

Adaptive Iterative Transformation Based Super Resolution Reconstruction of Medical Image Sequences

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Abstract. Image processing is the developing field recently. Many researches are going on in different areas. One of that important area is Medical Image Processing. There are various techniques used for Super Resolution of images. Here we are trying to enhance low resolution medical MR Images by Adaptive Iterative method. This paper gives a brief idea regarding enhancement of low resolution images. There are many parameters which affects the quality of image. Due to limitations of sensors, images are often down sampled and transmitted at low bit rates, resulting in low resolution images. High Resolution image can be reconstructed from several blurred, noisy and down sampled low resolution images using a computational process known as Super-Resolution.

Keywords: MR Images; Super-Resolution; Low Resolution; Adaptive iterative; High resolution; Blurred; Noisy and Down sampled.

1. Introduction

Super-resolution (SR), also known as High-resolution (HR), means that pixel density within an image is high, and therefore an HR image can offer more details that may be critical in various applications. All imaging systems have an upper limit on resolution. These limitations can arise in several ways:

- Diffraction of light limits resolution to the wavelength of the illuminating light.
- Lenses in optical imaging systems truncate the image spectrum in the frequency domain.
- Sampling of images limits the maximum spatial frequency to a fraction of the sampling rate.

The recent increase in the wide use of digital imaging technologies in consumer (e.g., digital video) and other markets (e.g., security and military) has brought with it a simultaneous demand for higher-resolution images. The demand for such high-resolution (HR) images can be met by algorithmic advances in super-resolution (SR) technology in tandem with hardware development. Such HR images not only give the viewer a more pleasing picture but also offer additional details that are important for subsequent analysis in many applications.

The current approach to obtaining HR images mainly relies on sensor manufacturing technology that attempts to increase the number of pixels per unit area by reducing the pixel size. However, the cost for high-precision optics and sensors may be prohibitive for general-purpose commercial applications, and there is a limitation to pixel size reduction due to shot noise encountered in the sensor itself. Therefore, a resolution enhancement (super-resolution) approach using computational, mathematical, and statistical techniques has received a great deal of attention recently.

One promising approach is to use signal-processing techniques to obtain an HR image (or sequence) from observed multiple low-resolution (LR) images. The major advantage of this approach is that it may cost less and the existing LR imaging systems can still be utilized. And with this High resolution images are frequently required in biomedical application, because HR images provides the accurate spatial and intensity information for correct diagnosis. In various MR imaging techniques, which are important for early medical diagnosis purposes, increasing the slice resolution may be impossible due to limitation of SNR or long

sequence repetitions time but with this approach, SR methods have been applied for the reconstruction of HR medical images by increasing slice resolution.

2. Previous Work

Simple resolution enhancement methods based on smoothing and interpolation techniques for noise reduction have been commonly used in image processing. Smoothing is usually achieved by applying various spatial filters such as Gaussian, Wiener, and median filters, least squares filters, geometric mean filter. Commonly used interpolation methods include bicubic interpolation and cubic spline interpolation [1]. Interpolation methods usually give better performance than simple smoothing methods. However, both methods are based on generic smoothness priors and hence are indiscriminate since they smooth edges as well as regions with little variations, causing blurring problems and checkerboard effect. More recently, different researchers have proposed some learning-based methods. Some methods make use of a training set of images [2, 3, 4, 5], while others do not require training set but require strong image priors that are either hypothesized [6] or learned from data [7]. Nevertheless, all these methods use the training data in a similar way. In particular, each element in the target high-resolution image comes from only one nearest neighbor in the training set. These methods typically require only one sample texture as input, possibly with some random noise or a target model [8]. Similar to learning-based methods for super-resolution, only one nearest sample texture is selected to generate each synthesized pixel. Many recently published work are based on the application of SR techniques to medical images. As a reference, in [9], H.Greenspan obtains results that demonstrate the potential of these techniques in practical medical application, as MRI and CT. On the other hand, the improvement in ultrasound images has been improved in [10] by D.Kouame and M.Ploquin.

3. Brief Literature Survey

Super-resolution is the problem of generating a high-resolution image from one or more low-resolution images. A new facet of image restoration research has begun to emerge in recent years. There are various algorithms that have demonstrated super resolution and discuss the common principles that they share which makes it possible for them to recover some of the lost bandwidth of object [11]. Image resolution depends upon physical characteristics of sensors, optics, density and special response of the detector elements [12].

Super resolution (SR) can be obtained by a technique whereby multi-frame motion is used to overcome the inherent resolution limitations of an LR camera system. Thus, most of the SR image reconstruction methods consist of three basic components: i) motion compensation, ii) interpolation, and iii) blur and noise removal. The performance of motion-based SR algorithms will ultimately be limited by the effectiveness of motion estimation and modeling. Another approach to obtain super resolution is by reconstructing frequency components, which lie above the cutoff frequency of the imaging system. One of the approaches is to use signal-processing techniques to obtain an HR image (or sequence) from observed multiple low-resolution (LR) images. The major advantage of this approach is that it may cost less and the existing LR imaging systems can still be utilized. Super Resolution (SR) image reconstruction is one of the most spot lighted research area, because it can overcome the inherent resolution limitation of the imaging system and improve performance of most digital image processing applications [13].

In Magnetic Resonance Imaging (MRI) the strength of the main magnetic field will affect image quality and the no of application for which the scanners can be used. The higher the strength, the better will be the quality of the image produced, because higher magnetic field provides a higher signal to noise ratio. The SNR is the most important parameter defining image quality in MRI. A low SNR means that the contrast between different tissues can be obscured by background noise [14]. This paper focuses on pathological anatomy images. These images usually presents deficient quality and in adequate characteristics as the limits used in equipments and the degradation of tissues during taking of samples these facts sometimes make the medical specialist unable to properly diagnosis without prior processing of images. SR algorithm based on dynamic Super resolution which reduces the computational cost and memory requirement [15]. The paper proposed regularized SR frame work which is tuned for MR image data. Exploring methods using, ridge detection algorithm along with degenerated segmentation schemes for estimating the intensity model parameters. Additional data set are being tested for healthy as well as pathological database [16].

4. Motivation for the Work

As the world is going towards new trends and technologies, image processing plays an important role in different valuable domains like Military, Medical, Security, etc. Due to the unique inherent advantages and wide spread use over the century for Medical and other applications Super Resolution is most preferred

method over others. Accuracy of the SR depends on the quality of the input image, preprocessing, feature extraction. Here we are concentrating on medical imaging specially on MR imaging. For proper diagnosis it is very important that MR images should be more clear and observable. Super Resolution helps to achieve best quality of MR images. The problems of SR imaging are complex, as the problem specifications are highly diverse and carry no unique, standardized solution; researchers have been suggesting many models, algorithms and techniques in this area. By proper selection of sensors (resolution), maintaining the physical parameters, good quality images can be acquired. However even with the utmost care, there is rotation and translation of the input image due to the position of the object on the input device. It is therefore decided to take up this problem and to develop a matching algorithm that is restoration and smoothening.

The literature survey reveals algorithms and the techniques provided by the researchers are based on lot of mathematical computations and are complex for implementation.

It is hence desirable to develop:

1. Effective Super Resolution image enhancement algorithm.
2. Comparatively simple but efficient and enhanced quality model for Super Resolution.

5. Objectives and Algorithm of Work

The main objectives of the proposed work are: I have keen interest in this area as well as inspiration to develop the relevant DSP techniques and to address the relevant signal processing technology for this SR approach to high-quality imaging. I aim to develop a method for solving single-image super-resolution problems. Given a low-resolution image as input, recover its high-resolution counterpart for a particular medical application. SR includes enhancement in spatial resolution for gray-scale images, suppression of signal dependent noise, and various other associated artifacts.

a) Objectives:

- To study of various medical images used for clinical diagnostic.
- To study various algorithms used for Super Resolution of MRI and Biomedical imaging.
- Study of SR algorithms for Biomedical imaging.
- To propose Super Resolution algorithm for MR (Brain) imaging.
- Study of original results obtained from individual implementation and proposed algorithm related to Biomedical imaging.

b) Methodology and Algorithm

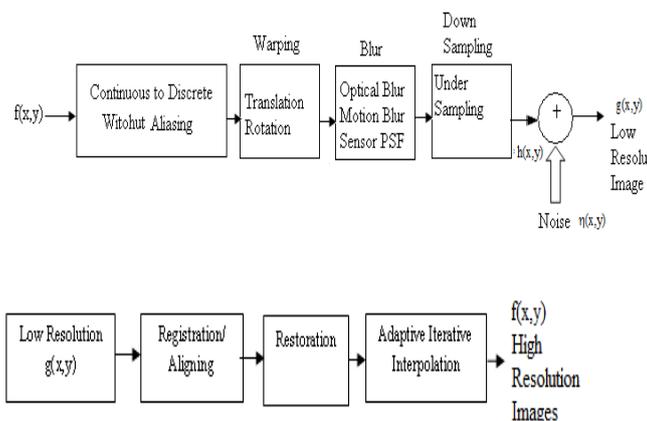


Figure1. Low Resolution Observation Model

Figure2. Super Resolution Reconstruction Model

While most methods have been proposed for super-resolution based on multiple low-resolution images of the same scene, the focus of proposed work is to study the method used for Super Resolution specially for Medical Images. To generating a high-resolution image from a single low-resolution image, with the help of one or more training set of images from scenes of the same or different types. Commonly this is referred as the single-image super-resolution problem.

The figure1 shows low resolution observation model with an additive noise operates on an input image $f(x,y)$ to produce low resolution image $g(x,y)$. $g(x,y)$ gives knowledge about degradation function H and some knowledge about additive noise in terms of $\eta(x,y)$.

$$g(x,y) = h(x,y)*f(x,y) + \eta(x,y) \quad (1)$$

Where $h(x,y)$ is the spatial representation of the degradation function it perform convolution operation with $f(x,y)$. Figure 2 shows super resolution reconstruction model, observed low resolution image sequence $g(x,y)$, is reconstructed with the help of adaptive iterative algorithm. An adaptive iterative expression for obtaining $f^{\wedge}(x,y)$ is as high resolution image.

$$f^{\wedge}(x,y) = g(x,y) - ((\sigma_{\eta}^2 / \sigma_L^2) [g(x,y) - M_L]) \quad (2)$$

Our proposed algorithm operates on a local region S_{xy} response of the algorithm based on four quantities. i) $g(x,y)$ the value of noisy mage at (x,y) . ii) σ_{η}^2 the variance of the noise corrupting $f(x,y)$ to form $g(x,y)$. iii) M_L the local mean of the pixels in S_{xy} . iv) σ_L^2 the local variance of the pixels in S_{xy} . We starts with a single high quality image as shown in figure 1, from which we can get an idea for enhancement of super resolution processing.

6. Experimentation

The experimentation is mainly for MR image development & implementation of algorithms for various operations as image enhancement, restoration, feature extraction, etc. The methodology used is as follows:

The database of MR images is prepared.

- 512 X 512 sizes of 10 images of same patient of different sense.
- The Machine: Hardware computing platform used P-IV desktop with 256 MB RAM with standard accessories.
- The software development platforms used isMatlab7.1 with Image processing Toolbox and its associated development tools/environment.
- After proper understanding the mathematical intricacies, the algorithms are implemented in software for various operations like pre-processing, noise removal, and post processing and proper diagnosis.
- For preprocessing operations like Enhancement, Deblurring, Filtering, Restoration standard algorithms like low pass filtering special filtering are implemented. An Iterative Adaptive based algorithm is developed.
- Out of number of pixels and interpixels are extracted and marked on image which is used for resolution
- Steps for resolution: we first apply initial level filtering and cropping the area of interest from image. Afterward selecting the scaling factor and zooming the image for super resolution.
- The results are prepared in the form of tables and graphs for analysis.
- Calculate PSNR and MSE of Images.
- Calculate the value of PPI for each image by iterative method.

Table 1 shows properties of different medical images used for experimentation. Also it gives brief information related to image format, pixels, size and resolution.

Table 1: properties of database for MR Images

Particulars	Se001	Se002	Se003	Se005	Se006	Se010
File format	JPG	JPG	JPG	JPG	JPG	JPG
Size	512 x 512					
Width (pixel)	512	512	512	512	512	512
Height (pixel)	512	512	512	512	512	512
H Resolution (dpi)	96	96	96	96	96	96
V Resolution (dpi)	96	96	96	96	96	96
Bit depth	8	8	8	8	8	8
Size (kb)	66.7	65.6	61.9	66.1	66.6	58.1

Figure 3 shows reconstructed image from low resolution image.

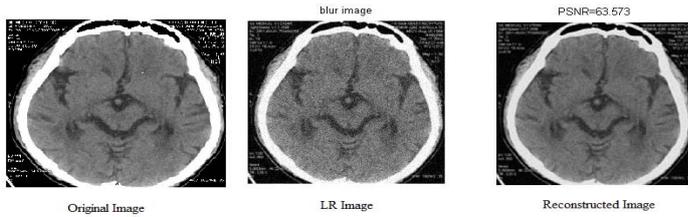
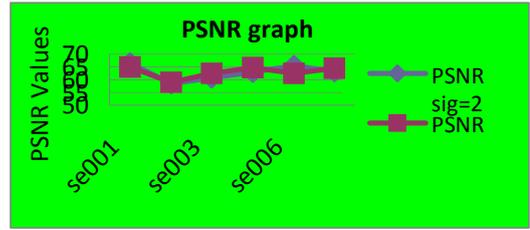


Figure 3: Reconstructed image from LR



Graph 1: PSNR Curve

PSNR and time values for different values of sigma by Taking Mean=0, variance=0.001

Table 2:- PSNR and Time Values at $\sigma=2,4$

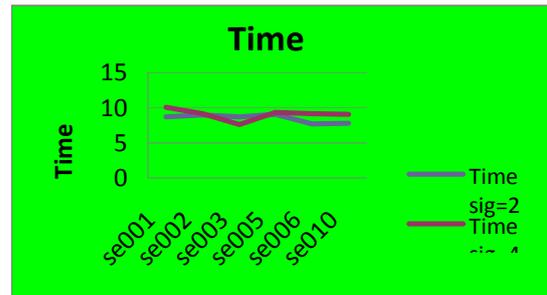
Images	PSNR $\sigma=2$	PSNR $\sigma=4$	Time $\sigma=2$	Time $\sigma=4$
se001	66.489	64.898	10.928	8.977
se002	58.606	58.94	8.874	9.178
se003	60.718	62.495	7.594	9.11
se005	63.065	64.701	8.86	9.114
se006	65.453	62.459	7.589	9.072
se010	63.166	64.568	6.465	9.02

PSNR and time values for different values of sigma by considering Mean=0, variance=0.002

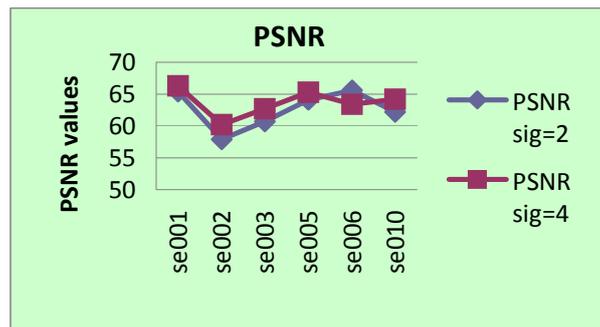
7. Conclusion



Graph 2: Time Curve



Graph 3: PSNR Curve



Graph 4: Time Curve

Table 3:- PSNR and Time Values at $\sigma=2,4$

Images	PSNR, $\sigma=2$	PSNR, $\sigma=4$	Time, $\sigma=2$	Time, $\sigma=4$
se001	65.398	66.319	8.6897	9.985
se002	57.862	60.156	8.938	9.092
se003	60.738	62.666	8.703	7.547
se005	64.12	65.335	9.016	9.279
se006	65.624	63.424	7.678	9.099
se010	62.247	64.17	7.761	9.01

In this study we have proposed an adaptive iterative based Super resolution reconstruction method for MR brain images. Aiming at improving the visibility of an image in order to obtain the optimum threshold

value used in proposed method, we have measured Peak signal to noise ratio and PPI of the image. The performance analysis demonstrate that the visibility have been much improved by this method.

8. References

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