referred by value of coordinates of array at that point. These digital images are used in various fields wherever there is a need to zoom the image or to analyze it to its depth such as medical, video surveillance, astronomy and many more. Therefore, if we enhance the resolution of the original picture it becomes easier for the observer to obtain any important information out of the image. A number of techniques have been used till date to get HR image from the original one. Super Resolution (SR) is one of the methods used for enhancement of the resolution of the image or video. High Resolution (HR) image has high pixel value. Pixel value is the value of the brightness at any point within the image.

1.2 Image Processing

It is a method to obtain a HR image or to take out some critical facts useful for further analysis by performing some mathematical operations. This is a process in which an image is given as input and output can be HR image or some features associated with it including contrast, sharpness, and many more. The major steps of image processing include:

i. Importing the image.
ii. Analysis and manipulation of image
iii. Output as image or features associated.

Following are the two types of image processing:-

a) Analog image processing- This type of processing is applied in hard copies of picture like printouts and photographs.

b) Digital image processing- This type of image processing is used in soft copy of digital images.

1.3 Digital Image Processing

Digital image processing involves a series of actions that is performed on a digital image to get the desired results. The digital images are manipulated through digital computer. The need of digital image processing is to improve the pictorial information for human interpretation or for analysis. Improvement of pictorial information includes improving the edges of an image to make it appear sharper, removing of noise and motion blur from an image. To get over these abnormalities images are required to be processed. Preprocessing, enhancement and information extraction are the three main phases an image has to endure, while using digital technique.

1.4 Super Resolution

SR is the technique of enhancing resolution of images or video to get a HR image from one or multiple LR images. The LR image has small pixel density within the image, therefore it offers fewer details. But HR image has large pixel density within an image, therefore it offers more information. The details of the original scene can be gathered more effectively with HR images. There are various fields such as medical imaging such as CAT, MRI; astronomy; video surveillance etc where HR images are required. The need for HR images is due to the areas where there is a need to zoom the image or to analyze it in deep. HR imaging is not always available. There are various sources of HR imaging but they are too expensive and inefficient due to sensor limitations and optics manufacturing technology.

Images can be obtained from one or multiple cameras. These images are to be associated to a regular framework. This process of association is called registration. Then SR procedures can be applicable to the particular field. Super Resolution is successful if a reliable alignment that is registration and construction of the image model is done. The three basic components that are used by most of the SR reconstruction algorithms:

1.4.1 Image Registration

The non-identical view-points of the same site can be observed by multiple LR images.

The process of wrapping the surface of one or more images of same location is called image registration. As images obtained from different sources or at different times are necessitated to be compared for the purpose of analyzing image or for decision making in many fields such as in medical to detect disease and in astronomy regarding actions in universe. Therefore, the misalignment between the images reduces the accuracy of analysis. So, this procedure is defined to align the two images geometrically. The two images used for alignment are known as reference image and sensed image. The reference image is referred to as source image on which algorithms of super resolution have to be implemented. The sensed image is called the target image. For image analysis, the most crucial step is image registration. The data sources like change detection, multichannel image restoration and image fusion all are combined to obtain final result. Image fusion forms an image with the combination of two or more images. Resultant fused image depicts more complete information of both the images than the single image. Change detection is the method to identify the regions of change in various images of the identical scene taken at different instant of times. This change detection is useful in various applications similar to surveillance, medical diagnosing and so on. Multiple Image Restoration is the technique to obtain the clean image from the corrupted or noisy image. This technique is different from image enhancement as image enhancement focuses on the features to make the image more agreeable. In order to align the non-identical images precisely, the very first step of super-resolution is image registration. In today's era, there is a tremendous development of image acquisition devices and therefore diversity of obtained images invokes automatic image registration. Following are some steps used in majority of registration methods:

- Detection of features: The features like corners, intersections, edges and many more are detected by means of segmentation method. These features are then represented by their representative points such as line endings or centre of gravity for further processing. In the literature these points are known as Control Points.
- Feature matching: Here the relation is established in between the detected features of sensed image to those of reference image. Some similarity measures combined

with spatial relationships are employed for matching of features of an image to that of reference image.

- Transform model estimation: The estimation of type and parameters of the so-called mapping function that are employed for aligning the sensed image with the reference image is done. The mapping function provides a method to link the various parts of an image without dividing the image. The parameters of the mapping functions are computed by means of the established feature correspondence

- Image re-sampling and transformation: The sensed image is transformed by means of the mapping functions. Transformation is done for aligning the image in correct position. Appropriate interpolation technique is used to compute image values in non-integer coordinates.

1.4.2 Interpolation

Interpolation is a method used to determine values of a function at any position in between the samples by using curve fitting equations. This method is used for enlarging and contrasting the digital image. It occurs in all digital images at some stage of resizing, zooming, magnification or remapping an image from one pixel grid to another. Image resizing is necessary when there is a need to change the value of total number of pixels that is to increase or decrease the pixels, whereas remapping can be done under variety of scenarios: correcting the lens distortion, changing perspective, and image rotation. Even if the same image is resized or remap, the results can vary significantly according to the applied interpolation algorithm. Usually resizing of image involves operations such as scaling up and scaling down. Due to this, the resized image has low quality but it can be retained by introducing new pixels. These new pixels are introduced on the basis of prediction or approximation. Therefore, image interpolation is the easiest way to enhance the quality of LR image. This may be achieved by curve fitting or regression analysis. Interpolation methods grouped into two categories: adaptive and non-adaptive. The methods that depend on what they are interpolating (sharp edges vs. smooth texture) are called adaptive, whereas the methods that treat all the pixels equally are known as non-adaptive.

1.4.2.1 Non-Adaptive Algorithms

These algorithms use a fixed methodology to handle all the pixels in the procedure of interpolation. The algorithm performs operations on the basis of local structure of image. In this linear and fixed computation is implemented at every pixel. The computational logic for non-adaptive remains fixed irrespective of features of images. Interpolation of new pixel values is done by combining sum of input data and interpolation kernel. Mostly non-adaptive is used in real life applications. Amongst them Nearest Neighbour, Bilinear, Bicubic, Spline, Sinc, Lanczos are prominent ones. While interpolating, depending on the complexity of algorithms these can be use anywhere from 0 to 255 adjacent pixels. If more adjacent pixels are included, the more appropriate these methods become, but there is a drawback that is large processing time. These methods are preferred as here computational cost is less.

1.4.2.2 Adaptive Algorithms

Here in the adaptive techniques different methods are used to locate pixels in the throughout procedure of interpolation. Non-linear types of computations are implemented depending on the sharp edges and smooth texture. The computational logic of these techniques is dependent on the intrinsic features and content of image. This includes many licensed software such as: Q image, Genuine Fractals and many more. The main objective of these algorithms is to minimize hideous interpolation artefacts. These are primarily modelled to maximize the artefact, therefore some cannot be implement to distort or rotate an image. These algorithms give better results than non-adaptive but have high computational cost as they require more hardware.

1.4.3 Reconstruction Of Images

The SR reconstruction aims at obtaining single high-resolution image either from degraded still images (single static image) or from several degraded multi frames (collection of images related by time or view).

1.4.3.1 Blind Image Super-Resolution

The blurring process is actually unknown in many practical applications. Due to this, blind SR algorithm is defined. This includes the identification of blur factor in SR restoration. The sensor PSF occurred due to camera lens is always ignored in the framework of blind SR. This means the HR images are affected by the sensor PSF. Image registration, image restoration and estimation of PSF is combined in one framework in this technique. While suppressing noise edges are preserved by partial differential equation (PDE).

1.4.3.2 Fast And Robust Super-Resolution

Estimation of HR image is not only based on LR measurements. The estimation also includes many hypotheses such as noise or motion models. For estimating HR image from noisy LR images, an appropriate estimation method is required to be chosen. The chosen method optimally estimates HR image, on the basis of assumptions of data and noise models. The methods which is limited only to data and noise models it may or may not be beneficial approach. Techniques not sensitive to models give stable results (robustness). The concept of breakdown is introduced to measure the robustness of an algorithm.

1.5 Application Areas Of SR Imaging

HR imaging is indispensable in various computer applications. The HR images are used to improve performance in pattern recognition. HR images also find their application in medical area. In many areas, HR image is required to analyze the area of interest. HR images are in great demand in various fields, such as medical, engineering, computer vision, pattern recognising, video production, and many more. It is not possible to get the images and videos of suitable resolution because such images and videos are obtained from various electronic devices that uses sensors, which includes X-Ray systems, remote sensing cameras etc and those sensors do not have desired resolution quality. HR image offers a bunch of assistance in:

- Remote sensing: It is defined as gathering information of an object without making physical contact. Remote sensing is used in various fields such as geography or earth science discipline. Therefore, images with high spatial resolutions are required in these areas.
- Surveillance video: to increase the resolution of any video so that we can easily upscale the area of interest.

- Medical imaging (CT, MRI, and Ultrasound etc): Most of the medical images are corrupted with noise and have LR. HR images are used for detecting any problem or analysis of specific part of body.

1.6 Super Resolution Classification

i. Multiple Image Frame Super Resolution

ii. Single Image Frame Super Resolution

1.6.1 Multiple Image Frame Super-Resolution

In multiple images SR, single SR is obtained from multiple LR images. This type of super-resolution refers to the case in which multiple images from the same scene are available. Various "looks" of the same scene are depicted by these multiple LR images. The changes in these LR images are due to camera zoom, camera or scene motion, focus and blur. Resolution of reconstructed image is above the limits of all imaging devices by using algorithm. It means these resolved images can depict more of the original scene's details than that of input images. The factors like blurring, geometrical transformation, and down sampling all come under degrading processes(decreasing resolution of image).The best case where SR can possible in these methods is to work when LR images have different sub pixel shifts and thus provide different information that is each image cannot be obtained from the others. The basic idea of preparation of training set based on any particular algorithm is prepared and with the help of that training set LR image can be further converted to HR image. It is of three types:

1. **Interpolation Based Approach**

   The technique of up-scaling the image or resizing the image by finding out the pixel values that are unknown and lies within the sample. It occurs in all digital images where you need to resize the image or remap (i.e. taking out the pixels from one image and locating them at other positions in new image) the pixels within the image. Resizing of image involves increasing or decreasing the number of pixels within the image whereas remapping involves distorting the pixels from one grid to other grid. There are various interpolation algorithms and the result of image depends on which interpolation algorithm is used by us. The two types of interpolation methods: adaptive and non-adaptive. Adaptive methods involve sharp and smooth texture and interpolation is done based on these two properties, whereas non-adaptive methods consider all points or pixel equally.

2. **Frequency Domain Based Approach**

   The main aim of SR methods is to get HR image from a set of LR images. All the LR images are of the same location. There is a method which correctly aligns high frequency and low frequency parts of the image. If the alignment of image is not perfect then this results in irregular image. This method has a number of benefits and is very simple. The relation between HR and LR image is clearly visible. The resolution of LR image is increased by finding out the high frequency details in image. This method has very low computational cost due to less calculation involved.

3. **Regularization Based Approach**

   Most of the SR algorithms add blur or noise to the image. This is the main problem of SR algorithms. Their motive is to decrease the number of possible solutions to stabilize the inverse operation. In this method, the information of unknown HR image is collected. It involves two methods:

   i. Deterministic regularization approach: The approach rely on the fact that, observation model can be completely specified with the estimation of registration parameters. Inverse problem is then solved by this approach by changing some knowledge about the solution.

   ii. Stochastic regularization approaches: The method adopts Bayesian approach, according to which the information can be extracted from the LR images about the unknown signal contained. In this method we find out PDF value of HR image is found with the help of observed HR image details and input LR image details.

1.6.2 Single Image Frame SR

In Single Frame SR is based on the single LR image. In this, only one single image is considered and processing is done on that image to convert it to HR version. The equation of single image SR can be written as

$$I_L = (I_H * b)_{s}, \tag{1.1}$$

where, I_L is LR image

I_H is HR image,

b is blur operator which adds blurriness to the image

The expression $_s$ denotes down sampling operation

The down sampling operation is implemented by a scale factor of s (possible value of s is positive integers).

There is a problem in single image SR, as there can be many HR images creating LR images that are identical. Single-image is like the interpolation, as both require the same thing that is one single input image. Interpolation methods like cubic, linear etc up-scale the image by finding out the missing pixel values. But interpolation does not consider edges as these are the most sensitive part of the image. Therefore, this results in addition of artifacts in the image and does not give us the smooth image. The main goal of SR is to get better HR image. Single-image SR algorithms involve two main methods: Learning-based method and Reconstruction-based methods.

a) **Learning-Based Single Image SR**

This technique of SR divides the image into patches. This is also called as Example based SR. In the method of image enhancement the input image is divided into patches where all patches are of same size. LR patches are converted into HR patches by using dictionary which is trained with the help of example images. The two dictionaries are created one having LR patch and other having HR patch. Firstly, input patch is matched with the LR dictionary. Then, LR dictionary patch and HR dictionary is used to reconstruct LR patch into HR patch.

b) **Reconstruction-Based Single Image SR**

This technique involves a process of building association between LR image and HR image. Its equation is:

$$L(y) = \int B(y,x)H(x)dx + E(y) \tag{1.2}$$

where, L(y) is continuous LR irradiance

H(x) is the continuous HR irradiance light-field on image plane

B(y, x) is the blurring kernel

E(y) is the noise

1.7 Various Interpolation Techniques

1.7.1 Cubic interpolation

It is the simplest methods of interpolation. If the value of a function f(x) and its derivative f'(x) is known at coordinate x=0 and x=1 than interpolate the function on the interval [0, 1] using three degree polynomial. Any four points within the image are used to find the unknown pixels values within the image. The equation for cubic interpolation is:

$$f(k_0,k_1,k_2,k_3,x_k)=(-0.5k_0+1.5k_1-1.5k_2+0.5k_3)x^3+ (k_0-2.5k_1+2k_2-0.5k_3)x^2+(0.5k_0+0.5k_2)x+k_1 \quad (1.3)$$

Where k_0, k_1, K2, k_3 are the values at x = -1, x = 0, x = 1, x = 2 and x_k is the unknown point

1.7.2 Nearest Neighbor interpolation

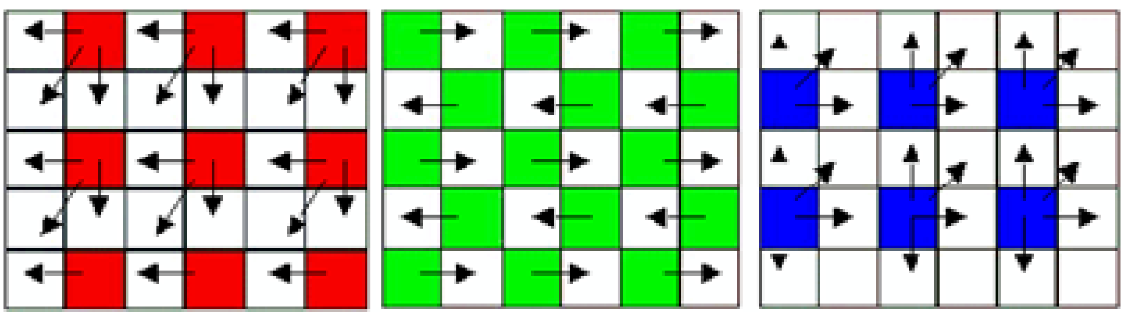


Figure 1.1: Nearest Neighbor Interpolation

The method given is very simple. It finds out the closest pixel value to specify the input pixel. After this step, it gives that value to the output pixel. This method does not find out new pixel values. It just copies the already present values as it does not change the existing values. The number of grid points needed for one-dimension nearest neighbor interpolation is two (one nearest point and one unknown point) and for two-dimensional is four (2 for x-axis and two for y-axis). For nearest neighbor method, the equation is:

$$u(s) = \begin{cases} 0 & |s| > 0.5 \\ 1 & otherwise \end{cases} \tag{1.4}$$

S is the distance between interpolated point and the point which is under consideration within the grid. Its coefficients ck = f (xk).

1.7.3 Bilinear Interpolation

Bilinear interpolation is used to find out the unknown pixel values within the sample with the help of given pixel values in 2-D grid. It is advanced version of Linear Interpolation. Firstly, linear interpolation is done in one direction of image. After this, it is performed in other remaining direction. It is a re-sampling method in which we find out the average of distance weight of 4 nearest pixels to find out the new pixel value. It is used to determine value of a point by using neighboring points assuming that surface is continuous and smooth and there is highly a correlation present between the neighboring points.

In Figure 1.2, the main aim is to find the value at the dot c having green color . The point c have the coordinates tx and ty. The value of c can be calculated by performing two linear interpolations in one direction i.e x axis so that we can get value of a and b. In the bilinear interpolation process, firstly value of a and b is calculated. In the similar way value of c is find out using a and b. c00, c01, c11, c10 are the four known pixel. c is the unknown pixel

$$b = (c11-c01) - tx; \tag{1.5}$$

$$a = (c10-c00) - tx; \tag{1.6}$$

$$c = (b-a) - ty; \tag{1.7}$$

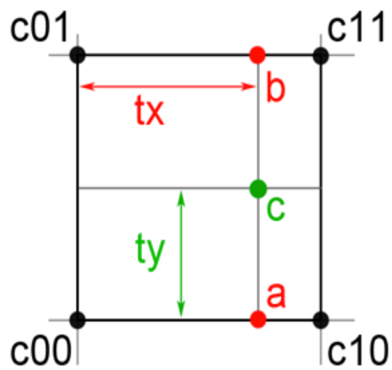


Figure 1.2: Bilinear Interpolations

1.7.4 Bicubic Interpolation

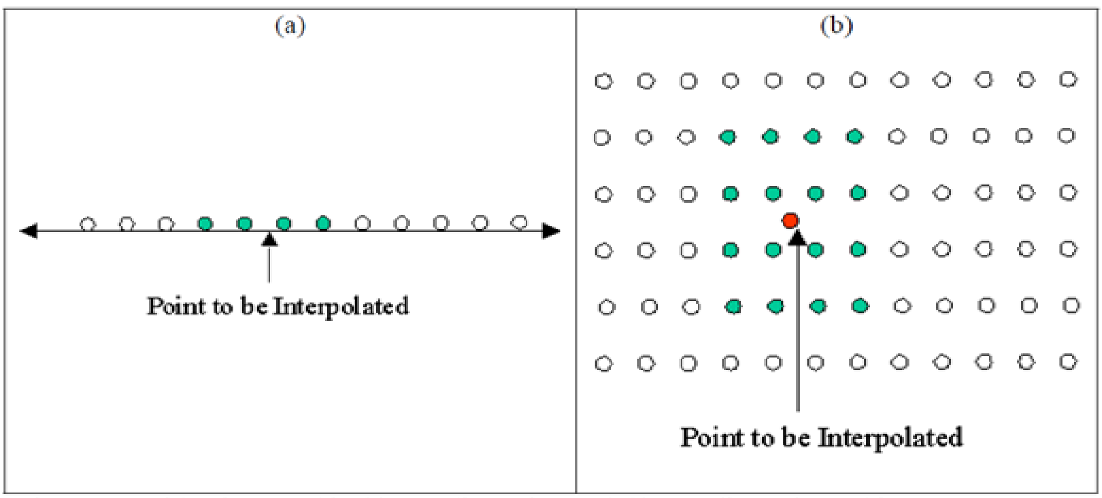


Figure 1.3: Bicubic Interpolation

Interpolation involves up-scaling the image or resizing the image by finding out the pixel values that are unknown and lies within the sample. It occurs in all digital images where you need to resize the image or remap the pixels within the image.

Bicubic interpolation is the improved version of cubic convolution interpolation method. Two dimensional interpolations are performed easily by one dimensional interpolation on each direction. The experimental result shows that performance of this method is better than linear interpolation and k-neighbor algorithm. Bicubic interpolation works on two dimensional grids whereas cubic works on one dimensional grid. The surface obtained in this is smoother than the surface obtained in bilinear and k-nearest interpolation algorithms. This method reconstructs the same surface between 4 starting pixels. This method provides zero artifacts. This method is hard to understand because of its tough calculation. In this information of sixteen pieces are extracted. Firstly, four horizontally 1-D cubic convolutions are performed in same direction. Then one more vertically 1-D cubic convolution is performed. Therefore, it is required to implement cubic interpolation in two dimensions. 16 grid points are needed. Figure 1.4 shows the effects of interpolation on the original image.

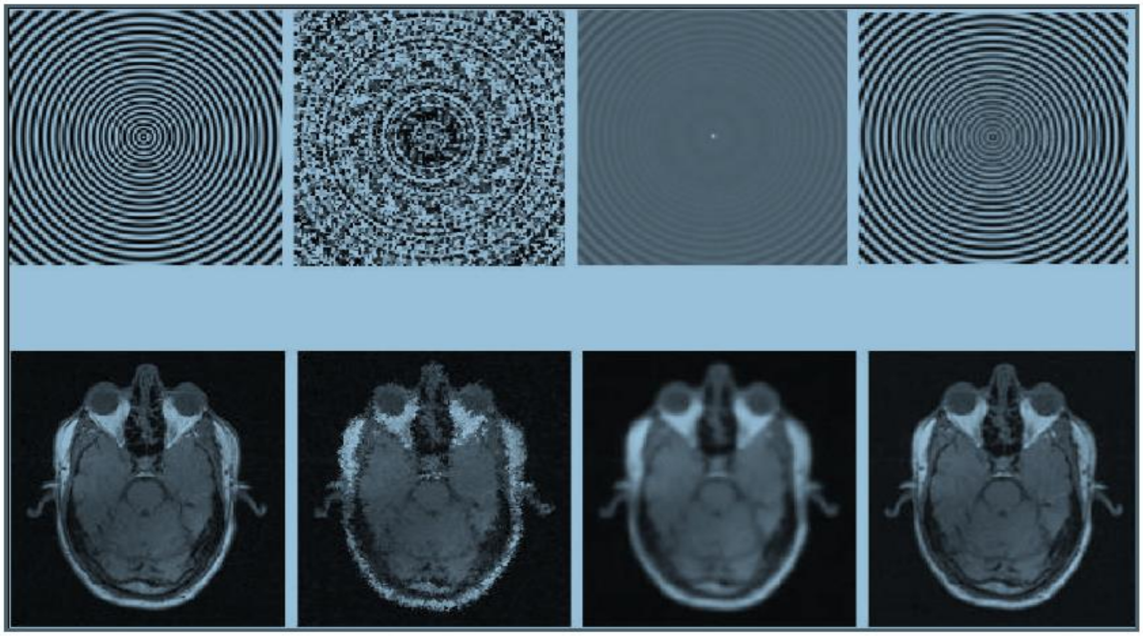


Figure 1.4: Effects of image interpolation (a) Original image, (b) Interpolated image using nearest neighbour, (c) interpolated image resulted from bilinear, and (d) interpolated image from bicubic [10]

1.8 Why Digital Image Processing Is Needed?

These days there is a tremendous increase in use of digital image processing and has brought up the demand of high resolution images for proper analysis in different fields. It involves a series of actions that is performed on a digital image to get the desired results. The digital images are manipulated through digital computer. The need of digital image processing is to improve the pictorial information for human interpretation or to analyze in deep. Improvement of pictorial information includes improving the edges of an image to make it appear sharper, removing of noise and motion blur from an image. To get over these abnormalities images are required to be processed.

In almost every field digital images are used. Similar way in the field of medical digital images such as CT scan, MRI is useful for studying and analyzing the certain problem. That’s why the topic of intensifying the medical images is very important. As high resolution images provide clear view of the image which makes the analyzing process easy and helps to take decision like A HR image could localize a tumor more accurately. The thesis defines the proposed technique which removes the noise and intensifies the medical image.

1.9 Thesis Outline

This section discusses the framework of this thesis, which is classified as follows:

Chapter 1 is an introduction which describes the central theme of the research. It consists of brief introduction and aspects to digital image processing and various Super resolution techniques.

Chapter 2 describes the review of the previous works and introduces some of the illustrations and concepts which are helpful for the proposed work.

Chapter 3 presents the research gaps, problem statement and objective of the thesis.

Chapter 4 discusses brief introduction of some definitions required to understand the algorithm. Then the proposed algorithm is described in this chapter.

Chapter 5 describes the methodology used to reach the goal, that is, solution to the problem formulated in chapter 3. Further Implementation details and results have been discussed in this chapter.

Chapter 6 presents the conclusions of this thesis and important future research directions in this field based on the findings.

CHAPTER 2

LITERATURE SURVEY

2.1 Interpolation Techniques

Interpolation is a method used to determine values of a function at any position in between the samples by using curve fitting equations. This method is used for enlarging and contrasting the digital image. Adaptive and Non-adaptive techniques are the two types of interpolation. In this paper, these techniques are studied and contrast in the terms of PSNR (Peak Signal-to-Noise Ratio) and shows adaptive techniques give better PSNR results than Non-adaptive [10].

Xudong Kang proposed a fusion method [8]. The basic idea is LR image is interpolated by using soft adaptive interpolation (SAI is an edge preserving interpolation technique) and bicubic interpolation. Than artifacts of SAI are estimated and those pixels are replaced by those from image which is interpolated by bicubic interpolation. Gaussian filter may be used to reduce the artifacts of edges of bicubic interpolated image and than a threshold value is calculated to detect the distortions caused by SAI. Gaussian filter is used to reduce the effect of noisy pixels and its performance is better than other conventional filters. Finally bilateral filter is used for smoothing the edges and the resulting HR image is achieved by weighed sum of the two HR image.

The Lanczos interpolation [23] is used to scale up the image. Scaling of image is required for better view of the image and to improve its resolution. The new unknown points are calculated from given points within the sample. It is performed on digital signals. This method is used to find the signal values within the samples. To find out the effect of every input pixel on the interpolated pixel, a reconstruction kernel L(x) is used. The kernel is called Lanczos kernel. It is defined as follow-

$$L(x) = \begin{cases} \mathrm{sinc}(x)\ \mathrm{sinc}(x/a) & \text{if } -a < x < a \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

An edge directed Interpolation method is given by [9]. The result shows that this algorithm gives better performance as it preserves the edges regularity whereas bilinear or nearest neighbor interpolations does not give strong edges(does not consider edges as edges have greater pixel value than other part of image and leave them as it is). Firstly, the covariance of LR image is calculated. Then that covariance value is used to perform interpolation at HR on the basis of geometry duality between LR and HR covariance's. This method is used for interpolation of grayscale images and reconstructing color images.

2.2 Various Enhancement Techniques

Sub regions Histogram equalization (SRHE) is presented by [26]. This method improves the texture of an image. This improvement is done by altering the intensity level of the pixels. This alteration is done on the basis of the intensity scattered over the input image. The method divides the image on the basis of the smoothed intensity values. Gaussian filter gives the smooth area of image. It also considers the values of intensity of the neighbour pixels. Implementation results depicts that the proposed method sharpens the image.

Edge directed algorithms focus on removing artifacts from edges and paying no attention towards the smoother regions. Y. Niu, W. Xiaolin et al. propose an approach where edges are reconstructed but also image details are also recovered [12]. In this approach, learning based details are combined with edge directed algorithm in a single framework. . In this approach, first edges are reconstructed in the LR input image. Then these details are combined with the missing details of example image. Succeeding this, learning based SR is performed. The implementation results depicts that the approach gives better performance results than the edge directed approach as the output image is irregular in edge directed algorithms whereas it gives an image having regular texture.

There is a method of creating the dictionaries of low and high resolution patches using example images so that these dictionaries perfectly fit the training set (there is a sparse association between LR patch and HR patch). In this algorithm, first the sparse coding matrix is produced using the present dictionary and then updating the dictionary atoms with the help of sparse representations. This algorithm overcomes the problem of creating and using over complete dictionary. This algorithm runs with any type of matching pursuit. The one of the type of sparse approximation is matching pursuit, which is used to find out the "best matching" projections of multidimensional data onto an over-complete dictionary. This algorithm is widely used in image processing, biology, face recognition, audio processing [17].

The k-nearest neighbor method given by [21] is very simple. It finds out the closest pixel value to specify the input pixel. After that it gives that value to the output pixel. This method does not find out new pixel values. It just copies the already present values as it does not change the values.

Jianchao Yang et al. proposed sparse representation technique to improve the resolution of an image and removing the noise [15]. Two dictionaries are prepared from examples. Dictionaries are prepared using k-SVD algorithm (this algorithm is already explained). It involves sparse association between the HR patch and LR patch. The basic idea behind this method is to represent the input vector as a weighted linear combination of small number of basis atoms. It is performed in two parts- First, training of dictionaries is done. In first phase, training is done on two dictionaries. One dictionary for LR patches and one for HR patches by using example images. Then, reconstruction of HR image is performed. In reconstruction phase, the method chooses patch from the low resolution dictionary that best represent the LR patch. This algorithm depends on sparse association between image patches. The experimental result show great results in robustness to image corruption. Its performance is much better than all other SRs method like interpolation and k-nearest neighbor method because it reduces the noise and blurriness effect as well as PSNR values of images enhanced using ScSR is greater than other conventional techniques.

Dinh-Hoan, Marie Luong et al. proposed a method sparse weighted super resolution (SWSR) and compare it with sparse coding nearest neighbor methods[24]. The basic idea behind this method is to show an input vector as a non-negative weighted linear combination of small number of basis atoms whereas ScSR deals with both negative and non-negative weighted linear combination. If there is negative average weight, a penalty is added. K-neighbor does not deal with noise whereas ScSR deals with only large amount of noise. SRSW deals with any amount of noise.

A new method is proposed for improving the resolution of a grayscale image [25]. In the first step, grey scale image is inputted. The LR image is interpolated using Lancoz interpolation. Then the features are extracted from interpolated image. Features are extracted using Lancoz and Gradient filter. The PCA is used get the most efficient information of feature extraction. Dictionary is trained using k-SVD algorithm. The database used consists of images with both HR and LR version. If the size of LR images is not same as that of the HR images, Lancoz interpolation is implemented to get the same size. The image is divided to get the block of 5*5 and these blocks are non-overlapping. Every column of block is concatenated column by column to form a vector. Than the “k-SVD method” is used to train the dictionaries. The two dictionaries are trained, one with LR blocks and second with HR blocks. Finally, both the dictionaries Dl (dictionary with LR blocks) and Dh (dictionary with HR blocks) are collected. The previous dictionary of LR blocks Dl and ScSR are used to obtain the sparse representation. Than the sparse representation reconstruction is done using the previous value and HR dictionary Dh. At last HR image is obtained.

Due to the advancement in the technologies such as 3-D imaging, the demand for HR depth images is increasing. All the traditional methods of depth super resolution reconstructs HR images by retrieving details of the image either internally from HR image or externally from the database of HR images. Therefore, H. Zheng et al. proposed a new method [29]. This new method exploits the both internal and external HR information to obtain high resolute images. This new joint regularization method formed with different constraints, allows solving HR image and sparse code simultaneously.

In Today's era, many applications require the images with high contrast and sharpness. Guang Deng presented a generalized unsharp masking algorithm [28]. The designed algorithm confronts the three issues: enhancing the contrast and intensity by method of isolated treatment of the components and the residue of model, how to reduce halo effect with the method of an edge-preserving filter, and to solve the problem of out-of-range using log-ratio and tangent operations. The properties of log-ratio approach eliminate rescaling process. In the proposed algorithm, there is availability to adjust the parameters which control the contrast and intensity to get the required results.

A new scaling algorithm of super resolution is introduced in [33]. This HR image obtained depicts more accurate details of edges. With this algorithm a given image can be enlarged to any size without uneven surface or blurring factors. Four steps are performed in the scaling process: firstly edge orientation is calculated, and then average is computed for the edge orientation, the third one is detection of edge patterns, and lastly interpolation. These all are pipelined to obtain efficient implementation. The performance is evaluated on the basis of SSIM index (Structural Similarity).

Zhaowen Wang, Ding Liu et al. discussed sparse coding model which is applied to enhance the resolution of an image is extended to improve performance of SR using key concepts of deep learning [38]. On the basis of LISTA (Learned Iterative Shrinkage and Thresholding Algorithm) network, a neutral network is implemented for every step of sparse coding processing. Training is provided to the sparse coding components through back propagation. Back propagation trains the network on the basis of gradient descent.

Trinh, Luong, Dibos et al. has jointly put forward a novel example-based method [39]. They proposed the method for noise removal and to increase the pixel density of medical images. In this method, resolution is improved by using database of HR and LR patches. Their main objective is estimation of HR images from a single noisy LR image. The non-negative sparse representation is used for the estimation of input patch. Both Denoising and SR are performed on each patch. The nonnegative sparse linear representation can be found for the input taken as a nonnegative quadratic equation.

The MRI (magnetic resonance imaging) systems are affected from poor out-of-plane resolution. Post-acquisition, SR filtering is a feasible and less expensive approach. A.Souza and R.Senn introduce a new SR framework [40]. This technique is implemented to improve resolution of tissues and contrast of acquired 3D MR images. The framework models the acquired information on the basis of thickness of slice and space in between slices. The available SR techniques have not considered the type of acquisition information that is sampling the data. This framework shows better results than existing method in the field of artificial data and MRI data of clinical knee.

Mingli Zhang et al. put forward a novel based SR algorithm [41]. This method exploits the sparse representation and nonnative similarity of patches. From this method, HR images are obtained from a technique based on ADMM (Alternating direction method of multipliers). To remove noise and artifacts from the reconstructed image an approach called back-propagation is used. Experimental results are calculated in terms of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structured Similarity Index).

CHAPTER-3

PROBLEM STATEMENT

3.1 Research Gaps

Most of the SR methods usually misplace or skip the areas of sharp edges. The main need for SR algorithms is to enhance the LR image details. Filters such as frequency filter and spatial filter add noise and do not give smooth image. There are many algorithms which have been used till date, to enhance the image quality. Some algorithms do not deal with the edges. The edges are the most sensitive part of the image, as the pixel value at edge is high than other neighbour pixel value. Whereas another set of algorithms focus only on edges leaving rest of the image as it is which makes the image irregular. Even interpolation used for increasing the resolution of the image does not focus on high frequency edges resulting in irregular image.

3.2 Problem Statement

HR images are useful in various fields including video surveillance, astronomy, medical etc. HR images are useful as they have high pixel density; it gives more clear view of image. Enhanced medical images are useful for critical examination of any body part to detect any disease and in astronomy it puts forward information about space.

HR imaging is not always available. Sensors can be used to enhance the resolution of the image. As the number of sensors grows, the resolution of the image also increases which result in high hardware cost. They also add physical artefacts (noise or blur) to the image. Due to these limitations, there is need of SR techniques.

Even after the arrival of various imaging sources, it is not an easy task to get the image with appropriate resolution. This is due to the physical imaging environment and factors that decrease the quality (noise and blur). These sources give blurred and irregular image. The only solution is SR techniques that help in increasing resolution of the image.

Various interpolation methods are implemented to upscale the image and enhance the resolution of the image. But it gives blurred up scaled image as output. So, interpolation is not efficient method for SR.

Filters are also used to improve low frequency pixels and finding high frequency information to enhance the resolution of the image. But the filters add noise in the image which gives a rough image as output.

There are many algorithms which are used to enhance the image quality. Some algorithms do not deal with the edges. The edges are the most sensitive part of the image, as the pixel value at edge is high than other neighbour pixel value. Some algorithms focus only on edges leaving rest of the image as it is which makes the image irregular.

3.3 Objective

(i) To achieve image super resolution by using sparse coding based network and interpolation.

(ii) To enhance image resolution by using the concept of deep learning.

(iii) Performance analysis of these techniques is performed in terms of SSIM, PSNR, and visual quality with existing ones.

3.4 Methodology

The research method used in this thesis is a combination of approaches with the beneficiaries of the study prior to the design of the output product with the experimental results to follow. First method removes the noise effects from the image to get better initial approximation. Then the denoised image is inputted to the network. This network firstly extracts the overlapping patches. Then these patches are encoded by using LR dictionary. Then encoded sparse coefficients are combined with HR dictionary for the reconstruction of HR patches. Then the overlapping patches are aggregated to obtain the final result. This network does not require learning of dictionaries explicitly.

CHAPTER-4

PROPOSED ALGORITHM: SR OF MEDICAL IMAGE

4.1 INTRODUCTION

Image SR is the dynamic field of image processing. Images and videos with high resolution are used in various fields like medicine, agriculture, pattern recognition etc. Despite the advancement in the technology used for acquisition and the performance of the reconstruction algorithms, it is not an easy task to get an image of required appropriate resolution due to the imaging environments, physical imaging system limitations and also the factors which limits the quality such as Noise and Blur. This problem can be solved by the use of Super Resolution (SR) methods. Therefore we proposed a technique to improve the pixel density of the medical image. The proposed method results are compared to the other methods (Table 5.1).

4.1 Sparse Coding Based Network For Image SR

When each item is expressed by a relatively small set of neurons, then this encoding is called sparse coding and the encoded code is called sparse code. When the natural images are implemented with sparse coding algorithm, the learned bases duplicates the receptive fields of simple cells in the visual cortex but localized bases are produced when it is implemented to other natural field that is speech and video. Even the biological neurons have same properties. This similarity makes the coding a credible model of the visual cortex.

Sparse coding SR algorithm is an example based SR method in which firstly overlapping patches are cropped from input image. Then these patches are ciphered by using LR dictionary. Then encoded sparse coefficients are linked with HR dictionary for the reconstruction of HR patches. Then the overlapping patches are aggregated to obtain the final result.

Deep learning is a branch of machine learning. It is also called deep structure learning. The learning is based on the algorithms which implements high-level abstractions in data. This abstraction is provided by using multiple processing layers or with convoluted structures. There can be more than one non-linear transformation.

The method is based on learning how to represent data. There are different ways to represent an image such as vector of intensity values per pixel. Image can also be expressed as a set of edges or regions having specific shape etc. For making the learning task easy some image representations defined above are better than other.

This technique is successfully implemented in different areas of computer vision, also in image restoration problems. This algorithm defines that conventional sparse coding model representation of the domain expertise is still valuable. To further accomplish improved results the sparse representation method it is combined with the elements of deep learning. The sparse coding model designed for SR can be incorporated as a neural network. This network learns an end-to-end mapping in between LR and HR images.

The sparse coding based network is the network in which sparse coding is extended with deep learning. This model is different from external example based approaches as there is no need to learn the dictionaries explicitly.

4.2 Proposed Algorithm

The proposed method involves both deep learning and sparse coding based network (Figure-4.1, 4.2, 4.3).

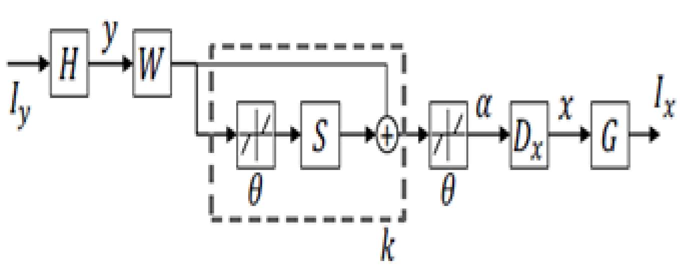


Figure-4.1: The SCN model

Step-1 In the first step of algorithm, LR medical image is denoised using filters such as ONLM, PRINLM. Denoising is employed on the inputted medical image for noise removal. As medical images are sensitive to noise and are corrupted by the noise.

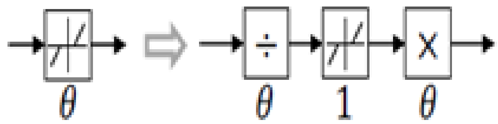


Figure-4.2: Decomposition of neuron

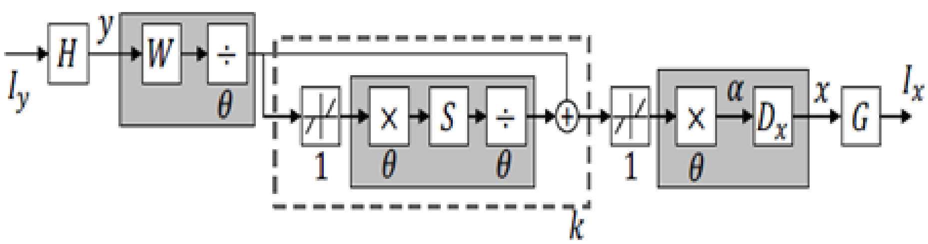


Figure-4.3: Structure of sparse coding based network

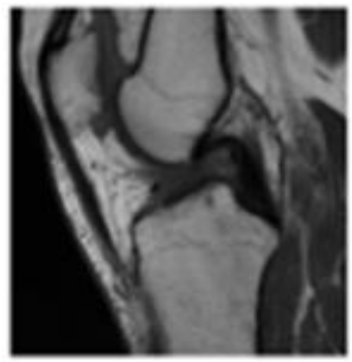
Step-2 I_y (LR denoised image) is inputted to the layer H. For each LR patch features are extracted in the H layer. The layer is the combination of two layers: the first layer consists of four trainable filters. The second layer shifts the filters to the 25 fixed positions. This layer has m_y filters and spatial size of these filters is $s_y \times s_y$. Therefore size for input patch is $s_y \times s_y$ and the feature representation y has m_y dimensions.

Step-3 Then each LR patch is provided to a LISTA network. (Learned Iterative Shrinkage and Thresholding Algorithm (LISTA), is defined as 'Updation of ISTA' model recursively. Iterative Shrinkage and Thresholding Algorithm (ISTA) are introduced to find sparse codes. This algorithm updates all the components in parallel and finds the approximated optimal code vector. The main idea behind this algorithm is that, for each iteration where the reconstruction error is great shift the current code in that direction. After that to enforce sparsity that is similarity in some domain, a component-wise shrinkage function is applied. A fixed number of iterations have been conducted to update the model. To minimize the previously described error loss of prediction for sparse code the parameters are learnt using stochastic gradient descent. Value of error gradient is computed using back-propagation.) LISTA network has finite number of k recurring section. Sparse code $\propto \in R^n$ is obtained as output from the LISTA.

Step-4 In the algorithm, at every point of LISTA it is made up of two linear layers. These layers are specified by $W \in R^{n \times m_y}$ and $S \in R^{n \times n}$. It also has a nonlinear neuron layer having activation function h_θ. The Figure 4.2 depicts how the decomposition of the original neuron having an adjustable threshold occurs. The decomposition of original layer is: two linear scaling layers and a neuron having unit-threshold. The weights of the scaling layers are depicted as diagonal matrices defined by $\theta \in R^n$.

Step-5 In the next layer obtained value of α that is sparse code is multiplied with HR dictionary $D_x \in R^{m_x \times n}$. This reconstructs HR patch x of size $s_x \times s_x = m_x$. In the final layer G, all the reconstructed patches are placed back to their respective positions in the HR image I_x. A fixed layer is present in layer G. This layer aligns the pixels of the overlapping patches and of a trainable layer. The overlapping pixels are combined using the weights of the trainable layer. The Figure 4.3 depicts, reorganized layer connections, some adjoining layers of the network can be combined to form a single layer. The example images used in database during sparse coding have both HR and LR versions. Four example images used in database are shown in Figure 4.4.

Training Image (a) **Training Image (b)**



Training Image (c) **Training Image (d)**

Figure 4.4: Example Images (a) CT scan of abdomen, (b) CT scan of thorax, (c)MRI image of ankle, (d) MRI image of knee.

Due to this merging computation load and also the redundant parameters are reduced in the network. Due to some extra nonlinear normalization performed on patches x and y, the H and G layers cannot be merged. Thus our network in total has five trainable layers: two are convolutional layers (that is H and G) and three are linear layers which are shown in gray boxes of Figure 4.3. The same weight is shared by all the k recurrent layers and therefore these are regarded as one. Peek to signal ratio (PSNR) is calculated as the cost function. PSNR is implemented to obtain quantitative results for comparison. It is defined as the remainder value obtained from the subtraction of the processed image and original image. The larger the PSNR value, the better will be image quality.

CHAPTER-5

IMPLEMENTATION AND TESTING

5.1 Implementation Setup

All the simulations have been developed in MATLAB on an Intel Core i5 desktop computer having specifications: 2.30 GHz processor, 4GB RAM, and Windows 7 operating System.

5.2 Performance Evaluation

The performance of the implemented algorithm is checked by measuring PSNR and SSIM value. PSNR stands for peek to signal noise ratio. It is maximum possible noise amount removed and improvement in image reconstruction.

$$PSNR = 10 * \log 10 (MAX\ P) - 10 * \log 10 (MSE) \qquad (5.1)$$

where MAX P describes the maximum value of power pixel of the image and MSE is the mean square error.

PSNR value of proposed and implemented algorithm is 25.43

SSIM stands for structured similarity of index. It is a method for predicting the perceived quality of images or videos. It is used to check the similarity between two images.

$$SSIM(x, y) = (2u_x u_y + c_1)(2_{xy} + c_2)/(u_x^2 + u_y^2 + c_1)(x^2 + y^2 + c_2) \qquad (5.2)$$

where u_x is the mean value of x;

u_y is the mean value of y;

x^2 is the variance of x;

y^2 is the variance of y;

$_{xy}$ is the covariance of x and y;

SSIM value of proposed and implemented algorithm is 0.75.

5.2 Results of Proposed Algorithm

Table 5.1: PSNR results of proposed Algorithm

Image	Noise(σ)	Proposed Network
Ankle Image	0	25.48
	5	25.51
	10	25.43

5.3 Comparative Analysis

Table 5.2: PSNR results for image super resolution

Image	Noise(σ)	Bicubic Interpolation	Sparse Coding	Proposed Network
Ankle Image	0	24.63	25.31	25.48
	5	23.57	24.79	25.51
	10	23,63	23.87	25.43

Table 5.3: SSIM results for image super resolution

Image	Noise(σ)	Bicubic Interpolation	Sparse Coding	Proposed Network
Ankle Image	0	0.73	0.74	0.78
	5	0.66	0.65	0.77
	10	0.54	0.58	0.75

The performance of proposed algorithm is better than bicubic interpolation and Sparse coding algorithm on the basis of PSNR value and SSIM value. The image obtained in bicubic interpolation is blurred as compared to proposed algorithm's image. The image we get is more clear than the bicubic interpolation and Sparse coding algorithm. The images as shown in the below Figures 5.1, 5.2, 5.3, 5.4:

The CT scan of the ankle is given below in figure 5(a). Proper analyzing of the scan is not possible as image is not able to provide the details required for analyze. Therefore, it is required to upscale the image, so that an observer can analyze it properly.

Figure 5.1: LR Input Image

Figure 5.2: Bicubic interpolation

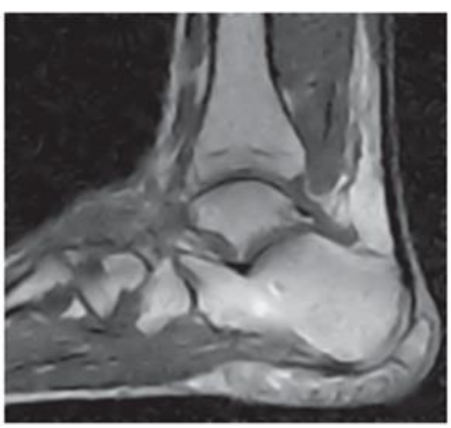


Figure 5.3: Sparse Coding

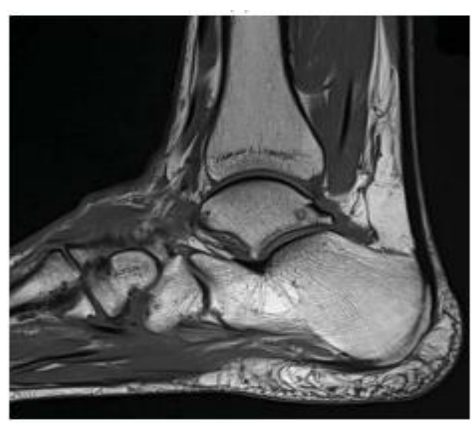


Figure 5.4: Output image(SCSN)

CHAPTER-6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In medical imaging HR images have great importance as medical images are more affected by noise due to acquisation systems. By increasing the number of sensors, resolution can be increased. But increase in the number of sensors will increse the hardware cost. So, this problem pushes to design an algorithm to increase the super resolution of the medical image. There are many methods for increasing resolution of images but still their results can be further improved.

In this thesis, a resolution-enhancement technique based on sparse coding has been proposed. In comparison with other resolution-enhancement methods (Bicubic interpolation and Sparse coding algorithm), experiment results show better performance. The performance is calculated and comparison with other methods is done by PSNR and SSIM values. The suggested method provides good results in case of both noise free image or noisy image. The contributions of the proposed method that has given the better experiment results in comparison with other methods are as follows:

- The proposed SR method employs Denoising to remove the noise from the image and take that image as input. After this, it uses sparse representation to increase the resolution of the images. Dictionaries are used for sparse representation.
- The proposed method provides good results in both the cases that is noise free image or noisy image.
- Besides producing the good SR results, there is also benefit in training speed and model compactness.

6.2 Scope For Further Research

This thesis has given various opportunities for future research. This proposed method can be extended to videos. This can be improved by using parallel processing to increase speed in accerlation. The interaction of deep networks of low level and high-level vision tasks can also be explored. The present algorithm can be enhanced further to get high PSNR and SSIM values as compared to the ideas discussed in this document.

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Video Link

https://www.youtube.com/channel/UCmd1H7J0t4vJdgKnzjH6YEQ

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